Explorations of Adaptive Resource Use and Technology Choice: Individual and Institutional Perspectives

Submitted in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

in

Department of Engineering and Public Policy

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December, 2022

Acknowledgements

The best parts of my graduate school experience were those I met along the way. I feel so grateful and humbled to have met, learned from, and worked with so many intelligent, creative, and compassionate individuals. I feel inspired to continue a career in research, and to do so while emulating the safe, inclusive, and welcoming environments I had the privilege to participate in over the past four years.

I would like to thank my committee: Dr. Mitchell Small, Dr. Gabrielle Wong-Parodi, Dr. Erin Belval, Dr. Jared Cohon, and Dr. Igor Linkov. My advisers, Mitch and Gabrielle, your support has meant the world to me. Mitch, thank you for inspiring and allowing me to pursue my curiosities and for exploring new research areas along with me. I remember our first conversation over the telephone before I joined EPP; from then until now, your humor, creativity, and compassion have helped alleviate so much stress. Gabrielle, you have been a role model academically and professionally. You have inspired and motivated me to engage in technical research areas as a social scientist. I will always admire your ability to communicate both as a researcher and as a mentor to myself and other students. Mitch and Gabrielle - the spaces you enter instantly feel warmer and brighter. Even if the spaces are Zoom meetings.

Ben Trump and Igor Linkov, thank you for instilling confidence in me as an earlier researcher, and for all the exciting research opportunities since. Your support has motivated me from start to finish of graduate school, and I am forever grateful to continue working with you in the next chapter of my career. Erin Belval, for taking time to collaborate with me, for teaching me wildland fire management 101. You have been the most excellent teacher, and I have looked forward to and learned so much through every one of our conversations. The EPP faculty, especially Dr. Jared Cohon, Dr. Baruch Fischhoff and Dr. Alex Davis, for opening my eyes to the possibilities for integrating social and engineering sciences. I am deeply inspired by your work, your teaching, and how welcomed you have made myself and other EPP students feel in your classrooms. I was intimidated to enter an engineering graduate program as a social scientist, but thanks to you, I am so excited to use all that I have learned to further explore the intersection of social and engineering sciences. I would also like to thank the hazard management personnel who participated in my work, for your time and insights that have informed my research. Beyond research, for your essential service in helping vulnerable communities affected by natural hazards. Talking with you has cemented my goal to do the same.

This work would not have been possible without generous financial support. I would like to thank the Risk and Decision Science Lab of the U.S. Army Engineer Research and Development Center for your continued financial support over the past four years. I would also like to thank Emerson and Elizabeth Pugh for awarding me your generous fellowship, and to the Society for Risk Analysis for your 'Young Research Travel Award' that allowed me to travel internationally for the first time in my life and present my work in South Africa. I would like to thank those at Carnegie Mellon who have support me along the way: the College of Engineering for your Presidential Fellowship, the Office of Graduate and Post-Doctoral Affairs for your Graduate Small project Help (GuSH) Research Grant, and the Department of Engineering and Public Policy for your continued financial support.

Most importantly, I would like to thank my family: Mom, Dad, Cullen, Brennan, Ruby, and Boz. On my darkest days, the creature comfort of living so close to each of you and looking forward to sitting out on the patio with you has been a constant reminder that love conquers all. My extended family, from Pittsburgh to Dallas. I am convinced that watching or rehashing every Steeler game got me through. Also, my chosen family: Alana, Alena, Alex, Paul, Shannon, Ricki. I feel like the luckiest person in the world to have had best friends like you since elementary school. Finally, but certainly not least, the friends I made within EPP, whose support, understanding, and friendship will keep us bonded for life. I will miss you so much, and can’t wait for what our futures hold.

Abstract

This thesis aims to explore the environmental factors, resources, and psycho-social considerations associated with the adaptive capacity of individuals and organizations facing chronic and/or compounding threats. The uncertainty, complexity, and occasional novelty of complex and compound threats may necessitate adaptive capacity and adaptive decision-making at the individual and organizational levels. Adaptive capacity is defined as processes, actions, or outcomes in a system that facilitate coping, managing, and adjusting to changing conditions, stressors, or hazards. For both individuals and organizations, built and natural environmental conditions can influence vulnerability and adaptive capacity. This thesis explores the intersection of adaptive capacity and enacted adaptive decision-making and behaviors by considering both internal barriers and external stressors that challenge the willingness and ability to adapt to current threat landscapes. Adaptive capacity and adaptive decision-making are contingent on a variety of factors internal and external to individuals and organizations, such as knowledge and concern about threats and vulnerabilities, the willingness and ability to engage in proactive behaviors, and the capacity to change existing behaviors (i.e., emergent technology use). Examples of adaptive capacity assessed in the current thesis include individual-level use of multi-modal, sustainable transportation modes (Chapter 1), compound threat management strategies and constraints (i.e., incident prioritization, availability and use of emergent technology adoption, use of decision support tools) (Chapter 2), and compound threat resource allocation (Chapter 3). Both quantitative and qualitative data are used to assess adaptive capacity, including quantitative surveys, qualitative data from semi-structured interviews, and quantitative historical data records of natural hazards. This thesis emphasized the relationship between adaptive capacity and resource availability, particularly in the context of chronic and/or compound threats. Findings across the three analytical chapters suggest that the availability of and access to resources alone is insufficient in capturing individual and organizational adaptive behavior. In addition to tangible resources, psycho-social factors such as personal experience, competing objectives, and risk perception and communication can constraint adaptive capacity. Chapters 2 and 3 focus on challenges presented by a variety of compounding threats, which are anticipated to increase in frequency, severity, and complexity moving forward. Overall, results focus on U.S. adaptive capacity of communities and federal hazard management agencies, who serve to help communities prepare for, respond to, recover from, and adapt to stressors and disruptions in the natural and built environments. Findings from Chapter 2 and Chapter 3 suggest that it is critical to support the essential hazard management workforce to adapt to compound threat events, particularly given the resource constraints and mental health concerns discussed in Chapter 2 and resource use implications presented in Chapter 3.

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Introduction Chapter

Individuals and institutions are confronted with a variety of natural and anthropogenic threats that occur over acute and chronic timeframes. These threats have affected a wide range of economic, infrastructure, human health, and ecological systems in the United States and other nations. According to the National Oceanic and Atmospheric Administration's (NOAA) *2021 Billion-Dollar Disaster Report*, 20 billion-dollar weather and climate disasters occurred in 2021, totaling $2.5 trillion in disaster-related costs. The number of billion-dollar disasters in 2021 was the second most of any recorded year, behind the 22 billion-dollar disasters that occurred in 2020 (Smith, 2022). Hurricanes and wildfires have imposed large losses over the past five years, accounting for 85% of total disaster-related costs in 2021 (Smith, 2022).

In addition to climate- and weather-driven hazards, anthropogenic sources of risk—which are defined as being primarily driven by human behavior and built environmental systems—are increasingly prevalent (UNDRR, 2022). For instance, there was an observed increase in global high-impact ransomware incidents against critical infrastructure organizations in 2021 that effected 14 of 16 US critical infrastructure sectors (Cybersecurity & Infrastructure Security Agency, 2022). Such attacks threaten to stall life-sustaining goods and services (i.e., emergency services, agriculture, information technology sectors). Yet, anthropogenic threats need not be malicious; for instance, the transportation sector was the highest contributor of US greenhouse gas emissions in 2021 (US EPA, 2022), exemplifying the association between daily individual-behavior and environmental change. Individuals and institutions simultaneously contribute to and are threatened by natural and anthropogenic hazards, and this thesis aims to understand if and how increasingly complex and interconnected threats influence individual- and institutional-level objectives and behavior.

Individual behavior is studied in Chapter 1 using classification tree models to classify transportation behavior based on survey data including a diverse set of demographic and individual preference data, as well as local environmental factors related to transportation mode accessibility and population dynamics (i.e., population densities) tailored to participating household addresses. The goal of this chapter was to evaluate if and how both personal and built environment factors were associated with more sustainable and multimodal transportation behavior for a representative sample of San Francisco Bay Area commuters with varying accessibility to emergent (i.e., bicycle/scooter sharing, car sharing, ridehailing) and conventional (i.e., public transport, private vehicle, bicycle) transportation modes. As such, Chapter 1 addresses individual-level decision-making and transportation behavior according to participant use of emergent and conventional transportation modes, assessing multimodal transportation behavior as a potential transition from personal vehicle use to more sustainable transportation modes.

Then, taking on an institutional perspective largely inspired by the COVID-19 pandemic[1], subsequent chapters address decision-making processes and resilience of US federal agencies involved in natural hazard management. Specifically, Chapters 2 and 3 will explore and assess if and how federal hazard management agencies prepare for, respond to, recover from, and adapt to compound threats. Compound threats are defined as two or more events that occur simultaneously or successively (Pescaroli & Alexander, 2018). The Intergovernmental Panel on Climate Change (IPCC) has defined compound hazards as (i) two or more extreme, co-occurring events, (ii) extremes derived from background conditions that amplify effects, or (iii) extremes derived from co-occurring “average” events (IPCC, 2012; Pescaroli & Alexander, 2018).[2] Examples of compound threats include concurrent natural hazard events (i.e., concurrent wildland fire incidents or complexes like the 2020 August Complex and LNU Lightning Complex) or successive natural hazard events (i.e., successive hurricanes like 2017 Hurricanes Harvey, Irma, and Maria). Further, though increasingly studied by climate scientists, compound threats can also include non-climatic threats, such as the confluence of natural hazards and the COVID-19 pandemic (Yusuf, 2020; Phillips et al., 2020). Compound threats are anticipated to increase in frequency and severity given climate change and our increasingly interconnected critical infrastructure systems (IPCC, 2022; Zscheischler et al., 2018). Compound threats are posited and shown to pose risks beyond the sum of their parts (Jay et al., 2018), threatening life, safety, and critical infrastructure functioning (Zscheischler et al., 2018). Interactions between multiple natural and/or anthropogenic risks can result in compounding overall risk that spans jurisdictions and sectors with the potential to present novel risks (IPCC, 2022). Compound hazards threaten public health, critical infrastructure, agriculture, and ecosystems (IPCC, 2022), presenting potential challenges to hazard management institutions in terms of incident prioritization and resource allocation. Multi-hazard risk assessment approaches are being developed to forecast compounding risk (Hariri-Ardebili, 2020). Beyond risk assessments, systems resilience and adaptation are necessary to maintain critical functioning despite the uncertainty and novelty presented by many compound threat scenarios, including those that might be difficult to capture in anticipatory risk assessments (Fox-Lent & Linkov, 2018; Zhang & Ng, 2021; Yadav et al., 2020).

Compound threats and hazards are expected to challenge the resilience of societies and systems globally (Quigley et al., 2020). In particular, hazard management agencies—who provide the critical services associated with hazard preparation, response, recovery, and adaptation—are required to make rapid decisions in complex, uncertain multi-objective decision spaces if and when presented with compound threats. Acute and chronic stress on government systems presented by the co-occurrence of natural hazards and COVID-19 exemplified the challenges that emergency response organizations face (Kruczkiewicz et al., 2021). For example, California was short hundreds of contracted wildland firefighters in 2020 when COVID-19 regulations prevented inmates from working on firefighting crews (Stark, 2020), and hurricane

[1] See Appendix A for list of organizational resilience and COVID-19 related publications based on my research involvement with the US Army Corps of Engineers’ Risk and Decision Science Lab.
[2] Where ‘extreme’ can be defined statistically or based on threshold exceedance (Pescaroli & Alexander 2018).

and tropical storm evacuation and sheltering protocols were constrained by inabilities to social distance (Whytlaw et al., 2021; Cegan et al., 2022). Compound threats including but not limited to those arising during the COVID-19 pandemic illustrate the need to understand compound risks and address current limitations in hazard communication, adaptive governance, and social justice (Kruczkiewicz et al., 2021).

To begin to understand compound hazard management, Chapter 2 focuses on how US federal hazard management agencies determine objectives and critical decision-making processes, including incident prioritization and resource allocation. This work will use both qualitative data based on the lived experiences of hazard management personnel, as well as quantitative analyzes using historical hazard management datasets. There is currently limited research on if and how federal agencies have adapted their operations and management strategies and maintained organizational resilience under compounding risks. As suggested by Kruczkiewicz et al., 2021, compound hazards implicate complex decision-making that should be further explored via existing and emergent knowledge and frameworks. Through a mixed-methods approach, the current thesis aims to learn from compound hazard experiences to understand how hazard management policies, objectives, strategies (i.e., incident prioritization, resource allocation), and constraints are influenced by compound threats. Narrative accounts from federal agency personnel (Chapter 2) as well as empirical data analyses (Chapter 3) will be used to inform future risk management and resilience-based directions for compound threat management, including applications of emergent technologies and decision-support approaches, communication and coordination channels, and multi-jurisdiction and multi-stakeholder decision support.

This thesis focuses on developing an understanding of the characteristics that facilitate decision-making processes in a rapidly changing world, focusing primarily on behavior related to technology adoption and use as well as organizational adaptive capacity and resilience in multi-objective decision spaces with uncertainty. Three chapters are outlined with the overarching goal of exploring and assessing the behavioral and sociotechnical properties and characteristics of individuals and institutions that may facilitate and inhibit adaptive capacity and resilience under a range of acute, chronic, and compound threats.

Chapter 1: Factors associated with emerging multimodal transportation behavior in the San Francisco Bay Area

Chapter 1[3] characterized how demographic, local transportation environment, and individual preferences for transportation attributes are related to multimodal transportation behavior in an urban environment with emergent transportation mode availability. Chapter 1 assessed commuting behavior based on a survey administered in the San Francisco Bay Area according to whether residents commuted (i) exclusively by vehicle, (ii) by a mix of vehicle and non-vehicle modes (i.e., multimodal behavior), or (iii) exclusively by non-vehicle modes. Multimodality has been considered a key component of sustainable,

[3] This work has been published in *Environmental Research: Infrastructure and Sustainability*. The full published text is presented in Appendix A: Wells, E. M., Small, M., Spurlock, C. A., & Wong-Parodi, G. (2021). Factors associated with emerging multimodal transportation behavior in the San Francisco Bay Area. *Environmental Research: Infrastructure and Sustainability*, *1*(3), 031004.

efficient, and resilient transportation systems, as this travel behavior can represent a shift away from personal vehicle use to more sustainable transportation modes, especially in urban environments with diverse transportation systems and emergent shared transportation alternatives (e.g., carsharing, ridehailing, bike sharing). However, it is unclear what factors contribute towards people being more likely to exhibit multimodal transportation behavior in modern urban environments.

A classification tree approach identified associations between commuting classes and demographic variables, preferences for transportation attributes, and location-based information. The characterization of commuting styles could inform regional transportation policy and design that aims to reduce vehicle use by identifying the demographic, preference, and location-based considerations correlated with each commuting style. Results suggested that transportation behavior was classified based on a variety of location-based and individual preferences. For instance, population density differentiated those who were multimodal from those who commuted by exclusively non-vehicle modes. Transportation preferences at the individual participant level suggested that the importance of engaging in other activities while commuting differentiated between those who exclusively used vehicles from those who were multimodal, and the importance of minimizing environmental impacts differentiated between those who were multimodal from those who exclusively did not use vehicles. Further, sensitivity analyses were conducted to assess if and how transportation behavioral outcomes might hypothetically shift given variations in select location-based and transportation preference factors.

Chapter 2: Organizational Absorptive Capacity and Resilience Under Compound Threats: Learning from Federal Agency Perspectives

The COVID-19 pandemic co-occurred with natural hazards and exemplified how emergency management can be challenged, constrained, and changed by the compound occurrence of two or more independent or inter-related threats. Chapter 2 will include interviews with hazard management professionals that describe their perspectives on how representative organizations have managed and potentially adapted to meet the challenges posed by compound threats. Specifically, this work focuses on federal agency perspectives. Federal agencies involved in hazard management are required to make rapid decisions in highly uncertain, often novel threats while operating under information and resource constraints. Federal agencies must find a balance among the multiple objectives of human health and safety, infrastructure, and ecological damage, while facing multiple sources of risks and constraints on resource limitations and social and political considerations. Chapter 2 explores the characteristics, properties, and protocols of federal agency decision-making in compound threats to generate hypotheses on knowledge gaps, needs, and concerns of federal agencies navigating complex, uncertain decision-spaces.

A qualitative, semi-structured interview approach is used to learn from past compound hazard experiences from the perspective of federal agency personnel. While existing research has assessed organizational resilience in the specific context of the COVID-19 pandemic and hurricane compound threat based on multi-stakeholder workshops (Yusuf et al., 2020; Whytlaw et al., 2021), Chapter 2 takes on broader definitions of compound threats to include COVID-19 pandemic related threats as well as other examples experienced by federal agency personnel. An interview-based approach was used to learn from the lived experiences of federal agency personnel involved in compound threat management, which can inform if and how their respective agency managed compound threats in the past. Interview topics included compound risk assessment and decision support processes used to faciliate incident prioritization and resource allocation decisions, as well as discussions of emergent factors that personnel expressed could be leveraged to enhance organizational resilience to compound threats, as well as other complex and uncertain threats.

A conceptual framework for federal compound threat management and resilience was developed based on existing empirical work (Cutter et al., 2008; Linkov et al., 2013; Resilient Organisations, 2019) and on the current qualitative interview data. The expressed strengths and weaknesses of federal agency compound threat management and resilience were explored according to deductive and inductive interview coding. Existing research stresses that resilience, or the ability to maintain critical functioning despite disruption, is achieved over multiple phases (i.e., preparation, response/absorption, recovery, adapation/mitigation) and multiple domains (i.e., physical, information, cognitive, social) (Cutter et al., 2008; Linkov et al., 2013). Thematic content analysis of interview data was conducted to explore and identify opportunities for federal hazard management agencies to adapt and maintain resilience under compound threats, such that critical functioning and decision-making processes are supported. Results provide insights on organizational structures, information needs, technology use that supports organizational mission fulfillment, adaptive capacity, and overall resilience under compounding threats. Interview results relate to the set of policies, resources, and emerging technologies and modeling approaches deployed in compound threats, and resulting themes relate to multi-objective decision making, resource constraints, and stakeholder engagement and coordination within and between federal, state, local, and community based organizations. Findings suggest that federal agency compound threat management is strained in part by by personnel availability and scarcity, which will be empirically assessed in Chapter 3.

Chapter 3: Are Compound Threats Associated with Changes in Resource Use? An Assessment of Wildland Fires Suppression Resources given the COVID-19 Pandemic

Chapter 3 builds from the results of Chapter 2. Chapter 3 aims to provide an empirical assessment of if and how wildland fire suppression resource use changed before and during the COVID-19 pandemic, both at national and regional levels. This work aims to assess the relationship between ground personnel resources used for daily fire suppression efforts before and during the COVID-19 pandemic via a Regression Discontinuity Design (RDD) approach. As compounding threats, such as wildland fires co-occurring during pandemics, are projected to increase in frequency and severity in the future (i.e., due to climate change and increasingly interconnected critical infrastructure systems) (Mora et al., 2022), it is essential to understand fire management changes under pandemic conditions, which may introduce high levels of complexity, uncertainty, and potential novelty. A combination of interview results from Chapter 2 as well as a review of interagency fire policy documents that outlined specific adaptations for wildland fire suppression strategies motivated the hypothesis that the COVID-19 pandemic strained firefighting resource use in 2020 and 2021 relative to prior recent years. COVID-related wildland fire policy documents, including the regional "Wildland Fire Response Plan: COVID-19 Pandemic" policy guidance, promoted early and aggressive initial attacks by way of increased aviation suppression efforts, as well as the increased use of unmanned aircraft systems (UAS) to minimize the potential for COVID-19 exposure and transmission within and between crews and affected communities (NIFC, 2020). However, it is currently unknown if and how trends in resource requests and use were empirically different for the 2020 and 2021 seasons relative to past fire seasons after controlling for environmental conditions of the regional landscapes and societal risks posed to nearby communities.

To statistically assess and model resource use given the compounding COVID-wildland fire threat, the current work compiled resource assignment data and controlled for daily fire behavior, societal risk factors, and geotemporal weather data for each fire incident across the western US that occurred between 2017 and 2021. Sharp Regression Discontinuity Design (RDD) models are being developed to predict resource use per fire day pre- and post- the COVID-19 pandemic at the national and regional levels. To capture and control for the range of tangible and intangible risk factors considered in suppression management, natural language processing was used to identify key risks and concerns discussed by Incident Management Team Incident Commanders (i.e., fire managers) in the 'Strategic Objectives' field of the Incident Command System 209 documentation for each fire day. Coding these narrative accounts can account for the social, economic, ecological, and political concerns that may have motivated resource requests and use. Thus, these models will integrate and control for diverse societal and ecological factors associated with wildland fire suppression, narrowing in on if and how the pandemic may have influenced resource use per fire day. These insights will provide empirical lessons learned for if and how wildland fire suppression absorbed simultaneous fire- and pandemic-related threats.

Chapter 1: Factors Associated with Emerging Multimodal Transportation Behavior in the San Francisco Bay Area

Peer reviewed citation: Wells, E. M., Small, M., Spurlock, C. A., & Wong-Parodi, G. (2021). Factors associated with emerging multimodal transportation behavior in the San Francisco Bay Area. *Environmental Research: Infrastructure and Sustainability, 1*(3), 031004.

1. Introduction

A range of traditional (e.g., personal vehicles, buses) and emergent (e.g., ridehailing such as Uber or Lyft, carsharing such as Zipcar, and bicycle/electric scooter sharing) transportation modes are available to a growing number of urban Americans. As emergent transportation mode availability has increased, reliance on personal vehicles could potentially decrease. Ideally, greater diversity in urban transportation alternatives promotes multimodal transportation behavior, which is the use of more than one transportation mode – such as a car and bus – over a defined time period [1 – 3].[4] Extant research on multimodal transportation behavior has focused on traditional transportation modes [1 – 2], yet less is known about this behavior in urban environments with emergent transportation modes.

Multimodal transportation systems and behavior are often framed as a key component of sustainable, resilient, and efficient transportation design and policy [4 – 6]. Shared transportation modes are often more sustainable, fuel-, and cost-efficient than some traditional modes [7 – 10], such as personal vehicles which contribute up to 60% of total annual US transportation emissions [11 – 13]. Hence, shifting to multiple modes may reduce GHG emissions, depending on individual travel [14]. Even occasional exposure to non-vehicle transportation modes has been shown to increase non-vehicle mode use and decrease intent to use personal vehicles over time [2, 7, 15 – 18]. Understanding how the local transportation environment, human behavior, and preferences are associated with multimodal behavior is essential for developing transportation policies to meet sustainability, resilience, and efficiency goals [19 – 22]. (See Appendix A for additional information on multimodal literature.)

As multimodal behavior may represent a shift away from personal vehicle use, the objective of this study was to identify (a) demographic, (b) location based, (c) transportation mode attributes, and (d) public transit accessibility factors differentiating (i) unimodal, (ii) multimodal, and (iii) non-vehicle commuters. This study incorporated a comprehensive set of both objective variables (i.e., demographics and location), as well as subjective variables (i.e., preferences for transportation mode attributes). The hypothesized correlations between explanatory variables and commuting classes are presented in Table 1. A non-parametric analysis was conducted using the Classification Tree (CT) modelling approach [23] with survey responses from 888 San Francisco Bay Area residents.

Table 1. The hypothesized direction of the correlation between input variables and commuting style classes based on findings from prior literature. The "+" symbol indicates a hypothesized positive correlation, "~" indicates a hypothesized weak or neutral correlation, and "-" indicates a hypothesized negative correlation.

Variable Category	Variable	Unimodal	Multimodal	Non-Vehicle	References
Demographics	Age (older)	+	-	-	[1, 2, 16, 17, 25]
	Female	-	+	+	[2, 26]
	Bachelor's degree or higher	-	+	+	[2, 7]
	Primary destination: Work	+	-	-	[2, 27]

[4] As in existent literature, the definition of multimodality encompassed *intermodality,* the combination of more than one mode of transportation over the course of one trip [1, 2].

	Primary destination: School	-	+	+	[2]
	Smartphone Ownership	-	+	+	[28]
	Household Income	-	+	+	[2, 29, 30]
	Young Children in Household	+	-	-	[2, 15, 17]
	Car availability	+	-	-	[1, 2, 7, 16, 17, 27, 31]
Location Based	Residential population density	-	+	+	[1, 2]
	Commute destination population density	-	+	+	[32]
	WalkScore	-	+	+	[33]
Preferences for Transportation Attributes	Low cost	+	~	-	[34 – 36]
	Predictable cost	+	~	-	[34 – 36]
	Short/Predictable travel time	+	+	-	[27, 37]
	Shelter from bad weather	+	~	-	[36, 38 – 41]
	Ability to easily make more than one stop	+	~	-	[36, 38 – 41]
	Ability to engage in other activities	-	+	+	[42 - 45]
	Ability to safely transport a child under 8 years old	+	~	-	[46, 47]
	Safety	+	~	-	[26]
	Minimizing environmental impact	-	~	+	[46, 48, 49]
Public transit accessibility	Access and egress travel times (walking)	+	~	-	[50, 51]
	Transfers	+	~	-	[50, 51]

Existing multimodal transportation behavior research tends to use multinomial logistic regression approaches to predict between pre-defined, categorical multimodal behavior [1 – 2], and post-hoc, data-driven multimodal behavior (i.e., latent class cluster analysis) [3, 22 52 – 53]. Here, however, a CT approach was used to predict commuting class outcomes. CT involves non-parametric data mining methodologies using recursive binary splitting of explanatory variables to predict multinomial outcomes across the sample. The CT approach offers advantages to logistic regression, as it is a non-parametric approach that does not assume a distribution for included explanatory variables [54]. For instance, CTs do not assume variable distributions and relationships, such as the Independence of Irrelevant Alternatives (IIA), which assumes that random error terms are independent and uncorrelated [54]. If such error term distribution assumptions are violated, regression results and implications may be invalid. Thus, while standard regression models assume that the same fitted relationship applies across the full input and output parameter space, CT divides the parameter space into subsets where different relationships may apply. Additionally, the CT approach can incorporate a variety of variable types (i.e., numeric, categorical, ratings, combinations), and the resulting tree structure is insensitive to monotonic transformations of explanatory variables [55]. CTs also handle multidimensional analyses that are sensitive to multicollinear explanatory variables [54]. In the transportation behavior context, this is particularly advantageous as transportation decisions occur in highly complex and multidimensional decision spaces based on individual, household, and local transportation environment factors. Finally, CTs provide a clear presentation of the output that is relatively simple to interpret, even for nontechnical stakeholders and decision makers [23, 55 – 56]. As such, they provide a tool to communicate findings and associations that may be otherwise more complicated to explain and interpret.

This papers made the following contributions to the transportation behavior literature: (i) a CT methodology was used to predict commuting classes while accounting for diverse variable types, (ii) diverse variable types included objective measures of the local transportation environment considering route-specific commute distances by vehicle, public transit, and foot, as well as subjective assessments of transportation attributes, and (iii) secondary model assessments, including the importance weights of explanatory variables and sensitivity analyses, were performed to generate further commuting behavior implications. Additionally, a case study approach was taken to better understand commuting behaviours in a modern metropolitan context with the presence of emerging transportation modes. Accordingly, the San Francisco Bay Area (herein, "Bay Area") was used as a case study, as the region often pioneers the deployment of emergent transportation technologies and may foreshadow adoption patterns in other urban U.S. regions [24]. The Bay Area has also instituted policies to disincentivize vehicle use and accelerate the uptake of sustainable transportation technologies, with varying levels of success. For instance, the Bay Area enacted the Commuter Benefits Program in 2014, an ordinance requiring that employers provide employee commuter benefits, such as public transit subsidies [57]. Yet, the Bay Area's Metropolitan Transportation Commission [58] fell short of its goal to reduce total non-auto mode share by 10% between 2011-2017, attaining a 4% reduction. This survey analysis using the CT approach can thus be used to inform ongoing transportation planning in the Bay Area to identify the explanatory factors that distinguish between commuting class outcomes and to assess whether commuting class outcomes are predicted primarily by demographic, location-based, transportation attributes, or public transit accessibility factors. Through further sensitivity analyses using CT, we explored which of these factors may be more or less likely to change due to uncertainty or future changes, either through public policy mechanisms, the increasing potential of novel capabilities via emergent transportation modes, or through trends in societal perceptions of transportation qualities and implications. This paper conducts sensitivity analyses to further assess importance of specific explanatory, which can in turn inform the local transportation environment factors and transportation mode attributes that influence SF Bay area commuting decisions. Addressing these variables may help target specific unimodality reduction efforts as the region strives to reduce personal vehicle use and transitions to more sustainable and emergent transportation modes.

2. Methods

2.1. Recruitment.

Data were collected through the SMART Mobility Consortium's WholeTraveler Transportation Behavior Study funded by the U.S. Department of Energy's Energy Efficient Mobility Systems (EEMS) program [24]. A random sample of 60,000 Bay Area household addresses were sent recruitment letters via paper mail between March and June 2018. A total of 1,045 respondents completed the online survey, yielding a response rate of 1.7%. This response rate was comparable to other surveys using similar unsolicited recruitment mailings with similar incentive payment levels. For instance, the 2015–2017 California Vehicles Survey had a 1.5% overall response rate [59]. A final sample of 888 Bay Area resident responses were included for analysis after excluding commuters who did not commute in the past week. (See Appendix B for more details.)

2.2. Respondents.

The average reported age was 46 years old (SD = 14.5), with 49% identifying as women. Eighty-six percent of respondents held at least a Bachelor's degree, and the median annual household income was $100-149K. Respondents resembled the local population [60] but were slightly more educated and affluent, perhaps due to the online format of the survey. (See Appendix B for more details.)

2.3. Commuting class definitions.

Respondents provided their past one-week commute behavior by indicating the mode(s) of transportation they used to get from their place of residence to their most frequently travelled destination (e.g., work, school, workplace of a household member). Reported mode use characterized respondents' commuting class (Table 2), and definitions of each mutually exclusive commuting class were adapted from Buehler and Hamre [2]. Commuting behavior was focused on, as commuting contributes to peak traffic congestion [61] and may be relatively consistent within respondents. A one-week timeframe was chosen to capture the typical variability of routine travel [1, 2, 17, 31].

Table 2. Definitions of commuting classes over past-week trips to respondent's primary destination.

Unimodal	Multimodal	Non-vehicle
Exclusively used a vehicle (as driver or passenger) to commute. Vehicle modes included: personal vehicle, carpooling, ridehailing, carsharing vehicles.	Used a vehicle mode as well as at least one other non-vehicle mode to commute.	Exclusively used non-vehicle modes to commute. A single mode or a mix of non-vehicle modes could have been used. Non-vehicle modes included: public mass transit, bus, private mass transit, walking, biking, telecommuting, motorcycle, electric scooter.

Note. This study used a pre-defined, categorical definition of commuting behaviors by adopting Nobis' (2007) broad definition of multimodality: "…any person who uses more than one mode of transportation within 1 week is classified as multimodal, regardless of the frequency of use" (pg. 36). We further modify this definition by including carsharing and ridehailing as possible vehicle modes.

2.4. Explanatory variables.

2.4.1 Objective variables. Demographic, location-based, and local public transportation environment variables were collected as objective input variables for the CT.

- *Demographics.* Participants reported their age, gender, education, primary destination type, household income, and whether children lived in their household.
- *Location-based.* Survey respondents indicated the address or cross streets of their most frequently visited primary destination (Figure 1). Location-based information was collected using confidential individual-level home and primary destination addresses. Residential and primary destination population densities at the census block group level (measured by thousands of people per square mile), driving distance between one's residence and primary destination address according to Google Maps application programming interface (API), WalkScore metric, and county-level dummy variables were additionally collected. The Google Maps API was used to collect travel time and distance estimates for four modes: vehicle, public transit, walking, and biking. Estimates were collected during peak commute hours, and comparisons of travel times by mode and time of day are assessed across the commuting classes in Appendix C. For the CT analysis, the vehicle travel distance according to Google Maps' time-minimizing route was selected.
- *Public transit accessibility.* The Google Map API generated public transit accessibility for each respondent's home to primary destination route using an existing R program [62]. The following data were pulled to access individual, commute-specific public transit availability: estimated walking time (minutes) between respondent's residence address and destination address and the nearest public transit stop along the route (access/egress), number transfers along the route, and number of alternative public transportation routes for each address pair.

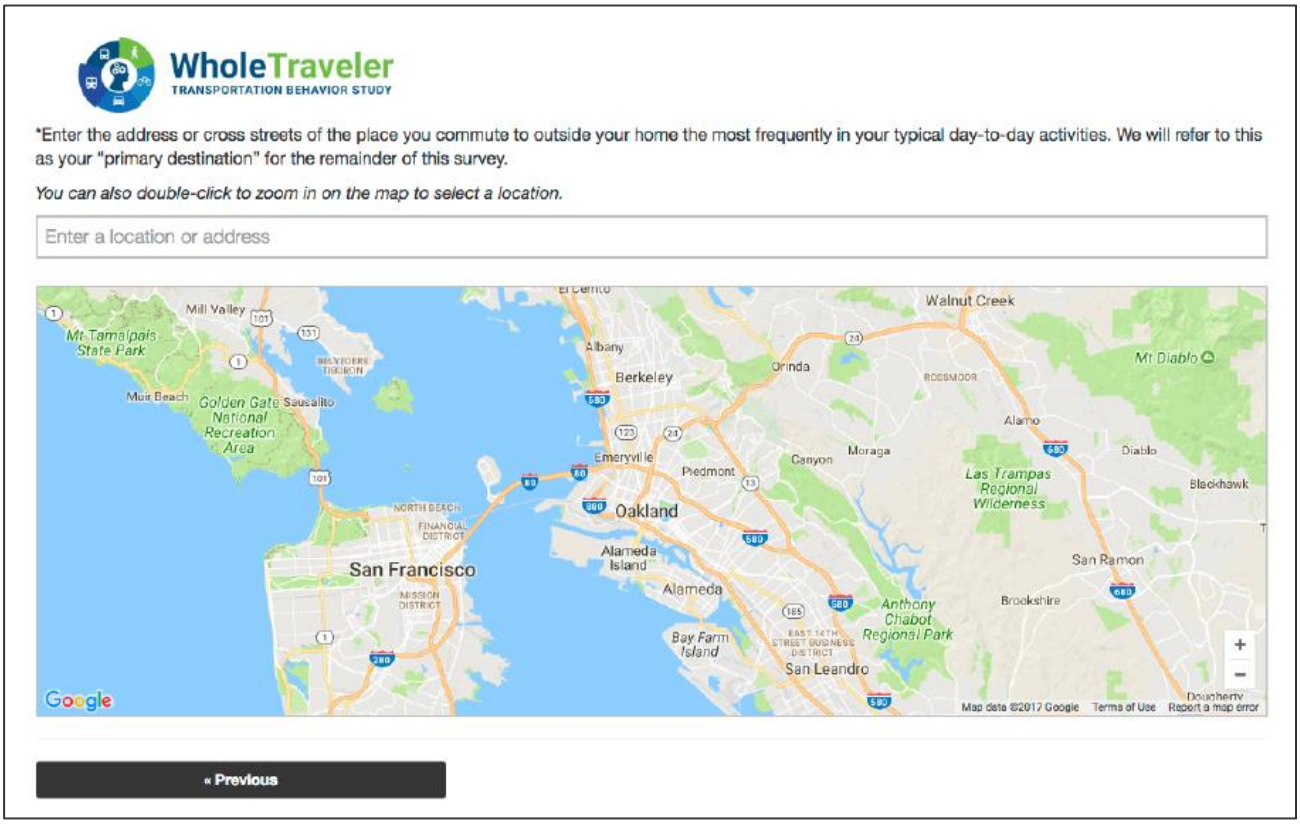


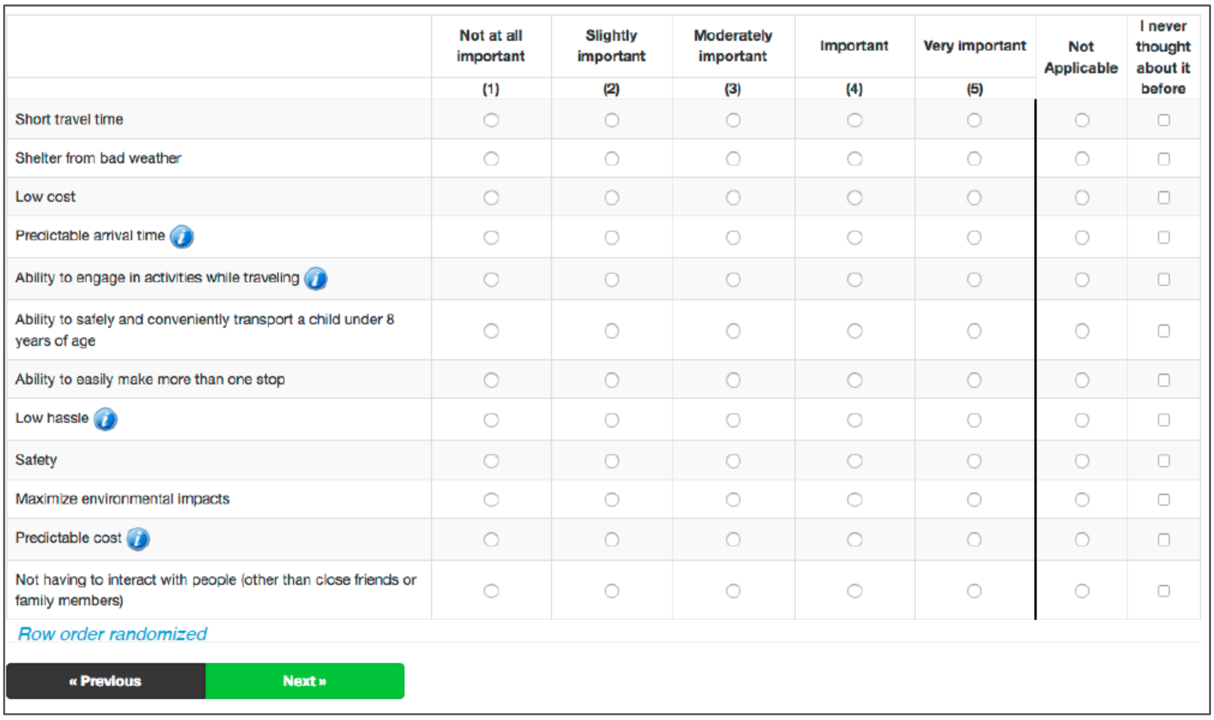
Figure 1. Primary destination address and map tool used to collect information regarding the destination that each survey respondent commuted to outside of their home the most frequently for day-to-day activities.

2.4.2 Subjective variables. In addition to the objective input variables, subjective ratings of "Preferences for transportation attributes" were reported by survey participants.

- *Preferences for transportation attributes.* Participants were asked to indicate how important each of the characteristics of transportation options were to their modal decision-making. Respondents rated the importance of transportation attributes when considering their commute to their primary destination (Figure 2) on a 5-point Likert scale (*1 = Not at all important* to *5 = Very important*). If respondents selected "Not applicable" for an attribute, it was coded as zero (Spurlock *et al* 2019).[5] For each of the transportation attribute items, survey participants were also presented with the option to select "I never thought about it before" for each transportation attribute. This was optional and independent of the Likert scale rating. However, due to the low correlation with "I never thought about it before" and importance, as well as the high correlation with the "Not applicable" response option, this measure was not assessed in the current work. The importance of social interaction and

[5] If respondents chose "Not Applicable" for Importance of Transportation Attribute variables, these scores were recoded with a score of zero, giving zero value to characteristics that a respondent deemed as factors that are not relevant to their commute mode choice [24]. Appendix E Table 3 shows the counts of "Not Applicable" responses, where the proportion of "Not Applicable" responses for 11 of the 12 attributes range from 0.5 – 4.4%. The exception is for the "Importance of transporting children" attribute, where 54.4% of respondents reported "Not Applicable". Appendix E Figures 3 and 4 show the CT results when these values are instead assigned a score of three or omitted entirely. Appendix E also shows that the main conclusions drawn from the CTs were unaffected by changes in the recoding of "Not Applicable" transportation attribute scores to either 3 (middle of Likert scale) or variable medians.

of minimizing environmental impact fell on a scale from -5 to 5 based on positive and negative survey item framings.[6, 7]



	Not at all important (1)	Slightly important (2)	Moderately important (3)	Important (4)	Very important (5)	Not Applicable	I never thought about it before
Short travel time							
Shelter from bad weather							
Low cost							
Predictable arrival time							
Ability to engage in activities while traveling							
Ability to safely and conveniently transport a child under 8 years of age							
Ability to easily make more than one stop							
Low hassle							
Safety							
Maximize environmental impacts							
Predictable cost							
Not having to interact with people (other than close friends or family members)							

Row order randomized

« Previous | Next »

Figure 2. Survey items for the Preferences for Transportation Attributes explanatory variables.

2.5. Data analytic approach.

2.5.1. Classification tree development. The rpart package [63] was used in R to run a CT to classify respondents into commuting class outcomes (Table 2). The CT methodology was used to develop predictive models of the three mutually exclusive commuting class outcomes (Table 2) [54, 64]. The CT method is a non-parametric data mining approach that involves the recursive binary splitting of explanatory variables to predict multinomial outcomes across the sample. The data are split such that within each of the tree's branches, the heterogeneity in the outcome variable is minimized [65 – 67]. CTs are represented through graphical trees in which each binary node has the predictor variable with the greatest discrimination ability among cases in that branch. The CT algorithm recursively partitions data to identify all possible splits of all explanatory variables and selects the optimal splits starting from the root node, and then selects the optimal splits for subsequent nodes [54, 65]. The Gini index was used to assess overall model splits, wherein the algorithm selected the splitting variable that maximized the explained variance of the class predictions [54].

Optimal tree size was determined using a 10-fold cross-validation technique that minimized CT complexity and misclassification rates [54, 64 – 67]. Cross-validation mimics the use of a test sample while extracting information from all cases of a data set to develop the model. The tree size with the lowest cross-validated prediction error was selected, as determined through 10-fold cross-validation. The tree was constructed from 35 candidate explanatory variables using the identified best tree size [23]. The full model classification tree was then simplified through a pruning process to produce the final model and corresponding classification statistics [55], importance weights, and sensitivity analyses. By pruning

[6] The environmental impact and social interaction variables are derived from two questions in the WholeTraveler survey instrument. First, respondents indicated whether they perceived environmental impact and social interaction each as a positive or negative transportation attribute (Appendix C Figure 4). If a respondent chose that those attributes were positive, they were then presented with "minimize environmental impact" and "ability to interact with others (other than close friends or family members)" (Figure 1) for evaluation of importance when determining mode choice. If perceived as negative attributes, the respondent was presented with "maximize environmental impact" and "not having to interact with other people (other than close friends or family)." Each respondent was shown one version of the questions. The survey items responses were coded to reflect either the positive or negative responses for both questions, coding a response to the negative form as a negative value from 1 to 5, and an answer to the positive version as a positive 1 to 5. A "Not Applicable" response was coded as a zero [24].

[7] For all WholeTraveler survey items used in this study, see Appendix C.

classification trees, nodes are systematically removed from the bottom of the tree. Nodes are removed that minimize tree complexity and misclassification rates [23]. (See Appendix E Table 3 for unpruned tree structure statistics). The final classification tree and subsequent analyses used the pruned CT due to its reduced complexity without significant loss of information. Loss of information was assessed using the No Information Rate (NIR). The NIR reflects observed (not predicted) outcome distributions without any input data, in that it reflects the largest proportion of the observed classes. As such, the NIR reflects the CT classification accuracy rate. The CT classification accuracy rate was compared to the No Information Rate classification rate, The tree's predictive power was characterized by the Area Under the Curve (AUC) from the Receiver Operator Characteristic (ROC) curve using macro-averaged AUCs calculated by taking the AUC for each classification versus all other possible categories, then averaging the AUCs from each classification [55]. The AUC provides an indicator for the diagnostic ability of a discrete classifier system based on the probability of true positive classification across the sample. (See Appendix E for further methodological detail).

2.5.2. Importance weights. To compare how influential explanatory variables classified the three commuting class groups, importance weights were estimated [54]. The measure of importance of an explanatory variable in relation to the final tree is defined as the weighted sum across all splits in the tree based on tree improvements when each variable is used as a primary or surrogate splitter. The variable importance of each variable is expressed in terms of a normalized quantity relative to the variable having the largest measure of importance, ranging from 0 to 100. The variable having the largest measure of importance scored as 100. The variable importance is expressed as the normalized quantity relative to the variable having the largest measure of importance [54].

2.5.3. Sensitivity analysis. Sensitivity analyses were conducted for each distinct explanatory variable retained in the pruned CT to derive a better understanding of how sensitive the classifications were for each retained explanatory variable. For each explanatory variable retained in the pruned CT, one standard deviation was independently added and then subtracted from each respondent's respective, original explanatory variable value. The updated dataset was entered into the original pruned classification tree to assess whether and to what extent the predicted commuting class outcomes shifted across the sample. A shift from one commuting class to another occurred when the additive change by one standard deviation per retained explanatory variable resulted in a participant's predicted reassignment to a different commuting class than originally predicted using the pruned CT. This sensitivity analysis approach was taken as CTs do not indicate individual explanatory variable effect size. As such, additively increasing and decreasing each retained explanatory variable in the pruned CT allowed for an assessment of how potential uncertainty in metric estimates could influence predicted commuting shares between the unimodal, multimodal, and non-vehicle outcomes. Alternatively, the sensitivity analysis results may be interpreted such that the additive changes in explanatory variables could reflect future changes in explanatory variables, as many of the local transportation environment and preference for transportation attribute variables are dynamic. For instance, public transit accessibility may evolve as transit routes change and extensions are established, and preferences for transportation attributes, such as the importance of minimizing environmental impacts, may be weighted differently across the sample in future years.

3. Results

3.1. Descriptive statistics.

Of the 888 respondents' commuting classes, 43.8% (*n* = 389) were unimodal, 35% (*n* = 313) were multimodal, and 21% (*n* = 186) were non-vehicle (Table 3).[8] Most multimodal commuters used personal vehicles, followed by telecommuting and commuting via bike, foot, or public mass transit. Within the multimodal commuting group, 25% used emergent transportation modes (e.g., ridehailing, carsharing) in the past week and used the most shared modes, including scooters, ridehailing, and carsharing. Conversely, only 3.8% of unimodal commuters used an emergent vehicle mode in the past week. Among the non-vehicle commuters, public mass transit, bike/foot, and bus were most used.

[8] See Appendix D Table 2 and Table 3 for past month and past day distributions of mode use by commuting class.

Table 3. The percent of each commuting class that used each specific transportation mode within the past week.

Unimodal vehicle	Multimodal	Non-vehicle
Personal vehicle (100%) Carpooling (16.5%) Ridehailing (Single) (1.5%) Ridehailing (Carpool) (1%) Carsharing vehicle (0.3%)	Personal vehicle (73.2%) Carpooling (28.1%) Ridehailing (Single) (15.7%) Ridehailing (Carpool) (16%) Carsharing vehicle (1%) Public mass transit (31.6%) Bus (16%) Private mass transit (8.9%) Walking/biking (43.1%) Telecommuting (44.1%) Motorcycle/electric scooter (2.2%)	Public mass transit (53.4%) Bus (32.8%) Private mass transit (6.9%) Walking/biking (52.4%) Telecommuting (24.9%) Motorcycle/electric scooter (1.1%)

Table 4 shows the mean and standard deviation for each explanatory variable included in the pruned CT.[9]

Table 4. Descriptive statistics (mean, standard deviation) for each explanatory variable across the sample (n = 888).

Variable Category	Variable Name	Variable Type	Mean	SD
Demographic	Birth year	Discrete	1974	14.6
Location-Based	Residence Population Density (thousand people per square mile)	Continuous	13.5	15.68
	Destination Population Density (thousand people per square mile)	Continuous	9.1	13.42
	Residence to Destination Drive Distance	Continuous	12.6	14.35
Importance of Transportation Attributes	Importance of Other Activities	Ordinal	2.6	1.44
	Importance of Environmental Impact	Ordinal	3.3	1.77
	Importance of Social Interaction	Ordinal	0.2	2.70
	Importance of Multiple Stops	Ordinal	3	1.51
Public Transit Accessibility	Transit Transfers	Discrete	1.9	0.99

3.2. Classification tree results. There were 13 total splits in the pruned, 10-fold cross-validated CT (Table 5).[10] The overall CT classification rate across the three commuting classes was 61.4% (95% CI: 58.1% - 64.6%). As there were three mutually exclusive outcomes, misclassification rates above 33% perform better than chance. The cross-validated error rate was 38.6% (95% CI: 35.4% – 41.9%), suggesting that the model may incorrectly predict respondents' commuting class 38.6% of the time. The classification tree prediction rates were compared to the No Information Rate (NIR) classification rate of 43.8%. The pruned classification tree had a statistically significantly lower misclassification rate than did the NIR model,

[9] Where possible, these sample statistics were compared to population-level statistics for the Bay Area (Appendix B). The set of sample statistics for all explanatory variables input into the model is shown in Appendix D Table 1.
[10] See Appendix E for unpruned classification tree structure and results.

suggesting that the classification tree performed better than chance. Finally, the Area Under the Curve (AUC) for unimodality was 72.7%, multimodality was 62.6%, and non-vehicle commuting was 70.9%.

Table 5. Pruned and unpruned classification tree statistics, including the number of splits, the (mis)classification rates and their 95% confidence intervals, the No Information Rate model, the p-value to assess the classification rate of the CT versus the NIR, and finally, the Area Under the Curve (AUC) for each commuting class outcome.

Pruned CT Statistic	**Estimate**
Number of splits	11
Classification Rate (95% CI)	61.4% (58.1% - 64.6%)
Misclassification (Error) Rate (95% CI)	38.6% (35.4 – 41.9%)
No Information Rate (NIR)	43.8%
p-value (Classification Rate > NIR)	P < 0.001
Unimodal AUC	72.7%
Multimodal AUC	62.6%
Non-Vehicle AUC	70.9%

General predicted patterns can be observed from the classification tree. Explanatory variables exert greater influence on classifications depending on their location within the fitted tree and their partition levels. These features of the fitted tree are generally consistent with hypothesized associations (Table 1). For example, those who (1) had greater residential and destination population densities, (2) placed greater importance on minimizing environmental impact and engaging in social interaction, and (3) placed less importance on making multiple stops along their commute were more likely to be classified as non-vehicle. The greatest difference between commuting classes was associated with residential population density – appearing as the first partition in the tree (Figure 3); those with greater density were predicted to be multimodal and those with less were predicted to be unimodal. We also observed that those who placed greater importance on minimizing environmental impact were predicted to be non-vehicle, whereas those who placed less importance were unimodal. Finally, those placing more importance on social interaction and making multiple stops were classified as multimodal, and those living closer to their destination were classified as non-vehicle.

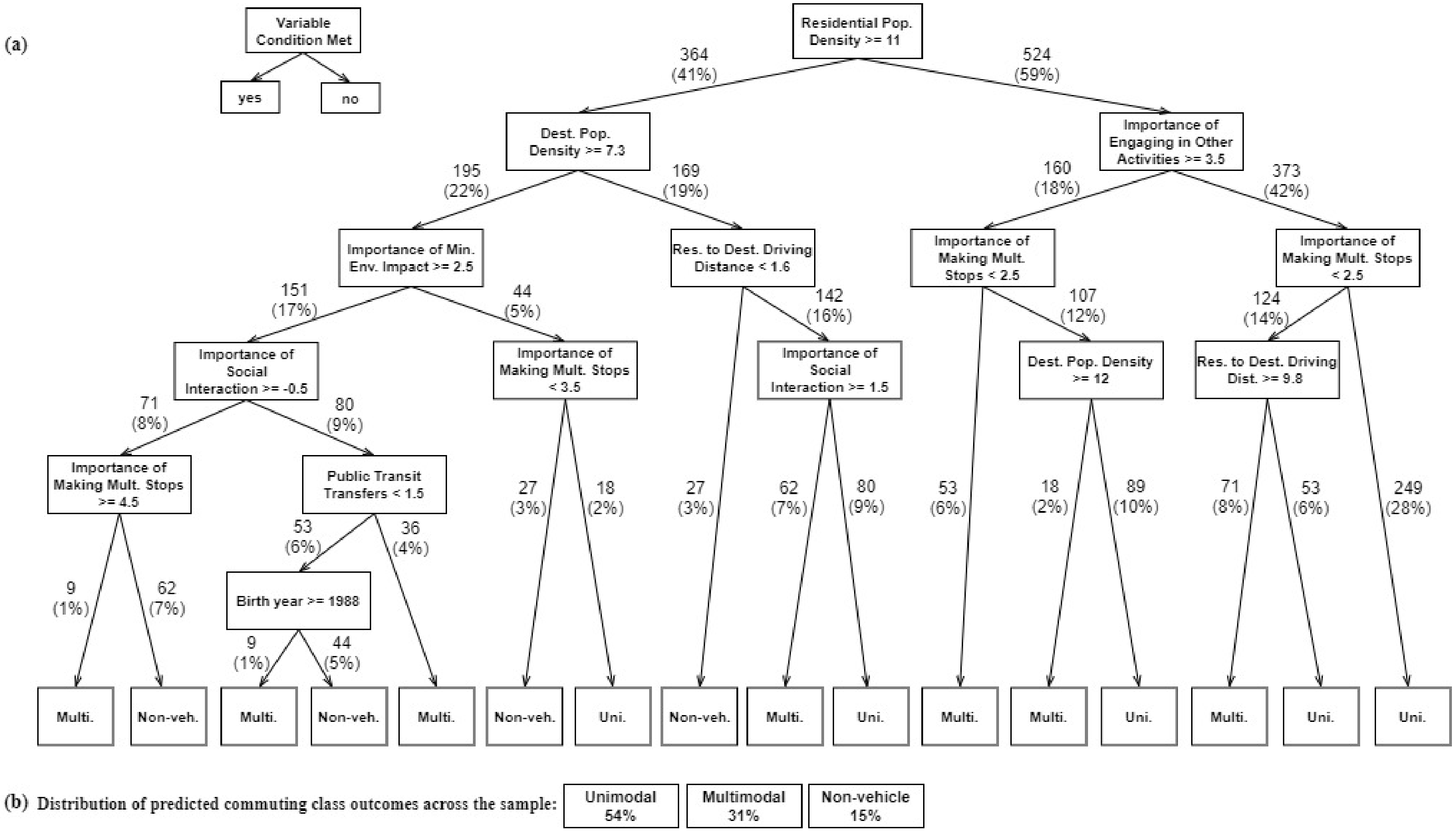


Figure 3A-B. The pruned, cross-validated CT developed using all 35 explanatory variables. The classification tree was trained on the full dataset (n = 888) using 10-fold cross validation. Each node in Figure 3 shows the predicted classification for that placement in the tree. The percent of respondents that fall in that placement of the tree is also shown in each node. The first node starts with 100% of the participants, and each subsequent branch shows the number and percent of the participants that did (left branches) or did not meet (right branches) that variable condition. Figure 3b shows the overall commuting class predictions across the sample based on the pruned CT structure.

