## GEOSPATIAL ANALYSIS OF THE ROUND FIRE:

## A REPLICATION OF BURN SEVERITY ANALYSES IN THE SIERRA NEVADA

by

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ACKNOWLEDGMENTS	ii
LIST OF TABLES	v
LIST OF FIGURES	vi
LIST OF ABBREVIATIONS	vii
ABSTRACT	viii
CHAPTER 1: INTRODUCTION	
1.1 Motivation	
1.2 Complexity of Wildfire	
1.2.1 Climate and Weather	
1.2.2 Vegetation	
1.2.3 Topography	
1.2.4 Fire history	6
1.3 Round Fire Incident	7
1.4 Research Objectives	9
1.5 Thesis Organization	
CHAPTER 2: BACKGROUND AND RELATED WORK	
2.1 Burn Severity	
2.1.1 Initial vs. Extended Assessments	
2.1.2. Field Techniques	
2.2 Remote Sensing of Burn Severity	
2.2.1 Timing of Image Acquisition	
2.2.2 Burn Severity Thresholds	
2.3 Related Work	
2.3.1 Monitoring Trends in Burn Severity	
2.3.2 California Rim Fire Analysis	
CHAPTER 3: DATA AND METHODOLOGY	
3.1 Study Area	
3.2 Data Sources	
3.2.1 Landsat Satellite Imagery	
3.2.2 CALVEG Land Cover Data	

# TABLE OF CONTENTS

3.2.3 National Elevation Dataset Topography Data	. 26
3.2.3. FRAP Fire Perimeters	. 27
3.2.4 BAER Soil Burn Severity Points	. 28
3.3 Methodology	. 30
3.3.1 Delineating Fire Perimeter	. 31
3.3.2 Differenced Normalized Burn Ratio	. 31
3.3.3 Setting Severity Thresholds	. 32
3.3.4 Normalized Difference Vegetation Index	. 35
3.3.5 Bivariate Correlation	. 35
3.3.6 Two-sample Kolmogorov-Smirnov Test	. 36
CHAPTER 4: RESULTS	. 39
4.1 Area Burned	. 39
4.2 Bivariate Correlation Results	. 41
4.3 Scatterplots	. 44
4.4 Pre-fire Land Cover	. 48
4.5 Pre-fire Fuel by NDVI	. 49
4.6 Topography	. 51
4.7 Study Area Fire History	. 55
4.8 Two-Sample K-S Test Results	. 57
CHAPTER 5: DISCUSSION AND CONCLUSIONS	. 61
REFERENCES	. 67
Appendix A: Attribute Table for Round Fire Soil Burn Severity Dataset	. 70
Appendix B: Round Fire Burn Severity Threshold Specifications	. 71
Appendix C: Pre-fire Land Cover of Study Area	. 72
Appendix D: Two-Sample K-S Test Statistics	. 73

# LIST OF TABLES

Table 1 Matrix of Soil Burn Severity based on Vegetation Type and Density	14
Table 2 Composite Burn Index Plot Breakdown	15
Table 3 Recommended Burn Severity Thresholds	18
Table 4 Rim Fire and Round Fire Study Area Comparisons	21
Table 5 Attributes from Round Fire Soil Burn Severity Field Data	29
Table 6 Pearson's Correlation Coefficients Matrix for Landscape Variables	42
Table 7 Pre-fire Land Cover Fractional Areas within Round Fire Burn Severity Classes	48
Table 8 NDVI Statistics by Burn Severity Classification for Round Fire	51
Table 9 Elevation Statistics by Burn Severity Classification	52
Table 10 Slope Statistics by Burn Severity Classification	54
Table 11 Two-Sample K-S Test Summary for Unburned and Very Low Burn Severity	58
Table 12 Two-Sample K-S Test Summary for Very Low and Low Burn Severity	59
Table 13 Two-Sample K-S Test Summary for Low and Moderate Burn Severity	60

## LIST OF FIGURES

Figure 1 Aftermath of the 2015 Round Fire	7
Figure 2 Round Fire BAER Soil Burn Severity Map	8
Figure 3 Temporal Scale of Burn Severity Surveys	. 12
Figure 4 Map of Fire Districts within the Study Area	. 23
Figure 5 Round Fire Examples of Low and Moderate Soil Burn Severity	. 28
Figure 6 Methodology Flowchart	. 30
Figure 7 Plot Showing Two-Sample K-S Statistic	. 37
Figure 8 Classified Burn Severity Map for 2015 California Round Fire	. 40
Figure 9 Round Fire Breakdown of Burn Severity	. 41
Figure 10 Scatterplot of Elevation and Slope Values Colored by Burn Severity	. 45
Figure 11 Scatterplot of Elevation and Slope Values Colored by Covertype	. 46
Figure 12 Scatterplot of Elevation and Slope Values Colored by Fire History	. 47
Figure 13 Round Fire Perimeter Overlaid on Pre-Fire NDVI	. 50
Figure 14 Histogram of Slope Values	. 53
Figure 15 Histogram of Aspect Values by Burn Severity Classification	. 55
Figure 16 Fire History of Study Area	. 56
Figure 17 Visualization of K-S Test Statistic for Fire History	. 58

# LIST OF ABBREVIATIONS

BAER	Burned Area Emergency Response	
CALFIRE	California Department of Forestry and Fire Protection	
CBI	Composite Burn Index	
dNBR	Differenced Normalized Burn Ratio	
DEM	Digital Elevation Model	
DN	Digital Number	
K-S	Kolmogorov-Smirnov	
LANDFIRE	Landscape Fire and Resource Management Planning Tools Project	
L1T	Level 1 Terrain	
MTBS	Monitoring Trends in Burn Severity	
NIR	Near-Infrared	
NBR	Normalized Burn Ratio	
NDVI	Normalized Differenced Vegetation Index	
RdNBR	Relative differenced Normalized Burn Ratio	
SWIR	Shortwave Infrared	
USFS	United States Forest Service	
USGS	United States Geological Survey	

#### ABSTRACT

Wildfires are a complex natural hazard that are destructive, yet essential to many ecosystems in the western U.S. Influenced by a variety of factors, they cause inevitable social losses and damage to economic resources despite the effort of humans to predict their occurrence and spread. While past research has improved the application of various fire management strategies and fuel treatment techniques, it has also indicated a trend of a growing wildfire season with more frequent large and intense fires. The state of California, with high amounts of burnable vegetation and plagued by drought, has experienced these changes first-hand. In early February of 2015, the Round Fire burned over 6,500 acres of public and private land in Inyo National Forest and neighboring Mono County of California. Primarily a brush fire, the wildfire spread quickly due to strong winds and dry conditions, destroying 38 residential structures. Occurring both outside the regular wildfire season and during a period of historic drought, the circumstances under which the Round Fire occurred make it an interesting target for analysis. The research objectives of this study were to create a remotely sensed burn severity map of the Round Fire using the differenced Normalized Burn Ratio (dNBR) and to provide descriptive and statistical summaries for the landscape variables pre-fire vegetation, pre-fire fuel, elevation, slope, aspect, and fire history. Linear correlation between landscape variables was determined using Pearson's bivariate correlation and all ordinal data was tested for significantly different distributions amongst samples between burn severity classifications using the two-sample Kolmogorov-Smirnov (K-S) test. An accuracy assessment of the dNBR was conducted using verified soil burn severity points collected post-fire by Burned Areas Emergency Response (BAER) teams. A geospatial analysis of the Round Fire will not only assist with short-term recovery efforts, but help forest managers predict and mitigate future wildfires.

viii

#### **CHAPTER 1: INTRODUCTION**

Since the early 1960s, the U.S. Forest Service (USFS) has used airborne infrared sensors to detect and map wildfires to assist fire management teams on the ground. By the mid-1980s, integration of satellite data into the domain of ecological monitoring had become a common sight (McCleese et al. 1991). Today, remote sensing plays a crucial role not only in wildfire monitoring, but for observing various types of temporal landscape level changes. With increasingly accessible mid- to high-resolution data for lesser to no cost, analyses can be performed with greater temporal variability on a global scale.

The two major applications of remote sensing in fire management have been to observe the immediate effects of fire on the landscape as well as the long-term process of regeneration. Examining characteristics such as fire perimeter and burn severity are important in determining how to direct short-term recovery efforts. On the other hand, monitoring long-term changes in vegetative distribution and composition provides insight into the extended effects of wildfire for future management policies. Many studies have used the Normalized Differenced Vegetation Index (NDVI) as a method to track rates of vegetative recovery, or long-term severity, following a wildfire. This thesis focuses on the first-order effects of the Round Fire near Bishop, California by examining short-term burn severity using the Normalized Burn Ratio (NBR) and the differenced Normalized Burn Ratio (dNBR).

## **1.1 Motivation**

Remote sensing makes an ideal method for observing and analyzing wildfire patterns due to the large-scale landscape changes associated with fire. In the Pacific North and Southwest regions, fires have been growing larger, with an average size during the period from 2000 to 2005 of 9,600 acres compared to just 6,700 acres from 1984 to 1999 (Schwind 2008). Additionally,

wildfires are becoming more of a year-round threat in many dry western ecosystems (Westover 2015). As both the number and size of wildfires are projected to be on the rise, remote sensing offers an efficient and cost-effective way to analyze these patterns.

Understanding how individual wildfires interact with external variables, and with respect to historical fire conditions is important because it benefits both society and the environment. Many of the social and economic losses caused by wildfire can be diminished through more informed planning and implementation of different fire management strategies. Additionally, by preserving the diverse role of wildfire in various ecosystems, many altered landscapes may slowly revert towards their historic land conditions. Many ecosystems, particularly forests, provide society with a vast range of natural resources, making it worthwhile to monitor both the short- and long-term changes associated with wildfire hazards. Since the patterns associated with wildfires also vary by region and over time, any qualitative or quantitative observations could be integrated into long-term research to help track these variations.

One particular reason for choosing to analyze wildfire in the Western U.S. was that severe drought has taken over the region for several years, going as far back as late 2011. A mixture of weak El Niño Southern Oscillation and possible climate change effects led to several seasons of mild winters followed by an early spring period with moist soil conditions. In the Sierra Nevada region of California, snowpack is traditionally at its peak by early April; however, on April 1<sup>st</sup> of 2015, surveys measured a depth of just 1.4 inches, the lowest amount recorded since 1950 (Carlson et al. 2015). With increased drought conditions, fires could potentially become more widespread and severe. Analyzing how fire patterns vary in these significant climatic conditions will aid in the effort to predict and when necessary prevent wildfire.

### **1.2 Complexity of Wildfire**

Wildfires are a well-researched hazard, yet continue to cause damage to natural and economic resources on an annual basis. Fire patterns, which are constituted by their extent and effects, are difficult to model and even harder to predict. However, through years of applied development in spatial analysis, experts have characterized many contemporary wildfire patterns across a range of fire-prone ecosystems (Miller et al. 2012). There are many different variables that can potentially influence the behavior of fire and no two wildfires are identical. In its most basic form, the wildfire potential of a site depends on the occurrence of flammable biomass and an ignition source (Ryan 1991). The availability of these variables, in turn, is influenced by a myriad of interrelated factors associated with more general changes in geography.

The sources affecting fire patterns can be roughly broken down into climate and weather, vegetation, topography, and fire history. The following subsections will broadly describe how these different elements impact the behavior of fire. While each of these elements could be explored in much greater detail, the aim is to highlight the general complexity behind the myriad of factors that drive wildfire.

#### 1.2.1 Climate and Weather

In traditional climatology, climate describes the mean state of the atmosphere at a given location while weather denotes the types of conditions experienced due to the climate at that location. The variables used to describe climate normally include temperature, atmospheric moisture, wind speed and direction, as well as atmospheric pressure (McGregor and Nieuwolt 1998). Both the climate and weather within a region are important factors driving fire patterns. Weather elements such as lightning strikes can serve as an ignition source for wildfire, while wind is often times a

dangerous cause for wildfire spread. Given the appropriate combination of weather conditions, the potential likelihood of a wildfire occurring can rise drastically in a short period of time.

