The Technical Efficiency of Wildfire Suppression in Alberta, Canada: A Stochastic Frontier Analysis

by

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Abstract

Wildfire management agencies are increasingly interested in the efficiency of wildfire suppression as they work to protect human lives and communities from wildfire damages under constrained management budgets. In Alberta, climate change is expected to increase the length of the wildfire season and increase annual area burned over the coming decades. These anticipated changes in the wildfire season reinforce the need for efficient use of suppression resources. This study uses stochastic frontier analysis to determine the efficacy of suppression resources and quantify the technical efficiency of wildfire suppression in Alberta's boreal forest zone. At the individual fire scale, we define the output of suppression resources, and therefore dependent variable of the suppression production function, as a held wildfire perimeter. Geospatial wildfire progression perimeter data from 34 wildfires were used to calculate the length of held perimeter for each observed day across all 34 wildfires. Suppression resources are included as production function inputs working to generate held perimeter while weather and fuel variables were included as factors effecting the level of suppression efficiency. Values at risk were included in the stochastic frontier models by using a satellite imagery machine learning dataset to identify inhabited structures within 30 km of active wildfire perimeters. Model results suggest ground equipment is the most effective suppression resource and positively contributes to average daily held perimeter. Average technical efficiency across all 34 wildfires was 26.89% and median technical efficiency was 23.61%. Alberta has no previous wildfire suppression efficiency research to establish a frame of reference for comparison of the efficiency estimates. The average suppression efficiency of 26.89% is lower than what was estimated in a similar study from the western United States which likely reflects Alberta's boreal forest's wildfire regime and coniferous fuels that are conducive to high intensity crown fires that are often difficult to contain. High drought codes and high percentages of coniferous fuels decrease the technical efficiency of containment. Technical efficiency of suppression was qualitatively higher for wildfires with nearby values at risk compared to wildfires with no nearby values at risk. Without considering values at risk, large wildfires had a low median technical efficiency of suppression that was similar to the smallest sample wildfires. After weighting the output to include values at risk, the technical efficiency of suppression for the largest wildfires was higher than the smallest wildfires in the sample. Results were robust across multiple model specifications and suggest there are opportunities to increase the efficiency of wildfire suppression in Alberta.

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Chapter 1: Introduction

1.1 Introduction

This chapter outlines the background and study location of this study and describes the motivations and purpose of the research. The research problem and objectives are presented, followed by specific research questions and hypotheses. The significant contributions of this research are presented followed by an outline of the organization of the thesis.

1.2 Background

Alberta's Boreal forest is well adapted to disturbances from climate, weather, insects, disease, and wildfire (Brandt et al., 2013). Stand-replacing wildfire is a dominant disturbance in Alberta's boreal zone and is a healthy ecosystem process that promotes forest regeneration (Weber and Flannigan, 1997). However, Alberta's wildfire seasons are expected to become longer on average and annual area burned is expected to increase by the end of this century because of the anticipated impacts of climate change (Flannigan et al., 2013; Tymstra et al., 2007). Longer wildfire seasons and increases to annual area burned will make it increasingly difficult for Alberta's wildfire management agency to protect human lives, communities, watersheds and sensitive soils, valuable natural resources, and infrastructure from being damaged by wildfire (MNP LLP, 2016). Wildfire management in Alberta is becoming increasingly expensive; expenditures have increased ten-fold since 1970 after adjusting for inflation and are expected to increase further as area burned increases and as more humans live and interact in wildfire environments (Hope et al., 2016; Stocks and Martell, 2016).

1.3 Research Problem

There is growing interest from wildfire management agencies seeking to increase the efficiency of wildfire suppression resources because they face constrained management budgets while working to achieve suppression levels that keep values at risk protected from wildfire. Wildfire suppression resources include crews, ground equipment, and aerial equipment that douse flames, remove fuels, and build wildfire containment lines in order to contain wildfires and prevent further growth (Plucinski, 2019a). The purpose of this study is to evaluate the efficiency of large wildfire suppression in Alberta. The broad objectives of this study are to:

1) develop a conceptual framework that defines the efficacy of wildfire suppression resources and the efficiency of large wildfire suppression in Alberta within an economic framework;
2) identify which factors are most likely to impact the efficiency of wildfire suppression by reviewing literature specific to wildfire management, wildfire growth, and wildfire suppression efficiency;
3) collect data on wildfire suppression and estimate stochastic frontier models to quantify the efficiency of wildfire suppression in Alberta; and
4) assess how the presence of values at risk (as proxied by inhabited structures) impact the efficiency of wildfire suppression in Alberta.

1.4 Significant Contributions of the Research

The type of efficiency analysis proposed in this study has not been conducted in Alberta and may provide valuable insight for managers seeking to understand how to increase the efficiency of wildfire suppression in Alberta. Efficiency analysis can increase understanding of the effectiveness of suppression resources and identify which variables significantly impact efficiency to assist in making management decisions that can optimize daily wildfire containment. The study uses stochastic frontier analysis to model the production of a held wildfire perimeter and assumes suppression resources such as crews, ground equipment, and aerial equipment are the inputs working to generate held perimeter as the output (Katuwal et al., 2016). Stochastic variables such as weather and fuels are included as predictors of the amount and variability of inefficiency in the production process. The specific research questions and hypotheses include:

1) What is the efficacy of wildfire suppression resources in Alberta?
    - Hypothesis: All types of suppression resources working on wildfire containment will, on average, contribute to increases in daily held wildfire perimeter and the empirical analysis will provide further information on the relative contribution of each category of suppression resource toward generating a held perimeter.
2) What is the efficiency of wildfire containment in Alberta?
    - Hypothesis: This type of analysis has not been conducted in Alberta's boreal zone so it is difficult to hypothesize absolute values of efficiency. However, Alberta's

wildfire regime and coniferous fuel types are conducive to high intensity crown fires that are difficult to contain which suggests efficiency estimates will likely be low, relative to those estimated in other jurisdictions.

3) Which variables significantly impact suppression efficiency?
    - Hypothesis: Weather and fuel variables that drive wildfire behaviour and intensity will significantly impact suppression efficiency.
4) How do nearby values at risk impact the efficiency of wildfire containment in Alberta?
    - Hypothesis: The presence of values at risk will result in higher average suppression efficiency.

Incorporating values at risk considerations into stochastic frontier model results is another significant contribution of this research. Existing research acknowledges that wildfire management seeks to protect values at risk but there are few examples of efficiency analysis that consider protecting values at risk as the model's output variable. The efficiency of wildfire suppression in Alberta is estimated with and without the incorporation of values at risk into the output variable which provides further insight to wildfire managers seeking to increase suppression efficiency while ensuring values at risk are protected. The causality and generalizability of results may be limited by incomplete progression perimeter data and uncertainty in the activities of suppression resources but developing a methodology that establishes initial estimates of suppression efficiency will inform future research and management decisions interested in improving efficiency in Alberta and other regions.

1.5 Organization of Thesis

This study is divided into six chapters. Chapter 1 provided a brief introduction to the study's objectives, research questions, key contributions, limitations, and organization. Chapter 2 provides background information on Alberta's boreal ecology and wildfire environment. Chapter 2 also introduces wildfire management in Alberta including what resources and strategies are used to suppress wildfires. Chapter 3 presents two case study wildfires from our sample dataset and examines the factors that motivate the allocation of provincial suppression resources. Chapter 3 also discusses how management objectives adapt within days or across days in response to changing wildfire behaviour, weather conditions, landscape features, and values at risk. Chapter 4 is a literature review that first defines effective and efficient wildfire suppression.

Chapter 4 then reviews the wildfire management literature and wildfire economics literature with specific interest in the efficiency of wildfire suppression. Chapter 5 presents this study's data, empirical methodology, and model results. Chapter 6 is a discussion of the implications of the model results, how the results compare to findings from other research, and concludes with a discussion of the limitations and possible policy implications of the results.

Chapter 2: Background

This chapter offers an overview of the history and future expectations of wildfires and wildfire management in Alberta, Canada. An overview of the boreal ecosystem provides an understanding of the wildfire environment and how the interplay between natural systems and human control can impact the efficacy and efficiency of wildfire suppression. A discussion on future expectations of wildfire in Canada under climate change highlights future management challenges. Finally, an overview of wildfire management in Canada and specifically Alberta helps to understand the resources and procedures used to contain wildfires. This study seeks to understand the efficiency of wildfire suppression in Alberta which requires a broader contextual understanding of how we arrived at today's management system.

2.1 Wildfires in Canada

The term wildfire is used interchangeably with forest fire, wildland fire, or fire and refers to any fire occurring in a natural environment that is burning out of control (Tymstra et al., 2020). Wildfires are a natural and essential process in Canada's forested ecosystems where an average of 7405 wildfires burn each year[1]. From 1990 through 2018 an average of 2.47 million hectares (Mha) were burned in Canada with annual area burned ranging from 0.63 Mha to 7.10 Mha (National Forestry Database, 2020). Figure 1 highlights the large variation in the number of wildfires and area burned in provinces and territories across Canada which reflects their unique climate, forest structure, and subsequent fire regimes (Boulanger et al., 2012)[2]. "Fire regime" is the intensity, frequency, seasonality, size, type, and severity of regional wildfires (Weber and Flannigan, 1997). Wildfires can threaten nearby communities and valuable timber resources but should not be viewed as natural disasters. The boreal forest is highly adapted to wildfires and depends on the burn-regeneration process for ecosystem health.

[1] According to 1990-2018 data from Canadian National Forestry Database.

[2] Excluding Nunavut which does not have regular wildfires.

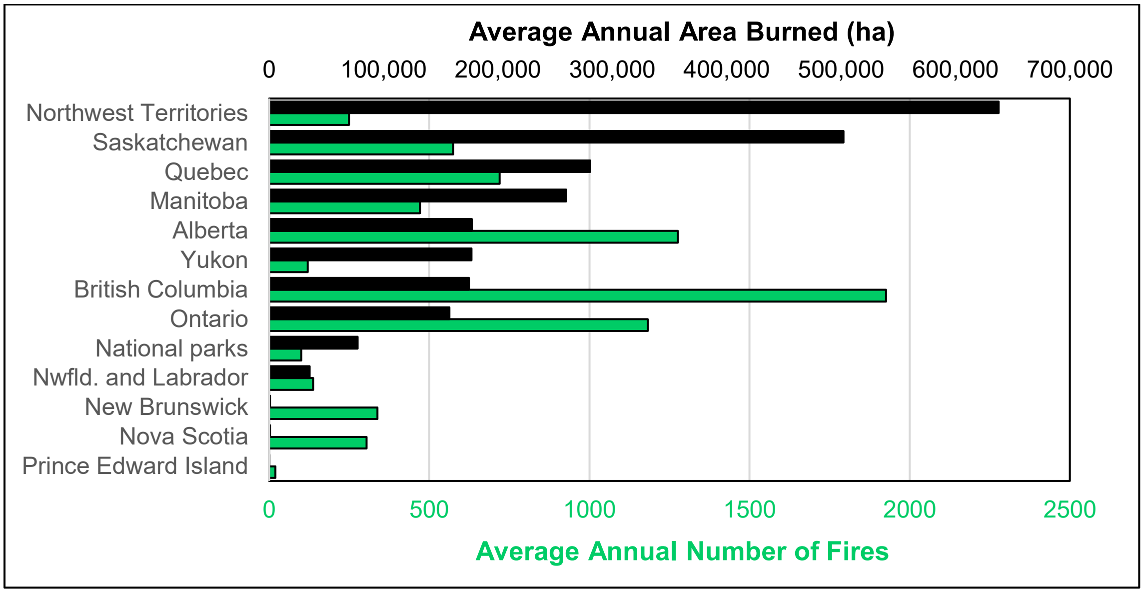


Figure 1. Annual area burned and number of wildfires in each Canadian province and territory (National Forestry Database, 2020).

2.2 Boreal Forest Wildfire Ecology

Canada's boreal zone covers 552 Mha and contains 75% of Canada's forested land (Natural Resources Canada, 2015). The boreal ecosystem is a primarily mixed-wood forest interspersed with a mosaic of coniferous forest, wetlands, peatlands, lakes, rivers, grasslands, and deciduous forests (Brandt et al., 2013). Boreal tree species are principally cold-tolerant coniferous trees *Picea glauca* (white spruce), *Picea mariana* (black spruce), and *Pinus banksiana* (jack pine) among others (Brandt et al., 2013). Natural disturbances from climate, weather, fire, insects, diseases, and their interactions are vital for boreal ecosystem health and rejuvenation (Brandt et al., 2013; Werner, 1986). Stand-replacing wildfire is the dominant process that shapes forest structure and pattern over the boreal's range (Weber and Flannigan, 1997). "Historically, fires swept [Canada's] prairies every two or three years; combusted its Cordilleran forests every five to fifty; and devoured its boreal forest, in immense chunks, every 50-120 years . . ." (Pyne 2007b, p. 959). The biota of the modern boreal resulted from centuries of evolutionary pressures selecting for plants and animals that cohabitate with fire (Keeley et al., 2011; McGee et al., 2015; Weber and Flannigan, 1997).

The boreal's fire regime is characterized by frequent small wildfires with 3% becoming large wildfires (≥ 200 ha) that go on to generate 97% of national area burned (Hanes et al., 2019; Stocks et al., 2002). Regular wildfires encourage biogeochemical cycling (Seedre et al., 2011;

Smithwick et al., 2005), create new open areas conducive to shade intolerant plants and animals, and promote forest regeneration for tree species that require the heat or combustion of fire to release their seeds or promote root sprouts (Pausas and Keeley, 2019; Weber and Flannigan, 1997). Humans also benefit from some positive elements of wildfire such as weed and pest control, increased soil fertility, and cleared understories for recreation or grazing (Keane et al., 2008; Keane and Karau, 2010). However, humans are not adapted to fire environments and resort to actively managing the forest around them to protect lives and communities.

2.2.1 Anthropogenic Influences on Boreal Wildfire Regime

Wildfire managers are in the challenging position of balancing the benefits of wildfire while protecting lives and communities. As colonial Europeans moved into Canada's forested and boreal-prairie transition zones, fire suppression became a priority (Pyne, 2007b). Indigenous communities moved freely in response to regular wildfire, but the colonizers wooden structures were threatened by free-burning fire (Pyne, 2007b). Around 1882, active fire suppression became the norm, and one observed effect was the southern edge of the boreal forest advanced southward roughly a kilometre per year through the early 20th century (Pyne, 2007b). Commercial forestry interests encouraged organized wildfire management through the federal government's Forestry Branch (est. 1899) and Canadian Forestry Association (est. 1900) who agreed forestry and fire protection must go hand in hand (Pyne, 2007b). During the 20th century, boreal wildfire suppression increased as firefighting techniques improved and resource towns developed in the boreal zone near energy and timber resources.

Prolonged, successful fire suppression means the ecosystem is not regularly burning which creates large swaths of mature and old-growth forest where closed crown fuels, thick undergrowth, and deep layers of organic ground fuel can increase the likelihood of high intensity fires after ignition if weather conditions permit (D. K. Thompson et al., 2017). Stands under 30 years old are less likely to produce intense wildfires and are easier for wildfire crews to contain (Bernier et al., 2016; Beverly, 2017). Successful suppression along with forestry, industry, and agriculture in the boreal zone are direct human impacts on boreal ecology. Anthropogenic climate change is a long-term, indirect effect on boreal ecology and health which has important implications for expected fire regimes and dynamics for the coming decades.

2.2.1.1 Climate Change and Wildfire in Canada and Alberta

Weather and climate are the most important natural factors influencing Canadian forest fires, through fuel moisture, lightning ignitions events, and wind conditions that propagate fire (Flannigan and Wotton, 2001). Historic data and climate models can predict how future climate and weather patterns may impact Canada's wildfire regimes and area burned (Flannigan et al., 2005). Annual temperatures have increased 1.7°C across Canada and 2.3°C in northern Canada since 1948 (Zhang et al., 2019). It is likely that more than half the observed warming in Canada is caused by human activities alongside natural climate variations (Zhang et al., 2019). If future anthropogenic emissions follow the low emissions scenario (RCP 2.6) where carbon dioxide emissions start declining by 2020 and go to zero by 2100, Canada is expected to warm 1.8°C by 2050 and plateau after that (Zhang et al., 2019). If a high emissions scenario is realized where emissions continue to rise throughout the 21st century (RCP 8.5) warming in Canada may reach 6°C by the late 21st century (Zhang et al., 2019). Summer precipitation, which is relevant to fuel moisture and wildfire intensity, is expected to decrease under the high emissions scenario (Zhang et al., 2019).

Higher temperatures and less precipitation have important implications for the future of wildfires in Canada. Flannigan et al. (2005) translate climate expectations into wildfire expectations using observed and modelled weather data and project annual area burned by wildfire will increase in every studied Canadian ecozone. Flannigan et al. (2013) used three general circulation models (climate models) and three emission scenarios and concluded that Canada's wildfire seasons will likely be more severe and 20 days longer, on average. Figure 2 shows a downward trend in number of fires since 1990 but total area burned is increasing (National Forestry Database, 2020). The general consensus is firefighters are skilled at putting out small fires which provide the greatest opportunity to minimize area burned and have been very successful with only 4% of fires in Canada exceeding 200 ha from 1990 to 2016 (Cumming, 2005; Hirsch et al., 1998; Tymstra et al., 2020). Observed and projected increases in area burned assume management agencies will likely be unable to maintain historic suppression levels given budget constraints and climate conditions that will create increased wildfire activity (Tymstra et al., 2020).

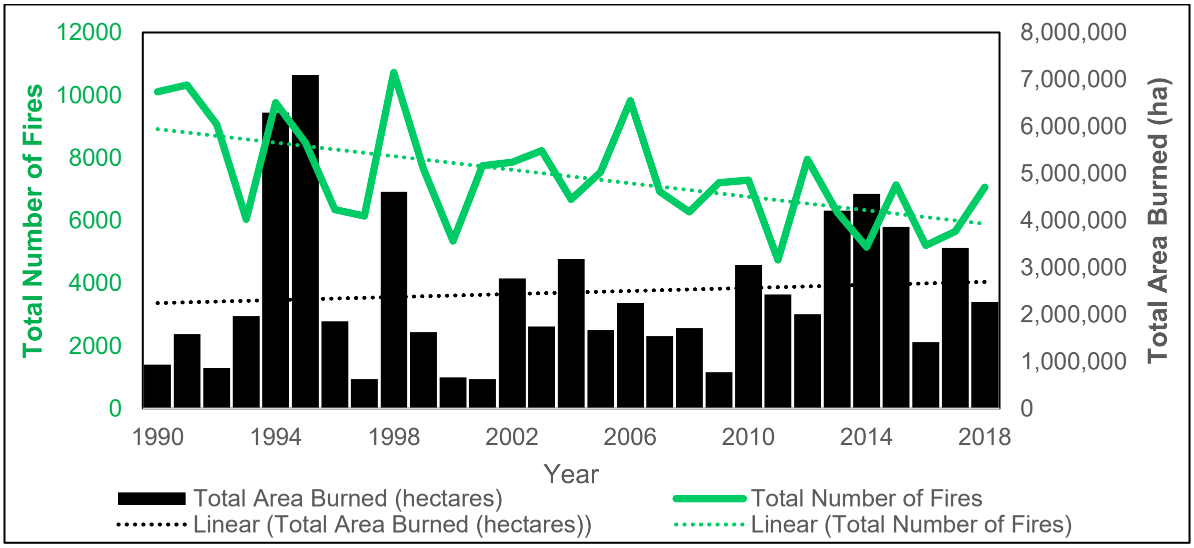


Figure 2. Time trend of number of fires and area burned in Canada from 1990 to 2018. (Updated from Tymstra et al. (2020) and National Forestry Database (2020))

2.3 Wildfires in Alberta

Alberta is second only to British Columbia in number of wildfire starts per year and fourth in area burned among all provinces and territories (National Forestry Database, 2020). Alberta has had significant historical wildfires; most recently the 2016 Horse River Fire burned houses and neighbourhoods in Fort McMurray becoming the most expensive natural disaster in Canadian history (McGee, 2019). Wildfire suppression is extremely important to protect the towns and Indigenous communities throughout Alberta's boreal zone but changing climate and resulting changes in wildfire regimes may make it difficult to achieve historic suppression levels.

Since 1950, almost all of Alberta has experienced significant increases in winter temperature from 0.5°C to 1°C per decade which may result in earlier and longer fire seasons (Beaubien and Freeland, 2000; Flannigan et al., 2005; Wotton and Flannigan, 1993). Spring wildfires are often the most severe because snowmelt uncovers dry, dead fuels that have not begun transpiration or "leaf out" (MNP LLP, 2020). In Alberta, increases in atmospheric CO_2 are expected to increase area burned by 12.9 to 29.4% compared to current weather and CO_2 (Tymstra et al., 2007). Longer fire seasons, increased area burned, and a continually expanding wildland-urban interface (WUI) will create more demand for personnel, equipment, and aircraft to fight fires in Alberta to keep communities, infrastructure, and valuable natural resources protected from fire.

2.4 Wildfire Management in Canada

Wildfire management is any action by wildfire agencies working toward wildfire protection and control and includes: 1) prevention, 2) mitigation, 3) preparedness, 4) response, 5) recovery, and 6) review (Tymstra et al., 2020). Prevention includes educating, regulating, and enforcing how humans interact with fire environments to avoid accidental ignition and minimize damage to property (Alberta Sustainable Resource Development, 2001). Highlighting the importance of prevention, from 1990 through 2018 the majority of wildfire ignitions were human caused and the remaining 47% lightning caused (National Forestry Database, 2020). Mitigation involves clearing fuels and minimizing the likelihood of wildfire starts or area burned after ignition. Preparedness is compiling a supply of wildfire detection and suppression resources that are skilled in anticipating future wildfire conditions and are ready to suppress, contain, and extinguish wildfires. Response is the actions taken, or not taken, by the suppression resources to contain and extinguish wildfires. Recovery includes efforts to repair or rebuild conditions during and after a wildfire (Tymstra et al., 2020). Review is the information gained from reviewing wildfire incidents and seasons that contribute to the evolving understanding of wildfire management across Canada. This study focuses on wildfire response but acknowledges wildfire management as a whole extends well beyond incident response (Tymstra et al., 2020).

Responsibility for public forest land management is divided between provincial/territorial governments and the federal government. Canada's provinces and territories are responsible for wildfire management of provincial forested resources (77% of Canada's total forested lands) (McGee et al., 2015). The federal government manages the remaining 16% within Indigenous communities, national parks, and military bases. The Canadian Wildland Fire Strategy (CWFS) national fire management strategy was developed in 2005 and updated in 2015 to unite and streamline fire management across all provinces and territories (Stocks and Martell, 2016). The CWFS acknowledges it will be challenging to maintain historic suppression levels given climate-change driven increases in area burned paired with an expanding wildland-urban interface and constrained fire management budgets (Stocks and Martell, 2016; Wildland Fire Management Working Group, 2016). Fire management is becoming increasingly expensive in Canada where expenditures have more than tripled since 1970 at $290 million to $900 million in 2013 (2013 CAD) (Stocks and Martell, 2016). Hope et al. (2016) expect future management costs to increase with area burned given all future climate scenarios. Alberta's wildfire situation is similar to national trends but has its own objectives, strategies, and challenges.

2.5 Wildfire Management in Alberta

Wildfire management in Alberta dates back to the early 1900s and acquired more skill and organization over the decades until becoming an established provincial government branch in the 1950s. Fire management costs increased steadily between 1970 and 1990 from around $40 M to $90 M (2013 CAD) (Stocks and Martell, 2016). There was a sharp increase after 1999 when total costs regularly exceeded $200 M. In 2019-2020 the Government of Alberta allocated $485 million for firefighting resources and a contingency fund of $680 million for emergency response needs. With these large financial commitments and expectations of increasing resource demand, there is growing interest to understand how efficiently resources are being used and how the phases of management can be adapted to maximize containment for public safety.

Alberta's forested lands, collectively called the "green area," consist of 10 forest management areas (FMA) where the provincial authority is responsible for wildfire management outside of national parks. The remainder of the province is the "white area" that is primarily private, unforested lands where municipalities manage wildfire. Provincial wildfire management in the green area prioritizes the protection of human life, communities, watersheds and sensitive soils, natural resources, and infrastructure in that order (MNP LLP, 2016, p. 2016). This list of priorities makes up the values at risk (VAR) that Alberta's wildfire managers seek to protect and guides resource allocation decisions. Wildfire management in Alberta follows the six-sided technique outlined by Tymstra et al (2020); prevention, mitigation, pre-suppression preparedness, suppression, recovery, and review. The Wildfire Prevention Section provides public education and regulates human-fire environment interactions which has resulted in a decrease of the number of human-caused fires to 53% in 2018 form previous highs of 74% in 2011 (MNP LLP, 2016). This thesis focuses on the suppression response component of wildfire management but acknowledges that fire management is a composite of all 6 facets of management.

The five stages of wildfire suppression initiated after a wildfire is discovered are:

1. Initial Attack,
2. Fireline Patrol and Observation (Assessment),

3. Fireline Holding (Sustained Action),
4. Mop-up,
5. Demobilization.

Alberta prioritizes early detection and initial attack (IA) because IA is generally regarded as the most effective and efficient method of fire containment (Beverly, 2017; Cumming, 2005; Hirsch et al., 1998). IA objectives are to: 1) initiate suppression before the fire exceeds two hectares in size and 2) contain fire spread within the first burning period (by 10 am the next day) (MNP LLP, 2016). The 10 am policy dates back to 1935 when the U.S. Forest Service deemed early detection and successful IA to be the most effective and efficient method to minimize losses while keeping suppression costs low by spending fewer days on each fire (Beverly, 2017; MNP LLP, 2016). Cumming (2005) describes IA effectiveness from 1968 to 1998 as the reason for decreases in escaped wildfires and area burned in Alberta's mixed-wood boreal forest. However, based on conditions and resource availability it is not always possible to meet IA objectives.

This study focuses on fires that have escaped IA and grow to at least 190 ha in size. Only 6.7% of new starts fail the 2 ha objective and 1.6% grow larger than 190 ha but these large fires are responsible for 98.2% of area burned in Alberta since 1990 (Alberta Agriculture and Forestry, 2020). When IA is unsuccessful or not feasible, crews will choose an appropriate containment strategy guided by values at risk, fuels, and fire behaviour, which is most often full suppression during sustained action (Tymstra et al., 2020; MNP LLP, 2020).

