Spring 5-1-2016

Fire and Fuels: Vegetation Change Over Time in the Zuni Mountains, New Mexico

Luke Wylie
University of Southern Mississippi

FIRE AND FUELS: VEGETATION CHANGE OVER TIME

IN THE ZUNI MOUNTAINS, NEW MEXICO

by

Luke Anthony Wylie

A Thesis
Submitted to the Graduate School
and the Department of Geography and Geology
at The University of Southern Mississippi
in Partial Fulfillment of the Requirements
for the Degree of Master of Science

Approved:

Dr. Bandana Kar, Committee Chair
Associate Professor, Geography and Geology

Dr. Grant Harley, Committee Member
Assistant Professor, Geography and Geology

Dr. George Raber, Committee Member
Associate Professor, Geography and Geology

Dr. Karen S. Coats
Dean of the Graduate School

May 2016

ABSTRACT

FIRE AND FUELS: VEGETATION CHANGE OVER TIME IN THE ZUNI MOUNTAINS, NEW MEXICO

by Luke Anthony Wylie

May 2016

The Zuni Mountains are a region that has been dramatically changed by human interference. Anthropogenically, fire suppression practices have allowed a buildup of fuels and caused a change in the fire-adapted ponderosa pine ecosystem such that the new ecosystem now incorporates many fire-intolerant species. As a result, the low-severity fires that the ecosystem once depended on to regenerate the forest are much reduced, and these low-severity fires are now replaced by crown-level infernos that threaten the forest and nearby towns. In order to combat these effects, land managers are implementing fuel reduction practices and are striving to better understand the local ecosystem.

In this study, a predictive fire spread model (FARSITE) was implemented to *predict spatio-temporal distribution of fire in the Zuni Mountains based on change in vegetation types that are most prone to fire*. Using Landsat imagery and historical fire spread data from 2001 to 2014, the following research questions were investigated: (1) *What variables are responsible for fire spread in the Zuni Mountains, New Mexico?* (2) *Which areas are prone to destructive and canopy level fires?* and (3) *How have the fuel model types that are most conducive to fire spread changed in the past twenty years?* The utilization of spatial modeling and remote sensing to understand the interaction of meteorological variables and vegetation in predicting fire spread in this region is a novel approach. This study showed that (i) fires are more likely to occur in the valleys and high

elevation grassland areas of the Zuni Mountains, (ii) certain vegetation types including grass and shrub lands in the area present a greater danger to canopy fire than others, and (iii) that these vegetation types have changed in the past sixteen years.

ACKNOWLEDGMENTS

I would like to thank my committee chair and major advisor Dr. Bandana Kar, and other committee members, Dr. George Raber and Dr. Grant Harley, for all their help and guidance throughout this project.

TABLE OF CONTENTS

LIST OF TABLES

Table

LIST OF ILLUSTRATIONS

Figure

LIST OF ABBREVIATIONS

KBDI	Keetch-Byram Drought Index
GCM	General Circulation Model
WUI	Wildland Urban Interface
ENSO	El Nino Southern Oscillation
PDO	Pacific Decadal Oscillation
SO	Southern Osicllation
EVT	Existing Vegetation Type
CC	Canopy Cover
CH	Canopy Height
ESP	Environmental Site Potential
FBFM	Fire Behavior Fuel Model
MRLC	Multi-Resolution Land Characteristics
VMR	Variance to Mean Ratio
NDVI	Normalized Difference Vegetation Index
USDA	United States Department of Agriculture

CHAPTER I

INTRODUCTION

1.1. Overview

While fire has been a part of many forests in the American southwest, the fire regime of this region has changed due in large part to Euro-American settlement. This large scale change of fire regimes has greatly affected the environment of the Zuni Mountains and is a major cause of concern today. The Sedgewick fire which ignited on May 10th in the northern part of the Zuni Mountains burned more than 8,000 acres and cost more than $900,000 dollars (*Albuquerque Journal 2*004). Because of this fire and other smaller fires in the Zuni Mountains, land managers have started implementing prescribed burning in this area to reduce fuel loads. In this study, vegetation types and meteorological variables were used to *predict the spatio-temporal distribution of fire in the Zuni Mountains based on vegetation types that are prone to fire.*

This chapter provides a brief history of wildfire throughout the United States, in American southwest, and specifically in the Zuni Mountains. A discussion of causes and consequences of wildfire, the trend of wildfire in the U.S., the role of climate change in the occurrence of wild fire is also presented here. Finally, the goals and objectives, research questions explored, and the significance of this research are discussed.

1.2. Wildfire in the United States

With the end of the Wisconsin Glaciation around 10,000 years ago, it is estimated that modern plant communities became comparatively stable for the past 6,000 years (Frost 1998). Thus, wildfire has been present in the United States' forest ecosystems since long before European settlers arrived in the 1500's on the continent, and many ecosystems evolved to become dependent on fire's rejuvenating properties. In the eastern United States, vegetation types evolved in sync with the occurrence of frequent fire and many of the plant species like the jack pine became dependent on it (Nowacki and Abrams 2008). The arrival of Europeans altered these fire regimes by either drastically increasing the occurrence of fire in some cases or by removing its presence all together (Figure 1*)* (Nowacki and Abrams 2008). In the south, fire regimes in the Holocene epoch were likewise characterized by low intensity brushfires that were utilized by Native Americans primarily for hunting and later for clearing fields for maize production (Fowler and Konopik 2007). With the advent of industrialization and widespread logging across the country, historical fire regimes were further shifted as loggers cut down entire stands, giving rise to more early succession forest types (Nowacki and Abrams 2008).

Federal involvement in fire protection began in 1886 when the U.S. Army became responsible for the management of Yellowstone National Park (Rothman 2005). After weathering some heavy fire seasons in Yellowstone, the National Park Service was created in 1916 and the U.S. Forest Service's policy of complete fire suppression began and remained the dominant policy until 1967 (Rothman 2005). In 1963, the Leopold Report questioned the fire suppression policy, and pointed out the negative effects of fire suppression efforts, most notably the overgrowth of thick underbrush that led to larger and more destructive fires, which eventually led to the passage of the Wilderness Act in 1964 (Rothman 2005). Now, the United States Department of Agriculture (USDA) Forest Service and other land managers strive to understand fire ecology and implement best practices of fire management in these critical ecosystems.

Figure 1. Fire regime change in the eastern United States (Nowacki and Abrams 2008).

The history of fire in the Southwest spans long before Euro-American settlement in this region. Native Americans in the region utilized fire to clear underbrush, replenish soils, and rejuvenate agricultural lands (Euler 1954; Petersen 1985). In northern New

Mexico, Hispanos used fire to clear areas for farmland and pastures (Allen 1984; Raish 2005). Many of these native groups including the Zuni Indians also used fire to aid in hunting, and produced large fires in the process (Raish 2005). A culmination of these activities could have produced large-scale effects on the fire regimes in this region even prior to westward expansion of human settlement.

Although the fire regimes in the Southwest shifted with Euro-American settlement, prior to this between 1870 and 1890 C.E., the region had experienced many low-intensity burns that regenerated the ecosystem (Fule 1997; Rother 2010). The first major suppression of fire occurred in 1880 due to cattle grazing by settlers and heavy logging with the arrival of the railroad (Dick-Peddie 1993). This suppression was followed by a complete halt in fires around 1940, which is linked to improved practices of fire suppression including smoke jumping by land managers in the area (Grissino-Mayer and Swetnam 1997). Since these suppression practices have been implemented, forest density has increased and species composition has shifted to a greater density of fire intolerant species (Fule 1997). These changes also caused more high-severity wildfires that damaged the ecosystem and settlements around it, and most researchers voiced the need to return these forests to their pre-settlement conditions (Fule 1997; Grissino-Mayer and Swetnam 1997).

An unintended consequence of this large scale ecological change in historically fire-prone ecosystems is a buildup of fuel sources which often result in catastrophic fires that damage the ecosystem and resets the process of ecological succession. This has resulted in the replacement of low-severity fires that the ecosystem once depended on by crown-level infernos that destroy the forest and many cities/towns in the West (Rother

2010). The primary ignition source of wildfire in this region is lightning with the majority of large fires originating on the highest peaks. In order to mitigate the effects of fuel buildup and decrease the number of crown level fires, crews in the Cibola National Forest are actively working to reduce potential fuels (USDA Forest Service 2014). In a widely supported proposal by the Collaborative Forest Restoration Program, the Forest Guild proposed to restore historic fire regimes "removing small excess trees" while protecting "old and large trees" (Zuni Mountain 2012). There have also been numerous Collaborative Forest Restoration Program grants issued for the purpose of returning the landscape to a more natural fire regime including the 2001 CFRP: Zuni-Cibola Forest Restoration Initiative, the 2004 Zuni Healthy Forest and Watershed Initiative, and the 2010 Bluewater Village Wildland Urban Interface and FireWise Project (Zuni Mountain, 2012).

Analysis of historical fire impact areas indicated that certain areas of the Zuni's are more susceptible to catastrophic burns than others. Therefore, this study focused on understanding the spatial and temporal variation of the vegetation types that are susceptible to fires will help forest managers target their efforts to reduce the buildup of fuels in specific areas and mitigate damage from future fires. On average, fuel reduction treatments can save $238-$600 per acre in suppression costs alone (Snider 2006; Zuni Mountain 2012). The methodology implemented in this study demonstrates the change in fire prone vegetation areas over time, which can be used to predict areas susceptible to fire, provide the forest service with valuable data to restore the ecosystem to a more sustainable fire regime, and help reduce fire suppression cost.

1.3 Causes of Fire and Fire Impacts

Most natural wildfires are caused by lightning; however human activity is now the foremost cause of wildfires. Some of these ignitions are intentional in cases like Native American's hunting methods, land clearing, or even arson. Other times accidental ignitions can occur due to careless hikers or campers. Climatically, it is believed that the future global warming trends will increase wildfire potential in much of the world (Liu *et al.* 2010). Fire potential is calculated using the Keetch-Byram Drought Index (KBDI), and when calculated using current general circulation models (GCMs), the current fire potential is shown to increase from low to medium in the United States (Liu *et al* 2010). If the trend of warming temperatures and decreased precipitation in the Southwestern United States continues, the prevalence and intensity of wildfire in the region can be expected to increase as well.

Figure 1. 10-Year Average of Wildland Fire Causes (1988-97)[3]

	HUMAN CAUSE	LIGHTNING CAUSE
Number of Fires	102,694	13,879
Percent of Fires	88	12
Acres Burned	1,942,106	2,110,810
Percent of Acreage	48	52

Figure 2. Sizes and causes of wildfires from 1988-1997 ("Wildland Fires" 2000).

A wildfire can impact society in different ways — ecologically, socially, and economically. Ecologically, a crown level fire, one that makes its way into the canopy, can cause severe damage to an ecosystem and significantly disrupt its ecological succession. A severe crown level fire can decimate the soils of an ecosystem and leave the area void of vegetation post-fire. However, a surface level fire that tends to remove clutter can prove beneficial to some ecosystems as it will encourage regrowth ("Wildland Fires" 2000).

Socially, it is important to address the issue of wildfire hazard as more people move closer to the wildland urban interface (WUI). During the 1990's, 13.6 million new housing units were built throughout the United States many of which were in areas adjacent to protected wilderness areas, leading one to believe that housing development in the WUI is bound to be of greater concern in the future (Radeloff *et al* 2005). During the 2013 fire season, 1,093 residences were destroyed by wildfires nationally; however, this is below the annual 10-year average of 1,394 residences (National Interagency Coordination Center 2013). The safety of fire crews is also of great concern with over 1,000 crews being dispatched in year 2013 alone (National Interagency Coordination Center 2013). A greater understanding of fuel reduction and mitigation techniques will enable planned evacuations and reduction of loss of life of both firefighters and civilians.

Economically, fire suppression is a huge expense to the Forest Service and other government agencies. In 2013, an estimated $1.7 billion of federal funds was spent in fire suppression to fight about 47 fires that burned approximately 4,319,546 acres of land (National Interagency Coordination Center 2013). The 2013 Rim Fire in the Sierra Nevada region of California alone was estimated to have cost $127 million in fire suppression (National Interagency Coordination Center 2013). The economic impact of wildfire is not limited to suppression cost alone. A wildfire may also disrupt economic activity in affected areas and/or destroy both commercial and residential buildings and infrastructures that will need to be rebuilt by the affected communities.

Figure 2. Selected Historically Significant Wildland Fires[11]

DATE	NAME	LOCATION	ACRES	SIGNIFICANCE
Oct 1871	Peshtigo	Wisconsin/Michigan	3,780,000	1,500 fatalities in Wisconsin
Sep 1894	Hinckley	Minnesota	Undetermined	418 lives lost
Sep 1894	Wisconsin	Wisconsin	Several million	Undetermined; some lives lost
Aug 1910	Great Idaho	Idaho/Montana	3,000,000	85 fatalities
1949	Mann Gulch	Montana	4,339	13 smokejumpers killed
Sep 1970	Laguna	California	175,425	382 structures destroyed
1987	Siege of '87	California	640,000	Valuable timber lost on the Klamath and Stanislaus National Forests
1988	Yellowstone	Montana/Idaho	1,585,000	Large acreage
Oct 1991	Oakland Hills	California	1,500	25 lives lost and 2,900 structures destroyed
Jul 1994	South Canyon	Colorado	1,856	14 firefighter fatalities
1998	Volusia Complex	Florida	111,130	Thousands of people evacuated from several counties
1998	Flagler/St. John	Florida	94,656	Forced the evacuation of thousands of residents
May 2000	Cerro Grande	New Mexico	47,650	Originally a prescribed fire; 235 structures destroyed; damaged Los Alamos National Laboratory

Figure 3. Significant Wildfires and their impacts ("Wildland Fires..." 2000).

1.4 Research Questions

Both climatic and anthropogenic disturbances to the ecosystem in the Zuni Mountains have been well documented and thoroughly explored. Oscillations in synoptic climatology like the El Nino Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) drive wet and dry periods in this area, which directly influence the frequency and severity of forest fire (Grissino-Mayer *et al.*, 1997). The implementation of fire suppression practices also allow a buildup of fuels and contribute to the growth of many fire-intolerant hardwood species. The result is crown-level infernos that have the potential to destroy the forest and nearby towns and cities in the West (Rother 2010). Although the causes of fire in this region have been well documented, the consequence of ecosystem changes on fire occurrence and spread is yet to be explored. The objectives of this study were to (1) implement a predictive fire spread model (FARSITE) to spatially and temporally model fire in the Zuni Mountains; (2) determine temporal variation of vegetation types susceptible to fire; and (3) propose management practices that are effective in reducing wildfire hazard based model outputs. The research questions that were examined in this study include:

1. What variables drive fire spread in the Zuni Mountains, New Mexico?
2. Which areas are prone to destructive and canopy level fires?
3. How have the fuel model types that are most conducive to fire spread changed in the past twenty years?

1.5 Outcomes and Significance

The data sets and maps resulting from this study will be shared with the land managers working for the Cibola National Forest to manage the Zuni Mountains. These outputs containing information about the areas susceptible to fire occurrence, the vegetation types responsible for fire occurrence, and potential fire spread zones will help land managers take appropriate mitigation actions to prevent future fire spread along the forest-urban interface and protect communities from fire impacts. Also, by displaying the spatial distribution of ignition points, these outputs will enable managers to efficiently target high risk areas for fuel reduction. Since land managers in the area understand the importance of reducing fuels and restoring the forest to its natural state, the findings will help them improve their restoration/mitigation plan.

This study will also pave the way for future studies exploring the expansion of fuel types using remote sensing imagery. Since most national forests have suppressed wildfires since the 1940's, the problem of fuel buildup and canopy fires is not one that is unique to the Zuni Mountains. By sharing the methodology with the Cibola National Forest GIS team, this study will help them and the USDA Forest Service implement such strategies in other similarly disturbed ecosystems. Furthermore, the methodology can be implemented longitudinally to explore the temporal variability of fire occurrence and fire spread in the Zuni Mountains after specific fire reduction policies and techniques have been implemented to determine the effectiveness of such policies and techniques.

1.6 Summary

A large crown fire has the potential to cost millions of dollars in suppression efforts and damages. Crown level fires also decimate vegetation leading to a disruption in ecological succession and a rapid increase in soil erosion. Thus, it is imperative to study this topic to allow planners to develop improved mitigation strategies for this region. The 2014 IPCC report identifies wildfire-induced loss of ecosystem integrity, property loss, human morbidity, and mortality as having a medium risk in the present and near term (2030-2040) and a very high risk in the long term due to global warming (Smith and Bustamante 2014). By integrating remote sensing and fire modeling techniques in this study, a methodology was developed that demonstrates how to identify areas in need of fuel reduction and track their growth over time.

This manuscript is organized into five chapters. The next chapter provides a comprehensive literature review of climatic and anthropogenic changes to fire regimes in the Zuni Mountains followed by a discussion of fire modeling and data sources needed to run the models. The methodology chapter provides an introduction of the study site, and discusses the research methodology used in this study (data sets, model parameters, image processing, and analysis). The findings of data analysis–remote sensing analysis, and fire prediction model–are presented and discussed in the results and discussion section following which the conclusion chapter summarizes the pertinent findings with regard to the research questions, identifies limitations and future research, and provides recommendations for forest managers from a policy perspective to reduce fire impact.

CHAPTER II

LITERATURE REVIEW

2.1 Overview

This chapter describes the complex relationship between climate and wildfire, explores the history of fire modeling, and provides an overview of data sources needed to run these models. A discussion about fire modeling and advancements in this area are presented to lay the foundation for implementing such models. Since remote sensing is critical to the production of many ecological data layers needed for this kind of modeling, a thorough discussion of the techniques used and their limitations are provided in this chapter as well.

