AN ABSTRACT OF THE FINAL REPORT OF

Diane M. Carrico for the degree of Master of Science (M.S.) in Environmental Sciences presented on January 5, 2023.

Title: Assessing the roles of aspect and wildfire intensity on vegetation recovery over time: the 2017 Eagle Creek Fire

Abstract approved:

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John D. Bailey

Following a century of fire suppression legislation within the United States, the increase in size and intensity of wildfires has highlighted the need for additional study on fire-landscape interactions. Fire suppression combined with increasing human spatial density and extent have contributed to an environment where fuel accumulation and location increases the risk of harm to both human-specific needs and environmental thresholds. This is especially the case in spaces that developed overburdened fuel loads and fire is no longer safe as a management practice. This generates further concern regarding how to address an ecological need for fire while protecting the well-being of community members. Scientifically informed land management practices would help address human and non-human environmental needs with respect to the current state of fuel conditions and practices.

Knowing how wildfire impacts the ecology within a landscape is part of informing land management practices. This may include determining where to concentrate intervention measures pre- and post-fire, what intervention measures to take, the relative risk factor of fire events, and the duration at which regeneration processes may occur. While there are several studies regarding singular characteristics of a post-fire environment, there is a lack of research comparing relative strengths of variable influences within them. This study adds to wildfire research by comparing vegetation, burn severity, and topographic features to characterize the relationships between these variables through post-fire ecological recovery. Using remote sensing tools and industry-vetted indices to represent selected variables, the goal is to describe what these indices and interactions convey within the study area and how they could apply to environmental decision-making.

The study area was the 2017 Eagle Creek Fire burn zone located near Cascade Locks, Oregon. The terrain is hilly, complex, and dominated by a mixed-conifer forest whose fire regime is on the scale of hundreds of years. This region exemplifies the rugged terrain of the Pacific Northwest, is culturally significant, adjacent to a dense urban area, and has a limited fire history due to long fire return intervals. Therefore, it is an appropriate case study to analyze the interplay of human, ecology, and land management objectives when limited information exists.

Assessing the role of aspect and wildfire intensity on vegetation recovery over time: the 2017 Eagle Creek Fire

by
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APPROVED:

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John D. Bailey, representing Environmental Science

I understand that my final report will become part of the permanent collection of the Oregon State. My signature below authorizes release of my final report to any reader upon request.

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Diane M. Carrico, Author

Dedication and Acknowledgement

When contemplating my career path, my desire for publication, and the body of my scientific work, I became increasingly aware of the struggles women face to be equitably recognized as valuable members of the community. Such a struggle, in fact, that women have felt compelled to consider hiding their gendered name to evade discrimination and bias when producing credible work. It is a tragedy when the tenets of scientific reasoning are forgotten in favor of denying the important discoveries of a fellow scientist.

I dedicate my work and my words to the women in science whose names have been buried beneath the heels of their community. I dedicate this to their allies, their families, and our collective communities and ecosystems that suffer at the hands of sexism. Your light is worth shining.

My name is Diane. I am a whole person. I am a scientist. This is my work.

Table of Contents

List of Figures

List of Tables

Introduction

Over the last century, the United States has experienced significant shifts in land management practices, human population dynamics, and fire-based natural disasters. Fire suppression legislation and practices implemented by government and land management officials in the early 1900s changed the landscape and ecosystem dynamics in ways that had not been anticipated (Nowacki et al., 2008, Steen-Adams et al., 2019, Robbins, 2021). Although suppression was enforced with the intent to protect people, economies, and ecosystems, the resulting megafires and ecosystem shifts have demonstrated the importance of fire and the error of using blanket suppression methods. Suppression efforts quite literally added more fuel to the fire and demonstrated the need for greater understanding and research into how fire interacts with the landscape and ecosystems.

The resultant fuel-laden landscape, climate change, and increasing human spatial density and extent have created an environment where severe wildfire threatens both human-specific needs and environmental thresholds (Robbins, 2021, Westerling et al., 2006). This is especially the case in spaces where fire is no longer a safe management practice due to the development of overburdened fuel loads. Now legislators and land managers are tasked with figuring out how we can address an ecological need for fire while protecting the well-being of community members. Scientifically informed land management practices would help address human and non-human environmental needs with respect to the current state of fuel conditions and practices.

Knowing how wildfire impacts the ecology within a landscape is part of informing land management practices and, in turn, informing associated legislation. This may include determining where to concentrate pre- and post-fire intervention measures, what intervention measures to take, the relative risk factor of fire events, and the duration at which regeneration processes may occur. While there are several studies regarding singular characteristics of a post-fire environment, there is a lack of research comparing the relative strengths of variable influences within them. This study adds to wildfire research by comparing vegetation, burn severity, and topographic features to characterize the relationships between these variables through post-fire ecological recovery. Using remote sensing tools and industry-vetted indices to represent selected variables, the goal of this project is to describe what relevant indices and interactions convey within the study area and how they could apply to environmental decision-making.

The fire of interest for this study was the 2017 Eagle Creek Fire (Figure 1). Analysis of the study site concentrated on the post-fire vegetation growth within the burn zone over time. The fire began in September 2017, was 100% contained in November 2017, and

remained burning into May 2018 (USGS, 2022). The study area is located near Cascade Locks, Oregon and sits east of Portland, Oregon. The terrain is hilly, complex, and dominated by a mixed conifer forest whose fire regime is on the scale of hundreds of years (USGS, 2022). This region exemplifies the rugged terrain of the Pacific Northwest (Figure 2), is culturally significant, sits adjacent to a dense urban area, and has a limited fire history due to long fire return intervals. Therefore, it is an appropriate space to analyze the interplay of human, ecology, and land management objectives when limited information exists.

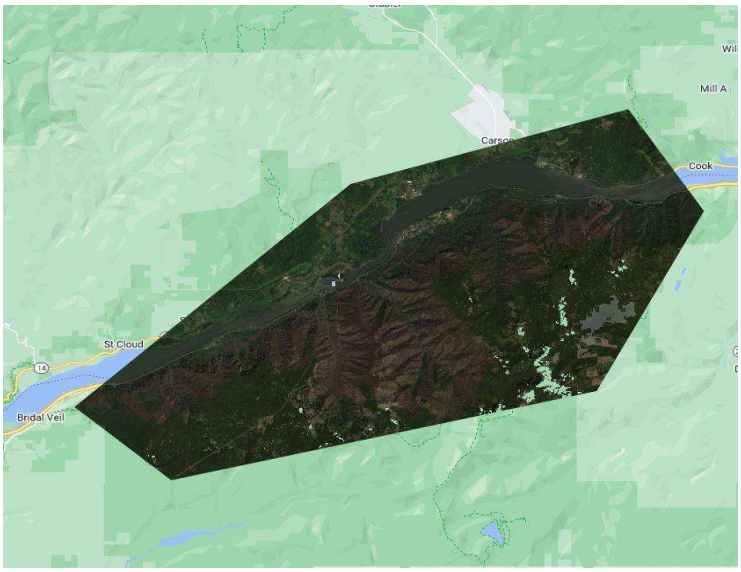

Figure 1: A Google Earth Engine image of the study area near Cascade Locks, Oregon. The post-fire true color image in the center indicates the study area and its boundaries.

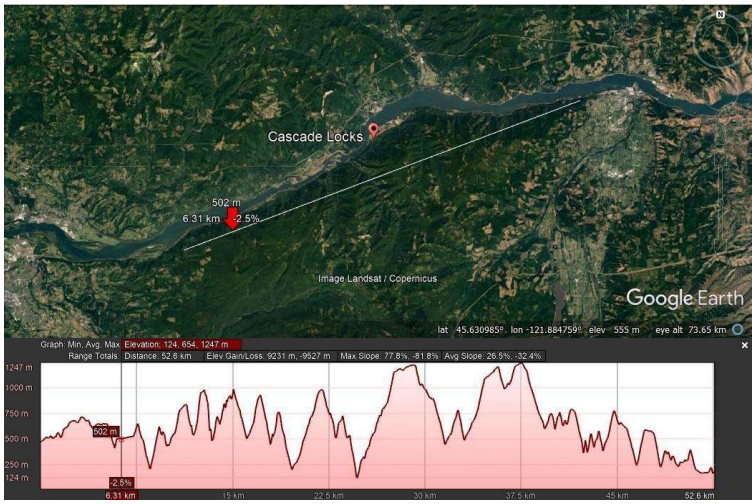

Figure 2: A Google Earth image and topographic profile of the Eagle Creek study area in Oregon. The line shown diagonally across the study area corresponds to the topographic profile. The red arrow on the map corresponds with the vertical marker line on the topographic profile.

While many factors can influence the growth of vegetation at various spatial and temporal scales (Solon et al., 2012), this study focuses on the control mechanisms of burn severity, topographic aspect, and their respective relationship with vegetation patterns through post-fire ecological recovery (Figure 3). Burn severity is a valuable control that measures how extreme a fire event was for a given area (Keeley, 2009). Burn severity is defined in this study as the amount of change on the surface of the earth detected by pre- and post-fire satellite imaging using the Difference Normalized Burn Ratio (dNBR) index. The effects of fire can alter environmental factors such as soil composition and exposure, vegetation and canopy density, and species composition. Aspect represents a comparatively static topographic feature and is related to relative atmospheric conditions such as exposure to sun, dominant winds, and amount of rain an area receives.

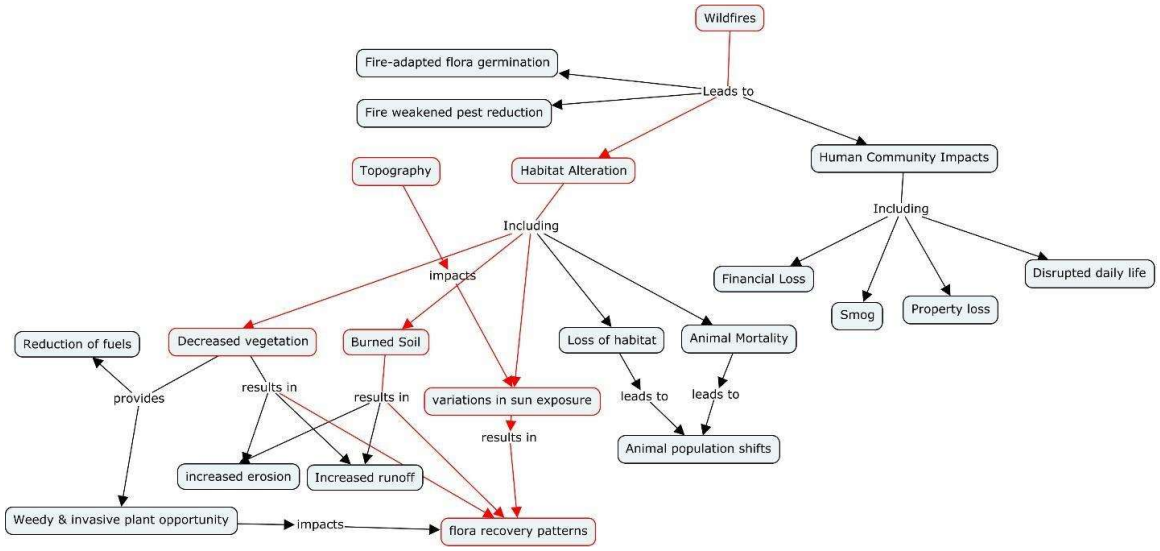

Figure 3: The concept map and focal pathway depicts the relationship and influences between wildfires and flora recovery patterns. The focal pathway indicates the variables and influences discussed in this study.

By considering vegetation and these control mechanisms over time, we can glean valuable information about how they influence vegetation and the duration of time any impacts are reflected within the vegetation indices. Additionally, by comparing multiple control mechanisms, we can analyze their relative strengths and how their level of influence may change through time. This knowledge can inform pre- and post-fire land management decisions when electing where, when, and how to intervene with ecological processes.

Due to limited access and the size of the study area, remote sensing tools and indices will be used. The Normalized Difference Vegetation Index (NDVI) will be used to represent vegetation with values ranging between -1 and 1 (Harris et al., 2011). The Difference Normalized Burn Ratio (dNBR) will be used to represent burn severity with values that range from -2 to 2. Topographic aspect is an indicator of orientation and will be measured in degrees ranging from 0 to 359.99. While NDVI cannot determine specific species, it is commonly used to represent characteristics such as the health and density of vegetation. Therefore, species-level discussion will be limited and the outcome of the study will be based upon the quantitative data provided by each respective index.

This study addressed three major goals:

1) to determine what, if any, pre-fire relationship exists between NDVI at Year 0 and the static values of burn severity and aspect, respectively. The Year 0 NDVI included a review of the years 2013-2017 prior to the onset of the fire. The establishment of "healthy" versus "browning" vegetation in this environment provides insight into how

fire might behave within this region. Comparing this initial analysis to post-fire data can validate the accuracy of an initial hazard assessment.

2) to analyze the post-fire environment's (Year 1) spatial relationships between NDVI for Year 1, aspect, and burned regions. This included an analysis of fire intensity and severity (dNBR) in terms of the percentages of low-, moderate-, and high-severity burns. The location of refugia (vegetation that survived within a fire perimeter) was compared to indices and environmental factors, then was cross-referenced to Year 0 NDVI to determine differences and spatial relationships of vegetation between years. While Year 0 represents the pre-fire environment, Year 1 represents one phenological cycle after the fire.

3) to determine if burn severity or aspect acts as the primary control mechanism on long-term (Year 2 - 4) post-fire vegetation recovery, how that relationship manifests, and how it behaves through time. This determines a.) if aspect or burn severity acts as a control mechanism on post-fire vegetation recovery; and b.) which one, if either, may act as a stronger control over another. By reviewing annual NDVI data, I determined over what length of time aspect or burn severity impacts post-fire vegetation growth.

The information gained from this project could be used in land management and wildfire-related decision-making when the burning or denuding of vegetation occurs. Knowing information about features that would impinge upon regrowth rates or have side effects such as increased erosion or changes to watershed dynamics could help inform land management practices. This could include determining where to concentrate pre- and post-fire intervention measures, where it is most appropriate to intentionally remove vegetation, where a fire may be likely to occur, and the duration at which regeneration processes may occur.

Ecology of the Ecosystem and Fire Adaptive Traits

The study site lies within the mesic forest zones of the Western Cascades in the state of Oregon and along the Columbia River Gorge. These forest zones are relatively moist, mixed conifer forests that are primarily composed of western hemlock (*Tsuga heterophylla*), silver fir (*Abies amabilis*), and Douglas-fir (*Pseudotsuga menziesii var. menziesii*) (Fire Management, 2022). Mesic forests can range between 0 and 2,133 meters in elevation with the aforementioned species being either dominant or co-dominant (Tesky, 1992, Uchytil, 1991). This wide elevation range accounts for variability of species ranges in both their northern and southern extent, the overlap in the species ranges, and the variability of moisture levels where respective species are found. Due to this variability, it can be difficult to pinpoint mesic areas based on species alone. Additionally, identifying specific fire regimes for these areas can be difficult when classifying regimes by species alone, as the species can be found within a range of regimes. The data points collected for this study ranged between 2 and 1461 meters.

Western hemlock grows well in environments that range from "very poor" to "medium" in nutrients (Tesky, 1992). It additionally tends to grow in dense stands and is a good habitat for lichen, which increases fuel continuity (Tesky, 1992). Douglas-fir does not tolerate temperature below 14 degrees Fahrenheit for longer than a week so tends to be restricted in elevations (Uchytil, 1991). It reaches diameters of 1.5-1.6 meters and heights around 76 meters at maturity with a lifespan up to 500-1,000 years (Uchytil, 1991). Silver fir is more commonly associated with western hemlock than Douglas-fir (Cope, 1992). It matures at 30-70 meters and 36-44 inches in diameter with a lifespan of 400-500 years in ideal conditions (Cope, 1992). The species is also shade tolerant and tends to be present in late seral or climax habitats but has a slow migration habit (Cope, 1992). Common understory shrubs include plants like vine maple (*Acer circinatum*), salal (*Gaultheria shallon*), huckleberry (*Vaccinium spp.*), Oregon grape (*Berberis nervosa*), and Beargrass (*Xerophyllum tenax*) (Uchytil, 1991, Cope, 1992). The dense stands and robust understory results in a large biomass, shade, and trapped moisture that will influence establishment and the growth of plant species. This trapped moisture and cool understory tends to discourage fires.

Fire Regime Adaptive Traits of Dominant or Key Species

The abundance, size, and shape of vegetation in these regions creates fuel continuity (or ladders) that can transfer fire from the ground into the tree canopy. The arrangement and physical properties of the plants can impact fire behavior and fire can, in turn, influence vegetation characteristics. Western hemlock is typically sensitive to fires (Tesky, 1992). High-severity fires often kill the trees and low-severity ground fires can damage the shallow roots. Fungal infections within fire-based wounds additionally increase postfire mortality rates (Tesky, 1992). The bark is thin and the tree has "shallow roots, highly

flammable foliage, and a low-branching habit" (Tesky, 1992). This results in a higher susceptibility to fire and a low threshold of fire resistance (Tesky, 1992). Some increased success with seedlings has been documented in burned versus unburned areas when prescribed burns removed competing vegetation (Tesky, 1992). However, sunscald from the open canopy has also killed plants that were germinating on top of burned humus (Tesky, 1992). The "fire adaptive trait" western hemlock has developed is to not be in fire-prone areas.

Silver fir typically grows in regions that tend to be humid and experience low fire occurrence and severity, which results in fire acting as a limiter to its range (Cope, 1992). Thin bark, shallow roots, and high flammability of foliage results in high susceptibility and mortality in fires (Cope, 1992). Furthermore, seedlings do not germinate well post-fire due to heat fluctuations in the burned soil (Cope, 1992). Like western hemlock, silver fir is fire avoidant and is at high mortality risk with increasing fire frequency.

Douglas-fir has thick bark on the lower bole and roots that protect it from heat damage in fires up to moderate intensity (Uchytil, 1991). Branches tend to be concentrated at the canopy, though lower branches tend to be present until the tree is around 100 years old (Uchytil, 1991). Reseeding is dependent on surviving trees, but the post-fire soils tend to be favorable for sprouting and seeds can mature inside scorched cones even if the tree was killed by fire (Uchytil, 1991). Douglas-fir is more likely to experience mortality during summer fires than late summer-fall fires due to growth cycles (Uchytil, 1991). Douglas-fir is more fire-adaptive than western hemlock or silver fir, so will have a higher chance of survival as fires become more prevalent.

Physical Geography

Rugged and steep terrain are typical in these areas (Fire Management, 2022). Soils are derived from igneous parent material, glacial till, or sedimentary rock and have an acidic pH (Meigs et al., 2020, Uchytil, 1991, Cope, 1992). Steep slopes and complex terrain results in the area being prone to landslides, rock falls, and debris flows (Fire Management, 2022). This geography can result in a short ecological gradient on steep slopes, hinder the ability for fire suppression, and increase the speed at which fire burns as upland vegetation is dried ahead of the fire.

The complex topography can also result in distinct regions of refugia or result in the ecosystem itself being a refugia site. Topographic features that promote moisture collection support spaces that are less prone to fire damage (Meigs et al., 2020). This can include spaces like the bottom of valleys, where cold air pools, or where there is dense vegetation growth (Meigs et al., 2020). Topography can also act as a bottom-up control on fires by affecting the type and arrangement of vegetation as well as supporting or hindering flame movement (Meigs et al., 2020). Meigs et al. (2020) found that important variables to determining where wildfire refugia will occur is the "local aspect, catchment

slope, and relative topographic position" with northern slopes, steeper slopes, and relative concavities having a higher probability of containing refugia. Refugia in the West Cascades is more likely to be present on northwest facing slopes that have a high biomass (Meigs et al., 2020). The tendency of this ecosystem to capture and retain moisture, cool the understory due to shade cover, and be present on complex topography with refugia spaces hinders fire presence.

Historical and Contemporary Fire regimes

The fire intervals in mesic, mixed conifer forests are typically thought to range between 100 and 400 years (Fire Management, 2022) and to experience infrequent, stand replacing fires (Tepley et al., 2013). For example, the Fire Effects Information System (FEIS) website shows that mesic western hemlock forests have a fire interval of 400+ years with fire severities of 29-100% replacement and 0-71% with mixed severity.

However, there is some disagreement about what historical and current fire regimes are for these areas. This appears to be due to how the ecosystems are defined and how fire regime data is collected for respective sites. For example, if a fire regime is classified by using a species range, that range may cover a variable scope of topographic features, latitudes, longitudes, and weather conditions that also influence fire and fire regime intervals. Therefore, a single species might experience regimes in the order of both tens of years and hundreds of years. Compare this to defining a fire regime purely by a geographic feature, such as a mountain range, which may incorporate multiple ecozones, weather patterns, and/or latitudes and longitudes. This complexity further demonstrates the need for additional research in pyrogeography and clarity on how a fire regime for any given area is defined.

Halofsky et al. (2020) analyzed the relationship between climate and fire in a study that looked at historical fire regime records using charcoal lake sediments, fire-scar, and tree-ring records in the Pacific Northwest. Their study found that early Holocene summers were comparatively warmer and dryer (Halofsky et al., 2020). These conditions supported more frequent fires in many areas (including regions currently housing moist forests) that created "a mosaic of forest successional stages" which resulted in more fire-adapted species being dominant and red alder (*Alnus rubra*) being dominant in early stages of mesic forests (Halofsky et al., 2020). These findings suggest that historical fire regimes resulted in a range of burn severities rather than being limited to stand-replacing fires (Halofsky et al., 2020). It also indicates that other vegetation species may have been dominant in the past within that same geographic space.

Indigenous communities have been present in what is now the state of Oregon for approximately 12,000 to 14,500 years (Dobkins et al., 2017). Harvesting of understory herbs like Beargrass and huckleberry occurred for Indigenous use and in conjunction with fire burning practices (Hart-Fredeluces et al., 2021). Hart-Fredeluces et al.'s (2021) study found Beargrass to be dominant or co-dominant with huckleberry and that fire regimes

with 100 year or more intervals would not sustain Beargrass populations. However, Indigenous burn intervals of low-severity fire every 10 years increased Beargrass populations (Hart-Fredeluces et al., 2021). This suggests that some measure of frequent fires occurred within mesic forests. However, information regarding Indigenous groups specifically burning in mesic areas could not be found. Therefore, it is unclear if this practice was restricted to drier parts of the ecosystem or if Indigenous groups burned into moist areas.

Based on Tepley et al. (2013) analyzing past fires in Douglas-fir/western hemlock forests, stand-replacing fires are evident but not dominant for old-growth forests within their study area. The majority of Douglas-fir trees older than 400 years showed signs of experiencing non-stand-replacing fires. Tepley et al. (2013) concluded that non-stand-replacing fires tended to leave at least 30 trees per hectare and result in an ecological trajectory shift rather than resetting to a stand-replacing fire regime. Tepley et al. (2013) concluded that the landscape indicated diversity in its fire history and ecological development patterns that promoted heterogeneity. This is significant, because it again indicates a deviation from the infrequent, stand-replacing fires mesic zones have been characterized by. However, this characterization is based upon a specific tree species and the associated range of that species, rather than a mesic zone itself being the target of the study. The use of a species as a metric presents the benefits and limitations previously discussed.

Data in the 20th and 21st Centuries have indicated that the western United States is experiencing warmer summers, increased droughts, and wildfires that are larger and more frequent than in the past (Robbins, 2021). A study in 2013 by Harvard University indicated that Northwest fire seasons would be three weeks longer, generate more smoke, and burn larger fires compared to 20th century fires by the mid-21st century due primarily to temperature change (Robbins, 2021). While scientists believed that the wetter forests of the Western Cascades would be resistant to drought and wildfire, the accumulation of large-scale wildfires between 2000 and 2020 that burned and reburned hundreds of acres indicates that a shift to a frequent fire regime is currently occurring and can be expected to continue in the future (Robbins, 2021). If we are to believe that historical fire regimes were more frequent and that indigenous groups practiced more frequent burns in this area, the study by Robbins et al. (2021) may suggest a potential return to historical regimes. However, an issue with this prediction is that the amount of fuel that has accumulated at this point could result in comparatively more severe fires when these regions experience burns again.

However, Halofsky et al. (2020) contradicts the implications of a frequent fire regime and states that moist forests are characterized by infrequent, high-severity, stand-replacing fires and will likely be more protected from fire events. Buotte et al. (2019) study on forest vulnerability to fire and drought further concludes that mesic forests have a low risk to fire and drought effects between 2020-2049. A study published in 2020 on fire refugia locations in the Pacific Northwest by Meigs et al. indicates that mesic forests

acted as refugia as a function of fire frequency. Meigs et al. (2020) also determined that spatial patterns of old versus young growth were based upon timber harvests more so than burn severity. This information adds to the complexity of how fire regimes in mesic areas with western hemlock, Douglas-fir, and silver fir are measured and defined.This uncertainty further supports the need for additional study.

Climate Conditions that Support the Ecosystem and Fire Regimes

Historical climate conditions were relatively warmer and drier with a higher frequency of fires, especially when warmer and drier spring and summer conditions were experienced (Halofsky et al., 2020). Warmer and drier climates would create drier fuels and a longer fire season.

Contemporary climate conditions include mild, wet winters and warm, dry summers with most precipitation occurring in Winter (Tepley et al., 2013). This results in fire seasons typically beginning in the Summer between August and September (Halofsky et al., 2020). Habitat ranges for Western Hemlock are between approximately 15 to 262 inches of mean annual precipitation, 32.5 to 52.3 degrees Fahrenheit mean annual temperatures, and frost-free periods averaging between 100 to 280 days (Tesky, 1992). Silver fir thrives in environments with annual precipitation between 38 and 262 inches of rain (Cope, 1992). The amount and timing of both precipitation and temperature ranges will influence the probability of fire, fire conditions, and when fires are likely to occur.

Occasional strong, gale-force, and dry winds from the eastern side of the Cascade Range have been reported to increase small fires into “megafires” during fire seasons in at least 1933, 1936, 1939, 1945, 1951, 2017, and 2020 (Robbins, 2021). These winds can blow continuously for multiple days and are accompanied by a relative humidity that remains low (Robbins, 2021). There is additionally some indication that drier conditions that occur with El Nino and the Pacific Decadal Oscillation every 20-30 years increases the likelihood of wildfire occurrence (Halofsky et al., 2020). Recognizing overarching climate patterns and temporal scales can help explain and anticipate major wildfire events.

Climate change that has resulted in increasing temperatures and drought are shown to be influencing fire frequency and size since the 1980s (Robbins, 2021). The increased warming of spring and summer results in snow melting earlier, evapotranspiration increasing, and decreased soil and fuel moisture sooner in the fire season and extending the fire season longer into the autumn (Halofsky et al., 2020). Awareness of climate change impacts on vegetation and fire regimes helps land managers develop action plans to meet long term management needs.

