

DISSERTATION

TOWARD INTELLIGENT WILDFIRE SYSTEMS: INTEGRATING MACHINE
LEARNING ACROSS MITIGATION AND SUPPRESSION

Submitted by

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ABSTRACT

TOWARD INTELLIGENT WILDFIRE SYSTEMS: INTEGRATING MACHINE LEARNING ACROSS MITIGATION AND SUPPRESSION

Wildfire management involves human judgment and decision-making across multiple temporal and operational scales, from long-term fuel treatment planning to real-time suppression under changing environmental and operational conditions. This dissertation examines different wildfire management activities through data-driven approaches that combine machine learning, spatial analysis, and historical datasets. Rather than prescribing optimal actions, this research focuses on identifying patterns in observed fuel treatment and aerial suppression decisions and relates them to measurable environmental and operational conditions.

The first chapter examines hazardous fuel treatment decisions in Colorado’s national forests using historical treatment records and spatial variables related to wildfire hazard, terrain, infrastructure, and human influence. Neural network models are used to analyze associations related to treatment type occurrence. The second chapter develops a deep learning approach for identifying likely aerial suppressant drop activity, providing a new way to infer aerial suppression execution from publicly available telemetry data. The third chapter uses ADS-B data to analyze cross-agency aerial response timing during initial wildfire response in California, quantifying how environmental and social conditions are associated with aircraft arrival patterns.

Together, these studies illustrate how machine learning and open operational datasets can make difficult-to-observe components of wildfire management more measurable. Collectively, they contribute new methods and empirical insight for studying wildfire management across operational scales.

DEDICATION

I dedicate this dissertation to my wife, my family, and my friends.

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Chapter 1

Introduction, Literature Review, and Dissertation Overview

1.1 Introduction

This dissertation develops and evaluates data science approaches that combine deep learning techniques with spatial analysis, with a dual focus on hazardous fuel treatment selection and aerial suppression strategies.

The first component of this dissertation examines fuel treatment decisions in Colorado's national forests, analyzing how environmental, operational, and socio-economic factors influence the selection of treatment types. By integrating geospatial records of historical treatments with spatial datasets, this study identifies the key drivers underlying these decisions and evaluates whether treatment strategies emphasize public safety, ecological benefits, cost efficiency, or logistical feasibility. Neural network models are used to assess patterns in fuel treatment choices, revealing the complex interactions that shape wildfire mitigation efforts across Colorado's national forests.

The second component examines aviation resource use in wildfire suppression, using publicly available Automatic Dependent Surveillance–Broadcast (ADS-B) flight data to analyze aerial suppressant drop activity. Deep learning models are used to detect patterns in aircraft behavior and drop timing, providing a framework for tracking and evaluating suppression operations. The use of ADS-B data is further extended to analyze seasonal and agency-specific deployment strategies by comparing aviation operations of the California Department of Forestry and Fire Protection (CAL FIRE) and the United States Forest Service (USFS). Time-to-response modeling techniques, including survival analysis, are applied to better understand operational response dynamics and resource mobilization

patterns. Together, these approaches address data gaps in aviation resource deployment during active wildfire events across California.

By integrating spatial analysis with machine learning methods, this dissertation contributes to a more comprehensive understanding of both proactive fuel treatment planning and reactive aerial suppression strategies. Neural network predictions are compared with empirical observations to evaluate the ability of these models to capture complex, nonlinear interactions in fire-prone landscapes. Ultimately, these findings aim to support fire managers and policymakers in making informed decisions that enhance wildfire resilience, reduce impacts on communities and ecosystems, and improve the efficiency of aviation-based suppression efforts.

1.1.1 Treatment Objectives

Hazardous fuel treatments advance multiple forest management goals, providing ecological, socio-economic, and community resilience benefits. Mechanical methods like thinning and prescribed burns lower fuel loads, reduce high-intensity fire risk, and create safer forest conditions near communities [1]. These treatments also contribute to long-term carbon storage by limiting carbon loss during wildfires [2–7] while increasing water yield and reducing drought vulnerability [8–11].

Beyond risk reduction, fuel treatments improve ecological resilience and biodiversity. By increasing understory diversity and improving habitat conditions, these practices support a broader range of species [12–14]. Additionally, effective treatment planning, particularly when involving local communities, helps align management objectives with priorities such as protecting watersheds and air quality while preserving ecosystem values [15,16].

1.1.2 Factors Influencing Fuel Treatment Decisions

Operational and Economic Constraints

Operational constraints present significant challenges to the implementation and effectiveness of fuel treatment strategies in wildfire-prone landscapes. Studies consistently highlight how operational and administrative factors restrict the scope of mechanical treatments. For instance, [17] underscores the limited availability of forest areas for mechanical treatment, with feasibility highly dependent on management's willingness to implement these treatments. [18] identifies difficulties in translating conceptual fuel treatment strategies into actionable plans due to the vast areas requiring treatment and the need for multifaceted decisions regarding treatment placement and intensity. Moreover, a shortage of trained personnel further constrains the capacity to carry out labor-intensive treatments, especially during the off-season [19,20].

Adding to these limitations, studies have emphasized the importance of cost considerations, suggesting that prioritizing treatments based on economic efficiency can help managers maximize impact within budget constraints [21,22]. Others have discussed how the prioritization of fuel reduction to protect water supplies and other natural resources is often constrained by cost and feasibility [23,24]. [25] reinforces this by noting that costs frequently pose barriers to both the implementation and continued maintenance of fuel treatments. [26] discusses the duality of fuel treatments, noting that while they can reduce the need for fire suppression, they are also costly and can pose risks to the people implementing them. High-hazard areas frequently demand multiple treatment stages, often starting with mechanical methods followed by prescribed fire when feasible [27], even though mechanical treatments are often prioritized despite prescribed fire being more effective in the long term [28]. Most studies suggest that fuel treatments are generally not financially sustainable for land management agencies when relying on revenue from forest products generated and carbon credits [15]. Moreover, the lack of accurate cost data further limits

the ability to prioritize fuel treatment activities and plan budget expenditures, making it difficult to allocate resources efficiently and evaluate long-term outcomes [15,29].

Environmental, Spatial, and Landownership Influences

Environmental constraints in wildland environments significantly limit the implementation of fuel treatments. For example, [30] discuss how air quality regulations and steep terrain restrict fuel treatment implementation in the Sierra Nevada. Existing vegetation and historical fire regimes also influence the type of treatments implemented; for example, prescribed fire may be prioritized in fire-prone vegetation types with historically low-severity regimes [31]. Severe drought conditions present additional challenges to forest restoration, diminishing the resilience benefits of treatments [32–34]. However, treatments can still mitigate drought impacts compared to untreated forests [35]. Furthermore, extreme fire weather can reduce the effectiveness of both fuel treatments and suppression efforts, as fire behavior is predominantly driven by weather under these conditions [36]. This underscores the importance of alternative management strategies, such as employing multiple forms of treatment (mechanical thinning plus prescribed fire) [1,37,38].

The placement of fuel treatments is constrained by factors including land ownership, which limits available locations [39]. Federal lands, typically remote and managed under a unified framework, present both opportunities and constraints for wildfire management. For example, structured tools have been developed to prioritize fuel treatment budgets on at risk lands including federal land, providing transparency but reducing flexibility as decision-making must align with standardized guidelines that may not always prioritize fuels management [40,41]. By comparison, treatments located near housing units focus directly on protecting assets, offering a more immediate benefit to residents than those applied to remote wildlands [42]. Private lands within the WUI are highly fragmented, with diverse ownership and management practices that often require a shift in resident mindset to build support for fuel treatment efforts [43], a willingness that is positively correlated with income and varies geographically [44]. Support for fuel reduction treatments on pri-

vate lands is often shaped by factors such as prior wildfire experiences, property damage concerns, familiarity with prevention programs, resident status (whether permanent or seasonal), forest land size, and the influence of neighboring landowners who have implemented similar treatments [45–47].

Given these environmental constraints, fuel treatment decision-making is inherently complex, shaped by operational limitations, land ownership and jurisdictional boundaries, environmental conditions, spatial factors, and evolving definitions of effectiveness. Managers, policymakers, and stakeholders must navigate a dynamic decision space that balances budgetary constraints, workforce capacity, and trade-offs between ecological benefits and socio-economic objectives. The scale, placement, and design of treatments further complicate the process, particularly where federal and private lands intersect with local community values.

1.1.3 Fuel Treatment Effectiveness

The definition of ‘effectiveness’ in fuel treatment research varies widely, reflecting diverse wildfire management goals and methodologies. At the landscape scale, research has emphasized how strategic fuel treatment placement can influence fire behavior, size, and suppression efforts across large areas, underscoring the need for careful planning to maximize positive impact [48,49]. Similarly, [50] review effectiveness by examining how treatments alter fire progression and severity at the landscape level, though noting the challenge of consistent measurement due to variable study designs. [51], through a meta-analysis, quantifies reductions in wildfire severity post-treatment, concluding that a combination of mechanical thinning and prescribed fire yielded the most significant reductions in hazards across the reviewed studies. However, while mechanical thinning alone can effectively meet fuel reduction and fire risk management objectives for several years, its long-term benefits may be constrained by environmental challenges, such as the difficulty of implementing prescribed fire [52,53]. When successfully implemented, the com-

bination of mechanical thinning and prescribed fire has been shown to effectively increase seedling density, improve water quality, reduce bark beetle mortality risk, lower wildfire risk, decrease fuel loads, and reintroduce low-severity fire to the landscape, among other benefits [38,53–57].

Supporting these perspectives, [39] reviews 86 simulation studies on landscape-scale fuel reduction treatments in North America, finding that treatments, particularly those strategically placed and frequently maintained, effectively reduce damaging wildfires. The review identifies factors such as treatment design, climate, and terrain as influential to effectiveness. For instance, establishing coordinated fuel breaks reduces wildfire exposure for residential and protected areas, directly benefiting communities [58–61]. [62] emphasizes the interaction between fuel treatments and fire occurrences, suggesting that effectiveness should account for the likelihood of a treated area encountering a fire and the frequency of treatment maintenance over time. Although concluding these instances to be infrequent, finding less than 7 percent of treatments encounter a subsequent wildfire, larger treatments or those positioned strategically across a landscape may increase the likelihood of interaction with fire events. Larger treatments are found to be more effective than smaller ones at landscape scales, and outperform smaller, disconnected treatments in reducing fire effects [63].

Highlighting the importance of spatial configuration, [64] and studies like the analysis of the 2014 Carlton Complex fire demonstrate that treatments on leeward slopes can reduce fire severity more effectively than those on windward slopes, particularly under extreme fire conditions. This finding underscores the need to align treatment placement with terrain and prevailing fire weather patterns to maximize effectiveness. Similarly, [65] achieved fuel treatment success in Canada’s boreal mixed wood forest by prioritizing treatment locations using a rule-based approach. This approach integrated factors such as burn probability, jurisdictional boundaries, and non-flammable landscape features to improve large-scale spatial effectiveness by lowering landscape-level burn probability. [66] showed

that strategically placed landscape fuel treatments in the northern Sierra Nevada effectively reduced wildfire severity and enhanced post-fire conifer regeneration, with treatments covering only 18 percent of the fire-affected landscape enhancing landscape resistance to fire and promoting forest recovery. Collectively, these studies underscore that effective fuel treatment strategies require a nuanced approach that considers spatial configuration, treatment scale, and maintenance frequency, as well as alignment with landscape features and constraints, to maximize resilience and reduce wildfire impacts across diverse objectives.

1.1.4 Federal vs. State-level Aerial Firefighting Strategies in California

Wildland firefighting agencies employ a diverse array of strategies and resources to combat wildfires, including the extensive use of aviation assets. Aerial resources, such as helicopters, air tankers, and lead planes, influence fire outcomes by delivering water, retardant, and personnel to locations in difficult terrain or areas with limited water access. In the United States, two prominent agencies, the U.S. Forest Service (USFS) and California Department of Forestry and Fire Protection (CAL FIRE), manage significant aviation operations to shape wildfire outcomes. While both organizations share the goal of wildfire suppression, their operational structures, resource allocation strategies, and aviation utilization differ due to variations in geographic scope, fire management policies, and institutional priorities [67,68].

The role of aviation resources in wildfire management was particularly evident during the 2020 California wildfire season, one of the costliest in the state's history [69]. Over 4.2 million acres burned statewide, including the historic August Complex Fire, which became California's first "gigafire," consuming more than 1 million acres [70]. CAL FIRE coordinated its aviation resources to address fire suppression in State Responsibility Areas (SRA) and Direct Protection Areas (DPA), including lands under federal jurisdiction [71]. This overlapping responsibility highlights the collaborative structure of wildfire management in California, where both state and federal agencies play roles in mitigating large-

scale fire events. By comparison, Region 5 of the USFS accounted for nearly a quarter of all aviation flight hours contracted by the agency, underscoring the demand for aerial support in California [72].

To respond to this increasing demand for aerial support and the growing scale of wildfire activity, the U.S. Forest Service significantly expanded its aviation expenditures in 2020 [73]. In 2020, the U.S. Forest Service utilized 458 contracted aircraft and 24 agency-owned aircraft, including helicopters, fixed-wing planes, airtankers, and water scoopers, to support wildfire outcomes and other missions. Aircraft operations focused heavily on fire-related missions, which accounted for 97.5 percent of the total 83,324 flight hours, a significant increase from previous years [72]. Helicopters played an important role, flying 43,248 hours and delivering approximately 123 million gallons of liquid, including 119.4 million gallons of water and 3.4 million gallons of retardant across the U.S. [72]. Airtankers contributed significantly as well, logging 8,574 flight hours and delivering 33.9 million gallons of retardant [72]. Currently, the USFS tracks the application of these liquids using Automated Telemetry Unit (ATU) to document resource use [74].

Although the USFS operates at a national scale, state-level agencies like CAL FIRE complement federal efforts with their own robust aerial firefighting programs. CAL FIRE operates the largest civil aerial firefighting fleet in the world, a component of its wildfire suppression strategy. With a mission to contain 95 percent of fires to less than 10 acres, CAL FIRE manages its fleet from 14 strategically located air tanker bases across the state. The agency's aviation program includes a diverse array of aircraft designed to deliver rapid fire suppression in California's challenging and often extreme wildfire conditions. CAL FIRE's aviation program plays a role in protecting property and natural resources in one of the most wildfire-prone regions in the world. As federal efforts increasingly emphasize the integration of advanced technologies for resource tracking and coordination, CAL FIRE's aviation operations stand as a model for state-level wildfire management.

1.1.5 Aviation Tracking Technology for Operational Insights

One such technology used to monitor aviation is Automatic Dependent Surveillance–Broadcast (ADS-B), which is already widely used in aviation for tracking and monitoring [75–77]. Federal Aviation Administration (FAA) regulations mandate the use of ADS-B Out transmitters in most airspaces, enabling the monitoring of CAL FIRE’s fleet using ADS-B flight tracking technology [78]. ADS-B technology has been successfully integrated into wildland fire operations to monitor unmanned aircraft systems (UAS) [79,80]. It has also been used to analyze aerial firefighting operations, highlighting the effectiveness and cost-efficiency of different aircraft types based on mission patterns, deployment techniques, and resource delivery [81]. Unlike the USFS, which is mandated to use ATU systems to track suppressant drop activities and ADS-B to monitor aircraft position, CAL FIRE is indirectly required to use only ADS-B technology.

The widespread implementation of ADS-B technology provides an opportunity to improve tracking to better understand CAL FIRE’s aviation response. Existing research has highlighted gaps in understanding aviation operations during wildfire suppression efforts, and ADS-B data from the OpenSky Network has been recognized as a valuable resource for addressing these gaps [82]. The OpenSky Network, a non-profit organization, provides open access to real-world air traffic control data collected through a global network of ADS-B and Mode S sensors. By offering detailed flight information, the network enables comprehensive analysis of aircraft activities, such as flight patterns and suppressant drops [83,84]. Integrating OpenSky data into CAL FIRE’s operations analysis presents a unique opportunity to enhance insights into state-managed aviation resources, complementing existing USFS-focused research. This approach not only bridges the knowledge gap in wildfire aviation operations but also lays the foundation for improved coordination and resource allocation across agencies.

1.1.6 Identified Gaps in Aerial Resource Data

The most current air tanker drop data, compiled by the USFS, records the activation and deactivation of the air tanker release mechanism, represented as a line to estimate where retardant or water was applied. This data has been used to characterize resource use at a national scale [85]. However, deficiencies in capturing the outcomes of individual retardant drops persist [86], and the need for improved data collection systems for airtankers has been previously highlighted [87].

The absence of CAL FIRE drop data further limits understanding of aerial suppression activity in California, requiring reliance on assumptions when modeling operational effectiveness. In addition, existing datasets are inherently incomplete because they are limited to aircraft actively conducting suppressant drops. A substantial portion of aviation resources—including reconnaissance platforms, air attack, lead planes, and other coordination or support aircraft—do not engage in drops and are therefore not represented in these datasets. As a result, current data products capture only a subset of aerial operations, omitting components of incident management and decision-making.

1.2 Literature Review

1.2.1 Overview of Wildfire Simulation Modeling Approaches

Wildfire management increasingly relies on modeling approaches to understand ignition patterns, fire spread, and behavior across complex landscapes. These models vary in structure and purpose, ranging from empirical regression to physics-based simulations and data-driven machine learning predictive models. Researchers integrate factors such as weather, vegetation, topography, and operational decisions to understand the dynamic nature of fire behavior. Using large-scale datasets, these models help quantify potential wildfire severity, extent, and economic impacts. By refining fire predictions and risk assessments, they play a role in informing policy decisions, guiding mitigation strategies,

and optimizing resource allocation, ultimately improving outcomes for communities and ecosystems.

1.2.2 Regression Modeling in Fuel Treatment Management

Empirical studies often use statistical methods, such as regression analyses, to assess fuel treatment effectiveness. These studies typically compare treated areas with untreated controls to evaluate changes in wildfire characteristics such as severity, spread rate, and extent. Variables such as treatment type, time since treatment, and weather conditions are included in regression models to understand their influence on wildfire outcomes [50].

For example, [37] used regression analysis to demonstrate that increasing the proportion of a landscape treated reduced the area experiencing high-severity fires. Their study showed a negative relationship between the percentage of area treated and the proportion of high-severity fire, highlighting the effectiveness of treatments beyond their immediate boundaries. [88] investigated the effects of prescribed fires on subsequent wildfire severity in dry coniferous forests in Idaho, using regression analyses to assess fire severity patterns in relation to the distance from prescribed burn edges. Their findings indicated that fire severity decreased within approximately 200 meters of treatment boundaries, demonstrating a landscape-level effect.

[89] examined the longevity and effectiveness of fuel treatments using sequential autoregression and found that combining thinning and prescribed burning effectively reduced fire severity. Many other studies have similarly employed regression techniques to quantify the relationships between fuel treatments and wildfire outcomes, while accounting for influencing factors such as weather, vegetation, and treatment characteristics [90–93, 93–96]. While regression-based methods are generally straightforward to implement and interpret, offering clear relationships between dependent and independent variables and the ability to handle multiple predictors, they rely on assumptions, such as

linear relationships, that may oversimplify the complex interactions among fuels, weather, and topography.

1.2.3 Evaluating Fuel Treatment Effectiveness Through Simulation Modeling

Simulation models excel at capturing complex interactions and spatial variability, while regression models are simpler and more interpretable for identifying direct relationships. Simulation approaches have been widely used to assess fuel treatment placement and effectiveness [39, 97], predicting fire behavior under various scenarios that include the presence or absence of fuel treatments. [98], for instance, estimated changes in wildfire size and risk due to fuel treatments by simulating wildfires with and without treatments. They found that treatments could reduce wildfire extent by an average of 7.2 percent, though variability among wildfires led to some with increased fire size in treated areas. Research using simulation models has repeatedly shown that strategically placed fuel treatments can reduce wildfire spread and severity by creating patterns that disrupt fire growth [99, 100]. One commonly applied simulation model in wildfire research is the FSIM fire modeling software, which has been applied to study avoided costs [101], evaluate different fuel management strategies [102], analyze fuel encounter rates [103], and explore fuel treatment trade-offs [104]. Additionally, optimization models often leverage outputs from fire simulation tools, like FlamMap or FSIM, to design treatment placements that reduce wildfire risk and enhance control opportunities [105, 106].

1.2.4 Neural Networks in Wildfire Prediction and Management

The increasing availability of diverse data inputs, including ground-based measurements, human-curated spatial datasets, and satellite imagery, signifies a shift toward a data-rich environment in wildfire management, which enhances analytical capabilities and decision-making but also presents challenges in data integration, standardization,

and computational demands [107]. Neural network models are particularly well-suited to leverage this amount of data [108]. Their ability to replicate complex decision-making processes makes them highly relevant for wildfire management, where extensive datasets document fire behavior, suppression strategies, and landscape conditions that wildland firefighters navigate. This alignment between neural network capabilities and the growing body of wildfire-related data underscores their potential to improve predictive modeling and support more effective management strategies.

Neural networks have emerged as a valuable tool for wildfire-related applications, particularly in mapping burned areas. Studies comparing neural networks to logistic regression for burn-scar detection from Landsat imagery have demonstrated superior model performance [109]. Similarly, neural networks have been applied to Landsat imagery to map burned areas, reducing commission errors associated with traditional approaches [110]. Additional research in Mediterranean regions has coupled neural networks with MODIS hotspot data, proving effective in burned area mapping [111]. Other studies have extended these methods by integrating multiple stages of analysis, leveraging MODIS, Sentinel-2, or even hyperspectral remotely sensed data alongside neural networks to improve burned-area detection accuracy [112–115]. Notably, all studies utilizing ANNs for burned area mapping rely on airborne imagery collection, but are often validated against ground based measurements [116].

Another common application of ANNs in wildfire management is fire detection, which is closely linked to response time and the ability to control a fire in its early stages. Several studies have utilized ANNs for fire detection tasks [117–121]. Additionally, ANNs have been incorporated into sensor networks to develop real-time wildfire detection systems [122–127]. For example, the You Only Look Once (YOLO) model has demonstrated its advantage over classical machine learning methods, achieving higher accuracy, reducing false positives, and enabling real-time wildfire detection on UAVs and other devices [128]. Within Colorado, recent efforts have integrated AlertWildfire software into fixed camera

networks, enhancing real-time wildfire detection capabilities using deep learning [129]. The primary function of fire detection algorithms is to identify changes in continually running quasi-static imagery and video feeds to support near-real-time detection of wildfire smoke plums.

Neural networks have also demonstrated potential for change detection and hybrid classification processes, particularly in analyzing changing environmental conditions. One line of work experimented with genetic algorithms for satellite-based change detection [130], while others combined ISODATA with neural networks to refine burned-area delineation [131]. Neural networks already showed promise in distinguishing change between fire occurrences and non-fire conditions, correctly predicting a high proportion of fire events [132]. Building on this foundation, additional research has leveraged neural-network-based approaches to assess post-fire vegetation recovery and ecosystem changes, utilizing methods such as Deep Embedded Clustering for vegetation change classification and Adaptive Generative Adversarial Neural Networks for re-vegetation assessment [133]. The success of these models in detecting fire-induced landscape changes has further motivated the development of neural-network-based frameworks for daily risk change estimation, integrating meteorological parameters and local fire history into a larger real-time management system [134,135].

Wildfire landscape control is another domain where ANN modeling has been applied. For example, ANN models have been used to assess forest fire susceptibility, revealing that factors such as population density influence fire risk in a nonlinear manner [136]. Understanding these relationships helps inform fire control strategies by identifying high-risk areas and optimizing resource allocation prior to wildfire events to improve landscape-scale wildfire control outcomes. Another notable method used to understand landscape level wildfire control is the PCL model, which identifies areas where a wildfire can be more effectively contained based on topographic, fuel, and environmental factors [135]. Originally developed using boosted logistic regression, the PCL model has recently under-

gone efforts to transition into an ANN-based framework, aiming to maintain or improve performance by capturing more complex, nonlinear relationships that influence wildfire behavior on the landscape.

1.2.5 Rationale for Applying Neural Networks

While machine learning is not a universal solution for wildfire research [107], neural networks are well-suited to problems where outcomes arise from complex, nonlinear interactions among environmental conditions, operational constraints, and human decision-making. The systems examined in this dissertation reflect these characteristics, as management actions emerge from the interaction of multiple factors rather than from simple, separable relationships.

Traditional statistical approaches offer interpretability but typically require assumptions about the interactions, which can limit their ability to represent complex dependencies among variables. Neural networks provide a more flexible alternative by allowing these relationships to be learned directly from data without prescribing their structure in advance. This flexibility is particularly relevant in wildfire applications because the relationships linking environmental conditions to management actions are not fixed, but instead emerge from interacting constraints that vary across space, time, and decision context.

In this dissertation, neural networks are used to estimate empirically observable relationships between conditions and decisions using historical data. The objective is not to produce mechanistic representations of decision-making, but to quantify how observed management actions vary as a function of environmental, logistical, social, and other factors. This approach is applied across multiple temporal scales, from long-term treatment allocation to real-time suppression activity, providing a consistent framework for analyzing decision processes from observational records.

In this context, neural networks function as a tool for approximating high-dimensional relationships in wildfire datasets, allowing the reconstruction of past decision patterns without requiring explicit specification of underlying decisions.

1.3 Dissertation Overview

1.3.1 A neural network model to study factors impacting the selection of hazardous fuel treatment types in Colorado’s national forests (S. Magstadt and Y. Wei, 2025)

This work presents a data-driven exploration of why certain hazardous fuel treatments are chosen in Colorado’s national forests, using a neural network model to uncover the main factors correlated with managers’ decisions over the past decade. At its core, the study seeks to improve our understanding of where and why treatments such as thinning, broadcast burning, and other practices occur by analyzing historical data on treatments recorded between 2015 and 2024. While there has been anecdotal or local knowledge about which factors influence the selection of treatment types, this research attempts to quantify and model those choices using spatial data and machine learning techniques.

A key part of this study is the focus on geospatial analysis. This research drew upon a variety of data sources, including the Forest Activity Tracking System (FACTS), which catalogues hazardous fuel treatments across national forests, and multiple spatial layers that describe wildfire risk, terrain, and human infrastructure. For example, topographic information (like slope and elevation) was combined with wildfire hazard metrics (such as burn probability) and measures of human influence (like distances to roads and structures). By transforming these factors into a consistent 30-meter grid, we created a framework that the neural network could interpret in a systematic way.

The neural network itself is designed to learn non-linear relationships between landscape conditions and the actual choice of treatment type on record. Where simpler statis-

tical methods might focus on a handful of predictors, a neural network can account for a wider range of overlapping influences, such as how steep slopes might discourage certain mechanical operations, or how high-risk fire zones might require more intensive interventions such as implementing multiple forms of treatments. This ability to handle complex interactions is particularly appealing in wildfire management, where local expertise, ecological conditions, and operational constraints all mix on the landscape.

From a high-level standpoint, the project found that land managers tended to favor prescribed fire in more remote or lower-risk areas, while mechanical methods like thinning were more common in places with denser fuels or higher perceived wildfire threat. In some cases, managers used combined approaches, referred to as “multi-treatment” strategies, particularly near communities or infrastructure. Although no single factor alone dictates a treatment choice, certain variables proved consistently important, wildfire hazard potential, elevation, and proximity to roads or buildings played significant roles in shaping these decisions.

In practical terms, the study provides a roadmap for incorporating advanced analytical methods into decision-making processes. By highlighting the variables that have historically correlate with treatment allocations, it offers a reference point for managers seeking to align future interventions with specific management goals such as wildfire risk reduction, ecological restoration, or protection of infrastructure. Ultimately, the work demonstrates how machine learning can complement traditional resource management expertise, providing a broader, evidence-based perspective on where different treatment methods might be most effective or feasible across Colorado’s diverse forest landscapes.

1.3.2 A Deep Learning Approach for Predicting Aerial Suppressant Drops in Wildland Firefighting Using Automatic Dependent Surveillance–Broadcast Data (S. Magstadt et al., 2024)

Wildfires are a growing challenge, and aerial firefighting plays a role in controlling them. Large aircraft, such as air tankers, drop fire retardants to slow the spread of wildfires, but tracking these drops has been difficult. Traditionally, data on suppressant drops is collected after flights and reported in different formats, making it challenging to analyze effectiveness and coordinate resources efficiently.

This study explores a new approach to tracking and predicting aerial suppressant drops using publicly available flight tracking data. By leveraging Automatic Dependent Surveillance–Broadcast (ADS-B) data, a system that continuously reports aircraft positions, this research provides a way to monitor firefighting aircraft in real time. The study combines ADS-B data with drop records from Automated Telemetry Units (ATU), which log the timing of suppressant releases, to train machine learning models capable of identifying when and where these drops occur.

Using historical flight data from 2017 to 2023, the study applies deep learning techniques to recognize patterns in aircraft movement that indicate a suppressant drop. The models analyze factors such as altitude, climbing rate, and speed to differentiate normal flight patterns from actual drop events. This method allows for more precise tracking of aerial firefighting operations without relying solely on manual data reporting.

The ability to predict and monitor suppressant drops in real time has significant benefits. Fire managers can gain insights into where and when drops are occurring, improving coordination with ground crews and resource allocation. This could lead to more effective wildfire containment strategies and better decision-making during active fires.

Beyond its immediate applications, this research highlights the potential of using open-source flight data and machine learning to enhance wildfire response. Future improvements could incorporate environmental factors like wind and terrain to further refine pre-

dictions. Expanding this approach to include helicopters and other firefighting aircraft would make it more valuable. By integrating technology and data-driven analysis, this study provides a framework for improving the efficiency and communication of aerial firefighting operations.

1.3.3 An Assessment of Aerial Firefighting Response Times Between Agencies During the 2020 Fire Season in California (S. Magstadt et al., 2026)

Rapid aerial response during the initial response phase of wildfires can influence early fire growth, firefighter safety, and suppression outcomes. In California, aerial firefighting operations are jointly conducted by the U.S. Forest Service (USFS) and the California Department of Forestry and Fire Protection (CAL FIRE) under shared responsibility agreements. Despite the importance of this coordination, quantitative evaluation of cross-agency aerial response has historically been limited by fragmented and agency-specific aviation records.

This study introduces a unified, ownership-agnostic framework for evaluating aerial firefighting response by leveraging Automatic Dependent Surveillance–Broadcast (ADS-B) telemetry. ADS-B provides continuous, second-by-second aircraft position data and is mandated across most U.S. airspace, allowing consistent tracking of both federal and state firefighting aircraft. Using ADS-B data from the OpenSky Network, the study reconstructs detailed flight trajectories for CAL FIRE and USFS aircraft during the 2020 California wildfire season and links these trajectories to wildfire ignition records.

Aircraft movements were spatially and temporally matched to 7,214 wildfire ignitions to estimate time to first aircraft arrival within the first 24 hours following discovery. Initial response was defined as the first detection of an aircraft within 5 km of the ignition point. The analysis applied competing-risks survival methods to quantify the probability that

each agency arrived first, alongside Cox proportional hazards models to evaluate how environmental, logistical, and social factors influenced response timing.

Results show that aerial response during initial attack is not front-loaded but instead accumulates gradually across the first 24 hours, indicating that aircraft are not routinely launched immediately upon fire discovery. Response times for CAL FIRE and USFS aircraft were broadly similar, reflecting coordinated dispatch under shared protection agreements rather than systematic differences between agencies. The survival models further reveal that aircraft are dispatched more rapidly under hotter temperatures, near higher population densities, and under anomalously dry live-fuel conditions, while greener vegetation and wetter fuels delay response. These findings highlight the role of human decision-making, values-at-risk, and evolving fire potential in shaping aerial suppression timing.

Beyond agency comparison, this work demonstrates how ADS-B data can be integrated with wildfire occurrence and environmental datasets to evaluate aviation response at scale. By providing a consistent, cross-agency view of aerial operations, the study establishes a foundation for real-time situational awareness, performance monitoring, and improved coordination across wildfire management organizations

Chapter 2

Modeling Hazardous Fuel Treatment Decisions in Colorado's National Forests

Chapter 2 is based on: Magstadt, S., Wei, Y. (2025). A neural network model to study factors impacting the selection of hazardous fuel treatment types in Colorado's national forests. *International Journal of Wildland Fire*, 34(1).

2.1 Introduction

2.1.1 Wildfire Impacts and the Need for Fuel Management

Colorado has experienced severe wildfires in recent years, causing significant damage to forests, communities and wildlife. For example, in 2020, Colorado experienced three of its largest wildfires on record, namely the Cameron Peak Fire, the East Troublesome Fire and the Pine Gulch Fire, which together burned over 540,000 acres (2185.3 square kilometers) [137]. The economic impact of these wildfires has been immense, with recent studies estimating that wildfires in the western United States, including Colorado, have caused billions of dollars in direct damages and long-term economic losses, including property destruction, firefighting costs and loss of ecosystem services [138]. Given these substantial costs and the growing frequency of large wildfires, proactive measures are increasingly necessary. Landscape fuel treatments are needed to reduce the severity of future destructive wildfires. By reducing vegetation fuels, these treatments not only diminish the potential for extensive, damaging wildfires but also foster forest configurations that can enhance resilience and post-fire recovery. This approach potentially lessens the necessity for excessive firefighting efforts and may lead to lower fire suppression expenses [26].