2.2 Climate and Wildfire Relationship

The exploration of the relationship between climate and fire in the Southwest is fairly a recent trend. A reconstruction of precipitation by Grissino-Mayer (1995, 1996) in the Southwest revealed that fire has historically been correlated to oscillations of wet and dry periods with increased fire frequency associated with periods of below average rainfall (Grissino-Mayer and Swetnam 2000). This idea of synoptic climatology influencing fire in the region was also propagated by Swetnam and Betancourt (1996) who demonstrated that changes in the amplitude and frequency of the wet-dry periods of the ENSO are highly correlated with fire frequency and severity in the Southwest. The biggest fires most often occurred when the ENSO switched from wet to dry periods (Grissino-Mayer and Swetnam 2000; Swetnam and Betancourt 1996).

Grissino-Mayer and Swetnam (2000) developed a tree-ring reconstruction of wildfire from a tree-ring chronology in northwestern New Mexico and compared it to a thousand year douglas fir and ponderosa pine reconstruction of precipitation to analyze the relationship between precipitation and fire in the Southwest (Grissino-Mayer 1995,1996). They defined three long term precipitation regimes. The first, with average rainfall, occurred between 1000 and 1400 C.E. and is associated with the Medieval Warm Period; the second, a period of below average rainfall between 1400 and 1790 C.E., which is associated with the Maunder Minimum ("The Little Ice Age"); and a period of above average rainfall between 1790 and 1992 C.E. This final period of above average rainfall was correlated with a decrease in fire frequency suggesting precipitation regimes play a heavy role in fire occurrence in the area. On a smaller temporal scale, Grissino-Mayer and Swetnam (2000) examined the importance of moisture in the years before fire to the production of fuels to be burned in wildfire and found that increased forest growth associated with wet years in the southwest produce more ground litter to be burned in dry years. Historically, fires resumed from 1795 to 1880 and then dropped off during 1881 and 1892, which indicates that settlement in the area, the introduction of cattle grazing, and anthropogenic fire suppression activities have influenced fire regimes in this region. Past research about fire regime supports that climate is a primary factors in fire occurrence, thereby leading to researches examining the ecosystem in the face of climate change.

Swetnam and Betancourt (1997) correlated multi-century, from 1700 to 2000, tree-ring reconstructions of multiple variables like drought, population change, and disturbance history to climate events across multiple temporal scales (from annual to decadal) and multiple spatial scales (from local, areas less than 10 square kilometers, to mesoscale, areas between 10,000 and 1,000,000 square kilometers) in the American

Southwest. The authors found that the proposed inter-decadal changes in fire-climate ran parallel to shifts in frequency and amplitude of the SO (Southern Oscillation) over the past three centuries — 1700 to 2000. When the SO experienced a rapid switch from wet to dry periods, the American Southwest experienced an increase in the frequency of fires. The greatest amplitude switch from wet to dry in the SO was from 1747 to 1748, and the largest fire observed in the study site occurred in 1748 (the fire was present in nearly ⅔ of all sampled sites). Swetnam and Betancourt (1997) also suggested that these synoptic fluctuations in climate may be aggravated by anthropogenic effects. The increase in fuels from fire suppression and shifts in the SO may be responsible for increases in area burned in both Canada (van Wagner 1988; Auclair and Carter 1993) and the American Southwest (Sackett et al 1994).

Rother (2010) explored the effects of climate and anthropogenic influences on ponderosa pine forests in the Zuni Mountains, New Mexico. She cross-dated over 800 fire scars on 75 tree-ring cross-sections to reconstruct fire regimes in the forests over three sites. Rother found that low severity wildfires occurred naturally in the area between 1700 and 1800 before the settlement of Euro-Americans in this region. Climatically, there was no relationship between fire and PDO (Pacific Decadal Oscillation), which indicates shorter term climate fluctuations between wet and dry periods were more often responsible for fires historically. Due to human settlement, fire frequency decreased during the 19th century in the Zuni Mountains and has been completely absent from all sites after 1920 because of anthropogenic disturbances like livestock grazing and fire suppression. While returning these forests to their pre-anthropogenic conditions sounds desirable, Rother errs on the side of caution, warning that due to the nature of climate change, returning to these conditions may not be possible or be the best option.

2.3 Wildfire Models

Wildfire modeling is an inter-disciplinary research are that draws from computer science, forestry, geography, mathematics, among others to mathematically model fires and their occurrence and spreading based on surroundings and climatic conditions (Andrews *et al,* 2003). Being a long standing discipline, a number of models have been developed over the years. While some of the earliest cell-based raster models were coarse in spatial resolution and lacked the complexity needed to accurately model the physics of a wildfire (Kourtz *et al*, 1977), the introduction of Percolation modeling in 1990, which assigns random barriers in a grid through which fire cannot pass, led to the development of more accurate and precise fire models.

One of the first computer models of forest fire was developed by Peter Kourtz, Shirley Nozaki, and William O'Regan in 1977, which was built in FORTRAN to run on a 32-bit personal computer. Their model pioneered the cell based wildfire model by partitioning the forest floor into a grid of two-hectare cells with homogeneous fuel types (Kourtz *et al,* 1977). The fire spreads through adjacent cells and the rate of spread is calculated based on fuel types, moisture content, and wind conditions (Kourtz *et al*, 1977). Despite its usability, several admitted shortcomings of this model include lack of spatial precision (with ½ a hectare grids being the smallest option); no conversion to crown level fire which burns hotter and is more destructive than a normal wildfire; no consideration of terrain conditions which is important to determining fire spread; and lack of simulation of spotting, where one fire turns into two.

The next major step in fire modeling occurred in 1986 with the introduction of percolation modeling that was applied to fire spread by Albinet *et al* (1986) and the accuracy of this model was later assessed by Tom Beer and I.G. Enting in 1990. The basic principle behind percolation modeling pertains to the statistical description of connectivity between random networks; this is applied to fire modeling to reflect uncertainty in spread through a regular landscape (Finney, 2004). For example, a user could input that 70% of the area is unburnable and the model would randomly select 70% of the grid cells and make them impassable, the model would then calculate how the fire "flowed" from the origin outward (Figure 4, 5, 6 *)*. In this model, the user specifies the size of a grid for analysis, percentage of unburned sites, the neighborhood size for fire to spread, number of desired time steps for burning, and threshold for ignition. Threshold for ignition is determined by heat input that is expressed as the number of burning neighbors. (Albinet, 1986; Beer and Enting 1990). When tested, the model did not reproduce laboratory results of burning matchsticks in the same grid pattern, a test which was meant to recreate the theory of fire modeling via percolation (Beer and Enting, 1990). The results of the study conducted by Beer and Enting (1990) indicated that "bushfire-spread models based on a two-dimensional grid with nearest neighbor ignition rules are also too naïve."

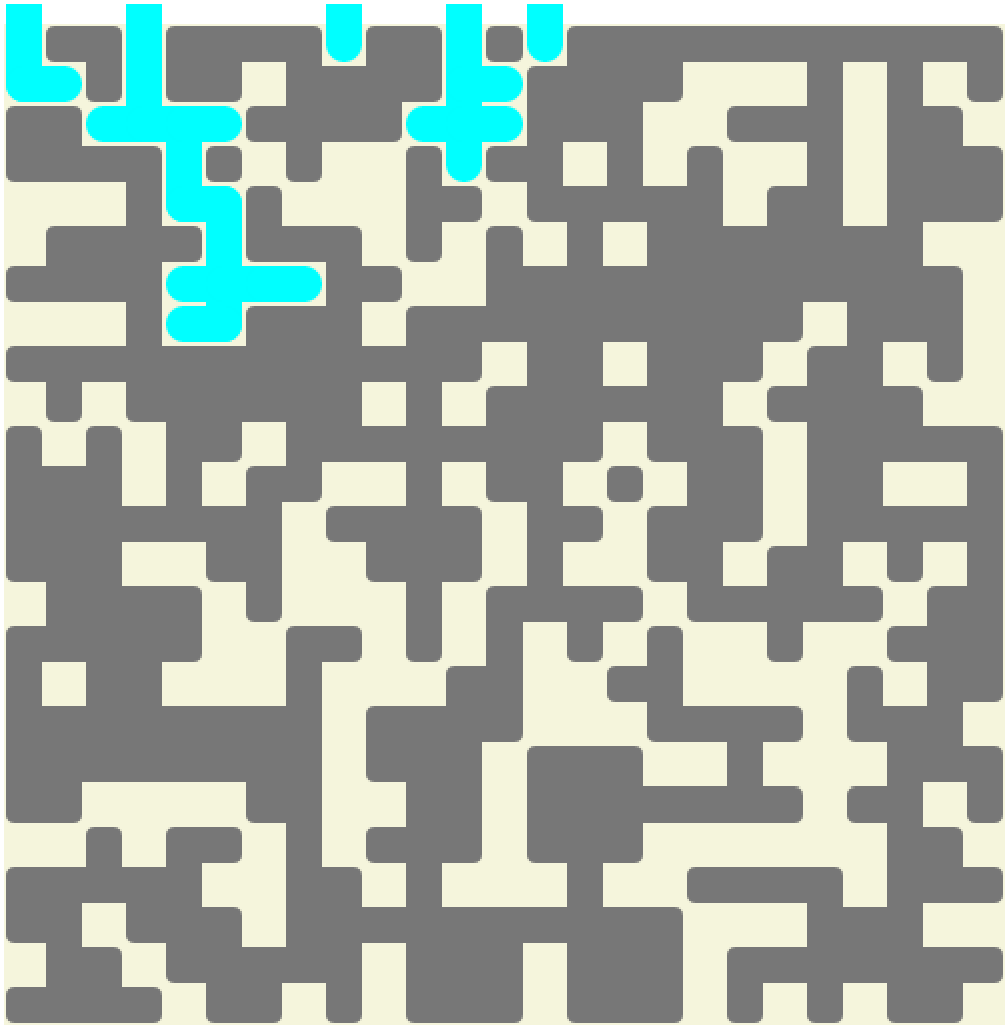

Figure 4. Low spread of fire, unburnable areas set at 70%.
Source: http://www.jeromecukier.net/projects/models/percolate.html.

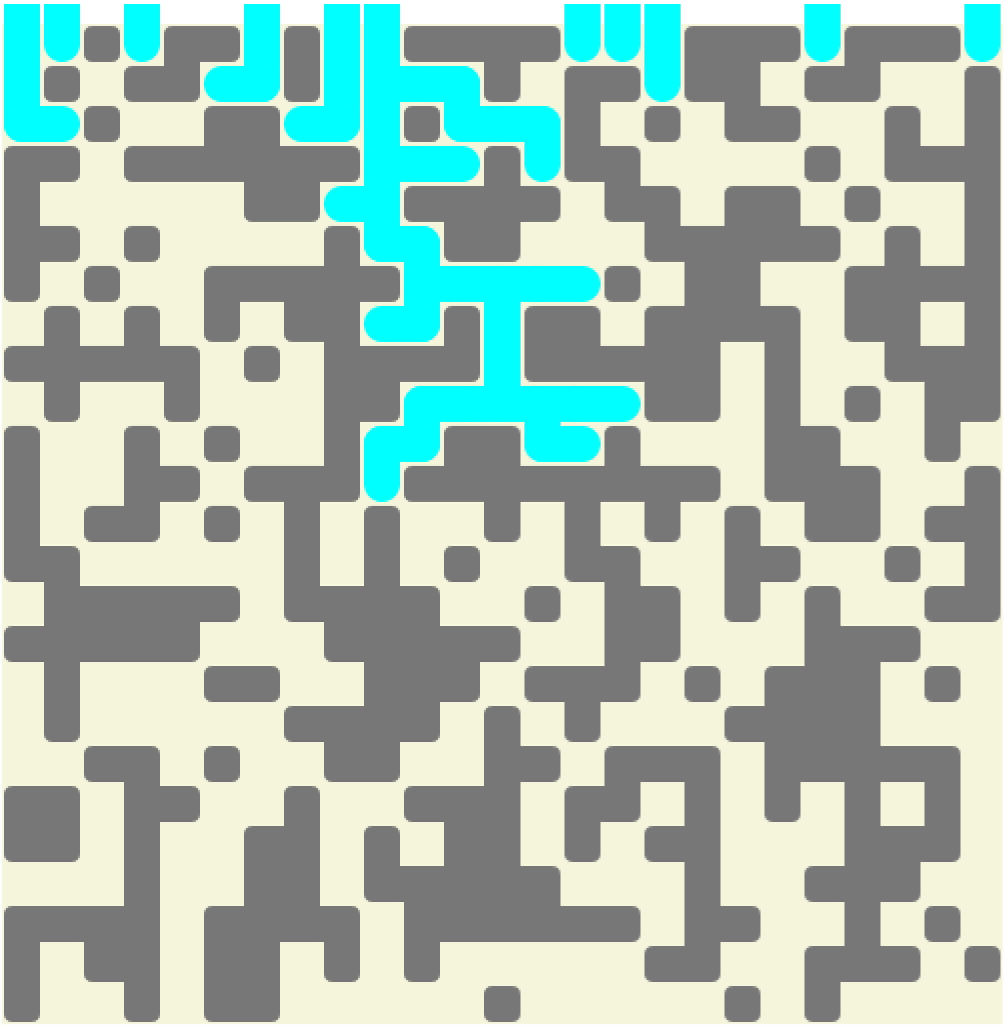

Figure 5. Medium spread of fire, unburnable areas set at 52%.
Source: http://www.jeromecukier.net/projects/models/percolate.html.

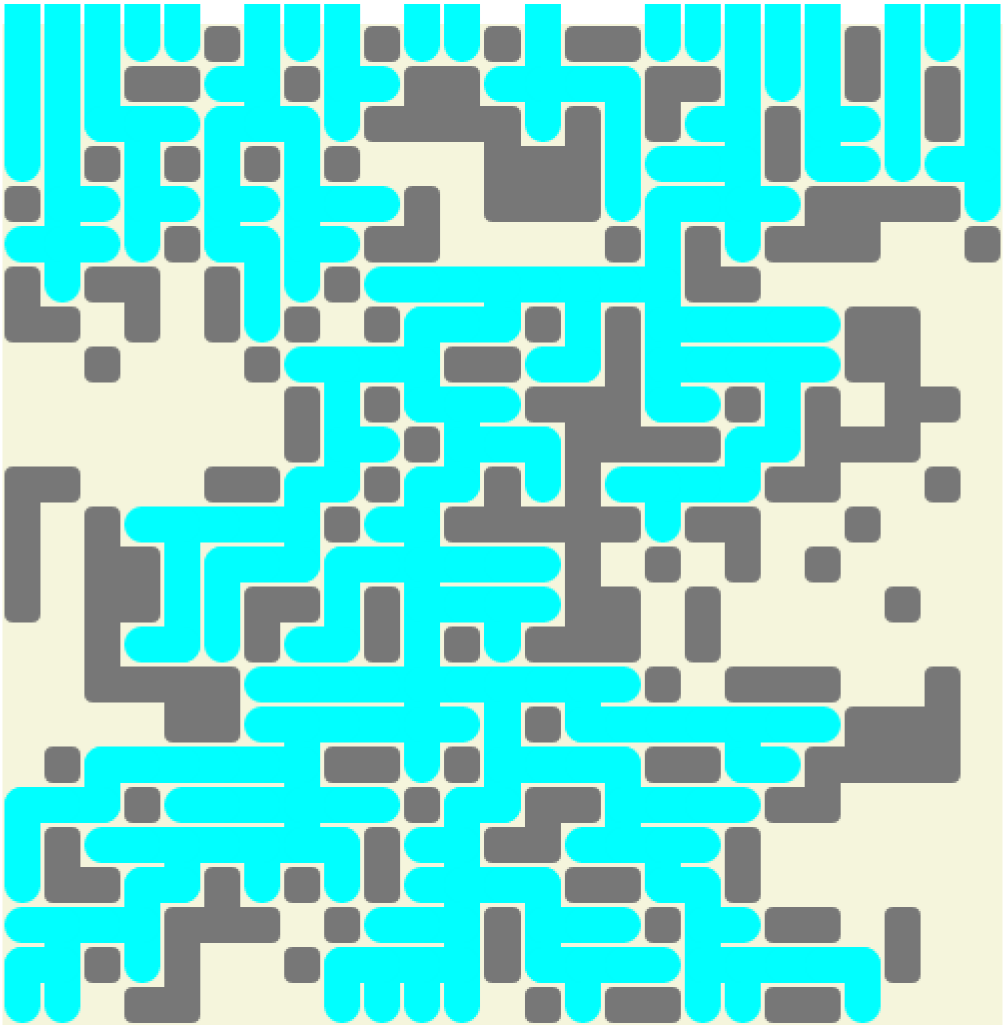

Figure 6. High spread of fire, unburnable areas set at 30%.
Source: http://www.jeromecukier.net/projects/models/percolate.html.

The FARSITE model was first built in 1994, and is commonly used among practicing foresters and land managers. Unlike most fire models that use cell-based raster calculations, the FARSITE model of 1994 is built on an elliptical model of fire spread based on Huygen's principle (Finney, 1994). This model has been in development for over twenty years and is now on its fourth major release.