Conservation and Restoration Concerns

As of 2013, restoration guidelines focus on biodiverse patches of vegetation as part of the presumption of stand replacing fire regimes (Tepley et al., 2013). Halofsky et al. (2020) suggests that intervention and conservation in mesic environments will be limited due to infrequent fires and suggests considering the creation of fire breaks (areas with relatively little vegetation) to protect important features. These restoration efforts focus on the lack of fire presence and accepting that stand-replacing fires will occur as part of the system.

Management concerns for western hemlock include the high risk of mortality in all fire severity levels, the tendency to grow in dense groves, and to form structures that facilitate the continuity of fire (Tesky, 1992). The logging of older western hemlock stands can further lead to an increase in leftover debris and subsequently an increase in fuel loads and fire danger (Tesky, 1992). Burning tends to be favored as a method of clearing debris and preparing for planting, especially when the management goal is to create a mixed forest of western hemlock and Douglas-fir (Tesky, 1992). Burning strategies are typically limited to controlling large accumulations of wood rather than low-severity broadcast burns, but are useful in controlling dwarf mistletoe infestations (Tesky, 1992). This species is very fire sensitive, which is problematic when fire reaches these regions, but is conversely useful when conducting management techniques to clear an area.

Douglas-fir is considered a major timber product in North America (Uchytil, 1991). Seedlings can be an important food for large game during Winter months when preferred forage is unavailable and seeds are a major food source for small rodents and birds (Uchytil, 1991). Old growth Douglas-fir is further a preferred nesting site for spotted owls (Uchytil, 1991). Douglas-fir beetles often attack fire-killed or weakened trees and are considered the most damaging insect to the tree (Uchytil, 1991). Managing Douglas-fir forests is an economic priority and ecologically important for spotted owls and other wildlife. Improper fire management could result in large economic losses, post-fire loss by beetle kill, and decreases in the threatened spotted owl population.

Silver fir can experience sunscald and sudden sun exposure can temporarily hinder growth (Cope, 1992). It can also be difficult to collect and store cones due to their delicate construction (Cope, 1992). The species is also susceptible to a wide range of infestations and diseases that are exacerbated by fire (Cope, 1992). Seeds are produced after the tree is 20-30 years old with production occurring every 2-3 years (Cope, 1992). Reproduction post-fire is limited due to seeds being sensitive to temperature fluctuations of burned soils (Cope, 1992). Silver fir is a comparatively delicate conifer species. Exposure to fire and improper fire management can lead to catastrophic declines in population and result in very slow recovery.

Management Controversies

Indigenous communities in the area tended to culturally view fire as a tool, but European immigrants culturally viewed wildfire as destructive (Robbins, 2021). The mass migration of European movement into North America eventually led to a dominant cultural shift in ideals in conjunction with the economics of lumber altering the historic interactions with the land (Robbins, 2021). The dominant cultural views of people within Oregon would influence and regulate the way fire was encouraged or discouraged in the landscape. This in turn would impact the ecology and the behavior of fire over time.

A series of fires within the western United States would further impact legislation and the way in which communities interacted with fire. State and federal governments began fire suppression efforts in 1910 following large fires in Montana, Idaho, and Washington (Robbins, 2021). The U.S. Forest Service began a "10 a.m. policy" in 1935 for the Pacific Northwest, in which fire control strategies were designed to have the fire under control by 10 a.m. the day after the fire started or by that time every subsequent day until the fire was put out (Robbins, 2021). The National Park Service created plans in the 1960s to allow natural fires to burn, but the Forest Service continued fire prevention and extinguishing protocols (Robbins, 2021). These policies continued the view that fires were destructive and promoted fire suppression policies that altered the landscape, increased fuel loads, and resulted in larger and hotter fires.

However, attitudes began to shift with an increase in scientific research on fire. Attempts by the Forest Service to sell fire-killed timber following a 2002 fire were met with protest when indications that salvage logging slowed post-fire ecological recovery (Robbins, 2021). Subsequent interest and research in climate, climate change, and fire relationships began in the 2000s and concluded that fire suppression led to biomass accumulation and the combination of warming climate and increased drought increased the risk of wildfires (Robbins, 2021). These new attitudes and growing contemporary knowledge have started shifting the way in which communities interact with fire.

Important Fire Events for the Area

The Eagle Creek Fire in 2017 burned 48,861 acres in the Eagle Creek drainage and resulted in 55% of the area as unburned or experiencing low burn severity, 30% moderately burned, and 15% severely burned (Fire Management, 2022). This area included private residences, railways, interstates, national forest trail systems and roads, bridges, state lands and parks, hatcheries, historic buildings and sites, and local power companies (Fire Management, 2022). Due to complex terrain, firefighting efforts primarily relied on air resources to suppress the fire (Fire Management, 2022). This fire made headlines due to the historic features at risk, the historic infrequency of the fire, and the intensity that allowed it to cross the Columbia River. This event symbolized an increase in fire events in the area.

In September 2020, a series of wildfires referred to as the “Labor Day Fires” were escalated due to an extreme east wind event (Robbins, 2021). These fires accumulated into 173,393 acres burned (including previously burned areas) and was dubbed a “megafire” (Robbins, 2021). According to Robbins (2021), similar strong east winds were the primary accelerant that resulted in large-scale fires in 1933, 1936, 1939, 1945, and 1951 with all but the 1951 fire ranging between 143,000 and 355,000 acres. These fire events drew public attention and indicated a growing concern for fire regime changes induced by climate change. While these fires did not cross the target area of this study, they occurred in zones with similar characteristics and influenced perspectives and understanding of fires across Oregon. No data was found indicating any historical, large fires that occurred prior to 2017 for the area of this study.

Supporting Research

Boer et al. (2008) refers to burn severity as " a measure of post-fire changes in forest canopy attributes" and compares Differenced Normalized Burn Ratio (dNBR) and Leaf Area Index (LAI) for the purpose of mapping burn severity (Figure 4). Their primary objective was to create and test a method to map burn severity as a change in LAI (dLAI) in a eucalyptus forest in Western Australia and compare it with results using dNBR (Boer et al., 2008). They propose that the change in LAI of a stand should be used to calculate burn severity of an area due to LAI being "...a key biophysical attribute of forests, and is central to understanding their water and carbon cycles." (Boer et al., 2008). They argue that although dNBR is commonly used to calculate burn severity, LAI may significantly contribute to both the dNBR and the composite burn index (CBI) that is often used with dNBR when assessing burn severity. Green vegetation cover is a visible attribute, is used to assess fire impact, and is a key input into calculating CBI and dNBR for burn severity in addition to informing ecosystem models that control photosynthesis and water use (Boer et al., 2008). LAI is therefore proposed as a defined and objectively measurable data point in the field and in remote sensing that can also provide information regarding flame length, which in turn provides information regarding fire intensity (Boer et al., 2008).

The study finds that dLAI is comparable to dNBR (Figure 4) when considering large-scale patterns and that both approaches agree on the identification of key features, such as highest burn severity and lowest burn severity (Boer et al., 2008). However, dNBR and dLAI were only moderately correlated at the pixel level and researchers were unable to determine which approach most accurately represented fire impacts on the ground (Boer et al., 2008). This may be due to dNBR being able to detect fire impacts beyond leaf canopy changes, whereas dLAI focuses on leaf canopy alone (Boer et al., 2008). However, incorporating a range of multiple impacts can result in difficulty determining

which specific ecological factor dNBR is identifying (Boer et al., 2008). In the case of this study, these features and limitations of dNBR resulted in the inclusion of unburnt areas of the forest that had experienced drying due to drainage (Boer et al., 2008). This means that dNBR may show positive values when there is comparable drying based upon topology or seasonal changes rather than explicitly from fire impacts (Boer et al., 2008).

Boer et al. concludes that, when analyzing this area of interest, dLAI produces maps similar to dNBR, measures burn severity based on a well-defined and recognized scale, allows comparisons between different sites within a single fire, allows comparisons of the same site through multiple fires, can be used to analyze burn patterns within different forest types, and can be related to other forest management concerns such as water production, productivity, and fuel loads. This method can be useful when considering large-scale burn severity patterns and when ecological questions related to LAI are part of the study. For the purpose of my study, I concluded that dNBR is an appropriate index, given that both dNBR and dLAI performs at similar levels and the dominant species of the area composes a mixed conifer forest where drying and leafing phenology would be comparatively limited.

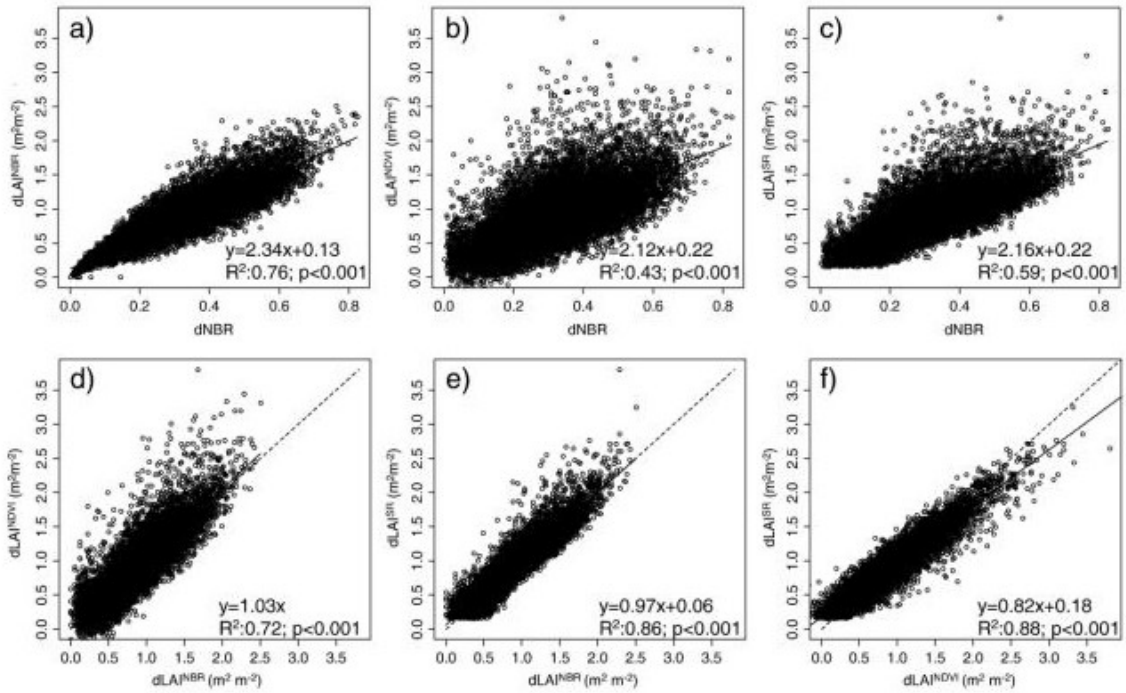

Figure 4: A graph from Boer et al. (2008) comparing dNBR and iterations of dLAI. The dashed black lines indicate a 1:1 relationship and the continuous curve shows a fitted trend. These graphs were used to help test the use of dLAI and dNBR in mapping burn severity.

Escuin et al. (2008) compares fire severity assessment methods using post-fire and pre/post-fire perspectives Normalized Burn Ratio (NBR) and Normalized Difference Vegetation Index (NDVI) indexes on LANDSAT TM/ETM images of three (3) fires located in southwest Spain. This region is commonly composed of heterogeneous vegetation, steep slopes, and complex topography (Escuin et al., 2008). This is similar to the topographic features in the Eagle Creek fire.

They divided fire severity into three (3) levels and defined fire severity as the "degree of change in the soil and vegetation caused by fire"(Escuin et al., 2008). They mention Burnt Area Index (BAI), Soil Adjusted Vegetation Index (SAVI), and Global Environmental Index (GEMI) as additional indices that can be used when assessing fire impacts, but do not focus on these methods in their study (Escuin et al., 2008). Their primary objectives revolved around comparing the NBR and NDVI indexes to pre and post fire conditions and to explore the limitations and impacts the index values have on the ability to distinguish severity levels (Escuin et al., 2008).

Researchers collected remote sensing images in addition to collecting field data where severity levels were divided into "extreme" (total consumption or scorched crowns), "moderate" (partially scorched crowns), and "unburned". NBR, NDVI, dNBR (the change in NBR between pre and post fire conditions), and dNDVI (the change in NDVI pre and post fire conditions) were then compared to pre, post, and pre/post fire images, respectively (Figure 5) (Escuin et al., 2008). Escuin et al. (2008) concluded that NBR was most sensitive to pre/post fire pixel displacement in the mid to near infrared spectrum, NDVI was more sensitive to pre/post fire pixel displacement in the red to near-infrared spectrum. Neither NBR nor NDVI were very sensitive to pre-/post-fire spectral changes in unaffected pixels (Escuin et al., 2008). Pre/post-fire dNBR and dNDVI were successful at discriminating between pixels that were burned and not burned with the dNBR being slightly better and indicating unburned-moderate severity (Escuin et al., 2008). The post-fire NBR and post-fire NDVI were better at identifying extreme and moderate severity pixels with the post-fire NBR having better results than the post-fire NDVI for moderate-extreme severity (Escuin et al., 2008). The post-fire NBR and dNBR were more suitable for detecting severity levels than the NDVI-based counterparts (Escuin et al., 2008).

Escuin et al. (2008) recommends that a two-step process be considered when determining fire severity. First, separating the "unburned" pixels (dNBR <107) from the rest of the pixels (Escuin et al., 2008). Second, separating the "extreme" (post-fire NBR <-73) from

the "moderate" severity pixels using their post-fire NBR values (Escuin et al., 2008).

Esceuin et al.'s (2008) research can be useful when determining how to create and differentiate between burn severity categories for wildfire assessment. The use of dNBR as an index to assess burn severity and the need for quantifying values to differentiate burn severity classes is supported here.

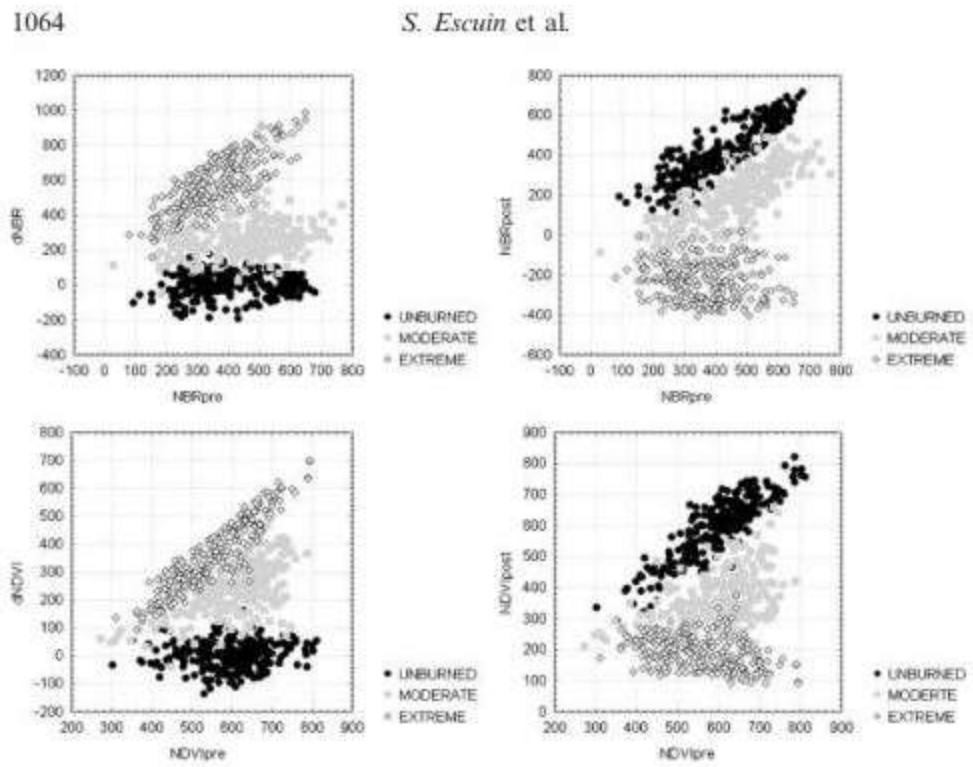

Figure 5: Scatterplots by Escuin et al. (2008) comparing NBR, dNBR, NDVI, and dNDVI with respect to burn severity. Strong correlations are shown between NBRpre vs dNBR and NDVI pre vs dNDVI, respectively, for extreme fire severity pixels. NBR pre vs NBRpost and NDVIpre vs NDVIpost, respectively, shows a strong correlation for unburned pixels (Escuin et al., 2008).

Leon et al.'s (2012) study analyzes the response of post-wildfire vegetation after three burn events in the Bandelier National Monument between 1999 and 2007 and compares them to three control sites nearby. They use the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) to assess "the average potential photosynthetic activity through the summer monsoon" and additionally consider topography, fire severity, and restoration treatment prior to the fire (Leon et al., 2012). In this study, fire severity is defined as "the change that we can

observe between before and after fire on vegetation cover"(Leon et al., 2012). Their primary goals were to analyze the impact of specific environmental conditions on post-fire vegetation response and to determine if pre-fire restoration methods had an impact on post-fire vegetation recovery (Leon et al., 2012) (Figure 6).

The pre-fire treatment categories were defined as receiving no treatment or as receiving treatment (Leon et al., 2012). NDVI is related to chlorophyll and photosynthesis in vegetation and was used as a measurement of plant productivity (Leon et al., 2012). A series of NDVI images were collected, averaged, then used to compare information between the fires and fire treatments (Leon et al., 2012). Imaging from Landsat TM5 and additional resources were collected to locate data on topography and fire severity (Leon et al., 2012). To quantify fire severity, Landsat TM5 images were selected from each fire and used to calculate the Difference Normalized Burn Ration (dNBR) (Leon et al., 2012). A Digital Elevation Model (DEM) at a 30-meter resolution was used to derive the elevation, aspect, and slope of the surface (Leon et al., 2012).

Leon et al. (2012) concluded that pre-fire management practices, topography, and fire severity are significant control mechanisms of post-fire vegetation response. Their models could discriminate between burned and unburned areas, but could not clearly identify between treatment categories. Elevation also appeared to influence post-fire vegetation responses. Leon et al. (2012) was useful for determining how to select remotely-sensed imaging for analysis and in identifying factors that influence vegetation response and recovery to post-wildfire events. It furthers the need to consider multiple variables when characterizing fire regimes and recovery.

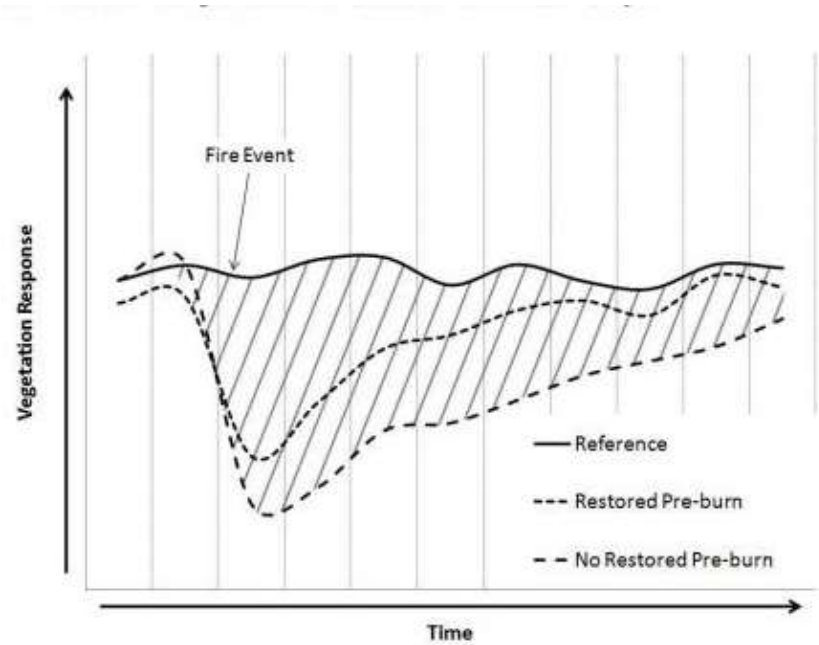

Figure 6: Chart from Leon et al. (2012) showing vegetation response over time to a burned environment. This is a conceptual model of vegetation response to disturbances related to the climate and other disturbances. Restored-burn areas are provided with some treatment and are expected to be less damaged by wildfires due to reduced fire severity (Leon et al., 2012).

Holden et al. (2009) relates severe fire occurrence to "elevation, aspect, slope, solar radiation, Heat Load Index, wetness", and ruggedness using information from 114 fires that are greater than 40 ha in the Gila National Forest between 1984 and 2004. They define burn severity as "the magnitude of ecological change associated with fire" and use Landsat images from the Monitoring Trends in Burn Severity (MTBS) project to compare images before and after the fire (Holden et al., 2009). The objectives of the study were to analyze burn severity information relative to topography and Potential Vegetation Type (PVT) and to develop a model that could be used to predict the probability of a severe fire relative to topographic features (Holden et al., 2009) (Figure 7).

The Relative Differenced Normalized Burn Ratio (RdNBR) was used to map the burned areas because it showed a stronger correlation to field data available for the study site compared to the Differenced Normalized Burn Ration (dNBR) (Holden et al., 2009). They digitized each fire using dNBR and Landsat images, used fire perimeter databases to locate names and dates of fires, then used RdNBR to cross reference fires of interest and exclude areas that had recently been reburned (Holden et al., 2009). The Composite Burn Index (CBI) was used to measure burn severity on site in 2004 and validate the

RdNBR data (Holden et al., 2009). The areas that were categorized as severely burned were then isolated and examined more closely for the study (Holden et al., 2009). The "Random Forest model" they created was then used to build a model surface of the study site (Holden et al., 2009).

Holden et al. (2009) concluded that severely burned areas occurred at a higher rate in higher elevations, in high elevation spruce-fir and mixed-conifer forests, on north and northeast facing slopes, on steep slopes, where solar radiation was low or moderate, and where the heat load index was very low or very high. Holden et al. (2009) concludes that burn severity and topography have a strong correlation and that vegetation-based topography correlation "breaks down" in wetter vegetation species (Holden et al., 2009).

Limitations of the study included the arbitrary nature of designating distinct burn severity measurements on a condition that contains a continuum and no or limited data on vegetation structure, climate, weather, and fire origin and direction. These limitations may be significant, as the origin and movement of the fire can impact the fuels fire has access to. For example, a fire moving northward may predominantly burn vegetation on south-facing slopes. If fires in that region historically travel northward, fuel may build up on north-facing slopes and result in a more severe burn compared to the south-facing counterpart. This study points out some significant considerations for future studies on fire effects and demonstrates how to assess fire impact over a long period in a specific area.

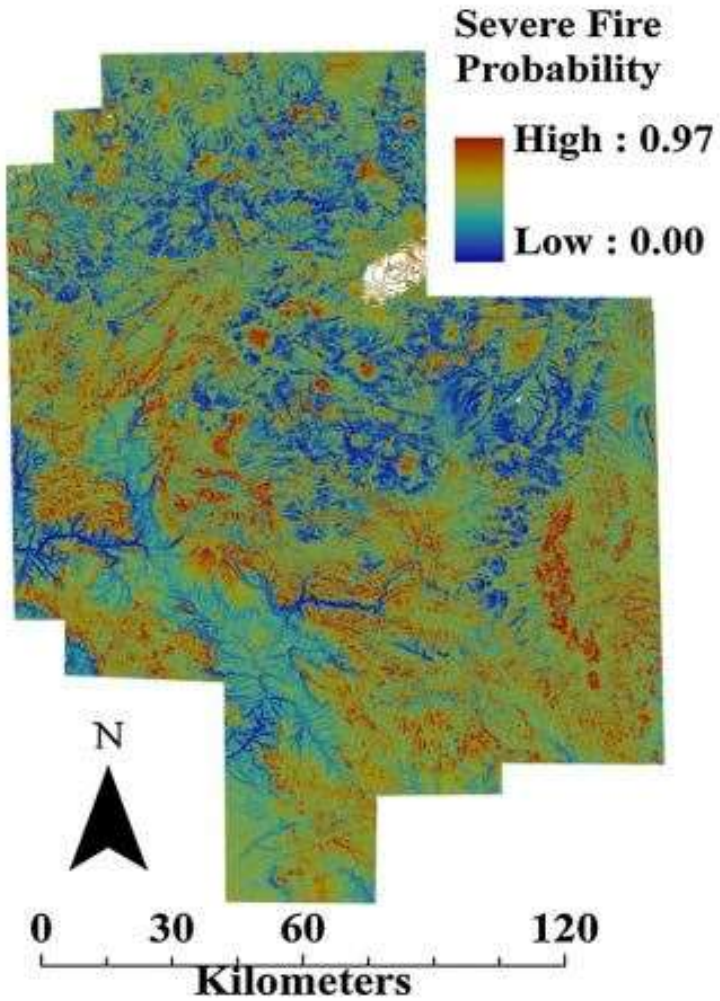

Figure 7: A map from Holden et al. (2009) showing the severe fire probability in the Gila National Forest based on a Random Forest model prediction. The burn severity probability is based on underlying topography.

Vlassova et al. (2014) analyzes the relationship between land surface temperature (LST) and fire severity in a pine forest in Spain using Landsat TM5 images over 27 months following the fire. The study area is hilly with elevations between 390m and 1280m and covers approximately 3000 ha of burned pine-dominant forest (Vlassova et al., 2014). The primary objectives of the study were to analyze changes in LST for two (2) years following the 2009 fire, detect any correlation between LST and differenced Normalized Burn Ratio (dNBR) values, and detect any correlation between Normalized Difference Vegetation Index (NDVI) and changes in LST (Vlassova et al., 2014) (Figure 8). They believed that the distribution of LST is related to burn severity and that the value range of

LST would be related to vegetation life cycles and time since the fire (Vlassova et al., 2014).
They used dNBR to determine burn severity and compared LST to the NDVI as they relate to burn severity categories (Vlassova et al., 2014). Field data was collected within the higher LST burned areas and compared to satellite imaging (Vlassova et al., 2014). Burn severity is defined as "the amount of change in a burned area with respect to the pre-fire conditions" (Vlassova et al., 2014). LST is described as a major factor that controls physical processes related to water, energy, and carbon dioxide on the land surface (Vlassova et al., 2014). Burn severity and vegetation regrowth (measured via NDVI) can be controlling factors in the spatial distribution of LST post-fire (Vlassova et al., 2014). The images used were composed of seven spectral bands and used a 30m resolution for six bands and 120m for the remaining thermal band. A digital elevation model (DEM) was used with ArcGIS software to get site information about slope and aspect and then atmospheric corrections were applied to the Landsat TM5 images (Vlassova et al., 2014). Categories of burn severity were defined via dNBR values as unburned, low severity, moderate-low severity, moderate-high severity, and high severity (Vlassova et al., 2014).