Beyond dictating changes in weather from season to season, slight shifts in climate can potentially have a strong influence on wildfire patterns. For example, a combination of elevated temperatures and decreased summer precipitation could be expected to increase both the length and severity of the fire season (Ryan 1991). In the Sierra Nevada region, drought cycles have been found to be associated with increased wildfire activity and larger fires (Evans et al. 2011). Decades of monitoring and tracking changes in fire patterns have allowed forest managers and fire experts to become more prepared to deal with the many risks of wildfire. By understanding how climate and weather have interacted with historical fire patterns, researchers can more accurately predict and prepare for future wildfire trends.

#### 1.2.2 Vegetation

Another important factor influencing regional fire patterns is the existing land cover or vegetation type. Shaped by local geography and climate, the distribution of vegetation varies based on the amount of land and resources available. In most cases, forests provide the greatest amount of fuel to burn in wildfires, followed by shrublands and then grasslands. However, due to an inverse relationship with moisture levels, fire frequency generally tends to increase with decreasing site productivity (Ryan 1991). Depending on the existing vegetation type, wildfire-related characteristics, such as rate of biomass accumulation, fire tolerance, and recovery patterns, will vary from region to region. Chaparral communities, for example, have a high susceptibility to fire which plays an important role in the vegetative cycle (Riano et al. 2002).

The relationship between vegetation and wildfire is a constantly changing cycle of growth and destruction. Long-term fire can alter the composition, structure, and heterogeneity of

forest landscapes (Scholl and Taylor 2010). While climate and vegetation type affect the general fire regime, individual vegetative properties can influence wildfire patterns and spread as well. In forest management, reductions in average tree diameter, tree density, and basal area have all been found to reduce the burning of tree foliage, also known as crown scorch, during wildfire (Pollet and Omi 2002). Other factors, like phenology, can be used to manipulate the natural fire cycle through timed prescribed burns. By exploring the complex interaction that vegetation has on wildfire, and vice versa, researchers can gain an upper hand to help mitigate potentially devastating damage.

#### 1.2.3 Topography

In addition to climate and vegetation, local topography also has many observable effects on general fire patterns. While the composition and structure of vegetation varies along latitudinal gradients due to shifts in climate, they also vary with changes in altitude due to distinct shifts in vegetative zones (Ryan 1991). In many western U.S. mountain ranges, an inverse relationship between elevation and fire frequency, measured by the fire return interval, has been repeatedly observed. Researchers have found that these patterns can be attributed to factors such as variations in fuel production, flammability of vegetation, and the length of snow-free periods (Gill and Taylor 2009). Of course, the effects on wildfire due to topography are closely interrelated with respective changes in climate and vegetation and will also vary with location.

Topography can also affect fire patterns due to changes in slope and aspect across the landscape. Both slope and aspect have a direct influence on the spatial distribution of vegetation as they help to specify the potential of different sites. In mixed-conifer forests, areas with middle to upper slopes often experience higher severity fire than lower slopes because of lower canopy cover and younger more densely-packed trees. On southern-facing slopes, fire frequency is often

higher than on northern-facing ones due to differences in solar insolation (Scholl and Taylor 2010). Knowledge of these patterns not only helps predict the general locations where wildfires may occur, but also enable forest managers to effectively employ fuel treatment techniques.

#### 1.2.4 Fire history

When discussing wildfires, the effects they have both on the likelihood and character of subsequent fires are important to take note of. While climate, vegetation, and topography are critical to individual fire patterns, wildfires are responsible in shaping the structure and fire regime of an ecosystem. In Sierra Nevada forests, a mixture of wildfires and historical land-use, through timber harvesting and burns, have led to changes in forest composition with frequent low to moderate severity fire return intervals (Evans et al. 2011). In other western regions, the lack of regular fire has led to increased tree density and homogenization of forests, reducing the overall fire frequency and area burned (Parks et al. 2014). Although some patterns may be more favorable than others, any shift from historical fire regimes will likely have some unintended consequences on the surrounding ecosystem.

When forest managers use fuel treatment techniques to mitigate potential future damage, they are also altering the fire history of a landscape. Various methods, such as thinning of trees and prescribed burns, have been employed in different combinations in attempts to control wildfire spread and severity. For the majority of the 20<sup>th</sup> century, the immediate response of suppressing fires in the Sierra Nevada led to distinct changes in vegetation types and structure. Fires became less frequent, but more severe, resulting in the development of more lenient policies towards direct suppression (McKelvey et al. 1996). While modern techniques are more respectful towards the role fire plays in many western ecosystems, there will continue to be landscape level changes due to past and future wildfires.

## **1.3 Round Fire Incident**

On the afternoon of February 6<sup>th</sup>, 2015, heavy winds from an incoming storm downed a power line which sparked a wildfire in Inyo National Forest and neighboring Mono County of California. Fueled by extreme weather conditions, the wildfire spread across the mixed Sierra Nevada landscape, destroying homes and forcing mandatory evacuations and road closures. Strong and shifting winds negated both ground personnel and aircraft from effectively containing the fire; however, early the next day, torrential rain fell and prevented any further movement of the wildfire (Gallegos and Ellsworth 2015). By the following day, 38 homes had been destroyed in the small towns of Swall Meadows and Paradise in Mono County (Thalhamer 2015). Additionally, field-data collected after the fire was fully contained mapped an estimated 6,535 acres of affected private and public lands at mostly low to moderate soil burn severity (Gallegos and Ellsworth 2015). While the timing and circumstances of what is now known as the Round Fire may be considered unusual, they highlight the danger and unpredictability wildfires pose to the landscape and its inhabitants.



Figure 1 Aftermath of the 2015 Round Fire (Photograph by Gary Swall)

A hand-mapped soil burn severity survey completed by BAER teams is shown in Figure 2 below with the fire perimeter outlined in red, moderate burn severity shown in yellow, low severity in blue, and very low severity in green. The map is reported to show 89% of low and moderate soil burn severity and the remaining 11% as very low to unburned. An estimated 24% of the total fire area burned at moderate severity (Gallegos and Ellsworth 2015).



Figure 2 Round Fire BAER Soil Burn Severity Map Source: Gallegos and Ellsworth 2015

#### **1.4 Research Objectives**

The Burned Area Emergency Response (BAER) assessment report for the Round Fire was released by Inyo National Forest on February 18<sup>th</sup>, 2015. At the time the report was released, satellite imagery was not available to cross-reference field-data taken on soil burn severity (Gallegos and Ellsworth 2015). Since the release of the report, satellite imagery more optimal for mapping wildfires had been captured to conduct a preliminary remote sensing burn severity analysis. With accurate field-data on fire effects, a burn severity map can be used to validate the application of the burn severity index within the region of the fire.

In addition, the widespread availability of fire-related geospatial data offers an opportunity to analyze wildfire patterns with respect to multiple landscape variables. If wildfire patterns are in some way driven by these landscape variables, their distributions would be expected to vary with changes in burn severity. An existing study of the 2013 California Rim Fire, which is discussed in detail in Section 2.3.2, uses a statistical test to validate this assumption (Potter 2014).

Using a mixture of satellite imagery and geospatial data layers, the objectives of this research study are to:

- Determine the initial extent and severity of fire across the Round Fire study area through the use of remote sensing.
- (2) Provide descriptive and statistical summaries for wildfire-related landscape variables within the fire perimeter.
- (3) Determine correlation and statistically test for significantly different distributions amongst landscape variables based upon their burn severity classifications.

(4) Compare the wildfire patterns observed in the Round Fire study area with those seen in the Rim Fire study using the same methods.

The dNBR was the primary index used for image analysis while the Pearson correlation coefficient and two-sample Kolmogorov-Smirnov (K-S) test were used for statistical testing. The landscape variables included in the spatial analysis were pre-fire land cover, pre-fire fuel, elevation, slope, aspect, and fire history. Since one assumption of the two-sample K-S test is that data is measured on an ordinal scale, all variables with the exception of pre-fire land cover and aspect were tested for significance. The resulting products of this study include a classified burn severity map, an analysis of bivariate correlation, statistical summaries of landscape variables, and results from two-sample K-S testing.

#### **1.5 Thesis Organization**

The remainder of this thesis consists of four chapters. The following Chapter 2 provides some background information and related work with regards to measuring wildfires and burn severity. Chapter 3 summarizes the data sources and methods used in the analysis. Chapter 4 presents the Round Fire burn severity map and results from analysis, and Chapter 5 offers some discussion, conclusions, and suggestions for future work.

#### **CHAPTER 2: BACKGROUND AND RELATED WORK**

Since wildfire patterns are driven by multiple external variables, one of the major struggles in fire ecology has been developing methods to uniformly measure wildfire effects. The following chapter provides a brief discussion on the meaning of burn severity with respect to other fire-related effects and explores some of the already established methods that are employed today. Two field-based methods, soil burn severity mapping and the Composite Burn Index (CBI), are described in the first section and the second section is dedicated to the calculation of burn severity through remote sensing and the use of the NBR. The chapter closes with a discussion of related work, including the current national burn severity mapping project and an overview of the Rim Fire Study by Christopher Potter. One of the objectives of this thesis was to replicate the methods of the Rim Fire Study in order to compare the application of the dNBR within the Sierra Nevada region of California.

#### 2.1 Burn Severity

The terminology associated with wildfire effects have been a topic of debate for many decades. While fire intensity and burn severity have similar connotations, fire intensity is defined as the energy output from an individual fire, while burn severity encompasses both the social impacts and ecological responses resulting from a wildfire. Although the responses associated with wildfires vary at different spatial and temporal scales, burn severity in fire ecology has traditionally been measured by the degree of organic matter loss occurring both above and below ground (Keeley 2008). From a landscape perspective, burn severity is more generally defined as the degree of environmental change due to wildfire (Key and Benson 2006; Gitas, di Santis, and Mitri 2009). Vegetative regeneration from wildfire is a long-term process so different effects will be observed and captured depending on when analysis takes place relative to the time of the fire.

## 2.1.1 Initial vs. Extended Assessments

As previously mentioned, the process of vegetative recovery from wildfire fluctuates with time, taking place over multiple growing seasons. Within the span of one year from a wildfire, an initial and extended burn severity assessment are typically completed. An initial assessment usually occurs within a few weeks of containment and is used to observe the most immediate effects of a fire, including the extent and severity as well as the various biophysical changes that occur during a wildfire (Key and Benson 2006). As seen in Figure 3 below, initial burn severity mapping is typically performed in coordination with forest experts during the completion of a BAER report and is useful for planning various recovery efforts such as dead tree or debris removal and other possible landscape level treatments. Determining the overall burn area immediately after a fire is also useful for setting a baseline to monitor long-term changes in the vegetative recovery process.





On the other hand, an extended assessment of short-term burn severity is typically

completed during the next growing season following a wildfire. By waiting until vegetation is at

its natural peak, an extended assessment in many ways is more representative of the long-term changes caused by wildfire. Since many fire-prone ecosystems show additional vegetative responses, such as the delayed mortality of plants, an extended assessment provides valuable details that may not be captured through an initial assessment alone (Key and Benson 2006). Figure 3 above shows how the net primary productivity of a forest site, shown by the blue line, changes after a fire relative to initial and extended assessments as well as for observations of long-term severity. At the time at which this thesis research project started, only an initial assessment was feasible given the amount of time elapsed since the Round Fire. It is highly recommended that an extended assessment is eventually completed for comparison with data on initial burn severity.

### 2.1.2. Field Techniques

In forest ecology, two standardized methods exist for collecting field data on post-fire burn severity. They are the traditional post-fire soil burn severity mapping techniques employed by the U.S. Forest Service (USFS) and CBI, used in the Monitoring Trends in Burn Severity (MTBS) joint project that is discussed in more detail in Section 2.3.1. Both measures have been used to correlate and calibrate remotely-sensed data.

Soil burn severity mapping is a routine process for BAER teams following a wildfire and takes place during the initial assessment of the landscape. It includes characterizations of various ground surface characteristics, such as char depth, organic matter loss, and altered color and structure due to wildfire (Parsons et al. 2008). Soil burn severity classifications can range from low, moderate, to high and are strongly correlated to pre-fire vegetative type and density. Most fire-prone vegetation types, for example, rarely experience high soil burn severity at under 20% canopy cover (Parsons et al. 2008). With the aid of specific descriptive severity indicators with

verified photos of soil burn severity conditions, researchers can confidently map the initial effects of a wildfire in preparation for recovery efforts.