3.3 Importance weights of pruned variables. 'Location based' explanatory variables (residential and destination population density, the importance of making multiple stops, and residence to destination driving distances) yielded the most heterogeneous data splits, followed by 'importance of transportation attributes' (Table 6). These weights reflect the explanatory variables from the pruned CT that established the most heterogeneous splits of the data. As such, these variables were instrumental in the classification of commuting styles based on the numeric splits presented in the pruned CT (Figure 2). For instance, residential population density and the importance of making multiple stops held the highest importance weights in the pruned CT.

Table 6. Importance weights for the unpruned classification tree. For the full set of importance weights, including those not directly presented in the pruned classification tree, see Appendix 1E.

Variable Category	Variable Name	Weight	Normalized Weight
Location Based	Residential Population Density	17	100%
Transportation Attributes	Importance of Multiple Stops	13	76.5%
Location Based	Residence to Destination Drive Distance	12	70.6%
Location Based	Primary Destination Population Density	9	52.9%
Transportation Attributes	Importance of Engaging in Other Activities	8	47.1%
Public Transit Accessibility	Public Transit Transfers	6	35.3%
Transportation Attributes	Importance of Social Interactions	5	29.4%
Demographic	Birth year	5	29.4%
Transportation Attributes	Importance of Min. Environmental Impact	4	23.5%
Public Transit Accessibility	Public Transit Access/Egress Walk Time to Stop	4	23.5%

3.4 Sensitivity analyses. For each of the variables retained in the pruned CT, standard deviations were calculated across the sample. Then, we decreased and increased individual-level values for each of these explanatory variables by one standard deviation to demonstrate resulting shifts in the predicted share of unimodal, multimodal, and non-vehicle commuters (Figure 4). Shifts in commuting class outcomes across the sample exemplified how sensitive the classifications were for each explanatory variable assessed. For instance, as shown in Figure 4f, given a decrease in each participant's "Importance of social interactions" rating by one standard deviation, the predicted share of unimodal commuters was predicted to increase by 7 percentage points (e.g., from a predicted 54% of the sample to 61% of the sample), while the predicted share of multimodal commuters would decrease by 9 percentage points (e.g., from 31% of the sample to 22% of the sample). Given an increase by one standard deviation from each participant's current value for "residential population density" (Figure 4a), there was a predicted 20 percentage point decrease in the share of unimodal commuting and a 15% increase in the predicted share of non-vehicle commuting. Similar results were found for increases in "destination population density", though the predicted increase in multimodal commuting was greater than the predicted increase in non-vehicle commuting. These results show how predicted commuting class shares may differ due to statistical uncertainty, as well as due to potential future changes in non-static, dynamic explanatory variables, such as population densities and the perceived importance of various transportation attributes.

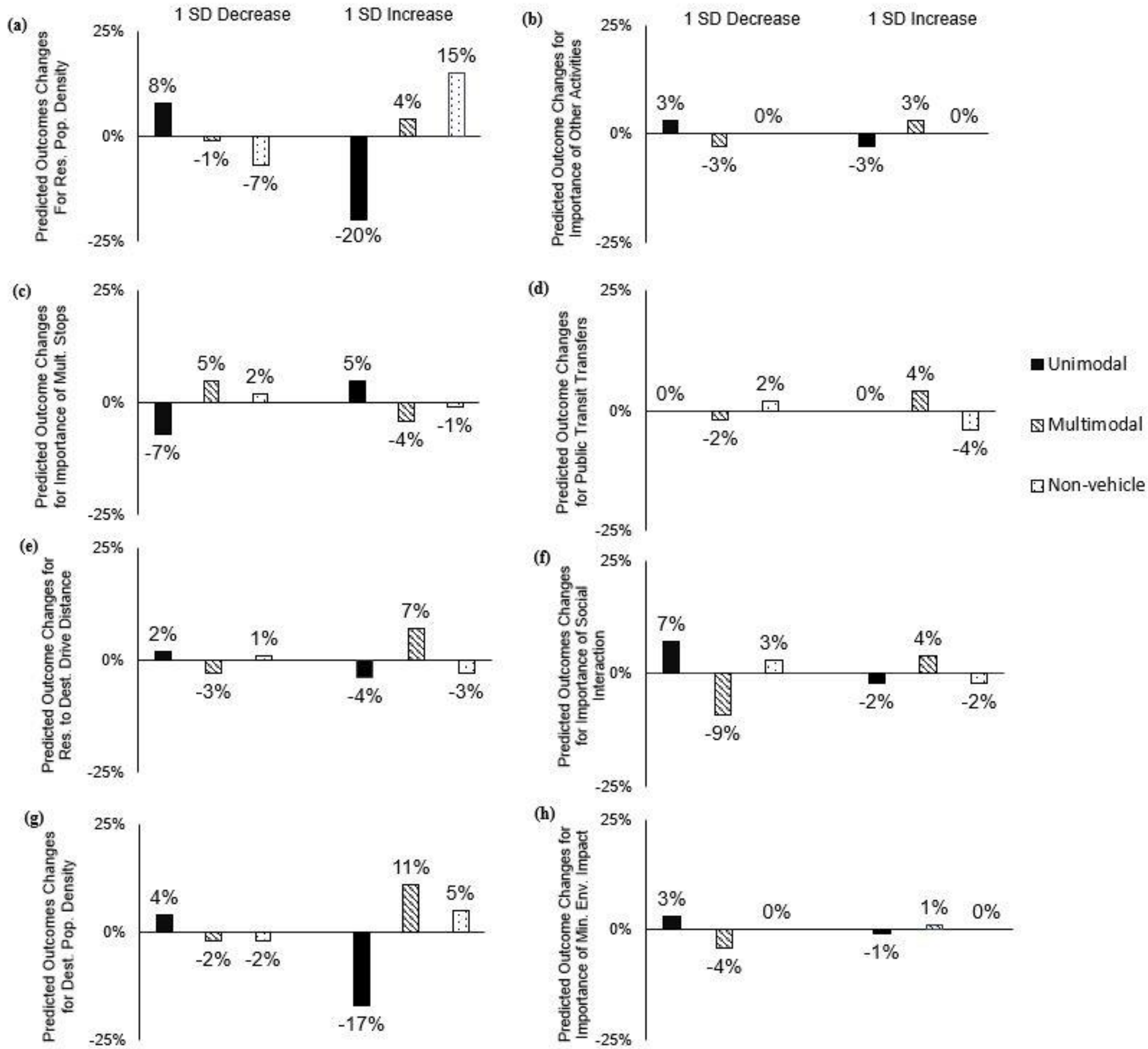


Figure 4. The distribution of CT predicted commuting classes based on modified input data for individuals based on the pruned classification tree. Within each bar chart, the left three bars on each chart show the effect of a one SD decrease in the explanatory variable, and the right three bars show the effect of a one SD increase in the explanatory variable.

4. Discussion

This survey analysis revealed the distribution of unimodal, multimodal, and non-vehicle commute behaviours for a sample of Bay Area residents, assessing individual-level use of traditional and emergent transportation modes. While approximately 74% of multimodal commuters indicated they used a personal vehicle in the past-week (Table 2), this commuting class also indicated the highest reported rate of past-week emergent transportation mode use. Conversely, only 3.8% of unimodal commuters used an emerging vehicle mode in the past week, indicating that they may be less inclined to use or adopt emergent transportation modes than multimodal commuters (Table 2).

A Classification Tree approach was used to assess which types of explanatory variables (i.e., demographic, location based, transportation mode attributes, and public transit accessibility) classified commuting classes. Attributes including residential and destination population densities, commute distance, and public transit transfers and walking accessibility were variables that distinguished commuting class outcome predictions (Figure 3A). Moreover, perceptions of the importance of making multiple stops, engaging in other activities, social interactions, and minimizing environmental impact also distinguished commute behavior (Figure 3A), which may provide key insights for policy makers aiming to incentivize shifts towards sustainable and emergent commuting behavior.

The ‘location based’ and ‘transportation mode attributes’ established the most heterogenous splits of the CT (Figure 3A). Residential population density was the most heterogeneous factor associated with commuting classes, aligning with existent research which has indicated population density is positively associated with public transportation use and negatively associated with personal vehicle use [2, 68]. The same relationship may hold for emergent transportation modes, including ridehailing. For instance, Wang and Mu [69] found that Uber accessibility was positively correlated with road network density, population density, and reduced commute times.

Various transportation attributes were associated with heterogeneous splits of the commuting class outcomes, exemplifying greater differences between commuting classes than most demographic and public transit accessibility factors (Figure 3A). The importance of making multiple stops along the route distinguished respondents’ commuting classifications suggesting that transportation may fulfil a critical need for flexibility (perhaps for childcare, taking care of errands, etc.). Flexibility in commuting travel stops may be a critical factor that differentiates exclusive versus occasional vehicle use, and more sustainable shared and mass transit travel modes could see increased ridership if their services better accommodated this need. Possible improvements might be more frequent stops or ticketing policies that allow for briefer stops to be made along a route or within a defined timeframe.

Additionally, multimodal commuters perceived engaging in other activities while commuting was to be more important than did unimodal commuters (Figure 3A). This aligns with hypotheses (Table 1) and may have implications for the adoption and use of emergent transportation modes that enable multitasking or passive travel, such as shared and/or automated vehicles. For instance, if this transportation attribute were to become more important or attractive to commuters, current sample sensitivity analyses show a potential shift in the share of unimodal commuting, which was predicted to decrease by 3% and redistribute to multimodal commuting (Figure 4). The sensitivity results suggest how the importance of engaging in other activities may offer policy implications for emergent transportation mode use or interest in use. Hardman [70] conducted interviews with partially automated vehicle users, who reported an increased ability to multitask while traveling. Multitasking has been defined as engaging in activities such as working, sleeping, eating, or reading while traveling [71]. Thus, if the ability to multitask becomes increasingly important to commuters, the sensitivity analysis results (Figure 4) predicted decreased unimodal, increased multimodal, and no change in non-vehicle commuting class outcomes. Policy implications include enhancing working or other multitasking experiences on commutes, such as through providing Internet access to riders [42].

Further, perceptions of engaging in social interaction emerged in the pruned CT (Figure 3A). Increased importance of social interaction was positively associated with multimodality, more so than both unimodal *and* non-vehicle commuting, despite non-vehicle commuters reporting more public transportation use, where exposure to social interaction is likely high. This aligns with prior work regarding the perceived importance and role of socialization for ridehailing users. Sarriera et al. [72] found that both social and negative social aspects of ridehailing motivated or deterred share ridehailing use, with a larger effect than personality or demographic characteristics. Amirkiaee and Evangelopoulos [73] found that social trust was a key factor predicting attitudes and use of ridehailing. Alternatively, non-vehicle commuters who biked or walked may have rated social interaction importance lower, thus leading to the observed heterogeneity.

The pruned CT also included the importance of minimizing environmental impact (Figure 3A). While the relationship between environmental worldviews and pro-environmental behavior remain uncertain [74], these results suggest greater environmental consciousness may be associated with more sustainable transportation behavior. Age was the only demographic differentiating factor, as those born after 1988 were classified as multimodal and those born before 1988 were classified as non-vehicle, aligning with previous research [75 – 78]. Younger individuals may be more flexible in their adaptation to multimodal transportation options while older individuals may experience reduced access to private automobile ownership and use.

The CT approach is well suited to reveal how multidimensional, even multicollinear, individual-, household-, and community-level factors can be structured to predict commuting classes. Though this approach does not overcome confounding factors such as residential selection present in studies of transportation choices [79 – 80], it does detect interrelations between explanatory variables, only including variables in the CT that establish the most heterogeneous splits across the sample. Thus, the CT approach revealed which explanatory variables were associated with heterogeneous commuting behavior. Though the relationships between explanatory and outcome variables were strictly correlational, the importance weights and sensitivity analyses provide insights as to how potential changes in dynamic explanatory variables may associated with a shift in commuting outcome distributions.

4.1. Limitations. Though the survey solicitation was designed to gain a representative sample, respondents were more affluent and educated than the average Bay Area residents, limiting representativeness and translation of results to other regions. Second, the study focused on commute behavior, but travel behavior may differ for other types of trips (i.e., recreational or social). Third, the survey-estimated use of each transportation mode was binary, offering only first order assessment of commuting behavior. However, Buehler and Hamre [2] compared model outcomes based on differing measures of multimodality (i.e., predefined definitions and according to intensity of vehicle use), finding the general relationships and effect sizes of covariates were consistent.[11] Fourth, the CT approach does not show the effect size for the relationship between each explanatory variable and outcome variables. Hence, we derived importance weights and sensitivity analyses. This sensitivity analysis approach assumed uniform, additive changes across the sample to detect how sensitivity CT predictions were to changes in explanatory variables, though we recognize that these shifts would be unlikely to occur uniformly across the full sample or population. Future analyses could integrate additional location-based information that has been associated with emergent transportation mode use. For instance, in their spatial assessment of shared electric scooter trips, Hosseinzadeh et al [81] included objective measures such as a mixed-use land index, percent of public and semi-public land, and densities of intersections, bike-lanes, and sidewalks.

Additionally, though outside the timeframe of the current analysis, it is informative to consider how social and societal issues may influence commuting behavior preferences, demand, and supply. For instance, the year 2020 presented a decline in both public transit supply and demand across the US given the COVID-19 pandemic. It is estimated that public transit ridership declined by approximately 73 – 79% across the US [82], compared with previous demand levels; ridership decline was particularly pronounced in places like the Bay Area with a large tech-based sector [83]. Urban areas in the US, including and especially the SF Bay Area, were predicted to experience risk for extreme traffic unless transit systems could return to COVID-19 safe transit systems with a high level of service, in terms of route availability, frequency, and capacity [84]. Further, for other urban regions in the US, Wilbur et al. [85] found that decreased transit ridership in 2020 tended to be lowest during peak commute hours—the focus of the current study. As such, we would expect that the results derived in the current analysis would look different for 2020 and perhaps 2021, such a decline in public transit ridership is expected and is hypothesized to lead to declines in both the multimodal and non-vehicle commuting classes, as these

[11] See Appendix A for further details on measures of multimodality.

commuting classes include public transit use. The decline in non-vehicle commuting class outcomes is expected to be most pronounced, as 53.4% of current non-vehicle commuters in the sample used public mass transit and 32.8% used buses (Table 3). Many of these transit riders would likely switch to personal vehicles to commute if they owned them, which would increase the unimodal commuting class rate in the sample as people return to their offices. Alternatively, as many non-essential workers had the option to work from home in 2020, there may have been an have been a shift towards remote work across the current sample in 2020 relative to 2018; as such, the share of non-vehicle workers would be expected to increase. In either case, the SF Bay Area is currently working towards a recovery plan to restore service, increase public transit accessibility, and increase public transit demand as of 2021 [86].

5. Conclusion

This study revealed associations between location-based metrics and reported importance of transportation attributes (e.g., making multiple stops, engaging in other activities) and commuting styles adopted by the public. Planning and policy implications of this work suggest the importance of taking these factors into consideration when designing transportation mode systems and investing in emerging technologies such as shared ridehailing services and automated vehicles. Future work should investigate whether these patterns hold in other urban regions, as well as over time to investigate how perturbations to the transportation system (e.g., closures or other adjustments made in response to COVID-19) and new technologies affect mode choice. A deeper understanding of the interactions between the transportation environment, human behavior, public health, and available technology may help target specific unimodality reduction efforts as urban regions in the U.S. strive to reduce personal vehicle use and transition to more sustainable and emergent transportation modes.

Chapter 2: Organizational Absorptive Capacity and Resilience Under Compound Threats: Learning from Federal Agency Perspectives

1. Introduction

Communities around the world are witnessing a rise in two or more natural and/or human-caused threats that co-occur (De Angeli et al., 2022; Ridder et al., 2022; Zscheischler et al., 2018; Cutter, 2018). These co-occurring threats—herein, compound threats—are predicted to increase in frequency and severity (IPCC, 2022). In the United States, governments and other hazard management organizations (e.g., American Red Cross) are responsible for preparing for, responding to, and mitigating the risks posed to humans, ecosystems, and critical infrastructure by compound threats. Thus, hazard management organizations must be resilient and adapt to highly uncertain and complex compound threats to fulfill critical missions and provide support for vulnerable communities (Quigley et al., 2020; National Response Framework, 2020; Seville et al., 2008). In these compound threats, federal agencies make critical operational decisions, such as where and when to allocate scarce resources; often, these decisions must be coordinated rapidly while balancing multiple objectives and considering multiple sources of risk (Izumi et al., 2022). For example, firefighters in recent years have had to combat increasingly severe wildland fires against the backdrop of the COVID-19 pandemic (Thompson et al., 2020). Additionally, severe weather events including the 2021 Texas Winter Storm have challenged public health agencies' ability to provide COVID-19 testing, vaccination, and treatment continuity (Traynor et al., 2021). It is projected that climate change and biodiversity degradation will increase the emergence and transmission of infectious diseases such as COVID-19 (Williams et al., 2021), showing the interconnectivity of and future potential for compound threats. Compound threats, including but not limited to infectious disease spread and natural hazards, are forecasted to increase in frequency and severity given climate change and increasingly interconnected critical infrastructure systems (IPCC, 2022; Zscheischler et al., 2018). Hence, there is an acute need to understand how hazard management organizations can be more resilient and adaptive in an everchanging compound threat landscape to meet the needs of communities more nimbly and successfully.

Hazard management describes the science of managing complex systems and multidisciplinary personnel to prepare for, absorb, recover from, and adapt to extreme events (U.S. Department of Health & Human Services, 2012). Organizations involved in hazard management must consider and weigh multiple, often conflicting, objectives, such as minimizing public and personnel health and safety risks, critical infrastructure impacts, and ecological damages (Marcot et al., 2012; de Almeida et al., 2017). As hazard management organizations face and manage disruption to protect communities, infrastructure, and ecosystems, their resilience is essential. Organizational resilience is defined as the continuity and restoration of organizational services and functions despite adverse events (Hutton et al., 2021; Lee et al., 2013; Connelly et al., 2017). Continuity of federal agency support and services over the course of threats and hazards may be vital for community wellbeing, particularly during compound threats (Hutton et al., 2021). In the threat and hazard context, organizational resilience is closely linked to the broader concept of disaster resilience, defined as a system's ability to resist, absorb, recover from, and adapt to the effects of a hazard(s) in a timely and efficient manner to preserve and restore critical functions (United Nations Office for Disaster Risk Reduction , n.d.). Federal agencies, such as but not limited to the Federal Emergency Management Agency (FEFMA), are often critical stakeholders involved in managing uncertain threats that involve rapid incident prioritization and resource allocation decisions to protect vulnerable communities and public lands (FEMA, 2019).

Organizational resilience characteristics are critical to identify and draw upon, as they may facilitate mission fulfillment, prioritization of response efforts, and equitable and timely distribution of critical resources. Various studies have assessed the characteristics and practices of organizations that facilitate or inhibit organizational resilience (Lee et al., 2018, Barasa et al., 2018). Largely inspired by COVID-19 co-occurring during natural hazards, recent work has started to explore organizational resilience and adaptive capacity under compound threats (Campbell et al., 2021). For instance, existing research has explored the organizational resilience of non-profits during the compound threat of the COVID-19 pandemic in hurricane-prone New Orleans through interview and survey-based approaches (Hutton et al., 2021). Similarly, research with government, non-profit, and community representatives in the Gulf Coast has explored hurricane evacuation and sheltering protocols during the COVID-19 pandemic (Marshall et al., 2021; Yusuf et al., 2021; Whytlaw et al., 2021; Shultz et al., 2020), characterizing organizational operations, constraints, and resilience. While there is conjecture about the challenges that hazard management agencies face under compound threats (Kruczkiewicz et al., 2021), relatively few studies have explored compound threat management from the perspective of practitioners, particularly for threats aside from the COVID-19 pandemic. Exploratory studies that use data from the perspective of practitioners who have responded to such events should be conducted to draw on lessons learned and efforts needed to support adaptive decision-making and organizational resilience for future compound threat events.

Compound threats may be natural and/or anthropogenic in nature and occur over acute to chronic timeframes. Here 'compound threats' are defined as the confluence of two or more individual threats that occur in the same geospatial location during the same time period, such that response and/or recovery efforts necessary to respond to one threat overlaps with the response and/or recovery efforts of another. This definition is intentionally broad to capture the diverse range of natural, anthropogenic, and socio-technical threats that may occur over a range of geo-temporal scales (UNDRR, 2021). Acute timeframes have definitive start and end points while chronic timeframes present ambiguous start and end points.

An example of a compound threat involving two acute threats include Hurricane Irma and Hurricane Maria. On August 30th, 2017, Hurricane Irma formed in the open Atlantic, growing in strength to a Category 5 hurricane. Irma struck Barbuda on September 6th, while sending strong winds and rains towards Puerto Rico. Irma caused significant, but limited damage along Puerto Rico's northern coast, disrupting power for over 1 million people, killing 4, and causing $700 million in storm damages (Cox et al., 2019). Irma's impact on the Virgin Islands and other Caribbean atolls was much larger: over $77 billion in damages and over 50 deaths. Two weeks later, while Hurricane Irma recovery efforts were ongoing, Hurricane Maria formed east of the Lesser Antilles, rapidly intensifying to a Category 5 storm. It struck Dominica on September 18th, weakened to a Category 4 Hurricane, and then struck Puerto Rico on September 20th. Almost 3,000 Puerto Ricans died, most of the island lost power, and over $90 billion in damages were left in the storm's wake (Cox et al., 2019). Although two weeks apart, the devastation of and limited recovery after Maria were exacerbated by the earlier arrival of Irma. Irma's direct impact on Puerto Rico was limited, but it drew the resources of federal and local agencies and left Puerto Rico underprepared for another storm. FEMA's only emergency stockpile in the Caribbean was located in Puerto Rico, and only 17% of the stockpile remained after Irma, with only 10% of FEMA's emergency water, tarps, and cots available for use during and after Maria. Hurricanes Irma and Maria exemplified the operational and logistical hurdles associated with incident prioritization and resource allocation given back-to-back disasters with overlapping hazard management cycles.

Overall, there has been limited research exploring organizational resilience in the context of compound threats, particularly for United States federal agencies. A focus on exploring the lived experiences of federal agency personnel who use US federal hazard management protocols, such as FEMA's National Incident Management System (NIMS), would be especially illuminating. To the author's knowledge, there has been limited empirical research on federal agencies' ability to cope with compounding threats based on predetermined hazard management decision-making processes and to adapt to evolving threat situations. The ability to cope (herein, absorptive capacity) and to adapt (herein, adaptive capacity) to evolving threats are considered key facets of organizational resilience (Lee et al., 2013; Linkov et al., 2018; Wood et al., 2019**).** Deeper understanding of how existing hazard management processes absorbed and adapted to compound threat events can help practitioners and researchers identify the internal barriers and external stressors that may hinder the resilience of federal hazard management organizations. As such, this exploratory study seeks to provide federal agency personnel insight into the characteristics and strategies that enable U.S. federal agencies to be resilient and adaptive when facing compound threats based on lived experiences. Interviews were used to characterize the field experiences of federal agency personnel, whose expertise and knowledge of organizational decision-making processes and lessons learned can yield insights to future systems-level improvements (Austhof & Brown, 2021; Timberlake et al., 2021; Kim et al., 2007). Here, U.S. federal agency personnel involved in threat management were interviewed and surveyed. Given the saliency of the COVID-19 pandemic co-occurring during other natural and anthropogenic threats and hazards, federal agency personnel perspectives and lessons learned were assessed regarding this global pandemic as well as other compound threat experiences.

1.1. Background

Existing and relevant federal hazard management frameworks, including coordination structures and decision support tools, were reviewed to contextualize existing federal and interagency hazard management processes. Organizational resilience definitions, characteristics, and actions were also reviewed to contextualize this study. When possible, both hazard management frameworks and organizational resilience are discussed in this study in the context of compounding threats.

Extension beyond risk. Multi-hazard risk analyses have been developed to assess the potential collective effect of two or more risks when they interact in compound threat scenarios (Wang and Wang, 2020; Center for Resilient Cities and Landscapes, 2020). Multi-hazard risk assessments can estimate the risks associated with complex simultaneous or subsequent threats, for which the combined, collective risk may be greater than the sum of its parts (De Angeli et al., 2022; IPCC, 2022; Center for Resilience Cities and Landscapes, 2020; Wang et al., 2020; Hariri-Ardebili, 2020). Further, given projections for increasing frequency and severity of compound threats, prior policy work has recommended that organizations use risk frameworks that adapt to risks over time, rather than eliminate them completely, which may require technical and institutional changes via social learning and adaptation (Essen et al., 2021). As there is limited research on local to regional feedback processes that may predict the occurrence and consequences of compound threats (IPCC, 2022; Prudhomme et al., 2014; Sillmann et al., 2017; Hao et al., 2018; Miralles et al., 2019), it is essential for federal organizations to address not only risk potential, but how they can be resilient if faced with novel and/or highly uncertain compound risks. Resilience presumes that various disruptions may occur over time and emphasizes the ability to recover while maintaining critical functions and subsequently adapt the system to improve planning and response processes for future threats (Linkov & Trump, 2019). The shift in thinking toward a resilience-based paradigm, which extends risk-based paradigms, signals a recognition that while risk-based approaches work well under conditions of relatively low uncertainty and complexity, compounding and cascading threat scenarios present novel, complex system-level constraints that can potentially exacerbate disruptions (i.e., resource constraints; cascading failures across interconnected critical infrastructure systems) (Pescaroli et al., 2021).

Importance of organizational resilience. Generally, resilience is a temporal and multidimensional, sociotechnical phenomenon that addresses how systems or individuals manage uncertainty (Linkov et al., 2013; Lee et al., 2013). The term ‘resilience’ has been studied across a diverse array of disciplines, such as psychology, public health, environmental science, engineering, and economics (Koliou et al., 2019; Haimes, 2009; Hicks-Masterson et al., 2014; Klein, Nicholls, & Thomalla, 2003; Manyena, 2006; Norris et al., 2008). Further, resilience has been applied across varying scales, from individual-level frameworks and metrics related to human psychology or infrastructure including bridges and dams to systems-level scales, such as social networks, socio-ecological systems, supply chains, and interconnected critical infrastructure networks (Koliou et al., 2019). Though resilience-based metrics and models differ by application areas and levels of analysis, they share the common understanding that resilience can enable systems to prepare for, respond to, recover from, and adapt to both foreseen and unforeseen disruptions (PPD-21, 2013; Linkov et al., 2013). Organizational resilience has been conceptualized and assessed based on factors internal to the organization (i.e., vertical or horizontal hierarchical structures, leadership, innovation) as well as on external considerations, such as effective partnerships (Resilient Organisations, 2019).

Resilient organizations are posited to be those that are prepared for and can adapt to stressors or disruptions, including novel or "worst-case scenarios" (Kantur et al., 2012), with the ability to learn (Weick et al., 2005), innovate (Kendra and Wachtendorf, 2003), and adapt (Vogus and Sutcliffe, 2012) to maintain critical functioning (Linkov et al., 2013). Various Presidential directives and orders have tasked U.S. federal agencies with improving resilience following catastrophic events such as Hurricane Katrina and Superstorm Sandy, emphasizing flexible and adaptive ways for critical services to recover given disruption (Larkin et al., 2015). Further, federal agencies have begun to adopt resilience-focused approaches to hazard management. It is particularly important for federal agencies to be resilient given their duty of care to the public; without critical infrastructure and critical service provision (i.e., water, transportation, healthcare, power, etc.), communities may be less apt to respond and recover from a hazard (Lee et al., 2013; Cutter et al., 2008).

Organizational resilience is linked to community resilience, which is defined as communities' ability to plan for, absorb, recover from, and adapt to natural and/or human-caused disruptive events (PPD-21, 2013; Koliau et al., 2019). Such disruptions can damage or hinder critical infrastructure systems (i.e., public and private built environments, cyber infrastructure, health care infrastructure, etc.), economic systems, and/or social systems. While this chapter focuses on organizational resilience rather than community resilience, the resilience of federal agencies involved in hazard management can support affected communities both directly and indirectly. Federal agencies have programs that can directly contribute to community resilience by addressing community emergency response, preparedness, security, risk mitigation and communication, as well as physical and economic recovery post-disruption (Koliou et al., 2019). For instance, the U.S. Department of Homeland Security has recently implemented the Building Resilient Infrastructure and Communities (BRIC) grant program to support states, local communities, and tribes to proactively invest in climate resilient infrastructure (US DHS, 2021). Federal resilience programs tend to evolve following disasters (e.g., Hurricane Katrina, Hurricane Sandy) to more adequately and equitably address community preparedness, emergency response, recovery, and mitigation based on community disruption experiences (Congressional Research Service, 2017). Organizational and community resilience are further linked in that short- and long-term community recovery post-hazard can indicate if and how organizations can improve their hazard management approach to better support the communities that they serve (Koliou et al., 2019). To facilitate community resilience to threats and hazards—including compound threats and hazards— hazard management organizations must be resilient themselves.

Compound threats may present complex decision spaces that are uncertain, and in some cases, novel, with the potential to pose multiplicative risks (Zscheischler et al., 2018). To be resilient in the face of compound threats, hazard management agencies must plan for and adapt to uncertainty in dynamic and complex socio-ecological systems (Essen et al., 2021; Nowell et al., 2018). Understanding the internal barriers and external stressors that challenge federal agency adaptive capacity in facing compound threats is particularly pertinent given changing conditions in the natural and built environments. To the author's knowledge, there is limited research that explores U.S. federal agency organizational resilience, adaptive capacity, and adaptive decision-making processes for compound threats.

Existing US hazard response frameworks. A brief review of existing U.S. federal hazard management frameworks helps to understand if and how federal agencies have adapted to compound threats, considering operations, inter-agency coordination, and decision-making processes.

Various directives, standards, and hierarchical structures are in place across the U.S. federal government that clarify jurisdictional and agency-specific responsibilities given a threat or hazard. Such frameworks provide a general organizational structure for incident response. Generally, if an incident affects a local community, local hazard management resources will be deployed. If the incident demands more resources than the community can supply, then state resources can be requested and deployed. Should the incident demand more resources than the state can supply, then federal resources can be requested and deployed after "emergency declarations" are filed (FEMA, 2022).

Following the 2001 terrorist attacks, the National Incident Management System (NIMS) was enacted by the U.S. DHS in 2003 to provide a nationwide and standardized approach for responding to any type of incident regardless of scope, size, or complexity. The NIMS addresses all phases of the hazard cycle: planning, response, recovery, and mitigation (FEMA, 2017). Further, NIMS was designed to integrate multi-jurisdiction governments, private sector organizations, tribes, and NGOs in hazard management; as such, it is considered applicable to all stakeholders with incident management and support responsibilities (FEMA, 2017). The NIMS provides a framework for multi-jurisdiction and cross sectoral coordination by clarifying hazard management responsibilities for the Incident Command System (ICS) teams, Emergency Operations Center (EOC) structures, and Multi-agency Coordination System (MACS) units. Hazard management responsibilities addressed by the NIMS include: (i) resource management, (ii) command and coordination, and (iii) communications and information management.

The NIMS provides guidance for resource management and coordination, as most organizations and jurisdictions do not own full fleets of critical resources that may be needed before, during, and after threats and hazards (FEMA, 2017). Thus, NIMS addresses multi-jurisdiction resource coordination and collaboration, while also addressing private sector and volunteer organization support. During an incident, incident objectives are determined and strategic decision-making processes guide the operational strategies and tactics necessary to fulfill those objectives. Then, the resources needed for response tactics are requested and may be allocated and mobilized to the incident if resources are available and the incident is prioritized (FEMA, 2017). After resources are no longer needed, they are demobilized back to their original location (FEMA, 2017).

The Incident Command System (ICS) is a critical component of NIMS' command and control approach to hazard management that is involved in resource management. ICS focuses on standardizing on-scene response to all hazards events across all responding organizations. The ICS is designed to clarify key response-related tasks and overcome any confusion that may arise when multiple agencies and jurisdictions mobilize during major disasters (Tierney, Lindell, and Perry, 2001). Theoretically, the ICS is designed to provide streamlined coordination structures to diverse threats and hazards types. As a system, the ICS is intended to standardize multi-agency and multi-jurisdiction organization and execution of hazard response (Jensen and Thompson, 2016, pg. 159). The ICS is designed to be flexible and scalable across incident types, complexity, durations, and sizes (Jensen and Thompson, 2016, pg. 160). Further, the ICS offers differing approaches to singular incident command and complex incident command, wherein complex incidents can include two or more concurrent threats/hazards occurring in similar geographic locations. Complex incidents, therefore, align with this chapter's definition of compound threats, and entail the deployment of Unified Command and Unified Area Command structures. Unified Command occurs when an incident spans multiple jurisdictions (i.e., if a wildland fire were to spread to both state and federally owned lands) and enables joint management of incident activities between multiple jurisdictions, though each unified jurisdiction maintains responsibility for its personnel (FEMA, 2017). When there are multiple hazards that co-occur geospatially and temporally, Unified Area Command may be enacted. Unified Area Command is relevant when entities responding to compound hazards request similar resources, such as during multiple, co-occurring wildland fires. Unified Area Command, therefore, is one organizational structure that federal and cooperating agencies have developed to manage complex, multi-incident events (FEMA, 2017).

Despite the intended flexibility and scalability of the ICS, practitioners and academics have different perspectives on its utility. For instance, some research has posited that the ICS system is inflexible, slow, and less adaptive to threats and task environments that require rapid decision making under uncertainty (Waugh, 2009, pg. 172). Academics have rarely studied ICS, and to the author's knowledge, there is very little research on the efficacy and resiliency of the ICS given compound threats. The characteristics of the ICS that are proposed to promote interagency hazard response (i.e., flexibility, adaptability, and applicability to a robust set of potential incidents) align with the characteristics associated with organizational resilience. However, command-and-control structures such as the ICS have been critiqued for their horizontal, hierarchical chain of command, which may give Incident Commanders and agency administrators disproportionate influence in strategic and tactical decision-making (Jensen and Waugh, 2014). Incident Commanders and Agency Administrators have exhibited cognitive decision-making biases, such as loss aversion, discounting, and *status quo* bias when evaluating and deciding between wildfire management strategies (Wilson et al., 2011; Rapp et al., 2020). Therefore, the hierarchical structure of ICS systems, as well as broader resource allocation systems such as the National Interagency Fire Center (NIFC), may be subject to human decision-making biases. More broadly, research has found that the intention of the NIMS to standardize emergency management is contingent on policy characteristics (i.e., objectives, incentives, financial and technical capacity), management preferences (i.e., perceived utility of NIMS), local resource capacities, and inter-organizational relationships (i.e., trust, cultural values) (Jensen and Youngs, 2015). Given the current contrast between the perspectives of practitioners and academics on the utility of NIMS and command-and-control systems, the current paper assesses the absorptive and adaptive capacities of current hazard management frameworks in the context of compound threats, with the goal of identifying potential strengths barriers to compound hazard management and resilience.

In addition to hazard management frameworks, technical advances in forecasting hazard occurrence probabilities in modeling loss potential via integrated weather and geospatial data may facilitate risk-informed decision-making (Rapp et al., 2020; Linkov et al., 2014). Further, some federal agencies have begun using decision support tools to streamline and make strategic, risk-informed decisions. For instance, the Wildland Fire Decision Support System (WFDSS) is used by wildland fire agencies to inform wildland fire response strategies based on integrated fire modeling and geospatial analyses (WFDSS). WFDSS supports broad and strategic decision-making for Incident Management Teams (IMTs) by integrating fire behavior, weather, and societal risk factors via spatial data layering (i.e., structures, communities) (Rapp et al., 2020). Using WFDSS, fire behavior analysts and fire managers can forecast fire behavior and spread probabilities based on current and forecasted weather, proximal fuels, and values at risk (Thompson, 2015). Decision-support tools like WFDSS are intended to facilitate risk communication and the development of strategic and tactical fire responses within and between firefighting crews. Similarly, HURREVAC is a decision support tool used by the National Hurricane Program, which is administered by FEMA, USACE, and NOAA through the National Hurricane Center. HURREVAC offers a web platform for government emergency management of hurricanes, storm surges, and floods (Becker et al., 2021; Kirlik, 2007). It includes the ability to forecast storm surges, excessive rainfall outlooks (1 – 3 days out with probabilistic forecasts) and includes Storm Simulator and Potential Track Area (Cone Error) to test potential scenarios based on NHC forecasting (NOAA, 2022).

Concept model. The “disaster resilience of place” (DROP) model (Cutter et al., 2008) and existing frameworks for organizational resilience given environmental threats (Lee et al., 2013; Linkov et al., 2013) were adapted to explore multi-phase, systems-level federal agency resilience to compound threat disruption. We adapted the core constructs from the DROP model to fit the organizational perspective, as Cutter et al. (2008) claimed that resilience given hazards is informed by inherent, antecedent conditions as well as adaptive capacities, both of which can be applied to infrastructure, institutional, organizational, social, and economic systems. Further, the DROP model’s cross-sectoral coordination structure aligns with federal hazard management frameworks, such as the “whole community” approach promoted by FEMA’s National Incident Management System (FEMA, 2022). Accordingly, the DROP model motivated the general framework of federal agency resilience under compound threats. The core constructs posited by the DROP model are defined in Table 1.

Table 1. Definitions for the deductive parent codes related to the DROP model (Cutter et al., 2008) and organizational resilience constructs.

Construct	Definition
Antecedent Conditions	"…multiscalar processes that occur within and between social, natural, and built environment systems. Antecedent conditions include both inherent vulnerability and inherent resilience…" (Cutter et al., 2008, pg. 602).
Absorptive Capacity	"Absorptive capacity (or threshold) is the ability… to absorb event impacts using predetermined coping responses…can be exceeded in two ways. First, if the hazard event is so large it overwhelms local capacity; and second if the event is less catastrophic, but existing coping responses are insufficient to handle the impact" (Cutter, 2008, pg. 603).
Adaptive capacity	The ability and capacity to adapt to changing environmental conditions through flexibility, improvisation, and organizational learning (Barasa et al., 2018; Cutter et al., 2008).
Recovery	"… degree of recovery [is] a continuum ranging from high to low. If… absorptive capacity is not exceeded, higher rates of the recovery are reached quickly. If the absorptive capacity is exceeded and the adaptive resilience process does not occur, a lower degree of recovery may result… if the absorptive capacity is exceeded and the adaptive resilience process does occur… more likely to achieve a higher degree of recovery" (Cutter et al., 2008, pg. 603).
Organizational Resilience	Organizational planning, absorptive capacity, adaptive capacity, and recovery that contribute to the organization's ability to maintain critical functioning during 'business as usual' and given disruption; contingent on internal and external relationships (Cutter et al., 2008; Lee et al., 2013; Barasa et al., 2018, Wood et al., 2019).

The antecedent conditions of the system (here, a federal agency) are characterized by social systems, natural environmental systems, and built environment factors. At some point, this system will face a disruption—in this case, a compound threat. Then, the system may absorb the disruption based on predetermined coping strategies, aiming to fulfill critical functioning and recover to a high degree. However, the system may face resource, time, and/or sociopolitical constraints that exceed its ability to absorb and efficiently recover from the disruption (Cutter et al., 2008). Agencies may need to adapt when presented with complex, sometimes novel compound threats (e.g., the confluence of COVID-19 and natural hazard); adaptation is needed when more conventional, predetermined coping processes (i.e., resources, information and decision-making processes, and coordination networks) prove insufficient to manage the current threat (Cutter et al., 2008). Thus, an organization's adaptive capacity—which has been considered a critical facet of organizational resilience—can influence how the organization copes with and recovers from disruption. Adaptive capacity has been associated with flexibility, innovation, improvisation, and learning (Barasa et al., 2018). As compound threats may pose greater risks than singular threats, absorptive capacity may be more likely to be exceeded, in which case adaptive capacity will be critical (i) to help cope with and recover from incidents and to (ii) provide insights for how organizations can mitigate and plan for future threats.

Adaptive capacity has been considered a core facet of organizational resilience (Lee et al., 2013), though organizational resilience is considered a broader set of planning, absorptive, and adaptive processes and characteristics that can facilitate organizational functioning despite disruption. Extant literature identifies characteristics associated with organizational resilience, including for organizations specializing in hazard response. The development of resilience-measurement scales is quickly evolving because such scales can facilitate interaction between academia, practitioners, and policymakers (Cutter and Derakhshan, 2019; Pescaroli et al., 2020). Organizational resilience is often conceptualized as a property, ability, or capability that can be improved over time (Ruiz-Martin et al., 2018; Larkin et al., 2015). As such, resilience is a continuously moving target that contributes to performance (i.e., provision of critical functions and services) that is maintained during hazards (Lee et al., 2013; Mitroff, 2005), and driven by the ability to plan for and adapt to complex and uncertain disruptions, such as compound threats. Organizational resilience can be assessed according to the physical properties of the organization (i.e., resource availability, resource scarcity, communication channels, technology, etc.), as well as according to organizational practices, standards, and culture (i.e., organizational structure, leadership, training, experience) (Cutter et al., 2008; Tierney and Bruneau, 2007). Here, organizational resilience indicators identified by the Relative Overall Resilience (ROR) framework (Lee et al., 2013) were used as deductive codes and were categorized by three main components found in existing empirical literature: (i) planning, (ii) adaptive capacity, and (iii) internal and external relationships (Organisational Resilience, 2019; Lee et al., 2013; Cutter et al., 2008; Larkin et al., 2015; Wood et al., 2019; Linkov et al., 2013).

1.2. Research questions.

Recent literature has identified that hazard management may be increasingly complex given compound threats, yet few articles have holistically addressed the unique challenges, constraints, and opportunities of compound threat management from the perspectives of practitioners. Literature that has assessed compound threat management from practitioner perspectives has tended to focus on threats involving the COVID-19 pandemic (Yusuf et al., 2020; Hutton et al., 2021). This work aims to capture a more diverse set of federal compound threat management approaches based on the lived experiences of U.S. federal agency personnel. To do so, we explore the following research questions using a qualitative approach:

1. What types of compound threat events have federal agency personnel experienced in the current threat landscape across the US, including but not limited to the COVID-19 pandemic?
2. How do federal agencies currently manage compound threats?
3. What internal and/or external challenges, constraints, and stressors do agencies face in adapting to compound threats, relative to their management of singular threats?
4. What organizational characteristics, practices, and resources support or inhibit organizational resilience and adaptation, particularly as they relate to compound threat operations?

2. Methods

Semi-structured interviews were conducted to obtain exploratory insights into federal agencies' self-reported compound hazard experiences, ability to absorb and adapt to compound hazards, and characteristics and actions taken to facilitate or inhibit organizational resilience. Complementary follow-up surveys were distributed to participants, and survey results were used to validate interview themes and capture broader perspectives on agency operations, constraints, and risks that may not have been discussed at the time of the interview.[12] Descriptive statistics of survey responses are included in Appendix 2C.

2.1. Interview protocol.

We used a set of guiding interview questions during each interview session, though conversations were not limited exclusively to these questions (Rapp et al., 2020; Patton, 2002). (See Appendix 2B for a full list of guiding interview questions). Interview questions were informed by existing federal hazard management frameworks and empirical organizational resilience models (FEMA, 2022; Resilient Organisations, 2019; Lee et al., 2013; Cutter et al., 2008). Conversations focused on identifying and

[12] After each interview session, participants were asked to complete a follow-up survey that was distributed via a Qualtrics URL. Survey responses were anonymous, and the average completion time was [7] minutes. Follow-up survey questions captured hazard management objectives and constraints as expressed in interviews, as well as variations in absorptive capacity and organizational resilience for singular versus compound threats (Wong-Parodi et al., 2016).

understanding the pathways between social and technical capabilities, coordination structures, and challenges that federal agencies face in compound threat management.

2.2. Data collection.

We recruited a total of 33 federal agency personnel to participate in the semi-structured interviews. Participants had been employed for at least one year by federal agencies involved in hazard management, and participants had expertise related to hazard preparation, response, recovery, and/or adaptation. Targeted federal agencies included those involved in environmental hazard management (i.e., FEMA, Army Corps of Engineers, US Forest Service). Participants were recruited from the author's professional and academic contacts through a purposive snowball sampling conducted between October 2021 and May 2022 (Rapp et al., 2020; Naderifar et al., 2017; Volken et al., 2017). Table 2 shows the federal agencies and U.S. geographic regions corresponding to the set of participants, as well as the mean years worked in their current agency. Participants were primarily employed by the U.S. Department of Homeland Security (DHS) (42%) and the U.S. Department of Agriculture (36%). Participants resided and operated across a diverse set of U.S. geographic regions to capture a range of natural and anthropogenic threat types. Approximately 45% indicated that the primary hazard that they respond to in their current position is wildland fires, followed by hurricanes (33%) and inland flooding (15%). Additionally, as hazard management is generally conceived across four phases, the hazard management phase(s) that each interviewee was primarily involved in at the time of the interview was captured. Across the sample, there was a particular focus on the 'response' of hazard management, which captured operations, logistics, and field work deployment (Khan et al., 2020). Over half of the participants (55%) were involved in the planning/preparation phase of hazard management.

Table 2. Participant characteristics of the 33 anonymous and confident federal agency personnel interviewed.

Years employed by federal agency mean (SD)	16.3	9.6
Participant Characteristics	***n***	**%**
Federal Department		
US Department of Homeland Security	14	42%
US Department of Agriculture	12	36%
US Department of Defense	4	12%
US Department of the Interior	3	9%
US Geographic Area		
National	5	15%
Western US (states)	8	24%
Eastern US (states)	6	18%
Southern US (states)	5	15%
Midwest (states)	4	12%
Primary Hazard Type		
Fire	15	45%
Other	18	55%
Role(s) within Hazard Management Phases		
Planning/Preparation	18	55%
Response	19	58%
Recovery	6	18%
Mitigation/Adaptation	2	6%

Semi-structured interviews were conducted using remote technology (Zoom) between November 2021 and May 2022. Interviews lasted 45 – 120 minutes. Calls were recorded, anonymized, and transcribed to remove identifiable information. Carnegie Mellon University's Institutional Review Board for the Protection of Human Subjects approved the research protocol (IRB approval number:

STUDY2020_00000248). Informed consent was secured from participants, who were not compensated for their participation. Two coders were trained by the author, and both were enrolled in graduate programs in public policy with experience in qualitative data analysis at the time of coding. The coders individually coded transcripts via deductive and inductive methods, and then codes were jointly compared and discussed across the research team to validate findings (Yusuf et al., 2021). The inter-rater agreement score of the coding team was 0.78 – 0.81, which is accepted as a valid level of inter-rater agreement representing mutual understanding of the codebook (McHugh, 2012) (See Appendix 2B for details on inter-rater agreement calculations).

2.3. Data analysis.

A master list of codes was developed during the transcript coding process. The coders used both inductive and deductive coding schemes to code each anonymized interview transcript via MAXQDA, a qualitative data analysis software. Deductive coding was based on both federal hazard management and operations policy and guidelines (i.e., National Response Framework) and resilience literature (i.e., Cutter et al., 2008; Linkov et al., 2013; Resilient Organisations, 2019). Thus, themes were connected to the broader literature on hazard management, public policy, and organizational resilience (Yusuf et al., 2021; Lee et al., 2013; Cutter et al., 2008; National Response Framework, 2019; Linkov et al., 2013). Additionally, inductive coding via thematic analysis was used to identify emergent patterns between participant responses. Inductive thematic analyses identified patterns across the qualitative interview data not identified by predetermined topics and constructs (Rapp et al., 2020; Braun and Clarke, 2006; Charmaz, 2014). After coding was complete, the author organized existing codes into themes related to compound hazard experiences, compound hazard absorptive capabilities (i.e., objectives, priorities, constraints), and organizational resilience in compound threats. (See Appendix 2B for details on codebook development.)

We developed a conceptual framework to explore federal agency antecedent conditions, absorptive capacity, and organizational resilience under compound threats (Table 1). Framework themes were developed for the following parent codes derived from existing literature on hazard management and resilience: (i) agency antecedent conditions and recalled compound threat experiences, (ii) compound threat absorptive capacity, (iii) compound threat adaptive capacity, and (iv) organizational resilience. The thematic analysis results reflect the coders interpretation of participant narratives (Wong-Parodi et al., 2017). Qualitative assessments of interview responses include interviewee quotes that clearly articulated a perspective on an interview response, as well as the count and percent of total participants who discussed a code. Further, we compared responses from personnel who are primarily involved in wildland fire management to participants primarily involved in other hazard types (e.g., hurricanes, flooding) to assess unique insights to compound threat management by hazard type. In addition to participant counts, themes were developed based on the total number of segments of text (e.g., 2-4 sentences in length) that were categorized to a given code (Browne et al., 2021). The same segment of text could contain multiple codes, referred to as code intersections (Browne et al., 2021).

Themes emerged across the data based on participant code counts, code segment counts, and code intersections (i.e., code co-occurrence). Follow-up survey results were assessed via descriptive statistics. Survey items quantitatively gauged singular and compound threat objectives, risks, constraints, and information and resource needs of federal agencies. However, the low sample size (n = 26) inhibits formal statistical significance tests. Descriptive statistical results are provided in Appendix 2C to offer informative first insights for hypothesis generation and research designs to improve understanding of compound threats and federal hazard management absorptive capacity.

3. Results and Discussion

3.1. Conceptual framework

We propose a conceptual framework of federal compound hazard management as informed by existing empirical work as well as analyses of the semi-structured interview transcripts. Figure 1 maps themes identified across the interview data according to their relation to the initial DROP and ROR conceptual frameworks. To adapt the DROP and ROR frameworks to the context of hazard management, the "absorptive capacity" and "recovery" phases—which served as parent codes in the coding scheme—included child codes that mirrored the hazard management responsibilities addressed by the NIMS include: (i) resource management, (ii) command and coordination, and (iii) communications and information management. Figure 1 identifies the deductive and inductive coding results that emerged from 33 interview transcripts to explore compound threat experiences, how federal agencies absorbed (i.e., responded to) these threats, and if and how they adapted to fulfill mission objectives given compound threats. Figure 1 acknowledges that federal agency hazard management is influenced by the broader social, natural, and built environment of their antecedent conditions; additionally, the current framework is informed by inductive factors related to individual characteristics of hazard management personnel (e.g., career experience and duration, agency of employment, and IMT participation). Using this framework, we address: (i) the types of compound threats that were experienced by federal agency personnel, (ii) decision-making processes during compound threat events (i.e., absorptive capacity), (iii) the internal and external barriers that they face in adapting to compound threat events (i.e., adaptive capacity), and (iv) opportunities to improve organizational resilience to enhance how agencies plan for, absorb, recover from, and adapt to compound threat events. Figure 1 integrates the deductive ROR model of organizational resilience (Resilient Organisations, 2019) with inductive interview data to address federal agency resilience considering compound threats across the deductive hazard management phases (i.e., antecedent conditions, absorptive capacity, recovery).