2.1.2 Hazardous Fuel Treatments: Types and Trade-offs

Hazardous fuel treatments (HFTs) are often classified into two main types, prescribed fire and mechanical treatment. Prescribed fires reduce surface fuels through combustion, whereas mechanical treatments reduce wildfire risk by changing the structure of forest fuels. Low-intensity surface fires are natural in many systems, and are critical in maintaining natural fire regimes and certain forest regeneration [139]. Prescribed fires play similar roles to low-intensity surface fires and are often more cost-effective, but come with a higher risk of implementation due to the potential to escape their implementation boundaries and pose a risk to surrounding resources and communities [140]. Moreover, prescribed fires require a strict set of weather conditions that may vary daily, limiting their implementation. Mechanical treatments manipulate the fuel continuity by altering vegetation biomass [141]. Several different types of mechanical treatments exist. For example, thinning removes vertical vegetation and reduces lateral forest fuel connectivity [99]. Yarding involves the removal of biomass from the landscape, whereas piling of fuels retains the biomass but rearranges it. Other important fuel treatment types commonly used in forested areas include mechanical mastication for crushing or chipping surface fuels [63], but because we did not find enough cases of those applications in our study area, we chose not to analyse them in this study. Although mechanical treatments carry less risk, they are more costly when implemented owing to the amount of labour and equipment required. Given funding and personnel constraints, forest management must prioritise restoration placement with suitable treatment types strategically to efficiently achieve landscape restoration goals [142].

2.1.3 Decision Complexity in Fuel Treatment Planning

Decisions for hazardous fuel treatments involve a multifaceted approach that integrates ecological, economic and social considerations. Science-based, quantitative guidelines for fuel management, particularly in dry forest ecosystems, are emphasised as im-

portant in recent research [143]. The need for a landscape-scale perspective in fuel management that iteratively assesses fire hazard, fuel treatments and wildfire behaviour to enhance ecological and social resilience to wildfires is also elaborated in a recent study [48]. Others have advocated for a nuanced approach to fuel treatment, emphasising the need for treatments to be part of an integrated fire management strategy that addresses both ecological health and wildfire mitigation [26]. Using tools like the Fire and Fuels Extension of the Forest Vegetation Simulator (FFE-FVS) allows managers to simulate and evaluate the stand level effectiveness of various fuel treatment options in reducing fire hazard and improving forest structure over time [144]. The Treatment Optimisation Model (TOM) identifies fuel treatment placement to minimise fire spread across the landscape [145]. Tools like ForSys can evaluate landscape scenarios to determine where to place restoration efforts to achieve multiple fuel management goals [146,147]. Others have used modelling approaches aimed at optimising fuel treatment locations [106,148–150]. Ultimately, the placement of fuel treatments is based on a combination of management tools, funding resources, strategic planning, scientific research, risk assessments, and community and stakeholder engagement.

2.1.4 Machine Learning Approaches to Wildfire Systems

Machine learning (ML) has become an essential tool in the domain of wildfire risk management, particularly with the increased availability of high-level computing power [107]. In the present study, we adopt the definition of ML as the automated detection of meaningful patterns in data [151]. ML algorithms often focus on the accuracy of predictions and probabilities of a natural system [152], and can be used to gain useful insight into the connection between explanatory variables and the response variable [153].

One ML method used to observe the interaction between explanatory and response variables is the feed-forward artificial neural network (ANN). In its most basic form, an ANN consists of a neuron, which is designed to mimic the biological function of brain

cells [154]. A neuron, often referred to as a perceptron, functions primarily as a linear regressor where the output is determined by calculating the dot product of inputs and weights plus a bias term. This value is then passed through a non-linear activation function, producing a continuous range of values. An ANN is a collection of combined perceptron units that act in parallel [155]. In a feed-forward ANN, neurons from one layer transmit signals to all neurons in the next layer, with the network computing collective outputs through non-linear activation functions. There are numerous examples of efforts to use this ML method to understand various aspects of wildfire processes. For example, fire weather plays an important role in influencing fire spread; understanding it helps us design mitigation strategies. One research effort used meteorological factors to build an ANN model to predict the scale and magnitude of wildfires on a fire ignition [156]. Studies have explored various neural network methods to predict wildfire occurrence [134, 157, 158]. For instance, a recurrent neural network was used to model the annual average area burned in Canada by utilising past wildfire risk to predict future landscape-scale burn area [159]. Attempts using ANNs have also been made to map wildfire susceptibility and vulnerability using density of wildfire occurrence [160–163].

2.1.5 Study Objective and Contribution

Although ANNs have been widely used in wildfire prediction and management, their application in studying hazardous fuel treatments has not been extensively explored. In our study, ANNs were leveraged to analyse and learn from historical fuel treatment data, gain insights into the factors associated with past hazardous fuel treatment strategies and provide suggestions to improve future hazardous fuel treatment allocation decisions. The dataset used in this study represents the outcomes of decisions made in multiple national forests over several decades in an evolving wildfire management system and reflects the spatial arrangement of the current fuel treatment strategy in national forests in Colorado. This study assesses past HFT locations and types based on both environmental and an-

thropogenic explanatory variables and evaluates the importance of these variables in explaining treatment decisions. Our findings from the analysis of historical fuel treatment decisions can help guide and enhance future treatment strategies in Colorado’s national forests.

2.2 Methods

2.2.1 Study Area

The study region encompasses a diverse 14.5-million-acre terrain across 11 national forests within Colorado, excluding the Manti–La Sal National Forest and the Comanche and Pawnee National Grasslands owing to insufficient data. To align with the US Forest Service administrative forest boundaries layer, which organises land by administrative units, we combined certain forests in our analysis. Specifically, the Arapaho and Roosevelt forests are grouped together, as are Grand Mesa, Uncompahgre and Gunnison, and Pike with San Isabel, owing to their ecological similarities and administrative proximity. This grouping resulted in seven distinct forest units used for our study (Figure 2.1). The elevation of the study region spans from approximately 1700 to 3800 m, home to an array of forest types including conifer, mixed conifer–hardwood, aspen, lodgepole pine, piñon–juniper, ponderosa pine, spruce–fir and oak shrublands, as well as riparian zones. This area features a mosaic of rural landscapes punctuated by urban centres, with tree density and canopy cover showing marked variability influenced by a variety of factors such as altitude, species mix and the presence of water sources. This heterogeneity is further shaped by human activities like timber harvesting and natural disturbances such as wildfires and pest outbreaks. Our analytical timeframe spanned 2015 to 2024. The HFTs during this period were implemented across all national forests in Colorado in diverse ecosystems.

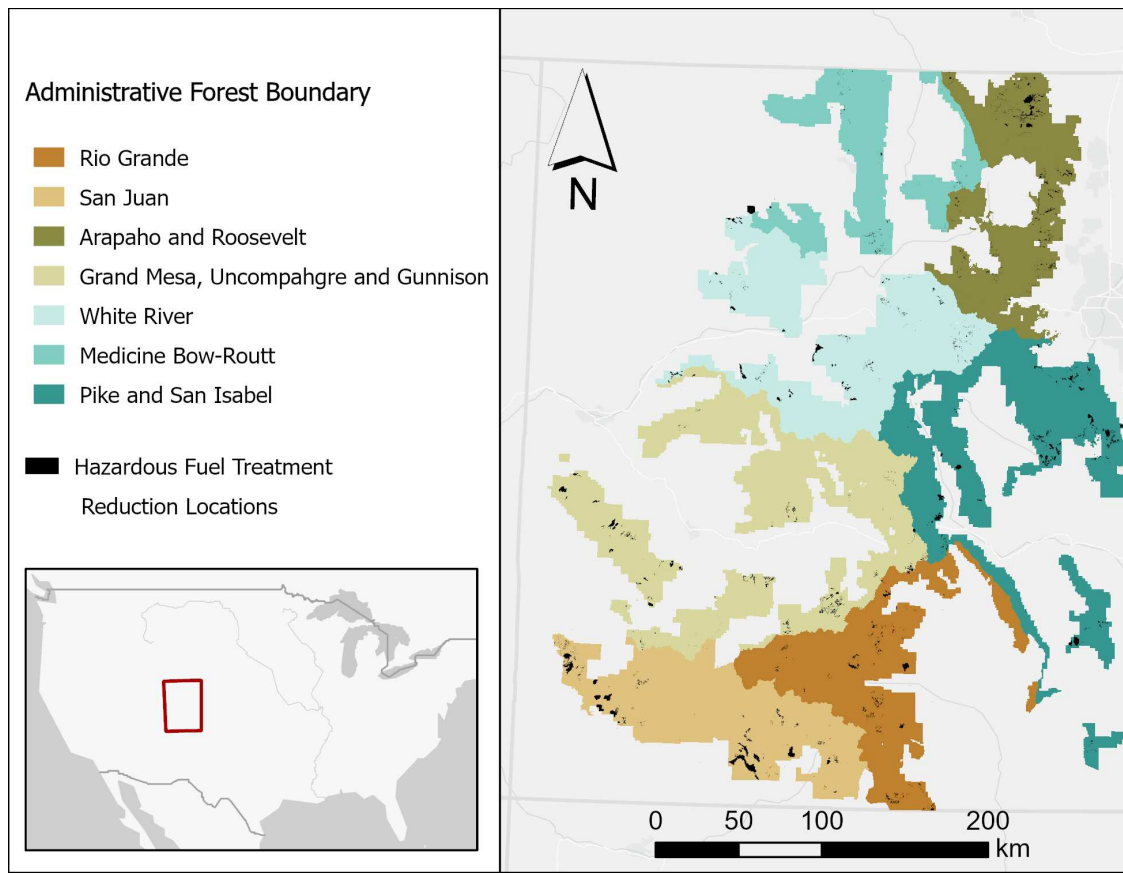


Figure 2.1: The administrative boundaries of the national forests in Colorado, highlighting the areas where hazardous fuel treatments have been implemented that are part of our study. The depicted black polygons represent the specific regions within these forests where fuel treatments have occurred from 2015 to 2024.

2.2.2 Hazardous Fuel Treatment Dataset

Hazardous Fuel Treatments

We sourced our historical HFT data from the georeferenced polygon dataset within the Forest Activity Tracking System (FACTS). This dataset comprises polygon locations of proposed HFTs across all US National Forests, reflecting the current treatment strategies adopted by the United States Forest Service (USFS). Our study was focused on Colorado, specifically utilising sites corresponding to fire risk reduction activities.

From the diverse range of different HFTs, we simplified our list of HFTs to include just six treatment classes. These included broadcast burning, which is the controlled application of fire to a predetermined area; burning of piled material, which involves setting fire to hazardous fuels previously accumulated either manually or mechanically; piling of fuels, a technique that entails collecting materials at a particular site; yarding, the act of extracting fuels from an area; and thinning for hazardous fuel reduction, a method that involves the selective cutting down of trees and shrubs for the exclusive purpose of fuel reduction. Piling of fuels is typically carried out as a preparatory treatment for prescribed fire but fuel often remains unburned in the study area, according to FACTS, likely owing to costs, liability associated with proximity to critical infrastructure and habitats, and concerns regarding smoke management near populated areas [164]. Additionally, we introduced a multi-treatment category to account for areas that underwent more than one type of treatment, where at least one of the treatments was mechanical and one was either prescribed fire or burning of piled material during the analytical timeframe. Treatments that underwent multiple mechanical interventions but no application of any controlled burning were excluded from the dataset to maintain focus on areas where both types of treatment were applied. Although our primary analysis timeframe spanned from 2015 to 2024, the earliest of the treatments in the multi-treatment cases may be prior to this timeframe and can extend as far back as 2001.

In our dataset, some fuel treatment polygons overlapped, indicating areas that underwent multiple mechanical treatments over time in Colorado’s national forests. We selected only the most recent treatment from 2015 to 2024 for overlapping polygons, resulting in 6291 treatment units covering approximately 152,000 ha treated over an area of 107,000 ha (Table 2.1). This approach avoided double counting the same area in our spatial analysis. Eight fuel treatment activities were omitted from our study owing to their limited sample size.

Table 2.1: Information about different fuel treatment methods, including the sample area in hectares (ha) that underwent each treatment.

Treatment	Sample area (ha)
Broadcast burning	42,232
Yarding	6,818
Burning of piled material	14,105
Piling of fuels	3,749
Thinning for HFR	4,691
Multi-treatment	27,501

2.2.3 Explanatory Variables and Preprocessing

Explanatory Variables

An integral component of neural network modeling lies in curating a robust set of explanatory variables that correspond meaningfully with the response variable. For this purpose, we harnessed both vector and raster datasets, standardising each to a 30-m resolution squared grid. We also calculated the closest Euclidian distance from each landscape location to the closest roads, structures and water bodies. Broadly, the explanatory variables in our study can be compartmentalised into three predominant categories, which are wildfire risk, landscape and anthropogenic elements.

To capture fire-regime characteristics within the hazardous fuel treatment polygons, we employed LANDFIRE geospatial data. This multi-agency initiative strives to develop

a uniform database of vegetation fuel metrics across the US [165]. Metrics such as the Percentage of Replacement-severity Fire (PRS), Percentage of Mixed-severity Fire (PMS) and Percentage of Low-severity Fire (PLS) were used in gauging fire severity within historical fire regimes. PRS measures the percentage of an area within a fire perimeter where fire severity caused more than 75 percent average top-kill, indicating extensive vegetation damage and replacement post-fire. PMS quantifies the percentage of an area within a fire perimeter with moderate severity, causing 25–75 percent average top-kill, leading to a mixture of killed and surviving vegetation.

Spatial datasets of landscape-level wildfire risk factors were used to assess wildfire risk within treatment zones. This analysis integrated several key variables to quantify wildfire risk, including wildfire hazard potential (WHP) [166,167] and flame length exceedance probability at 4 feet (1.2 meters) (FLEP4) and 8 feet (2.4 meters) (FLEP8) [167]. Additionally, we considered conditional risk to potential structures (CRPS) and conditional flame length (CFL), which are conditional on a fire occurring and represent the expected structure risk and flame length under such conditions [168,169]. We also considered burn probability (BP) [167]. BP is defined as the ratio of the number of times a cell is burned by a fire simulated by the FSim model to the total number of annual iterations simulated, and it serves as a quantitative measure for simulated wildfire exposure [170]. The proposed treatment data were extracted from the dataset version that most closely predated the analysed wildfire risk variables to ensure temporal consistency. These variables were used in evaluating the wildfire risk within each hazardous fuel treatment zone.

Our landscape characterisation incorporated spatial layers delineating slope (Slope), elevation (DEM) and proximity to water bodies (StreamEuc). For instance, terrains near water bodies predominantly feature riparian species, effectively excluding them as candidates for certain hazardous fuel treatment. Moreover, areas with steep inclines pose access challenges, and those at higher altitudes may offer limited value for treatment. Data on

elevation, slope and water bodies were obtained from the USDA Geospatial Data Gateway [171].

Acknowledging that hazardous fuel treatments serve dual purposes, such as reducing wildfire severity and safeguarding human infrastructure, we introduced anthropogenic variables. These variables aimed to portray the intersection of HFT decisions with human-centric factors. We collected vector lines and points representing existing Forest Service roads and structures, available from the USFS FSGeoData Clearinghouse and USDA Geospatial Data Gateway respectively. These data were then transmuted into a 30-m resolution raster layer, with each cell representing its proximity to the closest road (RoadEuc) or structure (StrucEuc).

Multicollinearity Testing and Variable Selection

Multicollinearity poses challenges in modelling when several explanatory variables share a strong linear correlation, thereby obscuring their distinct impacts on the model [172]. Although it may not inherently compromise the predictive ability of a neural network, multicollinearity can introduce redundancies in the interpretive process [173]. To identify and address potential collinearity in our dataset, we employed the variance inflation factor (VIF) as a diagnostic tool [174]. Conventionally, VIF values surpassing 10 demonstrate pronounced collinearity among explanatory variables. Conversely, values below 10 are generally indicative of negligible multicollinearity [175]. We omitted any explanatory variables with VIF values exceeding 10 [176]. In our analysis, conducted using Python 3.7, we assessed multicollinearity among independent variables using the `variance_inflation_factor` function from the `statsmodels.stats.outliers_influence` (statsmodels version 0.14.0) [177].

Feature Normalization

We addressed the challenge posed by the wide range of input variable values in the dataset by normalizing the explanatory variables. Feature normalisation is a technique

that transforms the independent variables to a common range, thereby ensuring equal weight is given to each explanatory variable [178]. We used the Min–Max scaling algorithm, which scales the distribution of the data from the minimum and maximum values of the variables to 0 and 1, respectively [179]. The transformation formula used for feature normalization is shown here:

$$z = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (2.1)$$

where z is the value after feature normalization, x_i is the variable value, $\min(x_i)$ is the minimum value of the variable range, and $\max(x_i)$ is the maximum value of the variable range. Feature normalisation was conducted on the training data after splitting the dataset into training and testing sets. The Min–Max scaling was then fitted on the training set and subsequently used to transform both the training and testing sets to maintain consistency. The feature normalisation was implemented in Python 3.7 using ‘scikit-learn’ [180].

2.2.4 Model Development

Hazardous Fuel Treatment Model Training

We designed our model based on a feed-forward ANN [154]. Given the complexity and non-linearity of large and varied datasets, ANNs are known for their proficiency in managing such data [181]. More specifically, we chose a ‘vanilla’ neural network architecture, which uses a feed-forward neural network trained using a backpropagation algorithm (Figure 2.2). This algorithm optimizes the network by adjusting weights and biases in response to errors, utilizing gradient descent [182].

The training and validation of our model were based on a dataset encompassing 770,774 training samples and 330,331 validation samples (Table 2.2). The neural network architecture was chosen for its compatibility with the categorical input data and the range of explanatory variables involved in our study. The architecture, with its single hidden layer,

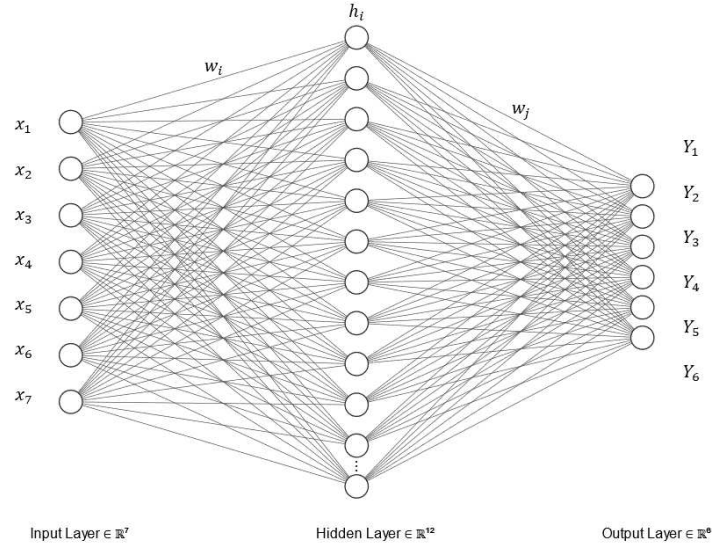


Figure 2.2: The model architecture of our feed-forward neural network with a single hidden layer. The network consists of an input layer with 9 neurons (denoted as $X_1, X_2, \dots, X_9$), representing the input features, a hidden layer with 64 neurons (denoted as h_i), and an output layer with 6 neurons (denoted as $Y_1, Y_2, \dots, Y_6$), corresponding to the output predictions. Each neuron in one layer is fully connected to all neurons in the subsequent layer through weights (w_i and w_j), which are adjusted during the model training process.

was chosen to balance model complexity and predictive power, minimising the risk of overfitting and maintaining the ability to generalise effectively to unseen data [183].

Table 2.2: Summary of training and testing datasets for hazardous fuel treatments distributed by national forest and treatment type. Values represent the number of 30-m resolution pixels.

National Forest	Broadcast burn	Yarding	Burning of piled material	Piling of fuels	Thinning for HFR	Multi-treatment
Rio Grande	28,565	42,527	7,129	114	1,042	37,727
San Juan	160,702	4,256	14,964	30,789	331	47,206
Arapaho and Roosevelt	36,932	3,680	4,794	6,373	138	113,408
Grand Mesa, Uncompahgre and Gunnison	65,877	1,256	84,658	710	2,444	18,081
White River	110,727	23,862	4,323	284	30	18,649
Medicine Bow–Routt	2,306	180	19,579	1	69	6,361
Pike and San Isabel	64,140	5	21,285	3,387	48,074	64,140

To identify the most effective hyperparameters for our model, we utilised ‘KerasTuner’ with a random search strategy [184,185]. This method facilitated an assessment of various node and activation function combinations to establish the model architecture. Our model was designed for a multiclass classification task, utilising the categorical cross-entropy loss function to optimise the model weights during training by measuring the discrepancy between the predicted probabilities and the actual class labels [186]. The Adam optimiser was selected for its computational efficiency and adaptability across varying model architectures [187]. The output layer utilised the softmax activation function, providing a probability distribution across the predicted classes [188]. The entire model was built using Python 3.7 and relied on the ‘Keras’ module, leveraging its high-level neural network application programming interface (API) for an efficient modelling process built on ‘TensorFlow’ [189,190].

2.2.5 Model Evaluation and Interpretation

Evaluation of Model Performance

For this study, we aimed to predict six distinct types of HFTs. To gauge our model’s robustness, we utilised the receiver operating characteristic (ROC) curve, deriving the area under the curve (AUC). We employed a 10-fold cross-validation approach to provide a more comprehensive assessment of the model’s performance across different data subsets. The AUC was not only applied in a macro context but was also measured for each fuel treatment type in contrast to the other classes [191–193]. To calculate the AUC for each class, we employed a one-vs-all approach. This method involves treating each class as the positive class and combining all other classes as the negative class, and then calculating the AUC for each scenario. For example, in the case of broadcast burning, we calculated its AUC by considering it as the positive class and all other treatment methods as the negative class. This process was repeated for each class, allowing us to assess the model’s performance for individual classes in addition to the overall performance.

We computed the area under the receiver operating characteristic curve (AUC) using the `roc_auc_score` function from the `sklearn.metrics` module (scikit-learn version 1.2.2) in Python 3.7 [194].

Feature Significance

We used permutation importance analysis to evaluate the significance of each feature in our ML model [195]. This approach involves shuffling the values of individual features and observing the subsequent changes in model performance. The resulting feature importance metrics offered transparency on the relative significance of each feature within the model's predictions. The permutation importance analysis was implemented using the 'eli5' Python module (eli5 version: 0.13.0). Then, using the 'sklearn.inspection' module (scikit-learn version 1.2.2), we generated partial dependence plots (PDPs) for explanatory variables to illustrate how individual variables influence the model's predictions for each response variable while holding other factors constant [194]. These plots reveal the marginal impact of each variable on the likelihood of the target outcome. Through these visual representations, we cite both the nature and the strength of the relationships between explanatory variables and the target.

2.2.6 Spatial Generalization and Landscape-scale Model Application

To mitigate the influence of spatial autocorrelation when modelling hazardous fuel treatments across various national forests, we implemented a leave-one-out cross-validation (LOOCV) method [153]. In this method, data from each national forest were segregated into a single test set with the remaining forests' data used for training. This procedure was repeated until each forest had been used as a test set, ensuring the model's evaluation reflected its effectiveness in predicting across separate geographical areas without the confounding effects of spatial dependencies. The application of the LOOCV method in this study was used to evaluate the generalisability of models designed to predict wildfire management practices across a diverse range of national forests.

We compiled a comprehensive dataset covering the 11 national forests in Colorado, intending to assess our model’s fit across these areas. To ensure the applicability of our model fitting, we implemented a filtering process based on the historical dataset used to train the model. Specifically, we compared each variable in the comprehensive national forests’ dataset against the corresponding minimum and maximum values found in our training dataset. This maintained consistency between the training and fitting conditions of the model. By enforcing this range-based filtering, we aimed to eliminate any areas within the national forests dataset that exhibited extreme values not represented in our training data, thus focusing the model’s predictions on regions with similar characteristics to those observed when building the model [196].

Finally, we fitted the model to this refined dataset, enabling us to examine the predictive dynamics within the ranges historically observed. We treated the model’s predicted values as probabilistic estimates, each informing the parameters of probability distributions for the respective response variables. This methodology allowed us to capture and represent the inherent uncertainty and variability in the predictions. We modelled the outcomes using a multinomial distribution, which reflects the diversity of potential values each response variable could assume based on the model’s forecasts.

2.3 Results

2.3.1 Variable Selection and Final Model Configuration

Due to high levels of multicollinearity, the variables FLEP4, CRPS, PRS, PMS, PLS were removed from the modelling dataset. Therefore, the modeling dataset consisted of the HFT label and nine explanatory variables: WHP, CFL, FLEP8, BP, StreamEuc, Slope, DEM, RoadEuc, and StrucEuc.

Our predictive model’s architecture, selected through a randomised grid search, consists of a single hidden layer with 64 neurons using rectified linear unit (ReLU) activation. We trained the model over 10 epochs, fine-tuning the model weights with a learning rate

of 0.001, employing the Adam optimiser and categorical cross-entropy as the loss function. The final model weights are visualised to provide a representation of the weight adjustments after the training process (Figure 2.3). The largest magnitude negative weight in the hidden layer is -15.2, connecting the input 'WHP' to hidden node 27, whereas the largest positive weight is 4.96, connecting 'WHP' to hidden node 40. In the output layer, the largest magnitude negative weight is -11.54, linking hidden node 29 to the output class 'piling of fuels', and the largest positive weight is 7.33, connecting hidden node 1 to the output class 'thinning for HFR'.

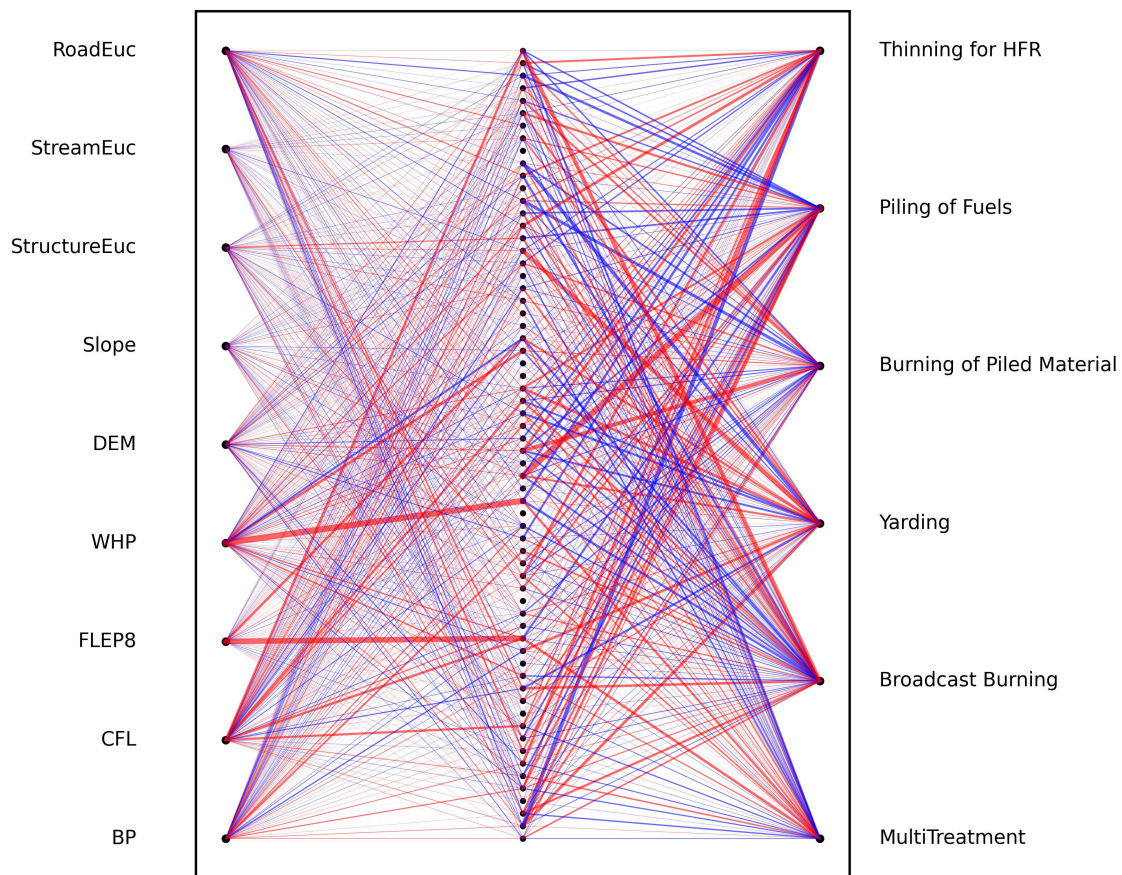


Figure 2.3: A neural network weight visualisation representing the connections and their significance between input features and outputs in a three-layer ANN. The input features include 'WHP', 'DEM', 'CFL', 'FLEP8', 'BP', 'StreamEuc', 'Slope', 'RoadEuc', 'StrucEuc'. Connections from input features to subsequent layers are depicted with lines, where the thickness indicates the weight magnitude and the colour represents the weight sign (blue for positive weights, red for negative weights).

2.3.2 Model Performance

After preparing the dataset and adapting it for our model, performance evaluation was conducted using distinct testing datasets. Our results yielded a macro-average AUC of 0.91 ± 0.0269 for the testing datasets. Among the classes, broadcast burning and thinning for HFR achieved the highest AUC score at 0.945 and 0.947 respectively, whereas the multi-treatment category had the lowest AUC score at 0.866 (Table 2.3).

Table 2.3: Testing AUC scores and bootstrap standard errors for each treatment class.

Prediction class	Testing AUC
Broadcast burning	0.945 ± 0.0003
Yarding	0.922 ± 0.0007
Burning of piled material	0.910 ± 0.0006
Piling of fuels	0.922 ± 0.0010
Thinning for HFR	0.947 ± 0.0011
Multi-treatment	0.866 ± 0.0008

2.3.3 Feature Importance and Response Patterns

Our permutation analysis highlights the significance of each feature within the model, revealing their order of importance. The most influential features, in descending order, are DEM, CFL, WHP, BP, FLEP8, StrucEuc, RoadEuc, Slope and StreamEuc (Table 2.4). DEM and CFL stood out with mean importance values of 0.221 and 0.171, indicating a notable decrease in performance when permuted. This was followed by WHP and BP, which showed mean importance values of 0.144 and 0.132. Slope and StreamEuc showed the lowest importance values of 0.0384 and 0.0345, respectively.

The likelihood of broadcast burning increases in areas with lower BP and WHP values, which are typically regions with reduced wildfire risk (Figure 2.4). Burning of piled material is more likely to occur in higher-elevation areas with lower BP values and closer to roads, i.e. regions with a lower baseline probability of burning but near roads. Broadcast burning is predicted to be more frequent in remote areas at greater distances from

Table 2.4: Variable importance and associated standard deviations for each explanatory variable used in the model.

Variable	Importance	s.d.
DEM	0.222	0.0007
CFL	0.717	0.0007
WHP	0.144	0.0007
BP	0.132	0.0005
FLEP8	0.131	0.0003
StrucEuc	0.0826	0.0004
RoadEuc	0.0467	0.0004
Slope	0.0384	0.0004
StreamEuc	0.0345	0.0004

structures and lower elevation. Piling of fuels is more expected in areas with greater CLF and higher WHP values where fuels are more likely to be piled as a preparatory step for future treatments such as burning. Thinning for hazardous fuel reduction is more likely in areas with a higher baseline probability of burning (BP) and greater flame length (CFL). The model also shows a higher likelihood of predicting multi-treatment approaches near structures, roads, and where CLF is lower.

2.3.4 Cross-forest Model Transferability

The LOOCV scores varied notably across different national forests, indicating the differential predictive power of the model in various forest environments. For instance, the model showed high predictive accuracy in the broadcast burning category in the Rio Grande NF, with a score of 0.928. The model also performed well for broadcast burning in the Medicine Bow–Routt NF, with an AUC of 0.923. This suggests the model is highly effective in predicting the implementation of this practice in these specific national forests. Conversely, the lower scores observed in the practice like burning of piled material in Pike and San Isabel NF point to a reduced predictive accuracy of the model for these practices in these environments.

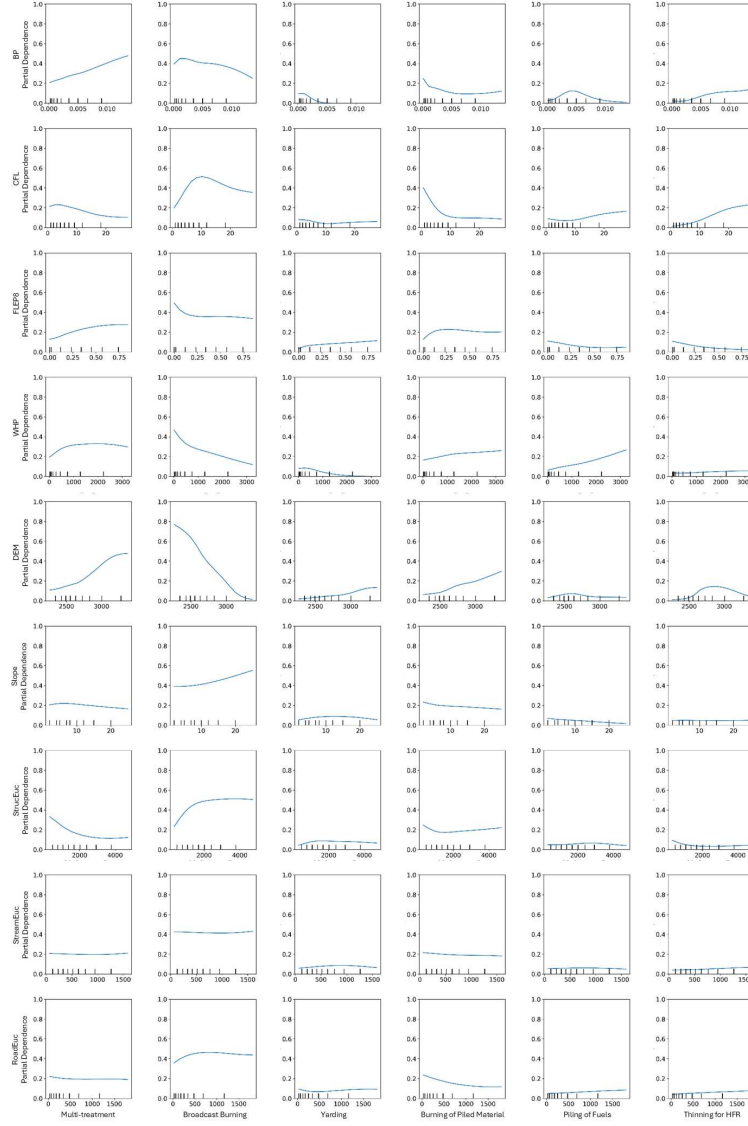


Figure 2.4: Partial dependence plots illustrate the influence of explanatory variables on different forest treatment activities. The plots depict the relationship between each explanatory variable and the following treatment activities: broadcast burning, yarding, burning of piled material, piling of fuels, thinning for HFT and multi-treatment.

