ASSESSING THE IMPACT OF LARGE FIRES, PROPERTY LOSS AND SIX CLIMATIC VARIABLES ON WILDFIRE SUPPRESSION COST AND A COMPREHENSIVE STUDY

by

NASIR QADIR

(Under the Direction of Bruno Kanieski Da Silva)

ABSTRACT

In the United States, wildfires have grown significantly in the past three decades. Therefore, wildfire management agencies like the United States Forest Service (USFS) are spending more to manage these fires. This study conducted a comprehensive review and used time series analysis to investigate: (1) the variables associated with increased suppression costs and (2) the seasonal trends of suppression costs and the influence of climatic and socio-environmental variables, in order to capture and understand the complex dependencies within the climatic and socio-environmental variables and suppression expenditures. However, a comprehensive review indicated that large fires (LF) and WPL (Wildfire Property Loss) have a positive correlation and the suppression expenditure, Niño 3.4 SST, NAO, and LF indicate seasonality. A positive dependency was observed between LF and SOI with suppression expenditure for USFS. This study suggests modeling suppression expenditure on the appropriate temporal scale to predict and understand different variables' impacts on expenditure.

INDEX WORDS: wildfires, suppression costs, socio-environmental loss, climate change, time series

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DEDICATION

I dedicate this thesis to my Family.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Wildfire occurrences have risen in forest and hardwood land vegetation during the early 20th century (Singleton et al., 2019). The rise in fuel load can be attributed to climate change, human intervention, and changes in land use (Olson et al., 2023). In 2021, a total of 58,900 thousand fires burned 7.1 million acres of land in the United States, resulting in a significant suppression expenditure of $4.3 billion. The fires resulted in a total of 4.3 thousand deaths and 12.4 thousand injuries. In the last decade, there has been a notable rise of 17.9% in the death rate resulting from fires. The U.S. Fire Administration has stated that a total of 353.5 thousand residential buildings and 116.5 thousand non-residential buildings were damaged in 2021 (NIFC, 2023a).

This study contributes to the current body of literature in many ways: (1) I have reviewed the current literature about wildfire suppression cost and investigated which climatic and socio-environmental variables effect on suppression costs; (2) I used monthly time series data to capture the seasonality as well as possible non-linear relationships.

This research has two chapters: (1) The second chapter includes a literature review on wildfire suppression from 1985 to 2022, as I have available nominal annual suppression cost data for the USFS and its regions. The main purpose of this chapter is to review the existing literature and investigate which socio-environmental variables affect the suppression costs, and (2) The goal of the third chapter is to find the seasonality and non-linear impact of multiple climatic and socio-environmental variables on suppression costs between 2005 and 2022 for the USFS and its regions (2005-2020).

CHAPTER 2

A SYSTEMATIC RVIEW OF WILDFIRE SUPPRESSION COST MANAGEMENT: A MODERN APPROACH[1]

[2]Qadir, N., Kanieski Da Silva, B., Abrams, J.B., Grala, R.K. To be submitted to Wildland Fire

Abstract

In the past two decades, the scale of the area consumed and suppression expenses by wildland fires have increased significantly. According to the National Interagency Fire Center (NIFC), the amount of suppression cost was $239 million in the year 1985, and in 2021, it increased to $4.389 billion. In addition to the monetary impact on public and private stakeholders' budgets, wildfires in 2021 resulted in an estimated 48 deaths (NCWLIFE, 2021) and caused significant environmental damage, including increased pollution due to the release of volatile and semi-volatile organic materials and nitrogen oxides as well as soil erosion from the loss of vegetation cover and soil heating, and impacts on biodiversity through habitat alteration or destruction, reductions in species diversity, and changes to ecosystem processes. The goal of this chapter was to systematically identify the variables causing the increase in wildfire suppression costs between 1985 and 2023. By conducting a rigorous evaluation of the available literature, this systematic review identifies gaps in knowledge and provides insights that can inform future research and policy decisions related to wildfire management and fire suppression costs. I used Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and used Google Scholar as the primary tool for collecting articles. After the initial screening of the articles, I investigated 166 scientific papers that mention wildfire and suppression cost/fire suppression cost in their abstract, text, keywords, or title. I gathered information about wildfire trends, the total area burned, and the total suppression expenditure in the United States to create a more reliable control system by determining the causes of the inconsistencies in the literature. I also gathered information about recent advances in terms of wildfire control and identified how it can empower firefighting agencies to plan better operations and actions. This paper identifies critical research gaps in the literature on wildfire and fire suppression costs, highlighting the need for further research to gain

insight into the long-term economic impacts of fires on local economies, timber values, policy, and ecosystem services.

Introduction

In the last few decades, wildfires have become increasingly frequent and have caused devasting damages in the US and other parts of the globe (Gao et al., 2023; Moody et al., 2013; Thapa et al., 2023a). The rise in those fires in recent years is attributed to the increased interface of urban wildlands, droughts, and climate change (Papadopoulos and Pavlidou 2011; Slavkovikj et al. 2014).

The damages of current wildfires are visible in various parts of the world, with events like the bushfires in Texas (2011), bushfires in Victoria State, Australia (2009), and wildfires in the area of Spain that is called Costa Del Sol (2012) (Slavkovikj et al., 2014). The occurrence of wildland -fires has been increasing at an annual rate of 3% across the western US, resulting in more severe, and larger burns (number of acres) compared to history (Liz Kimbrough 2022), extending to the Southwestern US, where the area burned has also expanded (Calkin et al., 2005; J. D. Miller et al., 2009a). However, more concerning is that a larger proportion of these fires have been burning with high intensity and societal impact (Dillon et al., 2011b).

These wildfires have significant consequences on forest regeneration, and ecosystem services across the United States (Thapa et al., 2023a). Some ecosystems, including those adapted to fire, rely on regular burns to maintain their health and promote regeneration (Kimmerer Robin Wall & Lake Frank Kanawha, 2001). However, the increasing severity of wildfires in the western United States is leading to extensive destruction of lands, infrastructure, and homes, and the degradation of ecological values (Ager et al., 2014a; J. Williams, 2013).

According to U.S. government statistical data, the United States faced significant fire-related challenges in 2021. There were 4,818 structures burned and a total suppression cost was $4.3 billion (NCWLIFE, 2021; NIFC, 2023b). The common reasons for forest fires in residential areas are associated with individual activities like campfires left unattended, the burning of waste, and tools use or malfunction that intentionally or accidentally caused the forest fires (San-Miguel-Ayanz, 2012).

Despite the variation in these fire statistics, one alarming trend stands out, that is the number of fire-related deaths per million. These statistics show an 18% increase over the past few decades, indicating a concerning lack of a consistent downward trend. In fire-related incidents a total of 13.0 persons per million lost their lives in 2021, marking a distressing peak. The previous year, 2020, also saw a 14% increase, with 11.4 deaths per million people. The increasing number of fire-related deaths in 2021 demands the attention of both authorities and the public (U.S. Fire Administration (FEMA), 2022). However, it is not just the number that is concerning, it is the broader impact on ecosystems, human lives, and society. Wildfires are among the most challenging issues facing natural and planted forests, urban infrastructure, and the well-being of communities (A.E. Cetin et al., 2013; Stipaničev et al., 2010).

These fires also pose a significant financial burden placed on governments, firefighting organizations, and impacted communities. The suppression-cost wildfires in the United States have been steadily rising, driven by both an increase in the number of incidents and severity (Ingalsbee, 2010). These challenges necessitate the allocation of more resources and advanced technology for effective firefighting efforts, making resource management a constant challenge for firefighting agencies. Due to the increasing frequency of wildfires, it is imperative to prioritize allocating resources to areas in the greatest danger. Policies for managing wildfires are crucial for preventing, reducing, and responding to these disasters. The wildland-urban Interface, where human life takes precedence, poses difficulties in wildfire control (National Academy of Public Administration, 2002). These places have a higher risk of wildfires affecting homes and infrastructure, necessitating substantial efforts in both suppression and prevention (Haas et al., 2013a).

This paper aims to identify the impact and causes of wildfires and the suppression expenditure spending on them. I use the systematic review technique PRISMA (Preferred Reporting Item for Systematic Reviews and Meta-Analysis) method. Our findings demonstrate that human-caused fires and natural fires both are significantly responsible for increasing suppression spending. This paper is organised as follows: (1) a review of the most recent studies on wildfires and suppression costs, (2) a discussion about the correlation between different variables, (3) an introduction of new fire-detecting techniques, (3) conclusion and potential pathways for future research.

Methodology

In this section, I present the focus and methodology employed in our research. This paper concentrates on peer-reviewed articles and reports starting from 1985 to 2023, reaching into the analysis of wildfire suppression costs. I employed a mixed approach in the review including a systematic literature review, and Pearson correlation coefficient to assess the relationships between the variable “time”, “large fires” and “wildland-urban Interface”, keywords co-occurrence analysis to obtain the cluster, and created a map by using the visualization of similarities (VOSviewer v.1.6.17) for the bibliometric study.

A literature review takes a qualitative approach and explores the methods and findings of the studies to provide a deep understanding of them. On the other hand, keyword analysis creates quantifiable relationships between papers and Pearson correlation coefficients identify the relationship between different variables.

Literature Search

We started with a comprehensive understanding of the first step outlined in the PRISMA 2020 guidelines (Rethlefsen et al., 2021) for the literature search. I followed the PRISMA protocol for the literature search and employed qualitative analysis. The descriptive variables (Table 1) and significant phase were involved in the preparation of keywords and database searches to retrieve relevant articles.

We scoured various scientific databases, including Web of Science, Scopus, and Google Scholar. Employing a strategic approach, I carefully selected key works such as "wildfires," "wildfire suppression," "suppression expenses," "suppression expenditure," and "wildland fires." In addition, I combined these keywords as follows: (i) ("fire" OR "wildfire" AND (suppression) (ii) ("expenditure" OR "costs*" OR "expenses"). Our diligent efforts resulted in the collection of 456 unique articles, integrating search results from the various databases.

Screening Procedure

In this section, I detail the two-stage screening procedure implemented to identify papers that contributed to the existing knowledge on wildfire suppression costs, with a particular focus on suggested formulations and solution approaches (Fig. 1). During the screening process, I strictly adhered to specific inclusion and exclusion criteria to ensure the relevance of selected papers. The criteria included: The paper's primary focus must be on wildfires and suppression costs.

In the initial screening, I scrutinized titles to eliminate duplicate papers, resulting in the removal of 48 duplicate papers. This initial screening returned a selection of 408 papers. Subsequently, I conducted a comprehensive review of titles, abstracts, and keywords to assess their suitability for our study. This rigorous screening procedure led to the exclusion of 242 papers that did not align with the focus of our research. Consequently, I arrived at a final selection of 166 papers.

Table 1. 1. Descriptive variables analysis

Variables	**Classifications**	**Explanation**	**Categories**
Journal	Continuous text	All the journals which publish the articles	Open
Title	Continuous text	Entire Headline	Open
Location	Discrete variable	Study area	USA
Year	Discrete variable	Date of Publication	1985 - 2023
Where	Discrete variable	Where the word wildfire and suppression costs appear.	Title Abstract Keywords
Contribution of paper	Discrete variable	The involvement of the article in terms of theories, new suggestions and especially in methodology.	Hypothetical Methodological Experimental
Major Research methods	Discrete variable	In the study which methodology was used. That helps us to understand the main objective and practical involvement in scientific research.	Case analysis Data analysis Observational Questionnaire

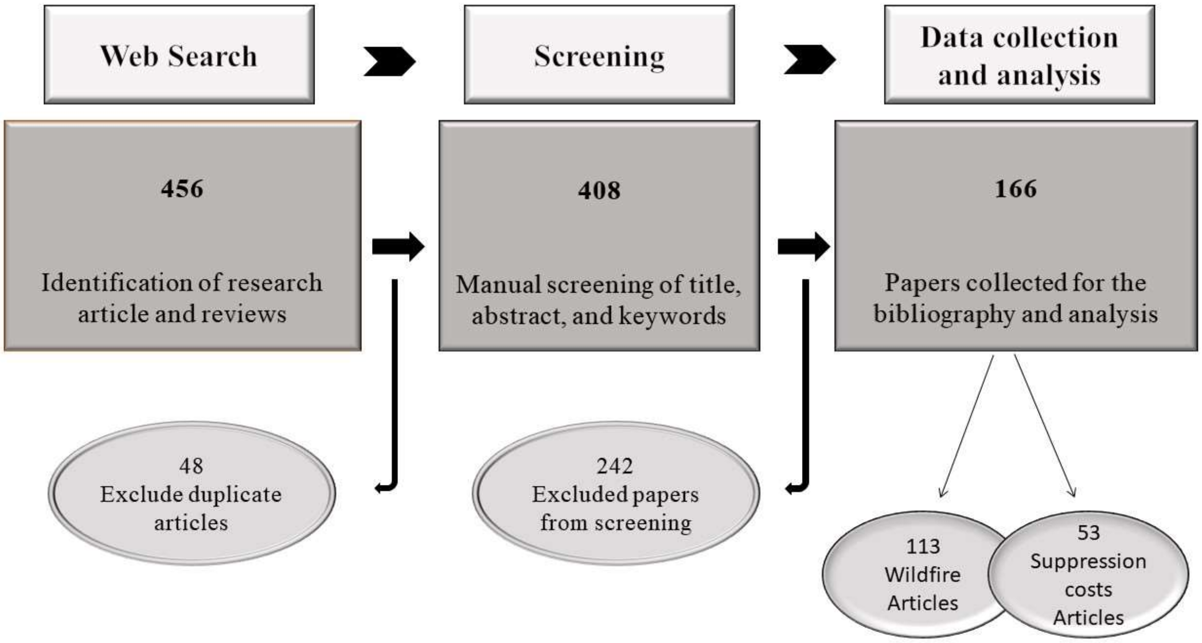

Figure 1. 1. The procedure of paper collection. Web Search: Google Scholar, Scopus, Web of Science

Results

Comprehensive Analysis of Articles

We gathered 166 articles, all published between 1985 and 2023, for detailed examination. Our analysis also encompassed a study of the publication trends over 33 years, as depicted in Figure 1.2, highlighting a consistent level of research output in this field.

We found that 3 journals contributed 10 or more papers to our review (Fig. 1.3). It is important to note that, although our literature search or filtering procedure was not limited to specific journals, all the journals focused on the subject matter. The three most popular journals in our study are the International Journal of Wildland Fire, Forest Ecology and Management, and the Journal of Forestry.

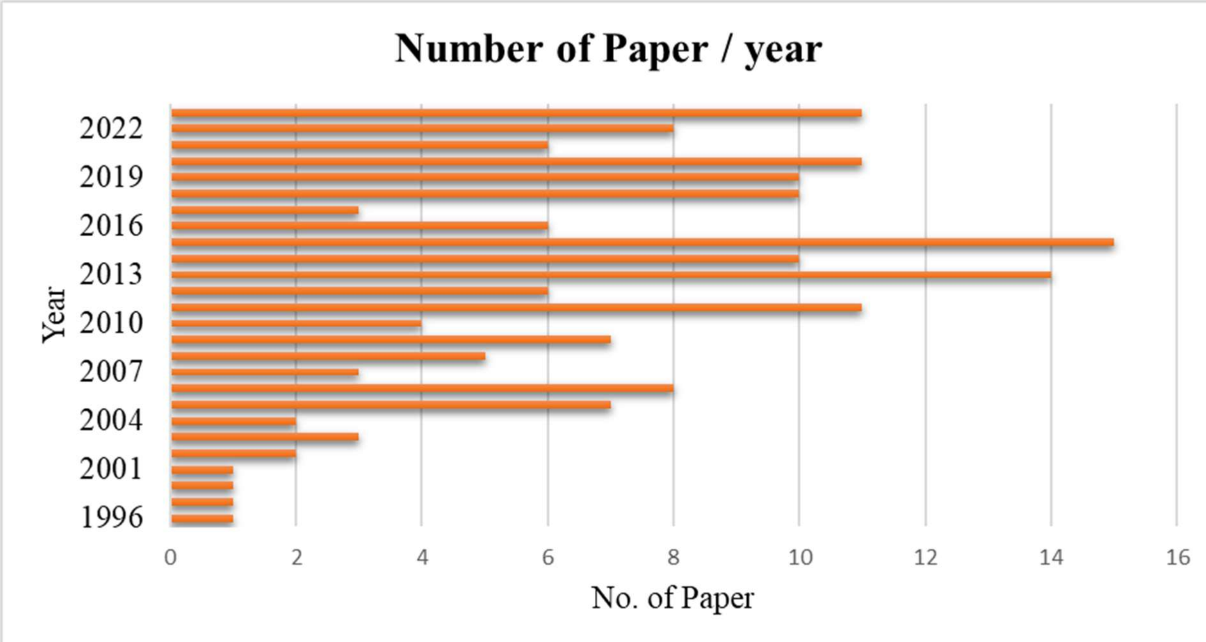

Figure 1. 2. Quantitative analysis and decade by decade exploration of annual paper collection trends: Uncovering patterns and evolution in research output over time.

Keywords Co-occurrence Cluster Results

This part is devoted to an author-keywords co-occurrence network analysis, which includes a thorough examination of keyword co-occurrence via a comprehensive evaluation of the literature. I first defined the minimal number of relationships inside author keywords co-occurrence. I created a map with 4 different clusters using VOSviewer (Fig. 4).