Vlassova et al. (2014) concluded that the burned zones averaged 7.6C warmer than the unburned areas and exceeded a 10C temperature difference between unburned and high burn severity zones. The variability of LST appeared to be directly related to burn severity (Vlassova et al., 2014). One month post-fire, LST differences decreased between unburned and burned areas, however differences between burn severity areas could be detected throughout the 2-year length of imaging (Vlassova et al., 2014). LST differences in burn severity categories were increased in areas that received more light, but these differences decreased over time with vegetation growth (Vlassova et al., 2014).

Vlassova et al.'s (2014) research correlates surface temperature, vegetation growth, and burn severity as controlling factors in post-wildfire environmental response and vegetation recovery. Methodology within the study additionally appears applicable to other regions with conifer-dominant forests and hilly terrain.

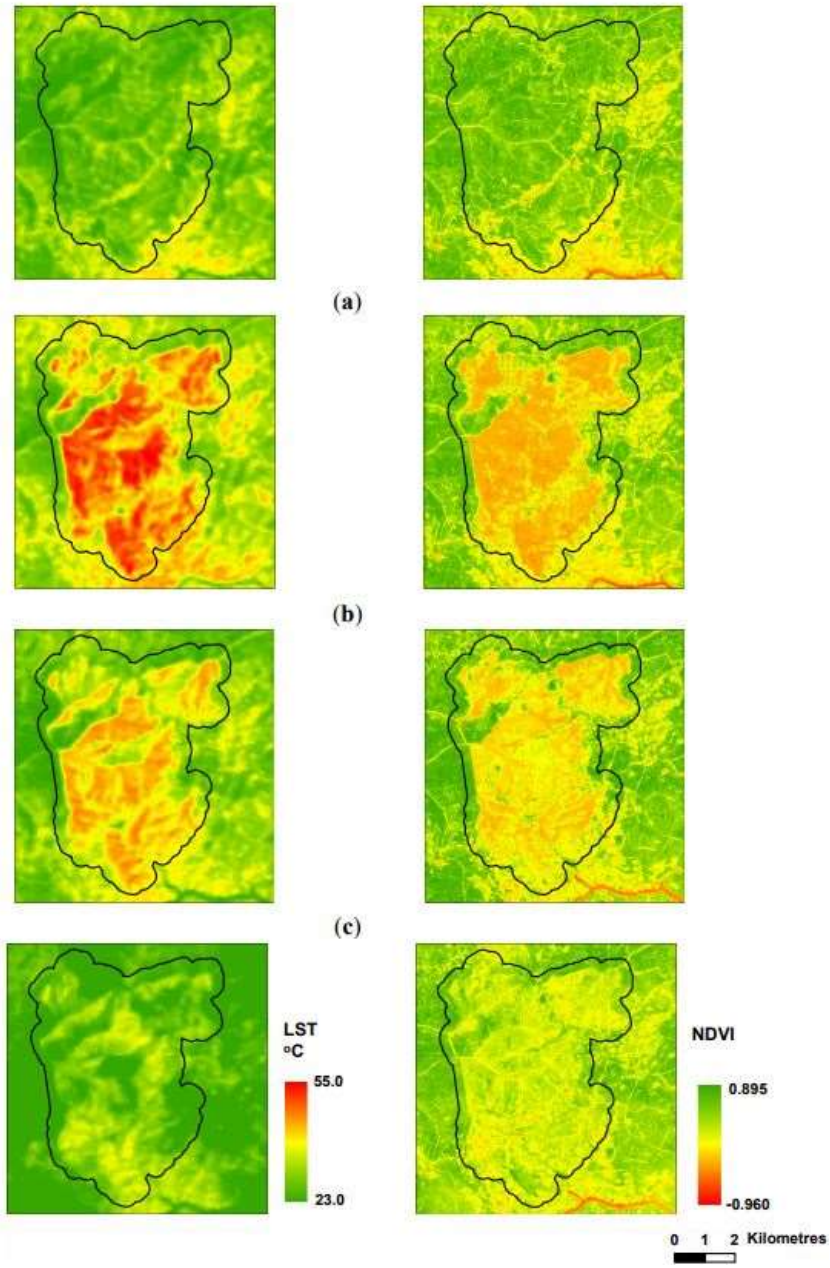

Figure 8: Index maps from Vlassova et al. (2014) comparing the spatial distribution of LST and NDVI. The left panel is LST and right panel is NDVI. From top to bottom, the events represent 7/13/09 (prefire), 7/29/09, 7/16/10, and 8/4/11.

Harris et al. (2011) used MODIS/ASTER data to analyze nineteen (19) fire severity spectral indices in chaparral areas of southern California to determine their relative

strengths and weaknesses as fire severity measuring tools. Their data was collected in 2007 and covered four (4) fires in a geographic region that experiences frequent fires. They describe fire intensity as related to "the physical combustion process in terms of energy release from organic matter" and expressed as "energy fluxes." They define fire severity as a measure of fire impact and "the amount of damage, the physical, chemical and biological changes or the degree of alteration that fire causes to an ecosystem.”. Their justification for the project is based upon the need to accurately assess fire and burn severity to estimate burn efficiency and to understand fire regimes and associated ecological impacts (Harris et al., 2011).

Researchers created 25 field plots within a month of the fires and based field procedures on the Fire Monitoring Handbook (Harris et al., 2011). The plots were recorded with GPS and visual ratings of unburned, very low, low, moderate, and high fire severity classes were assigned. Spectral imaging was acquired using the MASTER airborne simulator, georeferenced, and then applied to the spectral indices (Figure 9). Harris et al. (2011) concluded that Normalized Burn Ratio (NBR) is a "simple data layer to rapidly infer critical post-fire information in a cost-effective manner" for their study region and in Mediterranean shrublands. They further referenced NBR and dNBR as having a higher degree of correlation for forested ecosystems. Two other indices referred to as NIR-SWIR-Emissivity (NSE) and NIR-SWIR-Temperature Version 1 (NSTv1) had comparable correlations to NBR in the study area (Harris et al., 2011).

Harris et al. (2011) confirmed the usefulness of mid-infrared (MIR) spectral bands and indicated a potential for thermal imaging to support NBR data. This study compares a large number of spectral indices used in assessing fire/burn severity data using remote sensing. Comparing and quantifying this data assists in the appropriate selection of indices for assessing burn severity and demonstrates how to assess these indices within a target environment.

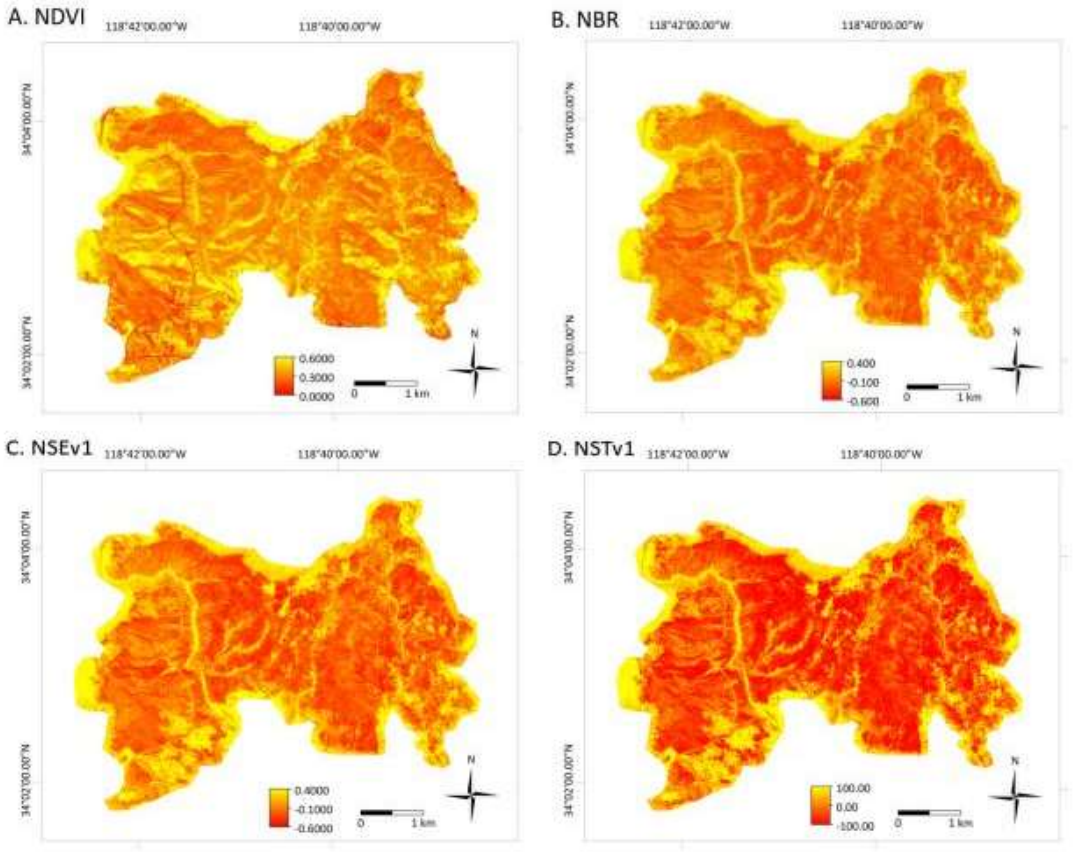

Figure 9: Spectral index maps from Harris et al. (2011) comparing the spatial distribution of NDVI, NBR, NSEv1, and NSTv1 of the October 2007 Canyon fire in California. These maps to compare the strengths and weaknesses of geospatial indices to measure fire severity.

This United Nations website titled "Step by Step: Burn Severity Mapping in Google Earth Engine | UN-SPIDER Knowledge Portal" (2022) provides step-by-step instructions on how to use Google Earth Engine (GEE) to map burn severity for an area of interest. They use the Normalized Burn Ratio (NBR) and Differenced Normalized Burn Ratio (dNBR) indexes, which are based on near-infrared and shortwave-infrared wavelengths (UN-SPIDER, 2022). They describe how NBR and dNBR are calculated and why they are appropriate for burn severity data (UN-SPIDER, 2022). The higher dNBR values are used to indicate higher severity damage and negative values show increased vegetation (UN-SPIDER, 2022). They use the classification created by the United States Geological Survey (USGS) to quantify their values UN-SPIDER, 2022). The website then walks through GEE code structure and satellite data options available for calculating burn severity, editing available to manage issues such as cloud cover, and code available to

produce data such as percentage of cover or the pixel count of any given burn severity class (UN-SPIDER, 2022). It is very useful in processing and quantifying burn severity data within an area of interest and is a quick, open access resource to accessing maps, satellite imaging, and data for burn severity and associated ecological impacts. In the end, it further verifies the use of dNBR and industry standards in burn severity classification.

Google Developers (2022) created a website titled “NDVI, Mapping a Function over a Collection, Quality Mosaicking | Google Earth Engine” that provides instructions on how to create code for the Normalized Difference Vegetation Index (NDVI) from Landsat images in Google Earth Engine (GEE) and explains the use of NDVI. The NDVI code creates values indicating photosynthesis for each pixel using the near infrared and red spectral wavelengths. Since NDVI values will differ based upon plant phenology, GEE created a code in which you could generate composite samples prioritizing "maximum greenness" in an area to compare data over the years at roughly the same phenological cycle. Visual representations of this index are overlaid within the GEE coding interface (Figure 10). The site additionally links to tutorials on processing and producing data (such as charts and values) from NDVI values within GEE (Google Developers, 2022). This website is very useful in locating remote sensing data and quantifying NDVI values within an area of interest. It is a cost-effective resource for accessing maps, satellite imaging, and data for NDVI and adheres to image analysis procedures modeled in peer-reviewed research.

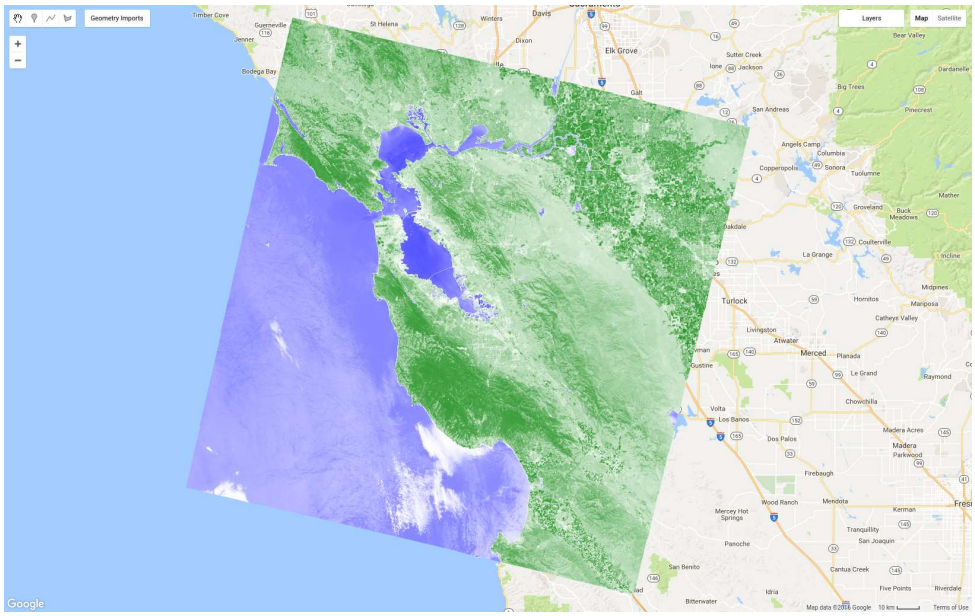

Figure 10: A Google Earth Engine sample of NDVI overlay imaging. NDVI values represent vegetation and have been color-coded so that dark green indicates high photosynthetic activity and blue indicates water. The darker the green, the denser and healthier the vegetation is.

Fire Intensity and Severity

Keeley (2009) discusses and defines the terms "fire intensity", "fire severity", "burn severity", and "ecosystem responses" based upon his perception of inconsistency and disagreement regarding definitions that previously existed and that is being further exacerbated by the increase in remote sensing tools and associated techniques in collecting data. In the latter case, he cites the issue as being the advancement of technology moving at a faster rate than our understanding of what the data means (Keeley, 2009).

He defines "fire intensity" as a description of the "physical combustion process of energy release from organic matter" measured as "the energy per unit volume multiplied by the velocity at which the energy is moving"(Keeley, 2009). This results in vector data that is applicable to physics applications and definitions. However, he finds this concept and definition limiting, as it creates a single value that does not describe multiple aspects of energy in the fire (Keeley, 2009). He proposes that additional metrics be considered to gain more detail, such as fireline intensity, residence time, and temperature (Keeley, 2009).

"Fire severity" is described as having definitions with varied complexity, but ultimately relating to some component of the loss of organic matter above and below ground (Keeley, 2009). A very broad definition is "the degree of environmental change caused by fire"(Keeley, 2009). This may be measured via crown scorch, ash characteristics, and other features related to biomass change (Keeley, 2009). LANDSAT imaging and the Normalized Difference Vegetation Index (NDVI) is determined to be relevant to measurements of fire severity in forest and woodland areas (Keeley, 2009). Keeley considers 'fire severity' to correlate to "fire intensity" and to be best used in environments with "forest trees that lack any resprouting capacity" (Keeley, 2009).

"Burn severity" is described as being often interchanged with "fire severity", which has similar metrics but differences come down to the extent of what is measured (Keeley, 2009). Remote sensing applications tend to prefer the term "burn severity" and use satellite imagery to create indexes such as the Normalized Burn Ratio (NBR) (Keeley, 2009). Keeley believes that using remote sensing terminology (e.g., NBR) when using associated tools is preferential over the term "burn severity", as it relates specifically to remote sensing applications (Keeley, 2009). "Burn severity" can also include a broader ecosystem response to fire than "fire severity" does (Keeley, 2009). Keeley recommends that, if "burn severity" and "fire severity" are going to be used interchangeably and "fire severity" and "ecosystem responses" are included in data collection, then fire/burn severity and ecosystem responses should be evaluated independently (Keeley, 2009).

"Ecosystem responses" encompasses a wide range of impacts from fire, including but not limited to erosion, community structures, and vegetation regrowth and could be measured directly and indirectly (Keeley, 2009). These are response variables to the impacts of how intense or severe a fire was (Keeley, 2009). Keeley concluded that "fire intensity" should not be used to describe fire impacts, but "fire severity" and "burn severity" are correlated to "fire intensity" and can be used to describe degrees of organic matter loss above and below ground (Keeley, 2009). He furthers that the distinction between these terms is important for land managers to properly assess resource questions (Keeley, 2009).

Keeley's (2009) paper is helpful with understanding and carefully defining separate but related nomenclature, methods, and metrics when assessing the impacts of fires (Table 1). It further impresses the need to use specific terminology when using GIS and remote sensing tools to collect and analyze data and supports the definition of burn severity used within this study.

Table 1: Summary of definitions, metrics, and usage of fire nomenclature as defined by Keeley (2009).

	Fire intensity	Fire severity	Burn severity	Ecosystem responses
Appropriate usage	Energy output from fire.	Aboveground and belowground organic matter consumption from fire.	Aboveground and belowground organic matter consumption from fire. Sometimes subdivided into 'vegetation burn severity' and 'soil burn severity'.	Functional processes that are altered by fire including regeneration, recolonization by plants and animals and watershed hydrology processes altered by fire.
Metrics	Strictly speaking it is the time-averaged energy flux in $W\ m^{-2}$, but more broadly can be measured as fireline intensity, temperature, residence time, radiant energy and other.	Aboveground measures include tree crown canopy scorch, crown volume kill, bole height scorch, skeleton twig diameter. Belowground and soil measures include ash deposition, surface organic matter, belowground organic matter contributing to soil structure, degree of hydrophobicity, and heat-induced oxidation of minerals. Mortality is a common measure that is best applied to non-sprouting trees in surface fire regimes. In crown fire regimes, aboveground mortality may be useful when fires are patchy.	Often used interchangeably with fire severity. Usually the term is applied to soils and designated 'soil burn severity'. In the USA, it is the preferred term used in post-fire Burned Area Emergency Response assessments and is considered to be the relative change due to fire, i.e. two soils with poor structure and low organic matter content may be rated differently if one was in that condition before the fire and another was not. Degree of severity may be influenced by socio-political concerns such as values at risk.	Vegetative cover, seedling recruitment, plant community composition and diversity, and plant and animal recolonization are important biotic parameters. Watershed hydrological processes such as dry ravel, erosion, and debris flows are the more important abiotic processes.
Inappropriate usage	Should never be used to describe fire effects such as those described under any of the remaining columns.	Should not include ecosystem responses. Also, in shrubland ecosystems, complete above- and belowground mortality should not be considered here because it depends on vegetation composition and the proportion of sprouting and non-sprouting species.	Should not include ecosystem responses. Also, this term should be restricted to field measurements and not be used to name remote-sensing indices because the interpretation of remote data is dependent on ground-truthing with field measurements of burn severity; calling both measures burn severity is circular.	Correlations between severity and ecosystem responses demonstrated in one system should not be considered universal for all ecosystems.

Steen-Adams et al. (2019) considers the "cultural fire regimes" (CFR) that tribal communities in the Confederate Tribes of Warm Springs (CTWS) of the Pacific Northwest historically used, and what the subsequent impacts of use were and are. The primary goals of the research were to determine how the CTWS tribes traditionally use fire in moist mixed conifer (MMC), dry mixed conifer (DMC) and shrub-grassland (SG) regions to create CFRs and to determine the structure of traditional knowledge systems and how the use of fire was involved in these communities (Steen-Adams et al., 2019).

Researchers created an "anthropological-landscape ecological GIS framework and traditional knowledge database" and integrated GIS tools into culturally relevant practices (Steen-Adams et al., 2019). They compared historical data, literature, oral history, and a GIS workshop with tribal participants to collect data and section their study area into MMC, DMC, and SG zones (Steen-Adams et al., 2019). Participants mapped features within the study area that were relevant to their community and used mapping features to indicate historical settlements, trails, and spatial zones with culturally relevant resources (Steen-Adams et al., 2019) (Figure 11).

Steen-Adams et al. (2019) determined that CTWS communities historically used high frequency, low-severity fire regimes predominantly in the MMC zone in order to promote huckleberry growth and harvesting. This resulted in opening the canopy and reducing understory plants that would compete with huckleberry (Steen-Adams et al., 2019). Additionally, the reduction in understory cover had a culturally positive correlation with

ease of movement through the site, accessibility to hunting large game, and reducing pests (particularly beetles) that damaged trees (Steen-Adams et al., 2019). Burn sites ranged from one-meter to landscape scales (Steen-Adams et al., 2019). While lower frequency and higher severity fires did occur by non-human means, these fires were comparatively less severe than modern fires due to CFRs reducing fuel loads (Steen-Adams et al., 2019). CFR activity was predominant in the East Cascade MMC region and was incorporated into "seasonal rounds" that involved setting fires during wetter seasons to control the burn (Steen-Adams et al., 2019). Human-induced burns in DMC and SG zones were less common due to the comparatively drier environment that had less vegetation competition for cultural resources and a higher frequency of non-human fires (Steen-Adams et al., 2019).

Steen-Adams et al. (2019) contributes to the cultural awareness of historical land management practices and how to incorporate GIS into culturally relevant land management studies. It demonstrates the impact that human-induced fire regimes may have on ecosystem structures and the non-human induced fire regimes that would subsequently impact post-wildfire vegetation structures. Looking at historical interactions with fire can inform sustainable practices into the future.

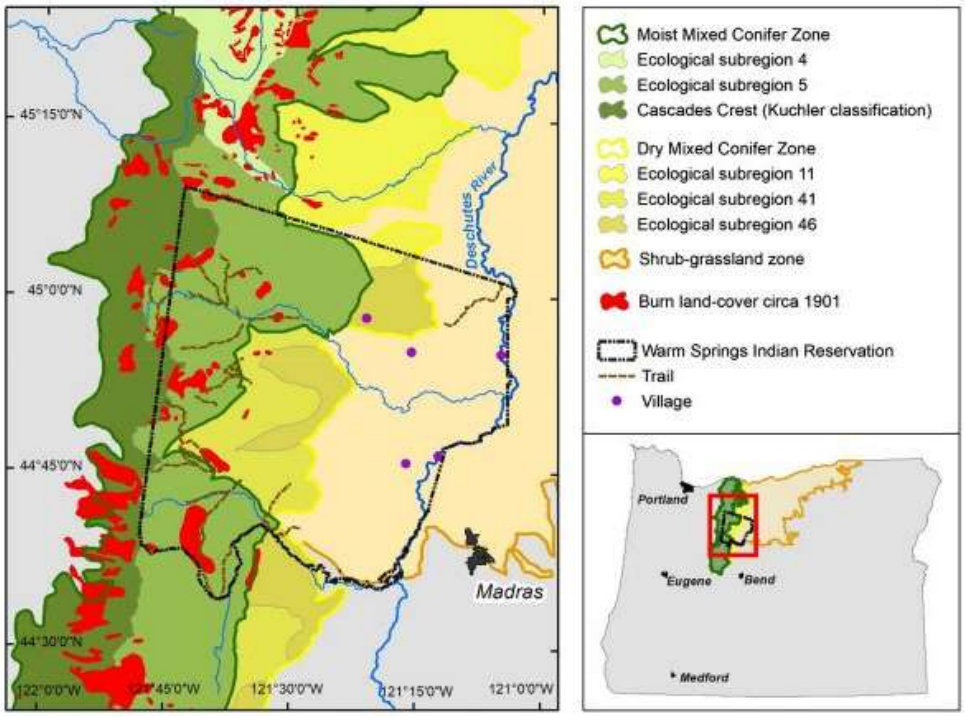

Figure 11: Map by Steen-Adams et al. (2019) depicting the historical spatial patterns of burn land cover within the Greater Warm Springs study area in Oregon. The map is generally divided into zones of moist mixed conifer forests and dry mixed conifer forests.

Crotteau et al. (2013) analyzed post-fire tree regeneration in a mixed-conifer, white fir and red fir dominated section of Lassen National Forest in northern California nine (9) and ten (10) years after a wildfire. The study site included four (4) burn severity categories and three (3) forest types for a total of twelve (12) regions (Crotteau et al., 2013). Their objectives were to "quantify post-fire tree seedling and woody shrub response" and "examine seedling and shrub species trends on the landscape" (Crotteau et al., 2013). The study area was 9,371 ha, ranged between 900m and 2100m in elevation, and in an environment where fires occurred between 9 and 110 years apart (Crotteau et al., 2013). Most of the study site had not experienced a fire approximately 100 years prior to the fire event this study is based upon (Crotteau et al., 2013).

The study site was divided into 12 sections (four fire severity types within three forest types) for stratified random sampling (Crotteau et al., 2013) (Figure 12). LANDSAT Thematic Mapper imaging was used to determine fire severity via the Relative differenced Normalized Burn Ratio (RdNBR) (Crotteau et al., 2013). This information was broken down into unchanged, low-severity, medium-severity, and high-severity fire

severity categories (Crotteau et al., 2013). A digital elevation model (DEM) was used to inform elevation thresholds and the study area was divided into mixed-conifer, low-elevation fir, and high-elevation fir regions (Crotteau et al., 2013). Five (5) sample points were set for each of the twelve (12) regions constructed for the study (Crotteau et al., 2013).

Crotteau et al. (2013) determined that the median value of seedling densities for conifers varied significantly by fire severity. The higher fire severity was associated with higher shrub coverage (Crotteau et al., 2013). *Abies spp*. regenerated most abundantly within the conifers and shrub cover in high fire severity regions was primarily *Ceanothus spp* (Crotteau et al., 2013). Fir regeneration was significant in the area, but the fire also resulted in diverse responses within the vegetation (Crotteau et al., 2013).

Crotteau et al. (2013) is a useful example of how to stratify sample plots for fire severity measurements and ecoregion classifications and introduces a modified NBR concept to measure fire severity. It also provides insight into post-wildfire vegetation dynamics over time and helps inform how NDVI may correlate to surface dynamics.