2.3.5 Landscape-scale Prediction across Colorado National Forests

By removing regions falling outside the historical range of all considered explanatory variables, 45.2 percent of the total area within Colorado's national forests was excluded from the model inference (Figure 2.5). The exclusion criteria particularly impacted regions with extreme topographical features such as very high mountain peaks, steep slopes, or at considerable distance from structures. This filtration step eliminated zones presumably beyond the scope of historical fuel treatment implementation. The model consistently predicted broadcast burning with higher frequency in the largely rural and less densely populated areas of the Colorado Western Slope. However, the more urbanised Eastern Slope exhibited a greater likelihood of the multi-treatment category. This highlights the model's ability to capture regional variations in fuel treatment strategies based on population density and land use.

2.3.6 Fine-scale Prediction in the Arapaho-Roosevelt National Forest

Additionally, the model's fine-resolution capabilities provided detailed, spatially explicit predictions for six primary treatments within the Arapaho–Roosevelt National Forest, showcasing its effectiveness in modelling complex landscapes and diverse treatment strategies (Figure 2.6). A notable trend is the model's prediction of a higher frequency of the multi-treatment category proximate to the Colorado Front Range. There is a discernible prediction pattern for prescribed burning in the northern areas of this forest, which is distinguished by its rural characteristics and lower housing density.

2.4 Discussion

2.4.1 Study Contribution and Conceptual Framework

The primary aim of this study was to leverage spatial data and artificial neural networks to analyse past HFT decisions in Colorado's national forests. Despite ANNs being recognised as valuable tools in fire management, their utilisation in modelling spatially ex-

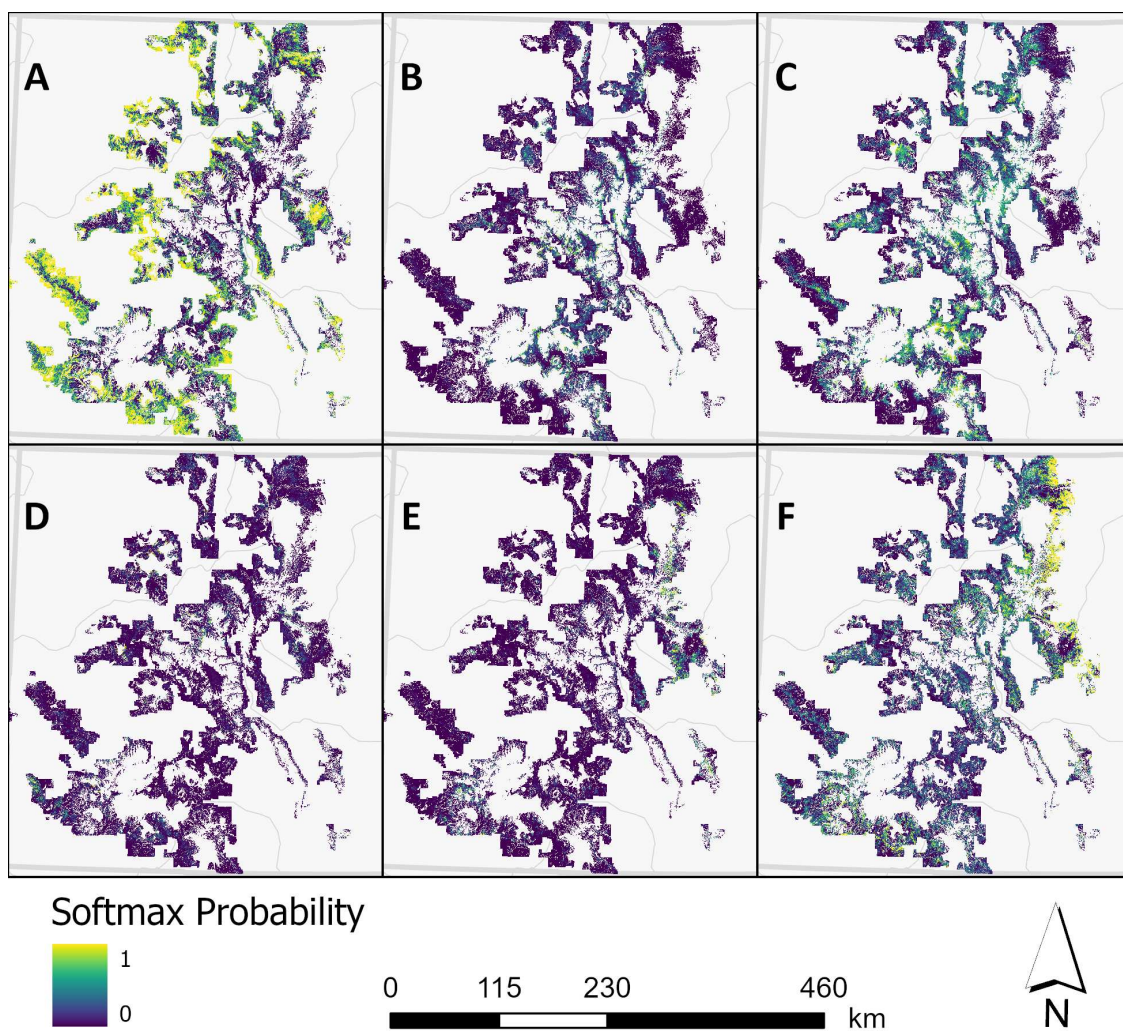


Figure 2.5: Map of softmax probability outputs generated from model prediction across 11 national forests in Colorado: (a) broadcast burning, (b) yarding, (c) burning of piled material, (d) piling of fuels, (e) thinning for HFT, (f) multi-treatment.

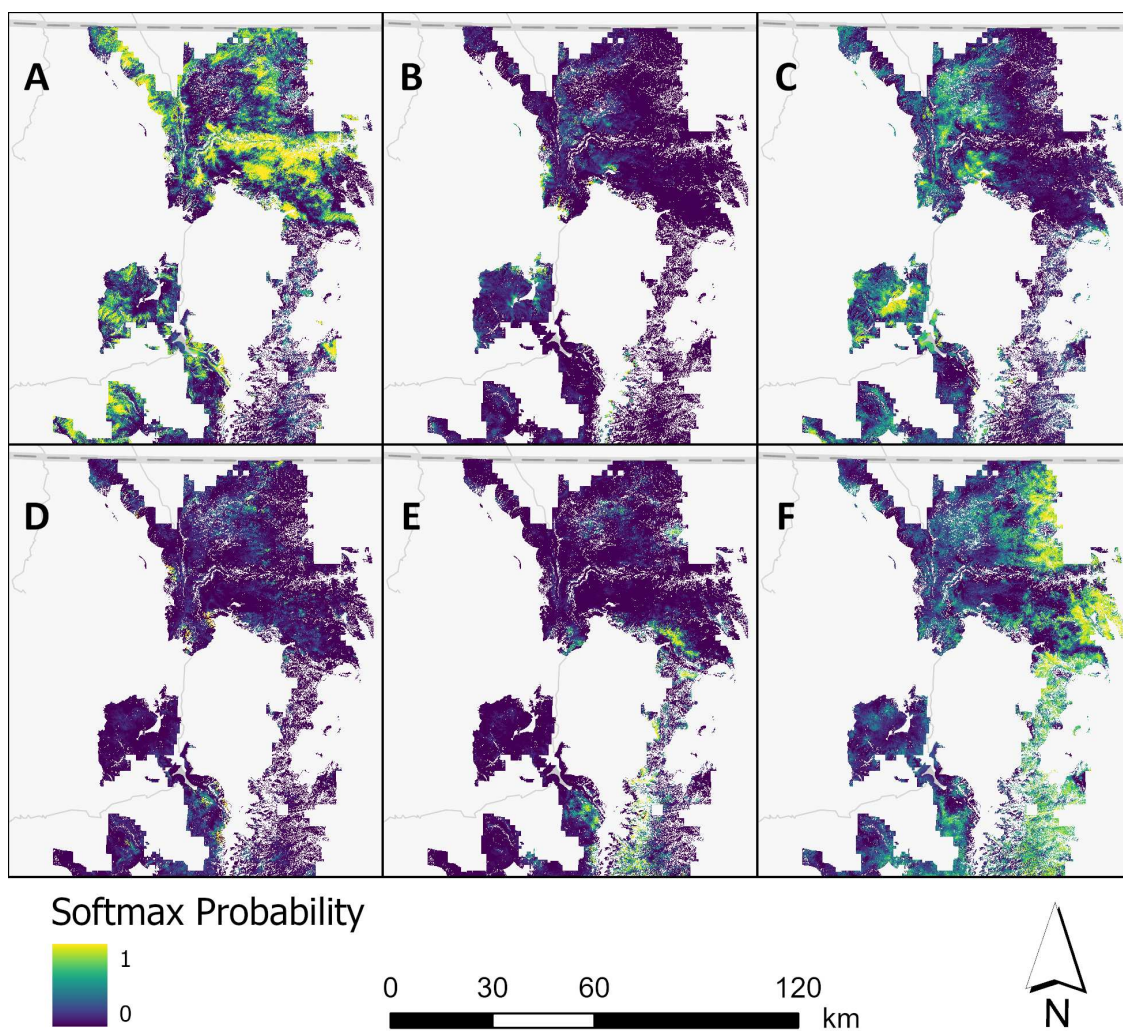


Figure 2.6: Map of softmax probability outputs generated from model within the Arapaho–Roosevelt NF in Colorado: (a) broadcast burning, (b) yarding, (c) burning of piled material, (d) piling of fuels, (e) thinning for HFT, (f) multi-treatment.

plicit treatments remained less explored [107]. The present study marks the first application of neural network modelling utilising past fuel treatment type selections as response variables, and notably, represents the first attempt at integrating human decision-making processes into a deep learning model for fuel treatment management.

Our study uses a historical analysis approach to study the nuanced operational considerations and human knowledge that land managers used to assign fuel treatment placement in the past. These treatment decisions often encapsulate expertise and understanding of the local ecological and operational dynamics. The variables considered in this study reflect both the specific objectives managers seek to address, such as reducing wildfire risk by enhancing forest health, and the operational constraints they face. This approach emphasises the value of empirical research in real-world settings [170]. The significance of this research lies in its ability to link data with historical treatment decisions in Colorado, offering an assessment of the key factors that influence past forest fuel treatment decisions. Using past management decisions as a reference provides a practical framework for understanding the choices and constraints that shaped treatment decisions.

2.4.2 Interpreting Fuel Treatment Decision Patterns

This research introduces a modelling approach that leverages historical land management decisions to create labelled data for assessing fuel treatments using an ANN. The creation of labelled data in this research relies on historical fuel treatment decisions, which are presumed to have been made with the intent of reducing wildfire risk. The success of these treatments is subjective and varies based on the objectives of different stakeholders [26]. Given the constraints inherent in the available dataset, our modelling efforts were focused on operational conditions rather than attempting to assess treatment or policy success. Although we were unable to conclusively determine if the treatment placements maximised objectives, this dataset represents a comprehensive resource for examining historical fuel treatment management practices spatially in Colorado. It is reasonable to infer that these

decisions were not made arbitrarily and were influenced by underlying strategic considerations and practical feasibility. Therefore, we chose to utilise this dataset to understand past decisions and to investigate the relationship between treatment locations and our explanatory variables.

We examined the individual effects of each variable within the model using permutation importance [197–199]. The high importance of burn probability and wildfire hazard potential and their inverse relationship with the likelihood of broadcast burning underscore a strategic choice in the past for reducing wildfire impacts through prescribed fires in lower-risk areas, potentially as a measure to maintain low fuel loads rather than reducing high fuel loads. Conversely, the partial dependence plot reveals a strategic approach where thinning is more likely to be implemented in areas with higher BP and CFL values, suggesting that in national forests in Colorado, the current strategy favours prescribed fires in less vulnerable areas while prioritising thinning practices in overstocked forests requiring urgent restoration interventions to mitigate wildfire risk [200].

The PDP plot revealed that the likelihood of the model predicting multi-treatment categories decreased as the distance from structures increased, suggesting an operational constraint that favours implementing multiple forms of treatments closer to the wildland–urban interface (WUI). Additionally, the analysis of variable influence using partial dependency implies that broadcast burning was more likely to be prescribed further from structures, aligning with the management strategy of conducting such burns in regions with sparse populations and lower structural density [31]. This approach indicates that Colorado’s current management chooses prescribed burns in less populated areas for wildfire hazard management while operational constraints drive the use of multi-treatments near infrastructure to minimise risks. Given that the WUI in the Colorado Front Range corridor is projected to shift to higher elevations in the future [122], the DEM variable becomes increasingly important to examine. Figure 2.5 suggests the multi-treatment categories are more likely to be prescribed in higher-elevation forest types, indicating that

the system could adapt to future WUI changes, allowing the continued implementation of diverse treatment strategies as urban areas expand into higher elevations. As nearly half of the WUI in the United States is in regions with high wildfire severity potential that historically experienced lower-severity fires [201], this approach addresses the increasing fire risks as urban development expands into new landscapes.

2.4.3 Operational Constraints and WUI Dynamics

WHP uses modelled probabilistic wildfire risk components to map areas where high-intensity wildfires may be difficult to manage and where fuel management may be needed [168]. The trend of decreased prediction of broadcast burning as WHP increases indicates the current management strategy favours concentrating prescribed burns in areas with lower wildfire hazard potential. Liability concerns are often noted as a significant barrier to the use of prescribed fire, particularly due to fears of legal repercussions if a fire escapes [202]. Despite the empirical risk of liability from escaped fires being minimal (below 1 percent), the fear of legal consequences persists, often exacerbated by sensational media coverage and a lack of accurate information about the safety and benefits of prescribed fire. If the current management strategies do not change, we can expect prescribed fires to continue being conducted primarily in areas where the wildfire risk is already low.

The greater housing density adjacent to the urban Colorado Front Range presents unique challenges and considerations for wildfire management [203]. Consequently, results suggest the need of considering a multi-treatment strategy at the complex urban–forest interface on the eastern slope of Colorado, indicating that diverse management approaches may contribute to effectively balancing wildfire risk reduction and urban protection (Figure 2.5, Figure 2.6). This approach inherently aligns with recent planning efforts in the Arapaho and Roosevelt National Forests and Pawnee National Grassland [204]. By combining mechanical treatments with prescribed burns, forest conditions can be effectively restored and ecosystem function enhanced [205]. This integrated approach is highlighted

in the Wildfire Crisis Strategy, which emphasises the critical role of managing fuel loads and mitigating wildfire risks, particularly in fire-adapted landscapes where ecological and community safety priorities intersect [200].

2.4.4 Implications for Management and Policy

Land management decisions regarding fuel treatments have been significantly influenced by policies aimed at addressing the accumulation of forest fuels. This build-up is largely due to extended periods of fire suppression, prolonged droughts and the escalation of disease, and insects and invasive plant infestations. In response, the National Fire Plan was established in 2000, initiating a comprehensive, long-term hazardous fuels reduction program [206]. Further supporting these efforts, the Healthy Forests Initiative and the Healthy Forests Restoration Act have provided land managers with additional tools to achieve their long-term objectives in reducing hazardous fuels and restoring fire-adapted ecosystems [207]. More recently, the Bipartisan Infrastructure Law provides funding support and policy guidance in Colorado to increase fuel treatments in regions with high wildfire hazard potential [208]. The underlying considerations of these policies provide essential guidance and resources for managing forest fuels in the future; yet the ultimate decision-making process integrates these policy frameworks with the expertise of local land managers. This combination ensures that land management actions are not only aligned with national objectives but are also adapted to the specific ecological and operational realities of their respective regions. By integrating these policy frameworks with practical insights from our analysis, land managers can make more informed decisions about fuel treatment strategies that consider both historical data and current ecological and operational realities.

This model helps identify key factors associated with the choice of fuel treatment types implemented across the Colorado national forest landscape. Although our study focuses on understanding factors linked to past fuel treatment decisions, validating the effective-

ness of different fuel treatment types across a diverse landscape is another important subject to study in future research. This analysis can help managers deliberately consider a minimum set of factors when selecting future fuel treatment strategies. For example, when selecting the suitable locations for broadcast burning, managers should at least analyse the following factors: conditional flame length, burn probability, wildfire hazard potential and distance to nearby buildings. More importantly, managers may want to reflect on the underlying reasons why those factors are important considerations for broadcast burning. For example, distance to nearby buildings may be less important if there are clear fire barriers between a building and a candidate prescribed burning site. It is also important to note that the factors tested in our model mainly focused on wildfire risk and anthropogenic considerations and did not encompass all potential variables. For example, certain vegetation characteristics in a specific location can influence treatment placement and treatment type selections. Future studies could employ higher temporal resolution satellite imagery or other forms of remotely sensed data such as LiDAR to better capture dynamic changes in vegetation structure and density. Managers may need to include some other restrictions, e.g. no mechanical treatment in certain wilderness areas, to determine suitable fuel treatment locations and types.

2.4.5 Limitations and Future Research Directions

By analysing historical trends, we aim to create a foundation for refining and informing future management strategies. These results can identify additional locations beyond historically treated areas and potential treatment types for hazardous fuel treatments. Furthermore, this approach serves as a diagnostic tool, refining future management decisions by recognising patterns of risk related to where treatments are implemented. Additionally, this model can facilitate better communication and collaboration among stakeholders by providing a transparent, data-driven approach to wildfire management. Given that over three-quarters of the public support active management strategies, such as prescribed fire

and mechanical thinning, recognising their importance over no management action [209], we must continue to develop strategies and solutions to improve the decision-making process.

Chapter 3

Deep Learning for Aerial Suppressant Drop Detection Using ADS-B Telemetry

Chapter 3 is based on: Magstadt, S., Wei, Y., Pietruszka, B. M., Calkin, D. E. (2024). A Deep Learning Approach for Predicting Aerial Suppressant Drops in Wildland Firefighting Using Automatic Dependent Surveillance–Broadcast Data. *Fire*, 7(11), 380.

3.1 Introduction

3.1.1 Aerial Firefighting and Operational Challenges

Wildfires have become increasingly prevalent across various global regions, resulting in increasing risks to human health and habitation, natural systems, as well as a corresponding increase in aviation suppression operations globally. Fixed-wing aircraft used in wildland firefighting, such as large air tankers (LATs), very large air tankers (VLATs), and scoopers, play an important role in the management of wildfires [73,210]. With their increased utilization, interest in effectiveness and safety has also increased [211,212]. However, monitoring and tracking their operations, including accurately pinpointing drop locations, pose significant challenges [213]. In the United States, individual contracted vendors are responsible for reporting the locations of suppressant drops. However, the lack of standardization in data reporting, with each vendor providing data in different formats, complicates the collection and post-processing efforts. These challenges hinder the availability of data for real-time tracking.

3.1.2 Aircraft Tracking Data and ADS-B Systems

Automatic Dependent Surveillance–Broadcast data (ADS-B) is a surveillance technology required by the Federal Aviation Administration (FAA) for all aircraft operating in

Class A airspaces nationwide [78]. The OpenSky Network, a real-time global flight tracking system, provides comprehensive flight trajectory data that could significantly enhance firefighting aircraft tracking and management, and thereby effectiveness [82,214]. This system's open-source nature allows researchers to access Mode S transponder data from each aircraft. By leveraging the OpenSky Network, raw trajectory data can be extracted for further analysis, identifying specific flight patterns and behaviors such as aerial suppressant drops. The integration of this spatial data with machine learning techniques enables us to train predictive models that consider flight characteristics during operations, thus predicting the drop locations.

3.1.3 Research Gap: Identifying Suppressant Drop Locations

Despite previous studies utilizing the OpenSky Network for automated flight pattern identification [84,215,216], research identifying suppressant drop locations using aircraft tracking remains unexplored. Aerial drops conducted by wildland firefighting aircraft are unique such that they reduce the plane's cargo load by up to 73.5 metric tons over a short distance [217]. This requires pilots to 'pitch up' and increase acceleration. This maneuver allows the aircraft to regain its lost altitude quickly and ensures safe clearance of trees and other potential obstacles in the wildland environment. The swift changes in flight dynamics during this operation make it an interesting case study for aerial trajectory analysis. Others have employed rule-based and statistical methods to discern take-offs, landings, and holding patterns related to firefighting, yet the identification of suppressant drop locations was not addressed [84].

3.1.4 Limitations of Existing Monitoring Approaches

Currently, the tracking of aircraft drop locations relies on automated telemetry units (ATU), necessitating post-flight data uploads by each contracted vendor, followed by additional data processing steps. This approach limits the tracking to known drop locations, omitting the aircraft's position during transit. Our methodology leverages real-time flight

tracking data, offering immediate and continuous aircraft location information, not just at drop locations. This enhancement in data availability significantly improves situational awareness for ground-based firefighting teams, thereby increasing safety and operational response effectiveness.

3.1.5 Study Objectives and Approach

Further, only aircraft contracted through the US Forest Service (USFS) are required to maintain and report the data. Thus, retardant drop data from airtankers contracted through the state of California and military aircraft using the Module Airborne Fire Fighting System (MAFFS) are not available through the ATU analysis process although these diverse aircraft from different management agencies will support the same fires. The absence of consistent ATU data may create an incomplete picture of fire suppression actions and limit our ability to understand the effectiveness of retardants. Implementing our methodology allows us to have a more complete picture of how aviation is supporting suppression actions. This study proposes an approach to collect ADS-B flight data of airtankers and combine them with the historically recorded airtanker suppressant drop data. Integrating both data sources may support future research in studying airtanker flight patterns and drop locations. To demonstrate the use of those data, we establish test cases by building sequential machine learning models to predict suppressant drop location during wildland firefighting operations.

In this study, we introduce a dataset derived from the detailed Mode S transponder data that reflects the flight behavior of firefighting aircraft. This dataset is part of an effort to improve the tracking and monitoring of aerial firefighting operations. We utilize sequential machine learning models, namely Long Short-Term Memory (LSTM) and 1D Convolutional Neural Networks (1DCNN), to analyze this data. Both these techniques offer unique advantages in processing sequential data to detect temporal patterns in flight

data [218,219]. Our goal is to better predict suppressant drop locations, aiding in the efficient deployment and monitoring of firefighting resources.

3.2 Materials and Methods

3.2.1 Study Area and Data Coverage

The map visualizes the spatial distribution of data gathered for our study within the western United States, encompassing latitudes from 30° to 50° North and longitudes from 125° to 100.5° West (Figure 3.1). The red dots indicate the precise locations of wildfire suppressant drops where comprehensive flight information was available from the OpenSky Network’s tracking data. These points align with regions historically impacted by wildfires, demonstrating where aerial suppression has been deployed and where our data collection was most reliable.

3.2.2 Aircraft Identification and Tracking Data Sources

Aircraft Identification using Mode S Codes

To distinguish individual aircraft within the OpenSky database, we collected a set of Mode S codes corresponding to aircraft contracted by the USFS for wildland firefighting tasks. This effort began by individually identifying tail numbers of aircraft known to participate in wildfire suppression (<https://fireaviation.com/>, accessed on 21 August 2023). Subsequently, we extracted the corresponding Mode S codes (Base 16/Hex) from the FAA flight registry (<https://registry.faa.gov/aircraftinquiry/Search/NNumberInquiry>, accessed on 21 August 2023). Through this process, we identified unique codes, each linked to a specific aircraft involved in firefighting operations. The identification of Mode S codes enables the targeted querying of individual aircraft data, which is needed for the detailed analysis and tracking of aircraft flight patterns during operation.

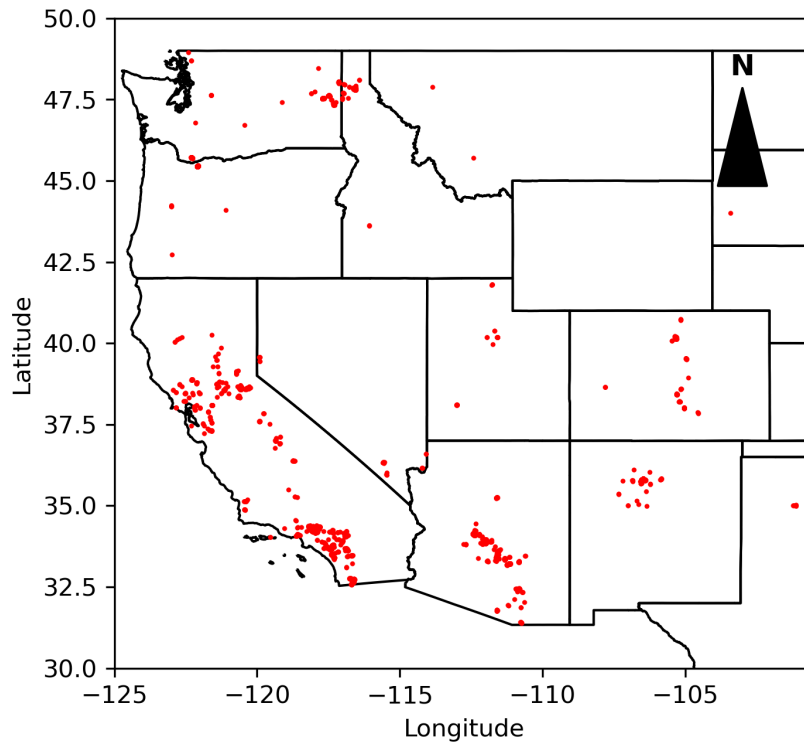


Figure 3.1: Map of documented wildfire suppressant drops in the western United States with available OpenSky Network ADS-B data. Red dots represent the locations of drops where flight data were successfully retrieved and analyzed. This subset of data points reflects instances where comprehensive flight tracking information was accessible, highlighting the geographical areas of active aerial firefighting efforts where data collection was feasible. The map is projected in the WGS 84 coordinate system (EPSG: 4326), matching the global positioning system used by the ADS-B data source.

ATU Drop Data

Our study relies on two main datasets: ADS-B data and ATU drop data. Both are needed for the precise identification and labeling of aerial drop locations in aircraft operations during wildland firefighting. The ATU data provide an established ground truth for the location of firefighting suppressant drops. These units are required on air-tankers contracted by the USFS, documenting the aerial application of water or fire suppressant during wildfire incidents. Spanning from 2017 to 2023, the data are represented as polyline records. These records estimate the opening and closing points of the aircraft's release door mechanism, indicating the start and end points of a drop. These insights into when and where an aircraft executed the drops serve as reference points. We align these points with ADS-B flight trajectory information, identifying known drop locations. This correlation process allows us to extract flight trajectory information that closely aligns with actual drop events.

ADS-B Trajectory Data

The ADS-B dataset, sourced from the OpenSky Network, offers a stream of flight tracking data, capturing the dynamics of an aircraft's flight patterns [82]. This dataset includes latitude, longitude, and time, which are needed in the construction of a space-time bounding box encapsulating the relevant drop data. The ADS-B data exhibits a two-dimensional array structure of form (t, n) . Here, 't' symbolizes discrete time intervals (measured at one-second intervals), while 'n' represents different flight characteristics. These attributes include altitude (m), speed (m/s), vertical climbing rate (m/s), and others that offer insights into the aircraft's operation. The data downloading process was implemented using the PyOpenSky API, which facilitated the retrieval of ADS-B data through structured requests [220, 221]. Using the ADS-B data together with ATU drop data, we developed a comprehensive dataset that integrates flight path information with fire suppressant drop locations, capturing the dynamic behavior of aircraft during active firefighting operations (Figure 3.2).

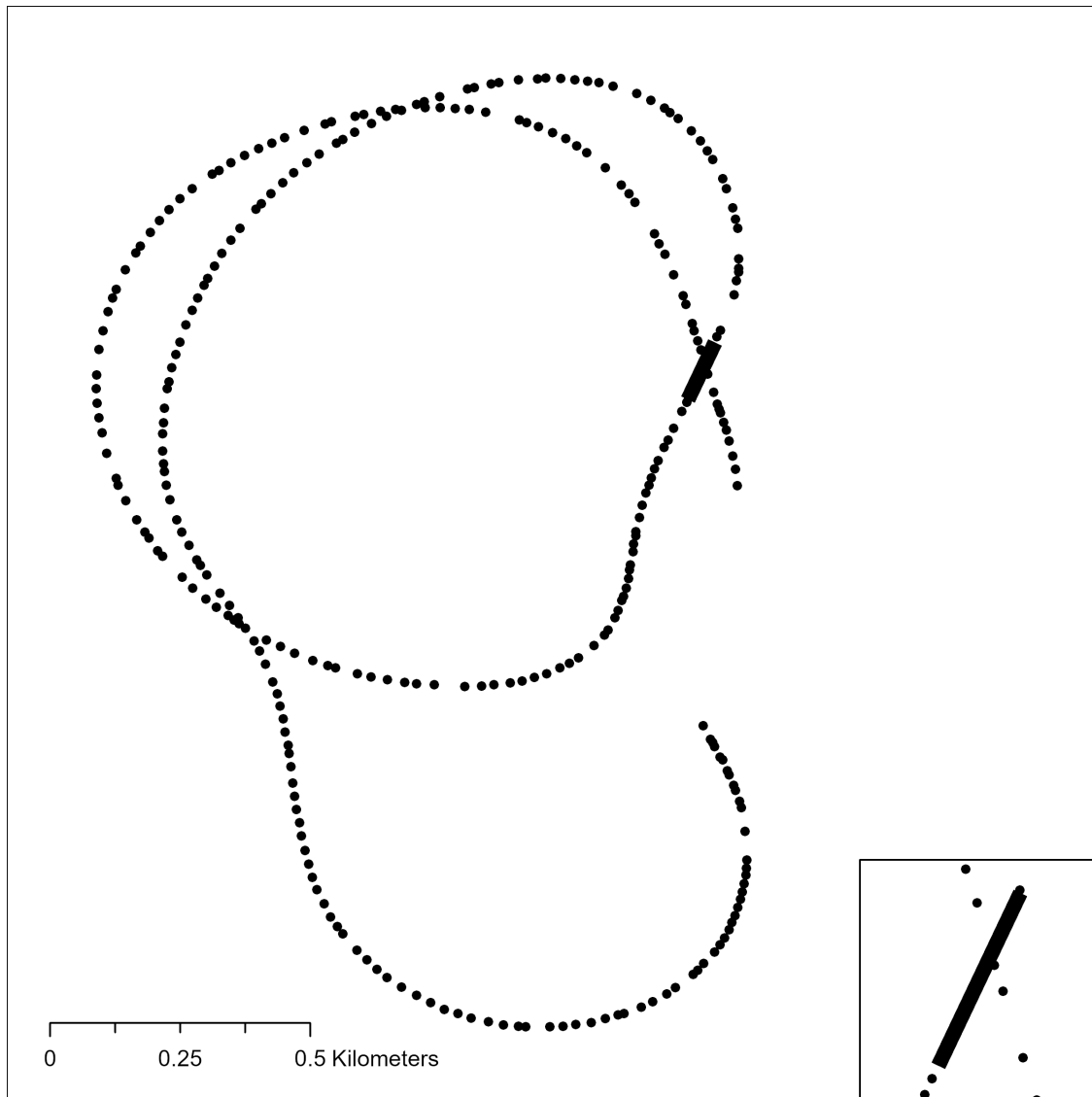


Figure 3.2: (a) Representation of flight paths derived from ADS-B data points, with the ATU drop path marked by a black line. (b) Enlarged view illustrating the congruence of ADS-B and ATU data points, demonstrating data consistency.)

3.2.3 Data Integration and Preprocessing

Above ground level (AGL) data acquisition is important for enhancing the understanding of aerial firefighting maneuvers, as aircraft must lower their AGL altitude for effective material drops with minimal dispersion [217]. We calculated the AGL drop height by leveraging the Google Earth Engine API [222] to obtain ground level surface elevations at specified drop locations and then determining the difference with the aircraft's altimeter readings from the ADS-B dataset. Consequently, our refined dataset includes ADS-B data, ATU drop data locations, and the calculated AGL height data, providing a complete view of aerial drop practices and associated flight characteristics including aircraft AGL.

ADS-B and ATU Data Alignment

To guarantee the reliability of our dataset in accurately identifying ADS-B data corresponding to drop events, we employed a comprehensive data labeling and preprocessing strategy. This strategy validated the spatial overlay between ADS-B flight trajectory data and ATU drop data, ensuring the dataset's integrity and applicability. First, we verified that each ADS-B data entry was correctly associated with its unique aircraft code. We queried the OpenSky Network request with the unique Mode S codes of each aircraft. This step confirmed that the designated aircraft were conducting the drops, aligning with the information from the ATU dataset. We then validated the spatial congruence between ADS-B and ATU drop data to ensure that the ADS-B data accurately reflected aircraft positions during firefighting suppressant drop events. This validation process involved comparing the geographical coordinates and timestamps from both data sources, ensuring precise correspondence and alignment, as exemplified by the flight paths and suppressant release locations depicted in the figure below (Figure 3.3). This alignment is important for accurately identifying the suppressant drop locations during aerial firefighting operations. By cross-referencing the ADS-B and ATU data, we ensure the precise

synchronization of drop events, enabling more accurate modeling and analysis of aerial suppressant operations.

