Quantifying Fuel for Fire in Waterton National Park.

By

Marcus Merlonghi

A Thesis submitted in partial fulfillment for the degree of

Bachelor of Science (Honors)

In Geography

Supervised by Dr. Laura Chasmer and Dr. Chris Hopkinson.

Department of Geography and Environment

University of Lethbridge

Abstract

This thesis investigates how the distribution of canopy fuel load (CFL) is changing within the context of a warming climate, and in the process, offers knowledge and recommendations to wildfire agencies regarding mitigation strategies to adapt to the changing distribution. While this thesis reviews wildfires in a general context, the analysis is primarily focused on Waterton National Park in Southern Alberta, Canada, where field measurements were conducted for the completion of this thesis. These field measurements guide an analysis which utilizes Lidar derived height metrics to predict the spatial distribution of CFL in Waterton National Park, and connects the predictions to slope, elevation, and aspect. The analysis discovered that north facing aspects were associated with more fuel availability, but decreased amounts of solar insulation on these slopes can inhibit moisture loss making the fuel less available to wildfire. Additionally, there existed a negative relationship between Elevation and CFL where CFL was lower at higher elevations. It is the hope of this thesis that the results be considered by wildfire managers in Waterton National Park as well as further defining the utility all wildfire agencies can find by using lidar derived data to predict the spatial distribution of fuel for fire.

Table of Contents

Chapter 1: Introduction.

Wildfires have been a focus for research in recent years due to their increasing threat in a climate change afflicted world. Wildfires are a unique type of hazard since they affect nearly all parts of the globe, with afflicted areas ranging from the boreal forest of Northern Canada to the tropical forests of Australia and Brazil (Coogan, et al, 2019). The spatial distribution of wildfire activity across the globe translates to a high degree of variation within wildfire research itself since understandings of fire in one ecosystem may not be applicable to another. Despite this, it is widely understood that wildfires are increasing in frequency, severity, extent, and duration when compared to historic norms (Tymstra, et al, 2020). The changing trends are thought to be a product of climate change and historic wildfire management strategies which placed a focus on fire suppression, leading to a buildup of fuels and the disruption of ecosystems, making contemporary forests more prone to wildfire (Coogan, et al, 2019. Vukomanovic, et al, 2019). Indeed, it is through disrupted ecosystems that wildfire can cause the most damage. This is because wildfires typically maintain a symbiotic relationship with ecosystems, a relationship where wildfire facilitates processes that are vital to ecosystem health such as nutrient cycling and plant succession (Zhao, et al, 2015).

Through the facilitation of such services, wildfires create landscapes that are adapted to the local wildfire regime, but when ecosystems are altered, either through anthropogenic or climate forcing's, then their ability to respond and recover from wildfire diminishes, creating ripe conditions for disastrous wildfires like the ones seen in recent years (Coogan, et al, 2019. Zhao, et al, 2015). These disruptions have laid the foundations for fire regimes to enter a new phase of unprecedented activity where there exists a large degree of uncertainty regarding how new fires will behave in a post climate change world. Therefore, a role of contemporary wildfire

research should be trying to understand these uncertainties and develop strategies for coping with wildfires in the face of new climatic norms. Furthermore, there exists a need to understand the local variation of wildfire activity within regions to develop more optimized approaches to wildfire response rather than the more traditional approaches focused on general application (Pausas & Riberio, 2013).

On the policy and management side of things, wildfire should be of particular concern since Climate change is predicted to raise the cost of wildfire suppression in Canada by 60% under a low warming scenario and 199% under a high warming scenario (Tymstra, et al, 2020). A near double in cost of wildfire fighting combined with increased fire size and severity would place significant strain on Canadian resources to combat increasingly damaging and costly events (Tymstra, et al, 2020). Indeed, the effect of wildfires on Canadian society has been increasing along with their activity, resulting in more public concern regarding the impacts of wildfire, concerns like lowered air quality, but also, through the destruction of communities and livelihoods. Indeed, wildfires are some of the most damaging disasters to afflict the Canadian Geography with the Slave Lake wildfires being the costliest disaster in Canadian History (Tymstra, et al, 2020). The impacts of wildfire on Canadian society and governance drive further need for understanding wildfire behavior and the optimization of management strategies under changing fire regimes.

It is within the changing wildfire context that this paper sets out to contribute to the understanding of wildfire within the context of Southern Alberta Rocky Mountains, a region that has been particularly hard hit by increasing wildfire activity due to a dry climate, a factor that makes fuel more readily available for combustion (Dennison, et al, 2014). Southern Albertas vulnerability to wildfires was made apparent during the 2017 Kenow Fire, a high severity

wildfire that burned majority of Waterton National Park (Eisenberg, et al, 2019). To help prevent future disasters such as the Kenow Fire, research is being undertaken to refine all facets of wildfire response ranging from fire prevention to recovery (Tymstra, et al, 2020). This paper aims to contribute to the fire prevention side of things by investigating the spatial distribution of Biomass and Canopy Fuel Load (CFL) to determine how factors like elevation and aspect alter their distribution. The outline for doing so will be to first conduct a literature review of the existing knowledge, then identify any gaps in current knowledge that require further investigation, and these gaps will will then guide the analytical chapter where results of this research are compiled and discussed.

Chapter 2: Understanding Wildfire Fuel and Management Strategies.

2.1: Introduction.

It should be of little surprise that climate change is making wildfires worse but why is this the case? Other than increasing temperatures, Climate Change does not affect the globe equally, this is evident when observing how some regions, like Canada, are warming faster than others, but the impacts of climate change become more complex when considering how it alters environmental systems and patterns (Coogan, et al, 2019). For example, some regions may be getting drier while others are predicted to receive more precipitation, or some regions may be exposed to altered precipitation patterns, changing how precipitation is received (Chileen, et al, 2020). So, understanding how climate change influences wildfire may be more complicated than it seems, and that is just climate change alone. There are many other variables influencing the outcomes of wildfires such as the presence of non-native species, geographical differences in the landscape, and even human forest interactions through policy and urban development (Dennison, et al, 2014). Understanding the variables influencing fire can give a better understanding on the variations seen in forest fuels, therefore allowing a connection to be made between environmental conditions and the distribution of fuels for fire. A review of current wildfire management strategies is undertaken to make recommendations on how to optimize strategies in a post climate change world. Specifically, the review will focus on the prevention and mitigation side of wildfire management through the identification of landscapes with abundant fire fuel that can be the sight of targeted wildfire defense strategies.

2.2: Objectives of the Review.

The first of the literature review will start by reviewing how wildfires might be enhanced or reduced by climate change, followed by the defining of fuels and characteristics of the

waterton wildfire regime, then a connection to what drives change in fuel flammability, finished by addressing the current state of wildfire management in Canada.

2.3: How Might Fuels be Enhanced or Reduced due to Climate Change.

With a rapidly changing climate and fire regime, comes a critical need to understand the current state of fuels to better predict how they might change under future conditions. For the near future, climate change posits the most notable way in which fuels for fire will change, but factors like human population, land-use, and agricultural practices also impose significant influence on the fire regime and should not be ignored. Therefore, the first objective of this literature review is to understand how fuels might be enhanced or reduced in respect to these variables.

The most obvious answer as to how climate change will impact the fire regime is that higher temperatures will increase the frequency and severity of drought like conditions, thereby enhancing the availability of dry vegetation, which is associated with an elevated risk of fire (Pausas & Riberio, 2013). Though it should be mentioned that not all forests follow this projection, but the Montane regions of Southern Alberta are certainly one of them where dry conditions are a driving force behind fire risk (Pausas & Riberio, 2013). Contemporary research describes fire regimes as being either weather dependent or fuel limited, where weather dependent regimes are reliant on hot and dry conditions to make fuel available for burning whereas fuel limited regimes require more moisture to enable the growth of fuel (Pausas & Riberio, 2013). Based on these descriptions Waterton can be inferred as having a weather dependent fire regime with the categorization being further supported by the *Out of the Ashes* paper, this paper notes how the high severity Kenow fire occurred in Waterton during the late season when conditions were particularly hot and dry (Eisenberg, et al, 2019). In contrast, the

study's early season prescribed burning was thought to be not as severe due to the abundance of moisture in the early season of the Rocky Mountains, suggesting that the hot and dry conditions of the late summer combined with an abundance of annual vegetation created the antecedent conditions necessary for the Kenow fire (Eisenberg, et al, 2019).

Additionally, climate change may promote the drying out of vegetation through earlier snowmelt and decreased snow precipitation, placing further stress on the Canadian Rocky Mountain system which receives a significant amount of moisture from spring snowmelt (Krawchuk & Moritz, 2011. Hopkinson, et al, 2012). Furthermore, a predicted decline in Canadian streamflow and precipitation would translate to a reduced level of moisture availability, placing stress on ecosystems in the Canadian Rockies and exacerbating the impact of the hot and dry summers in Waterton (Rood, et al, 2005). Other research shows a large drop in seasonal snowpack for elevations between 1600 m and 1845 m but a stable snowpack for higher elevations, it remains to be seen to how a drop in low elevation snowpack will impact moisture availability and how an increasing amount of precipitation received as rain instead of snow will impact Rocky Mountain Forested ecosystems (Harder, et al, 2015). Interestingly, Pausas and Keeley point out that climate change can lower fire risk in certain regions by limiting plant growth, which in turn limits fuel availability (Pausas & Keeley, 2009). The implication being that even if vegetation is drying out at an above normal rate, there might be other climatic forces at work limiting the effects of drier fuels.

Aside from climate change, the characteristics of an ecosystem's vegetation type influences the fire regime through determining the fuel structure. Fuel structure is important because it determines fire intensity and type. Fire intensity determines how severely the ecosystem is altered, for example, severe fires like Kenow fire are characterized as stand

replacing fires that destroy significant amount of organic material in the soil (Pausas & Riberio, 2013. Eisenberg, et al, 2019). A factor of vegetation type is the productivity of the vegetation, which is thought to be another factor influencing the fire regime. Productivity can be a key element to predicting fire behavior as research indicates it is the primary factor controlling the variability within an ecosystem (Pausas & Riberio, 2013). In other words, the reason some areas may burn more severely than others within the same ecosystem, can be attributed to variation in productivity (Pausas & Riberio, 2013).

Pausas and Keeley note 2 factors needed for wildfire that are particularly relevant to this study, those being Seasonality where climate variations create optimal conditions for fire, and fuel structure where the type of wildfire is determined, e.g. whether it is a surface level fire or stand replacing one. For Waterton, seasonality would be a dry season that transforms potential fuel into actual fuel, and fuel structure would support stand replacing fires as indicated by the high severity fire regime (Pausas & Keeley, 2009). These factors can be altered by climatic forcing's particularly high-pressure systems which are associated with dry conditions and an increase in risk of lightning strikes (Johnson & Wowchuk, 1993).

2.4: Defining Fuels and Characteristics of the Waterton Fire Regime.

The predominant method of understanding fuels comes from breaking down the components of the fire regime into 3 scales (Moritz, et al, 2005). The first of these occurs at the microscale where individual flames function, here oxygen, heat, and fuel interact over the course of seconds to generate flames which can turn into wildifres. Fuels at this level are influenced by overarching factors such as vegetation and moisture availability which determine whether the heat source is sufficient to generate a flame on a given piece of fuel. As for individual wildfire events, this occurs over the course of days and is determined by weather, topography, and fuels

(Moritz, et al, 2005). Here, a variety of factors determine not only fuel availability, but the characteristics of the wildfire itself such as its duration or the direction in which it spreads. Moisture availability seems to be the primary factor of concern as it is thought to play a critical role in determining the spread, frequency, and severity of wildfire (Holsinger, et al, 2016 & Schoennagel, et al, 2004). With fire frequency being the number of fire events and fire severity being defined by a combination of tree mortality, destroyed biomass, and/or heat penetration into the soil in the post-fire landscape (Zhao, et al, 2015).

Lastly, climate, ignitions, and vegetation interact to determine the fire regime over the course of decades. Here vegetation is the combination of factors influencing fuel availability such as vegetation type, forest structure, and biomass accumulation. As for ignition sources, lightning strikes are the primary source of ignition in the Canadian Rockies although human ignited fires have been common in the landscape since indigenous populations first inhabited the area and human caused fires from modern recreational activities is the next largest ignition source behind lightning (Eisenberg, et al, 2019. Tymstra, et al, 2020).

While moisture plays a critical role at all 3 stages, it is hard to quantify individual fuel moisture at the microscale (Kelsey, et al, 2018). This problem is made worse when considering how data from before the Kenow fire is limited, so this study will consider moistures impact on fuel availability over a larger scale in Waterton which will come with the added benefit of being translatable to other areas of similar climate. Therefore, to expand on how the fire triangle relates to moisture, the most obvious influence comes from climate where moisture availability is determined through factors such as precipitation and humidity, however individual weather events may play a strong role in creating fuel as was seen during the unusually hot summer which the Kenow fire occurred (Eisenberg, et al, 2019). Interestingly, topography may also play

a key role as aspect is thought to be an indicator of moisture availability (McCaffrey & Hopkinson, 2020). The thought here being that north facing slopes are cooler and therefore see less evapotranspiration, furthermore, snowpacks persist longer on north facing slopes which can provide an additional input of moisture onto north facing slopes (Moritz, et al, 2005).