The Huygen's principle of elliptical spread resolves some of the problems of cell based fire models such as changing wind speed and fuel moisture (Figure 7). The mathematical principles used to model fire based on Hyugen's principle were expounded by Richards (1995), which include a number of variables such as orientation of the vertex (the point at the foremost edge of fire), direction of maximum spread, shape of the fire calculated from fuel, and weather conditions at each vertex. Surface fire ellipsoids' rate of spread are calculated using Rothermel's spread equation which calculates fire spread by dividing the product of reaction intensity (determined by energy in kilojoules (kJ) per square meter, and wind and slope) by the product of dry bulk density and heat of pre-ignition (Rothermel 1972). The criteria for the surface fire to transition to a crown level fire is determined by Van Wagner's conditions laid out in his 1989 paper (Van Wagner 1988). This model incorporates fuel weights and moisture content, and if the rate of spread exceeds the "critical spread rate", the equation determines the fire has converted from a ground fire to a crown fire. If this condition is met, then the model will compute crown fire at the next computed vertex where the rate of fire spread across the canopy will be computed based on canopy bulk density (CBD) measured in *kg/m*^3. The required meteorological variables for this model include total daily precipitation, maximum and minimum temperatures, maximum and minimum relative humidity, and elevation. The elevation is used to adjust for adiabatic process across the landscape such that temperature decreases by 1°C per 100m of height and by 0.2°C per 100m humidity (Finney, 2004). Wind speed calculated hourly in (*mph)* is used along with its direction and is assumed to be parallel to the terrain. Both weather and wind variables are applied consistently across the landscape. Overall, the necessary inputs to run the model are extensive and include gridded datasets of: elevation, slope, aspect, canopy variables, and weather and wind data (Figure 8).

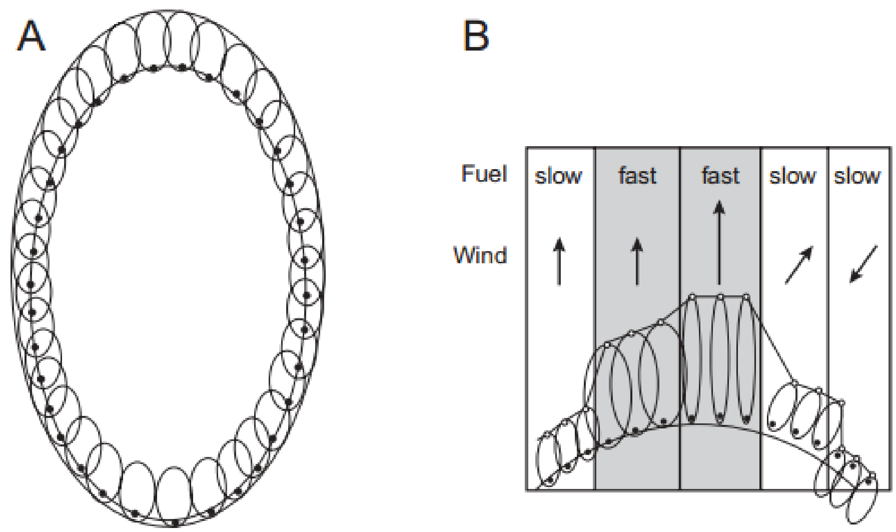

Figure 1—Illustration of Huygens' principle using elliptical wavelets. **(A)** Uniform conditions use wavelets of constant shape and size to maintain the elliptical fire shape over time. **(B)** Nonuniform conditions showing the dependency of wavelet size on the local fuel type but wavelet shape and orientation on the local wind-slope vector.

Figure 7. Hyugen's principle of elliptical spread (Finney, 2004).

Table 1—Raster inputs to *FARSITE* and their usage in the simulation.

Raster theme	Units	Usage
Elevation	m, ft	Used for adiabatic adjustment of temperature and humidity from the reference elevation input with the weather stream.
Slope	percent, °	Used for computing direct effects on fire spread, and along with Aspect, for determining the angle of incident solar radiation (along with latitude, date, and time of day) and transforming spread rates and directions from the surface to horizontal coordinates.
Aspect	° Az	See Slope.
Fuel model		Provides the physical description of the surface fuel complex that is used to determine surface fire behavior (see Anderson 1982). Included here are loadings (weight) by size class and dead or live categories, ratios of surface area to volume, and bulk depth.
Canopy cover	percent	Used to determine an average shading of the surface fuels (Rothermel and others 1986) that affects fuel moisture calculations. It also helps determine the wind reduction factor that decreases windspeed from the reference velocity of the input stream (6.1 m above the vegetation) to a level that affects the surface fire (Albini and Baughman 1979).
Crown height	m, ft	Affects the relative positioning of a logarithmic wind profile that is extended above the terrain. Along with canopy cover, this influences the wind reduction factor (Albini and Baughman 1979), the starting position of embers lofted by torching trees, and the trajectory of embers descending through the wind profile (Albini 1979).
Crown base height	m, ft	Used along with the surface fire intensity and foliar moisture content to determine the threshold for transition to crown fire (Alexander 1988; Van Wagner 1977).
Crown bulk density	kg m^{-3} lb ft^{-3}	Used to determine the threshold for achieving active crown fire (Van Wagner 1977, 1993).

Figure 8. Raster inputs necessary to the FARSITE model (Finney, 2004).

The development of fire models has continued beyond the development of the FARSITE model into more specialized models. A good example of this growth can be found in Phillip Dennison's and Tom Cova's WUIVAC (Wildland Urban Interface Evacuation) Model. This model creates evacuation triggers, a long standing tradition in hazards research, when a wildfire reaches a certain point in a landscape. Using traditional inputs like wind, fuels, and topography, WUIVAC determines the amount of time a fire will take to spread to a protected zone, which is used to set the evacuation trigger buffer. An evacuation trigger is a point that once crossed by a wildfire will trigger an evacuation response for a community (Dennison *et al*, 2007). WUIVAC incorporates FLAMMAP (a part of the FARSITE suite) to determine rate of spread along a landscape, and then reversing it to travel from a community cell until the specified trigger time is reached (Dennison *et al*, 2007).

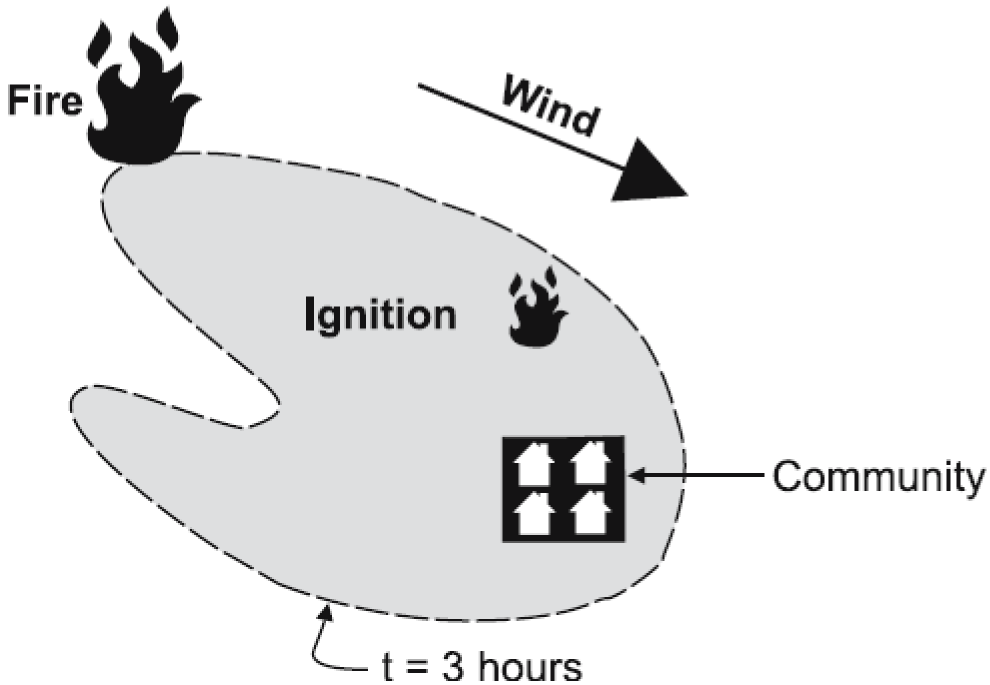

Figure 9. A representation of the WUIVAC model (Dennison *et al*, 2007).

2.4 Data and Variables for Wildfire Modeling

One of the main issues in wildfire modeling is obtaining accurate data to run and validate the model. Some data sources include historic fire atlases, dendrochronology, remote sensing data (e.g., fuel types), biophysical variables (e.g., canopy bulk density), and physiographic information (e.g., elevation) (Morgan 2001; Schmidt 2002; Keane, 2001). Modeling fuels is a complex endeavor and since much of the practice relies on the usage of space born remote sensing satellites, identifying ground based fuels can prove troublesome. The USGS's LANDFIRE program also provides geo-spatial products describing vegetation, fire regimes, and fuel across the United States (LANDFIRE 2010). One of the most important products generated by this program is the fuel model layer(s) critical to fire modeling. The methodology for developing these fuel models using a combination of remote sensing, biophysical variables, and local experts is discussed in Reeves *et al* (2006). However, there have also been research undertaken to model fuel by using only remote sensing. For instance, Van Wagtendonk and Root (2003) used Normalized Difference Vegetation Index (NDVI — an index that provides information about the greenness and health of vegetation) calculations over the course of a year to group vegetation types according to their phenological cycles, which represented fuel layer for fire modeling. Regardless of the methods used, the data produced by these fire models are valuable as they can be used by both land managers and citizens to more accurately predict future fire spread and help mitigate the damage.

Keane *et al.* (2001) described the challenges of modeling fuels, canopy complexity, fuel type diversity, fuel variability, and fuel model generalization, and offered insights about overcoming these challenges. The authors also mentioned that aerial imagery and satellite based sensors are unable to capture surface fuels because the ground is often obscured by a thick canopy. Also, a single weather event can alter the fuel load in an area dramatically by increasing the amount of dead and downed materials, thereby increasing the fuel load (Keane *et al,* 2001). The authors, therefore, identified four approaches to mapping this difficult phenomenon – (1) field reconnaissance, (2) direct remote sensing methods, (3) indirect remote sensing methods, and (4) biophysical modeling. The reconnaissance method involves traversing a landscape and recording fuel conditions on a map or on a notebook. However, this method is extremely cost ineffective and somewhat subjective. Using remote sensing to classify fuel types is a straightforward method and easy to ground reference, but typically it results in vegetation classification rather than fuels and is prone to canopy obstruction. Remote sensing maps ecosystem characteristics and uses them as surrogates for fuels; however, this method typically produces polygons too large to be of any use for accurate models. Finally, biophysical modeling uses environmental gradients like climate, topology, and disturbance to create fuel maps. Biophysical modeling shines when simulating fuel changes over time, but is extremely complex and requires lots of data, modeling, and analysis. Keane *et al.* (2001) proposed a method incorporating contemporary remote sensing and image processing techniques to model fuel distribution based on biophysical setting, species composition, and stand structure. They stressed the importance of these models to fire and land managers because of their applicability in modeling fire hazard. However, Keane *et al.* (2001) also discussed the need for more accurate fuel modeling by using specific and high quality geo-spatial data, high resolution remote sensors that can penetrate canopy layers, better field data, and more comprehensive ecosystem models.

Reeves *et al* (2006) pioneered a methodology to develop fuel products through the LANDFIRE project. Their methodology relies on: existing vegetation type (EVT), canopy cover (CC), canopy height (CH), environmental site potential which represents vegetation that could be supported at a given site (ESP), Landsat ETM imagery, and Digital Elevation Models (DEM). The authors, in conjunction with local fire experts, created rules to classify vegetation types for Fire Behavior Fuel Models (FBFM). For instance: EVT provides information about potential ground litter and vegetation type; canopy cover corresponds to the understory; canopy height provides information to distinguish between FBFMs; and ESP is sometimes used to determine xeric fuel beds (with little to no moisture) from mesic fuel beds (those with a moderate amount of moisture) (Reeves, 2006). All these data are available from the LANDFIRE project website. By combining EVT, CC, CH, and ESP and using rule sets for classification derived by local fire and fuel experts, the Anderson Fuel Model 13 is developed at 30x30 meter pixel size. Once the Fuel Model layer is created, the results are submitted to local experts for verification and fine tuning.

Table 1—Example LANDFIRE fuelbed assignments from a Great Basin Pinyon-Juniper Existing Vegetation Type. ESP is Environmental Site Potential.

Fuelbed #	Cover (%)	Height (m)	ESP	FBFM13[1]	FBFM40
1	0 - 50	Any	Xeric	6	SH1
2	0 - 50	Any	Mesic	2	GS2
3	50 - 100	≥ 3	Any	8	TL1
4	50 - 100	≤ 3	Any	6	SH1

[1]FBFM13 and FBFM40 are fire behavior fuel models from Anderson (1982) and Scott and Burgan (2005) respectively.

Figure 10. FBFM 13 and 40 assignments from Reeves et al's methodology (Reeves, 2006).

In contrast to Reeve's method of integrating EVT, CC, CH and ESP to determine fuel models, van Wagtendonk and Root (2003) analyzed multi-temporal Landsat Thematic Mapper data to map fuel models in Yosemite National Park. The authors used six images from May, June, July, September, October, and November 1992 and calculated their NDVI . First, to eliminate areas without significant vegetation the NDVI values with a maximum of 109 were masked, which typically indicate that some vegetation is present, but not enough for a fire. The authors then ran an ISODATA unsupervised classification in ENVI to define 30 unique spectral classes (van Wagtendonk and Root, 2003). NDVI mean and maximum values over time were plotted to see how the vegetation changed throughout the season and shapes of the curve were used to group similar classes. Elevation maps and a Digital Ortho Quadrangle were used to distinguish between fuel types with similar vegetation responses. Finally, 370 field plot locations were used to validate the findings, which resulted in 54.3% accuracy with a kappa coefficient of .391 (van Wagtendonk and Root, 2003). Overall, their method is useful for separating vegetation types with unique characteristics over time, but similar types and mixed stands prove problematic.

While a useful tool, an ISODATA classification like the one used by van Wagtendonk and Root (2003) can negatively impact the accuracy of a remote sensing classification. A more common image classification technique used in remote sensing is a supervised classification which utilizes training data and machine learning algorithms to classify pixels in a remotely sensed image. While there are a variety of methods and algorithms for this process, the methodology is almost always the same: decide on desired classification types, choose training data for each of the desired classes, use the training data to estimate a spectral signature for each class, use the trained algorithm to label every pixel in the image into one of the defined classes, and finally, visualize the spatial distribution of classes (Richards and Jia, 1994). The most commonly used algorithm for running a supervised classification is the Maximum Likelihood Classification algorithm. At its most basic, the Maximum Likelihood Classifier is a supervised classifier that uses the discriminant function to classify a pixel to the group with the highest spectral likelihood based on provided training data (Ahmed and Quegan, 2006).

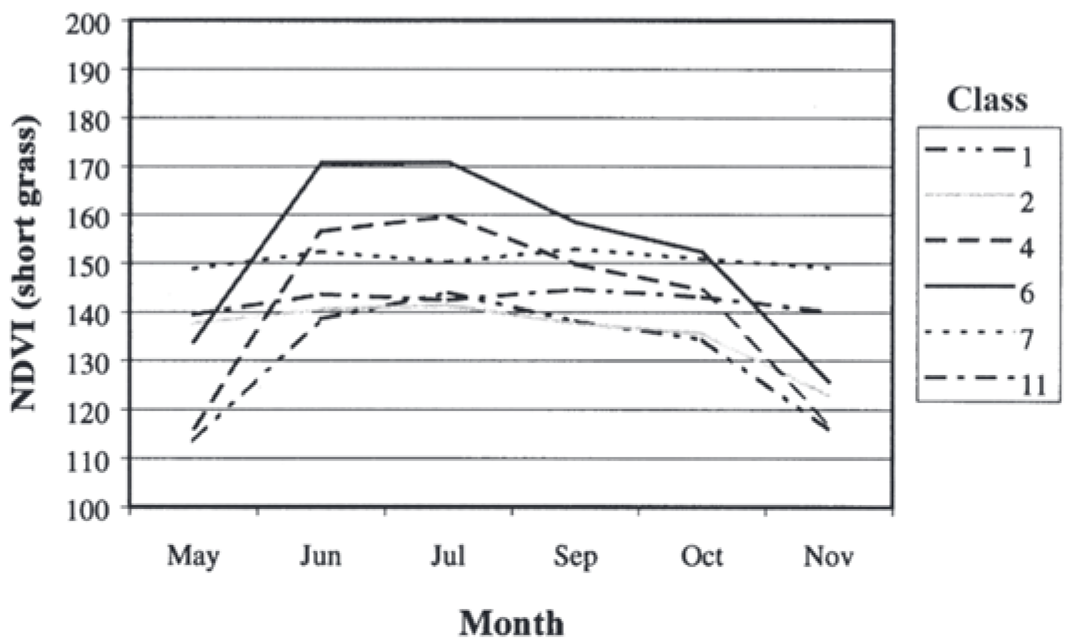

Figure 11. NDVI values for the short grass group (van Wagtendonk and Root, 2003).

2.5 Wildfire Prediction

The long history of wildfire models and their data requirements have long been stuck in the realm of research. However, with the development of Graphical User Interface (GUI) based programs and increased use of Geographic Information Systems and geo-spatial data, wildfire modeling is increasingly becoming useful to land managers and other professionals. In general, these models prove very useful for researching fire as an ecosystem process across an entire landscape (Finney, 1995). Now that most of the data to run these models is available from USGS's LANDFIRE project, a user can quickly predict the canopy-fire prone areas in a landscape and prescribe fuel treatment options to mitigate the risk. Stephens *et al.* (1997) used the FARSITE model to investigate how different forestry and fuel treatment practices affect potential fire behavior in the North Coast Creek watershed of Yosemite National Park. The authors used twelve categories of severity for the vegetation types, ranging from no treatment (0) to Group Harvest, Slash Treatment, and Fuel Management (12). The authors found that prescribed burns, thinning and biomassing before prescribed burns, and group selection with slash and fuel treatments produced the best results in terms of area burned, rate of fire spread, and heat (Stephens, 1997). When results like these are available to forest managers, the significance of wildfire prediction models is hardly understated.