2.5.1 Methods of Sustained Action

"Sustained action" encompasses all fire suppression and control activities after IA working toward a contained fire perimeter. Alberta Wildfire uses direct and indirect attack to carry out sustained action. "Direct attack" is action taken directly on flames such as airtankers or helicopters dousing flames with water or retardant, ground equipment smothering flames with dirt, or ground crews smothering flames with dirt, water, or shovels.

"Indirect attack" is crews and ground equipment constructing a control line away from the fire and burning out the fuel between the control line and the active fire perimeter. Fuels must be cleared to mineral soil and the line must be wide enough to prevent ignition beyond the control line. Fuel type and weather conditions designate how wide the fireline must be to prevent radiant heat or embers from igniting fuels beyond the control line (Byram, 1959). The effectiveness and efficiency of direct and indirect attack are influenced by fuel, weather, and fire conditions (Cole and Alexander, 1995; Wotton et al., 2017). Along with type of attack, when IA is transitioning to sustained action, management decides between full or modified suppression.

"Full suppression" refers to aggressive containment tactics used to contain the entire perimeter as quickly as possible. "Modified suppression" allows the wildfire to burn to an allowable size that maximizes the benefits of suppression while minimizing government expenditures. Alberta uses "appropriate response" tactics meaning every fire is assessed to choose the best suppression objevtive. A 2019 review noted there is some bias toward direct attack and total suppression when indirect attack or modified suppression may be more appropriate (MNP LLP, 2020). Johnson, Miyanishi, and Bridge (2001) critique direct attack in the boreal forest and imply that it is not possible to achieve effective suppression of large, boreal wildfires during extreme weather conditions.

2.6 Chapter 2 Summary

Wildfire is a natural component of Alberta's boreal ecosystem. With climate change it is expected fire seasons will be longer and area burned will increase in Alberta's boreal zone. Wildfire management agencies are interested in maintaining historic suppression levels to continue to protect communities from the threat of wildfire destruction. However, it will be challenging to maintain historic containment levels given the expected increases to annual area burned and an expanding wildland-urban interface that exposes more citizens to the potential dangers of wildfire. Wildfire management is expensive and as wildfire management agencies facing budget constraints are interested in understanding how effective suppression resources are at containing wildfires and how efficiently the containment is achieved.

This study will analyze the suppression of wildfires greater than 190 ha in Alberta's boreal zone excluding fires that are exceedingly large or complex such as the 2016 Horse River Fire that burned communities in Fort McMurray, Alberta. The objectives of this study are to gain an empirical understanding of the efficacy of suppression resources in Alberta's boreal zone, the efficiency of wildfire containment, which variables effect suppression efficiency, and how nearby values at risk may impact suppression efficiency. Wildfire management is a complex, dynamic process with suppression being affected by the stochastic nature of fuels, weather, and resource availability. The next chapter is an exploration of two case study wildfires to gain a deeper understanding of how wildfires in Alberta are assessed and what drives management decisions during sustained action.

Chapter 3: Case Studies

This chapter is an in-depth analysis of two wildfire events from our sample. The first objective of this chapter is to discuss the hierarchy of wildfire operations during sustained action and the flow of provincial suppression resources. The second objective is to use two case study wildfires to describe what motivates resource allocation requests from incident commanders, how provincial suppression resources are allocated after requests are received, and how resources are used throughout the phases of sustained action. A chapter summary will focus on when certain suppression resources are most effective and what weather, fuel, and fire behaviour conditions decrease the efficiency of containment by forcing suppression resources to retreat or change objectives.

3.1 Alberta Wildfire Management Hierarchy

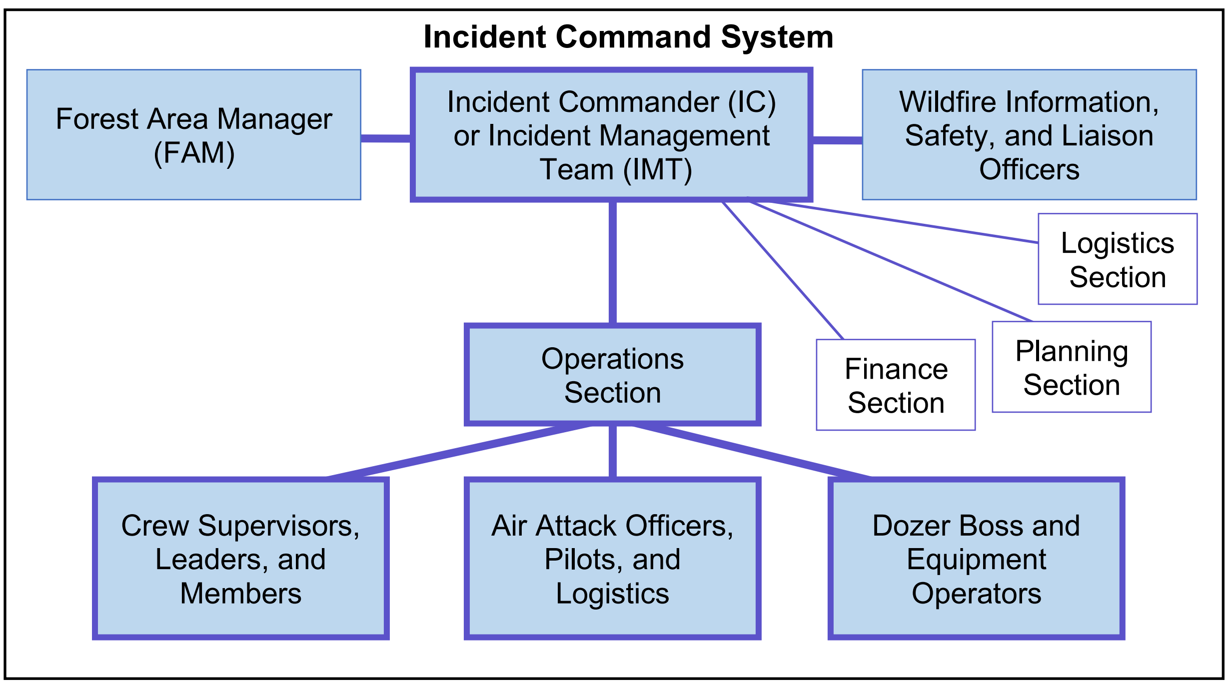


Figure 3. Hierarchy of Incident Command System for sustained action wildfire management in Alberta

Figure 3 outlines a simplified hierarchy of the operations section during sustained action wildfire management and shows how operations fit within Alberta's broader incident command system. The logistics, planning, and finance sections have their own hierarchy that are outside the scope of this study (Alberta Wildfire, 2012). There are 10 forest management areas in Alberta, each with its own Forest Area Manager (FAM). FAMs are responsible for all fire starts within their Forest Area jurisdiction. Incident commanders (ICs) are assigned to fires as they enter sustained action to set resource and crew directives for the duration of sustained action. If a fire is very large, complex, or threatens human life, an incident management team (IMT) takes over these decisions. ICs and IMTs assign suppression resources to meet the containment objectives agreed on by themselves, the Alberta Wildfire Coordination Centre (AWCC), and the FAM (MNP LLP, 2016). After setting daily objectives, ICs and IMTs request the number of suppression resources they need to achieve their objectives for the following day's activities. Figure 4 shows the flow of suppression resource requests to the AWCC who allocate resources based on provincial resource availability and the assessed values at risk (Alberta Wildfire, 2020a). It is possible some resource requests go unfilled if there are many concurrent wildfires and suppression resources are already fully committed given the high provincial fire load.

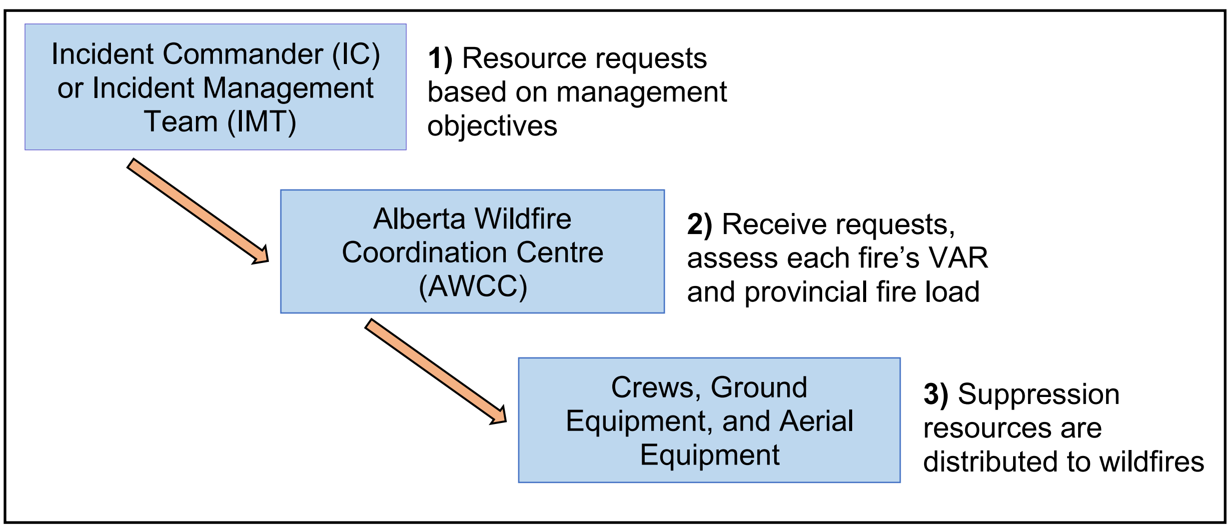


Figure 4. Flow of suppression resource requests and fulfillments to wildfires under sustained action in Alberta, Canada.

When provincial suppression resources are extremely limited, a Provincial Strategic Action Planning Group meets to assign a hierarchical priority to identified wildfires of concern. In May 2019, for example, six wildfires of concern were burning concurrently across the province and merited use of the strategic action planning group to efficiently prioritize and allocate suppression resources. Once suppression resources arrive to a fire, ICs assign resources to segments of the fire based on provincial VAR priority list:

1. Human Life (highest priority for resources, resources will be diverted from other values)
    - Public, firefighters, emergency responders, safe evacuation routes,
2. Communities
    - concentrated areas of permanent residence, infrastructure which has major impact on public safety or local economy, culturally significant areas (e.g. burial sites),
3. Watersheds
    - community watersheds/drinking water catchment areas,
4. Natural Resources
    - timber, critical wildlife habitat, aesthetics and recreation areas,
5. Critical Infrastructure
    - unoccupied/insurable residences and buildings and evacuated industrial camps (Alberta Wildfire, 2020a).

As part of the highest priority human life VAR, firefighter safety is prioritized by only deploying crews to sections of the perimeter where they can safely and efficiently work. In Alberta, crews are often placed at the rear and flanks of the fire to pinch off the head and they rarely work at the head of the fire because it is a dangerous position to work from (Alberta Wildfire, 2020b). In American jurisdictions, fire crews can be placed at the fire head but they are required to carry emergency fire shelters to deploy and protect themselves if the wildfire overruns their position (Chung, 2013).

Firefighting crews are one resource type available to incident commanders who also utilize ground equipment and aerial equipment to achieve their suppression objectives. In this study, crews, ground equipment, and aerial equipment are considered as the “inputs” available to wildfire managers to suppress and contain wildfires. Incident commanders choose a combination of inputs to contain wildfires and substitute between inputs to maximize wildfire containment given wildfire intensity and weather conditions.

3.1.1 Firefighting Crews and Personnel

Alberta has three types of wildfire crews: Unit, Firetack, and Helitack crews. Unit and Firetack crews are used during sustained action and work for longer periods of time to contain and extinguish wildfires. Unit and Firetack crews' daily activities can include dousing flames with backpack pumps, smothering flames with shovels and dirt, or helping to create containment lines using chainsaws and hand tools to remove fuels and expose mineral soil (Alberta Wildfire, 2020c, 2020b). Unit and Firetack crews also undertake mop-up activities which involve following behind a wildfire and extinguishing any remaining hotspots. Helitack crews focus on initial attack and are usually the first to reach a wildfire; quickly working to contain the wildfire within the first burning period before it reaches 2 ha in size (Alberta Wildfire, 2020c).

3.1.2 Ground Equipment

Ground equipment used during sustained action includes bulldozers, graders, tractors, excavators, wildland fire engines, pumps, water tankers, feller bunchers, mulchers, skidders, and various transport equipment. During sustained action, ground equipment operators work to build containment lines by creating firebreaks that can halt wildfire progression. Containment lines are built by dousing fuels with water pumps drawing from nearby water sources or water tanks; removing fuels using feller bunchers, mulchers, or skidders; and digging to expose mineral soil using bulldozers, graders, tractors, and excavators.

3.1.3 Aerial Equipment

Aerial equipment are capable of direct and indirect attack and are the only suppression resource that can directly attack the head of wildfires during high head fire intensities, if weather and fire conditions allow (Alberta Wildfire, 2020d, 2020b). Alberta Wildfire has access to light, intermediate, medium, and large helicopters for use during sustained action (Alberta Wildfire, 2020d). Helicopters contribute to sustained action by "bucketing" or dropping buckets of water or fire retardant directly on the fire head to douse flames or on areas ahead of the fire perimeter where containment lines are being built. Most helicopters used by Alberta Wildfire are capable of bucketing but the carrying capacity of the light and intermediate helicopters is around half the capacity for medium and large helicopters (Alberta Wildfire, 2020d). Light and medium helicopters can be used for other tasks including crew transport, medical evacuations, and deliveries to remote locations such as wildfire detection lookout towers (Alberta Wildfire, 2020d).

Alberta wildfire also makes use of fixed wing aircraft during sustained action. Airtankers are specialized airplanes fitted with tanks and equipment for dropping suppressants or retardants on wildfires (MNP LLP, 2020). The carrying capacity of airtankers ranges from 3,000 litres to 11,000 litres which is much larger than helicopter buckets (Alberta Wildfire, 2020e). Airtankers often operate in groups and are guided by smaller "birddog" aircraft that lead and direct airtankers to their target drop zones (Alberta Wildfire, 2020e).

The two case studies presented below will explore how suppression resource inputs are allocated to two wildfires from our study sample: one with no human life values at risk identified and the other with considerable human life and infrastructure values at risk. Over the length of sustained action, the case studies demonstrate how incident commanders react to changing wildfire behaviour and weather conditions by repositioning suppression resources and substituting between inputs to maximize wildfire containment while keeping firefighters and equipment operators safe.

3.2 Case Study 1 – No Assessed Human Values at Risk

This is a case study of a typical wildfire within our dataset. The fire was not large enough to require a large incident management team and was resourced based on information gained from the initial assessment that indicated no immediate VAR. The lightning caused fire was discovered on August 5, 2017 at 13:59 and resources dispatched by 14:03. Initial attack resources started for the fire at 14:11 and arrived by 14:40.

3.2.1 Initial Assessment

Wildfire assessors are among the first on scene to record initial assessment information on weather, fuels, immediate values at risk, and suggested suppression strategies. The initial assessment was completed by 14:42 when the fire was 35 ha large meaning IA objective one (action before 2 ha) was not met. The lightning caused fire was a crown fire burning in C-2 (Boreal Spruce) fuels. The fire spread rate was 5-6 $m \bullet min^{-1}$ driven by 30ºC temperatures, 40% relative humidity (RH) and 15 km/h NE winds. Timber was the only identified value at risk.

3.2.1.1 Wildfire Report

A medium helicopter and Helitack crew began suppression activities at 15:30. Water sources were sparse forcing the helicopter to travel 3 km to the nearest water source for bucketing. By 19:17 the fire was declared beyond limited resource capabilities and all resources were pulled off the fire. The fire was 944 ha when the resources were pulled.

3.2.1.2 Wildfire Assessment and Strategy

The wildfire analysis and strategy (WAS) form completed at 20:00 is more in-depth than the initial assessment and uses all available information including weather forecasts to create suppression objectives and strategies for sustained action crews. The wildfire was burning in C-2 fuels and was expected to overrun a nearby wildfire in the next burning period. Fuels north of the fire become broken and transition to lowland brush before intercepting the burn scar from the 2015 Moose Lake fire. Fuels to the east become broken with patchy aspen and some narrow, wet drainages. If the fire crosses the drainages, there are C-2 and M-2 fuels before D-2 predominates[3]. Mixed-wood patches broken by scrub grasslands and patches of C-1 extend to the northwest 10 km before D-1 fuels become dominant. Dry weather means grass and shrub fuels are promoted fire spread when they would not usually be of concern.

A cold frontal passage shifted winds from southerly to northwesterly creating dangerous firefighting conditions that prompted crew retreat. The cold front also would also bring relative humidity relief and potential for thundershowers that could increase fuel moisture in grass and shrub fuels creating better resistance to fire spread than was previously observed. Fire behaviour analysts are asked to project weather forecasts and fire growth behaviour for the next 72 hours but none were available in this circumstance, so the assessor provided a rough weather forecast and size estimate.

The next burning period (August 6) was expected to bring maximum temperatures around 18ºC, minimum RH of 55%, potential for precipitation, and northerly winds averaging 10 km/h. The fire was expected to grow to 1200 ha by end of day. August 7th and 8th maximum temperatures were expected to increase to 25ºC with minimum relative humidity around 30-40%,

[3] Refer to Appendix A for fuels information table.

little to no precipitation, and winds shifting back to the south-southwest averaging 15 km/h. The fire is expected to grow to 2500 ha and 3000 ha at the end of these burn periods.

Within the WAS the only noted VAR was timber. However, our GIS data analysis (Figure 5) indicates there were inhabited structures between 25 and 30 km north of the fire which may threaten human life and communities. As previously noted, to reach these northern structures the wildfire would have to cross lowland shrub fuels and a burn scar from a 2015 wildfire. It is unclear if the inhabited structures were not known to the assessor of if the assessor deemed the inhabited structures as not at risk given their distance, the lowland shrub fuels, and the historic burn scar. After the weather expectations, fire behaviour, and VAR analysis, the final section of the WAS form requires the assessor to develop management objectives and three strategies to achieve those objectives.

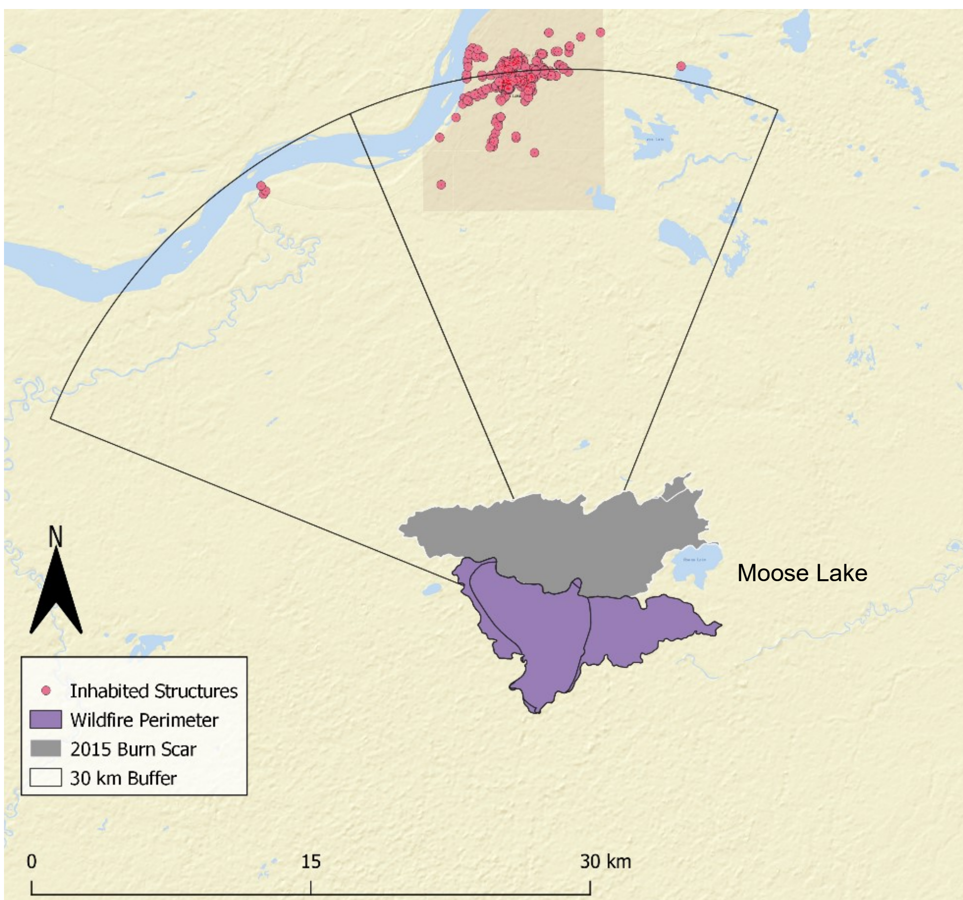


Figure 5. Inhabited structures north of active wildfire juxtaposed with historic burn scar.

The objective was to keep the fire south of Moose Lake and limit spread to the west and east with the overarching objective being containment and full extinguishment. The first proposed strategy is full containment which requires the most suppression resources of any strategy. The second proposed strategy was using ignition to tie fire into natural boundaries and fuel type changes then follow up with ground crews to reinforce lines. The strategies are proposed to the forest area office and the Alberta Wildfire Coordination Centre who agree with one of the proposed options usually based on resource availability and values at risk. The assessment result was immediate action following strategy one though the AWCC suggested the area consider option two given resource availability and no values at risk. After the strategy was agreed upon, the resource request for air tankers, Firetack crews, and bucketing was filled by the AWCC and resources were deployed to the fire for the next burning period. Incident command was transferred to the inbound sustained action operations team beginning the next day.

3.2.2 Sustained Action

The wildfire was assigned more resources over August 6-8 to limit fire progression and keep the wildfire south of Moose Lake. ICs use weather forecasts, information acquired on-site, and Prometheus fire growth model projections (when available) to continually update resource requirements based on growth and behaviour expectations (Tymstra et al., 2010). Figure 6 shows the change in suppression resources throughout sustained action. The spike in airtankers deployed on August 7 is likely because early wildfire intensities were too high for crews to safely or effectively contain the fire head. On August 7 at 19:25 the fire was designated as being held (BH) at 944 ha. However, the fire continued to grow after BH and the number of resources on the fire continued to grow through the end of August. The fire grew to 4994 ha and was designated under control (UC) on September 7, 2017 at 18:00. Helicopters and crews remained on the fire five days after UC presumably doing mop-up by extinguishing remaining hotspots. Figure 6 shows no ground equipment on the fire throughout sustained action seemingly because there was no road access to permit use of ground equipment. Scene photos and notes do not indicate any threat to values at risk other than timber throughout the length of the fire.

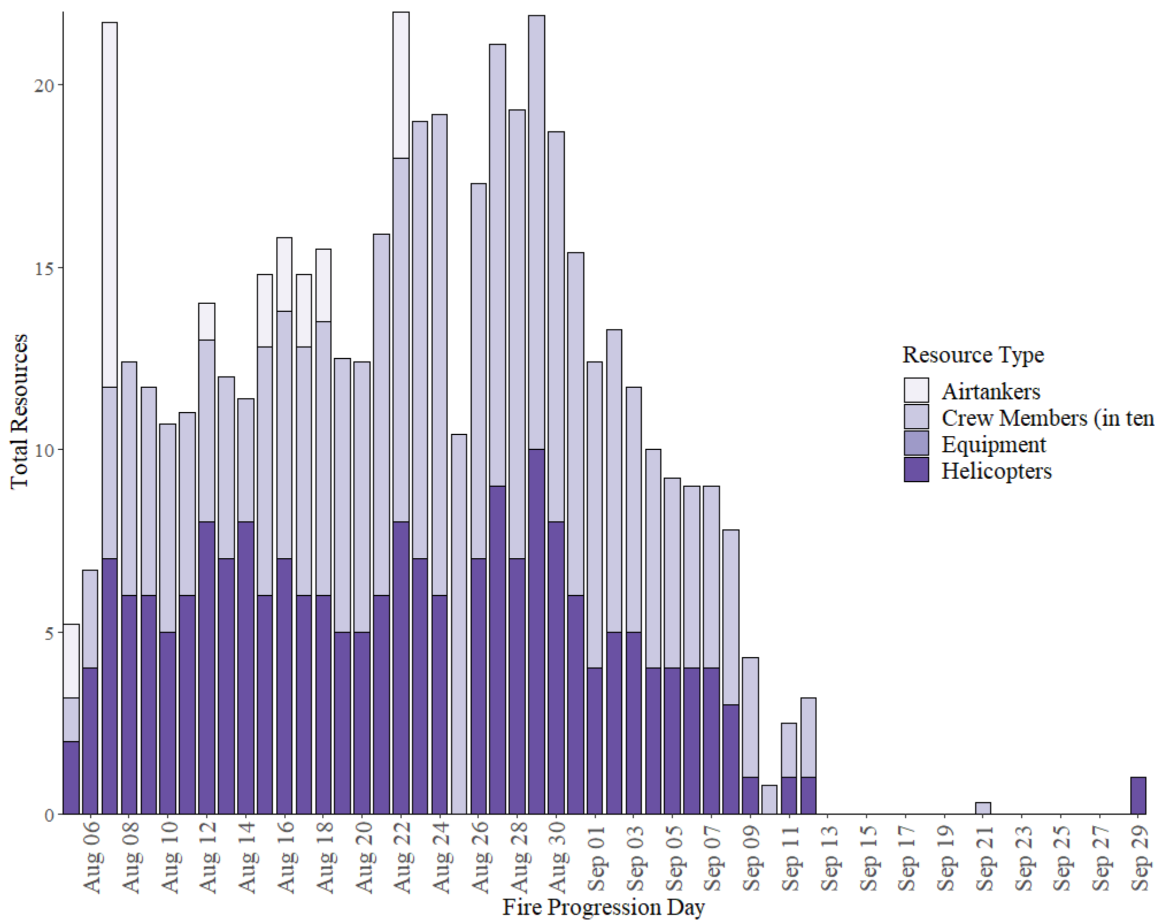


Figure 6. Case study 1 progression of suppression resources throughout length of fire.

3.3 Case Study 2 – Assessed Human Life Values at Risk

This is another typical fire from our dataset but differs from the previous case study because assessment notes indicate the presence of human and infrastructure values at risk. The lightning caused fire was discovered at 15:59 on May 26, 2018. Resources were dispatched at 16:02, started for the fire at 16:05, and arrived by 16:30.

3.3.1 Initial Assessment

The initial assessment was completed by 16:14 and the fire was 20 ha, failing to achieve the 2 ha IA objective. The crown fire was burning in C-2 fuels. Fire growth was influenced by 17°C temperatures, 57% relative humidity, and 25 km/h westerly winds.