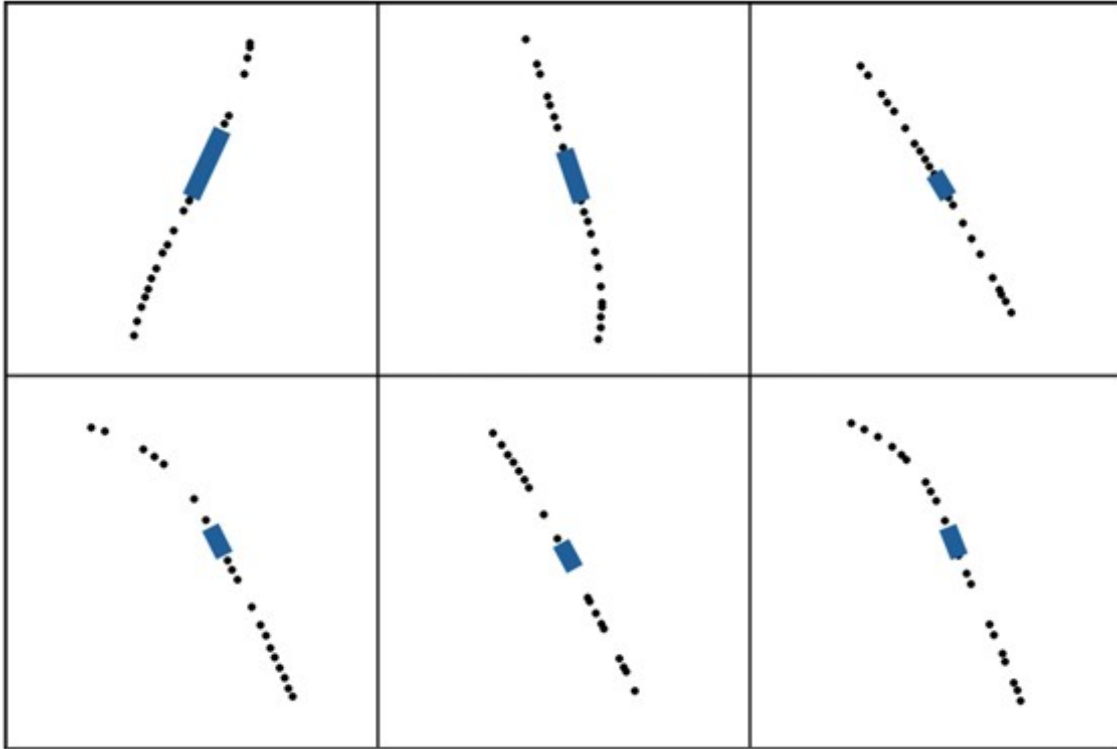


Figure 3.3: This figure compares two different data sources used in this study: flight trajectory points captured by ADS-B data, and ATU drop data within a 30 s window. Each panel illustrates a unique suppressant release event, showing flight paths marked by points at one-second intervals and suppressant release locations measured using the onboard ATU instrument, denoted by a solid blue rectangle. This figure demonstrates the spatial alignment between the two data sources used in the modeling process.

Signal Continuity Filtering

The OpenSky Network is a ground-based receiver network, which can result in interrupted signals from aircraft, particularly during low-altitude operations in mountainous areas commonly encountered in wildland firefighting [223]. To address this, we used a data filtering process. This process identified training samples that exhibit an almost uninterrupted stream of last contact timings. Specifically, we selected samples that contained 26 unique last contact numbers within the 30 s interval, enabling us to isolate and remove

samples with limited and inconsistent coverage. Consequently, this improves the quality of the dataset by ensuring a selection composed of samples that consistently document the moments leading up to and including the initiation of aerial drops. The resulting dataset offers a more accurate and reliable reflection of an aircraft's trajectory and operational patterns during drop and non-drop sequences (Figure 3.4).

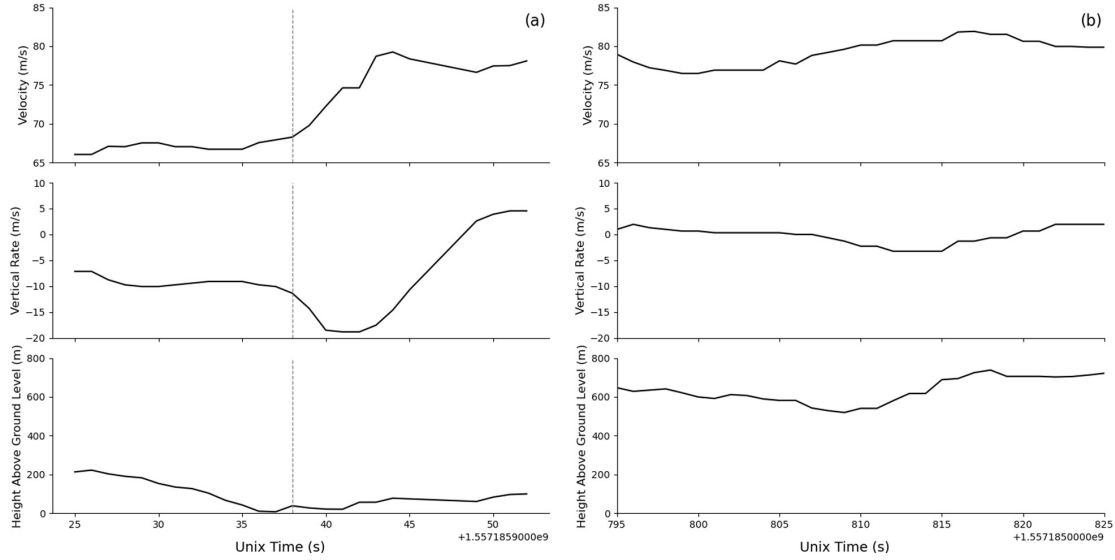


Figure 3.4: Comparative visualization of aircraft flight parameters during firefighting operations. (a) Represents a time series during an active suppressant drop event, highlighting the aircraft's velocity, vertical rate, and height above ground level. The dotted vertical line in (a) marks the timestamp of the start of the suppressant release, illustrated by a significant change in vertical rate and AGL, which is not present in (b). (b) Depicts a similar time series where no drop events occur, displaying steadier flight parameters throughout the observed period. These graphs provide a distinction between the aircraft's flight behavior during drop and non-drop sequences and visually show data with continuous coverage.

3.2.4 Sample Construction

Drop-event Time Window Selection

Given the short timing of aerial drop events, we chose a 30 s timeframe for data collection surrounding drop events. This decision was informed by the ATU dataset, which records the time the suppressant release mechanism was open, showing average drop times of 1.79 s for scoopers, 2.63 s for LATs, and 2.66 s for VLATs. By capturing informa-

tion 15 s before and after the start of drops identified in the ATU dataset, we ensured that our dataset contained comprehensive and contextually relevant information surrounding aerial drop events. This approach enabled a more thorough analysis of the operational dynamics during these maneuvers.

Creation of Drop and Non-drop Sequences

The process of creating 30 s samples for drop and non-drop activities involves segmenting continuous flight data into smaller time intervals, enabling the capture of specific operational events. In the context of aerial firefighting, these samples help us to analyze and understand the trajectory and operational patterns of fixed-wing aircraft. By dividing the data into these manageable segments, we derive understanding of the sequence of events leading up to and during aerial drops, facilitating a detailed examination of flight parameters such as altitude, velocity, and location during moments of operation. The flow of this segmented data into the model training process, from preprocessing to final prediction, is illustrated in Figure 3.5, providing a visual representation of the modeling workflow.

In the context of wildland firefighting operations, where aircraft activities are predominantly non-drop activities with the actual suppressant drops being relatively infrequent, there arises a natural imbalance in the dataset. This imbalance reflects the reality of operational flights, with most data representing transit or preparation phases compared to the less frequent suppressant drop events. This scenario poses a challenge for data analysis and model training, as a model trained on such a dataset might become biased towards predicting non-drop activities, neglecting the suppressant drop predictions.

In the data acquisition phase, we gathered ADS-B data for each aircraft engaged in wildfire suppression throughout the course of an entire day. To accurately differentiate between drop and non-drop activities, we applied the same filtering criteria across all data segments. We separated the drop segments from non-drop segments to ensure that non-drop samples were devoid of any ADS-B data from 15 s before to 15 s after an actual drop event.

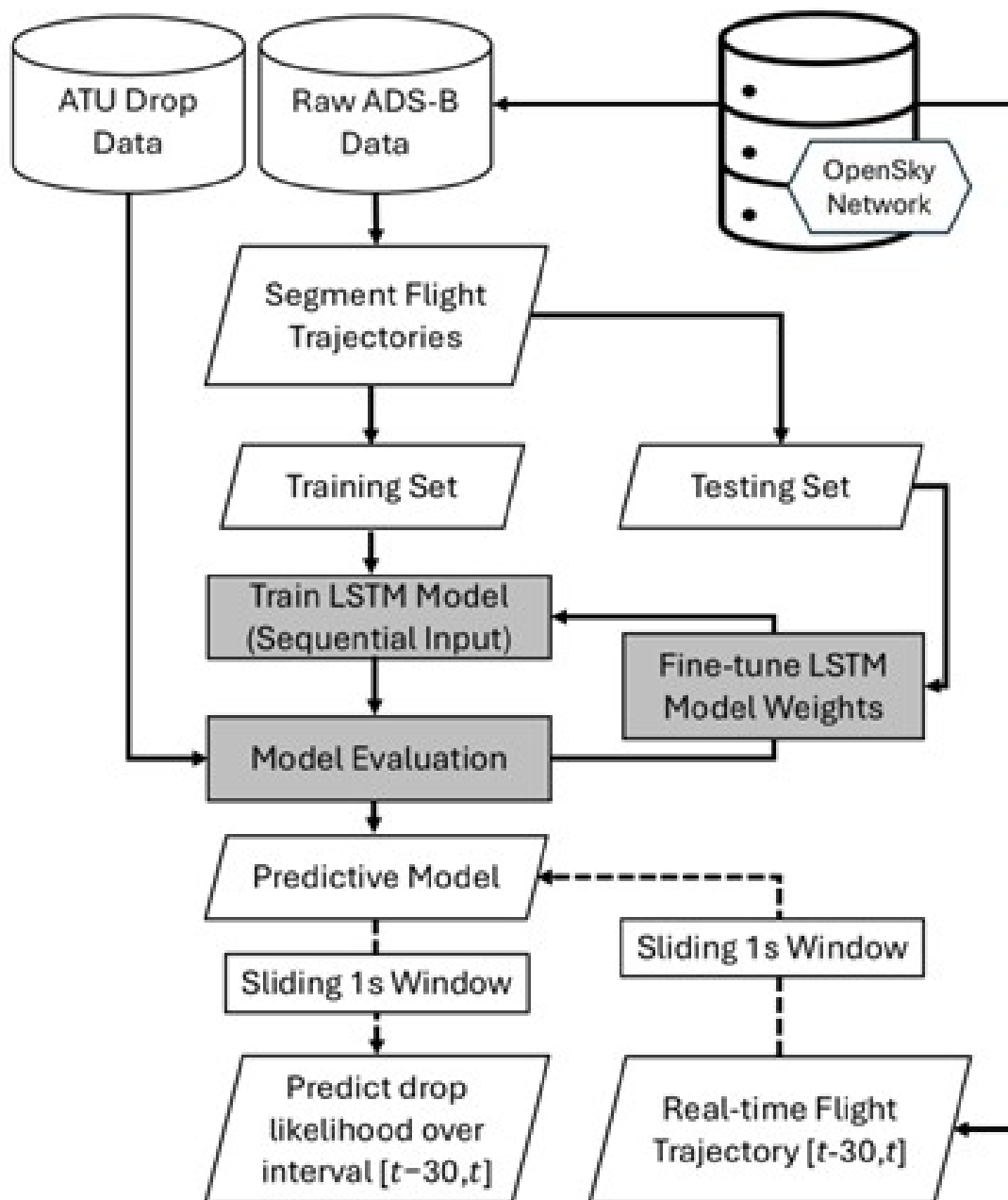


Figure 3.5: A flowchart depicting the workflow of integrating ATU and ADS-B data, segmenting flight trajectories, training the LSTM model, and generating suppressant drop predictions.

3.2.5 Sequential Model Development

1D Convolutional Neural Network

In our study, we designed two sequential neural network models using the Keras library in Python 3.10, which is integrated within the TensorFlow framework [189, 190]. This approach allowed us to leverage the Keras API to construct our model architectures to analyze sequential flight information. The architecture of the 1DCNN is structured with a Conv1D layer, employing 8 filters with a kernel size of 3 and a rectified linear unit activation function ('relu'). The input sequence, which has the shape (30, n), indicates 30 s time steps with n features at each step. Following the initial convolutional layer, a Max-Pooling1D layer with a pool size of 2 is applied. The model then flattens the pooled output and applies a dense layer with 64 neurons, utilizing a 'relu' activation function. A Dropout layer with a rate of 0.5 is included. The architecture concludes with a Dense output layer comprising a single neuron with a 'sigmoid' activation function. This configuration is chosen for binary classification tasks, where the output represents the probability of the input sequence being classified as a 'drop' event. The model is compiled with the 'adam' optimizer and 'binary_crossentropy' loss function [187].

Long Short-term Memory Model

The LSTM architecture begins with an LSTM layer consisting of 30 units. The LSTM layer's output is then fed into a Dropout layer with a rate of 0.5 to prevent overfitting by randomly omitting a portion of the features during training. This is followed by a Dense output layer with a single neuron and a 'sigmoid' activation function, suitable for binary classification tasks where the goal is to predict the likelihood of a 'drop' event occurrence. Like the 1DCNN model, the LSTM was compiled using the 'adam' optimizer and 'binary_crossentropy' loss function.

Training, Evaluation, and Covariate Testing

Both types of models were trained over 10 epochs, with 70 percent of the samples allocated for training and the remaining 30 percent reserved for performance evaluation. Given the imbalanced nature of the dataset, we specifically calculated precision, recall, and F1 scores to assess the models' performance, particularly their ability to accurately identify the less frequent suppressant drop events. The F1 score was particularly valuable in this context, as it provides a balanced measure of precision and recall, helping to ensure that the models are effective in predicting minority-class events. This evaluation provided an understanding of how well the models would perform in real-world scenarios, particularly in accurately detecting suppressant drop events.

During the validation phase, we tested different combinations of input covariates to determine which factors were most influential in the predictive accuracy of our models. Specifically, we examined various combinations of vertical climbing rate, aircraft velocity, and height above ground level to understand their impact on the models' ability to accurately identify suppressant drop events. This process involved evaluating the contribution of each covariate set to the models' precision, recall, and F1 scores, providing insights into which factors most significantly influenced the models' performance.

3.3 Results

3.3.1 Dataset Composition

Using our curated dataset, we identified 1,709 high-quality drop samples, each verified as a suppressant drop location based on our data filtering rules. Additionally, we compiled 21,536 non-drop samples, each representing a distinct 30 s flight interval during non-drop periods, ensuring no temporal overlap with the drop samples. These samples were used for training and validating our LSTM and 1DCNN models to capture the short-duration wildfire suppressant drop.

3.3.2 Model Performance

We validated the models' performance using a separate set of flight sequences not included in the training phase, assessing them on precision, recall, and F1 score metrics. The results demonstrated that both models were effective in identifying suppressant drop events. The LSTM model performed well when using vertical climbing rate and height above ground level as covariates. This model achieved an F1 score of 0.922, with a precision of 0.964 and a recall of 0.884 (Table 3.1).

Table 3.1: Performance metrics of LSTM and 1DCNN models using different covariate combinations for aerial suppressant drop event classification. Precision, recall, and F1-score are reported for each model using velocity (m/s) (V), height above ground level (m) (AGL), and vertical climbing rate (m/s) (Vert).

Covariates	LSTM			1DCNN		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Vert, AGL, V	0.940	0.838	0.886	0.832	0.914	0.871
Vert, AGL	0.964	0.884	0.922	0.933	0.911	0.922
V, AGL	0.834	0.775	0.803	0.859	0.897	0.878
Vert, V	0.946	0.874	0.909	0.911	0.802	0.853
Vert	0.863	0.769	0.814	0.880	0.823	0.851
AGL	0.894	0.840	0.866	0.878	0.866	0.872
V	0.857	0.228	0.347	0.680	0.290	0.407

3.3.3 Sequential Prediction of Drop Events

We also showcase the classifier's utility by employing an LSTM model trained on covariates including the vertical climbing rate and height above ground level. This model is applied to an unseen dataset comprising continuous flight data featuring a drop event at its midpoint. The LSTM model is initially fitted to the first 30 s window of the flight data sequence, and then it sequentially predicts the drop event likelihood, shifting the analysis window one second forward with each prediction. The input covariates and the corresponding model output predictions are visualized in Figure 3.6. The figure illustrates the sequential prediction output of an LSTM model applied to flight data during an aerial fire-

fighting operation. The top two plots display the flight data's input covariates: the vertical rate and the aircraft's height above ground level (AGL), over time. The vertical red line in these plots marks the start of the suppressant drop, serving as a reference point. The bottom plot presents the LSTM model's prediction, displaying the likelihood of a drop event occurring over time steps. The probability peaks around the actual drop event, reflecting the model's successful identification of the drop event based on the input covariates.

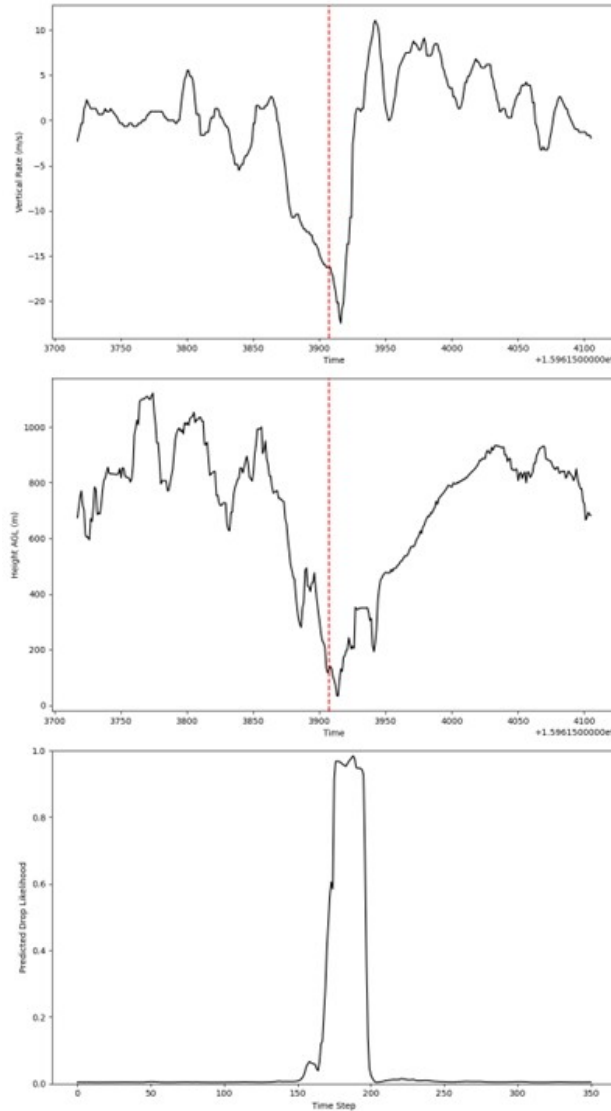


Figure 3.6: Visualization of LSTM model predictions for a fixed-wing aerial suppressant drop across time (Unix). The vertical red line indicates the start of the suppressant drop. The first two subplots depict the input covariates: vertical rate (m/s) and height AGL (m) over time. The input covariates were unseen during the model training. The third subplot illustrates the predicted drop likelihood over time.

3.4 Discussion

3.4.1 Model Performance and Interpretation

The performance metrics presented in Table 3.1, particularly the F1 score of 0.922 achieved by the LSTM model, highlight the model's effectiveness in accurately predicting suppressant drop events. The precision of 0.964 indicates that when the model predicts a suppressant drop within the 30 s window, it is correct 96.4 percent of the time. This suggests that the model is highly accurate, though much of the flight is spent in transit, making recall an important metric. The recall of 0.884 reflects the model's ability to correctly identify 88.4 percent of the samples that contained an actual drop event within the 30 s interval. For instance, if 100 samples contained actual suppressant drop events, the model would correctly identify approximately 88 of those. Figure 3.6 visually illustrates the model's performance by showing the relationship between the aircraft's vertical rate, height above ground level, and the predicted likelihood of a suppressant drop. The sharp peak in the bottom plot corresponds to the predicted drop event, demonstrating the model's ability to capture the flight dynamics of a suppressant drop. This level of performance suggests that the LSTM model could serve as a viable alternative to traditional ATU tracking, offering faster and potentially more reliable real-time predictions. By enhancing situational awareness and reducing the latency associated with post-flight data processing, this model has the potential to significantly improve the coordination and effectiveness of aerial firefighting operations, thereby supporting more informed decision-making during wildfire events.

3.4.2 Operational Implications for Aerial Firefighting

This approach represents a resource for developing machine learning algorithms aimed at predicting aerial suppressant drops. In this study, we acquired and labeled an open-source dataset with the intention of advancing real-time flight tracking machine learning models. Continued development of these models could greatly improve situational aware-

ness in the field. For example, ongoing initiatives such as the Colorado Team Awareness Kit (CoTAK) that provide real-time tracking of public safety aircraft positions can be further enhanced by this work. By integrating this model while expanding the ground-based collection of ADS-B data, fire managers could gain access not only to the real-time positions of aircraft but also to the precise locations of suppressant drops. This added layer of information could significantly enhance the coordination and effectiveness of firefighting operations, providing insights that aid in decision-making during active wildfire events.

3.4.3 Methodological Contributions and Novelty

The integration of real-time flight tracking data to predict aerial suppressant drops using deep learning is a novel approach that has not been previously explored in wildfire management [107]. While past studies have focused on analyzing holding flight patterns [84], this study is the first to specifically identify suppressant drop locations by combining ADS-B data with ATU drop records. Although the dataset used in this study was limited to fixed-wing aircraft, helicopters are widely recognized as a critical asset in wildfire suppression across the United States [224]. An extension of this work could involve incorporating helicopter drop data to enhance the model’s applicability across different types of aircraft.

3.4.4 Limitations and Future Research Directions

Future research could focus on improving the precision and accuracy of predicting the actual locations where suppressant is deposited, rather than identifying the aircraft’s position during a drop. By incorporating additional datasets, such as weather data (e.g., wind speed, wind direction) and topographical information (e.g., terrain slope, elevation), models could better account for the factors that influence where the suppressant disperses once it leaves the aircraft. The inclusion of real-time environmental variables, such as wind direction and wind speed, could provide insights into the dynamic conditions that affect the trajectory and spread of the suppressant after it is released. This would

enable the models to predict not just the moment of drop initiation but a more precise area of ground coverage that the suppressant will achieve.

3.4.5 Conclusions

Traditionally, the tracking of aircraft drop locations has relied on automated telemetry units, which require post-flight data uploads and subsequent processing by each vendor. This process limits tracking to known drop locations, excluding the aircraft's position during transit. By leveraging real-time flight tracking data, our methodology provides immediate and continuous location information for firefighting aircraft, extending beyond just the drop points. This advancement significantly improves situational awareness for ground-based firefighting teams, leading to better coordination, increased safety, and more effective operational responses. Ultimately, the integration of a standardized, real-time dataset represents a significant step forward in the management of aerial wildland firefighting strategies.

In conclusion, this model provides a standardized set of suppressant drop data, which addresses the challenges posed by the varying data formats used by different contractors. In accordance with the John D. Dingell, Jr. Conservation, Management, and Recreation Act, Section 1114, our research aligns with the legislative mandate to develop and operate a tracking system that remotely monitors the positions of wildland fire resources. The standardized workflow we have developed is not only compliant with this mandate but also enhances the overall safety and operational efficiency of firefighting efforts and could feasibly be utilized globally where ADS-B data are available.

Chapter 4

Cross-Agency Aerial Response Dynamics in Wildfire Initial Response

Chapter 4 is based on: Magstadt, S., Belval, E. J., Pietruszka, B. M., Wei, Y., O'Connor, C. An Assessment of Aerial Firefighting Response Times Between Agencies During the 2020 Fire Season in California. Available at SSRN 6099444.

4.1 Introduction

4.1.1 Aerial Firefighting Operations in California

Wildland firefighting agencies employ a diverse array of strategies and resources to combat wildfires, including the extensive use of aviation assets. Aerial resources, such as helicopters and air tankers, influence fire outcomes by delivering water, retardant, and personnel to locations in difficult terrain or areas with limited water access, while also providing critical intelligence to support decision-making on the ground. In California, two prominent agencies, the U.S. Forest Service (USFS) and California Department of Forestry and Fire Protection (CAL FIRE), manage significant aviation operations designed for wildfire response. Although CAL FIRE and the USFS are distinct organizations shaped by different mandates and missions, they are united by a shared responsibility for wildfire suppression and have legal agreements to work in coordination, particularly during the initial-response (IR) phase when aviation resources are rapidly mobilized [67,68]. CAL FIRE and the U.S. Forest Service operate under reciprocal Direct Protection Area (DPA) arrangements in California, whereby either agency may hold primary suppression responsibility on state or federal lands, including some areas under federal jurisdiction [71]. Additionally, Region 5 of the USFS (which is comprised of the state of California) accounted

for nearly a quarter of all aviation flight hours contracted by the agency, further illustrating the high use of aerial firefighting support in California [72].

4.1.2 Interagency Coordination During Initial Response

During the IR phase of wildfire response, both CAL FIRE and the USFS prioritize rapid aircraft dispatch using the closest resource concept, ensuring the nearest available aircraft responds to a fire regardless of agency ownership (National Interagency Coordination Center [225]). This cooperative approach enables the efficient use of limited aerial suppression assets across overlapping jurisdictions, particularly in California where state and federal responsibilities frequently intersect. Wildfire managers directly order aircraft from the administering airbase via intercom if the base is staffed; otherwise, they place requests through the Geographic Area Coordination Center (GACC), which manages aircraft availability and assignment statewide.

4.1.3 Motivation: the 2020 California Wildfire Season

The importance of this coordinated aerial response became especially evident during California's 2020 wildfire season, one of the most destructive and costly on record [69]. Firefighting agencies in California responded to 8,648 wildfires, which collectively burned more than 4.3 million acres across the state, more than double the recent previous state-record and representing nearly 4 percent of California's land area [226]. Among these, the August Complex Fire became California's first officially recognized gigafire, burning more than 1 million acres across seven counties [70]. The exceptional scale and intensity of these incidents placed demands on aerial resources, prompting both CAL FIRE and the U.S. Forest Service to heavily utilize aircraft to support suppression efforts across the state.

4.1.4 Aviation Resources and Operational Scale

To meet these demands, CAL FIRE operates the largest civil aerial firefighting fleet in the world, as a component of its wildfire suppression program. The agency's aviation

program includes a diverse array of aircraft designed to deliver rapid fire suppression in California's challenging and often extreme wildfire conditions. CAL FIRE manages its fleet of approximately 24 tankers, 25 helicopters, and 19 tactical aircraft from 14 strategically located air tanker bases across the state [67]. In comparison, Region 5 (California) accounted for the highest level of Forest Service aviation activity nationwide, with 20,550 flight hours, representing 24.7 percent of all Forest Service aviation use and more than double any other region [72]. The regional fleet included a mix of contracted and agency-owned helicopters, fixed-wing aircraft, airtankers, and water scoopers that supported wildfire suppression and other mission needs. Of these, helicopters played a particularly critical role, reflecting the region's reliance on rapid aerial suppression in steep and inaccessible terrain. Across the Forest Service, aircraft delivered over 122 million gallons of liquid, of which more than 119 million gallons were water and 3.4 million gallons were retardant, with a significant share occurring in California due to the region's extensive fire activity. Region 5 airtanker operations totaled approximately 1,616 flight hours (17.1 percent of national airtanker time).

4.1.5 Limitations of Existing Aviation Data Systems

Currently, the USFS tracks the application of these liquids using Automated Telemetry Unit (ATU) to document resource use [74]; however, comparable data for CAL FIRE operations are not publicly available, limiting direct comparisons between federal and state aerial suppression metrics. No unified aviation dataset exists that captures cross-agency aircraft activity during wildfire response, preventing evaluation of statewide IR coordination.

4.1.6 ADS-B as a Unified Aviation Tracking Framework

This lack of publicly accessible state-level aviation data underscores the value of leveraging independent, standardized tracking systems. Automatic Dependent Surveillance–Broadcast (ADS-B) technology, already mandated across most U.S. airspace, offers a solution by

providing continuous, high-resolution data on aircraft location and movement [75–77]. Federal Aviation Administration (FAA) regulations mandate the use of ADS-B Out transmitters in most airspaces, enabling the monitoring of firefighting aircraft [78]. ADS-B technology has been successfully integrated into wildland fire operations to monitor unmanned aircraft systems (UAS) [79, 80]. It has also been used to analyze aerial firefighting operations, highlighting the effectiveness and cost-efficiency of different aircraft types based on mission patterns, deployment techniques, and resource delivery [81]. Because ADS-B is present on all aircraft and the reporting is standardized across agencies, ADS-B technology offers a valuable opportunity to enhance the tracking and analysis of aviation operations, providing insights into state-managed aviation resources that can complement existing research focused primarily on USFS operations.

4.1.7 Study Objectives and Analytical Approach

The goal of this study is to use ADS-B flight tracking data and survival analysis techniques to quantify differences in IR response times, operational patterns, resource deployment strategies, and fleet usage between agencies involved in aviation operations in California in 2020. By applying Aalen-Johansen estimators and using Cox proportional hazards modeling approaches, the study seeks to generate empirical timelines of aircraft response times for these agencies during the IA phase. In addition to characterizing response patterns, the analysis will explore how physical, biological, social, and administrative attributes, such as topography, vegetation characteristics, and population density, influence the likelihood that a wildfire receives an aerial response during the first 24 hours of ignition. Ultimately, the goal is to bridge methodological gaps between real-time aviation tracking and operational analysis, helping to inform more effective cross-agency coordination and aviation resource management strategies during wildfire suppression.

4.2 Methods and Data

4.2.1 Data Acquisition and Fleet Identification

This study uses ADS-B data provided by the OpenSky Network to address gaps in understanding aviation activities during wildfire suppression efforts [82]. The OpenSky Network is a non-profit organization that offers open access to real-world air traffic control data collected through a global network of ADS-B and Mode S sensors. By providing detailed flight trajectories, timestamps, and aircraft identifiers, OpenSky enables comprehensive analysis of aerial firefighting operations, including flight patterns and suppressant delivery activity [83,84].

To evaluate aerial operations conducted by CAL FIRE and the USFS during the 2020 California wildfire season, all known firefighting aircraft were identified by tail numbers and cross-referenced with Federal Aviation Administration (FAA) registration data to confirm aircraft make, model, and associated ADS-B identifiers (<https://registry.faa.gov/aircraftinquiry/search/nnumberinquiry>). ADS-B flight records for these aircraft were collected from the OpenSky Network using a Python-based workflow that automated monthly data retrieval via the `pyopensky` package and a Trino query interface [82,221]. Tail numbers were converted to their corresponding ICAO24 codes, which served as unique identifiers within the OpenSky database. Retrieved data were subsequently processed into `GeoDataFrames` for spatial and temporal analysis of aerial suppression activity.

We accessed NASADEM tiles through the Planetary Computer STAC API [227], interpolated ground elevations at each aircraft location, and calculated height above ground level (AGL) by differencing geometric altitude from the surface elevation. Data were filtered to retain observations within a maximum 5000-meter AGL threshold to focus on operational flight segments relevant to wildfire suppression. Finally, monthly outputs were saved as shapefiles to analyze temporal patterns, deployment behaviors, and survival modeling. This approach enabled the construction of a detailed, elevation-corrected movement dataset across both agencies' aviation operations. The dataset spans January

2020 through December 2020 and includes high-resolution positional information (latitude, longitude, altitude, and timestamp) recorded at a 1-Hertz frequency (Figure 4.1). Data coverage is based on the OpenSky Network's ground-based sensor network, which exhibits geographically variable coverage due to terrain and sensor distribution [228].

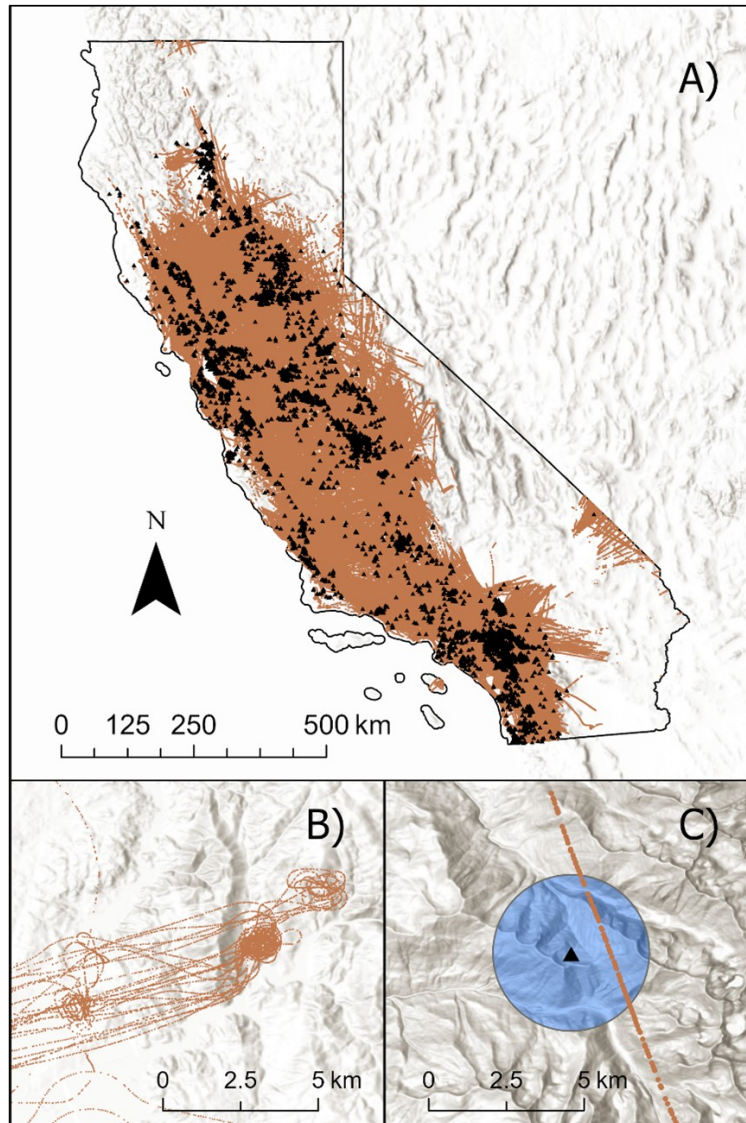


Figure 4.1: An overview of the study area (A), including aircraft flight paths derived from ADS-B data in orange and wildfire ignition points represented as triangles across California. Insets illustrate (B) aircraft circling patterns near active fires and (C) the 5 km detection radius used to assess aircraft arrival after ignition.