As for Waterton's fire regime, Holsinger and others note that fire regimes are controlled by biomass availability, climate, and ignition sources, which can be determined through factors such as soil moisture and NDVI (Holsinger, et al, 2016). Therefore, it would be of interest to use these parameters as a reference when categorizing Waterton's Fire regime. Waterton can be noted as having characteristics of a high severity fire regime, one of the three types of fire regimes identified by Schoennagel (Schoennagel, et al, 2004). The high severity fire regime is categorized by high elevation subalpine forests which experience infrequent stand replacing fires that destroy the forest canopy and occur at infrequent intervals (Zhao, et al, 2015). This is supported by research which indicates the Canadian rockies as being prone to infrequent, lightning strike fires, and that these ecosystems have fire return intervals of around 100 years, (Johnson & Wowchuk, 1993). Which in the case of Waterton, is supported by the fact that the last fire before the Kenow fire occurred 87 years ago (Eisenberg, et al, 2019).

Vegetation is an integral part of understanding fire's role in an ecosystem for a few reasons. One of those being how vegetation can either be fire adapted or fire intolerant species which would affect an area's risk for burning (Rogeau & Armstrong, 2017). Similarly, wildfire and vegetation seem to exist in a mutually influential relationship where changes in the fire regime may lead to major shifts in vegetation, landscape structure, and ecological functions such as productivity (Zhao, et al, 2015). Therefore, changes to one side of this relationship can influence the other, for example, it is known that non-native vegetation may alter fire risk and

was speculated to be a possible cause of the Kenow fire (Eisenberg, et al, 2019. Moritz, et al, 2005). In the Canadian Rockies, the major forest types include the mid-montane forest, consisting of Ponderosa Pine and Douglas fir, the high-Montane forest, and the subalpine forest, subalpine fir and whitebark pine (Zhao, et al, 2015). Of these species, lodgepole pine and douglas fir are identified as being fire-adapted species, while subalpine fir, white spruce, and englemen spruce are identified as fire-intolerant or fire-independent species (Schoennagel, et al, 2004. Rogeau & Armstrong, 2017). Although lodgepole pine is identified as fire-intolerant by the previous studies, another paper posits that Lodgepole pine is resilient to the high severity known to afflict the Canadian Rockies, propagating the idea that wildfire is a complex discipline which can change depending on the frame of reference (Chileen, et al, 2020). Lastly, aspen stands are known to inhabit Waterton Park and these stands are thought to increase the risk of wildfire (Eisenberg, et al, 2019). It is important to note that fire severity can change with weather conditions at the microscale but based on historical observations it can be inferred that Waterton generally falls under the high severity fire regime.

2.5 What Drives Change in Fuel Flammability.

Fire refugia has been defined as a patch of forest with an optimal geographic location that allowed for the patch to escape several fires and is older than three times the length of the mean fire return interval (Rogeau & Armstrong, 2017). The identification of fire refugia can be useful for forest management to both maintain existing refugia areas and protecting future ones (Rogeau & Armstrong, 2017).

With the current understanding of wildfires and their importance established, it is now necessary to explore how local variables may alter fuel flammability. Of previous note, NDVI has been used a predictor for wildfire through measuring vegetation health and productivity, with

NDVI even being described as “highly influential” when measuring wildfires in Glacier National Park, the U.S. national park bordering Waterton (Holsinger, et al, 2016). In fact, areas of low productivity have been shown to disrupt fire spread by acting as a break in the landscape (Holsinger, et al, 2016). NDVI measures have also been used as an indicator to measure forest recovery and fuel accumulation (Kellie, et al, 2015). Tree growth is related to biomass accumulation therefore larger trees would translate to higher degrees of biomass, making it interesting to note how tree crowding had a negative impact on tree growth, supporting the theory that competition between individuals is a key factor in determining forest population health (Buechling, et al, 2017). Conversely, higher elevations have been associated with increased growth rates, suggesting greater capability for ecosystem recovery at higher elevations than valley bottoms (Buechling, et al, 2017). Variation between species can also interact with wildfire risk. For example, subalpine fir has been demonstrated to experience higher rates of moisture loss whereas englement spruce has displayed greater control over moisture content (Kelsey, et al, 2018).

Seasonality is another factor that can cause significant changes in fuel flammability, with previous work showing that 97% of lightning started fires in the Canadian Rockies began in the late summer which is often characterized as being hot and dry, creating optimal conditions for the development of fuel (Johnson & Wowchuk, 1993). Though, interesting to note is how historical pollen analysis has shown that lodgepole pine populations remain stable under changes in temperature and fire regime, with precipitation being identified as the primary driver of vegetation change (Chileen, et al, 2020). This suggests that the species can help foster ecosystem resilient to wildfire, but it remains to be seen how other tree species in the Canadian Rockies react to similar changes (Chileen, et al, 2020). Topography has been shown to alter the

precipitation regime altering species composition, lightning strike frequency, and drying of vegetation through wind and solar radiation (McCaffrey & Hopkinson, 2020). Topography can also impede fire spread by creating breaks in the landscape, for example, features such as cliff bands or water bodies can disrupt fire continuity (Rogeau & Armstrong, 2017). Aspect has been shown to be a strong indicator of how topography can alter fire risk, with 72% of tree mortality during wildfire events occurring on SW, S, SE, and E facing slopes (McCaffrey & Hopkinson, 2020). Furthermore, south facing slopes show higher degrees of evapotranspiration (Kelsey, et al, 2018). As for elevation, increases in elevation have been shown to decrease wildfire burning by upwards of 33%, and Lidar studies have shown decrease in Canopy coverage at higher elevations suggesting less biomass available for wildfire (Rogeau & Armstrong, 2017. McCaffrey & Hopkinson, 2020). In fact, areas of both cool aspects and high elevation have been associated with the longest fire return intervals, suggesting that these areas host the highest potential for fire refugia to form Rogeau & Armstrong, 2017). Opposite to this, south and west facing aspects have been shown to have the shortest fire return intervals (Rogeau & Armstrong, 2017).

Along with the precipitation regime, topography can alter moisture availability through snowpack survival, with north facing snowpacks being 40% larger than snowpacks on south facing slopes, this translates to greater persistence throughout the spring and summer, providing melt water to support plant maintenance processes (McCaffrey & Hopkinson, 2020). Moisture availability has also been described as a factor influencing conifer seedling survival rates, and seedlings had a 48% lower chance of survival on south facing slopes, with insulated temperature, higher water content, and snow drifts increasing survival rates (Germino, et al, 2002).

2.6: Contemporary Wildfire Management in Canada.

The services provided by forests were briefly mentioned previously, but these services should be expanded upon to set the context for reviewing wildfire management strategies. Services can come in the form of economic benefits such as from commercial harvesting, recreational value through the establishment of national parks, cultural value through fostering livelihoods and ways of being, and even intrinsic value through services that bolster the health of the community itself, such as the nutrient cycling provided by wildfire itself (Vukomanovic, et al, 2019). Combined, these services mean that the health and maintenance of ecosystem functionality is of top concern for conservation efforts and wildfire management is a way of ensuring functionality despite wildfire disturbance. The other, more obvious reason for managing wildfire is to minimize the damage to human society, both through health and economic impacts. Financial impacts can cost millions and sometimes billions of dollars, as was seen in the Alberta Slave Lake wildfire which caused 3.84 billion dollars in damage, making it the costliest disaster in Canadian history (Tymstra, et al, 2020). Loss of community and relocation of evacuees is an increasing social impact of wildfires as the number of homes lost due to wildfire is increasing (Tymstra, et al, 2020). Long term health impacts of wildfire are not currently known but heavy smoke presence lowers air quality and can exacerbate respiratory illnesses (Coogan, et al, 2019).

As for the actual methodology managers use to handle wildfires, their strategies focus on 4 key phases; prevention, preparedness, response, and recovery. Tymstra and others defined these phases in her 2020 review of wildfire management in Canada as follows; “prevention focusing on preventing wildfires, and mitigation aiming to reduce the impacts when they do occur. Wildfire preparedness is those actions that contribute to a state of readiness to adequately manage wildfire arrivals and their possible consequences. The actions taken to manage a wildfire

incident when they do occur are referred to as response. The recovery phase includes all efforts to repair or rebuild conditions during and after a wildfire disaster." (Tymstra, et al, 2020). These are the pillars from which managers decide how a wildfire should be responded to. Canadian agencies vary by province, and each have their own wildfire response strategies, but they all generally follow a risk adverse approach. A risk adverse approach means wildfires are responded to when there exists any risk to areas of perceived value such as human settlements or forest stands with commercial value (Tymstra, et al, 2020). This often results in agencies responding to wildfires before the ecological benefits provided by fires can be attained, to combat this, research has suggested enhanced wildfire monitoring before initiating containment and engaging in alternative methods of mitigating damage (Tymstra, et al, 2020). Added to this, a call has been made for more horizontal cooperation between provincial wildfire agencies and other government bodies to make a national standard for wildfire fighting (Tymstra, et al, 2020). Resources for wildfire fighting have also been significantly underfunded when compared to the growing threat of wildfire, creating a need for innovative solutions to cope with the effects of underfunding (Tymstra, et al, 2020).

Methodology for wildfire prevention include prescribed burning and forest thinning which serve to lower the amount of fuel available for burning thereby reducing the severity of future wildfires and providing the valuable ecosystem services provided by fires. Strategies in Waterton National Park have explored the use of prescribed burning but no large scale implementation of prescribed burns have been applied as the effects of prescribed burning in Waterton are still being investigated (Eisenberg, et al, 2019). Therefore any insight into which areas in Waterton may benefit from prescribed burning could be of use to the researchers actively investigating prescribed burns in Waterton. Finally, it should be noted how contemporary wildfire

management primarily follows western approaches while largely ignoring indigenous relationships with wildfire. This is not only a disservice to indigenous communities, but is also a missed opportunity of wildfire agencies since it is known that indigenous North American populations have utilized wildfire to facilitate healthy ecosystems (Eisenberg, et al, 2019). Therefore, an investigation into indigenous relationships with wildfire, referred to as Traditional Ecosystem Knowledge (TEK), could be a promising methodology to help return contemporary ecosystems to their more resilient, historic states (Eisenberg, et al, 2019).

2.7: Conclusion.

A review of the outlined objectives has identified potential drivers of change in the wildfire landscape, with a particular focus being placed on fuel availability aspect of fires. With an understanding of how factors such as moisture or human development alter wildfires, connections can be made to fuels which is the Analytical Chapters variable of interest, and the primary object of study for the field work in Waterton National Park. Additionally, while Waterton has not been defined as belonging to one specific fire regime, exploring what characteristics Waterton shares with the different types of regimes provide a relational framework with which, the results of the Analytical Chapter can be related to as a reference point. Finally, the connection to wildfire management gives this paper a platform in which it can speak to the real-world implications for wildfire agencies and provide insight regarding how wildfires should be responded to in a world undergoing climatic warming.

Chapter 3: Gaps in the Current Understanding of Wildfire Fuels and Management Strategies.

To guide the discussions in the Analytical Chapter, an outline of the gaps in knowledge is provided to identify research that would be beneficial to understanding and managing wildfires in Waterton National Park. The most obvious of which is the growing need to understand how climate change may alter the contemporary fire regime in the context of factors restraining fire activity (Krawchuck, et al, 2011). The spatial examination of fuels is one way of addressing this gap since fuels are needed for wildfire activity and identifying environmental factors associated with either increased or reduced fuels can show areas at risk for increased fire activity. One such factor is elevation with research calling the need for a greater understanding between elevation and wildfire (McCaffrey & Hopkinson, 2020). Similarly, there is a gap in understanding how environmental factors impede fire spread, and this paper examines the distribution of fuels to contribute to that conversation (Holsinger, et al, 2016). Notably, Holsinger draws attention to the need to test wildfire constraints in wilderness areas minimally affected by human activity, providing the conditions needed to examine the constraints in an isolated framework (Holsinger, et al, 2016). Waterton National Park fits this description as it is fire managed but the areas of Rowe and Lineham are not actively fire suppressed (Eisenberg, et al, 2019).

As for wildfire management, there is a need to consider the specifics of the fire regime for management strategies. This is true both spatially and temporally. Temporal understanding is needed to consider the impact of the historical fire regime on current wildfire processes, and spatial understanding is needed to consider variation between regions and ecosystems that can contribute to different wildfire outcomes (Zhao, et al, 2015). Understanding the specifics of local fire regimes can allow for better optimized wildfire management as the management strategies

will specifically target the needs of the local fire regime (Pausas & Riberio, 2013). This is research that is lacking in the knowledge base since Wildfires are generally studied at large scale, leaving little explanation for wildfires behavior at the sub ecoregion level. For example, different wildfire regimes have been defined, but there is little research into the variability within fire regimes (Dennison, et al, 2014). Furthermore, it has already been observed how factors like aspect and vegetation productivity can influence wildfire on the sub regional scale, therefore an exploration into these variables within Waterton National Park can provide location specific insight into fire behavior and this understanding can set precedents for further exploration of these variables within the surrounding Montane regions such as Castle Provincial Park or Banff National Park (Dennison, et al, 2014).