Initial attack was undertaken by 3 airtankers, 8 helicopters and 1 operations team leader. Helicopters and airtankers made use of the nearest water source 1.2 km away for direct air attack.

By 16:56 the fire had quadrupled in size to 80 ha. Airtankers flanked the fire as they worked to contain it but large smoke columns and windy conditions limited visibility. Excessive wind gusts over 50 km/h made it unsafe for ground crew resources to assist the aerial attack. At 17:00 bulldozers attempted to gain access given the flat terrain but this was quickly dismissed 10 minutes later because wet muskeg eliminated access. By 17:14 airtankers were also called off the fire due to the windy conditions and fire volatility. Winds were notably shifting more northerly making poor burnout conditions. At 18:09 the northern flank was headed toward a historic burn and swamp that may be advantageous for containment. By 19:58 the fire was 2 to 2.5 km south of Firebag River.

3.3.1.1 Wildfire Assessment

The in-depth analysis WAS form was not available for this fire, so assessment information is derived from the initial assessment comments. The assessment noted a forestry base and cabin were values at risk of damage from the wildfire. The Firebag forestry base was 10 km from the fire's head at 16:27. By 17:36, the fire was between 6.5 to 8 km from the forestry base and the decision was made at 17:39 to drop retardant when airtankers could safely resume flying. At 18:43 dispatchers were notified of a cabin 3 miles east of the fire with possible people on site. The helicopter and crew onsite landed to tell residents to evacuate at 18:49 and confirmed no civilians were present. Our spatial VAR analysis in Figure 7 found no inhabited structures within 30 km of the wildfire which contradicts the assessment information. This discrepancy is likely caused by our inhabited structure dataset relying on satellite images that failed to detect the forestry base and cabin. This is a limitation that will be discussed further in Chapter 5. Our spatial VAR data also show two large oil and gas facilities 20 to 30 km to the west and southwest of the fire perimeter. Neither of these are noted as being at risk but may fall into category 4 (critical infrastructure) of VAR priority list. The assessment result was for no immediate action because the fire was beyond limited resource capabilities and there were no VAR despite the forestry base, cabin, and gas plants.

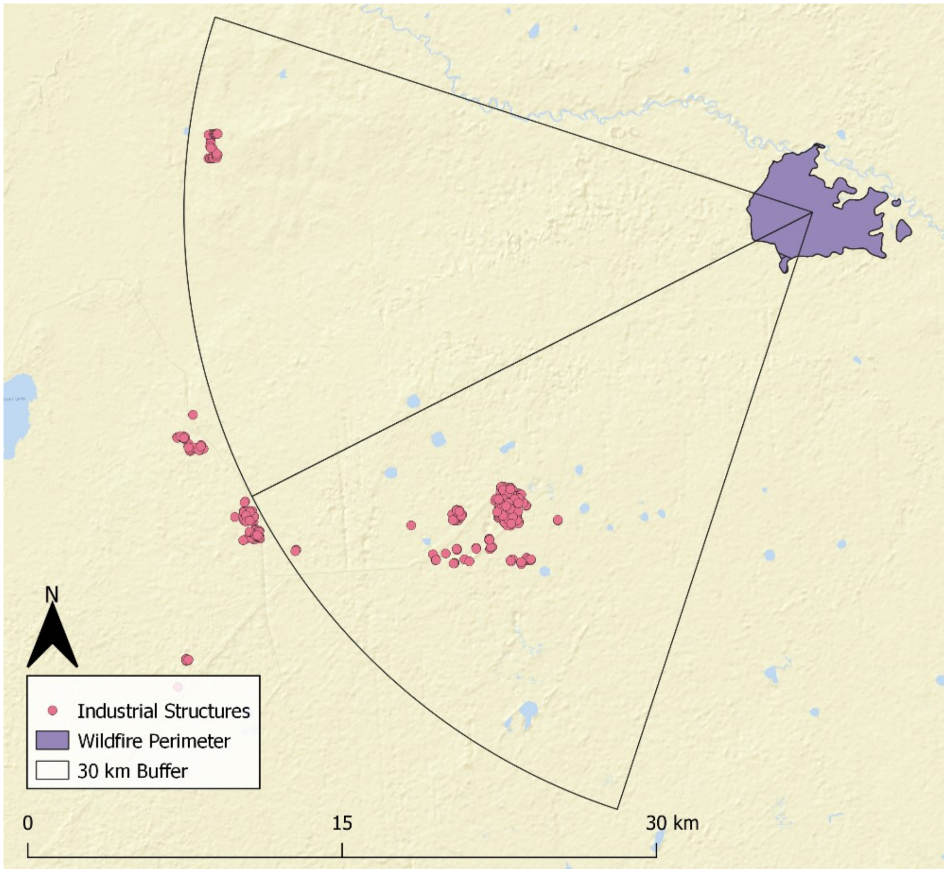


Figure 7. Uninhabited structures west and southwest of active wildfire.

3.3.2 Sustained Action

Ground firefighting commenced the next day, May 27, at 09:00 when 41 Firetack, Rappel and Strike Team crew members joined the airtankers and helicopters in containment activities with the fire at 260 ha. Figure 8 shows ground equipment (dozers, excavators, and water tankers) eventually gained access to the fire by May 28 to assist in sustained action. Airtankers were used while the wildfire was rapidly growing during early sustained action until the wildfire was declared being held (BH) on June 2 at a size of 2320 ha. Crew numbers remained consistent through June 5 when the fire was deemed to be under control (UC). Crews tapered off to zero by June 13 as Unit Crew members took over mop-up activities aided by ground equipment. Ground equipment continued mop-up until the fire was considered extinguished on June 20. Personnel returned to reassess fire conditions on July 4 when they decreased the estimated extinguished size to 2290 ha.

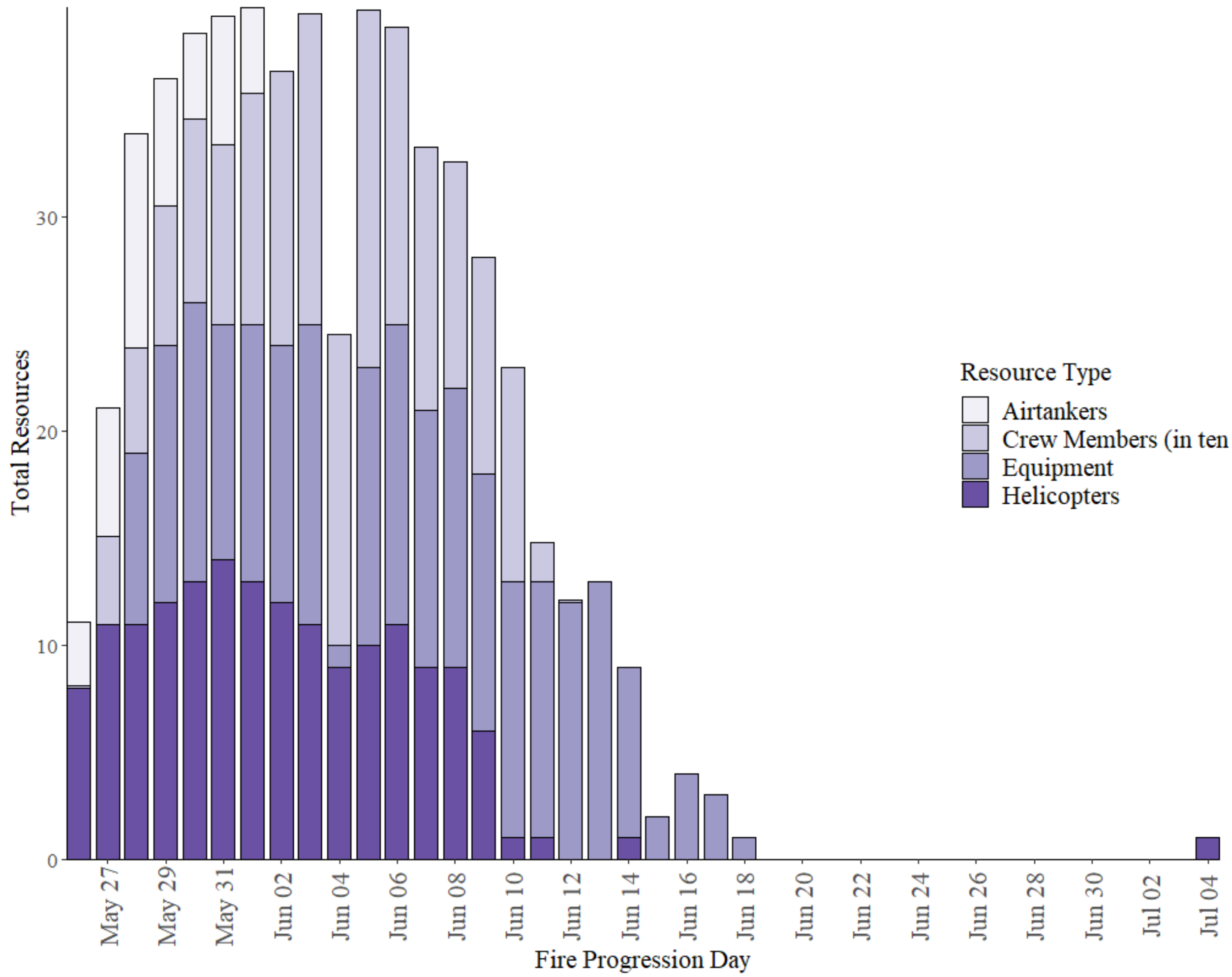


Figure 8. Case study 2 progression of suppression resources over length of wildfire.

3.4 Chapter 3 Summary

The presented case studies demonstrate the complexity of wildfire management in Alberta and the dynamic decision making required throughout sustained action. Alberta's Wildfire Management Branch uses the Incident Command System to streamline management and clearly establish the roles and duties of all operations section staff. Incident commanders manage wildfires by considering wildfire behaviour, current weather, forecasted weather, values at risk, firefighter safety, and containment goals in every management decision each day. Crews, airtankers, helicopters, and ground equipment are the suppression resource inputs incident commanders use to contain wildfires. In the case studies, airtankers were used early during sustained action when rapid wildfire growth made it difficult or unsafe for ground crews to effectively contain the fire. Crews were generally used throughout sustained action with early objectives of full containment that shifted to mop-up after containment to ensure nothing reignites. Ground equipment was also present throughout sustained action but required adequate roads and terrain to permit access which can be impeded by boreal peatlands and wetlands. When ground equipment was available, helicopters assisted with bucketing only during the containment phase. When ground equipment was unavailable, helicopters did participate in mop-up which highlights the substitutability between suppression inputs to achieve the same objectives.

Hot, dry, and windy weather conditions coincided with high wildfire intensities and rapid wildfire growth making containment difficult for suppression resources. Areas of grass and lowland shrub fuels were not concerning to incident commanders, but coniferous fuels generated high intensity crown fires that were difficult to contain. Weather and fuel conditions influenced how resources were utilized, the effectiveness of containment resources, and the efficiency of wildfire containment. Any attempts to model wildfire containment efficiency should consider how weather, fuels, and fire behaviour impact the effectiveness of suppression resources and can create inefficient containment conditions. The next chapter begins with a discussion defining effective and efficient wildfire containment, then presents a multidisciplinary literature review of wildfire management and containment research.

Chapter 4: Theory and Literature Review

This chapter is a literature review of past wildfire management research and economic efficiency analyses. First, a discussion on the definition of effective suppression is required to define the goal of wildfire management. Next, a review of wildfire economics research discusses the changing definition of optimal management effort since the early 20th century. The review outlines how management research has transitioned over the years from annual, regional models of wildfire suppression to the individual wildfire scale. Economic efficiency analysis models provide the methodology to quantify the efficiency of individual wildfire containment. Finally, a discussion on what resources are used to contain wildfires and which factors influence wildfire growth informs which variables to include in the efficiency analysis model.

4.1 Effective Wildfire Suppression (Defining Objective Variable)

Defining "effective" fire suppression simultaneously defines the output or goal of fire suppression. Effective suppression will have different definitions depending on the field of research, the scale of the problem, and the research question of interest (Plucinski, 2019b). Landscape-scale fire management scientists define effective suppression as a significant decrease in area burned over time or significantly lower area burned within actively managed forest areas compared to unmanaged areas (Cumming, 2005; Martell, 1996, 1994; Martell and Sun, 2008; Reimer, 2018). This definition aligns with the objectives of regional wildfire managers who oversee all wildfires in their province, state, or jurisdiction (MNP LLP, 2016). Observed and simulated data showing a significant decrease in area burned has been presented as evidence of effective regional fire suppression (Ward et al., 2001). Initial attack is considered the most effective suppression tactic because it quickly contains fire starts and prevents them from becoming large (Hirsch et al., 1998). A study from Ontario, Canada observed a larger proportion of small fires in managed forest areas as evidence of effective initial attack (Cumming, 2005).

Other researchers do not believe there is sufficient evidence to prove a relationship between area burned and suppression because it is challenging to construct a reasonable counterfactual to infer the impacts of wildfire suppression. Wildfire ecologists have argued changes in area burned are climate driven and independent of suppression because the boreal forest's fire regime has changed at least three times in the last 300 years and the fire management data record is not long enough for statistical inference (Johnson et al., 2001, 1998). They also argue that fewer small fires in unmanaged forests is because of less detection and not indicative of effective initial attack (Bridge et al., 2005). In the closed-canopy boreal system, the theory of fuel buildup from suppression does not explain changes to the fire regime or area burned because the regular large wildfires of the boreal occur under particular weather systems and are independent of fuel age or density (Arienti et al., 2006; Johnson et al., 2001). Cumming (2005) argues that the definition of "effective suppression" must be agreed on by all fields of research and defines effective suppression as a proportional decrease in area burned over a specified period, because proportion is independent of actual area burned. There is increasing interest to define effective suppression at the individual fire scale because it replicates how fire managers act on wildfires and is independent of landscape scale measurement error that makes it difficult to discern effective suppression from climate or weather influences.

Effective suppression of individual fires can be defined in terms of initial attack or sustained action. In Alberta, effective initial attack is defined as attacking a fire before it reaches 2 ha and containing it before 10 am the day after discovery; however, these small fires are not included in this study (MNP LLP, 2016). This study defines effective suppression at the incident level as a completely contained fire perimeter, regardless of the time it takes or number of resources used (M. P. Thompson et al., 2017). By extension, effective suppression resources must positively contribute to a held perimeter on average. This definition of effective suppression follows the economic definition broadly meaning to yield desirable outcomes (M. P. Thompson et al., 2017). Incident commanders take guidance from regional managers but work at the individual fire scale, managing resources to suppress wildfires of concern by limiting fire growth and area burned (Cumming, 2005). As discussed in Chapter 2, suppression is all combinations of direct and indirect attack to douse flames, remove fuels, and construct contained fireline. Other studies have defined effective suppression as protecting values at risk or minimizing expenditures on firefighting resources which reiterates the importance of a well-defined research question and outcome variable (Hesseln et al., 2010). Wildfire management agencies have long been interested in increasing their "effectiveness," but their use of the word "effective" actually refers to management productivity and efficiency (Hirsch and Martell, 1996; Plucinski, 2019b).

4.2 Efficient Wildfire Suppression

Suppression efficiency is defined as the generating maximum possible contained perimeter given a fixed set of suppression resource inputs (Coelli et al., 2005). This definition aligns with the definition of "technical efficiency" used by economists and differs from productivity which is the ratio of output produced to the inputs used. Technical efficiency also differs from cost-effectiveness which occurs when wildfire management agencies seek to minimize costs by increasing management effort to the point where marginal management cost equals marginal avoided damage (Sparhawk, 1925; M. P. Thompson et al., 2017). Similar to studying efficacy, the scale of the research question and the defined goal of suppression generate many ways to study wildfire suppression efficiency. Some landscape-level efficiency research analyzes the trade-offs between prevention and education programs, fuel reduction and mitigation, and fire suppression efficiency (Butry, 2009; Mercer et al., 2007). Mercer et al. (2007) developed a production function with simulated wildfire regime data in Florida and found prescribed fire significantly reduces wildfire area and wildfire intensity. Butry's (2009) propensity score model also suggests prescribed fire limits wildfire intensity which could make suppression more efficient. In Canada, the Canadian Wildland Fire Strategy suggested permitting natural fire in designated areas while vigorously protecting human life and communities to increase management efficiency and decrease expenditures (Stocks and Martell, 2016).

Individual fire efficiency research investigates which variables impact suppression efficiency including fire behaviour, the surrounding environment (weather, fuels, terrain, and accessibility), and the application of suppression (e.g. tactics, resources, and techniques) (Plucinski, 2019a). For example, two American case studies studied fuel treatments at the individual fire scale and found similar results to regional studies indicating mechanical fuel removal and previous large fires can increase suppression efficiency (Moghaddas and Craggs, 2007; Thompson et al., 2016). Improved efficiency was due to better retardant penetration to surface fuels, easier visual contact for crews, safer access, and faster suppression of new ignitions (Moghaddas and Craggs, 2007). Weather is the other stochastic variable regularly included in suppression efficiency analyses. Fernandes et al. (2016) conducted research in

Portugal from 2003-2013 and observed large fire suppression crews paired with low temperatures and little wind can significantly decrease large fire spread. Beverly (2017) studied how fuel age and weather affects small fire containment probability in Alberta's boreal forest. The author found extreme fire behaviour (estimated from high wind speed, high temperature, and low humidity) and longer time since previous wildfire decreases the likelihood of containment. Generalized linear mixed-models (GLMM) have also been used to model the probability of fire containment using real operations data and fire growth modelling (Finney et al., 2009). The GLMM results indicate fires are contained opportunistically during periods of moderate or low fire activity (Finney et al., 2009). These studies provide evidence that weather and fuels affect the efficiency of wildfire suppression and other efficiency research is interested in what maximizes the output of wildfire crews and resources.

Suppression efficiency at the fireline scale is referred to as "productivity" of suppression resources to contain fire perimeter (Plucinski 2019b). Wildfire management research dates back to the 1930s with interest in quantifying the output of fire crews and to understand substitutability between suppression resources (Hirsch and Martell, 1996). Observational studies have established baseline estimates of fireline produced per unit time for each suppression resource (Hirsch and Martell, 1996). A study from Ontario, Canada's boreal zone used expert elicitation to estimate how long it takes for initial attack crews to construct 2000 ft of fireline and found that crews work fastest in open fuel types with low intensity fires (Hirsch et al., 2004). Hirsch and Martell (1996) provide an overview of other productivity studies and Broyles (2011) calculated recent productivity estimates for American suppression resources. Fireline production rates were audited by sending people to observe fire crews and equipment and manually measure the length of fireline each resource dug to create an average hourly measure of what fire crews can create in grass, brush, and timber fuels (Broyles, 2011). Fire managers can then compare the contained fire perimeter to the total productive capacity from observation studies and any output below the observed output could be considered inefficient (Calkin et al. 2011). An American study used these quantified productivity rates to compare potential to observed output and found there was significant inefficiency in resource use, even when excluding crews not working on fireline containment (Katuwal et al., 2017). The above research generally concludes suppression efficiency is affected by weather, fire behaviour, fuel type, fuel conditions, terrain, and maximum productivity is rarely achieved. To the best of our knowledge there have been no equivalent efficiency analyses conducted on large wildfires in Alberta's boreal forest.

There is heightened interest in efficient wildfire management as Alberta undergoes continued population growth, with expanding wildland urban interface, and longer wildfire seasons associated with climate change (Tymstra et al., 2020, 2007). In response to increased threat of wildfires to human lives and communities, Alberta's wildfire managers are interested in increasing management efficiency to achieve historic levels of wildfire containment while under significant budget constraints, resource constraints, limited information, and other uncertainties which can be addressed by wildfire economics research.

4.3 Economic Models of Large Wildfire Management and Suppression

Wildfire economics studies the total costs and benefits of fire as another way to research the efficacy and efficiency of large wildfire suppression. In wildfire economics, the benefits of wildfire suppression are the prevented losses and effective suppression is not just contained wildfire, but is minimizing total damages caused by fire (M. P. Thompson et al., 2017). Efficient wildfire suppression occurs at the point where marginal benefits equal marginal costs meaning a balance between the benefits of suppression (avoided losses) and the costs of wildfire (burned forest, damaged resources, and wildfire management costs).

Some of the earliest wildfire economics research studied landscape-level suppression efficiency with the U.S. Forest Service. Headley (1916) was the first to address wildfire suppression efficiency and suggests the purpose of wildfire suppression is to prevent destruction of values at a cost less than the values in danger of destruction. Sparhawk (1925) least-cost plus loss model (LC+L) formalizes Headley's early ideas into an economic model seeking to minimize wildfire losses using presuppression management. The losses function (L) includes all damages incurred in spite of protection efforts plus suppression expenditures. Measuring losses or damages is challenging as early researchers acknowledged forests have timber, structural, and ecological values but lacked resources to measure net values. Total cost is the sum of presuppression expenditures and losses. Efficient or optimal fire management effort occurs at least cost, calculated at the minimum of the total cost function which requires a univariate function with one minima. Sparhawk's LC+L model incorrectly modelled the level of suppression as a model output that is dependent on fire occurrence instead of a decision variable for managers (Donovan and Rideout, 2003). Researchers in U.S.A. and Canada continued to use the LC+L theoretical model for many years with few addressing this specification weakness.

In Canada, Beall (1949) used size of burned area as a measurable form of damages and suggested a dollar value could later be applied to calculate an optimal allowable area burned using the LC+L framework. Mactavish (1965) touts the LC+L as theoretically useful and rightfully acknowledges multiple regression techniques would work to include stochastic variables such as rate of spread, fire intensity, fire load factors, and equipment used but failed to do so empirically. The LC+L literature argues that lack of data is the reason for the economic models not performing empirically. However, the early absence of empirical results was more so due to improper mathematical formulation of the economic problem and lack of a production function that explicitly relates management inputs to system output (Simard, 1976).

Parks (1964) successfully defined a deterministic model of fire suppression using the LC+L framework which could be mathematically solved for an optimal solution at the minimum of costs plus damages. Parks concludes that significant dollar savings can be achieved by increasing the size of fire suppression labour but did not include any suppression equipment costs. Simard (1976) added a production function to LC+L that links the cost and damage functions. In the production function, the fire management effort input is negatively correlated with the area burned output. This is the costs plus net value change model (C+NVC). Costs (C) are all costs associated with fire suppression and net value change (NVC) represents the net wildfire related damages. Marginality conditions of the C+NVC indicate optimal fire management effort occurs where marginal value (avoided fire damages) equals marginal management costs. Mills and Bratten (1982) FEES program minimizes C+NVC to achieve long-run economic efficiency while also allowing the incorporation of risk through expected values. C+NVC models impose dependability between presuppression and suppression expenditures and assume the sum of presuppression and suppression expenditures will always be negatively correlated with annual fire loss (Quince, 2009). Donovan and Rideout (2003) reformulate C+NVC so presuppression and suppression are independent inputs for NVC and optimal levels of each management curve occur at minimum C+NVC but there are persistent problems with generalizing the results.

LC+L and C+NVC models solve for optimal levels of management expenditures but fail to explain how to allocate these funds within departments or across regions. Production functions that define area burned as a function only of fire management effort ignore that area burned is largely influenced by weather, fuels, and fire behaviour which are outside of a management agency's control (Martell, 2001). Most of these landscape-level models fail to empirically include wildfire behaviour, regional weather, fuel conditions, and annual variations of these variables. Instead, emerging wildfire economic models suggest production theory better suits the individual wildfire management framework to address some of these issues.

4.4 Production Economics Framework for Large Wildfire Suppression

Davis (1965) and (Gamache, 1969) demonstrate a production economics framework can be applied to wildfire management (Gorte and Gorte, 1979). In recent years, production economics models have shown promising results toward understanding and quantifying the efficiency of large wildfire suppression (Holmes and Calkin, 2013; Katuwal et al., 2016). The benefit of the production economics framework is it allows the optimization problem to be framed at the individual fire scale. Instead of input data that are aggregated to the regional level and annual time scale, individual management resource inputs can be analyzed at a finer timestep and regional scale.

Microeconomic and producer theory study the behaviour of economic agents (producers) that take a set of inputs and transform them into a set of outputs (Greene, 2008). A "production function" defines the relationship of technology that transforms a set of inputs into a desirable output, where $\boldsymbol{y}$ represents output and $\boldsymbol{x}$ is a N x 1 vector of non-negative inputs.

$$\boldsymbol{y} = f(\boldsymbol{x}) \tag{1}$$

4.4.1 Properties of the Production Function

There are several properties of production functions that should be met in order to satisfy economic theory and do empirical analyses (Coelli et al., 2005).

1. Nonnegativity: The value of $f(\boldsymbol{x})$ is a finite, non-negative, real number.

2. Weak Essentiality: The production of positive output is impossible without the use of at least one input.
3. Nondecreasing in x (Monotonicity): Additional units of an input will not decrease output. If $\boldsymbol{x}^0 \geq \boldsymbol{x}^1$, then $f(\boldsymbol{x^0}) \geq f(\boldsymbol{x^1})$.
4. Concave in x: Any linear combination of the vectors x^0 and x^1 will produce output that is no less than the same linear combination of $f(\boldsymbol{x^0})$ and $f(\boldsymbol{x^1})$. This will satisfy the law of diminishing marginal productivity as all marginal products are constrained to non-increasing.

These properties are not all strictly necessary and some, for example monotonicity, can be relaxed in certain scenarios (Coelli et al., 2005). A production function defines the maximum possible output given the current state of technology and a fixed set of inputs. Basic microeconomic theory assumes producers are efficient profit maximizers or cost minimizers in the long run and therefore operate on the production frontier so long as there is perfect competition and no barriers to entry (Mankiw, 2014). Producers are technically efficient when producing the maximum amount of output given a fixed set of inputs and technology.

Historically, production frontiers were estimated with mathematical programming (Aigner and Chu 1968). The general form of the cross-sectional production function is shown in equation 2. Where $\boldsymbol{y}$ is output and $\boldsymbol{x}$ is a N x 1 vector of inputs. $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$ are parameters to be estimated by the model and $\boldsymbol{\varepsilon}$ is a N x 1 vector stochastic error $\boldsymbol{\varepsilon} \sim N(0, \sigma^2)$.

$$\boldsymbol{y} = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{x} + \boldsymbol{\varepsilon} \tag{2}$$

Linear programming that minimizes the sum of residuals and quadratic programming that minimizes the sum of squared residuals are more modern solving techniques that can successfully estimate production functions (Aigner and Chu, 1968; Schmidt, 1976). However, least squares estimation procedures actually estimate response (or average) functions by fitting the frontier through a set of observed combinations of inputs and outputs where all deviations are random and can be positive or negative, as opposed to the desired production frontier (Aigner and Chu, 1968; Battese, 1992). It is reasonable to assume some deviations from the production frontier are not random but instead are caused by producers not succeeding in maximizing outputs given their scale, technology, and inputs (Kumbhakar and Lovell, 2000a). In economic terms, the non-random deviations are caused by inefficiency, and efficiency literature addresses these concerns.