CHAPTER III

METHODOLOGY

3.1 Overview

This chapter discusses the methodology implemented in this study. The first section of this chapter introduces to the study site, and discusses the reasoning behind choosing this specific location and outlines some of the ecological history of the area. The second section discusses data sources and data processing steps implemented in this study. The third section of this chapter provides an in-depth discussion of the methodology employed to investigate the research questions: (1) What variables drive fire spread in the Zuni Mountains, New Mexico? (2) Which areas are prone to destructive and canopy level fires? and (3) How have the fuel model types that are most conducive to fire spread changed in the past twenty years? The last section discusses the reference data and steps implemented to validate the research findings.

3.2 Study Site

The Zuni Mountains are located at the southeastern edge of the Colorado Plateau and are a typical southwestern ecosystem dominated by ponderosa pine and douglas fir forests. The Zunis run southeast to northwest and range in elevation from around 2,000 meters to 2,800 meters at their highest point on Mt. Sedgewick. The area around the Zunis is sparsely populated with the presence of small towns of Grants and Gallup nearby. Precipitation in this mountain range is scarce with an annual average precipitation of 340mm and is very seasonal with a springtime drought followed by wetter conditions in summer and early fall (Sheppard *et al* 2002).

The area, which was mainly populated by Native Americans, experienced rapid change with the arrival of the Atlantic & Pacific Railroad through Grants, New Mexico in 1881. The arrival of the railroad facilitated the arrival of more settlers and an increase in livestock, namely sheep (Magnum, 1997). The arrival of the railway and subsequent population increase in Grants gave rise to logging in the Zuni's as well. On June 30, 1890 about 314,668.37 acres of land owned by William and Austin Mitchell were sold with the intent to use the land for its lumber (Glover and Hereford, 1986). Because of problems with logging activities, logging in this area was ceased in 1892 (Glover and Hereford, 1986). In 1901, the American Lumber Company purchased the rest of the Mitchell brothers' land and began a very successful timber harvesting venture that included the completion of the Zuni Mountain Railway that started by the Mitchell brothers (Figure 12)(Glover and Hereford, 1986). Numerous studies of fire that have been conducted in this area have demonstrated that fire was prevalent in the area until the late 1920s and has since been reduced in both frequency and spatial extent (Rother, 2010; Grissino-Mayer and Swetnam, 2000). This drop in fire hazard events could be due to an increased effort of fire suppression, and improvements in fire suppression techniques such as smoke jumping, timber harvesting and livestock grazing that reduce biomass, thereby reducing fuel sources in the area (Rother, 2010).

The imagery of the Zuni Mountains in 2010 (Figure 13) taken in shows that this area is occupied by a densely vegetated range that is surrounded by the New Mexico desert. Figure 14 shows the 2010 LANDFIRE fuel classifications of the Zuni Mountains and Table 1 shows a quick overview of each fuel model (Anderson 1982). According to the Anderson fuel model, the main fuel present in this area is fuel model 9 - a closed stand of trees with sparse surface litter like pine nettles (Anderson 1982; Albini 1976) followed by an abundance of fuel model 2 – an open stand of herbaceous materials like grasses between trees (Anderson 1982). The fuel model 5 (low dense shrublands), and fuel model 8 (closed canopy stands with surface litter like leaves and dead and downed wood) are also present in many of the valleys (Anderson SS1982).

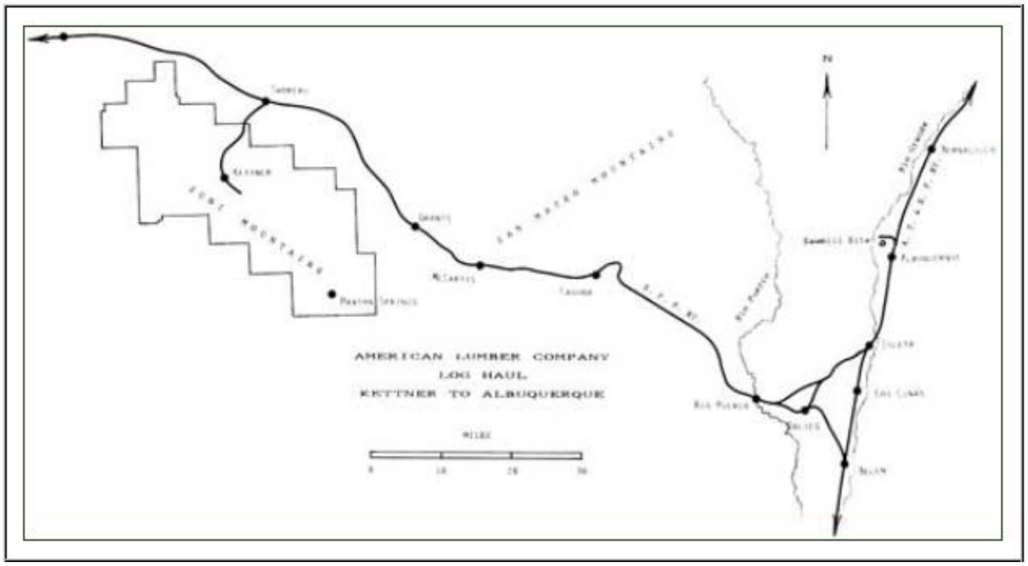

Figure 12. The American Lumber Company railroad route that ran from the heart of the Zuni's to the mill in Albuquerque (Glover and Hereford, 1986).

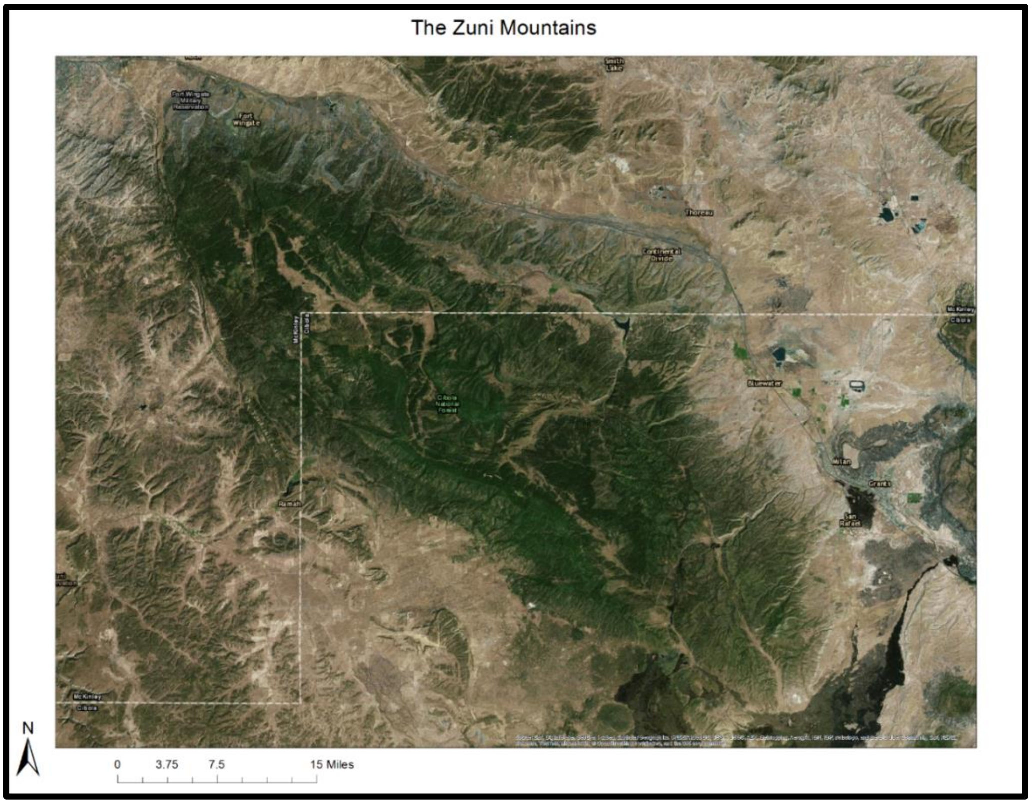

Figure 13. The Zuni Mountains.

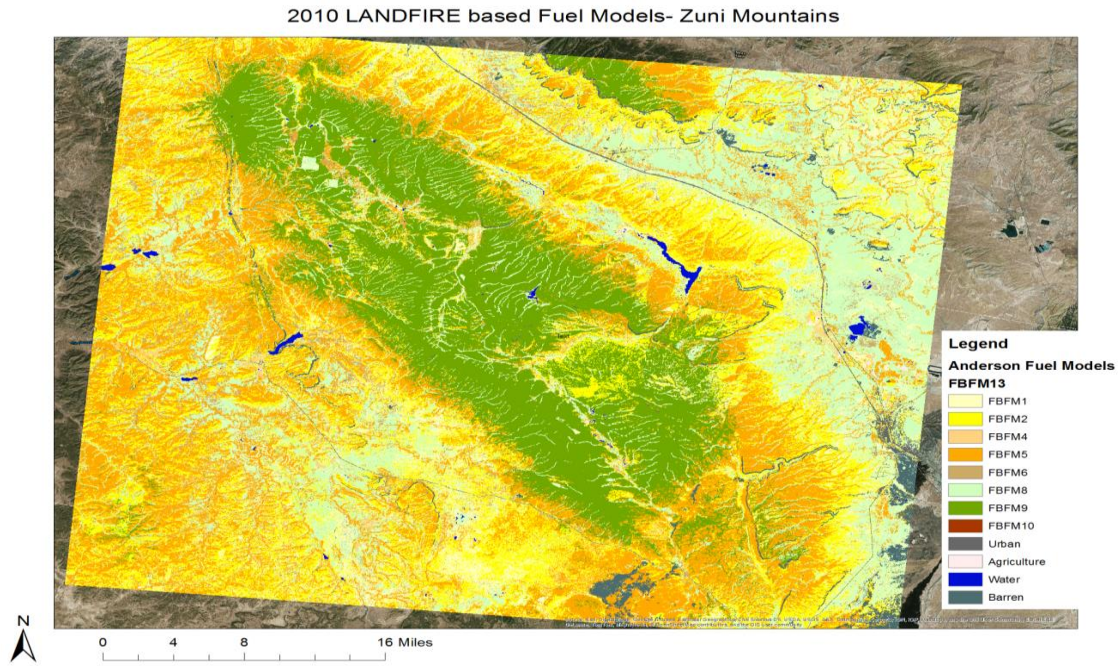

Figure 14. Fuel Models Present in the Zuni Mountains (LANDFIRE 2010).

Table 1

Fuel Model Descriptions present in the Zuni's (Albini 1976; Anderson 1982)

Fuel model	*Description*
FBFM1	*Short Grass (1 foot)*
FBFM2	*Grass understory and some canopy cover*
FBFM4	*Chapparral, high shrub*
FBFM5	*Lower brush (2 feet)*
FBFM6	*Dormant brush or hardwood slash*
FBFM8	*Closed canopy with surface litter*
FBFM9	*Timber litter with dead and downed*
FBFM10	*Heavy downed material*

3.3 Data Sources and Processing

Because this study focused on predicting the spatial distribution of potential future fire events, a large number of datasets were used to implement the fire and the fuel model, and validate the model output(s). Data about fuel types was collected in August 2014 for 220 points in the Zuni Mountains for supervised classification of the fuel types (Figure 15). In addition, the following spatial data sets were collected from different sources.

1. *Weather data*: To simulate the LANDFIRE's FARSITE fuel model, data about maximum and minimum temperature and precipitation were obtained from weather stations located at Grants, New Mexico (latitude of 35.17 and longitude of -107.9) for the duration of 1970 - 2014. Data about temperature (mean, min, and max), relative humidity (mean, min, and max), precipitation amount, precipitation duration, wind speed, and wind direction were also obtained from the NOAA's National Climatic Data Center from year 2000 onwards.

2.*Geo-spatial data:* Topographic data, especially, elevation layers depicting change in topography in this area is essential to implement the FARSITE model. The elevation data was obtained from the LANDFIRE project in 2010 (LANDFIRE 2010). A historic fire polygon layer - digitized by the USDA and workers in the Cibola National Forest – was obtained from the USDA Forest Service's GIS dataset (Figure 16). These fire polygons include all fires that impacted an area greater than 10 acres since 1970, and contain information about fire size, cause of ignition, date of fire occurrence and method of digitization. Ignition points for all fires in the Zuni Mountains containing the same attribute data as the fire polygons were also obtained from the USDA Forest Service's GIS dataset.

3. *Vegetation data:* Fuel models required to run the FARSITE model were procured from the LANDFIRE project. All the topographical and biophysical data for the model were acquired from the LANDFIRE project which included: LANDSAT data, elevation data, and plot level measurements from volunteers (Figure 17) in many sites to accurately predict the fuel types that are present in the area. All the data obtained from LANDFIRE projects are listed in Table 2 and the spatial extent shown in Figure 17.

4. *Reference data:* To validate the classification, the National Land Cover Dataset was obtained from the Department of Interior and the USGS Multi-Resolution Land Characteristics Consortium (MRLC), and Landsat multi-spectral imagery were obtained from the USGS's Earth Explorer. These data were used to determine the extent of vegetation change and specifically, determine the change in fuel models that is paramount for fire spread. Also, spectral signatures for different vegetation were obtained during sampling in order to classify the vegetation types into the Anderson Fuel Model classes.

Table 2

Spatial FARSITE Inputs

Layer	Source-Date	Spatial Resolution	Info
Forest Canopy Cover	LANDFIRE 2010	30m x 30m	Percent cover of tree canopy per pixel
Forest Canopy Height	LANDFIRE 2010	30m x 30m	Average height of top of vegetated canopy
Forest Canopy Bulk Density	LANDFIRE 2010	30m x 30m	Density of available fuel in canopy
Forest Canopy Base Height	LANDFIRE 2010	30m x 30m	Average height from forest floor to canopy bottom
Anderson FBFM	LANDFIRE 2010	30m x 30m	Anderson Fuel Model type
Elevation	LANDFIRE 2010	30m x 30m	Height above sea level
Aspect	LANDFIRE 2010	30m x 30m	Azimuth of sloped surfaces
Slope	LANDFIRE 2010	30m x 30m	Percent change elevation over an area

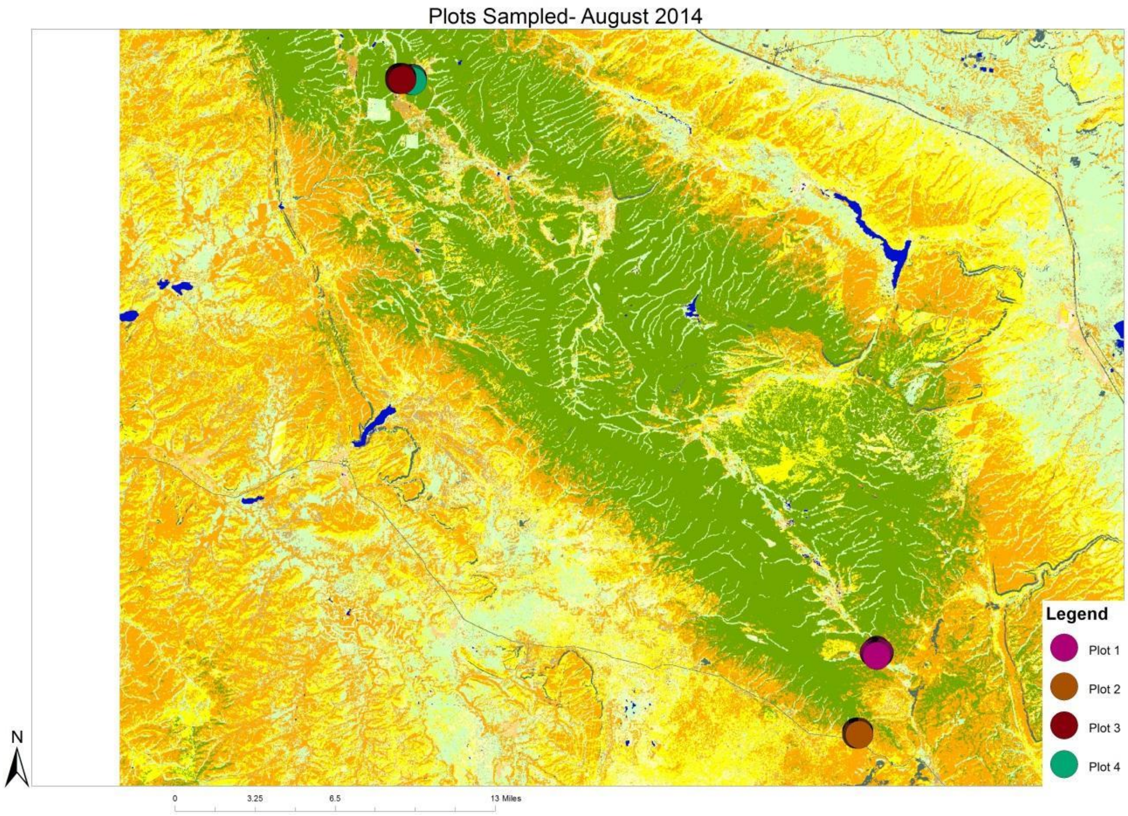

Figure 15. Locations of the four plots sampled August 2014.