Due to the corelation between vegetation type and density, the USFS provides the following matrix, shown in Table 1, to aid with the surveying and classification of soil burn severity. The likelihood of varying degrees of soil burn severity occurring is related to both the pre-existing vegetation type and density. While low soil burn severity is common across sparse, medium, and high densities of all vegetation types, high severity does not occur at sparse density for those same vegetation types. It should be noted that these are just guidelines and may not neceassarily be applicible for all fires (Parsons et al. 2008).

		Soil b	urn severity class	ses
Vegetation type	Density model <sup>a</sup>	Low	Moderate	High
Chaparral	Sparse	Cp	U	
	Medium	С	С	U
	High	С	С	U
Forest	Sparse	С	U	
	Medium	С	С	U
	High	С	С	С
Sagebrush	Sparse	С	U	
	Medium	С	С	U
	High	С	С	U
Grass	Sparse	С		
	Medium	С	U	
5	High	С	С	

**Table 1 Matrix of Soil Burn Severity based on Vegetation Type and Density** (Source: Parsons et al. 2008)

<sup>a</sup> Percent canopy cover for sparse, medium, and high density are approximately defined as: Sparse  $\leq 20\%$ ; Medium = 20–60%; and High  $\geq 60\%$ .

<sup>b</sup> Key: C = common; U = unlikely (but can occur in some circumstances); Gray cells = not applicable/does not occur.

The CBI was developed in 1996 when remote sensing was first integrated into large-scale wildfire monitoring as a multi-layered index of burn severity used to encompass the range of variation seen in fires. Using plots spread across a burn site, the CBI uses a decimal ranking

system from 0 to 3.0 to rate the magnitude of fire effects averaged across the vegetative structure of the plot (Key and Benson 2006). While it can be completed during an initial survey, the CBI usually takes place the following growing season as part of an extended assessment. Table 2 below shows the breakdown of levels that make up the CBI score of a plot, which are separated into categories by understory and overstory. By providing reports on burn severity both by strata and in composite form, a more complete representation of wildfire effects can be captured.

 Table 2 Composite Burn Index Plot Breakdown (Source: Key and Benson 2005)

Table LA-1—Three composite levels (A–C) encompass the five strata level (1–5). CBI scoring is completed for each strata and averaged to the desired composite level.		
A. Total plot	B. Understory	<ol> <li>Substrates</li> <li>Herbs, low shrubs and trees less than 3 ft (1 m)</li> <li>Tall shrubs and trees 3 to 16 ft (1 to 5 m)</li> </ol>
	C. Overstory	<ol> <li>Intermediate trees (pole-sized trees, subcanopy)</li> <li>Big trees (upper canopy, dominant/co-dominant trees)</li> </ol>

### 2.2 Remote Sensing of Burn Severity

Burn severity following a wildfire can be empirically measured using remotely sensed data through the implementation of the NBR. The NBR utilizes the near-infrared (NIR) and shortwave infrared (SWIR) multispectral bands in a ratio form as follows:

Normalized Burn Ratio = 
$$\frac{(NIR - SWIR)}{(NIR + SWIR)}$$
 (1)

Reflectance for the NIR band, which falls between 0.76–0.9 microns, reacts positively to leaf area and overall plant productivity. The SWIR band, falling between 2.08–2.35 microns, has an opposite reaction, responding positively to effects of drying and other non-vegetated surface characteristics. In the resulting NBR, with a range between -1 and 1, positive values represent areas where vegetative productivity increased while negative values indicate areas where the

effects of fire were present (Key and Benson 2006). During a wildfire, vegetation that is burned will shift from having high reflectance in the NIR and low reflectance in the SWIR band to low reflectance in the NIR and high reflectance in the SWIR band. By contrasting the reflectance signals between these two wavelengths, burned areas can be distinguished from unburned areas in a standardized measureable form.

## 2.2.1 Timing of Image Acquisition

For temporal analyses of burn severity, it is necessary to create an NBR image for both pre- and post-fire conditions. Selecting satellite data that truly represents the target of analysis, for example when performing an initial vs. an extended burn severity assessment, is a crucial step requiring knowledge of the local landscape. Understanding when a wildfire occurs relative to vegetative phenology and with respect to the normal fire season, for example, is important for interpreting or making conclusions derived from any NBR product.

Generally speaking, the best time of the year to obtain post-fire imagery is during the early to middle growing season, when green and unburned vegetation are most distinct from areas affected by wildfire. As the annual growing season nears its end, low burn severity and unburned areas become less distinguishable from one another (Key and Benson 2006). This is convenient for most assessments since wildfires tend to occur in the spring and summer seasons. For the purposes of an initial burn severity survey, as for the analysis of the Round Fire in this study, imagery should be selected that is as close to the date of containment as possible and such that is not obscured by the presence of smoke or clouds.

Selecting a pre-fire image is as important because it determines the conditions that are compared against the post-fire image. Since land cover and surface conditions change over time and with seasonality, avoiding large differences from scene to scene will help produce more

reliable dNBR results. In many cases, suitable pre-fire imagery may exist during the same year a fire occurs. In other cases, it is acceptable to use imagery from two to three prior growing seasons, given there were no major disturbances within the period. One exception is for the initial assessments of short-lived fires, where pre- and post-fire imagery can be obtained within roughly a month of one another (Key and Benson 2006). Due to the early occurrence of the Round Fire relative to the normal fire season, as well as major differences in seasonality compared to previous years, the optimal pre- and post-fire imagery for this analysis came from the same year, roughly a month and a half apart in time.

### 2.2.2 Burn Severity Thresholds

Another crucial step in creating a burn severity map is defining the thresholds that set the burn severity classification for the values in the final dNBR product. Satellite imagery taken from different periods of time in various regions of the world would ideally require the calibration of burn severity ranges for each individual set of wildfire scenes. In order to verify the accuracy of remotely-sensed data, classification ranges should be correlated with field-collected data on soil burn severity or CBI values and adjusted to obtain the highest accuracy possible.

It should be noted that in reality, there is always overlap in dNBR values between burn severity levels. Generally speaking, severity ranges can shift from roughly  $\pm 10$  to up to 100 or more points. Depending on the seasonality of images, type of assessment, and other related characteristics, the burned-unburned thresholds should be adjusted accordingly based upon scene specific information (Key and Benson 2006). Other important considerations when defining burn severity thresholds include the existing land cover type, delayed vegetative responses, and other factors possibly influencing the outcome of a remotely-sensed burn severity map. The MTBS project, discussed in Section 2.3.1, utilizes a system with five discreet severity classes, including increased post-fire response, unburned or unchanged, low severity, moderate severity, and high severity (Schwind 2008). These generally conform to the ordinal severity levels recommended by the developers of the CBI, seen in Table 3 below. While these thresholds work for most typical fires, they should not be blindly adopted due to differences in vegetation and phenology between remotely sensed images. It is highly recommended that there is consultation with forest and fire experts to help accurately set severity ranges.

Table 3 Recommended Burn Severity Thresholds (Source: Key and Benson 2006)

Severity level	dNBR range	
Enhanced regrowth, high	-500 to -251	
Enhanced regrowth, lo	-250 to -101	
Unburned	-100 to +99	
Low severity	+100 to +269	
Moderate-low severity	+270 to +439	
Moderate-high severity	+440 to +659	
High severity	+660 to +1300	
(dNBR value ranges are flexible; scene-pair dependent; shifts in thresholds $\pm 100$ points are possible. dNBR less than about -550, or greater than about +1,350 may also occur, but are <i>not</i> considered burned. Rather, they likely are anomalies caused by misregistration, clouds, or other factors not related to real land cover differences.)		

## 2.3 Related Work

The following section provides a brief overview of the history of remote sensing in burn severity studies. The MTBS project will be introduced, as well as a summary of the 2013 Rim Fire study by Christopher Potter, which served as a guiding model for this study. While there is extensive existing research related to the remote sensing of wildfire patterns, it should be noted that observations have varied both temporally and geographically.

Burn severity has been measured through means of remote sensing including aerial

photographs and satellite imagery for many decades due to its efficiency in analyzing large areas

of land at relatively low user cost. Spectral analysis of burn severity was developed as early as 1974 and has since integrated a range of sensors with varying spatial resolutions and a variety of analysis techniques including vegetation indices, image classification, and radiative transfer models. Additionally, while fire-prone ecosystems, including temperate forests and Mediterranean forests and shrublands, make up the majority of existing burn severity analyses, the techniques have been applied for wildfires in all types of natural environments (Gitas et al. 2009). With constant technological developments in the field of remote sensing, a satellite analysis of burn severity is now a routine process after most large wildfire events.

## 2.3.1 Monitoring Trends in Burn Severity

The MTBS project was launched in 2006 with the primary purpose of providing an analytical basis for analyzing national trends in fire severity. A joint project between the U.S. Geological Survey (USGS), the National Center for Earth Resources Observation and Science, and the USFS, the objectives of the multi-year study are to map the fire severity and burned areas of all wildfire activities greater than 500 acres in extent in the eastern U.S. and greater than 1,000 acres in extent across the western U.S. from 1984 onwards (Schwind 2008). MTBS provides national geospatial data for burned area boundaries and burn severity mosaics as well as individual fire-level burn severity data including pre-and post-fire imagery, NBR and dNBR products, themed severity maps, and other relevant wildfire data.

While the MTBS project aims to provide extended assessments for all fires within a year of their occurrence, data is usually not made publically available until certain periods of the year. Initial assessments are only completed for ecosystems that exhibit rapid post-fire vegetation responses, such as herbaceous and high productivity shrublands, due to difficulties in capturing post-fire data signals through satellite imagery (Schwind 2008). Throughout the time this project

was completed, no Round Fire data was published by the MTBS which was a motivating factor in choosing this topic. Therefore, a part of the objective of this study was to employ the MTBS methods to create an initial burn severity map for the Round Fire study area.

#### 2.3.2 California Rim Fire Analysis

In 2014, a study entitled *Geographic Analysis of Burn Severity for the 2013 California Rim Fire* by Christopher Potter was published in the Natural Resources Scientific Research Journal. The article focused on a remote sensing and statistical analysis of the Rim Fire, which burned over 250,000 acres in Stanislaus National Forest and Yosemite National Park in the central Sierra Nevada late in the summer season of 2013. Through employment of the RdNBR, a relative form of the dNBR, it was found that this substantial wildfire resulted in a mosaic of low, moderate, and high burn severity classifications patterns across a range of land cover types, primarily evergreen forest and shrubland (Potter 2014).

The Rim Fire analysis also integrated the use of landscape variables pre-fire land cover, pre-fire fuel, elevation, slope, aspect, and fire history to test for differences with respect to burn severity. The author chose to use the two-sample Kolmogorov-Smirnov (K-S) test, which tests the null hypothesis that two groups were sampled from populations with identical distributions, for example, the cumulative distributions of elevation across moderate and high burn severity areas. The K-S test is discussed in more detail in Chapter 3. At varying degrees of statistical significance, the author found differences amongst moderate and high burn severity areas for variables pre-fire fuel represented by an NDVI, elevation, slope, and fire history represented by the number of years since fire (Potter 2014)

The aim of this Round Fire study was partially to replicate the use of the dNBR and twosample K-S test in a similar but heterogeneous environment as the Rim Fire. By testing the same

landscape variables with respect to changes in burn severity, similarities and differences in wildfire patterns between the two study areas could be observed. Since there were distinct discrepancies observed between the two study areas prior to analysis, it was expected for there to be variations both in overall burn severity patterns and relationships with regards to various landscape variables. Table 4 below compares some of the relevant wildfire and landscape related characteristics for the Round and Rim Fire study areas.

**Table 4 Rim Fire and Round Fire Study Area Comparisons** (Source: Potter 2014; Gallegosand Ellsworth 2015)

Attribute	2013 Rim Fire	2015 Round Fire
Date	8/17/13 - 9/17/13	2/6/15 - 2/12/15
Region	Stanislaus National Forest	Inyo National Forest
	Yosemite National Park	Mono County
Size	257,314 acres	6,535 acres
Burn Severity	High/mid/low severity	Moderate/low severity
Elevation	250-3,250 m	1,500-3,500 m
Topography	Varied slopes and aspects	Varied slopes and aspects
Pre-fire land	Developed open, developed low,	Barren, conifer forest/woodland,
cover	barren, deciduous forest, evergreen	herbaceous, shrub, urban
	forest, shrubland, and grassland	
Fire history	Several historic fires throughout the	Mixture of wildfires and prescribed
	study area spanning over a century	fires going back as far as 1958

#### **CHAPTER 3: DATA AND METHODOLOGY**

The following sections provide a description of the Round Fire study area, information on various data sources included in the analysis, and the methods that were used for data preparation and processing. The data section is split into subsections by data source while the methodology section is separated by the techniques used throughout the duration of the analysis.