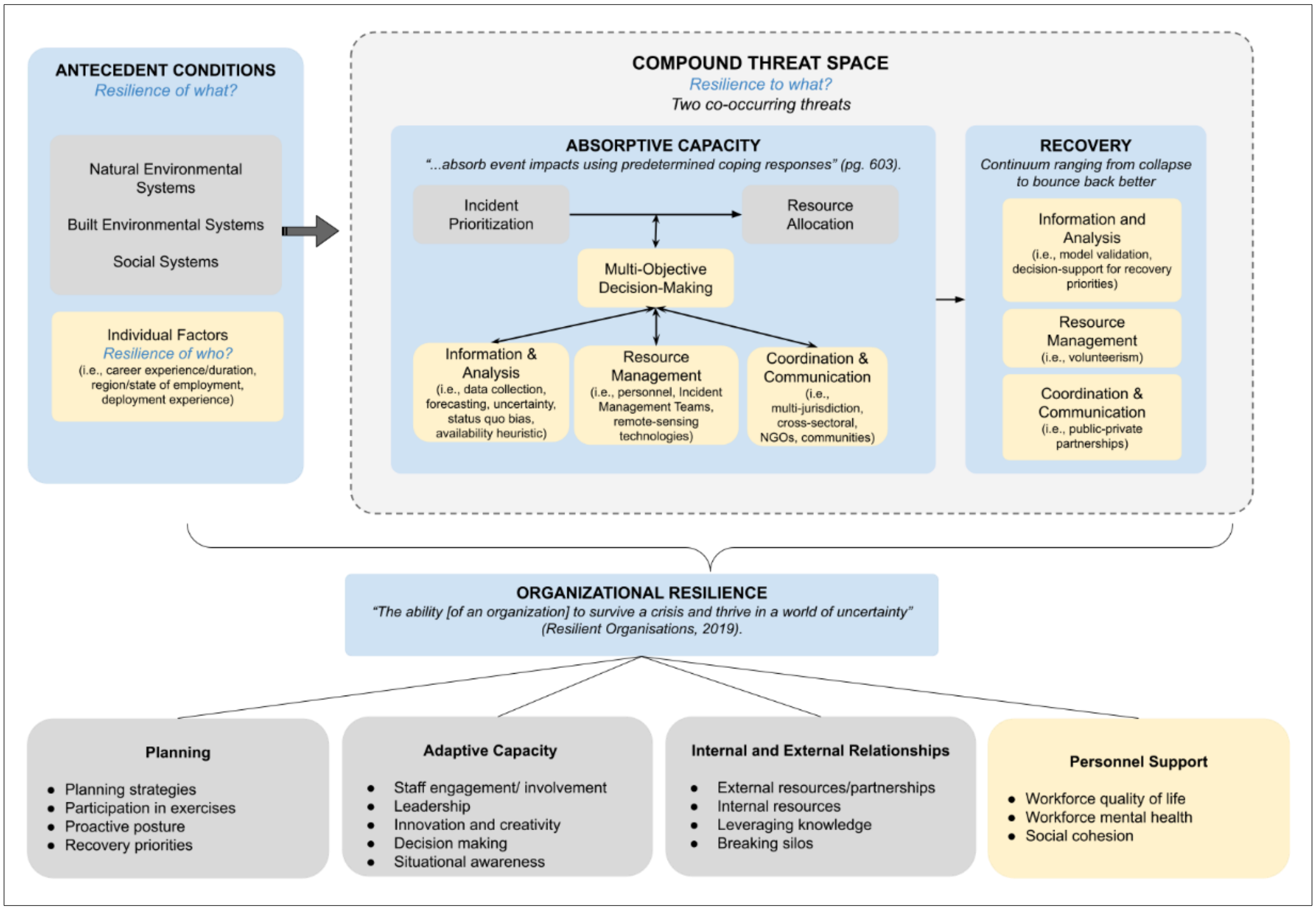


Figure 1. Concept model for compound threat management. Blue shaded boxes show the deductive parent codes related to the phases of hazard management and to the organizational resilience parent code. Grey shaded boxes show how deductive codes related to the hazard management phases and organizational resilience components that were discussed by participants. Yellow shaded boxes represent the inductive coding findings that emerged across interviews.

3.2.1. Federal agencies recall diverse compound threat experiences

All participants indicated that their agency tends to be mindful of and plan for the possibility of compound threat occurrences. Generally, participants expressed that compound threats are "…extremely common" (Interview 8), occurring "…at least once or more, sometimes, throughout the [year]" (Interview 20). This aligns with findings from existing literature in that compound threat frequency and severity may exacerbate risks to human health and safety (Wilhelmi et al., 2021; Santana et al., 2021), critical infrastructure systems (Wells et al. 2022), and ecological systems (Doherty et al., 2015). The awareness of and experience in compound threat management have related to the generally increasing intensity of natural and anthropogenic threats, as well as their intersection. Most participants indicated that they had observed increased frequency (n = 18, 55%) and/or severity (n = 18, 55%) of natural hazards over their career. Personnel who have primarily managed wildland fires discussed increased natural hazard frequency (n = 10, 67% of fire personnel) and severity (n = 11, 73% of fire personnel) at a greater rate than other participants. Eleven participants (33%) attributed evolving environmental conditions to climate change, some claiming that there has been "…increased attention towards the effects of climate change and the effects that those can have on increasing the severity of natural hazards" (Interview 2). Additionally, 13 participants (39%) noted that natural hazard seasons "are just getting longer" (Interview 20), evolving into year-round threats. This observation was pronounced among fire personnel (n = 9, 60% of fire personnel), one of whom stated, "It's kind of this elephant in the room that people are whispering about, but we're not quite taking hard enough action" (Interview 20). Though participants less frequently discussed anthropogenic hazards than natural, some discussed changes in anthropogenic hazard frequency (n = 5, 15%) and severity (n = 4, 12%). Participants attributed anthropogenic hazard changes to development in hazard-prone geographies (n = 8, 24%), such as within the wildland-urban interface (WUI) and flood-prone areas, and to increasingly interconnected and interdependent critical infrastructure systems (n = 5, 15%).

Participants recalled lived compound event experiences that they encountered over the course of their career. Table 3 presents all compound threat recollections that represent the lived experiences of participants, as well as the number of participants who recalled each compound threat type. The sample of compound threat recollections highlights that federal hazard management agencies have been tasked with managing natural, anthropogenic, and socionatural[13] threat types that range from chronic (e.g., COVID-19, invasive insect populations) to acute (e.g., hurricanes, solar eclipse) timeframes. Nineteen unique compound threat pairs were recalled, and participants recalled an average of 1.8 comound threat experiences for a total of 60 compound threat discussions. Approximately 69% of the threats discussed were natural threat sources, 8% were anthropogenic risk sources, and 29% were socionatural threat sources. Biological threats such as infectious disease outbreaks (including but not limited to COVID-19), injuries/fatalities, and invasive species events were considered 'socionatural' threats such that they are associated with combinations of natural and anthropogenic factors (i.e., transmission contingent on human behavior and protective measures) (UNDRR, 2022).

Table 3. Compound threat experiences recalled by participants based on their personal lived experiences working for their respective federal hazard management agency. In total, 120 unique threat types across 60 compound threat experiences were recalled by participants. Threat sources were then categorized as (i) natural, (ii) anthropogenic, and (iii) socionatural.

Compound Threat			**Threat Source**		
Threat 1	Threat 2	Count of Participant Mentions	Natural	Anthropogenic	Socionatural
COVID	Wildfire	15	1		1
COVID	Hurricane/Tropical Storm	6	1		1
COVID	Flood event	1	1		1
COVID	Earthquake	1	1		1
COVID	Cyberattacks	1	1	1	
COVID	Building collapse	1	1	1	
COVID	Chemical plant explosion	1	1	1	

[13] The United Nations Office for Disaster Risk Reduction defines natural hazards as "predominantly associated with natural processes and phenomena", anthropogenic hazards as "…induced entirely or predominantly by human activities and choices", and socionatural hazards as "…associated with a combination of natural and anthropogenic factors, including environmental degradation and climate change" (UNDRR, 2017).

Hurricane	Hurricane	8	1		
Hurricane	Damaged dam*	2	1	1	
Hurricane	Las Vegas shooting	1	1	1	
Hurricane	Disease outbreak	1	1		1
Hurricane	Earthquake	1	2		
Wildland fire	Wildland fire	11	2		
Wildland fire	Landslide	1	2		
Wildland fire	Personnel fatality*	3	1		1
Wildland fire	Solar eclipse viewing	2	1	1	
Wildland fire	Drought	2	2		
Wildland fire	Invasive insects	1	1		1
Heat wave	Remote music festival	1	1	1	
		120 unique threats	83 (69%)	9 (8%)	28 (23%)

* In this incidence, the dam was described to be damaged prior to the hurricane event.
** Personnel fatalities are referred to as "Incident-within-an-incident" situations are considered accidents and/or medical emergencies. Prior to deployment, personnel receive training for how to deal with these emergency situations. Incident-within-an-incident situations may not align with the current definition of compound threats, but are included in this table because these high risk situations were recalled by participants when asked about their compound threat experiences.

The most frequently recalled compound threat experience were two simultaneous natural hazards (i.e., two wildland fires or two hurricanes) that affected the same geographic area at approximately the same time. The frequencies of mentions of simultaneous natural hazards highlighted regional vulnerabilities to natural hazards. For instance, the 2020 August Complex fire in California was associated with 38 unique ignition points that burned over one million acres and has been attributed to extreme environmental conditions; a lightning storm ignited the incidents, and fires quickly spread over the ensuing days due to high winds, heat, and vapor pressure deficits (InciWeb, 2021; Zhuang et al., 2021). Similarly, compounding hurricanes, such as Hurricanes Irma and Maria, were recalled as compounding natural hazards that affected tropical cyclone-prone Caribbean islands and hurricane-prone Atlantic coast.

In addition to compound threat experiences that involved two or more natural hazards, some recalled anthropogenic threat types. For instance, one participant recalled the 2021 Surfside condominium collapse in Florida that occurred during the COVID-19 pandemic; FEMA and USACE were involved in search and rescue efforts while both were actively involved in and cognizant of COVID-19 transmission risks (FEMA, 2021). Another example includes the 2017 Las Vegas shooting, which occurred soon after Hurricane Maria – requiring resources deployed to Hurricane Maria response and recovery to be demobilized and deployed to support the community affected by the shooting. The examples of anthropogenic sources of risk in Table 2 exemplify the diverse range of compound threat event types; the diversity accentuates the need for federal agencies to absorb and adapt to complex, uncertain, and occasionally novel threats. The absorptive and adaptive capacity of federal agencies managing these events are discussed in the following sections.

3.2.2. Federal agency absorptive capacity to manage compound threats

Participants described their agency's absorptive capacity, or ability to cope, to fulfill mission objectives during compound threat events. Participants identified two critical decisions required in compound threat management: incident prioritization (n = 30, 91%) and resource allocation (n = 33, 100%). Incident prioritization was defined as the risk and decision analyses involved in prioritizing incidents when there are multiple, co-occurring threats or incidents. As "…there's always logistical limitations and resource limitations" (Interview 21), critical resource allocation decisions are based on incident prioritization and based on the tactical efficacy (i.e., chance of success) of resource deployment strategies. Federal agencies' absorptive capacity when faced with compound threats was described to involve strategic, multi-objective decision-making, including trade-off analyses of risks, objectives, and constraints (Dunn et al., 2017).

Participants reported that their respective federal agency plans for compound threats in part because they now frequently occur. Federal agency personnel expressed that they feel decision-making processes and organizational structures are in place to anticipate and respond to compound threats, though such threats present unique challenges to incident prioritization and resource allocation. Participants claimed that their agency plans for the "worst case" scenarios, which can include compound threats, particularly for natural hazard events which may co-occur due to weather and climate patterns. For instance, one participant explained that "…the products that the National Hurricane Center produce in terms of [storm] surge are very much worst case scenarios, and we need to be ready for either [the lower limit or worst case scenario]" (Interview 18).

During compound threats, incident prioritization was expressed as being particularly critical, as compound threats present multi-objective decision spaces with multiple sources of risk. Table 4 shows the number of participants who described each objective as critical in incident prioritization. Nearly all participants (n = 30, 91%) discussed minimizing public health and safety risks most heavily (Table 4). Similarly, 23 participants discussed minimizing personnel health and safety risks. Participants claimed that protecting public and personnel health and safety for communities facing immediate, acute risks drove incident prioritization decisions. While most participants described that incident prioritization was based on fulfilling health and safety objectives, other objectives were described with more nuance, potentially complicating incident prioritization and resource allocation decisions. The interview findings that prioritizing public and personnel health and safety align with 2001 US Federal Wildland Fire Policy, which indicates that protecting public and personnel health and safety should be of highest priority (Dunn et al., 2017). Most participants described minimizing critical infrastructure damage and private property protection (n = 29, 88%) in relation to incident prioritization, whereas fewer discussed minimizing ecological (n = 14, 42%) or cultural/historical site (e.g., cemeteries) (n = 14, 42%) damages.

While protecting public and personnel life and safety is the primary objective across jurisdictions, weighing objectives can be complicated when alternatives do not necessarily pose immediate life and safety risks, but rather threaten infrastructure and/or ecological, cultural, or historical sites. Hazard response decision-makers often need to weigh the protection of these valuable assets, also known as 'values at risk' (Dunn et al., 2017). The decision to prioritize incidents and resource allocation based on values at risk was expressed as particularly challenging among fire personnel, as wildland fire suppression efforts can actively protect certain values at risk over others. This leads to social/political pressures (n = 14, 93%) and ecological considerations (n = 10, 67%) that influence multi-objective decision-making, both during the response and planning phases of the hazard cycle. For instance, one participant described that "…the political and social side of things also affects decision making…history is a big driver in how we make decisions" (Interview 8), particularly if wildfires affect the same community in back-to-back years, as communities may still be recovering from prior fires. Economic considerations were discussed by fewer fire personnel (n = 7, 47%) than other hazard personnel (n = 13, 72%), suggesting potential differences in fire agency participant's perception of economic cost minimization, despite the increasing emphasis on cost constraints in recent wildfire management policies due to increasing fire activity across the U.S. (Dunn et al., 2017).

Table 4. Count of participants who discussed each objective as influencing decisions related to compound threat incident prioritization and resource allocation across the full sample (n = 33), for fire personnel (n = 15), and for other hazard personnel (n = 18).

Objective	Participant count (% of total sample)	Fire personnel count (% of total fire personnel)	Other hazard personnel count (% of total other hazard personnel)
Minimize public health/safety risks	30 (91%)	14 (93%)	16 (89%)
Minimize personnel health/safety risks	23 (70%)	13 (87%)	10 (56%)
Minimize critical infrastructure damage	29 (88%)	14 (93%)	15 (83%)
Minimize private property damage	11 (33%)	7 (47%)	4 (22%)
Minimize ecological damages	14 (42%)	10 (67%)	4 (22%)
Minimize economic costs/losses	21 (64%)	8 (53%)	13 (72%)
Minimize cultural/historical site damage	14 (42%)	7 (47%)	7 (39%)
Minimize social/political contention	26 (79%)	14 (93%)	12 (67%)

While incident prioritization and resource allocation were described to be informed by preferences for objectives, these decisions were also informed by situational awareness of various constraint types (Table 5). Personnel constraints (n = 29, 88%) and social/political constraints (n = 29, 88%) were the most frequently discussed constraints across participants, and these constraints were shared by fire and other hazard personnel. Field equipment/technology constraints were discussed by 61% (n =20) of participants and emergent technology constraints were discussed by 33% (n = 11) of participants. The least frequently discussed constraints included timeliness of hazard management actions (i.e., response actions and decision-making constrained by the immediacy of the threat/hazard) (n = 18, 55%) and access to emerging technology constraints (n = 11, 33%).

Table 5. Count of participants who discussed each constraint as influencing compound threat incident prioritization and resource allocation across the full sample (n = 33), for fire personnel (n = 15), and for other hazard personnel (n = 18).

Constraint type	Participant count (% of total sample)	Fire personnel count (% of total fire personnel)	Other hazard personnel count (% of total other hazard personnel)
Personnel	29 (88%)	13 (87%)	16 (89%)
Social/political	29 (88%)	14 (93%)	15 (83%)
Coordination/communication	28 (85%)	14 (93%)	14 (78%)
Time	18 (55%)	6 (40%)	12 (67%)

Data collection, availability	21 (64%)	10 (67%)	11 (61%)
Field equipment, technology	20 (61%)	7 (47%)	13 (72%)
Emerging technology	11 (33%)	8 (53%)	3 (17%)

Figure 2 illustrates the relationship between objective and constraint codes via coded segment intersection rates. Intersecting coded segments (approximately 2-4 sentences of transcripts) indicate if and how frequently constraints were discussed in the context of pursing objectives in compound threats. Constraints were grouped into three types: (i) resource management, (ii) information and analysis, and (iii) coordination and communication constraints. Constraint groups were formed based on constraint coded segment intersections (See Appendices 2C) and considering the deductive hazard management processes outlined in the NIMS. According to Figure 2, the economic efficiency and communication objective-constraint pair revealed the highest code intersection rate (32% of economic efficiency codes intersected with communication constraint codes), suggesting that economic efficiency objectives are met with social and political constraints during compound threat management. Exemplifying how objectives and constraints intersect, one participant explained that during compounding fire incidents:

> *"There's public perception. [Our state partners and private land owners] want to see us doing something… to keep [a fire] from coming onto private land. But largely those efforts aren't effective, and they cost a lot of money. They put a number of firefighters at risk, maybe doing work that we know doesn't have a high probability of success" (Interview 8).*

Similarly, Figure 2 revealed that 24% of discussions on meeting social and political objectives (e.g., reducing inter-agency and/or multi-jurisdiction context; appeasing public concern) intersected with information and coordination constraints, such as time and/or information constraints. Overall, coded segment intersections suggest that coordination and communication constraints were discussed most frequently for in the context of all objectives other than personnel life and safety. Personnel life and safety objectives were mentioned in 124 coded segments, and 24% of these intersected with the resource constraint code, suggesting that personnel life and safety protection may be constrained by resource limitations. Accessibility of and constraints to unmanned aviation systems (UAS) were mentioned by participants in this context, such that UAS "are a game changer" for real-time data collection during incidents and hazard management situational awareness that can "…take some of the risk out… doesn't have to be four people in a small aircraft flying around with that potential for catastrophic failure and death… The challenge now is just capacity, right? There's very few of them. And everybody needs it. … eventually would want to have that capacity on every incident (Interview 21).

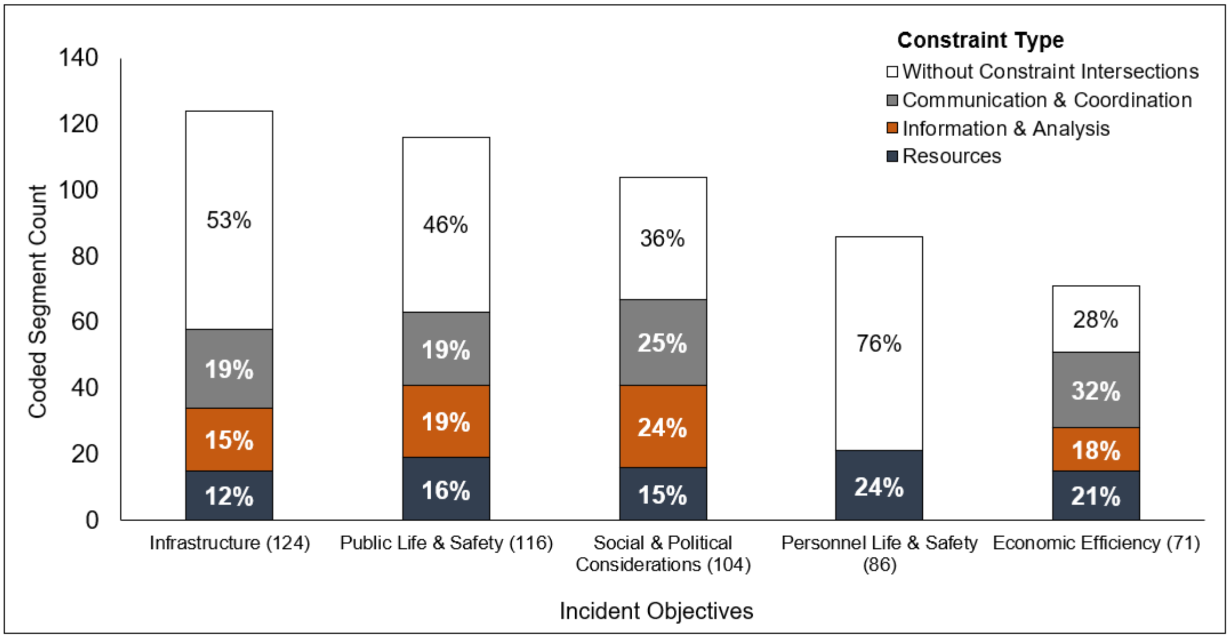


Figure 2. Coded segment intersections between coded segments for objectives and constraint codes within the absorptive capacity parent code. The numbers in parentheses indicate the total number of coded segments for each code, and the percentages along the links indicate the conditional probability that a constraint type intersected with each objective code.

3.2.1. Strategic planning and response strategy development for CTs via multi-objective decision-making processes.

Participants discussed knowledge transfer (n = 29, 88%), data collection and sharing (n = 33, 100%), and data analysis and decision support (n = 33, 100%) as critical operational processes for federal agency absorptive capacity when facing compound threats. These decision-making resources and processes were explained to facilitate informed decision-making regarding various objectives and constraints. Knowledge transfer was defined as "…communicating knowledge between both individuals and organizations across a range of domains and time scales (e.g., shift changes, best practices)" (DHS, 2010, pg. 3.14). Thus, knowledge transfer involves experiential knowledge, lessons learned, training, and intra- and inter-jurisdiction information sharing. Knowledge transfer was described as "…an art, it's a human factor, human piece" (Interview 21) that goes into strategic decision-making, such as resource allocation decisions. Qualitative knowledge transfer was described to occur within federal agencies and between jurisdictions; for instance, one participant described how "historic ground knowledge went into those [hazard response] discussions, and I think it really helped it. I think it would have been tougher if we didn't have the huge amount of local knowledge, historic knowledge there" (Interview 20).

Yet, given the complexity of compound threats, "Some people were very uncomfortable with making decisions, because basically, they were making life and death decisions… We have to be mindful of that, but we also have to give [decision-makers] the tools and techniques to make better informed decisions in… the 'fog of war'" (Interview 24). Accordingly, federal agency knowledge transfer was described to benefit from "…tying [analytics] to experiences" (Interview 15). The integration of experiential knowledge and analytics was supported by multiple participants (n = 10, 30%), who agreed that decision-making should balance between experiential "recognition-primed decision-making" (Interview 21) and data analytics. As discussed in judgement and decision-science literature, naturalistic decision making (NDM) implies that experts evaluate situations and make decisions based on experiential, tacit knowledge and intuition. Recognition-primed decision-making (RPD) is a form of naturalistic decision-making that posits expert decision-makers facing time constraints and uncertainty will assess how familiar a situation is and select a singular course of action that can then be modified, rather than evaluating the full set of potential alternatives and associated outcomes prior to or at the outset of an incident (Kahneman & Klein, 2009; Rapp et al., 2020). Currently, as decision-support tools that enable risk informed, multi-objective decision-making become more available, participants expressed a need to balance naturalistic RPD and data-driven decision-making. For instance, one participant claimed that:

> *"…you can't 100% rely on the model, and you can't 100% rely on the plan, because the plan is based on an assumption… have to be able to adapt based on what you see in the ground. And that's where the experience comes in. And not an over reliance on one thing or the other" (Interview 24).*

Regarding the current state of data-driven decision-making, participants primarily discussed two necessary components that facilitate compound threat response: (i) data collection (n = 22, 66%) and availability (n = 27, 82%), and (ii) data analytic capabilities (i.e., modeling, forecasting, decision support) (n = 29, 88%). Data collection technologies were described to have advanced in recent years via the adoption and use of remote sensing technologies including drones (n = 15, 45%), satellite imagery (n = 9, 27%), and infrared technologies (n = 10, 30%). Remote-sensing technologies were described to support real-time situational awareness during compound incidents, as well as during damage surveillance (n = 4, 12%) activities. Simultaneously, remote sensing technologies reduce personnel health and safety risk by offsetting the need to send personnel into potentially risky situations. Aviation assets (i.e., helicopters, large airtankers) were described by participants (n = 8, 24%) assisting in response activities, and some participants noted their increasing application in damage surveillance (n = 5, 15%).

Participants (n = 8, 24%) discussed how data collection and availability fuel multi-hazard risk assessments and forecasting monitor compound threat events. Modeling approaches that integrate the combined risk of multiple incidents and/or stressors have been posited to more accurately forecast multiplicative risks that arise from compound hazard incidents (De Angeli et al., 2022; Gill and Malamud, 2014; Marzocchi et al., 2012). As discussed by participants, multi-hazard risk assessment models inform hazard risk potential and inform incident prioritization, resource allocation, and response strategies. Generally, participants discussed how incidents are prioritized based on comparative risk assessments, wherein protecting public and personnel life and safety is the primary objective in this multi-objective decision space.

In addition to multi-hazard climatological models, participants discussed how decision-support tools have evolved such that federal agencies are now able to quickly forecast hazard occurrence, damage potential, and community vulnerabilities via integrated geospatial data. Modeling approaches facilitate incident prioritization and resource allocation decision-making and have evolved in a few key ways: (i) they have transitioned from deterministic to stochastic, accounting for uncertainty in risks (n = 3, 9%); (ii) they have incorporated multiple objectives, including social considerations (n = 16, 48%); (iii) they increasingly use real-time data if available (n = 7, 21%); and (iv) they increasingly account for changing environmental conditions (n = 3, 9%). Decision support tools assess the geotemporal probability of hazard occurrence and severity, and this information is paired with community damage and vulnerability projections (i.e., FEMA's National Risk Index for Natural Hazards). Moving beyond "simple risk" assessment (Essen et al., 2022), decision-support models are now equipped to integrate various data sources to assess and weigh risk based on multiple, predetermined objectives via "fair, equitable, and transparent processes" that are "…rigorous and defendable" (Interview 24). Examples of decision-support tools include the Wildland Fire Decision Support System (WFDSS) and the Hurricane Decision Support Tool (HURREVAC), both of which are intended for government hazard management (USGS, 2022; FEMA, 2022). Of note, one participant said "There are a lot of different decision making models and planning processes that we use, but there's not one that's stamped, saying you must do this. We have discretion in how we do that" (Interview 17).

In addition to modeling and decision-support tool use that has supported compound threat management, there are predetermined incident management structures for compound hazards (and/or otherwise complex incidents) as outlined in the NIMS ICS (see 1.1. Background section for more information). When compound threats occur across multiple jurisdictions (e.g., a natural hazard affects both federally- and state-owned land), participants (n = 3, 9%) indicated that Unified Area Command incident management protocols are engaged. Unified Area Command was discussed as reducing resource competition that might otherwise occur between jurisdictions during periods of resource constraints. As jurisdictions and teams are unified under this command structure, the competition for scarce resources was said to diminish as multiple jurisdictions work towards the same objectives in unison, reducing redundancy of effort and resource needs.

3.2.2. Federal agencies prioritize hazard response during COVID-19, while implementing socio-technical adaptations.

Despite efforts that federal agencies have taken to absorb CTs effectively and efficiently to maintain critical functioning and fulfill their mission objectives, novel risks presented by some CT events require adaptive decision-making and innovation. All participants were asked to describe how their agency absorbed and adapted to the compound threat of the COVID-19 pandemic during natural threats (e.g., wildfire or hurricane management given COVID-19 conditions). Almost all participants (n = 30, 91%) suggested that the COVID-19 pandemic influenced how their agency operated but did not necessarily change their mission objectives, duties of care, and incident prioritization processes. Though the primary objective to minimize health and safety risks was unchanged, many participants (n = 21, 64%) noted that operational changes occurred. Participants had mixed perceptions on the degree to which the COVID-19 pandemic influenced hazard management operations, ranging from minimal to extreme changes in operations and management. Though the pandemic introduced an environment with "no sense of normalcy" (Interview 7), some participants comment that "…the COVID environment has not changed the fact that we still have to show up in person when there's a disaster" (Interview 28). Relative to those involved in hazard preparation and mitigation, those involved in field deployments generally claimed fewer operational changes occurred because, relative to COVID-19 transmission, "…the bigger risk [for response units] is not being cohesive" (Interview 21), where cohesion has been defined as collective togetherness based on social relationships, trust, and orientation towards the common good and common goals (Schiefer and van der Noll, 2017).

The primary operational change during the COVID-19 pandemic was a transition to remote work (n = 28, 85%), which was viewed as a relatively comfortable transition for participants employed by the US DHS, who already had been developing remote work operations before the pandemic. Transitions to the remote work environment were perceived by some participants to increase coordination between federal, state, and local hazard management agencies as well as with the public (n = 11, 33%). Though fire suppression efforts required in-person deployments, participants representing federal agencies primarily involved in fire management described operational changes to minimize transmission risks within and between teams and the surrounding community (n = 12). These operational changes included fire crew re-organization into smaller, more contained units that were generally regarded as positive "learning opportunities" (Interview 15). For instance, fire agencies used smaller spike camps--defined as temporary or secondary camp sites for forestry crews (Haynes, 2019)--in lieu of larger base camps, where hundreds to thousands of crew members would sleep and eat during large wildland fire incidents. Additionally, fire agencies operated in "module of one" crew structures, defined as firefighting units that worked together the whole season with little to no personnel changes between crews (Symonds, 2021). Structural reorganizations were said to improve the health and quality of life of deployed personnel: "What came out of 2020 was really a COVID mitigation, and all the hot shots never want to go back. Because we've never been healthier [in terms of infectious disease transmission]… COVID made us leap forward with some of our practices." (Interview 15).

While effective in minimizing COVID transmission, remote work introduced operational constraints and challenges. Remote work was sufficient for intra-agency communication channels, but many hazard response operations were still required to be on site (i.e., for wildland fire suppression), with potential consequences for hazard response communication channels. Thus, fire personnel stated that remote work "…created more and more division… a whole combination of not only different perceptions, but different risk management" (Interview 25) approaches within agencies. Differing COVID risk management approaches challenged coordination structures and the ability to "…go work as a cohesive unit. How do we do that when we're not working together?" (Interview 25).

In addition to communication challenges, remote operations were not always conducive to typical hazard response procedures. Many participants (n = 17, 52%) observed "reductions in the workforce" (Interview 17), as contracted personnel were less available (n = 4, 12%), older or at-risk personnel felt the COVID-19 transmission risk was too high (n = 3, 9%), or because "their leadership kind of locked things down" (Interview 25).There were expressed difficulties in collaborative response efforts between response crews, as well as with volunteer community members. For wildland fire response in particular, participants noted that fire suppression strategies and tactics "…were less flexible" (Interview 8) such that inter-regional support was limited for fire regions facing resource scarcity.

The COVID-19 environment was posited to have presented "…a good opportunity to press our Chief Information Officer and Chief Technology Officer to bring us into current status with tools that are out there because we were forced to" (Interview 5). This participant, a DHS employee, continued by saying that the COVID environment "…was really the only moment in time where we sort of caught up" (Interview 5) in terms of adopting and using the latest available telecommunication technologies and data sharing platforms. Several participants reported that the pandemic was a window of opportunity for the adoption and use of emergent technologies such as drones and satellite imagery used in hazard preparation, response, and recovery. The pandemic may have catalyzed the rate of adoption of emerging "cloud based" (Interview 5) technologies across federal agencies based on perceived resource and information requirements to facilitate rapid decision making in complex threats. Further, participants discussed that federal agencies were increasingly attentive to data analytic applications in hazard management, leading to the recent establishment of data analytics units within FEMA's National Response Coordination Center (Interview 3). Data analytics are increasingly used by agencies such as FEMA to facilitate decision support for incident prioritization and resource allocation and were only recently stood up given "…an environment of scarcity during the pandemic" (Interview 3).

3.3. Federal agency adaptive capacity to manage compound threats (RQ3)

Table 6 summarizes the barriers to federal agency adaptive capacity in terms of the internal (i.e., within agency) and external (i.e., environmental and societal conditions; multi-jurisdiction and cross sectoral relationships) stressors (Lee et a., 2013; Kendra and Wachtendorf, 2003). Generally, participants expressed that "one of [federal agencies'] real challenges… is to be able to make decisions and to make change that allows us to actually adapt (Interview 21).

Table 6. Summary of the internal barriers and external stressors that participants mentioned as inhibiting the adaptive capacity of federal hazard management agencies in compound threats. The number in parentheses indicates the percent of total participants (*n* = 33) who mentioned each factor at least once.

	Internal barriers	**External stressors**
Resource management	Lack of access to field equipment (i.e., helicopters, large air tankers) (66%) Lack of access to emergent technologies (i.e., drones) (33%) Workforce quality of life (61%) Low workforce compensation (24%) Workforce attrition (i.e., aging workforce; reduction of applicants) (12%) Demobilization of resources (9%) Innovation and creativity (51%)	Technology acquisition (i.e., information security risks) (9%) Declining rates of volunteerism (9%) Longer hazard seasons (13%) Increasing cost of living (24%)
Information & analysis	Balancing experiential, recognition-primed and data-driven decision making (61%) Conflicting goals between leadership and modeling outcomes (16%) Inaccessibility of emergent data collection technologies (33%) Inaccessibility of models in remote locations/critical infrastructure disruption (9%) Lack of data and models focused on recovery prioritization (12%)	Changing climate conditions (18%) Limited data sharing between agencies; redundancy of efforts (39%) Model validation (i.e., comparison between outcomes and model predictions) (15%)
Communication & Coordination	Training (21%) Leadership *status quo* bias (48%) Resource competition (esp. within the Area Command ICS structure) (21%) Biased, exaggerated situational awareness reports (12%)	Lack of community trust (45%) Recurring hazards in communities (30%) Public risk perception (i.e., public prefers aerial attack for fire incidents, though strategy may be inefficient) (39%) Misalignment of inter-jurisdiction objectives (64%)

3.3.1. Barriers to adaptive capacity by workforce and emergent technology resource availability

Internal barriers. Table 6 summarizes the internal barriers to adaptive capacity related to resource availability and use. Participants discussed that both personnel and technology/equipment constraints influenced their agility and adaptive capacity. Specifically, barriers to innovation and creative problem solving were mentioned by 17 participants, and 58% of these deductive coded segments framed barriers to innovation and creativity as barriers to adaptive capacity. Federal agency personnel expressed that they "are behind the marketplace… We still have a long way to go to be as agile as we need to be in technology, whether it's communications, collaboration, file sharing… we're still a couple steps behind, which is a shame, but it's kind of the nature of the federal government" (Interview 5). This participant explained that federal government setbacks in adopting and using technology "have to do with security, verification, validation… there is a lot of area for improvement" (Interview 5). Another participant said that their federal agency "needs to eradicate the 'not-invented-here' syndrome" (Interview 24), referring to hesitancy to adopt and use science and modeling approaches developed by academia or the private sector.

Over half of the participants expressed interest in and/or use of the remote sensing technologies for real-time situational awareness and assessment. Yet, many participants noted that these emerging technologies are currently in the early stages of adoption across hazard response agencies and are considered a limited resource that hazard managers are "lucky" (Interview 25) to acquire. Frustration was expressed over the limited supply of these technologies, as other agencies do currently have adequate access to similar and more advanced remote sensing technologies (e.g., Department of Defense).

Another internal barrier to federal agency adaptive capacity was personnel workforce constraints. Twenty participants (61%) discussed that the working conditions and general treatment of federal hazard management personnel decrease personnel quality of life; this inductive finding was expressed more frequently among fire agency participants (n = 12, 80% of fire agency participants) relative to other hazard participants (n = 8, 44%). Diminished quality of life was attributed to the low wages for high-risk positions that often require being "…gone from their families for more than six months and living in awful conditions" (Interview 17). Federal agency personnel claimed that agencies have experienced increased attrition rates (n = 4, 12%) and decreased applicant rates, exacerbating the personnel scarcity problem and putting more pressure on current personnel. Participants expressed that the increased workload with minimal recovery time leads to "burning out a lot of people, you know, people are working a lot. There doesn't seem to be a lot of support from the agency with certain things" (Interview 22). Another participant explained:

> *"We have never built into our system, the ability to recover rest. It's been a system that is seasonal. What's worked in the past is, we ask folks to go really, really hard for a duration and that duration, you know, historically was 2-4 months. Now, that duration is 6-8 months. And then we turn around and ask them to do it again" (Interview 8).*

Personnel scarcity was cited as a limit to federal agency adaptive capacity during compound threats such that personnel scarcity adds pressure on the current workforce, who also face longer hazard seasons and increasingly complex threats. The relationship between strategic resource use and the external stressor of climate change was exemplified such that "the system for prioritization of resources… was built on the concept of overwhelming force. And the system is showing that it's really not adapting well... and really does not deal well with scarcity" (Interview 15) that was associated with increasing hazard severity and complexity. Adapting to the current natural and anthropogenic threat landscape may require shifts from prior approaches based on overwhelming force to more strategic, decision-making processes that consider longer-term objectives and constraints. Further, some participants expressed concern that the confluence of an aging workforce, increasing attrition rates, and decreasing application rates may have led to less experienced personnel—including those who received [partial] remote training during the COVID-19 pandemic—receiving promotions to management positions with insufficient training and ground experience.

Establishing recovery priorities was one of the least frequently discussed planning indicators across participants (n = 4, 12%), suggesting that some participating federal personnel may not be as apt to associate organizational resilience with participating in exercises or setting clear recovery priorities. Of total recovery priority coded segments, 70% were conveyed as organizational resilience inhibitors, or characteristics and practices of the agency that could be improved to become more resilient. Recovery priorities was defined as an agency-wide awareness and understanding of what priorities would be before, during, and after a compound threat, such that these priorities are clearly articulated by the agency and minimum operating requirements are maintained (Resilient Organisations, 2019; Lee et al. 2013).

In addition to resource availability, participants discussed the implications of resource allocation and use decisions such that the internal decision-making processes for resource allocation decisions limited agencies' ability to adapt to evolving compound threats. Most frequently, participants discussed how these constraints--which have been more apparent over the past 5 to 10 years--limited their agency's adaptive capacity. Participants expressed sentiments such as, "…working around staffing issues is always a concern, whether it's multiple events or even if it's just one" (Interview 13). Multiple participants (n = 3, 9%) discussed that the firefighting applicant pool dropped by 50 – 66% over the past two years, relative to past years. Participants attributed this to low compensation for high-risk jobs (n = 8, 24%), wherein "... we pay less than our local gas station for new employees, so there is competition for people to work" (Interview 25). In all, low compensation has exacerbated personnel scarcity while increasing demands on the current workforce. Further, agency adaptive capacity was said to be influenced by personnel constraints such that "Strategies have definitely changed how we're fighting fire… driven by lack of resources, increased fire behavior, increased fire growth… Over the past few years, we're told many times that we're just out of resources… so figure out a strategy with what you've got" (Interview 18). Thus, federal agency adaptive capacity is limited by personnel constraints that have become increasingly limited with increased hazard complexity by limiting the range of potential operational strategies and tactics.

Finally, mobilizing and demobilizing personnel and other resources during compound threat events was said to occur "more and more with the environment that we're working in and the increase of responses that we're making" (Interview18), alluding to climate change and other environmental stressors. Personnel safety concerns are further complicated by hazards that affect two or more different states, as each state is required to declare separate state-of-emergency declarations. One participant described how this requirement complicated hazard response in that "… you can't run just one operation to cover both states" (Interview 23). Natural hazards such as hurricanes with the potential to affect two or more states bifurcates response, which "…drains a little more of the resource capability that [FEMA has]" (Interview 23). Similarly, participants expressed difficulty in managing devolution and demobilization given "no notice type incidents" (Interview 5). This participant went on to say that federal agencies "need to be better than [current demobilization]. We need to be faster, we need to be automatic" (Interview 5), drawing on the time constraints associated with compounding threats and demobilizing deployed personnel and resources who may be vulnerable to secondary incidents. For instance, discussing how compound threats challenge personnel health and safety objectives when a secondary threat interferes with initial hazard response, one participant described that compound threats involve "... making sure that you're securing and protecting your staff… also trying to look forward, because now you realize… another event is happening. Can we get additional staff to start supporting the other event? They're going to be in a whole different part of the process… even if it's only a few days apart" (Interview 13).

External stressors. In addition to the internal barriers that limit federal agencies' adaptive capacity while facing compounding threats, external pressures limit resource availability and use. The decline in workforce availability was attributed to a variety of external stressors, including longer hazard seasons attributed to climate change (n = 6, 18%), an aging workforce and evolving generational values (n = 3, 9%), and increasing costs of living (n = 8, 24%). Participants noted that the hazard management workforce is inadequately compensated for the high risks faced by these personnel, particularly those that require field deployments. Economic stressors compounded by migration trends during the COVID-19 pandemic have led to situations such that "…people are moving away from population centers into rural areas, which is also driving up the cost of living… harder for an entry level firefighter to move [into a rural community]… There's no homes to buy or rent and it's become more difficult for people to live rurally now" (Interview 25). "Urban flight" to more rural areas during the COVID-19 pandemic has been empirically shown by cell phone mobility data, and was more prevalent for younger, wealthier, white populations with the ability to work remotely (Coven et al., 2022). Thus, particularly across the fire-prone western U.S. and hurricane- and flood-prone coastal U.S., there may be opportunities to reduce resource scarcity challenges if the federal workforce receives increased wages that enable personnel to live comfortably. Though interviews were conducted prior to the passing of the Biden-Harris Bipartisan Infrastructure Law in 2022 (Biden-Harris Administration, 2022), various participants (n = 5, 15%) discussed its potential to improve "work-life balance and mental health for people because it is taxing, you know? It's exhausting" (Interview 18). For instance, the Bipartisan Infrastructure Law requires that federal wildand firefighter salaries increase by either $20,000 per year or "50% of salary in specified geographic areas where it is difficult to recruit and retain the firefighting workforce (USDA, 2022)

In addition to the potential for reductions in the federal hazard management workforce, several participants (n = 3, 9%) noted declining rates of volunteerism over the course of their career. Declining rates of volunteerism were related to generational values and the ability and preference to donate money online rather than participate in in-person community volunteer efforts, which was exacerbated by COVID-19. Reductions in volunteerism were said to increase the pressure on the federal workforce such that outside support may be less bountiful or consistent now than in the past. Federal agencies, therefore, should acknowledge and account for reductions in volunteer support in developing compound threat response and recovery plans, especially in cases of infectious disease.

Related to technology acquisition and availability, participants expressed slow adoption of these technologies due to federal government bureaucratic processes, financial constraints, and information security risks that could threaten homeland security. One interviewee noted that there may be potential for hazard management agencies to acquire remote sensing data via contracts with other agencies who have access to such emergent technologies to alleviate current technology constraints following a hazard. More recently, the U.S. Senate has introduced the bipartisan Drone Infrastructure Inspection Grant (DIIG) Act, which aims to increase local, state, and federal access and training for infrastructural inspections and damage assessments via drone technology. The passage of this or similar grants can enable hazard management agencies from the local to federal levels to deploy drones for real-time data acquisition that can protect community and workforce health and safety, improving upon resource constraints mentioned by participants.

3.3.2. Barriers to adaptive capacity related to the adoption of modeling tools, and model validation

Internal barriers. As discussed in the "Absorptive Capacity" section, advances in quantitative decision-support tools have been effective in weighing if and how agencies should respond to compound threats based on values and communities at risk. Despite data analytics advancements, the "…cultural practice is experiential" (Interview 15). Some participants (n = 16, 48%) expressed a "success bias" (Interview 27) related preferring *status quo* approaches based on experiential decision-making. Participants described how those in leadership positions were "…still dependent on their experiential models in their head. And they just kind of culturally resist some of this stuff. But people are catching on to it pretty fast" (Interview 15). Participants (n = 5, 33%) discussed how decision-support tool incident prioritization and resource allocation optimization did not align with goals set forth by those in leadership positions, who are among the select few federal agency personnel who ultimately select the response objectives and priorities in compound threat risk management (FEMA, 2022). Reluctance to use decision-support and modeling outcomes was associated with ineffective and inefficient allocation of hazard response resources (Interview 15). Resource allocation inefficiencies may be particularly prevalent in uncertain, complex threats, as biases based on experience and existing knowledge can detract from optimal, resilient outcomes in light of unexpected event (Hariri-Ardebelli et al., 2020). Participants, particularly those representing fire agencies, expressed that those who were more reluctant to use emerging decision-support tools generally had more field experience (Interview 5), and therefore may be inclined to rely on "recognition primed decision-making" (Interview 27).

Participants claimed that reliance on RPD and reluctance to use decision-support and modeling tools was due to model uncertainty (n = 6, 21%), mistrust in model outcomes (n = 4, 12%), prior experiences with inaccurate model predictions (n = 3, 9%), and fundamental communication chain constraints that require officers to make decisions in the field under time and data availability constraints. One participant felt that *status quo* bias among leadership led to "…always trying to use that particular tool" (Interview 7). This participant went on to suggest, "... the way around [*status quo* bias] is to broaden understanding of various different tools and techniques… broaden the decision-making processes for... more of a consensus to [objective] decisions" (Interview 7).

Yet, given the complexity of compound threats, "Some people were very uncomfortable with making decisions, because basically, they were making life and death decisions… We have to be mindful of that, but we also have to give [decision-makers] the tools and techniques to make better informed decisions in… the 'fog of war'" (Interview 24). Accordingly, federal agency knowledge transfer was described to benefit from "…tying [analytics] to experiences" (Interview 15). The integration of experiential knowledge and analytics was supported by many participants (n = 20, 61%), who agreed that decision-making should balance between experiential "recognition-primed decision-making" (Interview 21) and data analytics. For instance, one participant claimed that "…you can't 100% rely on the model, and you can't 100% rely on the plan because the plan is based on an assumption… have to be able to adapt based on what you see in the ground… that's where the experience comes in" (Interview 24). For instance, another participant described "... a reliance on technology… makes us lazy in other areas that we need skills" (Interview 20). This participant described that "We have a lot of young guys that don't know how to use a map and compass" (Interview 20), which is sometimes necessary for fire suppression activities in austere environments. For instance, some noted that data-driven decision-making may be hindered by technical constraints, such as lack of internet or cell phone reception, which constrains data-driven decision-making; in these situations, personnel must make rapid, on-the-ground decisions based on field experience and knowledge.

External stressors. For both expertise- and modeling-driven decision-making, there was an expressed concern about the inability of mental models and technical modeling approaches to capture and forecast threats in the current natural and anthropogenic environments due to climate change and the interconnectivity of critical infrastructure systems. One participant described that "complexity in fire behavior and how frequently you have large growth days… really doesn't match your mental model anymore" (Interview 15). Thus, there is a need to incorporate changing environmental conditions and anthropogenic sources of cascading risk into incident prioritization decision making to proactively mitigate hazard complexity. Further, the changing climate and its atmospheric interactions have led to underestimations of model predictions of hazard frequency and severity; fire behavior modelers, for instance, are finding that "models aren't accurate anymore… wasn't true 10 years ago, and now it is. So, they're having to scramble and figure out something new to explain the phenomena" (Interview 15) associated with changing climates and fuel moisture, such as the "long-term drought" (Interview 15) in the western U.S.

Participants expressed current challenges in data sharing and model validation. Some participants expressed that data availability and transfer within and between government agencies of all levels could help support overall hazard management (n = 13, 39%). One participant said that "It's hard to get federal agencies to work together and figure out protocols for data transfer and, and there's always a security element to it" (Interview 11). There may be redundancy of data collection efforts, and some participants suggested that data collection efforts should be more widely available between agencies, jurisdictions, and the public to promote efficiency and transparency. Over time, this could help consolidate data for improved information dissemination. Further, five participants (15%) expressed that model validation is a useful but often neglected approach to understand if and how changing environmental and societal conditions as well as preparation, response, and mitigation actions promote recovery. Real-time data acquisition on damages accrued would help validate if and how model predictions differ from actual damage. This notion is supported by the IPCC (2022), who advocate for tracking adaptation progress over time given monitoring using continuous information gathering. Some participants noted that model validation in terms of damages incurred cannot currently rely on FEMA assistance or insurance claims given both over- and under-reporting of hazard-related damages to private property. For instance, one participant described how some affected community members are concerned with seeking or receiving federal financial assistance. One U.S. DHS participant described this in the context of the flood zone, where programmatic requirements dictate that during flood events, if your home is damaged and the damage is valued at 50% or greater of your home value, homeowners are required to mitigate for inspection. However, this participant described that inspectors, accordingly, will "…say the damage is valued at 47% the home value… not helping communities, and this is a common problem across the U.S. If [homeowners] don't have the resources… [homes] will essentially fall apart… Not really helping the community, but can buy them time" (Interview 26). This participant, along with three others, described that these communities tend to be smaller with fewer personal and local financial resources; they also tend to rely on coastal economies (e.g., fisheries) for employment, and have deep seeded historical and cultural ties to the coastal community in which they reside, such as owning "…homes passed from generation to generation" (Interview 26). Public concerns over reporting damage—while warranted—challenge the ability to validate the severity and extent of natural hazards, highlighting the intersection between policy, public perception, and model validation.

3.3.3. Barriers to adaptive capacity related to coordination and communication

Many participants described that coordination and communication constraints have influenced federal agency adaptive capacity. Coordination constraints were associated with internal coordination processes, as well as misalignment between cross-sectoral and multi-jurisdiction preferences in multi-objective decision spaces and capabilities, capacity, and coordination structures.

Internal barriers. Most participants (n = 28, 85%) discussed that federal agency adaptive capacity was constrained by internal coordination/communication structures and processes. Coordination constraints included lack of transparent priority setting within and between federal agencies (n = 11, 33%), inefficiencies and competition in resource allocation (n = 7, 21%), and knowledge transfer between response teams (n = 13, 39%). As discussed in prior absorptive capacity themes, critical and scarce resources are not necessarily allocated based on objective decision-support tool outcomes. Resource allocation inefficiencies have been described as "a huge problem" (Interview 11) attributed to financial incentives, such that "…agency administrators are trying to use [Congressional funding] in areas where there's more timber that is easier to extract from the land, or where there's acres that are easier to treat" (Interview 11).

Considering organizational structures, while some participants felt the Unified Area Command ICS structure reduced resource competition through unifying hazard response across jurisdictions, others claimed that the ICS enabled resource competition via the "Area Command" structure (n = 4). The Area Command ICS structure is enacted when an organization oversees and manages multiple incidents, a very large incident, or an evolving incident with multiple Incident Management Teams (IMTs) involved (FEMA, 2018). In these threats, IMTs usually have "similar needs", such that "they're all going to be competing for the same scarce resources" (Interview 30). Multi-Agency Coordination Systems (MACS) were described to "make the prioritization" and resource allocation decisions amidst incidents with similar needs, some of which "have life and death, huge property losses attached" (Interview 30). Another participant described that MACS have "differences of opinion on where [resources] should go… used to use word of mouth to make determination. Now, analytics can help with that, but that's where resistance comes in" (Interview 15).

Further, in describing the ICS resource request process, one participant noted a bias such that when requesting resources, "the best writer wins… those of us that can write well and explain what's at risk, and professionally exaggerate what's at risk… bias the agency administrators" (Interview 27). This bias has led to a system that allocates resources based on inaccurate knowledge transfer and situational awareness that has propagated throughout incident management systems. One participant remarked that

“You say it's lifesaving because you want to get to a higher priority, but if everything's lifesaving, nothing is lifesaving" (Interview 33). In addition to exaggerating risks to acquire resources, social connections can bias decision-makers to inefficient resource allocation. For instance, one participant said:

> *“…if somebody has a lot of experience and knows a lot of people, they’re going to get a lot of research advisors to their fire than another fire that may be much bigger, be more complicated and have more resource issues. If that lead doesn't know anybody and doesn't know how to work the system, they don't get very many people” (Interview 12).*

Social network connections were described to influence the allocation of scarce, specialized resources (e.g., search and rescue, hazardous waste management teams, research advisors, and ecologists). In addition to hazard response resource allocation, another participant mentioned that there are inefficiencies in administering grant programs across regions, as grants have been divided in ways that “were equal, but not… equitable” (Interview 31). As different regions and states have different economic resource needs, “…money isn’t going far enough” (Interview 31) when financial grant dispersal is based on equality rather than equity. For instance, this participant went on to explain that certain regions can use federal support to “…buy new office chairs every year… You tell them, hey, we're going to start reallocating equitably, and you are messing with people's money. You are messing with their staffing and… their livelihoods. They're going to bite you" (Interview 31). This participant described that “The squeaky wheel can [get resources], depending on who can call the governor… naive or in denial if you think that doesn't happen… watching affluent communities get resources in a manner that is disproportionate was tragic” (Interview 31). Additionally, inequities in financial support were described to be prevalent for rural areas (n = 3, 9%), which was attributed to generally more remote locations with fewer resources available than in urban areas.

External stressors. Land and hazard management was described as “a patchwork of ownership like federal, state and private” (Interview 11), wherein different government jurisdictions have “different personalities” (Interview 21). Local, state, and federal jurisdictions—which could each be affected by the same compound threat—were said to have “…misalignment…variation in mission and focus between state, local, and the federal agencies that has created a lot of stress on incidents and a lot of stress between them” (Interview 17). Personnel scarcity creates resource competition within and between federal agencies and state agencies. To overcome coordination barriers, participants described three key ways in which federal agency adaptive capacity could be bolstered through increased and diversified stakeholder engagement: (i) with local and state jurisdictions (n = 15, 47%), (ii) with community members (n = 13, 41%), and (ii) through the expansion of private-public partnerships (n = 6, 19%).

In multi-risk, multi-objective decision spaces, decision-makers often need to weigh the protection of these valuable assets, also known as ‘values at risk’ (Calkin et al., 2021). The decision to prioritize incidents and resource allocation based on values at risk was found to be particularly challenging for firefighting agencies, as wildland fire suppression efforts can better protect certain values at risk over others. Conflicting priorities entail social, political, and economic pressures that influence compound threat incident prioritization and resource allocation decisions during all phases of the hazard management cycle. To overcome multi-jurisdiction conflicts, several participants stressed “…the importance of interagency coordination and collaboration with stakeholders when responding to compounding threats, and if you're able to have that smooth coordination… makes it much easier to respond to these multiple, compounding threats” (Interview 14). Participants stressed that having “…all the federal agencies on the same page with that same [affected] community, with their state partners, singing the same song” (Interview 26) is essential to facilitating efficient decision-making and streamlining compound threat management. Participants described “a huge potential area for improvement with coordinating between federal land management agencies and state management agencies" (Interview 11) such that “there’s an absolute need for both robust government response at all levels and a robust volunteer response at all levels” (Interview 28). For instance, one participant who formerly worked for the American Red Cross claimed, “It's a people challenge. It's bridging the federal philosophy with the [NGO] philosophy. It's a resource issue on, you know, who pays for what? It is a control issue" (Interview 28).