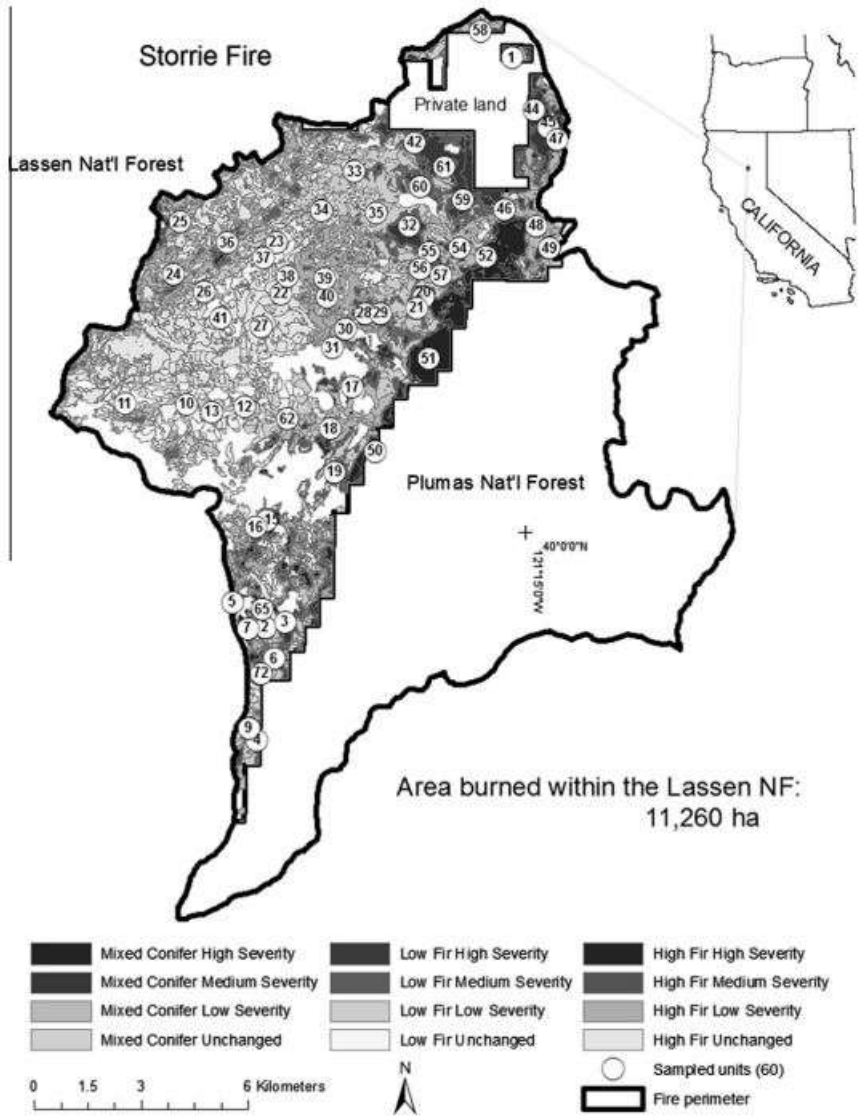

Figure 12: A map by Crotteau et al. (2013) indicating the area burned and study site delineation in the Lassen NF in California. It is stratified by four CBI values representing burn severity and three levels of forest type to separate ecosystem types (Crotteau et al., 2013).

Kane et al. (2015) analyzes the impact of environmental conditions on forest structures and fire using LiDAR airborne data. Their study area contains two forested regions within Yosemite National Park in California (Kane et al., 2015). The study area covered two regions, totaled approximately 27,000 ha, and excluded areas that burned before 1970, that were not forested at the time of the study, and that were not forested in 1937 (Kane et al., 2015). These exclusions were based on the desire to study regions where non-human fires were burned and the vegetation would therefore be altered via non-

human induced fire regimes (Kane et al., 2015). Sugar pine-white fir, Jeffrey pine, and red fir forest types were common in both study sites (Kane et al., 2015). The northern site contained an additional three (3) forest types (lodgepole pine, ponderosa pine, and western white pine (Kane et al., 2015).

LiDAR data was collected at a one (1) meter resolution and a digital terrain model (DTM) was created and metrics determined to indicate tall shrubs, short trees, and low foliage of tall trees (Kane et al., 2015). Fires that occurred between 1930 and 2010 were mapped and burn severity was determined using the Relativized differenced Normalized Burn Ratio (RdNBR) (Kane et al., 2015). Metrics for water balance and slope position were created and a random forest modeling algorithm was created to determine if there was correlation between variables (Kane et al., 2015). Comparison maps (Figure 13) were also created to visually inspect differences between variables.

Kane et al. (2015) determined that variations in the forest structure and fire could be predicted by environmental conditions through large portions of the study area. This included the number of times an area burned, variation in burn severity, variation in canopy cover, and forest structure after one and two fire events (Kane et al., 2015). They concluded that a "feedback mechanism" between local fire regimes, pre- and post-fire forest structures, and environments existed with water balance, slope position, and slope and insolation being primary control mechanisms (Kane et al., 2015).

Kane et al. (2015) provides an example of how to divide and structure a study area and isolate control mechanisms of vegetation behavior related to fire regimes. It further explains the relationship between specific control mechanisms and vegetation behavior.

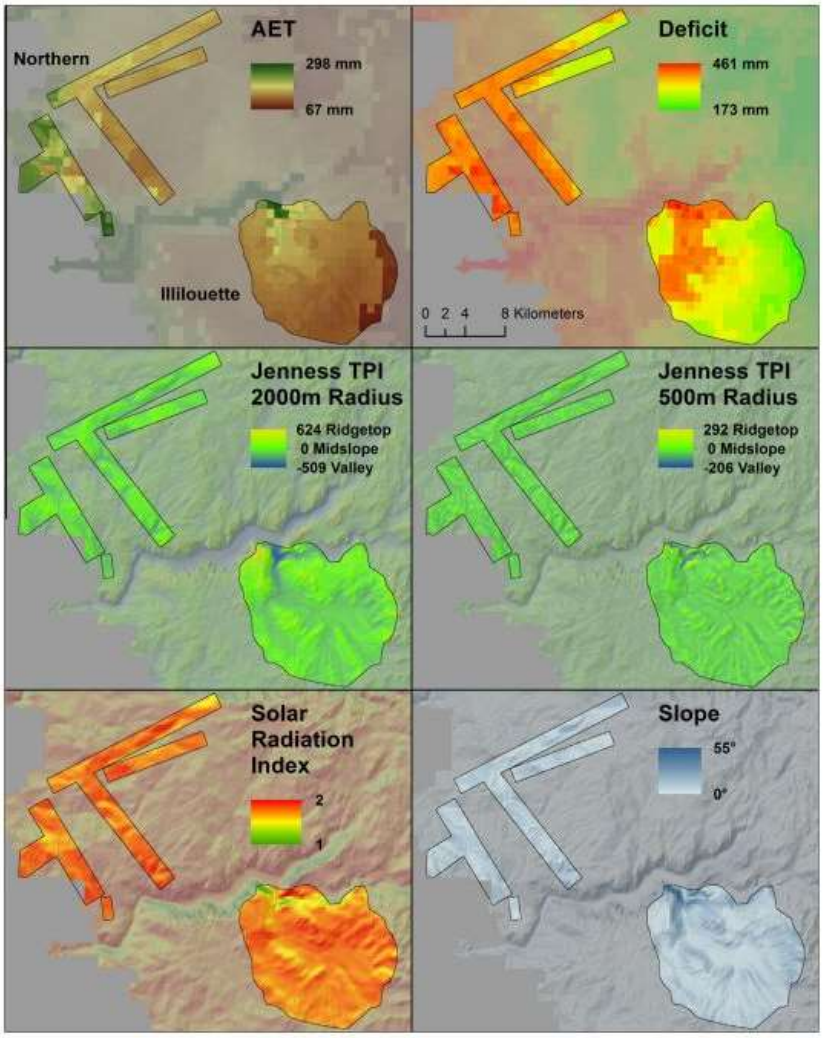

Figure 13: Map comparisons by Kane et al.(2015) mapping environmental conditions of the study sites in the Yosemite National Park in California. The Solar Radiation Index (bottom left) is a relative index where higher values correlates to greater solar radiation (Kane et al., 2015). The areas outline in black are the study sites, AET represents actual evapotranspiration, Deficit represents climatic water deficit, TPI represents topographic position index.

Riaño et al. (2002) studied "postfire regeneration" at two (2) locations in the Santa Monica Mountains, California that experienced burns and control sites that had not burned in at least 20 years. One location was composed of northern mixed chaparral and the other was composed of coastal sage scrub (Riaño et al., 2002). Fire return periods for this area range between ten (10) and forty (40) years (Riaño et al., 2002). The burns occurred in different years, but the flora community and environments (Riaño et al., 2002). The study had four (4) objectives that related to the effectiveness of remote

sensing data, validation of spectral indices, flora regeneration, and flora community dynamics over time (Riaño et al., 2002).

Site selection and data collection were based on remote sensing images *via* the AVIRIS in the Fall and Spring for imaging before and after fires, a Landsat TM- based vegetation map to compare information prior to the fires, a GIS layer of fire history since 1925, and a digital elevation model (DEM) (Riaño et al., 2002). Spectral thresholds related to vegetation were located ("endmembers") and then the normalized difference vegetation index (NDVI)was used to reflect flora regeneration (Riaño et al., 2002). Using this data, a regeneration index (RI) and normalized regeneration index (NRI) was created to analyze flora recovery (Riaño et al., 2002).

Riaño et al. (2002) concluded that 1) control plots were necessary to create regeneration indices, 2) using NDVI to generate RI and NRI performed better in the mixed chaparral environment than the sage scrub environment, 3) endmembers were more accurate in tracking regeneration over time compared to NDVI, and 4) an NRI calculation based upon the endmember termed "Green Vegetation" was better at estimating recovery at both study sites. They used remote sensing to go into deeper detail regarding the specific component of regeneration of vegetation, beyond the scope of NDVI valuation commonly used in remote sensing applications. Therefore, it provides an example of how to isolate specific plant behavior using remote sensing tools.

Veraverbeke et al. (2012) used MODIS imaging to study the effects of a wildfire in Greece on the surface albedo and the day and night surface temperatures (aka land surface temperatures or "LST") of the study site for up to two (2) years after the fire. The study location covers approximately 175,000 hectares in southern Greece and incorporates multiple fires that occurred in 2007 (Veraverbeke et al., 2012). The elevation ranges from 0 to 2404 meters and is dominated by limestone sediment and outcrops with some gravelly soils on the inland hills (Veraverbeke et al., 2012). The climate typically has hot and dry Summers with mild and wet Winters ("Mediterranean") (Veraverbeke et al., 2012). The flora includes Black pine as the dominant conifer, oak as the dominant deciduous species, olive groves, and shrubland (Veraverbeke et al., 2012). Research additionally aimed to determine if remotely sensed albedo and LST are appropriate to use as indicators for fire-burn severity (Veraverbeke et al., 2012). Fire severity is defined as "the effect of fire in pre-recovery recovery phase, accounting solely for direct fire effects" and burn severity is defined as "both the immediate effect of fire with ecosystems responses (mainly vegetation regeneration)"(Veraverbeke et al., 2012). Therefore, "fire-burn severity" relates to both of these effects on the landscape.

Veraverbeke et al. (2012) collected MODIS data and created GIS layers depicting the normalized difference vegetation index (NDVI), white-sky albedo (α), daytime LST (LSTd), night time LST (LSTn), and Quality Assurance (QA) . Control pixels were selected to compare data results. They concluded that land cover and fire-burn severity controlled, and was proportionally related to, post-fire vegetation changes, LST, and α values. A drop in post-fire NDVI values were significant, but α and LST were dependent on seasonality. Vegetation indices (VI) were effective in detecting burns and burn severity levels (Veraverbeke et al., 2012). Values for α decreased and LSTd increased after the fire, then varied by season or over time, respectively. LSTn values slightly decreased in conifer-dominant forests but were otherwise minimal.

Veraverbeke et al.'s (2012) study correlates vegetation response and environmental factors in the post-wildfire environment (Figure 14). The relationship between the "greenness" (NDVI) of the area and the shifts in albedo and surface temperatures can relate to vegetation response and growth patterns immediately after and in the years following a wildfire. The study further elects to use lower resolution spectral imaging with a higher temporal resolution in order to prioritize details within their target time scales. This demonstrates a consideration for identifying and prioritizing the quality of your data. In this case, the temporal scale was a significant priority.

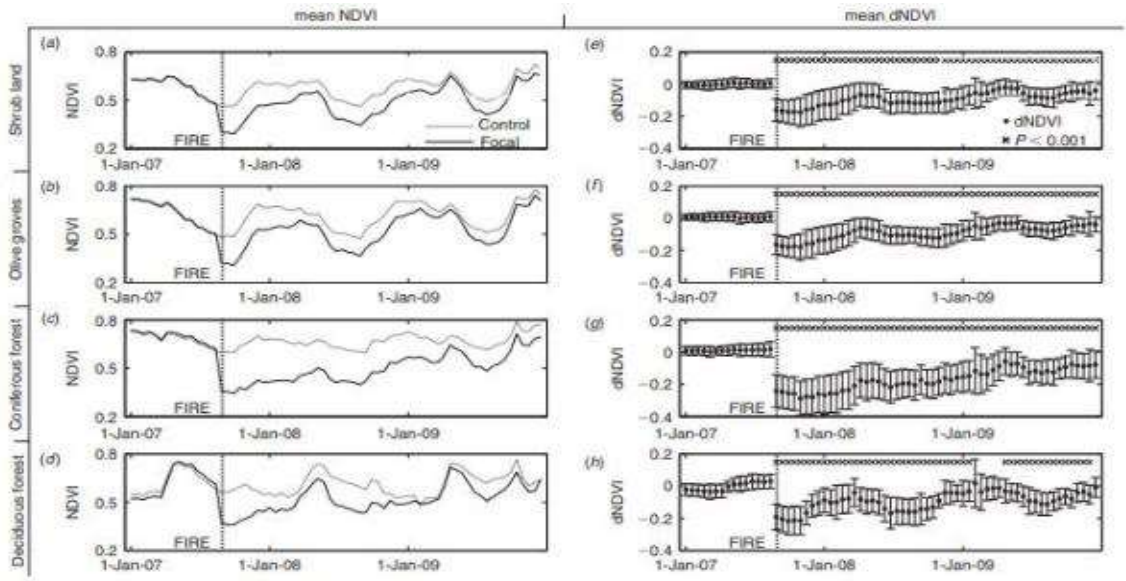

Figure 14: Graphs from Veraverbeke et al. (2012) depicting mean NDVI and mean dNDVI values over time relative to dominant vegetation cover before and after a fire event in Greece. NDVI represents the vegetation index value and dNDVI represents the difference between pre-and post-fire NDVI index values.

Materials and Methods

Analysis Steps

Step 1: Characterize pre-fire conditions of vegetation using NDVI.
- Average NDVI for sample points from 2013 - 2016.
- Characterize pre-fire environmental conditions, such as climate, topography, dominant species.
- Describe fire management history.

Step 2: Characterize dNBR from the fire event.
- Assign burn severity category to index value.
- Describe burn severity spatial relationships.

Step 3: Characterize post-fire conditions using NDVI over the following 4 years.
- Compare annual NDVI point values for all years.
- Compare each year of NDVI value to static aspect value.
- Compare each year of NDVI value to static dNBR value.
- Describe limitations of indices.
- Describe potential outside influences.

Step 4: Summarize relationship between NDVI and controls of dNBR and aspect.

This project uses Google Earth Engine (GEE) to process, review, and export data. A static polygon was generated to represent the study area and focus image processing.The Normalized Difference Vegetation Index (NDVI) was used to characterize vegetation (Boer et al., 2008; Escuin et al., 2008; Leon et al. 2012; Google Developers, 2022; Riano et al. 2002) and differenced Normalized Burn Ratio (dNBR) was used to characterize burn severity (Escuin et al., 2008; Holden et al. 2009; Harris et al., 2011; Google Developers, 2022; United Nations, 2022; Keeley, 2009; Crotteau et al., 2013). The data used to calculate aspect is the NASA Shuttle Radar Topography Mission Digital Elevation data set, which has a 30m spatial resolution and was processed to fill voids using open-source data (Farr et al., 2007). The data used to collect NDVI and dNBR values is the USGS Landsat 8 Surface Reflectance Tier 1 data set, which has a 30m spatial resolution and is atmospherically corrected to indicate surface reflectance (Google Developers, 2022; USGS, 2022). Data for Landsat 8 began in February 2013, so project data spans the years 2013 to 2021 in order to acquire data within the same phenological cycle (USGS, 2022). This data represents spatial analyses of vegetation growth, fire burn severity, and an indicator of how much relative sunlight an area receives, respectively. Images were compared between this data to determine a potential correlation between vegetation growth, burn severity, and aspect.

I identified a static value for burn severity using dNBR to indicate the severity of damage sustained for the duration of the burn (United Nations, 2022) and subdivided the classification into eight (8) categories in preparation for sampling. I took a static value for aspect, with the assumption that no significant post-fire topographic changes are taking place that would alter the directional face of the landscape (Farr et al., 2007; Kane et al., 2015; Vlassova et al., 2014). Aspect values were specified between 0 and 359.99 degrees then divided into eight (8) increments of 45 degrees for sampling. Those increments were further divided by the eight (8) classifications of dNBR. This made up the stratified random sampling zones with 25 points selected for each zone.

I took snapshots of the vegetation (NDVI) every year from 2013-2021 and at the same time of year to see what vegetation was like before the fire and how it changes over time after the fire (Escuin et al., 2008; Leon et al., 2013; Riano et al., 2002). When available, I used vetted, pre-written code. I additionally applied a cloud, cloud shadow, and snow mask to remove false values created by these features. All layers were clipped to the study area to reduce the amount of data and processing required. The image layers for aspect, NDVI, dNBR, and sample points were stacked into one feature and the combined data table was exported for further manipulation. Data values were also captured for elevation and an index representing solar radiation (CHILI). These data points are experimental features that were convenient to add to my GEE script code for additional consideration if time permitted.

The random sampling points taken from each zone were projected through the layer stack to collect multiple index values at each georeferenced point. Preliminary graphs were created comparing aspect, dNBR, and NDVI with aspect and dNBR separated by zones. I averaged NDVI for 2013-2016 to represent typical pre-fire point behavior over time, then annual post-fire NDVI for 2018 - 2021 was graphed against aspect, dNBR, and dNBR + aspect, respectively. Preliminary graphs were created in Microsoft Excel, however the file conversion necessary for this product resulted in errors that invalidated the data.

Additionally, I determined that results were uninteresting when comparing NDVI values with the classification systems created for aspect and dNBR. In contrast, comparing point-specific values for NDVI, aspect, and dNBR in various combinations indicated more scientifically interesting relationships between each index. Manipulating the data as continuous variables in JMP statistical software resulted in all viable graphs and charts being produced using JMP's Graph Builder.

While processing steps were similar for each index, special considerations and approaches were needed for each step. These differences are further described below.

Vegetation data - NDVI

Imaging from Landsat 8 Collection 1 Tier 1 was used to analyze the NDVI of the wildfire burn zone before and after the fire occurred. The Landsat 8 images use Landsat 8 spectral bands 4 (red, 0.64-0.67 μm) and 5 (NIR, 0.85-0.88 μm) to detect NDVI (NDVI, 2006). A cloud, cloud shadow, and snow mask were applied to the images to remove these features and reduce NDVI value errors during calculations. The images were further sorted to select a clear image, mosaicked, and scaled to the top of atmosphere reflectance.

NDVI is a calculation of the difference between near-infrared and red light and is a standardized way of measuring healthy vegetation or the 'greenness' of an area. NDVI values can be interpreted in multiple ways, described below. These definitions are considered during the analysis of quantitative values. NDVI only detects the presence of vegetation and does not provide details of flora composition. Therefore, only vegetation presence will be considered during this study.

According to USGS:
-1.0 - 0.1 = Barren rock, sand, or snow usually
0.2 – 0.5 = Sparse vegetation, shrubs, grasslands, senescing crops
0.6 - 0.9 = Dense vegetation, crops at peak growth stage

According to Earth Observing System:

Plant health:
-1 to 0 = dead plants or inanimate object
0 - 0.33 = unhealthy plant
0.33 – 0.66 = moderately healthy plant
0.66 – 1 = very healthy plant

Density:
0.2 - 0.4 = sparse vegetation
0.4 – 0.6 = moderate vegetation
0.6 – 1 = highest possible density of green leaves

Only images from the months of July to August for the years 2013 - 2021 will be considered. This range occurs when vegetation is more likely to be fully leafed and phonologically similar to pre-fire conditions. This date range is set due to the limitations of when the satellite collection became available (2013) and the last phenological year of available data prior to the completion of this study (2021).

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Burn Severity - dNBR

The Normalized Burn Ratio (NBR) and Difference Normalized Burn Ratio (dNBR) are similar in calculation and methodology to NDVI. Image sets were scanned for July - August 2017 to capture pre-fire conditions and January - May 2018 to account for the length of time the study area continued burning. The latter range was also necessary to reduce the cloud, snow, and smoke interference in satellite imaging. These dates additionally occur during a dormant period for relevant vegetation and would avoid errors caused by phenological cycle. The least cloudy image from each range was selected and clipped to the study area. A cloud and cloud-shadow mask was applied and then scaled to the top of atmosphere (TOA) reflectance.

NBR/dNBR considers near infrared (NIR) and shortwave infrared (SWIR) wavelengths and is used to highlight burnt areas in large fire zones. In regions that experience wildfires, there is a high reflectance of SWIR and low reflectance of NIR. This is the opposite of what healthy vegetation would reflect. Imaging with high NBR values indicates healthy vegetation, low values indicate bare ground or burnt areas, and values close to zero represent non-burnt areas.

The calculation of burn severity considers the difference between the pre-fire and post-fire NBR values (dNBR). The value of that difference is then used to estimate burn severity. Higher values of dNBR indicate more severe damage and negative values may indicate post-fire regrowth. dNBR values can regionally vary, so some field assessment may be required for interpretation.

$$\text{NBR} = \frac{NIR - SWIR}{NIR + SWIR}$$

$$\text{dNBR} = \left(\frac{NIR - SWIR}{NIR + SWIR}\right)_{\text{prefire}} - \left(\frac{NIR - SWIR}{NIR + SWIR}\right)_{\text{postfire}}$$

Table 2: Burn severity classifications proposed by USGS and color-coded by UN-SPIDER (2022). The burn severity classifications include all possible outcomes in the post-fire environment, including burned, unburned, and vegetation growth environments.

Severity Level	dNBR Range (scaled by 10^3)	dNBR Range (not scaled)
Enhanced Regrowth, high (post-fire)	-500 to -251	-0.500 to -0.251
Enhanced Regrowth, low (post-fire)	-250 to -101	-0.250 to -0.101
Unburned	-100 to +99	-0.100 to +0.99
Low Severity	+100 to +269	+0.100 to +0.269
Moderate-low Severity	+270 to +439	+0.270 to +0.439
Miderate-high Severity	+440 to +659	+0.440 to +0.659
High Severity	+660 to +1300	+0.660 to +1.300

Topography

Aspect is the orientation of a slope and is measured in degrees with 0 representing North, 90 representing East, 180 representing South, and 270 representing West. Google Earth Engine calculates aspect by comparing the elevation of each pixel to its four connected neighboring pixels. The software will identify the maximum rate of change in the downslope direction and assign a value to the pixel that represents the compass direction that the pixel surface faces. Due to the calculation structure, errors may occur at the edge of the image for those pixels that do not have a complete set of neighboring pixels. Pixels with an aspect will be labeled with values between 0 and 359.99. This is because 0 and 360 represent the same space on a circle. Pixels with a flat surface will have a negative value.

Elevation and slope were captured using the DEM as ancillary information but are not considered a primary focus of this study. No additional processing or masking was necessary for this layer.

CHILI

Data values were also captured for an index called CHILI (continuous heat-insolation load index). The CHILI index is meant to represent evapotranspiration and topographic shading to determine relative “cool” and “warm” areas of the map based on multiple static topographic features (Theobold et al., 2015). This index is based on the 10m NED DEM created by the USGS. These data points are experimental features that were convenient to add to my comparisons and provide visual input to vegetation and burn patterns. This data was initially used for early stages of visual analysis and incorporated

into sampling data points but was ultimately not used in the final analysis of this study due to time constraints and the complexity of the index.

Sampling

A stratified random sampling method was used to isolate the target controls of aspect and burn severity. Aspect was divided into eight sections of approximately 45-degree intervals with the upper limits of each section being placed at 45, 90, 135, 180, 225, 270, and 359.99 degrees, respectively. Burn severity was divided into sections based on the USGS burn severity classification (UN-SPIDER, 2022). Both stratified areas were then scaled and multiplied to create subregions where the quantified classification for the variables would be indicated via the tens and ones digits. E.g., the number 15 would indicate the 1st classification in burn severity and the 5th classification in aspect. This was used for quality control purposes to ensure sampling occurred as desired.

Quality control was performed by visually inspecting the layers in GEE to pinpoint obvious discrepancies such as sample points that fall outside of the study area, sample point distribution, masking application, and pre-masking image quality. Qualitative points were verified within the spreadsheet and graphing tools to check validity and outlier data. Three points were found to fall outside of mathematically possible NDVI ranges and were removed from the study.

Visual Study

Maps were created using burn severity, NDVI, CHILI, and aspect. Maps of NDVI values in 2017 and 2020 were visually compared to a map of burn severity overlaying CHILI data. The relationships between topography, burn severity, and NDVI were visually characterized and later compared to quantitative data. Major and minor ridgelines were identified in the study area, color-coded, and referenced when describing indice relationships. True color satellite images from GEE and Google Earth were used to inspect remote areas to correlate indices and their physical manifestations. While the CHILI data was ultimately not used, visual inspection correlated with topography accurately enough to define “primary” and “secondary” features used as a visual reference (Figure 15).

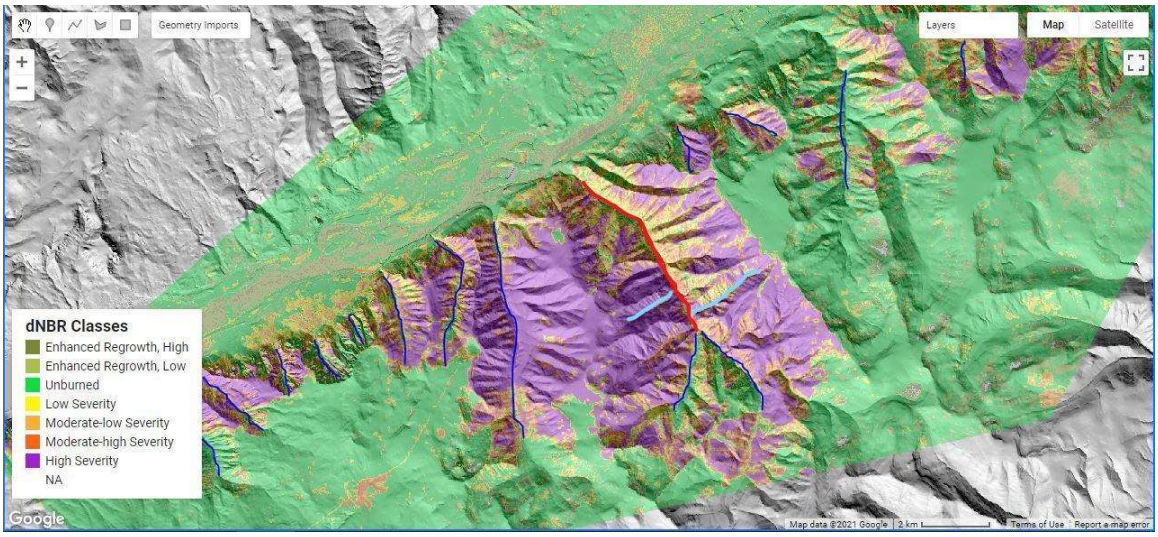

Figure 15: Google Earth Engine image of burn severity overlayed onto an image of CHILI data in the Eagle Creek study area in Oregon. The dark blue lines mark the "Primary" ridgelines and light blue lines indicate "Secondary" ridgelines. The red line marks a portion of the Eagle Creek Trail. The CHILI data uses topographic elements to indicate relative solar insolation.