Chapter 4: Modelling the Distribution of Biomass and Canopy Fuel Load in the Rowe and Lineham Valleys.

4.1: Introduction.

How does elevation, slope, and aspect influence the spatial distribution of Canopy Fuel Load (CFL) in Waterton National Park of the Southern Canadian Rockies? That question is the north star which will guide the Chapter to follow, and in answering this question, implications for wildfire management in Southern Alberta can be commented on. To do so, CFL will be measured across transects in Waterton National Park following the methodology outlined by the updated 2021 Canadian Forest Service's 11.3 m radius forest mensuration plots (Canadian Forest Service, 2021). These plots provide methodology for measuring forests which can be used to quantify fuel and predicting fire behavior. Additionally, these measurements will be paired with Lidar data to predict the spatial distribution of CFL in Waterton National Park, with the forest plots serving to calibrate Lidar derived raster files in ArcGIS. The results of predicting CFL can provide a foundation for further investigations regarding fuel variability within the greater surrounding regions, namely, Southern Alberta and the Canadian Rocky Mountain ecosystem. These questions and concerns are of interest since wildfire is becoming an increasing threat in Canadian society, so adding to the collective understanding of what influences fuel distribution should have high utility for land managers, disaster response teams, and conservationists (Coogan, et al, 2019). In effort to develop a better understanding of climate change's impact on fuel, the ArcGIS Solar Analyst tool will be used as a proxy for temperature across the study area to identify how the distributions of fuel align with areas of increased solar energy. The results will be used to connect CFL with slope, aspect, and elevation since these variables have been identified by preexisting knowledge as influencing wildfire activity. Most notable of the three is

aspect where northern aspects have been shown to be less afflicted by wildfire (McCaffrey & Hopkinson, 2020). This paper seeks to apply this connection to the spatial distribution of fuel. If the two are related, then the model of CFL should show lower quantities of CFL on north facing slopes when compared to south facing slopes. Similar results have been observed with elevation and aspect where lower amounts of vegetation are thought to be found at higher elevations and steeper slopes (McCaffrey & Hopkinson, 2020). Finally, this relationship is being investigated for the potential value it stands to offer contemporary Canadian wildfire management practices by identifying areas with an elevated risk for wildfire which can become a focus point for targeted fuel management strategies.

4.2: A Refined Review of Fuel and Wildfire Management.

To suite the intent of the Analytical chapter, the most relevant aspects of Chapter 2 will be reiterated here along with additional references to further expand upon any concepts particularly relevant to the analysis. Most notably, this short review will highlight the aspects of climate change most relevant to wildfire in Waterton National Park and use these aspects to identify which areas in Waterton are suspected to have an elevated risk for fire in the post climate change world. Then, a refined definition of fuels will be given to establish the specific type of fuels that this chapter aims to predict. Finally, wildfire management will be specifically related to Waterton National Park to set a basis for recommendations to wildfire management in Waterton itself, instead of wildfire management as a whole.

For Climate Change, the factor most relevant to Waterton is the increased prevalence of drought conditions and ecosystems becoming more moisture limited (Rood, et al, 2005). As previously outlined, Waterton is already a dry climate so enhanced drying will only worsen the effects (Dennison, et al, 2014). Climate Change will primarily facilitate drier conditions in

Waterton through decreased snowfall which will dampen the moisture provided by snowpacks, this can enable the curing of vegetation, priming them for combustion (Harder, et al, 2015). This change is thought to be more profound on South Facing Slopes as the higher amounts of solar radiation cause higher amounts of moisture loss when compared to north facing slopes (McCaffrey & Hopkinson, 2020). Climate Change may also increase the probability of wildfires occurring in any given year through a predicted increase in High-Pressure systems which would bring more lightning strikes (Johnson & Wowchuk, 1993). Therefore, since lightning strikes are the dominant source of wildifire ignition in the Canadian Rockies, the increased probability of ignition combined with drier vegetation will elevate the risks for disasters like the 2017 Kenow Fire to happen again in Southern Alberta (Johnson & Wowchuk, 1993). Shorter return intervals between wildfire events could be worrisome for fire managers in Waterton since historically, the park has had large temporal gaps between stand replacing wildfire events (Eisenberg, et al, 2019).

As for indicators of the wildfires themselves, they are described as being a function of Canopy Fuel Load (CFL), Canopy Bulk Density (CBD), Crown Base Height (CBH), and Foliage moisture (Cruz, et al, 2010. Cruz, et al, 2003). Where CFL represents the potential amount of energy that can be released from wildfire and can be estimated using Biomass obtained from field observations (Cruz, et al, 2003). Quantifying CFL is often derived through estimations based in Biomass since direct CFL measurements require destructive methods that enable parts of the tree to be analyzed in a lab setting (Cruz, et al, 2010). CBD represents the weight of fuel in each space and can be estimated by dividing total biomass by canopy volume and can be used for modeling wildfire behavior and activity using computer simulations (Reinhardt, et al, 2006). CBH can be measured via visual observations in the field and is the variable that links ground

fires to the crown providing a source of ignition for Canopy Fuels. However, with CBH, current wildfire simulations often do not account for indirect fuels that bridge ground to crown such as moss and Lichen, suggesting a greater degree of variability when linking CBH to wildfire based on quantification alone (Cruz et al, 2003). When measuring these variables, single tree or plot observations are hard to extrapolate for representation of entire forest stands as there is a high degree of variability in many of these metrics (Reinhardt, et al, 2006). Therefore, it is worthwhile to utilize Lidar Data as a means of providing data to support any field based statistical model, and this is not merely hypothetical, Lidar data combined with linear regression has already been shown to be appropriate methods for modeling these variables as was seen for the Gonzales-Ferreiro study (Gonzalez-Ferreiro, et al, 2014). In addition, research by McCaffrey & Hopkinson showed the use of Lidar to analyse vegetation metrics in the Southern Canadian Rockies, thereby supporting the use of Lidar data in the same study region to predict the distribution of CFL (McCaffrey & Hopkinson, 2020).

Due to this Chapters intent on identifying areas with excess fuels, it's recommendations to wildfire management will primarily be related to the prevention and mitigation phase of wildfire management by providing knowledge that will enhance the accuracy of targeted fuel management practices (practices such as prescribed burning). Reviews of current wildfire management has proposed a paradigm shift where agencies should focus on 3 principals; increased use of prescribed burns, increased ability to identify areas vulnerable to the effects of wildfire, and the strengthened capacity and capability of agencies (such as through increased funding) (Tymstra, et al, 2020). This research will focus on the first principal of increasing use of prescribed burns in areas with excess fuel. Prescribed burning is useful because it can dampen

the severity of future wildfires by removing fuel in the forest stand, thereby limiting the amount of energy released (Tymstra, et al, 2020).

Previously outlined were the potential benefits to be found in TEK and how managers might benefit from attempts to restore Waterton to a state similar to the one found before European colonization (Eisenberg, et al, 2019). However, these efforts should be approached with caution since it is impossible completely return Waterton to its pre-colonized state due to the large degree of uncertainty and unknown variables regarding historic conditions that contemporary knowledge may be entirely ignorant of, such as how non-native species altered the fire regime or the role now endangered species like bison had in maintaining historic ecosystem functionality (Eisenberg, et al, 2019). Since these unknowns have ceased to exist and were never catalogued or quantified before their disappearance, any efforts to restore Waterton to a historic state would be futile. Instead, it can be suggested that managers turn to TEK to seek out historic processes that could have modern benefits, benefits that would not make wildfires go away, but could make current ecosystems more resilient to the changing regimes (Eisenberg, et al, 2019).

Another consideration for management strategies should be seasonality. Research specific to Waterton has suggested that the effect of prescribed burning can vary based on when the burning was applied (Eisenberg, et al, 2019). Specifically, the researchers observed that early summer prescribed burning was less effective than late summer prescribed burning, this is thought to be a factor of the late ecosystem fostering a higher count of annual vegetation that has not had time to grow during the early season (Eisenberg, et al, 2019). Indeed, the notion of early season burns were to avoid the risk associated with understory growth, ensuring that managers could remain in control of the prescribed burn (Eisenberg, et al, 2019). This follows the risk adverse principals previously outlined that Canadian wildfire agencies follow, and while the

safety-first mindset is important, the ineffective early summer burning has proven some degree of risk is needed to prevent large scale wildfire disasters (Tymstra, et al, 2020).

4.3: Chapter 4 Objectives.

Since CBH is an indirect measure of wildfire activity and CBD is mostly utilized for simulating fire behavior, this study will choose to focus on on predicting the areas with greatest potential for wildfire with the fuel variable CFL being the primary indicator, and Biomass being a supplementary variable to ensure accuracy of the CFL model. This method is most appropriate for the study since it will allow for general inferences to be made on the degree of risk for wildfires in the study area rather than trying to predict the activity of wildfire itself as that would require the use of more complex metrics that are beyond the scope of this study. In other words, this study opts to use Biomass and CFL to indicate areas where there is an elevated risk for wildfire. Through this methodology, the results can be more applicable to wildfire management strategies by advising managers on which forest characteristics are associated with more fuel.

With the goals of the methodology established, the Analytical Chapter can now identify 3 core objectives that will be appropriate to research that uses CFL as the primary metric. The first objective will be to calculate CFL from the raw field data and correlate the raw data with Lidar derived forest metrics to identify the variables to be used in the predictive model. The Lidar data that will be coupled with the field measurements was provided by technicians at the University of Lethbridge's Artemis Lab and was flown after the events of the Kenow Fire in Waterton National Park. The Lidar data being provided to support field observations recorded by other lab members. That leads into the second objective where the model itself will be developed using linear regression and applied to the study area in ArcGIS pro using Raster calculator. A model applied with raster calculator allows for the observations at the plot level to be extrapolated to

the greater Lineham and Rowe valleys. With the spatial model, statistics can be generated that describe the relationship between CFL and variables like Elevation and Aspect. The final objective will be to describe the results of the predictive model and subsequent statistical analysis in respect to its implications for wildfire management strategies in Southern Alberta.

4.4: Methodology.

Study Area.

The study area for this paper focuses on the Rowe and Lineham valleys, a hill shaded DEM of the area can be seen in *Figure 1* to give a visual of the area. This region of Waterton National Park was unburned during the Kenow fire and can serve as a proxy for quantifying fuel availability in Rocky Mountain forests that have not burned in several decades. While these regions are not actively fire suppressed, likely due to their remoteness, Waterton National Park is fire managed therefore it can be assumed that fire management strategies in other parts of the park have had at least an indirect impact on the Rowe and Lineham Valleys (Eisenberg, et al, 2019). Furthermore, the study area provides ample room to investigate spatial variation in fuel loading. Specific to this study is an investigation into the variability between fuel elevation, slope, and aspect, with north facing aspects being represented by the Rowe observations and the south facing aspects being represented by the Lineham observations. Lastly, the Lineham plots were measured in late June while the Rowe plots were measured in late August, though the temporal variation in measurements is unlikely to affect the observations since they focused on the trees themselves rather sub canopy foliage like shrubs and weeds.

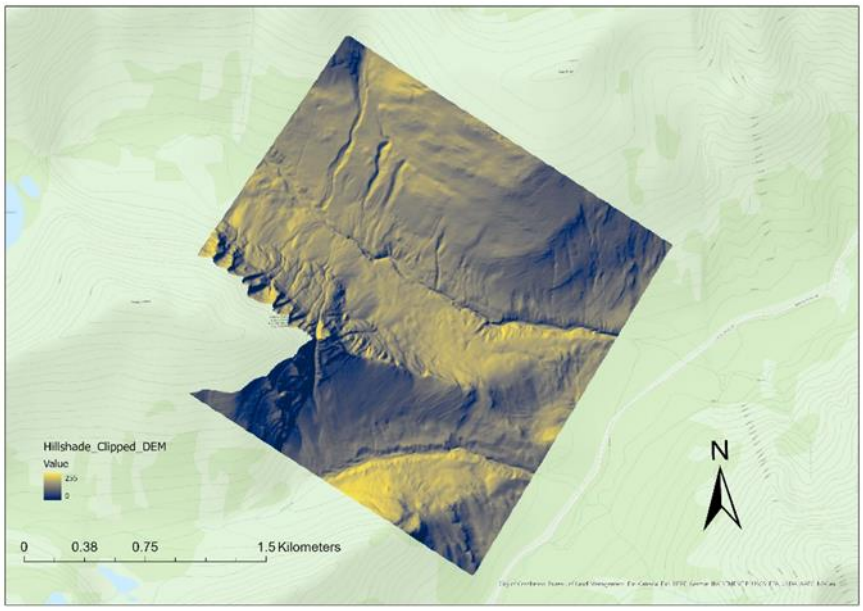

Figure 1: Hillshaded DEM of the Study area. The missing chunk is the area above 2300 m which was clipped out of the raster as it is above treeline.