4.5 Economic Efficiency Analyses

It is important to consider the efficiency of firms and managers because, if inefficiencies exist, it is possible to increase effectiveness and productivity through more efficient use of resources and inputs given current technologies. Increases in efficiency can increase outputs at no additional cost or can generate cost-savings if producers are comfortable at current levels of output and reduce their use of inputs to achieve identical results (Kumbhakar and Lovell, 2000a). Research in the 1950s began to explore and define theoretical efficiency models and methods for empirical analysis.

Koopmans (1951) began by not presupposing that marginal cost is known to managers and instead managers use comparative statics to explore different resource allocation combinations that compose an "efficient set" when they reach the point of zero profit. Farrell (1957) builds on Koopman's work and decomposes production efficiency into two components: technical efficiency and allocative (price) efficiency. Technical efficiency is a firm producing the maximum possible output given a fixed set of inputs. Allocative efficiency is a firm using inputs in optimal proportions given their prices and the production technology. In this study we are strictly interested in the output decision and focus on technical efficiency which can be input oriented or output oriented depending on the production problem the producer faces.

Farrell's (1957) measure of technical efficiency used an output-oriented model with a single output, constant returns to scale, and constant technology across all producers. Output oriented efficiency is producing the maximum amount of output with inputs and technology held fixed. The producer maximizes output by proportionally expanding output as far as possible while inputs remain fixed. Both input and output oriented models produce the same efficient frontier but generate a different technical efficiency estimate so it is important to consider the producer's behaviour (i.e. which vector the producer has control over) when deciding between models. Input oriented efficiency is using the least amount of inputs to produce a fixed amount of output at current levels of technology. In the input-oriented model, the producer seeks to contract the input vector as much as possible while producing a fixed set out output.

In the case of wildfire management in Alberta, this study assumes output-oriented efficiency because wildfire management resources are often assigned to specific fires and the incident management teams work with the assigned resources to contain the growing wildfire in the most efficient manner. Given our definition of effective suppression is a contained fireline, we assume that fire managers seek to maximize the length of fireline that is contained given the resources and technology available for each wildfire. Though there is an increased interest in economic evaluation to inform resource allocation decisions, Australian survey results indicated wildfire managers have limited familiarity with the information derived from economic evaluation results which indicates there is opportunity for improved communication of research results with managers (Clayton et al., 2014).

4.6 Efficiency Measurement Methods

Several non-parametric and parametric methodologies have been developed in response to Farrell (1957) to quantify the efficiency of various producers and industries.

4.7 Data Envelopment Analysis

Data envelopment analysis (DEA) is a non-parametric method of measuring economic efficiency. The non-parametric efficiency model benefits from requiring fewer assumptions and avoids the risk of introducing bias by assuming an incorrect functional form (Schmidt, 1985). DEA is a linear programming model that defines a sector's efficient frontier based on the performance of a large sample of generic "decision making units" (DMUs) (Charnes et al., 1978). A linear piece-wise frontier is fit based on the output of best performing DMUs and any DMU whose output falls under the efficient frontier is operating inefficiently, given their inputs and technology (Charnes et al., 1978). The benefit of DEA is it can measure the productivity and efficiency of single or multi- output and input models with large numbers of variables and constraints (Cooper et al., 2004). DEA also benefits from not requiring assumptions about technology, except convexity, or distributional assumptions about efficiency. However, DEA assumes any variation between DMUs is interpreted as inefficiency and does not allow for random variation which can be a limitation (Hjalmarsson et al., 1996). Statistical inference is challenging in DEA because efficiency estimates are free of a functional form meaning all variation between DMUs is interpreted as inefficiency though some research has derived a DEA estimator (Hjalmarsson et al., 1996; Schmidt, 1985; Simar and Wilson, 2000). Efficiency can also be measured using a parametric framework with an assumption of the functional form of the inefficiency term which allows for parametric estimation and statistical inference.

4.8 Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) is an extension of production function models that builds from Farrell's (1957) work to calculate efficiency by quantifying any deviations from the frontier production function. SFA determines if the deviations from the frontier are due to stochastic variance (random error) or technical inefficiency. This methodology was first documented by two concurrent manuscripts by Meeusen and van Den Broeck (1977) and Aigner, Lovell, and Schmidt (1977) who suggest a composite error term that consists of stochastic shock and technical inefficiency. Battese and Corra (1977) published months later with a similar specification that only differs slightly in the inefficiency's density function. The cross sectional SFA model is shown in equation 3.

$$y_i = \boldsymbol{\alpha} + \boldsymbol{\beta} x_i + \varepsilon_i \tag{3}$$

$$\varepsilon_i = v_i + u_i, \quad i = 1, \dots, N$$

Distributional assumptions are required for both components of the SFA error term where v_i, unobservable random error, is assumed to be independently and identically distributed with a mean of zero and positive variance. The inefficiency term, u_i, is independent of v_i, non-negative, and can follow a number of different density functions including truncated normal, half normal, exponential, or gamma (Aigner et al., 1977; Greene, 2005a, 2008; Meeusen and van den Broeck, 1977). u_i is interpreted as a firm's technical inefficiency of production while v_i is the stochastic error associated with the uncontrollable factors of the production process (Battese 1997). If u_i is absent from the error term, the model collapses to a classic production function.

Output oriented SFA uses observations of inputs and outputs over a study period to estimate the efficient frontier. Technical inefficiency is measured as the distance between observed output and estimated maximum output which is demonstrated in Figure 9 assuming a simple single input-output production process (Aigner et al., 1977).

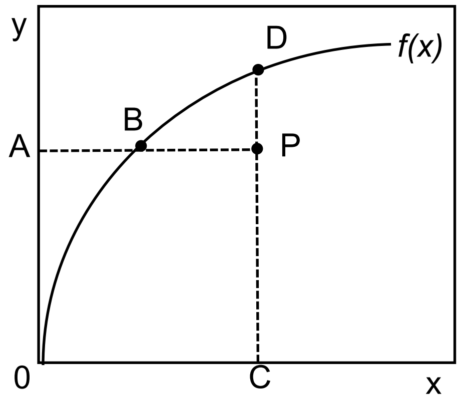


Figure 9. Output oriented technical efficiency. *f(x)* represents the efficient production frontier. Point P is an inefficient producer. Distance PD represents output-oriented technical inefficiency. Producer P could increase output (y) to point D using the same amount of input (Coelli et al. 2005).

In Figure 9, technical efficiency is calculated as TE = CP/CD (Coelli et al., 2005). Technical efficiency is the ratio between observed output of a producer and potential output of the producer had they been operating on the frontier at the known amount of input (equation 4) (Hjalmarsson et al., 1996).

$$TE(y,x) = \frac{y}{f(x)} \leq 1 \tag{4}$$

SFA is generally fit by maximum likelihood because ordinary least-squares and generalized method of moments estimators have been shown to be inefficient (Belotti et al., 2013; Schmidt, 1976). The log likelihood function is derived from the probability density function of ε_i which is the convolution of v_i *and* u_i's component densities (Belotti et al., 2013). Closed form point estimates of u_i and TE are possible with the truncated normal, half-normal, and exponential error distribution (Jondrow et al., 1982; Stevenson, 1980). All other model specification can be solved by simulation that relies on asymptotic properties (Belotti et al., 2013).

The benefit of stochastic frontier analysis is the ability to quantify producer's inefficiency instead of assuming all deviations from the frontier are stochastic measurement error. SFA is more suitable to panel data than DEA, allows for formal hypothesis testing, and construction of confidence intervals for all estimates (Hjalmarsson et al., 1996). Cross sectional SFA analysis is limited to providing a snapshot of producers and their efficiency at one point in time but panel data allows tracking of performance over time (Kumbhakar and Lovell, 2000a).

4.9 Panel Stochastic Frontier Analysis

Panel SFA observes the same producer over time which can loosen model restrictions by allowing inefficiency to change over time and differentiate inefficiency from other producer characteristics (Pitt and Lee 1981; Battese 1992; Battese and Coelli 1995). Panel models have been developed where all time-invariant unobserved heterogeneity is inefficiency (e.g. Pitt and Lee 1981), inefficiency can vary over time (e.g. Battese and Coelli 1992), and all time-invariant unobserved heterogeneity is ruled out of the inefficiency (Greene 2005). Greene's (2005) “true random effects” (TRE) specification differentiates time-varying inefficiency and unit-specific time-invariant unobserved heterogeneity as shown in equation 5:

$$y_{it} = (\alpha + w_i) + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} \pm u_{it} \tag{5}$$

$$i = 1, \dots, N, t = 1, \dots, T$$

where y_{it} is the output of ith producer at time t, x_{it} is a vector of factor inputs, and α_i and $\boldsymbol{\beta}$ are vectors of unknown parameters to be estimated. v_{it} is a vector of random errors assumed to be independent and identically distributed N(0, σ^2). u_{it} are associated with technical inefficiency of production and are assumed to be independent and identically distributed and can follow many distributions including half-normal, truncated normal, and exponential (Belotti et al., 2013). $\boldsymbol{w}_i$ is the time-invariant random effect specific to each producer (Greene, 2005a). Model and density function selection should not just follow the popular literature but be guided by the sample data being analyzed (Greene, 2005a). The TRE model can be extended to allow for a heteroskedastic error term.

4.9.1 Heteroskedasticity

The consequence of heteroskedasticity in SFA analysis is biased estimates of technical efficiency and therefore it is important to test and control for if present (Kumbhakar and Lovell, 2000b). Caudill and Ford's (1993) Monte Carlo analysis showed that heteroskedasticity in the one-sided error of a Cobb-Douglas stochastic frontier production function leads to overestimation of the intercept and underestimation of the slope parameters. Inefficiency measures rely on the residuals derived from frontier estimation and model misspecification can create sensitivity in the residuals which is passed on to the inefficiency estimates (Caudill et al., 1995). A model where the variance of inefficiency is a function of an independent set of parameters can control for heteroskedasticity (Le, 2018).

4.9.2 Exogenous Determinants of Inefficiency

Standard SFA allows us to observe the efficiency of each producer. It remains possible that there are variables that are neither inputs nor outputs but affect producer output. Most wildfire management agencies are interested in learning what variables affect efficient production and to what extent. It is possible to include explanatory variables of inefficiency by extending the basic SFA model. The basic SFA model (equation 3) assumes the inefficiency term (u_i) is time invariant and homoskedastic. If there is unaccounted heteroskedasticity in u_i, technical efficiency estimations will be biased (Belotti et al., 2013; Wang and Schmidt, 2002). Early research used 2-stage SFA estimation to account for heteroskedasticity but produced biased estimates (Schmidt, 2011; Wang, 2002). Instead, a simultaneous estimation procedure is preferred to include variables that explain heteroskedasticity while creating unbiased results (Battese and Coelli 1995).

This study uses the true random effects (TRE) model developed by Greene (2005a; 2001) that allows for unobserved heterogeneity across fires and time-varying, heteroskedastic inefficiency (Caudill, Ford, and Gropper 1995; Battese and Coelli 1995; Hadri 1999). The random effects model is suitable to fire management because there are likely to be unobservable differences in manager and crew experience across different fires (Hesseln et al., 2010). All time-invariant effects are treated as unobserved heterogeneity and the inefficiency component varies over time (Greene, 2008).

$$y_{it} = (\alpha + w_i) + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} \pm u_{it} \tag{6}$$

$$i = 1, \dots, N, t = 1, \dots, T$$

$$v_{it} \sim N(0, \sigma^2_{vit})$$

$$u_{it} \sim E(\mu_i, \sigma_{uit}^2)$$

$$w_i \sim N(0, \Theta^2)$$

$$\sigma_{uit}^2 = e^{z_{it}'\boldsymbol{\delta}} \tag{7}$$

In equation 6, u_{it} (technical inefficiency) and v_{it} (stochastic noise) are iid of each other and the other regressors. $\boldsymbol{w}_i$ is the time-invariant random effect specific to each fire (Greene, 2005a). Equation 7 defines the heteroskedasticity of the technical inefficiency (σ_{uit}^2) as a parametric function where $\mathbf{z}_{it}'$ is a (1 x m) vector of exogenous variables with a constant term and $\boldsymbol{\delta}$, the inefficiency effects, is a (m x 1) vector of unknown parameters to be estimated. If all elements of $\boldsymbol{\delta}$ are zero, then the technical efficiency effects are not related to the z-variables and the model collapses to basic panel SFA (equation 5) (Battese and Coelli 1995). To solve the TRE model with heteroskedastic inefficiency, σ_{uit}^2 is substituted into the likelihood function anywhere σ_u^2 appears (Kumbhakar et al., 2020). In equation 7, the variance of u_{it} is an exponential function to ensure variance is positive for all $\boldsymbol{z}$ and $\boldsymbol{\delta}$ (Hadri, 1999; Parmeter, 2014)**.**

Under the TRE specification, there is no closed form solution for the two-sided disturbance and unobserved heterogeneity term, so simulation is used to maximize the log likelihood function and estimate technical efficiency (Greene, 2001, 2005a). The generalized log likelihood function is;

$$\log L = \sum_{i=1}^{N} \log \left[u_{i_i} \left(\prod_{t=1}^{T(i)} g(y_{it}, \beta' \boldsymbol{x_{it}}, u_{it}, \theta) \right) h(u_{it} \mid \theta) du_{it} \right., \tag{8}$$

where θ is a vector of ancillary parameters. Greene (2001) outlines how simulation methods can be used to estimate the first integral which is an expectation

$$u_i \left(\prod_{t=1}^{T(i)} g(y_{it}, \beta' x_{it}, u_{it}, \theta) \right) h(u_{it} \mid \theta) du_{it} = E[F(u_{it} \mid \theta)], \tag{9}$$

that can be computed using the law of large numbers:

$$plim \frac{1}{R} \sum_{r=1}^{R} F(u_{itr} \mid \theta) = E[F(u_{it} \mid \theta)]. \tag{10}$$

Estimating the integral requires simulation using a random number generator and then the integral is inserted into the log likelihood for maximization and parameter estimation. Point estimates of firm level technical inefficiency are estimated using the mean or mode of the conditional distribution of u given ε (Kumbhakar et al., 2020). With heteroskedasticity defined in equation 7, the mean of u following the exponential distribution is

$$E[u_{it} \mid z_{it}] = e^{\frac{1}{2} z_{it}' \delta_{it}}. \tag{11}$$

Technical efficiency (TE) is estimated following the procedure developed by Jondrow et al. (1982) by substituting equation 11 into equation 12.

$$TE_{it} = exp(-E[u_{it} \mid z_{it}]) \tag{12}$$

The efficiency estimates from stochastic frontier analysis create a greater understanding of how efficiently individual producers operate over time. In wildfire science this is useful to understand if resources are being used efficiently over the length of sustained action or if there are opportunities to increase output, given inputs and technology. Stochastic frontier analysis is useful to draw statistical inference from parameter estimates but there are some challenges associated with misspecification that must be controlled before interpreting or generalizing results.

4.10 Identified Limitations in Stochastic Frontier Analysis

Stochastic frontier analysis has the same specification requirements as standard production function estimation (Griliches and Mairesse 1995). Careful attention must be given to unobservable quality characteristics, functional form selection, sample selection bias, omitted variable bias, and output endogeneity. Panel models control for unobservable quality characteristics (heterogeneity) in the random effects model by observing the same production units over time but distributional assumptions and endogeneity must be addressed (Greene, 2005b).

4.10.1 Distributional Assumptions

Choosing the correct distribution of $\boldsymbol{u}$ is important because studies that have compared efficiency estimates from simulated data of different distributions show efficiency estimates are biased if fit to the wrong distribution (Belotti et al., 2013). If there is only interest in ranking each producer based on their technical efficiency score, the rank is robust to distributional choice (Kumbhakar and Lovell, 2000a). In this study we are interested in quantified estimates of technical efficiency for each wildfire on each day, so the distribution is chosen based on best model performance and model fitness criteria such as R-squared and Akaike information criteria.

4.10.2 Endogeneity

Endogeneity is another challenge for SFA because ignoring endogeneity leads to biased and likely inconsistent estimates (Kumbhakar et al., 2020). Endogeneity violates the model assumption that $\boldsymbol{x}$ is independent of $\boldsymbol{u}$ and $\boldsymbol{v}$. Stochastic frontier models are typically estimated by maximum likelihood (MLE) and consistent parameter estimation requires causality to be unidirectional and independent variables not be correlated with the error term (Kumbhakar et al., 2020). In economic terms this means the estimation procedures require strict exogeneity of the independent variables (input variables in the production context).

Statistical endogeneity arises from omitted variables, simultaneity, or measurement error (Kumbhakar et al., 2020). Simultaneity occurs when output is jointly determined with inputs (Griliches and Mairesse, 1995). Economic endogeneity can occur because the production process is rarely instantaneous meaning inputs are not converted to outputs as soon as the allocation decision is made (Marschak and Andrews 1944). It remains possible that producers may observe shocks (v) or be aware of their inefficiency (u) and adjust inputs ($\boldsymbol{x}$) creating endogeneity (Kumbhakar et al., 2020). Other times, producers will make their input decisions based on expected output making output endogenous resulting in reverse causality bias (Torres and Morrison Paul 2006). It can be argued that this behavior arises for wildfire managers when making their resource allocation decisions based on expectations of fire behaviour and growth.

Endogeneity can be dealt with using instrumental variables and a corrected two stage least squares estimation procedure (2SLS), but it is often difficult to find accurate instruments and the model may not robust to the choice of instruments (Amsler et al., 2016). Limited information maximum likelihood (LIML) can be used and is similar to 2SLS but is estimated as a system that contains the reduced form equations for the endogenous variables (Amsler et al., 2016; Anderson and Rubin, 1949). LIML estimators rely on correct reduced from model specification and it is still possible the endogenous variables are correlated with the white noise and the inefficiency requiring joint estimation which is not simple to model (Amsler et al., 2016). Finally, the method of moments estimator can maximize the likelihood function using first order conditions which creates valid estimates regardless of endogeneity (Kumbhakar et al., 2020). Endogeneity is important and we can not guarantee it is fully absent from our analysis which is a limitation of using production function analysis. After ensuring correct model specification, we will consider how to capture the inherent quality differences of suppression resource inputs.

4.11 Input Prices as a Quality Adjustment

Input quality differences can drive measured differences in firm productivity (Fox and Smeets, 2011). If differences in input quality are not accounted for, it may be incorrectly measured as inefficiency when modelling output and productivity (Fox and Smeets, 2011). Input prices are quality indicators of the productivity, scarcity and average component cost of production inputs (Cleveland and Stern, 1998). Prices can therefore be included in the measure of inputs used in production to capture inherent quality differences (Gandhi et al., 2019). Alberta Wildfire's different airtankers are an example of how inputs within a category can differ in quality. The Convair CV 580 airtankers can carry 7950 litres of retardant and operate independently while the Air Tractor 802F airtankers can carry 2955 litres of retardant and operate as a group of four (Alberta Wildfire, 2020e). The production function will be estimated with and without input prices of suppression resources to control for quality differences of input resources and assess for significant changes to estimates.

4.12 Technical Efficiency Analyses of Large Wildfire Suppression

Wildfire suppression economic efficiency models analyze the technical efficiency of suppression and can explicitly include weather, fuel, and other variables that are associated with fire growth and behaviour. Technical efficiency in the following wildfire economics studies refers to containing the maximum possible wildfire perimeter or area given a fixed set of suppression inputs. A DEA study from Greece observed different regional fire stations had significantly different wildfire suppression efficiencies (Fotiou, 2000). Another DEA analysis found significant differences in the efficiency of Portugal's wildfire management municipalities at containing wildfire and area burned (Martinho, 2018). Importantly, these DEA models observed differences in efficiency of containment but could not explain what caused the observed efficiency differences.

Holmes and Calkin (2013) used estimated fire perimeters and a Cobb-Douglas production function to measure the mean productivity of suppression inputs. Results indicated Type 1 incident management teams could enhance fireline production rates. This study could not explicitly estimate the technical efficiency of suppression because they used estimated fire perimeters instead of measured fire perimeters, meaning the error term could not be decomposed into the stochastic and systematic components. Holmes and Calkin (2013) also found weather variables such as wind speed were insignificant suggesting collinearity with variables not included in the model which indicates there are opportunities to improve model specification.

Katuwal, Calkin, and Hand (2016) used stochastic frontier analysis to assess the efficiency of large wildfire suppression. This thesis was heavily motivated by their SFA methodology that used GIS fire perimeters to calculate length of daily held perimeter as the dependent variable. They found bulldozers and fire engines positively contribute to held fireline but air equipment had no effect and crews negatively affected held perimeter. Mean efficiency was around 47% but there were challenges identifying significant variables that influenced inefficiency. Only lagged maximum relative humidity increased inefficiency and relative age of fire decreased inefficiency though they included wind, timber, rivers, roads, suppression tactic, and previous wildfires as explanatory variables of inefficiency with zero significance.

Hesseln, Amacher, and Deskins (2010) used stochastic cost frontier analysis to assess if access to GIS technology during suppression affected suppression efficiency. Stochastic cost frontier analysis is a type of SFA that models a cost function, instead of a production function, where the dependent variable is total firefighting expenditures (Hesseln et al., 2010). Cost frontiers assume a cost-minimization objective where wildfire protection efficiency is achieved at the combination of assets that control fires at the lowest cost. Inefficiency is the non-random deviations from the minimum cost or loss frontier. Hesseln, Amacher, and Deskins (2010) used a random effects model which acknowledged there is unobserved heterogeneity across wildfires because of different fire managers, experience of crews, and timing of suppression resource arrival to fire. Their study of large fires from U.S.A's northern Rocky Mountains revealed the costs of GIS technology are outweighed by avoided damages that are realized by improving the efficiency of firefighting assets. They also found that area burned, fire complexity, and lodgepole pine fuels significantly increase suppression costs while weather variables were insignificant (Hesseln et al., 2010).

A major critique of economic efficiency models is they are unable to account for resources being used for management objectives other than fireline containment (Plucinski, 2019b). Another criticism is that the efficiency analyses fail to model the complexity of the large fire decision environment where response strategies can be dynamic within each fire day (M. P. Thompson et al., 2017). Information on the resource activities is tracked by some wildfire management agencies and filtering the inputs to only those participating in fireline containment would control for some of these complexities. Thompson et al. (2017) also assert the models fail to account for containment lines that are built and do not engage in fire or are burned over. We argue firelines built for containment on future days create a lag in inputs until their fireline is engaged which is an argument for the use of panel data models that observe output throughout sustained action. Other challenges in modelling suppression efforts and efficiency include little understanding of the substitutability of suppression resources and limited monitoring of containment efficiency. Trade-off analysis and generation of efficient frontiers can help mangers balance multiple objectives without reducing everything to monetary terms (M. P. Thompson et al., 2017). This argument supports the use of stochastic frontier analysis because SFA quantifies technical efficiency and the marginal impact of suppression resources which informs the substitutability.

From a management perspective, operating on the efficient frontier should not be considered a fire suppression objective as it is often not realistic to achieve. It is essential that the decision maker understands the full limitations of scope of this model. Thompson et al. (2018) suggest key performance indicators can be generated after efficiency analysis to generate realistic management objectives. One possible performance indicator calculates the "productive capacity" of suppression resources assuming perfect efficiency and ranks performance based on the ratio of "productive capacity" to actual held perimeter. This study will use the information gained from past economic efficiency of wildfire suppression research to adapt these models to large wildfires in Alberta's boreal zone.

4.13 Suppression Resource Input Variables

Wildfire suppression resources are the production function input variables. Suppression resources include crews, ground equipment, and aerial equipment that work to douse flames and create breaks in fuel that are large enough to prevent the fire from growing larger. The effectiveness of suppression resources decreases as fire intensity increases and incident commanders will substitute between different containment strategies and suppression resource types depending on the fire intensity (Cole and Alexander, 1995). Table 1 outlines what resources are most effective given the fire intensity class. Head fire intensity classes describe expected fire behaviour given the fuel type, moisture content, and weather conditions.

Table 1. Effectiveness of suppression resources under five different fire intensity classes

Fire Intensity Class	Description of Fire Potential and Implication for Wildfire Suppression in C-2 (Boreal Spruce) Fuels [A]
1 (< 10 kWm^{-1})	Moist surface fuel conditions make control very easy as fires generally do not spread far beyond their origin point.
2 (10 – 500 kWm^{-1})	Surface fuels can sustain ignition and combustion. Direct manual attack by firefighters "hotspotting" with only hand tools and backpack pumps is possible. A light helicopter with a bucket is also effective. Containment line built with hand tools should hold.
3 (500 – 2000 kWm^{-1})	Flames over 1.5 m and intermittent crown fire can occur. Moderately difficult to contain. Hand-constructed containment lines are likely to be challenged and the opportunity to "hotspot" diminishes. Water under pressure (fire pumps with hose), heavy machinery, and "intermediate" helicopters with buckets are generally required.
4 (2000 – 4000 kWm^{-1})	Critical burning conditions as intermittent crown fire and short-range spotting is common. Control is very difficult and direct attack on head of fire by ground resources is only possible immediately after ignition. Any other head fire suppression should be done by medium and heavy helicopters with buckets or fixed wing aircraft dropping retardant. Successful control is uncertain.
5 (> 4000 kWm^{-1})	Crown fires are prevalent. Control is extremely difficult and all efforts at direct control are likely to fail. Suppression must be restricted to the flanks and back of fire. Indirect attack with aerial ignition may be possible.

[A] Table modified from (Cole and Alexander, 1995)

Suppression crews use hand tools and backpack water pumps to directly attack the entire wildfire perimeter or they will focus on hotspots. "Hotspotting" involves crews extinguishing the hottest, most intense sections of the fire which rapidly reduces the rate of fire spread by bringing the fire under control in its earliest stages (Alberta Wildfire, 2020b). Crews also use hand tools to create mineral earth containment lines and support the lines built by equipment or airtankers (Plucinski, 2019a). However, the general effectiveness of crews with hand tools and backpack pumps requires light fuels, shallow soil and a head fire intensity class less than 2 (Table 1). These conditions are not common in Alberta's boreal zone.