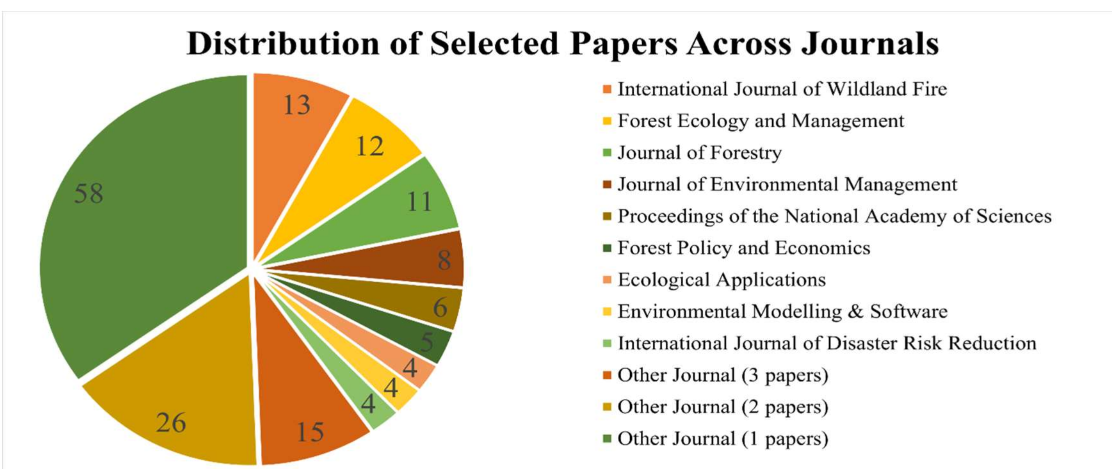

Figure 1. 3. Number of Top Journals that were Recognized in Our Literature Collection.

Keywords Co-occurrence Cluster Results

This part is devoted to an author-keywords co-occurrence network analysis, which includes a thorough examination of keyword co-occurrence via a comprehensive evaluation of the literature. I first defined the minimal number of relationships inside author keywords co-occurrence. I created a map with 4 different clusters using VOSviewer (Fig. 1.4). The importance of this cluster analysis lies in its ability to provide a comprehensive overview of the existing literature. This could help find new trends, areas that need to be focused on for future research, and gaps in the current literature.

Red Cluster: There are four author keywords in this cluster, including wildfire, wildfire suppression, burn severity, fire behavior, fire severity, fire effect, and climate change. These keywords belong to the articles of Thapa, Jenkins, and Westerling (2023b), Fitch et al. (2018a), Stasiewicz and Paveglio (2022), Bayham et al. (2022), Cardil et al. (2021), J. D. Miller et al. (2009b), Riley et al. (2018), Michaletz and Johnson (2007), Flannigan et al. (2006).

Yellow Cluster: his cluster includes two keyword terms such as wildfire risk and burn probability. These keywords can be seen in these articles (C. Miller & Ager, 2013), (Ager et al., 2014b),

Blue Cluster: In this cluster, there are three keywords, including wildfire management, suppression cost, and risk assessment. The articles include the above keywords Mattioli et al. (2022), Prestemon, Abt, and Gebert (2008a), Thompson et al. (2013a), (Calkin et al., 2014), S. Zhou and Erdogan (2019a).

Green Cluster: It includes the following four author keywords wildland fire, forest economics, wildland-urban Interface, and optimization. These terms can be found in the following articles

Haas, Calkin, and Thompson (2013b), Finney (2005), Kennedy and Johnson (2014), Thompson et al. (2017a), Gebert and Black (2012a), Gude et al. (2013a).

Overall, this cluster analysis provides a broad summary of the key themes and research areas in the wildfire suppression costs literature, with an emphasis on the multidisciplinary nature of wildfire research and the importance of accounting for a variety of variables in the wildfire management plan, such as risk assessment, economic considerations, and climate change.

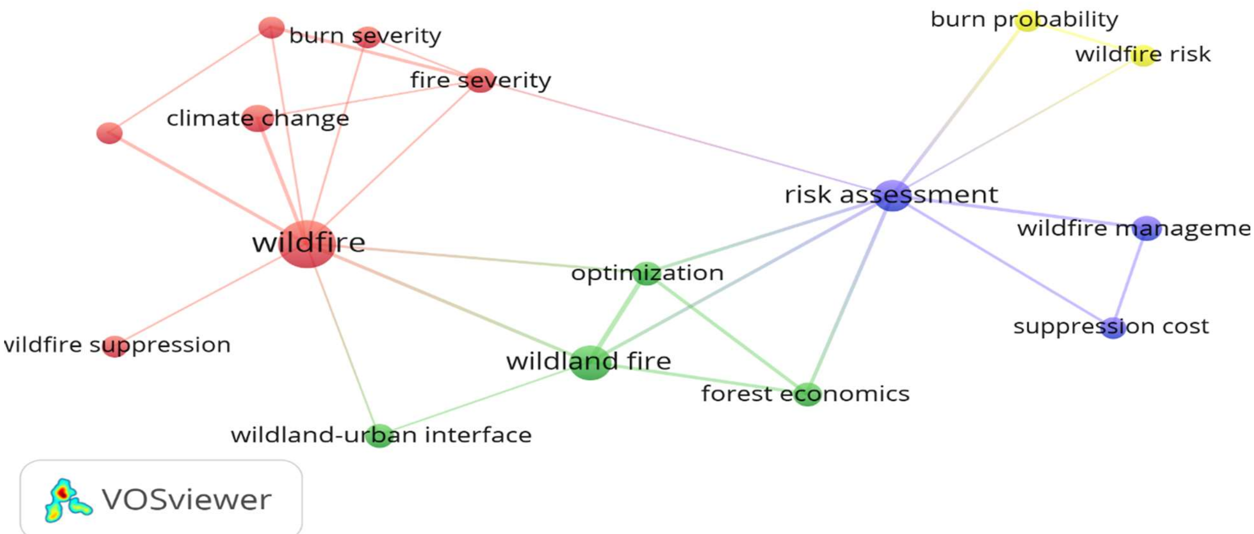

Figure 1. 4. keywords co-occurrence VOSviewer map

Results of Historical Analysis

According to twentieth-century history studies, Native Americans, used fire as an intentional method to control landscapes throughout the Inland Northwest. It was claimed that fire was the most essential weapon available to them for altering natural settings in order to enhance food supply (Pyne, 1982; White, 1991). Barrett, (1980) asserted that the Native American habit of employing fire to increase subsistence gathering exhibited a high level of technical skill. This was reinforced by tree-ring fire chronologies, which revealed that fires were intentionally started during specific seasons and with fuel that allowed for low-intensity burns, optimizing their beneficial benefits.

Fire regimes are influenced by Native American burning, which is a place-specific ecology. In other words, Native Americans torched the areas where it suited them and allowed them to do so successfully (Clar, 1959). The use of fire by Native Americans to preserve huckleberry crops and adjacent woodlands, particularly subalpine glades, has been identified in several sites. In the Washington Cascades, the slopes of Mount Adams are one example. However, it appears that these are well-known and rare situations (French, 1999).

Native Americans practiced an early form of agriculture that involved the intentional burning of dry grasslands and woods in order to cultivate a large number of plants. They used fire to suppress certain plant species while fostering the development, fruiting, and proliferation of others (Hessburg & Agee, 2003).

Frequent burning could have prevented the growth and domination of shade-resilient tree species like Douglas-fir, white fir, and grand fir, while preserving fire-resilient, early seral species like ponderosa pine and western larch tree (hessburg et al., 1999). It is unable to identify individual impacts on changes in vegetation cover because of the combined effects of stopped Native American burning, fire suppression, animal grazing, and selective cutting, which have produced identical successional trajectories and outcomes. The ponderosa pine forest and juniper woodland have grown more rapidly as a result of the lack of fire. Ecosystems where ponderosa pine was the predominant early seral species, it is expected that the main consequence of fire exclusion was to increase tree evenness or decrease tree clumping, leading to enhanced overall tree density within area covers (Harrod et al., 1999).

In the western United States suppression efforts are failing to contain severe flames leading to extensive destruction of lands, infrastructure, and homes, and the degradation of ecological values (Ager et al., 2014a; J. Williams, 2013). A financial burden has been placed on governments, firefighting organizations, and impacted communities as the expense of suppressing wildfires has increased in the United States (Ingalsbee, 2010).

In 1908, the United States Congress passed the Forest Fires Emergency Act (Pyne, 2017). After three years of operation, the United States Forest Service (USFS), allowed local governments to help cover the costs of wildfire suppression management when there was a deficit (ask help to cover the suppression costs) (Ingalsbee & Raja, 2015). This decision, through the Forest Fires Emergency (FFE) Act, unexpectedly disrupted local plans as it merged suppression strategies with standard financial plans for the local government (Dombeck et al., 2004).

By the 1910 fires, the USFS (United States Forest Service) had spent over $1 million for the first time. In the 20th century, annual suppression costs escalated from $1 million to over $1 billion, leading to an increase in the daily suppression cost for large fires (Economics, 2009). The mid-1990s saw numerous proposals aimed at enhancing liability and cost-containment strategies (Schuster, 1997). In recent years, the rising cost suppression has become a central concern, extensively discussed in research publications and management reports (Krista M. Gebert et al., 2008).

Since the mid-1980s in the United States, the suppression expenditure of forest fires has been on the rise (Prestemon et al., 2008b). Holmes, Huggett, and Westerling (2008) reported that 94% of suppression expenditure from 1980 to 2002 was dedicated to controlling fires on national forest land. Reducing suppression expenditure has gained significant public attention in the United States (Abt L. Karen et al., 2009). Over the past two decades, the frequency and duration of wildfires, as well as suppression expenses and burned areas, have increased (Donovan et al., 2011). The substantial increase in the area destroyed by forest fires can be attributed to factors such as soil temperature, drought, snowmelt, and fuel expansion, all linked to prior suppression efforts (Westerling et al., 2006).

In recent years, between 1999 to 2010, the federal government allocated over $16 billion to control wildfires, but during this time, 1179 homes were still consumed by fire (Gude et al., 2013b). The United States observed suppression costs exceeding $1 billion in the years 2002, 2006, 2007, 2008, and 2012. Between 2010 and 2013, suppression costs increased by approximately $2 billion annually (NIFC, 2014). According to the Independent Large Wildfire Cost Panel 2007, in 2006, the largest forest fire occurred, burning a total area of 9.99 million acres nationwide. In Northern California, the United States Forest Services allocated over 30% of the nationwide budget to control the two lightning-caused fires, highlighting the significant costs associated with major fires (Ingalsbee & Raja, 2015). During the years 1995 to 2004, California experienced an average suppression cost of $420 per acre (North et al., 2012).

In 2017, the California Fire Protection Department reported over 250 forest fires across 43 different areas, displaced more than 100,000 people, and damaged more than 1300 buildings (Ertugrul Mustafa et al., 2021; Stockmann et al., 2010). These fires engaged 245,000 acres burned and around 11,000 firefighters, resulting in over-suppression expenditures. Remarkably, a majority of forest fires can be controlled with varying suppression efforts, highlighting the disparity between major fires and smaller incidents (Calkin et al., 2014). Research has shown that a mere 1% of major fires are responsible for 83%-96% of the lands burned (David E. Calkin, 2005).

In recent years, wildfires have posed a serious threat to people and animals residing near the urban-wildland boundary (Zhou and Erdogan 2019). The challenge of wildfire control has become increasingly daunting, with annual occurrences worldwide (T. Zhou et al., 2020). Despite substantial financial investments, achieving full control remains elusive (Yan, 2017).

Countries like Portugal, Australia, and the United States are now at higher risk from WPL (Wildland-urban Interface) fires compared to previous times (Stephens et al., 2009). The expansion of the urban-wildland Interface (UWI) has significantly contributed to the rapid increase in suppression expenditure (Gorte 2013; Gebert, Calkin, and Yoder 2007). To protect lands and homes threatened by wildfires, communities and policies often exert pressure on fire officers. In the Private lands (not under federal jurisdiction) the cost of suppressing wildfires sometimes higher than the economic value of those lands, which means that the expenses incurred in fighting fires on these private lands may outweigh the potential or profits that could be gained from those lands (Hesseln, 2001). However, the fire in both North and South California in 2017 resulted in losses exceeding $10 billion (Liang et al., 2008).

Pearson Correlation Results

A comprehensive analysis of the articles indicates a significant pattern in the discussion of suppression costs and their relationship with the large fires and wildland-urban Interface (WPL). I employed correlation analysis to examine the trend in the number of research articles over time, aiming to determine if there has been an increase related to the wildland-urban Interface (WPL) and large fires research articles over time. The analysis was based on the different years that the authors mentioned in the articles, which indicated that WPL and large fires were the causes that increased the suppression costs. Our results showed a strong positive correlation of coefficient 0.7809, indicating a noticeable increase in the research related to human development interfaced with wildland environments. The analysis also revealed a moderate positive correlation, with a correlation of coefficient 0.4959. Figure 1.5 demonstrates the trend of research articles over time, potentially showing an upward-sloping line or curve to highlight how the frequency of research articles related to large fires and WPL has been gradually increasing over time.

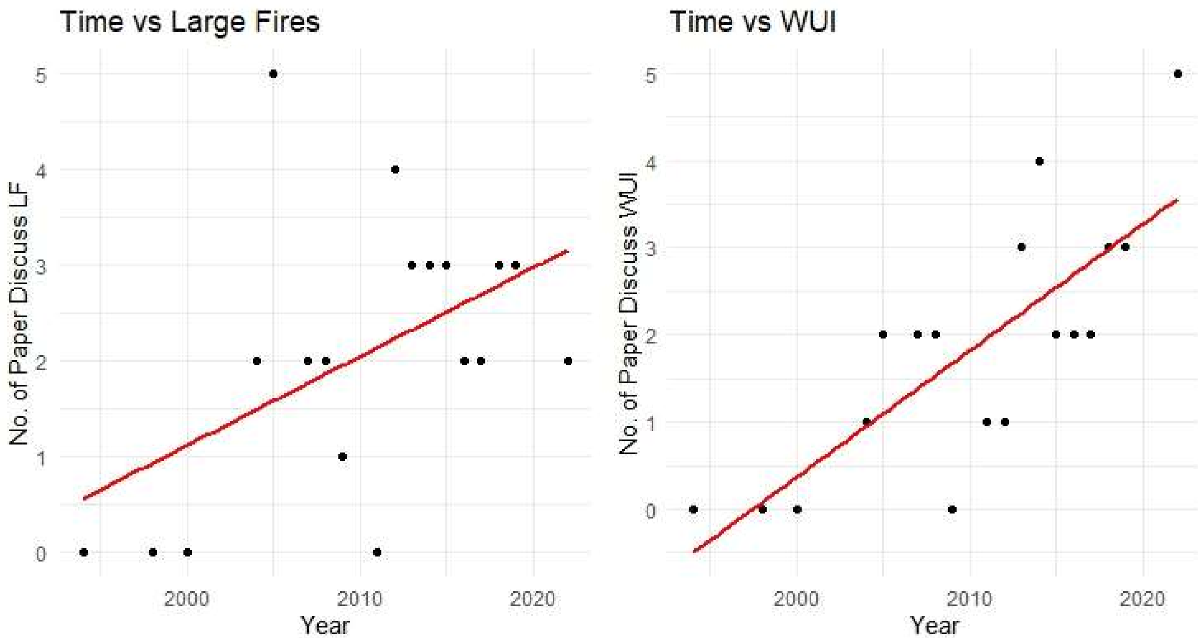

Figure 1. 5. Correlation between the discussion of the wildland-urban interface and large fires research articles over time.

Literature Results

Several statistical models were developed to determine the total fire suppression expenditure in terms of fire size, fire duration, and burned acres (Calkin et al., 2005; Gebert et al., 2007; Houtman et al., 2013; Roman Mees et al., 1993). The study by Liang et al., (2008) showed USFS pays a significant amount of money putting out wildfires. In the results, they suggested that 58% of the change in expenditure is due to private lands and fire size.

Abt L. Karen., et al., (2009) developed regression models to predict the expenses for fire suppression paid by federal forest regions. The models were developed for forecasting horizons of two and three years. The study's objectives were to ascertain whether historical seasonal fire suppression expenditure influenced current expenses and to assess how effectively time sequence models built on historical suppression expenditure forecast expenditures for the next fire seasons. As a result, they proposed that more precise methods of correcting for variances in budget requests might come from modifications to the funding of suppression expenditures that have been implemented recently.

Yoder and Gebert study outlined the method for making predictions about the fire and the associated costs per acre. These forecasts are based on fire characteristics that were visible at the time of first ignition or before the end of suppression efforts. In the result, they said that bivariate models are more useful than univariate ones for prediction (Yoder & Gebert, 2012).

A comprehensive model for calculating annual suppression costs was developed by combining a model for simulating wildfires with a model for the cost of suppression. The authors used the cost modeling for a group of expensive National Forests, highlighting variations in expected costs caused by factors that increase economic risk. As a result, their cost models can be used for forecasting expenditure, better decision-making, and improved risk management in adverse budgetary situations (Thompson et al., 2015).

Fitch et al., (2018) analyzed previous fires in the northern Arizona region to identify key fire performance patterns that could be predicted before actual wildfires occurred and had a significant impact on calculating the costs of suppression. In determining how much it will cost to put out wildfires, the study emphasized the importance of burn severity and the potential to reduce fire severity and wildfire management costs. The results suggest that, for reducing suppression expenditure, more aggressive techniques and approaches frequently have a better success rate, except in the case of extreme weather conditions.

Keyser and Westerling (2019) created statistical models to forecast the size of the high-severity area burned in the western region of the US, as well as in the other three subregions: Rockies, Sierra, and Southwest. The models were created to identify the potential consequences of significant wildfires in these regions. In the result, they mentioned that climate change has an impact on the high severity of burned fires.

(Rossi et al., 2022) used forecast models in the research to provide insight into how supervisors' decisions to completely suppress accidental fires are affected by the updated FIRE Act policies. In the results, they mentioned that there is no significant difference in the suppression costs after the policy change.