Field Measurements.

To quantify biomass metrics, forest plots were measured in Rowe and Lineham valleys. These plots were a part of a transect that had each plot spaced by a distance of at least 100 m and at least a 100 m change in elevation. 5 plots were measured for the Lineham valley, and 3 plots were measured for the Rowe valley. Each plot was surveyed with a GNSS satellite transceiver supported by a base station to obtain plot coordinates which was then used for the study's analysis.

At each plot, a hypsometer was used to measure tree height, base of the live crown (LCBH), and base of the dead crown (DCBH). For LCBH, this was indicated by the lowest point of a tree still having living needles whereas DCBH was measured to be the lowest point with dead crown present e.g. brown needles. In addition, Diameter at breast height (DBH), species identification, and tree condition were also measured. DBH was measured from measuring tape or calipers and only trees with a DBH greater than 3 cm were included in the 11.3 m forest plot,

trees with a DBH less than 3 cm were considered saplings and counted in the understory plot which was not incorporated into this study. The species of the tree was identified based on visual characteristics such as the bark color, trees identified for this study were Subalpine Fir (SAF), Lodgepole Pine (LP), Engelman Spruce (ES), Douglas Fir (DF), and White Spruce (WS). The condition of the tree was indicated by visual characteristics and fell into any of the following categories Living (L), Dead (D), dead with needles (DWN), dead without needles (DWON), snag (S), and Dead with loose bark (DLB). Final mentions about the field measurements is regarding the use of flagging ribbons to keep track of measured trees to ensure there were no repeats, and the site NP2 was only half completed but the results were multiplied by 2 to account for the other half of the plot.

Once the forest plots were measured, the data was entered into excel where biomass calculations were performed. These calculations are based on the allometric equations described by Ung and Lambert where Wood, Bark, Stem, Foliage, Branches, and Crown are quantified based off the field measured DBH and Height combined with constant values for the specific tree species provided by Ung and Lambert, all the variables were then added together to get total Biomass in kg per cubic m (Lambert, et al, 2005 & Ung et al, 2008). To surmise the calculations, they use DBH, tree height, and tree species to calculate aboveground biomass of forest data along with specifying the biomass found in specific components of the tree such as its bark or stem. The results of the Biomass calculations were then used to estimate CFL using the formulas outlined by Reinhardt where CFL is a product of foliage added to half of the branch material, providing a quantified measure of CFL in kg per cubic meter (Reinhardt, et al, 2006).

Although not the target of the study, Canopy Bulk Density (CBD) was also calculated as CBD is another common metric used to describe risk for fire so this paper quantified the metric

to see if there were any significant results. The CBD calculations followed the formulas outlined by Canadian Forest Services (Canadian Forest Services, 2021). By their definition, Canopy Bulk Density is the density of total live biomass dry weight measured in kg per cubic meters. The formula used for Canopy bulk density was “Canopy Fuel load / (Height-Crown Base Height)” With crown base height being either the base of the live crown or base of the dead crown, whichever was closer to the ground.

GNSS Processing.

To process the data obtained by the GNSS transceiver, the data was uploaded as .tps files to the computers in the Artemis Lab at the University of Lethbridge, and then sent to Natural Resources Canada’s Geomatics website where their Precise Point Positioning feature provided detailed pdfs of the surveyed data including the gps coordinates (Natural Resources Canada, 2021). The GNSS outputs was processed in NAD83 coordinate system and contained detailed description of the Precise Point Positioning data including the plot coordinates. These coordinates were pulled from the pdf’s and entered into ArcGIS using the create point feature which allowed for the manual entering of the GNSS coordinates into the study’s workspace in ArcGIS.

Lidar Processing.

Lidar points were classified into ground and non-ground points and coded in a .laz file, which then allowed metrics like vegetation height to be calculated using the ground points as a baseline. The .laz file was then used with the ArcGIS toolbox LasTools, a toolbox containing a variety of Arc tools that can process Lidar data. For this study, LasHeight was used to normalize the point cloud by replacing the z coordinate value with a height value, this makes vegetation heights relative to the ground surface rather than the elevation above sea level. LasCanopy outputs were produced as 5 m resolution .tif rasters using

the height normalized .las file. The outputs from LasCanopy included height percentiles (H01, H05, H25, H75, H90, H95, and H99), statistical descriptions of the height profiles (Kurtosis, Skewness, Average, Standard Deviation, Minimum, and Maximum), Canopy Density, and Canopy Cover. Lastly, LasDEM provided a 5 m resolution DEM of the study area based on the height normalized .las file.

Statistical Analysis.

Following the application of LasCanopy, the plots were added to ArcGIS using the coordinates provided by Natural Resources Canada. Then, 11.3 m shapefiles were created around each plot and zonal statistics was applied to each radius, outputting the mean height percentile associated with each plot. This data was then entered into excel where a Correlation Matrix was developed using the correlation tool, a tool that is apart of Excels Data Analysis add on, the results of the correlation matrix can be seen in *Table 2*. The field calculated Biomass and CFL were used to calibrate the regression model, providing a point of reference for the lidar derived height metrics. The height percentiles were utilized due to their known value in predicting forest metrics such as stand density and crown height, displayed by the work of Watt and others which show that lidar height percentiles are an appropriate metric to correlate with Biomass and CFL (Watt, M.S., et al, 2013).

Canopy Fuel	*Load (kg p*	*Biomass*	*H99*	*H95*	*H90*	*H75*	*H25*	*H10*	*H05*	*H01*
Canopy Fue	1									
Biomass	0.852523	1								
H99	0.345967	0.752738	1							
H95	0.461938	0.71688	0.848036	1						
H90	0.345391	0.761519	0.996807	0.845936	1					
H75	0.341139	0.762105	0.993354	0.843943	0.999321	1				
H25	0.435078	0.783091	0.964974	0.947743	0.960323	0.956454	1			
H10	0.469254	0.772379	0.929082	0.976581	0.92117	0.916208	0.990194	1		
H05	0.465832	0.755207	0.901244	0.991109	0.89605	0.892639	0.979779	0.995697	1	
H01	0.461938	0.71688	0.848036	1	0.845936	0.843943	0.947743	0.976581	0.991109	1

Table 2: Correlation Matrix used to determine the Lidar metrics that are most associated with CFL and Biomass.

Once the Correlation matrix was developed, several methods were investigated to develop the best regression for modeling CFL in ArcGIS Pro. A simple linear regression with a 95% confidence interval served as the starting point for modelling CFL, from there, non-parametric regression was explored using methods such as power function, multiple regression, and chi square testing. The goal of non-parametric testing was to obtain a higher R^2 for the model, which succeeded, but in doing so, lowered the p value of the dependent variable coefficients. Therefore, the linear regression was decided to be the most appropriate fit with the thought being that it is better to explain less variability with stronger confidence, than to explain more variability with weaker confidence.

Once a model was decided upon, the processing moved to ArcGIS Pro where the Rasters were clipped above 2300 m as this is generally considered to be the upper limit for treeline in the Southern Canadian Rockies, beyond this point there would be a lack of vegetation that would interfere with this study's statistical analysis (McCaffrey & Hopkinson, 2020). Then raster calculator was implemented to apply the results of the regression, giving the predicted values of CFL and Biomass across the Rowe and Lineham valleys. To support the weaker linear model of CFL, Biomass was also modelled using raster calculator to ensure the results matched what was seen with the CFL. Since CFL is a derivative of Biomass, the two should have similar distributions. Slope and Aspect rasters were derived from the DEM, and the Reclassify Tool was used on the Slope, Aspect, and DEM raster to create stratified zones which would later be used for zonal statistics. These zones can be seen in *Figures 2, 3, and 4*. The stratified Slope, Aspect, and DEM layers served as the input zones for analysis with Zonal Statistics and randomly generated points, and the modeled CFL raster was used to derive statistics within each zone. This

methodology of connecting CFL to stratified Slope, Aspect, and Elevation zones allowed for an investigation into the link between CFL across the different variable zones.

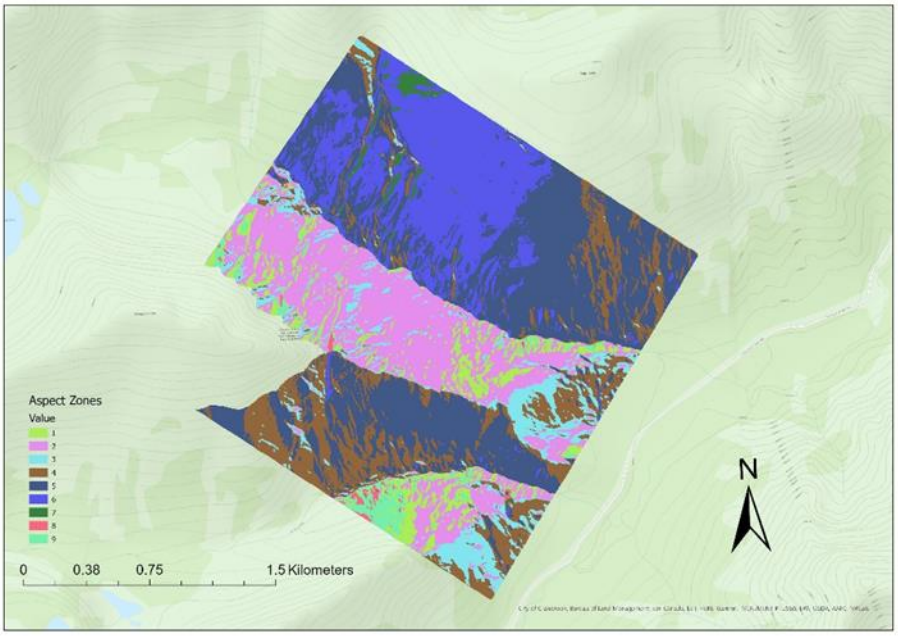

Figure 2: Aspect classified into zones for use with the ArcGIS Zonal Statistics tool.

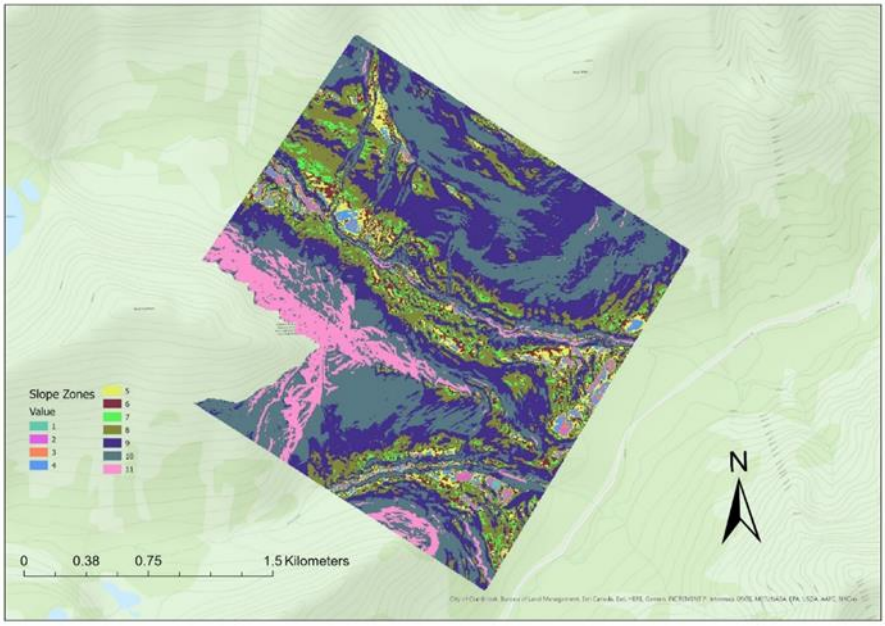

Figure 3: Slope classified into zones for use with the ArcGIS Zonal Statistics tool.