To examine CAL FIRE’s aviation operations, the study focused on its permanently maintained, state-funded fleet, comprising 77 aircraft. As of 2025, this fleet included 25 Grumman S-2T airtankers, 7 Lockheed C-130H Hercules airtankers, 12 UH-1H Super Huey helicopters, 12 Sikorsky S-70i helicopters, 18 Rockwell OV-10 aircraft, and 2 King Air A200 aircraft [67]. A summary of aircraft types and counts included in this study is provided in Table 4.1. In contrast to CAL FIRE’s permanent fleet model, the USFS relies on a dynamic combination of exclusive-use and call-when-needed contracts to secure its aerial firefighting resources. To focus specifically on aircraft capable of performing retardant drops, this study used ATU drop logs, which are required for all USFS-contracted aircraft capable of this operation, including airtankers and type one helicopters. Any aircraft that conducted at least one recorded retardant or water drop between 2017 and 2024 was included in the analysis. These aircraft were then cross-referenced with OpenSky ADS-B data to compile comprehensive flight histories. The USFS fleet identified in this dataset includes a range of helicopters and fixed-wing airtankers. Among the heavy-lift Type 1 helicopters, the most commonly used models included Boeing CH-47D, Sikorsky S-70i, Kaman K-1200, Sikorsky UH-60A, Sikorsky S-64E, and CH-54B helicopters. The mid-lift Type 2 helicopter fleet primarily included Bell UH-1H, Bell 205A-1, Airbus MBB-BK117 D-3, and Sikorsky S-58 variants. For fixed-wing airtankers, the USFS operated a variety of aircraft models including Bombardier DHC-8, Lockheed C-130, Boeing 737-3H4, McDonnell Douglas DC-9-87 and MD-87, British Aerospace AVRO 146-RJ85A and Bae 146, Bombardier CL-415, Canadair CL-215-6B11, and McDonnell Douglas DC-10. Overall, the USFS dataset captured four very large airtankers (VLATs), 48 large airtankers (LATs), 83 Type 1 helicopters, and 42 Type 2 helicopters actively engaged during the study period.

The USFS dataset covers helicopters and fixed-wing aircraft involved in wildfire suppression from 2017–2024, matching the full span of available ATU records. Because USFS helicopter ATU drop logs were anonymized, we did not have an exact year-by-year list of helicopters used; instead, we compiled a comprehensive 2017–2024 roster of USFS con-

Table 4.1: Summary of aircraft types and counts included in the ADS-B analysis for CAL FIRE and USFS aviation resources during the 2020 California fire season.

Agency	Aircraft Category	Aircraft Model	Count
CAL FIRE	Airtanker	Grumman S-2T	25
CAL FIRE	Airtanker	Lockheed C-130H Hercules	7
CAL FIRE	Helicopter	UH-1H Super Huey	12
CAL FIRE	Helicopter	Sikorsky S-70i	12
CAL FIRE	Tactical	Rockwell OV-10	18
CAL FIRE	Tactical	King Air A200	2
USFS	Very Large Airtanker (VLAT)	Multiple models	4
USFS	Large Airtanker (LAT)	Multiple models	48
USFS	Type 1 Helicopter	Multiple models	83
USFS	Type 2 Helicopter	Multiple models	42

tracted aircraft and, for California, considered helicopters in-scope if they were wildland-mission capable, based in or regularly operating in the state, and had a plausible operational range for responding to California wildfires. Together with CAL FIRE, these datasets provide a detailed operational portrait of California’s aerial firefighting and underpin our survival analyses.

4.2.2 Aviation Use Summary Statistics

To complement the survival models, we developed a set of descriptive statistics that summarize aviation workload, response timing, and spatial deployment patterns for CAL FIRE and the USFS during the 2020 season. Using the full ADS-B dataset, we first calculated the number of unique active aircraft per day for each agency, producing a daily time series of fleet utilization. These daily activity profiles capture seasonal patterns in aircraft use and provide a baseline context for interpreting when each agency was most operationally engaged.

We then examined how proximity to airbases related to response outcomes by mapping all ignition points alongside airbase locations and classifying each fire by its first-arriving agency. For each ignition, we summarized response time metrics (mean, median, and percentile values), enabling a comparison of typical arrival times. Rather than relying

solely on averages, we constructed empirical response-time distributions for both agencies to show how arrival times varied across the full IR window.

To assess spatial patterns of aviation activity, we rasterized all ADS-B flight trajectories to produce gridded density surfaces for CAL FIRE and USFS separately. Each raster records the cumulative number of aircraft-seconds per grid cell across the study period. We also generated a difference surface (CAL FIRE minus USFS), which highlights areas where one agency operated more intensively than the other. This product provides a spatially explicit view of how aircraft from each agency used airspace over the course of the season and supports comparisons of regional deployment patterns.

4.2.3 Aircraft Response Timing to Initial Fire Discoveries

The OpenSky dataset provided timestamps, geographic positions, and unique aircraft identifiers (ICAO24 codes), which we processed to construct time series visualizations and to detect aircraft presence near wildfires. Wildfire occurrence data were obtained from the Fire Program Analysis Fire-Occurrence Database [229], which includes discovery date, discovery time (HHMM format), fire size, and ignition coordinates. Of the 10,198 wildfires reported in California in 2020, 8,213 had valid discovery time and date information.

To calculate aviation response times, we spatially and temporally matched wildfire discovery records with ADS-B flight detections. Aircraft detections were filtered to those occurring within 5 km of a fire’s ignition point and within 24 hours following its discovery. The 5-km radius was selected to accommodate the positional uncertainty of ignition records, which are typically reported at section-level accuracy, ensuring that aircraft detections are captured even when discovery coordinates are offset from the true ignition location. We defined initial response as the first 24 hours following discovery, consistent with federal guidance that treats this period as the typical length of the initial operational window before a fire transitions to extended response [230]. For each fire, response time

was defined as the elapsed minutes between discovery and the first qualifying aircraft detection. As a sensitivity check, we repeated the analysis using alternative spatial thresholds of 7 km and 9 km; response time estimates were qualitatively similar across radii, indicating that results were not sensitive to the specific distance threshold chosen.

Fires with no recorded aircraft activity and no detections within this radius were excluded, as they likely occurred outside the effective surveillance range of the ADS-B network rather than reflecting a deliberate decision not to respond. This filtering step removed 1,003 fires from the dataset and ensures that subsequent analyses reflect operational patterns within the ADS-B-observable portion of the state.

4.2.4 Initial Response Analysis

The data was structured so that each row represented a single response time observation per fire. The reshaped datasets were concatenated, and for each fire, the minimum recorded response time across both agencies was selected to define the duration to first aircraft arrival. Each fire was assigned an event code: one if CAL FIRE arrived first, two if USFS arrived first. Fires without a recorded response within the observation window were right-censored by setting their duration to the maximum observed time (24 hours from ignition) and assigning an event code of zero.

The resulting dataset (FPA_ID, duration, event_type, Agency) was then used to fit a nonparametric competing risks model using the Aalen–Johansen estimator [231]. For each unique event time, transition intensity matrices were constructed to represent the probability of transition into each of the two groups (CAL FIRE first, USFS first). These matrices were cumulatively multiplied to derive the cause-specific cumulative incidence functions (CIFs), which quantify the probability over time that each agency is the first to respond. CIFs were then plotted to visualize how these probabilities evolve, appropriately accounting for the competing nature of response events and censoring. Unlike standard survival

curves, CIFs account for the fact that multiple outcomes can prevent the occurrence of one another, in this case, the arrival of one agency precludes the other from arriving first.

While the competing risks model identifies which agency is more likely to arrive first, it does not examine the factors influencing response timing. To study the influence of landscape, weather, and operational conditions on aircraft arrival, we applied a Cox proportional hazards model [232]. Using the same fire level dataset, we kept each fire's observed duration and flagged the event indicator as 1 when an aircraft from either agency arrived and 0 when no aircraft arrived within 24 hours. The model was fitted using the Breslow method for baseline hazard estimation and standard errors [233]. Estimated hazard ratios represent the multiplicative effect of each covariate on the instantaneous rate of aircraft arrival, holding other variables constant. Model fit and proportional hazards assumptions were assessed using the Schoenfeld residual-based diagnostics [234].

We estimated three separate Cox proportional hazards models. Each model incorporated the same covariates but differed in stratification approach. In the first model, we included no stratification to provide a baseline specification. The second model added fixed effects stratified by time of day, derived from the fire discovery time (`DISCOVERY_TIME`), based on prior evidence that large airtanker activity peaks during afternoon hours when fire behavior typically intensifies [235, 236]. Fires were categorized into three periods based on local discovery hour: Morning (06:00–12:59), Afternoon (13:00–20:59), and Night (21:00–05:59). This classification allowed us to account for operational rhythms and diurnal variation in fire behavior and aircraft dispatch likelihood. The third model introduced stratification by DPA, which delineates zones of primary suppression responsibility across federal, state, and local fire agencies, to account for differences in fire management arrangements, resource availability, and dispatch practices across protection zones. This stratified modeling framework allowed us to evaluate the stability of covariate effects while accounting for temporal and jurisdictional heterogeneity in aerial response behavior.

4.2.5 Covariate Selection

Vegetation and fuel characteristics have been shown to affect airtanker use and deployment patterns [213], making vegetation and fuel characteristics an important factor for modeling aerial suppression decisions. To characterize live fuel conditions consistently across California’s diverse ecosystems, we used the Normalized Difference Vegetation Index (NDVI), which provides continuous spatial coverage and reflects live photosynthetic activity across forested, shrubland, grassland, and developed environments [237]. NDVI captures short-term variability in vegetation greenness that can influence ignition potential, flame intensity, and tactical considerations during the IR phase. Because vegetation stress typically appears as reduced greenness, negative NDVI anomalies, departures below a site’s recent mean, have been linked to elevated wildfire potential [238–240]. We therefore derived a standardized day-prior NDVI anomaly (NDVI_ANOM) for each fire using the following formulation:

$$\text{NDVI_ANOM} = \frac{\text{NDVI}_{d-1} - \text{NDVI}_{\text{mean},m}}{(\text{NDVI}_{\text{max},m} - \text{NDVI}_{\text{min},m}) / 4} \quad (4.1)$$

where NDVI_{d-1} is the NDVI on the day before discovery, and $\text{NDVI}_{\text{mean},m}$, $\text{NDVI}_{\text{max},m}$, and $\text{NDVI}_{\text{min},m}$ are the mean, maximum, and minimum NDVI values for the corresponding calendar month, computed over the preceding 12 months. We scaled anomalies by dividing by the month-specific NDVI range, $(\text{NDVI}_{\text{max},m} - \text{NDVI}_{\text{min},m}) / 4$, where the range is computed from the same calendar month over the preceding 12 months. This anomaly highlights departures from expected seasonal conditions, offering an indicator of live-fuel conditions that can shape how aircraft are used during initial response. Because unusually low NDVI anomalies signal stressed, more flammable live fuels, they also serve as a proxy for conditions under which initial response is more difficult to contain with ground resources.

To complement the live-fuel signal provided by NDVI, we included 100-hour dead fuel moisture (fm100) as a measure of background fuel aridity, a variable that strongly influ-

ences fire behavior and is a component of fire danger rating systems [241,242]. Not only does it strongly influence fire behavior, lower dead-fuel moisture increases the likelihood of ignition, rate of spread, and fireline intensity; 100-hour fuel moisture is also an input to operational fire-behavior models, underscoring its importance [243].

Topographic constraints were represented using slope steepness from LANDFIRE terrain data. Steeper slopes can limit ground access, reduce handline effectiveness, and increase reliance on aerial resources [235,244]. Additionally, steep slopes tend to elevate firefighter risk by increasing flame exposure, entrapment potential, and the difficulty of safe escape route construction, conditions that often require greater suppression [245].

Weather-driven fire danger was characterized using wind speed at 10 m (vs), maximum temperature (tmmx), and the Burning Index (bi), all from GridMET [246]. These variables capture environmental conditions that are closely associated with periods of intensified fire behavior and increased demand for aerial support [235,244,247]. Because weather is one of the primary situational cues used by incident commanders, these factors are often incorporated, consciously or intuitively, into assessments of potential fire behavior and suppression needs [170]. Together, these weather variables provide a dynamic representation of conditions that influence both fire growth and the likelihood of early aircraft deployment.

Operational logistics were represented through distance to water bodies (dist_to_water_km), used as a proxy for dip-site availability. Proximity to suitable water sources has been shown to influence both airtanker and helicopter deployment patterns [248], making it an important consideration for IR response.

Finally, values-at-risk covariates were included to capture the influence of human exposure on aerial suppression decisions. The Global Human Modification Index (GHM) and 1-km population density (Popo_1km) from WorldPop were used to represent development pressure and wildland–urban interface proximity, consistent with findings that aircraft deployments often concentrate near populated areas [213].

With the exception of distance to water sources, all covariates were sourced from the FPA FOD-Attributes dataset [237]. Table 4.2 provides the full list of variables, definitions, and data sources.

Table 4.2: Covariate names, descriptions, and data sources used in the survival analysis of aerial initial response.

Variable Name	Description	Source
fm100	100-hour dead fuel moisture (%)	[246]
NDVI_ANOM	Standardized day-prior NDVI anomaly computed from day-prior NDVI and monthly mean, maximum, and minimum NDVI over the preceding 12 months	[237, 249]
Slope	Terrain slope (0–90 degrees)	[165]
dist_to_water_km	Distance to nearest waterbody (km)	[250]
vs	Wind velocity at 10 m above ground (m/s)	[246]
bi	Burning index (NFDRS fire danger index)	[246]
tmmx	Maximum temperature (K)	[246]
GHM	Cumulative measure of human modification of lands within 1 km of the fire ignition point	[251]
Popo_1km	Average population density within a 1 km radius of the fire ignition point	[252]

4.3 Results

4.3.1 Aircraft Activity and Seasonal Patterns

We obtained 17,884,545 positional records (4,968 flight hours) for USFS aircraft and 21,925,926 records (6,090 hours) for CAL FIRE aircraft, representing second-by-second tracking across the 2020 season where ADS-B data was available. CAL FIRE activity (4.2, top) increased through the summer, peaked in September, and declined in November. USFS aircraft showed a broadly similar seasonal pattern but with a slightly later and more diffuse peak and fewer individual aircraft active on a typical day (Figure 4.2, bottom).

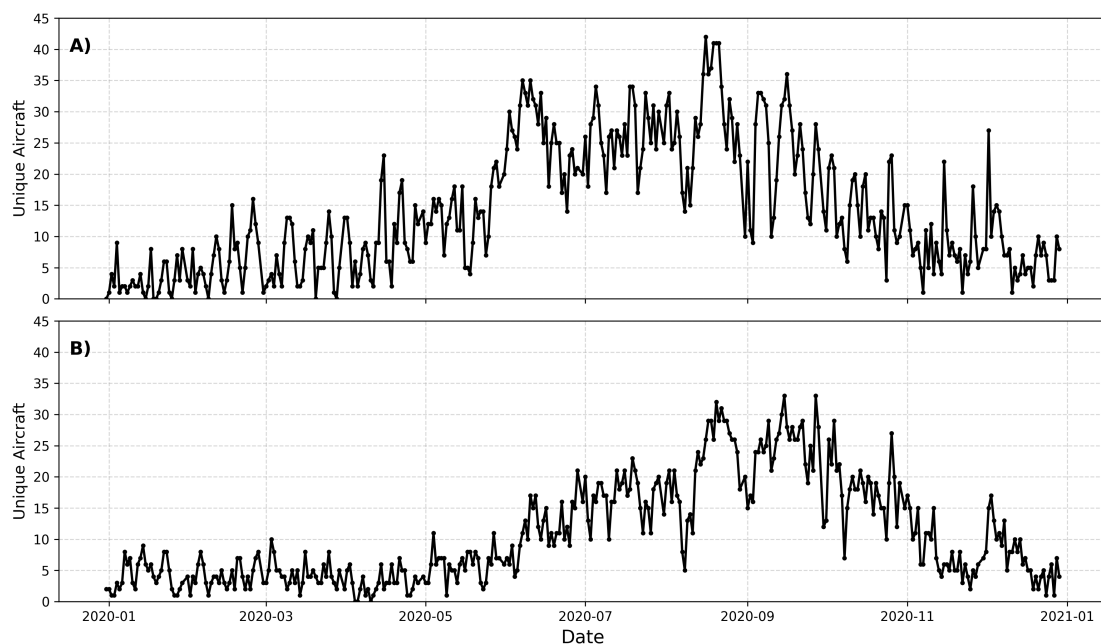


Figure 4.2: Line plot illustrating the distribution of unique aircraft activities (CAL FIRE top, USFS bottom) by day for 2020.

To compare spatial patterns of airspace use, we generated a density-difference surface representing USFS aircraft density minus CAL FIRE aircraft density at a 3-kilometer resolution (Figure 4.3). Positive values indicating areas more frequently traversed by USFS aircraft and negative values indicating higher CAL FIRE activity. The map shows dense flight-path corridors and incident hubs across the state, with pockets of higher CAL FIRE

activity indicated by dark purple values and pockets of higher USFS activity indicated by bright yellow values.

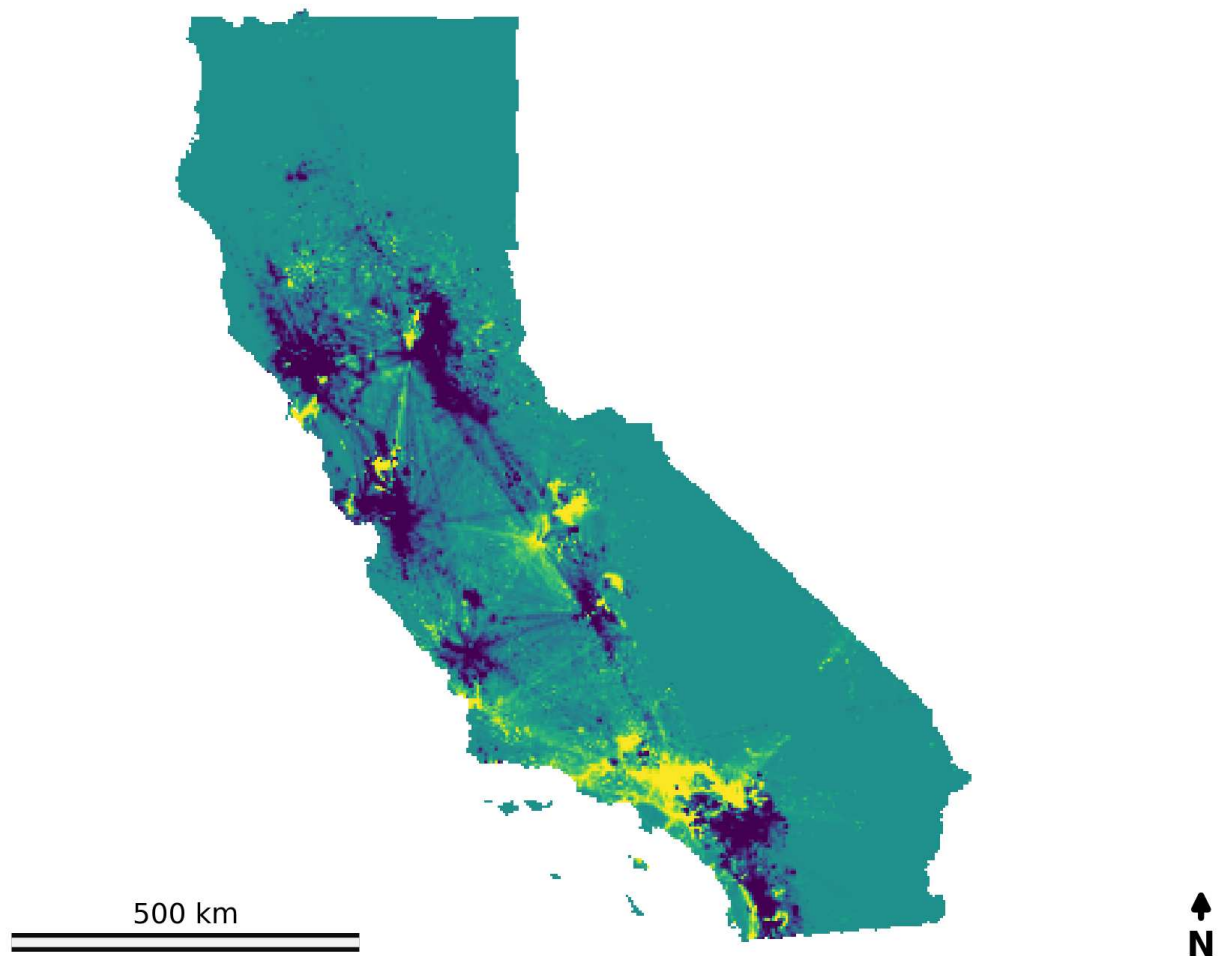


Figure 4.3: Difference in ADS-B–derived aircraft density between USFS and CAL FIRE aircraft across California during the 2020 fire season. Values represent USFS minus CAL FIRE cumulative aircraft-seconds per 3-km grid cell, with bright yellow areas indicating more frequent USFS use and dark purple areas indicating more frequent CAL FIRE use.

4.3.2 Incident Summary and Response Times

A total of 7,214 wildfire incidents were included in the analysis. Of these, 1,476 received an aerial response within 24 hours of discovery (840 CAL FIRE, 637 USFS), while 5,737 had no recorded aerial response and were classified as “NoResponse.” Response times were right-censored at 1,440 minutes (24 hours). Among incidents with a recorded response, CAL FIRE arrival times averaged 700 minutes (median 751; IQR: 387–1007), and USFS arrival times averaged 673 minutes (median 680; IQR: 406–962). Fifty-five incidents had an initial response within 20 minutes (37 CAL FIRE, 18 USFS).

4.3.3 Proximity to Airbases

Distances from ignition points to the nearest CAL FIRE airbase ranged from about 0.25 to 254 km across all fires (Figure 4.4). Mean distances were 33.5 km for CAL FIRE-first responses ($n = 840$), 35.6 km for USFS-first responses ($n = 637$), and 46.9 km for No Response fires ($n = 5,737$). Medians showed a similar pattern: 29.7 km (CAL FIRE-first), 35.4 km (USFS-first), and 42.7 km (No Response). Although the distributions overlapped across response types, fires that received an initial aerial response were generally closer to an airbase, while No Response fires exhibited both the largest mean and median distances.

Across all three panels in Figure 4.5, ignition locations are distributed statewide with a broad north–south pattern along the Sierra Nevada, Coast Range, and southern California foothills. No Response fires (Panel A) are widely dispersed across the same areas where responded fires occur. CAL FIRE-first responses (Panel B) and USFS-first responses (Panel C) show overlapping geographic footprints, with both agencies’ initial responses appearing throughout northern, central, and southern California. CAL FIRE airbases (triangles) are positioned across the state, and incidents of each response type occur in proximity to multiple bases rather than clustering around any single region.

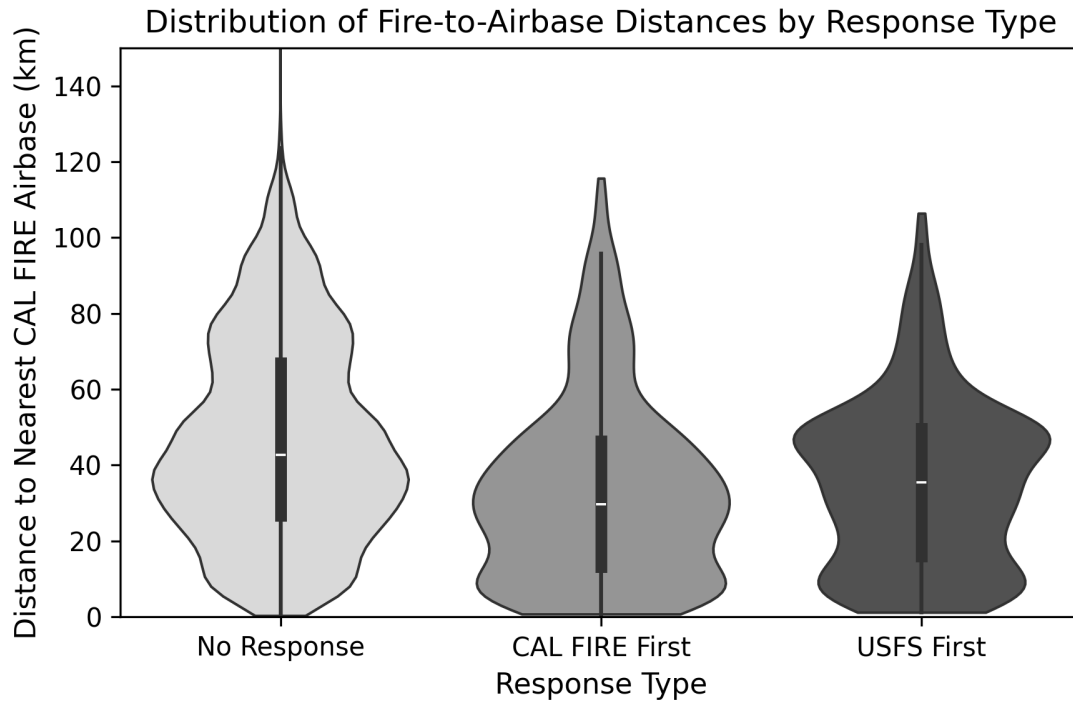


Figure 4.4: Violin plots showing distances from fires to the nearest CAL FIRE airbase, grouped by response type (No Response, CAL FIRE first, USFS first)

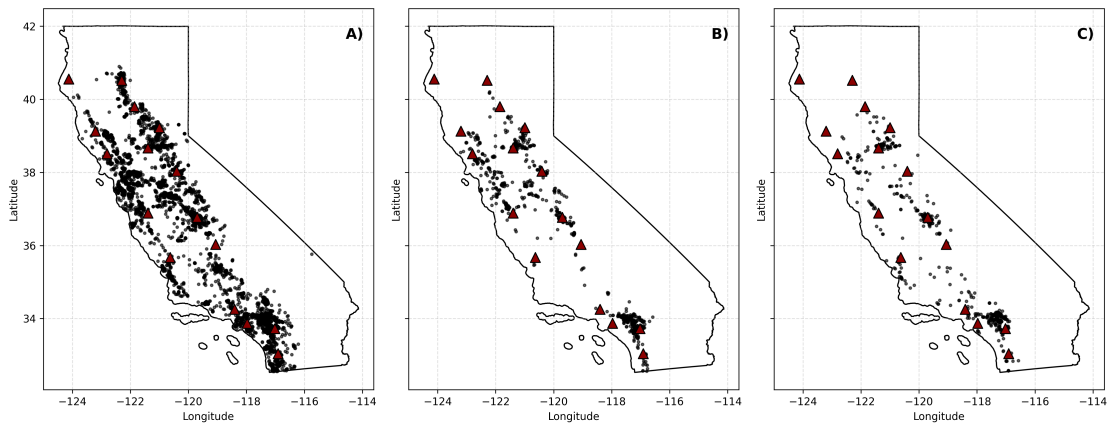


Figure 4.5: Spatial distribution of fire response types and CAL FIRE airbases across California. Panels show (A) incidents with no aerial response, (B) incidents where CAL FIRE aircraft responded first, and (C) incidents where USFS aircraft responded first. Black points represent incident locations, and red triangles indicate airbase locations.

4.3.4 NDVI Results

Across all 7,214 fires, standardized day-prior NDVI anomalies (NDVI_ANOM) ranged from roughly -8 to $+5$, with most values falling between -2 and $+2$ and a slight tendency toward more negative anomalies during the core 2020 fire season (Figure 4.6). When grouped by event type, NDVI_ANOM distributions for fires that received no aircraft and those that received an aerial response were broadly similar, with medians near zero and strongly overlapping interquartile ranges (Figure 4.7). In the Cox models, however, NDVI_ANOM consistently had a negative and highly significant coefficient ($\beta \approx -0.10$, $p < 0.001$ in all three specifications; Table 4.3), indicating that, after accounting for fuel, weather, exposure, and distance-to-water covariates, increasingly positive NDVI anomalies were associated with lower estimated hazards of aircraft arrival and increasingly negative anomalies with higher hazards.

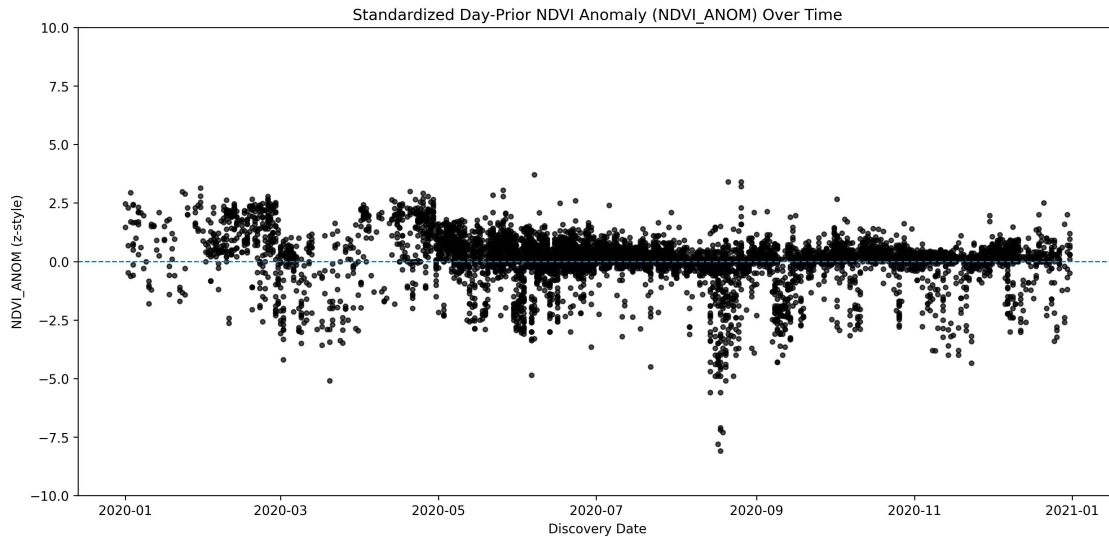


Figure 4.6: Spatial distribution of fire response types and CAL FIRE airbases across California. Panels show (A) incidents with no aerial response, (B) incidents where CAL FIRE aircraft responded first, and (C) incidents where USFS aircraft responded first. Black points represent incident locations, and red triangles indicate airbase locations.

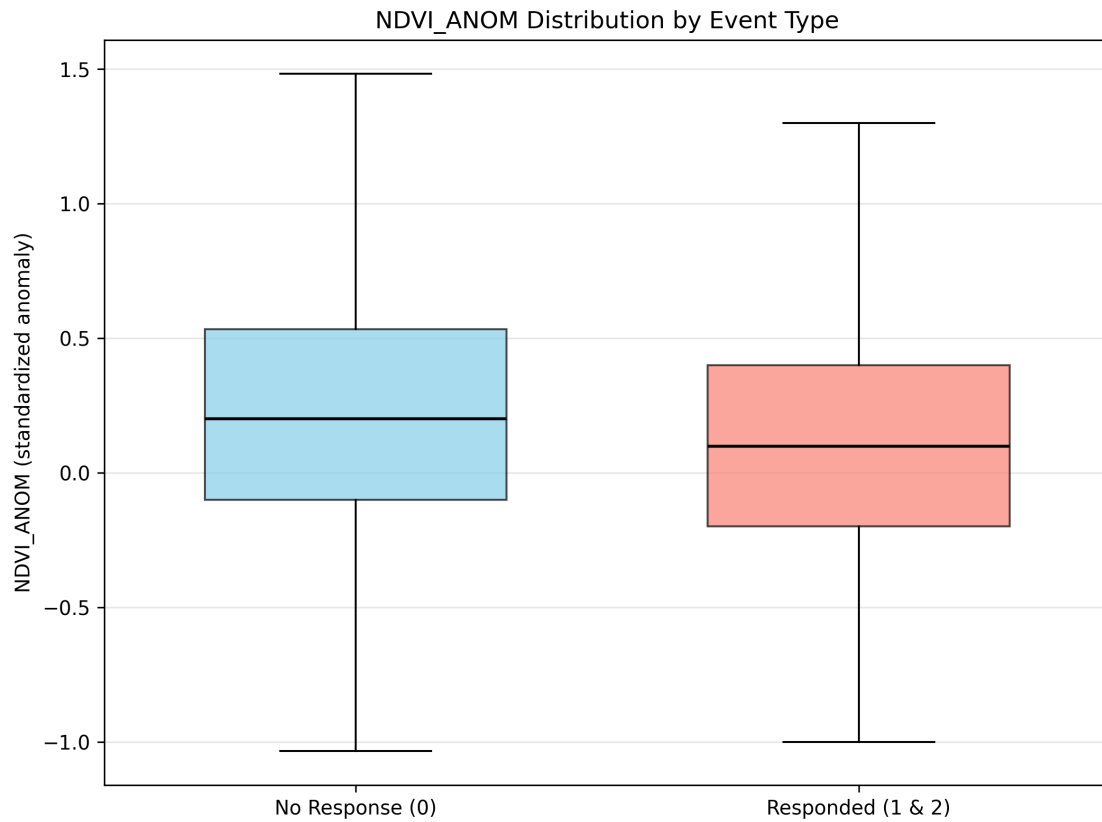


Figure 4.7: Spatial distribution of fire response types and CAL FIRE airbases across California. Panels show (A) incidents with no aerial response, (B) incidents where CAL FIRE aircraft responded first, and (C) incidents where USFS aircraft responded first. Black points represent incident locations, and red triangles indicate airbase locations.