Results

Visual Study

Vegetation regrowth patterns on secondary features appear to be oriented in a north versus south slope orientation rather than fixed upon an east vs. west slope orientation. Regrowth on primary features appear to be oriented in an east versus west orientation. Values near -1 (indicative of water) appear on large swaths of some slopes (Figure 16) but are later determined to be bare earth.

Primary north-south oriented valleys have low values (indicating reduced growth), but higher values on primary ridgelines. Regrowth on northern and southern secondary slopes are varied in terms of orientation-based pattern, but rate of regrowth appears bounded by the secondary ridgelines. Primary eastern slopes show more dominant regrowth than corresponding western slopes. These marked differences in growth appear to be bounded by ridgelines.

Overall, there is revegetation in most areas with the most prominent growth between 2018 and 2019. NDVI values that increased over time appeared concentrated around primary ridgelines. By 2020, higher NDVI values were present in most areas except deep valleys (Figure 17).

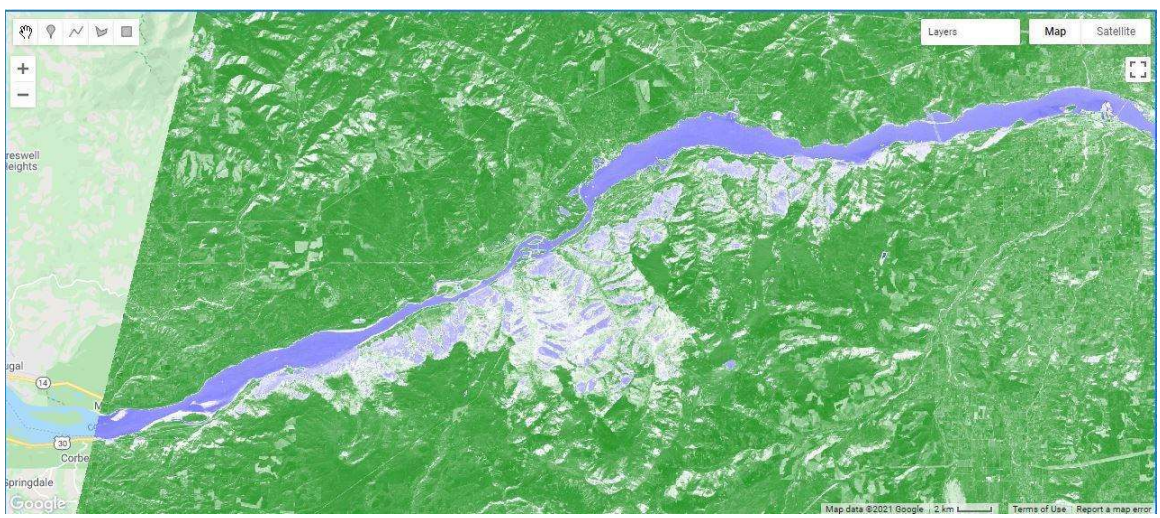

Figure 16: Google Earth Engine NDVI image of the Eagle Creek Recreation Area post-fire, 2017. Green represents vegetation with darker shades representing healthier or dense vegetation. The white represents bare earth or soil. The blue sections on the hillslope are a technical error likely exacerbated by smoke and are bare rock or soil.

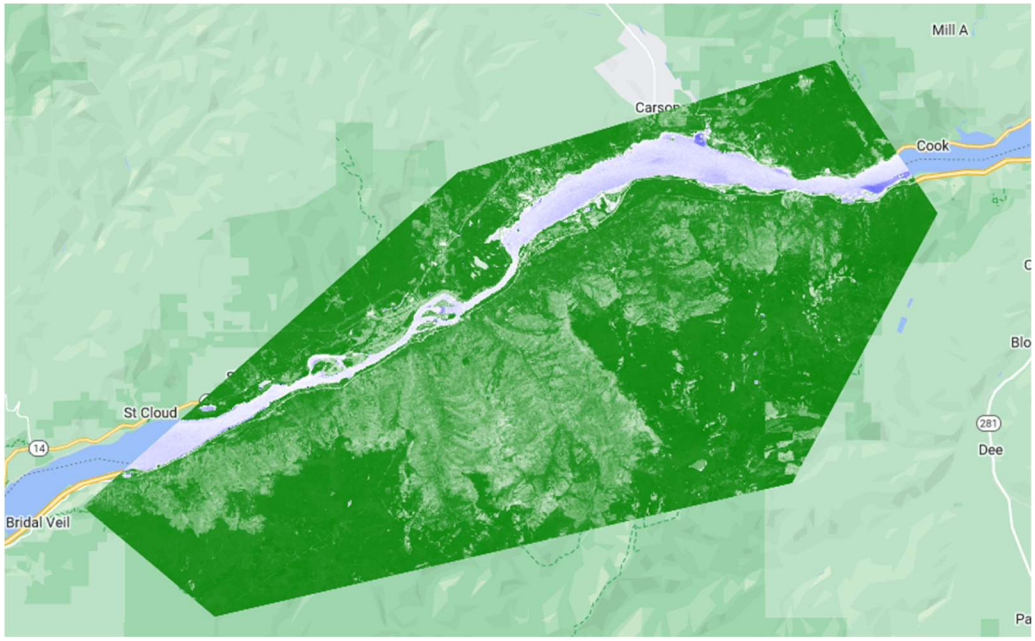

Figure 17: Google Earth Engine NDVI image of Eagle Creek Recreation Area post-fire, 2020. Green represents vegetation with darker shades indicating greater health or density. The white represents bare earth or soil. The blue sections on the hillslope are a technical error and are bare soil.

Data Analysis

Initial graphing was completed by exporting data from Google Earth Engine (GEE) then importing that file into Microsoft Excel. A series of graphs were generated using exact values for NDVI and the stratified sampling classifications for aspect and dNBR (Figure 18). While Excel could read this file type, the software's interpretation of data values was inconsistent with how the GEE spreadsheet represented data. This was a function of software coding and how the two spreadsheets treat numbering rather than reflecting issues with raw data validity. Therefore, the Excel graphs were erroneous in visualizing the raw data. Further, the error resulted in false representation when graphing exact values for all indices and did not introduce scientifically interesting data. All graphs using Excel and stratified sampling classifications were subsequently removed from the study. JMP Graph Builder was used for final graphing analysis.

There were 1,425 sample points taken in total with 1,346 (or 94% of the study area) indicating some level of vegetation pre-fire in 2017. Of those vegetated samples, 1,075 were healthy/dense vegetation (NDVI 0.6 -1), 228 were moderately dense/healthy vegetation (NDVI 0.3 - 0.6), and 43 were unhealthy/sparse vegetation (NDVI 0.1 - 0.3). There were 779 sample points that experienced some severity of burn.

Figure 18: Graphs comparing NDVI and dNBR + Aspect for 2018 through 2021 for the Eagle Creek fire in Oregon. The values grafted are based upon the classification system used to generate sample points. Note that the tens column represents dNBR values and the ones column represents Aspect values.

Experimenting with comparing data while emphasizing NDVI, dNBR, and aspect, respectively, highlighted relationships between indices (Figures 19-21) and showed that pre-fire NDVI-based analysis was the most useful in this case. When tracking the change in NDVI over time while holding 2017 NDVI sample points static, I divided the plots into categories based on initial 2017 NDVI values. In this way, data reflected what happened to points that started with healthy, moderate, and sparse vegetation, respectively.

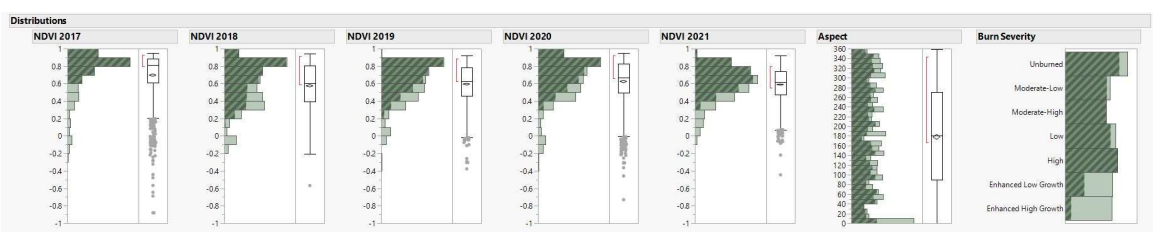

Figure 19: A figure of NDVI-based plot dynamics over time showing relationships between aspect and burn severity for the 2017 Eagle Creek Fire in Oregon. The darkened parts of the histogram represent sample points that had NDVI values between 0.6 - 1 beginning in 2017.

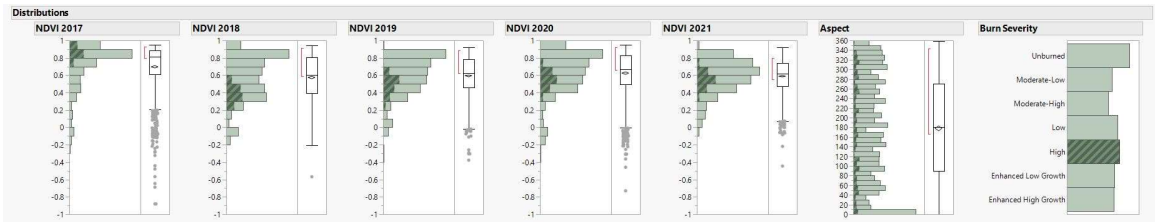

Figure 20: A figure of burn severity-based plot dynamics over time showing relationships between aspect and NDVI for the 2017 Eagle Creek Fire in Oregon. The darkened parts of the histogram represent sample points that experienced High severity burning.

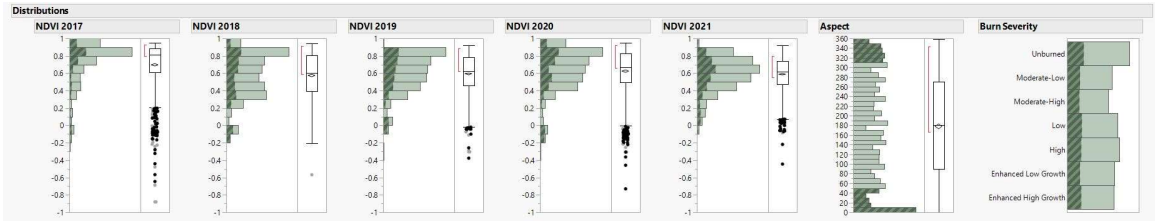

Figure 21: A figure of aspect-based plot dynamics over time showing relationships between burn severity and NDVI for the 2017 Eagle Creek Fire in Oregon. The darkened parts of the histogram represent sample points with an aspect of 310 - 50 degrees.

When graphing the distribution of sample points amongst topographic features, the point distribution amongst aspect ranges were relatively equal with the maximum difference between the number of points being less than 25. Most of the sample points had slope values between 0 - 40 degrees with the greatest number of points per column at 27.5 - 30 degrees and 0 - 5 degrees. Highlighting the peak slope values provided additional input regarding the distribution of topographic data and how they relate. Most of the points within these slope ranges also occurred at elevations under 100 meters and had aspects between 0 - 45 degrees (Figure 22).

Using the same graph from Figure 22 and emphasizing the elevation distribution of 0-100 meters, most of the points within this range also occurred on slopes of 0 - 10 degrees with a larger number of points per column being on slopes between 0 - 2.5 degrees. Similar to the slope-emphasized graph, the aspect of 0- 45 also had the most points per column (Figure 23).

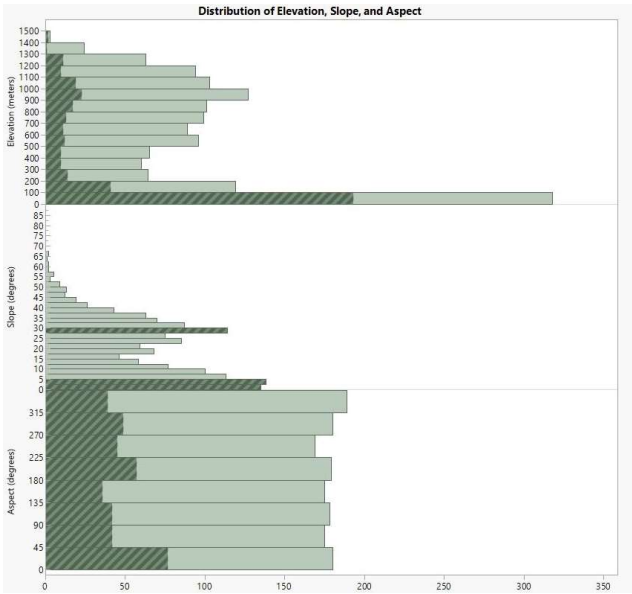

Figure 22: A graph of the distribution of sample points in relation to elevation, slope, and aspect in the Eagle Creek fire in Oregon. Elevation is graphed in 100 meter increments. Slope is graphed in 2.5 degree increments. Aspect is graphed in 45 degree increments. The darkened sections represent points that are associated with the selected Slope range (30 degrees). Note the aspect distribution is roughly equal due to the stratified random sampling method used.

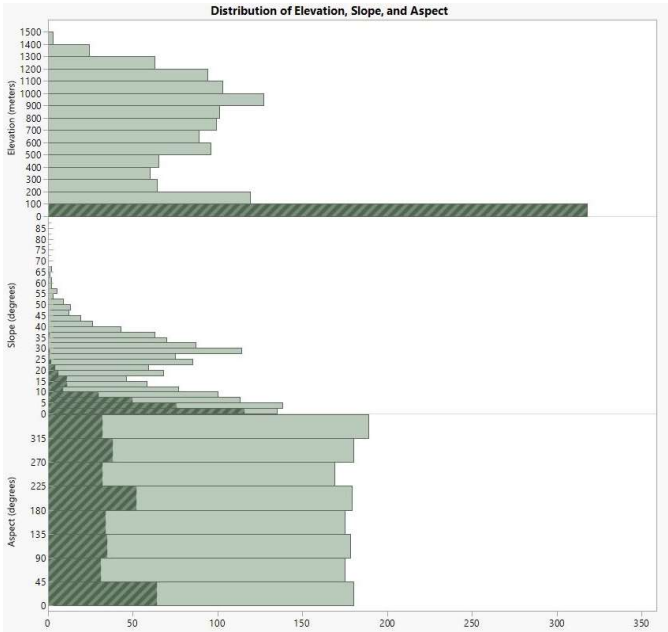

Figure 23: A graph of the distribution of sample points in relation to elevation, slope, and aspect in the Eagle Creek fire in Oregon. Elevation is graphed in 100-meter increments. Slope is graphed in 2.5-degree increments. Aspect is graphed in 45-degree increments. The darkened sections represent points that are associated with the selected Elevation range (0-100 meters). Note the aspect distribution is roughly equal due to the stratified random sampling method used.

NDVI values from 2013 to 2017 are relatively static and comparable with inconsequential deviations (Figure 24). For the years 2013 - 2016, the averaged median NDVI value is 0.82 and the averaged mean value is 0.71. This is comparable to the 2017 NDVI median value of 0.81 and mean value of 0.70.

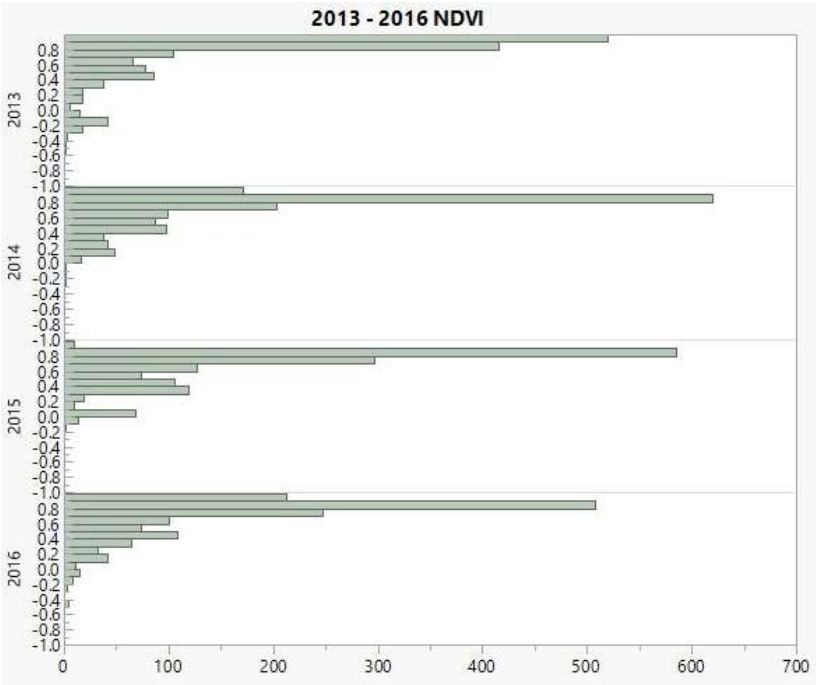

Figure 24: A graph of the distribution of sample points in relation to NDVI values for years 2013 - 2016, respectively, in the Eagle Creek Fire (Oregon) burn zone. NDVI values are grouped in 0.1 increments and represent vegetation health with 0.1-0.3 being sparse vegetation, 0.3-0.6 moderate vegetation, and 0.6-1 dense/healthy vegetation.

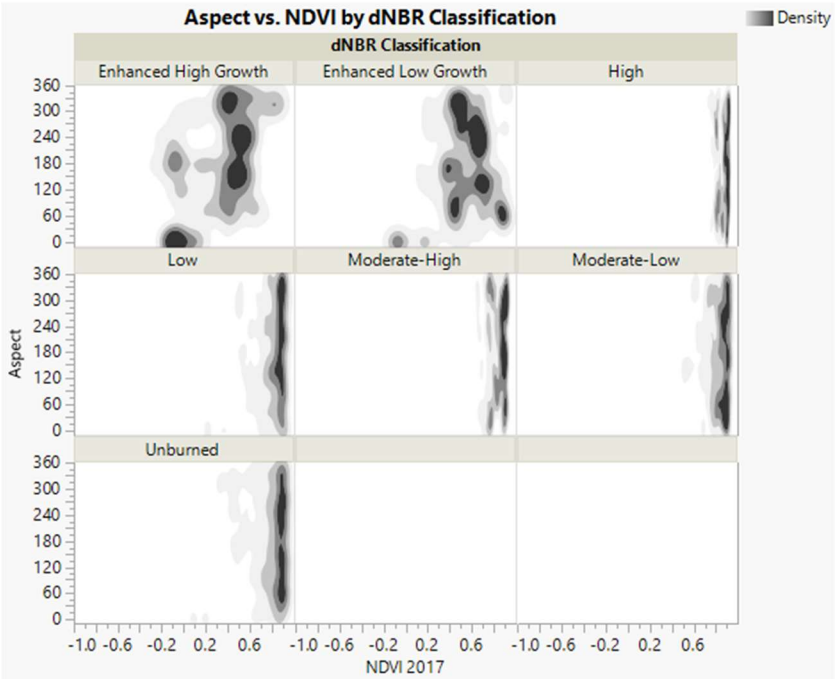

Figure 25: A graph of aspect vs. pre-fire NDVI for 2017, divided by burn severity, unburned, and growth classifications in the Eagle Creek study area. This graph shows the relative density of sample points broken into four tiers with darker color equating to increased density. This graph represents the 2017 NDVI distribution prior to the fire.

Graphs of the sample point density of aspect *vs*. NDVI for years 2017 to 2021, respectively, were created to visually represent changes over time (Figures 25 - 29). Degree of darkness indicates the relative density of point distribution. Zones of growth are added for interest, but not the focus of the study so will not be discussed here. These graphs are intended to provide a snapshot of relative distribution of....

The 2017 NDVI values in unburned and burned zones are concentrated within higher NDVI ranges (0.6 - 1), meaning that ... These values change significantly after the fire in all areas experiencing wildfire with the most change occurring in Moderate-High and High zones of the wildfire. The point distribution within each zone additionally becomes broader relative to 2017 distribution, but then narrows by 2020.

Post-fire, there are distinct distribution changes between burn severity classes with the unburned zone showing greater concentration at high NDVI values across aspect range with a slight gap around 150 - 200 and 340 - 40 degrees. The unburned zone shows the least variance in NDVI and greatest variance in aspect.

NDVI value distributions in low-severity zones are concentrated around values of 0.6 - 0.9, Moderate-Low zones around 0.6 - 0.8, Moderate-High zones around 0.4 - 0.7, and

High zones around 0.4 -0.6. Over time, the distribution of NDVI values become narrower within each zone as the zone values also move toward higher NDVI average values. The distribution of aspect values becomes patchy and inconsistent between burn zones with some higher density maintained on the equivalent of northern slopes. However, like NDVI, aspect distribution becomes more linear over time. Neither aspect nor NDVI have returned to pre-fire conditions by 2021.

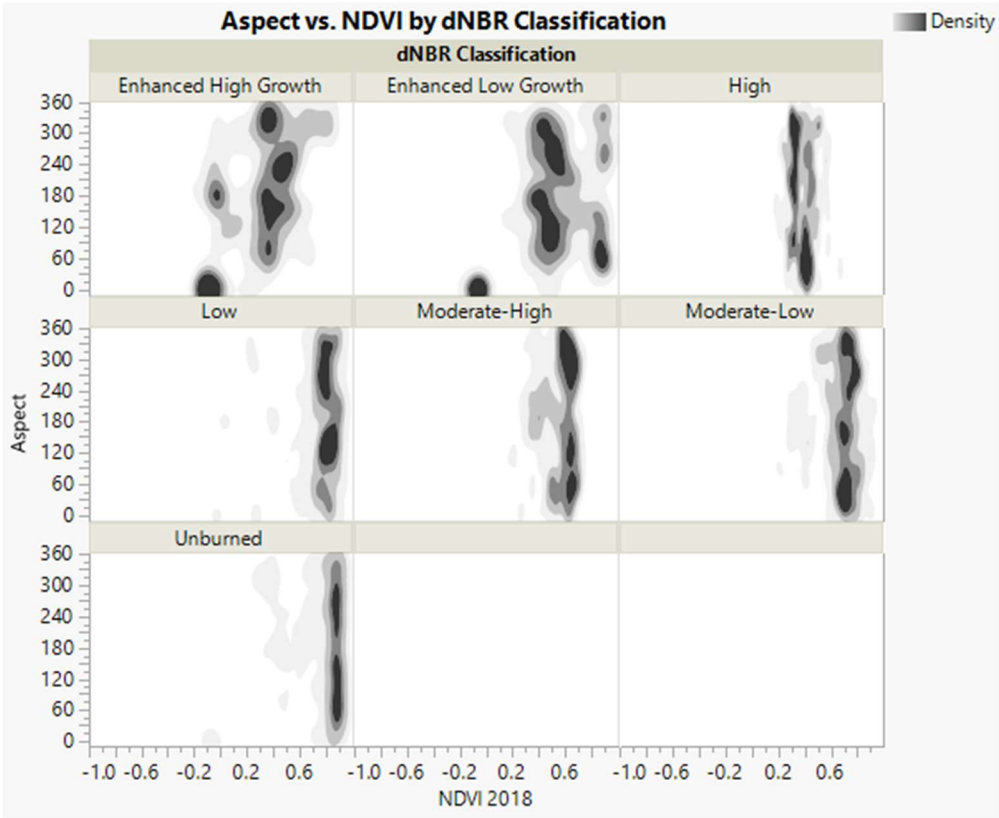

Figure 26: A graph of aspect vs. NDVI for 2018, divided by burn severity classifications in the Eagle Creek (Oregon) study area. This graph shows the relative density of sample points broken into four tiers with darker color equating to increased density. This graph represents the NDVI distribution one year after the fire.

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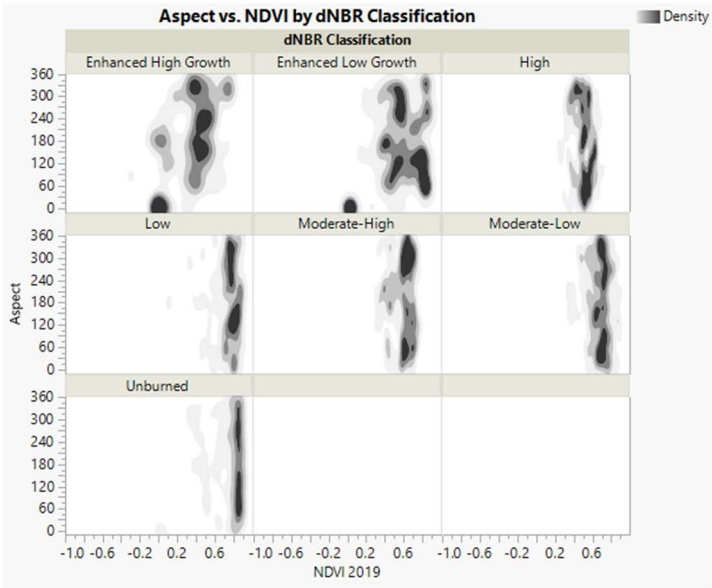

Figure 27: A graph of aspect vs. post-fire NDVI for 2019, divided by burn severity classifications in the Eagle Creek (Oregon) study area. This graph shows the relative density of sample points broken into four tiers with darker color equating to increased density.