Establishing volunteer and community-level engagement was expressed as a way to increase awareness of and sensitivity to local needs, preferences, and values. While establishing such connections "…takes some work… [as] all the programs have different timing, have different requirements…" (Interview 26), localized coordination facilitates situational awareness, information and knowledge dissemination, and has the potential to integrate local objective preferences and reduce resource competition and/or redundancy of hazard management efforts (Interview 26). For instance, one participant described that their federal unit "…sought out a specific fire behavior analyst that used to be a fuels person in that area. She knew the terrain and the topography and the weather influences there… sought her out to do multiple fire behavior analyses… having all that local knowledge and experience really helped weigh that decision" (Interview 20). Generally, participants expressed that federal agencies are increasingly aware of and pursue local and tribal knowledge, having established programs such as the Silver Jackets, who leverage local knowledge into flood risk management assessments, and federal ICS Liaison positions to support "the state and local agencies in collaborating with us because, realistically, they are the ones that know the community the best" (Interview 14). Thus, the general consensus across participants who discussed external coordination was that "the better relationships that we have been able to develop and maintain, have made for a lot easier time, even with the COVID stuff… the better relationships that you have with [local and state] cooperators, or even between agencies, it just makes for a better outcome… regardless of what happens on the other side, on so many different levels" (Interview 20).

In addition to federal-state agency coordination, participants acknowledged that the "federal community has to leverage the state and locals to help… bridge the gap to the community, and in order to be able to effectively communicate" (Interview 14). Expressed contention between federal agencies and affected communities was attributed to: (i) federal lack of transparency, (ii) differing preferences for response and recovery decisions between communities and agencies, and (iii) general lack of trust of federal agencies. The relationship between federal agencies and communities was expressed to be a needed focus area for federal hazard management, as "local communities are threatened by federal presence… they get defensive, they don't want to be told what to do" (Interview 23) and "hiding things behind the curtain does not win anybody any favors" (Interview 16). As hazards, such as wildland fires, were described to "evoke an emotional response" (Interview 25), it is "really crucial that we can… communicate risks appropriately" (Interview 14), as well as corresponding objectives and management strategies to the public. Similarly, one USDA participant expressed that "…the agency is struggling to be relevant within the communities. You know, we've lost that tide of the community… [affected communities] may not like a team… that was there making decisions about certain things. I think the agencies struggle with that overall" (Interview 22).

In addition to engaging with local and community level organizations, several participants suggested that continued development of public-private partnerships can establish a holistic, community-based approach to hazard resilience, though there is currently "misalignment… that is pretty prevalent" (Interview 17). For instance, one interviewee noted that Walgreens provides prescription drugs to community members affected by a natural hazard for 30 days after the hazard, which supports community recovery and eases public health concerns that federal, state, or local governments may otherwise face.[14] Conversely, some participants discussed how public-private partnerships have negatively affected hazard management; for instance, the "fire industrial complex" (Interview 21) was attributed to the investment in heavy equipment (i.e., large air tankers, dozers) for fire suppression tactics, pushing the notion that across the U.S., fires have been "villainized" (Interview 21) and some of which consistently lead to aggressive suppression strategies with adverse, long-term ecological consequences.

[14] https://www.walgreens.com/images/adaptive/pharmacy/healthcenter/b2b/pdfs/377-Walgreens_DisasterPreparedness_WhitePaper_012921_AccessFixed.pdf

3.4. Understanding federal agency opportunities through comprehensive perspectives on organizational resilience

Figure 3 shows the total number of participants who discussed each Relative Overall Resilience (Lee et al., 2013) and each inductive resilience indicator (values in parentheses). Within the "planning" component of organizational resilience, "maintaining a proactive posture" (n = 21, 64%) and "planning strategies" (n = 16, 48%) were discussed by the most participants, and in the "adaptive capacity" component, "staff engagement" (n= 20, 61%) and "leadership" (n = 20, 61%) were discussed by most participants. "Internal resources" (n = 22) and "leveraging knowledge and information" (n = 19, 58%) were the most frequently discussed "relationships" components. Additionally, inductive resilience indicators emerged; inductive indicators included workforce quality of life (n =20, 61%), mental health (n = 16, 48%), social cohesion (n = 8, 24%), and flexibility (n = 8, 24%). The percentages in the bar chart reflect the total percentage of coded segments that were discussed as a facilitator (dotted bars) or inhibitor (solid bars) to organizational resilience.

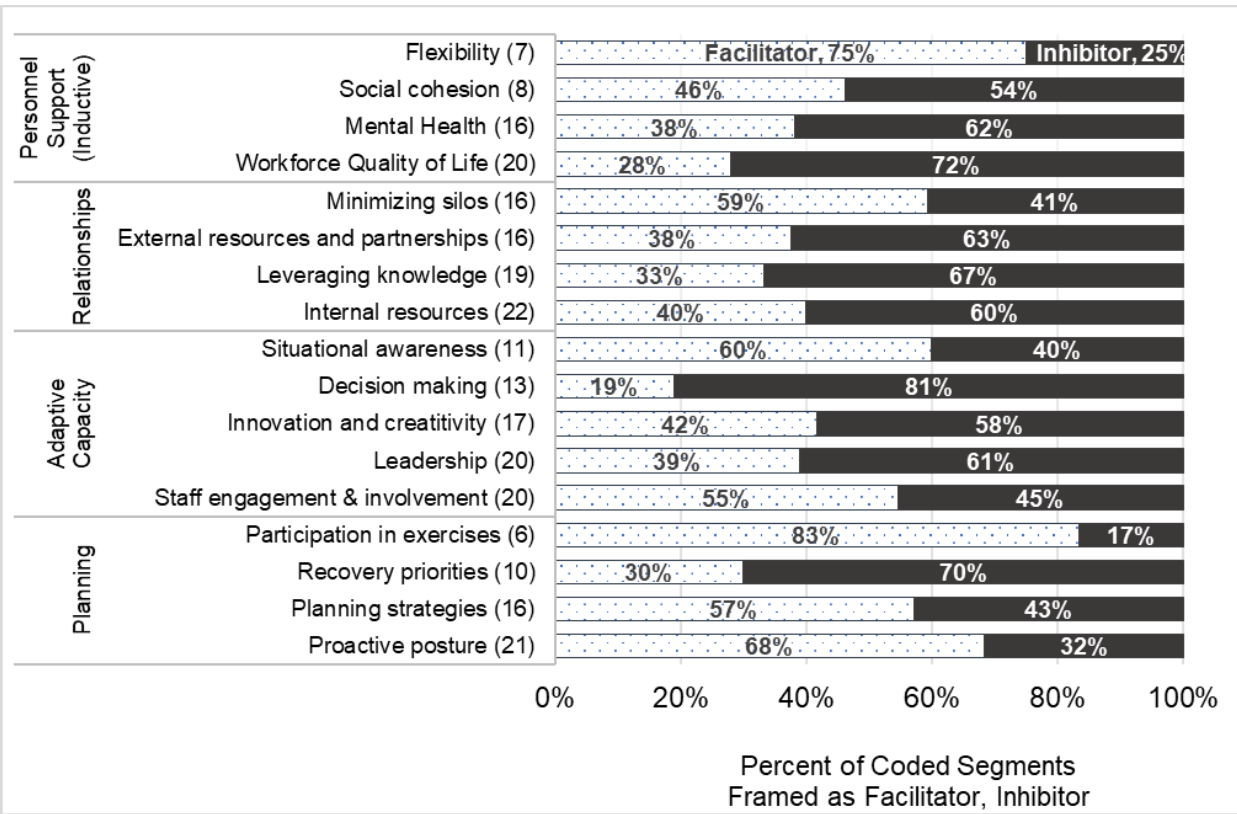


Figure 3. Mentions of organizational resilience indicators across interviews. The organizational resilience factors were based on a deductive coding scheme including existent indicators (Lee et al., 2013; McManus et al., 2008). The value in parentheses represents the number of times each indicator was discussed across the full set of interviews. The percentages represent the percent of coded segments for which participants expressed the indicator facilitated (dotted bars) or inhibited (solid bars) organizational resilience.

3.4.1. Organizational resilience exemplified through planning strategies, proactive postures, inclusivity, and flexibility.

While the preceding themes of this work pertain to many of the adaptive capacity indicators defined by the ROR, planning component indicators were also mentioned in interviews. Participants most frequently discussed the proactive posture (n = 21, 64%) and planning strategy (n = 16, 48%) indicators

(Figure 3). Both indicators involve preparation and foresight of future conditions and actions and to address vulnerabilities in the antecedent context (Lee et al., 2013). Of the planning strategy coded segments, 57% of segments were coded as facilitating overall organizational resilience. One participant employed by a fire management agency reported planning strategies are developed "every single day based on what we're doing. Does it work? No? How do we adjust it? … fire organizations as a whole are incredibly good at adapting to changing environments and changing conditions" (Interview 18). Planning strategies were described as critical to organizational resilience because if plans of action are not addressed and understood by the workforce in advance of a threat or hazard, "It's distracting your attention from actually dealing with the incident and saving lives" (Interview 3). Of the proactive posture coded segments, 68% of segments were coded as facilitating overall organizational resilience by enabling "…strategic and behavioral readiness to respond to early warning signals of an organization's internal and external environment before they escalate into crisis" (Lee et al., 2013). Proactive postures were described to be particularly critical when personnel had not experienced a hazard type in recent history; for instance, one personnel described that proactively having "communication channels open" (Interview 13) between divisions, jurisdictions, and personnel who are more experienced with certain hazard types is essential to strategic decision-making. Yet, it is worth noting that some participants felt that their agency took on a more reactive stance, particularly in terms of technology adoption. Taken together, federal agency personnel had generally positive outlooks on the development of planning strategies and proactive postures, suggesting that federal agencies have implemented effective planning protocols and practices that have facilitated organizational resilience, indicating a paradigm shift from reactivity to proactivity.

3.4.2. Organizational resilience could be improved by individual-level support

Though we were primarily interested in federal agency perspectives of compound threat management and organizational resilience at the agency-level, many participants defined and discussed organizational resilience as it related to individual-level personnel resilience. Inductive themes pertaining to individual-level mental health, workforce treatment (i.e., wages, work-life balance, deployments), and inter-personal workforce social cohesion emerged across interviews: "[resilience is] really how well we take care of ourselves, and how well we take care of each other" (Interview 9). Another participant explained that they thought of resilience "more like human capital type things… less about strategies and mitigation options to ensure that we can manage our risks… there is a space for these different flavors of resilience to coordinate, coexist, overlap… I don't think anybody is there yet" (Interview 32).

Mentions of mental health were included as inductive codes, and workforce mental health was perceived to be negatively associated with organizational resilience such that 62% of mental health coded segments were discussed as an agency weakness or opportunity for improvement. Participants discuss that workplace pressure leads to "…what [they] perceive to be a high divorce, suicide, depression rate" (Interview 17), as well as fatigue, burn out[15], and other mental health concerns such as substance abuse, PTSD, and anxiety. Personnel mental health support following an incident was related to agency recovery priorities; participants claimed that increased focus on individual-level mental health support and recovery should be considered a recovery priority set forth by hazard management agencies. Participants described that organizations will only be resilient if the individuals that comprise the organization are resilient, which they directly related to mental health concerns.

Though federal agencies are increasingly aware of the toll of hazard management on mental health due to repeated exposure to traumatic events, participants and existing empirical literature have found that workforce mental health is inadequately addressed across federal hazard response agencies, leading to fatigue and attrition (Belval et al., 2018).[16] Mental health was frequently embedded in

[15] Burnout is defined as "a syndrome conceptualized as resulting from chronic workplace stress that has not been successfully managed." (World Health Organization, 2020).

[16] Belval, E. J., Calkin, D. E., Wei, Y., Stonesifer, C. S., Thompson, M. P., & Masarie, A. (2018). Examining dispatching practices for Interagency Hotshot Crews to reduce seasonal travel distance and manage fatigue. *International journal of wildland fire*, *27*(9), 569-580.

conversations of personnel shortages, leading the current hazard workforce to work long hours over back-to-back deployments, aligning with anecdotal perspectives brought to light in recent years (Rott, 2021).[17] ICS Incident Management Team personnel are deployed to an incident and then resume work at their typical day job with minimal financial incentive; for instance, USFS Forest Managers may be deployed for 2-3 weeks as an Incident Commander or Operations Section Chief on an IMT, then must return to the USFS Forest Manager duties post-deployment, which stresses the workforce as "… being on an Incident Management Team is not anybody's primary job…. It puts a lot of strain on their home life because somebody else has to carry the load for them while they're gone. If nobody's taking over for their regular job, then when they come back, their workload is just crazy" (Interview 18). Additionally, participants discussed that while federal agencies are apt to invest in heavy equipment such as helicopters, there is a lack of investment in training opportunities for firefighters interested in incident command, operations, and logistics.

In addition to workforce mental health, social cohesion emerged as an inductive code that was mentioned by 8 (24%) participants. Social cohesion was defined by participants as "…the idea of synergy…" (Interview 21) between federal agency personnel during hazard management, and participants said that resilience often comes down to:

> *"How are we taking care of our personnel and ourselves, there's really a bottom line. And there's no science to that. There really isn't a model for that there's really a tool for that. It's really the ability to mentally focus on each other, and then understand the differences that we all bring to the table when something happens that's so far out of what we expected" (Interview 9).*

Participants had mixed views on if and how federal agencies currently promote social cohesion, as 54% of related coded segments portrayed that lack of social cohesion can inhibit organizational resilience. Social cohesion was described as being difficult for IMTs, such that these teams "…don't have existing [interpersonal] relationships. You don't have trust, or you have to build it… it's really hard in a 14-day period to build synergy where you're greater than the sum of the parts, right?" (Interview 21). Other participants felt their agency's "training and exercise requirements facilitate resilience… place us in positions to execute on what we will be asked to execute upon in the real world, and the act of doing things together builds camaraderie" (Interview 7). This participant explained that camaraderie is "really important, because my resilience may be at a different level than your resilience" (Interview 7). Thus, social cohesion may bolster individual resilience such that social cohesion has been association with decreases in individual-level mental health disorders (Zemba et al., 2019; Wood et al., 2017; Breslau et al., 2016). Considering compound threats, some participants claimed that personnel were encouraged and inspired to "… jump on any anything that comes up, we help each other to support each other… and we get the work done, no matter what it is [headquarters] throw at us" (Interview 10). For instance, FEMA had little to no historical involvement with infectious disease management and support, but were assigned to be critical stakeholders in COVID-19 testing, treatment, and vaccination efforts (Interview 2). Participants felt that cohesion and defining a common goal helped orient and engage agency personnel, particularly those deployed on IMTs: "I think about an IMT. What makes it successful? I would say, common mission, common objectives… it's also their values and importance in the work we're doing. That's one of the real strengths of wildland firefighting and being part of the organization is that you are part of something bigger than yourself, right?" (Interview 21).

Related to cohesion, the deductive organizational resilience indicator "minimization of silos" was described as facilitating federal agency organizational resilience. Minimizing silos involves the breaking down of "divisive social, cultural, and behavioral barriers, which are most often manifested as communication barriers creating disjointed, disconnected, and detrimental ways of working" (Lee et al., 2013). Multiple participants (n = 5, 33%) described their agency as inclusive and diverse, offering "an integration of different viewpoints into how we attack problems" (Interview 7). Participants expressed

[17] Rott, N. (2021). As fires worsen, a mental health crisis for those battling them. *Capitol Public Radio*.

that a sense of inclusivity was necessary for organizational resilience, such that team members felt comfortable sharing their knowledge and ideas with each other (i.e., horizontal information dissemination) and with leadership (i.e., vertical information dissemination). Further, participants explained that "building that respect, and that trust" prevents "pointing fingers at each other… We are all responsible… let's learn from it, get better, and move forward" (Interview 21). Several participants expressed that divisions and units within their agency were becoming increasingly collaborative and "changing back to where everyone's helping each other do different things… if we work more as a team, all together, not just in fire, but the whole organization, and there will be more resilient and be able to tackle bigger issues" (Interview 25).

3.5. Limitations

The current interview findings should be considered exploratory given the sample size (n = 33) and unit of analysis (i.e., federal hazard management agencies). While current insights and participant perceptions of federal compound threat management tend to align with existing empirical, theoretical, and policy-oriented work, this set of exploratory findings may not apply to all federal agencies and/or units. Results may vary by agency and according to the geographic vulnerabilities that participants have been exposed to. While the federal resources are often shared and while the NIMS and similar hazard management frameworks are designed to be generalizable and scalable to different threat types and geographies, findings from the interview-based study may not portray all federal personnel experiences with compound threat management.

4. Conclusion

Understanding and identifying barriers to federal agency resilience and management of compound threats is critical, as compound threat events are projected to increase in frequency, severity, and complexity over longer-duration natural hazard seasons (De Angeli et al., 2022; Ridder et al., 2022; Zscheischler et al., 2018; Cutter, 2018). Compound threats may complicate how federal hazard management agencies prioritize co-occurring incidents, which may share competing resources (Phillips et al., 2020). Using qualitative data based on semi-structured interviews with federal hazard management personnel, federal agencies were found to face internal resource constraints primarily attributed to workforce scarcity and external stressors associated with community and local government coordination. Resource constraints were associated with: (i) increasing duration of natural hazard seasons that limited off-season recovery for the workforce, (ii) fatigue, burnout and other mental health concerns, (iii) increasing costs of living across much of the United States at the time of the interviews, and (iv) potential reductions in on-site volunteer efforts. Coordination between federal hazard agencies and local governments and vulnerable communities also constrained federal adaptive capacity to compound threats such that local and federal preferences for incident prioritization, objectives, and resource allocation may diverge and complicate the multi-objective, multi-threat decision space. Considering that adaptive capacity is a core component of organizational resilience, results suggest that federal agency hazard management and organizational resilience would benefit from increased focus on community involvement and on prioritizing mental health of the workforce.

Chapter 3: Are Compound Threats Associated with Changes in Resource Use? An Assessment of Wildland Fires Suppression Resources given the COVID-19 Pandemic

1. Introduction

The severe 2020 and 2021 wildfire seasons in the US were further complicated by the compounding threat of the COVID-19 pandemic. From 2020 through 2021, there were approximately 55 million reported cases of COVID-19, responsible for nearly 825,000 deaths in the US (US CDC, 2022). Concurrently, there were nearly 59,000 wildfires in both 2020 and in 2021, burning over 10 million acres in 2020 and 7 million acres in 2021 across the US (NIFC, 2021). Fire frequency, duration, severity, and spread have increased across the US since 2000 with an estimated eight-fold increase of high-severity fire between 1985 and 2017 (Westerling, 2016; Singleton et al., 2019; Mueller et al., 2020; Abatzoglou and Williams, 2016; Schultz et al., 2021). Increasingly intense fire seasons strain local, state, and federal firefighting critical workforces. Wildland firefighters work increasingly long fire seasons, facing a variety of physical and mental risks including smoke inhalation, post-traumatic stress disorder (PTSD), depression, anxiety, and fatigue (Groot et al., 2019; Koopmans et al., 2022). Additionally, wildfire smoke inhalation has been associated with amplified COVID-19 health outcomes due to added strain on the respiratory system (Henderson, 2020). The risk of infected personnel coincides with community transmission and supply chain constraints, wherein supply chain constraints challenged the deployment of critical firefighting resources to fire lines. Thus, the compounding threat of wildland fires and COVID-19 has challenged fire agencies and responding organizations, whose primary objective to is protect vulnerable communities. As such, it is necessary to examine if and how wildland fire suppression strategies may have been constrained or otherwise changed under the compounding risk of COVID-19.

Infectious disease transmission, including but not limited to COVID-19, can propagate within and between fire crews and other personnel, particularly across wildland fire camps (Belval et al., 2022; Thompson et al., 2020). Fire camps are sites where hundreds to thousands of dispatched firefighters from across the country are based while they respond to fire incidents and where fire crews are provided with food, water, shelter, and sanitary services (Thompson et al., 2020). "Camp crud" is a contagious annual respiratory illness often transmitted at fire camps (Wildland Fire Lessons Learned, 2020), exemplifying how fire camps may be "ideal settings" for COVID-19 transmission (Thompson et al. 2020, pg. 1). Historically, noroviruses have spread through fire camps, such as during the 2011 Idaho Black Canyon Fire response when approximately 27% of responders contracted the norovirus (Britton et al., 2014). Studies of COVID-19 transmission within the firefighting workforce have revealed that incidence rates of COVID-19 were higher for the firefighting workforce relative to surrounding communities (Newberry et al., 2021), and COVID-19 transmission within fire crews has persisted through 2022 (Schmid, 2022).

Viral outbreaks at fire camps threaten workforce health and safety and constrain critical scarce resources (Belval et al., 2022). Fire agencies approached the 2020 fire season with limited knowledge of best wildfire management practices given pandemic conditions (Thompson et al., 2020), where the projected fire season severity was met with the potential for disease transmission for fire crews and fire prone communities alike. An international survey analysis (including 40% U.S. participants) conducted by Stoof et al. (2020) showed that fire managers and firefighting personnel perceived increased risk and concern regarding COVID-19's impact on organizational operations, management, and performance such that 63% of study participants were moderately to very worried about COVID-19's impact on the operations of their respective fire agency. Additionally, fire agencies also faced limitations in terms of contracted fire crews and volunteer personnel that typically assist in wildland fire suppression. For instance, less than half of California's inmate firefighting crews were active for duty in the summer of 2020 due to COVID-19 transmission concerns – a reduction of over 1,000 wildland firefighters (Stark, 2020).

To mitigate the compounding risks presented to personnel and community by the confluence of wildland fires and COVID-19, national and multi-jurisdiction fire management organizations proposed various adaptations to *status quo* wildfire management practices. Several guiding policy documents, as well as early literature reviews of these policy documents (Moore et al., 2020), have recommended several changes to the wildland fire management paradigm. Policy guidelines that informed adaptations in fire management addressed five key fire management areas: (i) firefighter health safety, (ii) community health and safety, (iii) suppression strategies, (iv) use of suppression resources, and (v) use of other technology (i.e., to enable remote work). For instance, the National Interagency Fire Center's (NIFC) *Wildland Fire Response Plan: COVID-19 Pandemic* (2020) included prescriptive guidance to minimize within crew COVID-19 transmission which included: (i) reconfiguration of fire camps to reduced "spike" camps to promote social distancing, (ii) behavioral COVID-19 hygiene, sanitation, and screening practices (i.e., regular COVID-19 testing, use of personal protective equipment (PPE), and sanitation of vehicles, equipment, camps); (iii) clear plans and preparation for possible outbreaks; and (iv) increased remote work when possible. Various policy guidelines outlined potential changes to fire suppression strategies and tactics (see Appendix 3A for table of proposed wildland fire management changes under COVID-19), including for suppression strategy selection and the use and distribution of resources to fulfill suppression strategies:

- "Utilize suppression strategies that minimize the number of assigned personnel and incident duration… Use predictive services and professional judgement to balance assigned resources and incident duration" (NIFC, 2020, pg. 16).
- "Evaluate opportunities for application of aviation and mechanized assets to reduce assigned personnel" (NIFC, 2020, pg. 17).

While these and other wildland fire management policies and guidance were recommended to mitigate the compound COVID-19 threat, it is unclear if and how federal fire agencies adapted to the compound threat via the adoption of these policies and recommendations. Many guidance documents advocated for reduced personnel assignment and use, primarily by way of increased use of predictive services and applications of aviation and mechanized assets. While anecdotal evidence suggests that wildland fire management resources and strategies were constrained by the COVID-19 pandemic, there are limited empirical analyses regarding how U.S. wildland fire agencies have adapted to changing societal conditions presented by the COVID-19 pandemic. Accordingly, we assessed potential shifts in wildland fire suppression resource use using a Regression Discontinuity Design (RDD) modeling approach that evaluated and compared ground personnel resource use prior to and during the COVID-19 pandemic. The RDD approach developed here used a quasi-experimental design with relatively weak conditions compared to other quasi-experimental techniques (i.e., instrumental variables method, matching method) (Hidano et al., 2015). The RDD models approximated if and how ground personnel resources used during the pandemic changed from pre-pandemic conditions while controlling for fire behavior, weather, and societal risk factors.

Objectives and policy implications. Various interagency policy guidelines promoted earlier, more aggressive initial attacks given the pandemic. Aggressive initial attacks were thought to minimize the potential for fire spread that would require additional firefighting personnel, increasing the risk of COVID-19 transmission between personnel. It is currently unknown whether trends in personnel resources used during the pandemic were empirically different for the 2020 and 2021 seasons relative to past fire seasons. This chapter assessed if and how wildfire suppression resource use changed during pandemic conditions, controlling for environmental conditions of the regional landscapes as well as proximity and threats to nearby communities (i.e., public health and safety, property damage, critical infrastructure damage). Specifically, RDD models are developed to examine fluctuations in ground personnel resource use during wildland fire suppression (i.e., the response to extinguish a fire incident) . By comparing wildland fire incidents across the Western U.S. from 2017 to 2021, I aim to provide empirical insights as to the organizational adaptive capacities[18] of U.S. fire agencies facing simultaneous fire and COVID-19 risks. Adaptive capacity will be assessed by using daily fire suppression ground personnel used per day for each fire incident (herein, "fire days") as the unit of analysis, which is measured using historical records of fire incidents and resource use data.

This assessment builds from the interviews conducted in Chapter 2 such that Chapter 3 quantitatively assesses if and how the COVID-19 pandemic constrained resource allocation and use in the wildland fire suppression context based on historical fire management data. According to group workshops with fire managers and personnel hosted by the USFS' Human Performance & Innovation and Organizational Learning team (2020), "Whatever actions are taken this season should not be looked at as a temporary fix for a temporary situation… possible permanent changes to how we fight fire into the future that make us, as a group, more resilient" (pg. 1). As such, the compound threat of fire and COVID-19 presented in 2020, 2021, and perhaps beyond may have presented a window of opportunity for fire agencies to adapt their wildfire response (Wildland Fire Lessons Learned Center, 2020). Historical data analyses of wildland fire suppression personnel resource use can help identify if and how resource constraints changed during the compounding wildland fire and COVID-19 pandemic threat. Understanding resource use as a gauge for the adaptive capacity of fire agencies will help to provide empirical lessons learned for if and how pandemic conditions influence wildland fire resource use. This analysis can be used to inform anticipatory action and governance surrounding suppression management given the emergence of other future infectious diseases (Bacciu et al., 2022; Mora et al., 2022).

1.1. Research questions

- Across the western US, if and how did suppression resource use per fire day differ during the pandemic relative to recent prior years?
- Were there regional differences in resource use per fire day during the COVID pandemic?

Considering the NIFC management guidelines and the potential for COVID-19 transmission, the 2020 and 2021 fire years were hypothesized to show reductions in total ground personnel used per fire day (i.e., daily observations for each unique fire incident) relative to prior recent years after controlling for weather, fire behavior, societal risks, strategic objectives, and regional Preparedness Levels (PL).[19] This hypothesis is motivated by the guidance set forth by the NIFC regarding wildland fire response under COVID-19 pandemic conditions. As COVID-19 was a national risk, there were no anticipated differences in ground resource use per fire day for different U.S. fire regions. In addition, each region recommended similar wildland fire management protocol for handling COVID-19.

2. Methods and Materials

I developed sharp Regression Discontinuity Design (RDD) models to evaluate ground personnel resource use per fire day for wildland fire suppression efforts across the western U.S. from 2017 to 2021. Specially, these models assessed ground personnel resource use before versus during the COVID-19 pandemic. Figures 1A and 1B show aggregate ground personnel used per fire acre burned (Figure 1A) and per fire acre burned per fire (Figure 1B) on a daily basis from January 1, 2017 through December 31, 2021 with the official declaration of the COVID-19 pandemic depicted on March 10, 2020 (WHO, 2020). Daily resource aggregate resource use trends show that, controlling for fire acres and fire incidents, there was an apparent reduction over time in ground personnel resources used across daily fires in the western

[18] Adaptive capacity is defined as a system's ability to adjust to change, moderate the effects, and cope with a disturbance (Cutter et al., 2008, pg. 600); adaptive capacity is often exemplified through a system's ability to improvise and/or engage in social learning (Cutter et al., 2008).

[19] Preparedness Levels (PLs) are published by the National Interagency Fire Center within the daily Incident Management Situation Report (NIFC, n.d.). PLs are determined by the National Multi-Agency Coordination Group (NMAC) and are dictated by fuel and weather conditions, fire activity, and fire suppression resource availability throughout the country. PLs are included in fire suppression management models to serve as a proxy for resource scarcity.

U.S. according to Resource Ordering and Status System data. The aggregate resource use trends show that there were fewer ground resources used per fire acre and per fire acre per fire from 2020 through 2021 relative to 2017 through 2019, suggesting reductions in ground personnel resource use per fire acre after March 10, 2020. The locally weighted smoothing (LOESS) curves represent timeseries trends that show reductions in ground resource use on a daily basis across the western U.S., and the RDD modeling approach then evaluates these trends by assessing ground resource use considering environmental and societal conditions for each individual fire incident day. The “fire day” unit of analysis is used throughout the remainder of this chapter to assess ground resource use outcomes by controlling for the unique environmental, societal, and managerial conditions that occur on daily bases.

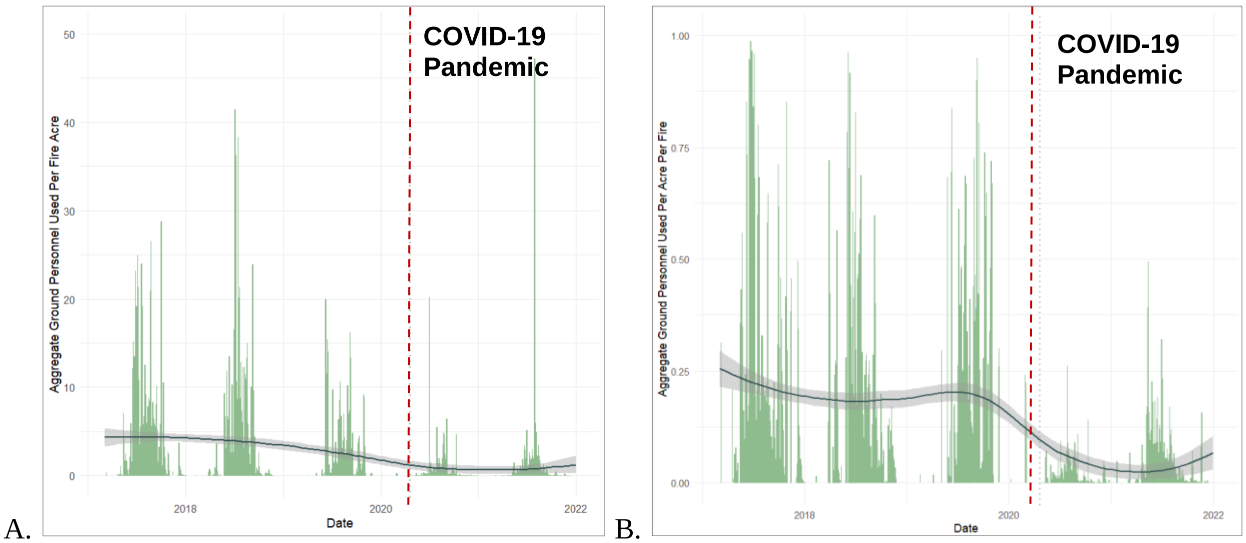


Figure 1A-B. Daily aggregate ground personnel resources used (A) per fire acre burned and (B) per fire acre burned per fire. The vertical dashed line shows when the COVID-18 pandemic was declared. The curved line represents the locally weighted smoothing (LOESS) curve with standard errors (gray shaded curve) between the timeseries data and the ground personnel resource use outcome (Jacoby, 2000).[20] The loess curve signals that there were fewer ground resources used per fire acre per fire in 2020 relative to 2017-2019, and ground personnel resources used per fire acre per fire began increasing in 2021 relative to 2020.

2.1. Scope.

The United States is divided into 10 geographic fire regions (Figure 2) referred to as Geographic Area Coordination Centers (GACCs). This analysis focused on GACCs located in the western US (i.e., ONCC, OSCC, PNCC, SWCC, RMCC, GBCC), as wildland fires are more prevalent and pose greater risks in these GACCs than GACCs located in the Eastern US. Models were developed to estimate total personnel use via global (i.e., all western US GACCs combined) and local (i.e., individual GACCs). The timeframe of 2017 – 2021 was selected because heavy equipment (i.e., dozers, engines, helicopters, air tankers) used for fire suppression has been relatively consistent since 2017 (Stonesifer et al., 2021).

[20] The locally weighted smoothing (LOESS) curve in Figure 1A-B is a non-parametric curve of best fit that is a generalization of least squares methods (Jacoby, 2000). This smoothing technique is suitable for showing the relationship between timeseries data and an outcome when the dataset may include sparse data points (i.e., fire days during the off-season that have no reported resources used, fires, or fire acres burned).

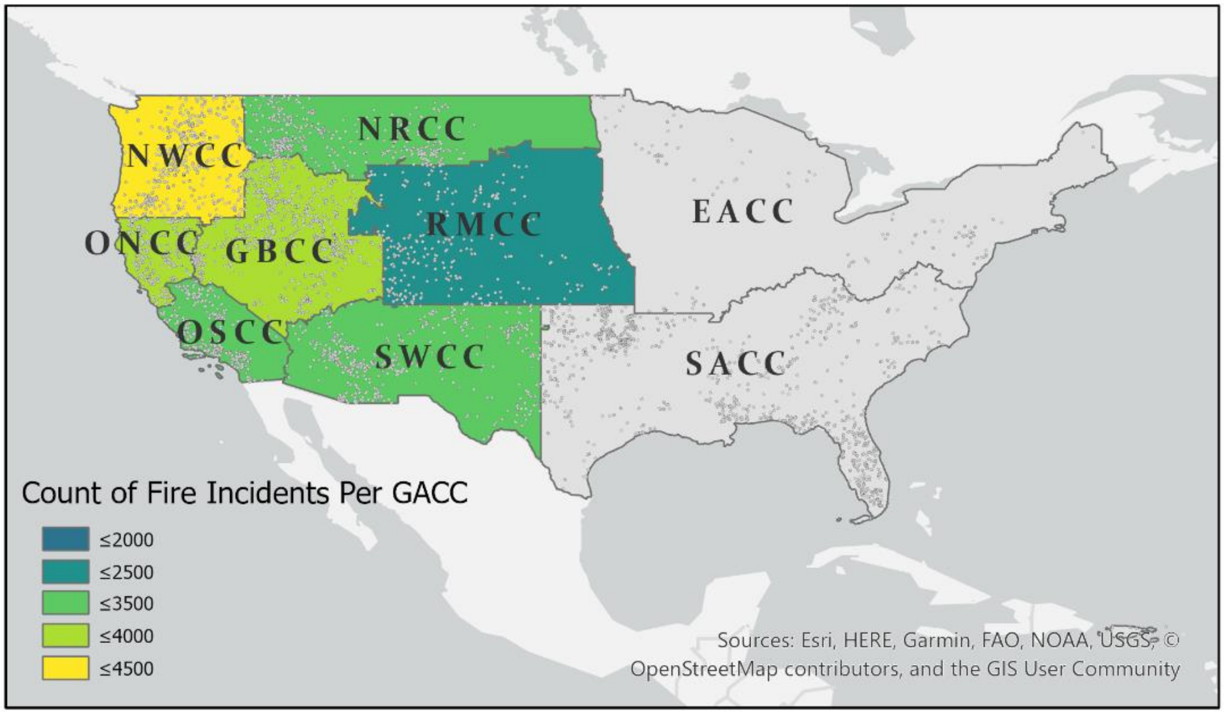


Figure 2. Map of contiguous U.S. GACCs (i.e., fire regions). GACCs shaded in green or yellow represent those included in this analysis. The gray dots represent fire incident origin locations for each large fire incident that occurred between 2017 – 2021.

The analysis focused on fire day resource use for wildland fires of categorized Fire Complexity Types 1, 2, or 3 (NIFC).[21] Complexity Types 1 are designated to the most complex fire incidents, and Complexity Types 5 are the least complex and most common. For the current analysis, Complexity Types 1, 2, and 3 were selected because generally, for large wildland fires that are of Complexity Types 1, 2, or 3, necessary ICS-209 data are reported by fire managers on a near daily basis to monitor the incident (NIFC, n.d.). Additional data cleaning mechanisms were used to finalize the fire day sample for the current preliminary results (Appendix 3B). There were a total of 22,022 fire day observations used in the analysis, which represented 1,916 unique fire incidents. Of these, 11,093 fire day observations occurred prior to the COVID-19 pandemic (i.e., between January 1, 2017 and March 10, 2020) and 10,929 fire day observations occurred during the COVID-19 pandemic (i.e., between March 11, 2020 and December 31, 2021). Table 1 provides an annual overview of the number of unique fire incidents, reported fire days across incidents, and the number of fire days categorized as having Complexity Types 1, 2, or 3 fires per year.

[21] Fire complexity is ranked from Types 1 to 5 per incident; this ranking is determined by fire agency administrators and is used to facilitate personnel assignment decisions (NIFC, 2004). Type 5 incidents are of the lowest level of complexity, and Type 1 are the most complex. Type 5 incidents are the most common and require no more than five personnel to manage, whereas Type 1 incidents involve 500+ personnel (NIFC, 2004).

Table 1. Counts of annual total fire incidents and ICS-209 reports (which represent individual fire days), including the distributions and annual percentages of fire days categorized by fire managers as Complexity Types 1, 2, and 3.

Year	Fire Incident Count	Fire Day ICS-209 Report Count	Complexity T1 Count (%/Year)	Complexity T2 (%/Year)	Complexity T3 (%/Year)
2017	523	4803	986 (21%)	1495 (31%)	2322 (48%)
2018	382	4581	1037 (23%)	1312 (29%)	2232 (49%)
2019	199	1703	155 (9%)	264 (16%)	1284 (75%)
2020	525	6408	1343 (21%)	1764 (28%)	3301 (52%)
2021	288	4527	986 (22%)	1525 (34%)	2016 (45%)
TOTAL	1917	22022	4507 (20%)	6360 (29%)	11155 (51%)

2.2. Concept model.

The declining trends in ground resources used per fire day motivated the sharp RDD methodology, as this quasi-experimental approach has been used to evaluate how policy interventions or historical interventions influence hazard management outcomes pre- versus post-intervention (Young et al., 2020; Hidano et al., 2015). Sharp RDD models were developed for samples including: (i) all western U.S. large fire incidents, (ii) by U.S. fire region (iii) by fire complexity types, and (iv) by national Preparedness Levels (PLs). Further, RDD models were used to assess resource use sensitivity across different timeframes of analysis—referred to as the model bandwidths in RDD (Young et al., 2020). Figure 3 shows the concept model for this modeling approach that predicts ground personnel (i.e., crew and equipment personnel) used per incident per fire day. The model inputs include the primary variable of interest and RDD threshold variable, which was the date of the fire day. Strategic objectives identified by fire managers (i.e., minimize infrastructural damage, minimize ecological damage, minimize historical/cultural site damage), societal risks (i.e., structures at risk of damage, evacuations, etc.), fire behavior characteristics, weather conditions, strategic objectives, and national and regional PLs are used as model controls.

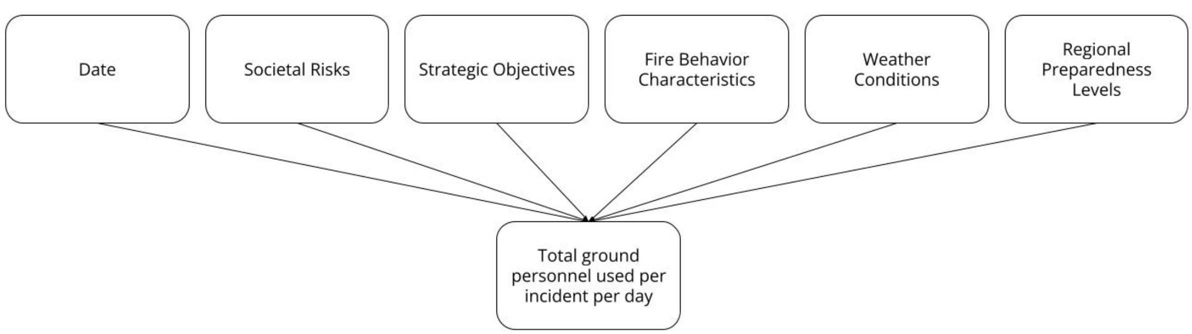


Figure 3. Concept model illustrating model inputs and the predicted model outputs – ground personnel used per incident per day.

2.3. Model Inputs.

Table 2 summarizes the model covariates, data sources, data types, and descriptive statistic for the sample for large wildland fire incidents that occurred across the western US between January 1, 2017 to December 31, 2021. See Appendixes 3B for these covariate distributions and statistical tests of comparative distributions in the pre-COVID and during-COVID subsamples.

Table 2. The variable categories, measurement types, mean, standard deviation (SD), median, and inter-quartile range (IQR) used for the set of model covariates.

Variable Category	Variable	Variable Type	Mean	SD	Median	25th Percentile	75th Percentile
Dependent variable	Ground personnel used per fire day (untransformed)	Continuous	190.2	478.6	56	18	153
	Ground personnel used per fire day (ln)	Continuous	3.9	1.8	4.03	2.9	5.0
Incident Overview (ICS-209)	During-COVID Threshold	Binary	0.5	0.5	0	0	1
	Human-caused	Binary	0.1	0.3	0	0	0
Fire Behavior (ICS-209)	Complexity Type 1	Binary	0.2	0.4	0	0	0
	New fires in GACC	Continuous	16.4	15.3	13	7	22
	Complexity Type 2	Binary	0.3	0.4	0	0	1
	Complexity Type 3	Binary	0.5	0.5	0	0	1
	Current fire size (ha)	Continuous	33,395	81,797	5,444	956	26,354
	Current fire size (ha)	Continuous – log scale	8.5	2.3	8.6	6.9	10.2
	Percent incident contained	Continuous	46.5	35.8	0.01	10	45
	Fire behavior: minimal	Binary	0.5	0.5	0	1	1
	Fire behavior: moderate	Binary	0.2	0.4	0	0	0
	Fire behavior: active	Binary	0.2	0.4	0	0	0
	Fire behavior: extreme	Binary	0.05	0.2	0	0	0
Weather conditions (GridMet)	Energy release component (percentile)	Continuous	0.8	0.2	0.9	0.8	0.9
	Daily accumulated precipitation (mm)	Continuous	0.6	2.9	0	0	0
	Vapor-pressure deficit (kPa)	Continuous	1.7	0.8	1.58	1.1	2.2
Societal Risk Factors (ICS-209)	Evacuations in progress or planned	Binary	0.04	0.2	0	0	0
	Area closure	Binary	0.01	0.1	0	0	0
	Structures threatened*	Continuous	405	3224	0.03	0.03	0.03
	Public injuries and fatalities	Continuous	2.1	5.8	0	0	0
	Responder injuries and fatalities	Continuous	0.1	/0.9	0	0	0
Strategic Objectives (ICS-209)	Historical, cultural concerns	Binary	0.2	0.4	0	0	0
	Public land ecological concerns	Binary	0.02	0.1	0	0	0
	Social considerations	Binary	0.2	0.4	0	0	0

	Economic considerations	Binary	0.1	0.3	0	0	0
	Personnel health and safety concerns	Binary	0.1	0.3	0	0	0
	Public health and safety concerns	Binary	0.2	0.4	0	0	0
Regional PL (SIT Reports)	PL 1 or 2	Binary	0.2	0.4	0	0	0
	PL 4 or 5	Binary	0.5	0.5	0	0	1
Daily COVID-19 caseloads (CDC)	New daily COVID-19 cases per state and across western U.S.**	Continuous	2077	3612.9	637	262	2712

* Including residential, commercial, and other structure types

** Only used COVID-19 caseloads in models that assessed 2020 versus 2021

For each day of a large fire incident, fire managers' report and submit an Incident Command System 209 Report (ICS-209) (FEMA, n.d.). The Federal Emergency Management Agency's (FEMA) ICS-209 Reports are used to assess daily fire incident situations, including daily fire behavior, estimated societal risks, and strategic objectives for each incident per reporting period. Generally, for large wildland fires that are of fire complexity 1 through 3, these reports are filed daily to monitor the incident (NIFC, n.d.). Additionally, FAMWEB's Situation Reports were to assess "Preparedness Levels" (PLs), which reflect wildland fire frequency and severity at the national and regional levels. PLs are used as model controls because they serve as a proxy for resource scarcity.

Fire managers request and use fire suppression resources in part based on the suppression strategy selected. The suppression strategy is selected based on how it fulfills multiple objectives that are considered by fire managers (Belval et al., 2015; Calkin et al., 2016). Multiple, sometimes competing objectives address the minimization of health and human safety risks to affected communities and personnel, the minimization of social and/or political tensions, the minimization of infrastructural damage, the minimization of damage to historical and/or cultural sites, and the minimization of ecological damage. Weighting schemes for incident objectives have been developed at the regional level to facilitate incident prioritization and suppression resource allocation decisions. Fire managers, such as Incident Commanders on Incident Management Teams (IMTs), report on a near daily basis if and how these objectives may be fulfilled by suppression strategies and tactics. These reports support resource requests sent to regional Multi-agency Coordinating Group Systems (MACS), who make final resource prioritization and resource allocation decisions. To communicate if and how certain resources are needed to satisfy the multi-objective decision space of each fire incident, fire management fills out a narrative field in the FEMA ICS-209 report on a fire day basis. To capture strategic objectives, natural language processing (NLP) was used to codify and pull key phrases indicative of the set of objectives considered in the decision-weighting scheme for incident prioritization and resource allocation (California Wildland Fire Coordinating Group, 2021) (Figure 4). NLP was used to integrate data for each fire incident related to the "harder-to-quantify" and/or intangible objectives that fit into resource allocation and use decision making, including social and political factors that influence such decisions (Figure 4).

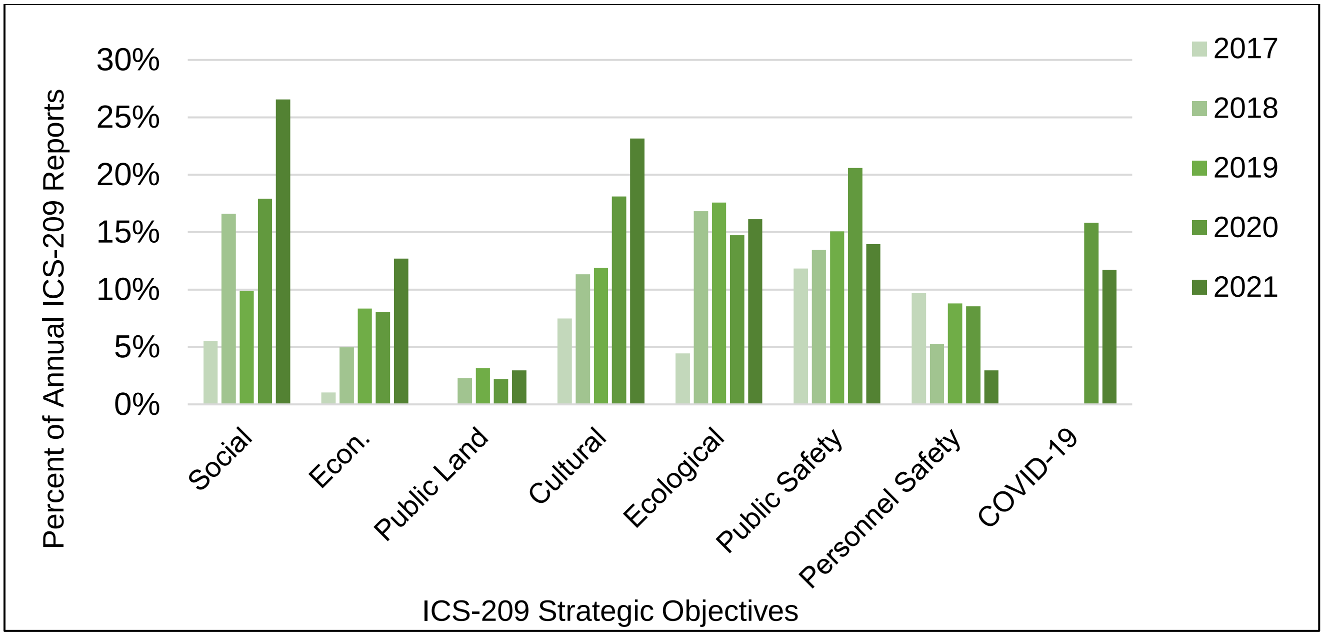


Figure 4. Natural language processing results of the “Strategic Objectives” narrative field filled out in ICS-209 Reports.

Additionally, an interaction term for off-peak fire season fire days that were of Complexity Type 1 (i.e., most complex fire incidents) was included to control for complex fire days that occurred in off-peak periods when fire suppression resources were available in higher quantities. Generally, these fires were assigned high quantities of ground personnel both due to their complexity and availability of resources given limited resource competition with other co-occurring fire incidents (e.g., the December 2017 Thomas Fire and the November 2018 Camp Fire, both in California). This interaction was included to account for large fires with highly rated complexity levels that occurred during periods with fewer competing fires.

2.4. Predicted model outcomes.

Total ground personnel used per fire day was the outcome of interest, where ground personnel include personnel working on fire crews and personnel who operate heavy equipment (i.e., fire engines, bulldozers, etc.) (Belval et al., 2020). Ground personnel resource use per fire day (i.e., daily quantities of personnel types used for each individual fire incident) were collected via the Resource Ordering and Support System database (ROSS) (NWCG, 2020) and Interagency Resource Ordering Capability (IROC) (NWCG, 2022). The ROSS and IROC databases also include overhead personnel used per fire day (i.e., those working in administration, logistics), though these positions were not included in this analysis because of the potential to work remotely. Personnel working in overhead positions may not have faced the same COVID-19 – wildfire risks as ground personnel, who were unable to conduct remote work.

Table 3 shows the summary statistics for ground personnel resources used per fire day for fire incidents that occurred over all fire days during 2017 to 2021, for the pre-COVID fire days, and for the during-COVID fire days. The mean ground personnel per fire day pre-pandemic was 328 (SE = 640) relative to the during-pandemic mean total ground personnel per fire day of 55 (SE = 90). Reductions in ground personnel were observed according to pre- and during-COVID group means, medians, and inter-quartile ranges (IQR). These descriptive statistics clearly show a reduction in ground personnel used per fire day, which was further explored through multivariate RDD modeling controlling for weather, fire behavior, and societal risk factors.

Table 3. Descriptive statistics of ground personnel resource use per fire day according to the full dataset (*n* = 22,022) and according to the pre-COVID (January 1, 2017 through March 10, 2020) and during-COVID (March 11, 2020 through December 31, 2021) timeframes of analysis. The arithmetic and geometric means are included as the model uses the natural log of ground personnel as the predicted outcome, and regressors share a multiplicative relationship with this predicted outcome.

Timeframe	**Arithmetic Mean (SD)**	**Geometric Mean**	**Median**	**IQR**
2017- 2021 (*n* = 22,022)	190 (479)	49 (5.8)	56	18 – 153
Pre-COVID (*n* = 11,093)	328 (640)	117 (4.4)	127	48 - 323
During-COVID (*n* = 10,929)	55 (90)	20 (4.7)	23	8 – 62

2.5. Modeling approach.
A sharp Regression Discontinuity Design (RDD) approach was used to assess federal agency ground resource use to suppress fires on a fire day basis before and during the COVID-19 pandemic.[22] Sharp RDD modeling approaches have been conducted to provide a quasi-experimental regression approach suitable for investigating how an intervention (i.e., a policy) may influence an outcome (Young et al., 2020).[23] Specifically, a sharp RDD modeling approach was developed to assess ground personnel use outcomes before and during the COVID-19 pandemic.

Sharp RDD is characterized by a deterministic treatment assignment that is based on whether an observation falls above or below a cut-point threshold of a continuous variable, generating a discontinuity in the probability of treatment receipt at that point according to different model slopes (Young et al., 2020). RDD can be used *post hoc* to conduct analyses of the association between an intervention and a predicted outcome. Here, RDD models were developed to assess whether the NIFC's *Wildland Fire Response Plan: COVID-19 Pandemic* (2020) may have had an influence on (Y_1) total ground personnel used per fire day. Sharp RDD was used to assess and compare trends in ground personnel per fire day before and after WHO officially declared the COVID-19 pandemic on March 11, 2020 (WHO, 2020). Thus, the RDD models explored what association, if any, between the COVID-19 pandemic and ground personnel resource use per fire day (Y_1).[24] We theorize each response (Y_1) to be defined by:

$$Y_1 = \beta_0 + \beta_1 X_i + \beta_2 F_i + u_i$$

[22] In addition to the sharp RDD modeling design, mixed-effect regression models were developed to further validate trends in resource use per fire day across western GACCs by accounting for region-specific weather, fire behavior, and societal risk factors. Mixed-effects models are well suited to account for geographic variation in that may occur between different GACCs given their ability to estimate within-group variation (Schielzeth et al., 2020). Mixed-effects models can be developed on 2017 – March 9, 2020 data and tested on March 10, 2020 – December 31, 2021 data to validate if and how resource use per fire day in 2020 could be used to forecast resource use per fire day in 2021.

[23] This approach to assessing fire suppression change was inspired by Young et al. (2020), who assessed wildland fire strategies and acres burned before and after the implementation of the federal *2009 Guidance for Implementation of Wildland Fire Management Policy*, which aimed to encourage fire managers to adopt "expanded strategies" aside from aggressive suppression for wildland fire response (Young et al., 2020). Using the RDD approach, Young et al. (2020) found that the 2009 policy corresponded with an estimated 27 – 73% increase in the number of fires managed with expanded strategies options and limited evidence of an increase in size or annual area burned (pg. 587).