Socio-Environmental Factors

Prestemon et al., (2008a) employed a technique to predict the US Forest Service's fire control expenses ahead of the fire seasons in their research. The authors' focus was on creating empirical models that included a variety of meteorological conditions, such as drought, sea level pressure, and ocean temperature, taking them into account. The particular temporal trends and past expenses of the US Forest Service locations were considered. The research aimed to use these criteria to accurately predict the expenses of fire suppression for the USFS (United States Forest Service). As a result, there was no difference between the spring and fall suppression expenditures forecast for the upcoming season.

To evaluate the impact of residential properties on daily fire suppression expenditures, Gude et al. (2013) used linear mixed probabilities while accounting for changes within all fires. The result indicates that the presence of residential properties is linked to increased wildfire suppression expenses. Gude et al. (2013) study found results that are consistent with the findings of Bayhman and Yoder (2020). Their data showed that the cost of combating wildfires increased in direct proportion to the number of residential structures. The study demonstrates the effect of housing increase on the price of containing and extinguishing wildfires. Clark et al., (2016) also investigated both the price of fire control and the spatial distribution of housing expansion. They used data from 281 fires that occurred in the North Region of the Rockies. The study aimed to determine the effect of Wildland-urban Interface (WPL) development on suppression costs, paying particular attention to the geographical model of expansion. As a result, they mentioned that policies that control the WPL development can be almost as impactful as policies that entirely prohibit such development.

Bayham and Yoder (2020) examined the socio-environmental elements that affected the expenses related to fighting wildfires. The panel dataset included 500 fires in the western US, to which an economic model was applied. They uncovered that priority was given to fires that presented a threat to residential structures when allocating "suppression resources" such as hand workers and engines. Additionally, they found that more aircraft were sent to the scene when fires occurred close to properties with higher economic value. Gebert and Black (2012) also supported the concept that a less aggressive approach was linked to lower per-unit expenses, reinforcing the importance of effective fire management strategies in the face of increasing suppression costs due to housing expansion.

S. Zhou and Erdogan (2019) study introduced a stochastic linear programming paradigm with two stages for integers. The model considers both the allocation of resources for fighting fires and the evacuation of residents. The results indicated that in a short time model can create the solution for the complex WPL wildfire problems.

Thompson et al. (2017) proposed a modelling framework that combined optimization and simulation methodologies, expanding on the research into suppression costs. The study aimed to acquire a comprehensive understanding of the efficiency of fuel management solutions, considering factors such as housing expansion. Thompson et al. (2013) also indicated that the increase in suppression cost is due to Wildland-Urban Interface (WPL) development, aligning with the earlier work of Gude et al., (2013).

Unique Fire-Detecting Techniques

Different strategies for detecting and localizing fires in diverse settings are compared. The approaches used are determined by considerations such as cost, practicality, mobility, precision, and the application's specific requirements. Wireless sensor networks (WSNs) that make use of sensor-based methodologies are regularly mentioned in literature as a useful, affordable solution. These stationary appliances use sensors to identify fires and provide details about the location and behavior of the fire. Their range of motion is constrained, and depending on the technology, the interval between detection and notification can change. Fire localization mistakes and false alarm rates are typically relatively low (Aslan et al., 2012; Bayo et al., 2010; Bouabdellaha et al., 2013; Hefeeda & Bagheri, 2007, 2009).

Camera-based solutions that involve image and video processing are more expensive but give high-resolution data. They provide you with the ability to broaden your search parameters and find fires throughout vast tracts of forest. They cannot offer data on fire behavior and are less practical than sensor-based systems. False alarm rates are moderate, and the time between detection and reporting may be quite considerable. The difficulties in precisely finding the fire frequently led to errors in fire localization (B. C. Ko et al., 2009; Zhang et al., 2018).

Neural network-based techniques use artificial intelligence to detect fires by analyzing data like temperature and smoke levels. They provide valuable insight into fire behavior, but their practicality isn't particularly great. Since these techniques are rarely used in literature, more research needs to be done on them. False alarm rates can alter, even though there is frequently minimal time between detection and notification. Fire localization errors in neural network-based techniques are rather minimal (Hong et al., 2022; Muhammad et al., 2018; Saeed et al., 2020; Satir et al., 2016).

The use of Satellite fire detection systems is common because of their capacity to cover large areas. However, because of their practical limitations, they are quite expensive and rarely used. These methods can offer insight into the behavior of fires. However, it usually takes a long time for a fire to be noticed and reported. Fire localization errors can be very significant, while false alarm rates are generally minimal (Cuomo et al., 2001; Filizzola et al., 2016; Mark A. Cochrane, 2013; Oliva & Schroeder, 2015; Rauste et al., 1997).

In UAV/airborne strategy, unmanned aerial vehicles are employed to locate fires. They offer a practical, transportable solution for a fair price. These techniques, which are mentioned frequently in literature, can provide details regarding fire behavior. The proportion of false alarms is moderate, and the average detection to notification time is significant. Fire localization errors typically arise because it is challenging to accurately identify fire locations from aerial perspectives (Krüll et al., 2012a; Tomkins et al., 2014).

Fuzzy logic-based approaches offer a solution with a low false alarm rate, affordability, and utility. They hardly ever appear in literature and are only sporadically appropriate. However, they do not cover the entire area of interest, these strategies could only be able to partially provide information on precise fire behavior. The time between fire detection and reporting is typically short, therefore fire localization difficulties are frequently unimportant (Bolourchi & Uysal, 2013; B. Ko et al., 2014).

Animals used as mobile sensors are rarely used in practice, although they provide a novel means of detecting fires. They are not particularly successful despite their vast coverage area and mobility. Because they provide no insight into how fires behave, these tactics are rarely referenced in the literature. Despite the short time between detection and notification, a significant proportion of false alarms may occur. Because it is difficult to discern fire sites based on animal behavior, fire localization errors are especially common (Bousack et al., 2015; Sahin, 2007). Radio-acoustic techniques are a distinct and specialized method of detecting fires. These tactics are hardly used in literature and have minimal utility. They don't give you any information on fire behavior, and the interval between detection and reporting is brief. False alarm rates are high, as are fire location inaccuracies (Sahin & Ince, 2009).

The Use of Multiple Sensors to Control Fire

According to (Chowdary et al., 2018a), sensors have been widely utilized to detect and monitor a wide range of environmental conditions those are listed below (Figure 1.7 (a&b). Barometric pressure sensors track changes in air pressure. These sensors can be used to identify pressure changes brought on by fire-related phenomena like smoke plumes or thermal updrafts. Firefighters and other emergency personnel can learn vital details about the fire's dynamics and make well-informed decisions about their firefighting tactics by keeping an eye on pressure changes. Temperature sensors are frequently used to detect temperature changes, but they can also be used to measure temperature differences induced by humidity variations. The use of these sensors provides useful information related to environmental conditions by monitoring the temperature differences in the weather change (Kaiser, 2000; J. Li et al., 2019).

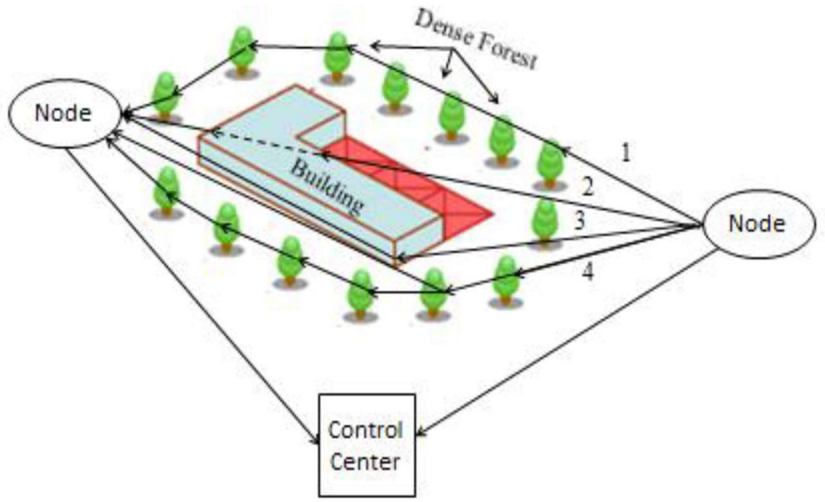

Figure 1. 6 (a). Fire Identification in a Limited Area of Interest (Reproduced with the permission of Chowdary et al., 2018)

There is another sensor available called a humidity sensor to detect changes in the humidity levels. The humidity sensor provides the proper monitoring of a controlled environment (Kou et al., 2020). Smoke sensors are effective for detecting fire. The sensor picks up the smoke and frequently gives alerts that there is a fire present. In buildings, and commercial places smoke sensors are widely used. This smoke sensor quickly identifies the smoke identical and triggers the alarm to take quick action against the fire to limit possible damage (S. J. Chen et al., 2007; Ho, 2009; Sebastien Frizzi et al., 2016). Carbon monoxide gas, which is typically released during a fire, can be detected with CO sensors. These sensors are essential in identifying potentially fatal situations like carbon monoxide leaks or fires that emit large amounts of this dangerous gas because carbon monoxide has no flavor or color.

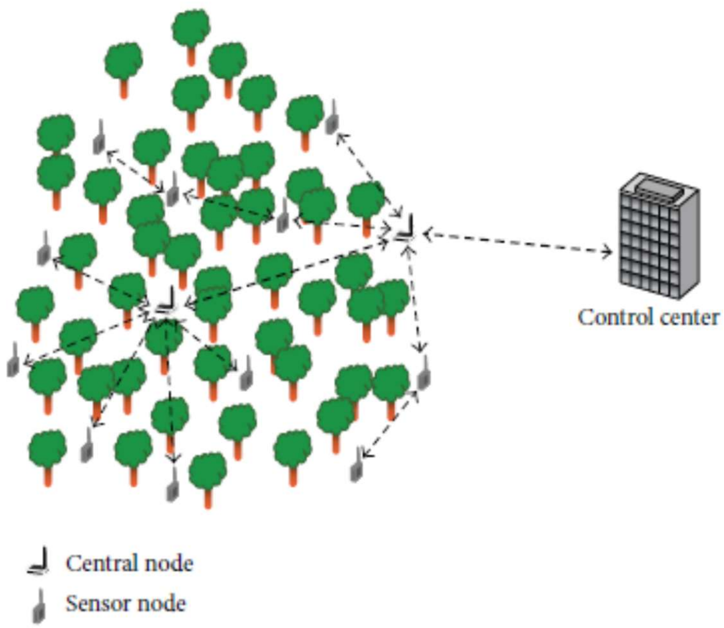

Figure 1.7 (b). Fire detection of overall forest (Reproduced with the permission of Chowdary et al., 2018)

These sensors aid in ensuring occupant safety by continuously monitoring CO levels and offering early warning of hazardous conditions (Gutmacher et al., 2012; Qiu et al., 2019). Infrared (IR) sensors are frequently employed in fire detection systems as fire indicators. When smoke or other obstacles could prevent eye detection, these sensors can quickly identify fires by detecting the infrared radiation that fires release. Infrared sensors help with quick action and effective fire management by quickly alerting authorities (Arrue et al., 2000; Ramiro Martínez-De Dios et al., 2005; Xavier & Nanayakkara, 2022).

Microwaves used by passive microwave imaging sensors can pass through thick smoke. As a result, they are particularly useful in firefighting situations where heavy smoke may make it difficult to use traditional visual or infrared imaging techniques. The place and range of a fire may be determined in real-time by these passive microwaves imaging sensors, enabling more accurate fire mapping, and improved situational awareness for firefighters (Alimenti et al., 2008; Kempka et al., 2006; Krüll et al., 2012b; Varotsos et al., 2020).

Discussion and Conclusion

Our research provides a new perspective by extending the temporal range from 1985 to 2023, in contrast to the previous work by Mattioli et al., (2022, "Estimation Wildfire Suppression Costs: A Systematic Review"). This long period allows us to analyze the wildfire suppression costs computation developing area, giving us valuable information about how the techniques and goals of the research have changed over time. A comprehensive literature review, a Pearson correlation coefficient analysis, and a keywords co-occurrence analysis are all part of our mixed-method approach, in contrast to the prior study, which concentrated on the diversity and fragmentation of methodological techniques. This study does not focus only on the qualitative methods and findings of the prior studies but also quantifies the relationship between different variables such as "suppression cost," "large fires," "WPL," and "time." In addition, VOSviewer's inclusion for keywords co-occurrence analysis enhances our study and offers a new and insightful perspective on the research landscape by graphically mapping clusters and linkage. Our study presents an extensive, long-term, and diverse analysis of wildfire suppression expenditures assessment, giving depth and modification to the academic understanding of this crucial topic.

This systematic review investigates the existing literature on wildfire suppression costs. The initial step involves an analysis of the various models of these wildfire suppression costs. Large fires and wildland-urban Interface are positively correlated with the suppression cost. Large fires and WPL are the main sources because of that suppression costs rise over time. Governments, communities, and people are currently facing enormous financial burdens because of the intensity and frequency of wildfires that have increased in recent years. The size, intricacy, topography, weather, and proximity to populated areas are some of the variables that affect how much it takes to put out a wildfire. The costs of containing wildfires tend to rise exponentially as they become more severe and difficult to control. Furthermore, wildfire collateral damage, such as the destruction of homes, infrastructure, and natural resources, adds to the economic pressure. Climate change-induced droughts, the spread of human settlements into fire-prone areas, and the accumulation of combustible debris in forests because of years of fire suppression strategies are all factors contributing to this rise. Although most of the publications derive closed-form solutions for their models. There is also a large presence of articles offering unique solution models and early fire detection technologies. Each technique has its strengths and limitations. I think that future studies should continue to improve our enhance their effectiveness in different scenarios. There is a need to investigate and build models that are more accurate and systematic and that consider many elements such as fire behavior, environmental conditions, resource allocation, and the efficacy of suppression tactics. The use of sensor systems, early fire detection technologies, such as satellite monitoring systems and the incorporation of artificial intelligence and machine learning techniques into fire management systems could be helpful.

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CHAPTER 3

ASSESSING THE EFFECT OF LARGE FIRES, PROPERTY LOSS AND SIX CLIMATIC VARIABLES ON WILDFIRE SUPPRESSION COSTS: A COPULA APPROACH[2]

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Abstract

In the last three decades, there has been a significant increase in the number of wildfires, leading to higher costs for wildfire management agencies like the United States Department of Agriculture Forest Service (USFS). This study employs time series analysis and monthly data to identify the significant seasonal effects, predict the impact of variables on suppression costs, and assess the joint distribution of variables using copulas to uncover potential nonlinear dependencies. The analysis focuses on the suppression expenditure of the USFS, Nino3.4 SST, NAO (North Atlantic Oscillation), and LF (large fires), revealing significant seasonality. A strong positive dependency was observed between Nino3.4 (1.38) and suppression expenditure in the Western aggregated regions of the USFS, with an upper tail dependency (0.35). The PDO (Pacific Decadal Oscillation) exhibits a dependency value of 0.34 and lower tail (0.87), while the PDSI (Palmer Drought Severity Index) shows a negative dependency (-0.09) with no tail dependency. On the other hand, only Nino3.4 SST exhibits a negative dependency with the suppression expenditure in the Southern region, whereas AO (Arctic Oscillation) shows a positive dependency (0.59), with no tail dependency. The suppression expenditure of both regions exhibits different results with other variables. This study suggests the importance of modeling suppression expenditure at an appropriate temporal scale to predict and understand the impact of different variables on expenditure.

Introduction

The term "wildfires" has become prominent and spread worldwide, given its extreme impact on the environment, economy, and social life (Gill et al., 2013; Jolly et al., 2015). The catastrophic damages from wildfire events were seen in various parts of the world, such as the forest fire in Texas (2011), Victoria State, Australia (2009), and Costa Del Sol, Spain (2012) (Slavkovikj et al., 2014). The occurrence of wildland fires has been increasing at an annual rate of 3% across the western US, resulting in more severe, and larger burns (number of acres) compared to history (Liz Kimbrough, 2022).

Human activities have significantly contributed to the recent rise in the occurrence of fires (Hantson et al., 2015). In the United States, almost 85% of forest fires are caused by humans (NPS, 2023). These fires also cause a significant threat to humans and their belongings in communities with the wildland-urban interface (WPL) (Argañaraz et al., 2017). In 2021, residential and non-residential fires caused a $12.5 billion loss in the United States (USFA, 2021).

In addition, PM2.5 (particles with a diameter of 2.5 micrometer or smaller) emissions can negatively impact human health (Fann et al., 2018). In 2011, wildfire smoke affected around 212 million humans in the United States who lived near the fire area (Knowlton, 2013). Fann et al., (2018) study estimated that in different States (e.g., East Florida, Louisiana, Georgia, West Idaho, and Northern Oregon and California) deaths and respiratory problems have increased due to wildfires, including economic value loss between $11 to $20 billion ($2010) annually in short-term exposures and long-term exposure estimated value between $76 to $130 billion ($2010) annually.

Suppression costs in the U.S. have increased from $239 million to $4.3 billion between 1985 and 2021 (NIFC, 2023b). Climate change has increased and the interaction between wilderness areas and urban development, leading to more severe wildfires and greater losses. The 7.5 million acres of land burned, 3790 deaths, and $3.5 billion in damage in 2022 highlight the impact of these changes (NSC, 2023). Furthermore, the 20% increase in wildfire risk in California due to rising temperatures and drought shows the need for effective wildfire management strategies, which create more favorable conditions for wildfires to start and spread (Goss et al., 2020).

The duration of the fire season is expanding, and the initiation and spread of fires is more likely in hot and arid climates. Researchers have established a correlation between prolonged irregular weather patterns and the incidence of wildfires in the Southwestern and Southeastern regions of the United States (Brenner, 1991; Swetnam & Betancourt, 1990). The effects of environmental change on boreal forestlands may result in a 50% rise in the frequency of wildfires by the century's end (2100) (Flannigan et al., 2009).