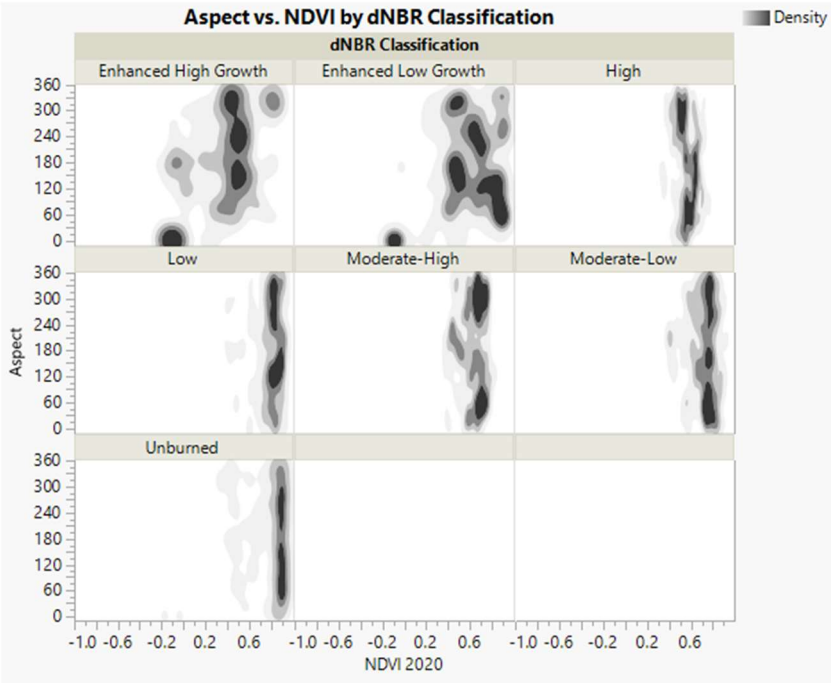

Figure 28: A graph of aspect vs. post-fire NDVI for 2020, divided by burn severity classifications in the Eagle Creek (Oregon) study area. This graph shows the relative density of sample points broken into four tiers with darker color equating to increased density.

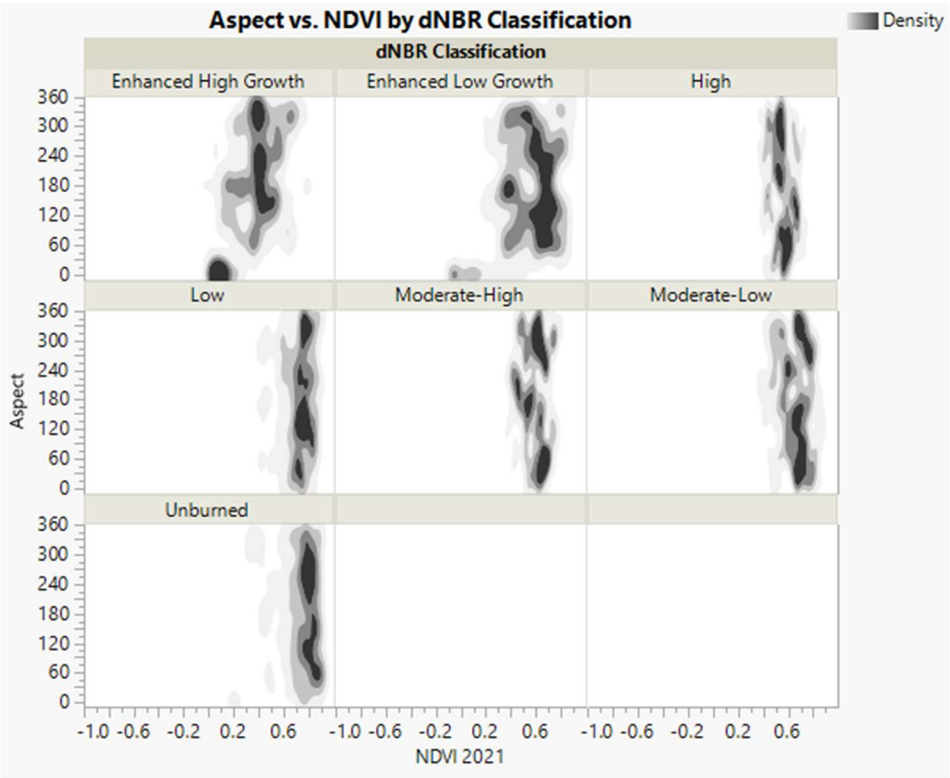

Figure 29: A graph of aspect vs. post-fire NDVI for 2021, divided by burn severity classifications in the Eagle Creek (Oregon) study area. This graph shows the relative density of sample points broken into four tiers with darker color equating to increased density.

Sample points with NDVI values related to healthy or dense vegetation (values 0.6 - 1) in 2017 showed a wide range of responses in post-fire years. These sample points continued to dominate high-NDVI point distribution over time. Most of these sample points remained at values of 0.2 (sparse or unhealthy vegetation) and above with all relevant points reaching values of above 0.3 by 2020 (Figure 30). The total number of sample points with NDVI values of 0.6 - 1 in 2017 totaled 1,075 or 80% of all sample points in 2017 with values of 0.1 - 1. The number of points that maintained values of 0.6 - 1 over time are 65 % in 2018, 70% in 2019, 76% in 2020, and 68% in 2021. The distribution of these 2017 points in NDVI ranges of 0.3 - 0.6 were 34% in 2018, 29% in 2019, 23% in 2020, and 32 % in 2021. The distribution of these 2017 points in NDVI ranges of 0.1 - 0.3 were 5% in 2018, 1% in 2019, 0% in 2020, and 0% in 2021. See Tables 3-5 and Figures 27-29.

Sample points with NDVI values related to moderately dense or healthy vegetation (values 0.3 - .6) in 2017 show a slight increase of their distribution range to predominantly values of 0.2 - 0.6 beginning in 2018. However, the 2017 distribution

remains relatively static with 86% in 2018, 88% in 2019, 82% in 2021, and 86% in 2021 points remaining in the 0.3 - 0.6 NDVI range. There are some sample points showing increases in NDVI, but this comprises 4% in 2018, 9% in 2019, 15% in 2020, and 11% in 2021 points originally measured at 0.3 - 0.6 in 2017 (Figure 31).

Sample points with NDVI values related to sparse or unhealthy vegetation (values 0.1-0.3) in 2017 only comprised 43 sample points (or 3.3% of 2017 samples with vegetation). These sites largely experienced a downward distribution in NDVI values with less than 5 sample points experiencing growth above values of 0.3 (Figure 32).

The distribution of 2017 NDVI values from 0.1 - 1 over time can be seen in Tables 3 - 5 and Figure 33. Most sample points within each NDVI category remained within that category over time. The only areas that experienced high burn severity were densely vegetated sample points with NDVI values ranging between 0.6 - 1. Low and moderately vegetated areas predominantly experienced low-severity burns. Densely vegetated areas experienced all levels of burn severity with 16 - 20% of associated samples within each burn category.

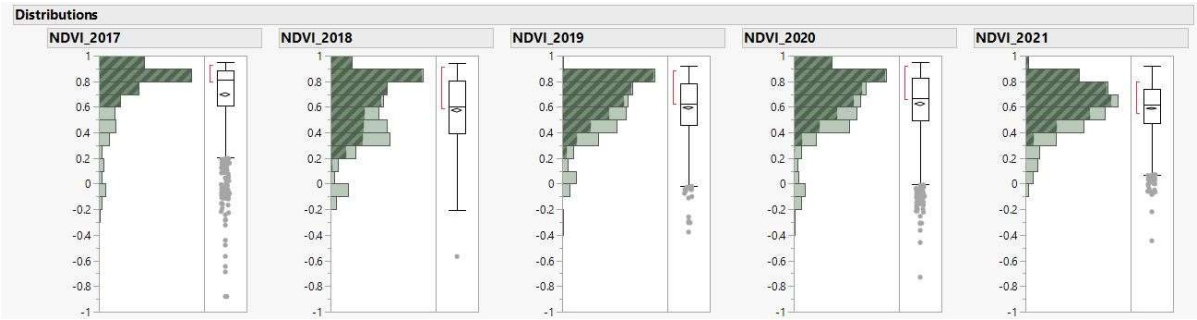

Figure 30: A histogram showing the relative change of NDVI values per sample point over time in the Eagle Creek (Oregon) study area. The dark sections represent sample points that had NDVI values between 0.6 - 1 in 2017. There are 1,075 sample points in this NDVI range.

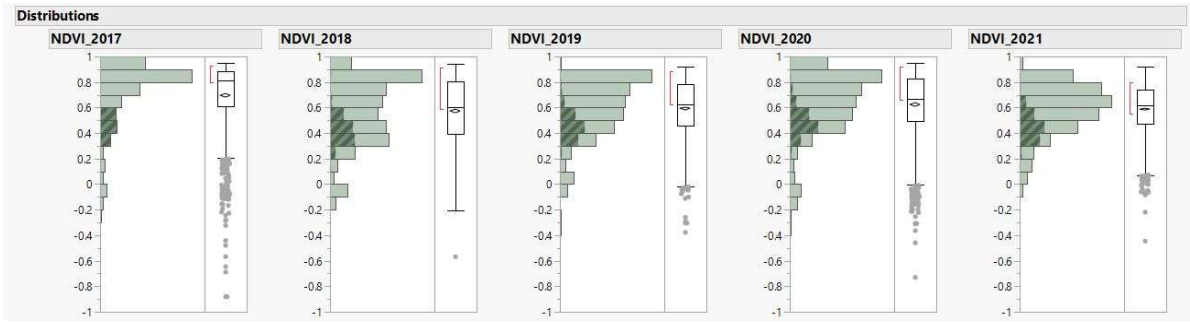

Figure 31: A histogram showing the relative change of NDVI values per sample point over time in the Eagle Creek (Oregon) study area. The dark sections represent sample points that had NDVI values between 0.3 - 0.6 in 2017. There are 228 sample points in this NDVI range.

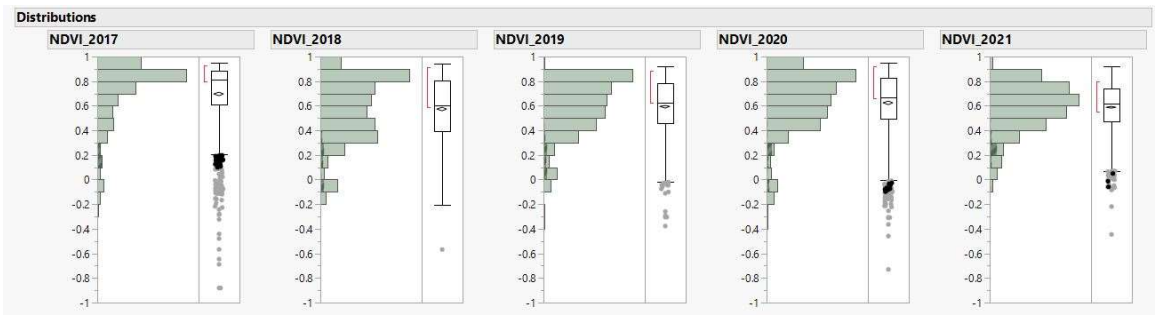

Figure 32: A histogram showing the relative change of NDVI values per sample point over time in the Eagle Creek (Oregon) study area. The dark sections represent sample points that had NDVI values between 0.1 - 0.3 in 2017. There are 43 sample points in this NDVI range.

Table 3: Distribution of sample points in 2017 with NDVI values of 0.6 - 1 in the Eagle Creek (Oregon) study area. The 2018 - 2021 values show the distribution (as a percent) of these sample points over time. The Low - High values show the distribution (as a percent) of burn severity of the sample points.

NDVI	2017 (pts)	2018 (%)	2019 (%)	2020 (%)	2021 (%)	Low (%)	M-Low (%)	M-High (%)	High (%)
0.6 - 1	1075	65	70	76	68	17	16	16	20
0.3 - 0.6	-	34	29	23	32	-	-	-	-
0.1 - 0.3	-	5	1	0	0	-	-	-	-

Table 4: Distribution of sample points in 2017 with NDVI values of 0.3 - 0.6 in the Eagle Creek (Oregon) study area. The 2018 - 2021 values show the distribution (as a percent) of these sample points over time. The Low - High burn severity values show the distribution (as a percent) of burn severity of the sample points.

NDVI	2017 (pts)	2018 (%)	2019 (%)	2020 (%)	2021 (%)	Low (%)	M-Low (%)	M-High (%)	High (%)
0.6 - 1	-	4	9	15	11	-	-	-	-
0.3 - 0.6	228	86	88	82	86	70	5	0	0
0.1 - 0.3	-	9	5	5	7	-	-	-	-

Table 5: Distribution of sample points in 2017 with NDVI values of 0.1 - 0.3 in the Eagle Creek (Oregon) study area. The 2018 - 2021 values show the distribution (as a percent) of these sample points over time. The Low - High values show the distribution (as a percent) of burn severity of the sample points.

NDVI	2017 (pts)	2018 (%)	2019 (%)	2020 (%)	2021 (%)	Low	M-Low	M-High	High
0.6 - 1	-	2	0	2	0	-	-	-	-
0.3 - 0.6	-	14	23	19	21	-	-	-	-
0.1 - 0.3	43	49	51	51	72	9	0	0	0

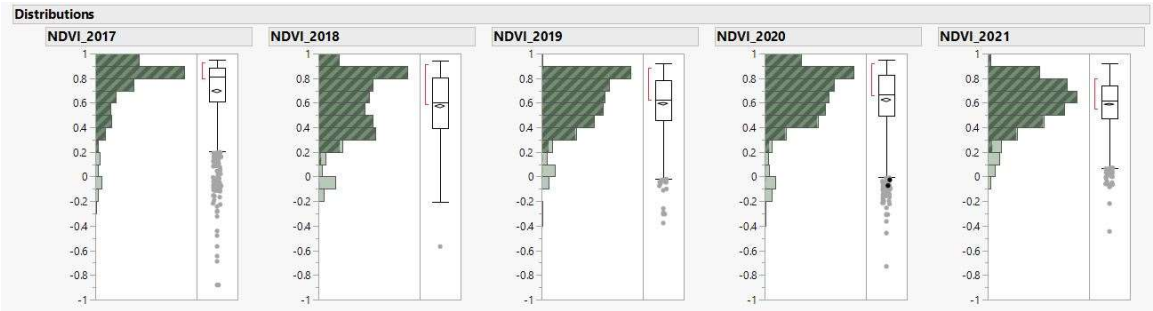

Figure 33: A histogram showing the relative change of NDVI values per sample point over time in the Eagle Creek (Oregon) study area. The dark sections represent sample points that had NDVI values between 0.1 - 1 in 2017. There are 1,346 sample points in this NDVI range.

The 2017 pre-fire NDVI values show a connection with the burn severity zones (Figure 34). Samples that experienced some level of burn also had NDVI values of 0.1 - 1 with a 25th quartile at 0.61, median value of 0.81, and mean value of 0.70. The sample points are roughly evenly distributed through burn zones due to the stratified random sampling method used. Table 6 shows the statistical values of the 2017 NDVI values based upon burn severity for all zones that experienced burn. These values indicate the state and distribution of NDVI values of the sample points immediately before the fire. All values are associated with dense, healthy vegetation.

Figure 34: Histograms of pre-fire 2017 NDVI, with subsequent dNBR values and burn severity for the Eagle Creek Fire in western Oregon. The darker columns represent the sample points that experienced some level of burning during the wildfire. There is a total of 779 sample points that burned.

Table 6: Median 2017 Pre-fire NDVI values by Burn Severity classification (low-moderate, low-high, and high severity), with quartiles and medians, for the Eagle Creek Fire in western Oregon. Values may be slightly higher in future high-severity zones; lower means than medians show skewing to lower values.

	Low	**Mod-Low**	**Mod-High**	**High**
25th %	0.76	0.76	0.76	0.80
Median	**0.86**	**0.84**	**0.84**	**0.90**
75th %	0.90	0.89	0.90	1.00
Mean	*0.80*	*0.81*	*0.82*	*0.86*

NDVI median, quartile and mean values show the greatest change from pre-fire values in high-severity burn zones (Tables 7-14, Figure 35-38). These high-severity zones register moderate vegetation reflective returns?? in 2018 and remain there for all but the 75th quartile beginning in 2020. With low-severity burn zones registering dense, healthy

vegetation by 2018, mod-low burn zones registering dense, healthy vegetation (though reduced) by 2018, mod-high burn severity zones registering moderate vegetation in 2018 and moderate to healthy/dense vegetation in 2019.

Low and moderate-low burn zones experienced a mean NDVI value decrease in 2018, 2019, and 2021. High and moderate-high burn zones experienced a mean NDVI value decrease in 2018 but only moderate-high experiencing a decrease in 2021 (Tables 11 – 18, Figure 35-38). Only low-severity zones reached near-pre-fire conditions. All other zones ranged between 0.11 and 0.31 NDVI points lower at their peak recovery period in 2020. All but the high severity burn zone experienced a reduction in mean NDVI values between 2020 and 2021.

Table 7: Median NDVI Values over time in High-Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in western Oregon.

High	**2017**	**2018 - post Eagle Creek Fire**	**2019**	**2020**	**2021**
25th %	0.80	0.32	0.42	0.49	0.49
Median	**0.90**	**0.39**	**0.50**	**0.56**	**0.55**
75th %	1.00	0.45	0.57	0.63	0.62
Mean	*0.86*	*0.39*	*0.50*	*0.55*	*0.55*

Table 8: Median NDVI Values over time in Moderate-Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Mod-High	**2017**	**2018**	**2019**	**2020**	**2021**
25th %	0.76	0.47	0.48	0.50	0.66
Median	0.84	0.58	0.61	0.65	0.59
75th %	0.90	0.64	0.68	0.70	0.51
Mean	0.82	0.54	0.58	0.61	0.58

Table 9: Median NDVI Values over time in Moderate-Low Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Mod - Low	**2017**	**2018**	**2019**	**2020**	**2021**
25th %	0.76	0.61	0.60	0.64	0.56
Median	0.84	0.70	0.69	0.74	0.67
75th %	0.89	0.77	0.74	0.79	0.74
Mean	0.81	0.67	0.66	0.70	0.65

Table 10: Median NDVI values over time in Low-Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Low	**2017**	**2018**	**2019**	**2020**	**2021**
25th %	0.76	0.72	0.70	0.75	0.65
Median	0.86	0.76	0.77	0.82	0.73
75th %	0.90	0.85	0.82	0.87	0.79
Mean	0.80	0.75	0.73	0.78	0.70

Table 11: Median difference between NDVI in 2017 and the given year in High-Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

High	**2018**	**2019**	**2020**	**2021**
25th %	-0.48	-0.38	-0.31	-0.31
Median	-0.51	-0.40	-0.34	-0.35
75th %	-0.55	-0.43	-0.37	-0.38
Mean	-0.47	-0.36	-0.31	-0.31

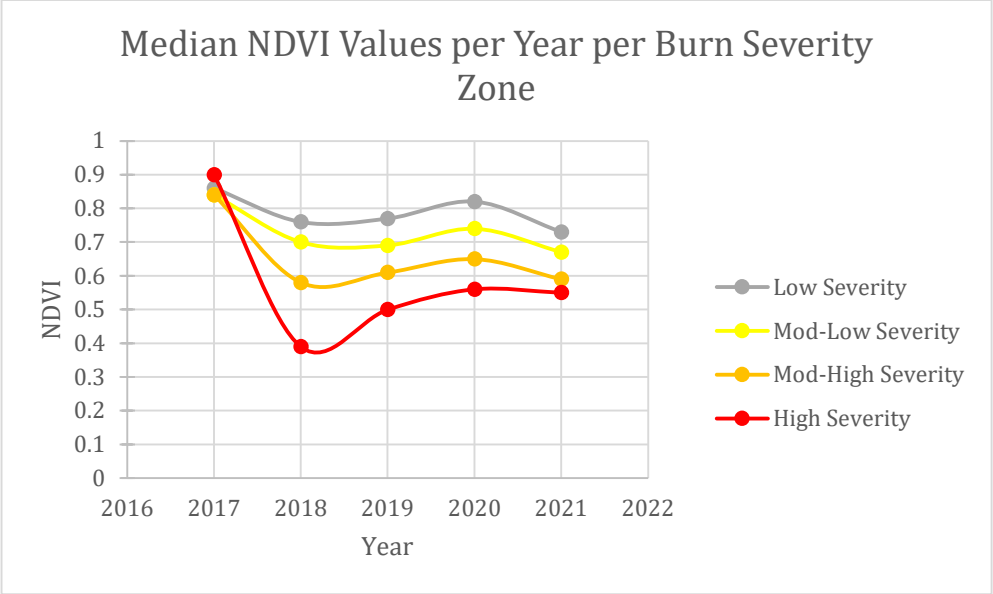

Figure 35: A graph of Median NDVI values per Year per Burn Severity Zone. Each line represents a burn severity classification. Median values for high severity fires decrease the most and remain lower than other burn areas through time.

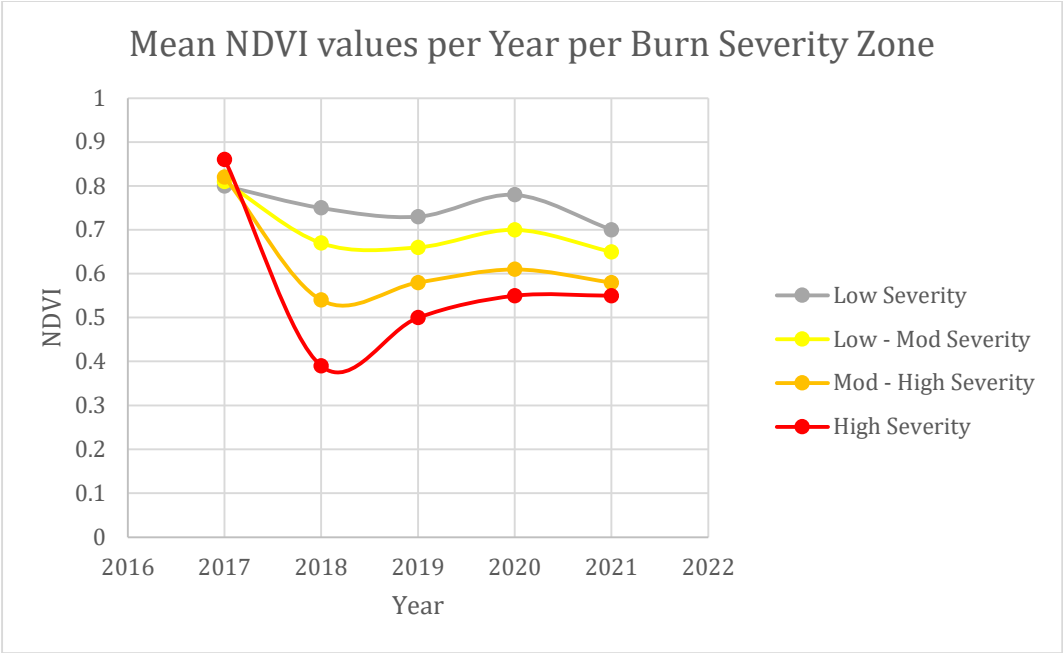

Figure 36: A graph of Mean NDVI values per Year per Burn Severity Zone. Each line represents a burn severity classification. Median values for high severity fires decrease the most and remain lower than other burn areas through time.

Table 12: Median difference between NDVI in 2017 and the given year in Moderate-High Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Mod- High	**2018**	**2019**	**2020**	**2021**
25th %	-0.29	-0.28	-0.26	-0.10
Median	-0.26	-0.23	-0.19	-0.25
75th %	-0.26	-0.22	-0.20	-0.39
Mean	-0.28	-0.24	-0.21	-0.24

Table 13: Median difference between NDVI in 2017 and the given year in Moderate- Low Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Mod - Low	**2018**	**2019**	**2020**	**2021**
25th %	-0.15	-0.16	-0.12	-0.20
Median	-0.14	-0.15	-0.10	-0.17
75th %	-0.12	-0.15	-0.10	-0.15
Mean	-0.14	-0.15	-0.11	-0.16

Table 14: Median difference between NDVI in 2017 and the given year in Low-Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Low	**2018**	**2019**	**2020**	**2021**
25th %	-0.04	-0.06	-0.01	-0.11
Median	-0.10	-0.09	-0.04	-0.13
75th %	-0.05	-0.08	-0.03	-0.11
Mean	-0.05	-0.07	-0.02	-0.10

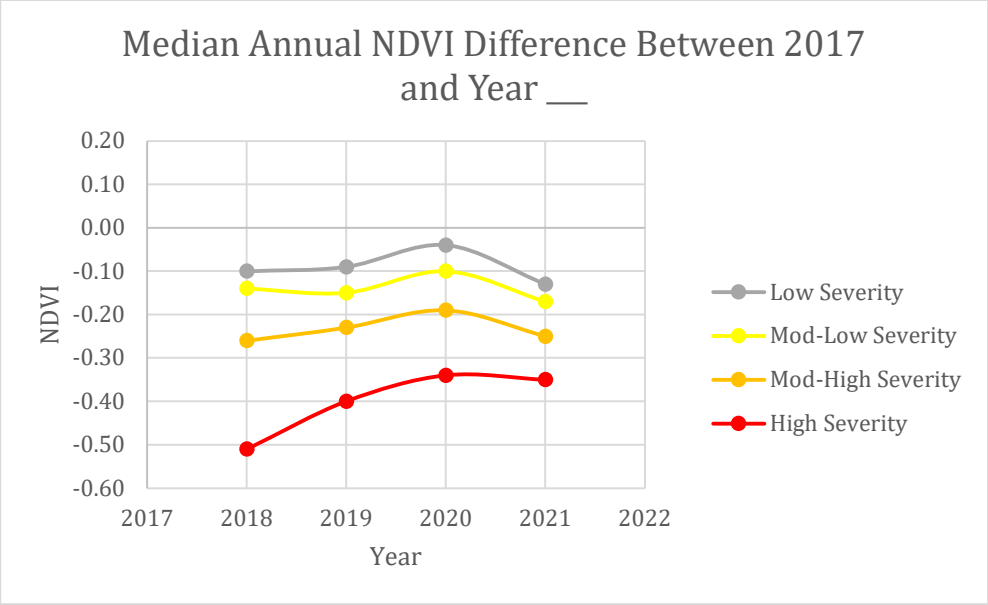

Figure 37: A graph of the median annual rate of NDVI difference between 2017 and the given year. This graph shows the relative distance between pre-fire NDVI values in 2017 and the year in the x-axis. A value of 0 would indicate no difference between pre- and post-fire NDVI values.

Table 15: Median annual rate of NDVI change in High Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

High	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
25th %	-0.48	0.1	0.07	0
Median	-0.51	0.11	0.06	-0.01
75th %	-0.55	0.12	0.06	-0.01
Mean	-0.47	0.11	0.05	0

Table 16: Median annual rate of NDVI change in Moderate-High Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

NDVI Annual Change Between Years for Moderate-High Burn Severity Zones

Mod - High	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
25th %	-0.29	0.01	0.02	0.16
Median	-0.26	0.03	0.04	-0.06
75th %	-0.26	0.04	0.02	-0.19
Mean	-0.28	0.04	0.03	-0.03

Table 17: Median annual rate of NDVI change in Moderate-Low Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Mod - Low	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
25th %	-0.15	-0.01	0.04	-0.08
Median	-0.14	-0.01	0.05	-0.07
75th %	-0.12	-0.03	0.05	-0.05
Mean	-0.14	-0.01	0.04	-0.05

Table 18: Median annual rate of NDVI change for Low-Severity Burn Zones, with quartiles and means, for the 2017 Eagle Creek Fire in Oregon.