[24] As in Young et al. (2020), we assumed that fire managers were aware of and complying with the *Wildland Fire Response Plan: COVID-19 Pandemic* (2020), and as such, a sharp rather than fuzzy regression discontinuity design was conducted (Jacob et al., 2019).

such that

$$X_i = \begin{cases} 1, & W_i \geq c \\ 0, & W_i < c \end{cases}$$

where (X_i) represents an indicator variable equal to 1 if the fire day (*i*) occurred after March 11, 2020, the threshold *c* of the running variable, which is fire day date (W_i,) in the current model (Young et al., 2020). *F* represents a vector of wildland fire variables (i.e., behavior, weather, societal risks, strategic objectives) used as controls in the model. Sharp RDD includes deterministic treatments that are discontinuous at the cut-off: all observations with $W_i < c$ do not receive treatment and all observations where $W_i \geq c$ do receive treatment. Additionally, β_1 is the average treatment effect for individuals with $W_i = c$, which is assumed to be a good approximation to the treatment effect in the population. Global model results for all western U.S. fire days across the full timeframe (2017 – 2019 vs. 2020 – 2021) used every observation in the sample to model the outcome as a function of the rating variable and treatment status. This approach "borrows strength" from observations far from the cut-point score to estimate the average outcome for observations near the cut point score and the estimation of treatment effects as a "discontinuity at the cut point" (Jacobs et al., 2019). To minimize bias, different functional forms for the rating variable (linear, quadratic) were tested by conducting F-tests on higher-order interaction terms and inspecting the residuals (Appendix 3C).

RDD approaches can include fuzzy or sharp forms, where sharp regression discontinuity applies uniform (rectangular) kernel weighting and fuzzy regression applies heterogenous kernel weighting (Jacob et al., 2012; Young et al., 2020). Sharp RDD forms are used in the current analysis given the wide timeframe bandwidths of the global model and because fire days that occurred during the COVID-19 pandemic could deterministically be assigned to the quasi-"treatment" group (Perraillon, 2020). First, linear and quadratic univariate models were assessed to observe the relationship between the pre-COVID and during-COVID threshold effect on predicted logged ground personnel outcomes (Lee and Lemieux, 2010; Jacob et al., 2012; Young et al., 2020). Then, multi-variate models were developed that included weather, fire behavior, strategic objective, and societal risk covariates to control for fire day characteristics that may be attributed predicted ground personnel resource use. Multi-variate sharp RDD methods were developed with different functional forms (i.e., linear, quadratic), and local and global linear models are included in the main text.[25] We examined underlying distributions of the data-generating process and fitted the appropriate global model. Global models assume a functional form that is consistent before and during the COVID-19 pandemic.[26] The current results use log-level linear regression to meet the following Gauss-Markov linear regression assumptions: (i) linearity, (ii) independence of residuals, (iii) homoscedasticity (natural log of ground personnel use per fire day)[27], (iv) normality (residuals normally distributed), (v) omitted variable bias. A natural log transformation of the dependent variable—ground personnel resources used per fire day—was used for final model results to mitigate heteroskedasticity. As approximately 18% of fire day observations (*n* = 3,964) had zero ground personnel assigned, a monotonic transformation was applied by adding one ground personnel to each fire day observation (including those with greater than zero ground personnel resources used) such that the natural log for each fire day could be estimated with minimal bias (i.e., not yield negative infinity) (Davis, 2018). This handling of fire day observations with zero ground personnel observed was further explored in Appendix 3B by testing model results with different treatments of fire days with zero ground personnel used; overall, the modeling results were consistent despite the handling of fire days with zero ground personnel used.

[25] Model results and goodness of fit as measured by the adjusted R^2 for quadratic model forms did not significantly deviate from linear regression results, and therefore, linear regression results are presented in the main text. See Appendix 3C for model results using quadratic model forms.
[26] See Appendix 3B for pre-COVID and during-COVID distributions of covariates.
[27] For distributions of untransformed ground personnel use and log-transformed ground personnel use, see Appendix 3B.

Using the natural log of dependent variable approach, the relationships between covariates and the logged dependent variable are multiplicative, thus altering the interpretations of model coefficients relative to model interpretations of the untransformed dependent variable (Wooldridge, 2009). Continuous, untransformed covariates are interpreted such that a one unit increase in X is associated with a $100 \times B_1$ percentage change in the dependent variable. For binary covariates—including the main effect of interest, the "during-COVID threshold" that differentiated pre-and during-COVID fire days—when the binary variable switches from 0 to 1 (i.e., from pre- to during-COVID), the percentage change of Y is $[100 \times ((e^{B_1}) - 1)]$ (Halvorsen and Palmquist, 1980). These coefficient interpretations indicate percentage changes in Y (i.e., natural log of ground personnel used per fire day), but do not indicate how many ground personnel were predicted to change. To do so, it is first necessary to differentiate the model with respect to the "during-COVID threshold" variable after inverting the log to derive the number of Y (ground personnel) that are predicted to change if input changes by one unit.

$$Ground\ personnel\ used = e^{\beta_0 + \beta_1 X_i + \beta_2 W_i} - 1$$

$$\frac{\partial}{\partial\ During - COVID\ Threshold} = B_1 \times e^{\beta_0 + \beta_1 X_i + \beta_2 W_i}$$

where B_1 reflects the "During-COVID Threshold" binary variable for fire day observations that occurred during the pandemic (i.e., March 11, 2020 – December 31, 2021). For a one unit increase in the "During-COVID Threshold" variable (i.e., from pre-COVID to during-COVID, holding covariates constant), we would expect $B_1 \times e^{\beta_0 + \beta_1 X_i + \beta_2 F_i}$ fewer ground personnel used. This implies a multiplicative relationship between covariates and the logged dependent variable, thus altering the interpretations of model coefficients relative to model interpretations of the untransformed dependent variable.

Various bandwidths were selected to compare model outcomes across different timeframes (Young et al., 2020). By adjusting model bandwidths, model outcomes were compared for different timespans between 2017 and 2021. The global models include all fire day observations that occurred between 2017 and 2019 versus all fire day observations that occurred between 2020 and 2021. Local models included narrower bandwidths to compare ground personnel resources used. Comparing different bandwidths allows for balancing precision with consistency (i.e., accuracy) to further explore the sensitivity of results. Narrow bandwidths suggest more consistent and less biased results if there are many observations proximal to the policy treatment (Young et al., 2020; Imbens and Lemieux, 2008; Lee and Lemieux, 2010). By adjusting the bandwidth, this analysis assessed the sensitivity of ground personnel resource use considering different timeframe comparisons.[28] For instance, ground personnel resource use changes specific to peak fire season observations (May through September) were compared pre- and during-COVID fire days, fire days in 2019 were compared to those in 2020, and fire days in 2020 were compared to 2021 to assess during-COVID resource use fluctuations. In models assessing resources used for 2020 relative to 2021 fire days, additional COVID-19 related covariates were included: (i) fire management mentioning COVID-19 within their discussion of strategic objectives for that incident in ICS-209 reports, and (ii) daily statewide COVID-19 caseloads at the start of each fire day (CDC, 2022). COVID-19 related covariates were included for the 2020 versus 2021 bandwidth to better assess if and how fluctuations in the pandemic were associated with shifts in ground personnel resource use. Additionally, the sharp RDD multivariate linear regression model for all western U.S. fire days across the global bandwidth (i.e., 2017 – 2021) covariates were assessed and presented in terms of their respective t-statistic. The t-statistic ($t_{\hat{\beta}}$) reflects the "variable importance" (Grömping, 2009) when each covariate is added to the model by deriving:

[28] For instance, 2019 and 2020 were quite different in terms of the fire risks posed; however, 2018 and 2020 were comparable in terms of the fire risks posed. Therefore, it may provide deeper insights to compare these years directly.

$$t_{\hat{\beta}} = \frac{\hat{\beta} - \beta_0}{SE(\hat{\beta})}$$

where $\hat{\beta}$ is the estimate of the covariate, β_0 is a non-random known constant (i.e., intercept), and $SE(\hat{\beta})$ is the standard error of the estimator (Kennedy and Cade, 1996). The t-statistic provides a commonly used measure of the relative extent to which the absolute value of the slope will change when each covariate is added to the model, such that higher t-statistics suggest greater changes in the predicted outcomes.

3. Results

3.1. Global RDD results for western U.S.

Univariate and multivariate sharp RDD model results indicate that the COVID-19 pandemic had a significant effect on the number of ground personnel used per fire day across the western U.S. Figure 5B shows scatterplots and univariate linear regression relationships between pre-COVID and during-COVID fire days on (A) untransformed ground personnel resources used and (B) natural log ground personnel resources used per fire day. Untransformed outcomes are included to illustrate the scale of ground personnel changes pre- and during-COVID, though to satisfy linear regression assumptions, the core results use the natural log + 1 transformed ground personnel and changes in covariates reflect percentage changes in average predicted ground personnel used per fire day.

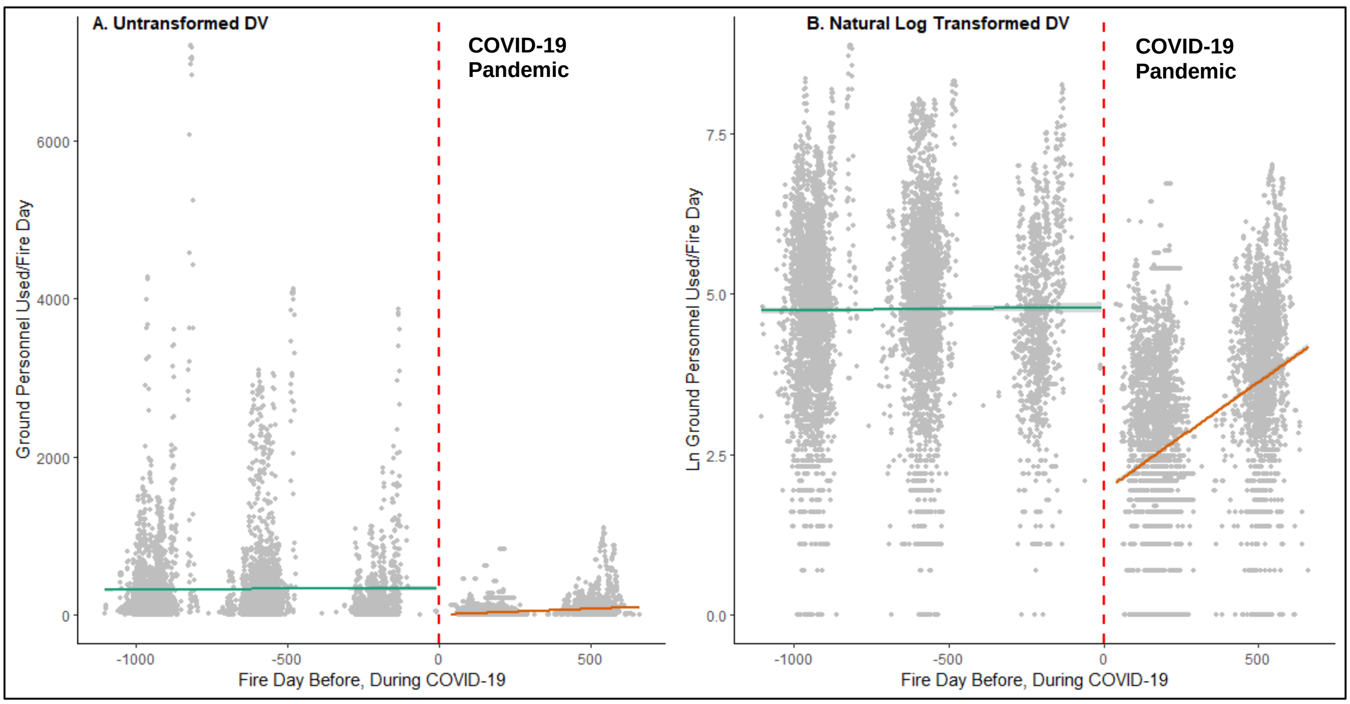


Figure 5. Scatterplot and fitted univariate linear regression line for the effect of the "During-COVID Threshold" variable on predicted (A) ground personnel and (B) natural log transformed ground personnel used per fire day. The dots represent observed ground personnel use per fire day. Negative x-axis values reflect fire days that occurred pre-COVID. The vertical red dashed line represents March 11, 2020 – the date the WHO declared the COVID-19 pandemic, which served as the threshold date for the RDD to compare ground personnel use across the Western US. Pre-pandemic there were a total of 11,093 fire days representing individual incidents per date. Pre-COVID, the mean ground personnel used was 328 personnel (SD = 640) per fire day. During the pandemic, the mean ground personnel used was 55 ground personnel (SD = 90) per fire day. Both the (A) untransformed and (B) natural log transformed relationships are illustrated to contextualize the predicted scale of the reduction in ground personnel during-COVID.

Table 4 shows the global sharp RDD results for a multivariate linear regression model that included all covariates. We focused on the change in logged ground personnel used before and during the

COVID-19 pandemic to meet linear regression assumption of homoscedasticity (i.e., constant variance of residuals). Table 4 results compared the bandwidth of 2017 – March 10, 2020 fire days to March 11, 2020 – December 31, 2021 fire days. The coefficient for the "During-COVID-19 Threshold" variable predicted that, holding covariates constant, ground personnel used on during-COVID fire days were predicted to reduce by an average of 92.2 – 93.2% ($p < 0.001$) relative to pre-pandemic fire days, which had an observed geometric mean of 122 (SE = 4.4) ground personnel resources used per fire day. This percentage reduction in ground personnel was derived such that when the binary variable switches from 0 to 1 (i.e., from pre- to during-COVID), the associated percentage change of Y is $[100 \times ((e^{B_1}) - 1)]$ (Halvorsen and Palmquist, 1980). Here, the 95% confidence intervals around the coefficient results in Table 4 predict a reduction by $[100 \times ((e^{-2.69}) - 1)] = -93.2\%$ to $[100 \times ((e^{-2.69}) - 1)] = -92.2\%$. The multivariate modeling results were consistent with the univariate global RDD model, which revealed an average predicted reduction of 93 - 94% ($p < 0.001$) of ground resources used per during-COVID fire day relative to pre-COVID. Details and further results on univariate models (i.e., level-level models, log-level models in linear and quadratic forms) are presented in Appendix 3C.

Table 4. Sharp RDD linear regression results for global pre-COVID (2017 – March 10, 2020) versus during-COVID (March 11, 2020 – December 31, 2021) model predictive of the natural log + 1 transformation of ground personnel used per fire day. This table includes the coefficient estimates for the natural log transformation on the dependent variable, standard error (SE), lower-bound of the 95% Confidence Interval (CI Lower), upper-bound of the 95% Confidence Interval (CI Upper) and coefficient p-values. The adjusted R2 for this model was 0.47 ($p < 0.001$). Covariates are ordered by their relative model importance according to the t-statistic when the covariate is added to the multivariate regression model that includes all other covariates.

Predictors	Est.	t-stat	SE	Lower CI	Upper CI	P-value
Intercept	3.32	--	0.07	3.19	3.46	<0.001
During-COVID threshold	**-2.61**	**70.2**	**0.04**	**-2.68**	**-2.54**	**<0.001**
Fire Complexity Type 1	0.95	33.4	0.03	0.89	1.01	<0.001
Fire Complexity Type 2	0.71	30.3	0.02	0.67	0.76	<0.001
Region: ONCC	0.93	23.3	0.04	0.86	1.01	<0.001
Region: OSCC	0.92	22.5	0.04	0.84	1.01	<0.001
Off-peak fire days * Complexity Type 1	1.47	14.2	0.10	1.26	1.67	<0.001
Regional PL 4 or 5	-0.26	13.7	0.02	-0.30	-0.22	<0.001
Current incident area (log)	0.07	13.5	0.01	0.06	0.08	<0.001
Region: NWCC	0.39	10.8	0.04	0.32	0.47	<0.001
Region: GBCC	0.41	10.6	0.04	0.34	0.49	<0.001
Off-Peak Fire Day	-0.45	8.0	0.06	-0.56	-0.34	<0.001
General fire behavior: active	0.23	7.9	0.03	0.18	0.29	<0.001
Cause: Human	0.24	7.8	0.03	0.18	0.30	<0.001
VPD (kPa)	0.08	6.1	0.01	0.05	0.09	<0.001
Objective: Public land	-0.38	5.9	0.06	-0.51	-0.26	<0.001
General fire behavior: moderate	0.15	5.8	0.03	0.10	0.20	<0.001
Evacuations planned or progressing	0.25	5.6	0.04	0.16	0.34	<0.001
Region: SWCC	0.24	5.4	0.04	0.15	0.32	<0.001
Public Injuries/Fatalities * Regional PL 4 | 5	-0.12	5.2	0.02	-0.17	-0.09	<0.001
Structures threatened (log)	0.01	4.2	0.00	0.01	0.02	<0.001
General fire behavior: extreme	0.17	3.6	0.05	0.08	0.26	<0.001
Region: NRCC	-0.13	3.5	0.04	-0.21	-0.06	<0.001
Public injuries or fatalities	0.06	3.3	0.02	0.02	0.10	0.001
Percent Fire Contained	0.01	3.2	0.00	0.00	0.01	0.001
Objective: Responder health and safety	0.11	3.1	0.04	0.04	0.18	0.002
Responder injuries or fatalities	0.01	3.0	0.00	0.01	0.01	0.003
ERC Percentile	-0.11	2.4	0.05	-0.21	-0.01	0.038
Objective: Social consideration	0.07	2.3	0.03	0.0	0.13	0.016

Objective: Human health and safety	0.05	2.1	0.03	0.01	0.11	0.042
Daily precipitation (mm)	0.01	1.3	0.00	-0.01	0.01	0.214
Regional new fires	0.01	1.3	0.00	-0.01	0.0	0.167
Area restriction in progress	0.11	1.3	0.08	-0.06	0.27	0.2
Objective: Cultural resources	-0.02	0.8	0.03	-0.08	0.04	0.546
Objective: Economic consideration	0.02	0.2	0.04	-0.06	0.10	0.579
Observations	22,022					
Adjusted R^2	0.466					

The covariates in Table 4 (aside from the Intercept) are ordered from those found to be the most important to least important to model results, which was calculated by evaluating models that did and did not include each covariate one at a time according to changes in the absolute value of the t-statistic of the model (see Appendix 3C for more details on covariate importance and scaling). The binary "During-COVID Threshold" variable that separated pre- from during-COVID fire days was found to be the most important variable according to the t-statistic, followed by the categorization of fire days by their fire complexity type. While the relationship between the "During-COVID Threshold" variable and the predicted ground personnel use per fire day outcome variable is of primary interest, the relationships between the covariates and the predicted model outcome also shed light on factors associated with resource use on large wildland fires. Additionally, indicators for fire days that occurred in the northern (ONCC) and southern (OSCC) California fire regions were found to be important according to the t-statistic, and were predicted to increase ground personnel resource use by 150 – 153% on average, relative to the reference fire region, the Rocky Mountain Coordination Center (RMCC), holding covariates constant. Comparatively, fire days that occurred in the NRCC were predicted to decrease ground personnel resource use per fire day by 12% on average relative to those in the RMCC.

Complexity Types 1 and 2 are considered most complex in that they require more rigorous management approaches, including the establishment of multiple branches to manage suppression efforts (NIFC, 2004). Relative to complexity type 3 fires (least complex of those included in dataset), complexity type 1 fires were predicted to increase ground personnel by an average of 159% ($p < 0.001$) and complexity type 2 fires were predicted to increase ground personnel by an average of 107% ($p < 0.001$) holding covariates constant. We controlled for fire days with high complexity and that occurred during the western U.S. off-peak fire season (i.e., January through March and November through December of each year), such as the December 2017 Thomas Fire in California. These off-peak fire days were positively correlated (Pearson $r = 0.24$, $p < 0.001$) with ground resource use, potentially due to increased resource availability in winter months. Accordingly, we included an interaction term to capture off-peak, highly complex fire days (e.g., "Off-Peak * Complexity Level Type 1"). These fire days predicted that, on average, personnel use would increase by 333%, holding covariates constant. Additionally, fire days that occurred in northern California (ONCC) or southern California (OSCC) were considered important covariates of the sharp RDD model, as was the natural log of the current incident area (ha). Additionally, we included an interaction term for the relationship between regional PL 4 or 5 (i.e., fire days that occurred during days with high regional fire activity and resource scarcity) and public injuries and fatalities. These were included to further highlight the relationship between resource use, resource scarcity, and public safety risks.

3.2. Global RDD bandwidth sensitivity results.

Table 5 shows the main effects of pre-COVID versus during-COVID fire day resource use according to different bandwidth selections. The main effects reflect the difference in the estimated number of personnel used per fire day for during-COVID fire days, relative to pre-COVID fire days, according to different model forms and bandwidths. Preliminary results are contingent on the model form (i.e., linear, quadratic, cubic). Various model forms are being tested because when all models identify a significant effect, the estimated policy effect can be considered more robust to alternative model specifications (Young et al., 2020). Generally, there was a predicted decrease in total personnel used per fire day on average across the western US, after controlling for weather, fire behavior, strategic objectives, and societal risk covariates. This association was consistent across model forms and bandwidth comparisons, increasing confidence in the revealed negative association between during-COVID fire days and resource use. The negative association was strongest when comparing 2018 to the 2020 during-COVID treatment group, suggesting a potentially significant reduction in personnel use in 2020 relative to 2018, though both fire years were similar in large wildland fire frequency and severity.[29] For this 1-year bandwidth comparison, it was estimated that, on average, during-COVID fire days used approximately 110 to 1300 fewer personnel per fire day, contingent on model form.

Table 5. Sharp RDD regression results of the main effect of the "During-COVID Threshold" variable on average predicted changes in ground personnel resources used per fire day. Models A – E vary the bandwidths used to compare fire day observations using multivariate linear regression with a logged dependent variable. All covariates were included in these models. The predicted percentage change in ground personnel reflect average predicted changes when fire days occur during the "Treatment" group relative to the "Control" group specified by each model.

	Pre-COVID			**During-COVID**		
Bandwidth Selection (total *n*)	***n***	**Obs. Geom. Mean (SD)**	**Obs. Median**	***n***	**Obs. Geom. Mean (SD)**	**Obs. Median**
(A) Global (*n* = 22022)	11093	117 (4.4)	127	10929	20 (4.7)	23
(B) Global (omit outliers, influential) (*n* = 19475)	9742	117 (3.2)	124	9733	22 (3.9)	24
(C) Peak Fire Season (*n* = 19127)	10087	105 (4.6)	118	9040	20 (4.6)	25
(D) Narrow Bandwidth (*n* = 8111)	1703	108 (4.3)	105	6408	9 (4.7)	11
(E) Exclude only 2019 (*n* = 20319)	9390	116 (4.9)	130	10929	20 (4.8)	23
(F) During-COVID (*n* = 10935)	6408	9 (4.3)	11	4527	40 (3.6)	49

(A) Global: 2017 – 2019 versus 2020 - 2021 (R^2 = 0.467)
(B) Global: 2017 – 2019 versus 2020 - 2021 without outliers, highly influential obs. (R^2 = 0.455)
(C) Peak Fire Season Observations: 2017 - 2019 versus 2020 – 2021 (R^2 = 0.412)
(D) Narrow Bandwidth Observations: 2019 versus 2020 (R^2 = 0.516)
(E) Exclude 2019 Observations: 2017 – 2018 versus 2020 – 2021 (R^2 = 0.447)
(F) During-COVID Observations: 2020 versus 2021 (R^2 = 0.447)

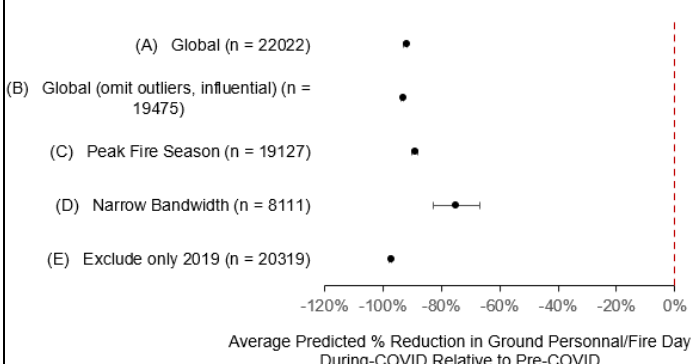
In summary, Table 5 shows that various model bandwidths that compare pre-COVID to during-COVID fire day observations based on sample sizes, the observed geometric mean, standard deviation, and median based on the historical data. Observed data comparing pre- and during-COVID groups shows that, across all selected bandwidths, the pre-COVID group had approximately 105 to 117 ground personnel assigned per fire day based on the geometric mean. Conversely, the during-COVID fire days had approximately 9 to 22 ground personnel per fire day based on the geometric means of various bandwidth selections. These results were consistent across timeframe bandwidths. Bandwidth selection F in Table 5 shows the comparison between 2020 fire day observations and 2021 fire day observations. Observational results for the 2020 versus 2021 bandwidth suggest that ground personnel reductions that were observed and predicted in 2020 recovered slightly in 2021, such that the observed geometric mean

[29] In 2018, there were 58,083 recorded wildland fires that burned 8.8 million acres across the US. In 2020, there were 58,950 wildland fires that burned 10.1 million acres across the US (NIFC, n.d.)

ground personnel increased from 9 (SD = 4.3) to 40 (SD = 3.6) per fire day. This suggests that the average observed reduction in ground personnel rebounded in 2021 relative to 2020.

To further understand ground personnel changes based on sharp RDD multivariate regression, Figure 6 shows the average predicted reduction in ground personnel by an average of 67 to 98% during-COVID fire days relative to pre-COVID fire days, holding covariates constant. All during-COVID threshold main effects were statistically significant at the $\alpha < 0.001$ level. Further, Figure 6 shows that, relative to the (A) global model comparing all western U.S. fire incidents between 2017 – 2019 to 2020 – 2021, when comparing (B) peak fire season fire day observations in this same timeframe results in a smaller percentage reduction of ground personnel used per fire day during-COVID relative to pre-COVID. The reduction of ground personnel used per fire day by 88 – 90% suggests that during peak fire season (April – October of each year), the change in ground personnel used was not as extreme. Next, we modeled a narrower bandwidth, comparing only 2019 (n = 1,709 fire days) to 2020 (n = 6,402 fire days) fire day observations (Table 5 Model C). Narrow bandwidths tend to yield more consistent and less biased results, as observations can be considered more similar if they occur closer together (Young et al., 2020; Imbens and Lemieux, 2008). However, as shown in Table 5, the 2019 fire year had fewer overall fire day observations and was considered a mild fire year across the western U.S. Accordingly, there was an average predicted percentage decrease in ground personnel used per fire day by 67 – 83% on during-COVID relative to pre-COVID fire days. This reduction is relatively less extreme than in the (A) global and (B) peak fire season models. As 2019 was considered a relatively mild fire season with fewer and less severe fire days, the percentage reduction in ground personnel used was not as extreme as in models (A) and (B).

Considering the unique 2019 fire season, we then excluded 2019 fire day observations when deriving Table 5 Model D; in this model, the percentage reduction from pre-COVID to during-COVID ground personnel used per fire day was greater than for the (A) global and (B) peak fire season models that integrated 2019 data. By excluding 2019 fire day observations, during-COVID ground personnel used per fire day was predicted to decrease by 96 to 98% on average relative to pre-COVID fire days, holding covariates constant. Finally, we compared ground personnel resource use per fire day for 2020 relative to 2021 fire day observations to assess potential changes in ground personnel resource use over the course of the pandemic (Table 5 Model E). Results suggest that there was an average predicted increase in the percentage of ground personnel resources used per fire day in 2021 relative to in 2020 by 803 to 1118%, holding covariates constant. This suggests that fire day observations in 2021 used more ground personnel resources than in 2020, highlighting the drop in ground personnel resources used in 2020 began to recover in 2021.



Est.	Lower CI	Upper CI	Pred. Geom. Mean Pre-COVID
-92%	-92%	-93%	122 (4.4)
-93%	-94%	-93%	117 (4.5)
-89%	-90%	-88%	107 (4.5)
-75%	-67%	-83%	274 (4.2)
-97%	-98%	-97%	338 (4.6)

Figure 6. Forest plot for the effect sizes of the binary "During-COVID Threshold" variable across the bandwidth model types developed across western U.S. fire days, corresponding with the results presented in Table 5. The error bars show the 95% confidence interval for the change in the percentage of ground

personnel used per fire day for during-COVID observations relative to pre-COVID observations. The predicted geometric mean is included to provide a baseline for the average model prediction of pre-COVID ground personnel used per fire day, holding covariates constant. All “During-COVID Threshold” effects and models were statistically significant at the $\alpha < 0.001$ level.

In addition to assessing different bandwidth selections that compare pre- and during-COVID fire day observations, bandwidths were selected that compared 2020 and 2021 fire day observations. Figure 7 shows the average predictive changes in ground personnel use during 2021 relative to 2020 using sharp RDD fitted univariate linear regression trend lines. Generally, the further fire days occurred from the start of the COVID-19 pandemic in early 2020, the greater predicted ground personnel resources were used per fire day according to the (A) untransformed dependent variable and (B) natural log transformed dependent variable models. This suggests the potential for recovery of ground personnel resources used as the pandemic progressed from 2020 and into 2021**.**

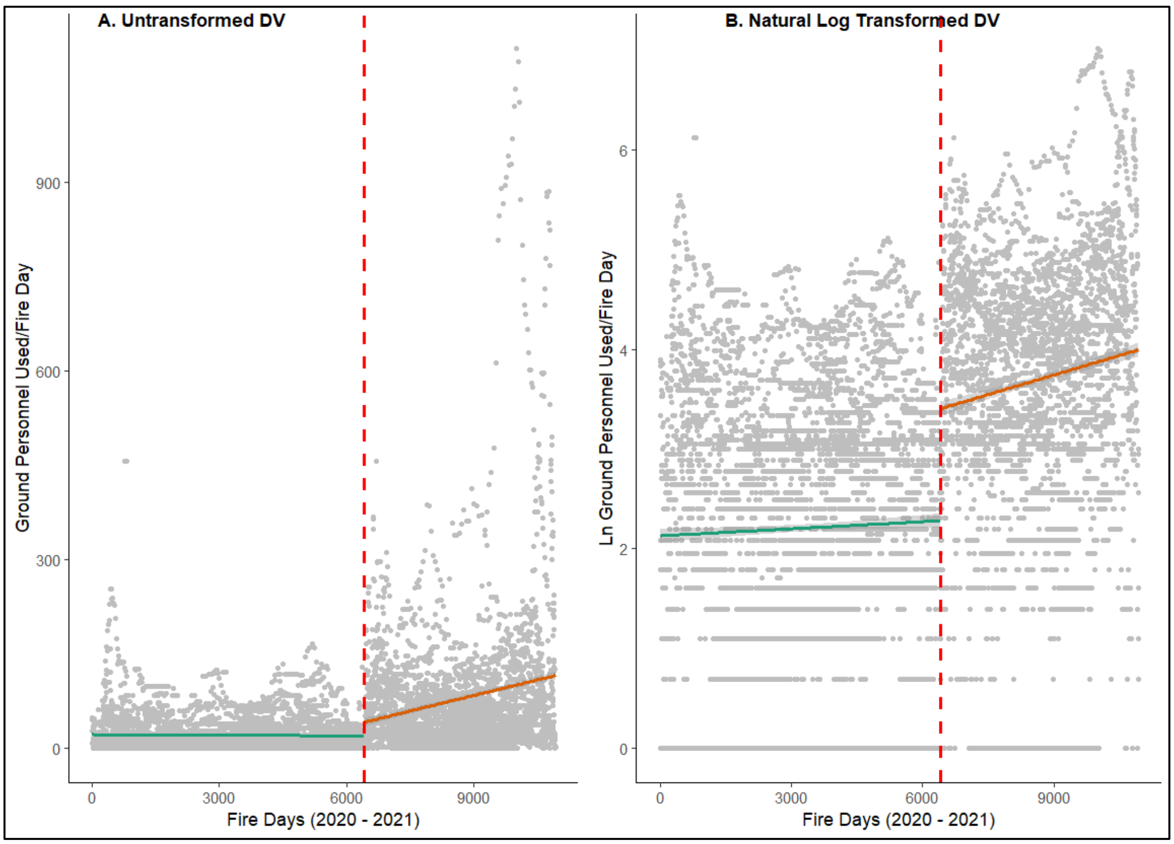


Figure 7. Scatterplot and fitted univariate linear regression line for the effect of the “During-2021 Threshold” variable on predicted (A) ground personnel and (B) natural log transformed ground personnel used per fire day. Dots represent the observed ground personnel use per fire day. The dashed vertical line represents the “During-2021 Threshold” cutoff of December 31, 2020, which served as the modeling threshold variable.

3.3. Regional sharp RDD results.

Sharp RDD models were developed for individual GACCs to assess if and how ground personnel resources used before and during COVID-19 changed within specific fire regions across the western U.S. In addition to exploring where resource use trends tended to occur over the western U.S., studying each region in isolation can also help understand when resource use shifts may have occurred by region. Figure 8 shows the total ground personnel used per calendar date from 2017 through 2021, illustrating how certain GACCs exhibit earlier fire season severity according to the relative proportion of ground personnel use. For instance, the pink shaded bars show the Southwest Coordination Center (SWCC), which tends to have the earlier fire seasons, whereas the blue shaded bars illustrate how California (ONCC and OSCC) tend to exhibit greater relative resource use in later months of the year.

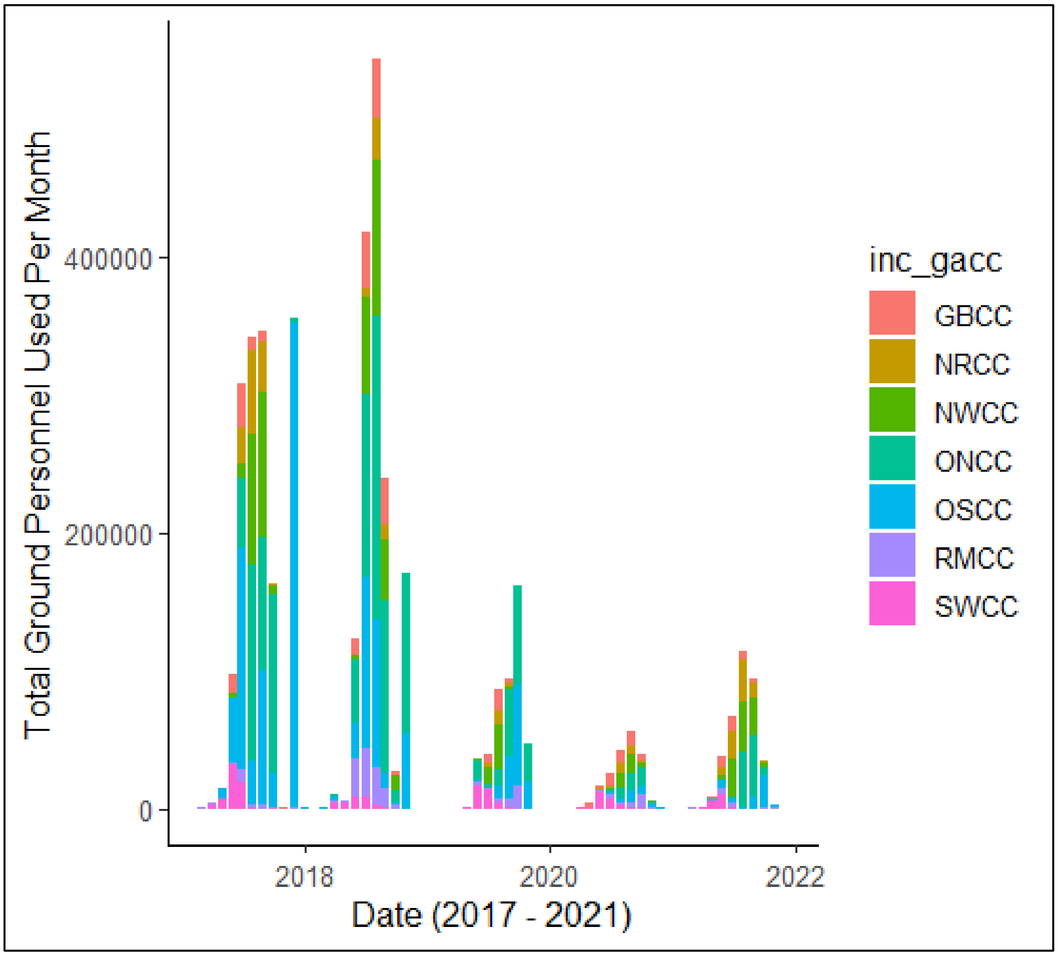


Figure 8. Total daily ground personnel used from 2017 through 2021 as summed across western U.S. GACCs according to integrated ICS-209 and ROSS/IROC data.

When comparing resource use trends across GACCs, it is also helpful to first understand the observed frequency, median, and average ground personnel resource at the regional level to inform predicted changes in natural log ground personnel used. Table 6 shows the total fire day observations for each GACC, the pre- and during-COVID arithmetic means and standard deviation, and the pre- and post-COVID geometric means. ONCC and OSCC exhibit the highest ground personnel use per fire day pre-COVID, such that the observed geometric mean for the ONCC was 376.5 (SE = 4.1; median = 387) ground personnel used per fire day. By comparison, the NRCC revealed a geometric mean of 65.9 (SE = 3.9; median = 82) ground personnel per fire day, highlighting that regional trends in resource allocation and use may be critical to further evaluate under the sharp RDD univariate and multivariate linear regression approach.

Table 6. Observed count of regional fire day observations (n), geometric means, and standard deviations from the geometric means of ground personnel resources for pre- and during-COVID fire day observations according to observed ICS-209 reports.

	Pre-COVID			**During-COVID**		
GACC (total *n*)	*n*	Geometric Mean (SD)	Median	*n*	Geometric Mean (SD)	Median
GBCC (3208)	1463	65.9 (3.9)	82	1745	24.3 (3.8)	29
NRCC (4083)	2499	53.8 (3.9)	69	1584	17.3 (4.4)	23
RMCC (1983)	1063	69.7 (4.2)	92	920	11.6 (3.9)	13
SWCC (2125)	945	77.2 (3.2)	80	1180	11.2 (5.8)	14
NWCC (4815)	2316	112.9 (3.9)	132	2499	28.9 (3.3)	30
OSCC (2683)	1544	323.3 (4.2)	387	1139	17.6 (4.9)	20
ONCC (3125)	1615	376.5 (4.1)	434	1510	28.9 (4.8)	31

At the regional GACC level, univariate sharp RDD models across the global bandwidth (2017 – 2019 versus 2020 – 2021) indicated that there were statistically significant percentage reductions in ground personnel resources used per fire day for during-COVID relative to pre-COVID fire days. Figure 9 shows the univariate sharp RDD linear regression trends for natural logged ground personnel used pre- relative to during-COVID fire days.

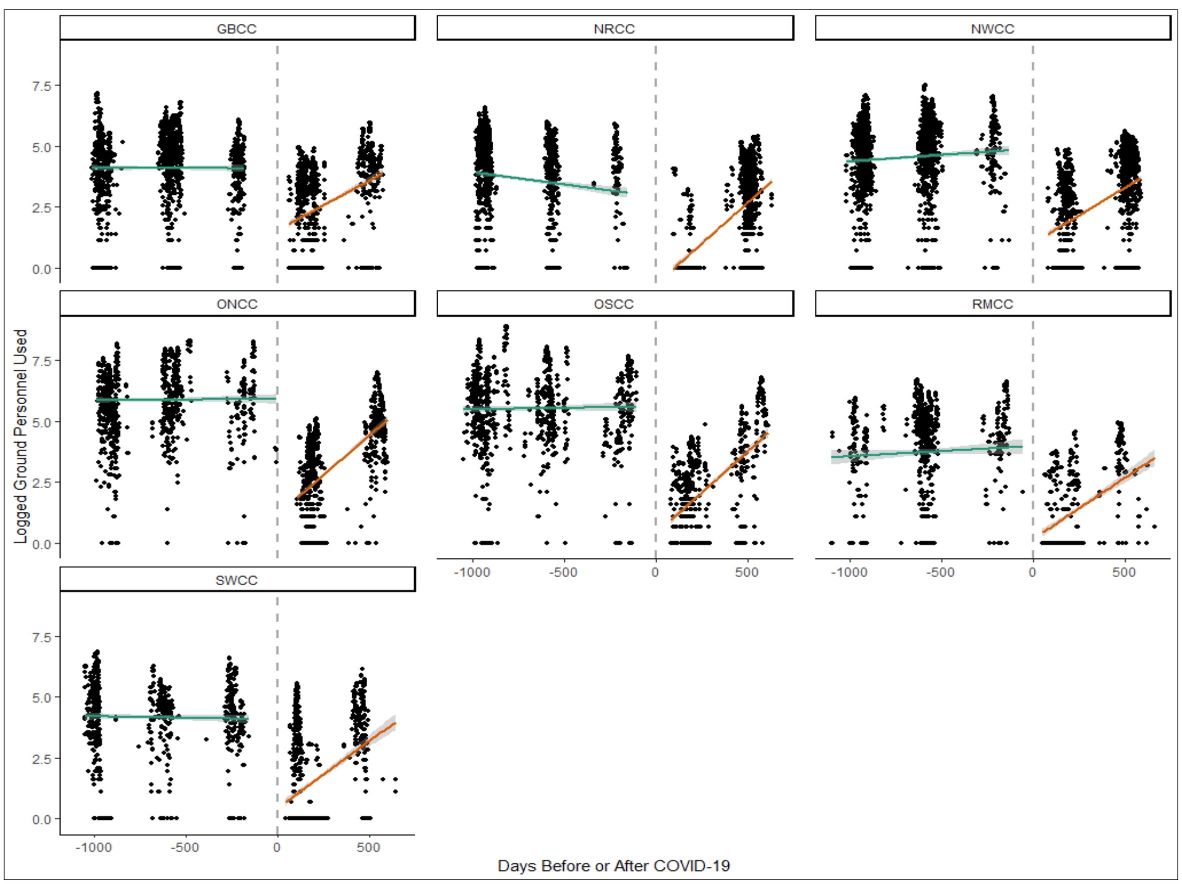


Figure 9. Univariate sharp RDD results for global model (2017 – 2019 v 2020 – 2021) for each GACC using the full dataset. The fire observations to the right of the dashed gray line show during-COVID fire days.

In addition to univariate trends, Figure 10 shows the average predicted "During-COVID Threshold" per GACC main effect results for the sharp RDD multivariate linear regression models using the global bandwidth, holding covariates constant. Figure 10 orders western GACCs according to average predicted percentage change in ground personnel used per fire day during-COVID, after holding all regional-level covariates constant.

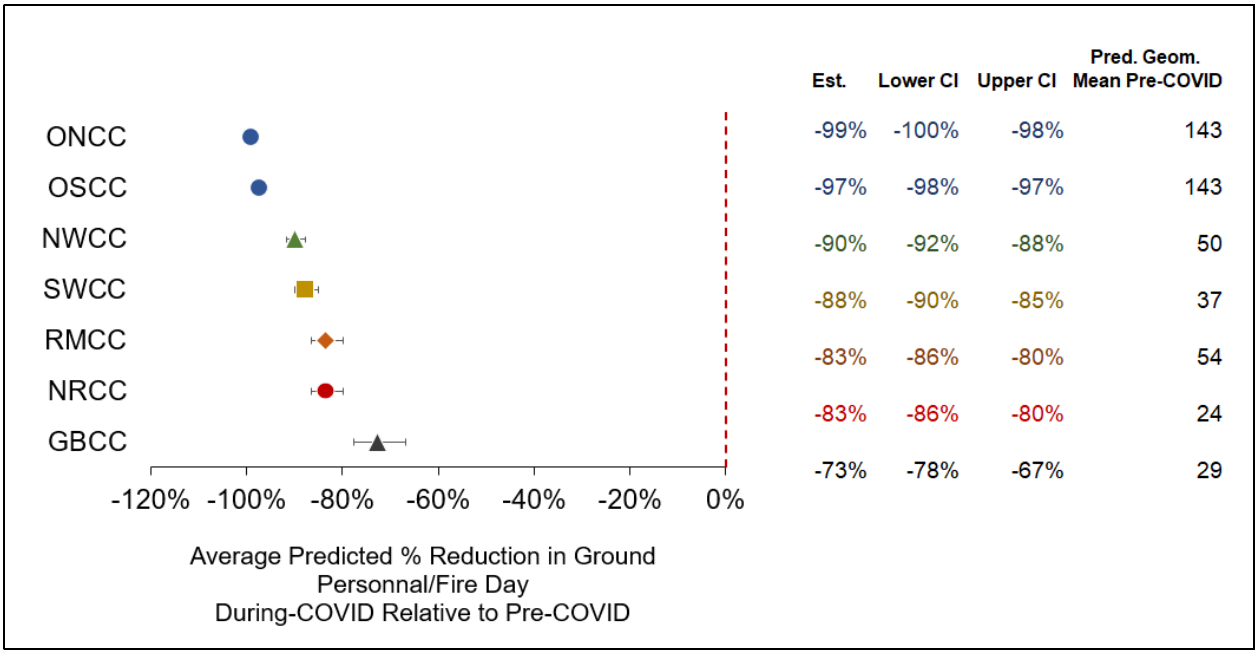


Figure 10. Forest plot showing the average predicted percentage change in ground personnel resource use during- relative to pre-COVID using sharp RDD multivariate regression models developed for each GACC (global bandwidth; 2017 – 2021). The effect sizes of the binary "During-COVID Threshold" variable are visually represented in the figure, and adjacent values in the data table align with each GACCs "During-COVID Threshold" estimate, the corresponding 95% CI, and the predicted geometric mean for pre-COVID fire days. The predicted geometric mean is included to provide a baseline for the average model prediction of pre-COVID ground personnel used per fire day, holding covariates constant. All "During-COVID Threshold" effects and models were statistically significant at the $\alpha < 0.001$ level.

All GACCs shown in Figure 10 were predicted to have reductions in the percentage of ground personnel used per fire day during-COVID relative to pre-COVID fire days, holding covariates constant. As shown in Table 6 and Figure 6, the ONCC (northern California) fire region was predicted to have the greatest average reduction in ground personnel used per fire day, such that there was a predicted average reduction of ground personnel by 98 – 100% during-COVID fire days relative to pre-COVID fire days, where there was a mean of 773 ground personnel used per pre-COVID fire day. Similar findings held for OSCC (southern California), where ground personnel resource use for pre-COVID fire days was predicted to reduce by an average of 97 – 98% during-COVID fire days, holding covariates constant. The global sharp RDD multivariate linear regression model predicted that the GBCC, NRCC, and RMCC fire regions had a lesser, though still strategically and tactfully impactful, reduction in the average predicted reduction in ground personnel used for during-COVID fire days relative to pre-COVID. To further assess why certain regions, such as the GBCC, NRCC, and RMCC, were predicted to have less extreme average reductions in ground personnel than other regions. Figure 11 illustrates the relative proportions of total ground personnel used per year per GACC according to general fire behavior, categorized by fire management teams along a 1 to 4 categorical scale (i.e., *1 = Minimal to 4 = Extreme fire behavior*).

4. Discussion

Sharp RDD model designs were developed to assess ground resource use per fire day across the western U.S. and by fire regions before and during the COVID-19 pandemic. Model results inform if and how fire suppression management may have changed over the course of the pandemic, controlling for a wide range of weather, fire behavior, societal risk factors, and strategic objectives as identified by fire managers. While anecdotal evidence has suggested potential reductions in personnel use per fire day during the COVID-19 pandemic, the extent of this reduction was formerly unclear. As such, the sharp RDD modeling approach aimed to inform if and how fire suppression resource use may have shifted or adapted over nearly two years of the pandemic. To do so, we focused on ground personnel (i.e., crew members, equipment operators), who are typically required to work in the field and therefore unable to work remotely, unlike overhead personnel (i.e., administration, fire behavior modeling, etc.).

Comparing fire days that occurred in the western U.S. between 2017 and 2021, sharp RDD univariate and multivariate regression results indicated significant percentage reductions in ground personnel used per fire day for during-COVID fires relative to pre-COVID fires. Ground personnel reductions were found to be consistent across bandwidths and according to the model that did versus did not include outliers and highly influential data points (Table 5, Model B). Generally, average reductions in ground personnel were predicted to be approximately 70 to 98% of pre-COVID fire days, controlling for weather, societal risk factors, strategic objectives, regional PLs, and GACCs. Using the 2020 versus 2021 model bandwidth, there was an average predicted percentage change in ground personnel resource use such that approximately 8 times as many ground personnel were used per 2021 fire day relative to 2020 fire days. By the end of 2021, the average predicted ground personnel resources used per fire day nearly aligned with pre-COVID rates.

Regionally, we found observed and predicted reductions in ground personnel resource use between pre- and during-COVID fire days for all western U.S. fire regions (i.e, GACCs). Predicted reductions were particularly pronounced in California. In the ONCC (i.e., northern California), the sharp RDD multivariate model using the global bandwidth and all fire day observations predicted an average reduction in ground personnel used per fire day during-COVID by 98 to 100% ($p < 0.001$) relative to pre-COVID fire days. Similarly, average reductions by 97 to 98% ($p < 0.001$) were predicted in the OSCC (southern California). Though the current model does not incorporate or distinguish between personnel agency affiliation (i.e., state, federal, contracted ground personnel), resource scarcity in California has been discussed and linked to reductions in California inmate crew personnel (Tillman, 2020). Reporting on workforce composition for the 2018 – 2019 fire year, CAL FIRE (California's state fire agency) reported that inmates composed approximately one-quarter of their total workforce (i.e., 3,500 ground personnel) (CAL FIRE, 2018; Tillman, 2020). While some inmate crew members were released from prison due to overcrowding concerns associated with COVID-19 transmission, other inmate crews experienced COVID-19 transmission within fire camps (Stark, 2020). In July 2020, it was reported that 94 of the 192 state inmate crews were active (Stark, 2020). California's use and treatment of inmate crews has been criticized, as these critical ground personnel are estimated to make \$2 to \$7 per fire day (Lowe, 2021). Further, those who have served on inmate crews and who have been released from prison have faced barriers in that—despite their experience—state and local agencies have not hired people with criminal records (Lowe, 2021). Future work is needed to tease apart where, when, and why California ground personnel resource use reductions have occurred over the course of the pandemic, though reasonable speculation may connect overall ground personnel reduction to reductions in inmate crew availability. From the author's perspective, perhaps this also indicates that career opportunities should be made available to those who have endured the fire line and are subsequently released from prison, despite convictions.

Though there were consistent reductions in predicted ground personnel use during-COVID fire days across each GACC, the degree of the reduction varied. As discussed, the highest percentage reductions were observed and predicted for California's ONCC and OSCC. The Southwest region (SWCC) has consistently had the earliest peak fire season in the western U.S., which co-occurred during the beginning of the COVID-19 pandemic in March 2020. Further, the SWCC fire season was particularly active, burning nearly 1 million acres in Arizona alone – the states most active fire season in the past decade (Vandell, 2021). Sharp RDD models predicted an average reduction of 85 to 90% ($p < 0.001$) of ground personnel on during-COVID fire days, compared to pre-COVID fire days. Considering that the SWCC had the earliest peak fire season that co-occurred during the start of the pandemic, assessments of SWCC fire management perspective and experiences in strategic and tactical operations at the start of the pandemic may be useful to inform whether the observed and predicted ground personnel reductions were attributed to COVID-19 risk management concerns, resource availability, or potential data inconsistencies outlined in the Limitations section. Finally, the GBCC (i.e., Utah, Nevada, southern Idaho, western Wyoming) had observed and predicted reductions of ground personnel per fire day to a lesser degree than other fire regions. Comparative differences between regions affirm that it may be preferable to interpret results at the regional level, as resource use changes were disproportionate by GACC.

Overall, the reductions in resource use in 2020 exhibited here—whether associated with COVID-19 risk management, workforce availability, or other considerations—may be of concern to both fire management agencies as well as vulnerable communities.

4.1. Future work.

Immediate next steps in the current analytic plan include running models by national and/or regional PLs to assess if and how fire days with varying resource scarcity classifications were associated with observed and predicted changes for ground personnel use during-COVID relative to pre-COVID fire days. Univariate sharp RDD results for the predicted changes in ground personnel use according to the global model bandwidth (2017 – 2019 versus 2020 – 2021) are included in Appendix 3D. To extend this work beyond resource use assessments, future projects can align these models with wildland fire suppression outcomes, including: the ratio of structures damaged to threatened, lives lost, suppression costs, and other metrics of net societal damages (i.e., perceived value of cultural/historical site damages, including monetary and non-monetary, through preference weighting). Extending models in this way will help determine if and how potential resource use changes led to different fire outcomes. For instance, structural equation modeling could be used to link models of fire characteristics, resource use, and fire outcomes at the fire day or fire incident level to assess the relationship between pre- and during-COVID resource use and fire outcomes. While the current analysis suggests significant ground personnel resource reduction during fire days that occurred during the COVID-19 pandemic relative to prior recent years, this analysis does not assess fire outcomes in terms of specific or net societal losses incurred as related to this reduction in ground personnel resource use. We believe the relationship between resource use and fire outcomes may be worth assessing to evaluate if and to what extent fire agencies can better prepare for and adapt to the evolving fire landscape met with predicted increases in infectious disease spread attributed to climate change (Baker et al., 2022).

To derive a first order approximation of the relationship between ground resource use and fire outcomes, we aggregated total public and personnel injuries and fatalities at the monthly level across the current dataset. Then, we calculated the ratio total injuries and fatalities per fire incident from 2017 to 2021 (Figure 11).[30] We elected to assess injuries and fatalities rather than fire acres burned for the first order assessment of fire outcome changes that may be associated with during-COVID reductions in ground personnel use per fire day (Kolden, 2020).

[30] We also derived the ratio of total injuries and fatalities to total monthly fire incidents. See Appendices 3D for more information.