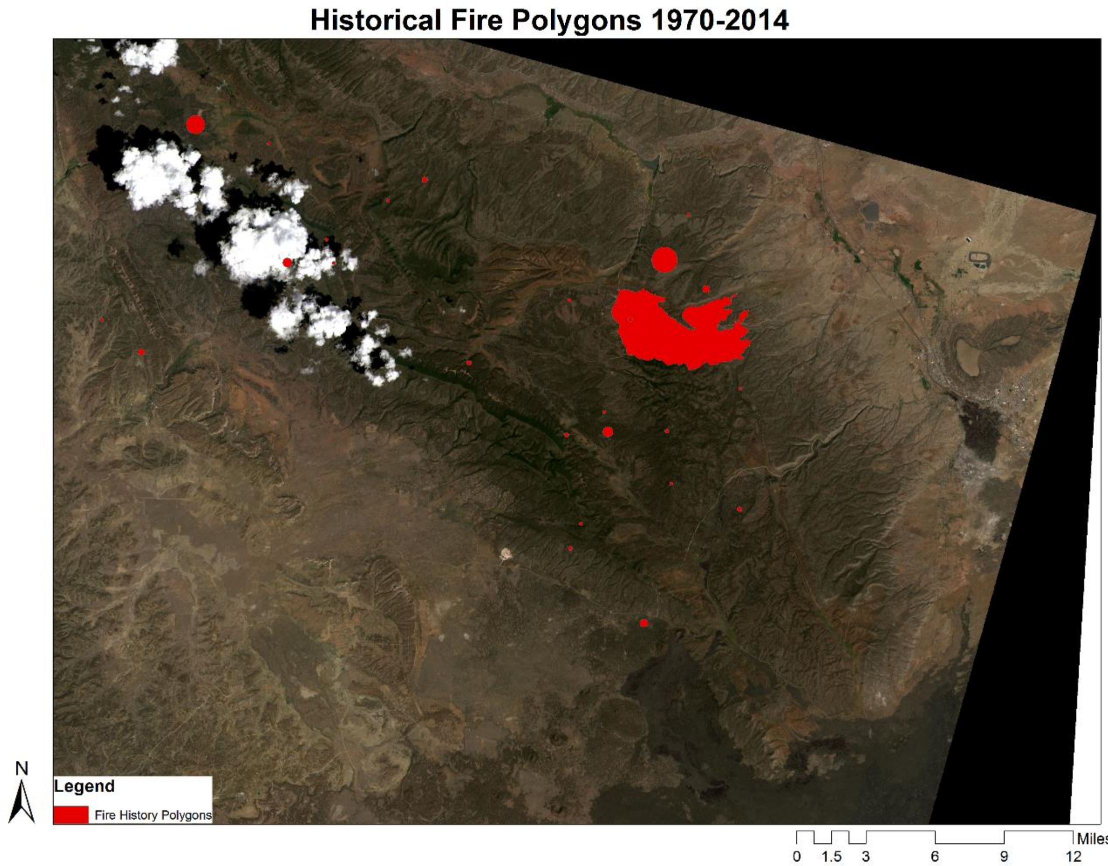

Figure 16. Historical Fires in the Zuni Mountains.

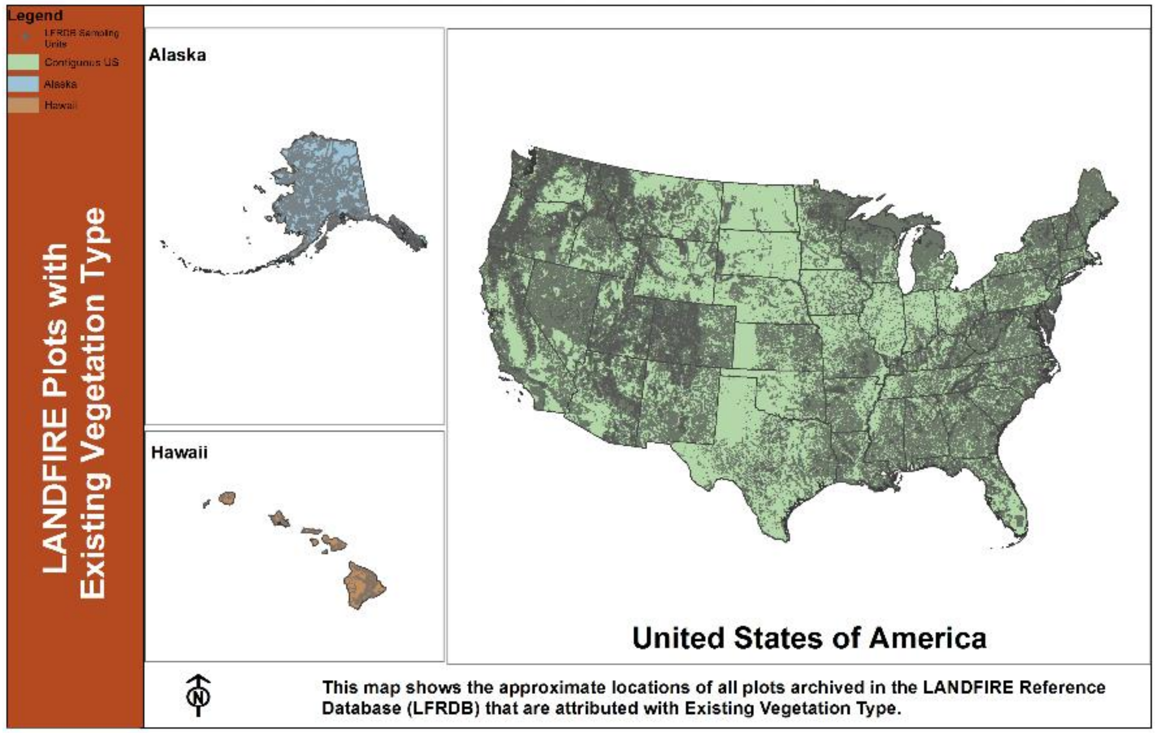

Figure 17. Locations covered and ground measurements taken in the LANDFIRE Reference database.

3.4 Research Methods and Techniques

An exploratory research design was implemented to examine the research questions. Integrating fire modeling with a vegetation change analysis is a novel approach in fire research that has broader impacts for a number of stakeholders. To determine the main drivers of large scale fires in the study area, climate variables were statistically analyzed. To discover the areas in the Zuni Mountains most prone to destructive fires, the FARSITE model was implemented. Finally, to track the changes in vegetation types most prone to canopy level fires, a vegetation change analysis was implemented using Remote Sensing techniques.

3.4.1 Statistical Methods

To address the first research question, it is necessary to provide a quantitative analysis of meteorological variables and past fire in the Zuni Mountains. The meteorological data contained daily weather observations beginning during 1970 from the nearby airport in Grants, New Mexico. Prior to 2000, the data contained only measurements for maximum temperature, minimum temperature, and total precipitation. However, since 2000, more observations like wind speed and wind direction have been included in the dataset. In order to analyze the climatic drivers of fire spread, statistical techniques including quadrat analysis, Pearson-R correlation, and discriminant analysis were implemented to compare the historic fire polygons to climatic variables.

To model fire based on weather conditions that facilitate the largest spread possible, it is important to determine the climatic factors that have historically been associated with large fires in the area. To determine fire spread, the climatic variables that produce a wildfire and burn the most area were identified by using weather data and fire polygon information in a discriminant analysis. The 145 fire events that occurred during 2010 – 2012 due to lightning (the most common cause of fire in the area) were used in the discriminant analysis to categorize fires into the following groups - small fires that burn between 0 and .25 acres, medium fires between .26 and 9.9 acres, larger fires between 10 and 99.9 acres, and extremely large fires greater than 100 acres. The following climatic variables: maximum relative humidity, minimum relative humidity, wind speed, wind direction, minimum temperature, maximum temperature, precipitation amount, and precipitation duration for the day of ignition were used as independent variables and matched with their respective fires (dependent variable) in the discriminant analysis. To investigate the correlation between these meteorological variables before a fire and area burned during a fire, a Pearson-R correlation was implemented between acreage burned (dependent variable that was estimated from the historic fire polygons in the Zuni's) and independent variables (meteorological data - mean of the maximum temperature, minimum temperature, and precipitation averages for the day of ignition and the three days prior to 28 major fire events).

Finally, a pattern analysis was conducted to determine the spatial pattern of natural fires (not caused by humans) in relation to specific fuel types in the Zuni's. The ignition point data obtained from the USDA was used to extract ignition points representing ignition from lightning. A quadrat analysis was conducted to identify if the points are dispersed or clustered. A variance to mean ratio and chi-square value were calculated to determine if clustering occurred, and if it was statistically significant.

3.4.2 FARSITE Modeling

To address the second research question, the FARSITE fire model was implemented. The model was run using a weather (WTR) file that contained no precipitation, and temperatures ranging from 90 and 95 degrees Fahrenheit. Because statistical analysis revealed that relative humidity has a negative correlation with fire size and August temperatures hover around 90 degrees Fahrenheit (Figure 21). A Wind File (WND) was held constant with winds blowing west at 15mph. After entering all the weather and biophysical data [table 2] into the FARSITE model, the fuels on the ground were "conditioned" using weather data described above for three days prior to running the model. When setting the parameters for the model, a 15 minute interval was used as a timestamp to calculate new ellipsoids, and each fire simulation was run for 24 hours.

Weather data was held constant throughout each 24 hour period. Once the model was initiated, fire growth was calculated by: aggregating the fires environment, calculating fuel moistures, finding the orientation angles of each vertex, calculating surface fire if there is no canopy cover, calculating crown fire if there is canopy cover, and then computing fire area and perimeter for that timestamp (Finney, 2004). After the simulation was run, fire polygons were saved, and area burned and perimeter of each fire after the 24 hour simulation were recorded.

3.4.3 Vegetation Change Analysis

The third question requires tracking the spatial distribution of vegetation types most prone to canopy fires over time. For this purpose, Landsat multispectral imagery was used to explore the temporal and spatial change of the vegetation types identified by the LANDFIRE project. Since major fires, those greater than 100 acres, occurred on average every 4.25 years between 1993 and 2010, vegetation type was analyzed using cloud free imagery at approximately five year intervals. If cloud free imagery was not available, seasonal imagery from the next available year was used. The remote sensing imagery was obtained between July 15th and September 15th because the ground reference data was obtained during this time period in 2014. For classification of these imagery to identify fuel types and their spatial distribution, the spectral signatures were acquired from the JPL spectral library, which were then used to run a supervised classification to identify the grasslands, ponderosa pine forests, shrublands, deserts, and Malpais Lava in each image. The fuel classification outputs obtained for the years 2014, 2011, 2006, and 2001 were compared to the LANDFIRE fuel classifications in the Zuni Mountains.

For supervised classification, five distinct land cover types including desert, Malpais lava, grasslands, shrub lands, and ponderosa pine/douglas fir forests were identified, and cloud free imagery was obtained from the USGS's Earth Explorer, for all years, where cloud free imagery was available, and spectral bands were stacked using the composite bands tool. Training/spectral data were gathered using the 220 sample points taken in the field to assist in classification of the 2014 imagery and high resolution imagery from Google Earth was used to assist in classification of the older imagery. Once training data was aggregated, reference polygons were drawn on the Landsat imagery to define classes for the maximum likelihood classifier. The ArcGIS image analyst extension was used to apply a maximum likelihood classification to Landsat 5 images collected for 2011, 2006, and 2001.

Figure 18. Spectral Signatures generated for fuel classes 2, 5/8, 9, and Desert land cover types.

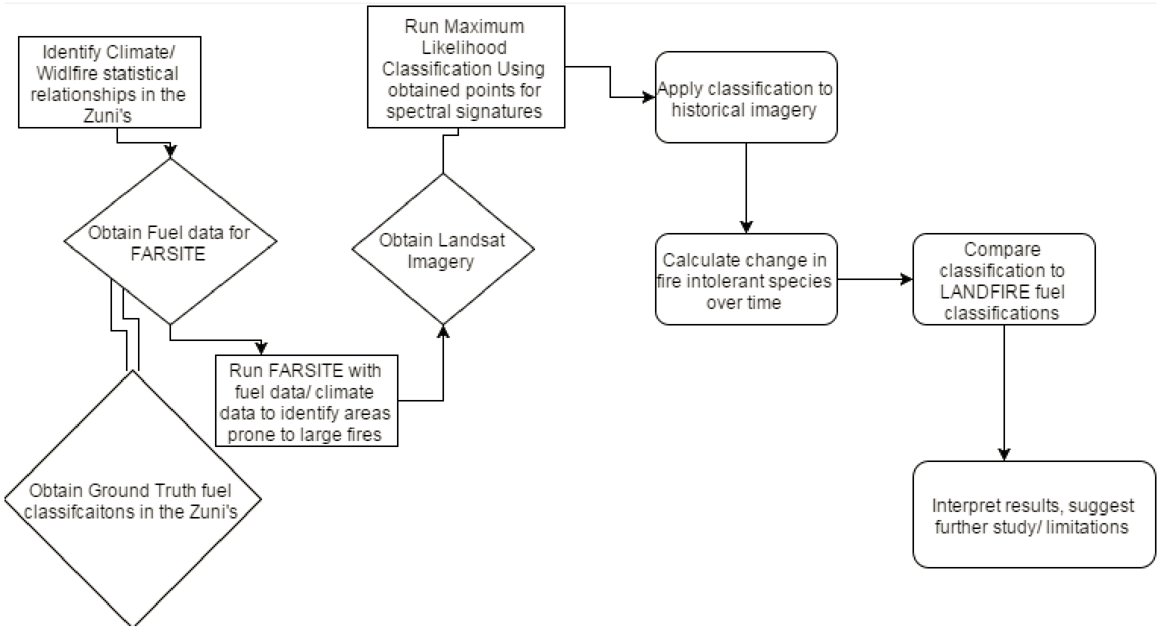

Figure 19. Flow diagram of study methodology.

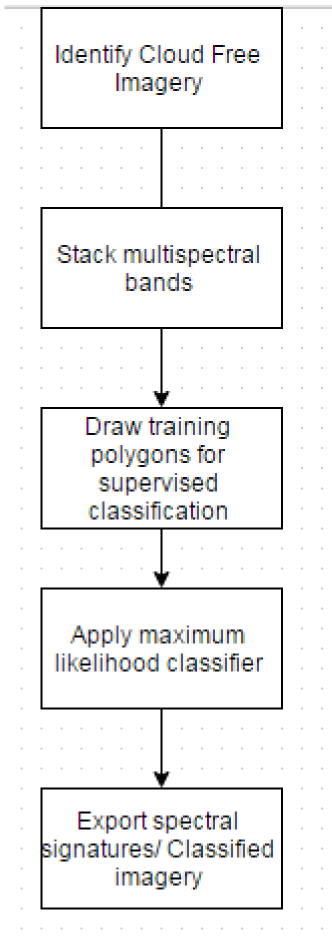

Figure 20. Supervised Classification workflow.

3.5 Validation

Validating the classified output from remote sensing imagery is critical to ensuring the accuracy of the final results before using it for other purposes. The in situ data were collected in 2014 and used for validation. Specifically, the best available imagery of the Zuni's around late August were classified using maximum likelihood classifier, and the accuracy of the results of the classification model were assessed using a confusion matrix to determine where type I and type II errors occurred in the probabilistic classifier. An independent data set – fuel classifications from the LANDFIRE program – was compared with the maximum likelihood classification output using pattern analysis to further assess the accuracy of the supervised classification. Validation using these measures helped quantitatively assess accuracy without *a-priori* information as well as determine where the maximum likelihood classifier produced erroneous output.

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Overview

Statistical results revealed that there is a statistically significant clustering of ignition points in the Zuni Mountains in areas of higher elevation and that fire size is primarily affected by relative humidity on the day of original ignition. The fire modeling results demonstrated that fuel types 1 and 2 (grasslands) (Figure 26) are responsible for large fires, types 5 and 8 (shrub dominated areas) (Figure 27) result in moderate fires, and type 9 (typically ponderosa pine) (Figure 28) generally cause small fires in the Zuni's when climatic variables are held constant. A discussion of all results generated from statistical and spatial analyses is presented in the following sections.

4.2 Statistical Results

The first test was run to discern if there was a significant difference between the climatic drivers of large and small fires in the Zuni Mountains. The analysis revealed that the only variable that made it into the function was the maximum relative humidity. While minimum relative humidity and precipitation duration had higher correlations with fire size, they never met the criteria for inclusion. The Eigenvalue for the function is .097 and explains 100% of the variance. Using this strong negative correlation as a basis, when running the FARSITE model, the fuels with no prior precipitation were used; thus keeping the relative humidity very low for maximum fire spread in the model.

Structure Matrix

	Function
	1
RHMax	1.000
RHMin[a]	.784
PPTDUR[a]	.612
TmpMax[a]	-.447
WS[a]	-.384
PPTAMT[a]	.341
TmpMin[a]	-.130
WDir[a]	-.023

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Figure 21. Structure Matrix showing correlations from the Discriminant Analysis.

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.097[a]	100.0	100.0	.297

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.912	13.076	3	.004

Figure 22. Eigenvalues showing the percent of variance found in the Discriminant Analysis.

Classification Results[a,c]

		Group	Predicted Group Membership 1.00	2.00	3.00	4.00	Total
Original	Count	1.00	51	0	17	15	83
		2.00	23	1	6	12	42
		3.00	4	3	1	6	14
		4.00	0	0	2	4	6
	%	1.00	61.4	.0	20.5	18.1	100.0
		2.00	54.8	2.4	14.3	28.6	100.0
		3.00	28.6	21.4	7.1	42.9	100.0
		4.00	.0	.0	33.3	66.7	100.0
Cross-validated[b]	Count	1.00	51	0	17	15	83
		2.00	23	1	6	12	42
		3.00	4	3	1	6	14
		4.00	0	0	2	4	6
	%	1.00	61.4	.0	20.5	18.1	100.0
		2.00	54.8	2.4	14.3	28.6	100.0
		3.00	28.6	21.4	7.1	42.9	100.0
		4.00	.0	.0	33.3	66.7	100.0

a. 39.3% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 39.3% of cross-validated grouped cases correctly classified.