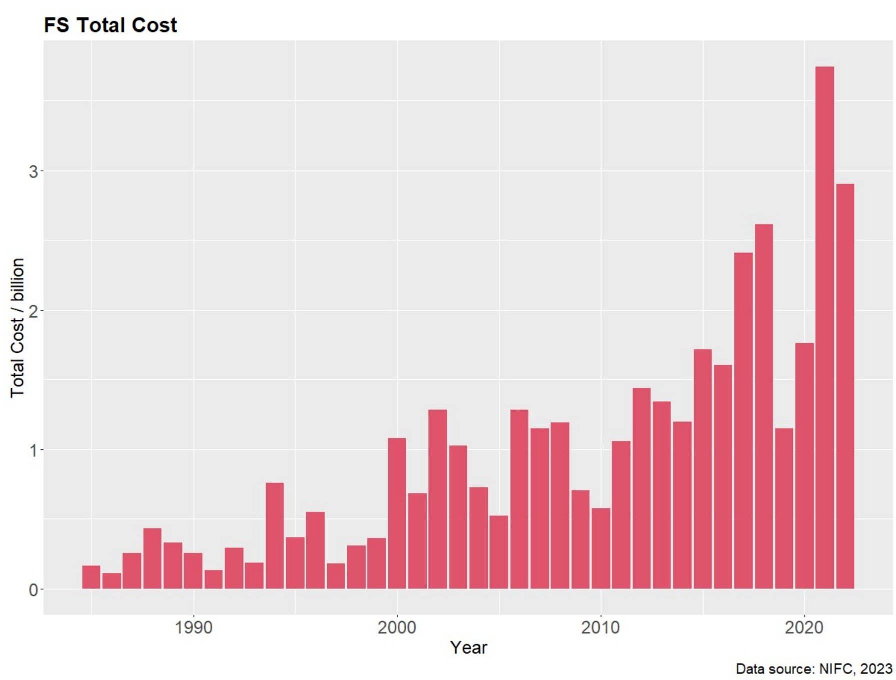

Figure 2. 1. Annual historical expenditure for the USFS (Forest Service) over United States.

Understanding the seasonal effects on wildfire dynamics and predicting the influence of variables on suppression expenditures are important steps in determining effective wildfire management strategies. Additionally, assessing the joint distribution of variables using copulas allows for the determination of potential nonlinear dependencies, enabling more accurate predictions and risk assessment. The objective of this chapter is to investigate the significant seasonal effects, predict the impact of variables on suppression costs and assess the joint distribution of variables by using copulas (potential nonlinear dependencies) with socio-environmental and climate-related variables.

I employ regression analysis and copula analysis to comprehend the linear and non-linear correlation between suppression expenditure and other variables. The results of my research indicate that some climate and socio-environmental variables both have a significant correlation with the suppression cost by the Forest Service. This chapter is structured as follows: (1) a comprehensive examination of the most relevant studies on wildfires and the costs associated with their suppression, (2) an introduction to the methods used for time series analysis, (3) a thorough discussion of the findings, and (4) conclusions and suggestions for potential future research directions.

Literature

Early studies have focused on the association between climate variables and wildfires, which alternatively affect the suppression costs (Abt L. Karen et al., 2009; Addington et al., 2015; A. Chen, 2022; Prestemon et al., 2008a; Riley et al., 2013; A. P. Williams et al., 2013). Prestemon et al. (2008) used climate variables and showed that there were positive trends in suppression expenditures across most regions (on average, ~80% of USFS (United States Forest Service) suppression expenditure are allocated to regions 1-6), after accounting for climate variables. The March (lag) PDSI (Palmer Drought Severity Index) exhibits a negative influence on suppression costs. Suppression costs tend to decrease when drought conditions are less across the western United States. Additionally, their study also determined a potential increase in suppression expenditure over time.

Abt L. Karen et al., (2009) developed regression models to forecast USFS wildfire suppression costs. In the United States suppression expenditure and the techniques used for suppression activities have put significant burdens on the budgets of land management organizations for the fire management and other activities. Their regression model could enhance the accuracy of budgeting, though it remains uncertain how the agencies will adapt to more unpredictable budget requests with the current assumptions system. However, their findings suggested that recent changes to how suppression costs are funded could provide a more accurate means to adjust to the variability in budget requests.

Gebert & Black, (2012) study used wildfire suppression costs and fire characteristics datasets, and investigated which factors (e.g., fire size, duration, and strategy) impact suppression expenditure. Their findings show management strategies affect the suppression costs. The main results of the study indicate that less aggressive fire management strategies lead to lower costs for federal agencies compared to a strategy of full perimeter control. Specifically, a strategy of limited suppression reduces expenditures per acre by 52%.

Gebert et al., (2007) determined suppression costs per acre for different wildland fires larger than one hundred acres. Their research focuses on expenses per acre and does not include an approximation for a fire range estimate to describe sample limitations regarding fire range. These models, which depend on spontaneous estimations of the whole fire area, are being employed for forecasting during a fire. As a result, they mentioned that a study of low-cost fires could discover a low-cost firefighting strategy.

Prestemon & Donovan (2008) studied improving decision-making for the agencies and governments who need to decide on unknown environmental conditions in the future. The study developed a new single-stage model that can effectively minimize spending on fire suppression, specifically during times of enhanced fire activity due to global warming. Their results showed that using a single-stage method is beneficial as compared to a two-stage method to reduce fire suppression costs. The study also indicates that during periods of higher wildfire activity, potentially attributed to global warming, the cost savings from the single-stage method compared to the two-stage method are greater.

The study by Bayham & Yoder, (2020) determined the impact of resource allocation during a fire season on the expenses associated with the suppression expenditure. Their investigation uncovered a rise in suppression costs because of extra firefighting and crew to control the fires that endanger valuable residential and commercial buildings. Additionally, they predicted that due to the high rate of housing growth in California, suppression costs might increase up to $24 million annually.

The modification of policy guidelines may have increased the possibility that managers would apply strategies other than full suppression. Rossi et al. (2022) work established the decision-making process, employed by wildfire incident managers, focusing particularly on the impact of environmental and socioeconomic variables. The authors built a model called CREL (Correlated Random Effects Logit) and a Difference-in-Differences method to examine the variables that affect suppression decisions both before and after a modification in federal fire policy. The authors of the study reported that climate variables (e.g., humidity), show a greater influence on decisions on wildfire suppression associated with other variables (e.g., policy change). However, the rise in funding for suppression effectively responded to this effect, resulting in no noticeable variation in probabilities following the implementation of the policy modification.

Current studies highlight the importance of climate variables, past costs, and trends in predicting wildfire suppression costs. However, there is a research gap in integrating socio-environmental variables into existing climate models and understanding the effects they have on the expenses associated with suppressing wildfires.

The focus of my research is to enhance the existing analysis by adding the following key aspects: (1) the creation of a monthly forecast model that accurately accounts for the seasonal variations in suppression spending patterns; (2) the demonstration that specific climate variables have no direct impact on monthly suppression expenditures; and (3) the finding of valuable insights into the interdependency among the suppression expenditure and climatic and socio-environmental variables through copula analysis.

Comparison of Wildfire Drivers Between Southern and Western United States

Wildfires in the Southern and Western United States show that a variety of factors influence fire behavior. Understanding the various drivers of wildfires in each region is crucial for developing successful fire control and mitigation strategies. The table 2.1 below contrasts these reasons, demonstrating the disparities in fire behavior between the South and West, each factors provides vital information about the challenges and potential for the wildfire management.

Western Regions of United States

The federal government owns around 87% of wildfire-affected land in the western United States, which influences management strategies. Federal entities, such as the United States Forest

Service and the Bureau of Land Management, play a significant role in wildfire management on public lands (USDA FS, 2016).

A variety of factors contribute to more extreme fire behavior in Western wildfires. The hot, dry weather in the area causes the foliage to dry out, fueling the flames. Strong winds, which are typical in the Western United States, contribute to the rapid spread of fires, making suppression more difficult. The region's mountainous terrain complicates firefighting operations by making it more difficult to confine and access flames. These elements frequently exacerbate wildfires in the Western United States (L Westerling et al., 2003).

The western area contains a variety of habitats, including chaparral, sagebrush steppe, and coniferous woods, each with its own set of fuel properties. Coniferous forests, which are predominantly composed of pine, fir, and spruce trees, can create exceptional flammable conditions, particularly during dry season. Chaparral ecosystems exist in mediterranean climates and are distinguished by dense, readily ignited woody bushes. The sagebrush steppe's vegetation is dominated by sagebrush and other drought resistant plants. Its fine, dry fuels burn hot and ignite quickly. Give the large range of fuel sources (Wibbenmeyer & McDarris, 2021).

In the western regions, different fuel treatments are used depending on a number of criteria, including as resource availability, land ownership patterns, and management aims. In some regions, such as national parks or wilderness areas, fuel treatments may be fully prohibited or controlled in order to preserve natural ecosystems (NPS, 2023). Treatment methods also differ; some places prioritize creating defensible space around buildings, while others use controlled burning and mechanical thinning (USDA FS, 2022).

Lighting is one of the most common natural fire sources in the western United States, is responsible for approximately 44% of wildfires that start there. Lightning strikes have the potential to complicate firefighting efforts by sparking flames in remote, sometimes inaccessible regions. Several factors, including climatic trends and environmental variables, influence the frequency and intensity of lightning strikes (NASA, 2021).

In the Western United States, fire is also necessary for the regrowth of other plants such as ponderosa pine. Because these species evolved to survive in fire-prone settings, their seeds frequently need the heat of a fire to open and germinate. Fire can be used to clear vegetation that is in the way of future development. In the absence of fire, these plants may struggle to rejuvenate because dense understory growth makes it difficult for seedlings to establish themselves (Korb et al., 2019).

Southern Region of United States

The southern United States has more private land ownership and local control over fire management than western regions. Approximately 37% of land in the southern United States is federally owned (USDA FS, 2016).

Fires in the southern region are usually less intense than those in the western regions, owing to increased humidity and less harsh weather. Because of the higher humidity in the southern region, the trees may be less combustible and spread more slowly. The south experiences more frequent rainfall and cooler temperatures, which helps reduce the risk of wildfires. Despite relatively low fire intensities, the south has significant wildfire issues, particularly where human development overlaps with wildlands (Wibbenmeyer & McDarris, 2021).

The South is characterized by pine forests, meadows, and shrublands, which have an impact on fire behavior. Periodic fires are required to sustain the biodiversity and overall health of the habitats that are most suited to them. Pine forests are resistant to low intensity flames due to their thick bark and self-pruning branches. There are two types of forests: slash pine and longleaf pine.

Grasslands and shrublands, like the Southeastern Coastal Plain, are fire-adapted; many species rely on fire to promote seed germination or to lessen competition from woody plants (Paysen et al., 2000).

Prescribed fire is commonly utilized in the area because it supports fire-adapted ecosystems such as longleaf pine forests, which rely on frequent burning for maintenance and regrowth. Several groups actively advocate the benefits of managed fire, and the Southeast has a long history of fire-based land management. This proactive strategy to manage fire promotes the ecological health of the region's diverse landscapes while reducing the risk of uncontrolled wildfires (NRCS, 2012).

Lightning-caused wildfires are less prevalent in the South than in the West, owing to increased humidity and fewer thunderstorms. Plant aridity can be reduced in the South due to higher relative humidity, which reduces the risk of lightning-caused plant fires. In addition, the South has fewer thunderstorms than the West, where dry lightning strikes regularly cause wildfires. Even while wildfires sparked by lightning are less common in the South, they can still occur, especially during dry spells or other conditions that encourage lightning activity (NASA, 2021).

Overall, in the both regions of United States, rapid urbanization near wildlands raises the possibility of human-caused fires and makes fire control more challenging. As more people move into these areas, there is a greater possibility of unintended ignitions from sources including power lines, autos, and outdoor activities. Additionally, the existence of residential and infrastructure in wildland urban interface (WUI) areas creates challenges for firefighters, who are tasked with preserving both natural landscapes and human populations (AMWINS, 2023).

Table 2. 1. Wildfire Drivers Between Southern and Western United States

Aspect	Southern US	Western US	Reference
Fire Behavior and Intensity	Fires in the South tend to exhibit lower intensity due to higher humidity levels and less extreme weather conditions.	Western wildfires often experience more intense fire behavior, driven by drier fuels, strong winds, and rugged terrain.	(L Westerling et al., 2003; Wibbenmeyer & McDarris, 2021)
Fuel Types	Pine forests, grasslands, and shrublands dominate the South, influencing fire behavior.	The West boasts diverse ecosystems, including coniferous forests, chaparral, and sagebrush steppe, each with distinct fuel characteristics.	(Wibbenmeyer & McDarris, 2021)
Prescribed Burns	The Southeast leads in using prescribed fire for vegetation management, burning approximately 6 million acres annually.	Implementation of fuel treatments varies within the West.	(Martinson & Omi, 2013; Wibbenmeyer & Dunlap, 2022)
Ignitions causes	Lightning-triggered wildfires are less common due to higher humidity and fewer thunderstorms.	Approximately 44% of Western U.S. wildfires are ignited by lightning.	(NASA, 2021)
Topography and Slopes	Generally flatter terrain with fewer steep slopes.	Rugged mountains and steep slopes increase fire challenges.	(Zhai et al., 2023)
Land Ownership and Management	More private land ownership and local control over fire management.	Nearly 70% of wildfire-affected land is federally owned, impacting management strategies.	(USDA FS, 2016)
Fire-Adapted Species	Species like longleaf pine have evolved with frequent fire.	Ponderosa pine and other species also rely on fire for regeneration.	(Korb et al., 2019; Wibbenmeyer & McDarris, 2021)
Smoke Exposure	Smoke impacts are significant but less widespread.	Smoke from large wildfires affects air quality across broader regions.	(Wibbenmeyer & McDarris, 2021)
Wildland-Urban Interface (WUI)	Growing WUI areas contribute to fire risk near cities.	Rapid urbanization near wildlands exacerbates fire danger.	(AMWINS, 2023)

Methodology

I investigated the impact of climatic and socio-environmental variables on wildfire suppression for the USFS across different regions. USFS manages a significant amount of public land (193 million acres), with an overall budget of $2.97 billion allocated for wildfire management (USFS, 2023). Details about the data that were used and their corresponding sources are given in the next section.

Dataset of Wildfire Suppression Expenditure

The USFS recorded monthly data on wildfire control costs from 2005 to 2022 and for the Western aggregated (Region 1-6) and Southern regions (Figure 2.2), comparable data were available from 2013 to 2020. From 2005 to 2022, the Forest Service spent an average of $117.27 million per month on suppression overall in the United States; the Western aggregated regions spent an average of $66.65 million per month and the Southern region spent an average of $3.24 million per month from 2013 to 2020 (Figure 2.3).

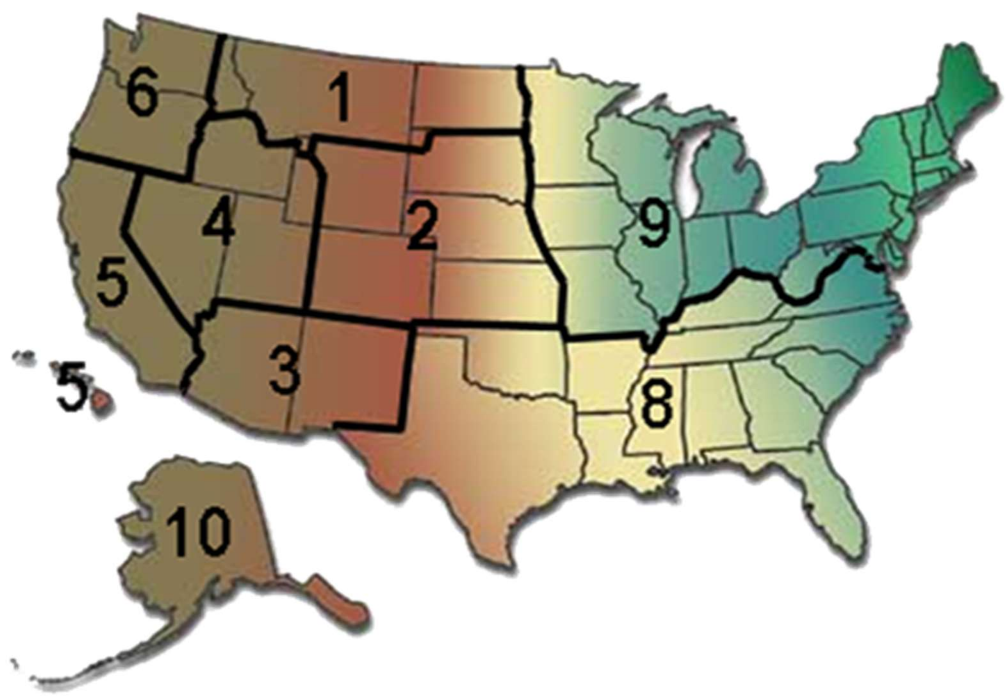

Figure 2. 2: U.S. Department of Agriculture Forest Service map

These series also have "negative" expenditures because federal ledgers were adjusted to reflect payments from states or other agencies for suppression expenditures made on their behalf in the previous month as well as contract costs (like aviation) that were not related to the current wildfire activity. Inferences for the Forest Service could be especially affected by the accounting framework's ability to mask anticipated links between spending and climate factors. I show specifications that adding lags to expenses in model specifications helps mitigate the accounting effect. On the other hand, the USFS monthly data since 2005 shows negative values for March 2006, December 2012, March 2012, May 2015, and August 2020 in the graph of Figure 2.4.