Aerial suppression resources include helicopters and airtankers that can drop water or fire retardant to aid in containment activities (Plucinski, 2019a). Aerial equipment will locate their suppressant drops to either directly douse flames as part of direct attack or to wet fuels and build retardant containment lines ahead of the fire during indirect attack (Plucinski, 2019a). Table 1 describes airtankers and helicopters as the only suppression resource that can be effective at HFI 4 or higher and they are regularly used during sustained action in Alberta's boreal zone (Hirsch and Martell, 1996).

Ground equipment removes fuels and moves earth to build mineral soil containment lines around wildfires (Plucinski, 2019a). Canadian wildfire management agencies also utilize the abundant natural water sources by using ground water tankers and engines with pumps and hoses that knock down flames or wet fuels in the path of the wildfire during sustained action (Plucinski, 2019a). Ground equipment can effectively contain fire perimeter for HFI classes 3 and below but effectiveness above HFI 3 becomes uncertain (Table 1).

4.14 Suppression Resource Allocation

Suppression resources are allocated based on threats to values at risk, wildfire behaviour, growth potential of today's wildfires (current load), and future wildfire starts (forecasted load) (Tymstra et al., 2020). Alberta Wildfire allocates resources by prioritizing the protection of values at risk (human life, communities, sensitive watersheds and soils, valuable natural resources, and infrastructure) as discussed in Chapter 3. Incident commanders deploy resources to sections of the perimeter that maximize VAR protection and wildfire crews use containment resources at their disposal to prevent further growth (MNP LLP, 2020, 2016).

Incident commanders have said they would prefer to use fewer suppression resources but risk tolerance and socio-political pressures can potentially compel incident commanders to allocate more resources than necessary given the values at risk (Calkin et al. 2013). Strategic behaviour can also affect suppression efficiency because incident commanders compete to secure resources from their regional dispatch and retain them over long periods (Bayham and Yoder, 2020). Donovan, Prestemon, and Gebert (2011) were interested in how the political affiliation of local congress representatives and the amount of newspaper coverage impacted the costs of wildfire suppression. Their use of instrumental variable regression showed that newspaper coverage and the seniority of local congressperson were associated with increased expenditures on fire suppression. Firefighter safety is also of critical importance to wildfire managers and fire management teams with lower risk tolerance have been shown to be less efficient at fire suppression (Hand et al., 2017; Katuwal et al., 2017). Canadian wildfire management agencies are interested in improving suppression efficiency but will not risk firefighter safety for a chance of increased efficiency. Suppression resources balance the objective of wildfire containment with the objective of maintaining firefighter safety and will change their strategy or tactic away from direct attack if conditions are too dangerous for firefighters. Wildfire suppression resources do their best to contain wildfires but are working against the random nature of weather, fuels, and landscape features which influence fire growth but are outside the control of suppression crews.

4.15 Wildfire Growth and Containment Efficiency Variables

Fire behaviour during containment efforts regulates fire suppression effectiveness (Beverly, 2017). Fire behaviour and area burned are related to vegetation (fuel), weather, and level of suppression (Martell and Sun, 2008). The majority of fire growth occurs during "spread days" when hot, dry, and windy weather conditions are ideal for wildfire ignition and spread (Wang et al., 2017). Conversely, suppression resource success is usually opportunistic during extended periods of moderate weather (Finney et al., 2009). Maximum wind speed, minimum relative humidity and maximum air temperature have been used in models to capture the current day's weather (Katuwal et al., 2016). Resourcing decisions are often made the evening before assignment based on forecasted weather conditions and expectations of fire behaviour in the next burning period (MNP LLP, 2016). To capture these expectations, evening forecast variables can represent expectations for tomorrow's burning period. Fire growth and behaviour are also influenced by long-term and large-scale weather patterns (Lagerquist et al., 2017; Skinner et al., 1999).

The Canadian Forest Fire Weather and Index System (CFFWIS) captures long-term regional weather trends (Van Wagner, 1987). CFFWIS calculates three fire behaviour indices and three fuel moisture codes. Fire behaviour codes: initial spread index (ISI), buildup index (BUI), and fire weather index (FWI) are proxies for the rate of fire spread, amount of combustible fuel, and potential fire intensity. These behaviour codes represent long-term weather systems as opposed to present day weather. Fuel moisture codes: fine fuel moisture code (FFMC), duff moisture code (DMC), and drought code (DC) estimate the fuel moisture in three layers of forest floor fuel material. FFMC is considered a short term indicator of fuel flammability (18 hour) and DC represents long-term resistance to extinguishment (52 days) (de

Groot, 1998). FFMC and DC fuel indices can be readily incorporated into the SFA model because they are linear indices that are rarely censored at the top or bottom of their distribution.

Fuels above the forest litter layer (surface, ladder, and crown) are another important predictor of fire growth because the density and moisture content of these layers influence the transition from surface to crown fires (Forestry Canada Fire Danger Group, 1992). The boreal's coniferous and C-2 (Boreal Spruce) stands are particularly flammable with deep sub-surface organic layers, feather moss, continuous shrubs, and tree crowns that extend nearly to the ground acting as ladder fuels that propagate surface fires to high intensity crown fires (Beverly et al., 2020).

The spring burning period in Alberta is conducive to rapid fire spread after snowmelt reveals dry, dead fine fuels from last season prior to vegetation green-up (Pickell et al., 2017; Tymstra et al., 2007). Foliar moisture content is also at a minimum in coniferous trees during this period termed the "spring dip" that would likely decrease suppression efficiency due to the extreme burning conditions. Lightning events that coincide with extremely dry fuels create surges in wildfire ignitions when resource demand can quickly exceed resource availability (Tymstra et al., 2020). Alberta's full response approach defaults to a risk-based appropriate response when a wildfire load surge occurs (Tymstra et al., 2020). The number of new daily fire starts can be used to proxy the provincial fire load and control for supply constraints (Martell, 2001).

Landscape features such as roads and large waterbodies can serve as natural firebreaks with potential to generate gains in efficiency as suppression resources can focus on other sections of the wildfire (Arienti et al., 2006; Katuwal et al., 2016). Historic wildfires can also increase suppression efficiency because active wildfires that overlap historic burn scars from the last nine years can increase initial attack effectiveness (Beverly, 2017; Parks et al., 2016; Thompson et al., 2016). The percent of the wildfire perimeter that overlaps roads, waterbodies, and burn scars from the past 9 years can be included in models to capture the landscape features that influence containment efficiency.

4.16 Chapter 4 Summary

In summary, this study uses stochastic frontier analysis to determine the efficiency of large wildfire suppression in Alberta, Canada. Effective suppression resources positively contribute to a contained wildfire while efficient suppression is producing the longest possible contained fireline while using the fewest resources. To study the efficiency of wildfire suppression, the SFA model incorporates crews, ground equipment, and air equipment as production inputs that contain wildfires. Past research indicates efficient suppression relies on extended periods of tempered wildfire behaviour and weather conditions. Stochastic variables for weather, fuels, and natural fire breaks will be included to predict the amount and variance of technical inefficiency. From this analysis, we hope to gain an understanding of which suppression resources are most efficient at containing large wildfire and which stochastic variables are the largest barriers to efficient suppression. The next chapter outlines the data sources, model specification, and model results.

Chapter 5: Data, Empirical Methodology, and Model Results

The objective of this study is to understand the efficacy of wildfire suppression resources and estimate the efficiency of large wildfire suppression in Alberta's boreal zone. Stochastic frontier analysis is used to estimate technical efficiency of wildfire suppression and will incorporate wildfire suppression resources as production function inputs. Stochastic variables that affect wildfire growth and behaviour will be incorporated as determinants of the level and variability of inefficiency. The objective of Chapter 5 is to present and discuss the parametric results of the stochastic frontier models. First, the sample selection procedure and data sources for the analysis are discussed. Next, the model results are presented, and estimated coefficients are discussed. Then, the technical efficiency estimates are derived from model parameters. Finally, a summary of the model results and implications is presented.

5.1 Sample Selection

This study focuses on large, prolonged wildfires that have exceeded initial attack objectives and are undergoing sustained action by wildfire crews in Alberta. In this study, large wildfires are any wildfire larger than 190 ha. This definition includes all class E wildfires that exceed 200 ha at extinguishment and select fires that are just short of the 200 ha threshold. Some American studies use 121 ha to define large wildfires, however this study is specific to Alberta and therefore uses Alberta's classification system (Calkin et al. 2014). Extremely large, complex wildfires were also removed from the analysis because wildfires large enough to threaten many lives or communities are extremely complex to manage with factors influencing management decisions beyond what are considered in this study such as newspaper coverage and political pressure (Donovan et al., 2011). All sample fires are from the boreal zone of Alberta's forested region (48% of Alberta's land base) and explicitly exclude wildfires in the foothills and Rocky Mountain regions to control for the added complexity terrain, slope, and elevation introduce to wildfire management (Linn et al., 2007). In addition to these initial selection criteria, sample selection was limited by the availability of progression perimeter data which are necessary for the analysis. Table 2 outlines the number of available fires from 2013 through 2019 that meet the selection criteria of which 24.4% had sufficient progression perimeter data to be considered for analysis.

Table 2. Sample wildfires that meet selection criteria and have sufficient data available.

Year	Fires ≥ 190 ha	Sample Fires	Fraction Available for Analysis
2013	6	2	0.333
2014	5	0	0.000
2015	44	17	0.386
2016	10	1	0.100
2017	17	4	0.235
2018	18	4	0.222
2019	14	6	0.429
Total	**114**	**34**	**0.244**

5.2 Data Sources

The data required for this study come primarily from Alberta Wildfire's data catalogue and are supplemented with publicly available and open access datasets. Wildfire perimeter data are from Alberta Wildfire's geographical information systems (GIS) data catalogue. Resource data are from Alberta's Fire Information Resource System (FIRES) that is internal to the Government of Alberta's Wildfire Management Branch. Meteorological data from lookout towers and automated weather stations are also from the FIRES database but only have two observations per day (AM and PM). Hourly weather data (temperature, precipitation, wind, and relative humidity) were downloaded from Alberta Agriculture and Forestry's historical weather station data viewer and are from the same automatic weather stations used by Alberta Wildfire's incident management teams and wildfire managers (Government of Alberta, 2020a).

5.2.1 Progression Perimeters

The progression perimeter data are a combination of wildfire perimeters from aerial GPS delineation, ground-borne GPS, digitized from aerial photography, and, in rare circumstances, hand-drawn perimeters. Held perimeter is the model's dependent variable. It is calculated as any section of the daily wildfire perimeter that does not grow any larger, minus previously held perimeter (equation 13).

$$\boldsymbol{y} = HeldPerimeter = DailyHeld - PreviouslyHeld \tag{13}$$

Figure 10 shows how the intersect feature from any spatial data analysis software is used to calculate held perimeter as the length of progression perimeter that intersects final perimeter; meaning it does not grow larger.

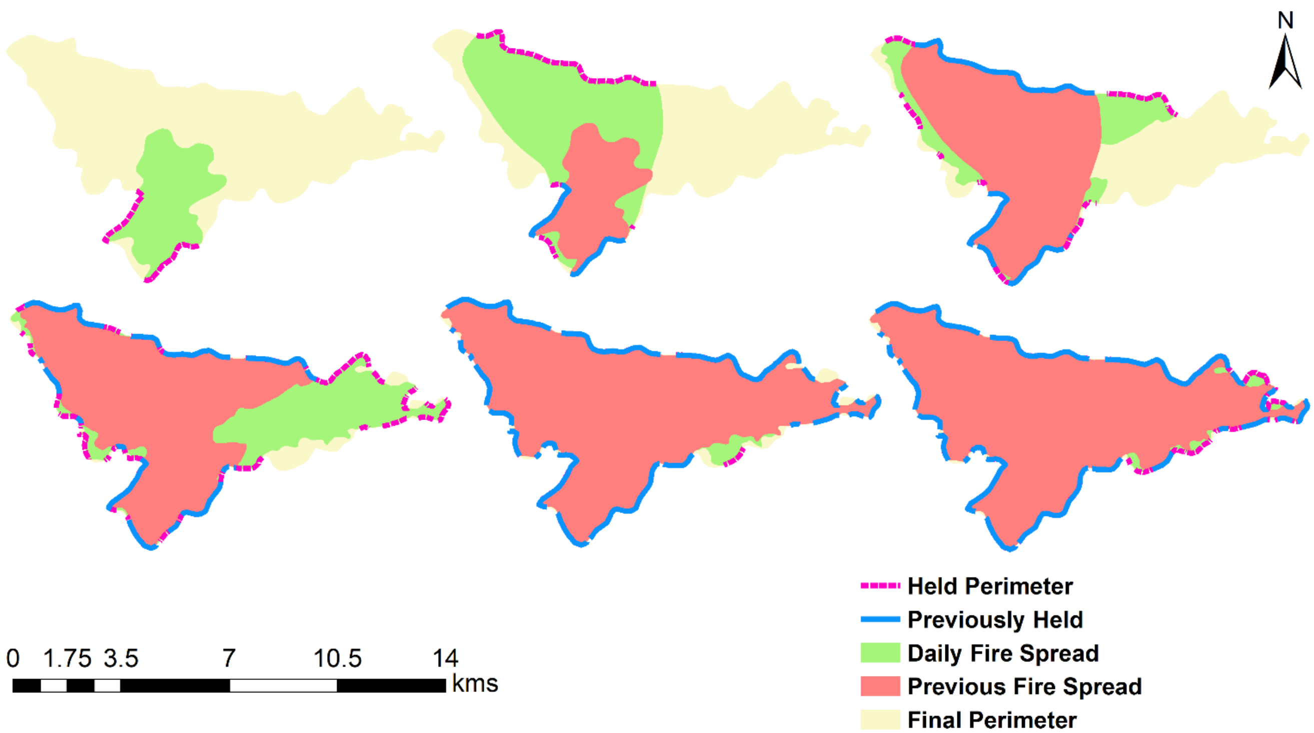


Figure 10. Example calculation of daily held perimeter from a sample wildfire.

Progression perimeters are not recorded daily as they are in American jurisdictions (Katuwal et al., 2016). The sporadic updating of progression perimeters creates "gaps" in the observed held perimeter in what would otherwise be a panel dataset. The SFA input variables are all observed daily but because held perimeter, the dependent variable, is not observed daily the input variables are averaged across the length of the gap meaning the length of time between observations of the dependent variable. This is not

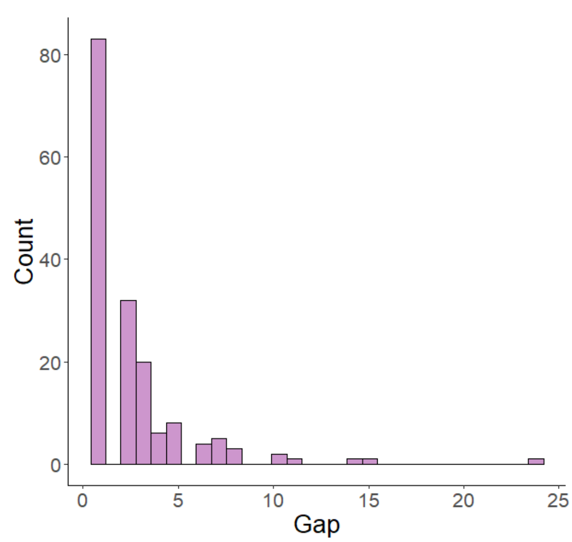


Figure 11. Histogram of gap length (in days) between observed GIS perimeters

ideal because the averages can understate the influence of stochastic variables but is similar to techniques used by other researchers facing this same problem (Collins et al., 2007). The gap variable is included in the model to control for the various gap lengths between observed held perimeters. The histogram in Figure 11 shows 96% of the gaps are under 10 days and 50% of the gaps are 1 day long as they would be in a true panel as used by Katuwal, Calkin, and Hand (2016).

5.2.2 Values at Risk

Held perimeter as the output or dependent variable assumes incident commanders treat all segments of the wildfire perimeter as equal. However, when incident commanders are setting priorities and allocating resources they consider firefighter safety, values at risk, present and forecasted weather, and probability of success (Alberta Wildfire, 2020a). These considerations lead to the strategic positioning of suppression resources to prioritize the containment of certain perimeter sections that are most valuable and likely to be contained. The values at risk (VAR) that receive priority protection by Alberta Wildfire follow the hierarchy: human life, communities, watersheds and sensitive soils, valuable natural resources, and critical infrastructure.

To capture VAR in the model, this study proxies the human life and community VAR by using inhabited structures adjacent to active wildfires. This requires a georeferenced, polygonised dataset that can be used in conjunction with the wildfire progression perimeter dataset. Microsoft recently released a complete dataset of building footprints across Canada (Microsoft, 2019). Machine learning used 3 million satellite images to segment images and isolate all pixels containing structures. After segmenting, the second stage required polygonization to approximate the prediction pixels into building footprint polygons which achieved 98.7% precision. In the Alberta dataset, erroneous polygons were manually observed and removed, then “inhabited” structures were identified through visual reference in QGIS.

To incorporate VAR into the econometric model, a weighting procedure is applied to the held perimeter. The held perimeter was divided into eight segments (octants) and a buffer generated that extends 30 km out from the centroid of the daily wildfire perimeter (Figure 12). The buffer was spatially overlayed with inhabited structures to generate a count of all inhabited structures that fall within 30 km of the wildfire perimeter. 30 km was chosen as the furthest distance that wildfire assessors noted structures as being at risk during values at risk assessments during a manual review of assessment notes. A weighting statistic for held perimeter is calculated using the count and distance of structures within each 30 km buffer. There are many possible weighting statistics including inverse distance and inverse distance squared (Parks, 2014).

The weighting statistic for inverse distance is $W_j = \sum_{i=1}^{N_j} \frac{1}{d_{ij}}$ where j ∈ Z: j ∈ [1,8] representing the octants and i ∈ Z: i ∈ [1,N_j] representing all inhabited structures that fall within the 30 km buffer of each octant. The inverse distance squared weighting statistic is calculated as $W_j = \sum_{i=1}^{N_j} \frac{1}{d_{ij}^2}$. The held perimeter is recalculated to include VAR by the formula: $y_{VAR} = \sum_{j=1}^{8} y_j(1 + W_j)$ where y_j is the length of held perimeter in each octant and W_j is the weighting statistic for each octant. Inverse distance squared was chosen as the most appropriate weighting method because it produced consistent model convergence that was not achieved under other weighting procedures. The SFA model will be estimated with and without VAR to evaluate if incorporating VAR into the model significantly impacts technical efficiency measures of wildfire containment. In Figure 12, the east and southeast octants have the most structures threatened by the wildfire. If suppression management decisions are motivated by the provincial VAR priority list, we hypothesize weighting the held perimeter to include VAR will increase the estimated technical efficiency of suppression resources and wildfire containment.

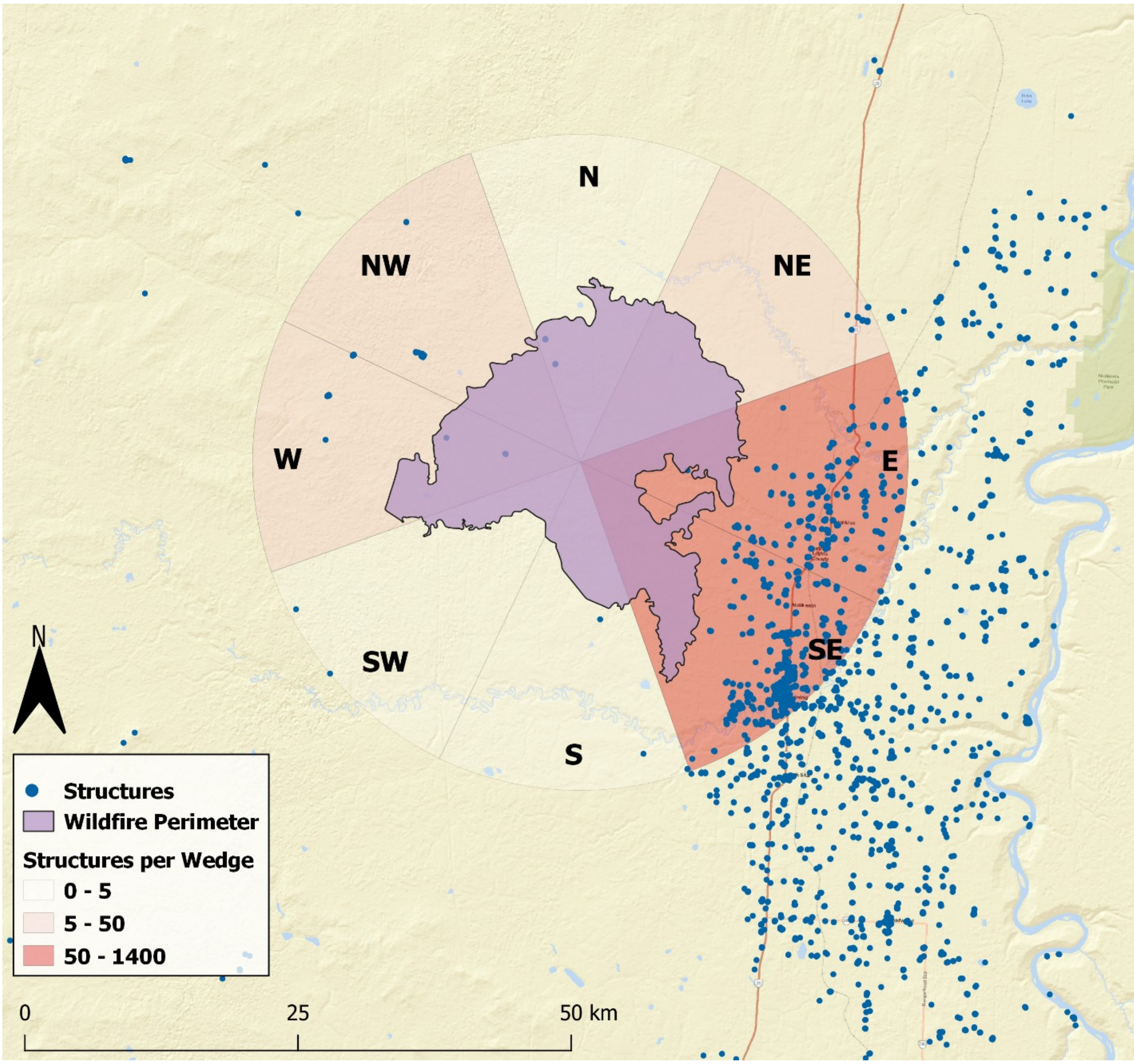


Figure 12. Example of 30 km octant buffers and structures from the values at risk dataset.

5.2.3 Wildfire Containment Resource Inputs

Wildfire containment resources are the production function input variables. As described in the previous chapters, suppression resources work to contain fires by dousing flames, wetting fuels, building containment lines by removing fuels, excavating surface fuels down to mineral soil, and using controlled ignition to tactfully backburn fuels before the fire can reach them. The FIRES database includes the number and type of aerial equipment, ground equipment, and personnel that were present on each fire per day.

Crew resource information was filtered to only include members and leaders of Helitack, Firetack, and Unit Crews that work on fireline containment as production function inputs. The filtering procedure excludes non-incident command personnel such as camp staff, finance officers, and safety personnel. Crews are an important input resource but the effectiveness of crews is challenged at head fire intensity (HFI) class 2 or higher and wildfires that escape initial attack in Alberta's boreal zone regularly exceed that threshold when crews will work in support of other suppression equipment (Table 1; Cole and Alexander 1995).

Aerial containment resources include fixed wing and rotary wing aircraft. The fixed wing input only includes airtankers that are capable of dropping water or retardant and can engage in fireline containment. For the rotary wing input, intermediate, medium, and large helicopters that are capable of bucketing were selected. This excludes light and small helicopters because their smaller bucket capacity is only effective at HFI class 2 and lower and the lighter helicopters are mostly used for reconnaissance and transport during high intensity fires (Alberta Wildfire, 2020b; Cole and Alexander, 1995).

The ground resources include a range of equipment dedicated to clearing and dousing fuels including excavators, bulldozers, graders, water tankers, pumps, loaders, tractors, skidders, feller bunchers, and mulchers. Ground equipment was filtered to select only equipment that would engage in fireline containment and removed equipment such as trucks and trailers that would not be working on containment. Given the information from previous literature and the wildfire containment manual, the efficiency of suppression resources is influenced by wildfire intensity and behaviour that are also included in our model.

5.2.4 Fire Weather Indices and Weather Variables

Meteorological data are recorded twice daily (AM and PM forecasts) at lookout towers and hourly at automatic weather stations deployed in a network across Alberta owned by a combination of Alberta Agriculture and Forestry, Environment Canada, and local municipalities. The PM weather is used to form expectations for the next day's burning conditions as a pre-suppression forecast (Alberta Wildfire, 2019a). Each study fire was paired with the nearest weather station or lookout tower of similar elevation and no weather station was more than 100 km away (Tymstra et al., 2010). Daily weather variables were averaged across the length of the gap between observed progression perimeters. There is some loss of variability when averaging these weather variables as was observed by Collins et al. (2007).

5.2.5 Fuels

The fire behaviour prediction fuels raster dataset is derived from satellite data and is updated annually by Alberta Wildfire's GIS group. The fuel dataset consists of 32 fuel-type categories ranging from O-1 (Grass), C-2 (Boreal Spruce), S-1 (Jack or Lodgepole Pine), and various M- categories representing mixed-wood stands as shown in Appendix A. Coniferous fuels and C-2 in particular are highly likely to create fire intensities that cannot be effectively contained by suppression crews due to low foliar moisture, low canopy base height, and high canopy bulk density creating continuous vertical and horizontal crown fuels that allow surface wildfires to transition to high intensity crown fires (Beverly, 2017; Van Wagner, 1983). The percent of wildfire perimeter that overlaps coniferous and C-2 fuel types is calculated as model input variables to capture the impact of fuels on efficiency.

5.2.6 Landscape Features

Landscape features such as large water bodies and roads can act as natural firebreaks that prevent the growth of fire perimeters that meet the firebreaks. Spatial data layers for waterbodies and roads were retrieved from Alberta's open data portal (Government of Alberta, 2020b). The percent of daily held perimeter that intersects waterbodies and roads is calculated as two possible variables to include in the model. Previous wildfires within the last 9 years have been shown to increase the efficiency of initial attack in Alberta's boreal zone by clearing the dense ground fuels of forested stands permitting easier access to crews and equipment (Beverly, 2017). The percent of held perimeter that intersects previously burned wildfire areas from the past 9 years is calculated as another possible model input variable.