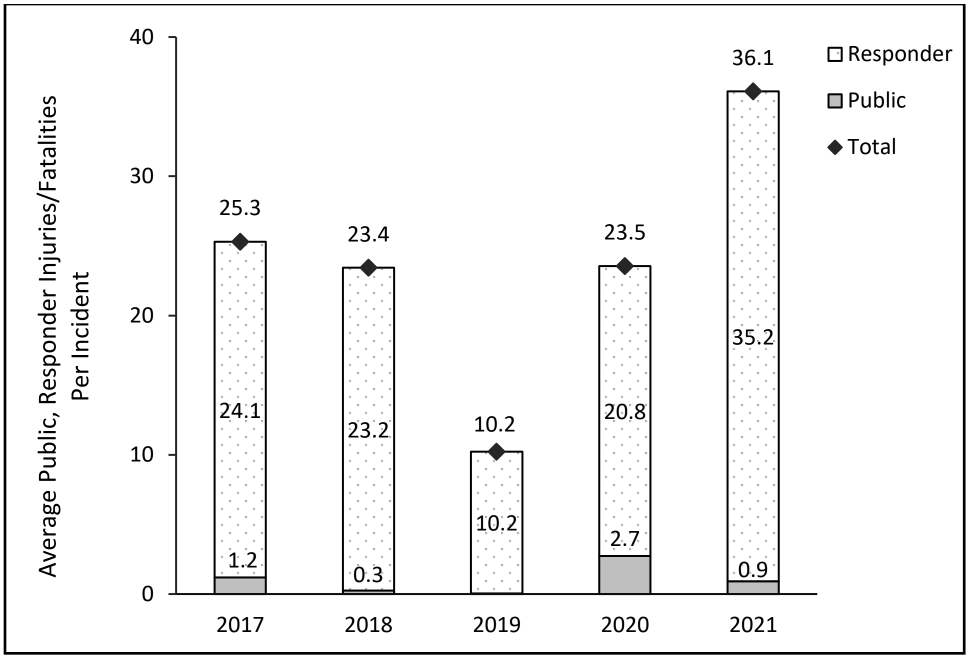


Figure 11. Average combined public and personnel injuries and fatalities per fire incident by year.

Results from Figure 11 suggest that the average public and personnel injuries and fatality rates at the fire incident unit of analysis may have disproportionately increased 2021, despite ground resource use recovery in 2021 relative to 2020 as predicted by the sharp RDD multivariate model. The average number of injuries and fatalities in 2021 was 36.1 responders and public community members, relative to 23 to 25 injuries and fatalities per incident in 2017, 2018, and 2020. The reduction in injuries and fatalities in 2019 is likely attributed to overall fewer fire incidents and less complex fire incidents, as shown in Table 1. While Figure 11 does not control for factors such as weather conditions or national/regional PLs, the first order results suggest that it may be worth assessing how ground personnel resource reduction during the pandemic was associated with societal damages and costs, including but not limited to injuries and fatalities.

Finally, evaluations of the Biden-Harris Infrastructure Law can be conducted to assess if and how other factors, such as rising costs of living that occurred during the COVID-19 pandemic, might be related to resource availability and subsequently resource use. As discussed in Chapter 2, the Biden-Harris Infrastructure Law will increase federal firefighting salaries by $20,000 per year, or up to 50% of their current salary depending on if they work in a region that is predetermined to have scarce resources (Biden-Harris Administration, 2022). Similar sharp RDD models could be developed to evaluate trends in resource use per fire day before and after the passage of the Infrastructure Law, which can further inform how the observed and predicted ground resource use reductions shown in this study where related to workforce compensation and resource availability. Finally, this dataset did not include information on COVID-19 transmission within crews; which would be useful to include to assess ground personnel resource use under conditions of within or between crew transmission of COVID-19 or other infectious diseases (Belval et al., 2022; Thompson et al., 2020). There may be opportunities to integrate predictive epidemiological models with historical data here to test if and how national and regional shifts in resource use may be linked to infectious disease transmission within and between firefighting units

4.2. Limitations.

While RDD models are considered “quasi-experimental”, we believe that these relationships should be considered correlational as resource use per fire day may be influenced by various societal, political, and economic considerations. While we attempted to capture fire management objectives through NLP processing of Incident Commander "Strategic Objectives" summaries in the ICS-209 data, learned information from Chapter 2 (i.e., interviews on compounding threat management) suggests that resource allocation can be influenced by social networks as well as the career experiences of fire management personnel. As such, while this modeling approach captured a range of physical and societal considerations that might influence resource allocation and subsequent use, there may be other management-related variables not captured in the current set of models. Additionally, resource use per fire day is most likely correlated with and constrained by the number of available resources on any given day. Resource availability data at the national and regional levels was considered to be sensitive information and my access was therefore restricted. Resource availability may have reduced overall given the pandemic, such as was likely the case in California, where approximately half of inmate firefighting crews were unable to participate in fire suppression activities due to COVID-19 transmission risks.

Further, wildland fire agencies transitioned from the ROSS to IROC resource management systems in early 2020, right around the same time as the COVID-19 pandemic began. Fire managers report resource requests, assignments, and use via this system. As global models of overhead, rather than ground, personnel resources used (Appendices 3B) did not reveal this same reduction despite being logged on the same resource monitoring and tracking platform, we have reason to believe that the observed reduction in ground personnel resources used was not greatly influenced by potential data inconsistencies that could have occurred given the transfer to new software. If this reduction were attributed to database inconsistences/errors, national fire management should adjust for this for future operations and research purposes.

5. Conclusion

Chapter 3 used historical records of fire days from 2017 through 2021 to assess if and how ground personnel resource use changed between pre-COVID and during-COVID periods. Using sharp RDD univariate and multivariate linear regression models at the western U.S. and western U.S. fire region scales, we show that during-COVID, there was an average predicted reduction in ground personnel used per fire day by approximately 70 – 99%, relative to pre-COVID fire days. Observed and predictive reductions in ground personnel used per fire day were consistent across bandwidths (i.e., timeframes) of analysis and for each of the western U.S. fire regions (albeit to different degrees of observed and predicted reduction). When modeling 2020 to 2021 fire day observations, there was an observed and predicted increase in ground personnel used per fire day. Finally, to estimate how changes in ground personnel might be associated with fire outcomes, we included a first order assessment of aggregate public and personnel injuries and fatalities per fire day observation from 2017 through 2021. First order results suggest that their may be an association between reductions in ground personnel use and estimated public and personnel injuries and fatalities; future work is recommended to further assess the implications of ground personnel reductions for wildland fire suppression efforts.

Conclusion Chapter

This thesis focuses on developing an understanding of the characteristics that facilitate and inhibit adaptive capacity and adaptive decision-making processes given increasingly complex threats, focusing primarily on behavior related to adaptive technology and resource use in chronic and/or compounding threats. Three chapters use qualitative and quantitative data to explore and assess the behavioral, geospatial, and sociotechnical properties and characteristics of individuals and institutions that may facilitate and inhibit adaptive capacity and resilience under a range of chronic and compound threats. Together, findings converge on the "capacity-adaptation relationship" (Mortreux and Barnett, 2017, pg. 7), a complicated relationship wherein prior research has found that the availability of and access to assets and resources are insufficient in predicting and capturing enacted adaptive behavior. Adaptive capacity has been associated with psycho-social factors including risk perception and attitudes, personal experience, trust and expectations in authorities, place attachment, and competing objectives or concerns (Wong-Parodi, 2022; Mortreux and Barnett, 2017; Fazey et al., 2007).

Chapter 1 assessed San Francisco Bay Area commuting behavior by integrating transportation alternative accessibility, demographic, and socioeconomic factors with preferences for transportation attributes. In doing so, I aimed to capture psycho-social facilitators and barriers to sustainable, multimodal commuting behavior by weighing if and how adaptive transportation behaviors were informed by geospatial and socioeconomic factors, as well as personal preferences and competing concerns related to socializing, multi-tasking, and minimizing environmental impacts. Soon after, I was exposed to the stressors, constraints, and competing objectives involved in hazard management during the COVID-19 pandemic through my experience as a student contractor for the U.S. Army Corps of Engineers. Realizing, and to a small extent partaking in, the hazard management responsibilities that fall on local, state, and federal agencies, I aimed to connect individual perspectives of adaptive hazard management to organizational and institutional objectives, constraints, and overall resilience. Thus, Chapter 2 used a semi-structured interview approach to learn from the lived experiences of federal hazard management personnel, who faced compounding threats including but not limited to the COVID-19 pandemic co-occurring during natural hazards. An interview approach was taken to capture a broad range of institutional and socio-technical barriers and facilitators to federal agency adaptive capacity that might be otherwise difficult to quantity, but that influenced incident prioritization, resource allocation, and coordination processes during compounding threats, which have been empirically associated with multiplicative risks (Zscheischler et al., 2018). Inductive findings related to workforce fatigue, mental health, and attrition motivated Chapter 3. Chapter 3 aimed to measurably assess if and how wildland fire suppression resource use changed over the course of the COVID-19 pandemic. While prior research on organizational and institutional adaptive capacity is often limited by lack of data or evidence of adaptive behaviors (Mortreux and Barnett, 2017), I aimed to empirically assess the capacity-adaptation relationship for western U.S. wildland fire agencies faced with increasingly long, frequency, and severe fire seasons compounded by the COVID-19 pandemic.

Chapter 1 Overview:

Based on integrated survey and geospatial analyses of commuter transportation behaviors in the San Francisco Bay Area, Chapter 1 focused on identifying if and how multimodal transportation behavioral patterns emerged via a Classification Tree approach. Demographic, socioeconomic, transportation preference, and geospatial commute characteristics of participants were used as inputs to predict whether participants were unimodal (i.e., vehicle only commuters), non-vehicle (i.e., walking, biking), or multimodal (i.e., use vehicle at least once and other transportation mode at least once) over a week. Chapter 1 introduced a method that integrated participant preferences with geospatial data to classify behavioral outcomes and emerging transportation adoption in an urban environment with a growing population that has encouraged multimodal and non-vehicle transportation choices through various incentives and disincentives. Further, at the time of data collection, the San Franscisco Bay Area had a host of emergent and sustainable transportation modes available to the public, with varying degrees of accessibility based on participant residential and workplace addresses. Classification Tree results suggested that while environmental factors, such as residential population density at the zip code level, were predictive of commuting behaviors, participant preferences for general attributes of transportation mode alternatives were also determinants in predicting commuting behavior. For instance, the "importance of engaging in other activities", the "importance of making multiple stops along the route" and the "importance of minimizing environmental impact" were associated with reported commuting behaviors.

The results in Chapter 1 offer deeper understanding of the interactions between the transportation environment, human behavior, public health, and available technology. These insights help target specific unimodality reduction efforts as urban regions in the US strive to reduce personal vehicle use and transition to more sustainable and emergent transportation modes. Future work could use this survey and modeling approach to assess if and how preferences for transportation attributes and commuting behavior shifted over the course of the COVID-19 pandemic. Additionally, this model could be used to assess if and how multimodality in California will shift along the lifecycle of the California Air Resources Board's newly proposed zero-emission vehicles rule, which mandates that 100% of vehicles sold in California will be plug-in hybrid electric, electric, or hydrogen fuel cell by 2035 (California Air Resources Board, 2022). Longitudinal studies using this and similar commuting behavior models can detect trends and factors associated with transitions to more sustainable commuting, including multimodal and non-vehicle commuting. Implications from the legislation in California may inform shifts in preferences for and adoption of transportation alternatives, including electric vehicles as well as public transit, bicycling, scooters, and walking modalities.

Chapter 2 Overview:

The association between preferences and geospatial data on technology use inspired subsequent thesis chapters, which pivoted from a focus on transportation behavior at the individual level to organizational behavior and adaptation to compound threats. Chapter 2 involved deductive and inductive thematic content analysis to explore if and how federal hazard management agencies adapted to and were resilient in light of compound threats, according to agency personnel perspectives. Particular emphasis was placed on wildfire and hurricane management agencies, with representation also from federal agencies involved in flood and tornado events.

Semi-structured interview results explored how federal agencies manage compound threat events based on lived experiences, perceived strengths, and perceived opportunities to adapt federal hazard management to meet the mounting risks presented by compound threats. Interview results suggest that the sampled federal hazard management personnel were aware of compound threat potential, indicating that hazard management has involved increasingly frequent, severe, and complex incidents. The compound threat of COVID and other hazards was discussed in each interview, and generally, participants expressed that the COVID-19 pandemic instigated positive change and new management practices, including the acquisition and use of improved remote communication systems within and between agencies and communities, as well as positive operational adaptations (e.g., spike camps, module-of-one concept in fire management). Beyond COVID-19, many participants attributed the increasingly complex threat to climate change and/or interconnected critical infrastructure systems. Emergent modeling approaches and remote sensing technologies were described as useful in adapting to compound threat management by offsetting personnel risk, collecting real time data for forecasting, situation monitoring, and conducting damage assessments in hazard-affected areas. However, participants described the internal barriers and external stressors that limit the absorptive and adaptive capacities of federal agencies managing compound threats. Absorptive and adaptive capacity were found to be constrained by: (i) lack resource availability and scarcity, (ii) lack of consensus or validation of predictive decision-support tools, and (iii) inter- and intra-agency coordination constraints, including balancing objectives in multi-objective decision spaces that necessitate "pretty rapid-fire" (Interview 2) decision making processes under uncertainty with resource competition.

A central theme that emerged from the interviews was that there is a current scarcity of hazard management personnel at all levels of government. This was attributed to an increase in hazard season durations and severity, wages not meeting the rising cost of living, and general mental health concerns for personnel exposed to high levels of physical and emotional stress. The "degrading workforce" (Interview 27) amidst intensifying threats has constrained the range of strategic operations and may be adding to the workload of individuals working in federal hazard management, particularly those who are deployable. Participants expressed that resource availability and adjacent hiring practices and workplace culture do not promote adaptation to current threats (i.e., sufficient recovery periods post-deployment). These participant perspectives, however, seem to be acknowledged institutionally such that the Biden-Harris Infrastructure Law will increase the compensation of wildland firefighters.

Additionally, the interviewees expressed a view that community engagement may improve equitable hazard management given compound threats, such that "…there's a shift across the board with federal agencies looking at social equity… And you know, that has a big role to play in compounding threats" (Interview 14, USACE). Equitable hazard management is essential given the disproportionate risks faced by marginalized communities (Lukasiewicz, 2020). Compound threat management decisions based on benefit-costs analysis alone can perpetuate inequities experienced by marginalized communities. This is particularly concerning for compound threats, which may pose unforeseen and/or compounding risks to vulnerable communities. The United Nation's Sendai Framework and many other risk assessments do not currently integrate structural inequities or social injustice (Kruczkiewicz et al., 2021). As threats and stressors beyond acute natural hazards, including but not limited to the COVID-19 pandemic, have also disproportionately affected lower socioeconomic and Black, Indigenous, People of Color (BIPOC) communities, it is imperative for federal agencies to establish decision-making processes that consider and weigh the risks faced and resources needed by affected communities. Chapter 2 participants discussed opportunities for making hazard support processes more equitable. For instance, emergent data collection and analytic capabilities within the Federal Emergency Management Agency (FEMA) were described as helping them to identify if and how FEMA financial assistance has been distributed equitably to support hazard-affected homeowners and small business owners.

Future work could extend these exploratory interview findings to guide the development of broader data collection processes, such as surveys that could be distributed across federal agencies. For instance, survey approaches could probe if and how decision-making processes, incident priorities, and constraints differ between compound and singular threats. Such information could inform existing compound threat management approaches, such as the “Unified Area Command” approach within the ICS, by garnering more data on workforce perceptions of the competing objectives and resources during compound threat scenarios. Insights might benefit from more localized place-based and/or hazard-based assessments (Cutter et al., 2008). Additionally, future research can quantitatively assess if and how resource availability and use have historically changed over time, particularly in the contexts of compound threats (i.e., wildland fires and COVID-19) and in light of recent introductions and passages of federal resource support (i.e., the Biden-Harris Bipartisan Infrastructure Law, FEMA’s emergent Building Resilient Infrastructure and Communities support, and the Drone Infrastructure Inspection Grant Act). To do so, historical FEMA ICS data could be used to evaluate societal risks (i.e., structures damaged/destroyed, public and personnel injuries and fatalities) and resource allocation in singular versus complex incident types over time and by region.

Chapter 3 Overview:

A core finding that compound threat management is constrained by personnel scarcity motivated Chapter 3, which assessed and compared wildland fire suppression resource use and before and over the course of the COVID-19 pandemic. While Chapter 2 focused on identified the core constraints that limit federal agency adaptive capacity, Chapter 3 focused on if and how the perceived personnel constraint found in Chapter 2 was manifested in wildland fire suppression efforts. In Chapter 3 historical datasets of daily fire management situation reports, weather conditions, and resource scarcity are used to develop sharp Regression Discontinuity Design models that predict daily ground resource use for fire suppression efforts, controlling for weather conditions and societal risk factors from the perspective of fire managers. Models developed at the western U.S. and fire region scales consistently reveal that ground resource use per wildland fire days is predicted to have been reduced during the COVID-19 pandemic by an average of 70 – 98%, holding covariates constant. Thus, even when controlling for a wide variety of weather, fire behavior, and societal risk factors, ground personnel resource use declined in 2020 and in 2021, relative to 2017 – 2019. Future work can be extended by developing models, such as structural equation models, that assess if and how the observed and predicted reductions in ground personnel resources used are associated with fire outcomes (i.e., public and personnel injuries and fatalities, structures damaged, suppression costs, etc.). Further, as personnel and other resources were expressed to hinder the absorptive and adaptive capacity in compound threats, evaluations of how federal agencies have operationalized compound threat-specific management by assessing historical resource allocation data can help to identify and evaluate thresholds for which agency practices and technologies facilitate or hinder adaptive capacity during compound hazard management. These considerations will help to inform further extensions of Chapter 3 of this thesis, which assesses wildland fire suppression resource use before and during the COVID-19 pandemic.

Concluding Remarks and Directions for Future Work:

There is increasing recognition that current resources and decision-making processes from the individual to institutional scales may be inadequate in preparing for, responding to, and adapting to the changing climate. This thesis emphasized the relationship between adaptive capacity and resource availability – but that the availability of and access to resources alone is insufficient in capturing individual and organizational adaptive behavior. In addition to tangible resources, psycho-social factors such as personal experience, competing objectives, and risk perception and communication can constraint adaptive capacity. Chapters 2 and 3 focus on challenges presented by a variety of compounding threats, which are anticipated to increase in frequency, severity, and complexity moving forward (Phillips et al., 2020). While the authors agree that the U.S. government, corporations, and citizens should engage in sustainable behaviors that limit environmental and atmospheric degradation (such as transitioning to more sustainable transportation alternatives as explored in Chapter 1, or more preventative management of hazards as raised in Chapter 2 interviews), global societies also need to understand how to overcome the internal barriers and external stressors that limit our ability to adapt to this changing world. The adaptive capacity of the United States is in part contingent on the resilience of local, state, and federal hazard management agencies, who serve to help communities prepare for, respond to, recover from, and adapt to stressors and disruptions in the natural and built environments. Thus, it is critical to support this essential workforce, particularly given the resource constraints and mental health concerns discussed in Chapter 2 and resource use implications presented in Chapter 3. Consistent with the findings presented in this thesis, various policy changes are underway that may enhance hazard management adaptive capacity and resilience. For instance, the Biden-Harris Bipartisan Infrastructure Bill was recently enacted with the intent to bolster support for physical infrastructural resilience and adaptation, as well as support essential workforces involved in hazard management, such as wildland firefighters. Future work can evaluate federal agency adaptive capacity through the lens of resource availability before and after the implementation of workforce benefits received under the passage of the Biden-Harris Infrastructure Bill (Biden-Harris Administration, 2022). Additionally, the bipartisan Drone Infrastructure Inspection Grant (DIIG) Act aims to increase local, state, and federal access and training for infrastructural inspections and damage assessments via drone technology (H.R. 5315, 2022). The passage of this or similar grants can enable hazard management agencies from the local to federal levels to deploy drones for real-time data acquisition that can protect community and workforce health and safety, improving upon resource constraints mentioned by participants. While the benefits costs of these policies and grants are yet to be evaluated, their introduction and passage suggest that the federal government acknowledges current and future threats and has weighed if and how our current federal hazard management workforce can be supported to absorb and adapt to such threats. Enhanced resource capabilities may facilitate resilience of the agencies themselves as well as the communities that they protect by offsetting personnel safety risks. Future research, which I hope to participate in, can empirically evaluate the efficacy, efficiency, and equity of these emergent policies.

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Conclusion References

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APPENDIX 1: Factors associated with emerging multimodal transportation behavior in the San Francisco Bay Area

Appendix 1A: Literature Review

Multimodality has been defined across the literature as the use of at least two modes of transportation during a predetermined time period [1 – 3]. Intermodality, the combination of more than one mode of transportation over the duration of one trip, is a subset of multimodality [1, 2]. As in existent literature, intermodal behavior was enveloped within the multimodal class in the current study.

Classifying whether an individual exhibits multimodal transportation behavior has been executed both qualitatively and quantitatively [4]. The qualitative classification of multimodality requires strict, predetermined definitions of transportation behavior groups, and an individual's behavior determines which behavioral group they fall into [1, 2]. Classification of transportation behavior groups via qualitative means are heavily dependent on the predefined definitions of the groups. Alternatively, behavior groups have been established according to data-driven methods, such as latent class cluster analysis. Data-driven approaches establish behavioral groups across data patterns, and individuals' classifications are based on which latent behavioral group they belong to [4, 5, 6].

Data sources of multimodal information. According to Buehler and Hamre (2015), there are three types of data typically used in multimodality research: (1) multi-week travel diaries, (2) week travel diaries, or (3) one-day travel surveys with questions regarding prior travel behavior (e.g., over the past year) [1, 7]. While multi-week travel diaries capture occasional transportation behavior, they suffer from smaller sample sizes. As such, the majority of related literature uses past-week transportation behavior information [1 – 3, 7].

Appendix 1B: Sample Recruitment Details

The WholeTraveler survey was distributed across the nine counties of the San Francisco Bay Area in 2018. Recruitment letters were sent to approximately 60,000 randomly selected household addresses across the SF Bay Area. The recruitment letters were sent via a paper mail invitation and follow-up postcard. The recruitment letters specifically asked the household member over 18 years old with the most recent birthday to participate. This was done to randomly select one person from a given household. Participants completed the survey via an online web page between March and June 2018. The survey was presented in English only. Participants were compensated with a $10 Amazon gift card for completing the survey. Of the 60,000 households that were sent a recruitment letter, 1,045 participants completed the portion of the online survey used for this analysis. The average survey completion time was 28 minutes. A final sample of 888 participants was used for analysis after data preprocessing. A total of 157 participants were not included in the final analysis because they indicated that they did not commute to their identified primary destination within the past week.

Appendix 1C: Sample vs. Population

Table 1 compares the final 888 respondents from the WholeTraveler survey to the Bay Area population as collected by the American Community Survey (ACS) Public Use Microdata Sample (U.S. Census Bureau, 2018). The ACS PUMS Bay Area data represents over 377,000 residents and over 157,000 households across the SF Bay Area. The ACS PUMS data represents the 2017 data collection cycle; as the WholeTraveler survey data was collected in 2018, there may have been minor differences between the 2017 and 2018 Bay Area populations. As there were age restrictions for participation in the WholeTraveler survey such that all participants had to be at least 18 years of age, the age distributions within each survey difficult to compare directly.

Table 1. WholeTraveler survey sample representation of San Francisco Bay Area population according to population-weighted ACS PUMS data (U.S. Census Bureau, 2018).

	Percent of PUMS Bay Area	Percent of WholeTraveler Sample
Female	51	49
At least HS Educ.	75	98
At least Bachelor's Educ.	39	86
Born 1930s	4	1
Born 1940s	8	7
Born 1950s	13	14
Born 1960s	14	18
Born 1970s	14	21
Born 1980s	14	28
Born 1990s	12	10
HH Inc < $75 K	36	25.4
HH Inc $75 - 150 K	29	34.4
HH Inc $150 - 200 K	12	14.6
HH Inc > $200 K	22	25.6
Alameda County	25	22
Contra Costa County	14	15
Marin County	3	3
Napa County	1	2
San Francisco County	16	11
San Mateo County	8	10
Santa Clara County	23	25
Solano County	4	6
Sonoma County	6	6

Population and demographic information across the San Francisco Bay Area counties are derived from the 2017 American Community Survey (ACS) Public Use Microdata Sample (PUMS) as collected by the U.S. Census Bureau.

Appendix 1D: Descriptive Statistics Results

Table 1. Descriptive statistics (mean, standard deviation) for each explanatory variable input into the Classification Tree across the sample (n = 888).

Variable Category	Variable Name	Variable Type	Mean	SD
Demographic	Birth year	Discrete	1974	14.6
	Female	Binary	0.49	0.50
	Education	Categorical (1 – 8)	Bachelor's	NA
	Destination: School	Binary	0.04	0.21
	Destination: Work	Binary	0.73	0.45
	Destination: Other	Binary	0.19	0.39
	Income	Categorical (1 – 12)	$100 - $150K	NA
	Any child	Binary	0.15	0.36
Location Based	Alameda County Resident	Binary	0.26	0.44
	Contra Costa County Resident	Binary	0.14	0.34
	Sonoma County Resident	Binary	0.06	0.23
	Santa Clara County Resident	Binary	0.22	0.42
	San Mateo County Resident	Binary	0.08	0.28
	Marin County Resident	Binary	0.03	0.17
	Napa County Resident	Binary	0.01	0.11
	Solano County Resident	Binary	0.04	0.18
	San Francisco County Resident	Binary	0.17	0.37
	Residence Population Density (thousand people per square mile)	Continuous	13.5	15.68
	Destination Population Density (thousand people per square mile)	Continuous	9.1	13.42
	Residence to Destination Drive Distance (miles)	Continuous	12.6	14.35
Importance of Transportation Attributes	Importance of Other Activities	Ordinal	2.6	1.44
	Importance of Child Transport	Ordinal	1.2	1.81
	Importance of Environmental Impact	Ordinal	3.3	1.77
	Importance of Social Interaction	Ordinal	0.2	2.70
	Importance of Low Cost	Ordinal	3.8	1.22
	Importance of Low Hassle	Ordinal	4.4	0.95
	Importance of Multiple Stops	Ordinal	3	1.51
	Importance of Predictable Cost	Ordinal	3.6	1.30
	Importance of Predictable Time	Ordinal	4.4	0.90
	Importance of Safety	Ordinal	4.2	1.08
	Importance of Shelter	Ordinal	3.7	1.30
	Importance of Short Travel	Ordinal	4.3	0.93
Public Transit Accessibility	Access/Egress Walk Time (min) to Transit	Continuous	17	12.12
	Transit Transfers	Discrete	1.9	0.99
	Alternative Transit Routes Available	Discrete	3.8	0.66

Table 2. Distribution of transportation mode use of each commuting class when past-month behavior is assessed.

	Unimodal	Multimodal	Non-vehicle

Personal Vehicle	1.00	0.82	0.13
Carpool	0.26	0.40	0.05
Ridehail (Single)	0.07	0.25	0.13
Ridehail (Carpool)	0.03	0.24	0.13
Carshare	0.00	0.03	0.01
Telecommute	0.08	0.53	0.38
Bike, Foot	0.03	0.47	0.55
Public Mass Transit	0.04	0.41	0.60
Bus	0.02	0.23	0.36
Private Mass Transit	0.02	0.12	0.08
Motorcycle/Scooter	0.01	0.02	0.07

Table 3. Distribution of transportation mode use of each commuting class when past-day behavior is assessed.

	Unimodal	Multimodal	Non-vehicle
Personal Vehicle	0.51	0.31	0.00
Carpool	0.03	0.09	0.00
Ridehail (Single)	0.00	0.01	0.00
Ridehail (Carpool)	0.00	0.01	0.00
Carshare	0.00	0.00	0.00
Telecommute	0.00	0.12	0.07
Bike, Foot	0.00	0.16	0.23
Public Mass Transit	0.00	0.09	0.19
Bus	0.00	0.05	0.08
Private Mass Transit	0.00	0.03	0.04
Motorcycle/Scooter	0.00	0.00	0.00

Table 4. Descriptive statistics of the location-based variables. The population densities are reported as thousands of people per square mile. The WalkScore is a standardized score from 0 to 100 that estimates walking accessibility to various amenities (e.g., stores, schools, libraries, etc.) (Carr et al., 2011). Primary distance is the estimated driving distance (miles) between participants' residence and primary destination address according to Google Maps.

Input Variable	Mean	SD	Q1	Median	Q3
Residence Population Density (thousands of people/mi)	13.5	15.7	4.7	9.1	17
Primary Destination Population Density (thousands of people/mi)	9.1	13.4	1.7	5.7	11.1
Primary Distance (miles)	13	14.6	2.8	8.3	17.2
WalkScore (1-100)	55	28.7	33	58	80

Table 5. Descriptive statistics of the preference for transportation attribute variables. Each attribute was ranked in terms of importance to the participant along a 5 point Likert-scale (1 = *Not at all important* to 5 = *Very important*).

	Mean	SD	Median
Activities	2.6	1.4	3
Child transportation	1.2	1.8	0
Environmental impact*	3.3	1.7	4
Social interaction*	0.2	2.7	1
Low cost	3.8	1.2	4
Low hassle	4.4	0.9	5
Multiple stops	3.0	1.5	3
Predictable cost	3.6	1.3	4
Predictable time	4.4	0.9	4
Safety	4.2	1.1	4
Shelter	3.7	1.3	4
Short travel	4.3	0.9	5

* *Note:* The importance of environmental impact and social interaction were scored along a -5 to 5 scale, as participants were randomly presented with either positive or negative framings of these transportation attributes.

	Other Activities	Child Transport	Min. Env. Impact	Social Interaction	Low Cost	Low Hassle	Mult. Stops	Pred. Cost	Pred. Time	Safety	Shelter	Short Travel
Other Activities	1.00											
Child Transport	0.08*	1.00										
Min. Env. Impact	0.16**	0.02	1.00									
Social Interaction	0.11**	0.18**	0.11**	1.00								
Low Cost	0.11**	0.06	0.25**	0.06	1.00							
Low Hassle	0.07*	0.07*	0.11**	-0.12**	0.24**	1.00						
Mult. Stops	-0.02	0.19**	-0.03	0.05	0.09*	0.21**	1.00					
Pred. Cost	0.14**	0.10**	0.23**	0.03	0.57**	0.32**	0.13**	1.00				
Pred. Time	0.02	0.07*	-0.01	-0.08*	0.20**	0.34**	0.16**	0.32**	1.00			
Safety	0.14**	0.17**	0.11**	0.01	0.28**	0.28**	0.18**	0.34**	0.27**	1.00		
Shelter	0.05	0.09*	0.02	-0.07*	0.16**	0.31**	0.24**	0.24**	0.30**	0.36**	1.00	
Short Travel	-0.01	0.00	-0.04	-0.10**	0.29**	0.41**	0.19**	0.26**	0.36**	0.18**	0.25**	1.00

** $p \leq 0.01$

* $p \leq 0.05$

Table 6. Correlation matrix showing the Pearson *r* correlation coefficients between perceived 'Importance of Transportation Attributes' explanatory variables. The transportation attribute pairs sharing the strongest positive correlations included: Predicable Cost and Low Cost ($r = 0.57$), and Short Travel and Low Hassle ($r = 0.41$). The transportation variable pairs sharing the strongest negative correlations included: Social Interaction and Low Hassle ($r = -0.12$), and Social Interaction and Short Travel ($r = -0.10$). The statistical significant of each 'Importance of Transportation Attribute' explanatory variable pair is also shown (** $p \leq 0.01$ and (* $p \leq 0.05$). The majority of relationships were statistically significant at the alpha = 0.05 level, except for between: Other Activities and Multiple Stops ($p = 0.62$), Other Activities and Predictable Time ($p = 0.54$), Other Activities and Shelter ($p = 0.15$), Other Activities and Short Travel ($p = 0.76$), Child Transport and Min. Environmental Impact ($p = 0.50$), Child Transport and Low Cost ($p = 0.09$), Child Transport and Short Travel ($p = 0.92$), among others.

Table 7. Public transit accessibility metrics estimated by the Google Maps API averaged during peak commute hours (8AM and 5PM).

	Mean	SD	Min	Q1	Median	Q3	Max
Available	0.938	0.25					
Transfers[1]	1.9	1	1	1	2	3	4
Transfers[2]	2	0.9	1	1	2	2	6
Alt. Routes[1]	3.8	0.7	1	4	4	4	4
Alt. Routes[2]	3.8	0.7	1	4	4	4	4
Access + Egress Walking Time (min)[1]	17.3	12.6	0	8.5	14	22.6	87.9
Access + Egress Walking Time (min)[2]	15.5	8.7	0	9.4	15.5	18.8	87.9
Access + Egress Walking Time (min)[3]	22.4	21.9	0	9	14.9	25.7	87.9

[1] If PT routing data unavailable, missing values were omitted.
[2] If PT routing data unavailable, missing values were set to sample mean.
[3] If PT routing data unavailable, missing values were set to sample max.

Table 8. The Google Maps API travel time estimates for 8AM and 5PM were averaged for each mode. The correlations between transportation mode travel times were estimated using Pearson r coefficient. 95% confidence intervals are shown in parentheses. The correlations between the estimated travel times for each mode across the sample show strong positive correlations, indicative that higher travel times for one mode will be associated with higher travel times of another. For this reason, these travel time estimates were not including in the logistic regression models due to high multicollinearity and variance inflation factors.

	Drive	Transit	Bike	Walk
Drive	1			
Transit	0.72 (0.68, 0.75)	1		
Bike	0.89 (0.89, 0.90)	0.79 (0.76, 0.81)	1	
Walk	0.86 (0.84, 0.87)	0.8 (0.77, 0.82)	0.98 (0.98, 0.98)	1

Table 9. Descriptive statistics of the residence to primary destination commute variables collected via the Google Maps API estimates. Travel time estimates were run during and averaged over peak commuting hours (8AM and 5PM).

	Mean	St. Dev.	Q1	Median	Q3
Vehicle	30	24	11.4	24.4	40.3
Public Transit	67.5	59	29	55.4	87.8
Bicycle	75	53	16	42.6	96.5
Walk	227	276	48.3	121.4	303.2

Table 10. Analysis of variance tests were conducted to assess whether the differences in mean weekly travel time by mode were statistically significantly different between commuting classs.

	df	sum sq	mean sq	F	P
Drive Time (min)	2	437129	218565	4.8	0.008
Public Transit Time (min)	2	7794721	3897360	16.8	0
Bicycle Time (min)	2	3616214	1808107	3.8	0.022
Walk Time (min)	2	34240000	17120187	3.8	0.023
PT Access/Egress Walk Time (min)	2	32971	16485	3.8	0.02

Table 11. A Tukey multiple comparisons of the means test was conducted. The difference in the means of weekly commute travel times is shown for each transportation mode, with the 95% confidence interval for the mean difference shown in parentheses. The *p*-values for these differences in means are also presented. P-values below the significance level of 0.05 indicate that the weekly travel time was significantly different for that set of commuting classes.

	Drive diff	*p*	Transit diff	*p*	Bicycle diff	*p*	Walk diff	*p*	Access diff	*p*
Non-vehicle - Multimodal	-29.2	0.3	-188.5	0	-166.7	0.03	-547.4	0.02	-7.2	0.5
Unimodal - Multimodal	-25.9	0.005	65.1	0.2	-110.6	0.1	-241.7	0.3	9.6	0.2
Unimodal - Non-vehicle	-22.7	0.5	253.6	0	56	0.6	305.7	0.3	16.8	0.02

Appendix 1E: Classification Tree Development and Extended Results

Appendix 1E.1. Summary of Classification Tree Methodology and Rationale

While multimodal transportation behavior work tends to use multinomial logistic regression approaches to predict between pre-defined, often categorical [1, 2] or post hoc, data-driven (i.e., latent class cluster analysis) classifications of multimodal behavior [4 – 6]. CT approach offers certain advantages to logistic regression in that it is a non-parametric approach that does not assume a distribution for included explanatory variables [8]. Additionally, the CT approach can incorporate a variety of variable types (i.e., numeric, categorical, ratings, combinations) [8, 9]. CTs also handle multidimensional analyses that are insensitive to multicollinear explanatory variables [10]. In the transportation behavior context, this is particularly advantageous as transportation decisions occur in highly complex and multidimensional decision spaces based on individual, household, and local transportation environment factors. Finally, CTs provide a clear presentation of the output that is relatively simple to interpret, even for nontechnical stakeholders and decision makers [9 – 11]. Each of the following sets of explanatory variables input into the CART algorithm: (i) Demographic, (ii) Location Based, (iii) Transportation Mode Attributes, and (iv) Public Transit Accessibility.

Appendix 1E.2. Classification Tree Development

To classify participants into commuting class outcomes, the CT algorithm sequentially divided explanatory variable data to maximize homogeneity across participants [10]. The CT algorithm recursively partitions data to identify all possible splits of all explanatory variables and selects the optimal splits starting from the root node, and then selects the optimal splits for subsequent nodes [10]. The Gini index was used to assess overall model splits in the CTs, wherein the algorithm selected the splitting variable that maximized the explained variance of the class predictions [10].

The rpart package was used [12] in R. The CT algorithm parameters were set such that a minimum of 20 observations per node was required for a partition to be attempted and a minimum improvement of 0.01 on the complexity parameter was required for a partition to be considered successful [13]. Through partitioning, the tree grows, which can result in over-fitted, complicated models which many branches, while a tree that is too small might not capture the important structure of the data. Thus, determining an optimal tree size an important task in constructing a classification tree [11] In this study, the optimal tree size was determined by using the 10-fold cross-validation technique. Cross-validation mimics the use of a test sample while extracting information from all cases of a data set to develop the model. The tree size with the lowest cross-validated prediction error was selected, as determined through 10-fold cross-validation [9]. While tree size was selected by prediction error, future analyses could base tree size selection according to the tradeoff between tree size and misclassification and prediction error [14]. The tree was constructed from 35 candidate explanatory variables using the identified best tree size [11].

The full model classification tree was then simplified through a pruning process. By pruning classification trees, nodes are systematically removed from the bottom of the tree. Nodes are removed that minimize tree complexity and misclassification rates [11]. This pruned classification tree was used as the final model for which importance weights and sensitivity analyses were performed. The final classification tree and subsequent analyses used the pruned classification tree due to its reduced complexity without significant loss of information, and because it performed better than the No Information Rate classification rate.[31] The CT classification accuracy rate is compared to the No Information Rate classification rate, which captured the largest proportion of the observed classes. The tree's predictive power was characterized by the Area Under the Curve (AUC) from the Receiver

[31] See Appendix E Table 1 for unpruned tree structure statistics.

Operator Characteristic (ROC) curve using macro-averaged AUCs calculated by taking the AUC for each classification versus all other possible categories, then averaging the AUCs from each classification [9].

Appendix 1E.3. Classification Tree Results

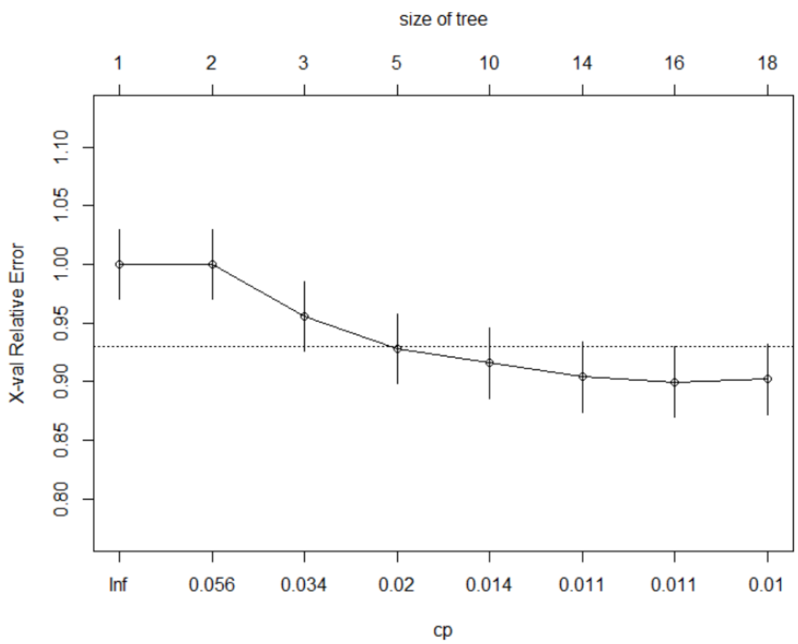


Figure 1. The complexity factor ("cp") versus the 10-fold cross validated relative error for the unpruned Classification Tree with all 35 explanatory variables included. As the crossed validated relative error rate is minimized for 16 splits, there were 16 splits in the unpruned classification tree.

Table 1. Unpruned, cross-validated CT confusion matrix.

		Observed		
		Unimodal	Multimodal	Non-Vehicle
Predicted	Unimodal	331	138	46
	Multimodal	45	131	47
	Non-Vehicle	13	44	93

Table 2. Pruned, cross-validated CT confusion matrix.

		Observed		
		Unimodal	Multimodal	Non-Vehicle
Predicted	Unimodal	311	128	44
	Multimodal	65	141	49
	Non-Vehicle	13	44	93

Table 3. Pruned and unpruned classification tree statistics, including the number of splits, the (mis)classification rates and their 95% confidence intervals, the No Information Rate model, the p-value to assess the classification rate of the CT versus the NIR, and finally, the AUCs for each outcome.

Statistic	**Unpruned**	**Pruned**
Number of splits	16	11
Classification Rate (95% CI)	62.5% (59.2 – 65.7%)	61.4% (58.1% - 64.6%)
Misclassification Rate (95% CI)	37.5% (34.3 – 40.8%)	38.6% (35.4 – 41.9%)
No Information Rate (NIR)	43.8%	43.8%
p-value [Classification Rate > NIR)	P < 0.001	P < 0.001
Unimodal AUC	74.1%	72.7%
Multimodal AUC	62.9%	62.6%
Non-Vehicle AUC	70.9%	70.9%

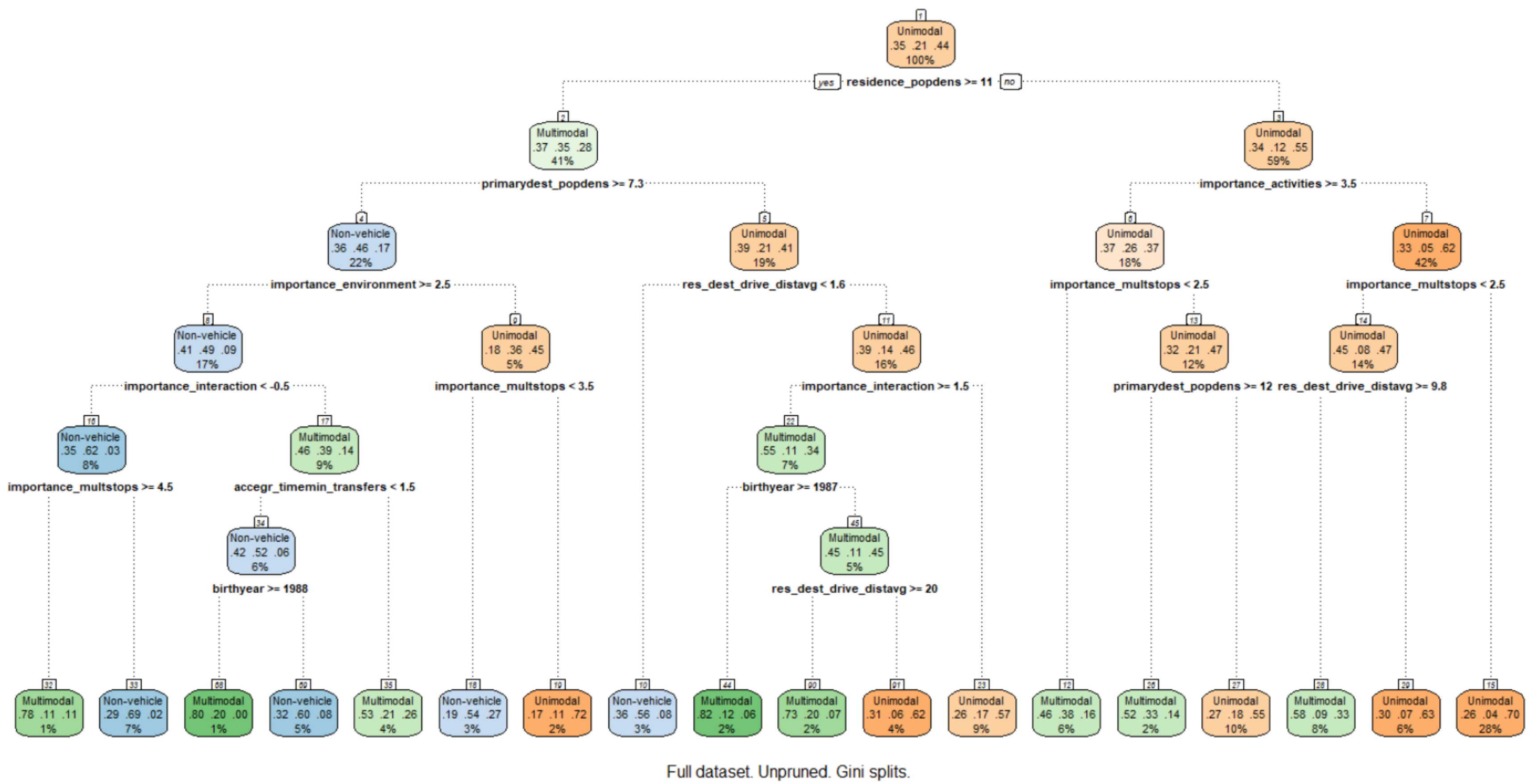


Figure 2. The unpruned classification tree developed using all 35 explanatory variables. The classification tree was trained on the full dataset (n = 888) using 10-fold cross validation.

Appendix 1E.4. Unpruned classification tree interpretation

Figure 2 shows the unpruned classification tree that was developed using all 35 explanatory variables. The 10-fold cross-validation approach was used to develop Figure 2. Figure 2 is annotated with the predicted outcomes across the sample at that point in the tree. The tree's first node, for stance, starts with 100% of the respondents and has a predicted outcome of unimodal commuting behavior, as this commuting class had the greatest frequency across the sample. The node is partitioned according to the explanatory variables that establish the two most heterogeneous groups of survey respondents according to their commuting class outcomes. The top node is split by whether residential population density, a continuous variable, was above or below 11 (thousand people per square mile) for each respondent's residential address. This partitioning process is repeated along each branch of the tree according to other explanatory variables until the data splitting yields insufficient differentiation among respondents with respect to the commuting class outcomes.

Table 4. Counts of "Not Applicable" scores for the Importance of Transportation Attribute variables across the full sample (n = 888).

Transportation Attribute Variable	Count of "Not Applicable" Responses (Percent of Total Sample)
Importance of Other Activities	31 (3.5%)
Importance of Child Transport	483 (54.4%)
Importance of Environmental Impact	15 (1.7%)
Importance of Social Interaction	34 (3.8%)
Importance of Low Cost	10 (1.1%)
Importance of Low Hassle	10 (1.1%)
Importance of Multiple Stops	39 (4.4%)
Importance of Predictable Cost	21 (2.4%)
Importance of Predictable Time	4 (0.5%)
Importance of Safety	10 (1.1%)
Importance of Shelter	21 (2.4%)
Importance of Short Travel	5 (0.6%)

Appendixes 1E.5. Alternative CTs based on alternative handling of 'Not Applicable' Transportation Attribute Variables

We present two comparative assessments of handling 'Not applicable' responses on the 'Importance of Transportation Attribute' explanatory variables. For each of the 12 transportation attributes, survey respondents rated how important the attribute was to the transportation decision making along a Likert-scale from 1 = Not at all important to 5 = Extremely important. Alternatively, respondents could select 'Not applicable' rather than rate the Transportation Attribute along the Likert-scale. In the main text, the 'Not applicable' scores were set to zero. Here, we assess and compare two alternative handlings of 'Not applicable' scores: (1) Not applicable scores were set to 3 along the Likert scale, and (2) Not applicable scores were set to the variable median.

Overall, we found that alternative CTs One and Two included an extra branch for female gender, such that female gender was associated with higher multimodal commuting class frequencies relative to the non-vehicle commuting class. This may be attributed to different handlings of 'Not applicable' variables, such that 483 respondents selected 'Not applicable' for the child transportation attribute, potentially leading to the inclusion of the gender variable. Otherwise, the 'Importance of Transportation Attribute' variables generally align with the pruned CT found in the main text. For instance, importance of minimizing environmental impact, engaging in other activities, engaging in social interaction, and making multiple stops along the route remain in the pruned, alternative CTs presented in Figures 3 and 4 in this section.

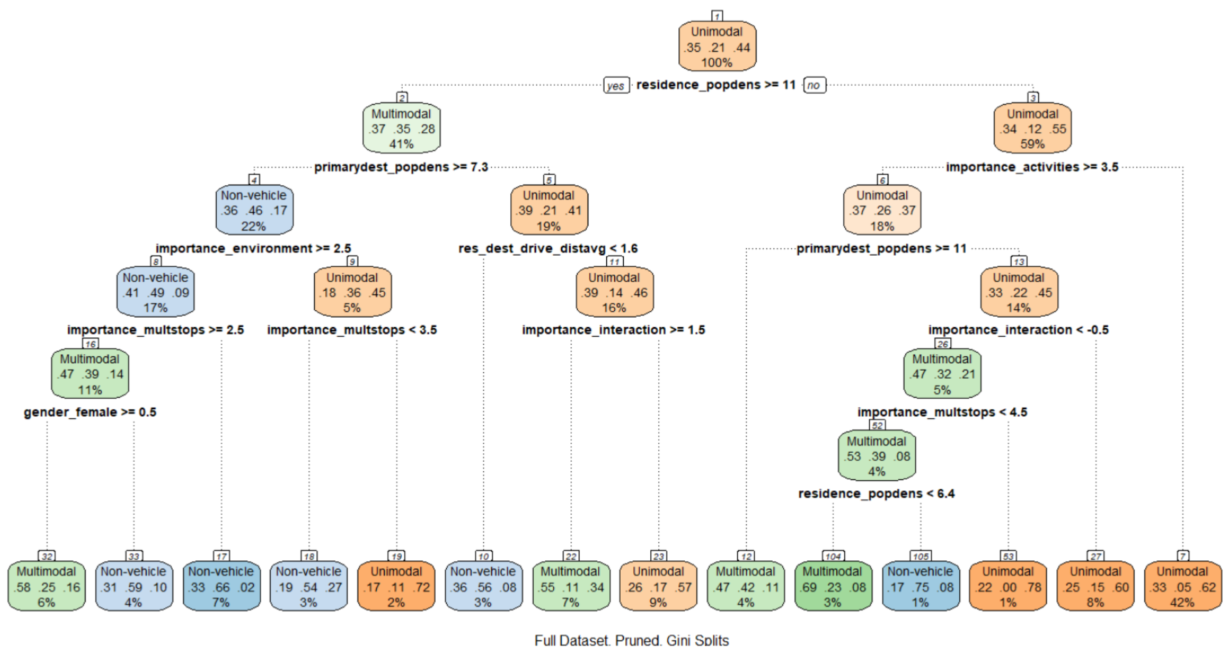


Figure 3. Pruned classification Trees after setting "Not Applicable" scores of Importance of Transportation Attributes variables to 3 along the Likert scale from 1 to 5.

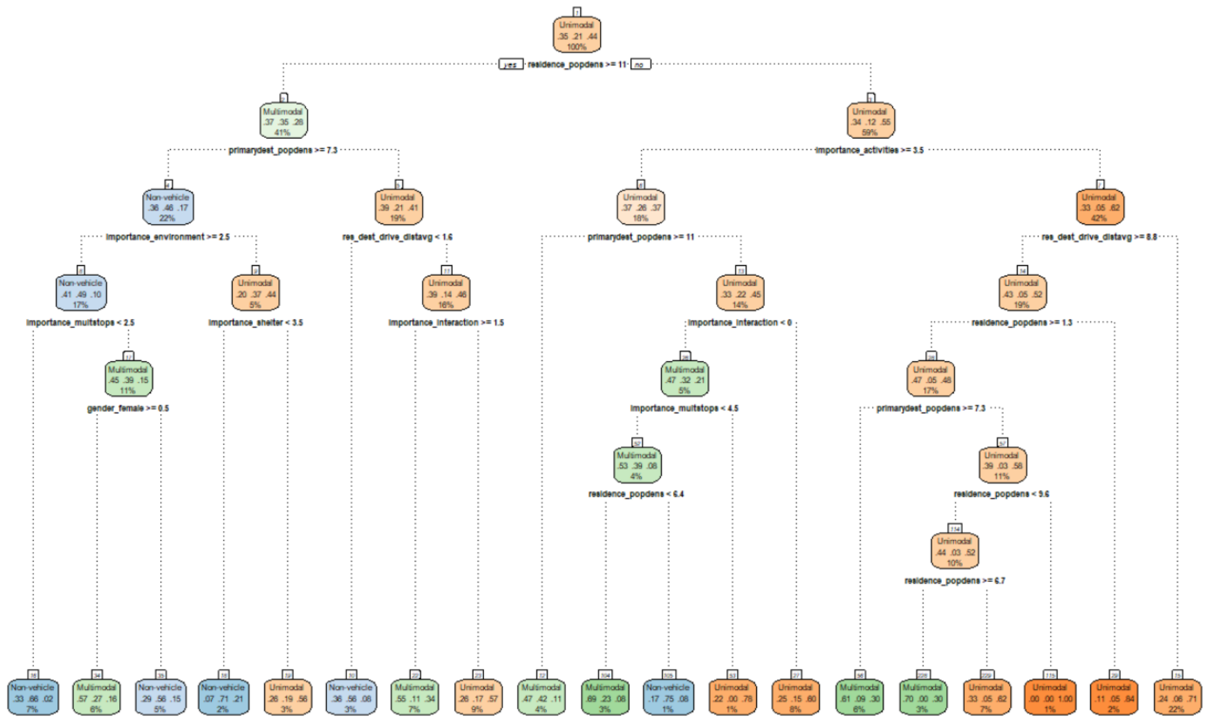
Appendix 1E.6. Importance of Transportation Attribute Alternative CT One: Set NA to 3

While similar, this pruned CY includes a node for female gender, where those who indicated that they identify as having a female gender were classified as multimodal as opposed to non-vehicle. This may indicate that by setting the rated importance of transporting a child to 3 rather than 0 for the "Not

Applicable" response option, the multicollinear role of gender is retained as an explanatory factor that classifies commuting classes.