Table 4.3: Coefficient estimates and standard errors from three Cox proportional hazards models examining factors associated with time to initial aircraft arrival on wildfires in California during the 2020 fire season. Model 1 is unstratified, Model 2 is stratified by time of day, and Model 3 is stratified by DPA. Values are log hazard coefficients with standard errors in parentheses. Positive coefficients indicate faster aircraft dispatch. Statistical significance is denoted by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, and + $p < 0.10$. Each model includes 7,214 wildfire events.

Covariate	Model 1 Coef. (SE)	Model 2 (Time strata) Coef. (SE)	Model 3 (DPA strata) Coef. (SE)
fm100_z	-0.074 (0.054)	-0.078 (0.054)	-0.064 (0.054)
NDVI_ANOM_z	-0.100*** (0.024)	-0.101*** (0.024)	-0.099*** (0.024)
Slope_z	0.043 (0.031)	0.043 (0.031)	0.008 (0.035)
dist_to_water_km_log_z	-0.060* (0.026)	-0.060* (0.026)	-0.037 (0.027)
vs_z	-0.056 (0.041)	-0.056 (0.041)	-0.053 (0.040)
bi_z	0.044 (0.058)	0.038 (0.058)	0.049 (0.058)
tmmx_z	0.448*** (0.038)	0.445*** (0.038)	0.464*** (0.038)
GHM_z	0.119* (0.051)	0.117* (0.051)	0.193*** (0.054)
Popo_1km_log_z	0.146** (0.047)	0.148** (0.047)	0.166*** (0.048)
Num. Obs.	7,214	7,214	7,214
BIC	25,567.6	22,441.0	23,740.2

4.3.5 Cumulative Incidence of First Response

Cause-specific cumulative incidence functions (Figure 4.8) show the probability of each agency being first to arrive over time. By 1,440 minutes, the cumulative incidence reached approximately 0.12 for CAL FIRE and 0.09 for USFS. Confidence intervals (shaded bands) reflect uncertainty around each estimate.

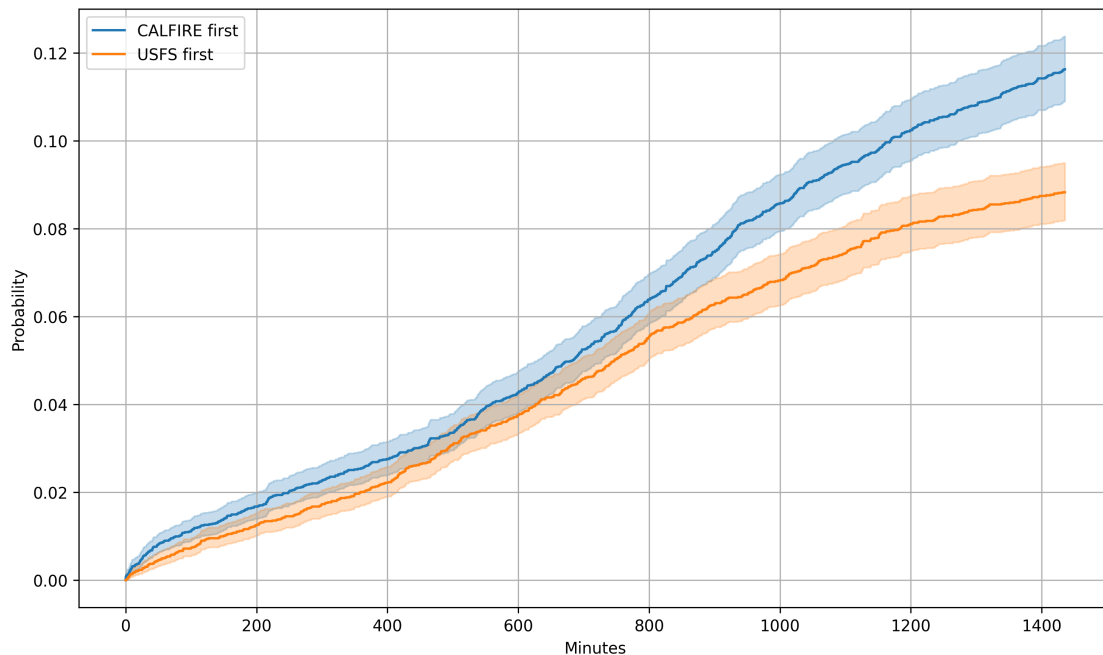


Figure 4.8: Difference in ADS-B–derived aircraft density between USFS and CAL FIRE aircraft across California during the 2020 fire season. Values represent USFS minus CAL FIRE cumulative aircraft-seconds per 3-km grid cell, with bright yellow areas indicating more frequent USFS use and dark purple areas indicating more frequent CAL FIRE use.

4.3.6 Cox Proportional Hazards Models

We estimated three Cox proportional hazards models: (1) an unstratified baseline model, (2) a model stratified by discovery time (Morning/Afternoon/Night), and (3) a model stratified by DPA region (Table 4.4). Schoenfeld residual diagnostics are provided in (Figure 4.9), and robustness checks excluding covariate groups are shown in (Table 4.5).

Schoenfeld Residuals - Model 3 (Stratified by DPA Group)

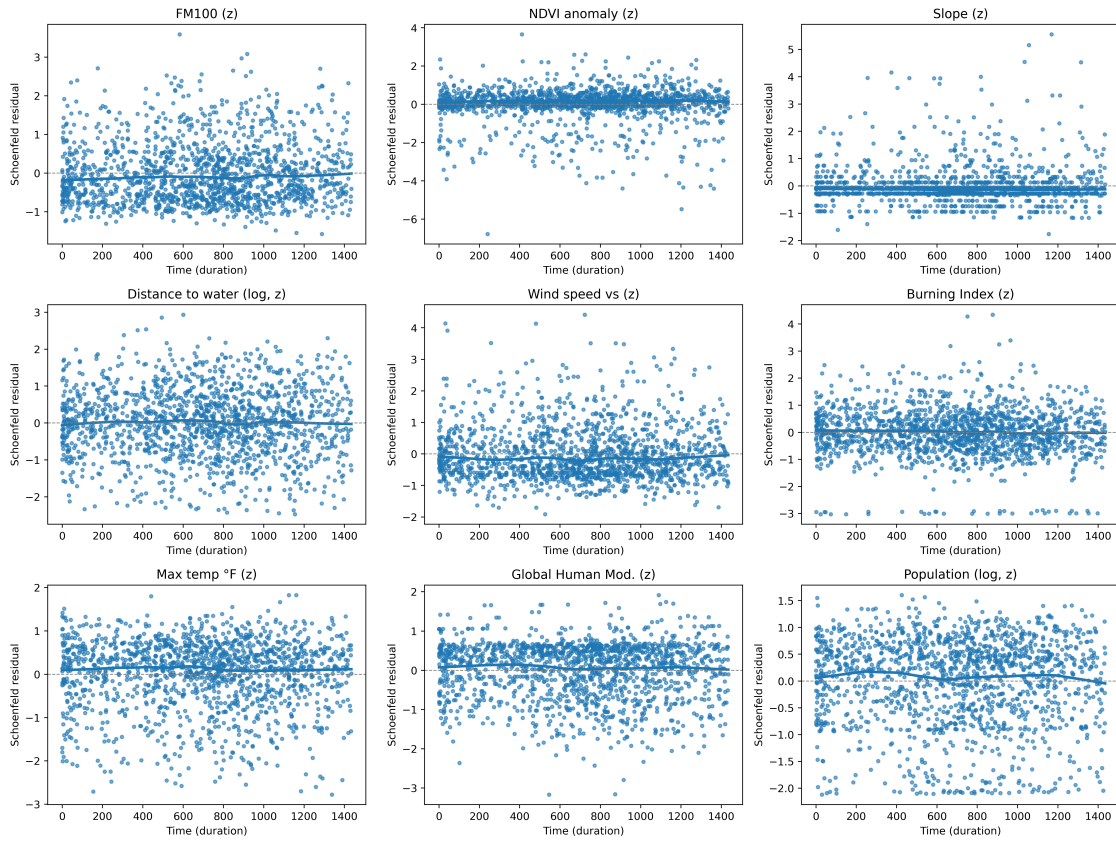


Figure 4.9: Difference in ADS-B–derived aircraft density between USFS and CAL FIRE aircraft across California during the 2020 fire season. Values represent USFS minus CAL FIRE cumulative aircraft-seconds per 3-km grid cell, with bright yellow areas indicating more frequent USFS use and dark purple areas indicating more frequent CAL FIRE use.

Table 4.4: Cox proportional hazards regression results for initial aircraft arrival timing. Model 1 is unstratified. Model 2 is stratified by time of day. Model 3 is stratified by Direct Protection Area (DPA). Values are log hazard coefficients with standard errors in parentheses. Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Model 1	Model 2 (Time strata)	Model 3 (DPA strata)
fm100_z	-0.074 (0.054)	-0.078 (0.054)	-0.064 (0.054)
NDVI_ANOM_z	-0.100*** (0.024)	-0.101*** (0.024)	-0.099*** (0.024)
Slope_z	0.043 (0.031)	0.043 (0.031)	0.008 (0.035)
dist_to_water_km_log_z	-0.060* (0.026)	-0.060* (0.026)	-0.037 (0.027)
vs_z	-0.056 (0.041)	-0.056 (0.041)	-0.053 (0.040)
bi_z	0.044 (0.058)	0.038 (0.058)	0.049 (0.058)
tmmx_z	0.448*** (0.038)	0.445*** (0.038)	0.464*** (0.038)
GHM_z	0.119* (0.051)	0.117* (0.051)	0.193*** (0.054)
Popo_1km_log_z	0.146** (0.047)	0.148** (0.047)	0.166*** (0.048)
Num. Obs.	7214	7214	7214
BIC	25567.6	22441.0	23740.2

Table 4.5: Coefficient estimates and standard errors from Cox proportional hazards models examining sensitivity to covariate exclusion. Columns report the full model and models excluding slope, population, fuel, or weather covariates. Values are log hazard coefficients with standard errors in parentheses. Positive coefficients indicate faster aircraft dispatch. Statistical significance is denoted by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, and + $p < 0.10$. Each model includes 7,214 wildfire events.

	Full	No_Slope	No_Pop	No_Fuel	No_Weather
GHM	0.892*** (0.193)	0.799*** (0.178)	nan	0.861*** (0.192)	0.986*** (0.193)
NDVI_ANOM	-0.097*** (0.025)	-0.098*** (0.025)	-0.090*** (0.025)	nan	-0.108*** (0.025)
Popo_1km	0.006+ (0.004)	0.007+ (0.004)	nan	0.006 (0.004)	0.007+ (0.004)
Slope	0.009 (0.007)	nan	-0.015* (0.006)	0.009 (0.007)	0.003 (0.007)
bi	0.003 (0.003)	0.003 (0.003)	0.004 (0.003)	0.006** (0.002)	nan
dist_to_water_km	-0.034** (0.011)	-0.035** (0.011)	-0.039*** (0.011)	-0.036** (0.011)	-0.031** (0.011)
fm100	-0.021 (0.015)	-0.021 (0.015)	-0.003 (0.015)	nan	-0.109*** (0.009)
tmmx	0.034*** (0.003)	0.034*** (0.003)	0.035*** (0.003)	0.036*** (0.003)	nan
vs	-0.041 (0.027)	-0.041 (0.027)	-0.056* (0.027)	-0.054* (0.024)	nan
Num. Obs.	7,214	7,214	7,214	7,214	7,214
BIC	25,569.5	25,562.2	25,612.7	25,567.4	25,703.1

We evaluated the proportional hazards assumption of the Cox regression models using Schoenfeld residuals, visualized via the `CoxPHFitter` function in the `lifelines` library. These plots assess whether residuals remain independent of time, a key requirement for the validity of proportional hazards modeling. As shown in Figure 4.9, most covariates exhibit residuals that fluctuate randomly around zero, suggesting reasonable adherence to the assumption. Although formal statistical tests flagged minor violations for some covariates, these are likely artifacts of the large sample size or the continuous nature of the predictors rather than substantive departures from proportionality [253]. Given the stability of effect estimates across stratified model specifications and the lack of strong temporal patterns in residuals, we interpret the models as appropriately specified for estimating how landscape, weather, and exposure factors influence aircraft dispatch timing during the initial response phase.

Across all three Cox model specifications, coefficient signs and magnitudes were consistent (Table 4.3). Maximum temperature (`tmmx`), nearby population density (`Popo_1km`), and human-modified landscape values (`GHM`) had positive coefficients in every model, indicating higher estimated hazards of aircraft arrival when increased. `NDVI_ANOM`, distance to water, and `fm100` had negative coefficients across models. Slope, wind speed (`vs`), and burning index (`bi`) showed coefficients near zero with no meaningful variation across specifications. Effect sizes for the major covariates were stable across Models 1–3, and no coefficient changed sign between models. The time-of-day–stratified model produced the lowest BIC value, indicating slightly better fit relative to the baseline and DPA-stratified models. Hazard ratios and confidence intervals from all three model specifications are shown in Figure 4.10.

The baseline survival functions for the DPA-stratified model (Model 3) differed across the three DPA groups (Figure 4.11). STATE-managed fires ($n = 2,006$) showed the steepest decline in survival probability over the 24-hour window, indicating a higher baseline hazard of aircraft arrival under this stratification. LOCAL DPAs ($n = 5,088$) exhibited the

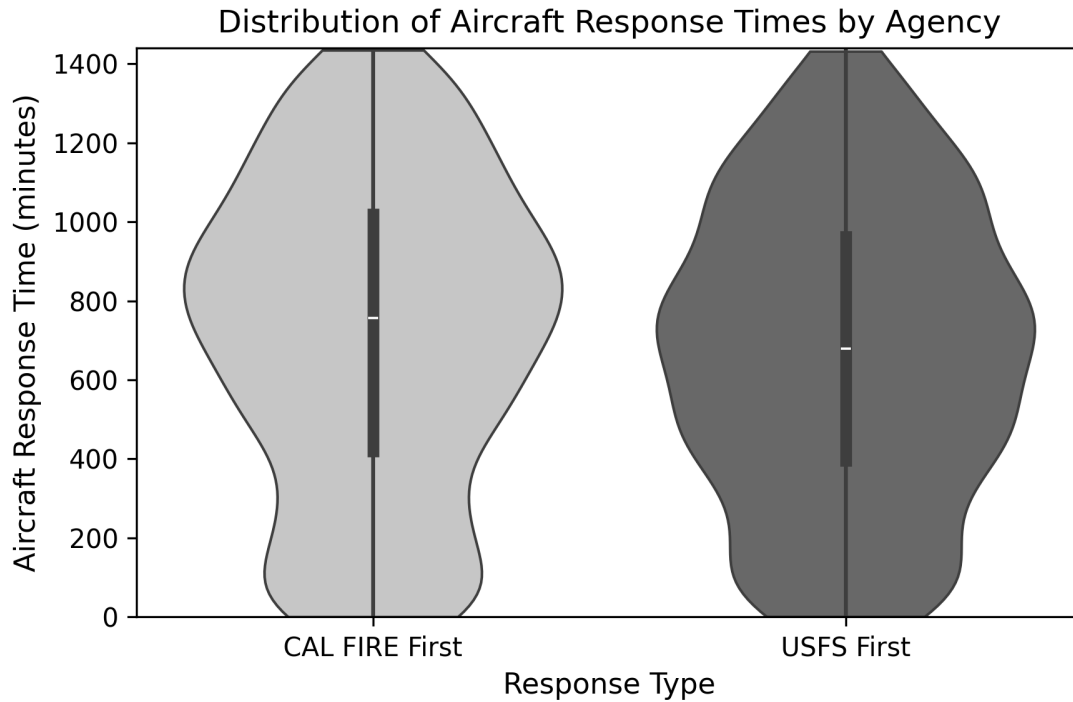


Figure 4.10: Violin plots comparing aircraft response times for fires first reached by CAL FIRE versus USFS during the 2020 season.

slowest decline, maintaining the highest survival probabilities for most of the time range. FEDERAL DPAs ($n = 120$) showed an intermediate trajectory, though the curve displayed more irregular step patterns compared to the other groups, reflecting the smaller sample size for FEDERAL-managed fires. All curves steadily decreased, consistent with the accumulation of aircraft arrival events over the observation period

4.4 Discussion

4.4.1 Response Timing and Operational Decision-making

The cause-specific cumulative incidence curves rise steadily rather than showing an early step change, indicating that the probability of receiving an aircraft is relatively diffuse across the first 24 hours during the IR phase (Figure 4.8). If aircraft were commonly launched immediately at discovery, we would expect a sharp initial jump; instead, both agencies exhibit a near-linear accumulation, with only a small fraction of fires receiving

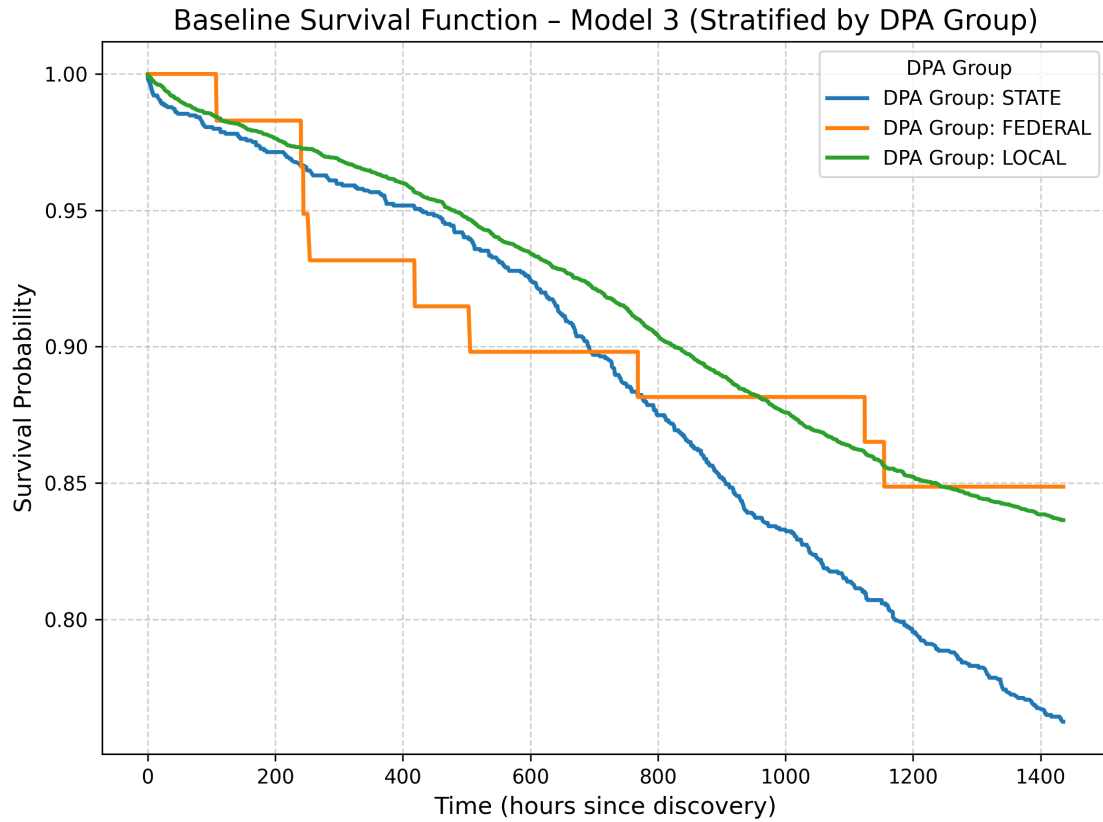


Figure 4.11: Baseline survival functions from the DPA-stratified Cox model (Model 3). Curves show the estimated probability that no aircraft has arrived as a function of time since fire discovery for STATE, FEDERAL, and LOCAL Direct Protection Areas.

aircraft in the first 20 minutes. This pattern is consistent with the absence of any single, predictable “clock” governing when aircraft are dispatched after a fire’s discovery.

Responding to wildfire involves balancing multiple, sometimes competing priorities, including firefighter safety, suppression costs, public expectations, and the anticipated ecological outcomes of different response strategies, among others, which together shape when and how resources are deployed [254,255]. As a result, the timing of aerial response reflects the combined influence of fuel moisture, weather, slope, access to water, proximity to people and infrastructure, and the evolving fire situation, factors that seldom align uniformly across incidents. Operationally, dispatch is also mediated by availability (what’s on base, what’s already committed), airspace and smoke constraints, and maybe most importantly, human decision-making under uncertainty [170]. That last element introduces real variability. Incident commanders weigh consequences, alternatives (ground attack, wait for IR/size-up), and risk thresholds differently, so two similar ignitions may lead to different call-up times. Together, these environmental, logistical, and human factors produce a broadly increasing, rather than front-loaded, arrival profile, with modest early responses and a persistent chance of first arrival throughout the IA window. Practically, this means that improving situational awareness, coordination, and decision support tools may do more to contribute to timely and effective aerial response than any single operational change alone.

4.4.2 Environmental and Logistical Influences on Aircraft Arrival

Building on this broader understanding of how response decisions unfold, the modeled results further show that aircraft are more likely to be mobilized under conditions of higher temperatures, patterns consistent with prior studies of aerial suppression behavior [213,235]. This suggests weather, and more specifically hotter temperatures, may influence dispatch decisions. Wind speed, by contrast, had a small negative but statistically non-significant effect on the hazard of aircraft arrival, indicating no clear evidence

that stronger winds systematically accelerate or delay aerial response in this dataset. This is consistent with operational practice, where incident commanders will still launch aircraft across a wide range of wind speeds when safety envelopes allow, even though higher winds are known to reduce drop effectiveness by increasing drift and making it harder for water or retardant to reach the target fuels [256]. Additionally, steep terrain has historically been a focal point for retardant operations, our models show no statistically significant association between slope and the hazard of aircraft arrival [235]. This may reflect either genuinely weak slope sensitivity in IA decision-making or the fact that ADS-B coverage is concentrated in lower-elevation terrain where slope variation is smaller and operational patterns differ from high-slope wilderness settings.

These same terrain- and weather-driven challenges also intersect with logistical considerations such as access to water. In our results, the distance-to-water term does not exhibit a consistently strong signal, suggesting that water availability may influence aviation use in some contexts but not uniformly across incidents. Several factors could explain this muted relationship. In remote areas where accessible water sources are scarce, longer ferry distances and fewer drop sites can constrain operations and shift reliance toward ground-based tactics [257]. Distance to water may also shape the type of aircraft used, the feasibility of placing water or retardant drops, and broader suppression strategies, but these influences may not manifest as a simple, statewide pattern.

Beyond logistics, distance to water is correlated with environmental characteristics that vary substantially across California's landscapes. Fires farther from water often occur in settings with lower fuel continuity or reduced vegetation productivity, where aerial support may offer limited marginal benefit compared to ground attack. For example, [258] note that ecosystems with lower net primary productivity, common in arid regions distant from riparian areas, tend to have sparser or more discontinuous fuels, which constrain fire growth potential and may reduce the need for intensive aerial suppression. Thus, the weak statistical relationship observed here may reflect the combined influence of op-

erational constraints, longer ferry distances, ecological gradients, and differences in fuel structure rather than a direct, statewide effect of water proximity alone.

Across all three Cox models, the NDVI anomaly term (NDVI_ANOM) is negative and highly significant, indicating that live-fuel conditions exert a consistent influence on whether aircraft are dispatched quickly. Because the anomaly was constructed so that negative values represent below-normal greenness for that location and month (drier, more stressed live fuels) and positive values represent greener-than-usual conditions, the negative coefficient means that fires igniting under more stressed vegetation are more likely to receive aircraft earlier. In standardized units, a one-standard deviation increase in NDVI_ANOM (toward greener-than-expected vegetation) reduces the likelihood of aircraft arrival by roughly 10 percent, whereas a one-standard deviation shift toward more negative anomalies increases the likelihood of using aircraft. This pattern is consistent with prior work showing that NDVI anomalies and departures from “normal” greenness track live fuel moisture and elevated fire potential [238–240] and with recent efforts to incorporate improved live-fuel moisture representations into fire danger systems [242]. Together, these results suggest that incident commanders are more inclined to mobilize aircraft under conditions when live fuels appear unusually dry for the season, not just when background dead fuels are dry, and that NDVI-derived indicators provide information about response decisions beyond what is captured by fm100 or composite fire-danger indices alone. This emphasis on anomalously dry fuels aligns with broader evidence from the 2020 season that unusual fuel conditions contributed to concerns about late-season large-fire potential and shaped strategic planning for suppression capacity [259].

4.4.3 Values at Risk and Human Drivers of Aerial Response

While these environmental and logistical factors help explain where aircraft are less likely to be deployed, human and social factors appear equally important in determining where they are. Aviation deployments during initial response tend to intensify where

high value property are at stake [260]. Our model reproduces this pattern through positive coefficients on both the GHM and Popo_1km. Multiple empirical studies indicate that proximity to people and property is a strong driver of aerial suppression decisions. A nationwide analysis of large air tanker missions during 2010–2014 showed that aviation assets were disproportionately concentrated within about 10 km of the wildland–urban interface, where population density and infrastructure are highest [213]. A more detailed review of 2012 operations in Montana found the median distance from drop locations to mapped WUI values was only 2.8mi, underscoring how protection of communities shapes deployment patterns [86]. Consistent with these case studies, the U.S. Forest Service’s Air Firefightin Use and Effectiveness (AFUE) program reported that most of the drops in all types of aircraft occurred in fires where values were threatened during the event, signaling that resource considerations -at risk routinely influence the flight tasking at the national scale [211]. Taken together with our findings, these studies reinforce that aircraft are preferentially mobilized when fires threaten concentrated assets, whether homes or infrastructure, explaining the strong population proximity signal in our hazard models.

4.4.4 ADS-B Coverage Limitations and Interpretation of Results

While these results capture genuine operational behavior, they also reflect the spatial and technical constraints of ADS-B data. Line-of-sight reception means that ground-based ADS-B networks provide denser coverage in populated corridors and lower-elevation valleys, especially the Central Valley and Sierra foothills, while reception drops off in remote, mountainous regions such as far-northern coastal California, the high Sierra, and the southeastern deserts. To avoid conflating absent detections with absent response, we excluded 1,003 fires with no ADS-B messages within 5 km in 2020; however, this necessary filter shifts the analytic sample toward areas with robust sensor coverage, greater airbase density, and higher WUI exposure. Consequently, the estimated probabilities and timing of aerial response may be somewhat upward-biased relative to true statewide patterns,

and differences between agencies may be muted if one agency more frequently serves wilderness and high-elevation terrain. Our findings should therefore be interpreted as describing IR activity that is observable via ADS-B, rather than representing all IR operations statewide. Future work could reduce these gaps by incorporating satellite-based ADS-B reception or by outfitting aircraft with onboard, internet-connected systems capable of relaying position data in real time.

4.4.5 Implications of ADS-B for Wildfire Aviation Research

Despite these coverage limitations, ADS-B nevertheless provides a uniquely comprehensive view of aerial activity compared with traditional data sources. Existing wildfire aviation studies have relied primarily on ATU drop logs, which are mandatory for federally contracted airtankers but not for state fleets such as CAL FIRE. As a result, analyses using only ATU data (e.g., [85,261]) omit substantial portions of aerial suppression performed by state and private aircraft. ADS-B addresses much of this limitation, because all transponder-equipped aircraft broadcast their position every second, open networks like the OpenSky Network provide ownership-agnostic, continuous records of aircraft movement. Prior work has already shown that straightforward pattern-recognition methods applied to ADS-B tracks can identify CAL FIRE airtankers, map circling orbits over active fires, and reconstruct operational timelines without access to mission logs [84].

ADS-B's strengths stem from its open broadcast architecture; low-cost receivers can collect signals wherever line-of-sight exists, and community archives now contain billions of messages [223]. When integrated with incident records or the subset of federal ATU drops, these data support new spatial analyses of fleet utilization. Yet the system remains incomplete: coverage is uneven, mountainous terrain can obscure reception, and some aircraft still operate without broadcasting ADS-B even within mandated airspace. Advancing wildfire aviation research will therefore require hybrid data systems that merge terrestrial and satellite ADS-B, agency-specific telemetry, and emerging unmanned-aircraft sensors.

Such integration would produce a more comprehensive and resilient picture of aerial fire-fighting activity and extend performance analyses beyond federal fleets to the state and local resources that increasingly shoulder IR responsibilities.

4.5 Conclusion

Figure 4.4 shows that the spatial distribution of response types is broadly consistent across California, with no discernible geographic clustering that would indicate systematic spatial bias in whether CAL FIRE or the USFS responds first. Incidents with no aerial response, CAL FIRE–first responses, and USFS–first responses all occupy the same statewide footprint, which aligns with the fact that CAL FIRE airbases are strategically located to provide wide and relatively uniform coverage. Because the airbase network is intentionally designed to minimize spatial gaps, a strong geographic signature in response patterns is not expected. The violin plot Figure 4.4 shows a slight tendency for incidents receiving an initial aerial response to occur at somewhat shorter distances from CAL FIRE airbases compared with no-response incidents. This weak proximity signal is operationally intuitive, closer fires are more likely to receive aircraft simply because travel times are shorter and aircraft can be committed more efficiently. Overall, proximity to airbases appears to play a modest role in shaping response likelihood and sequencing, but it does not produce a pronounced spatial pattern across the state.

The results of this study indicate a cooperative balance in aviation workload between CAL FIRE and the U.S. Forest Service, reflecting the intertwined responsibilities defined under California’s Direct Protection Area agreements. Despite differences in fleet composition and mission scope, the expected response times for the two agencies are nearly identical within the ADS-B–observable portion of the state (Figure 4.10). This similarity suggests that, operationally, both agencies are contributing comparably to IR aviation response during high-activity periods.

Workload patterns further reinforce this shared commitment. The seasonal activity curves for the two fleets exhibit a nearly unimodal, parallel structure, with both agencies showing a midsummer–early fall pulse in aircraft activity (Figure 4.2). The similarity in these seasonal pulses indicates that both fleets scaled up and sustained aviation effort during the same fire-season periods, consistent with coordinated IR responsibilities. Spatial patterns also suggest a roughly even division of effort: the distribution of incidents first reached by each agency (Figure 4.5) shows substantial geographic overlap, rather than a clear partitioning of responsibility.

This balanced pattern of effort and engagement aligns with prior work documenting shared federal–state response structures and cooperative aviation management under DPA agreements and closest-resource dispatch protocols [68, 225]. It is also consistent with findings from [213], who showed that large airtanker use is requested at the incident level through a national dispatch system and is concentrated near populated areas, indicating that deployments are driven by operational needs and proximity to values at risk rather than purely by jurisdictional boundaries. Together, these results suggest that the combined CAL FIRE and USFS aviation systems operate less as two separate fleets than as a jointly involved suppression network responding to similar environmental triggers and workload pressures.

This study demonstrates that ADS-B’s global, second-by-second telemetry provides a uniquely comprehensive lens on wildfire aviation use, allowing us to quantify when, where, and under what conditions CAL FIRE and USFS aircraft launch during initial response, something that has not been possible with traditional, agency-specific records. By linking aircraft trajectories with survival analysis, we show how terrain, weather, water access, and values-at-risk shape deployment timing and reveal patterns that were previously obscured by fragmented reporting systems. Rather than comparing agencies per se, our analysis illustrates how a unified, ownership-agnostic data stream can illustrate the broader operational environment in which both systems operate. As ADS-B contin-

ues to expand, further integration with federal and state tracking systems, shared data protocols, and more consistent coverage will strengthen its potential as the foundation for real-time coordination, performance assessment, and long-term planning. Together, these advances point toward a future in which a consolidated monitoring architecture supports more transparent, equitable, and strategically informed use of aviation resources during wildfire response.

Chapter 5

Synthesis and Contributions

5.1 Overview

Wildfire management involves decisions and actions that unfold across multiple temporal and organizational scales. Decisions made years in advance through fuel treatment planning may shape the landscape conditions under which future fires occur. Following ignition, dispatch and initial response decisions often unfold over hours as agencies allocate aviation and ground-based resources to address different changing weather, fire behavior, and values-at-risk conditions. Within those broader response activities, suppression actions such as aerial delivery occur at much finer temporal scales.

This dissertation examines related wildfire management processes across three temporal scales. Rather than prescribing how decisions should be made, it focuses on identifying patterns in observed outcomes and relating those patterns to measurable environmental, spatial, and operational conditions.

At the longer time scale, this work models hazardous fuel treatment allocation in Colorado's national forests using historical treatment records and spatial covariates describing hazard, terrain, and infrastructure. At the incident time scale, it analyzes initial aerial response timing by reconstructing aircraft arrivals relative to reported ignition events and modeling time to arrival as a function of environmental and social factors. At the execution time scale, it develops a framework for inferring likely suppressant drop activity from ADS-B flight telemetry, providing a new way to characterize suppression activity from operational aviation data.

5.2 From Landscape Mitigation to Real-Time Suppression

Although each chapter of this dissertation examines a distinct wildfire management activity, the chapters are related by a broader temporal structure in which longer-term planning and landscape conditions form part of the context for later suppression decisions. This dissertation does not model those relationships as a single end-to-end process. Instead, it develops and evaluates analytical components that help describe different layers of that broader management context independently.

At the landscape scale, hazardous fuel treatments can modify fuel continuity, vertical structure, and vegetation pattern, which may in turn affect burn probability, flame length potential, and other indicators of wildfire hazard. Chapter 2 examines where these treatments were historically allocated, using spatial covariates to characterize patterns associated with treatment placement.