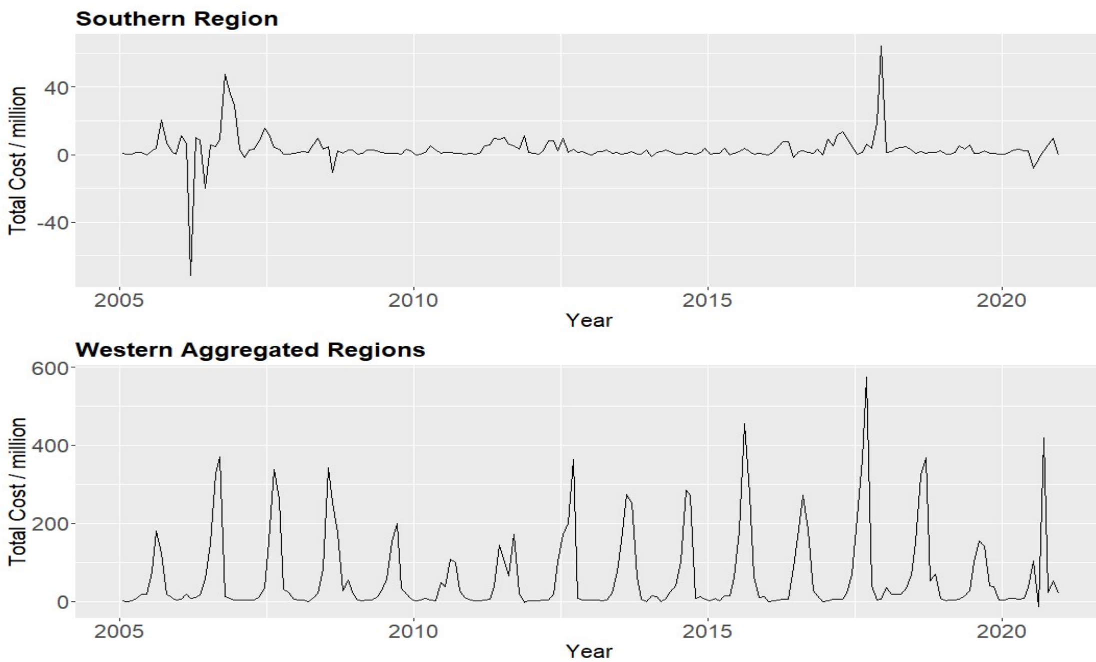

Figure 2. 3. USFS Western aggregated and Southern regions (2005 – 2020) monthly wildfire suppression

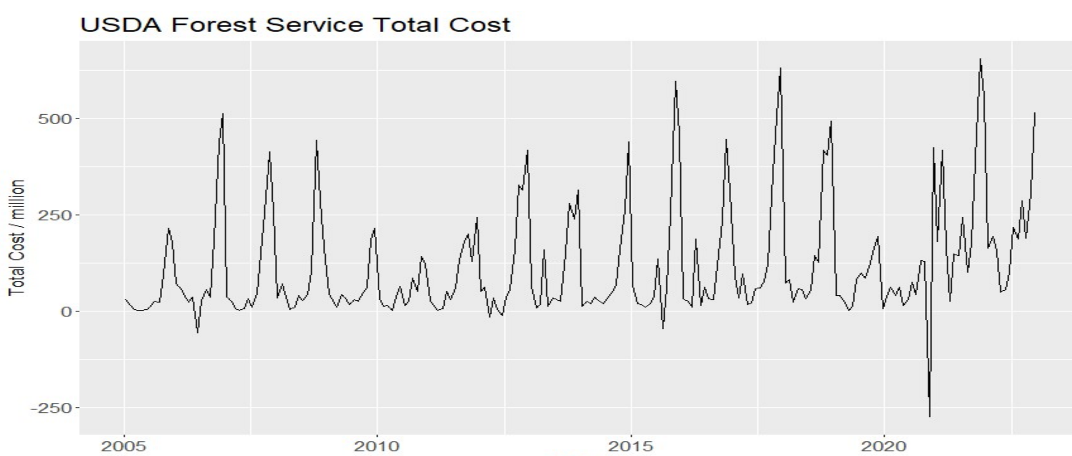

Figure 2. 4. United States Department of Forest Service (2005 – 2022) monthly wildfire suppression

Climate Factors

Niño 3.4 SST Index

Niño 3.4 index represents the sea surface temperature (SST) in the Pacific Ocean near the equator. The Niño 3.4 SST variation measures the average temperature over 5 years. NOAA (2024) defines La Niña as an SST anomaly of less than -0.4 degrees Celsius, and El Niño as an anomaly of more than +0.4 degrees Celsius for six months or more. The primary emphasis of this study is the Niño 3.4 (SST), rather than its variation.

Palmer Drought Severity Index (PDSI)

A regional drought index that measures the severity of drought conditions for land areas is the PDSI (Alley, 1984). PDSI values that are negative indicate low soil moisture conditions, whereas positive values indicate higher soil moisture conditions (NCAR, 2024). I collected and aggregated the PDSI data from the western U.S. climate divisions, such as Forest Service Regions 4 (Intermountain), 5 (Pacific Southwest), and 6 (Pacific Northwest), for the western aggregated regions and regions 8 (Southern) for the southern region. These three regions receive significant emphasis in prioritization due to their elevated historical wildfire activity.

Arctic Oscillation (AO)

There is a significant link between the Arctic Oscillation (AO) and the North Atlantic Oscillation (NAO) (Hamouda et al., 2021). (Christiansen, 2002) states that the AO index is based on atmospheric pressure and covers a larger area in the Northern Hemisphere than the NAO, which only covers the Atlantic region. Depending on its strength, AO variation produces storms in certain parts of Earth. Stormier weather is typically found in the southern United States when air mass movement is weaker (negative values). On the other hand, stormier climate throughout the northern part of the U.S. is correlated with positive values (NOAA, 2024).

North Atlantic Oscillation (NAO)

The NAO is obtained by subtracting the Surface Sea-level Pressure (SSP) of the Subpolar low from that of the Subtropical high (Azores). A positive North Atlantic Oscillation (NAO) indicates above-average pressure and heights in the North Atlantic, Eastern US, and Western Europe. North Atlantic high latitudes have below-average heights and pressure. On the other hand, the negative phase shows a different pattern of pressure and height anomalies in these areas (NOAA, 2024).

Pacific Decadal Oscillation (PDO)

PDO is a climatic metric based on ocean temperature. PDO index measures the difference in the sea surface temperature in the Pacific Basin and North America. The PDO is categorized into warm or cool periods based on the differences observed in the ocean temperature of the Northeastern and Pacific Oceans. This categorization is carried out in combination with the El Niño-Southern Oscillation (Mantua et al., 1999; NOAA, 2024).

Southern Oscillation Index (SOI)

SOI is a standardized metric that quantifies the difference in sea level pressure seen in the Pacific Ocean, called the second part of the El Niño-Southern Oscillation. During the El Niño, the index exhibits a positive value, but during the La Niña, it shows a negative value. The Eastern Tropical Pacific has variations in ocean temperatures that are associated with the SOI (NOAA, 2024).

Socio-environmental Variables

Large Fire (LF)

Wildfires categorized as "large" are defined as those exceed one thousand acres in the western United States, five hundred acres in the eastern United States, and in the other regions, one hundred acres in timberland or three hundred acres in grasslands. In addition, wildland fires that do not meet the criteria for classification as large fires but are assigned a nationally recognized incident management team are also included in the IMSR (e.g., <100) (EPA, 2021; NIFC, 2023b).

Wildfire Property Loss (WPL)

The wildfire property loss data includes comprehensive information on the destruction caused by wildfires to residential and commercial structures. This dataset encompasses the number of houses and other structures that have been burned or damages due to wildfires in each regions of USFS (Economics, 2023).

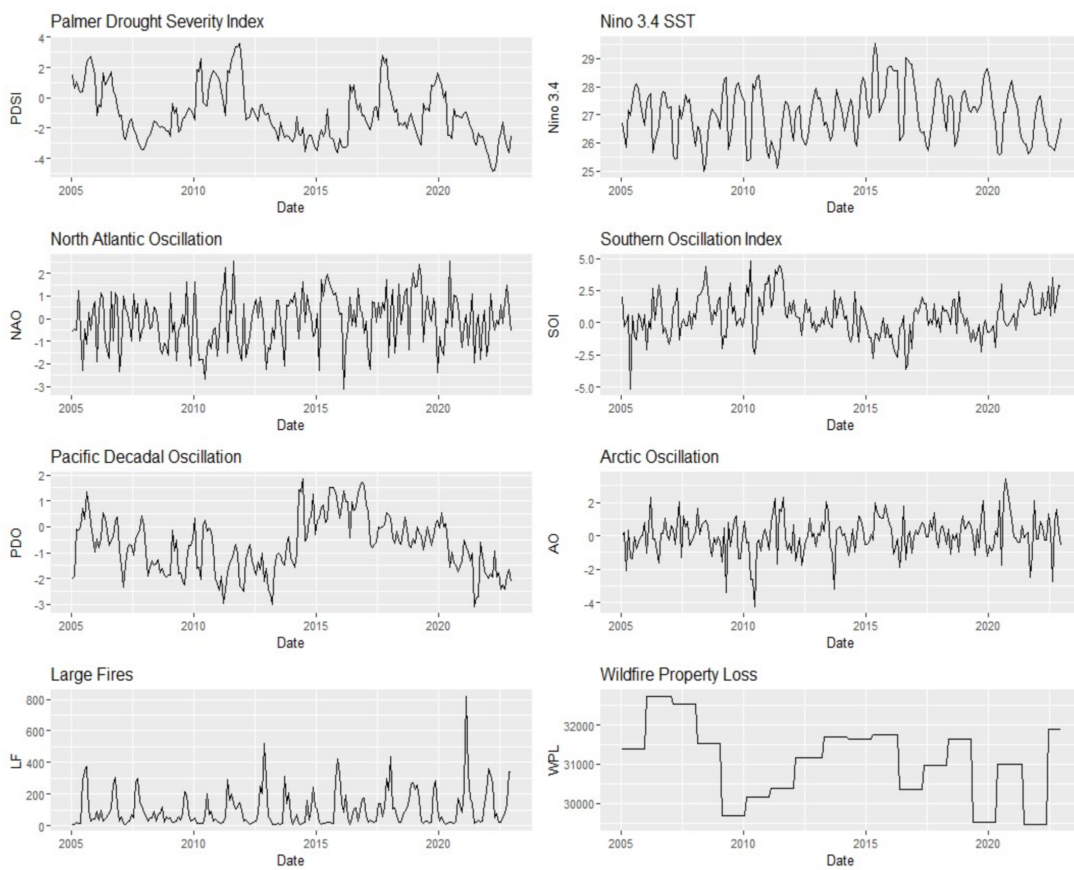

Figure 2. 5. Monthly dataset of climatic and socio-environmental variables (2005 – 2022)

Statistical Analysis

Seasonality Test

I began the investigation by calculating the monthly seasonality of all variables using equation (1).

$$Y_t = \sum_{i=1}^{12} \beta_i D_{it} + \varepsilon_t \qquad (1)$$

The variable Y_t represents the amount of expenditure, D_{it} is a binary variable for each month i in period t, ε_t is an independently and identically distributed error term, and t (t = 1,…, T) denotes time. The null hypothesis states that all beta coefficients (β_1, β_2, ..., β_{12}) are equal to zero. If a test of the null hypothesis fails to be rejected, there is no seasonality in the data. In addition, I also applied the non-parametric Kruskal-Wallis test to evaluate the sensitivity of my results (Kruskal & Wallis, 1952).

$$H = \frac{12}{(N-1)(N+1)} \sum_{i=1}^{12} \frac{T_i^2}{n_i} - 3(N+1) \qquad (2)$$

Where N is the total number of observations, n_i is the number of observations for the ith month, and T_i is the sum of the ranks for the ith month.

Unit Root Test

I employed the ADF (Augmented Dickey-Fuller) tests to determine for stationarity in the dataset under three different assumptions, to avoid any spurious correlations or external relationships between all the variables which could affect the validity of results.

$$\Delta Y_t = \alpha + \beta_{t-1} + \gamma t + \sum_{k=1}^{K} \phi_k \Delta Y_{t-k} + \varepsilon_t \qquad (3a)$$

$$\Delta Y_t = \alpha + \beta_{t-1} + \sum_{k=1}^{K} \phi_k \Delta Y_{t-k} + \varepsilon_t \qquad (3b)$$

$$\Delta Y_t = \beta_{t-1} + \sum_{k=1}^{K} \phi_k \Delta Y_{t-k} + \varepsilon_t \qquad (3c)$$

The variable $\Delta Y_t = Y_t - Y_{t-1}$, t represents the time trend and $\sum_{k=1}^{K} \phi_k \Delta Y_{t-k}$ is a method used to manage and analyze data that exhibits serial correlation. In equation (3a), I evaluate the null hypothesis H0, which states that α, β, and γ are all equal to zero ($H_0 = \alpha = \beta = \gamma = 0$). In equation (3b), the null hypothesis is that α and γ are both equal to zero ($H_0 = \alpha = \beta = 0$). Finally, in equation (3c), the null hypothesis is that β is equal to zero ($H_0 = \beta = 0$).

Pearson Correlation

Prior to performing regression analysis, the Pearson correlation test is used to evaluate potential correlation between the selected variables (Suppression expenditure, Niño 3.4, PDO, NAO, AO, SOI, PDSI, WPL, and LF). The Pearson correlation coefficient is used to assess the strength and direction of the linear relationship between variables. This coefficient goes from -1 to 1, with -1 being a perfect negative correlation, 1 representing a perfect positive correlation, and 0 indicating no linear association.

Endogeneity Test

Before conducting the OLS regression, Wu-Hausman test was employed to assess whether endogeneity exists in the regression model or not. I built 17 different models, each specifying a unique combination of these (e.g., Niño 3.4, PDSI, NAO, AO, SOI, PDO) instrumental variables for LF (Large Fires) and WPL (Wildfire Property Loss). I selected the best model (combination instrument variables) based on the significance values of Wu-Hausman Test.

I used the equation (4) to estimate the coefficient, Where Y_t is the endogenous variable (LF and WPL), $X_1, \dots, X_n$ is the instrument variables (e.g., Niño 3.4, PDSI, NAO, AO, SOI, PDO), β_0 *and* $\beta_1, \dots, \beta_n$ are the coefficients of instrument variable and v_t is the error term.

$$Y_t = \beta_0 + \beta_1 X_1 + \dots + \beta_n X_n + v_t \tag{4}$$

From the above equation I obtained the value of $\hat{Y}_t$ (which is predicted value of Y_t and the value of $\hat{v}_t$ (estimated residuals).

$$SC_t = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \gamma_1 \hat{v}_t + \epsilon_t \tag{5}$$

Where SC_t is the dependent variable (suppression cost), $\hat{v}_t$ is the estimated values of v_t, $X_1, \ldots, X_n$ are the other independent variables., β_0 and $\beta_1, \ldots, \beta_n$ are the coefficients.

I ran the regression with suppression cost as a dependent variable and all other variables as independent variables, including predicted value of v_t. The results of coefficient of equation (5) helped me to find the endogeneity test of LF and WPL. I test the following hypothesis that $H_0 : \gamma_1 = 0$, there is no endogeneity and alternate hypothesis $H_1 : \gamma_1 \neq 0$, the LF and WPL is endogenous (if the results are significant).

Regression Modeling

The 2SLS (2 Stage Least Square) method is used to estimate the coefficient in the regression model, the first stage estimates the endogenous variable using an instrument variable. After identifying the endogeneity and correlated variables, I estimated an equation for overall Forest Service costs, individual region, and western aggregated regions using ordinary least square (OLS) method. By using the predicted values from the first stage (formula 4) in the second stage regression, addresses the issue of endogeneity and provides unbiased and consistent estimates of the coefficient in the regression model.

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon_t \tag{6}$$

where Y_t represent the dependent variable (Suppression Cost) at time t , $X_1, \ldots, X_n$ represents the independent variables (e.g., $\widehat{LF}$ (used predicted values from stage one), WPL, Niño 3.4, PDSI, NAO, AO, SOI, PDO), $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are the coefficients of the independent variables, and ϵ_t is the error term.

The steps involved a specification that included dummy variables for the months of October, November, and December since the average of suppression costs these months were more than others (possibly due to end of year financial practices such as budget allocation), as well as up to twelve lags of the dependent variable (only for USFS overall). The decision to include variables in the comprehensive statistical model was made by looking at the correlation between suppression costs and the potential variables. If there was a notable correlation, the variables were included in the model. I removed variables that had no significant impact and re-estimated the equation with the remaining variables. I also added a lag of six-month, and a lag of twelve-month for climatic and socio-environmental conditions mentioned earlier in the variables by using the following model.

Copula Modeling

The Pearsons correlation coefficient is used to measure linear relationships and is particularly useful for the normal distributed data. However, it is not suitable when dealing with the non-Gaussian (not normal) distributed data. Copula analysis provides a solution by allowing for the flexibility required to model dependencies in non-Gaussian data. This technique allows for a more accurate representation of complex dependence and their co-movement (Patton, 2006).

$$C(u, v\,; \theta) = c(u, v; \theta_1, \theta_2, \ldots, \theta_n) \qquad (7)$$

Where C represent the copula function, u and v are the marginal cumulative distribution function (CDFs) of the two variables, and $\theta_1, \theta_2, \ldots, \theta_n$ are the parameters depending on the specific copula family, which may include one or more parameters.