Table 5. Importance of Transportation Attribute Alternative CT One confusion matrix. The rows indicate the commuting class outcomes as predicted by the pruned CT, and the columns indicate the commuting class outcomes observed across respondent survey data.

		Observed		
		Unimodal	Multimodal	Non-Vehicle
Predicted	Unimodal	337	164	46
	Multimodal	37	102	98
	Non-Vehicle	15	47	98



Full Dataset. Pruned. Gini Splits

Figure 4. Pruned classification Trees after setting “Not Applicable” scores of Importance of Transportation Attributes variables to each survey item’s median value along the Likert scale from 1 to 5.

Appendix 1E.6. Importance of Transportation Attribute Alternative CT Two: Set NA to Median

While similar, this pruned CY includes a node for female gender, where those who indicated that they identify as having a female gender were classified as multimodal as opposed to non-vehicle. This may indicate that by setting the rated importance of transporting a child to the variable median rather than 0 for the “Not Applicable” response option, the multicollinear role of gender is retained as an explanatory factor that classifies commuting classes.

Table 6. Importance of Transportation Attribute Alternative CT Two confusion matrix. The rows indicate the commuting class outcomes as predicted by the pruned CT, and the columns indicate the commuting class outcomes observed across respondent survey data.

		Observed		
		Unimodal	Multimodal	Non-Vehicle
Predicted	Unimodal	315	116	44
	Multimodal	63	154	48
	Non-Vehicle	13	43	94

Table 7. Statistics for pruned CTs that differentially handle 'Not applicable' responses for 'Importance of Transportation Attribute' variables, including the number of splits, the (mis)classification rates and their 95% confidence intervals, the No Information Rate model, the p-value to assess the classification rate of the CT versus the NIR, and finally, the AUCs for each outcome.

Statistic	**Alternative CT One (NA = 3)**	**Alternative CT Two (NA = median)**
Number of splits	13	16
Classification Rate (95% CI)	60.5% (57.2 – 63.7%)	63.4% (60.1 – 66.6%)
Misclassification Rate (95% CI)	39.5% (36.3 – 42.8%)	36.6% (33.4 – 39.9%)
No Information Rate (NIR)	43.8%	43.8%
p-value [Classification Rate > NIR)	P < 0.001	P < 0.001
Unimodal AUC	72.3%	74.5%
Multimodal AUC	59.4%	65.1%
Non-Vehicle AUC	71.9%	71.3%

As shown in Table 7, the statistics Alternative CTs One and Two yielded similar results, such that their accurate classification rates were comparable in terms of the point statistic (60.5% versus 63.4%), as well as their 95% confidence intervals. The classification rates for both alternative CTs performed better than the null model with statistical significant (P < 0.001). Both alternatives classified unimodal commuting outcomes with the greatest accuracy (AUC = 72.3% versus 74.5%), and multimodal commuting with the least accuracy (AUC = 59.4% versus 65.1%).

APPENDIX 2: **Organizational Absorptive Capacity and Resilience Under Compound Threats: Learning from Federal Agency Perspectives**

Appendix 2A: Background Information

Relative Overall Resilience definitions

The organizational resilience indicators according to the Relative Overall Resilience (ROR) framework are defined in Table 1; these indicators were used to code interviews and to develop the survey tool (Resilient Organizations, 2019; Lee et al., 2013; McManus et al., 2008). These definitions were used for deductive interview coding, as well as for the follow-up survey Likert-scale question on organizational resilience strengths and weaknesses. Previously, the ROR was used to

Table 1. Organizational resilience attributes and corresponding indicators with corresponding definitions according to the Relative Overall Resilience framework (Resilient Organisations, 2019).

Resilience Attributes	Resilience Indicator	Definition
Leadership and Culture	Leadership	Strong crisis leadership to provide good management and decision making during times of crisis, as well as continuous evaluation of strategies and work programs against organizational goals.
	Staff engagement	The engagement and involvement of staff who understand the link between their own work, the organization's resilience, and its long term success. Staff are empowered and use their skills to solve problems.
	Situation Awareness	Staff are encouraged to be vigilant about the organization, its performance, and potential problems. Staff are rewarded for sharing good and bad news about the organization including early warning signals and these are quickly reported to organizational leaders.
	Decision making	Staff have the appropriate authority to make decisions related to their work and authority is clearly delegated to enable a crisis response. Highly skilled staff are involved, or are able to make, decisions where their specific knowledge adds significant value, or where their involvement will aid implementation.
	Innovation and creativity	Staff are encouraged and rewarded for using their knowledge in novel ways to solve new and existing problems, and for utilizing innovative and creative approaches to developing solutions.
Networks and relationships	Effective partnerships	An understanding of the relationships and resources the organization might need to access from other organizations during a crisis, and planning and management to ensure this access.
	Leveraging knowledge	Critical information is stored in a number of formats and locations and staff have access to expert opinions when needed. Roles are shared and staff are trained so that someone will always be able to fill key roles.
	Breaking silos	Minimization of divisive social, cultural and behavioral barriers, which are most often manifested as communication barriers creating disjointed, disconnected and detrimental ways of working.
	Internal resources	The management and mobilization of the organization's resources to ensure its ability to operate during business as

		usual, as well as being able to provide the extra capacity required during a crisis.
Planning	Unity of purpose	An organization wide awareness of what the organization's priorities would be following a crisis, clearly defined at the organization level, as well as an understanding of the organization's minimum operating requirements.
	Proactive posture	A strategic and behavioral readiness to respond to early warning signals of change in the organization's internal and external environment before they escalate into crisis.
	Planning strategies	The development and evaluation of plans and strategies to manage vulnerabilities in relation to the business environment and its stakeholders.
	Stress testing plans	The participation of staff in simulations or scenarios designed to practice response arrangements and validate plans.

Appendix 2B: Methodological details

Semi-structured interview protocol. The first focus area was addressed to contextualize the current threat environment, as well as the technologies and policies employed by federal agencies to manage such risks. The second focus area ('Organizational decision-making between singular and compound threats') was designed to elucidate if and how the risk assessment and risk management approaches associated with singular versus compound threats spaces were similar and different, as well as to identify opportunities for agencies' ability to prepare, respond to, and adapt to compound threats. Interviewees were asked to recall and reflect upon if and how their agency deviated from singular threat response to handle compounding threats by outlining their operations and risk management procedures, information and resource needs, and the potential for social and culture influence on decision-making. Finally, the third focus area ('Organizational resilience and adaptive capacity') offered a broader exploration of how federal agency personnel define organizational resilience, and they were asked to identify characteristics and actions of their respective agencies that they perceived facilitated and inhibited organizational resilience.

Table 2. Interview topic areas and questions asked during interview sessions.

Interview Section	Qualitative Questions (Interview)
Part 1. Organizational role and temporal changes within each organization.	**Overview:** Derive sense of career and if and how organizations may have adapted over interviewees careers. (Time: 10 minutes) Interviewer: Thank you again for participating in this interview. I will start with a few open-ended questions about your role and experiences within [organization]. 1. Can you tell me about your role within [organization] and what interested you about working in this field? 2. What year did you enter this field? 3. Since [year started], have you noticed any changes in the environmental conditions and threats that your agency might respond to? a. If yes: What changes? b. If no: Can you comment on why you think that environmental conditions and threats conditions have been consistent? 4. Since [year started], have you observed changes in data collection, analysis, and modeling technologies and techniques used by your agency? a. If yes: What are these technologies? What do you use them for? b. If no: What technologies have you been using? Do you feel existing technologies are sufficient to carrying out your agency's mission and functions? 5. Since [year started], have you observed changes in technologies used in the field by your agency? a. If yes: What are these technologies? What do you use them for? b. If no: What technologies have you been using? Do you feel existing technologies are sufficient to carrying out your agency's mission and functions? 6. Since [year started], have policies changed that have influenced how your organization functions? a. If yes: What types of policy changes? How have they changed your organization's functioning and objectives? b. If no: Are there any policies—at the local, state, or federal level—that you think should be changed? 7. Tell me what your job has been like during [the COVID-19 pandemic]. What was it like last summer (2020)? How about this summer?
Part 2. Compound threat hazard management decision-making (i.e., absorptive, adaptive capacity)	**Overview:** Within separate conversations on single and multiple incidents, derive a sense of risk management and decision-making processes (i.e., intuitive versus naturalistic). Also discuss objectives and inter-agency coordination for singular and compound threats. Elicit understandings of how and when expert intuition versus objective data sources/decision support models are used. The theoretical foundation for these questions is based on Okoli et al. (2016): work on intuitive and naturalistic decision-making for fire managers. (Time: 20 minutes) Interviewer: Imagine that your organization is responding to an incident when another occurs within approximately the same timeframe and location. Imagine that your organization is now responding to multiple incidents simultaneously. 1. Can you tell me of a time when you responded to a similar circumstance and had to respond to multiple incidents at the same time. *[If they can't think of anything, bring up COVID example]* 2. Starting at the beginning of the incident, how did you make decisions in this context? What were your organization's objectives? a. For notable decisions: You mentioned that your organization needs to [make X decision]. How do you approach this? b. If and how might multiple incidents influence your organization's decision making? c. Can you recall any times when decision-making processes differed from the norm? 3. What information would you need to decide how to respond to multiple threat incidents? a. Where do you get this information (i.e., colleagues, data, models, etc.)? b. Do you feel your organization have sufficient information or data on [information type mentioned]? Why [or why not]? 4. What risks does your organization face during [single threat]? a. How does your organization approach these risks?

	b. How could your organization's risk management processes be improved? 5. What types of <u>constraints</u> or limitations does your organization face? (i.e., resources, personnel, technology, time) a. How do these constraints effect your organization's ability to function? b. Are these constraints different from the single threat incidents? If so, how? c. Has your organization started using or is currently considering using new technologies or resources given [compounding threat]? Resource scarcity? d. Can you describe the time pressure involved in making decisions? 6. What <u>challenges</u> did your organization face? a. How are these challenges for multiple threats similar to those you face during single threats? b. How are they different? 12. Please describe how your agency <u>communicates</u> or coordinates with other government agencies, organizations, or community stakeholders.
Part 3. Organizational resilience	**Overview:** This portion of the interview will serve to understand the key factors associated with organizational resilience under single and multiple threats. The structure and order of the questions relates to the National Academy of Science's phases of resilience: prepare, absorb, recover, and adapt. Absorb is not addressed in this section because it is thoroughly addressed in Part 2 of the interview. (Time: 15 minutes) Interviewer: Next, I would like to talk about your organization's ability to prepare for, recover from, and adapt to multiple threat incidents. 1. What, if anything, does the term "organizational resilience" mean to you? 2. Organizational resilience is defined as "…ability to survive, and potentially even thrive, in times of crisis" (Seville et al., 2008). Stated another way, organizational resilience is the ability to prepare, absorb, recover, and adapt to stressors to maintain functioning. a. What are some key factors that facilitate organizational resilience under multiple threats? b. What are some key factors that inhibit organizational resilience under multiple threats?
Part 4. Transition to survey.	Finally, I would like to ask you to participate in a brief survey. I will send you the link in the chat window now. The survey is confidential and should take approximately 5-10 minutes. Please let me know if you have any questions as you complete the survey.
Part 5. Closing.	Thank you for participating in this interview. Your time and insights are greatly appreciated. To continue gaining understandings of federal emergency response organizational resilience, I wanted to close by asking if you might be willing and able to connect me with two colleagues who similarly work for a federal emergency response, public health, or environmental engineering agency. If so, their name and contact information would be much appreciated.

Survey design. After each interview session, interviewees were asked to complete a follow-up survey that was distributed via a Qualtrics URL. Survey responses were anonymous, and the average completion time was [7] minutes. Follow-up survey questions captured similar information as interview questions by following the same general interview focus areas presented in Figure 1 and were used to estimate the prevalence of views expressed in interviews (Wong-Parodi et al., 2016), as well as demographic and individual career-specific information. Survey questions were designed to provide a more direct and quantitative comparison between singular and compound threat risk perception, mission objectives, resource/information needs, and constraints. Many questions included 5-Point Likert Scale responses that separately addressed singular and compound threat management objectives, information needs for decision-making, and the likelihood of a variety of potential risks and constraints faced by the agency. Risks included personnel and community health and safety, infrastructural impacts, resource access, information access, timeliness of response, and ecological impacts. These risks assessed were designed to mirror the variety of risks posed by natural and anthropogenic threats, as identified in existent literature.

Constraints assessed included operational, resource, personnel, communication, and information constraints, which were also identified according to existing literature. Survey data that differentiated between singular and compound threats allowed for a structured approach to assess if and how singular and compound threat risk spaces were perceived differently by federal agency personnel, and whether compound threats were perceived to change hazard management objectives, information needs, risks, and/or constraints relative to singular threats. The survey also included a series of questions related to the strengths and weaknesses of organizational resilience when facing a compound threat, and which adopted indicators were believed to be indicative of organizational resilience (Lee et al., 2013; McManus et al., 2008; OrgRes Diagnostics, 2021) (Figure 1 of main text).

Thematic coding of qualitative interview data

Intercoder Agreement.

Three coders coded the anonymous interview transcripts. The lead author of this chapter coded all interview transcripts, and the other two coders coded a random sample of half of the interview transcripts. The coders first coded a random selection of two interviews together by using a deductive set of interview codes. Then, the coders independently coded transcripts, meeting on a weekly basis to discuss coding questions and iteratively refining the codebook to include clear definitions, examples, and counterexamples of each mutually agreed code definition.

To assess how similarly the coders interpreted and applied the deductive codes, intercoder reliability scores were calculated as a percentage of coding agreement based on the ensemble of all codes. The qualitative software package used for this project, MAXQDA, assesses intercoder reliability via the kappa calculation (Brennan & Prediger, 1981). The kappa calculation assumes that the transcripts are independent from one another and that the research team independently coded transcripts (Brennan & Prediger, 1981). Kappa is calculated based on the percent of coded transcript segments (approximately 1 – 3 sentences in length) that two coders applied the same code relative to the percent chance that two coders would apply the same code. This is calculated using the following set of equations, as applied to the coding agreement results between Coder 1 (lead author) and Coder 3.

		Coder 1		
		1	**0**	
Coder 2	**1**	a = 3395	b = 637	4032
	0	c = 301	0	301
		3696	637	4333

P(observed) = Po = a / (a + b + c) = 0.78

P(chance) = Pc = 1 / Number of codes = 1 / 96 = 0.01

Kappa = (Po - Pc) / (1 - Pc) = 0.78

If there is an unequal number of codes per segment or if only one code is to be evaluated:

P(chance) = Pc = Number of codes / (Number of codes + 1)^2 = 0.01

Kappa = (Po - Pc) / (1 - Pc) = 0.78

The final intercoder agreement rate between Coder 1 (lead author) and Coder 2 was *kappa* = 0.78, and the intercoder agreement rate was *kappa* = 0.81 between Coder 1 and Coder 3. To improve the interrater reliability score as measured by the Kappa coefficient, the coders have refined "Organizational resilience" codes as well as the "Risk Management" codes to increase interrater reliability score.

Thematic coding: Antecedent Context of Organizational Hazard Management. The individual-level career information for each interviewee was captured, including: (i) the agency they worked for, (ii) the number of years they were employed by their current agency, (iii) the U.S. geographic region that they served, (iv) the phase of the disaster management system (i.e., preparation, response, recovery, adaptation/mitigation) that most closely aligned with their job title and described job responsibilities. Deductive coding was used to capture individual-level roles to assess how the set of interviewees represented the hazard management cycle. Additionally, interviewees were asked to describe the current threat landscape that their agency faces according to environmental, data/technology, and social/political changes that have evolved over the course of their career, which served to define the "Antecedent context" (Figure 1). Organizational changes in objective setting, operations, and constraints under the specific compound threat of the COVID-19 pandemic were thematically coded to identify if and how federal agency hazard management changed over the context of the COVID-19 pandemic. This case study also served to exemplify a salient example of compound threat management for the set of interviewees.

Thematic coding: Absorptive and Adaptive Capacity under Compound Threats. Next, interviewees were asked to recall one or more compound threat incidents that they have been professionally involved in over the course of their career, as represented by the "Compound threat" component of Figure 3. Compound threats could include any combination of natural or anthropogenic shocks (acute) or stressors (chronic) that presented compound risk. Then, questions regarding if and how their agency's "absorptive capacity" was exceeded, based on discussions of decision-making procedures, information/resource needs, constraints, and inter-agency coordination, and thematic coding was used to identify themes in if and how compound threats led to exceedances in organizational absorptive capacity. The deductive coding scheme was in part adapted from Cutter's 'disaster resilience of place model', and interview questions probe organizational absorptive capacity in hazard response, as well as organizational resilience (Figure 3). Absorptive capacity refers to the ability to absorb hazard impacts using predetermined coping strategies, and organizational resilience includes the ability to plan for and adapt to complex threats, such as compound threats, that may lead to constraints to system functioning (Cutter et al., 2008). Absorptive capacity and organizational resilience are thought to influence the degree of recovery after hazard impact has occurred. Absorptive capacity exceedance is conceptualized to be more common for compound threat events, therefore challenging organizational recovery from compound threats. Interviewees expressed how their respective agencies managed and operated under compound threats, which provided information on if and how agency absorptive capacity can be exceeded in these threats. An agency's absorptive capacity is associated with how they can respond to and recover from a threat in the shorter term, and as such, absorptive capacity is in part contingent on antecedent planning and mitigation efforts of the agency. Thus, the full range of preparation, response, recovery, and mitigation efforts considering compound threats was thematically coded to identify current strengths and potential weaknesses in compound threat management across all phases of the hazard cycle. Additionally, as the antecedent context of the agency is grounded in social systems, natural environment systems, and the built environment, the identified themes in compound threat response were codified according to four domains (i.e., physical, information, cognitive, and social) (Linkov et al., 2013).

Thematic coding: Organizational Resilience. Organizational resilience was conceptualized to allow for recovery despite absorptive capacity exceedance (Cutter et al., 2008). Organizational learning and adaptive capacity have been shown to be contingent on factors like the adequacy of resources, decision flexibility, management structures, which were explored through interviews. Deductive coding was used to assess interviewee's definitions of organizational resilience, as well as characteristics and actions (or lack thereof) that they perceived facilitated or inhibited their agency's organizational resilience. Interview questions build from existing theories and measurement scales of organizational resilience, focusing on organizational ability to prepare for, respond to, recover from, and adapt to compounding threats (Lee et al., 2013; Linkov et al., 2013). Interviews and surveys borrowed from existing organizational resilience measurement scales to assess both internal factors (i.e., command structure, culture, and the prioritization of response actions and resource allocation) as well as interagency factors (i.e., communication channels, interagency command structure, deliberation, etc.).

Appendix 2C: Extension of results

Table 3. Deductive and inductive parent and corresponding child codes, along with the total number of participants who discussed each child code at least once, the percentage of total participants who discussed each child code, and the number of coded segments (i.e., code applications over 2-4 sentences within transcripts). The percentage of for coded segments is derived from the number of coded segments per child code over the total number of coded segments for its respective parent code.

Parent Code	Child Code	Interview Count	Percentage of Total Interviews	Coded Segment Count	Percentage of Coded Segments
Job Role				**248**	
	Deployment/Field Work	15	45%	25	10%
	Recovery	5	15%	6	2%
	Mitigation/Adaptation	4	12%	22	9%
	Incident Commander	11	33%	13	5%
	Planning	24	73%	47	19%
	Logistics	18	55%	26	10%
	Public Information	12	36%	14	6%
	Safety	5	15%	7	3%
	Liaison	10	30%	23	9%
	Finance/Administration	7	21%	7	3%
	Operations	29	88%	58	23%
Operations and Management				**1323**	
	Resource Allocation	32	97%	281	21%
	Incident Prioritization	30	91%	124	9%
	Knowledge Transfer	29	88%	131	10%
	Situational Awareness	24	73%	63	5%
	Analysis and Decision Support (+)	32	97%	164	12%
	Information Security	5	15%	7	1%
	Info Collection, Sharing	32	97%	122	9%
	Risk Governance (Current)	32	97%	255	19%
	Risk Management Improvements	28	85%	176	13%
Relevant Policies				**112**	
	Funding	9	27%	11	10%
	Multi-Jurisdiction Policy Change	7	21%	11	10%
	Social/Political	13	39%	32	29%
	Operations	30	91%	35	31%
	Mission	8	24%	11	10%
	Presidential Administration	7	21%	12	11%
Field Technology Changes				**72**	
	Aviation Assets	8	24%	13	18%

	Infrared Technologies	10	30%	14	19%
	Satellites	9	27%	16	22%
	Drones (UAVs)	15	45%	29	40%
Data/Information Technology Changes				**130**	
	Analyst Job Roles	5	15%	8	6%
	Assessing/Forecasting Hazard Vulnerabilities	8	24%	10	8%
	Assessing/Forecasting Hazard Consequences	10	30%	21	16%
	Assessing/Forecasting Hazardous Event Occurrence	10	30%	20	15%
	Data Availability	20	61%	32	25%
	Data Collection	22	67%	39	30%
Environmental Changes				**124**	
	Work Conditions	13	39%	25	20%
	Anthropogenic Hazard Severity	4	12%	5	4%
	Anthropogenic Hazard Frequency	5	15%	7	6%
	Natural Hazard Frequency	17	52%	33	27%
	Natural Hazard Severity	17	52%	28	23%
	Threat/Hazard Type	7	21%	10	8%
	Climate Change	11	33%	16	13%
COVID Absorption and Adaptation				**305**	
	Objectives	16	48%	33	11%
	Operations	18	55%	126	41%
	Transmission Risk	21	64%	49	16%
	Remote Work	27	82%	63	21%
	Personnel Availability	16	48%	34	11%
Compound Threat				**158**	
	Chronic Hazard	15	45%	24	15%
	Acute Hazard	28	85%	54	34%
	Anthropogenic Hazard	13	39%	19	12%
	Natural Hazard	28	85%	61	39%
Objectives				**576**	
	Public Life and Safety	30	91%	116	20%
	Personnel Life and Safety	23	70%	86	15%
	Infrastructure	29	88%	124	22%
	Economic Considerations	21	64%	71	12%
	Ecological Resources	14	42%	43	7%
	Cultural/Historical Resources	14	42%	32	6%
	Social/Political Considerations	26	79%	104	18%
Constraints				**594**	
	Social/Political Constraints	29	88%	152	26%
	Coordination/Communication Constraints	28	85%	111	19%
	Time Constraints	18	55%	32	5%
	Emerging Technology Constraints	11	33%	16	3%
	Technology/Field Equipment Constraints	20	61%	51	9%
	Data/Information Constraints	21	64%	63	11%
	Personnel Constraints	29	88%	169	28%
Information and Analysis				**301**	
	Expertise	26	79%	89	30%
	Data/Information Availability	27	82%	87	29%
	Modeling Capabilities	27	82%	125	42%

Coordination				**815**	
	Community Coordination	27	82%	121	15%
	Private Sector Coordination	12	36%	32	4%
	NGO Coordination	8	24%	22	3%
	Local Coordination	23	70%	113	14%
	State Coordination	24	73%	124	15%
	Regional Coordination	18	55%	46	6%
	Federal Coordination	32	97%	357	44%
Organizational Resilience				**492**	
	Workforce Treatment	20	61%	51	10%
	Mental health	16	48%	41	8%
	Cohesion	8	24%	20	4%
	Proactive Posture	20	61%	30	6%
	Recovery Priorities	9	27%	14	3%
	Participation in Exercises	6	18%	10	2%
	External Resources	16	48%	23	5%
	Planning Strategies	16	48%	6	1%
	Situation Monitoring and Reporting	11	33%	16	3%
	Decision Making	13	39%	24	5%
	Information and Knowledge	19	58%	45	9%
	Staff Engagement and Involvement	20	61%	54	11%
	Leadership	19	58%	40	8%
	Minimize Silos	16	48%	34	7%
	Innovation and Creativity	17	52%	31	6%
	Internal Resources	21	64%	53	11%

Code intersections.

Table 4. The total coded segments intersections between objective codes. The values in the shaded cells represent the percentage of code co-occurrence, calculated by the count of two codes applied to the same transcript segment over the total segments for that row.

Code	Code Frequency (Segments)	Cultural/ Historical Resources	Ecological Resources	Economic Considerations	Infrastructure	Personnel Life and Safety	Public Life and Safety	Social/ Political Considerations
Cultural/Historical Resources	32		16%	4%	8%	1%	4%	20%
Ecological Resources	43	22%		15%	15%	0%	14%	9%
Economic Considerations	71	9%	26%		17%	5%	14%	18%
Infrastructure	124	31%	42%	30%		12%	39%	21%
Personnel Life and Safety	86	3%	0%	6%	8%		13%	6%
Public Life and Safety	116	16%	37%	23%	36%	17%		24%
Social/Political Considerations	104	66%	21%	27%	18%	7%	22%	

In addition to deriving the total participants who discussed each objective as influencing compound threat management and overall absorptive capacity, Figure 3 shows the relational findings for the number of coded segments across interview transcripts that contained multiple objective codes. Figure 3 shows that of the 116 total “minimize public life and safety risks” coded segments, 45 coded segments (39%) intersected with “minimize critical infrastructure damages”, suggesting that these objectives tend to be discussed by participants as complementary objectives. Conversely, of the 86 “minimize personnel life and safety risks”, 10 coded segments (12%) intersected with the “minimize critical infrastructure damage” objective code. As noted by a few participants (n = 6, 18%), there can often be trade-offs between minimizing personnel life and safety risks and minimizing infrastructure damages. For instance, one interviewee noted that “…wildland firefighter is not certified to attack a structure fire” (Interview 27), as they do not have the same protective equipment necessary for building protection. Thus, protecting critical infrastructure and protecting personnel life and safety objectives can be at odds, though the relationship between critical infrastructure protection and public life and safety are framed as complementary.

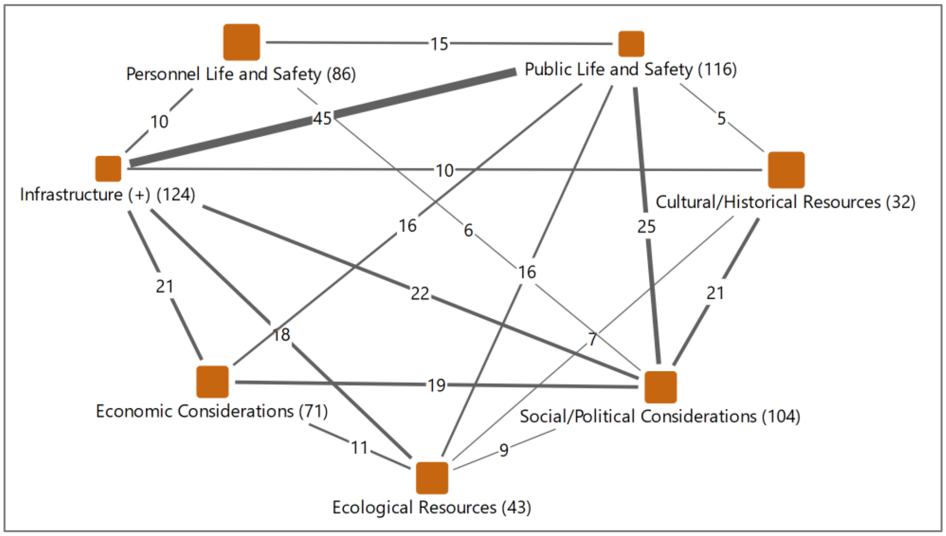


Figure 1. Relational findings for the code segment co-occurrence for stated objectives in compound threat management. The number in parentheses next to each node indicates the number of coded segments there were for each objective across the 33 interview transcripts. The number of each line indicates the number of segments with code intersections between two objective codes.

In addition to assessing the degree of code intersections, compound threat management can be informed by code pairs with fewer intersections, such as when comparing coordination/communication constraints, time constraints, and field equipment/technology constraints. Of the 111 coordination/communication constraint segments, 6 segments intersected with field equipment/technology and 6 segments intersected with time constraints, indicating that coordination/communication constraints may not involving timing or field equipment constraints as much as personnel and social/political constraints.

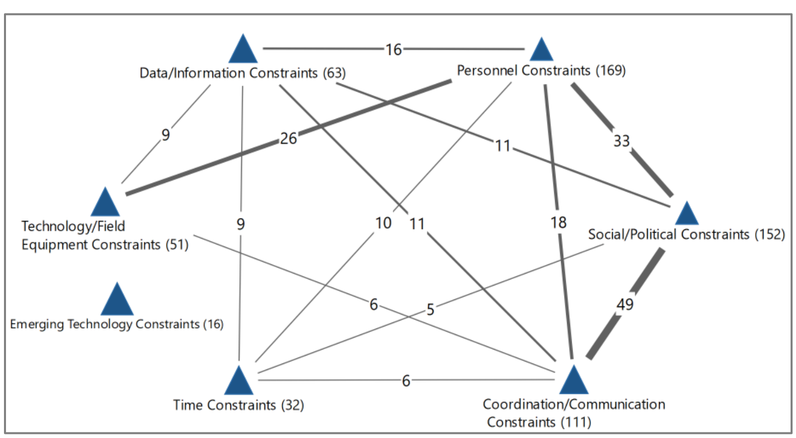


Figure 2. Relational findings for the code segment co-occurrence for stated constraints in compound threat management. The number in parentheses next to each node indicates the number of coded segments there were for each objective across the 33 interview transcripts. The number of each line indicates the number of segments with code intersections between two constraint codes.

Post-interview survey results

Follow-up surveys were sent to each participant following their interview session. Surveys were used to quantitatively evaluate singular and compound threat objectives, constraints, information needs, and organizational resilience factors. Though not the primary focus of this chapter, descriptive survey results can be found following this link.

APPENDIX 3: Are Compound Threats Associated with Changes in Resource Use? An Assessment of Wildland Fires Suppression Resources given the COVID-19 Pandemic

Appendix 3A: Background material

Table 1 shows proposed wildland fire suppression management guidance published across the United States during the 2020 COVID-19 pandemic.

Table 1. US fire agency policy and management guidelines proposed at the start of the 2020 wildfire season to mitigate viral transmission and other risks associated with the COVID-19 pandemic.

Policy Objective	**Specific policy proposal**	**Source proposing policy**
Firefighter safety	Reconfigure camps: "Utilize line spike and small spike camps as much as possible"	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
	Remote work: "Minimize briefing size and limit face-to-face contact as much as possible"	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
	COVID testing	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
	PPE / sanitation	Center for Disease Control and Prevention (2020)
Suppression strategies	10AM Policy: "Hit it hard. Go back to the 10 AM policy for the season; utilize aircraft more on IA to keep fires small."	USFS (2020)
	Aggressive initial attack	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020) USFS (2020)
	Point protection: "Explore opportunities for more indirect attack, focused use of heavy equipment, and designation of management action points using natural barriers"	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
Suppression resources	Minimize responding personnel: "Create suppression strategies to minimize assigned personnel and incident duration… Use predictive services and professional judgement to balance assigned resources and incident duration".	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
	"Utilize more heavy equipment and less crews"	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020) USFS (2020)

	"Evaluate opportunities for application of aviation and mechanized assets to reduce assigned personnel"	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
Technology use and innovation	Utilize decision support centers and tools	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)
	Use of unmanned aerial vehicles when possible	National Interagency Fire Center - Wildland Fire Response Plan COVID-19 Pandemic (May 2020)

Appendix 3B: Methodological details

Data cleaning and sample selection.

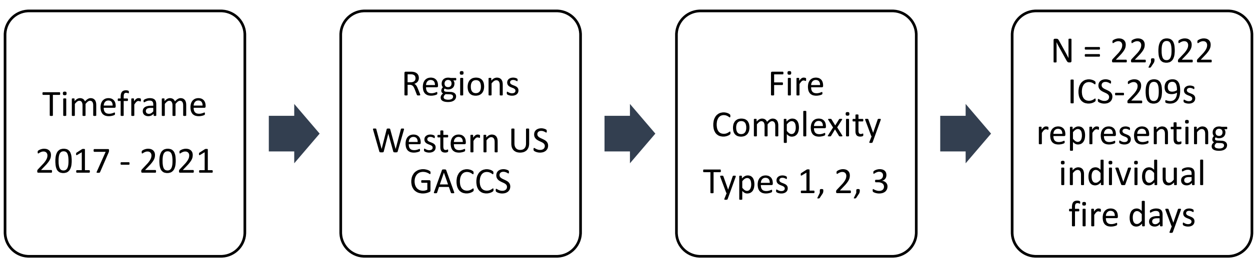


Figure 1. Data cleaning process used to derive the final set of fire day observations.

Data sources.
FEMA ICS-209: ICS-209 Reports are intended to report information for significant incidents. These reports contain basic information used to support decision-making across all levels of government, wherein decision-makers include the agency/jurisdiction where the fire incident occurs, as well as the multi-agency coordination system (MACS) agencies ([FEMA, n.d.).](FEMA, n.d.) Incident information is reported as a way to provide situational monitoring such that the appropriate local, regional, state, or national jurisdiction can decide if, when, and how many resources to allocate to the incident. While these forms can be used for a variety of incident hazard types, it is estimated that 98% of them are used for wildland fire incidents (St. Denis et al., 2020).

ICS-209 reports were used for fire incidents that occurred between 2017 – 2021 and were of fire complexity 1, 2, or 3. Fire complexity is determined by agency administrators and are used to facilitate personnel assignment (NIFC, 2004). Type 5 incidents are of the lowest level of complexity, and Type 1 are the most complex. Type 5 incidents are the most common and require no more than five personnel to manage, whereas Type 1 incidents involve 500+ personnel (NIFC, 2004). Only ICS-209 reports with of complexity Types 1, 2, or 3 were included in this analysis.

National Interagency Coordination Center (NICC) Incident Management Situation Report (IMSR): The IMSR provides an overview of the national wildland fire activity of the previous day. The report is produced daily when national Preparedness Levels (PLs) are Level 2 or above (NICC, 2019). The NICC Predictive Services Intelligence Section reviews the national and regional fire activity, which is used to generate national and regional PLs per day (NICC, 2019). Fire activity updates are provided from the ICS-209 reports, and are used to inform daily national and regional PLs. More specifically, PLs are determined by the fire activity levels, the number and kind of resources committed to incidents, weather conditions, and fuel conditions (NICC, 2019). National and regional PLs range from Levels 1 to 5, and each level includes specific management actions such that higher PLs reflect greater levels of wildland fire activity and resources committed (NIFC, n.d.). As such, they are used in the current analysis as a proxy for resource scarcity per fire day at both the national and regional levels.

GridMet: GridMet is a database of daily high resolution meteorological data that covers the contiguous US from 1979 – yesterday. The dataset provides a spatially and temporally complete gridded weather dataset at ~4km resolution. The energy release component (ERC) for each incident site on each fire day was pulled via the climateR R package (Johnson, 2021). This package accesses gridded sources of climate data using consistent parameter sets. Specifically, it pulls weather data from the Gridded Meteorological Dataset, a dataset of daily high-spatial resolution (source). The "energy release component" was pulled for each incident at the daily level to control for weather conditions in this analysis. ERC is a calculated output related to the available energy (BTU) per unit area (square foot) within the "flaming front at the head of a fire" (USDA FS, n.d.). The ERC is used for the National Fire Danger Rating System (NFDRS), and reflects potential fire intensity via a composite fuel moisture index including the contribution of live and dead fuels (USDA FS, n.d.). As the ERC fluctuates based on the fuel moisture index over time per unit area, the ERC was expressed as a percentile for each incident site. The ERC is used by fire managers and planners both to prepare for upcoming fire seasons, as well as to monitor daily fire behavior, which can facilitate decision support for personnel and equipment assignments.

NICG Resource Ordering and Support System (ROSS) / Interagency Resource Ordering Capability (IROC): ROSS and IROC both have served as centralized resource ordering and tracking platforms and were used to provide historical data on resources used per fire day from 2017 – 2021 in the current analysis. In 2020, IROC replaced ROSS as the centralized resource ordering and tracking platform in 2020, though both datasets contain the same information (NICG, 2020). IROC is a modernized and more flexible and scalable resource ordering platform for all hazard incidents that is supported by both PCs and mobile devices (NICG, 2020). ROSS and IROC have been used to provide the dispatch community with a reliable system of tracking where, when, and which resources are allocated to incidents, even during peak capacity (NICG, 2020). In the current analysis, ROSS/IROC datasets were used for total personnel resources used per fire day—the predicted output of interest in model development.

Weather variable descriptions

Three variables related to weather conditions and fire landscapes were collected for this analysis: (i) accumulated precipitation per day (mm), (ii) vapor pressure deficit, and (iii) energy release component (ERC) percentiles. These data were extracted from GridMet via the climateR package in R (Johnson, 2020). ERC percentiles were derived from historical, site-specific ERC values pulled for each day over the past 10 years, as described below.

Definitions:

- **Accumulated precipitation (mm)**: Total accumulated precipation (mm) per day measured at the incident origin point.
- **VPD:** Difference between the amount of moisture in the air and how much moisture the air could potentially hold when it is saturated; a higher VPD implies that the air can hold a large amount of water; independent of air temperature (Wollaeger & Runkle, n.d.)
- **ERC values**: ERCs are a fire characteristic (link). ERCs are derived from predictions of: (i) the rate of heat released per unit area during flaming combustion and (ii) the duration of flaming (SWCC, 2022). The primary operational weather inputs to ERC are daily maximum and minimum temperature and relative humidity; temperature and relative humidity at the local observation time of 1300, and precipitation amount and duration for the previous 24-hours from the observation time (Brown et al., 2014). The primary operational weather inputs to ERC are daily maximum and minimum temperature and relative humidity; temperature and relative humidity at the local observation time of 1300, and precipitation amount and duration for the previous 24-hours from the observation time (Brown et al., 2014). Weather data used to calculate ERCs are collected and calculated via the Parameter-elevation Regressions on Independent Slopes

Model (PRISM) and validated/augmented with data from the Remote AutomatedWeather Station (RAWS) network weather data (Bayham et al., 2020). For each fire incident location, daily weather data (and automatically calculated ERC values) are collected from a network of land management agency RAWS across the U.S.

- **ERC Percentiles:** As ERCs are unitless values derived relative to location, the ERC values of different incident locations cannot easily be compared. As such, percentiles are used in fire behavior modeling. Daily ERC values pulled from a 10-year timeframe for each incident location are preferred to derive ERC percentiles, which will be used as model covariates. However, deriving 10-year ERC data for all ~2000 unique incident locations included in this analysis may be computationally challenging, as the climateR code used to pull ERC values runs (prohibitively) slowly.

Weather variable summary statistics

Table 1. Summary statistics for the weather variables as related to each incident origin point (longitude, latitude provided on ICS-209 Reports.

	Mean (SD)	**Median**	**IQR**
Precipitation (mm)	0.6	0.00	0.00 – 0.00
VPD	1.7	1.6	1.1 – 6.5
ERC values	69	70	59 - 116
ERC percentiles	0.8	0.9	0.8 – 0.9

Weather variable correlations

Table 2. Correlations between the weather variables. As there was a moderately strong, positive correlation between the ERC value and ERC percentile, only the ERC percentile was included in final models.

	Precipitation	VPD	ERC (value)	ERC Percentile
Precipitation	1			
VPD	-0.23	1		
ERC (value)	-0.07	-0.32	1	
ERC Percentile	-0.02	-0.01	0.61	1

ERC Percentile Derivation

Fire management personnel commonly use the ERC to assess current fire danger and develop management plans for both suppression and fire use. The calculated ERC is the available heat per unit area (kilojoules/m^2). ERCs are based on the estimated potential energy released per unit area at the flaming front of a fire (SWCC, 2022). Daily variations of ERC are attributed to changing moisture content of local fuels (SWCC, 2022). ERC values tend to range from 0 to 100, though they can be higher given weather extremes and fuels modeling. The larger the ERC value, the “hotter” and potentially more severe the fire. Fire management decision makers commonly use ERCs, which are a calculated output of the National Fire Danger Rating System (NFDRS) (NIFC, 2022). According to Brown et al. (2014), ERCs are used by fire managers as an indicator of both fire severity (i.e., potential amount and extent of fire activity) and fire business (i.e., decision-making and economics involved in fire suppression and fuel treatment approaches). ERCs are provided in the NFDRS to improve information available to fire management decision makers; the goal is to “…inform decision makers for proactive wildland fire management, thus better protecting lives and property, reducing firefighting costs and improving firefighting efficiency” (NIFC, 2022). ERCs help depict seasonal trends offering a comparison tool against prior years. ERCs are one of the indicators used to determine a region’s Preparedness level. ERCs are also used in models that predict fire behavior (Young et al., 2020) and in models that predict fire management fire risk perception and related suppression decision-making (i.e., resource allocation, suppress strategies, incident prioritization) (Bayham et al., 2020).

Daily ERC values are used to inform fire management strategies and planning. According to Brown et al. (2014), fire specialists have indicated that ERC values of 40 and 60 might be useful thresholds that can be related to management strategies and planning. They also note that “…a fire danger index such as ERC is meant to represent an aspect of fire potential. As such, there can be many days with a high ERC value in which there is no fire occurrence, and therefore it is not surprising that simple linear correlations are difficult to obtain” (Brown et al., 2014). Though small fires can occur with virtually any value of ERC, large fires (> 400 hectares) tend to be associated with ERC values of 60 or higher (and thus, are often associated with higher economic fire costs) (Brown et al., 2014). For this and other analyses that use ERC values, "…the ERC was calculated for the day of the fire start based on historical weather records from the Western Regional Climate Center's RAWS archive. If the nearest RAWS did not have complete data for the day of the fire start, then the next nearest RAWS was selected, and so on" (Brown et al., 2014). The distance between a RAWS location and fire incident location may be up to 50 km, as ERC tends to be broad in spatial scale (Brown et al., 2014).

Using Predictive Service Areas (PSAs) to pull 10-year ERCs: Rather than pulling daily ERC values over 10-years for each specific incident included in the model, PSAs may be useful in approximating this data. PSAs are defined as:

> *"… geographic areas for which national-level fire weather or fire danger services and products are produced by wildland fire agency meteorologists and intelligence staffs in support of resource allocation and prioritization. A PSA boundary defines areas where 2 or more weather elements or National Fire Danger Rating System (NFDRS) indices exist with a high correlation to historical significant fire size. "Significant fires" are the 95th percentile fire size for the PSA" (NIFC).*

There are 251 PSAs across the US, and 138 PSAs across the western US, which are used to communicate current and forecasted fire potential (Figure 2). As PSAs are used in meteorological and fire management risk assessments and decision-making frameworks, I used PSAs as geographic units of analysis from which 10-year ERC values were pulled. Then, each individual incident location included in my dataset can be matched to the PSA in which it is located (each PSA centroid location is subsequently matched in the nearest RAWS weather station, where data is collected). The incident ERC percentiles can then be estimated according to the 10-year ERC distribution for each PSA (rather than for each specific incident location/coordinate pair). For instance, to assess if and how using PSA centroid locations to approximate incident 10-year (2011 – 2021) ERC percentiles, I pulled daily ERC values for California's 25 PSA centroid locations (Figure 3). Each CA PSA in Figure 2 has associated daily ERC values for 2011 - 2021. The deciles for daily ERC values for each CA PSA were calculated, as shown in Figure 4. Match each incident location with each PSA - match to closest by distance. Finally, I calculated the percentile for each raw ERC value (at the incident-level) according to the ERC distribution of its associated PSA.

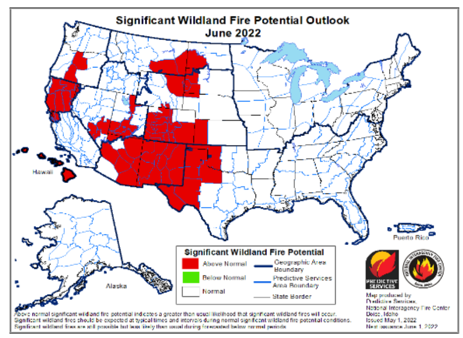


Figure 2. Map that represents the cumulative forecasts of the eleven Geographic Area Predictive Services Units and the National Predictive Services Unit (NIFC).

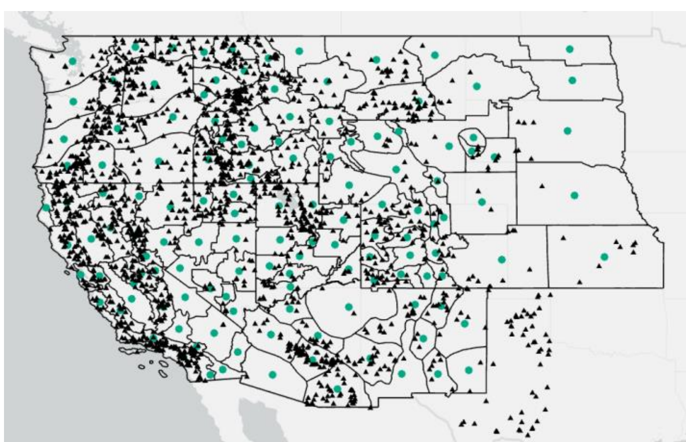
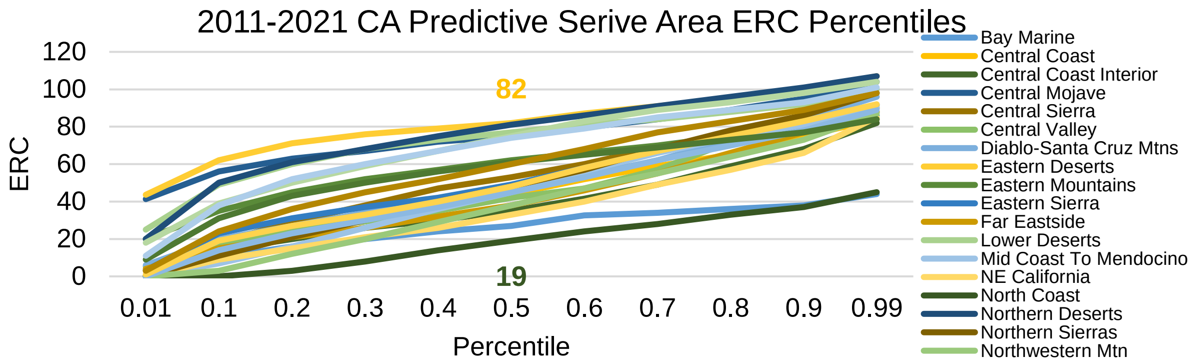
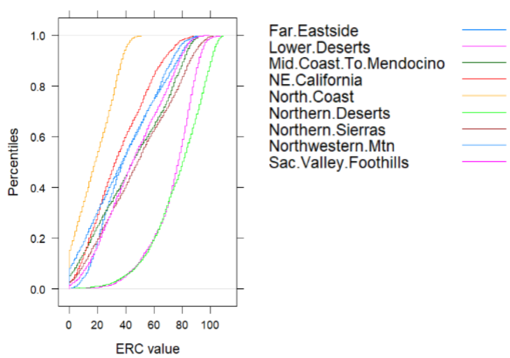


Figure 3. Map of all 2017 – 2020 fire incident locations (black triangles) in the western US Geographic Areas. The black outlined boundaries represent the western US Predictive Service Areas (PSAs), and the green dots represent each PSA centroids. The 10-year ERC values were pulled for each of California's PSAs.

Example using Figures 3 and 4: The nearest PSA centroid to a fire incident location is the Eastern Deserts PSA. The ERC value for that fire incident (based on incident origin coordinates) is 82 one day that the fire is burning (i.e., one fire day). Based on the 10-year ERC distribution for the Eastern Deserts PSA, the ERC value of 82 falls into the 50th ERC percentile for that incident on that fire day. (Same logic for Central Coast Interior.





B.

Figures 4A-4B. (A) The 10-year ERC percentiles for each of CA's 25 PSAs. For instance, the 50th percentile for the **Central Coast Interior** PSA has an ERC value of 19, whereas the 50th percentile of the **Eastern Deserts** PSA has an ERC value of 82. In (B), the ERC values are presented along the x-axis for a select number of PSA locations with corresponding percentiles presented along the y-axis, like an empirical cumulative distribution function for daily ERC values from 2011 – 2021.

Figure 5 shows the distances between each of the 2017 - 2020 incident location distances from the nearest PSA centroid point.

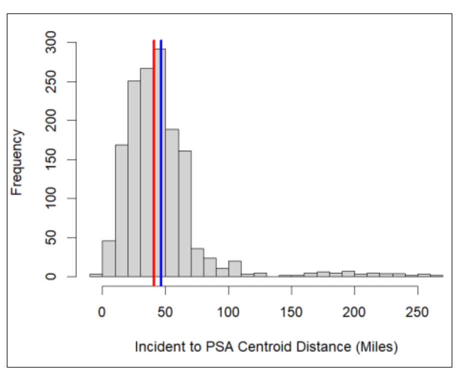
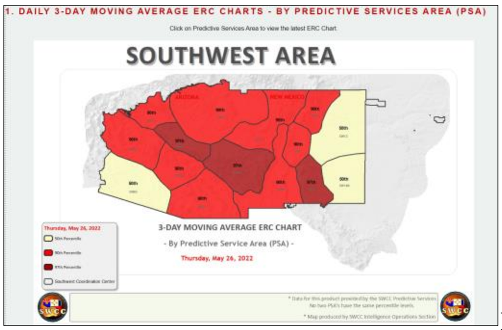
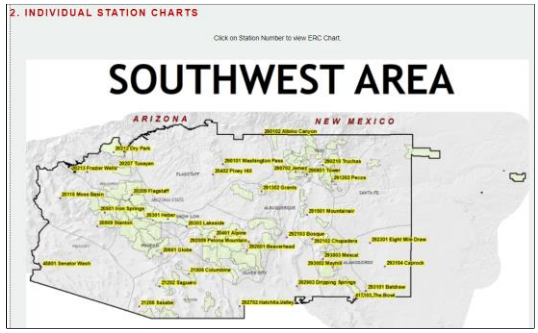


Figure 5. The distances (miles) between each of the 2017 - 2020 incident location distances from the nearest PSA centroid point. The red vertical line shows the sample median distance and the blue vertical line shows the sample mean distance. According to Brown et al. (2014), The distance between a RAWS location and fire incident location may be up to 50 km (32 miles), as ERC tends to be broad in spatial scale (Brown et al., 2014).

Limitations of 10-year ERC Distributions at the PSA level. Using the 10-year ERC values for each PSA will provide an approximate ERC value distribution that each fire observation used in the model can be paired to. While

PSA ERC data can be used to approximate ERC percentiles for each incident location, this approach will not be as high resolution as pulling incident location specific ERC values. While not as high resolution as pulling historical daily ERC values at the incident level, regional Geographic Area Coordination Centers (GACC) use PSAs to assess and communicate ERC percentiles. For instance, Figure 5 (below) shows how the Southwest Coordination Center uses PSA boundaries to communicate ERC percentiles (SWCC, 2022).

A. 

B. 

Figures 6A-6B. The Southwest Coordination Center (SWCC) uses (A.) PSAs to communicate ERC percentiles, an indicator of general trends in seasonal conditions used to assess how the season is processing relative to prior years. (B.) Units throughout the SWCC produce local, site specific charts that are higher resolution than the PSAs via Automated Weather Stations, which are strategically located throughout the National Forests of the SWCC. Each day around 1400 local time, this data is uploaded via satellite to the National Weather Information System (WIMS) (SWCC, 2022).

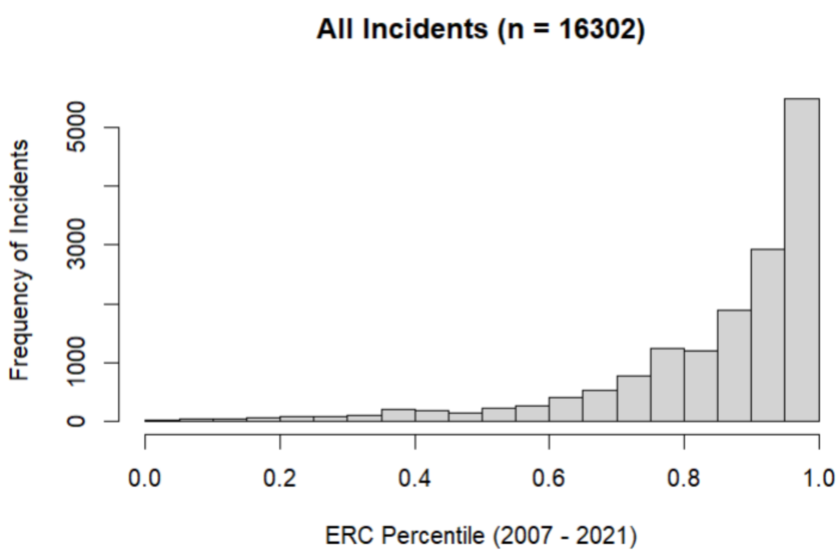


Figure 7. The histogram of ERC percentiles corresponding to each daily fire day ERC value, wherein percentiles were derived from historical 10-year ERC values for each PSA centroid.

Collinearity between DV (logged ground personnel use and covariates)

Table 3. Pearson *r* correlations and *p*-values between the dependent variable (natural log of ground personnel used per fire day). The strongest negative correlation was with the “During-COVID threshold” variable (binary; 1 = fire day occurred during COVID) ($p < 0.001$) and the strongest positive correlation was with fires of Complexity Type 1 ($p < 0.001$).