#### 3.1 Study Area

The 2015 California Round Fire occurred in the White Mountain Ranger District of Inyo National Forest, bordering the southeastern Sierra Nevada Mountains. With its perimeter intersecting the boundary between Inyo and Mono counties, roughly between Mammoth Lakes and the city of Bishop just west of California Highway 395, the fire affected a variety of federal, state, National Forest, and privately owned lands. The towns of Swall Meadows and Paradise Valley were also located within the fire perimeter.

The burn site, situated in the Rock Creek watershed, consists of a variety of habitat types including sagebrush, bitterbrush scrub, desert scrub, pinyon, east-side pine, montane chaparral, aspen, and some meadow habitat. Elevation within the study area ranges from roughly 1,500 to 3,500 m. The western part of the burn borders Wheeler Ridge, which is very rocky, while the southern portion borders irrigated rangeland (Gallegos and Ellsworth 2015). The wildfire occurred in a region with a Mediterranean climate, characterized by warm dry summers and cool wet winters. Since the eastern slopes of the Sierra Nevada generally experience reduced precipitation, mixed conifer forests tend to be found at higher elevations than in other parts of the region (Evans et al. 2011). Due to these conditions, fire is a regular disturbance that is important in shaping the composition and structure of vegetation in the region including study area.

Figure 4 below shows the Wheeler Crest and Paradise fire districts, which serve the towns of Swall Meadows and Paradise, respectively. The lower portion of the map shows the southern part of Mono Country, which borders the northern limit of Inyo County. The rocky slopes of Wheeler Ridge can be identified by the topography seen on the left side of the map while Lower Rock Creek is seen from the center top to the bottom right of the map.



Figure 4 Map of Fire Districts within the Study Area Source: Mono County GIS

### **3.2 Data Sources**

This section describes the geospatial data sources integrated into the Round Fire analysis. All data was obtained at or converted to 30 m spatial resolution and re-projected to Universal Transverse Mercator Zone 11N using the World Geodetic Survey 1984 coordinate system. A separate discussion on data quality, potential sources of error, and other factors possibly influencing the results of the analysis is provided for each data source.

#### 3.2.1 Landsat Satellite Imagery

Level 1 Terrain (L1T) corrected Landsat 8 satellite pre- and post-fire imagery was downloaded from the USGS Global Visualization Viewer online image browser. L1T Landsat products are terrain corrected and come in Digital Number (DN) units (USGS 2014). The pre-fire scene is dated January 1<sup>st</sup>, 2015 while the post-fire scene was taken on February 19<sup>th</sup>, 2015. Subsets of the study area were created from the 30 m spatial resolution data located in the scene corresponding to Worldwide Reference System 2 path 42 and row 34. The NBR uses SWIR and NIR bands, which correspond to bands 5 and 7, respectively for Landsat 8. The maximum cloud cover from the two scenes is 14%, with no major obstructions of the study area as determined from the accompanying LandsatLook Quality images.

Unlike the Enhanced Thematic Mapper plus sensor aboard the previously launched Landsat 7, the Landsat 8 satellite carries the Operational Land Imager and Thermal Infrared Sensors which are capable of detecting a new deep blue visible channel and new infrared channel for a total of 11 bands (Riebeek et al. 2012). While the Landsat orbit return interval remains 16 days, data quality and radiometric quantization is higher on Landsat 8 than on all previous Landsat instruments, providing significant improvements for image analysis. Additionally,

Landsat 8 returns a minimum of 400 scenes per day, roughly 150 more scenes than Landsat 7, increasing the chances of capturing cloud-free images for users (Riebeek et al. 2012).

Landsat 8 captures panchromatic, multispectral, and thermal bands at 15, 30, and 100 m, respectively (Riebeek et al. 2012). Dealing with infrared and NIR bands at 30 m spatial resolution, some generalization of landscape features is inevitable due to the large pixel size relative to the objects being observed on the ground. While issues of spectral confusion between vegetative characteristics, for example shaded and unshaded burned vegetation, have been witnessed in past research, moderate spatial resolution Landsat imagery has been the sensor traditionally used in burn severity studies (Gitas, de Santis, and Mitri 2009).

## 3.2.2 CALVEG Land Cover Data

Land cover polygon data was downloaded from the USFS CALVEG database for the Pacific Southwest Region. The CALVEG classification system conforms to the upper levels of the National Vegetation Classification Standard and provides attribute data on vegetation types based on a variety of nominal and descriptive categories, as well as data on other forest structural characteristics. The Round Fire perimeter crosses into the South Sierran and Great Basin mapping zones, corresponding to zones 4 and 8 of the region, respectively. The most recent land cover data was selected, which was 2008 for the South Sierran dataset and 2009 for the Great Basin dataset. To shorten processing times, the two datasets were merged into a single file, then clipped to the study region for further analysis.

The attribute chosen to classify pre-fire land cover was COVERTYPE, which is defined within the metadata as the vegetation cover type. It includes the categories agriculture, barren, conifer forest, hardwood forest, herbaceous, mixed conifer and hardwood forest, shrub, urban, and water. When choosing a classification type, there are also generalizations being assumed

about the nature of the landscape. Land cover boundaries, like ecosystems, both change over time and often overlap one another. Since the datasets being used go as far back as 2008, there are likely some changes in cover type which lowers the degree of certainty of any assumptions drawn from the analysis. CALVEG provides an accuracy assessment of the classifications using a system of fuzzy ratings, which rank the degree of correctness between digital and field-verified land cover classifications (USDA Forest Service Pacific Southwest Region 2003).

#### 3.2.3 National Elevation Dataset Topography Data

Topographic data, including a digital elevation model (DEM), slope, and aspect layers for the study area were downloaded via the USGS Landscape Fire and Resource Management Planning Tools Project (LANDFIRE) data distribution portal. LANDFIRE is a multiagency program that offers national geospatial data for fire modeling and to assist with management decisions. All topographic layers were derived from the National Elevation Dataset, which provides spatially consistent 30 m spatial resolution raster data for the entire U.S., with even higher resolution data in certain regions of the country. The outputs of both the slope and aspect layers are dependent upon the elevation values of the DEM. The slope layer represents the percent change of elevation measured in degrees, while the aspect layer represents the azimuth of the surface measured from 0 to 360 degrees.

For analysis of burn severity, 30 m resolution raster data was deemed sufficient enough to capture variations in elevation and topography that could potentially influence fire patterns. With moderate spatial resolution data, there is a likelihood for smaller topographic details to be obscured by larger scale landscape changes. The western portion of the Round Fire, for example, lies on a rocky ridge with many abrupt changes in elevation along an increasing slope. While modeling these details to a sub-meter level could provide deeper insight into the relationship between fire and topography, they are not necessary for analyzing the general topographic trends associated with wildfire. At a 30 m pixel size, the topography across the study area showed enough variation to highlight the essence of the landscape.

#### 3.2.3. FRAP Fire Perimeters

Fire perimeter polygons were obtained from the California Department of Forestry and Fire Protection's (CALFIRE) Fire Resource and Assessment Program. CALFIRE assesses the amount, extent, and conditions of forests and rangelands to assist with fire management policies throughout the state of California. The database includes statewide perimeters for all known wildfires, prescribed fires, and other non-fire fuel modification projects going as far back as 1878 and up to 2013. While prescribed burns have occurred around the region of the Round Fire, only wildfire and non-burn treatment polygons lie within the fire perimeter. Additionally, only events intersecting the fire perimeter were selected for analysis. Attributes for wildfires included fire size in acres, agency who tracked the fire, cause, and ignition dates. The non-fire modification dataset included information on treatment type and year, management agency, acreage, and preand post-treatment condition classifications.

CALFIRE attempts to map all fires greater than 10 acres in size by collecting data from multiple national agencies; however, there are reported gaps in the datasets. While the database is quite extensive, some fires go unreported while the records of others get lost or destroyed over time. Additionally, standards of mapping wildfires have evolved over time, making it hard to consistently monitor long-term changes in wildfire patterns (CALFIRE 2009). As time progresses, methods of mapping wildfires will become more standardized, easing the effort required to compare them with both historical conditions and with other regions. Since there were no major disturbances within the study area since the dataset was last updated, this

particular dataset was appropriate for the creation of a spatial layer depicting fire history within the fire perimeter.

## 3.2.4 BAER Soil Burn Severity Points

Soil burn severity field data points collected by BAER teams during the week following the fire were obtained from representatives of the USFS and used in the creation and calibration of the remotely-sensed burn severity map. The dataset included a total of eight field-verified points located within the fire perimeter with detailed attribute information ranging from ash color and depth to various soil and land cover-related characteristics as well as observed responses and measurements from conducted soil burn severity tests. Figure 5 below shows photographs from the survey that were provided for reference between low and moderate soil burn severity areas and were useful for understanding the range of burns within the context of the landscape.



Figure 5 Round Fire Examples of Low (left) and Moderate (right) Soil Burn Severity Source: Brad Rust, USFS
The observed soil burn severity of the field-collected points ranged from very low to low and moderate. While the surveyed points were located across a range of slope gradients, lengths, and positions, they were all found on southeastern facing aspects with the exception of one point with a southern aspect. Additionally, the majority of points were from areas where sagebrush was the dominant existing vegetation type, occurring at either low or high density. One of the data points, whose existing vegetation classification is unspecified, notes the presence of riparian trees in the comments section. A table with selected attributes from the surveyed points is provided below (Table 5). The full attribute table from the soil burn severity point dataset is provided in Appendix A.

Point #	Observed	Slope %	<b>Slope Position</b>	Pre-fire	Vegetation
	Severity			Vegetation	Density
1	Moderate	40	Midslope	Sagebrush	Low
2	Moderate	40	Midslope	Sagebrush	Low
3	Moderate	20	Foot Slope	Sagebrush	High
4	Low	3	Valley Bottom	Sagebrush	Other
5	Moderate	15	_	_	_
6	Moderate	20	Foot Slope	Sagebrush	High
7	Moderate	3	Valley Bottom	Other	High
8	Very Low	0	Valley Bottom	Sagebrush	Low

 Table 5 Attributes from Round Fire Soil Burn Severity Field Data (Source: Brad Rust, USFS)

# 3.3 Methodology

This section describes the techniques that were used to complete the analysis of burn severity for the 2015 Round Fire. All remote sensing and image analyses was performed in IDRISI Selva, an integrated GIS and image processing software authored by Ron Eastman and colleagues (Clark Labs 2015). Esri's ArcGIS version 10.3 desktop environment was used for data management and spatial analysis of burn severity and landscape variables (Esri 2015). And finally, IBM's SPSS predictive analytics software was used to carry out all related statistical tests (IBM 2015). The methodology flowchart replicated in Figure 6 shows the data that was acquired in green, the data that was created in orange, and the work (i.e. processing) that was performed in blue.



**Figure 6 Methodology Flow Chart** 

## 3.3.1 Delineating Fire Perimeter

One of the most important steps in creating a burn severity map is delineating a digital fire perimeter to represent the overall area affected by a wildfire. Accurate delineation is a crucial procedure because the perimeter layer was used in many of the subsequent geoprocessing steps.

The Round Fire perimeter polygon was manually digitized in ArcGIS using a post-fire NBR image of the study area created in IDRISI. The NBR was computed using the image calculator by adding the SWIR and NIR bands, then dividing them by their difference, as explained in Equation (1) previously in Section 2.2. The burn scar is most apparent in the post-fire NBR due to contrasting low levels of reflectance of green vegetation across the SWIR band and high levels of reflectance from low moisture levels across the NIR band.

For digitizing fire perimeter polygons, a recommended display scale of 1:24,000 was used to faithfully maintain the character of the burn area at smaller spatial scales (Key and Benson 2006). The burn patterns along the western and eastern boundaries of the Round Fire were rather heterogeneous, so extra care was exercised digitizing these zones. After a first manual attempt, additional vertices were added to help distinguish the overall fire boundary. The perimeter polygon was then smoothed using a polynomial approximation with an exponential kernel function using a tolerance of 5 m. In addition, the digitized perimeter was checked against the BAER field mapped soil burn severity data as well as pre- and post-fire false-color composite satellite imagery to ensure accurate delineation.