To estimate the parameters for each bivariate model of copula family, I used a specific method that was related. I examined five types of copulas: Gaussian (Normal), t, Clayton, Gumbel, and Frank to determine which one best captured the relationship between variables (X. Y. Li et al., 2016; Sukcharoen et al., 2014). For the Gaussian and t copulas parameters I estimated the correlation coefficient (ρ), Gumbel copula parameters estimated by using Kendall's tau method, Clayton copula parameters estimated through specific formula based on the Kendall's tau, and for the Frank copula parameters I used the maximum pseudo-likelihood method; copula is suitable for all these relationships and measure (Hu, 2004). These methodologies helped me to determine the optimal parameters for each copula family.

Once the parameters were estimated, I selected the most appropriate copula family for each bivariate model on their performance based on likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). These criteria helped me identify the copula that provided the best fit for my data, allowing me to model the dependencies between variables more accurately.

Results and Discussion

Seasonality Test

The seasonality test reveals that out of eight variables examined, five exhibit some degree of seasonality. The Niño 3.4 (SST), LF and the wildfire suppression expenditure by both the Western Aggregated regions, Southern region, and overall USFS exhibit seasonality that is significant at a level of (1%) and NAO shows statistically significant seasonality at a level of (10%). Previous studies (L Westerling et al., 2003) indicated that in the western United States wildfires are strongly seasoal. On the other hand, the remaining variables, PDSI, PDO, AO, and SOI did not exhibit any seasonality (Table 2.2). The absence of seasonal variation observed in the other variables was unexpected, considering their known tendency to fluctuate over different seasons.

Table 2. 2. Seasonality test (F and KW test)

Variables	**F-value regression**	**KW-value**
Suppression expenditure – USFS	22.90***	110.81***
Suppression Expenditure – Southern	44.37***	145.59***
Suppression Expenditure – Western Aggregated	1.14	32.86***
PDSI	0.32	0.65
Niño 3.4 SST	7.49***	69.96***
NAO	1.73*	17.73*
SOI	0.54	3.87
PDO	0.80	8.40
AO	0.65	8.71
LF	13.4***	116.92***

Note: The symbols "***" represent a p-value below 1%, "**" represents a p-value below 5%, and "*" represents a p-value below 10%. There was a combined total of 216 observations for all climatic and socio-environmental variables and Forest Service suppression expenditure and a separate total of 192 observations for Western aggregated and Southern suppression expenditure.

Unit Root Test

All variables under consideration showed significant indication of stationary, as indicated by the diverse unit root test criteria. The only anomaly was observed in the Niño 3.4 (SST), which did not exhibit stationarity under no-drift and no-trend conditions (Table 2.3). The results shown in Table 2.3 provide valuable insight into the optimal specification and the correlation between suppression costs and climate and socio-environmental variables. Based on the results of stationarity in all variables, I developed a suppression model that is dependent on the level of all variables.

Table 2. 3. Augmented-Dickey Fuller Test for Stationary (Unit root)

Variables	Trend	Drift	No drift, No Trend
Suppression Expenditure – USFS	-8.00***	-7.56***	-5.03***
Suppression Expenditure – Southern	-8.64***	-8.62***	-7.63***
Suppression Expenditure – Western Aggregated	-8.14***	-8.13***	-6.23***
PDSI	-3.91***	-3.69***	-3.14***
Niño 3.4 SST	-7.69***	-7.72***	-0.25
NAO	-9.15***	-8.95***	-8.92***
SOI	-5.94***	-5.94***	-5.41***
PDO	-4.35***	-4.33***	-3.48***
AO	-8.77***	-8.67***	-8.68***
LF	-8.02***	-7.93***	-5.11***

Note: The symbols “***” represent a p-value below 1%, “**” represents a p-value below 5%, and “*” represents a p-value below 10%. There was a combined total of 211 observations for all climatic and socio-environmental variables and Forest Service suppression expenditure, and a separate total of 192 observations for Western and Southern suppression expenditure.

Pearson Correlation

The Pearson correlation coefficient for the suppression expenditure of the USFS (overall US), Western aggregated regions, and the Southern are displayed in Figures 2.5, 2.6 and 2.7, respectively. Each variable distribution is shown on the diagonal, variables-related scatter plots are shown in the bottom triangle, and the Pearson coefficient is shown in the top triangle. To be more precise, the first column represents the relationship between each climatic and socio-environmental condition and suppression costs, and the first row represents the Pearson correlation.

Since the USFS data ended in 2022 and the regional data ended in 2020, I determined a correlation study of the variables for each. For overall USFS, PDSI and suppression costs were significantly correlated negatively. On the other hand, the Western aggregated and Southern regions did not show significant results.

Several climatic and socio-environmental variables exhibit significant relationships. The most significant association is found between the Niño 3.4 SST and the SOI with a correlation coefficient of -0.62 (FS overall), -0.60 (western aggregated regions) and -0.60 (southern). The Niño 3.4 SST and the PDO showed a significant positive correlation coefficient of +0.54 (FS overall) and +0.17 (western aggregated regions), align with the prior study of Prestemon et al., (2008a) that PDO is highly correlated with Niño 3.4 SST. The Niño 3.4 SST and the LF also showed a significant positive correlation coefficient of +0.32 (FS overall) and +0.21 (western aggregated regions), respectively.

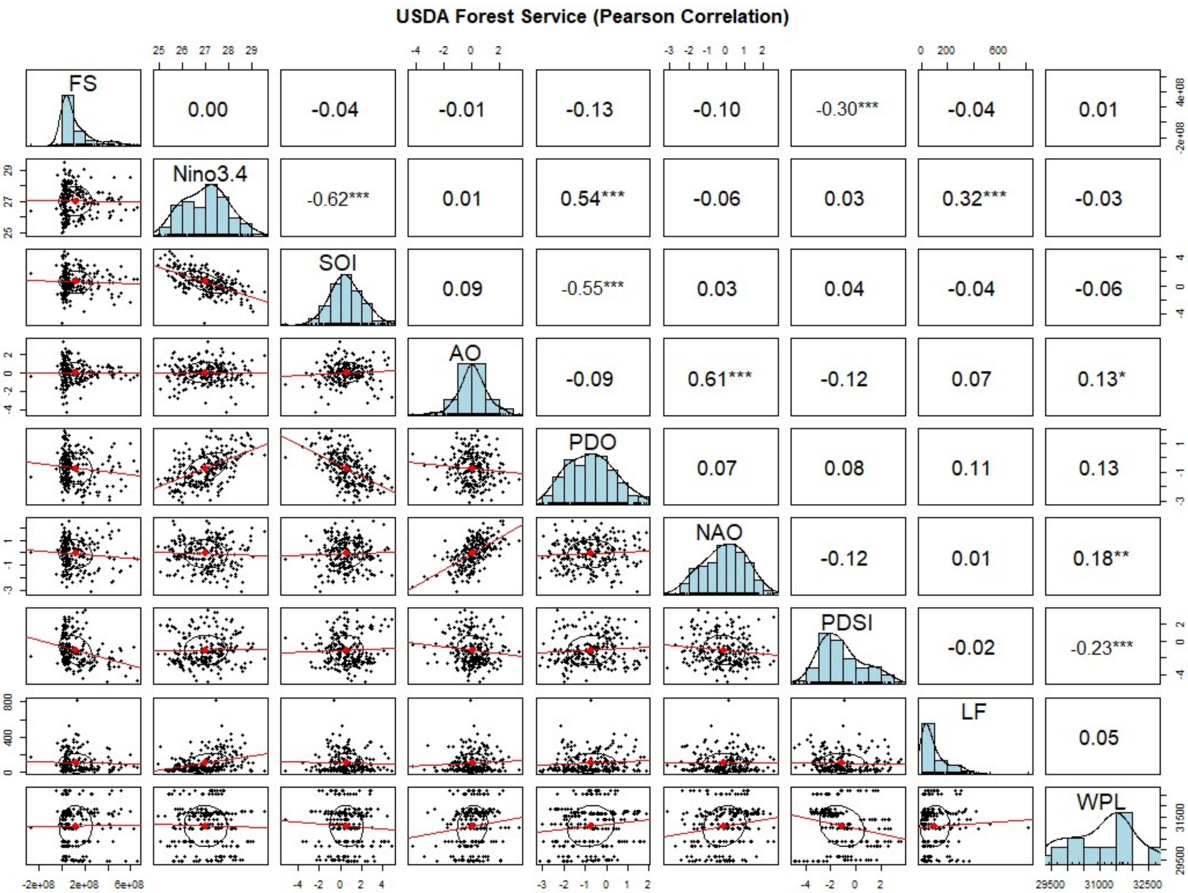

Figure 2. 6. Pearson correlation coefficient USFS (Total Observation = 216)

The SOI and PDO exhibit a negative correlation of -0.55 (FS overall), -0.52 (western aggregated Regions), and -0.52 (southern). The precise causes for the association between AO and NAO showed a positive correlation coefficient of +0.61 (FS overall), 0.62 (western aggregated Regions), and 0.62 (southern) have not been completely explored (Báez et al., 2013). The correlation coefficient between the PDSI and SOI showed a positive coefficient of 0.04 (FS overall) and showed a significant positive coefficient of 0.16 (western aggregated regions) and negative coefficient -0.28 (southern). LF showed a negative correlation coefficient (-0.02) with the PDSI (FS overall), which aligns with the prior study of (Riley et al., 2013).

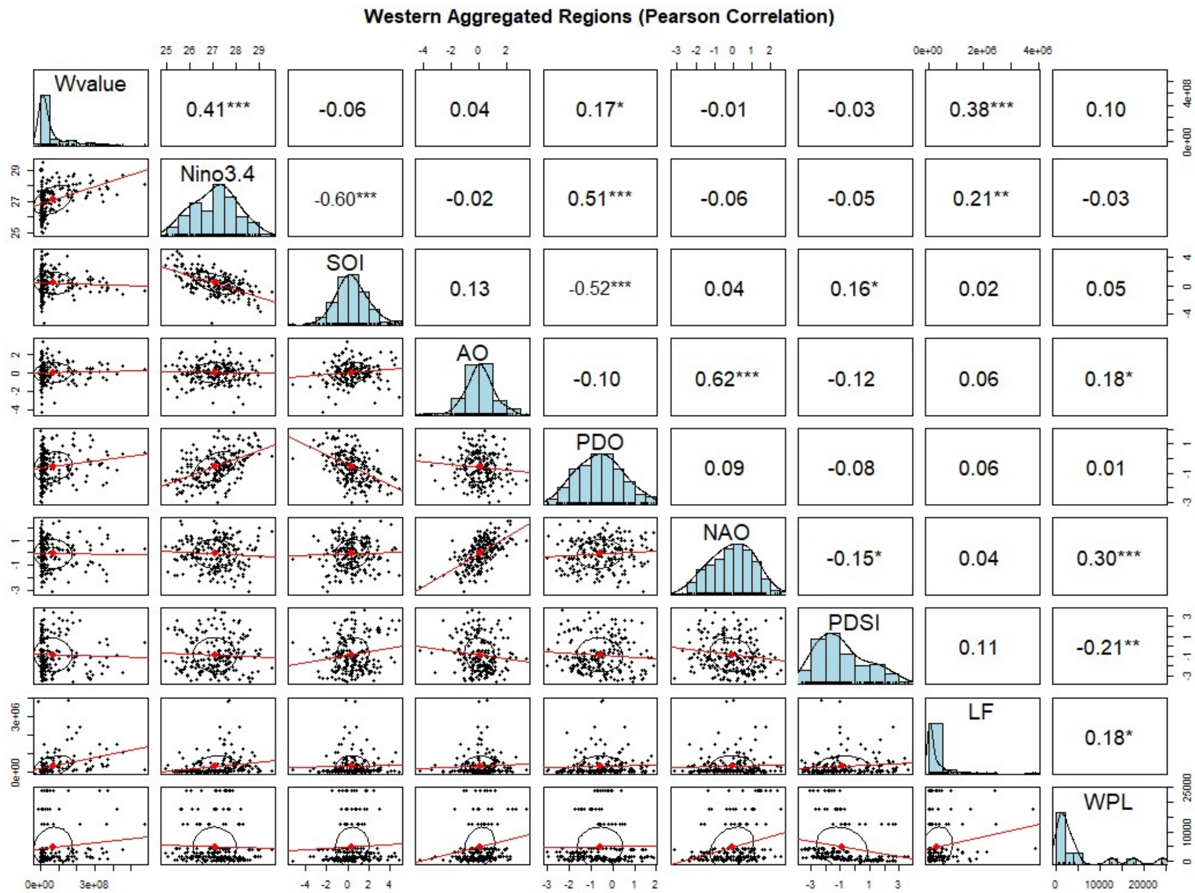

Figure 2. 7. Pearson correlation coefficient USFS Western aggregated Regions (Total Observation = 192)

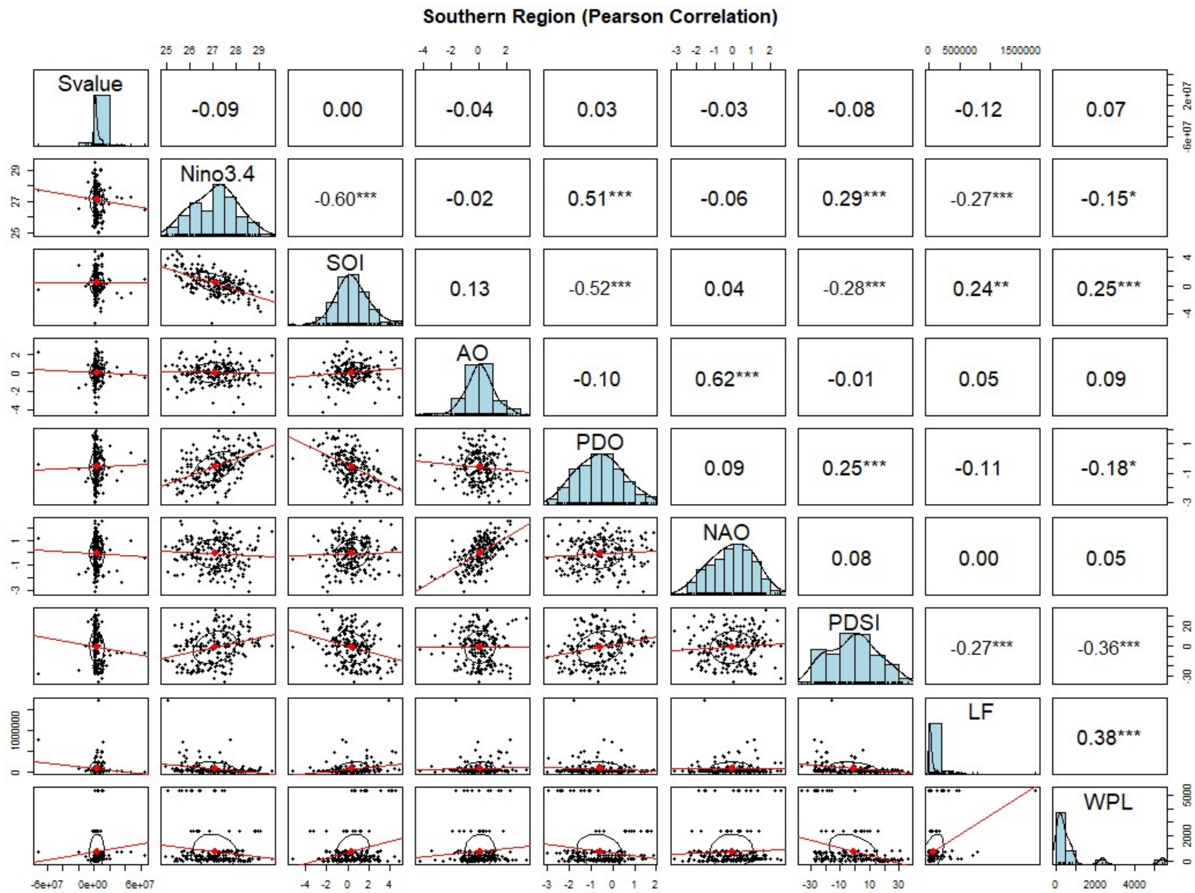

Figure 2. 8. Pearson correlation coefficient USFS Southern Region (Total Observation = 192)

Endogeneity test

Based on the diagnostic tests, model 5 (PDSI and NAO) performed as a good combination of instrument variables for the USFS (overall) and southern region. The Wu-Hausman test demonstrated the presence of endogeneity (p-value = 0.013 and 0.000). For the western aggregated regions, model 9 (Niño 3.4 SST and SOI) performed as the best combination of instrumental variables. The Wu-Hausman test demonstrated the presence of endogeneity (p-value = 0.000); for the full details of the results please see appendix A (Table A2.1, A2.2, A2.3).

For the USFS and both regions (western aggregated regions and southern region), WPL did not show endogeneity with any combination of instrumental variables. The Wu-Hausman test demonstrated non-significant results for each combination of models; for the full details of the results please see appendix B (Table B2.1, B2.2, B2.3).

Regression Modeling

The expenditures associated with USFS are presented along the nine different model parameters in Table 2.3, respectively. The model includes dummy variables for October, November, and December, and suppression costs lag in the univariate model that is presented in column 1 of the table. All climatic and socio-environmental variables and their lags (Niño 3.4 SST, SOI, PDO, AO, NAO, PDSI, LF, WPL) are represented in columns 2 through 9.

The USFS suppression cost model performed best with the first, fourth, and tenth lags. The regression results indicate a considerable seasonal impact on the suppression expenditure (FS overall). Among the months listed, November had the most significant effect on the USFS suppression expenditure model, with a correlation coefficient of $242 million. The coefficients for October ($113 million) and December ($234 million) were significantly smaller than November coefficient $242 million (Table 2.4, column 1).