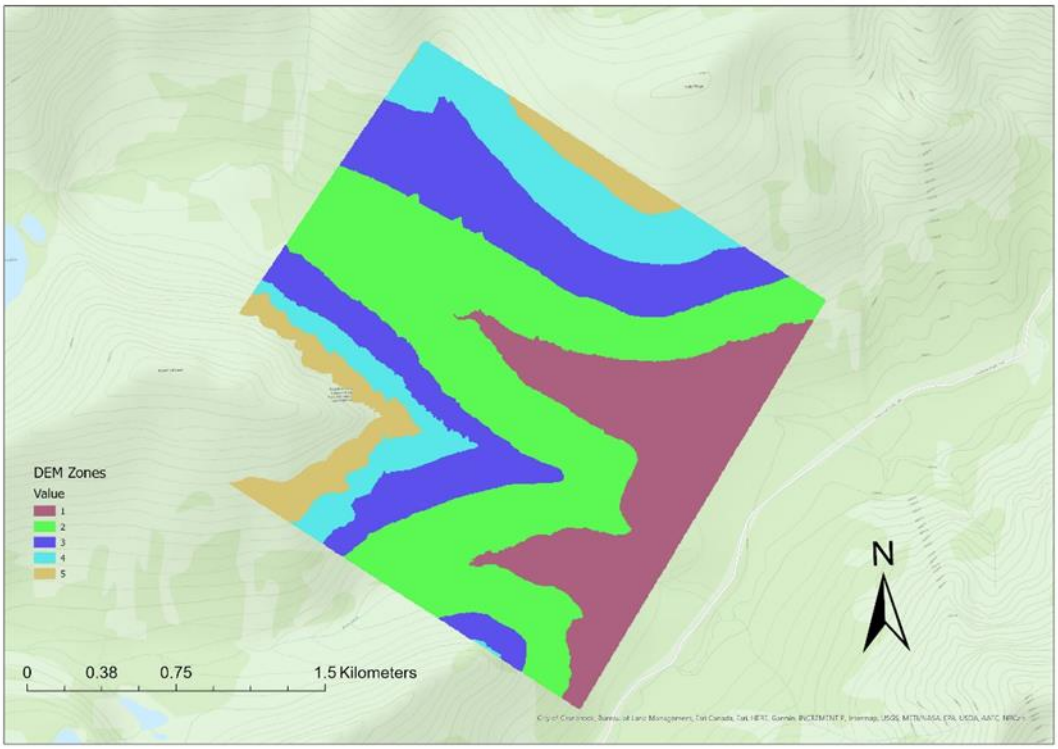

Figure 4: DEM classified into zones for use with the ArcGIS Zonal Statistics tool.

4.5: Results.

Field Measurements.

The results of the field observed CFL and Biomass calculations were converted from kg per cubic meter to kg per meter squared by dividing the metrics by 400 since there is 400 m^2 in each 11.3 m radius plot. With the units converted, Biomass and CFL were then compiled in *Table 1* found in Appendix B. The range of the field Biomass observations is 6.94 kg m^2 to 32.99 kg m^2 and the range of the CFL observations is 1.59 kg m^2 to 5.83 kg m^2. With the Biomass and CFL quantified, the values were then charted onto *Figures 5 and 6* with elevation as the x variable, these graphs establish a preliminary exploration of the relationship between elevation, Biomass, and Fuel before diving into the Lidar processing. Once charted, the field observations could then be compared to the Lidar modelling to see if the results match up and the charts also

offer a visual representation of the field observed CFL and biomass. The charts do not indicate any strong correlation on their own due to a small sample size of 8 plots (hence why Lidar was utilized in conjunction with field measurements), but the charts do suggest a slight negative relationship between Biomass and Elevation in the south slopes, whereas the CFL for the south slopes shows less variability. The data provided by the field observations are insufficient to interpret any possible relationship between the north slopes and CFL due to such a small sample size high degree of variability seen on the north slopes. Therefore the results of the Lidar analysis will be the primary method of investigating the relationship between CFL and the study variables.

	Canopy Fu	Biomass	H99	H95	H90	H75	H25	H10	H05	H01
Sp1	2193.73	13199	24.46938	4.394375	22.1175	19.89375	14.59438	10.345	8.08375	4.394375
Sp2	2108.79	11273	20.83563	3.918125	18.6675	16.76	11.26563	8.535625	6.72125	3.918125
Sp3	2141.94	10449	17.01053	2.321579	14.2979	12.32737	8.076842	5.840526	4.174211	2.321579
Sp4	2070.2	10649	16.45143	2.591429	14.18214	12.51857	8.161428	5.729286	4.527143	2.591429
Sp5	2333.59	9230	10.914	1.599333	8.978	7.522	4.007333	2.749333	2.156	1.599333
NP3	635.74	2776	10.9625	1.57875	8.753125	7.3025	3.913125	2.686875	2.151875	1.57875
Np2	1699.9	11091	19.36688	2.4525	17.90313	16.29875	8.915	5.74	4.315	2.4525
NP1	1457.91	8807	19.89476	2.078095	17.38429	15.35048	8.327619	5.288571	3.759048	2.078095

Table 1: Raw data pulled from field measurements and Lidar before being processed using statistical analysis. Canopy Fuel Load and Biomass are measured in kg per cubic meter whereas the height percentiles represent the number of Lidar laser points returned at different intervals.

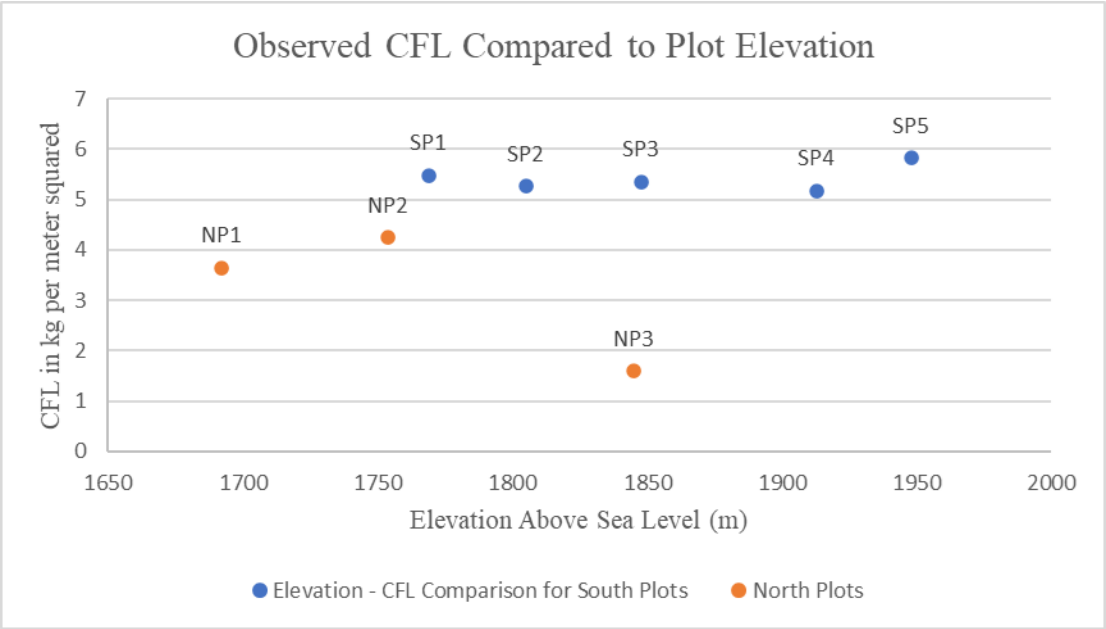

Figure 5: Observed Canopy Fuel Load derived from the raw field data compared to plot elevation.

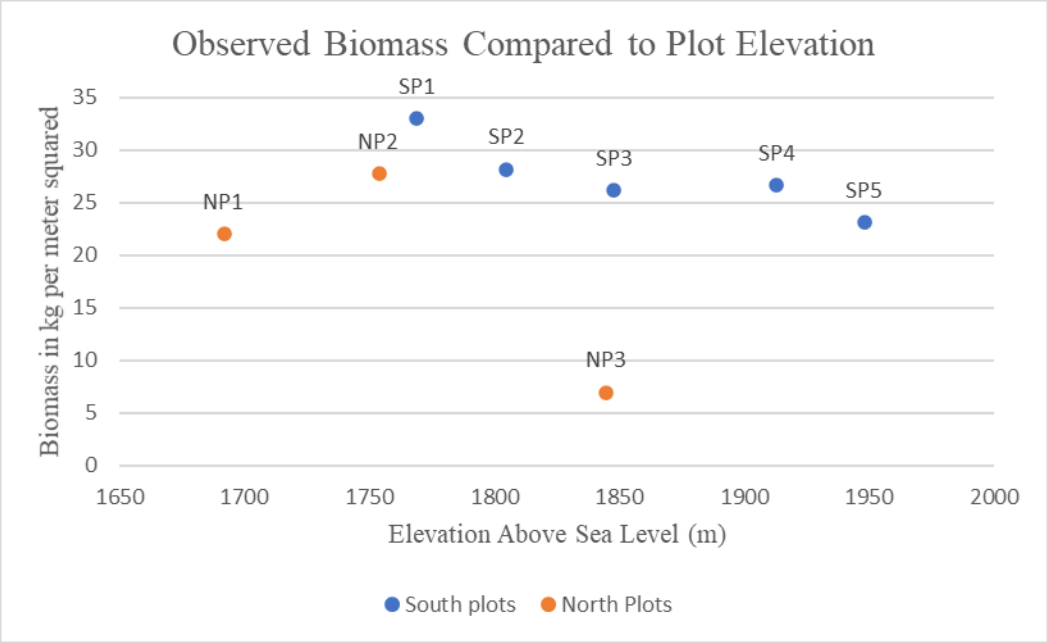

Figure 6: Observed Biomass derived from the raw field data compared to plot elevation.

Results of the Regression Model.

Along with the field measurements, *Table 1* displays the results of the LasCanopy height percentile metrics derived from LasTools. A correlation matrix was then developed based on this

data, the matrix being visible in *Table 2*. Here, the height metrics are correlated with Biomass and CFL to see which height metric would be most appropriate for regression modelling. As displayed in the table, “H10” was the most correlated metric with a CFL correlation of 0.47 and a Biomass Correlation of 0.77. Then, each metric was used as the independent variable in a regression model where CFL and Biomass were the dependent variables, the results of the regression can be seen in *Tables 3 and 4*. As previously mentioned, linear regression was not the ideal model but an R^2 of 0.22 was still worth exploring due to the sufficient correlation value. Furthermore, the p value for H10 is 0.24 in the linear regression, whereas H10 had a p value of 0.40 in the power function model. Similarly, multiple regression was attempted with other variables like canopy density, but this resulted in unrealistic model results such as negative CFL values in the output raster. Therefore, the linear regression models were decided to be the most appropriate. However, to compensate for the weaker R^2 in the CFL linear regression model, biomass was also linearly regressed with H10 and had a significantly stronger model with an R^2 of 0.59 and a H10 p value of 0.07. If the CFL model were to be at least somewhat accurate, then the results should match up with the Biomass model, and indeed this is what was seen when Raster Calculator was used to implement these models in ArcGIS Pro.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.772379							
R Square	0.596569							
Adjusted F	0.52933							
Standard I	2123.634							
Observati	8							
ANOVA								
	df	*SS*	*MS*	*F*	*gnificance F*			
Regressior	1	40013026	40013026	8.87242	0.024679			
Residual	6	27058927	4509821					
Total	7	67071954						
	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	4294.87	1958.929	2.192459	0.070834	-498.456	9088.196	-498.456	9088.196
H10	918.999	308.5276	2.978661	0.024679	164.0592	1673.939	164.0592	1673.939

Table 2: Results of the Biomass-H10 linear regression.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.469254							
R Square	0.2202							
Adjusted R Square	0.090233							
Standard Error	534.7531							
Observations	8							
ANOVA								
	df	*SS*	*MS*	*F*	*gnificance F*			
Regression	1	484497.3	484497.3	1.694278	0.240778			
Residual	6	1715765	285960.8					
Total	7	2200262						
	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	1237.185	493.2786	2.508086	0.046022	30.17601	2444.195	30.17601	2444.195
H10	101.1254	77.69045	1.301645	0.240778	-88.9763	291.227	-88.9763	291.227

Table 3: Results of the CFL-H10 linear regression.

For Biomass, the model was represented by the equation “y = 4294.87 + (918.999 * X)” where X is the H10 raster that was derived from LasCanopy, this created an output raster of predicted Biomass values across the study area provided by the H10 raster. The output raster of the Biomass model was derived from Raster Calculator and can be seen in *Figure 7*. For all output raster’s, a sliding colour scale was to show areas with higher concentrations of CFL or Biomass red was the color of choice to indicate higher risk due to the greater amount of potential

energy available during a fire event. The range of values for the Biomass raster is 10.73 kg m^2 to 108.86 kg m^2. For CFL, the model was represented by the equation "y = 1237.18 + (101.125 * X) where X is the same H10 raster used in the Biomass modeling and the output raster was of the same extent and area coverage, the only difference being that the output raster predicts CFL rather Biomass. The results of the CFL model applied to ArcGIS using Raster Calculator can be seen in *Figure 8*. The missing chunk in the CFL model is from the area clipped above 2300 m, this was not performed on the Biomass model since statistical analysis was only being applied to CFL, not Biomass. The range of values for the CFL raster is 3.09 kg m^2 to 9.17 kg m^2. Additionally, *Figure 9* is the same raster from *Figure 8* but offers a zoomed in view of the study area where the field measurements were conducted and showcases the area of the map with the highest concentration of fuel. The original units of the Biomass and CFL models were kept in kg per cubic meter but were revised with Raster Calculator to divide the values by 400 to translate them to kg per m^2.