#### 3.3.2 Differenced Normalized Burn Ratio

In order to create a classified burn severity map, a post-fire NBR is first subtracted from a prefire NBR to generate a differenced Normalized Burn Ratio (dNBR) image, as follows:

$$dNBR = prefire NBR - postfire NBR$$
(2)

To temporally difference two images taken on different dates, the DN values reported in Landsat L1T data must first be converted to radiance, and then to top-of-atmosphere reflectance units. IDRISI offers RADIANCE and ATMOSC image processing and restoration modules to handle these conversions. The RADIANCE module provides methods for converting DN to calibrated radiance values while the ATMOSC module provides parameters to compensate for differences due to atmospheric effects in remotely sensed data. Using accepted radiometric calibration coefficients and the radiance and reflectance offset and gain values reported in the metadata of the pre- and post-fire Landsat scenes, the DN values were converted in IDRISI to a band-specific ratio of detected surface brightness, falling between the values of 0 and 1 (Chander, Markham, and Helder 2009).

Since the conversion to reflectance integrates the solar angle for the center of the scene, the pre- and post-fire NBR images were subset to the study area after the conversion to reflectance. After ensuring the images were geometrically registered, they were differenced using the image calculator in IDRISI. While a dNBR, scaled by $10^3$ , has a theoretical range of -2,000 to +2,000, it rarely exceeds the range of -550 to +1,350. Because the dNBR is a difference of normalized ratios, its units simply measure the magnitude of change in the NBR (Key and Benson 2006). Negative dNBR values typically indicate vegetative regrowth while positive values correspond to different degrees of burn severity. Resulting dNBR values falling within  $\pm 100$  from 0 generally represent areas where little change due to fire occurred.

## 3.3.3 Setting Severity Thresholds

Next, the dNBR raster was opened in ArcGIS to manually set thresholds for the final burn severity map. The raster was first classified using the break values suggested by the MTBS project seen previously in Table 2, with the exception of the lower limit for the unburned severity level, which was extended to include all negative values representing both low and high levels of enhanced regrowth. The thresholds for low, moderate-low, moderate-high, and high severity were left unchanged. Field-verified soil burn severity points were then overlaid on the classified dNBR and individually checked for accuracy. Since the collected points ranged from very low, low, to moderate severity, they were correlated with the MTBS dNBR ranges low, moderate-low, and moderate-high, respectively. Using these ranges, only three of the eight soil burn severity points were located in areas that were correctly classified. While the MTBS ranges work well with forest fires, they are not particularly suitable for the conditions of the Round Fire.

In order to correlate the field-collected points with the remotely-sensed data, the dNBR values at each surveyed point were extracted to a table for further analysis. One of the weaknesses of the field-data was that there were only one point surveyed at both low and very low soil burn severity. The point with very low severity had a dNBR value of 122.37 while the low severity point had a value of 148.84. The remaining six moderate severity points had a dNBR range of 150.36–737.97 with a mean of 431.83 and standard deviation of 188.32. Using this new data, the thresholds were readjusted to compensate for the lower severity ranges witnessed in the primarily shrub fire.

By increasing the range of the moderate severity class to encompass both the moderatelow and moderate-high MTBS classes and dividing the low severity range into very low and low severity levels, new ranges that were more suited for the characteristics of the Round Fire were set. For the second iteration of burn severity thresholds, ranges were defined as: Unburned <54, Very Low 55–123, Low 124–299, Moderate 300–738, and High >739. The break value for the unburned range was determined by sampling a group of unburned pixels located outside the fire perimeter. Applying these ranges, six of the eight surveyed soil burn severity points were correctly classified. The two incorrectly classified points were surveyed at moderate severity but located in areas classified as low severity.

The objective for the third iteration was for all surveyed soil burn severity points to be correctly classified. In order to achieve this, the only change was to the lower limit of the moderate burn severity level, which was decreased from 299 to 150. While these thresholds fit the entire dataset of field-collected points, they disproportionately distributed the area that each severity level made up of the total burned area. To better understand the new ranges, the areas for each level were calculated by dividing the pixel count of each range by the total number of pixels in the clipped dNBR. Using the third set of thresholds, 64.38% of the total area was classified as moderate or above, just 9.38% of the area at low, and the remaining 26.14% at unburned or very low. Compared to the second iteration of thresholds, with 22.92% of the area at moderate severity or above and 50.84% at low severity, the area of moderate burn areas was highly overestimated while the low areas were underestimated. A table showing each set of applied threshold ranges, field-verified accuracy, pixel counts, and percent total area burned is provided in Appendix B.

It was determined that a suitable range of severity thresholds would be a midway point between the second and third iterations. Since the area burned at moderate severity is slightly under the estimated 24% of total area using the second iteration and more than double the estimated area using the third iteration, the moderate severity range was readjusted to encompass the greater of the two misclassified moderate severity points. The final severity ranges applied were: Unburned <54, Very Low 55–123, Low 124–249, Moderate 250–738, and High >739. Using these thresholds, only one surveyed moderate burn severity point, with an extracted dNBR value of 150.36 was misclassified in an area of low burn severity.

#### 3.3.4 Normalized Difference Vegetation Index

An NDVI of the study area was produced from the 30 m spatial resolution pre-fire Landsat 8 image to create a data layer representing pre-fire fuel. NDVI has been used to measure various biomass related characteristics such as leaf area, plant productivity, and other temporal vegetative changes. It is also a common measure of vegetative recovery for long-term burn severity assessments (Key and Benson 2006). The formula for the NDVI is similar to the NBR, but substitutes the red or visible band in place of the SWIR band as shown below:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}$$
(3)

Chlorophyll in live green vegetation appears dark across the visible, particularly red, wavelengths and contrasts the spectral reflectance from the cell structure of leaves within the NIR wavelengths. The NDVI, like the NBR, is also a ratio index with resulting values falling between -1 and 1, where a value of 0 indicates no vegetation and a value of 1 represents the highest possible density of green leaves (Weier and Herring 2000). For the purposes of this project, the NDVI was also scaled by 10<sup>3</sup> to achieve an integer format for comparison with the dNBR. Analysis with respect to pre-fire fuel conditions could be indicative of many burn severity patterns that are not apparent and provide additional insights into the complex relationship between fuel and fire.

## 3.3.5 Bivariate Correlation

In order to determine the relationship between explanatory landscape variables influencing the severity of the Round Fire, bivariate correlation was conducted using Pearson's correlation coefficient in SPSS. The Pearson's coefficient compares the values of two variables in each pixel or cell location for the entire extent of the Round Fire and identifies the strength and whether or not a significant positive or negative linear relationship exists between them (Rogerson 2015). It

tests the null hypothesis that there is no linear association between two variables. The resulting coefficient has a range of -1 to 1 and identifies both the strength and direction of the relationship. Generally speaking, test results with an absolute value between 0.1–0.3 indicate small or weak, between 0.3–0.5 indicate medium or moderate, and 0.5 and above indicate large or strongly correlated variables (Cohen 1988).

Before running the test, several data layers required additional processing for purposes of determining linear correlation. The land cover layer was used to represent tree cover by creating a binary raster with tree cover indicated by the land cover types conifer, hardwood, and mixed conifer and hardwood forests. All other land cover categories were classified as non-tree cover for this portion of the analysis. Since the original aspect layer was measured on a circular scale from 0 to 360°, it was converted into north-south (northness) and east-west (eastness) variables by calculating the cosine and sine of the aspect raster. The resulting layers were measured on a continuous scale from -1 to 1. For the measurement northness, values close to 1 indicate north, -1 indicates south, and 0 indicates east and west facing aspects. The same pattern follows for the variable eastness, with 1 indicating east, -1 indicating west, and 0 indicating north and south facing aspects (Palmer 1993). Finally, the number of years since the last fire event occurring was used to represent fire history, with no past wildfires assigned a value of 0.

### 3.3.6 Two-sample Kolmogorov-Smirnov Test

In order to make confident assumptions about the relationship between burn severity levels and the landscape variables included in the analysis, the two-sample K-S test used in the Rim Fire Study introduced in Section 2.3.2 was employed.

The two-sample K-S test is a non-parametric test of variance, meaning that no assumptions are being made regarding how the underlying data is distributed (Rogerson 2015).

Non-parametric statistical methods are based on ranks and deal exclusively with ordinal data. More specifically, the two-sample K-S test compares the maximum difference between the cumulative frequency distributions of two independent samples. If the two samples were drawn from the same population, it would be expected for their cumulative frequency distributions to be close to identical. If there is a significant difference at any point along the two distributions, it could be concluded that there is a high likelihood the samples come from different populations (Sheskin 2003). The two-sample K-S statistic is illustrated by the black arrow in Figure 7 below.



Figure 7 Plot Showing Two-Sample K-S Statistic Source: https://commons.wikimedia.org/wiki/File:KS\_Example.png

Applied to burn severity classifications, the null hypothesis for the variable elevation, for example, was that samples from low and moderate severity classified areas would come from identical distributions of elevation. Dealing with raster data, all pixels classified under the same severity level were sampled and run in the two-sample K-S test in SPSS. Depending on the p-value used, varying degrees of statistical significance can be inferred. When the p-value used with the statistic is small, there is a higher likelihood that the two groups were sampled from

populations with significantly different distributions due to a lower chance for more extreme results to exist (Potter 2014).

The two-sample K-S test has both strengths and weaknesses. One benefit of using the K-S test is that its only required assumptions are for data to be measured on an ordinal scale and that the observations from the two samples are randomly selected and independent from one another (Sheskin 2003). On the other hand, the two-sample K-S test, like many non-parametric statistical methods, lacks statistical efficiency in that little can be drawn from conclusions made, only that they are significantly different (Lehmann 2006).

#### **CHAPTER 4: RESULTS**

This chapter presents the results of the Round Fire analysis including a final classified burn severity map, results from bivariate correlation, summaries of all landscape variables, and results for variables that were statistically analyzed using the two-sample K-S test. The results are presented in a series of sections discussing the fire extent and patterns as well as their relationship with pre-fire land cover, pre-fire fuel, topographic variables, and fire history.

### 4.1 Area Burned

An enlarged version of the final remotely-sensed burn severity map can be found on the following page in Figure 8. It should be noted that the severity levels used in the map do not conform with the MTBS range of unburned, low, moderate-low, moderate-high, and high severity. Through an iterative process in consultation with experts, the break values between thresholds were adjusted to redistribute dNBR values to meet the circumstances of the Round Fire. In Figure 8, the classified dNBR is overlaid on the pre-fire NBR clipped to a 3 km buffered bounding box with unburned areas represented in dark green, very low burn severity in light green, low severity in yellow, moderate severity in orange, and high severity in red.

Based upon the manually digitized perimeter, it was determined that the fire perimeter had a length of 38.6 km and encompassed an extended area of 25.9 km<sup>2</sup> or 6,406 acres. When calculating the fire extent using the pixel count or converted polygon areas, there were a total of 6,407 acres. Due to the use of moderate spatial resolution Landsat 8 imagery, the corners of pixels along the outer perimeter of the fire were both under- and over-approximated in varying parts of the map. Because the portions of pixels landing outside the perimeter boundary exceeded the unclassified area falling inside the perimeter, the total area was slightly greater than when calculated from the perimeter area alone.



Figure 8 Classified Burn Severity Map for 2015 California Round Fire

Looking at individual levels of burn severity, there were a variety of patterns observed within the Round Fire. Using the finalized set of thresholds, just 1.34% or 85 acres burned at high severity and 32% or roughly 2,052 acres burned at moderate severity. Next, approximately 40% or 2,587 acres burned at low severity and another 15% or 970 acres at very low severity. The remaining area was detected as unburned, but was still counted towards the total affected area. Looking at the spatial distribution of burn patterns, it is evident that the majority of area burned at either low or moderate severity with very low and unburned areas scattered around the perimeter and clustered in other areas of the fire. The makeup of burn severity for the Round Fire is shown in a pie chart in Figure 9 below.