The determination of climatic and socio-environmental variables reveals a significant correlation effect on USFS suppression expenditure. Increased frequency and severity of El Niño occurrences may increase drought and wildfires (Cochrane, 2003). The Niño3.4, Niño3.4$_{t-6}$ (six-month lag), and Niño3.4$_{t-12}$ (twelve-month lag) conditions of El Niño have a considerable influence on suppression expenditure. To be more specific, the Niño3.4 variable has a positive impact with a coefficient of $4.80 million, while the Niño3.4$_{t-6}$ (six-month lag) variable has a notable positive influence, indicated by a coefficient of $12.6 million. (Cochrane, 2003). It's important to note that this effect is relatively minor when considering the annual spending of over $1 billion on wildfire suppression. Suppression expenditure has a negative correlation with increasingly negative values of the SOI, which indicates a coefficient of $-1.67 million and SOI_{t-6} (six-month lag) has a positive coefficient of $4.92 million. The coefficient of PDO_{t-12} (twelve-month lag) indicates a positive coefficient of $7.39 million.

The AO also has a positive coefficient of $1.13 million and AO_{t-12} (twelve-month lag) has a greater impact on suppression cost, increasing to $3.11 million. The NAO consistently exerts a negative impact, as shown by an NAO value of $-4.45 million. The PDSI has a significant negative correlation coefficient ($-11.4 million) with suppression expenditure. $PDSI_{t-6}$ (six-month lag) has a significant negative coefficient of $-0.303 million, similarly, this result aligns with earlier study linking higher drought seasons and more intense wildfires (A. Chen, 2022). $\widehat{LF}$ (used fitted values) indicated a significant positive correlation with the suppression cost with a coefficient of $0.14 million and WPL showed a significant positive relation at WPL_{t-6} (six-month lag) with a coefficient of $0.17 million and a significant negative coefficient of $-0.18 million at WPL_{t-12} (twelve-month lag).

The determination of variables reveals different significant correlations with western aggregated regions' suppression expenditure (Table 2.5). The PDO_{t-12} (twelve-month lag), and $PDSI_{t-12}$ (twelve-month lag) conditions have a significant influence on suppression expenditure. To be more specific, the PDO_{t-12} variable has a positive impact with a coefficient of $13.14 million, while the $PDSI_{t-12}$ (twelve-month lag) variable has a notable positive influence, indicated by a coefficient of $4.15 million. The $PDSI_{t-6}$ showed a negative correlation coefficient ($-4.11 million). In the western U.S., there is a difference in the impact of negative and positive anomalies on precipitation from north to south (Fan et al., 2017), and this result aligns with Addington et al.,

(2015) that drought condition is strongly associated with wildfires. The impact of Niño3.4 ($5.80 million) showed a positive coefficient on suppression expenditure, higher value of Niño3.4 might be linked to extended drought and wildfires (Wooster et al., 2012). Suppression expenditure has a negative relationship with SOI, which indicates a coefficient of $-1.47 million. SOI_{t-6} (six-month lag) has a negative coefficient of $-2.0 million. Fuller & Murphy, (2006) reported a significant relationship between fires and the SOI and Niño3.4 index.

The AO also has a positive coefficient of $1.31 million and AO_{t-6} (six-month lag) has a significant negative impact on suppression cost ($-9.68 million). The NAO indicated a negative impact, as shown by a NAO value of $-0.14 million and NAO_{t-6} (six-month lag) has a positive relation with a coefficient of $9.65 million. Similarly, the impact of AO (negative) and NAO (positive) aligns with earlier study of Prestemon et al., (2008a). The PDSI has a significant positive correlation coefficient ($3.19 million) with suppression expenditure. $\widehat{LF}_{t-12}$ (twelve-month lag) indicated a significant positive correlation with the suppression cost with a coefficient of $39.84 million. The significant negative correlation of WPL_{t-12} ($-36.26 million) is surprising. This result may suggest a non-linear relationship between suppression costs and WPL. Later, a non-linear model better explained this unexpected result.

The exploration of southern regions' suppression expenditure also indicated a different relationship with each variable (Table 2.6). The Niño3.4 and $Niño3.4_{t-6}$ (six-month lag) and conditions of El Niño have significant influence on suppression expenditure with the negative coefficients ($-4.16 and $-1.85 million). Suppression expenditure showed a negative correlation with SOI, which indicates a coefficient of \$-0.65 million and SOI_{t-12} has a significant positive coefficient (\$1.51 million).

The coefficient of PDO and PDO_{t-6} (six-month lag) indicated a significant positive coefficient (\$2.00 and \$1.92 million). The AO shows a positive coefficient (not significant) (\$0.05 million), AO_{t-6} (six-month lag) has a significant positive coefficient of \$1.58 million, which aligns with the prior study (Justino et al., 2022) that in the different regions of United States wildfires increased during the positive phase of AO. The NAO indicated a negative impact, as shown by an NAO value of \$-0.87 million and NAO_{t-6} (six-month lag) indicates a significant coefficient (\$-1.65 million). The PDSI has a positive coefficient (\$0.00 million) with suppression expenditure, and $PDSI_{t-6}$ (six-month lag) has a similar positive relation with a coefficient of \$0.02 million, which is like the study of Prestemon et al., (2008a). $\widehat{LF}$ indicated a significant negative correlation with the suppression cost with a coefficient of \$-0.76 million. WPL showed positive significant correlation of coefficient (\$12.59 million).

Table 2. 4. Suppression cost estimates USFS 2005 – 2022 (2SLS Regression)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Y_{t-1}	0.25^{***}	0.26^{***}	0.25^{***}	0.25^{***}	0.25^{***}	0.26^{***}	0.22^{***}	0.29^{***}	0.24^{***}
Y_{t-4}	0.72^{*}	0.95^{**}	0.70	$0. 76^{*}$	0.67	0.78^{*}	0	0.13^{***}	0.67
Y_{t-10}	0.28^{***}	0.24^{***}	0.25^{***}	0.27^{***}	0.27^{***}	0.28^{***}	0	0.23^{***}	0.28^{***}
October	113^{***}	115^{***}	114^{***}	113^{***}	115^{***}	107^{***}	114^{***}	123^{***}	113^{***}
November	242^{***}	240^{***}	246^{***}	249^{***}	248^{***}	240^{***}	248^{***}	247^{***}	251^{***}
December	234^{***}	242^{***}	242^{***}	245^{***}	243^{***}	244^{***}	245^{***}	247^{***}	246^{***}
Niño3.4		4.80							
Niño3.4$_{t-6}$		12.6^{*}							
Niño3.4$_{t-12}$		1.38							
SOI			-1.67						
SOI$_{t-6}$			4.92						
SOI$_{t-12}$			-1.11						
PDO				-5.29					
PDO$_{t-6}$				-3.52					
PDO$_{t-12}$				7.39					
AO					1.13				
AO$_{t-6}$					0.25				
AO$_{t-12}$					3.11				
NAO						-4.45			
NAO$_{t-6}$						-4.27			
NAO$_{t-12}$						-5.95			
PDSI							-11.4^{***}		
PDSI$_{t-6}$							-0.303		
PDSI$_{t-12}$							6.29^{*}		
$\widehat{LF}$								0.14^{**}	
$\widehat{LF}_{t-6}$								-0.98	
$\widehat{LF}_{t-12}$								0.39	
WPL									-0.36
WPL$_{t-6}$									0.17^{*}
WPL$_{t-12}$									-0.18^{**}

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10

Table 2. 5. Suppression cost estimates Western Agg. Regions2013 – 2022 (2SLS Regression)

Variables	**Coefficient**	**Std. Error**	**Probability**
Y_{t-1}	0.15**	0.06211	0.0156**
Y_{t-11}	-0.07	0.08766	0.4508
Y_{t-12}	0.64***	0.07109	0.0000***
Niño3.4	5.80	8498000	0.4957
Niño3.4$_{t-6}$	2.54	7890000	0.7478
Niño3.4$_{t-12}$	3.05	8958000	0.7341
SOI	-1.47	4870000	0.7626
SOI $_{t-6}$	-2.00	4659000	0.6685
SOI $_{t-12}$	3.11	4625000	0.5019
PDO	2.10	7535000	0.7811
PDO $_{t-6}$	-7.45	7212000	0.3032
PDO $_{t-12}$	13.14*	7158000	0.0683*
AO	1.31	6302000	0.8360
AO $_{t-6}$	-9.68	6251000	0.1237
AO $_{t-12}$	2.62	6229000	0.6742
NAO	-0.14	6000000	0.9816
NAO $_{t-6}$	9.65	6258000	0.1253
NAO $_{t-12}$	0.06	6007000	0.9925
PDSI	3.19	4252000	0.4550
PDSI $_{t-6}$	-4.11	3497000	0.2416
PDSI $_{t-12}$	4.15	3954000	0.2952
$\widehat{LF}$	0.00	0.04595	0.9536
$\widehat{LF}_{t-6}$	12.79	11	0.2467
$\widehat{LF}_{t-12}$	39.84***	14.84	0.0081***
WPL	40.79	1076	0.9698
WPL$_{t-6}$	1001	1290	0.4390
WPL$_{t-12}$	-36.26***	1175	0.0024***

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10

Table 2. 6. Suppression cost estimates southern regions 2005 – 2020 (2SLS Regression)

Variables	Coefficient	Std. Error	Probability
Y_{t-1}	0.22***	0.07459	0.0034***
Y_{t-3}	0.18**	0.07779	0.0256**
Y_{t-4}	-0.18**	0.07559	0.0162**
Niño3.4	-4.16***	1083000	0.0002***
Niño3.4$_{t-6}$	-1.85*	1079000	0.0889*
Niño3.4$_{t-12}$	1.40	1125000	0.2161
SOI	-0.65	647900	0.3205
SOI $_{t-6}$	0.06	637800	0.9266
SOI $_{t-12}$	1.51**	650900	0.0220**
PDO	2.00*	1042000	0.0567*
PDO $_{t-6}$	1.92**	972400	0.0497**
PDO $_{t-12}$	0.89	920800	0.3330
AO	0.05	863800	0.9509
AO $_{t-6}$	1.58*	854900	0.0660*
AO $_{t-12}$	0.46	866700	0.5941
NAO	-0.87	813800	0.2874
NAO $_{t-6}$	-1.65**	801900	0.0415**
NAO $_{t-12}$	-0.53	781600	0.5020
PDSI	0.00	54580	0.9281
PDSI $_{t-6}$	0.02	64100	0.7649
PDSI $_{t-12}$	-0.12*	64230	0.0739*
$\widehat{LF}$	-0.76**	0.2966	0.0113**
$\widehat{LF}_{t-6}$	-3.69	4.637	0.4270
$\widehat{LF}_{t-12}$	0.53	4.796	0.9118
WPL	12.59*	734.3	0.0885*
WPL$_{t-6}$	-74.57	764.3	0.3308
WPL$_{t-12}$	72.59	683.1	0.2896

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10

Dependency Modeling with Copulas

In this part, I determined the copula modeling technique as an effective tool to understand and capture the dependence among the variables (Figure 2.8). Copulas offer a flexible method for modeling dependencies, making them well-suited for tail dependencies due to their adaptability (Nelsen, 2006).

The analysis of climatic and socio-environmental variables reveals different insights into their interdependencies and potential impacts on the USFS suppression expenditure (Table 2.7). LF indicates a positive dependency (0.30), indicating that an increase in LF occurrences is associated with suppression costs. However, lower dependency (0.1) exhibits extreme influences in the lower range. WPL indicates a positive dependency (1.03), suggesting a correlation with the USFS suppression costs (an increase in one variable leads to an increase in the other variable), and exhibits upper tail dependencies (0.04), signifying extreme effects in the upper range values.

Table 2. 7. U.S. Forest Service suppression costs and variables (Copula Dependency)

Variables	**Dependency**	**Tail Dependencies**	
		Lower	Upper
Large Fire	0.30	0.10	0
WPL	1.03	0	0.04
PDSI	-0.32	0	0
Niño 3.4	0.19	0.02	0
NAO	-0.64	0	0
SOI	0.15	0.01	0
PDO	-0.18	0	0
AO	0.10	0	0

The climatic variables indicated different dependencies with USFS suppression expenditure. PDSI indicates a negative dependence (-0.32), indicating that an increase in PDSI correlates with a decrease in the suppression expenditure. Niño3.4 and SOI both show a positive dependency with values of (0.19 and 0.15), exhibiting that an increase in Niño3.4 and SOI is correlated with an increase in the suppression costs (FS overall), and both variables exhibit a low lower dependency value (0.02 and 0.01) that indicates that potential influence in the lower range. Prior studies have shown that the severity of wildfire are influences by El Niño in the different regions of United States (Jones et al., 2014; Swetnam & Betancourt, 1990). On the other hand, NAO and PDO both exhibit a negative dependency (-0.64 and -0.18), indicating that an increase in one variable is correlated with a decrease in the suppression expenditure. AO shows a positive dependency (0.1) with both lower and upper dependency values (0), showing that an increase in AO is correlated with an increase with an increase in the suppression expenditure of USFS. Figure 2.8 provides a graphical representation of the dependency values of the USFS suppression and climatic and socio-environmental variables.

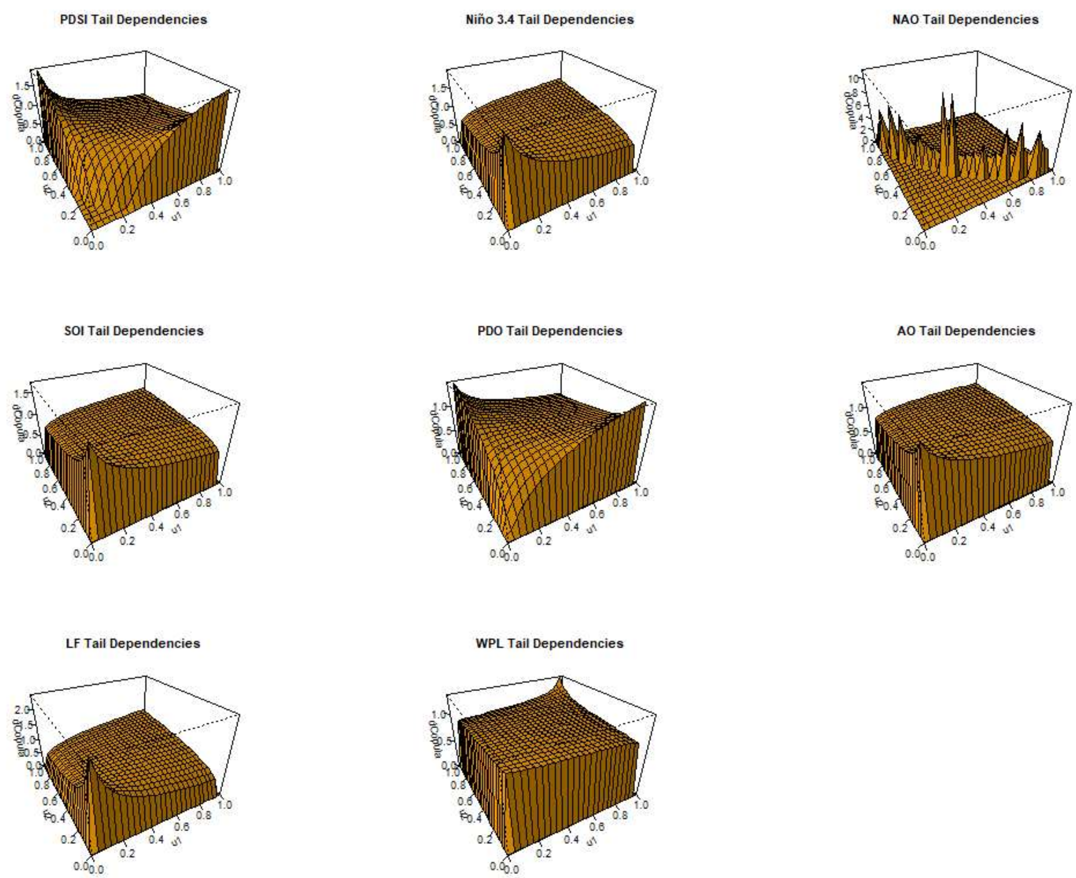

Figure 2. 9. Dependency between the USFS suppression costs and climatic and socio-environmental variables.

The analysis variables uncover fascinating insight into their interdependencies and potential impacts on the suppression expenditure of western aggregated regions (Table 2.8). LF indicates a strong positive dependency (5.58), indicating that an increase in LF occurrences is associated with suppression costs. WPL also indicates a positive dependence (0.16), with no tail dependence. PDSI indicates a negative dependency (-0.09), indicating that an increase in PDSI correlates with a decrease in the suppression expenditure and NAO also indicates a negative dependency (-0.05). Niño3.4 shows a positive dependency with the value of (1.38), with an upper tail dependency of (0.35) indicating a potential influence in the upper range, higher value of Niño3.4 could be linked to extended drought and wildfires (Wooster et al., 2012).. SOI exhibits a substantial positive dependency (0.05), indicating that an increase in SOI is correlated with an increase in the suppression expenditure. PDO shows a positive dependency (0.34), with a lower tail dependency (0.87) indicating a potential extreme influence in the lower range. AO exhibits a positive dependency (0.09) indicating that an increase in AO is correlated with an increase in the suppression expenditure of western aggregated regions (Figure 2.9).

Table 2. 8. USFS (western aggregated regions) suppression costs and variables (Copula Dependency)

Variables	Dependency	Tail Dependency	
		Lower	Upper
PDSI	-0.09	0	0
Niño 3.4	1.38	0	0.35
NAO	-0.05	0	0
SOI	0.05	0	0
PDO	0.34	0.87	0
AO	0.09	0	0
LF	5.58	0	0
WPL	0.16	0	0

The investigation between southern region suppression costs and variables uncovers different interdependencies and potential impacts on the suppression (Table 2.9). LF indicates a positive dependency (1.6), indicating that an increase in LF occurrences is associated with suppression costs. WPL also indicates the positive dependence (1.64), with no tail dependence. PDSI indicates a negative dependency (-1.76), and NAO also indicates a positive dependency (0.11), with a lower tail dependency (0.001). Niño3.4 shows a negative dependency with the value of (-0.55). SOI exhibits a substantial positive dependency (0.36), indicating that an increase in SOI is correlated with an increase in the suppression expenditure. PDO shows a positive dependency (0.006), and AO also exhibits a positive dependency (0.59) indicating that an increase in AO is correlated with an increase in the suppression expenditure of western aggregated regions, which aligns with the prior study (Justino et al., 2022) that in the different regions of United States wildfires increased during the positive phase of AO (Figure 2.10).