Table 3 provides a summary of all input variables that were considered in this study. Not all variables were included in the final model because many variables are highly collinear and others did not exhibit enough variability to be useful during the econometric analysis. The final model includes 34 wildfires from 2013 through 2019 in Alberta's boreal zone. There are 167 observations across 34 wildfires.

Table 3. Summary statistics of available input variables.

Variable	Var. Name	Mean	St. Dev.	Median	Min	Max
Held Perimeter (m)	*held*	16883.5	26798.71	7477.25	0	212571
Inverse Distance^2 Held Perim. (m)	*id2_held*	26871.21	81869.7	9251.23	0	891560.1
Fire Age (days)	*age*	7.72	6.85	6	1	31
Gap (days)	*gap*	2.62	2.94	2	1	24
Airtanker	*air*	3.45	5.25	0	0	29
Ground Equipment	*equip*	24.96	49.23	0	0	262
Helicopter	*heli*	11.23	13.92	7	0	95
Crew Member	*crew*	98.81	165.69	38	0	1283
% C2 (Boreal Spruce) Fuel	*c2 %*	37.61	19.67	35.38	8.93	100
% Coniferous Fuel	*conif %*	57.87	18.5	58.72	15.86	100
% Held Large Waterbodies	*water %*	8.31	8.15	6.65	0	52.62
% Held Road	*road %*	0.35	1.15	0	0	10.34
% Past Fires	*past %*	3.06	6.56	0	0	36.05
Build-up Index	*bui*	74.8	28.21	75.37	13.5	162.3
Drought Code	*dc*	406.61	106.23	415.8	168.8	644.5
Daily Severity Rating	*dsr*	6.38	6.77	4.41	0	45.33
Fine Fuel Moisture Code	*ffmc*	83.42	10.55	87.2	36.1	96.8
Fire Weather Index	*fwi*	18.37	12.4	16.51	0	59.85
Initial Spread Index	*isi*	6.35	4.97	5.1	0	35.95
Max Temperature (°C)	*tempmax*	23.16	4.91	23.29	10.4	32.8
Max Wind Speed (km h^{-1})	*windmax*	8.22	4.04	7.9	0.1	20.35
Rain Total (mm)	*rain*	2.43	8.49	0	0	84.4
Relative Humidity Max (%)	*rhmax*	84.88	14.78	89	41.4	101.4
Relative Humidity Min (%)	*rhmin*	33.53	11.72	32.1	9	69.1
Year	*year*	2016.54	1.84	2016	2013	2019

5.2.7 Outlier Analysis

Outlier analysis was conducted using plots of fitted estimates versus estimated residuals as well as Cook's Distance and QQ plots. One fire was deemed to be an outlier due to it being the largest fire in the sample as well as the timing of this fire being concurrent with four other significant fires burning in Alberta in 2019. When there are enough concurrent wildfires threatening values at risk, the provincial strategic action planning group assesses the provincial situation and prioritizes which wildfires are most important. HWF-066-2019 was consistently ranked as lowest priority on May 28, 29, and 30th 2019. Given the fire was large and complex enough to potentially be excluded based on size criteria, as well as the known suppression resource supply constraint noted in the provincial strategic action planning group meeting documents, HWF-066-2019 was excluded from the final analysis. No other significant outliers were observed and all other selected fires were included in the final analysis.

5.3 Model Specification

5.3.1 Empirical Model

The stochastic frontier model presented in equation 14 is an extension of the true random effects (TRE) panel stochastic frontier model that incorporates explanatory variables into the inefficiency term (Greene 2005b; Battese and Coelli 1995). The random effects model is estimated using maximum likelihood as discussed in Chapter 4.

$$y_{it} = (\alpha + w_i) + \boldsymbol{\beta}' \mathrm{x}_{it} + v_{it} - u_{it}(z_{it}' \boldsymbol{\delta}) \tag{14}$$

$$i = 1, \dots, N, t = 1, \dots, T$$

$$u_{it} = z_{it}' \boldsymbol{\delta} \tag{15}$$

$$u_{it} \sim E(\mu, \sigma_{uit}^2)$$

$$\sigma_{uit}^2 = e^{z_{it}' \boldsymbol{\delta}}$$

$$v_{it} \sim \mathcal{N}(0, \sigma_{vit}^2)$$

$$w_i \sim \mathcal{N}(0, \boldsymbol{\theta}^2)$$

z_{it} is a (1 x m) vector of explanatory variables associated with technical inefficiency of production such as weather and fuels for *i* number of fires across *t* time periods. $\boldsymbol{\delta}$ is the corresponding (m x 1) vector of unknown technical inefficiency coefficients to be estimated (Battese and Coelli 1995). w_i is a time invariant, random term meant to capture heterogeneity across fires (Greene, 2005b). Unobserved heterogeneity captures characteristics unique to each fire that cannot be observed but can still affect wildfire containment such as incident commander or crew experience. As discussed in Chapter 4, the model parameters are estimated using simulated maximum likelihood because $w_i, u_{it}, and\ v_{it}$ compose a 3-part error term which requires the simulated likelihood function estimation to be conditioned on w_i (Greene, 2005b). The dummy variable formulation suggested by Battese (1997) allows for logged input variables with zero values. The zero-value input is a challenge that has also been addressed by the inverse hyperbolic sine transformation in recent literature (Bellemare and Wichman, 2020). An inverse hyperbolic sine transformation approximates the natural logarithm, which is useful for right skewed data, while retaining zero-valued observations which makes model estimation possible without dropping any observations (Bellemare and Wichman, 2020). The model was estimated with the inverse hyperbolic sine transformation but the model would not converge across all specifications. The stochastic frontier model is specified as a Cobb-Douglas production function

$$\begin{gathered} ln(y_{it}) = \alpha + \beta_1 air\_d + \beta_2 heli\_d + \beta_3 equip\_d \\ +\beta_4 \ln(max(air, air\_d)) + \beta_5 \ln(max(heli, heli\_d)) + \beta_6 \ln(max(equip, equip\_d)) \\ +\beta_7 \ln(notheld) + \beta_8 \ln(gap) + v_{it} - u_{it} \end{gathered} \quad (16)$$

$$u_{it} = \delta_0 + \delta_1(water\ \%) + \delta_2(conif\ \%) + \delta_3(dc) + \delta_4(ffmc) + w_{it}, \quad (17)$$

where y_{it} is held perimeter. The inefficiency term's explanatory variables (z_{it}) are not included as production function inputs because incident commanders and fire crews have no control over these variables, but we hypothesize the variables will impact the level of inefficiency when producing held perimeter. The dummy variables (*air_d*, *heli_d*, and *equip_d*) are formulated so *air_d* = 1 when *air* = 0 as an example (Battese 1997). This dummy variable formulation allows for the estimation of the logarithmic Cobb-Douglas production function while allowing observations of zero resource inputs. Cobb-Douglas was chosen as the most parsimonious production function that is globally convex but has some limitations including constant returns to scale. Other specifications such as Box-Cox translog models and quadratic functional forms are regularly used (Greene, 2008).

All model variables are standardized by their geometric mean except the percent variables. The resource inputs *air, heli,* and *equip* are the cumulative sum of all respective resources used on the fire since the previous progression perimeter observation. *not_held* is the length of fire perimeter from the previous observation that was not contained and is therefore available to be held on the current day. *gap* is the length of time between each wildfire's observed progression perimeter.

water % and *conif %* are the percent length of fire perimeter that overlaps with large water bodies and coniferous fuel stands. We expect efficiency increases with *water %* as the perimeter is being contained by natural features and decreases with conif % as it is more challenging to contain wildfire in coniferous stands compared to deciduous or grass vegetation.

dc is drought code, a fuel moisture code for the deep organic duff layer, representing seasonal drought and long-term (52 day) resistance to extinguishment. *dc* is calculated using the previous day's *dc,* noon temperature, rainfall, and current month to account for daylength (Van Wagner and Pickett, 1985). A possible limitation of the drought code variable is *dc* tends to increase as the summer wildfire season progresses. A drought code anomaly variable should be considered in future analyses because it differentiates rare drought events from the regular seasonal variation in drought code (Field et al., 2004). *ffmc* is a measure of litter layer fuel moisture and is a short term (18 h) measure of the ease of ignition and flammability of fine fuels. *ffmc* is calculated using yesterday's *ffmc,* precipitation, relative humidity, and noon air temperature (Van Wagner and Pickett, 1985). *dc* and *ffmc* are proxies for fuel moisture using local weather conditions interpreted as long- and short-term weather conditions that will influence fire behaviour.

These codes were chosen because they increase linearly and are rarely censored at the top or bottom of their distributions. As the fuel moisture codes increase, we expect inefficiency to increase. Raw weather variables such as wind speed and direction are important predictors of wildfire growth however wind speed is highly variable within days making it difficult to include wind in a contemporaneous model that predicts the efficiency daily wildfire containment (Linn et al., 2007). Fire weather and fuel moisture indices are what incident commanders refer to when making management decisions which suggests including codes is an appropriate representation of what motivates incident commander decisions (Alberta Wildfire, 2019b).

5.3.2 Estimation Procedure

An iterative estimation procedure first estimates ordinary least squares (OLS) regression models to identify any model specification issues such as multicollinearity before moving to stochastic frontier models. Next, cross sectional stochastic frontier models are estimated that treat all observations as independent and ignore the repeated observations within individual fires. Finally, the true random effects panel SFA is estimated which allows for time variant inefficiency and unobserved heterogeneity across fires.

5.4 Results

5.4.1 Ordinary Least Squares Regression

Table 4 presents the results of OLS regressions including estimates of variance inflation factors (VIF) that measure the impact of collinear input variables. VIFs below 5 are acceptable and those above 5 should be investigated because high multicollinearity artificially inflates variance and makes it difficult to interpret individual coefficients but does not bias the estimates. The VIF for the crew input variable indicated high collinearity with other resources (Table 9, Appendix A). Large wildfires that escape initial attack are likely to be too intense for crews to be effective working direct attack on the fire perimeter (Table 1). For high intensity fires, crews are more likely to be working on the flanks supporting aerial and ground equipment (Alberta Wildfire, 2020b). This strategic management technique is a possible explanation of the high collinearity between crews and other inputs so crews are removed as a model input.

Table 4. Ordinary least squares regression results with variance inflation factors (VIF) and standard errors clustered by fire.

	Model 1 - No VAR Coefficient (se)	**Model 2 - VAR** Coefficient (se)	VIF	**Model 3 - No VAR** Coefficient (se)	**Model 4 -VAR** Coefficient (se)	VIF
constant	-1.104	-1.655		2.650	1.925	
	(0.92)	(1.10)		(2.03)	(2.03)	
air_d	1.544*	2.332**	3.41	0.867	1.384	3.53
	(0.82)	(1.03)		(0.84)	(0.97)	
heli_d	-2.600**	-2.674**	1.81	-2.698**	-2.644**	2.04
	(1.01)	(1.01)		(1.04)	(1.00)	
equip_d	0.00872	0.129	4.00	-0.781	-0.816	6.17
	(0.55)	(0.57)		(1.04)	(1.03)	
lnair	0.325	0.448	3.29	0.254	0.292	3.50
	(0.35)	(0.40)		(0.38)	(0.37)	
lnheli	0.273	0.386	2.73	-0.251	-0.160	3.75
	(0.32)	(0.32)		(0.59)	(0.57)	
lnequip	-0.0407	0.0859	4.51	-0.168	-0.121	4.99
	(0.19)	(0.20)		(0.22)	(0.21)	
lnnotheld				0.0322	0.0261	1.51
				(0.05)	(0.05)	
lngap				1.202*	1.183*	1.68
				(0.63)	(0.62)	
water (%)				3.196	2.414	1.20
				(2.34)	(2.31)	
conif (%)				-2.682**	-3.232**	1.32
				(1.31)	(1.32)	
dc				-1.592**	-1.563*	1.54
				(0.77)	(0.79)	
ffmc				0.558	1.506	1.22
				(1.92)	(1.90)	
log lik.	-427.5	-436.7		-417.1	-420.5	
p	0.0307	0.00224		0.0000175	0.0000349	

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, N = 167.

The VIFs from OLS models 1 and 2 with resource inputs and their dummy variables are all below 5 so we move forward confident multicollinearity is not a significant concern. Models 3 and 4 include the stochastic fire growth variables that are not considered as production function inputs but still influence wildfire growth. The equipment dummy's VIF is above 5 in models 3 and 4 but the benefit of added information from including the equipment dummy variable outweighs the impact of including slightly collinear variables.

The expected sign on the dummy variables is negative assuming no resources on the fire decreases length of held perimeter. The airtanker dummy is positive and significant in Model 1 and 2 without VAR which is counterintuitive and will be investigated further in the stochastic frontier models. The dummy variable coefficients in Models 2 and 4 flip from helicopter to being positive to airtanker being positive and significant. The changing signs on the dummy variables may be indicative of collinearity obfuscating the effects of the three resource inputs.

The expected sign on the total resource coefficients is positive assuming more suppression resources on a wildfire contributes positively to held perimeter. The estimated coefficients are all positive except for total equipment in the non-VAR models (1 and 3) and total helicopters in the full models (3 and 4). The negative signs on total equipment and helicopter are counterintuitive but insignificant. The stochastic variables in Models 3 and 4 all have the expected coefficients but show little statistical significance. Other variables that were not included in the final model include a season dummy which was intended to capture Alberta's spring fire season when dry conditions regularly lead to escaped wildfires. Percent of perimeter held on roads and percent of overlap with historic burn scars were also considered but had insufficient variability to establish any relationship with held perimeter.

5.4.2 Stochastic Frontier Analysis

The stochastic frontier models expand on the OLS models by allowing for a two-part error term that consists of stochastic noise and technical inefficiency. After refining model input variables in the OLS models, a cross-sectional SFA was estimated that treats all observations as independent. Finally, we estimate the true random effects model accounting for unobserved heterogeneity across fires and defined heteroskedasticity in the time-variant technical inefficiency term.

5.4.2.1 *Cross Section SFA*

Table 5. Cross section stochastic frontier model results with exponential error distribution and standard errors clustered by fire.

	Model 5 No VAR	**Model 6 VAR**		**Model 7 No VAR**	**Model 8 VAR**
	Coefficient (se)	**Coefficient (se)**		**Coefficient (se)**	**Coefficient (se)**
constant	2.730**	3.757**	constant	1.391***	3.354***
	(1.249)	(1.657)		(0.290)	(0.318)
air_d	0.0373	-0.0548	air_d	0.0663	-0.114
	(0.430)	(0.466)		(0.382)	(0.361)
heli_d	-1.541*	-1.084	heli_d	-1.202	-0.633
	(0.900)	(1.163)		(0.731)	(1.039)
equip_d	-0.389	-0.255	equip_d	-0.131	0.218
	(0.320)	(0.325)		(0.267)	(0.287)
lnair	-0.0472	-0.113	lnair	-0.0289	-0.118
	(0.160)	(0.182)		(0.147)	(0.171)
lnheli	-0.603**	-0.560*	lnheli	-0.494**	-0.372*
	(0.264)	(0.289)		(0.195)	(0.212)
lnequip	0.132*	0.280***	lnequip	0.142**	0.311***
	(0.0714)	(0.0834)		(0.0675)	(0.112)
lnnotheld	0.0751**	0.0940***	lnnotheld	0.0789***	0.104***
	(0.0334)	(0.0254)		(0.0290)	(0.0246)
lngap	1.026***	0.918***	lngap	0.883***	0.724***
	(0.339)	(0.347)		(0.242)	(0.232)
			Inefficiency		
water (%)	0.468	-1.324	water (%)	-2.498	-2.785
	(1.425)	(1.482)		(1.754)	(1.786)
conif (%)	-0.249	-0.778	conif (%)	2.103***	2.302**
	(0.923)	(1.038)		(0.733)	(0.902)
dc	0.189	0.449	dc	1.424***	1.490***
	(0.510)	(0.545)		(0.510)	(0.456)
ffmc	0.491	-0.0577	ffmc	-0.736	-1.600
	(0.869)	(1.079)		(1.514)	(1.353)
$ln\ \sigma_u^2$	2.018***	2.112***	$ln\ \sigma_u^2\_cons$	0.157	0.920
	(0.219)	(0.318)		(1.314)	(1.140)
$ln\ \sigma_v^2$	-1.097***	-1.076	$ln\ \sigma_v^2$	-1.035***	-0.834**
	(0.298)	(0.666)		(0.243)	(0.346)
log. lik.	-366.0	-372.8	log. lik.	-360.2	-367.3
chi^2	122.0	149.2	chi^2	56.73	54.18
p	2.42e-20	8.15e-26	p	2.03e-09	6.38e-09
σ_u	2.742***	2.875***	$E(\sigma_u)$	2.686	2.773
	(0.300)	(0.458)		CI: (2.57 – 2.81)	CI: (2.64 - 2.91)
σ_v	0.578***	0.584***	σ_v	0.596***	0.659***
	(0.086)	(0.195)		(0.072)	(0.114)
λ	4.747***	4.92***	E(λ)	4.507	4.208
	(0.315)	(0.594)			

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

N = 167, y_{it} = ln(held perimeter) in models 5 & 7, and y_{it} = ln(I.D.^{2} weighted held perimeter) in models 6 & 8

Table 5 presents results from cross-sectional stochastic frontier models estimated from 34 fires and 167 observations assuming an exponential error distribution and standard errors clustered by fire. Models with bootstrapped standard errors showed similar results but the clustered standard errors were chosen because the cross-sectional models do not account for the panel structure of the data. Clustering by fire adds information to the cross-sectional models that controls for not all observations being spatially independent because some observations are from the same fire on different days. Models 6 and 8 include VAR in the dependent variable by weighting held perimeter using the inverse distance squared weighting procedure based on the number of inhabited structures within 30 km of the active fire perimeter.

In models 5 and 6 all variables are included as inputs to the production function with no exogenous determinants of technical efficiency. The helicopter dummy variable coefficient is negative and significant which was expected indicating days with no helicopters on the fire have a decreased held perimeter. Total equipment's coefficient is significant and positively related to held perimeter which is expected assuming equipment effectively contains the fire perimeter. Total helicopter's coefficient is negative and significant which is unexpected because it implies the more helicopters assigned to a fire the less held perimeter that is generated. This will be explored further in the panel SFA models. The coefficient for perimeter not held since the previous observation is positively related to held perimeter. A positive relationship is expected because more perimeter not held on previous days means more is available to be held on the current day. The positive, significant coefficient on *gap* was expected because as the gap length between observation increases, there is more time for crews and natural features to contain the fire perimeter. $ln\ \sigma_u^2$ is significant indicating technical inefficiency is present and the use of SFA is preferred to OLS. Models 7 and 8 moves the set of stochastic variables to be explanatory variables for the amount and heteroskedasticity of technical inefficiency.

In general, moving the stochastic variables to the inefficiency term in models 7 and 8 results in a better qualitative model fit because of more significant coefficients. There are no significant dummy variables and the remaining production function inputs have the same coefficient and interpretation as the non-heteroskedastic inefficiency models 5 and 6. In the heteroskedastic models 7 and 8, the inefficiency coefficients are interpreted as affecting inefficiency where variables with positive coefficients would increase average technical inefficiency.

Percent of held perimeter that is coniferous fuels is positive and significant in models 7 and 8 meaning more coniferous fuels create inefficient fire containment. The drought code's coefficient is also significant and positive indicating as drought code increases, it is more difficult to contain the fire perimeter and the suppression resources are less efficient at containing fireline. Fine fuel moisture code is insignificant and does not affect efficiency which suggests drought code is a stronger predictor of weather conditions that control the efficiency of suppressing wildfires (Van Wagner, 1987). The cross-sectional pooled models do not account for time variant inefficiency or repeated observations from 34 sample fires.

5.4.2.2 Panel SFA

Panel stochastic frontier models are used because the dataset contains repeated observations of the same wildfire over time. The panel model specification can explicitly account for unobserved heterogeneity specific to each wildfire and allows technical efficiency to vary over time which is not possible in cross-sectional models. Table 6 presents results from panel stochastic frontier models estimated following Greene's (2005b) true random effects model specification (equation 14 and 15).

Table 6. Panel stochastic frontier model results with exponential error distributions and standard errors clustered by fire.

	Model 9 No VAR Coefficient (se)	**Model 10 VAR Coefficient (se)**		**Model 11 No VAR Coefficient (se)**	**Model 12 VAR Coefficient (se)**
constant	2.731**	3.758**	constant	3.129***	3.354***
	(1.247)	(1.657)		(0.245)	(0.318)
air_d	0.0372	-0.0548	air_d	0.0667	-0.114
	(0.430)	(0.466)		(0.382)	(0.361)
heli_d	-1.542*	-1.084	heli_d	-1.201	-0.633
	(0.899)	(1.163)		(0.735)	(1.039)
equip_d	-0.389	-0.255	equip_d	-0.130	0.218
	(0.321)	(0.325)		(0.266)	(0.287)
lnair	-0.0472	-0.112	lnair	-0.0279	-0.118
	(0.160)	(0.182)		(0.148)	(0.171)
lnheli	-0.603**	-0.560*	lnheli	-0.494**	-0.372*
	(0.264)	(0.289)		(0.195)	(0.212)
lnequip	0.132*	0.280***	lnequip	0.142**	0.311***
	(0.0714)	(0.0835)		(0.0666)	(0.112)
lnnotheld	0.0751**	0.0940***	lnnotheld	0.0792***	0.104***
	(0.0334)	(0.0254)		(0.0291)	(0.0246)
lngap	1.025***	0.919***	lngap	0.882***	0.724***
	(0.339)	(0.347)		(0.242)	(0.232)
			Inefficiency		
water (%)	0.467	-1.324	water (%)	-2.500	-2.785
	(1.425)	(1.482)		(1.748)	(1.787)
conif (%)	-0.250	-0.778	conif (%)	2.107***	2.302**
	(0.922)	(1.038)		(0.741)	(0.902)
dc	0.176	0.449	dc	1.534***	1.490***
	(0.473)	(0.545)		(0.553)	(0.456)
ffmc	0.485	-0.0580	ffmc	-0.748	-1.600
	(0.859)	(1.079)		(1.546)	(1.353)
$ln\ \sigma_u^2$	2.018***	2.112***	$ln\ \sigma_u^2\ \ cons$	0.157	0.920
	(0.219)	(0.318)		(1.314)	(1.140)
$ln\ \sigma_v^2$	-1.099***	-1.076	$ln\ \sigma_v^2$	-1.042***	-0.834**
	(0.299)	(0.666)		(0.245)	(0.346)
$ln\ \Theta^2$	0.0228	0.00392	$ln\ \Theta^2$	0.0490	-0.00000335
	(0.0341)	(0.0161)		(0.194)	(0.0268)
log.lik.	-366.0	-372.7	log.lik.	-360.2	-367.3
chi^2	121.4	149.2	chi^2	56.87	54.17
p	3.27e-20	8.18e-26	p	1.91e-09	6.40e-09
σ_u	2.743***	2.875***	$E(\sigma_u)$	2.687	2.773
	(0.300)	(0.458)		CI[A] (2.57-2.81)	CI (2.64-2.91)
σ_v	0.577***	0.584***	σ_v	0.594***	0.659***
	(0.086)	(0.194)		(0.073)	(0.114)
λ	4.751***	4.924***	$E(\lambda)$	4.523	4.208
	(0.315)	(0.594)			
AIC	763.9	777.5		752.4	766.5
BIC	813.8	827.4		802.3	816.4

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$,

[A] CI is 95% Confidence Interval. In the heteroskedastic model σ_u is $E(\sigma_u) = E(z_{it} \times \delta_{it}) = e^{0.5 z_{it} \delta_{it}}$

i = 34, N = 167, y_{it} = ln(held perimeter) in models 9 & 11, and ln(I.D.^{2} weighted held perimeter) in models 10 & 12

The model specification in Table 6 assumes an exponential error distribution, unobserved heterogeneity across fires, and time-variant inefficiency. A large number of draws is required to reasonably estimate the true likelihood function so the estimation uses 100 Halton draws, roughly equivalent to several hundred draws, as suggested by Greene (2005). In the heteroskedastic inefficiency models 11 and 12, the standard deviation of u_{it} is measured at the mean $E(\sigma_u)$.There is no p-value but a confidence interval (CI) is presented. Θ represents the standard deviation of the unobserved heterogeneity (w_i) and λ is the signal to noise ratio calculated as σ_u/σ_v. The estimated coefficients from the panel SFA in Table 6 are very similar to the cross-sectional coefficients in Table 5. This is likely because the Θ parameter representing the standard deviation of unobserved heterogeneity is insignificant in the panel model. However, the panel specification is still preferred over the cross-sectional specification because there are repeated observations of the same wildfires. Clustering the standard errors by wildfire captures some expected heteroskedasticity but the panel structure explicitly accounts for the presence of repeated observations.

Models 9 and 10 have no defined inefficiency variables and assume all variables are inputs to the production function. The dummy variable coefficients are mainly insignificant except *heli_d* which is negative and significant in model 9. A negative coefficient is expected because it suggests when no helicopter resources are present on the wildfire, less held perimeter is generated. In these models, the inefficiency coefficient, $ln\ \sigma_u^2$, is significant indicating inefficiency is present and SFA is the preferred estimation technique over OLS. The heterogeneity coefficient, $ln\Theta^2$, is insignificant suggesting the variance of unobserved heterogeneity is equal to zero. Models 11 and 12 have moved the stochastic variables to the inefficiency term. Based on the log likelihood values and information criteria (AIC and BIC), moving the variables to the inefficiency term create better performing models. There are generally more significant coefficients in the heteroskedastic inefficiency models 3 and 4 which qualitatively suggests better model fit. Given the information gained from the cross-section models (Table 5) and models 9 and 10, TRE models 11 and12 are the preferred specification in this study and the following discussion will focus on models 11 and 12.

Ground equipment's coefficient (*lnequip*) is positive and significant indicating ground resources positively contribute to held perimeter. Ground equipment such as feller bunchers, bulldozers, and graders work to produce contained fireline by removing fuels then digging to mineral soil meaning their objective directly aligns with the assumed output variable of the model. The total airtanker coefficient (*lnair*) is insignificant and has no measurable effect on held perimeter. The total helicopter coefficient (*lnheli*) is negative and significant. These results are important because they suggest aerial suppression resources are ineffective at containing large wildfires in Alberta's boreal zone meaning they do not contribute to an increase in held perimeter, on average. It is possible that airtankers and helicopters are engaged in activities other than fireline containment such as transport and reconnaissance or the resources are working to build containment line that will engage the perimeter on future days which means a held perimeter on the current day is not part of their daily objectives. It may also be true that aerial resources are "ineffective" because they are being used in scenarios that exceed fireline intensity thresholds of effectiveness (Cole and Alexander, 1995; Wotton et al., 2017). Fireline intensity thresholds dictate that ground resources begin to be ineffective at 2 MWm^{-1} and aerial resources are ineffective beyond 4 MWm^{-1} when water drops may evaporate before reaching the ground and the fire can spot across chemical retardant barriers (Hirsch and Martell, 1996; Wotton et al., 2017). Without more immediate information on the activities of the aerial resources and head fire intensities we cannot yet determine the absolute cause of ineffective aerial suppression resources. Perimeter not held on previous days (*lnnotheld*) and the length of the gap between observed perimeters (*lngap*) coefficients are positive and significant as expected because more perimeter available to be held and a more time to work toward containment is expected to increase held perimeter output.