Figure 9 Round Fire Breakdown of Burn Severity

## **4.2 Bivariate Correlation Results**

The results from bivariate correlation are summarized in Table 6. The row and column headers feature the same explanatory variables, in this case, tree cover, NDVI, elevation, slope, northness, eastness, and fire history, while each individual cell displays the Pearson's Correlation Coefficient, the two-tailed p-value, and the number of 30 x 30 m pixels that were used in the calculations for each set of corresponding variables. Additionally, correlations significant at the

		Tree Cover	NDVI	Elevation	Slope	Northness	Eastness	Fire History
Explanatory	Variables							
	Pearson Correlation							
Tree Cover	Sig. (2-tailed)							
	Ν							
	Pearson Correlation	0.295**						
NDVI	Sig. (2-tailed)	0.000						
	Ν	28315						
	Pearson Correlation	0.203**	0.256**					
Elevation	Sig. (2-tailed)	0.000	0.000					
	Ν	28315	28809					
	Pearson Correlation	$0.080^{**}$	-0.028**	0.679**				
Slope	Sig. (2-tailed)	0.000	0.000	0.000				
	Ν	28315	28809	28809				
	Pearson Correlation	-0.008	-0.017**	0.004	0.003			
Northness	Sig. (2-tailed)	0.173	0.003	0.515	0.575			
	Ν	28208	28329	28329	28329			
	Pearson Correlation	0.008	0.004	-0.024**	-0.014*	0.002		
Eastness	Sig. (2-tailed)	0.189	0.452	0.000	0.016	0.782		
	Ν	28208	28329	28329	28329	28329		
	Pearson Correlation	0.239**	0.354**	0.501**	0.042**	0.009	-0.016**	
Fire History	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.119	0.009	
	Ν	28315	28809	28809	28809	28329	28329	

# Table 6 Pearson's Correlation Coefficients Matrix for Landscape Variables

\*\*. Correlation is significant at the 0.01 level (2-tailed).

\*. Correlation is significant at the 0.05 level (2-tailed).

0.01 level were marked with two asterisks while those significant at the 0.05 level were marked with one.

Amongst all pairs of correlated variables, the relationships between elevation and slope and elevation and fire history exhibited the highest positive coefficients with values of 0.679 and 0.501, respectively. The pattern observed between elevation and slope was expected because higher elevations are generally associated with more rugged and mountainous terrain. The significant positive relationship between elevation and fire history indicated that higher elevations within the Round Fire had experienced more past wildfire events. Elevation also had a significant, but weaker positive correlation with variables tree cover and NDVI, likely due to the greater prevalence of trees at higher elevations. One significant negative linear correlation flagged was for the relationship between the variables elevation and eastness, with a coefficient value of -0.024. This indicated that moving from lower to higher elevations, surface aspects tended to move from east to west-facing. This was understandable because the western border of the Round Fire was along a steep east-facing incline, with the perimeter of the fire likely slowing once reaching the western aspects past the ridgeline of Wheeler Ridge.

Other notable relationships included that between tree cover and NDVI as well as their individual correlations with slope and fire history. While tree cover and NDVI measure relatively similar subjects, their differences are important to take note of when correlated with other variables. Tree cover simply represents areas whose typical land cover type has trees while the NDVI is a direct measurement of green biomass derived from satellite imagery. Using the pre-fire NDVI captured during the winter season, tree cover and NDVI exhibited a significant positive correlation with a coefficient value of 0.295. Considered a weak to moderate correlation, comparing these two variables with respect to other landscape variables showed some notable

patterns. Both tree cover and NDVI, for example shared significant positive linear correlations with fire history. This made sense because the presence of biomass, particularly trees, serves as a source of fuel for fires. However, tree cover and NDVI had opposite linear correlations when examined with the variable slope. While it is difficult to pinpoint the exact cause of this pattern, it is likely attributed to low NDVI values occurring where tree cover normally exists, particularly in areas with higher slopes.

Among all the variables tested, the aspect measurements northness and eastness showed the least overall number of correlations with respect to other landscape variables. Northness was only correlated with NDVI, with a weak negative correlation significant at the 0.01 level. It indicated that north facing aspects had smaller NDVI values, which coincides with the fact that southern aspects in the northern hemisphere usually receive more sunlight for vegetation to grow. In addition to eastness and elevation, eastness and slope also exhibited a weak negative correlation; however, only at the 0.05 significance level. This relationship not only holds true for the same reasons eastness and elevation are correlated, but because elevation and slope share a strong positive linear correlation. In reality, landscape variables interact on multiple levels, making it necessary to investigate their relationships when attempting to look at burn severity.

### **4.3 Scatterplots**

In order to gather more insights about the spatial distribution of landscape variables and their interactions with one another, a series of scatterplots was created showing the relationships between elevation and slope with respect to burn severity, cover type, and fire history. Working with raster data, the landscape variable values at each pixel within the Round Fire extent were extracted using a location raster and the sample tool within ArcGIS. The resulting attribute table was used in SPSS to create the following color coded scatterplots.

While most of the explanatory variables were flagged as statistically significant at the 0.01 level, the linear relationship between slope and elevation, with a coefficient value of 0.679, showed the strongest positive relationship out of all combinations of variables. A scatterplot displaying the slope and elevation values of all pixels falling within the Round Fire perimeter is reproduced in Figure 10 below and is color coded with the legend used in the classified burn severity map presented in Section 4.1. A strong positive linear relationship is observable, as well as the tendency for high burn severity to be associated with higher elevations and gentler slopes across the study area. While pixels ranging from unburned to moderate severity are seen throughout most of the scatterplot, high severity pixels tend to be clustered towards the middle to high elevations, around 2,200 m, and in areas with slopes less than 25°. Additionally, the moderately classified pixels show a higher trend of elevation and slope than the low ones.



Figure 10 Scatterplot of Elevation and Slope Values Colored by Burn Severity

Next, the slope and elevation scatterplot was reproduced and colored using the CALVEG cover type value as seen in Figure 11 below. The land cover categories displayed in the legend are listed in order from the most to the least commonly found within the Round Fire perimeter. Two different shades of green and dark brown were used to represent categories with tree cover. Both conifer and mixed conifer/hardwood are associated with higher slopes and elevations while the hardwood cover type displays a distinct preference for low elevations and slopes within the Round Fire. With the exception of the barren cover type, the other land cover categories were quite clustered around certain slopes and elevations. The R<sup>2</sup> value shown in the upper right hand corner of the plot measures how well the variation of one variable explains the variation in the other, or close the data are to the fitted regression line (Frost 2013). In this case, 45.3% of the variation in elevation is explained by the variation in slope and vice versa.



Figure 11 Scatterplot of Elevation and Slope Values Colored by Covertype

Finally, the same scatterplot was recreated but symbolized using information from the fire history data layer. Rather than assigning color by the year of occurrence, pixels that had experienced any wildfire history were colored red, those with treatment history were colored in green, and those with no fire history were colored in black. Like the distribution of pixels with respect to tree cover, in Figure 11, the majority of pixels that were affected by wildfire were located above the fitted regression line. This confirms the observed correlation that higher elevations were more commonly affected by fire, as determined using Pearson's correlation coefficient. Additionally by comparing Figures 11 and 12, the significant correlation between tree cover and fire history can be visualized. Looking at the distribution of green points in Figure 12, the hand pile burn prescribed treatment from 2006 was employed in an area that had commonly experienced wildfires in the past.



Figure 12 Scatterplot of Elevation and Slope Values Colored by Fire History

## 4.4 Pre-fire Land Cover

The land cover for this study was classified using the COVERTYPE attribute derived from the CALVEG datasets. Over 82.9% of the area burned had a preexisting land cover classification of shrub, followed by conifer forest, covering 7.8% of the burned area. The herbaceous and hardwood forest cover types made up 3.8% and 3.1% of the total extent, respectively. The barren cover type, defined by rock, soil, sand or snow, made up just 1.8%, while the remaining classifications agriculture, mixed conifer and hardwood forest, and urban accounted for a mere 0.7% of the total burned area combined.

Next, pre-fire land cover type was correlated with burn severity by cross-tabulating the areas between the two variables. The fractional areas that each land cover class contributed to each separate burn severity range were converted to percentages and are shown in Table 7 on the following page. This table is best interpreted by looking at the columns, with the values in each column, rounded to the nearest tenth, adding up to 100%. The final column shows the percent total area burned separated by land cover class, as discussed in the previous paragraph. The classified land cover map that was used can be found in Appendix C and a table with cross-tabulated area measurements for each land cover class and burn severity level can be found in Appendix D.

Using information derived from the cross-tabulation of pre-fire vegetation and burn severity classifications, several observations can be inferred about the relationship between land cover type and severity for the Round Fire. The predominant land cover class across all burn severity levels was shrub, with percentages ranging from 44.5% for high burn severity areas to 91.2% of all low severity areas. Conifer forests and woodlands followed, with the exception of high burn severity areas, whose second most common pre-fire vegetation type was hardwood

forests. In addition to hardwood forests, the mixed conifer and hardwood forest cover type also burned a significantly larger fraction that expected across the high severity class. Across the moderate severity range, the herbaceous cover type burned more area than expected, while the lower severity levels of unburned, very low, and low, consisted of high amounts of conifer, barren, and herbaceous cover types.

Land Cover Class	% Unburned	% Very Low	% Low	% Moderate	% High	% Total burned area
A	0.2		0.1	0.5	0.0	0.2
Agriculture	0.2	0.2	0.1	0.5	0.0	0.2
Barren	4.5	2.8	1.3	1.0	0.7	1.8
Conifer	10.7	8.4	4.9	10.3	2.0	7.8
Hardwood	0.6	0.9	1.1	6.0	38.6	3.1
Herbaceous	2.1	2.2	1.3	8.0	1.5	3.8
Mixed*	0.0	0.0	0.0	0.6	12.7	0.4
Shrub	81.8	85.4	91.2	73.4	44.5	82.9
Urban	0.1	0.2	0.0	0.0	0.0	0.1

Table 7 Pre-fire Land Cover Fractional Areas within Round Fire Burn Severity Classes

\*Mixed = Mixed conifer and hardwood forest

# 4.5 Pre-fire Fuel by NDVI

To account for flammable biomass, the NDVI ratio was calculated using a combination of bands 4 and 5 from the pre-fire Landsat 8 image. Resulting NDVI values within the fire perimeter, scaled by 10<sup>3</sup>, had a range from -42 to 282, indicating relatively low amounts of burnable vegetation prior to the Round Fire. This was not an unexpected result since the pre-fire image came from the middle of the winter season, when productivity was near its annual minimum. Additionally, drought effects in California have caused increased stress on vegetation,

weakening the spectral signature that is picked up by satellites. Figure 13 shows the pre-fire NDVI image displayed in greyscale and subset to a 3 km bounding box from the fire perimeter with healthier green vegetation represented by lighter shades of grey. It should be noted that the NDVI range for the bounding box includes a lower limit of -66, compared to the minimum of -42 found within the Round Fire extent.



Figure 13 Round Fire Perimeter Overlaid on Pre-Fire NDVI

Zonal statistics for the NDVI based on burn severity classification are provided in Table 8 below. Moving from unburned to high severity, both the maximum and mean NDVI values increased, with the exception for low severity. While the maximum NDVI value for low severity fell between that of the unburned and very low severity classes, the mean value for that same class was even less than for unburned areas. This could have been potentially caused by the large proportion of land that burned at low severity relative to other classes, or simply due to a low NDVI average from the shrubbery that made up the majority of pre-fire land cover. Additionally, the mean value for the high severity class was substantially higher than the other classes and could possibly be attributed to a higher presence of hardwood and mixed conifer trees, indicated by the positive linear correlation between tree cover and NDVI.

dNBR Severity Class	Maximum	Mean	Standard Deviation
Unburned	215	81	28
Very Low	237	85	28
Low	228	80	24
Moderate	270	96	40
High	282	160	58

 Table 8 NDVI Statistics by Burn Severity Classification for Round Fire

## 4.6 Topography

A 30 m DEM was used to represent elevation across the study area. Elevation within the fire perimeter ranged from 1,384 to 2,752 m. Table 9 on the following page provides the minimum, maximum, and mean elevation values as well as their respective standard deviations for each dNBR burn severity class. With the exception of high severity, all other classes, including unburned, had a minimum starting elevation of 1,385 m  $\pm 1$  m. The minimum elevation for the high severity class was just over 100 m greater. On the other hand, the maximum elevation

values, ending at 2,709 m for unburned areas, increased with increasing severity up to 2,752 m for the moderate severity level. The maximum elevation detected at high burn severity did not follow the same trend and was more than 135 m less than that of the unburned class.

dNBR Severity Class	Min	Max	Mean	STD*
Unburned	1,385	2,709	1,791	302
Very Low	1,384	2,730	1,782	288
Low	1,386	2,745	1,788	242
Moderate	1,386	2,752	1,987	292
High	1,493	2,573	2,191	115

 Table 9 Elevation (meters) Statistics by Burn Severity Classification

\*STD = Standard Deviation

While the elevation ranges, separated by class, show some interesting patterns, the mean values listed in the fourth column of Table 9 are more telling of the relationship between elevation and wildfires. Based on the results, it is apparent that within the study area there was a positive relationship between elevation and burn severity. Averaging the very low and low burn severity levels, the mean elevation of burned areas increased from 1,785 to 1,987 and 2,191 m for the moderate and high severity classes, respectively. This means that for the Round Fire, average elevation increased roughly 200 m from low to moderate and moderate to high severity. The mean elevation for unburned areas was slightly higher than that of the very low and low classes, and could have been caused by the presence of unburned pixels being detected at high elevations along Wheeler Ridge which marked the western border of the Round Fire.