Figure 23. Classification results for discriminant analysis.

A Pearson-R correlation was run to determine if there was a relationship between acres burned (in square meters), and precipitation, minimum temperature, and maximum temperature for three days prior to 28 major fire events in the Zuni Mountains. All three variables had a negative correlation with acres burned, but no results proved to have statistical significance. Therefore, the null hypothesis that there is no significant correlation between acres burned (dependent variable) and precipitation, minimum and maximum temperature, and acreage burned for three days before a major fire event (independent variables) in the Zuni Mountains was accepted.

Correlations

		AcresBurned m2	Precipitation	TempMin	TempMax
AcresBurnedm2	Pearson Correlation	1	-.095	-.033	-.059
	Sig. (2-tailed)		.631	.866	.765
	N	28	28	28	28
Precipitation	Pearson Correlation	-.095	1	.428*	.054
	Sig. (2-tailed)	.631		.023	.784
	N	28	28	28	28
TempMin	Pearson Correlation	-.033	.428*	1	.775**
	Sig. (2-tailed)	.866	.023		.000
	N	28	28	28	28
TempMax	Pearson Correlation	-.059	.054	.775**	1
	Sig. (2-tailed)	.765	.784	.000	
	N	28	28	28	28

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

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

Figure 24. Pearson R correlation between Acres Burned, Precipitation, Minimum Temperature, and Maximum Temperature.

The next test was designed to determine if ignitions caused by lightning in the Zuni Mountains are random or clustered in certain areas. The points per quadrat were tallied and used to calculate a mean point density of 9.05 points per quadrat, a List variance of 44.79, a variance to mean ratio of 4.95, and a chi-square value of 425.7, which translates to a significance value less than .000. The Variance to Mean Ratio (VMR) and small p-value indicate that the point pattern for lightning based ignitions is significantly more clustered than random. Visual analysis also revealed that many of these ignitions are clustered around the peaks of the Zuni's, offering valuable insight for where fuel reduction is most needed. These results indicate that the fire risk is higher in the higher elevations.

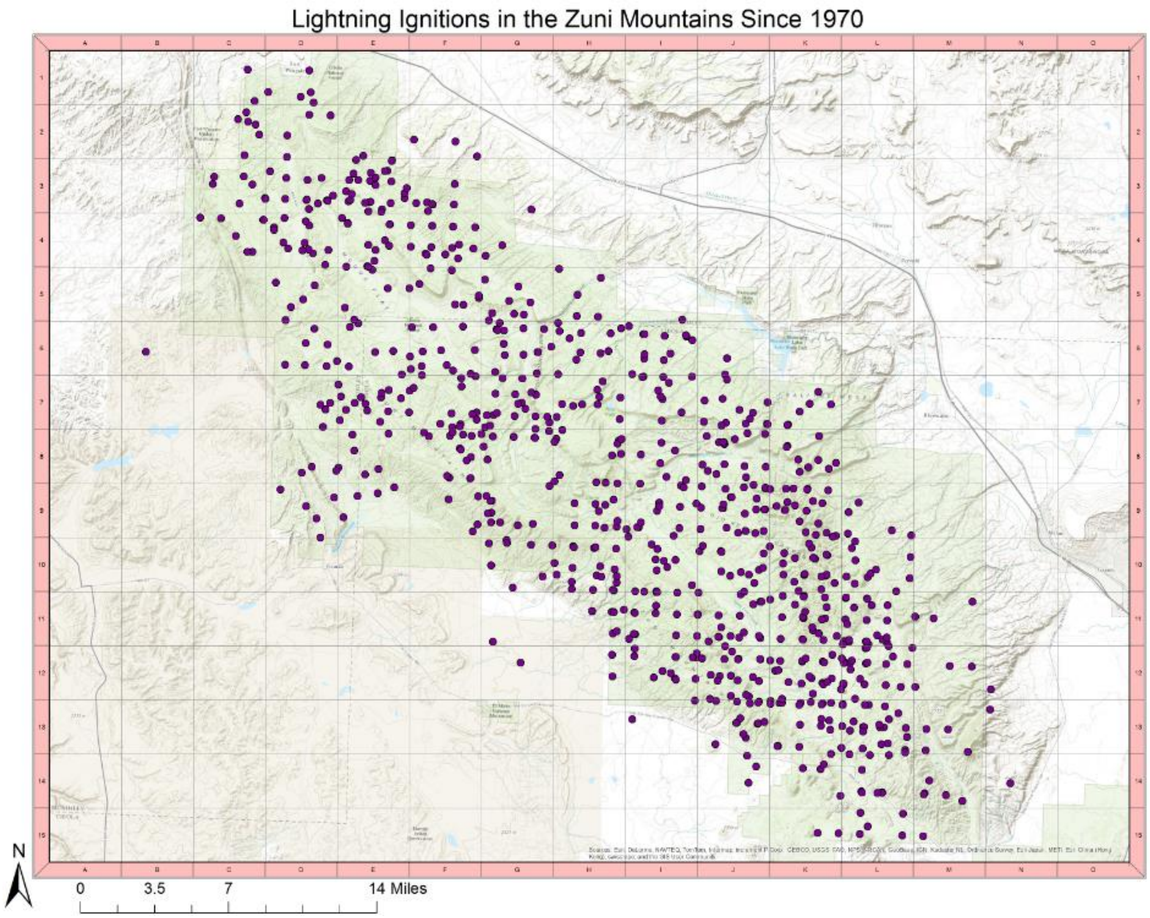

Figure 25. Clustered Lightning ignitions in the Zuni Mountains since 1970. Source: USDA Forest Service.

4.3 FARSITE Modeling

The results of FARSITE modeling of fires based on different fuel types in the Zuni Mountains revealed distinctly different fire sizes. The first simulation (Figure 26) simulated a fire in a grassland environment (FBFM 2), which is typically found in lower elevations in the Zuni's and used for cattle grazing. The largest area burned because of this fuel type was found to be an area of 1,033.26 hectares. In the next simulation (Figure 27), fire spread was determined based on fire in a shrub land environment with sparse trees, typical of a ponderosa pine forest that has not been cleared naturally or otherwise, represented by FBFM 5 and FBFM 8. The largest area burned by this fuel type was 414.29 hectares within a 24 hour period. The third simulation modeled fire in a typical ponderosa pine/douglas fir forest (Figure 28), which resulted in 64 hectares of maximum area that burned by this fuel type over a 24 hour simulation.

These results indicate that the areas occupied by fuel type FBFM 2 are at high risk for catastrophic fires, areas occupied by fuel type FBFM 5 and FBFM 8 are at medium risk, and areas occupied by FBFM 9 are at low risk. These results also support the theory that anthropogenically induced changes to the fire regime (cattle grazing and fire suppression) lead to larger and more dangerous fires than would be possible in a ponderosa pine forest with natural fire regimes. The next step of this research was to track and extrapolate the spread of the high risk vegetation types to help mitigate the risk of crown level fires in these areas.

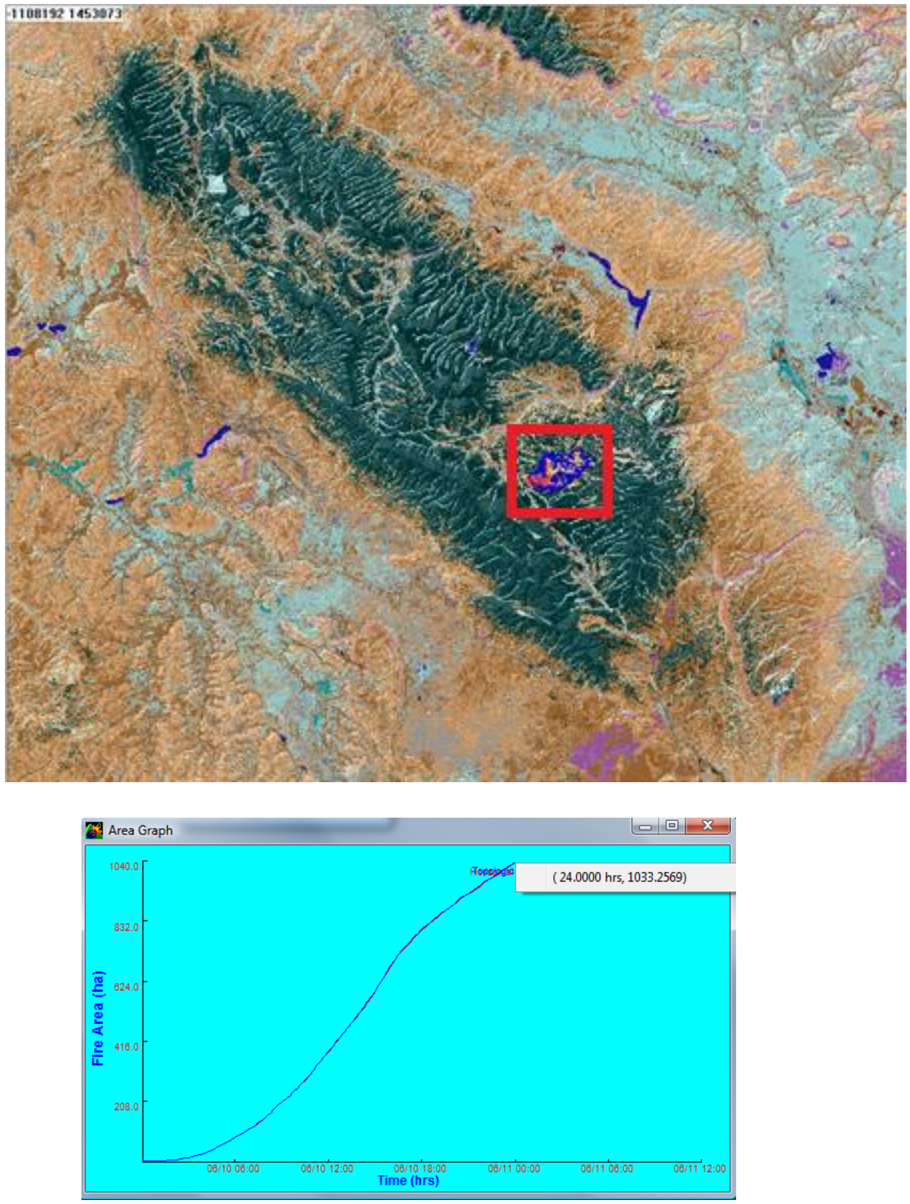

Figure 26. A FARSITE Simulation of fire run for 24 hours in FBFM 2 vegetation.

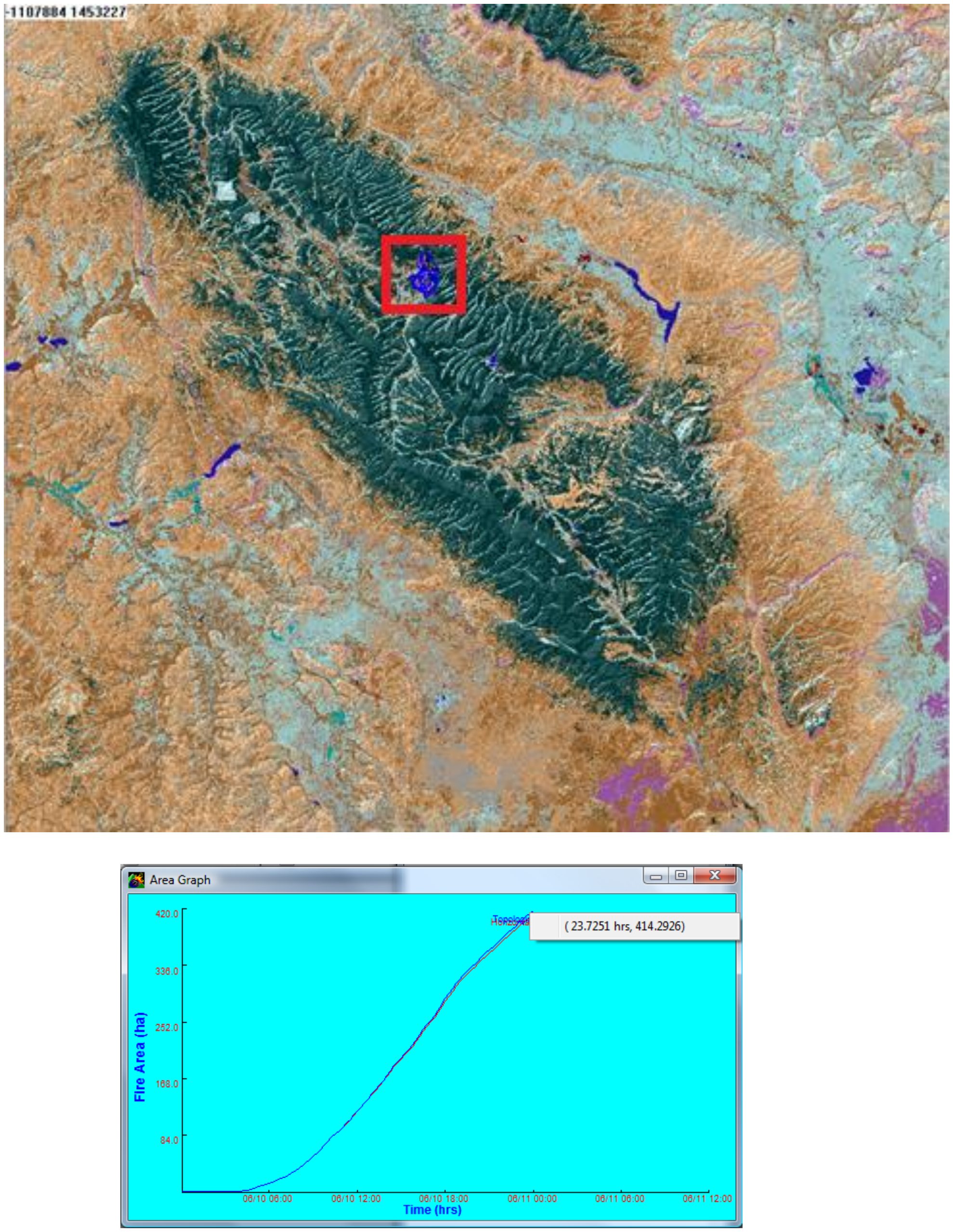

Figure 27. A FARSITE Simulation of Fire run for 24 hours in FBFM 5 and 8 vegetation.

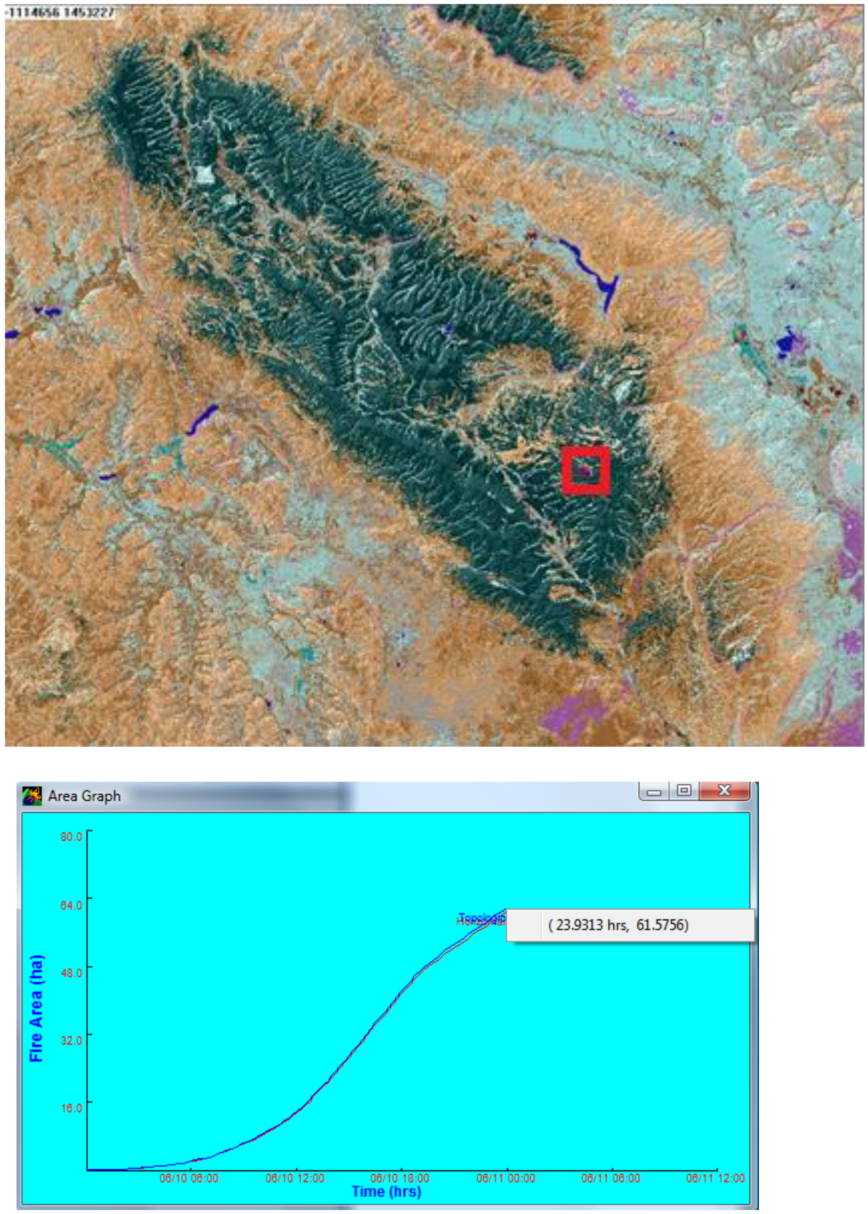

Figure 28. A FARSITE Simulation run for 24 hours in FBFM 9 vegetation.