In models 11 and 12, stochastic variables become the exogenous determinants of technical inefficiency. Technical inefficiency is the deviation from the observed held perimeter output compared to the maximum possible output estimated by the efficient frontier (Katuwal et al., 2016). The percent coniferous fuels coefficient is positive and significant when explaining technical inefficiency. This indicates as more of the perimeter is coniferous fuels, technical inefficiency increases. This was hypothesized because wildfires in coniferous fuel stands are usually more difficult for resources to contain as dense ground fuels are difficult for crews to navigate and coniferous trees create ladder fuels that become can more easily transition to high intensity crown fires (Beverly et al., 2020). Drought code's coefficient is also positive and significant meaning as drought code increases, inefficiency increases which is expected because higher drought codes indicate dryer fuel conditions caused by high temperature and little precipitation. Percent held on waterbodies and fine fuel moisture code are insignificant and have no effect on technical inefficiency.

It is difficult to determine if weighting the dependent variable using VAR improves model fitness or explanatory power because traditional model fitness statistics such as Akaike information criteria and the coefficient of determination (R^2) rely on models having the same dependent variable. Model 12 has a lower signal to noise ratio compared to model 11 which suggests a qualitative improvement to model fitness. We can test the hypothesis that including VAR increases the technical efficiency of suppression by calculating technical efficiency using estimated parameters.[4]

5.5 Technical Efficiency

Table 7 presents the estimates for technical efficiency (TE) using the procedure proposed by Jondrow et al. (1982) that estimates technical efficiency at the mean of inefficiency where

$$TE = e^{-E(u|e)}. \tag{18}$$

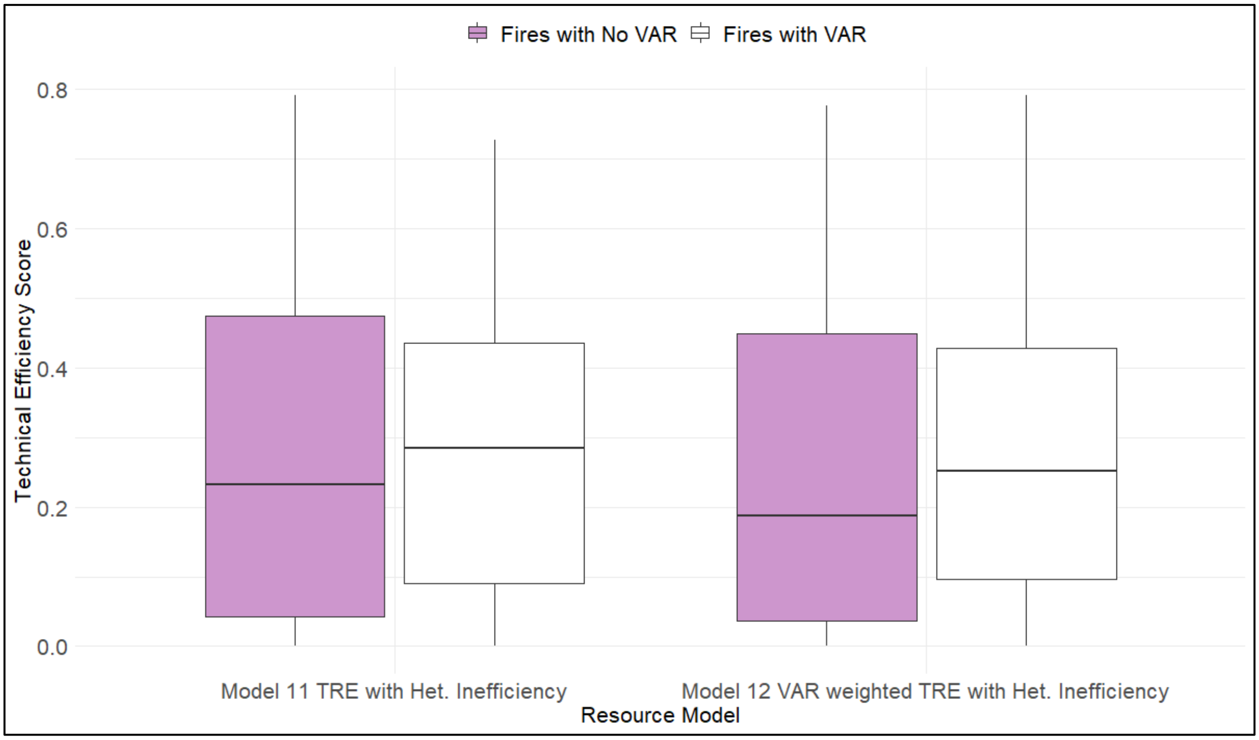
Table 7. Technical efficiency estimates for resource input stochastic frontier analysis models*

Model	Mean TE	Median TE	Lower 95% CI	Upper 95% CI	Min	Max
Cross Section SFA (5)	0.2612	0.2190	0.1022	0.5550	0	0.7926
Cross Section SFA with VAR (6)	0.2486	0.1791	0.0965	0.5313	0	0.7874
Cross Section SFA with Het. (7)	0.2730	0.2478	0.1052	0.5767	0	0.7917
Cross Section SFA with Het. & VAR (8)	0.2648	0.2247	0.0937	0.5899	0	0.7915
TRE SFA (9)	0.2612	0.2192	0.1023	0.5547	0	0.7926
TRE SFA with VAR (10)	0.2486	0.1790	0.0965	0.5313	0	0.7874
TRE SFA with Het. (11)	0.2730	0.2475	0.1055	0.5757	0	0.7917
TRE SFA with Het. & Var (12)	0.2648	0.2247	0.0937	0.5899	0	0.7915

** SFA = stochastic frontier analysis, VAR = values at risk weighted output variable, Het. = heteroskedastic inefficiency, TRE = "true random effects" panel SFA model specification, CI = confidence interval.*

[4] Models using expenditures on suppression resources as the input variables were also examined because the literature suggests that such models may be able to address input quality differences. However, the results from the expenditure models did not differ greatly from the resource models presented in Table 6. The coefficients on the inefficiency variables were significant and consistent with Table 6 which suggests robust model specification. The full expenditure model specification, results, and analysis can be found in Appendix B.

In general, average technical efficiency ranges from 24-27% and median TE ranges from 18-25% across all model specifications (Table 7). SFA analysis of wildfire suppression across the western United States estimated average efficiency ranging from 47-68% from their sample data (Katuwal et al., 2016). It is difficult to compare TE estimates across models or across studies because TE is a relative measure based on the frontier estimated for each model specification but the difference between our estimates of TE in Alberta's boreal compared to the western United States is large enough to garner further discussion. Our average TE estimates are lower than the previous study which potentially reflects the different fuels and wildfire regime in Alberta's boreal zone. From our study's sample fires, 58% occurred in coniferous fuel stands with 38% of those being in highly flammable C-2 Boreal Spruce. This suggests the fuel types in this study are more conducive to generating high intensity wildfires that are difficult to efficiently contain compared to the American study that had 68% "timber" fuels, not differentiating between coniferous or deciduous, with the remaining being shrub, grassland, or non-vegetative fuels (Katuwal et al., 2016). Average technical efficiency between 24-27% is lower than previous research but with no other study of this type done in Alberta's boreal zone, we speculate the coniferous fuels and long return period of wildfire generate wildfires that are difficult to suppress which creates the lower average technical efficiency compared to the western United States (Stocks et al., 2001). Next, we explore how inhabited structures as values at risk may have impacted efficiency estimates.



Model 11 = true random effect panel stochastic frontier model, y = held perimeter with defined inefficiency variables
Model 12 = panel stochastic frontier model, y = inverse distance squared weighted held perimeter using inhabited structures as values at risk, with defined inefficiency variables

Figure 13. Boxplots of technical efficiency scores for resource input true random effects models.

Our first hypothesis is technical efficiency will be higher for wildfires with nearby values at risk. In the sample dataset, 10 fires had inhabited structures within 30 km of the wildfire, while the remaining 24 fires had no inhabited structures at risk. In Figure 13, the comparison between the white boxplots representing fires with VAR and the pink boxplots meaning wildfires with no VAR allows us to visualize if TE is significantly different for the 10 fires with VAR. Across both model specifications, the median TE is higher for fires with VAR. The overlapping interquartile range suggest this difference is not statistically significant but the results being robust across both models suggests future research should investigate this trend.

Our second hypothesis is estimated technical efficiency will be higher in models that weight the held perimeter output to include VAR, the number and distance of houses within 30 km of the fire's perimeter. In Table 7, average and median TE is lower in models that use the VAR weighted held perimeter compared to their non-weighted counterpart model which does not align with our hypothesis. In Figure 13, this hypothesis can be analyzed with caution by comparing boxes of matching colours in model 11 and model 12 because the models have different dependent variables and the estimates of TE are relative to each model's unique frontier. Median efficiency is slightly lower in model 12 with the VAR weighted dependent variables which does not align with our hypothesis. The overlapping interquartile range suggest there is no significant difference in technical efficiency after weighting the dependent variable using values at risk. This is unexpected because we hypothesized the weighted held perimeter would reflect how incident commanders may prioritize the containment of perimeter sections nearest VAR as outlined in Alberta Wildfire's training documents (Alberta Wildfire, 2020a). Further analyses of technical efficiency by wildfire size and observing TE over time may explain why the weighting procedure did not noticeably impact median TE.

5.5.1 Wildfire Size Technical Efficiency

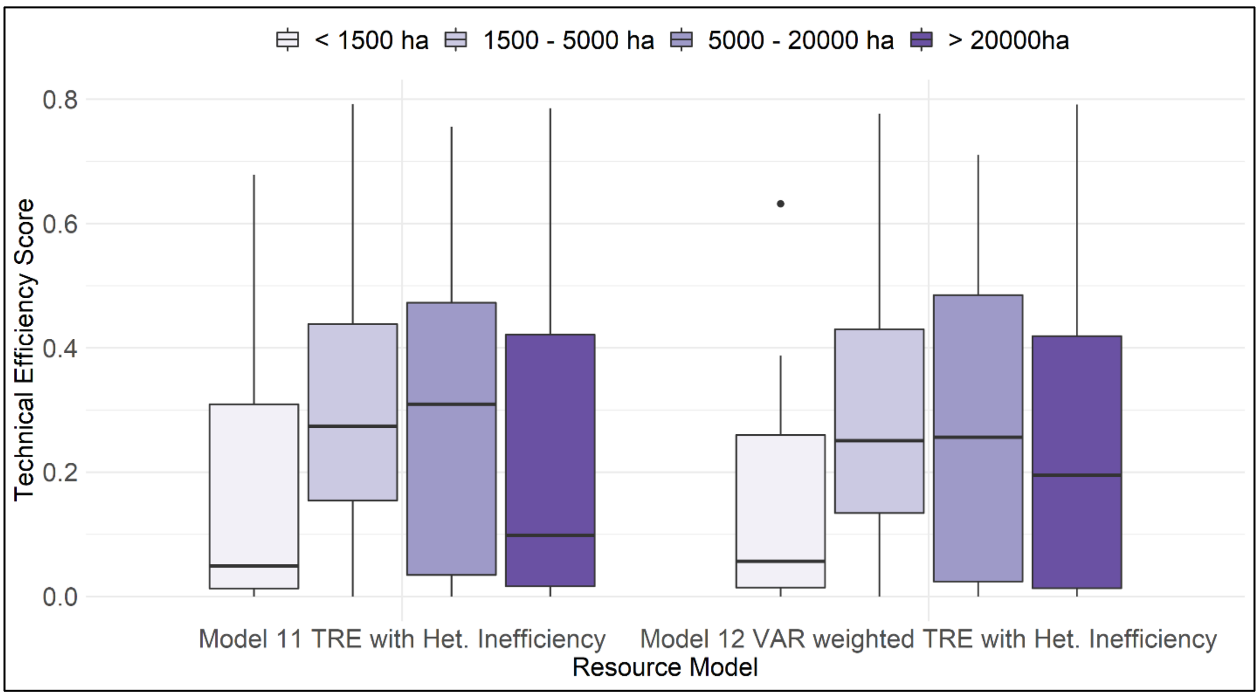


Figure 14. Technical efficiency of sample wildfires separated into four different size categories based on final size at extinguishment.

Figure 14 presents the technical efficiency of the sample wildfires separated into four different size categories. The number of observations in each bin is distributed evenly. In model 11 with no values at risk considered, the smallest and largest wildfires categories have the lowest technical efficiency. For the small wildfires, this may be due to having a small wildfire perimeter meaning there is less available to be held. The model's output variable is length of held perimeter and one suppression resource input may be sufficient to effectively contain the small wildfire but it does not generate much held perimeter because the perimeter is already short. For the large wildfires, the low efficiency may be due to the increased difficulty in containing larger wildfires because of their intensity that challenges the effectiveness of suppression resources (Cole and Alexander, 1995; Wotton et al., 2017).

In model 12, after weighting for values at risk, the median technical efficiency for the largest wildfire category is higher. This suggests there were considerable values at risk in the largest wildfire category and recalculating the output variable to include VAR increased the median efficiency of the largest wildfires.

5.5.2 Technical Efficiency Over Time

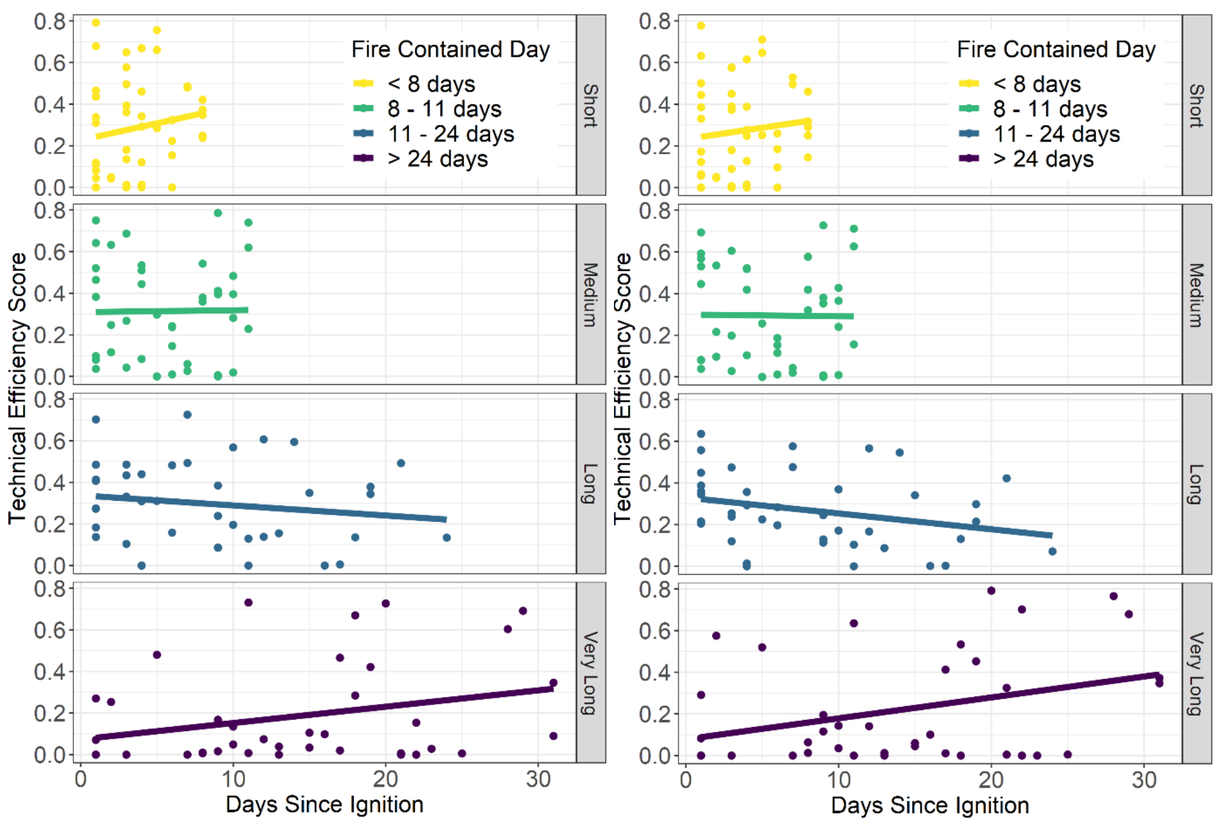


Figure 15. Technical efficiency of sample wildfires throughout sustained action separated into four different length categories. Model 11 on the left, y = held perimeter, Model 12 on the right, y = inverse distance squared held perimeter.

To explore how technical efficiency changes throughout sustained action, TE estimates were plotted over time and the sample fires were separated into four different categories based on age (in days) at containment. The number of observations in each bin is evenly distributed. In Figure 15, the shortest wildfires that were contained in 7 days or fewer had increasing technical efficiency on average. Medium length wildfires had flat efficiency over time suggesting no change in technical efficiency of containment at the beginning of the fire compared to the end. Long wildfires had a negative trend in efficiency suggesting the suppression resources present on the fires during later stages were contributing little to held perimeter. However, the longest category with wildfires burning the more than 24 days had the opposite trend showing increasing efficiency over time. This suggests the longest burning wildfires were difficult to contain during early stages of sustained action when efficiency was challenged and containment efficiency increased near the end of suppression activities. There is no discernible difference between model 11 with no values at risk and model 12 that considers values at risk when observing TE over time in Figure 15. This time trend analysis reveals that technical efficiency of containment does not always increase as sustained action goes on. There is no clear trend to suggest efficiency could be increased by reallocating resources to earlier or later stages of sustained action.

5.5.3 Technical Efficiency of Select Fires Over Time

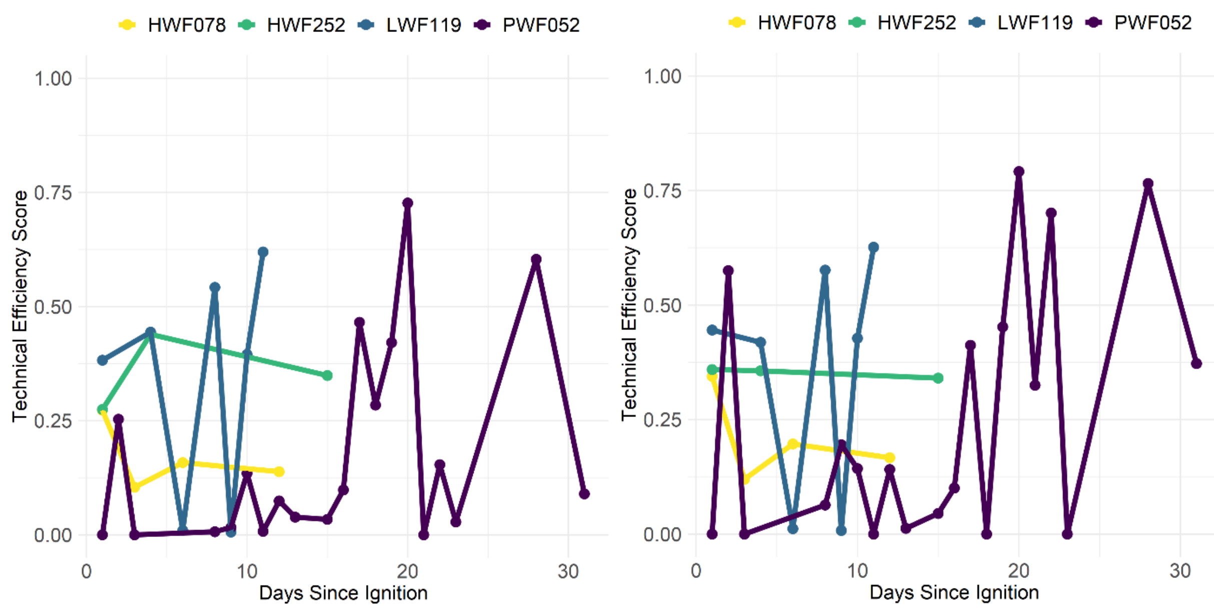


Figure 16. Technical efficiency over time of four select wildfires from sample throughout sustained action. The left graph presents the estimates from model 11 where output is held perimeter. The right graph presents the estimates from model 12 where output is values at risk weighted held perimeter.

Figure 16 presents the technical efficiency estimates from four wildfires in the sample dataset to demonstrate the day-to-day variability in technical efficiency. Figure 16 highlights the large variability technical efficiency over time which was observed for most wildfires in the dataset. HWF078 and HWF252 had no values at risk present while LWF119 and PWF052 did have values at risk. Comparing the left to right graph, there is a noticeable increase in the technical efficiency for PWF052 (purple) when it is non-zero. The remaining three wildfires are less noticeably impacted by the weighting procedure. Another analysis of technical efficiency compared early season to late season wildfires and is shown in Appendix A Figure 17. The seasonal analysis shows significant temporal clustering where the majority of wildfires start at the same time during the season. An analysis of the ignition source of the wildfires indicates 32 of the 34 sample fires were lightning caused while just 2 were human-caused. The temporal clustering of wildfire starts likely coincides with significant lightning events occurred in the province and may explain why there are no significant differences in TE of early season compared to late season wildfires.

5.6 Chapter 5 Summary

This chapter presents the results of stochastic frontier models that estimate the efficacy of containment resources and the technical efficiency of large wildfire containment in Alberta's boreal zone from 2013-2019. The results indicate ground equipment is effective at containing held perimeter and positively contributes to held perimeter on large wildfires in Alberta's boreal zone. However, results suggest that helicopters and airtankers are ineffective at containing the sampled wildfires. Some limitations of our analysis prevent us from saying definitively if this result is because aerial suppression equipment is being used when wildfire intensity is too high for the resource to be effective. It is also possible the aerial resources are being used for management tasks besides fireline containment or resources are working on containment line that will hold the perimeter on future days. The estimation procedure and conclusions may be limited by the sample size constraining the generalizability of the results or potential endogeneity impeding our ability to determine causality.

Average technical efficiency of containment is 26.89% and model results support specifications with exogenous variables that determine technical inefficiency. Wildfires occurring in more coniferous fuels and high drought codes (high temperatures and little precipitation) have a lower technical efficiency of wildfire containment. These results are robust in many different model specifications. From 34 sample fires, 10 fires had nearby values at risk and these 10 wildfires had slightly higher median containment efficiencies. However, applying a weighting procedure to include values at risk in the output variable had no noticeable impact on model and efficiency estimates. The smallest and largest wildfires were the least efficient at generating held perimeter however, including values at risk noticeably increased median efficiency of the largest sample wildfires. Technical efficiency of containment did not increase over time for wildfires of all ages and there is no consistent trend on technical efficiency over time. The final discussion and conclusion chapter will discuss the implications of these results.

Chapter 6: Discussion

Improving the efficiency of large wildfire containment is of growing importance to wildfire management agencies who are interested in achieving historic containment levels while faced with increasing budget constraints and anthropogenic climate change which is expected to create more frequent and severe wildfires (Coogan et al., 2019). This study used stochastic frontier analysis to estimate the technical efficiency of large wildfire suppression in Alberta's boreal zone. Stochastic frontier models were estimated with suppression resources as input variables. Variables that were expected to affect efficiency, such as weather, fuel, and large water bodies, were included to explain the amount and variability of technical efficiency of containment. The analysis objectives were to assess the efficacy of suppression resources, the efficiency of wildfire containment, and the impact of values at risk on the containment efficiency of wildfires greater than 190 ha in Alberta's boreal zone.

6.1 Efficacy of Suppression Resources

The first objective of this study was to determine the efficacy of large wildfire suppression resources. We define effective suppression as any actions that contribute to a contained wildfire perimeter meaning effective resources will positively contribute to held perimeter on average. Our results suggest ground equipment such as bulldozers, graders, fire engines, and feller bunchers are the most effective suppression resource when containing boreal wildfires in Alberta. Our results also indicate airtankers, medium helicopters, and large helicopters do not appear to significantly contribute to held perimeter. These results are similar to those from Katuwal, Calkin, and Hand (2016) who found bulldozers and fire engines contributed to held perimeter while helicopters and airtankers had no relationship with held perimeter.

The apparent lower efficacy of helicopters and airtankers could be caused by a number of factors. It is possible the aerial equipment is not working on fireline containment making held perimeter irrelevant to their daily objectives (Katuwal et al., 2016). It is also possible the aerial resources are being used when head fire intensities are too high for the resources to be effective (Cole and Alexander, 1995; Hirsch and Martell, 1996; Wotton et al., 2017). Information on wildfire intensity and the daily objectives of aerial resources would improve our model's explanatory power and help provide recommendations on when to use suppression resources to maximize wildfire containment.

6.2 Efficiency of Wildfire Containment

The second objective of this study was to quantify the average efficiency of large wildfire suppression in Alberta's boreal zone and identify which variables affect inefficiency. Average technical efficiency for all eight models was 26.89% and median was 23.61% under the true random effects specifications with unobserved heterogeneity across fires. These are lower efficiency estimates compared to past research of large wildfires across the western United States that found 47-68% average technical efficiency (Katuwal et al., 2016). Technical efficiency is a relative measure so it is difficult to compare across models or studies but the difference in average efficiency may be due to the different wildfire regime of Alberta's boreal zone compared to the western United States. Only a few regions in the western U.S. have closed-canopy coniferous fuels and weather conditions capable of generating high-"severity" crown fires similar to those observed in Alberta's boreal zone (Sommers et al., 2011). It is possible that inherent differences in fuels and wildfire intensity produce higher containment efficiencies in the western United States compared to northern Alberta.

The other possible explanation of efficiency differences between models is the previous American study did not account for unobserved heterogeneity across fires and simulation studies have shown significantly different efficiency estimates after including unobserved heterogeneity (Belotti et al., 2013). We believe the random effects specification is preferable because the random effects model controls for potential differences in incident commander experience, crew experience, incident commander risk aversion, political pressure, or newspaper coverage which may effect management decisions (Donovan et al., 2011; Hesseln et al., 2010; Wilson et al., 2011).