Moving on to other topographic variables, there were a variety of slope gradients seen throughout the fire perimeter ranging from flat land to rocky ridges as steep as 61°. A histogram of extracted slope values is reproduced in Figure 14. Looking at the shape of the curve, it is quite evident that the data is right skewed. This means that the majority of area burned over relatively gentle terrain, falling between 1–10°. For the Round Fire, substantially less area burned at increasing slope gradients; however, this was simply an observed trend and not conclusive of general wildfire patterns. Even less of the area burned towards the upper end of slope ranges, on slopes of 45° and greater. Based on the elevation and slope scatterplots shown in Section 4.3, higher elevations were found to be positively correlated with slope. Additionally there were no areas with slopes of 30° or greater located below an elevation of 1,600 m. These patterns reflect the gradual sloped terrain found throughout the majority of the Rock Creek watershed vs. the more rugged terrain of Wheeler Ridge.



Figure 14 Histogram of Slope Values (%)

Next, zonal statistics defined by burn severity class were calculated using the slope raster values and are provided in Table 10 on the following page. When examining slope characteristics by severity level, there was much less discrepancy observed from class to class. The range between the highest and lowest observed means covered just 4.3°. Both the unburned and very low burn severity levels had a mean slope value of 13.7°, which was greater than the mean value of the low and less than that of the moderate burn severity class. Despite having the

lowest range of slope values, the high burn severity class had the highest observed mean of 16.2° and lowest respective standard deviation. Looking at the scatterplot in Figure 10, the greater mean elevation and slope values of the moderate severity class (orange) compared to the low severity class (yellow) is clearly observable.

dNBR Severity Class	Min	Max	Mean	STD
Unburned	0	61	13.7	14.6
Very Low	0	57	13.7	13.5
Low	0	58	11.9	11.0
Moderate	0	53	14.6	10.7
High	2	42	16.2	6.6

 Table 10 Slope (%) Statistics by Burn Severity Classification

Finally, a surface aspect layer was created from the DEM to identify the slope direction throughout the study area. By viewing the histogram of aspect values within the entire fire perimeter, it was determined that the most common aspect directions were east and southeast, with near equal proportions accounting for almost 63% of the total burned area. The northeastern and southern aspect directions, which border the eastern and southeastern directions respectively, followed and combined to contribute another 30% of the affected area. The few remaining pixels fell in areas with aspects directions ranging from southwest, moving clockwise, to northeast. While determining the distribution of surface aspects across the fire perimeter can be useful in understanding the study area terrain, analysis with respect to burn severity may be more telling of underlying wildfire patterns.

Figure 15 below shows the histogram of aspect values, separated by burn severity classification as determined from the remote sensing portion of this analysis. Each bar on the graph represents the pixel count within a severity level corresponding to an individual aspect

direction with a range of 45°. While this histogram visualizes the distribution of surface aspects by severity level, it can also be used to compare overall burned area through overall histogram size. Based on Figure 15, the dominant aspect direction of burned areas varied from class to class. For the two largest classes, low and moderate severity, the east and southeast aspect directions were most common. The unburned and very low burn severity classes had substantially less eastern facing, but relatively more southern facing aspects.



Figure 15 Histogram of Aspect Values by Burn Severity Classification

# 4.7 Study Area Fire History

The final landscape variable analyzed was the fire history of the study area. Using the CALFIRE perimeter dataset, a fire history layer, shown in Figure 16 on the following page, was created including all incidents intersecting the digitized Round Fire perimeter. There were a total of five wildfires, labeled with their year of occurrence and displayed in different shades of red, as well as one fuel modification project, shown in green, occurring within the fire perimeter. The earliest of these events was a small fire occurring in 1958 towards the southeastern region of the study

area. The most recent recorded wildfire, excluding the Round Fire, was from 2002, which just borders the northern perimeter of the Round Fire. The single fuel modification project that occurred was a 102 acre hand pile burn that was performed by the USFS less than a decade ago in 2006. It was located completely within the perimeter of the Round Fire and overlapped two previous historic wildfires in 1974 and 1981.



Figure 16 Fire History of Study Area

Referring to Figure 16 above, the wildfire incidents in the northern half of the Round Fire covered substantially more area than those in the southern half of the fire. While two fires were

recorded in the southern region from the years 1958 and 1983, only a minimal amount of overlap with the Round Fire perimeter occurred. On the contrary, there were both overlap of existing fires and extensive overlap with the Round Fire occurring towards the upper half of the map. Looking specifically at the fire from 1974, only a sliver of area falls within the Round Fire perimeter that was not overlapped by more recent incidents. In the case of overlap during sampling, the uppermost (i.e. most recent) value was used to define both the temporal and spatial representation of fire history.

## 4.8 Two-Sample K-S Test Results

The results from two-sample K-S testing are provided next. Comparisons between the frequency distributions of landscape variables within the Round Fire extent for unburned and very low severity, very low and low severity, and low and moderate severity will be discussed in separate paragraphs. The landscape variables tested included tree cover as determined from the covertype layer, NDVI, elevation, slope, and fire history measured by years since fire. Additionally, all tests were run using a 2-tailed asymptotic method with a significance level of 0.01 and confidence interval of 95% unless noted otherwise. Summaries for each set of comparisons are provided within this section, while the actual statistics, including most extreme differences and determined K-S value for each test, are provided in Appendix D. For the purposes of analysis, the unburned level was assigned a value of 1, low severity assigned a value of 2, and so on up to high severity which was assigned a value of 5.

The first two-sample K-S test were run between the unburned and very low burn severity levels. Sampling all related pixels within the Round Fire extent, it was determined that the landscape variables tree cover and fire history had distributions that were the same, while variables NDVI, elevation, and slope exhibited significantly different distributions across

8	Null Hypothesis	Test	Sig.	Decision
1	The distribution of TreeCover is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.601	Retain the null hypothesis.
2	The distribution of NDVI is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
3	The distribution of Elevation is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
4	The distribution of Slope is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.001	Reject the null hypothesis.
5	The distribution of FireHistory is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.356	Retain the null hypothesis.

 Table 11 Two-Sample K-S Test Summary for Unburned and Very Low Burn Severity

Asymptotic significances are displayed. The significance level is .01.

unburned and very low burn severity areas. A summary of tests between unburned and very low severity can be found in Table 11 above. The K-S p-values for NDVI, elevation, and slope were well below the significance level of 0.01, while variables tree cover and fire history had p-values greater than 0.3. A visualization of the two-sample K-S test between unburned and very low severity for the landscape variable fire history is provided in Figure 17 below. By comparing the frequency distributions of fire history or years since fire, it was determined that their distributions were the same across unburned and very low severity areas.



Figure 17 Visualization of K-S Test Statistic for Fire History

Next, the two-sample K-S test was run between all very low and low burn severity pixels using the same test options as noted previously. Contrary to the observations made between unburned and very low severity pixels, all landscape variables tested showed statistically significant differences in frequency distributions of very low and low burn severity areas. The null hypothesis that distributions of variables tree cover, NDVI, elevation, slope, and fire history were the same across levels of severity was rejected. It should be noted the ratio of low burn severity to very low burn severity areas was greater than 2.5:1, meaning there were substantially more pixels sampled at low burn severity than at very low burn severity. When the difference between sample sizes is sufficiently large, it is common to reject the null hypothesis because the cumulative distribution functions of each sample are likely to be considerably different (Lehmann 2006). This notion weakens the conclusion that the distribution of landscape variables differs by burn severity because the difference could also be caused by variations in sample size.

Table 12 Two-Sample K-S Test Summary for Very Low and Low Burn Severity

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of TreeCover is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.004	Reject the null hypothesis.
2	The distribution of NDVI is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
3	The distribution of Elevation is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
4	The distribution of Slope is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
5	The distribution of FireHistory is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .01.

Finally, the same test was run comparing all low and moderately classified burn severity pixels within the Round Fire perimeter. The ratio of low burn severity to moderate burn severity areas, roughly 1.25:1, was much more balanced compared to that of very low and low severity areas. The p-values for all landscape variables tested were extremely small, indicating that the distributions of tree cover, NDVI, elevation, slope, and fire history were significantly different across low and moderately classified areas. Of the total burned area, nearly 75% was classified as low or moderate. One particular issue with the two-sample K-S test, and non-parametric tests in general, is that there is a higher likelihood of rejecting the null hypothesis with increasing sample sizes. In this case, the comparison between low and moderate burn severity includes the greatest number of samples. Despite being robust with regards to sample size in that all classified pixels were included in calculations, these same results may not have been reproduced if, for example, only 500 points were sampled from each severity level.

Table 13 Two-Sample K-S Test Summary for Low and Moderate Burn Severity

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of TreeCover is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
2	The distribution of NDVI is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
3	The distribution of Elevation is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
4	The distribution of Slope is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.
5	The distribution of FireHistory is the same across categories of Severity.	Independent- Samples Kolmogorov- Smirnov Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .01.

#### **CHAPTER 5: DISCUSSION AND CONCLUSIONS**

The objectives of this study were to map the extent and burn severity of the Round Fire, which occurred on February 6<sup>th</sup>, 2012 in the Southern Sierra Nevada Basin of California. By integrating free mid-resolution Landsat 8 satellite imagery and a variety of publically available fire-related geospatial data, a detailed analysis of the Round Fire with respect to various landscape variables was conducted. In addition, the application of the dNBR within the region was tested and compared against results from a similar event, the Rim Fire, one of the most significant wildfire incidents that has occurred in the state of California.

This final chapter presents an extended summary and discussion of the results as well as some concluding remarks and suggestions for future work. By understanding how wildfire patterns are influenced by various landscape variables, forest managers and fire experts can develop new approaches to help mitigate future damages and preserve the health and balance of our fragile ecosystems.

As expected, a remote sensing analysis of the Round Fire posed a number of challenges, due to the nature and timing of the fire. While methods have been developed to measure wildfires during the peak fire season, generally from early spring to the late summer, there have been far fewer opportunities to examine wildfires occurring outside that time frame. Additionally, unlike forest fires, the nature of shrub fires requires extra calibration to highlight the lower ranges of burn severity. Due to seasonal and phenelogical differences, the process of setting burn severity thresholds required the addition of field-collected data to both calibrate and validate the accuracy of remotely sensed data. While a remotely sensed burn severity map generalizes fire patterns into discrete ordinal levels, often times lacking the accuracy of field data, the amount of time and money saved makes the pursuit of using these methods worthwhile.

Comparing the remotely sensed results with the acreage stated in the BAER Assessment Report, there were slight discrepancies in the total fire extent and makeup of burn severity for the Round Fire. Through the analysis of satellite imagery, roughly 100 fewer acres, or just 1.5% of the fire extent, burned than compared to initial ground reports. The under-reporting of the fire extent could be attributed to the manual process of digitizing the fire perimeter, or possibly due to very low and low burn severity areas being indistinguishable from unburned areas. While there were unburned areas found near the perimeter of the fire, particularly the east and western borders, it was difficult to clearly separate them from burned areas due to the mosaic of burn patterns witnessed in the case of the Round Fire.