4.4 Supervised Classification

Using a remote sensing approach to study vegetation change in the Zuni Mountains presented some unique challenges. Since the Oso Ridge is part of the continental divide, orographic lift is commonplace, which makes availability of cloud free images difficult. Also, using Landsat imagery to study an area through the early 2000’s requires either correcting for Scan Line Failure of the Landasat 7 project, or settling for Landsat 5 imagery. To overcome these challenges, the images obtained between July and mid-September were used every four years to find a balance between cloud free imagery and match the phenological cycle of the training data, which were captured in August. Landsat 5 imagery was also chosen instead of Landsat 7 to avoid interference from Scan Line Correction. All images were captured at WRS2 Path 35 Row 36 to keep the study area the same. As such the following images and sensors were used for classification:

2014: Landsat 8 OLI captured August 11, 2014

2011: Landsat 5 TM captured July 1, 2011

2006: Landsat 5 TM captured September 6, 2006

2002: Landsat 5 TM Captured September 7, 2001

A supervised classification was run on each of these images using the image analyst extension of ArcGIS 10.3.1. A training set and spectral signature were developed for each of the following classes: grasslands, shrublands, ponderosa pine/ douglas fir forests, old lava for the malpais lavaflow to the southwest, and desert for the large area surrounding the Zuni Mountains. A study boundary was drawn around the southern boundary through the North West section of the Zuni Mountains to assess vegetation across different areas including farms, peaks, ridges, and valleys.

Once the supervised classification was complete, the classified raster layers were clipped to the defined study area and converted to integers in the raster calculator.

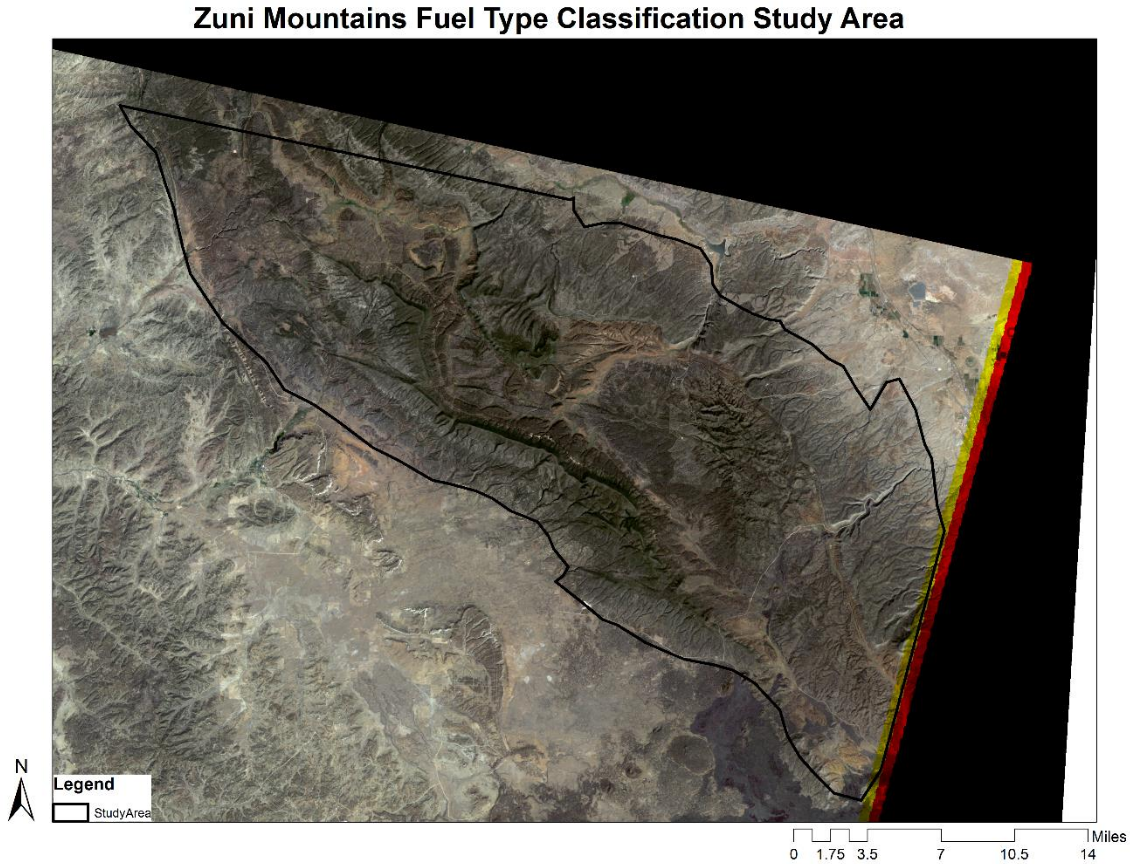

Figure 29. Supervised Classification Study Area.

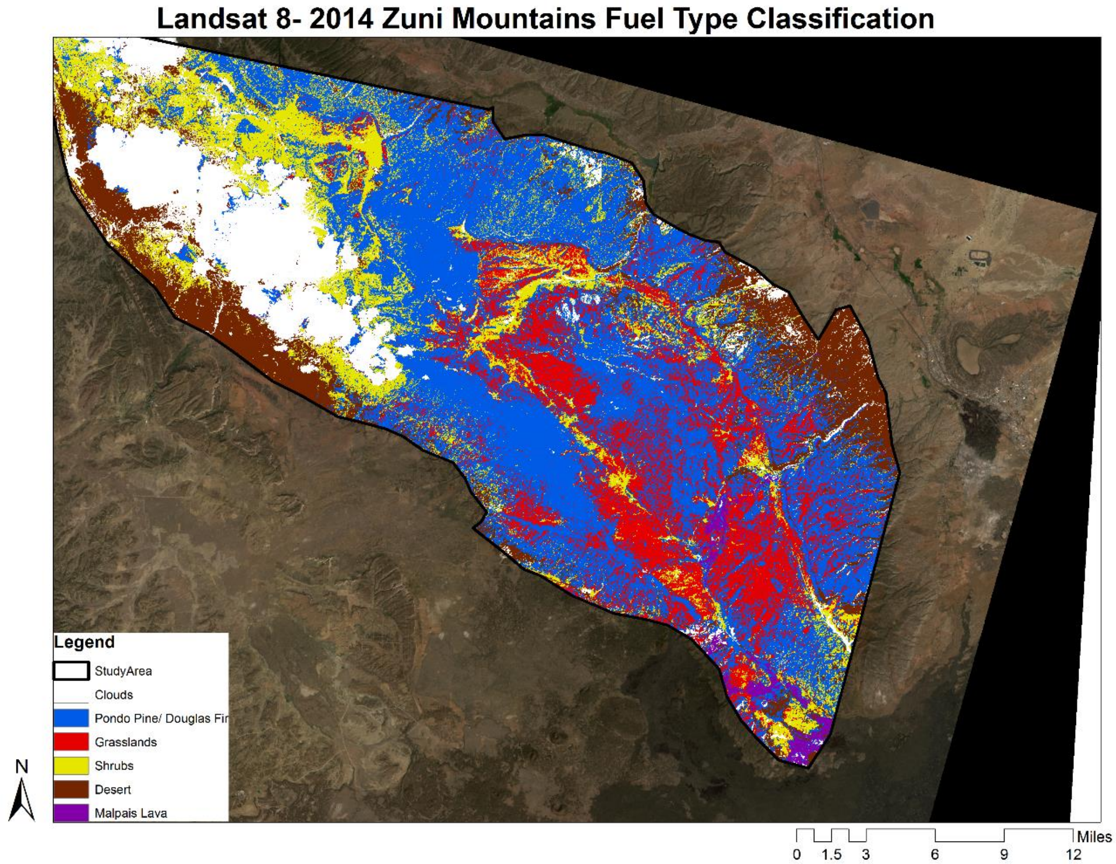

Figure 30. Supervised Classification Results 2014.

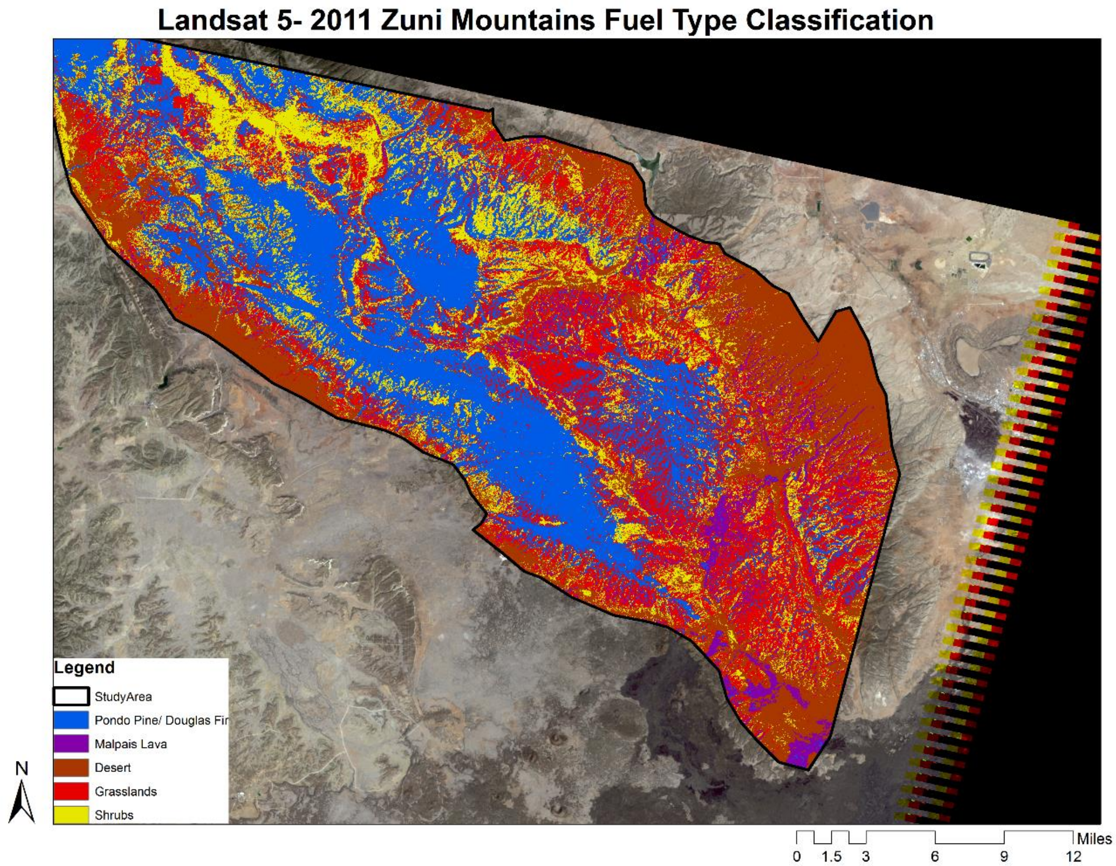

Figure 31. Supervised Classification Results 2011.

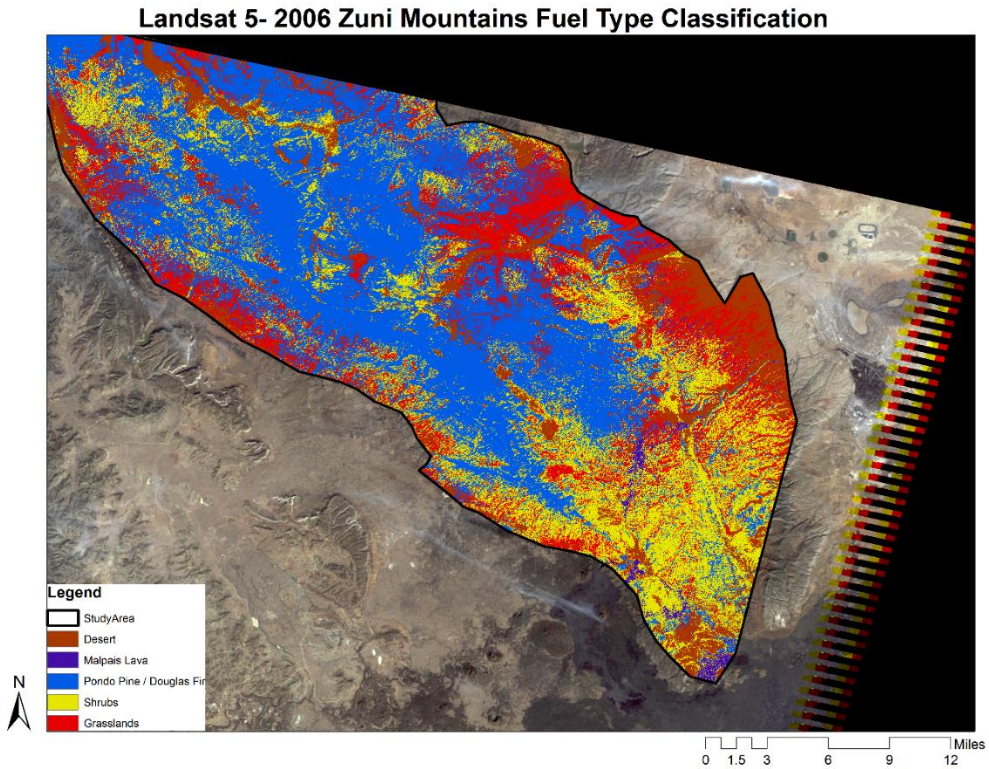

Figure 32. Supervised Classification Results 2006.

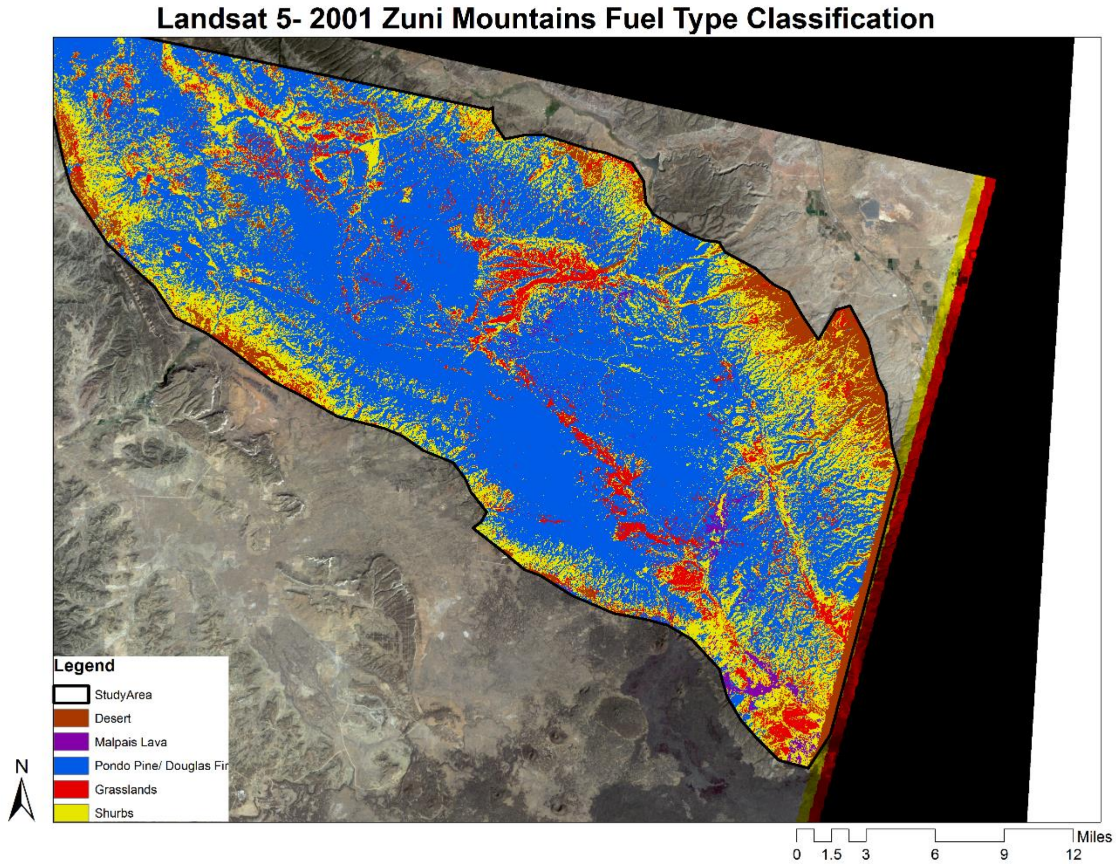

Figure 33 Supervised Classification Results 2001.

These results suggest an interesting shift in vegetation types through the Zuni's since the early 2000's. The estimated area for each fuel type (Table 3) as per the classification results within the study area demonstrate a decrease in the volume of ponderosa pine and douglas fir forests as well as shrublands and an increase in grasslands. The fuel types and the area covered by them as per the LANDFIRE classifications of the same area (Table 4) show a similar trend, although less drastic than the supervised classification. While the supervised classification showed an increase of 1,075.70 hectares (119,522 pixels) for grasslands over the 13 year study period, the Landfire classification suggests the increase was only 205 hectares (22,833 pixels).