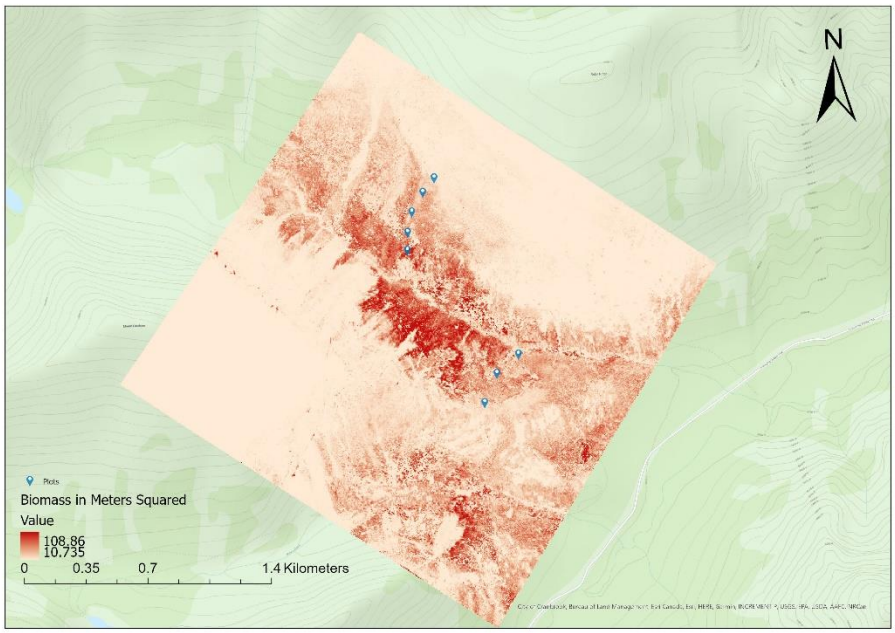

Figure 7: Results of the Biomass Model measured in kg per m^2.

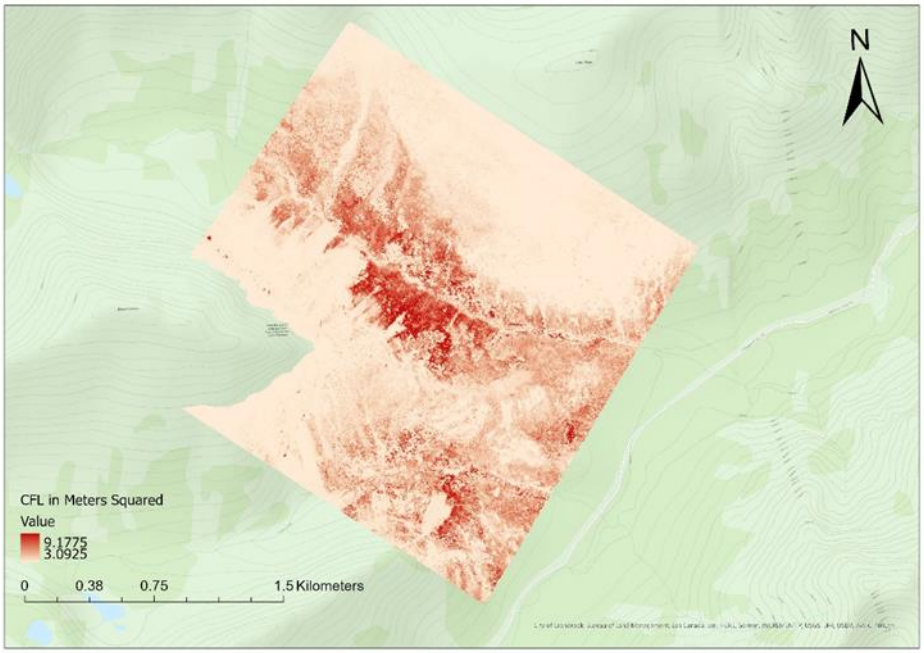

Figure 8: Results of the CFL Model measured in kg per m^2.

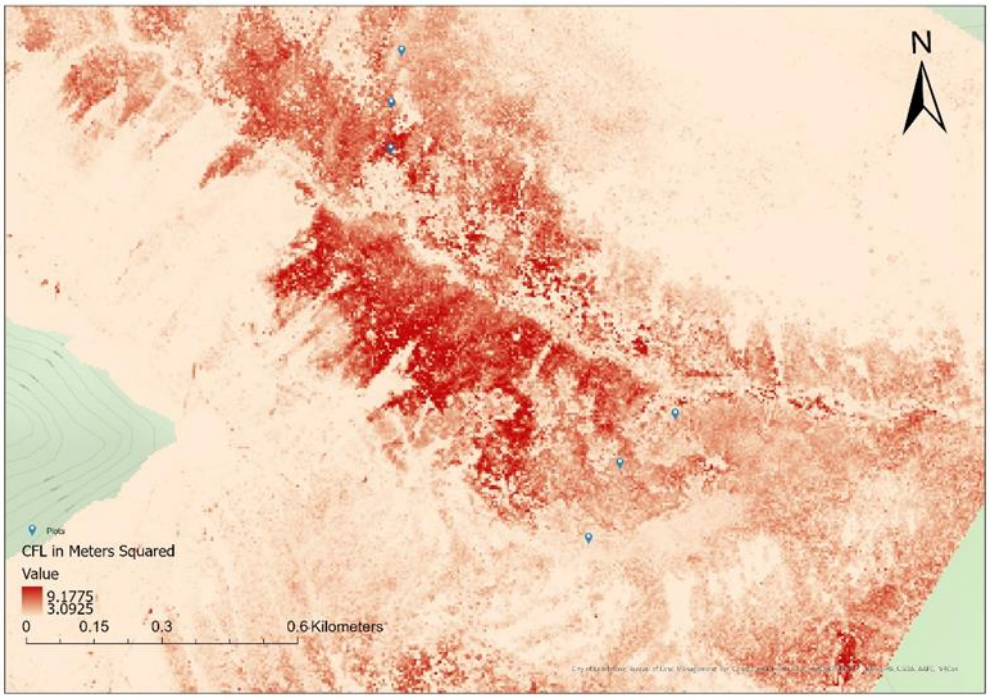

Figure 9: Results of the CFL Model zoomed into the Rowe and Lineham Valleys, results are measured in kg per m^2.

The range of output values for CFL and Biomass seem to follow a similar pattern suggesting the CFL model has accuracy since CFL would be a derivative of Biomass.

Furthermore, the results of the CFL model align with the field observations as indicated by the standard error which can be seen in *Tables 3 and 4* which display the linear regression model where the standard deviation of the predicted model fall within the expected values that were extracted from each plot. The plots that fall outside the standard deviation are NP3 and SP5, as shown in table 5. The leading explanation would be attributed to human error in the field measurements since these two plots were the highest in elevation (implying more physical exertion in reaching these plots), and it seems unlikely for the error to be a factor of the Lidar processing since it would suggest that false results were returned for the top plots but not any other areas.

OBJECTID	Shape *	Plot	Latitude	Longitude	Z	Observed CFL	Expected CFL
1	Point Z	SP1	5439735	717157.64	1769.962	2194	2503.09
2	Point Z	SP2	5439837	717159.5	1805.92	2109	1432.172
3	Point Z	SP3	5439952	717182.36	1848.194	2142	1945.889
4	Point Z	SP4	5440064	717244.89	1913.251	2070	1743.638
5	Point Z	SP5	5440146	717308.72	1948.967	2334	1505.994
6	Point Z	NP1	5439148	717787.47	1692	1457	1918.585
7	Point Z	NP2	5439038	717665	1754.422	1700	1934.765
8	Point Z	NP3	5438872	717595.8	1845	635	1551.5

Table 5: The shapefile attribute table of the field plots exported from ArcGIS Pro as an excel sheet, shows the results of CFL from the field (observed) compared to the results of CFL from the linear regression model (expected).

Statistical Interpretation of the Regression Model.

Once the raster output of the linear model was generated, Zonal Statistics and randomly generated plots were used to apply a statistical analysis to the results. For Zonal statistics, mean CFL was the statistical metric of choice due to the unequal area coverage between slope, DEM, and Raster. In other words, the zones used for zonal statistics were not equal in their area coverage, South slopes had an area coverage of 1636800 meters whereas Northwest slopes had an area coverage of 24225 meters, so to account for this, average CFL was used since the

average would account for the spatial variability between zones. The results of this analysis can be seen in *Figures 10, 11, and 12*. For elevation, a negative relationship can be seen with the lowest elevation zone containing the heights of 1570 meters to 1715.8 meters having the highest average CFL with a value of 4.37 kg m^2, then the mean progressively gets lower for each zone ending with the highest elevation zone containing heights from 2153 meters to 2299 meters and having an average CFL of 3.179 kg m^2. For aspect, the statistical zones were categorized as belonging to one of the following: Northeast, East, Southeast, South, Southwest, West, Northwest, or North. The Northeast, Northwest, and North aspects had the highest average CFL with values of 4.29 kg m^2, 4.16 kg m^2, and 4.05 kg m^2, respectively. In contrast, the South, West, and Southwest aspects had the lowest average CFL with values of 3.76 kg m^2, 3.73 kg m^2, and 3.78 kg m^2, respectively. Finally, for slope, the zones were categorized by degree angle and the trend follows a concave pattern where CFL peaks in the middle slopes and tapers off to the sides. Specifically, the zone covering angles between 8.53 and 11.3 degrees had the highest average CFL with a value of 4.59 kg m^2, and the zone covering angles between 45 and 90 degrees had the lowest average CFL with a value of 3.51 kg m^2.

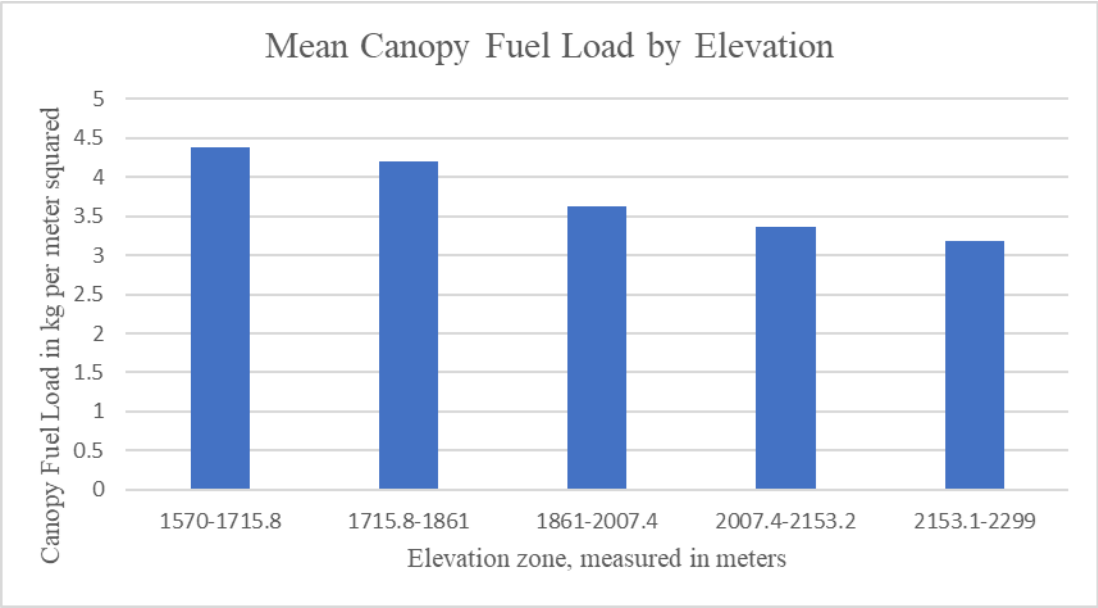

Figure 10: The average CFL charted against each respective Elevation Zone.

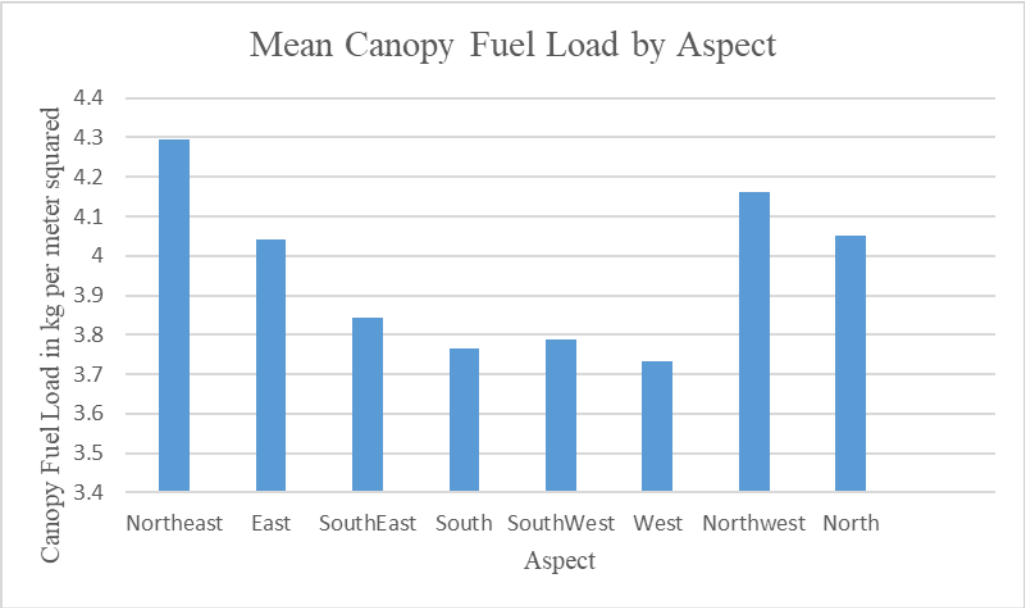

Figure 11: The average CFL charted against each respective Aspect Zone.