Low	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
25th %	-0.04	-0.02	0.05	-0.1
Median	-0.10	0.01	0.05	-0.09
75th %	-0.05	-0.03	0.05	-0.08
Mean	-0.05	-0.02	0.05	-0.08

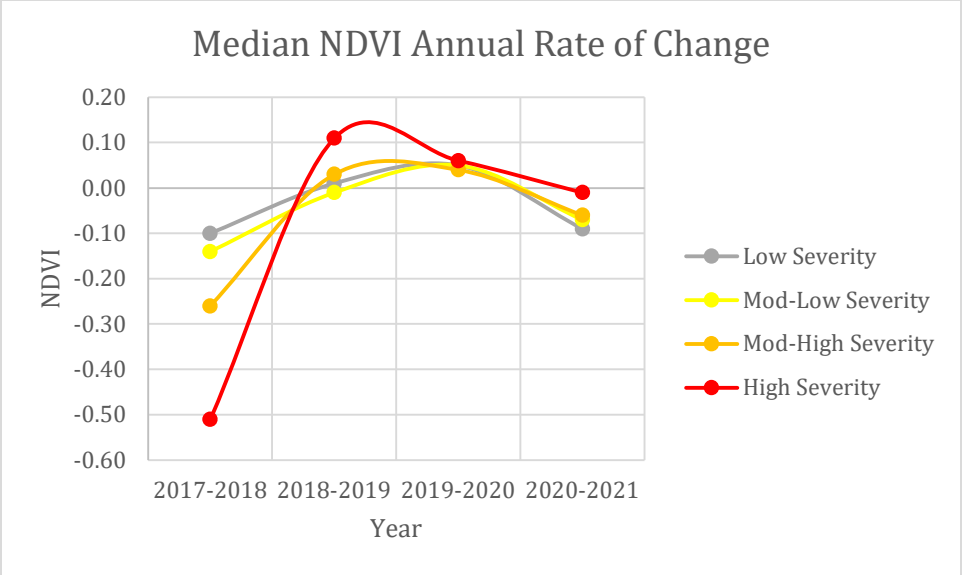

Figure 38: A graph of the Median NDVI Annual Rate of Change. This graph depicts how much the NDVI values changed between each year. Note that previous graphs showed NDVI the lowest in high severity burn zones, but the rate of positive NDVI change remains higher in the post-fire years.

Relationship Between NDVI and Aspect

Preliminary graphs comparing NDVI from 2017 to aspect does not indicate any significant aspect-based deviations. NDVI values at all aspects appear uniform (Figure 39). Density graphs of NDVI from 2017 - 2021, respectively, indicate linear and uniform distribution of high NDVI values across all aspects in 2017 (Figure 40). From years 2018 - 2021, NDVI shows a broader distribution of values consistent with previous observations of reduced vegetation. This reduction affects all aspect values, but aspects at 160 - 225 degrees and 340 - 10 degrees experience a greater spread of NDVI values and slower return to pre-fire NDVI values.

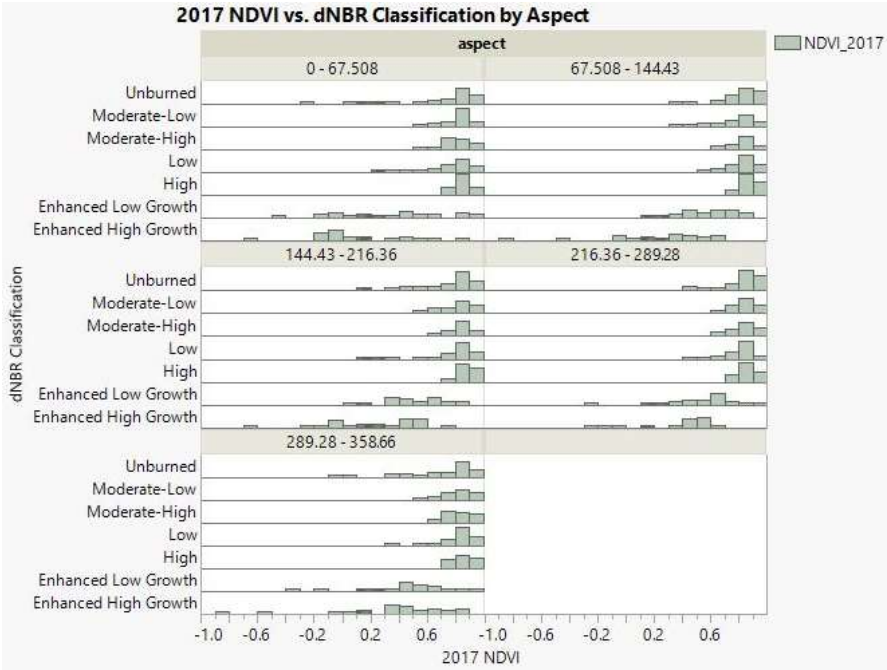

Figure 39: A histogram of *2017 NDVI* vs *burn severity* broken into increments of aspect *for the 2017 Eagle Creek Fire in Oregon*. Note the JMP Graph Builder analyzes data distribution and automates categorical breakdown when applying data overlays.

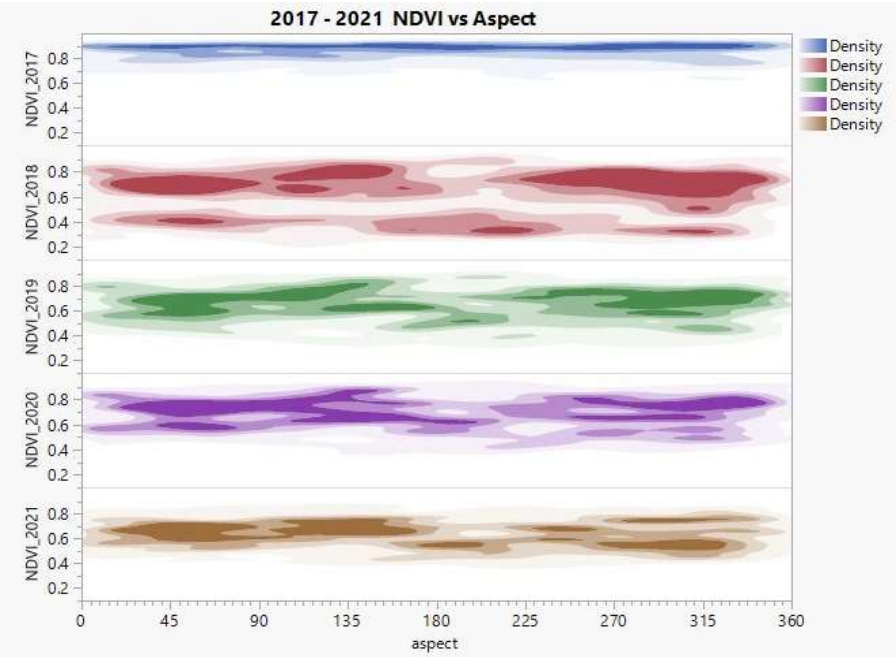

Figure 40: A density graph of aspect vs 2017-2021 NDVI *for the 2017 Eagle Creek Fire in Oregon*. Each color *scheme represents the NDVI year on the y-axis.* The density is broken into four tiers with the darkest color representing the higher density.

Plotting the mean, median, and rate of change for NDVI values through years 2017 to 2021 according to aspect shows little deviation between NDVI within the respective year (Tables 19 – 26. Figure 41-44). Consistent with previous findings, NDVI values decrease between 2017 and 2018, increase in 2019 and 2020, and decrease between years 2020 and 2021 through all aspect ranges. Based upon the mean values, there are inconsequential differences between aspects measured in 45-degree increments based upon the cardinal directions of north, south, east, and west (Table 19 -21, Figure 41-44).

Assessing the median values of NDVI produced the highest values at 90 -135 degrees in years 2019 - 2021 and lower values 180-225 degrees in years 2018-2021 (Table 22, Figure 42). In 2017-2018, aspects of 180-225 experienced the greatest negative rate of change but the highest positive rate of change from 2018-2019. Aspects of 0-45 experienced the highest positive rate of change in 2020. Aspects of 0-45 and 225-270 experienced a negative rate of change in 2018-2019 while all others experienced a positive rate of change. Aspects of 270-315 experienced the smallest positive rate of change in 2019-2020. In 2020-2021, aspects 0-45 and 135-180 experienced the smallest negative rate of change while all but aspects 90-135 had double the negative rate.

Based upon the direction of north, south, east, and west, the relationship between the directions of south and west experienced mirrored changes in median NDVI values in all years except changes between years 2020-2021. They had the highest negative rate of change in 2018 and highest positive change in 2019. West had the highest negative rate of change in 2021. North and east were similarly mirrored with the relatively higher rate of change in 2020. East experienced the smallest negative rate of change in 2021. All directions experienced negative rates of change in 2021.

Table 19: Mean NDVI values per aspect range per year within burned zones for the 2017 Eagle Creek Fire in Oregon. Aspect is divided into 45-degree increments. Values represent plots that experienced some severity of burn.

Mean NDVI Per Aspect	**2017**	**2018**	**2019**	**2020**	**2021**
0-45	0.80	0.58	0.61	0.66	0.62
45-90	0.82	0.59	0.63	0.68	0.64
90-135	0.82	0.59	0.63	0.67	0.64
135-180	0.82	0.58	0.61	0.66	0.62
180-225	0.83	0.56	0.60	0.64	0.60
225-270	0.84	0.59	0.62	0.66	0.62
270-315	0.84	0.59	0.62	0.66	0.62
315-0	0.83	0.59	0.62	0.67	0.63

Table 20: Mean annual change in NDVI values per aspect range per year within burned zones for the 2017 Eagle Creek Fire in Oregon. Aspect is divided into 45-degree increments. Values represent plots that experienced some severity of burn.

Annual Change in Mean NDVI per Aspect	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
0-45	-0.22	0.03	0.05	-0.04
45-90	-0.23	0.04	0.05	-0.04
90-135	-0.23	0.04	0.04	-0.03
135-180	-0.24	0.03	0.05	-0.04
180-225	-0.27	0.04	0.04	-0.04
225-270	-0.25	0.03	0.04	-0.04
270-315	-0.25	0.03	0.04	-0.04
315-0	-0.24	0.03	0.05	-0.04

Table 21: Mean annual change in NDVI values per cardinal direction per year within burned zones for the 2017 Eagle Creek Fire in Oregon. Aspect is divided into 180-degree increments. Values represent plots that experienced some severity of burn.

Mean Annual Change in NDVI per Aspect	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
N	-0.94	0.13	0.19	-0.16
S	-0.99	0.14	0.17	-0.15
E	-0.92	0.14	0.19	-0.15
W	-1.01	0.13	0.17	-0.16

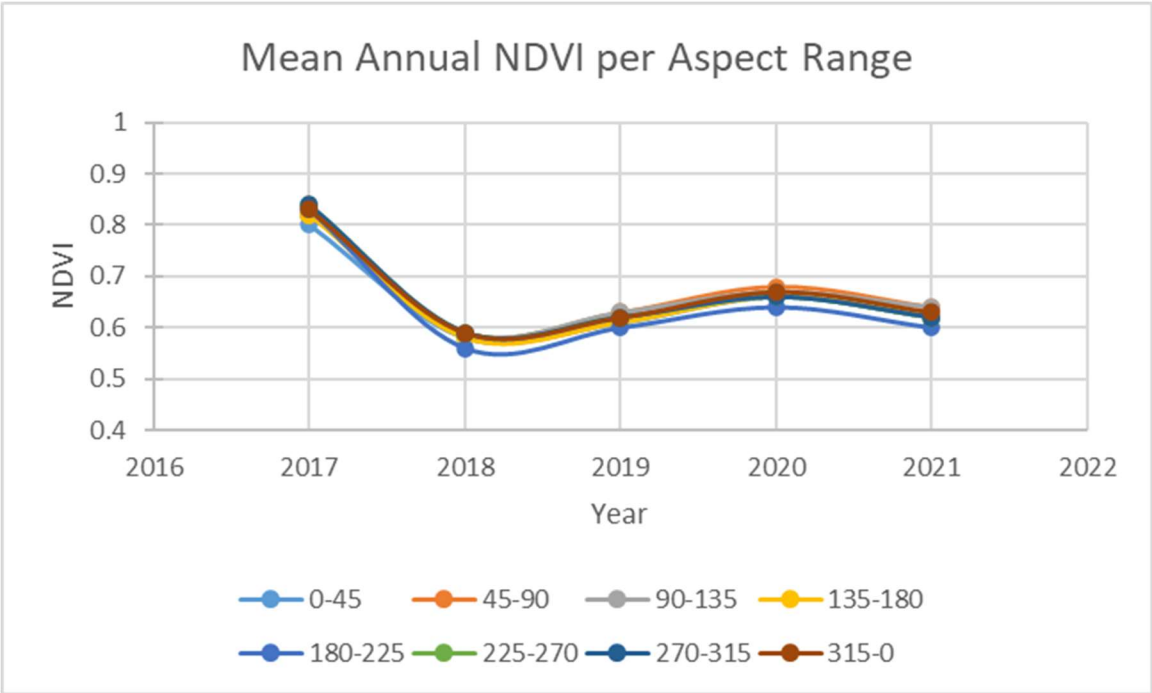

Figure 41: A graph of Mean Annual NDVI per Aspect Range. The averaged NDVI values follow a similar trajectory and value range with sample points in the 180-225 range falling slightly lower than other aspect ranges.

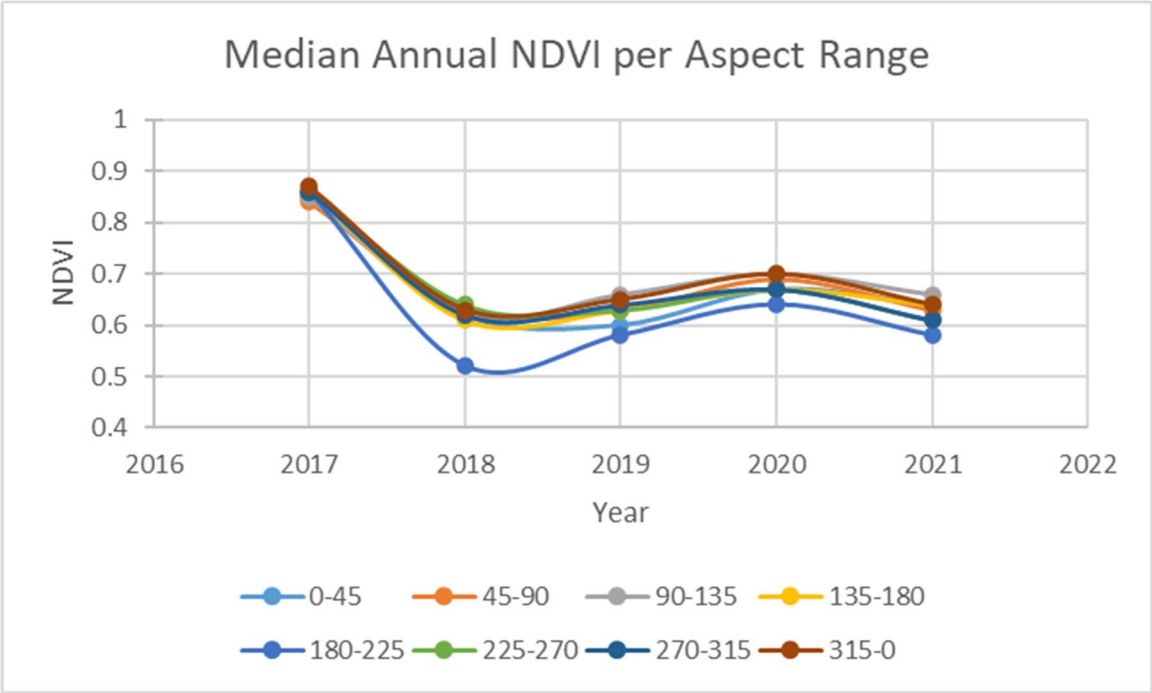

Figure 42*: A graph of Median Annual NDVI per Aspect Range. The averaged NDVI values follow a similar trajectory like the mean values, but with greater deviation. The sample points in the 180-225 range fall slightly lower than other aspect ranges in post-fire years.*

Table 22: Median NDVI values per aspect range per year within burned zones for the 2017 Eagle Creek Fire in Oregon. Aspect is divided into 45-degree increments. Values represent plots that experienced some severity of burn. Annual lowest values are in blue. Annual highest values are in red.

Median NDVI Per Aspect	**2017**	**2018**	**2019**	**2020**	**2021**
0-45	0.85	0.62	0.60	0.67	0.64
45-90	0.84	0.63	0.63	0.69	0.63
90-135	0.84	0.62	0.66	0.70	0.66
135-180	0.87	0.61	0.63	0.67	0.64
180-225	0.86	0.52	0.58	0.64	0.58
225-270	0.86	0.64	0.63	0.67	0.61
270-315	0.86	0.62	0.64	0.67	0.61
315-0	0.87	0.63	0.65	0.70	0.64

Table 23: Median annual change in NDVI values per aspect range in years 2017 -2021 within burned zones for the 2017 Eagle Creek Fire in Oregon. Aspect is divided into 45-degree increments. Values represent plots that experienced some severity of burn. Annual lowest values are in blue. Annual highest values are in red.

Change in Median NDVI per Aspect	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
0-45	-0.23	-0.02	0.07	-0.03
45-90	-0.21	0.00	0.06	-0.06
90-135	-0.22	0.04	0.04	-0.04
135-180	-0.26	0.02	0.04	-0.03
180-225	-0.34	0.06	0.06	-0.06
225-270	-0.22	-0.01	0.04	-0.06
270-315	-0.24	0.02	0.03	-0.06
315-0	-0.24	0.02	0.05	-0.06

Table 24: Median annual change in NDVI values per cardinal direction in years 2017 - 2021 within burned zones for the 2017 Eagle Creek Fire in Oregon. Aspect is divided into 180-degree increments. Values represent plots that experienced some severity of burn. Annual lowest values are in blue. Annual highest values are in red.

Median Annual Change in NDVI per Aspect	**2017-2018**	**2018-2019**	**2019-2020**	**2020-2021**
N	-0.92	0.02	0.21	-0.21
S	-1.04	0.11	0.18	-0.19
E	-0.92	0.04	0.21	-0.16
W	-1.04	0.09	0.18	-0.24

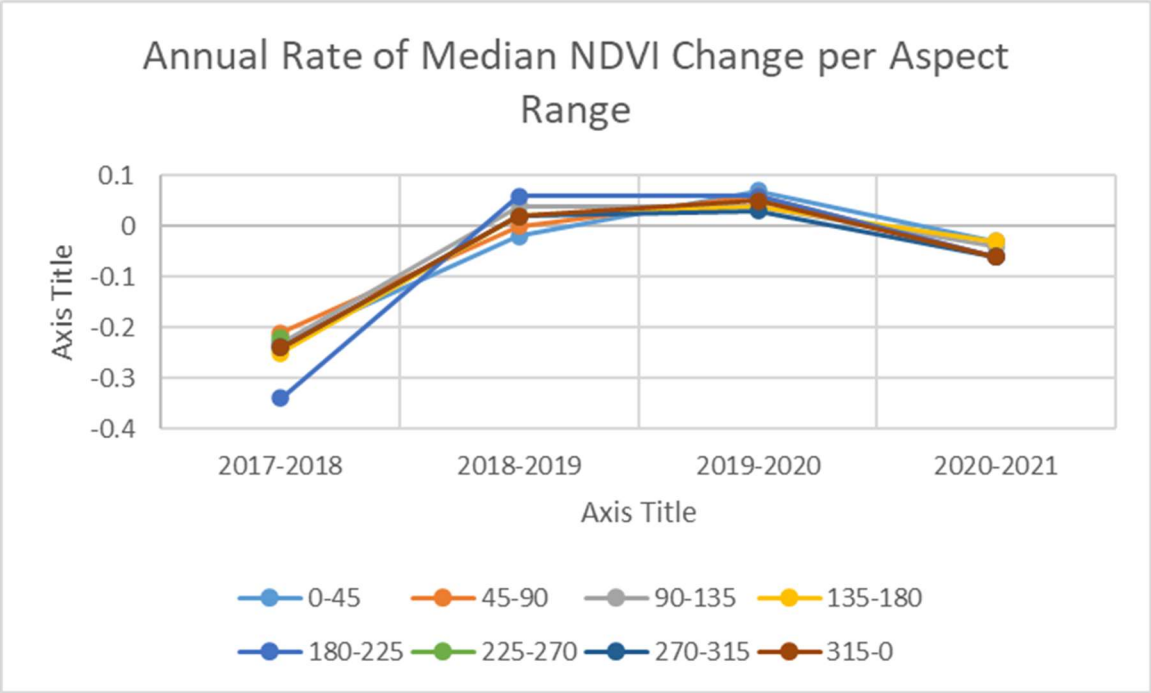

Figure 43: A graph of the Annual Rate of Median NDVI Change per Aspect Range. This graph shows how much NDVI values changed each year. Note that sample points in the 180-225 range decreased the most between 2017-2018 and increased the most in 2018-2019.

Table 25: Median 2017 NDVI values within aspect ranges of 45 degrees, with quartiles and median, for the 2017 Eagle Creek Fire in Oregon. These values represent points that experienced some level of burn.

2017 NDVI	**0-45**	**45-90**	**90-135**	**135-180**	**180-225**	**225-270**	**270-315**	**315-0**
25th %	0.76	0.79	0.79	0.90	0.79	0.80	0.79	0.76
Median	0.85	0.84	0.85	0.86	0.86	0.86	0.86	0.87
75th %	0.9	0.90	0.89	0.80	0.90	0.89	0.91	0.90
Mean	0.8	0.82	0.82	0.82	0.83	0.84	0.84	0.83

Table 26: Point distribution of 2017 NDVI values over ranges of aspect for the 2017 Eagle Creek Fire in Oregon. These points represent both burned and unburned samples. The field values represent the number of sample plots in each category. The values in red indicate a deviation in the distribution pattern.

NDVI	**2017**	**0-45**	**45-90**	**90-135**	**135-180**	**180-225**	**225-270**	**270-315**	**315-0**
0.6 - 1	1075	116	144	138	131	132	132	135	147
0.3 - 0.6	228	11	24	30	38	25	30	33	37
0.1 - 0.3	43	13	5	3	4	8	2	6	2
Total:		140	173	171	173	165	164	174	186

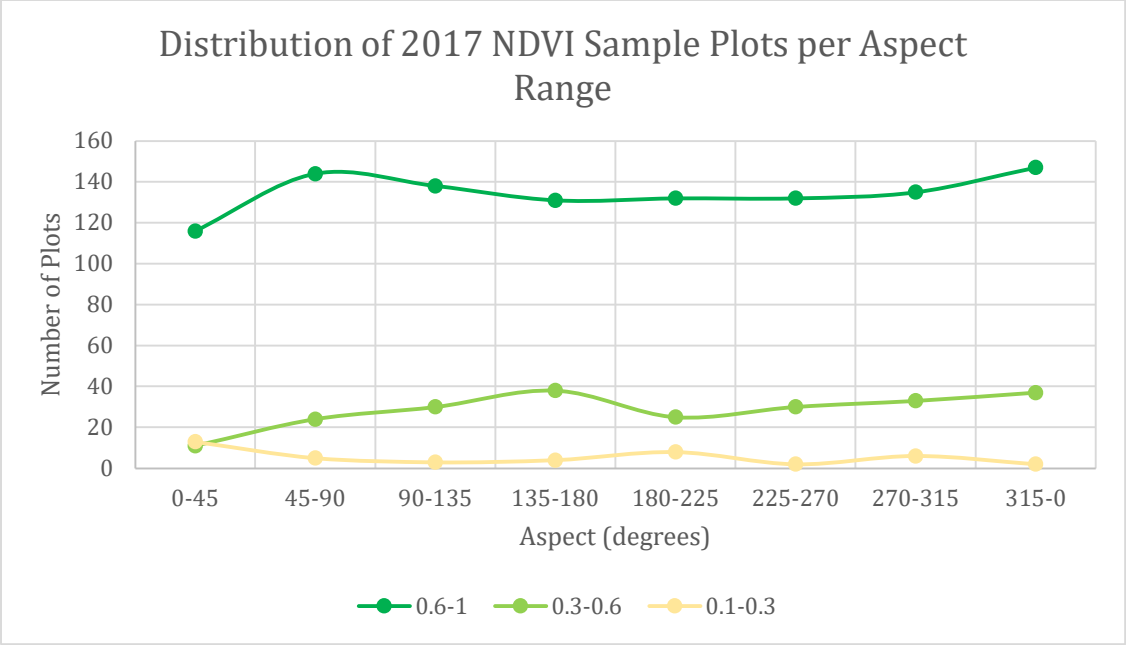

Figure 44: A graph of the Distribution of 2017 Sample Plots per Aspect Range. This breaks down the NDVI values from the pre-fire 2017 sample points and shows how they were distributed into each aspect range. Values of 0.6-1 are dense/healthy vegetation, 0.3-0.6 are moderate, and 0.1-0.3 are sparse vegetation. Note that there are roughly equal numbers of moderate and sparse vegetation at 0-45 degrees, but a stepwise disbursement in other ranges. In all ranges, dense/healthy vegetation is dominant.

Discussion

Analysis Approach:

While research targeting a single fire-related variable was readily available, research comparing multiple variables was sparse. This resulted in the credibility of the aspect (Leon et al., 2012, Holden et al., 2009, Vlassova et al., 2014) , dNBR (Boer et al., 2008, Escuin et al., 2008, Leon et al., 2012, Holden et al., 2009,Vlassova et al., 2014), and NDVI (Escuin et al., 2008, Leon et al., 2012, Vlassova et al., 2014) indices being verified while requiring some novelty to the multivariate approach required in this study. Research by Ireland et al. (2015) used a method similar to this study, though incorporated a digital elevation model rather than isolating aspect. Ireland et al. (2015) did not detail how samples were selected when defining sample plots. In their case, the burn index is divided by severity and aspect is divided as a binary north versus south feature (Ireland et al., 2015). However, the mechanics of their site selection with respect to creating direct comparisons of the indices is unclear. Eg, if the plot was divided by one index and then subdivided by the other or if each index was treated as separate sampling environments and then compared.

Creating a method in which the same sample point was queried each year over time was essential in this experiment and allowed direct comparison of conditions and responses at the pixel level. This was accomplished by using stratified random sampling to break the study area down by burn severity and then again by sub-categorizing aspect within each burn zone (Ireland et al., 2015). This allowed the data to isolate what happens within each burn zone, what happens within each aspect range, and subsequently the comparison between indices at each point. This ensured that any NDVI value change was a function of actual surface change rather than due to variances that would be caused by random sampling of each year or index separately.