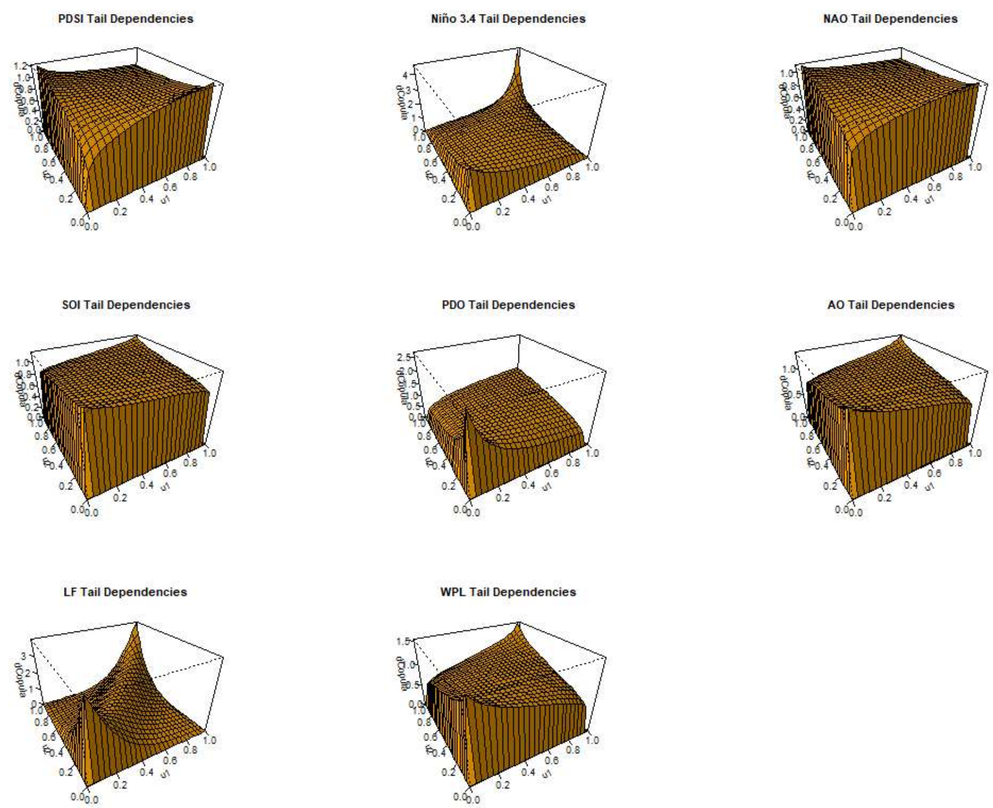

Figure 2. 10. USFS (western aggregated regions) suppression costs and variables (Copula Dependency)

Table 2. 9. USFS (southern) suppression costs and variables (Copula Dependency)

Variables	Dependency	Tail Dependency	
		Lower	Upper
PDSI	-1.76	0	0
Niño 3.4	-0.55	0	0
NAO	0.11	0.001	0
SOI	0.36	0	0
PDO	0.006	0	0
AO	0.59	0	0
LF	1.6	0	0
WPL	1.64	0	0

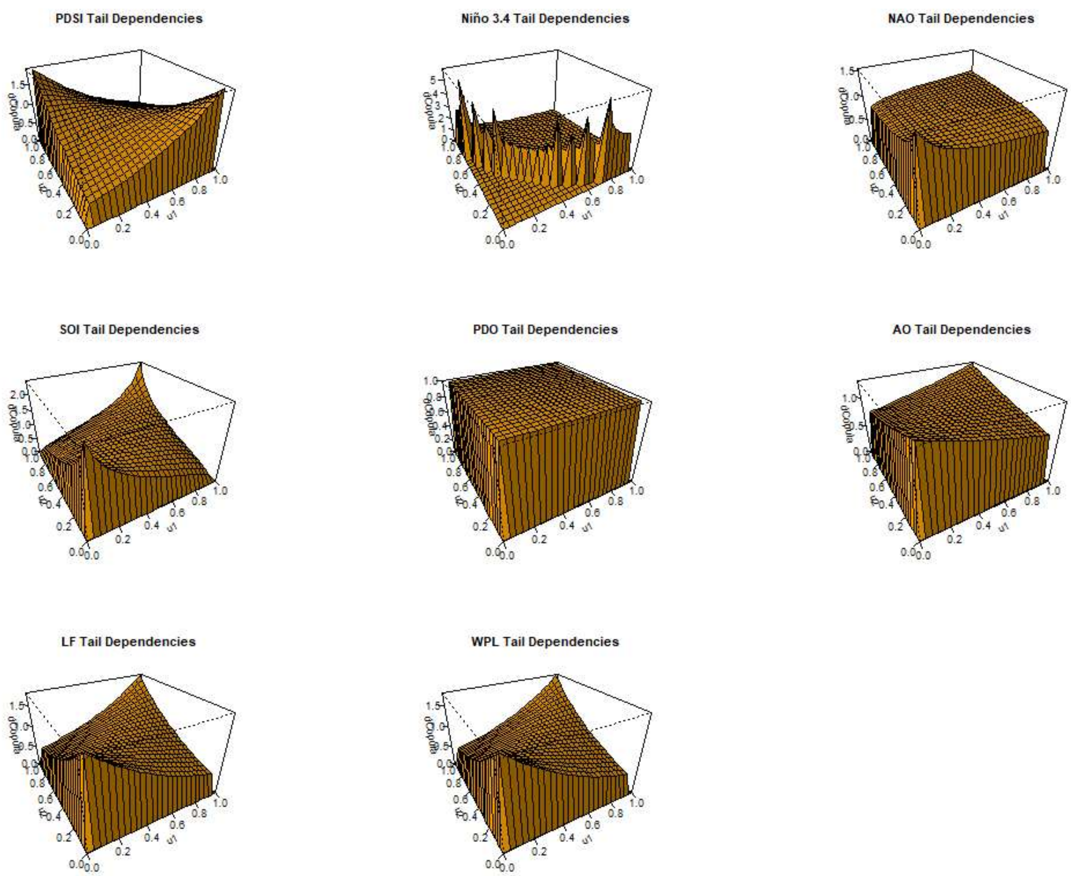

Figure 2. 11. Forest Service (southern) suppression costs and variables (Copula Dependency)

Conclusion

Wildfire impacts land management planning, budgets, and resource allocation in the United States (Ager et al., 2010; Calkin et al., 2011). The study reveals how the creation of models and analysis of cost-influencing variables advance in predicting future expenditures, facilitating agencies to better plan budgets and allocate resources for wildfire management in the future.

I determined the variables that influence the amount of money spent on suppressing fires for the USFS and its regions by using the monthly data (2005 - 2022 for USFS and 2005 - 2020 for other regions). This study used the monthly dataset of only USFS suppression costs and its western aggregated regions which includes regions 1-6 and southern region (8). This study did not include the Eastern and Alaska regions.

I employed a non-linear copula model to analyze the complex relationships between suppression costs and all variables. This advanced modeling approach allowed me to capture the complex dependencies and non-linear relationships among variables. By using copula model, I was able to uncover nuanced patterns and dependencies that would have been overlooked by traditional linear models.

The study findings align with previous studies in different ways. Prestemon et al., (2008a) noted increased wildfire suppression costs during the negative AO and positive NAO, consistent with this study results for AO and NAO. Fuller & Murphy, (2006) found a significant relationship between fires and SOI and Niño 3.4, corresponding negative correlation between SOI and suppression costs. The study of Justino et al., (2022) demonstrated that increased wildfires during the positive phase of AO, aligns with significant positive relationship between AO and suppression costs.

Wildfires have significant economic impacts beyond just suppression costs, including property damage. Understanding the factors driving suppression expenditures can help policymakers and agencies quantify the full economic impact of wildfires and develop strategies to mitigate these impacts. This study can inform long-term planning efforts for wildfires management. By recognizing the trends and patterns in the data, agencies can develop strategies that are effective not just in the short term but also in the long term.

Understanding of the factors that influence wildfire suppression expenditures can also benefit local communities. By educating residents about these factors, communities can better prepare for wildfire seasons and work with agencies to implement preventative measures. Overall, this study highlights the importance of adopting a comprehensive approach that considers a wide range of climatic and socio-environmental factors when formulating wildfire management practices.

Future studies could be focused on including economic and social factors in the analysis of cost determinations for wildfire suppression to achieve a comprehensive understanding of drivers. Factors such as land use patterns, population density, and socioeconomic status can significantly impact the costs associated with managing wildfires. Exploring the potential of technological advances, such as remote sensing is another way to improve wildfire management for the future. These technologies have potential to revolutionize how wildfires are monitored, predicted, and managed, ultimately reducing suppression expenditures.

Appendix A

Table A2. 1: Endogeneity (Wu-Hausman Test) Results of LF (Large Fires) for USFS (overall) (Model Comparison)

Model	df1	df2	Statistic	p-value
model1	1	213	0.1049701	0.746263
model2	1	213	0.8117368	0.368625
model3	1	213	0.1874850	0.665456
model4	1	213	0.3651427	0.546307
model5	1	213	15.3037264	0.000123***
model6	1	213	5.9540769	0.015501**
model7	1	213	0.4048432	0.525282
model8	1	213	1.0265765	0.312114
model9	1	213	0.1318403	0.716892
model10	1	213	0.0000032	0.998573
model11	1	213	0.6079404	0.436430
model12	1	213	0.0163056	0.898512
model13	1	213	3.5390140	0.061305*
model14	1	213	0.0542908	0.815982
model15	1	213	5.4171439	0.020879**
model16	1	213	3.2087448	0.074665*
model17	1	213	0.1180876	0.731457

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10, df1 represents the degree of freedom associated with a statistical test, where df1 is the numerator degree of freedom and df2 is the denominator degrees of freedom (total number of observation).

Table A2. 2: Endogeneity (Wu-Hausman Test) Results of LF (Large Fires) for Western Aggregated Regions (overall) (Model Comparison)

Model	df1	df2	Statistic	p-value
model1	1	189	26.4067610	0.00000069***
model2	1	189	18.3963810	0.00002859***
model3	1	189	16.8642210	0.00005972***
model4	1	189	22.0177010	0.00000517***
model5	1	189	1.6295310	0.20333420
model6	1	189	1.5544293	0.21402570
model7	1	189	0.0908779	0.76339546
model8	1	189	0.9448263	0.33228208
model9	1	189	36.4224077	0.00000001***
model10	1	189	24.0796018	0.00000199***
model11	1	189	30.1860139	0.00000013***
model12	1	189	25.0203719	0.00000129***
model13	1	189	2.7465222	0.09912521*
model14	1	189	1.0411439	0.30885990
model15	1	189	2.6310579	0.10645880
model16	1	189	3.3425437	0.06908661*
model17	1	189	0.0174351	0.89509160

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10, df1 represents the degree of freedom associated with a statistical test, where df1 is the numerator degree of freedom and df2 is the denominator degrees of freedom (total number of observation).

Table A2. 3: Endogeneity (Wu-Hausman Test) Results of LF (Large Fires) for Southern Region (overall) (Model Comparison)

Model	**df1**	**df2**	**Statistic**	**p-value**
model1	1	189	3.481228	0.0636181*
model2	1	189	3.747011	0.0543941*
model3	1	189	3.4808766	0.0636314*
model4	1	189	3.4115018	0.0663068*
model5	1	189	6.180665	0.0137830**
model6	1	189	0.8438556	0.3594672
model7	1	189	3.1488448	0.0775906*
model8	1	189	5.9021744	0.0160574**
model9	1	189	1.258286	0.2633989
model10	1	189	2.0801594	0.1508797
model11	1	189	2.3986929	0.1231095
model12	1	189	2.4948964	0.1158880
model13	1	189	0.1813369	0.6707114
model14	1	189	0.1377048	0.7109891
model15	1	189	0.1535391	0.6956174
model16	1	189	0.360278	0.5490709
model17	1	189	0.125018	0.7240486

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10, df1 represents the degree of freedom associated with a statistical test, where df1 is the numerator degree of freedom and df2 is the denominator degrees of freedom (total number of observation).

Appendix B

Table B2. 1: Endogeneity (Wu-Hausman Test) Results of WPL (Wildfire Property Loss) for USFS (overall) (Model Comparison)

Model	df1	df2	Statistic	p-value
model1	1	213	2.0427030	0.1544026
model2	1	213	1.3942660	0.2390028
model3	1	213	6.1925970	0.1359480
model4	1	213	20.6140895	0.9394160
model5	1	213	6.2414910	0.1323515
model6	1	213	21.1874170	0.7153620
model7	1	213	7.7727640	0.5783800
model8	1	213	16.8396380	0.5796480
model9	1	213	0.7512825	0.3870458
model10	1	213	1.8640015	0.1736039
model11	1	213	5.7558856	0.1729487
model12	1	213	0.0148327	0.9031806
model13	1	213	4.6013554	0.3307864
model14	1	213	1.2840203	0.2584267
model15	1	213	4.4018410	0.3707908
model16	1	213	3.0434800	0.8250440
model17	1	213	0.0509678	0.8216042

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10, df1 represents the degree of freedom associated with a statistical test, where df1 is the numerator degree of freedom and df2 is the denominator degrees of freedom (total number of observation).

Table B2. 2: Endogeneity (Wu-Hausman Test) Results of WPL (Wildfire Property Loss) for Western Aggregated Regions (Model Comparison)

Model	df1	df2	Statistic	p-value
model1	1	189	0.113191700	0.7369126
model2	1	189	0.925746300	0.3372000
model3	1	189	1.003053000	0.3178000
model4	1	189	1.492742000	0.2233000
model5	1	189	0.247610300	0.6193000
model6	1	189	0.065277120	0.7986000
model7	1	189	0.002107577	0.9634000
model8	1	189	0.059775820	0.8071000
model9	1	189	5.525270000	0.1977000
model10	1	189	1.066036000	0.3032000
model11	1	189	29.968699400	0.1384000
model12	1	189	1.019738000	0.3139000
model13	1	189	0.694233500	0.4058000
model14	1	189	0.679222700	0.4109000
model15	1	189	0.621787200	0.4314000
model16	1	189	0.621043900	0.4316000
model17	1	189	0.020660490	0.8859000

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10, df1 represents the degree of freedom associated with a statistical test, where df1 is the numerator degree of freedom and df2 is the denominator degrees of freedom (total number of observation).

Table B2. 3: Endogeneity (Wu-Hausman Test) Results of WPL (Wildfire Property Loss) for Southern Region (Model Comparison)

Model	df1	df2	Statistic	p-value
model1	1	189	0.385817	0.535255
model2	1	189	1.537066	0.216592
model3	1	189	3.323132	0.698920
model4	1	189	4.533526	0.345315
model5	1	189	1.472280	0.226501
model6	1	189	0.892987	0.345876
model7	1	189	1.631052	0.203124
model8	1	189	0.755411	0.385871
model9	1	189	0.116911	0.732789
model10	1	189	2.566679	0.110807
model11	1	189	0.001557	0.968567
model12	1	189	1.180476	0.278643
model13	1	189	1.865613	0.173602
model14	1	189	0.177597	0.673925
model15	1	189	0.280753	0.596830
model16	1	189	1.260290	0.263020
model17	1	189	0.375135	0.540954

Note: ***: p-value less than 1%, **: p-value less than 5% and *: p-value less than 10, df1 represents the degree of freedom associated with a statistical test, where df1 is the numerator degree of freedom and df2 is the denominator degrees of freedom (total number of observation).

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CHAPTER 4

CONCLUSIONS

There are two key chapters in this study. The purpose of chapter 2 was to determine the variables that contributed to the rise wildfire suppression expenditures between 1985 and 2023. This review determined study gaps and provides insights that can drive future wildfire management and suppression policy decisions by evaluating the current available literature. Google Scholar is used as a primary tool for collecting articles and final articles selected by using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) screening and selection procedure. Following the initial screening of the articles, I investigated 166 articles that mentioned wildfire and suppression cost/fire suppression cost in the abstract, text, keywords, or title. I collected data on wildfire trends, total area burned, and total suppression expenditures in the United States. I also gathered information regarding recent technological developments in wildfire control, monitoring, and determined how they can help firefighting agencies plan better operation. Future research could be focused on to gain insight into the long-term economic impacts of fires on local communities, economy, timber market, ecosystem, and policy.

The goal of chapter 3 was to identify the key research gaps, highlighting the need for additional research to better understand the long-term economic impacts of fires. The characteristics of impacting the money spent on fire suppression for the USFS and its regions were identified using monthly data from 2005 to 2022 for the USFS (overall) and 2005 to 2020 for the other regions. The study examined the relationship and tail dependency between suppression costs and variables: Niño 3.4, PDSI, SOI, AO, NAO, PDO, WPL, and LF. Various tests were employed to investigate the characteristics of these variables and determine the presence of unit roots and seasonality. The study discovered that all variables tests showed evidence of stationary except of WPL (due to its change from yearly to monthly). Five factors show substantial seasonality. Copula dependencies revealed that five variables were positively dependent on USFS western aggregated costs. The analysis identified that monthly variables have a considerable impact on USFS (overall) suppression, in USFS (overall) suppression, in western aggregated regions, and in the south.