Covariate	Pearson *r* Correlation	p-value
During-COVID Threshold	-0.49	0.00
CAUSE_HUMAN	0.05	0.00
COMPLEXITY_LEVEL_T1	0.24	0.00
COMPLEXITY_LEVEL_T2	0.16	0.00
COMPLEXITY_LEVEL_T3	-0.19	0.00
CURR_INCIDENT_AREA_LOG	0.23	0.00
ERCPercentile	-0.05	0.00
EVAC	0.07	0.00
GBCC	-0.02	0.00
GEN_FIRE_BEHAVIOR_ACTIVE	0.12	0.00
GEN_FIRE_BEHAVIOR_EXTR	0.01	0.04
GEN_FIRE_BEHAVIOR_MIN	-0.15	0.00
GEN_FIRE_BEHAVIOR_MOD	0.05	0.00
new_fire_gacc	0.05	0.00
non_peak	0.02	0.02
NRCC	-0.13	0.00
NWCC	0.04	0.00
obj_culturalresources	0.04	0.00
obj_economic	0.01	0.09
obj_firefightersafety	0.01	0.08
obj_humansafety	0.03	0.00
obj_publicland	-0.05	0.00
obj_social	0.04	0.00
ONCC	0.18	0.00
OSCC	0.12	0.00
prcp	0.00	0.78
PROG_AREA_RESTR	0.01	0.12
public_inj_fatal	0.02	0.00
r_PL_4_5	0.01	0.14
responder_inj_fatal	0.09	0.00
STRUCT_THR	0.02	0.00
STRUCT_THR_LOG	-0.09	0.00
SWCC	-0.12	0.00
vpd	0.02	0.01

Collinearity between all IV and DV covariates

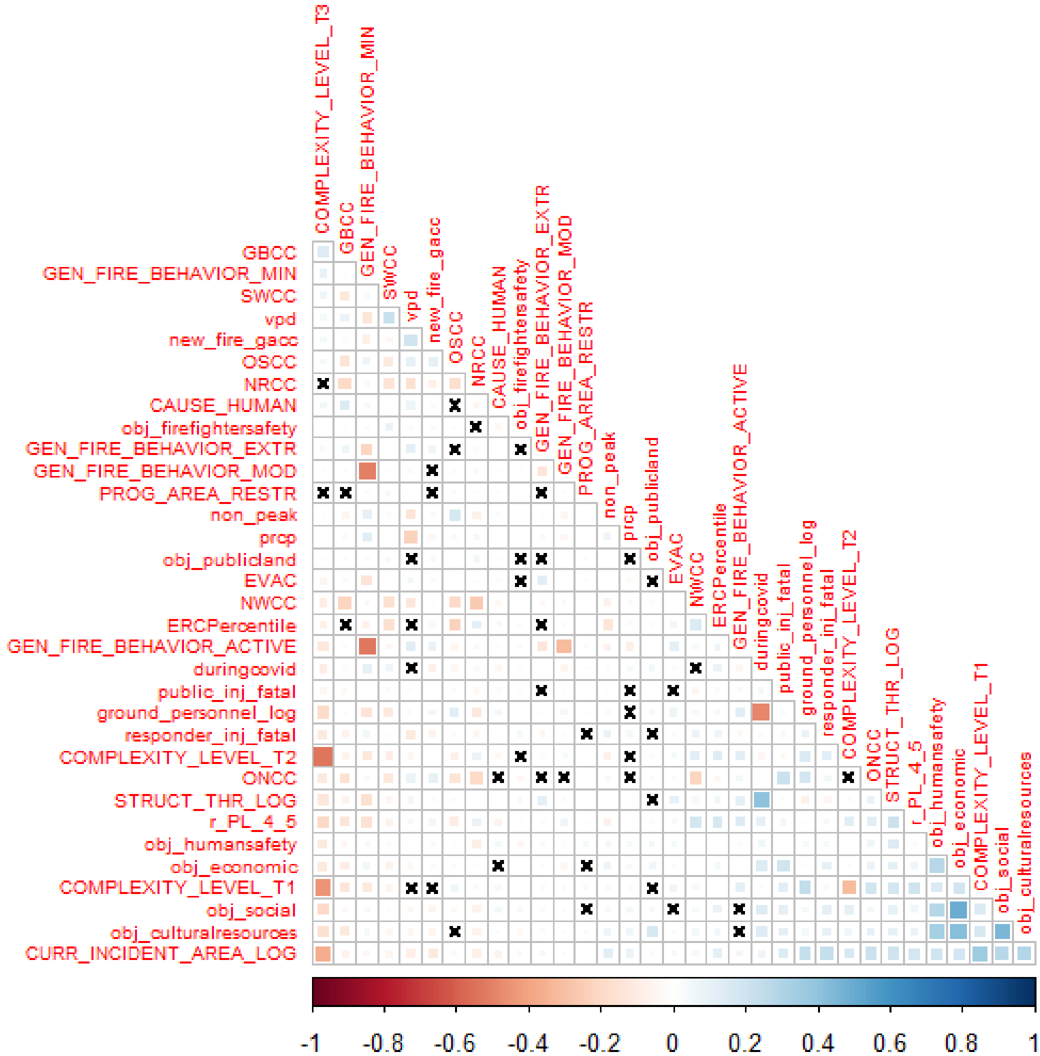


Figure 8. The correlation matrix between all model covariates, including the "During-COVID Threshold" main effect (i.e., *duringcovid* in the figure) and the dependent variable (i.e., *ground_personnel_log*). Small black x's indicate statistically insignificant correlations (α < 0.05) between variable pairs.

Comparative distributions and tests of covariates between the pre- and during-COVID observations

To meet the RDD assumption that the groups of data before and after the threshold of the running variable (i.e., before and after the COVID-19 threshold date), we calculated and compared the distributions for each covariate according to grouped data (i.e., pre-, during-COVID subsets). These comparative tests allowed us to determine if and how covariates aside from the "During-COVID Threshold" effect may have led to predicted changes in ground personnel used per fire day. We then conducted formal statistical tests to compare statistically significant differences between the groups; F-tests were used to compare group means for normally distributed continuous covariates, and Chi-Squared tests were used to compare the relative expected proportions of binary variables. Additionally, for continuous and log-continuous variables, we created grouped density plots and then conducted F-statistic to compare group means and Chi-Square tests of proportions for binary variables.

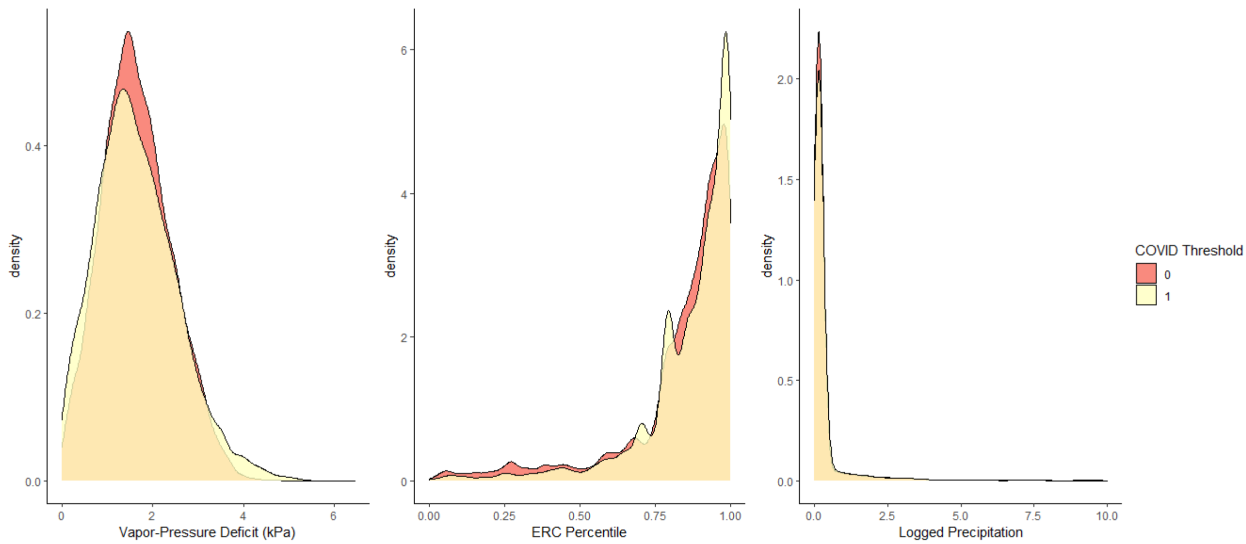


Figure 9. Density plots for the weather-related covariates including (i) the vapor-pressure deficits (kPa), (ii) the ERC percentile, and (iii) the logged precipitation accumulation per fire day for the 0 = pre-COVID fire days and the 1 = during-COVID fire days.

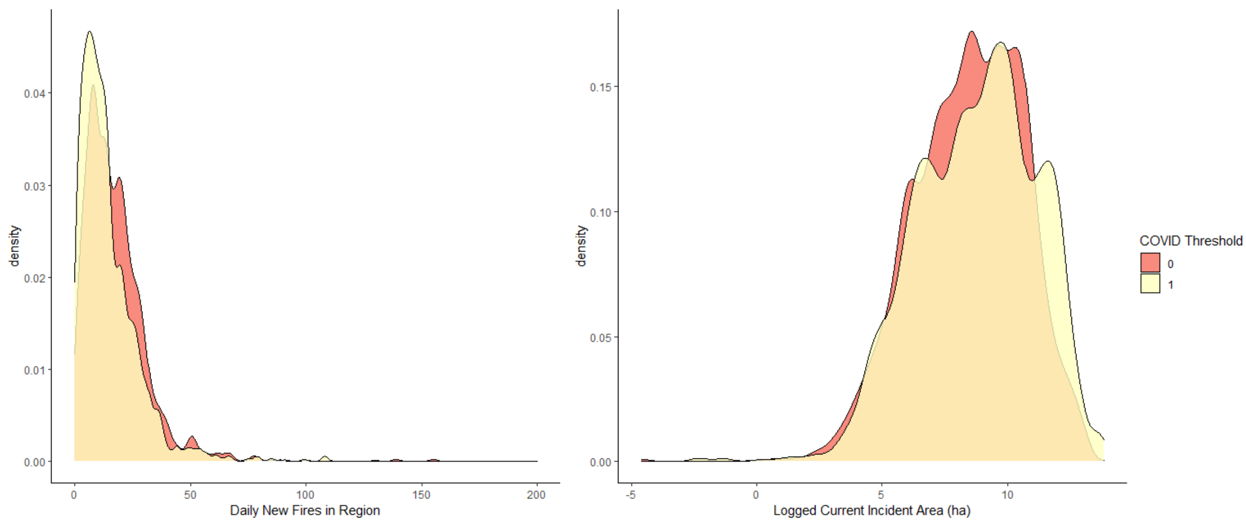


Figure 10. Density plots for the fire condition covariates including (i) the total new regional fires and (ii) the natural logged current incident area (ha) per fire day for the 0 = pre-COVID fire days and the 1 = during-COVID fire days.

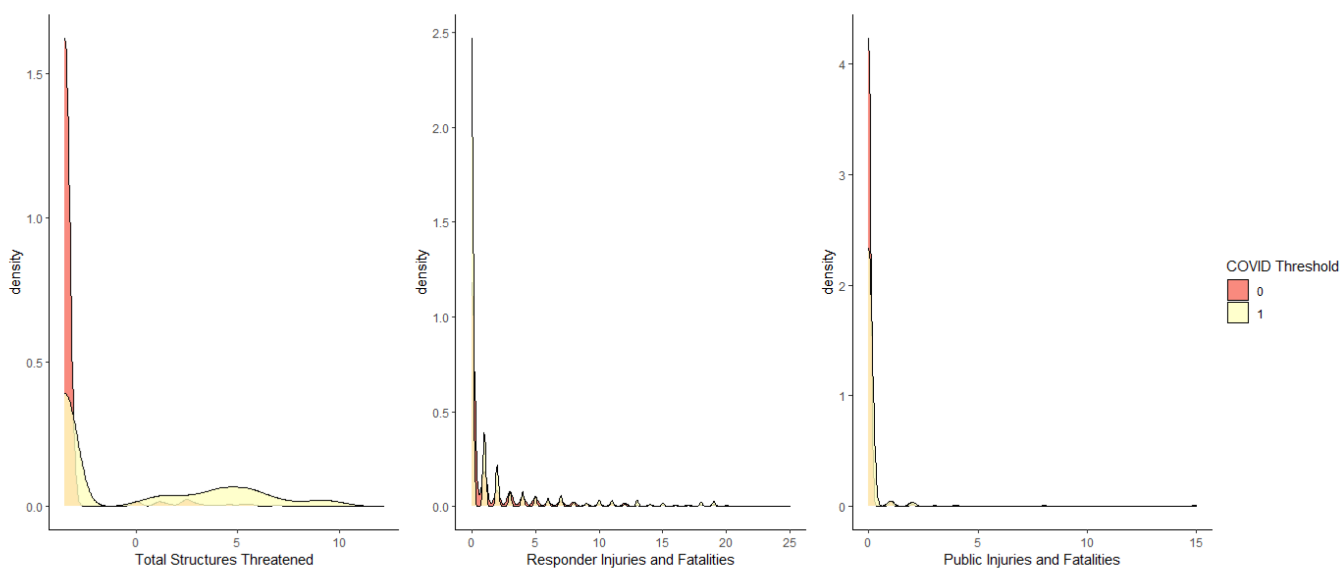


Figure 11. Societal risk factor covariates including (i) the logged total structures threatened, (ii) the number of responder injuries and fatalities, and (iii) the number of public injuries and fatalities per fire day for the 0 = pre-COVID fire days and the 1 = during-COVID fire days.

Table 4. Dependent variable and covariate distributions for the pre-COVID (n = XXX) and during-COVID (n = xxxx) groups.

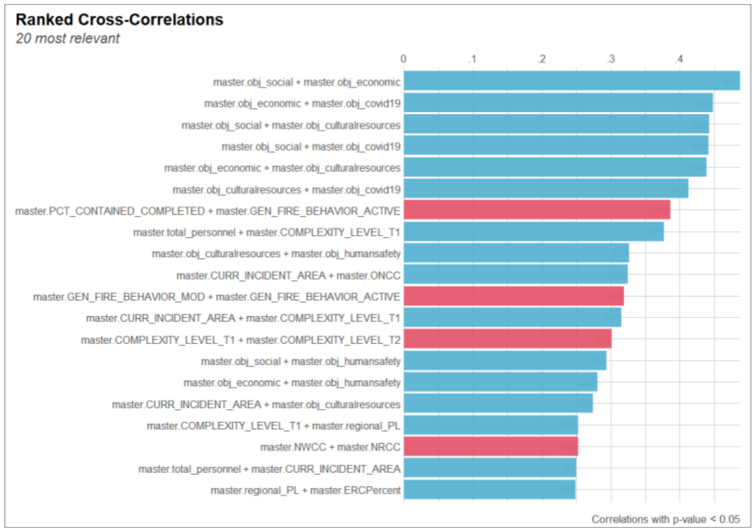
	Pre-COVID Fire Days									
Variable	N	Mean	SD	Median	N	Mean	SD	Median	F Statistic	Chi-Squared
Ground personnel used per fire day	11093	327.91	639.14	127	10929	50.5	90.34	23	F=2019.105***	
Ground personnel used per fire day (ln)	11093	4.76	1.55	4.84	10929	3.01	1.49	3.14	F=7303.603***	
Human caused incident	11093	0.1	0.3	0	10929	0.08	0.28	0	F=17.263***	X2=17.057***
Off-Peak fire day	11093	0.03	0.18	0	10929	0.05	0.21	0	F=17.079***	X2=16.783***
Current incident area (ha)	11091	22687	53764	4190	10928	44263	101556	7763.25	F=389.757***	
Current incident area (ln ha)	11091	8.22	2.2	8.34	10928	8.75	2.37	8.96	F=291.325***	
PCT_CONTAINED_COMPLETED	11093	44.96	35.47	42	10926	48.03	36.09	50	F=40.442***	
General fire behavior: minimal	11041	0.42	0.49	0	10792	0.5	0.5	1	F=136.83***	X2=135.673***
General fire behavior: moderate	11041	0.27	0.44	0	10792	0.21	0.41	0	F=83.703***	X2=83.102***
General fire behavior: active	11041	0.26	0.44	0	10792	0.23	0.42	0	F=21.521***	X2=21.356***
General fire behavior: extreme	11041	0.05	0.23	0	10792	0.05	0.23	0	F=0.118	X2=0.099
Fire Complexity Type 1	11093	0.2	0.4	0	10926	0.2	0.4	0	F=1.327	X2=1.289
Fire Complexity Type 2	11093	0.28	0.45	0	10926	0.26	0.44	0	F=11.283***	X2=11.176***
Fire Complexity Type 3	11093	0.53	0.5	1	10926	0.39	0.49	0	F=428.869***	X2=420.159***
Total structures threatened	11093	27	415	0.03	10929	788	4526	0.03	F=310.382***	
Evacuations in progress or planned	11093	0.05	0.21	0	10929	0.04	0.19	0	F=11.051***	X2=10.825***
Area restriction in progress	11093	0.01	0.1	0	10929	0.01	0.11	0	F=4.608**	X2=4.339**
Responder injuries or fatalities	11093	2.12	5.87	0	10929	1.93	5.73	0	F=5.977**	
Public injuries or fatalities	11093	0.07	0.67	0	10929	0.16	1.17	0	F=49.054***	
Regional PL 1 | 2	11093	0.29	0.46	0	10902	0.16	0.37	0	F=549.247***	X2=535.171***
Regional PL 4 | 5	11093	0.38	0.49	0	10902	0.55	0.5	1	F=614.657***	X2=597.339***
New fires in region	11092	17.77	14.57	15	10929	15.02	15.96	12	F=177.673***	
Daily precipitation (mm)	11093	0.47	2.4	0	10929	0.7	3.31	0	F=37.039***	
ERC Percentile	11093	0.81	0.21	0.88	10929	0.86	0.17	0.92	F=349.499***	
VPD (kPa)	11093	1.66	0.77	1.6	10929	1.66	0.9	1.56	F=0.005	
ONCC	11093	0.15	0.35	0	10929	0.14	0.35	0	F=2.491	X2=2.43
OSCC	11093	0.14	0.35	0	10929	0.1	0.31	0	F=63.095***	X2=62.594***
NWCC	11093	0.21	0.41	0	10929	0.23	0.42	0	F=12.738***	X2=12.616***
NRCC	11093	0.17	0.37	0	10929	0.2	0.4	0	F=44.285***	X2=43.97***
GBCC	11093	0.16	0.36	0	10929	0.13	0.34	0	F=24.334***	X2=24.121***
SWCC	11093	0.09	0.28	0	10929	0.11	0.31	0	F=32.816***	X2=32.509***
Objective: Social consideration	11093	0.11	0.32	0	10929	0.22	0.42	0	F=475.259***	X2=464.481***
Objective: Economic consideration	11093	0.05	0.21	0	10929	0.11	0.31	0	F=308.925***	X2=303.792***
Objective: Public land	11093	0.01	0.12	0	10929	0.02	0.16	0	F=30.177***	X2=29.608***
Objective: Cultural resources	11093	0.11	0.31	0	10929	0.21	0.41	0	F=449.341***	X2=439.618***
Objective: Human health and safety	11093	0.14	0.35	0	10929	0.18	0.38	0	F=69.133***	X2=68.617***
Objective: Responder health and safety	11093	0.07	0.26	0	10929	0.06	0.24	0	F=15.769***	X2=15.547***

Multivariate Linear Regression Assumptions

Multivariate linear regression assumptions were checked to ensure validity in model results and interpretations. The key assumptions of multivariate linear regression include:

1. Linearity in the relationship between input variable (x) and predicted outcome variable (y). To test whether this assumption held, residual versus fitted data was assessed.
2. Independence of input variables was assessed via tests of collinearity between input variables. Correlation matrices as well as variance inflation factors (VIF) were assessed. As all correlation coefficients between variable pairs were below $r = 0.5$ and all VIF values were below 5, the independence of input variable assumption was satisfied.

A.



B.

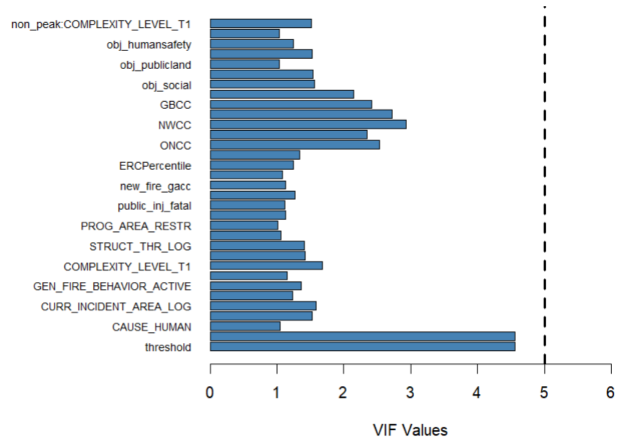


Figure 12A-B. (A) Correlation coefficients between input variables as ranked by their correlation coefficient, *r*. Each correlation coefficient shown here was statistically significant at the alpha < 0.05 level. (B) The highest variance inflation factor (VIF) values of all model covariates. Each is below the commonly used threshold of $VIF = 5$.

3. Normal distribution of residuals assumption was assessed according to the distribution of residual error terms. This assumption is conducted to ensure that there were no other relationships that could explain the variance that were not taken into account by the linear regression. To assess this, Q-Q plots were used to visualize if standard residuals were normally distributed.
4. Homoscedasticity or equal variance of variables was tested to determine if error terms are the same across different levels of the outcome variable (y). To assess this, we plotted the spread of the

residuals, wherein residuals should exhibit constant spread. Heteroskedasticity apparent in Residuals vs. Fitted graphs of model results. Heteroskedasticity is likely to bias model results due to the right skew of the dependent variable (ground personnel used per fire day).

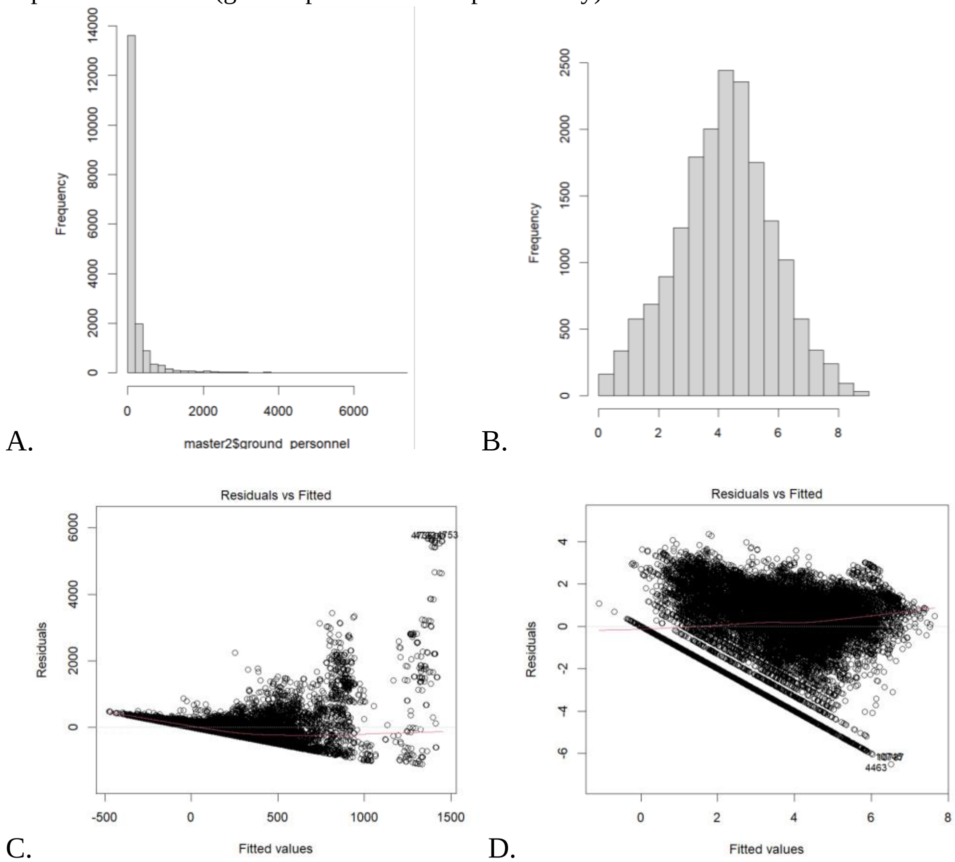


Figure 13A-B. Histograms for the ground personnel resources used DV given (A) untransformed data and (B) log transformed data. The residual versus fitted graphs for the: (C) untransformed values of ground personnel used per fire day using the full sample (including outliers, high leverage) and (D) log transformed values of ground personnel used per fire day using the full sample (including outliers, high leverage)

Handling Fire Days with Zero Ground Personnel Used

The final dataset (n = 22,022) included 4,121 fire day observations for which zero ground personnel were assigned. Pearson correlation coefficients for fire characteristics and societal risk factors showed weak, negative correlations with fire days with zero ground personnel used. As zero ground personnel fire days were not associated with fire characteristics or societal risk factors, we assume that zero ground personnel fire days were not strategic or intentional, as might be the case for a managed burn response to a wildland fire (i.e., if an incident occurred on public land that did not threaten structures or communities).

Table 5. Pearson r correlation coefficients between observations with zero ground personnel and various physical fire characteristics and societal risk factors. All correlation coefficients were statistically significant at the alpha = 0.001 level, and the *r* values show weak, negative correlations between fire incident characteristics and zero ground personnel used at the fire day unit of analysis.

Fire Characteristic and Societal Risk Variables	Zero Ground Personnel Used
Current Incident Area	-0.07
Fire Complexity T1	-0.13
Fire Complexity T2	-0.11
Fire Complexity T3	-0.01
Structures Threatened	-0.04
Evacuations	-0.04

As we took the natural log of ground personnel used per fire day (the dependent variable) to avoid modeling issues of heteroskedasticity, observations with zero ground personnel used will yield negative infinity. To overcome this in the current analysis, various approaches were tested (Table 2) and predicted outcomes were compared. Generally, the predicted outcomes of logged ground personnel used per fire day were relatively consistent across different treatments of zero ground personnel fire days. Ultimately, to avoid omitting fire day observations, maintain a normal distribution, and to reduce the potential for bias by setting zero ground personnel fire days to their respective incident median or mean, we opted to set zero ground personnel fire days to the number of ground personnel used on that incident according to the closest report date. Figure 1 shows the histogram of the distribution after this transformation, and Table 2 shows the RDD results after conducting various transformation types to the zero ground personnel fire days.

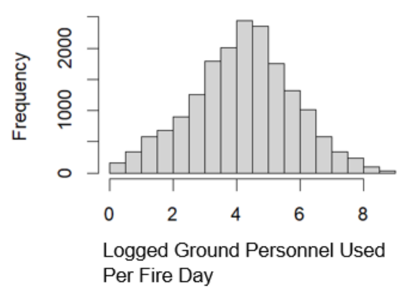


Figure 14. Histogram of the logged ground personnel used per fire day after setting zero ground personnel assignments to the number of ground personnel used on that incident according to the closest report date.

Table 6. Global linear RDD model results after conducting various transformations to the zero ground personnel fire day observations. Generally, the predicted outcome coefficients, p-values, and model R^2 results were consistent across transformations.

Functional Form Sample	**Pre-COVID**	**During-COVID**	**Sample Size**	**COVID Threshold Coef.**	**SE**	***p*-value (threshold)**	**R^2**	***p*-value (model)**
Linear Log transformed DV								
0 GP → 1 GP	2017 – 2019	2020 - 2021	20,022	-2.9	0.05	< 0.001	0.44	< 0.001
0 GP → Incident Med. GP	2017 – 2019	2020 – 2021	20,022	-2.5	0.04	< 0.001	0.45	< 0.001
0 GP → Closest Incident GP by Date	2017 – 2019	2020 – 2021	20,022	-2.5	0.04	< 0.001	0.45	< 0.001

Appendix 3C: Result Extensions and Sensitivity Analyses

Univariate Sharp RDD regression results (western U.S. fire day observations)

The linear and quadratic functional forms were developed and evaluated for final model form selection. Table 2 shows the comparative univariate model results for linear and quadratic models.

Table 1. Global model results (2017 – 2019 vs 2020 – 2021) for the univariate sharp RDD regression results including untransformed and log transformed dependent variables using linear and quadratic functional forms. The sample size for all univariate global model results was 22,022 fire day observations.

Functional Form Sample	Threshold Est.	SE	*p*-value (threshold)	R^2	*p*-value (model)
Linear Untransformed DV	-362	12	< 0.001	0.1	< 0.001
Linear Log transformed DV	-2.73	0.04	< 0.001	0.295	< 0.001
Quadratic Untransformed DV	-251.7	18.47	< 0.001	0.088	< 0.001
Quadratic Log transformed DV	-2.71	0.07	< 0.001	0.318	< 0.001

Multivariate Sharp RDD regression results: Assessing Functional Forms

The linear and quadratic functional forms were developed and evaluated for final model form selection. Table 2 shows the comparative multivariate model results for linear and quadratic models.

Table 2. RDD regression main effect results according to varying bandwidths and model forms. No covariates were included in these models. The "Main Effect" column includes the beta-coefficient that represents the fire incident days occurring during the pandemic; the effect size shows the association held between during-pandemic fire days and total personnel outcomes.

Functional Form Sample	Sample Size	Threshold Coef. Estimate	SE	*p*-value (threshold)	R^2	*p*-value (model)
Linear Untransformed DV						
Full Data	22,022	-301	13	< 0.0001	0.44	< 0.0001
Exclude Influential and Outlier Observations	21,193	-162	4	<0.0001	0.42	<0.0001
Linear Log transformed DV						
Full Data*	22,022	-2.61	0.04	< 0.001	0.466	< 0.001
Exclude Influential and Outlier Observations	19,475	-2.73	0.03	< 0.001	0.455	< 0.001

* The model that included the full set of observations with a natural logged dependent variable was selected for use in the main manuscript.

Interpretation of a beta-one in Log-Level Regression

We took the natural log of the dependent variable (ground personnel resources used per day) given the heteroskedasticity of the right-skewed untransformed dependent variable. Thus, in multivariate linear regression, interpretations of covariate coefficients changes from multivariate models with untransformed DVs. To interpret coefficient values for different model covariate types (i.e., binary, continuous, logged continuous), we used the following coefficient interpretations (Halvorsen and Palmquist, 1980)**:**

- **Continuous covariates:** Multiply by 100; If X increased by one percent, we expect ground personnel use to change by (+/-) percent.
- **Logged continuous covariates:** Coefficient is the expected change in percent of ground personnel used when X is increased by one percent.
- **Binary covariates:** When X switches from 0 to 1, the predicted percentage change of Y is $[100 \times (e^{B_1} - 1)]$

Multivariate sharp RDD model variable importance

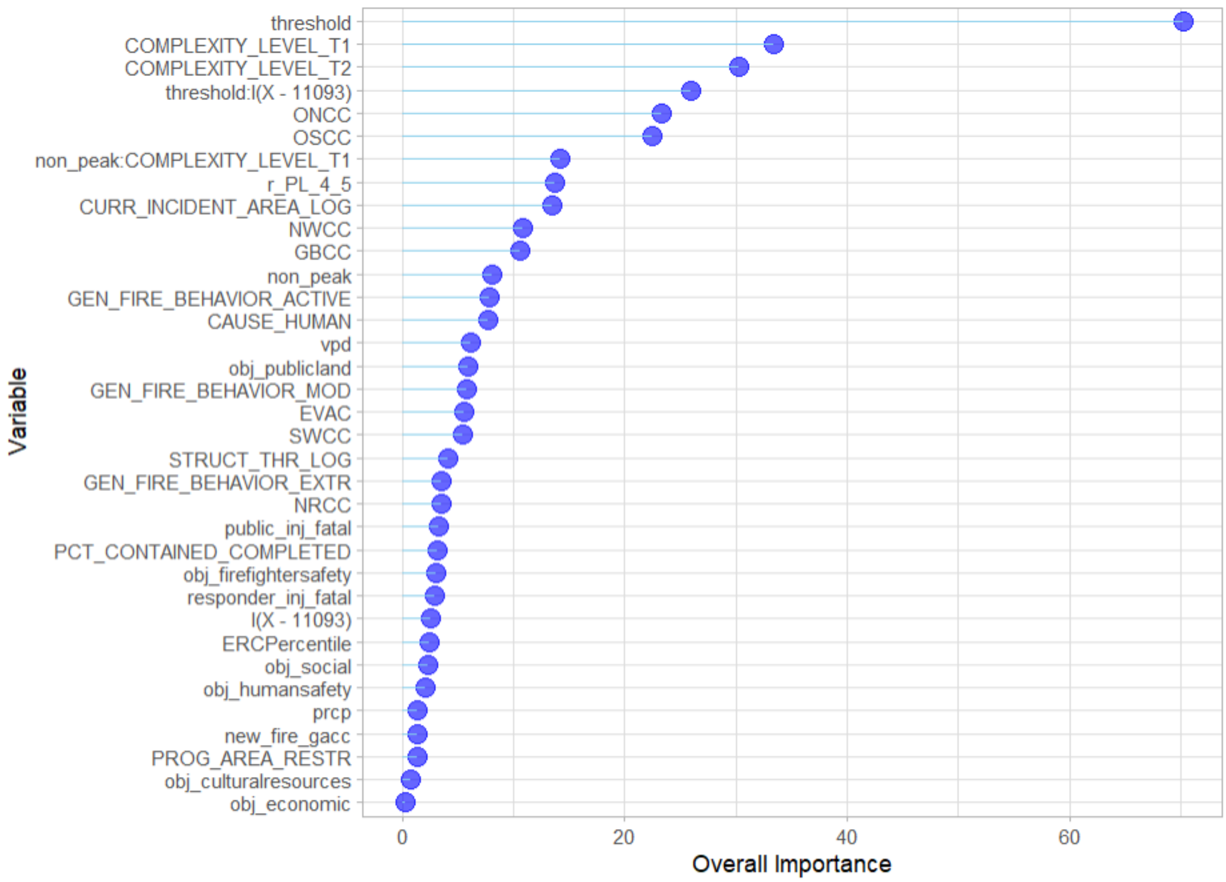


Figure 15. Overall importance of each of the covariates included in the global multivariate sharp RDD model. Importance was calculated by evaluating models that did and did not include each separate covariate one at a time according to changes in the absolute value of t-statistic of the model. The R^2 statistic is calculated for the model against the intercept of the null model, which includes only the intercept. Relative importance was scaled to account for the different variable types included (i.e., binary, continuous, log-continuous). Overall, the COVID-19 Threshold (wherein a score of 1 indicated that a fire day occurred during COVID) was most important in variable associated with model fit.

Multivariate sharp RDD model results: Sensitivity of results after removing outliers and highly influential observations

After RDD models predictive of ground resource use per fire day were developed for the 2017 – March 10, 2020 versus March 11, 2020 – 2021 bandwidths, Cook's distance metrics were calculated to detect and omit highly influential fire day observations from the dataset to assess if and how resulting effect sizes changed. Influential observations are defined as those that disproportionately influence any component of regression analyses, including the predicted outcome or slope coefficients. While outliers (i.e., extreme values of *y)* and high leverage points (i.e., extreme values of *x*) may also be influential observations, additional analyses are needed to assess whether they are influential. Cook's distance is a commonly used assessment to detect highly influential observations (Cook, 1979).[32] Cook's distance calculates the influence exerted by each observation on the predicted outcome, such that the change in the fitted $\hat{Y}$ is calculated with and without each observation *i*. This indicates the degree to which each observation *i* influences the fitted values. Cook's distance is calculated by the equation:

$$\text{Di} = \frac{\sum_{i=1}^{n} (\hat{Y}_i - \hat{Y}_{i(-k)})^2}{(p+1)\hat{\sigma}^2} = \frac{\sum_{i=1}^{n} (\hat{Y}_i - \hat{Y}_{i(-k)})^2}{P*MSE}$$

Where $\hat{Y}_j$ is the prediction for observation *i* based on all the data, $\hat{Y}_{i(-k)}$ is the prediction for observation *i* for a regression where observation *k* is removed, *p* is the number of parameters in the model, and the MSE is the mean squared error of the regression that includes all covariates (Davis, 2018).

Generally, observations with a Cook's distance greater than 3 times the mean Cook's distance are regarded as influential, though this threshold is not definitive. For the current sample and RDD model, there were 1,826 fire day observations that had Cook's distances greater than 3 times the mean Cook's distance, and these were influential observations. After removing highly influential observations, we identified observations (*n* = 500) with outlier values for the natural logged ground personnel used. We assessed the multivariate sharp RDD results for the global model results after omitting both highly influential and outlier observations, resulting in a total sample of n = 19,475. Of these, there were 9,742 fire day observations that occurred pre-COVID and 9,733 fire day observations that occurred during-COVID. For both the models that did and did not include outlier and highly influential observations, the portion of fire day observations that occurred during-COVID was approximately 50%. As shown in the global multivariate sharp RDD model results in Table 1 (below), the effect of the "During-COVID Threshold" variable was relatively consistent between the model that did include outlier and highly influential observations ($n = 22{,}022$; $B_{during} = -2.6, p < 0.001$) and the model that omitted outlier and highly influential observations ($n = 19{,}475$; $B_{during} = -2.7, p < 0.001$). As outliers and highly influential observations did not bias the global model results, we included all observations in the final model of Chapter 3.

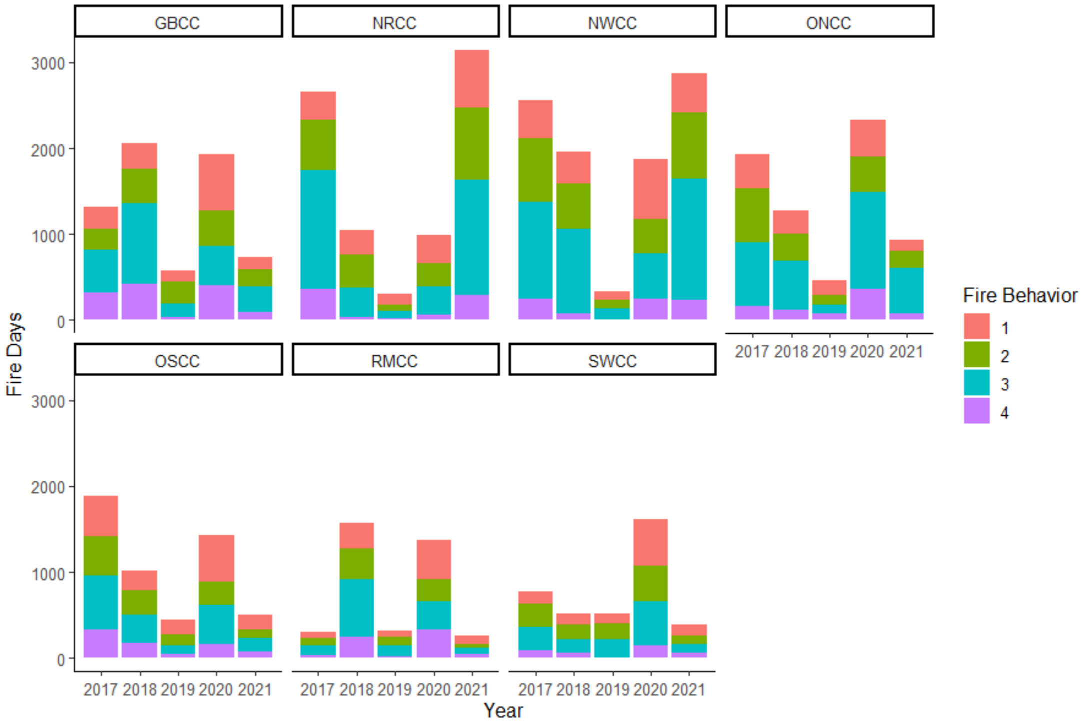
Table 1. RDD models predictive of ground resource use per fire day were developed for the 2017 – March 10, 2020 versus March 11, 2020 – 2021 bandwidths after outlier ground personnel observations and highly influential fire day observations were omitted from the analyses (*n* = 19,475).

Predictors	**Estimates**	**std. Error**	**Lower CI**	**Upper CI**	**p**
(Intercept)	3.59	0.06	3.478	3.709	**<0.001**
During-COVID threshold	**-2.73**	**0.03**	**-2.787**	**-2.664**	**<0.001**
Cause: Human	0.22	0.03	0.168	0.273	**<0.001**
Off-Peak Fire Day	-0.40	0.05	-0.501	-0.303	**<0.001**
Current incident area (log)	0.05	0.00	0.038	0.055	**<0.001**
Percent Fire Contained	0.00	0.00	0.000	0.001	**0.007**

[32] Cook, R. D. (1979). Influential observations in linear regression. Journal of the American Statistical Association, 74(365), 169-174.

General fire behavior: moderate	0.12	0.02	0.081	0.164	**<0.001**
General fire behavior: active	0.17	0.02	0.126	0.220	**<0.001**
General fire behavior: extreme	0.17	0.04	0.089	0.247	**<0.001**
Fire Complexity Type 1	0.94	0.02	0.891	0.986	**<0.001**
Fire Complexity Type 2	0.80	0.02	0.766	0.843	**<0.001**
Structures threatened (log)	0.02	0.00	0.011	0.021	**<0.001**
Evacuations planned or progressing	0.46	0.04	0.386	0.537	**<0.001**
Area restriction in progress	0.17	0.08	0.018	0.321	**0.029**
Responder injuries or fatalities	0.01	0.00	0.002	0.008	**0.001**
Public injuries or fatalities	0.10	0.03	0.049	0.153	**<0.001**
Regional PL 4 or 5	-0.22	0.02	-0.255	-0.189	**<0.001**
Regional new fires	0.00	0.00	0.001	0.003	**0.001**
Daily precipitation (mm)	0.01	0.00	-0.000	0.012	0.054
ERC Percentile	0.02	0.04	-0.064	0.108	0.618
VPD (kPa)	0.04	0.01	0.024	0.065	**<0.001**
Region: ONCC	0.73	0.03	0.660	0.795	**<0.001**
Region: OSCC	0.71	0.04	0.642	0.779	**<0.001**
Region: NWCC	0.25	0.03	0.191	0.311	**<0.001**
Region: NRCC	-0.31	0.03	-0.367	-0.243	**<0.001**
Region: GBCC	0.35	0.03	0.282	0.408	**<0.001**
Region: SWCC	0.30	0.04	0.226	0.371	**<0.001**
Objective: Social consideration	0.06	0.03	0.007	0.103	**0.024**
Objective: Economic consideration	0.00	0.04	-0.073	0.066	0.925
Objective: Public land	-0.24	0.07	-0.372	-0.116	**<0.001**
Objective: Cultural resources	-0.06	0.03	-0.107	-0.008	**0.024**
Objective: Human health and safety	0.16	0.02	0.116	0.204	**<0.001**
Objective: Responder health and safety	0.19	0.03	0.126	0.243	**<0.001**
Off-peak fire days * Complexity Type 1	1.01	0.21	0.608	1.416	**<0.001**
Public injuries/fatalities * Regional PL 4 or 5	-0.13	0.03	-0.190	-0.079	**<0.001**
Observations	19475				
R^2 / R^2 adjusted	0.558 /	0.558			

A.



B.

Figure 11A-B. The (A) annual GACC fire days classified according to the general fire behavior categories (i.e., *1 = Minimal to 4 = Extreme fire behavior*) and (B) corresponding annual proportions of each fire behavior category over all regional fire days.

Figure 11A-B shows general fire behavior classification counts over all regional fire days by year to explore regional differences in fire behavior as categorized and reporting by fire managers on a fire day basis. Figure 11 intends to capture if and how fire behavior on individual fire days may be associated with regional resource use; for instance, given the lesser predicted percentage reduction in ground personnel used during-COVID in the GBCC, NRCC, and RMCC relative to pre-COVID use, one might expect that these regions could have had fewer proportions of active and extreme fire behaviors over total fire days during-COVID fire days relative to pre-COVID fire days in the region. While Figure 11 captures that in the GBCC, approximately 60% of pre-COVID fire days (excluding 2019, an outlier year in terms of western U.S. fire activity) were classified as having active or extreme fire behavior. This reduced to approximately 40 to 50% for during-COVID fire days. The ONCC, with the greatest predicted average reduction in ground personnel used for during- relative to pre-COVID fire days, exhibited a relative increase in active and extreme fire behaviors per total annual fire days in the region.

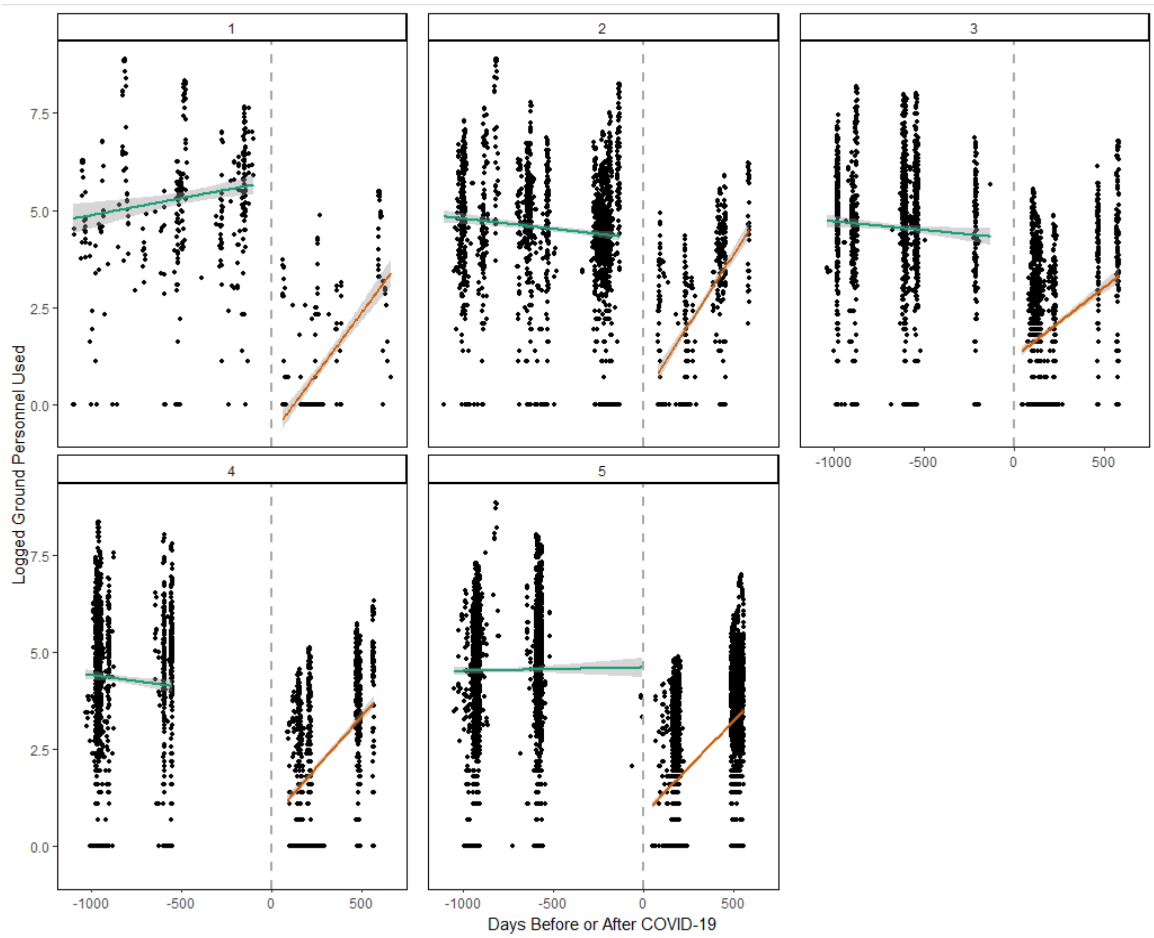


Figure 16. Univariate sharp RDD linear regression trends for each of the five national Preparedness Level (PL) categories (*1 = Lowest fire activity category to 5 = Highest level of wildland fire activity*).

Appendix 4: Hazard management and organizational resilience related publications

Vecherin, S., Chang, D., **Wells, E.,** Trump, B., Meyer, A., Desmond, J., ... & Linkov, I. (2022). Assessment of the COVID-19 infection risk at a workplace through stochastic microexposure modeling. *Journal of exposure science & environmental epidemiology*, 1-8.

- Abstract: The COVID-19 pandemic has a significant impact on economy. Decisions regarding the reopening of businesses should account for infection risks. This paper describes a novel model for COVID-19 infection risks and policy evaluations. The model combines the best principles of the agent-based, microexposure, and probabilistic modeling approaches. It takes into account specifics of a workplace, mask efficiency, and daily routines of employees, but does not require specific inter-agent rules for simulations. Likewise, it does not require knowledge of microscopic disease related parameters. Instead, the risk of infection is aggregated into the probability of infection, which depends on the duration and distance of every contact. The probability of infection at the end of a workday is found using rigorous probabilistic rules. Unlike previous models, this approach requires only a few reference data points for calibration, which are more easily collected via empirical studies. The application of the model is demonstrated for a typical office environment and for a real-world case. The proposed model allows for effective risk assessment and policy evaluation when there are large uncertainties about the disease, making it particularly suitable for COVID-19 risk assessments.

Wells, E. M., Cummings, C. L., Klasa, K., Trump, B. D., Cegan, J. C., & Linkov, I. (2021). Real-time Anticipatory Response to COVID-19: A Novel Methodological Approach. In *COVID-19: Systemic Risk and Resilience* (pp. 35-59). Springer, Cham.

– Abstract: The SARS-CoV-2 novel coronavirus 13 (COVID-19) pandemic has revealed the technical requirements needed to enhance scientific analysis and epidemic modelling, but also the social and institutional challenges of operating in a global crisis. The large-scale and turbulent nature of the pandemic has exemplified that healthcare and public health safety organizations resilience is critical for maintaining function and community support in times of crises with unclear outcomes and implications. Conceptualizations of organizational resilience need support swift organizational decision-making that simultaneously prepares for and responds to adverse events and system strains under uncertainty. This chapter presents a modelling approach towards bolstering organizational resilience for healthcare organizations facing COVID-19 called "real-time anticipatory response," which considers how organizations concurrently prepare for and respond to the pandemic under conditions of high pressure and high uncertainty. The framework supports strategic planning based on limited information and immediate need for organizational response which can be applied to a vast array of natural disaster and other crises that require stakeholders to enact quick decisions that facilitate organizational preparation and response simultaneously

Cegan, J. C., Trump, B. D., Cibulsky, S. M., Collier, Z. A., Cummings, C. L., Greer, S. L., Jarman, H., Klasa, K., Kleinman, G., Surette, M.A., **Wells, E**., & Linkov, I. (2021). Can Comorbidity Data Explain Cross-State and Cross-National Difference in COVID-19 Death Rates?. *Risk Management and Healthcare Policy*, *14*, 2877.

– Abstract: Many efforts to predict the impact of COVID-19 on hospitalization, intensive care unit (ICU) utilization, and mortality rely on age and comorbidities. These predictions are foundational to learning, policymaking, and planning for the pandemic, and therefore understanding the relationship between age, comorbidities, and health outcomes is critical to assessing and managing public health risks. From a US government database of 1.4 million patient records collected in May 2020, we extracted the relationships between age and number of comorbidities at the individual level to predict the likelihood of hospitalization, admission to intensive care, and death. We then applied the relationships to each US state and a selection of different countries in order to see whether they predicted observed outcome rates. We found that age and comorbidity data within these geographical regions do not explain much of the international or within-country variation in hospitalization, ICU admission, or death. Identifying alternative explanations for the limited predictive power of comorbidities and age at the population level should be considered for future research.

Zemba, V., **Wells, E. M**., Wood, M. D., Trump, B. D., Boyle, B., Blue, S., ... & Linkov, I. (2019). Defining, measuring, and enhancing resilience for small groups. Safety Science, 120, 603-616.

- Abstract: Resilience is increasingly recognized as a factor that improves the functioning and performance of individuals and communities; however, it is underexamined in smaller groups or teams. We performed a comprehensive literature review to examine how resilience is defined, measured and used in small teams. Additionally, we evaluated the effectiveness of trainings or interventions on teams towards increasing unit resilience and performance. Following a literature review, 74 measures across 37 articles were assessed. Study eligibility criteria include English-language publications between 1980 and 2017 that included output from a research trial or survey on military or civilian groups pertaining to their resiliency to adverse events. Resilience of units/teams was assessed across the four phases of resilience defined by NAS: prepare, absorb, recover, adapt. Our review found that while the concept of resilience is not often studied in small groups empirically, the focus of available studies is on recovery with limited attention given to absorption and adaptation. This work reveals a potential mechanism to improve team/unit performance via unit resilience training and improved unit cohesion. Training had small but significant effects on the preparation ($r = 0.03$, $k = 5$) and recover ($r = 0.05$, $k = 6$) phases of unit resilience. In order to improve resilience in small groups, training programs and other interventions must be appropriately focused on the essential phases of resilience associated with mission execution.

Wood, M. D., **Wells, E. M.,** Rice, G., & Linkov, I. (2019). Quantifying and mapping resilience within large organizations. Omega, 87, 117-126.

- Abstract: To complement risk assessment, large organizations need to be resilient in order to maintain critical functioning in the face of uncertain future threats (whether the threat is environmental, cyber, security-related, social, etc.). Given the complexity of both large organizations and future threat, it is challenging to enact programs and protocols that ensure resilience across whole organizations. We propose that large organizations can map current organizational resilience across threat event cycle phases (Plan, Absorb, Recover, Adapt) and context-specific resilience domains (Physical, Information, Cognitive, and Social) to contextualized resilience metrics. Subcomponents then can be compared to one another through dashboards or quantitative indices to facilitate decision making for resilience through identifying organizational strengths, weakness, synergies, and redundancies across its subcomponents in the context of their associated missions and capabilities. The United States Department of the Army is used as a case study example of how resilience approaches of large, complex organizations can be visualized to enable resilience insights using this methodology.