Stratifying the study area in this manner further supported ensuring enough sample points to make comparisons between each burn zone and the aspect values within them. This strategy allowed the ability to see how NDVI behaves within all iterations of burn severity and aspect at each pixel location. This is key to controlling the validity of the data and being able to make the direct comparisons desired. In contrast, random sampling irrespective of burn severity or aspect could result in an issue with capturing enough points within any given category to make a comparison. For example, if we have 1000 points at 360 degrees and only 5 at 180 degrees, that data would be an unreasonable comparison when we know it does not accurately represent the terrain.

How data can be presented in a way that allows for practical analysis and interpretation is an additional issue when setting up a sampling strategy. Selecting an adequate number of sample points without overburdening the analysis process or visual elements of the analysis is necessary when visually drawing out relationships. Too many points clutter

the chart and can be visually misleading. For example, there may be 100 points sitting on an NDVI value of 0.2 and only one at 1, but visually it looks the same. Too many points can result in the data being too bulky to process in a timely manner and exacerbating issues with visually presenting the data or sorting through attributes within a reasonable timeframe. Selecting a smaller number of sample points can be visually easier to plot and read through data but may not be enough points to accurately represent the study area. Twenty-five sample points per subdivided category was arbitrarily selected in this study due to the ability to meaningfully graph data without visual or processing overburden.

A significant strategy to detect the index relationships was determining pre-fire NDVI values and holding the associated sample points static through the comparisons over time. This included comparing pre-fire NDVI values to the dNBR values that would not become present until late 2017. Treating dNBR values as static on the landscape allowed the data to show what NDVI conditions were in each zone that fire would occur. Although it is not possible for the 2017 event's burn severity to have an impact on pre-fire vegetation, it allowed some analysis regarding what conditions may have contributed to the burn pattern that would come. It also indicates that the NDVI values for the pre-fire period were influenced by other factors that eventually led to the burn pattern in the 2017 fire dNBR index.

Pre-wildfire baseline conditions:

The study area was described as a mesic, mixed conifer forest that had not experienced fire on the scale of hundreds of years. While there is not hundreds of years of remote sensing data available, the NDVI values for the years 2013 - 2017 were similar in distribution and consistent with the expected vegetation characteristics. Therefore, the 2017 NDVI values can be considered to accurately represent the baseline, long-term vegetation conditions of the study area. Further, comparing the 2017 values to aspect showed no obvious bias between indices. Both mean and median values of NDVI were similar within aspect ranges and confirmed that NDVI values were clustered around dense/healthy vegetation. This was expected, as the area is a dense, mixed-conifer forest with a thick understory that is supported by the climate conditions and fire regimes with long intervals (Fire Management, 2022, Tesky, 1992, Uchytil, 1991, Cope, 1992, Meigs et al., 2020). The aspect at this juncture would represent the hundreds-years fire regime scale of NDVI response to wildfire. Given this information, pre-fire NDVI values indicate that aspect does not act as a control at this time scale.

Post-fire conditions:

In total, the Eagle Creek Wildfire burned 48,861 acres in the Eagle Creek Drainage and resulted in 55% of the area as unburned or experiencing low burn severity, 30% moderately burned, and 15% severely burned (Fire Management, 2022). Refugia tended to remain along peaks and slopes protected by ridgelines (Figure 45). The high-severity portion of the fire was centered around the ignition point of the fire and coincides with

the first hours and days of rapid spread under severe fire weather conditions. Vegetation recovery patterns follow this burn pattern, with vegetation moving from refugia areas and into denuded areas. As of 2021, all but the deeper valleys indicate some level of vegetation growth. This could be caused by conditions such as physical limitations in access for seed or severe burn conditions creating an inhospitable environment due to changes in sun exposure, soil chemistry, and increased runoff.

This deviates from the study by Meigs et al. (2020) that suggests topography such as valleys, places with dense vegetation, or other areas that promote cool temperatures or where moisture may accumulate would likely act as spaces for refugia. However, as Meigs et al. (2020) suggested, topography does appear to have some measure of influence in the spatial pattern due to relative topographic positions that also influenced the spatial vegetation recovery patterns.

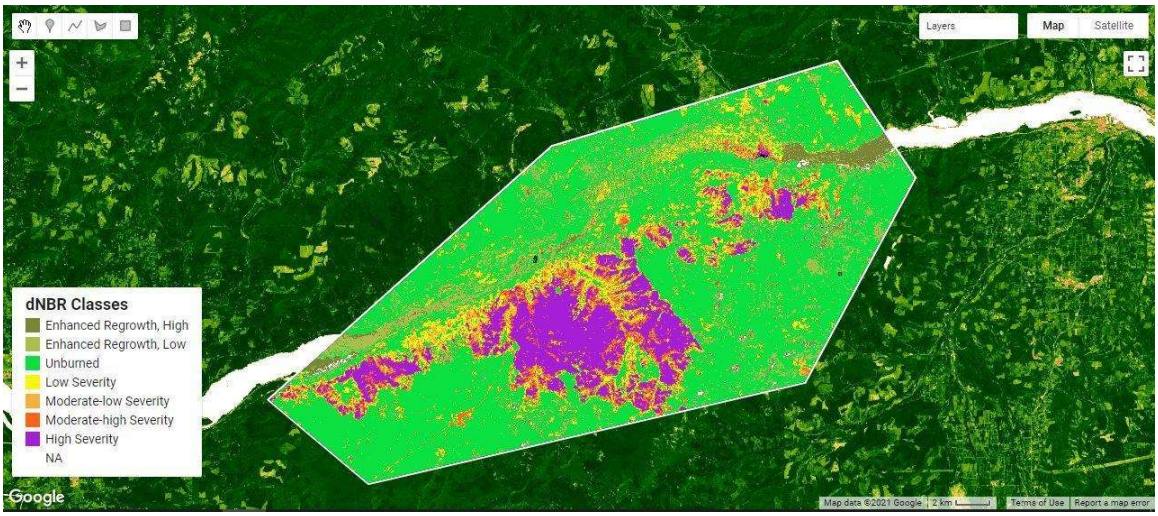

Figure 45: Google Earth Engine dNBR image of Eagle Creek Recreation Area comparing images from July 2017 to October 2017 to determine burn severity. Note the purple, red, orange, and yellow areas that represent burned regions. The large, high severity burn area in the center-left portion of the study area signifies the starting location of the fire.

Due to the burnt condition of the evergreens, it is possible that NDVI values we see are related primarily to understory growth or leafing of deciduous trees that survived the fire (Figure 46). Cooler regions indicated in the preliminary study with CHILI data overarchingly align with low NDVI values and lack of regrowth (Theobold et al., 2015). This suggests some topographic control on NDVI may be present, though not due in part or whole to aspect.

Figure 46: A close up Google Earth satellite image of Eagle Creek in September 2018. Note the sections of refugia that still show spots of green within the burned area.

NDVI calculations are limited to indicating the 'greenness' of an area and do not provide fine details such as species type or topographic information (Google Developers, 2022). Rather than being completely barren in low NDVI areas, the landscape is covered with burnt stands of evergreen trees and fallen logs (Figure 38). These trees present similar NDVI values to bare soil or rock due to their color and subsequent spectral reflectance. While they may be alive and in a slow state of recovery, they are predominantly brown vegetation with few leafy or green parts and do not register within NDVI values as what we interpret as live, healthy vegetation. As suggested in the study by Boer et al. (2008) when analyzing the leaf area index (LAI), correlating field data with satellite imagery may reveal additional information about the health and status of vegetation in these areas.

The relationship between NDVI and aspect remained homogeneous in pre- and post-fire environments. While NDVI values changed across all aspect ranges after the fire, the scale and direction of change remained comparable with only slight deviations in post-fire environments. This deviation was reflected by the degree of spread within annual NDVI values. The mean post-fire values remained fairly consistent amongst aspect ranges within each year. They additionally showed that NDVI stayed at or near values representing healthy/dense vegetation. However, the post-fire median values showed a slight, but patterned shift in the range of values within each sample area. When the mean and median values deviate from each other, it indicates a wider distribution of values. In this case, greater NDVI variation means more complex or patchy vegetation occurred in some areas at some time more than others, even though the average annual values were

similar.

Overall, post-fire vegetation patterns remained healthy/dense according to aspect-based evaluations. When holding the pre-fire NDVI values static, a post-fire deviation within the aspect ranges of 0-45 degrees appeared that was not consistent with other ranges. This deviation was manifested as an equal number of scarce and moderately vegetated points whereas all other rangers showed a 3+ fold difference between scarce and moderately vegetated points. This range faces the north-north-east direction, but this same pattern is not reflected in other north or eastern ranges that might provide obvious answers for these differences. Kane et al. (2014) discovered similar results when analyzing digital elevation models and concepts of solar radiation exposure as predictors in the vegetation structure and burn severity patterns in western forests. Kane et al. (2014) used a more complex set of topographic elements compared to this study, but ultimately determined that their influences were minor within their study area. However, when studying boreal forests that contained mixed conifers, Fang et al. (2015) discovered that topography, including aspect, played a significant role in burn patterns. In their case, the topography was considered an influence on the type and connectivity of the vegetation, which therefore would impact fire behavior (Fang et al., 2015). However, the 2017 Eagle Creek fire had a homogeneous vegetation composition and has been analyzed at the pixel level whereas Fang et al. (2015) analyzed multiple areas at the patch level with greater deviations in vegetation type and structure. This suggests that scale may also play a factor in index relationship patterns and influence.

Like aspect, the mean and median pre-fire 2017 NDVI values were homogenous across what would become the burn severity types. This suggests that all pre-fire burn severity zones contained a majority of healthy, dense vegetation and did not provide a clear indication as to which areas were more susceptible to future burn relative to others. However, separating pre-fire sample points via their vegetation health/density and analyzing how they changed over time revealed dynamics particular to burn severity.

The dominant post-fire vegetation categories remained consistent between the pre-fire years and the years after the Eagle Creek Fire. Approximately 80% of the densely vegetated sample points were burned to some degree but were roughly equally distributed between the four burn severity categories. Only 25-30% of sample points transitioned to moderate vegetation but little, if any, transitioned into sparse vegetation relative to pre-fire healthy vegetation. This suggests that healthy, densely vegetated areas in similar environments and fire weather conditions experience a mixed-severity fire rather than a stand-replacing fire (Meigs et al. 2020). While dense vegetation and heavier fuels burn hotter in a fire, my results indicated that it does not necessarily do so nor does high-severity fire comprise the majority of the area burned. This is also consistent with regional studies (Tepley et al., 2013). Additionally, high-severity burn areas experienced a faster annual rate of vegetative regrowth after the fire compared to other burn severities as remotely measured by greeness.

Moderately healthy/dense vegetation predominantly burns at low severity across a range of wildfire conditions. In this analysis of the Eagle Creek Fire, a few areas burned at moderately-low severity and little, if any, that burned at moderately-high and high severity. Approximately 25% of the points did not experience any burning, with 4-15% that experienced vegetation growth. These areas were less vegetated and therefore had less fuel available to burn (Meigs et al., 2020, Fang et al., 2015). The fire would be less likely to reach the same intensity levels as areas that have more fuel. They may also be less likely to have ladder fuels that would carry fire into the canopy or connect with other vegetation. Due to experiencing some level of burning, the relatively reduced competition and clearing of debris could be what allowed increased growth of refugia or removed competition for other species (Meigs et al., 2020). These areas responded in a stable manner even though some event(s) in 2021 decreased NDVI in areas that began with dense or sparse vegetation.

Sparse/unhealthy vegetation with sparse fuels experienced low-severity burning only given fuel limitations. This was consistent in the Eagle Creek Fire and is expected, as there would be little fuel present to burn and/or reduced connectivity of the vegetation (Meigs et al., 2020, Fang et al., 2015). While moderate and healthy vegetation points predominantly stayed within their original NDVI ranges, sparse vegetation only remained within this category for about half of the points until 2020. This suggests that vegetation growth and denuding occurred in the post-fire environment, but some event in 2021 resulted in a significant decline of vegetation in these same areas by 2021.

The Eagle Creek Fire burn pattern contradicts the notion of widespread, stand-replacing fires previously considered for this area and forest type (Tepley et al., 2013, Halofsky et al., 2020). Halofsky et al. (2020) concluded their study by characterizing modern mesic forests as experiencing infrequent stand-replacing fires with limited need for intervention beyond protecting high value features. This was based on the notion that fires only occur in these areas under extreme conditions (Halofsky et al., 2020). However, the findings here support the continuation of the historical mixed-severity fire regime characterized by Halofsky et al. (2020) and observed by Tepley et al. (2013). In the case of Tepley et al. (2013), their study found that high-severity, stand-replacing fires occurred in some areas of a burn zone but were not the dominant burn severity within a fire event. Tepley et al. (2013), further concluded that fire events promoted an ecological trajectory shift and a heterogeneous environment. Given the growth rate and habit of the dominant conifer species and common understory shrubs (Tesky, 1992, Uchytil, 1991, Cope, 1992, Fire Management, 2022), it can be reasonably concluded that the increased NDVI values within the four post-fire years analyzed here is not the same conifer-dominant composition. This notion aligns with the ecological shift proposed by Tepley et al. (2013).

Future study:

Accessing an updated version of the Landsat 8 data would be useful in furthering these results and for similar studies, as these images have been superseded by a new version (Google Developers, 2022). Initial attempts to swap satellite data in my code resulted in multiple reference errors, and I could not properly load referenced bands; either the coding errors need to be corrected or the validity of the current satellite data verified. The Landsat imaging used in this study was pre-corrected to the surface reflectance, but the masking was designed to scale values to the top of atmosphere reflectance (Chander et al., 2009). There was also some ground surface obstruction due to smoke, snow, and clouds. This may be unavoidable due to the presence of smoke during fires and the fire season clearing during wetter, colder months.

The data set used to calculate aspect assigns a negative value to flat surfaces (Farr et al., 2007). The aspect ranges emphasized in the study did not include negative values nor were any found in the sampling points prior to graph analysis. The study area is hilly and may not have a significant number of flat surfaces, but is an unknown element not represented in the data and may impact application to other regions with a larger expanse of flat surfaces. Further, the classification designation used to break aspect into 45-degree increments for stratified sampling was arbitrary. Additional research may indicate a more useful classification for this feature that may reveal information not found here.

When reviewing data in the data table, three NDVI calculations went outside of the -1 to 1 range. NDVI values should fall within this range due to how this index is calculated (Escuin et al., 2008; Boer et al., 2008; Leon et al., 2012; Google Developers, 2022; Riano et al., 2002;). I considered these values to be errors and removed those data points. Further work could be done to determine why these errors occurred, as they should be mathematically impossible.

Determining what pre-fire relationships represent when dNBR values symbolize an event that has not occurred can impact the ability to determine what may happen in the future. This proved difficult in the study and it may be useful to use NDVI as a tool to stratify sampling points if the objective is to project risk related to fire. Locating data on the last fire event known in the area or locating a fire event with similar conditions and comparing outcomes would help determine if fire behavior patterns exist or are unique to study sites.

Since healthy and green vegetation reflects more near-infrared and absorbs more red light, NDVI calculation can provide some information about the status of health or state of leafing in a forest. My preliminary studies considered representation values close to -1 as indicative of water, values close to 0 as indicative of bare soil or rock, and values close to 1 as indicative of healthy vegetation. The higher the NDVI value is, the 'greener' the area is. This also means that forests will have seasonal changes in NDVI as plants go through their life cycles. NDVI only detects the presence of vegetation and does not provide details

of flora composition. Therefore, only vegetation presence could be considered during this study and only pre-fire vegetation could be specified.

While data in this study can provide broad spatial information about vegetation patterns, it is important to consider that seasonal fluctuations, weather patterns for the year, and sensor or calculation errors can make it difficult to directly compare growth patterns over time. For example, ideal seasonal conditions could have resulted in vegetation 'greenness' peaking in June of one year and in August for another. In this case, comparing images in August for each year would allow comparison of vegetation state within August for each year, but would not indicate the full spatial extent of vegetation growth between years. This may account for why there appears to be more growth between some years that did not present as strongly in others.

Research indicated that NDVI and dNBR indices have been thoroughly vetted and determined to be reliable indicators of on-ground conditions. Therefore, I did not complete a field-based statistical cross-analysis of my data for validation. Collecting images of a sample point or series of sample points over time could help characterize on-ground conditions relative to NDVI values and add depth to the study. In this study, the dominant vegetation was evergreen conifers. Given the habit and growth dynamics, it is presumed that vegetation recovered during the time of the study could not be dominated by these same species. However, visual aid of surface conditions could add depth to land management proposals when monitoring for desirable or undesirable species or determining how future fire may move through the landscape. Additionally, the presence of cloud cover proved challenging for consistent image acquisition, so selecting each year's specific peak extent of vegetation was not possible. This supports the benefit of confirming data in the field and/or examining NDVI values from aerial footage to avoid cloud cover issues that present with satellite imaging.

It is also important to note that the distribution of aspect and dNBR within this study does not represent the attribute ratio of the study site itself. The sampling method forced an equal number of points to be distributed throughout each aspect and burn category. The surface area of any given degree of aspect, for example, might not be equal and therefore equal representation would not accurately reflect the terrain. Breaking aspect into sections of 45 degrees each with the assumption that randomization within each range may have compensated to some degree. This method subsequently restricted the usefulness of some data comparisons, such as the ability to evaluate the relationship between aspect and burn severity. Future studies may consider stratifying the study area based on ratios so that sample points can reflect the on-ground distribution of various characteristics of the site.

Areas that were unburned or experienced growth were incorporated into some of the graphs for ancillary information but were not the focus of analysis. Some of these areas deviated noticeably from their counterparts and may be worth studying in isolation or in conjunction with burn zones.

While this study focused on what happened within the pixels that were burned, additional study on the unburned pixels and related spatial patterns may be of interest. This could add to the knowledge of how refugia sites are formed and how they may act as a source for vegetation recovery. Though recovery primarily followed the burn pattern, there are a few refugia sites that remained densely vegetated and fell outside of what may be spatially expected. For example, Figure 47 indicates an area of refugia (circled in red) with dense vegetation within one of the most severely burned areas of the site. Circled in blue, a ridgeline marks a stark contrast between densely vegetated and burned areas. Additionally, the area circled in black indicates a pattern related to farmland but registered as "burned" on the dNBR and NDVI data due to the change in vegetation.

While the red and blue areas would not have been incorporated into vegetation changes in the burned-pixel data, the black area would have. Having details on the flight paths and drop points of air-based firefighting efforts and additional data on nearby farmland could be beneficial to answering these questions. Some of these refugia sites may be explained by fire-retardant drops that targeted rescuing hikers (Figure 48) or focusing on specific high-value areas. Data on farmland could clarify if embers reached the tracts of land and burned vegetation or if the change is a result of agricultural activities.

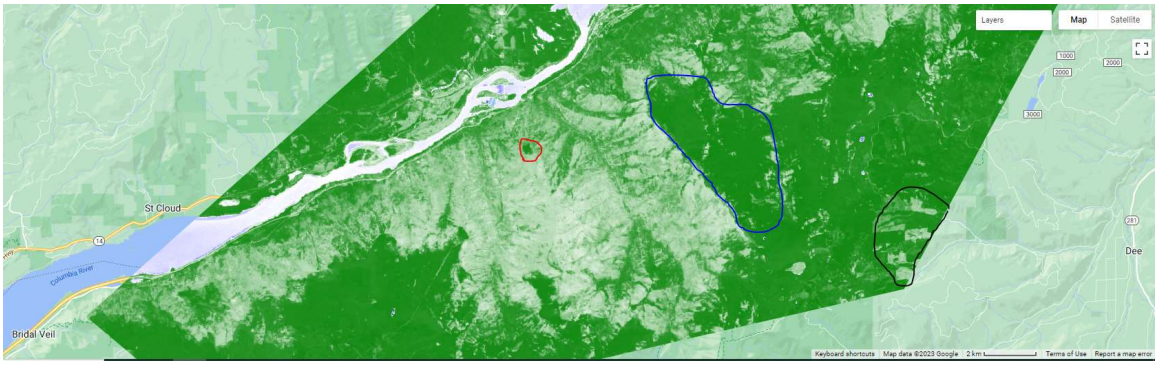

Figure 47: Google Earth Engine image of 2018 NDVI. The red encircles a refugia site that deviates from other refugia patterns. The blue encircles a spatial pattern of vegetation that may have been influenced by air-based firefighting efforts. The black encircles pixels associated with farmland.

Figure 48: A 2023 Google satellite image of a refugia site in the Eagle Creek Fire burn zone. This is a close-up view of the area circled in red from Figure 47. The satellite image shows the confluence of hiking trails within the refugia zone. Knowing the flight paths and drop zones of air-based fire-fighting efforts or accessing on-site data may provide insight into how this area of refugia remained within one of the most severely burned areas of the site.

Summary and Conclusions

Three goals were set out originally for this study:

1) Determine what, if any, pre-fire relationship exists between NDVI at Year 0 and the static values of burn severity and aspect, respectively, with a review of years 2013-2017 and vegetation condition.

2) Analyze the post-fire environment (Year 1) spatial relationships between NDVI for Year 1, aspect, and burned regions and compare to Year 0. Including an analysis of dNBR in terms of burn low, moderate, and high severity burns and the locations of refugia.

3) Determine if burn severity or aspect acts as the primary control mechanism on long-term (Year 2 - Year 4) post-fire vegetation recovery, how that relationship manifests, and how it behaves through time.

The annual NDVI values between the years of 2013-2017 presented as homogenous both temporally and with respect to dNBR and aspect indices. Under the assumption that the historical fire regime in this area is on the scale of hundreds of years, neither aspect nor dNBR alone or in combination could conclude a long-lasting impact on NDVI value distribution at these regime scales in this study area. Therefore, these indices were not helpful in determining historical wildfire patterns prior to the 2017 wildfire or spatial displacement of wildfire when NDVI was approached as an overarching value across the study area.

However, some patterning emerged once the pre-fire NDVI values were separated into vegetation categories and then the changes in NDVI viewed at these points over time. Overarchingly, the starting NDVI values were predominantly maintained in the high and moderate burn severity zones with dense/healthy vegetation experiencing a homogenous mix of all burn severity types. Moderate and sparse vegetation tended to only have low-severity burns and a mix of growth and decline of vegetation.

The findings of this study suggests that we can anticipate some fire behavior based on pre-fire NDVI values when considering the 30 meters by 30 meters scale of pixels used in this study. Using the pattern demonstrated post-fire, it may also be possible to analyze NDVI in reverse years to see changes over time that could be representative of historical fire patterns. As expected, areas with higher pre-fire NDVI values tended to experience a higher severity of burn. This makes sense when considering that higher concentrations of fuel means there is more fuel to burn during a fire. Considering this area's fire regime is

on the scale of hundreds of years, it is reasonable to consider pre-fire NDVI vs aspect relationships to represent what the state of the relationship between these indices might look like over long temporal scales. However, it only provides a snapshot of what the area looked like before a fire event and not what the progression of regrowth characteristics were like between events.

Burn severity appears to be the dominant control mechanism in post-fire vegetation recovery with the pre-fire NDVI being an indicator of future burn severity, which in turn influences vegetation recovery. This demonstrates the inherent relationship between vegetation and fire consistent with many studies (Meigs et al., 2020, Fang et al., 2015, Riano et al., 2002, Holden et al., 2009, Steen-Adams et al., 2019, Crotteau et al., 2013, Leon et al., 2012, Nowacki et al., 2008). It also demonstrates that a burn zone in this environment is complex. The denser or healthier the vegetation is, the more likely a fire in that area will be high severity in at least some regions of the burn zone (Meigs et al., 2020, Fang et al., 2015, Kane et al., 2014). This supports the notion that fire suppression leads to larger fires and, by proxy, larger zones of higher intensity fires due to areas of fuel accumulation becoming denser and larger (Meigs et al., 2020, Fang et al., 2015, Kane et al., 2014). Fire is a natural part of the system and continued blanket suppression harms the ecosystem and encourages greater loss when a fire does occur (Tesky, 1992, Uchytil, 1991, Cope, 1992, Fire Management, 2022, Dobkins et al., 2017, Hart-Fredeluces et al., 2021, Meigs et al., 2020, Fang et al., 2015, Kane et al., 2014).

The objectives of land managers will influence the perception of the fire and what is considered an acceptable loss. For example, on the pixel level, some sample points experienced high severity fires and denuding of vegetation. If that pixel represented a particular asset of importance, the loss may be unacceptable. However, if the entire study area is considered as one unit, the NDVI values within the burn zone relatively continue to approximate pre-fire value ranges (aka healthy, dense vegetation) except for high severity zones that approach these ranges around Year 2-3. As a single unit, the rate at which NDVI is increasing in higher severity zones suggests that pre-fire NDVI may resemble pre-fire values in a matter of years. Within this study, NDVI values were short only around 0.05 units from being considered healthy, dense vegetation.

Subsequent decisions around intervention and recovery will be based upon land management goals and values around accepting fire as a natural part of the system. Findings demonstrate that it is possible for fires to influence dense vegetation accumulation while allowing fire to be part of the system. For example, if the goal is to reduce unwanted outcomes from high severity fires, maintaining moderate NDVI values can encourage the majority of burning to be no greater than low-severity. Alternatively, targeting high-severity areas for post-fire aid could speed vegetation recovery. Each approach subsequently has multiple iterations to obtain the desired species and spatial arrangement to meet the target goals for the land.

For this study area, recommendations for management based on this study are to monitor moderate-high and high-intensity burn zone environments for invasive species encroachment and recovery rate. The study area is relatively remote though the fire ignition point began near a popular hiking trail. Reducing access and disturbance to severely burned areas would reduce the chance of personal injury due to loose soil or downed trees and allow the area to establish vegetation that would stabilize steep slopes. Safeguarding refugia sites would also assist in regenerating vegetation within or close to prior ecological thresholds. The most severely burned areas are predominantly measured as moderate vegetation values and would likely experience a low-severity, if any, burn at this time. If the desire to introduce or establish specific species is present, focusing on locations of lower NDVI that previously registered as moderate to high NDVI values may be the most successful due to lack of competition.

It is important to note that this study does not measure the conditions of fauna populations and subsequent recovery. Both flora and fauna populations are part of a healthy, sustainable ecosystem. The presence of vegetation or habitat does not guarantee the return of fauna populations if those populations do not have adequate connectivity to those habitats. Therefore, land management objectives related to wildlife would need to engage with additional measures to determine ecosystem recovery as a whole, rather than purely based on vegetation indices.

This study adds to the limited knowledge of relative control mechanisms on vegetation recovery in post-fire environments. It sets an example of methodology and provides multiple avenues to expand on additional research. Parallel research in similar environments and locations would be beneficial to creating standards in which to characterize fire regimes and associated behavior.

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