Another major obstacle in classifying the burn severity of the Round Fire was that the dominant pre-fire land cover type was shrubland. While the MTBS methods have been developed for forest fires, shrub fires generally experience a smaller range of burn severity due to the nature of shrub vegetation as a source of flammable biomass. Unlike the MTBS severity levels of unburned, very low, moderate-low, moderate-high, and high, the Round Fire BAER report integrated severity levels unburned, very low, low, and moderate. This meant that a finer distinction between burn severity levels had to be achieved vs. adopting the MTBS methods alone.

The inclusion of field-verified soil burn severity points proved to be an integral source for both calibrating and validating the remotely sensed burn severity map, but also created challenges because of the small size of the dataset and lack of diversity of surveyed points. With just eight data points, six of which were classified as moderate burn severity, determining suitable threshold ranges was a slow iterative process which resulted in a lower than expected accuracy while still staying true to the nature of the Round Fire. Before the process had begun, it

was expected that correctly classifying all eight points would result in a fairly accurate burn severity map; however, it was found that the amount of moderate burn severity areas was highly overestimated and low severity areas was underestimated. In the end, with six of eight points falling in areas matching their classified burn severity, a 75% accuracy of field-verified points was relied upon to meet the field-reported acreages of burn severity.

After determining burn severity, raster data for landscape variables pre-fire vegetation, NDVI, elevation, slope, aspect, and fire history were assembled and used to analyze the Round Fire. Using the extent of the Round Fire, correlations between variables were analyzed using Pearson's coefficient. While determining correlation was not made an objective until after the analysis started, it proved to be an informative process which was telling of many of the underlying relationships between the variables influencing wildfire. While some results were expected, such as the strong positive correlation between elevation and slope, others, for example that between elevation and fire history, helped highlight how several variables interact with one another. The addition of colored scatterplots also showed some underlying patterns, such as the fact that higher severity burn levels were directly associated with tree cover on gentler slopes at higher elevations.

Analysis of landscape variables with respect to classified burn severity levels was also conducted to learn more about the nature of the Round Fire and how it compared with more general fire trends that have been observed in the past. Relationships between vegetation and burn severity were determined by cross-tabulating burn severity classifications with pre-fire land cover categories. While shrub was both dominant across all severity levels, and throughout the entire Round Fire, land cover types with tree cover had a notable presence at higher severity levels. By calculating zonal statistics for NDVI, elevation, and slope, other notable patterns

became more apparent. All three of these variables showed a positive relationship with burn severity, with mean values increasing with rising severity. While the low burn severity level had a tendency to deviate from these patterns, it covered the greatest extent within the Round Fire which likely skewed the results. Finally, the integration of wildfire data helped illustrate how historic wildfires and prescribed treatments have influenced the study area in the past. Visually inspecting the single hand pile burn which occurred within the study area, it could be concluded that it had some effect in curtailing both the spread and severity of the Round Fire.

Finally, the two-sample K-S test was used to verify that distributions of landscape variables were significantly different across very low and low burn severity areas as well as low and moderate burn severity areas. Comparisons across unburned and very low burn severity areas also showed significant differences in the distribution of landscape variables, with the exception of the variables tree cover, as determined from pre-fire vegetation cover, and fire history measured by the number of years since fire. This meant that tree cover and fire history were not significantly different in areas classified as unburned and very low severity within the Round Fire. This did not come as a major surprise because the distinction between unburned and very low severity areas was minimal relative to comparisons involving other burn severity levels.

Using the Rim Fire study both as a model to replicate and compare results, the patterns exhibited through the implementation of the two-sample K-S test were consistent across both fires occurring in the Sierra Nevada region. Despite being different with regards to dominant prefire vegetation, size, and range of severity, all tested landscape variables showed significantly different frequency distributions when comparing levels of burn severity. While the Rim Fire study focused on comparing low and high burn severity areas, an objective of this study was to compare burn severity classifications that were quantitatively more similar in an attempt to find
discrepancies between the two study areas. However, with the exception of tree cover and fire history for unburned and very low burn severity areas, all variables showed notable differences.

As previously stated, fire patterns are driven by multiple factors and no two wildfires are identical. The application of the dNBR in the Sierra Nevada region of California is no different. In order to apply remote sensing techniques to map wildfires, a thorough understanding of prefire conditions, timing relative to the wildfire season, and wildfire patterns in general are crucial for accurately determining burn severity. Despite the modern convenience and accessibility of powerful remotely sensed data for analysis, coordination with forest managers and fire experts is just as important. The availability of field-data provides an invaluable source for calibrating remotely sensed results and also gives users the opportunity to verify results with ground truthed data. While a burn severity map produced from satellite data is both cost and time effective, without the integration of field data, it is impossible to verify the accuracy of subsequent classifications.

Now that more time has elapsed since the Round Fire, it would be useful to conduct an extended burn severity assessment to monitor the lengthy process of recovery. Performing an initial assessment aids with immediate recovery efforts, but often times does not fully represent the nature of the fire. Due to the delayed regenerative response of many fire-prone ecosystems, collecting CBI data within the study area would be beneficial for mapping long-term severity and directing future fire policies. Integration of additional landscape data, such as vegetative density and climatological variables, would also assist in understanding the complex interaction of variables influencing wildfire. The density of vegetation has been found to be directly related to wildfire patterns and could explain the variation of burn severity witnessed throughout the

65

Round Fire. Climatological data, such as wind direction or moisture levels during the fire itself, could also be useful for understanding the spread and progression of fire within a landscape.

Finally, for future individual wildfire studies, there may be better statistical tests to apply than the two-sample K-S test. While non-parametric tests are relatively straightforward and easy to use, the opportunity to draw confident conclusions from their use was limited due to the simplicity of the null hypotheses. By applying zonal statistics, a tool that is inherent in GIS programs and geospatial analysis, a more detailed representation of landscape variables with respect to burn severity classification can be achieved. While the addition of bivariate correlation was an easy and informative method to learn about how the landscape variables included in the analysis interacted with one another, more advanced statistical methods could also be adopted. Spatial autocorrelation, for example, measures the degree of clustering or dispersion between two variables and can be used to quantitatively determine how burn severity is influenced by different landscape variables. While beyond the scope of this project, spatial autocorrelation would be worth pursuing in future studies of fire behavior.

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Attribute	Point 1	Point 2	Point 3	Point 4	Point 5	Point 6	Point 7	Point 8
dNBR Value	737.97	542.06	150.36	148.84	483.35	276.76	400.49	122.37
Survey Date	2/11/15	2/11/15	2/11/15	2/12/15	2/12/15	2/14/15	2/14/15	2/12/15
Soil Burn Se	verity							
Ground	20-50	0-20	0-20	0-20	0-20	0-20	0-20	0-20
Cover (%)								
Ash Color	Black	Black	Other	Black	Black	Mixed	Black	_
Ash Depth	5	0	0	0	0	2	5	0
( <i>MM</i> )								
Soil	Slightly	Slightly	Slightly	Original	Slightly	Slightly	Slightly	Original
Structure	Altered	Altered	Altered	Structure	Altered	Altered	Altered	Structure
Root Alt	Very Fine	No	Very Fine	No	Very Fine	Very Fine	Very Fine	Unchanged
	Consumed	Change	Consumed	Change	Consumed	Consumed	Consumed	
Infiltration	Water	Water	Water	Water	Water	Water	Water	Water
Method	Drop	Drop	Drop	Drop	Drop	Drop	Drop	Drop
Infiltration	Moderate	Moderate	Strong	Moderate	Weak	Moderate	Strong	Weak
Time (sec)	10–40	10–40	>40	10–40	<10	10–40	>40	<10
Infiltration	>8 mL	>8 mL	>8 mL	>8 mL	>8 mL	>8 mL	>8 mL	>8 mL
Amount								
Observed	Moderate	Moderate	Moderate	Low	Moderate	Moderate	Moderate	Very
Soil Burn								Low
Comment	WR* to 3	WR to 1	No cover	No	PP**	WR to 1	Riparian	Open
	inch	inch		vegetation	Sagebrush	inch	Trees	Canopy
Topography								
Aspect Direction	Southeast	Southeast	Southeast	Southeast	Southeast	South	Southeast	Southeast
Slope %	40	40	20	3	15	20	3	0
Slope	200	500	500	200	0	750	50	5
Length (FT)								
Slope	Midslope	Midslope	Foot	Valley	-	Foot	Valley	Valley
Position Soil Texture	Other	Other	Slope	Bottom	Other	Slope	Bottom	Bottom
Soll Texture	Other 30	Other 40	Other 30	5 Other	Other	Other 45	Other	Other
Rock %	50	40	50	5	0	45	0	0
Soil	Silt-loam	Silt-loam	Coarse	Coarse	Silt-loam	Gravel	Silt-loam	Silt-loam
Comments			sandy loam	sandy loam		coarse sandy loam		
Vegetation								
Pre-fire	Sagebrush	Sagebrush	Sagebrush	Sagebrush	Sagebrush	Sagebrush	Sagebrush	Sagebrush
Vegetation Pro fire Veg	Low	Low	Uigh	Othor		Uigh	High	Low
Density	LOW	LOW	nigii	Other	_	rigii	nigii	LOW
Vegetation	Moderate	Sage	All burned	Moderate	_	Sagebrush/	Locust	_
Comment	veg burn		off			Bitterbrush	along creek	

## Appendix A: Attribute Table for Round Fire Soil Burn Severity Dataset

\*WR =Water Repellency

\*\*PP = Pinyon Pine

Source: Brad Rust, USFS

Appendix	B: Round	l Fire Burn	Severity	Threshold	<b>Specifications</b>
FF					

MTBS Severity Thresholds			New Severity Ranges	2 <sup>nd</sup> Iteration	3 <sup>rd</sup> Iteration	Final Iteration
Unburned	<99		Unburned	<54	<54	<54
Low severity	99–269	$\rightarrow$	Very low severity	54–123	54–123	54–123
Moderate-low	270–439	$\rightarrow$	Low severity	124–299	124–150	124–249
Moderate-high	440–659	$\rightarrow$	Moderate severity	300–738	151–738	250–738
High severity	660+		High severity	739+	739+	739+
Accuracy check	3/8		Accuracy check	6/8	8/8	7/8

# Burn Severity Makeup of Total Area

MTBS Severity Thresholds							
Unburned	20%						
Low severity	51%						
Moderate-low	19%						
Moderate-high	8%						
High severity	2%						

	New Severity Ranges	2 <sup>nd</sup> Iteration	3 <sup>rd</sup> Iteration	Final Iteration
	Unburned	11%	11%	11%
$\rightarrow$	Very Low Severity	15%	15%	15%
$\rightarrow$	Low Severity	51%	9%	40%
$\rightarrow$	Moderate Severity	22%	63%	32%
	High Severity	1%	1%	1%



Appendix C: Pre-fire Land Cover of Study Area (CALFIRE COVER TYPE)

### Appendix D: Two-Sample K-S Test Statistics

		Tree Cover	NDVI	Elevation	Slope	Fire History
	Absolute	.018	.066	.066	.046	.021
Most Extreme	Positive	.018	.041	.066	.046	.000
Differences	Negative	.000	066	063	035	021
Kolmogorov-Smirnov Z		.765	2.836	2.853	2.005	.927
Asymp. Sig. (2-tailed)		.601	.000	.000	.001	.356

#### Test Statistics for Unburned and Very Low Burn Severity

Test Statistics for Very Low and Low Burn Severity

		Tree Cover	NDVI	Elevation	Slope	Fire History
	Absolute	.031	.098	.182	.108	.091
Most Extreme	Positive	.031	.098	.105	.091	.091
Differences	Negative	.000	011	182	108	.000
Kolmogorov-Smirnov Z		1.754	5.524	10.268	6.110	5.150
Asymp. Sig. (2-tailed)		.004	.000	.000	.000	.000

#### Test Statistics for Low and Moderate Burn Severity

		Tree Cover	NDVI	Elevation	Slope	Fire History
	Absolute	.101	.321	.313	.202	.298
Most Extreme	Positive	.101	.321	.313	.202	.298
Differences	Negative	.000	056	032	014	005
Kolmogorov-Smirnov Z		7.195	22.967	22.384	14.454	21.334
Asymp. Sig. (2-tailed)		.000	.000	.000	.000	.000