Those landscape conditions form part of the context in which incident-level suppression decisions are made. Initial aerial response may be associated with anticipated fire behavior, weather, values at risk, accessibility, and other aspects of landscape setting, some of which are related directly or indirectly to fuel conditions. Chapter 4 examines this incident-level layer by modeling time to aircraft arrival as a function of environmental and social covariates. Although fuel treatments are not modeled explicitly as a covariate in that chapter, some of the hazard-related conditions may still be part of the broader situational context managers consider when deciding whether and how quickly to deploy aviation resources.

Once aviation resources are mobilized, suppression activity depends not only on whether aircraft arrive, but also on how operations are carried out in space and time. Chapter 3 develops a framework to infer likely suppressant drop activity from ADS-B flight telemetry, making it possible to characterize realized aerial suppression activity more directly than with dispatch records alone. These reconstructed patterns provide a way to examine how aerial suppression is carried out at finer temporal resolution.

Taken together, the chapters examine related processes that unfold across multiple temporal scales. Fuel treatment allocation over years is associated with the landscape conditions present during future fire events. Those conditions, together with weather, accessibility, and values at risk, help define the setting in which aviation response decisions occur over hours. Aviation mobilization then creates the conditions under which suppressant delivery is carried out at much finer time scales. The dissertation does not study this full sequence within a single integrated model, but it does provide an example for examining several connected components of a complicated wildfire management system using complementary empirical approaches.

5.3 Methodological Contributions

This dissertation contributes a set of empirical methods for studying wildfire management from incomplete and heterogeneous observational data. Across chapters, the methodological innovations center on three related challenges by modeling complex nonlinear allocation patterns, reconstructing operational timing from telemetry, and inferring suppression activity from raw movement data.

First, this dissertation demonstrates the use of neural network models as a flexible framework for representing nonlinear and interacting covariate relationships in historical fuel treatment allocation. This is methodologically important because treatment placement is unlikely to follow a simple rule-based structure and instead reflects multidimensional associations among hazard, infrastructure, terrain, and human influence. The neural network approach provides a way to learn these relationships across heterogeneous landscapes.

Second, this dissertation extends wildfire aviation research through event reconstruction from aircraft telemetry. By linking ADS-B trajectories with ignition records, it becomes possible to estimate aircraft arrival timing in a consistent observational framework. This provides a methodological alternative to relying only on dispatch documentation and

demonstrates how telemetry can be used to recover incident-level response metrics across agencies and incidents.

Third, this dissertation develops a classification-based framework for inferring likely suppression activity from high-frequency flight trajectories. Methodologically, this contribution lies in converting raw aircraft movement data into an empirical representation of likely suppression execution. This creates a new way to study operational activity at fine temporal resolution using open telemetry data, even where direct suppression records are absent or incomplete.

Taken together, these contributions show how machine learning, event reconstruction, and telemetry-based inference can expand the empirical toolkit available for wildfire management research. More broadly, they demonstrate how previously underused observational data streams can be transformed into analyzable representations of planning, response, and suppression activity.

5.4 Limitations and Scope

The analyses in this dissertation are based on observational data and are intended to describe patterns within specific contexts. The fuel treatment models are trained on historical data and reflect the conditions, policies, and constraints present during the study period. They approximate past decision patterns but do not represent prescriptive strategies or imply optimal treatment placement. Instead, the modeled patterns reflect realized decisions shaped by operational and environmental constraints rather than an optimized allocation of treatments across the landscape.

The wildfire aviation suppression reconstruction framework depends on ADS-B telemetry, which may vary in coverage and completeness. Therefore, the reconstructed results should be interpreted as an approximation of observed activity rather than a complete record of suppression operations.

The response-timing analysis provides a simplified representation of how observed arrival times relate to measured environmental and social variables, but it does not capture the full complexity of dispatch and operational decision-making, including factors such as resource availability, competing aircraft demands, and other operational constraints at the time of dispatch.

More broadly, the relationships identified in this work are associative rather than causal. The models show how observed decisions and actions are related to environmental and operational variables, but they do not demonstrate that those variables directly caused the observed outcomes.

This dissertation examines several components of wildfire management across temporal scales without attempting to unify them within a single integrated model. Instead, the focus is on describing patterns within each process using the data available.

5.5 Looking Ahead

Looking ahead, new datasets and new modeling approaches will likely make it possible to ask better and more connected questions about wildfire management. As records continue to improve, so will the ability to study how these different parts of the system relate to one another across time and space. That creates room for future work that is more integrated, more detailed, and better able to examine processes that have traditionally been difficult to observe. In that sense, this dissertation is not only a set of individual studies, but also part of a broader shift toward new ideas in wildfire management.

Bibliography

- [1] Emily G Brodie, Eric E Knapp, Wesley R Brooks, Stacy A Drury, and Martin W Ritchie. Forest thinning and prescribed burning treatments reduce wildfire severity and buffer the impacts of severe fire weather. *Fire Ecology*, 20(1):17, 2024. Publisher: Springer.
- [2] John L Campbell, Mark E Harmon, and Stephen R Mitchell. Can fuel-reduction treatments really increase forest carbon storage in the western US by reducing future fire emissions? *Frontiers in Ecology and the Environment*, 10(2):83–90, 2012. Publisher: Wiley Online Library.
- [3] Matthew Hurteau and Malcolm North. Fuel treatment effects on tree-based forest carbon storage and emissions under modeled wildfire scenarios. *Frontiers in Ecology and the Environment*, 7(8):409–414, 2009. Publisher: Wiley Online Library.
- [4] Duncan C McKinley, Michael G Ryan, Richard A Birdsey, Christian P Giardina, Mark E Harmon, Linda S Heath, Richard A Houghton, Robert B Jackson, James F Morrison, Brian C Murray, and others. A synthesis of current knowledge on forests and carbon storage in the United States. *Ecological applications*, 21(6):1902–1924, 2011. Publisher: Wiley Online Library.
- [5] Malcolm P North and Matthew D Hurteau. High-severity wildfire effects on carbon stocks and emissions in fuels treated and untreated forest. *Forest Ecology and Management*, 261(6):1115–1120, 2011. Publisher: Elsevier.
- [6] Scott L Stephens, James D McIver, Ralph EJ Boerner, Christopher J Fettig, Joseph B Fontaine, Bruce R Hartsough, Patricia L Kennedy, and Dylan W Schwilk. The effects of forest fuel-reduction treatments in the United States. *BioScience*, 62(6):549–560, 2012. Publisher: American Institute of Biological Sciences Circulation, AIBS, 1313 Dolley

- [7] Eric M Winford and James C Gaither Jr. Carbon outcomes from fuels treatment and bioenergy production in a Sierra Nevada forest. *Forest Ecology and Management*, 282:1–9, 2012. Publisher: Elsevier.
- [8] Alexis A Bernal, Jeffrey M Kane, Eric E Knapp, and Harold SJ Zald. Tree resistance to drought and bark beetle-associated mortality following thinning and prescribed fire treatments. *Forest Ecology and Management*, 530:120758, 2023. Publisher: Elsevier.
- [9] William D Burke, Christina Tague, Maureen C Kennedy, and Max A Moritz. Understanding how fuel treatments interact with climate and biophysical setting to affect fire, water, and forest health: A process-based modeling approach. *Frontiers in Forests and Global Change*, 3:591162, 2021. Publisher: Frontiers Media SA.
- [10] Sharon M Hood, Justin S Crotteau, and Cory C Cleveland. Long-term efficacy of fuel reduction and restoration treatments in Northern Rockies dry forests. *Ecological Applications*, 34(2):e2940, 2024. Publisher: Wiley Online Library.
- [11] Harold SJ Zald, Chance C Callahan, Matthew D Hurteau, Marissa J Goodwin, and Malcolm P North. Tree growth responses to extreme drought after mechanical thinning and prescribed fire in a Sierra Nevada mixed-conifer forest, USA. *Forest Ecology and Management*, 510:120107, 2022. Publisher: Elsevier.
- [12] Evan E Hjerpe, Melanie M Colavito, Amy EM Waltz, and Andrew Sánchez Meador. Return on investments in restoration and fuel treatments in frequent-fire forests of the American west: A meta-analysis. *Ecological Economics*, 223:108244, 2024. Publisher: Elsevier.
- [13] Allison K Rossman, Charles B Halpern, Richy J Harrod, Lauren S Urgenson, David W Peterson, and Jonathan D Bakker. Benefits of thinning and burning for understory diversity vary with spatial scale and time since treatment. *Forest Ecology and Management*, 419:58–78, 2018. Publisher: Elsevier.

- [14] Liubov Volkova, Alexander G Weiss Aparicio, and Christopher J Weston. Fire intensity effects on post-fire fuel recovery in Eucalyptus open forests of south-eastern Australia. *Science of the total environment*, 670:328–336, 2019. Publisher: Elsevier.
- [15] Molly E Hunter and Michael H Taylor. The economic value of fuel treatments: a review of the recent literature for fuel treatment planning. *Forests*, 13(12):2042, 2022. Publisher: MDPI.
- [16] Nima Karimi, Patrick Mahler, and Jennifer L Beverly. Optimizing fuel treatments for community wildfire mitigation planning. *Journal of Environmental Management*, 370:122325, 2024. Publisher: Elsevier.
- [17] George A Woolsey, Wade T Tinkham, Mike A Battaglia, and Chad M Hoffman. Constraints on Mechanical Fuel Reduction Treatments in United States Forest Service Wildfire Crisis Strategy Priority Landscapes. *Journal of Forestry*, page fvae012, 2024. Publisher: Oxford University Press US.
- [18] Brandon M Collins, Scott L Stephens, Jason J Moghaddas, and John Battles. Challenges and approaches in planning fuel treatments across fire-excluded forested landscapes. *Journal of Forestry*, 108(1):24–31, 2010. Publisher: Oxford University Press.
- [19] Erin J Belval, Jude Bayham, and Shayne Magstadt. Retention of highly qualified wildland firefighters in the Western United States. *Forest Policy and Economics*, 158:103115, 2024. Publisher: Elsevier.
- [20] Courtney A Schultz, Heidi Huber-Stearns, Sarah McCaffrey, Douglas Quirke, Gwen Ricco, and Cassandra Moseley. Prescribed fire policy barriers and opportunities: a diversity of challenges and strategies across the West. 2018. Publisher: Ecosystem Workforce Program, Institute for a Sustainable Environment

- [21] Jason Kreitler, Matthew P Thompson, Nicole M Vaillant, and Todd J Hawbaker. Cost-effective fuel treatment planning: A theoretical justification and case study. *International journal of wildland fire*, 29(1):42–56, 2019. Publisher: CSIRO Publishing.
- [22] Douglas B Rideout and Philip N Omi. Estimating the cost of fuels treatment. *Forest Science*, 41(4):664–674, 1995. Publisher: Oxford University Press.
- [23] Benjamin M Gannon, Yu Wei, Lee H MacDonald, Stephanie K Kampf, Kelly W Jones, Jeffery B Cannon, Brett H Wolk, Antony S Cheng, Robert N Addington, and Matthew P Thompson. Prioritising fuels reduction for water supply protection. *International Journal of Wildland Fire*, 28(10):785–803, 2019. Publisher: CSIRO Publishing.
- [24] David L Peterson and Morris C Johnson. Science-based strategic planning for hazardous fuel treatment. *Fire Management Today*. 67 (3): 13-18, 2007.
- [25] Theresa B Jain, Ilana Abrahamson, Nate Anderson, Sharon Hood, Brice Hanberry, Francis Kilkenny, Shawn McKinney, Jeffrey Ott, Alexandra Urza, Jeanne Chambers, and others. Effectiveness of fuel treatments at the landscape scale: State of understanding and key research gaps. *JFSP PROJECT ID: 19-S-01-2. Boise, ID: Joint Fire Sciences Program*. 65 p., 2021.
- [26] Elizabeth D Reinhardt, Robert E Keane, David E Calkin, and Jack D Cohen. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. *Forest Ecology and Management*, 256(12):1997–2006, 2008. Publisher: Elsevier.
- [27] Nicole M Vaillant and Elizabeth D Reinhardt. An evaluation of the Forest Service Hazardous Fuels Treatment Program—Are we treating enough to promote resiliency or reduce hazard? *Journal of Forestry*, 115(4):300–308, 2017. Publisher: Oxford University Press Oxford, UK.

- [28] Dirac Twidwell, Carissa L Wonkka, Michael T Sindelar, and John R Weir. First approximations of prescribed fire risks relative to other management techniques used on private lands. *PLoS one*, 10(10):e0140410, 2015. Publisher: Public Library of Science San Francisco, CA USA.
- [29] David Calkin and Krista Gebert. Modeling fuel treatment costs on Forest Service lands in the western United States. *Western Journal of Applied Forestry*, 21(4):217–221, 2006. Publisher: Oxford University Press.
- [30] Malcolm North, April Brough, Jonathan Long, Brandon Collins, Phil Bowden, Don Yasuda, Jay Miller, and Neil Sugihara. Constraints on mechanized treatment significantly limit mechanical fuels reduction extent in the Sierra Nevada. *Journal of Forestry*, 113(1):40–48, 2015. Publisher: Oxford University Press Oxford, UK.
- [31] Robert N Addington, Brian G Tavernia, Michael D Caggiano, Matthew P Thompson, Jason D Lawhon, and John S Sanderson. Identifying opportunities for the use of broadcast prescribed fire on Colorado’s Front Range. *Forest Ecology and Management*, 458:117655, 2020. Publisher: Elsevier.
- [32] Robert N Addington, Stephen J Hudson, J Kevin Hiers, Matthew D Hurteau, Thomas F Hutcherson, George Matusick, and James M Parker. Relationships among wildfire, prescribed fire, and drought in a fire-prone landscape in the south-eastern United States. *International Journal of Wildland Fire*, 24(6):778–783, 2015. Publisher: CSIRO Publishing.
- [33] Jamie M Lydersen, Brandon M Collins, and Carolyn T Hunsaker. Implementation constraints limit benefits of restoration treatments in mixed-conifer forests. *International Journal of Wildland Fire*, 28(7):495–511, 2019. Publisher: CSIRO Publishing.
- [34] ZL Steel, MJ Goodwin, MD Meyer, G Andrew Fricker, HSJ Zald, MD Hurteau, and Malcolm P North. Do forest fuel reduction treatments confer resistance to beetle

- infestation and drought mortality? *Ecosphere*, 12(1):e03344, 2021. Publisher: Wiley Online Library.
- [35] Michael J Vernon, Rosemary L Sherriff, Phillip van Mantgem, and Jeffrey M Kane. Thinning, tree-growth, and resistance to multi-year drought in a mixed-conifer forest of northern California. *Forest Ecology and Management*, 422:190–198, 2018. Publisher: Elsevier.
 - [36] TD Penman, L Collins, OF Price, Ross A Bradstock, S Metcalf, and DMO Chong. Examining the relative effects of fire weather, suppression and fuel treatment on fire behaviour—A simulation study. *Journal of environmental management*, 131:325–333, 2013. Publisher: Elsevier.
 - [37] Jamie M Lydersen, Brandon M Collins, Matthew L Brooks, John R Matchett, Kristen L Shive, Nicholas A Povak, Van R Kane, and Douglas F Smith. Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. *Ecological Applications*, 27(7):2013–2030, 2017.
 - [38] Míriam Piqué and Rut Domènech. Effectiveness of mechanical thinning and prescribed burning on fire behavior in *Pinus nigra* forests in NE Spain. *Science of the total environment*, 618:1539–1546, 2018. Publisher: Elsevier.
 - [39] Jeffrey E Ott, Francis F Kilkenny, and Theresa B Jain. Fuel treatment effectiveness at the landscape scale: a systematic review of simulation studies comparing treatment scenarios in North America. *Fire Ecology*, 19(1):1–29, 2023. Publisher: Springer.
 - [40] Federico Della Croce, Marco Ghirardi, and Rosario Scatamacchia. Improved solution of the Budget constrained Fuel Treatment Scheduling problem and extensions. *Computers & Industrial Engineering*, 168:108139, 2022. Publisher: Elsevier.
 - [41] Keith M Reynolds, Paul F Hessburg, Robert E Keane, and James P Menakis. National fuel-treatment budgeting in US federal agencies: Capturing opportunities for

- transparent decision-making. *Forest Ecology and Management*, 258(11):2373–2381, 2009. Publisher: Elsevier.
- [42] Matthew P Thompson, Kevin C Vogler, Joe H Scott, and Carol Miller. Comparing risk-based fuel treatment prioritization with alternative strategies for enhancing protection and resource management objectives. *Fire Ecology*, 18(1):26, 2022. Publisher: Springer.
 - [43] Gregory J Winter, Christine Vogt, and Jeremy S Fried. Fuel treatments at the wildland-urban interface: Common concerns in diverse regions. *Journal of Forestry*, 100(1):15–21, 2002. Publisher: Oxford University Press.
 - [44] Susan H Walker, Douglas B Rideout, John B Loomis, and Robin Reich. Comparing the value of fuel treatment options in northern Colorado’s urban and wildland–urban interface areas. *Forest Policy and Economics*, 9(6):694–703, 2007. Publisher: Elsevier.
 - [45] Sarah McCaffrey. Crucial factors influencing public acceptance of fuels treatments. *Fire Management Today*, 69(1):9, 2009.
 - [46] Anusha Shrestha, Robert K Grala, Stephen C Grado, Scott D Roberts, and Jason S Gordon. Landowner concern about wildfires and implementation of fuel reduction treatments. *Journal of Forestry*, 119(3):251–265, 2021. Publisher: Oxford University Press US.
 - [47] Christine A Vogt and Stanley J Cindrity. *A changing landscape in the wildland-urban interface: Permanent and seasonal home owners, recreation and fuel management*. Department of Agriculture, Forest Service, Northern Research Station, 2003.
 - [48] Sharon M Hood, J Morgan Varner, Theresa B Jain, and Jeffrey M Kane. A framework for quantifying forest wildfire hazard and fuel treatment effectiveness from stands to landscapes. *Fire Ecology*, 18(1):33, 2022. Publisher: Springer.

- [49] Alexandra K Urza, Brice B Hanberry, and Theresa B Jain. Landscape-scale fuel treatment effectiveness: lessons learned from wildland fire case studies in forests of the western United States and Great Lakes region. *Fire Ecology*, 19(1):1, 2023. Publisher: Springer.
- [50] Shawn T McKinney, Ilana Abrahamson, Theresa Jain, and Nathaniel Anderson. A systematic review of empirical evidence for landscape-level fuel treatment effectiveness. *Fire Ecology*, 18(1):21, 2022. Publisher: Springer.
- [51] Kimberley T Davis, Jamie Peeler, Joseph Fargione, Ryan D Haugo, Kerry L Metlen, Marcos D Robles, and Travis Woolley. Tamm review: A meta-analysis of thinning, prescribed fire, and wildfire effects on subsequent wildfire severity in conifer dominated forests of the Western US. *Forest Ecology and Management*, 561:121885, 2024. Publisher: Elsevier.
- [52] Matthew A Albrecht and Brian C McCarthy. Effects of prescribed fire and thinning on tree recruitment patterns in central hardwood forests. *Forest Ecology and Management*, 226(1-3):88–103, 2006. Publisher: Elsevier.
- [53] Daniel T Stark, David L Wood, Andrew J Storer, and Scott L Stephens. Prescribed fire and mechanical thinning effects on bark beetle caused tree mortality in a mid-elevation Sierran mixed-conifer forest. *Forest Ecology and Management*, 306:61–67, 2013. Publisher: Elsevier.
- [54] James M Furlaud, Grant J Williamson, and David MJS Bowman. Mechanical treatments and prescribed burning can reintroduce low-severity fire in southern Australian temperate sclerophyll forests. *Journal of Environmental Management*, 344:118301, 2023. Publisher: Elsevier.
- [55] TM Loupe, WW Miller, DW Johnson, JS Sedinger, EM Carroll, RF Walker, JD Murphy, and CM Stein. Effects of mechanical harvest plus chipping and prescribed fire

- on Sierran runoff water quality. *Journal of environmental quality*, 38(2):537–547, 2009. Publisher: Wiley Online Library.
- [56] Richard F Miller, Jaime Ratchford, Bruce A Roundy, Robin J Tausch, April Hulet, and Jeanne Chambers. Response of conifer-encroached shrublands in the Great Basin to prescribed fire and mechanical treatments. *Rangeland Ecology & Management*, 67(5):468–481, 2014. Publisher: Elsevier.
- [57] Scott L Stephens, Daniel E Foster, John J Battles, Alexis A Bernal, Brandon M Collins, Rachelle Hedges, Jason J Moghaddas, Ariel T Roughton, and Robert A York. Forest restoration and fuels reduction work: Different pathways for achieving success in the Sierra Nevada. *Ecological Applications*, 34(2):e2932, 2024. Publisher: Wiley Online Library.
- [58] Bruno A Aparício, Fermín Alcasena, Alan Ager, Woodam Chung, José MC Pereira, and Ana CL Sá. Evaluating priority locations and potential benefits for building a nation-wide fuel break network in Portugal. *Journal of environmental management*, 320:115920, 2022. Publisher: Elsevier.
- [59] Tiago M Oliveira, Ana MG Barros, Alan A Ager, and Paulo M Fernandes. Assessing the effect of a fuel break network to reduce burnt area and wildfire risk transmission. *International Journal of Wildland Fire*, 25(6):619–632, 2016. Publisher: CSIRO Publishing.
- [60] Volker C Radeloff, Roger B Hammer, Susan I Stewart, Jeremy S Fried, Sherry S Holcomb, and Jason F McKeefry. The wildland–urban interface in the United States. *Ecological applications*, 15(3):799–805, 2005. Publisher: Wiley Online Library.
- [61] Alexandra D Syphard, Jon E Keeley, and Teresa J Brennan. Comparing the role of fuel breaks across southern California national forests. *Forest Ecology and Management*, 261(11):2038–2048, 2011. Publisher: Elsevier.

- [62] Kevin Barnett, Sean A Parks, Carol Miller, and Helen T Naughton. Beyond fuel treatment effectiveness: characterizing interactions between fire and treatments in the US. *Forests*, 7(10):237, 2016. Publisher: MDPI.
- [63] James K Agee and Carl N Skinner. Basic principles of forest fuel reduction treatments. *Forest ecology and management*, 211(1-2):83–96, 2005. Publisher: Elsevier.
- [64] Susan J Prichard, Nicholas A Povak, Maureen C Kennedy, and David W Peterson. Fuel treatment effectiveness in the context of landform, vegetation, and large, wind-driven wildfires. *Ecological Applications*, 30(5):e02104, 2020. Publisher: Wiley Online Library.
- [65] Marc-André Parisien, David R Junor, and Victor G Kafka. Comparing landscape-based decision rules for placement of fuel treatments in the boreal mixedwood of western Canada. *International Journal of Wildland Fire*, 16(6):664–672, 2007. Publisher: CSIRO Publishing.
- [66] Carmen L Tubbesing, Danny L Fry, Gary B Roller, Brandon M Collins, Varvara A Fedorova, Scott L Stephens, and John J Battles. Strategically placed landscape fuel treatments decrease fire severity and promote recovery in the northern Sierra Nevada. *Forest Ecology and Management*, 436:45–55, 2019. Publisher: Elsevier.
- [67] CAL FIRE. Aviation Program, 2025.
- [68] U.S. Forest Service. Aviation Strategic Plan 2022-2026, 2023.
- [69] Hugh D. Safford, Alison K. Paulson, Zachary L. Steel, Derek J. N. Young, and Rebecca B. Wayman. The 2020 California fire season: A year like no other, a return to the past or a harbinger of the future? *Global Ecology and Biogeography*, 31(10):2005–2025, April 2022. Publisher: Wiley.
- [70] JE Keeley and AD Syphard. Large California wildfires: 2020 fires in historical context, *Fire Ecol.*, 17, 22, 2021.

- [71] Ken Pimlott, John Laird, and Edmund G Brown Jr. Wildfire activity statistics. *California Department of Forestry and Fire Protection Office of the StateFire Marshal*, pages 1–45, 2015.
- [72] U.S. Forest Service. CY2020 U.S. Forest Service Aviation Annual Report, 2021.
- [73] Crystal S Stonesifer, David E Calkin, Matthew P Thompson, and Erin J Belval. Is this flight necessary? The Aviation Use Summary (AUS): a framework for strategic, risk-informed aviation decision support. *Forests*, 12(8):1078, 2021. Publisher: MDPI.
- [74] U.S. Forest Service. Interagency Aviation Information Bulletin 2021-08, 2021.
- [75] Busyairah Syd Ali. System specifications for developing an Automatic Dependent Surveillance-Broadcast (ADS-B) monitoring system. *International Journal of Critical Infrastructure Protection*, 15:40–46, 2016. Publisher: Elsevier.
- [76] Mauro Leonardi. ADS-B anomalies and intrusions detection by sensor clocks tracking. *IEEE Transactions on Aerospace and Electronic Systems*, 55(5):2370–2381, 2018. Publisher: IEEE.
- [77] Mihály Varga, Zsolt Alfréd Polgár, and Horia Hedeşiu. ADS-B based real-time air traffic monitoring system. In *2015 38th International Conference on Telecommunications and Signal Processing (TSP)*, pages 215–219. IEEE, 2015.
- [78] Federal Aviation Administration. Electronic Code of Federal Regulations: 14 CFR § 91.225 - Automatic Dependent Surveillance-Broadcast (ADS-B) Out equipment and use, 2020.
- [79] Deborah L Bakowski, Lynne Martin, Gil Dustin, and Chris Mariano. Incorporating UAS Traffic Management into Wildland Firefighting Operations: Initial Findings of Subject Matter Expert Interviews. In *2024 AIAA DATC/IEEE 43rd Digital Avionics Systems Conference (DASC)*, pages 1–10. IEEE, 2024.

- [80] Lynne Martin, Yasmin Arbab, Lauren Roberts, Joey Mercer, Charles Walter, William McCarty, and Charles Sheehe. Developing an Unmanned Aircraft System Pilot Kit (UASP-kit) for Wildland Fire UAS Operators. In *AIAA AVIATION 2022 Forum*, page 4003, 2022.
- [81] A Struminska and A Filippone. Flight performance analysis of aerial fire fighting. *The Aeronautical Journal*, pages 1–29, 2024. Publisher: Cambridge University Press.
- [82] Matthias Schäfer, Martin Strohmeier, Vincent Lenders, Ivan Martinovic, and Matthias Wilhelm. Bringing up OpenSky: A large-scale ADS-B sensor network for research. In *IPSN-14 Proceedings of the 13th International Symposium on Information Processing in Sensor Networks*, pages 83–94. IEEE, 2014.
- [83] Shayne Magstadt, Yu Wei, Bradley M Pietruszka, and David E Calkin. A Deep Learning Approach for Predicting Aerial Suppressant Drops in Wildland Firefighting Using Automatic Dependent Surveillance–Broadcast Data. *Fire*, 7(11):380, 2024. Publisher: MDPI.
- [84] Xavier Olive, Junzi Sun, Adrien Lafage, and Luis Basora. Detecting events in aircraft trajectories: Rule-based and data-driven approaches. In *Proceedings*, volume 59, page 8. MDPI, 2020. Issue: 1.
- [85] Crystal Stonesifer, Cal Bryan, Jude Bayham, David Calkin, and Erin Belval. Firefighting Aircraft: Understanding Current Practices to Shape Future Response in a Changing World. *Environmental Sciences Proceedings*, 17(1):50, 2022. Publisher: MDPI.
- [86] Crystal S Stonesifer, Matthew P Thompson, Dave Calkin, and Charles W McHugh. Characterizing large airtanker use in United States fire management. In *In: Keane, Robert E.; Jolly, Matt; Parsons, Russell; Riley, Karin. Proceedings of the large wildland fires conference; May 19-23, 2014; Missoula, MT. Proc. RMRS-P-73. Fort Collins, CO:*

- US Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 314-316., volume 73, pages 314–316, 2015.*
- [87] Jerry D Tagestad, Troy M Saltiel, and André M Coleman. Rapid Spaceborne Mapping of Wildfire Retardant Drops for Active Wildfire Management. *Remote Sensing*, 15(2):342, 2023. Publisher: MDPI.
 - [88] Robert S Arkle, David S Pilliod, and Justin L Welty. Pattern and process of prescribed fires influence effectiveness at reducing wildfire severity in dry coniferous forests. *Forest Ecology and Management*, 276:174–184, 2012. Publisher: Elsevier.
 - [89] Susan J Prichard and Maureen C Kennedy. Fuel treatments and landform modify landscape patterns of burn severity in an extreme fire event. *Ecological Applications*, 24(3):571–590, 2014. Publisher: Wiley Online Library.
 - [90] Marco A Contreras, Russell A Parsons, and Woodam Chung. Modeling tree-level fuel connectivity to evaluate the effectiveness of thinning treatments for reducing crown fire potential. *Forest Ecology and Management*, 264:134–149, 2012. Publisher: Elsevier.
 - [91] Eva Marino, Carmen Hernando, Javier Madrigal, Carmen Díez, and Mercedes Guisjarro. Fuel management effectiveness in a mixed heathland: a comparison of the effect of different treatment types on fire initiation risk. *International Journal of Wildland Fire*, 21(8):969–979, 2012. Publisher: CSIRO Publishing.
 - [92] Erik J Martinson and Philip N Omi. Performance of fuel treatments subjected to wildfires, 2002. Publication Title: FIRE, FUEL TREATMENTS, AND ECOLOGICAL RESTORATION.[vp]. 16-18 Apr.
 - [93] Susan J Prichard, David L Peterson, and Kyle Jacobson. Fuel treatments reduce the severity of wildfire effects in dry mixed conifer forest, Washington, USA. *Canadian Journal of Forest Research*, 40(8):1615–1626, 2010.

- [94] Hugh D Safford, Jens T Stevens, Kyle Merriam, Marc D Meyer, and Andrew M Latimer. Fuel treatment effectiveness in California yellow pine and mixed conifer forests. *Forest Ecology and Management*, 274:17–28, 2012. Publisher: Elsevier.
- [95] Scott L Stephens, Ralph EJ Boerner, Jason J Moghaddas, Emily EY Moghaddas, Brandon M Collins, Christopher B Dow, Carl Edminster, Carl E Fiedler, Danny L Fry, Bruce R Hartsough, and others. Fuel treatment impacts on estimated wildfire carbon loss from forests in Montana, Oregon, California, and Arizona. *Ecosphere*, 3(5):1–17, 2012. Publisher: Wiley Online Library.
- [96] Michael C Wimberly, Mark A Cochrane, Adam D Baer, and Kari Pabst. Assessing fuel treatment effectiveness using satellite imagery and spatial statistics. *Ecological Applications*, 19(6):1377–1384, 2009. Publisher: Wiley Online Library.
- [97] Jimmie Chew, J Greg Jones, Chris Stalling, Janet Sullivan, and Steve Slack. Combining simulation and optimization for evaluating the effectiveness of fuel treatments for four different fuel conditions at landscape scales. In *Systems Analysis in Forest Resources: Proceedings of the Eighth Symposium, held September 27–30, 2000, Snowmass Village, Colorado, USA*, pages 35–46. Springer, 2003.
- [98] MA Cochrane, CJ Moran, MC Wimberly, AD Baer, Mark A Finney, KL Beckendorf, J Eidenshink, and Z Zhu. Estimation of wildfire size and risk changes due to fuels treatments. *International Journal of Wildland Fire*, 21(4):357–367, 2012. Publisher: CSIRO Publishing.
- [99] Mark A Finney. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. *Forest Science*, 47(2):219–228, 2001. Publisher: Oxford University Press.

- [100] Mark A Finney. A computational method for optimising fuel treatment locations. *International Journal of Wildland Fire*, 16(6):702–711, 2007. Publisher: CSIRO Publishing.
- [101] Mark Buckley, N Beck, P Bowden, ME Miller, B Hill, C Luce, WJ Elliot, N Enstice, K Podolak, E Winford, and others. Mokelumne watershed avoided cost analysis: why Sierra fuel treatments make economic sense. *Report prepared for the Sierra Nevada Conservancy, The Nature Conservancy, and USDA Forest Service.* (Sierra Nevada Conservancy: Auburn, CA) Available at <http://www.sierranevadaconservancy.ca.gov/mokelumne> [Verified 22 June 2015], 2014.
- [102] Joe H Scott, Matthew P Thompson, and Julie W Gilbertson-Day. Examining alternative fuel management strategies and the relative contribution of National Forest System land to wildfire risk to adjacent homes—A pilot assessment on the Sierra National Forest, California, USA. *Forest Ecology and Management*, 362:29–37, 2016. Publisher: Elsevier.
- [103] Matthew P Thompson, Karin L Riley, Dan Loeffler, and Jessica R Haas. Modeling fuel treatment leverage: Encounter rates, risk reduction, and suppression cost impacts. *Forests*, 8(12):469, 2017. Publisher: MDPI.
- [104] Alan A Ager, Michelle A Day, and Kevin Vogler. Production possibility frontiers and socioecological tradeoffs for restoration of fire adapted forests. *Journal of Environmental Management*, 176:157–168, 2016. Publisher: Elsevier.
- [105] Woodam Chung. Optimizing fuel treatments to reduce wildland fire risk. *Current Forestry Reports*, 1:44–51, 2015. Publisher: Springer.
- [106] Yu Wei, Douglas Rideout, and Andy Kirsch. An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. *Canadian Journal of Forest Research*, 38(4):868–877, 2008.