Our results found the environmental variables that significantly affected technical efficiency were percent coniferous fuels, and drought code. It was expected drought code would decrease technical efficiency of suppression because long-term drought conditions create dry fuels where fire can spread rapidly at high intensities that are difficult to contain (Van Wagner, 1983). Percent coniferous fuels also decreases efficiency as coniferous stands tend to have denser ground fuels and low canopy base heights which act as ladder fuels that facilitate the transfer of surface fires upward to high intensity crown fires that are difficult to contain (Omi and Martinson, 2010).

When analyzing wildfires over time, our results also indicated no clear trend in efficiency over time. Wildfires that burned for the shortest and longest amount of time had increasing efficiency over time, but mid-length wildfires had negative or unchanged efficiency over time meaning there are no implications that efficiency could improved by reallocating resources to earlier or later in sustained action. When analyzing wildfires by size, our results suggest smallest and largest wildfires were the least efficiently contained but including values at risk noticeably increased the efficiency of the largest wildfires; a finding that is discussed in the next section.

6.3 Values at Risk and Containment Efficiency

The third objective was to understand if values at risk during wildfire containment significantly affect the estimated technical efficiency of suppression. Inhabited structures within 30 km of the wildfire perimeter served as a proxy for the human life and community values whose protection is prioritized by Alberta Wildfire. Qualitative analysis indicated the 10 sample fires with values at risk within 30 km of their perimeter had higher median technical efficiency than fires with no VAR across all models. This suggests there is some prioritization of containing wildfires with nearby inhabited structures as opposed to those without.

To further understand the influence of VAR on wildfire containment efficiency, we explored if sections of wildfire perimeters nearest values at risk are more important during containment. Held perimeter, the dependent variable, was weighted using an inverse distance squared weighting procedure based on inhabited structures within 30 km of the wildfire perimeters. The weighted dependent variable acknowledges wildfire management in Alberta does not view all held perimeter as equivalent and prioritizes protecting values at risk (Alberta Wildfire, 2020a). After weighting the dependent variable to include VAR, the results suggest no discernible difference in estimated technical efficiency compared to the unweighted models even though wildfires with nearby VAR were seemingly more technically efficient. The only observed effect in the weighting procedure was on wildfires in the largest category (> 20,000 ha) that had noticeably higher median efficiency after weighting for VAR. This suggests when wildfires are large enough and near values at risk, sections of the large wildfires nearest VAR were given priority containment.

After wildfires in Alberta escape initial attack, the wildfire management branch chooses an "appropriate response" based on values at risk, availability of suppression resources, and the provincial fire load (Tymstra et al., 2020). Alberta's boreal zone has a low population density and only 10 of the 34 sample fires had inhabited structures within 30 km. The output variable was unchanged for 24 wildfires after the weighting procedure which may explain why there was almost no observed effect on average technical efficiency except on the largest wildfires. The unchanged average technical efficiency after including values at risk may also suggest containing perimeter sections nearest VAR is not always achieved. Future research should seek to increase sample size to include more wildfires with nearby VAR and include information on what section of the perimeter suppression resources are working on containing each day to understand where effort is focused and not assume effort is distributed across the entire perimeter simultaneously.

Alberta's 2019 provincial wildfire review indicated a management bias towards direct attack and full suppression when indirect attack and modified suppression are sometimes more appropriate (MNP LLP, 2020). This observation is another possible explanation why including VAR had little noticeable effect on average efficiency because the majority of Alberta wildfires undergoing sustained action will receive full suppression tactics. Budget constraints and climate change impacts on wildfire seasons in Alberta will likely necessitate a further transition to a wildfire risk management approach wherein not all wildfires receive full suppression. Wildfire risk management incorporates residential structures and the wildland-urban interface (WUI) into management decision making tools (MNP LLP, 2020; Tymstra et al., 2020). Spatial data on inhabited structures can identify regions where fire mitigation and protection should be prioritized to maximize the benefits of wildfire management (Thompson et al. 2011). We believe our weighting procedure using inhabited structures to construct a weighted output variable is an important contribution of this research because this technique has not been used before, to the best of our knowledge, and is a novel method to include protection of VAR as part of the output of wildfire management effort.

6.4 Limitations and Future Research

The limitations of this analysis are outlined to acknowledge some shortcomings of the current study and provide recommendations for future analyses. The first limitation is we cannot claim causality because there is the possibility of endogeneity in the estimates. A stochastic cost frontier analysis could control for endogeneity by assuming the input prices as exogenous and should be explored in future analyses. The Cobb-Douglas functional form of the production function was chosen as the most parsimonious model that produced consistent model estimates however, the Cobb-Douglas functional form is limited because returns to scale are forced to be constant. It is possible returns to scale are not constant and other functional forms should be explored or adding a squared output term should be explored in future analyses (Price et al., 2017). The chosen exponential distribution of the error term presents another possible limitation because it monotonically increases in technical inefficiency which may produce efficiency estimates that are higher than other distributions may estimate (Kumbhakar et al., 2020). Further exploration of the distribution of the error term is suggested for future analyses.

Another limitation is the potential for sample selection bias which makes it difficult to generalize the results beyond this study. Fire progression perimeter data were available for 24.4% of wildfires that fit the size and location selection criteria. It is unknown which wildfires are chosen for GIS perimeter data updates or why, but it is possible there is selection bias from this limitation. The quality and accuracy of fire progression perimeters can also be highly variable depending on the data source. Regular, high-precision measurement of wildfire progression would greatly improve efficiency analyses and future studies that seek to understand wildfire management at the daily, individual fire scale.

Not having daily wildfire perimeters was another limitation for this type of analysis. It creates gaps in the output variable where wildfire growth in-between observed wildfire perimeters is unknown. Total suppression resource input variables had to be summed across these gaps and stochastic variables such as weather had to be averaged across the length of these gaps. Averaging across these gaps suppresses the variability of the stochastic variables and makes it challenging to observe a relationship between the input variables and held perimeter (Collins et al., 2007). Updating wildfire perimeters daily at the end of each burning period would improve model results and the explanatory power of efficiency analyses of individual fires.

Another possible limitation exists in using the drought code variable because it tends to increase from May through August. A drought code anomaly variable should be considered in future analyses because it differentiates rare drought events from the regular seasonal variation in drought code (Field et al., 2004).

The sample size of 34 fires with 167 observation is another potential limitation of the analysis. Maximum likelihood estimation requires sample sizes large enough to achieve asymptotic properties of the estimates. A larger dataset could also allow for the exploration of interaction and multiplier effects of containment resources. Crews often work to support aerial and ground equipment and including crews as a production function input could capture the potential multiplicative effects of resources working together (Cole and Alexander, 1995). A larger dataset could also allow for the exploration of lag effects of suppression activities. Indirect attack can have a lagged effect on wildfire containment because suppression resources working on backburn operations or digging fire containment lines are often working to contain the wildfire on future days (Alberta Wildfire, 2020b). Indirect attack may seem inefficient at containing the current day's perimeter, but the objective being to contain the wildfire perimeter on future days implies a lagged effect on held perimeter. Other studies have also suggested weather variables can have a lag effect on daily suppression efficiency which may not have been entirely captured by our fuel moisture code variables (Bayham et al., 2020). A full exploration of lead and lag effects of suppression resources and inefficiency variables would increase understanding of wildfire containment but requires a larger dataset with no gaps between observed progression perimeters to generate lagged variables. The values at risk analysis relied on satellite imagery to identify inhabited structures. There were some discrepancies in the satellite imagery dataset compared to assessment notes which reiterates the need for a provincial values at risk map that can be quickly deployed to identify all values at risk during initial assessment routines. Despite these limitations, we believe our methods and conclusions contain multiple important contributions and the knowledge gained during this analysis allows us to provide suggestions for future research.

Future research seeking to assess the efficiency of large wildfire suppression at the individual fire scale would benefit from daily, high-precision spatial wildfire perimeter data for all active wildfires undergoing sustained action. Daily wildfire perimeter data is available for wildfires in the United States and Canadian jurisdictions could benefit from this type of record keeping (Katuwal et al., 2016). Future analyses could further explore differences between small and large wildfire containment by separating small and large wildfires into separate models or using dummy variables to assess potential differences in efficiency estimates or significant input variables. Initial attack is often cited as the most efficient wildfire containment strategy by containing wildfires within a day after discovery, before the wildfire reaches 2 ha in size (Arienti et al., 2006; Beverly, 2017; Hirsch et al., 2004; Hirsch and Martell, 1996; Murphy et al., 1991). Future research could quantify the suppression efficiency of initial attack compared to sustained action in order to increase understanding of efficiency during different phases suppression. To address potential endogeneity, we suggest future analyses opt for models that correct for endogeneity or use stochastic cost frontier models when possible because prices are often exogenous which allows for greater interpretation of the causality of model results (Hesseln et al., 2010). This study considered wildfires greater than 190 ha in Alberta's boreal zone so the average efficiency estimates establish a baseline for wildfire management in Alberta. Future research could compare suppression efficiency across different Canadian jurisdictions to better understand and compare how different management techniques and wildfire regimes impact the efficiency of wildfire suppression across Canada.

6.5 Conclusion

This study is a stochastic frontier analysis of 34 wildfires greater than 190 ha in Alberta's boreal zone. The research questions of this study assessed the efficacy of suppression resources, the efficiency of wildfire containment, and the effect nearby inhabited structures have on containment efficiency. Use of stochastic frontier analysis to measure technical efficiency of wildfire containment has not been done in Alberta's boreal zone. This study builds on past research by including fuel moisture codes as inefficiency variables that capture the long-term (52 day) and short-term (18 hour) weather conditions of each wildfire. We also included the impact inhabited structures may have on containment efficiency by using spatial data analysis and a novel wildfire perimeter weighting procedure to adjust the dependent variable based on values at risk.

Our results suggest ground equipment such as bulldozers and fire engines are effective suppression resources while airtankers and helicopters do not appear to be effective when containing large wildfires. The stochastic frontier analysis estimated 26.89% average technical efficiency of large wildfire containment in Alberta's boreal zone. It is difficult to know if this estimate is high or low because this type of analysis has not previously been done in Alberta's boreal zone but the coniferous fuels that dominated the study region are capable of generating high intensity crown wildfires which makes 26.89% average efficiency plausible compared to 47% efficiency estimated in the western United States (Katuwal et al., 2016). Coniferous fuels and high drought codes are related to decreases in technical efficiency. Wildfires with nearby inhabited structures had slightly higher median technical efficiencies of containment which suggests the provincial management agency prioritizes protection of wildfires with nearby values at risk. However, weighting the dependent variable to include inhabited structures as immediate values at risk had no discernible effect on technical efficiency of suppression except on the largest wildfires that saw an increase in efficiency after including values at risk. In general, our results suggest fuel and weather conditions conducive to high intensity wildfires and extreme wildfire behaviour can challenge the efficacy of suppression resources creating inefficient wildfire containment conditions. Policy seeking to improve the efficiency of wildfire containment in Alberta's boreal zone may consider modified response during wildfire days when the efficacy of suppression resources will be challenged and wildfires become unmanageable (Wotton et al., 2017).

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Appendix A

Table 8. Fuel classification and percent cover throughout wildfire management zone as of 2019 fire season in Alberta, Canada.

Count	Percent Cover (%)	Fuel Type	Description
3598117	4.812	C-1	C-1 (Spuce - Lichen Woodland)
10388455	13.892	C-2	C-2 (Boreal Spruce)
3407564	4.557	C-3	C-3 (Mature Jack or Lodgepole Pine)
1607726	2.150	C-4	C-4 (Immature Jack or Lodgepole Pine)
165148	0.221	C-5	C-5 (Red and White Pine)
190	0.000	C-6	C-6 (Conifer Plantation)
255432	0.342	C-7	C-7 (Ponderosa Pine - Douglas-Fir)
9040650	12.089	D-1/D-2	D-1/D-2 (Aspen)
20900	0.028	S-1	S-1 (Jack or Lodgepole Pine Slash)
25743	0.034	S-2	S-2 (White Spruce - Balsam Slash)
181	0.000	S-3	S-3 (Coastal Cedar - Hemlock - Douglas-Fir
21663898	28.970	O-1	O-1 (Grass)
3662457	4.898	Non-Fuel	Non-Fuel
2886649	3.860	Water	Water
10365518	13.861	Vegetated Non-Fuel	Vegetated Non-Fuel
369	0.000	M-1/M-2 (10 PC)	M-1/M-2 (Boreal Mixedwood - 10%
3597	0.005	M-1/M-2 (15 PC)	M-1/M-2 (Boreal Mixedwood - 15%
645065	0.863	M-1/M-2 (20 PC)	M-1/M-2 (Boreal Mixedwood - 20%
171616	0.229	M-1/M-2 (25 PC)	M-1/M-2 (Boreal Mixedwood - 25%
423151	0.566	M-1/M-2 (30 PC)	M-1/M-2 (Boreal Mixedwood - 30%
259829	0.347	M-1/M-2 (35 PC)	M-1/M-2 (Boreal Mixedwood - 35%
549203	0.734	M-1/M-2 (40 PC)	M-1/M-2 (Boreal Mixedwood - 40%
393279	0.526	M-1/M-2 (45 PC)	M-1/M-2 (Boreal Mixedwood - 45%
2442932	3.267	M-1/M-2 (50 PC)	M-1/M-2 (Boreal Mixedwood - 50%
682875	0.913	M-1/M-2 (55 PC)	M-1/M-2 (Boreal Mixedwood - 55%
505289	0.676	M-1/M-2 (60 PC)	M-1/M-2 (Boreal Mixedwood - 60%
291737	0.390	M-1/M-2 (65 PC)	M-1/M-2 (Boreal Mixedwood - 65%
383502	0.513	M-1/M-2 (70 PC)	M-1/M-2 (Boreal Mixedwood - 70%
194282	0.260	M-1/M-2 (75 PC)	M-1/M-2 (Boreal Mixedwood - 75%
744025	0.995	M-1/M-2 (80 PC)	M-1/M-2 (Boreal Mixedwood - 80%
1669	0.002	M-1/M-2 (85 PC)	M-1/M-2 (Boreal Mixedwood - 85%
341	0.000	M-1/M-2 (90 PC)	M-1/M-2 (Boreal Mixedwood - 90%
74781389	**100**		

Table 9. Variance inflation factors from ordinary least squares models including crew total

Variable	VIF	1/VIF
lncrew	7.36	0.135954
lnheli	5.24	0.190759
lnequip	4.62	0.216227
lnair	3.31	0.302399
equip_d	4.38	0.228454
crew_d	3.57	0.280287
air_d	3.49	0.286660
heli_d	2.13	0.470073

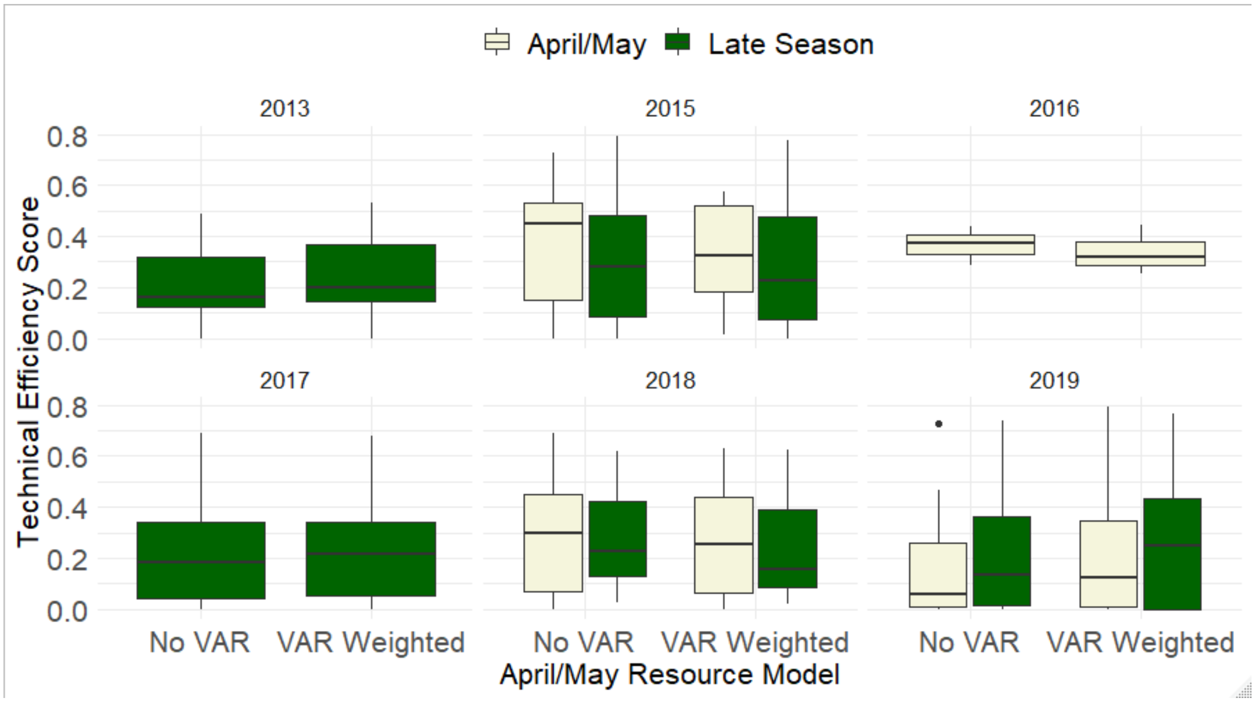

Figure 17. Boxplot of technical efficiency score for all sample fires. The boxplots are separated by wildfires burning in April and May (beige) or late season (green). VAR indicates values at risk.

Appendix B

Expenditure Models

Suppression Resource Expenditure Data

Another model specification was considered that included expenditure data in the production function to capture potential quality differences of suppression resources within each category. Capturing these potential quality differences may explain why the aerial suppression resources appear to be ineffective in the resource models that treat all inputs in each category as equivalent quality. The suppression resource expenditure data from the FIRES resource database. The expenditure data are separated into expenditures on aircraft rental, aviation fuel, retardant dropped, contracted equipment, and various manpower categories.

The database does not differentiate between airtanker and helicopter rental costs or retardant drops so all aerial rental, fuel, and retardant expenditures are summed into one "air" expenditure that represents all aerial firefighting equipment expenditures. The expenditure data also does not differentiate for resources that specifically work on fireline containment so the data could not be filtered to the same extent as the resource models. The SFA dependent variable remained as the natural logarithm of held perimeter, so this is not a cost frontier but is a production function that incorporates expenditures as a way to capture the inherent quality differences of suppression resources (Fox and Smeets, 2011; Gandhi et al., 2019). The models were run with expenditure inputs alone which did not provide valuable insights because of the aggregate nature of the expenditure data. The model was also run by calculating an average "unit price" that divided total expenditures by the count of resources in each category. The average unit price was then multiplied by the quantity of containment resources that was used in the resource models (Table 6).

$$\begin{gathered} ln(y_{it}) = \alpha + \beta_1 \ln(air\_d) + \beta_2 \ln(equip\_d) + \beta_3 \ln(max(air\_d, air * \$)) \\ +\beta_4 \ln(max(equip\_d, equip * \$)) + \beta_5 \ln(not\_held) + \beta_6\, ln\,(gap) + v_{it} - u_{it} \end{gathered} \tag{189}$$

$$u_{it} = \delta_0 + \delta_1(water\ \%) + \delta_2(conif\ \%) + \delta_3(dc) + \delta_4(ffmc) + w_{it}. \tag{20}$$

Expenditure Panel SFA Results

The same iterative estimation procedure was followed as previously done with OLS and cross-section SFA models used to refine input variable and evaluate model performance. Results from the total expenditures model inputs were mainly insignificant and suggested suppression resources were not related to held perimeter (Appendix B, Table 10). The insignificance is likely because we were unable to filter the expenditure data specifically for resources that work on fireline containment. Results from the expenditure model using "unit prices" were very similar to the resource model (Table 6) and did not add more information because the assumptions used to calculate the unit price resulted in no variation in the price that could possibly explain quality differences (Appendix B, Table 11). The estimated coefficients for the inefficiency variables were consistent with Table 6 which suggests robust model specification. Future research will further explore other methods to determine the prices of inputs in order to capture potential quality differences of suppression inputs.

Table 10. True random effects stochastic frontier panel model with total expenditure inputs, exponential error distribution, and standard errors clustered by fire. Model 1 did not converge.

	Model 13 - No VAR	**Model 14 - VAR**		**Model 15 - No VAR**	**Model 16 - VAR**
	Coefficient (se)	Coefficient (se)		Coefficient (se)	Coefficient (se)
constant		3.219^{***}	constant	3.024^{***}	3.017^{***}
		(1.090)		(0.300)	(0.233)
air_d		-2.503	air_d	-3.760	-2.208
		(1.877)		(2.335)	(1.934)
equip_d		1.279^{**}	equip_d	0.833	1.062
		(0.629)		(1.130)	(0.702)
lnairexp		0.0398	lnair	-0.0624	0.0463
		(0.165)		(0.175)	(0.166)
lnequipexp		0.106	lnequip	0.0567	0.0826
		(0.0656)		(0.0922)	(0.0685)
lnnotheld		0.108^{***}	lnnotheld	0.0972^{***}	0.106^{***}
		(0.0283)		(0.0341)	(0.0297)
lngap		0.550^{***}	lngap	0.514^{***}	0.547^{***}
		(0.154)		(0.176)	(0.157)
			Inefficiency		
water (%)		-0.00701	water (%)	-0.0148	-0.0271
		(0.0149)		(0.0210)	(0.0205)
conif (%)		-0.00114	conif (%)	0.0170^{**}	0.0188^{**}
		(0.00823)		(0.00730)	(0.00882)
dc		0.166	dc	1.595^{***}	1.604^{***}
		(0.435)		(0.513)	(0.510)
ffmc		-0.109	ffmc	-0.0902	-1.186
		(0.749)		(1.516)	(1.348)
$ln\ \sigma_u^2$		2.114^{***}	$ln\ \sigma_u^2\_cons$	-0.423	0.619
		(0.266)		(1.267)	(1.283)
$ln\ \sigma_v^2$		-0.906^{***}	$ln\ \sigma_v^2$	-1.353	-0.719^{**}
		(0.261)		(0.953)	(0.351)
$ln\ \Theta^2$		0.0148	$ln\ \Theta^2$	0.0452	0.0966
		(0.0307)		(0.185)	(0.492)
log.lik.		-375.4	log.lik.	-361.9	-369.5
chi^2		455.5	chi2	708.0	376.7
p		1.37e-91	p	1.15e-149	2.82e-78
σ_u		2.877	$E(\sigma_u)$	2.812995	2.756919
		(0.3828)		CI:(2.69 - 2.93)	CI:(2.63 - 2.88)
σ_v		0.636	σ_v	0.508	0.698
		(0.08293)		(0.242)	(0.1225)
λ		4.525082	E(λ)		
		(.391687)			
AIC		778.7605		751.7527	766.9186
BIC		822.4124		795.4046	810.5706

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

i = 34, N = 167, y_{it} = ln(held perimeter) in models 13 & 15, and ln(I.D.^{2} weighted held perimeter) in models 14 & 16

Table 11**.** True random effects stochastic frontier panel model with "unit price" expenditure inputs, exponential error distribution, and standard errors clustered by fire.

	Model 17 - No VAR Coefficient (se)	**Model 18 - VAR** Coefficient (se)		**Model 19 - No VAR** Coefficient (se)	**Model 20 - VAR** Coefficient (se)
constant	2.087^{**}	2.764^{***}	constant	2.892^{***}	3.147^{***}
	(0.890)	(1.065)		(0.230)	(0.275)
air_d	-0.659	-1.890	air_d	-0.574	-1.694
	(1.883)	(1.995)		(1.932)	(1.903)
equip_d	0.704	2.214^{**}	equip_d	0.690	2.226^{**}
	(1.078)	(0.939)		(0.917)	(1.040)
lnairexp	-0.0784	-0.201	lnairexp	-0.0729	-0.172
	(0.153)	(0.174)		(0.158)	(0.165)
lnequipexp	0.0790	0.254^{***}	lnequipexp	0.0699	0.237^{**}
	(0.0985)	(0.0945)		(0.0856)	(0.108)
lnnotheld	0.0975^{***}	0.112^{***}	lnnotheld	0.0916^{***}	0.106^{***}
	(0.0311)	(0.0238)		(0.0276)	(0.0236)
lngap	0.560^{***}	0.514^{***}	lngap	0.533^{***}	0.502^{***}
	(0.185)	(0.153)		(0.173)	(0.149)
			Inefficiency		
water (%)	0.00980	-0.0109	water (%)	-0.0243^{*}	-0.0269^{*}
	(0.0200)	(0.0129)		(0.0139)	(0.0140)
conif (%)	0.00479	-0.000704	conif (%)	0.0212^{***}	0.0224^{***}
	(0.00666)	(0.00716)		(0.00753)	(0.00855)
dc	0.0356	0.385	dc	1.639^{***}	1.608^{***}
	(0.439)	(0.459)		(0.487)	(0.460)
ffmc	0.544	0.331	ffmc	-0.915	-1.617
	(0.784)	(0.792)		(1.518)	(1.328)
$ln\ \sigma_u^2$	2.102^{***}	2.203^{***}	$ln\ \sigma_u^2\_cons$	0.151	0.874
	(0.231)	(0.307)		(1.293)	(1.095)
$ln\ \sigma_v^2$	-1.215^{***}	-1.340^{**}	$ln\ \sigma_v^2$	-1.096^{***}	-0.852^{***}
	(0.297)	(0.602)		(0.253)	(0.269)
$ln\ \Theta^2$	0.0232	0.00390	$ln\ \Theta^2$	-0.149	0.00278
	(0.0346)	(0.00776)		(0.257)	(0.0186)
N	167	167	*N*	167	167
log.lik.	-370.1	-375.7	ll	-363.7	-369.2
chi^2	75.01	78.07	chi2	51.52	42.35
p	4.74e-12	1.20e-12	p	2.33e-09	0.000000157
σ_u	2.861^{***}	3.008^{***}	$E(\sigma_u)$	2.768651	2.825122
	(.3306542)	(.4621281)		CI: (2.66 – 2.90)	CI: (2.69 – 2.96)
σ_v	0.545^{***}	0.512^{***}	σ_v	0.578^{***}	0.653^{***}
	(.0809173)	(.1540891)		(.0732026)	(.0877442)
AIC	768.2911	779.304		755.3166	766.3218
BIC	811.943	822.9559		798.9685	809.9737

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

i = 34, N = 167, y_{it} = ln(held perimeter) in models 17 & 19, and ln(I.D.^{2} weighted held perimeter) in models 18 & 20