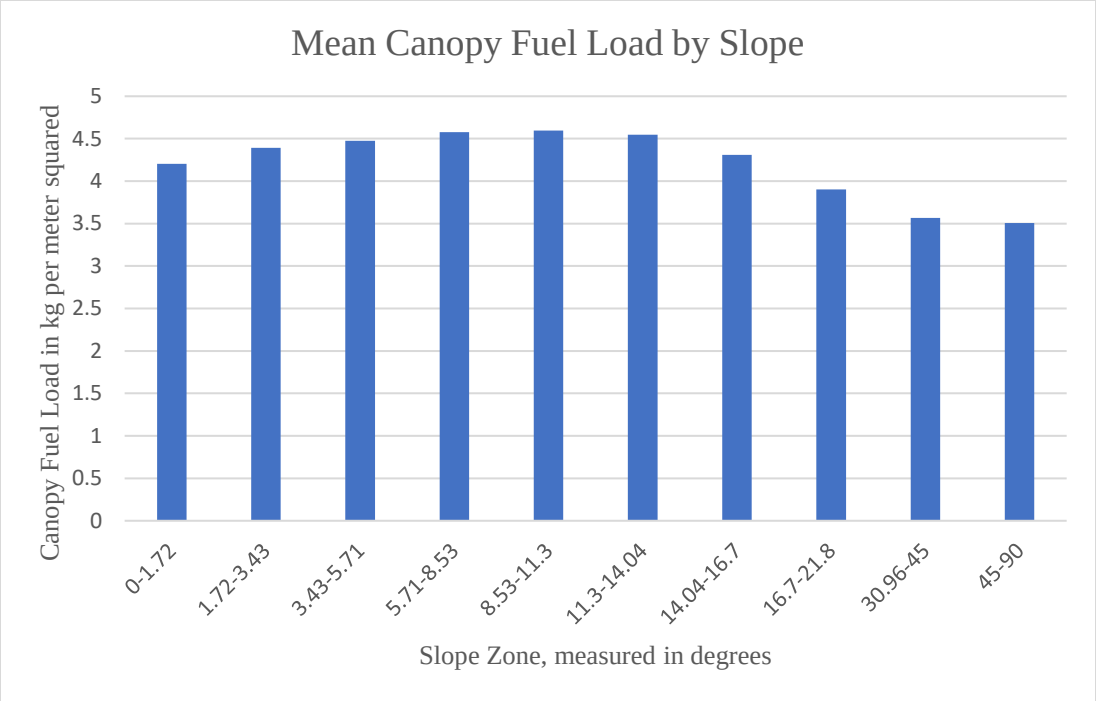

Figure 12: The average CFL charted against each respective Slope Zone.

For the randomly generated plots, the ArcGIS tool "Create random points" was used to create 500 random points and distribute them across the zones generated for each variable of interest (Slope, DEM, and Aspect). Once the random points were generated, the CFL value from the predicted raster were extracted onto a scatter plot shown in *Figure* 13, this plot allows the results of the random plots to be analyzed and compared to the field observations. The Scatter plot shows that the randomly generated plots support both the field observations, and the results of Zonal Statistics. This is because the Scatter plot shows a negative relationship with CFL and Elevation where lower elevations have more fuel.

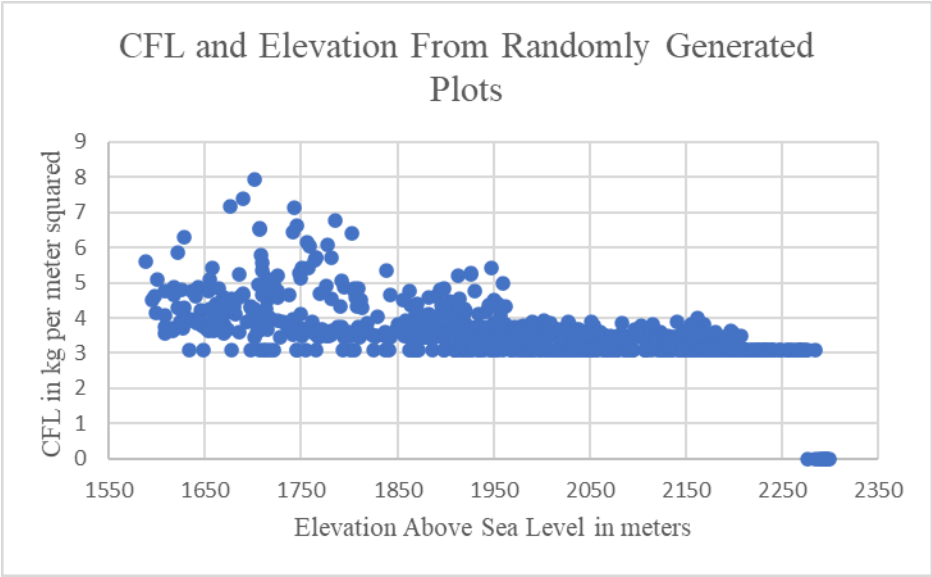

Figure 13: 500 randomly generated plots plotted by their predicted CFL value and Elevation.

Finally, the average CFL from the randomly generated plots were compared to the raw field observations by using a paired t test with a 95% confidence interval to see if the predicted CFL holds up to what was observed in the field. The results of this T test can be seen in *Table 6*. The results of the T test show a correlation metric of 0.12 and a t stat of 0.41, indicating that the CFL predicted using the linear regression matches the CFL observed in the field.

t-Test: Paired Two Sample for Means		
	Field	*kg in m2*
Mean	4.575563	4.375862
Variance	1.96452	0.055467
Observations	8	8
Pearson Correlation	0.122117	
Hypothesized Mean	0	
df	7	
t Stat	0.405597	
P(T<=t) one-tail	0.348575	
t Critical one-tail	1.894579	
P(T<=t) two-tail	0.697149	
t Critical two-tail	2.364624	

Table 6: Results of the T test comparing the CFL observed in the Field to the average CFL from randomly generated points across the predicted raster.

Results of Solar Analyst.

To further contribute to the discussion on areas at risk for fire, the ArcGIS Solar Analyst tool was used in conjunction with the CFL predictions to provide a proxy for temperature. The solar insulation was calculated based on June 21st, 2021, and incoming solar radiation was compounded by hourly intervals, the output raster can be seen in *Figure* 14. By providing a proxy for temperature, the results of the solar analysis tool allow for the identification of areas that receive more solar energy and in doing so, represent areas with a greater potential for drying of fuels, a factor that is associated with an increased risk for fire (Pausas & Keeley, 2009). The results show that the Lineham Valley, characterized by south facing aspects, receives more solar radiation than the Rowe Valley which is characterized by north facing aspects. This is an interesting result because the quantity of fuel and potential for drying seem to pose to contradictory risk factors for fire managers. On one hand, the area with more fuel availability is relatively cool and moist, but the area with less fuel availability has increased potential for

drying. Therefore, the guiding question for the discussion to follow will be which valley is at greater risk for wildfire, the dry slopes with less fuel, or the moist slopes with abundant fuel?

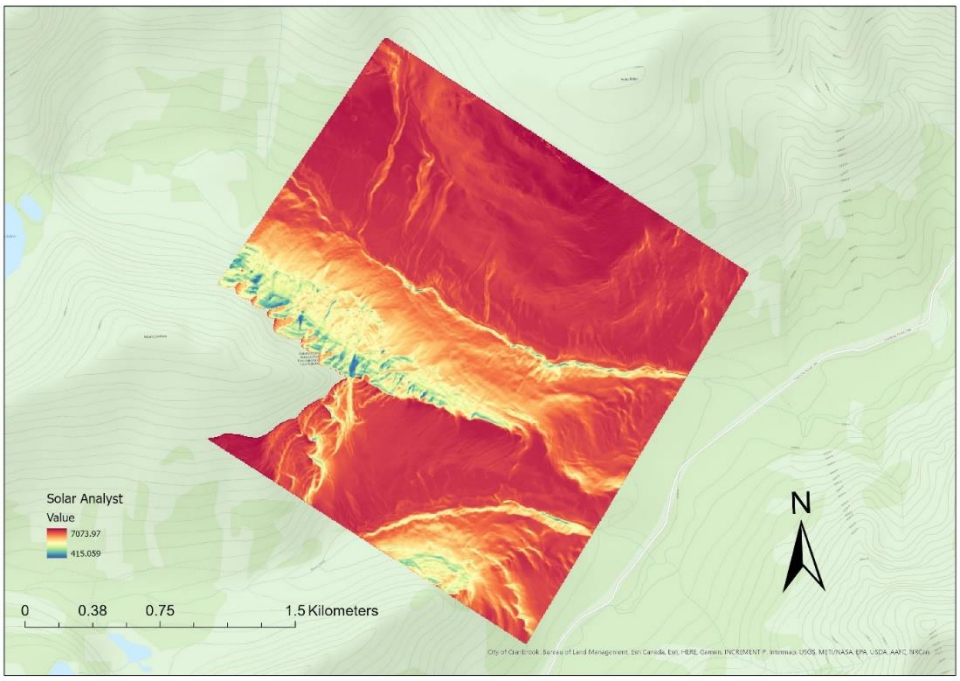

Figure 14: Results of Solar Analyst. Input values were calculated for incoming solar radiation over hourly intervals in the study area on the solar solstice, June 21st, 2021.

4.6: Discussion.

When interpreting the predicted distribution of CFL, fuel load does not appear to be a contributing variable to decreased wildfire activity on north slopes. If north slopes were less vulnerable to wildfire because of decreased fuel loading, then the results of the analysis would have shown more fuel on the south facing slopes, instead, the opposite was true. This is particularly evident when examining *Figure 9* which shows a stark decrease in CFL on South Facing slopes as opposed to north ones, even when accounting for size difference. This conclusion also aligns with the predicted Biomass values seen in *Figure 7*. Here too, the results show a decrease in vegetation on North Facing Slopes. Therefore, there must be some other driving force behind the decrease in wildfire activity on North Slopes. Moisture availability is a

potential variable of interest since previous studies have highlighted how moisture abundant areas inhibit the spread of wildfire (Schoennagel, et al, 2004). To compliment this notion, the results of Solar Analyst can be drawn upon where the decreased amount of solar radiation on North Slopes would translate to decreased rates of Potential Evapotranspiration (PET). Therefore, decreased PET levels could be future variable of interest when investigating areas that have less risk to wildfire. However, future studies would be needed to verify the correlation between PET and CFL since the results of solar analyst alone are not sufficient to draw that conclusion. Regardless of the causation behind the decreased risk of fire in north slopes, it can be recommended to land managers to focus on south slopes when employing fire mitigation strategies, but managers should be aware of the fact that north slopes may have higher amounts of fuel loading. This observation is of importance to managers because it means that certain conditions such as drought can make this fuel more readily available for burning, with external conditions such as drought having the potential to transform the relatively low risk north slopes into high-risk areas with abundant fuel. Therefore, land managers would benefit from exploring variables that are showing decrease burning on north slopes to better understand what sort of conditions could transform the north slopes into high-risk zones.

Returning to PET, the relationship this variable shares with risk for fire should be of particular concern to researchers when considering changing climate which is set to make drought like conditions more common in the Waterton region (Rood, et al, 2005). As conditions dry, the north slopes could make large quantities of fuel available for wildfire which would pose a significant risk if the slopes were to ignite. The abundance of fuel on northern slopes could enable the proliferation of wildfire disasters in the coming decades if these north aspect fuels undergo transformations that make the excess CFL readily available for combustion. To better

prepare for drier conditions, the causation for decreased fire risk on north slopes should be a focus of future research since it is evidently not related to limited fuel loading.

As for the relationship between decreased fire risk and elevation, the results of this analysis align with the findings of Rogeau and Armstrong where they displayed increases in elevation decrease wildfire burning by upwards of 33% (Rogeau & Armstrong, 2017). The predictive model of this study's analysis shows decreased amounts of CFL at higher elevations with a negative relationship between average CFL and elevation being shown in *Figure 10*. Additionally, the Biomass model also saw decreased amounts of Biomass at higher elevations, matching the findings of the CFL model. Therefore, limited fuel availability can be regarded as a contributing factor to decreased risk for fire at higher elevations however the causation for limited CFL at higher elevations cannot be determined based on this analysis. Meaning, the source of lower fuel loads at higher elevations was beyond the scope of this study. This is also supported by the comparison between observed and predicted CFL verified by a t test between the two, also showed a negative relationship between elevation and CFL when arranged in the *Figure 13* scatter plot. Here, the randomly generated plots followed similar trends to the predicted values, further supporting decreased fuel at higher elevations.