Similarly, while the supervised classification showed a decrease in fuel model 9 area by of 2,700 hectares (300,012 pixels), the Landfire classification suggested a decrease of only 341 hectaures (31,891 pixels) in ponderosa pine and douglas fir forests.

Table 3

Counts of classes within the Study Areas (in hectares)post classification

Ground Class	2014	2010	2006	2001
Clouds	2201.184	N/A	N/A	N/A
PP/DF (FBFM9)	5,982	4,669	6,769	8,683
Shrublands (FBFM5/8)	1,967	2,418	3,312	3,616
Grasslands (FBFM2)	2,237	3,608	2,531	1,162
Malpais Lava	170	684	220	21
Desert	2,002	3,181	1,818	888

Table 4

Counts of classes within the corresponding LANDFIRE classifications (in hectares)

Ground Class	2013	2010	2006	2001
Clouds	N/A	N/A	N/A	N/A
PP/DF (FBFM9)	7,055	7,056	7,072	7,342
Shrublands (FBFM8)	1,359	1,366	1,548	1,346
Grasslands (FBFM2)	17,211	1,761	1,547	1,516
Shurblands (FBFM5)	3,396	3,438	3,325	3,625
Desert	N/A	N/A	N/A	N/A

CHAPTER V

CONCLUSION

5.1 Overall Conclusions

This chapter discusses what is going to happen in Zuni mountains moving forward in terms of fire given the changes in different tree species and the distribution of these potential fire zones with regard to population concentration. The specific answers to the research questions and recommendations for emergency managers to prevent fire spread and its potential impact are also presented here.

There seems to be a slow decline of ponderosa pine and douglas fir forest within the Zuni Mountains. Whether this change is anthropogenic or climatically induced is still unknown. However, it is evident that a shift from fire tolerant forest compositions to less fire tolerant vegetation does not bode well for fire intensity or frequency in areas previously studied (Snider, 2006). Fortunately, human settlement in the Zuni Mountains is sparse and is mainly populated by livestock farmers in the valleys, so large scale fires in the area do not pose a large threat to human populations.

Climatically, there does not exist any significant correlation between climatic variables and acreage burned during historical fires in the area. When investigating the first research question (*What variables drive fire spread in the Zuni Mountains, New Mexico?)*, it was found that ignitions due to lightning in the area (the most common source of ignition) are statistically clustered around areas of high elevation. Also, a higher maximum relative humidity has historically been associated with smaller fire size. These results give land managers an idea of where to target fuel reduction efforts to best reduce risk of canopy fire and a better understanding of fire risk due to relative humidity.

Although fuel classifications like Anderson's 1982 classification are well understood in how they contribute to fire spread, they have not been used to study fire in the Zuni Mountains at the time of this study (Anderson, 1982). To answer the second research question (Which areas are prone to destructive and canopy level fires?), the FARSITE model was used to identify the areas and fuel types susceptible to fire spread. Fuel Model 2 was found to be responsible for spreading fire across large areas over a smaller time frame. Fuel Models 5 and 8 were found to be moderately conducive to fire spread and Fuel Model 9 was the least conducive. Although these results were expected, they provide a frame of reference when classifying fuel models through historic imagery of the area.

Implementing a remote sensing approach helped track the spread of these fuel types that are conducive to canopy fires back through time and answer the third research question (How have the fuel model types that are most conducive to fire spread changed in the past twenty years?). By understanding fire spread based on spatio-temporal distribution of fuel types responsible for catastrophic canopy fire, the fire managers can make more informed decisions about fire management in the area moving forward.

A gradual decline in ponderosa pine and douglas fir forests (Fuel Model 9), over the past 13 years was found. These species have slowly been replaced with fuel types more conducive to fire spread (Fuel Models 5/8 and 2). The classification results estimated a decrease of ponderosa pine and douglas fir forests by 31% in the past 13 years whereas the LANDFIRE fuel classification estimated a decrease of 3.1%. Although these rates may be due to differences in the phonologic cycle in which the images were taken and cloud cover, the maximum likelihood classification implemented in this study suggested a rapid encroachment of fuel types 5, 8, and 2 along the lower elevations in the Zuni Mountains in the southeastern and northern parts of the study area.

It is also interesting to take note of the changing precipitation amounts in the Zuni Mountains over the study period. A drought in 2000s in this area may have contributed to the decline of ponderosa pines (Figure 34). The sharp decline in precipitation seen between 2002 and 2003 would likely have led to a decline in ponderosa pine in the 2006 imagery. To illustrate this, annual precipitations for the Zuni Mountains were pulled from the National Climatic Data Center (NCDC) from a weather station located in Zuni, New Mexico (COOP:299897) Mountains at from 2001 to 2010 and graphed below.

A supervised classification of fuel types on such a small scale as the Zuni Mountains is rarely performed. Increasing the spatial and spectral resolution of the remote sensing data could potentially yield a more detailed overview of vegetation change in the area. Also, if private imagery at a high spatial resolution was available, a better validation could be performed instead of simply comparing one fuel model classification to another. Since the accepted fuel type classification from LANDFIRE is performed on a continental scale, it would be interesting to see if accuracy could be increased by focusing their methodology on smaller areas.

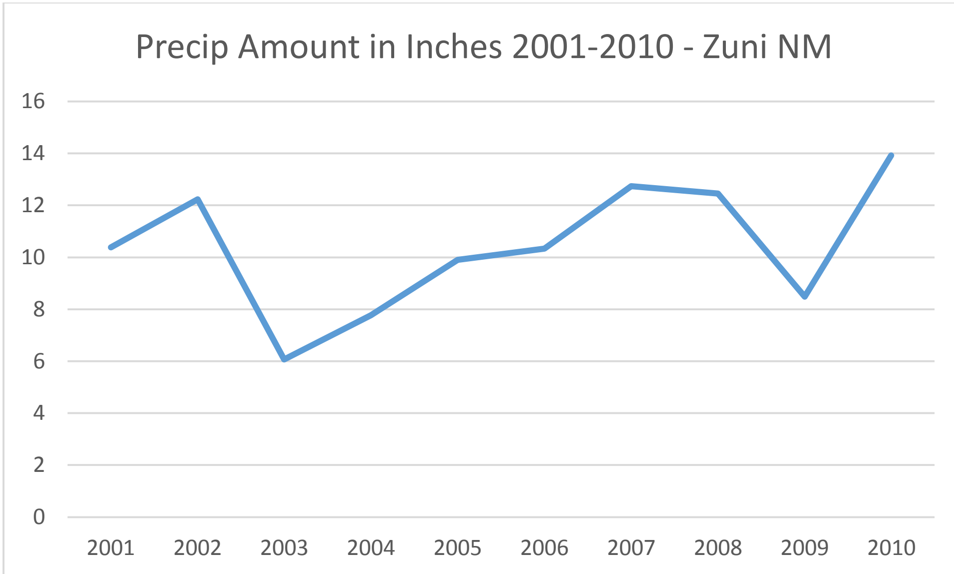

Figure 34. Historical precipitation amounts in Zuni, New Mexico (NCDC 2015).

REFERENCES

Allen, CD. 1984. Montane Grassland in the Landscape of the Jemez Mountains. MS thesis, University of Wisconsin.

Albinet, G. Searby, G. Stauffer, D. 1986. Fire propagation in a 2-D random medium. Journal de Physique 47. 1:1-7.

Albini, FA. 1976. Computer-based models of wildland fire behavior: a user's manual. Intermountain Forest and Range Experiment Station, Forest Service, US Department of Agriculture.

Anderson, H.E. 1982. Aids to determining fuel models for estimating fire behavior. USDA For.Serv. Gen. Tech. Rep. INT-122

Andrews, PL. Collin DB. Robert, CS. 2003. *BehavePlus Fire Modeling System: Version 2.0: User's Guide*. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Ahmed, A. Quegan, S. 2012. Analysis of Maximum Likelihood Classification on Multispectral Data. *Applied Mathematical Sciences. Vol 6:129. 6425-6436.*

AuClair AND, Carter, TB. 1993. Forest Wildfires as a recent source of CO2 at norther latitudes. *Canadian Journal of Forest Research.* 23: 1528-1536.

Azizi, Z. Najafi, A. Sohabi, H. 2008. Forest Canopy Density Estimating, Using Satellite Images. *The International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences. Vol XXXVII. Part B8.*

Beer, E. Enting, IG. 1990. Fire spread and percolation modeling. *Mathematical and Computer Modeling.* 13(11):77-96.

Dennison, P. Cova, T. Mortiz, M.A. 2007. WUIVAC: A Wildland Urban Interface Evacuation Trigger Model applied in Strategic Wildfire Scenarios. *Natural Hazards. 41:181-199.*

Dick-Peddie, WA. 1993. New Mexico Vegetation: past, present and future. Albuquerge NM: University of New Mexico Press: 244pp.

Euler, RC. 1954. Environmental adaptation at Sia Pueblo. *Human Organization.* 12(4) 27-30.

Finney, MA. 1994. Modeling the spread and behavior of prescribed natural fires. *Proc. 12th Conf. Fire and Forest Meterology*. 138-143.

Finney, MA. 1998. *FARSITE: Fire Area Simulator—model development and evaluation.*Res. Pap. RMRS-RP-4. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 47 p.

Finney, MA. 2004."FARSITE: Fire area simulator: model development and evaluation.".

Finney, MA., Ryan, K.C., 1995. *Use of the FARSITE fire growth model for fire prediction in the US national parks.* In: Sullivan, J.D., Luc Wybo, J., Buisson, L. Eds.., International Emergency Management and Engineering Conference. International Emergency Management and Engineering Society. Nice, France, pp. 183–189.

Flannigan, MD. Harrington, JB. 1987. A Study of the Relation of Meteorological \ Variables to Monthly Provincial Area Burned by Wildfire in Canada (1953-1980). *Journal of Applied Meteorology*. 27:441-452.

Flannigan, MD. Wotton, BM. 2001. Climate, Weather, and Area Burned. *Forest Fires: Behavior and Ecological Effects.* Academic Press. 335-357.

Frost, CC. 1998. *Presettlement Fire Frequency Regimes of the United States: A First Approximation*. Tall Timbers Fire Ecology Conference Proceedings No 20. 70-80.

Fule, P. 1997. Determining Reference Conditions for Ecosystem Management of Southwestern Ponderosa Pine Forests. *Ecological Applications.* 7(3): 895-908.

Fowler C. Konopik, E. 2007. The History of Fire in the Southern United States. *Human Ecology Review*. 14: 165-176.

Glover, VJ. Hereford, JP. 1986. Zuni Mountain Railroads Cibola National Forest, New Mexico. *Cultural Resources Management Report No 6. http://www.foresthistory.org/ASPNET/Publications/region/3/cibola/cultres6/index.htm* (Accessed March 3, 2015).

Grissino-Mayer, HD. Swetnam, T. 1997. Multi-century history of wildfire in the ponderosa pine forests of El Malpais National Monument. *New Mexico Bureau of Mines & Mineral Resources.* 156.

Keane, RE. Burgan, R. van Wagtendonk, J. 2001. Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, GIS, and biophysical modeling. *International Journal of Wildland Fire*. 10:301-309.

Kourtz, P. Nozaki, S. O'Regan, WG. Fisheries and Environment Canada. 1977. Forest Fires in the Computer. A model to predict the perimeter location of a forest fire. *Information Report FF-X-65*.

LANDFIRE.[Homepage of the LANDFIRE Program, U.S.Department of Agriculture, Forest Service; U.S. Department of the Interior], [Online]. Available: http://www.landfire.gov/index.php [2010, October 28].

Littell, JS. McKenzie, D. Peterson, DL. Westerling, AL. 2009. Climate and wildfire area burned in western U.S. ecoprovinces, 1916-2003. *Ecological Applications.* 19(4):1003- 1021.

Liu, Y. Stanturf, J. Goodrick, S. 2010. Trends in global wildfire potential in a changing Climate. *Forest Ecology and Management.* 259(4):685-697

Magnum, NC. 1997. In the land of frozen fires: history of human occupation in El Malpais country. *New Mex. Bur. Mines Miner. Resour. Bull.* 156:173-182.

Morgan, P. Hardy, C. Swetnam, T. Rollins, M. Long, D. 2001. Mapping fire regimes across time and space: Understanding coarse and fine-scale patterns. *International Journal of Wildland Fire*. 10: 329-342.

National Interagency Coordination Center. *Wildland Fire Summary and Statistics Annual Report2013. http://www.predictiveservices.nifc.gov/intelligence/2013_Statssumm/annual_report_2013.pdf*

NCDC. *Climate Data Online.* 2015 http://www.ncdc.noaa.gov/cdoweb/datasets/ANNUAL/stations/COOP:299897/detail (accessed December 30, 2016).

Nowacki, GJ. Abrams, MD. 2008.The Demise of Fire and the "Mesophication" of Forests in the Eastern United States. *Bioscience*. 582): 123-138.

Petersen, KL. 1985. The History of the Sagehen Flats: the pollen record. US Department of the Interior, Bureau of Reclamation, Denver, CO. 229-238.

Raish C. Gonzalez-Caban, A. Condie, CJ. 2005. The importance of traditional fire use and management practices for contemporary land managers in the American Southwest. *Environmental Hazards.* 6:115-122.

Radeloff, VC. Hammer, RB. Stewart, SI. Fried, JS. Holcomb, SS. McKeffry, JF. 2005. The Wildland-Urban Interface in the United States. *Ecological Applications.* 15(3):799-805.

Reeves, MC. Kost, JR. Ryan, KC. 2006. Fuels Products of the LANDFIRE Project. *USDA Forest Service Proceedings.* RMRS-P-41.

Richards, GD. 1995. A General Mathematical Framework for modeling two-dimensional wildland fire spread. *International Journal of Wildland Fire.* 2:63-72.

Richards, JA. Jia, X. 2006. *Remote Sensing Digital Image Analysis.* Germany: Springer-Verlag, Berlin, Heidelburg. 2006.

Rother, M. 2010. Influences of Climate and Anthropogenic Disturbances on Wildfire Regimes of the Zuni Mountains, New Mexico, U.S.A. *M.S. Thesis*.

Rothman, HK. 2005. *A Test of Adversity and Strength: Wildland Fire in the National Park System*. US Department of the Interior, National Park Service.

Rothermel, RC. 1972. A Mathematical model for predicting fire spread in wildland fuels. *USDA For. Serv. Gen. Tech. Rep. INT-143.*

Sacket, S. Haase, S. Harington, MG. 1994. Restoration of Southwestern ponderosa pine ecosystems with fire. *Proc. Sustainable Ecological Systems: Implementing an Ecological Approach to Land Management*, Flagstaff, AZ, USDA Forest Service General Tech. Rep. RM-247, 115-121.

Snider, G. Daugherty, PJ. Wood, D. 2006. The irrationality of continued fire suppression an avoided cost analysis of fire hazard reduction treatments versus no treatment. *Journal of Forestry*. 104(8):431-437

Smith, P. Bustamanta, M. "IPCC, 2014: Climate Change 2014: Agriculture, Forestry, and Land Use Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change." *Transport* (2014).

Stephens, SL. 1997. Evaluation of the effects of silvicultural and fuels treatments on potential fire behavior in Sierra Nevada Mixed Conifer Forest. *Forest Ecology and Management.* 105:21-35.

Schmidt, KM. Menakis, JP. Hardy, CC. Hann, WJ. Bunnell, DL. 2002. Development of Coarse Scale Spatial Data for Wildland Fire and Fuel Management. *USDA Forest Service General Technical Report.* RMRS-GTR-87.

Swetnam, T. Betancourt, J. 1997. Mesoscale Disturbance and Ecological Response to Decadal Climatic Variability in the American Southwest. *Journal of Climate.* 11:3128-3147.

Sheppard, PR. Comrie, AC. Packin, GD. Angersbach, K. Hughes, MK. 2002. The Climate of the US Southwest. *Climate Research.* 21:219-238.

U.S. Fire Administration. *Wildland Fires: A Historical Perspective.* 1(3). October 2000. http://nfa.usfa.dhs.gov/downloads/pdf/statistics/v1i3-508.pdf

USDA Forest Service. “Mt Taylor RD Planning Perscribed Burn”. 2014. http://www.fs.usda.gov/detail/cibola/news-events/?cid=STELPRD3794949 (accessed May 15 2014).

Van Wagner, CE. 1988.The historical patterns of annual burned area in Canada. *For. Chron.* 64:182-185.

Van Wagtendonk, JW. Root, RR. 2003. The use of multi-temporal Landsat Normalized Difference Vegetation Index (NDVI) data for mapping fuel models in Yosemite National Park, USA. *International Journal of Remote Sensing*. 24(8):1639-1651.

Veblen, TT. Kitzberger, T. Donnegan, J. 2000. Climatic and Human Influences on Fire Regimes in Ponderosa Pine Forests in the Colorado Front Range. *Ecological Applications.* 10(4):1178-1195.

Westerling, AL. Gershunov, A. Brown, TJ. Cayan, DR. Detting, MD. 2003. Climate and Wildfire in the Western United States. *American Meteorological Society*. 84(5): 595-605.

Westerling, AL. Hidalgo, HG. Cayan, DR. Swetnam, TW. 2006. Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity. *Science.* 313: 940-943.

"Zuni Mountain Fire Exceeds 8,000 Acres". *Albuquerque Journal*. June 16, 2004 http://www.abqjournal.com/fire/apzuni06-16-04.htm

"Zuni Mountain Landscape Strategy Collaborative Forest Landscape Restoration Program: Proposal for funding". 2012. *ForestGuild.org*, http://www.forestguild.org/CFLRP/Documents/ZuniMountainLandscapeStrategy.pdf