- [107] Piyush Jain, Sean CP Coogan, Sriram Ganapathi Subramanian, Mark Crowley, Steve Taylor, and Mike D Flannigan. A review of machine learning applications in wildfire science and management. *Environmental Reviews*, 28(4):478–505, 2020. Publisher: NRC Research Press 1840 Woodward Drive, Suite 1, Ottawa, ON K2C 0P7.
- [108] Oludare Isaac Abiodun, Aman Jantan, Abiodun Esther Omolara, Kemi Victoria Dada, Nachaat AbdElatif Mohamed, and Humaira Arshad. State-of-the-art in artificial neural network applications: A survey. *Heliyon*, 4(11), 2018. Publisher: Elsevier.
- [109] Ruiliang Pu and Peng Gong. Determination of burnt scars using logistic regression and neural network techniques from a single post-fire Landsat 7 ETM+ image. *Photogrammetric Engineering & Remote Sensing*, 70(7):841–850, 2004. Publisher: American Society for Photogrammetry and Remote Sensing.
- [110] Aitor Bastarrika, Emilio Chuvieco, and M Pilar Martín. Mapping burned areas from Landsat TM/ETM+ data with a two-phase algorithm: Balancing omission and commission errors. *Remote sensing of Environment*, 115(4):1003–1012, 2011. Publisher: Elsevier.
- [111] Israel Gómez and M Pilar Martín. Prototyping an artificial neural network for burned area mapping on a regional scale in Mediterranean areas using MODIS images. *International Journal of Applied Earth Observation and Geoinformation*, 13(5):741–752, 2011. Publisher: Elsevier.
- [112] Leigh B Lentile, Zachary A Holden, Alistair MS Smith, Michael J Falkowski, Andrew T Hudak, Penelope Morgan, Sarah A Lewis, Paul E Gessler, and Nate C Benson. Remote sensing techniques to assess active fire characteristics and post-fire effects. *International Journal of Wildland Fire*, 15(3):319–345, 2006. Publisher: CSIRO Publishing.

- [113] Varun Mithal, Guruprasad Nayak, Ankush Khandelwal, Vipin Kumar, Ramakrishna Nemani, and Nikunj C Oza. Mapping burned areas in tropical forests using a novel machine learning framework. *Remote Sensing*, 10(1):69, 2018. Publisher: MDPI.
- [114] Seyd Teymoor Seydi, Mahdi Hasanlou, and Jocelyn Chanussot. Burnt-Net: Wildfire burned area mapping with single post-fire Sentinel-2 data and deep learning morphological neural network. *Ecological Indicators*, 140:108999, 2022. Publisher: Elsevier.
- [115] Kathiravan Thangavel, Dario Spiller, Roberto Sabatini, Stefania Amici, Sarathchandrakumar Thottuchirayil Sasidharan, Haytham Fayek, and Pier Marzocca. Autonomous satellite wildfire detection using hyperspectral imagery and neural networks: A case study on australian wildfire. *Remote Sensing*, 15(3):720, 2023. Publisher: MDPI.
- [116] George P Petropoulos, Krishna Prasad Vadrevu, Gavriil Xanthopoulos, George Karantounias, and Marko Scholze. A comparison of spectral angle mapper and artificial neural network classifiers combined with Landsat TM imagery analysis for obtaining burnt area mapping. *Sensors*, 10(3):1967–1985, 2010. Publisher: Molecular Diversity Preservation International (MDPI).
- [117] KR Al-Rawi, JL Casanova, A Romo, and EM Louakfaoui. Integrated Fire Evolution Monitoring System (IFEMS) for monitoring spatial-temporal behaviour of multiple fire phenomena. *International Journal of Remote Sensing*, 23(10):1967–1983, 2002. Publisher: Taylor & Francis.
- [118] K Angayarkkani and N Radhakrishnan. An intelligent system for effective forest fire detection using spatial data. *arXiv preprint arXiv:1002.2199*, 2010.

- [119] Ying-Qing Guo, Gang Chen, Yi-Na Wang, Xiu-Mei Zha, and Zhao-Dong Xu. Wild-fire identification based on an improved two-channel convolutional neural network. *Forests*, 13(8):1302, 2022. Publisher: MDPI.
- [120] Zhanqing Li, Alexandre Khananian, Robert H Fraser, and Josef Cihlar. Automatic detection of fire smoke using artificial neural networks and threshold approaches applied to AVHRR imagery. *IEEE Transactions on geoscience and remote sensing*, 39(9):1859–1870, 2001. Publisher: IEEE.
- [121] Hamdy Soliman, Komal Sudan, and Ashish Mishra. A smart forest-fire early detection sensory system: Another approach of utilizing wireless sensor and neural networks. In *SENSORS, 2010 IEEE*, pages 1900–1904. IEEE, 2010.
- [122] Zhihua Liu, Michael C Wimberly, Aashis Lamsal, Terry L Sohl, and Todd J Hawbaker. Climate change and wildfire risk in an expanding wildland–urban interface: a case study from the Colorado Front Range Corridor. *Landscape Ecology*, 30(10):1943–1957, 2015. Publisher: Springer.
- [123] Saima Majid, Fayadh Alenezi, Sarfaraz Masood, Musheer Ahmad, Emine Selda Gündüz, and Kemal Polat. Attention based CNN model for fire detection and localization in real-world images. *Expert Systems with Applications*, 189:116114, 2022. Publisher: Elsevier.
- [124] Jerome Miller, Kirk Borne, Brian Thomas, Zhenping Huang, and Yuechen Chi. Automated wildfire detection through artificial neural networks. *Remote Sensing and Modeling Applications to Wildland Fires*, pages 293–304, 2013. Publisher: Springer.
- [125] Khan Muhammad, Jamil Ahmad, Zhihan Lv, Paolo Bellavista, Po Yang, and Sung Wook Baik. Efficient deep CNN-based fire detection and localization in video surveillance applications. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 49(7):1419–1434, 2018. Publisher: IEEE.

- [126] Sergio Saponara, Abdussalam Elhanashi, and Alessio Gagliardi. Real-time video fire/smoke detection based on CNN in antifire surveillance systems. *Journal of Real-Time Image Processing*, 18:889–900, 2021. Publisher: Springer.
- [127] Rudresh Deepak Shirwaikar, Lincy Mathews, and others. CNN-Based Video Surveillance for Fire and Localization Detection. In *2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP)*, pages 1–8. IEEE, 2022.
- [128] Dmitriy Alexandrov, Elizaveta Pertseva, Ivan Berman, Igor Pantiukhin, and Aleksandr Kapitonov. Analysis of machine learning methods for wildfire security monitoring with an unmanned aerial vehicles. In *2019 24th conference of open innovations association (FRUCT)*, pages 3–9. IEEE, 2019.
- [129] AlertWildfire. AlertWildfire, 2022.
- [130] Turgay Celik. Change detection in satellite images using a genetic algorithm approach. *IEEE Geoscience and Remote Sensing Letters*, 7(2):386–390, 2010. Publisher: IEEE.
- [131] F Sunar and C Özkan. Forest fire analysis with remote sensing data. *International Journal of Remote Sensing*, 22(12):2265–2277, 2001. Publisher: Taylor & Francis.
- [132] Cristina Vega-García and Emilio Chuvieco. Applying local measures of spatial heterogeneity to Landsat-TM images for predicting wildfire occurrence in Mediterranean landscapes. *Landscape Ecology*, 21:595–605, 2006. Publisher: Springer.
- [133] R Shanmuga Priya and K Vani. Vegetation change detection and recovery assessment based on post-fire satellite imagery using deep learning. *Scientific Reports*, 14(1):12611, 2024. Publisher: Nature Publishing Group UK London.
- [134] Amparo Alonso-Betanzos, Oscar Fontenla-Romero, Bertha Guijarro-Berdiñas, Elena Hernández-Pereira, Maria Inmaculada Paz Andrade, Eulogio Jiménez, Jose

- Luis Legido Soto, and Tarsy Carballas. An intelligent system for forest fire risk prediction and fire fighting management in Galicia. *Expert systems with applications*, 25(4):545–554, 2003. Publisher: Elsevier.
- [135] Christopher D O’Connor, David E Calkin, and Matthew P Thompson. An empirical machine learning method for predicting potential fire control locations for pre-fire planning and operational fire management. *International journal of wildland fire*, 26(7):587–597, 2017. Publisher: CSIRO Publishing.
- [136] Li-Ming Li, Wei-Guo Song, Jian Ma, and Kohyu Satoh. Artificial neural network approach for modeling the impact of population density and weather parameters on forest fire risk. *International Journal of Wildland Fire*, 18(6):640–647, 2009. Publisher: CSIRO Publishing.
- [137] National Interagency Fire Center (NIFC). Spatial Fireline Records, 2020, 2020. Place: Boise, ID, USA.
- [138] Douglas Thomas, David Butry, Stanley Gilbert, David Webb, Juan Fung, and others. The costs and losses of wildfires. *NIST special publication*, 1215(11):1–72, 2017.
- [139] Mark E Harmon. Survival of trees after low-intensity surface fires in Great Smoky Mountains National Park. *Ecology*, 65(3):796–802, 1984. Publisher: Wiley Online Library.
- [140] Paulo M Fernandes and Hermínio S Botelho. A review of prescribed burning effectiveness in fire hazard reduction. *International Journal of wildland fire*, 12(2):117–128, 2003. Publisher: CSIRO Publishing.
- [141] Teresa J Brennan and Jon E Keeley. Effect of mastication and other mechanical treatments on fuel structure in chaparral. *International Journal of Wildland Fire*, 24(7):949–963, 2015. Publisher: CSIRO Publishing.

- [142] Ana MG Barros, AA Ager, MA Day, and P Palaiologou. Improving long-term fuel treatment effectiveness in the National Forest System through quantitative prioritization. *Forest ecology and management*, 433:514–527, 2019. Publisher: Elsevier.
- [143] Morris C Johnson, David L Peterson, and Crystal L Raymond. Managing forest structure and fire hazard—A tool for planners. *Journal of forestry*, 105(2):77–83, 2007. Publisher: Oxford University Press Bethesda, MD.
- [144] Elizabeth D Reinhardt. *The fire and fuels extension to the forest vegetation simulator*. United States Department of Agriculture, Forest Service, Rocky Mountain . . . , 2003.
- [145] Mark A Finney. An overview of FlamMap fire modeling capabilities. In *In: Andrews, Patricia L.; Butler, Bret W., comps. 2006. Fuels Management-How to Measure Success: Conference Proceedings. 28-30 March 2006; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 213-220, volume 41, 2006.*
- [146] Fermín J Alcasena, Alan A Ager, Michele Salis, Michelle A Day, and Cristina Vega-Garcia. Optimizing prescribed fire allocation for managing fire risk in central Catalonia. *Science of the total environment*, 621:872–885, 2018. Publisher: Elsevier.
- [147] Alan A Ager, Cody R Evers, Michelle A Day, Fermin J Alcasena, and Rachel Houtman. Planning for future fire: Scenario analysis of an accelerated fuel reduction plan for the western United States. *Landscape and Urban Planning*, 215:104212, 2021. Publisher: Elsevier.
- [148] James Minas, John Hearne, and David Martell. An integrated optimization model for fuel management and fire suppression preparedness planning. *Annals of operations Research*, 232:201–215, 2015. Publisher: Springer.

- [149] Ramya Rachmawati, Melih Ozlen, Karin J Reinke, and John W Hearne. An optimisation approach for fuel treatment planning to break the connectivity of high-risk regions. *Forest Ecology and Management*, 368:94–104, 2016. Publisher: Elsevier.
- [150] Dmytro Matsypura, Oleg A Prokopyev, and Aizat Zahar. Wildfire fuel management: network-based models and optimization of prescribed burning. *European Journal of Operational Research*, 264(2):774–796, 2018. Publisher: Elsevier.
- [151] Shai Shalev-Shwartz and Shai Ben-David. *Understanding machine learning: From theory to algorithms*. Cambridge university press, 2014.
- [152] Diogo V Carvalho, Eduardo M Pereira, and Jaime S Cardoso. Machine learning interpretability: A survey on methods and metrics. *Electronics*, 8(8):832, 2019. Publisher: MDPI.
- [153] Max Kuhn and Kjell Johnson. *Applied predictive modeling*, volume 26. Springer, 2013.
- [154] Frank Rosenblatt. The perceptron: a probabilistic model for information storage and organization in the brain. *Psychological review*, 65(6):386, 1958. Publisher: American Psychological Association.
- [155] Christopher M Bishop. *Neural networks for pattern recognition*. Oxford university press, 1995.
- [156] Hao Liang, Meng Zhang, and Hailan Wang. A neural network model for wildfire scale prediction using meteorological factors. *IEEE Access*, 7:176746–176755, 2019. Publisher: IEEE.
- [157] Christos Vasilakos, Kostas Kalabokidis, John Hatzopoulos, George Kallos, and Yiannis Matsinos. Integrating new methods and tools in fire danger rating. *International Journal of Wildland Fire*, 16(3):306–316, 2007. Publisher: CSIRO Publishing.

- [158] George E Sakr, Imad H Elhajj, and George Mitri. Efficient forest fire occurrence prediction for developing countries using two weather parameters. *Engineering Applications of Artificial Intelligence*, 24(5):888–894, 2011. Publisher: Elsevier.
- [159] Tao Cheng and Jiaqiu Wang. Integrated spatio-temporal data mining for forest fire prediction. *Transactions in GIS*, 12(5):591–611, 2008. Publisher: Wiley Online Library.
- [160] MJ Perestrello De Vasconcelos, Sara Silva, Margarlda Tome, Margarlda Alvim, and JM Cardoso Pereira. Spatial prediction of fire ignition probabilities: comparing logistic regression and neural networks. *Photogrammetric engineering and remote sensing*, 67(1):73–81, 2001.
- [161] Mar Bisquert, Eduardo Caselles, Juan Manuel Sánchez, and Vicente Caselles. Application of artificial neural networks and logistic regression to the prediction of forest fire danger in Galicia using MODIS data. *International Journal of Wildland Fire*, 21(8):1025–1029, 2012. Publisher: CSIRO Publishing.
- [162] Yunes Jafari Goldarag, Ali Mohammadzadeh, and AS Ardakani. Fire risk assessment using neural network and logistic regression. *Journal of the Indian Society of Remote Sensing*, 44(6):885–894, 2016. Publisher: Springer.
- [163] Hamed Adab. Landfire hazard assessment in the Caspian Hyrcanian forest ecoregion with the long-term MODIS active fire data. *Natural Hazards*, 87:1807–1825, 2017. Publisher: Springer.
- [164] Alison H Berry, Geoffrey Donovan, and Hayley Hesseln. Prescribed burning costs and the WUI: economic effects in the Pacific Northwest. *Western Journal of Applied Forestry*, 21(2):72–78, 2006. Publisher: Oxford University Press.

- [165] Matthew G Rollins. LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire*, 18(3):235–249, 2009. Publisher: CSIRO Publishing.
- [166] Gregory K Dillon and Julie W Gilbertson-Day. Wildfire Hazard Potential for the United States (270-m), version 2020. 2020.
- [167] Gregory K Dillon, Joe H Scott, Melissa R Jaffe, Julia H Olszewski, Kevin C Vogler, Mark A Finney, Karen C Short, Karin L Riley, Isaac C Grenfell, Matthew W Jolly, and Stuart Brittain. Spatial datasets of probabilistic wildfire risk components for the United States (270m), 2023.
- [168] Gregory K Dillon, James Menakis, and Frank Fay. Wildland fire potential: A tool for assessing wildfire risk and fuels management needs. In *Proceedings of the large wildland fires conference*, pages 60–76, 2014.
- [169] Joe H Scott, Julie W Gilbertson-Day, Christopher Moran, Gregory K Dillon, Karen C Short, and Kevin C Vogler. Wildfire Risk to Communities: Spatial datasets of landscape-wide wildfire risk components for the United States. 2020.
- [170] Matthew P Thompson and Dave E Calkin. Uncertainty and risk in wildland fire management: a review. *Journal of environmental management*, 92(8):1895–1909, 2011. Publisher: Elsevier.
- [171] USDA-NRCS. Geospatial data gateway. 2014. Publisher: Natural Resources Conservation Service Washington, DC.
- [172] Edward R Mansfield and Billy P Helms. Detecting multicollinearity. *The American Statistician*, 36(3a):158–160, 1982. Publisher: Taylor & Francis.
- [173] Richard D De Veaux and Lyle H Ungar. Multicollinearity: A tale of two nonparametric regressions. In *Selecting models from data: artificial intelligence and statistics IV*, pages 393–402. Springer, 1994.

- [174] Aylin Alin. Multicollinearity. *Wiley interdisciplinary reviews: computational statistics*, 2(3):370–374, 2010. Publisher: Wiley Online Library.
- [175] Scott W Menard. *Logistic regression: From introductory to advanced concepts and applications*. Sage, 2010.
- [176] Eric Vittinghoff, David V Glidden, Stephen C Shiboski, Charles E McCulloch, Eric Vittinghoff, David V Glidden, Stephen C Shiboski, and Charles E McCulloch. Predictor selection. *Regression methods in biostatistics: linear, logistic, survival, and repeated measures models*, pages 395–429, 2012. Publisher: Springer.
- [177] Skipper Seabold and Josef Perktold. Statsmodels: Econometric and statistical modeling with python. In *Proceedings of the 9th Python in Science Conference*, volume 57, pages 10–25080. Austin, TX, 2010. Issue: 61.
- [178] Iratxe Nino-Adan, Eva Portillo, Itziar Landa-Torres, and Diana Manjarres. Normalization influence on ANN-based models performance: A new proposal for Features’ contribution analysis. *IEEE Access*, 9:125462–125477, 2021. Publisher: IEEE.
- [179] GOPAL Patro and Kishore Kumar Sahu. Normalization: A preprocessing stage. *arXiv preprint arXiv:1503.06462*, 2015.
- [180] Matthias Feurer and Frank Hutter. Hyperparameter optimization. *Automated machine learning: Methods, systems, challenges*, pages 3–33, 2019. Publisher: Springer International Publishing.
- [181] Michael Egmont-Petersen, Dick de Ridder, and Heinz Handels. Image processing with neural networks—a review. *Pattern recognition*, 35(10):2279–2301, 2002. Publisher: Elsevier.
- [182] Robert Hecht-Nielsen. Theory of the backpropagation neural network. In *Neural networks for perception*, pages 65–93. Elsevier, 1992.

- [183] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.
- [184] James Bergstra and Yoshua Bengio. Random search for hyper-parameter optimization. *Journal of machine learning research*, 13(2), 2012.
- [185] Tom O’Malley, Elie Bursztein, James Long, François Chollet, Haifeng Jin, Luca Invernizzi, and others. Keras Tuner, 2019.
- [186] Zhilu Zhang and Mert Sabuncu. Generalized cross entropy loss for training deep neural networks with noisy labels. *Advances in neural information processing systems*, 31, 2018.
- [187] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
- [188] Christopher M Bishop. *Neural networks for pattern recognition*. Oxford university press, 1995.
- [189] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems, 2015.
- [190] Francois Chollet. *Deep learning with Python*. Simon and Schuster, 2021.

- [191] Kevin Woods and Kevin W Bowyer. Generating ROC curves for artificial neural networks. *IEEE Transactions on medical imaging*, 16(3):329–337, 1997. Publisher: IEEE.
- [192] Alberto Jiménez-Valverde. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species distribution modelling. *Global Ecology and Biogeography*, 21(4):498–507, 2012. Publisher: Wiley Online Library.
- [193] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International conference on machine learning*, pages 1321–1330. PMLR, 2017.
- [194] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, and others. Scikit-learn: Machine learning in Python. *the Journal of machine Learning research*, 12:2825–2830, 2011. Publisher: JMLR. org.
- [195] André Altmann, Laura Toloşi, Oliver Sander, and Thomas Lengauer. Permutation importance: a corrected feature importance measure. *Bioinformatics*, 26(10):1340–1347, 2010. Publisher: Oxford University Press.
- [196] Xuenan Cao and Roozbeh Yousefzadeh. Extrapolation and AI transparency: Why machine learning models should reveal when they make decisions beyond their training. *Big Data & Society*, 10(1):20539517231169731, 2023. Publisher: SAGE Publications Sage UK: London, England.
- [197] Marcos Rodrigues and Juan De la Riva. An insight into machine-learning algorithms to model human-caused wildfire occurrence. *Environmental Modelling & Software*, 57:192–201, 2014. Publisher: Elsevier.

- [198] Bahareh Kalantar, Naonori Ueda, Mohammed O Idrees, Saeid Janizadeh, Kourosh Ahmadi, and Farzin Shabani. Forest fire susceptibility prediction based on machine learning models with resampling algorithms on remote sensing data. *Remote Sensing*, 12(22):3682, 2020. Publisher: MDPI.
- [199] Binh Thai Pham, Abolfazl Jaafari, Mohammadtaghi Avand, Nadhir Al-Ansari, Tran Dinh Du, Hoang Phan Hai Yen, Tran Van Phong, Duy Huu Nguyen, Hiep Van Le, Davood Mafi-Gholami, and others. Performance evaluation of machine learning methods for forest fire modeling and prediction. *Symmetry*, 12(6):1022, 2020. Publisher: MDPI.
- [200] U.S. Department of Agriculture. Wildfire Crisis Strategy: Confronting the Wildfire Crisis. Technical report, U.S. Department of Agriculture, Forest Service, Washington, D.C., 2022.
- [201] David M Theobald and William H Romme. Expansion of the US wildland–urban interface. *Landscape and Urban Planning*, 83(4):340–354, 2007. Publisher: Elsevier.
- [202] John R Weir, Urs P Kreuter, Carissa L Wonkka, Dirac Twidwell, Dianne A Stroman, Morgan Russell, and Charles A Taylor. Liability and prescribed fire: Perception and reality. *Rangeland Ecology & Management*, 72(3):533–538, 2019. Publisher: Elsevier.
- [203] Jessica R Haas, David E Calkin, and Matthew P Thompson. Wildfire risk transmission in the Colorado Front Range, USA. *Risk analysis*, 35(2):226–240, 2015. Publisher: Wiley Online Library.
- [204] U.S. Department of Agriculture. Black Diamond Landscape Resiliency and Risk Reduction Project. Technical report, U.S. Forest Service, 2023.
- [205] Elizabeth L Kalies and Larissa L Yocom Kent. Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. *Forest Ecology and Management*, 375:84–95, 2016. Publisher: Elsevier.

- [206] USDA–USDI. A report to the President in response to the wildfires of 2000. Technical report, 2000.
- [207] U.S. Congress. Healthy Forest Restoration Act of 2003, 2003.
- [208] U.S. Congress. Infrastructure Investment and Jobs Act, 2021.
- [209] James K Agee. The fallacy of passive management managing for firesafe forest reserves. *Conservation in Practice*, 3(1):18–26, 2002. Publisher: Wiley Online Library.
- [210] David E Calkin, Crystal S Stonesifer, Matthew P Thompson, and Charles W McHugh. Large airtanker use and outcomes in suppressing wildland fires in the United States. *International Journal of Wildland Fire*, 23(2):259–271, 2014. Publisher: CSIRO Publishing.
- [211] U.S. Department of Agriculture, Forest Service. Aerial Firefighting Use and Effectiveness (AFUE) Report. Technical report, U.S. Department of Agriculture, Washington, D.C., March 2020.
- [212] Crystal S Stonesifer, David E Calkin, Matthew P Thompson, and Jeffrey D Kaiden. Developing an aviation exposure index to inform risk-based fire management decisions. *Journal of Forestry*, 112(6):581–590, 2014. Publisher: Oxford University Press Oxford, UK.
- [213] Crystal S Stonesifer, David E Calkin, Matthew P Thompson, and Keith D Stockmann. Fighting fire in the heat of the day: an analysis of operational and environmental conditions of use for large airtankers in United States fire suppression. *International Journal of Wildland Fire*, 25(5):520–533, 2016. Publisher: CSIRO Publishing.
- [214] Junzi Sun, Huy Vũ, Xavier Olive, and Jacco M Hoekstra. Mode S transponder comm-B capabilities in current operational aircraft. In *Proceedings*, volume 59, page 4. MDPI, 2020. Issue: 1.

- [215] Simon Richard Proud. Go-around detection using crowd-sourced ADS-B position data. *Aerospace*, 7(2):16, 2020. Publisher: MDPI.
- [216] Zhongrui Xu, Xiaoguang Lu, and Zhe Zhang. Aircraft go-around detection employing open source ADS-B data. In *2021 IEEE 3rd International Conference on Civil Aviation Safety and Information Technology (ICCASIT)*, pages 259–262. IEEE, 2021.
- [217] USDA Forest Service. Standards for Airtanker Operations. 2019.
- [218] M Vijaya Kumar, SN Omkar, Ranjan Ganguli, Prasad Sampath, and S Suresh. Identification of helicopter dynamics using recurrent neural networks and flight data. *Journal of the American Helicopter Society*, 51(2):164–174, 2006. Publisher: Vertical Flight Society.
- [219] Anvardh Nanduri and Lance Sherry. Anomaly detection in aircraft data using Recurrent Neural Networks (RNN). In *2016 Integrated Communications Navigation and Surveillance (ICNS)*, pages 5C2–1. Ieee, 2016.
- [220] Junzi Sun, Huy Vũ, Joost Ellerbroek, and Jacco M Hoekstra. pymodes: Decoding mode-s surveillance data for open air transportation research. *IEEE Transactions on Intelligent Transportation Systems*, 21(7):2777–2786, 2019. Publisher: IEEE.
- [221] Junzi Sun and Jacco M Hoekstra. Integrating pyModeS and OpenSky Historical Database. In *OpenSky*, pages 63–72, 2019.
- [222] Noel Gorelick, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote sensing of Environment*, 202:18–27, 2017. Publisher: Elsevier.
- [223] Matthias Schafer, Martin Strohmeier, Matthew Smith, Markus Fuchs, Rui Pinheiro, Vincent Lenders, and Ivan Martinovic. OpenSky report 2016: Facts and figures on SSR mode S and ADS-B usage. In *2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC)*, pages 1–9. IEEE, 2016.

- [224] Matthew P Thompson, David E Calkin, Jason Herynk, Charles W McHugh, and Karen C Short. Airtankers and wildfire management in the US Forest Service: examining data availability and exploring usage and cost trends. *International Journal of Wildland Fire*, 22(2):223–233, 2012. Publisher: CSIRO Publishing.
- [225] National Interagency Coordination Center (NICC). *National Interagency Mobilization Guide*. National Interagency Fire Center, Boise, ID, 2023 edition, March 2023.
- [226] Thomas W Porter, Wade Crowfoot, and Gavin Newsom. Wildfire Activity Statistics. *California Department of Forestry and Fire Protection: Sacramento, CA, USA*, page 46, 2020.
- [227] NASA JPL. NASADEM Merged DEM Global 1 arc-second V001 [Data set], 2020. Published: NASA Land Processes Distributed Active Archive Center.
- [228] Martin Strohmeier, Xavier Olive, Jannis Lübke, Matthias Schäfer, and Vincent Lenders. Crowdsourced air traffic data from the OpenSky Network 2019–2020. *Earth System Science Data*, 13(2):357–366, 2021. Publisher: Copernicus Publications Göttingen, Germany.
- [229] Karen C Short. Spatial wildfire occurrence data for the United States, 1992-2020 [FPA_fod_20221014]. 2022.
- [230] Congressional Research Service. Federal Interagency Wildfire Response Framework. Technical Report IF12384, Library of Congress, 2023.
- [231] Odd O Aalen and Søren Johansen. An empirical transition matrix for non-homogeneous Markov chains based on censored observations. *Scandinavian journal of statistics*, pages 141–150, 1978. Publisher: JSTOR.
- [232] David R Cox. Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, 34(2):187–202, 1972. Publisher: Wiley Online Library.

- [233] Norman Breslow. Covariance analysis of censored survival data. *Biometrics*, pages 89–99, 1974. Publisher: JSTOR.
- [234] David Schoenfeld. Partial residuals for the proportional hazards regression model. *Biometrika*, 69(1):239–241, 1982. Publisher: Oxford University Press.
- [235] Matthew P Thompson, Christopher J Lauer, David E Calkin, Jon D Rieck, Crystal S Stonesifer, and Michael S Hand. Wildfire response performance measurement: current and future directions. *Fire*, 1(2):21, 2018. Publisher: MDPI.
- [236] K. Reinke, S. Jones, S. Ramsey, and N. Trihantoro. Utility of Himawari-8 Observations to Explore Aerial Suppression Activities. Research Report, CSIRO and Bushfire and Natural Hazards CRC, Melbourne, 2021.
- [237] Yavar Pourmohamad, John T Abatzoglou, Erin J Belval, Erica Fleishman, Karen Short, Matthew C Reeves, Nicholas Nauslar, Philip E Higuera, Eric Henderson, Sawyer Ball, and others. Physical, social, and biological attributes for improved understanding and prediction of wildfires: FPA FOD-attributes dataset. *Earth System Science Data Discussions*, 2023:1–29, 2023. Publisher: Göttingen, Germany.
- [238] Robert E Burgan. *Using NDVI to assess departure from average greenness and its relation to fire business*, volume 333. US Department of Agriculture, Forest Service, Intermountain Research Station, 1996.
- [239] Emilio Chuvieco, David Cocero, David Riano, Pilar Martin, Javier Martinez-Vega, Juan De La Riva, and Fernando Pérez. Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sensing of Environment*, 92(3):322–331, 2004. Publisher: Elsevier.
- [240] Bennett Sall, Michael W. Jenkins, and James Pushnik. Retrospective analysis of two northern California wild-land fires via Landsat five satellite imagery and Normal-

- ized Difference Vegetation Index (NDVI). *Open Journal of Ecology*, 3(4):311–323, 2013.
- [241] Patricia L Andrews, Don O Loftsgaarden, and Larry S Bradshaw. Evaluation of fire danger rating indexes using logistic regression and percentile analysis. *International Journal of Wildland Fire*, 12(2):213–226, 2003. Publisher: CSIRO Publishing.
- [242] W Matt Jolly, Patrick H Freeborn, Larry S Bradshaw, Jon Wallace, and Stuart Brittain. Modernizing the US National Fire Danger Rating System (version 4): Simplified fuel models and improved live and dead fuel moisture calculations. *Environmental Modelling & Software*, 181:106181, 2024. Publisher: Elsevier.
- [243] Richard C Rothermel. *Modeling moisture content of fine dead wildland fuels: input to the BEHAVE fire prediction system*. Number 359. United States Department of Agriculture, Forest Service, Intermountain ..., 1986.
- [244] Melanie Wheatley, B Mike Wotton, Douglas G Woolford, David L Martell, and Joshua M Johnston. Modelling decisions concerning the dispatch of airtankers for initial attack on forest fires in Ontario, Canada. *Canadian Journal of Forest Research*, 53(4):217–233, 2022. Publisher: Canadian Science Publishing 1840 Woodward Drive, Suite 1, Ottawa, ON K2C 0P7.
- [245] Wesley G Page and Bret W Butler. Fuel and topographic influences on wildland firefighter turnover fatalities in Southern California. *International journal of wildland fire*, 27(3):141–154, 2018. Publisher: CSIRO Publishing.
- [246] John T Abatzoglou. Development of gridded surface meteorological data for ecological applications and modelling. *International journal of climatology*, 33(1):121–131, 2013. Publisher: John Wiley & Sons, Ltd. Chichester, UK.
- [247] Heather Simpson, Michael Storey, Matt Plucinski, and Owen Price. Investigating the suitability of aviation tracking data for use in bushfire suppression effective-

- ness research – Black Summer final report. Technical Report 725.2022, Bushfire and Natural Hazards CRC, 2022.
- [248] Matt Plucinski. Review of aerial suppression effectiveness research literature. 2025.
- [249] Eric Vermote. NOAA climate data record (CDR) of AVHRR normalized difference vegetation index (NDVI), version 5. *NOAA National Centers for Environmental Information*, 10:V5ZG6QH9, 2019.
- [250] California Department of Fish and Wildlife. California Lakes, 2025.
- [251] Christina M Kennedy, James R Oakleaf, David M Theobald, Sharon Baruch-Mordo, and Joseph Kiesecker. Managing the middle: A shift in conservation priorities based on the global human modification gradient. *Global change biology*, 25(3):811–826, 2019. Publisher: Wiley Online Library.
- [252] WorldPop and CIESIN. Global high-resolution population density (1\,km) – UN adjusted: United States of America, 2020, 2018.
- [253] Patricia M Grambsch and Terry M Therneau. Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, 81(3):515–526, 1994. Publisher: Oxford University Press.
- [254] Mary A Taber, Lisa M Elenz, and Paul G Langowski. Decision making for wildfires: A guide for applying a risk management process at the incident level. *Gen. Tech. Rep. RMRS-GTR-298WWW. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 59 p., 298, 2013.*
- [255] Stephen D Fillmore, Sarah McCaffrey, Rachel Bean, Alexander M Evans, Jose Iniguez, Andrea Thode, Alistair MS Smith, and Matthew P Thompson. Factors influencing wildfire management decisions after the 2009 US federal policy update. *International journal of wildland fire*, 33(1), 2024. Publisher: CSIRO Publishing.

- [256] Liam Fogarty and Alen Slijepcevic. The influence of wind speed on the effectiveness of aerial fire suppression. *Fire Technology Transfer Note*, (17), 1998.
- [257] Edward G Keating, Andrew R Morral, Carter C Price, Dulani Woods, Daniel M Norton, Christina Panis, Evan Saltzman, and Ricardo Sanchez. *Air attack against wildfires: understanding US Forest Service requirements for large aircraft*. Rand Corporation, 2012.
- [258] Joe R McNorton and Francesca Di Giuseppe. A global fuel characteristic model and dataset for wildfire prediction. *Biogeosciences*, 21(1):279–300, 2024. Publisher: Copernicus Publications Göttingen, Germany.
- [259] Pedro Belavenutti, Alan A Ager, Michelle A Day, and Woodam Chung. Designing forest restoration projects to optimize the application of broadcast burning. *Ecological Economics*, 201:107558, 2022. Publisher: Elsevier.
- [260] Jude Bayham and Jonathan K Yoder. Resource allocation under fire. *Land Economics*, 96(1):92–110, 2020. Publisher: University of Wisconsin Press.
- [261] Jude Bayham and Calvin Bryan. The Economics of Wildland Firefighting Aviation Procurement and Effectiveness. In *Western Economics Forum*, volume 21, pages 43–52, 2023. Issue: 2.