Moving to slope, *Figure* 12 shows that the prime angles that promote fuel availability are between 5.71 and 14.04 degrees. This is a factor that should be taken into consideration by land managers when identifying areas for fuel management since angles within this range have higher amounts of fuel availability. However, it is important to note that this study did not isolate for slope and other compounding variables could have influenced this conclusion, such as increased moisture availability on those angles. This prevents the direct correlation between slope and fuel availability, but the observation adds another variable land managers can consider when

examining areas to conduct fuel management and creates room for a future study to isolate the influence of slope on fuel availability to confirm whether there is a direct correlation between slope and fuel load.

The modelling demonstrated by this study show the utility Lidar has in identifying areas with an elevated risk for wildfire via the presence of excess fuel load, with the identification of such areas holding being of particular value to wildfire managers who can then implement proper mitigation strategies to lower fire risk. Of notable interest to future predictions of CFL would be the coupling of Lidar metrics with ground observations as this could yield promising results when modelling wildfire risk over large areas. Further refinement of such coupling should be investigated to identify specific Lidar metrics that can be used on larger scales. This study has shown the benefits of the H10 CFL coupling but other studies would be needed to see how this applies to other forests across Canada. If standard Lidar metrics are developed for predicting CFL, then Lidar could be used to model CFL over large spatial areas, such as the entirety of Waterton National Park, along with the modelling of regions that are difficult to measure in the field. Indeed, the use of Lidar data to predict CFL distributions has high utility for remote regions that are hard to access, added accuracy could be enabled if field measurements are sampled along access roads while Lidar metrics provide data to quantify the rest of the areas fuel load.

4.7: Areas for Future Research.

This paper identifies areas for future research that can contribute to a better understanding of wildfires in the Canadian Rockies. Primarily, a study investigating the potential for northern slopes to facilitate wildfire disasters by drying out and creating a large source of CFL, researching this topic will help wildfire agencies develop dynamic strategies that will be

beneficial to lowering the damage done by wildfires in the climate change afflicted world. Something future investigations regarding the moisture-wildfire relationship should consider is the influence of species on moisture retention as different species have previously been shown to utilize water in different ways (Kelsey, et al, 2018). Primary species of interest in the Waterton area could include Subalpine fir which is thought to be more prone to moisture loss, and Englemen Spruce which is thought to be better suited for moisture retention (Kelsey, et al, 2018). Additionally, studies investigating the causation behind decreased CFL at higher elevations to further explore the connection made to higher elevations and decreased risk for wildfire, and a study that isolates the relationship between slope and fuel would also be of benefit to wildfire agencies. By researching these topics, managers can optimize their fuel management strategies by enhancing the accuracy of targeted efforts to maximize the effectiveness of the practices, ensuring that fuels are treated in the most ideal locations.

4.8: Conclusion.

The findings of this paper have shown that areas at higher elevations, north facing aspects, and slopes above 14.04 degrees tend to have less quantities of crown fuel available for fire. Therefore, it can be recommended that wildfire managers in Waterton National Park focus efforts of prescribed burning on areas that fall outside of those parameters. Though it is important to recognize that other factors such as moisture availability or seasonal variation may alter the fuel availability of the predicted distribution. Creating a need for a study investigating how fuel availability changes on a temporal scale and under different environmental conditions. The call for a dynamic approach to understanding fuel distribution demonstrates the need for wildfire managers to take a holistic approach when considering strategies as there exists a need to account for how areas at risk for fire, characterized by elevated fuel availability, can alter with

changing environmental conditions. A dynamic understanding of fuel availability would further support notions that suggest turning away from standardized management practices, and instead, shift towards adaptive strategies that change based on current conditions and location specific variables (Pausas & Riberio, 2013). One potential tool for a dynamic management system could be the utilization of Lidar derived metrics to predict fire risk over large spatial scales.

Chapter 5: Conclusion.

To summarize, this thesis has investigated potential factors influencing the spatial distribution of fuel in the Rowe and Lineham valleys of Waterton National Park using a combination of field observations and Lidar derived height metrics to address the increasing threat wildfires pose to modern society (Tymstra, et al, 2020). The factors influencing the distribution were studied in effort to better understand what environmental conditions allow for excess fuel loading and to contribute to the contemporary understanding of wildfire behavior in a climate change afflicted world. Understanding the distribution of fuel will be crucial in the coming decades as wildfire managers seek to optimize mitigation strategies to adapt to an increasingly active wildfire regime holds utility to wildfire managers when employing mitigation strategies (Tymstra, et al, 2020). Additionally, this study offers location specific information regarding the fire regime in Waterton, addressing calls for location specific wildfire management strategies that account for the large degree of variability between forest ecosystems (Pausas & Riberio, 2013). While this study helps contribute to that need, it is only one small step towards a greater understanding of contemporary wildfires and there still exists large areas further research should explore. In exploring these research areas, modern society can become more resilient to changing wildfire regimes as the world faces continuous warming from climate change, but only with the proper understanding, can this resilience be achieved (Coogan, et al, 2019).

Bibliography

Buechling, A., Canham, C., Martin, P. (2017). Climate and competition effects on tree growth in Rocky Mountain forests. *Journal of Ecology*, vol. 105, iss. 6, pp. 1636-1647. https://doi.org/10.1111/1365-2745.12782

Canadian Forest Services. (2021). Fuels in the Context of the Next-Generation Canadian Forest Fire Danger Rating System (NG-CFFDRS). *The Fire Danger Group of the Canadian Forest Service of Natural Resources Canada*

Chileen, B. V., McLauchlan, K. K., Higuera, P. E., Parish, M., & Shuman, B. N. (2020). Vegetation response to wildfire and climate forcing in a Rocky Mountain lodgepole pine forest over the past 2500 years. *The Holocene*, 30(11), 1493–1503. https://doi.org/10.1177/0959683620941068

Coogan, Sean C.P., et al. (2019). "Scientists' warning on wildfire--a Canadian perspective." Canadian Journal of Forest Research, 49(9), 1015+.

Cruz, M.G., et al. (2010). Comment on 'estimating canopy fuel characteristics in five conifer stands in the western United States using tree and stand measurements'. *Canadian Journal of Forest Research*, 40(11), 2262+.

Cruz, M.G., Alexander, M.E., Wakimoto, R.H. (2003). Assessing Canopy Fuel Stratum Characteristics in Crown Fire Prone Fuel Types of Western North America. *International Journal of Wildland Fire*, 12(1), 39-50.

Dennison, P., Brewer, S., Arnold, J., Moritz, M. (2014). Large wildfire trends in the western United States, 1984–2011. *Geophysical Research Letters*, 41(8), 2928 – 2933. https://doi.org/10.1002/2014GL059576

Eisenberg C, Anderson CL, Collingwood A, Sissons R, Dunn CJ, Meigs GW, Hibbs DE, Murphy S, Kuiper SD, SpearChief-Morris J, Little Bear L, Johnston B and Edson CB (2019). Out of the Ashes: Ecological Resilience to Extreme Wildfire, Prescribed Burns, and Indigenous Burning in Ecosystems. *Front. Ecol. Evol.* 7(436). 10.3389/fevo.2019.00436

Germino, M. J., Smith, W. K., & Resor, A. C. (2002). Conifer Seedling Distribution and Survival in an Alpine-Treeline Ecotone. *Plant Ecology*, 162(2), 157–168. http://www.jstor.org/stable/20051292

Gonzalez-Ferreiro, Eduardo, et al. (2014). Modelling Canopy Fuel Variables for Pinus Radiata D. Don in NW Spain with Low-Density LiDAR Data. *International Journal of Wildland Fire*, 23(3), 350-362.

Harder, P., Pomeray, J., Westbrook, C. (2015). Hydrological resilience of a Canadian Rockies headwaters basin subject to changing climate, extreme weather, and forest management. *Hydrological Processes*, 29(18), 3905-3924. https://doi.org/10.1002/hyp.10596

Holsinger, L., Parks, S., Miller, C. (2016). Weather, fuels, and topography impede wildland fire spread in western US landscapes. *Forest Ecology and Management*, 380, 59-69. https://doi-org.ezproxy.uleth.ca/10.1016/j.foreco.2016.08.035

Hopkinson, C., et al. (2012). Spatial snow depth assessment using LiDAR transect samples and public GIS data layers in the Elbow River Watershed, Alberta. *Canadian Water Resources Journal*, 37(2), 69-87. https://doi.org/10.4296/cwrj3702893

Johnson, E.A. & Wowchuk, D.R. (1993). Wildfires in the southern Canadian Rocky Mountains and their relationship to mid-tropospheric anomalies. *Canadian Journal of Forest Research*, 23(6), 1213-1222. https://doi.org/10.1139/x93-153

Kellie A. Uyeda, Douglas A. Stow & Philip J. Riggan (2015). Tracking MODIS NDVI time series to estimate fuel accumulation, Remote Sensing Letters, 6(8), 587-596. 10.1080/2150704X.2015.1063736

Kelsey, K.C., Redmond, M.D., Barger, N.N. et al. (2018). Species, Climate and Landscape Physiography Drive Variable Growth Trends in Subalpine Forests. *Ecosystems* (21), 125–140. https://doi-org.ezproxy.uleth.ca/10.1007/s10021-017-0139-7

Krawchuck, M. & Moritz, M. (2011). Constraints on global fire activity vary across a resource gradient. *Ecology*, vol. 92, pp. 121-132. https://doi.org/10.1890/09-1843.1

Lambert, M.C., Ung, C., Raulier, F. (2005). Canadian national tree aboveground biomass equations. Canadian Journal of Forest Research, 35(8), 1996-2018. https://doi.org/10.1139/x05-112

McCaffrey, D., Hopkinson, C. (2020). Repeat Oblique Photography Shows Terrain and Fire-Exposure Controls on Century-Scale Canopy Cover Change in the Alpine Treeline Ecotone. *Remote Sensing*, vol. 12, Iss. 1569, p. 1569. https://doi.org/10.3390/rs12101569

Moritz, M. A., Morais, M. E., Summerell, L. A., Carlson, J. M., & Doyle, J. (2005). Wildfires, complexity, and highly optimized tolerance. *Proceedings of the National Academy of Sciences of the United States of America*, *102*(50), 17912–17917. https://doi.org/10.1073/pnas.0508985102

Natural Resources Canada. (2021). Precise Point Positioning. Natural Resources Canada. https://webapp.geod.nrcan.gc.ca/geod/tools-outils/ppp.php?locale=en.

Pausas, J. & Keeley, J. (2009). A Burning Story: The Role of Fire in the History of Life. *BioScience*, 59, 593-601. https://doi.org/10.1525/bio.2009.59.7.10

Pausas, J. & Riberio, E. (2013). The global fire-productivity relationship. *Global Ecology and Biogeogrpahy*, 22, 728-736. https://doi.org/10.1111/geb.12043

Reinhardt, E., Lutes, D., Scott, J. (2006). FuelCalc: A Method for Estimating Fuel Characteristics. *USDA Forest Service.*

Rogeau, M.P. & Armstrong, G. (2017). Quantifying the effect of elevation and aspect on fire return intervals in the Canadian Rocky Mountains. *Forest Ecology and Management*, 384, 248-261. https://doi.org/10.1016/j.foreco.2016.10.035.

Rood, S., Samuelson, G.M., Weber, J.K., Wywrot, K.A. (2005). Twentieth-century decline in streamflows from the hydrographic apex of North America. *Journal of Hydrology*, vol. 306, iss. 1-4, pp. 215-233. https://doi-org.ezproxy.uleth.ca/10.1016/j.jhydrol.2004.09.010

Schoennagel, T., Veblen, T., Romme, W. (2004). The Interaction of Fire, Fuels, and Climate across Rocky Mountain Forests. *BioScience*, 54(7), 661–676, https://doi-org.ezproxy.uleth.ca/10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2

Tymstra, C., Stocks, B., Cai, X., Flannigan, M. (2020). Wildfire management in Canada: Review, challenges and opportunities. *Progress in Disaster Science, 5, 100045.* https://doi.org/10.1016/j.pdisas.2019.100045.

Ung, C., Bernier, P., Guo X.J. (2008). Canadian national biomass equations: new parameter estimates that include British Columbia data. *Canadian Journal of Forest Research*, 38(5), 1123-1132. https://doi.org/10.1139/X07-224

Vukomanovic, J., Steelman, T. (2019). A Systematic Review of Relationships Between Mountain Wildfire and Ecosystem Services. *Landscape Ecol*, 34, 1179–1194 https://doi-org.ezproxy.uleth.ca/10.1007/s10980-019-00832-9

Watt, M.S., Meredith, A., Watt, P. et al. (2013). Use of LiDAR to estimate stand characteristics for thinning operations in young Douglas-fir plantations. N.Z. j. of For. Sci. 43, 18. https://doi.org/10.1186/1179-5395-43-18

Zhao, F., Keane, R., Zhu, Z., Huang, C. (2015). Comparing historical and current wildfire regimes in the Northern Rocky Mountains using a landscape succession model. *Forest Ecology and Management*, 343, 9-21.