

**TWENTY YEAR (1984-2004) TEMPORAL AND SPATIAL
BURN SEVERITY PATTERNS INFERRED FROM SATELLITE IMAGERY
IN THE GILA NATIONAL FOREST, NEW MEXICO**

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AUTHORIZATION TO SUBMIT DISSERTATION

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ABSTRACT

Recent increasing trends in fire extent have been documented, yet little is known about how climate, vegetation and topography influence the patterns of burn severity (defined here as the magnitude of vegetation change one year post-fire relative to pre-fire conditions) of those fires. Here, I use satellite-derived burn severity data to infer 20-year patterns of burn severity relative to topography and climate. A time series of Landsat Thematic Mapper (TM) satellite images were used to map 114 fires (195,600 hectares burned) on the Gila National Forest from 1984-2004. Burn severity of each fire was inferred from the Relative Differenced Normalized Burn Ratio (RdNBR), a derivative of the differenced Normalized Burn Ratio. Data from nearby weather and Snowpack Telemetry (SNOTEL) stations were used to evaluate the influence of Snow Water Equivalent (SWE) and precipitation patterns on severe fire occurrence. Vegetation and Digital Elevation Model-derived Geographic Information System (GIS) layers were used to analyze the spatial patterns of severe fire occurrence on the 1.4 million-hectare Gila National Forest.

Severe fire occurred more frequently at high elevations, in mesic spruce-fir and mixed-conifer vegetation types, on north-facing slopes and where solar radiation and heat load index values were low. Within drier Potential Vegetation Types, severe fire occurred more frequently where moisture was more available. However, this pattern shifts at higher elevations, where areas with high heat load indexes and exposed south-facing slopes increased the probability of severe fire occurrence during this twenty-year period. Random Forest predictions of severe fire occurrence using topographic variables as predictors yielded classification accuracies of 82% and 63% for two (high severity vs. other) and three (low, moderate, high severity) class burn severity grids.

Spring precipitation, SWE and precipitation-free periods during the fire season (April-July) were significantly related to area burned and area burned severely, with the length of dry periods explaining most of the variation in fire extent and severity. These precipitation metrics were strongly correlated with 17-year patterns of spring and early summer vegetation green-up inferred from the Advanced Very High Resolution Radiometer (AVHRR).

Spectral indices used in this study were derived from the Landsat TM sensor. However the life of this sensor may be limited and other remotely sensed data on burn severity patterns

will likely be sought in the future. Using pre and post-fire images from 4 different satellite sensors with varying spatial and spectral resolutions (Quickbird, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Landsat TM and the Moderate Resolution Imaging Spectroradiometer (MODIS)) correlations between ground-based Composite Burn Index (CBI) plots and satellite-derived indices were compared. ASTER and Quickbird-derived indices performed as well or better than the Landsat-derived dNBR.

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CHAPTER 1

INTRODUCTION

Motivation and Study Area

Only in the last three decades have land managers and policy makers begun to accept the critical role that fire plays as a disturbance agent in most vegetation types in the United States. The shift from a paradigm of fire as destructive force (symbolized by suppression of all fires), to recognition of its critical ecological role is still underway. The role fire plays in ecosystems and its interactions with topography, vegetation and climate are typically described in terms of fire regimes. Fire regime attributes include descriptors like extent (area burned), rotation (time necessary for an area of a particular size to burn), and severity (magnitude of change caused by fire) (Agee 1993, Morgan et al. 2001). Scientists have learned a great deal from tree ring (Swetnam and Betancourt 1990, Kitzberger et al. 2007) and fire atlas data (Morgan et al. in press) about how general climate and vegetation patterns influence fire occurrence. However, beyond purely theoretical distributions that describe the probability of severe fire occurrence within vegetation types (Agee 1993, Thode 2005), little is known about the temporal and spatial aspects of fire severity. Research in this area is needed to advance our understanding of fire ecology, assist in the management of fire-prone forests and provide the context for future fire management decisions.

Remote sensing, the art and science of inferring land surface characteristics and change from a distance using airborne or spaceborne instruments is also a relatively new science. Combined with rapid increases in computing power and developments in Geographic Information Systems (GIS), remote sensing has opened new opportunities for studying broad-scale ecological patterns, and in particular characteristics of fire and post-fire effects. The Landsat TM 5 sensor, launched in 1982, has been continuously collecting information about the earth's surface since 1984. With a spatial resolution of 30 meters and blue, green, red, near-infrared and mid-infrared wavelength-specific bands, this sensor is well suited for inferring characteristics about changes in vegetation caused by fire. With more than 20 years

of data now available, Landsat offers uniquely rich temporal and spatial characteristics with which to evaluate post-fire ecological effects through time and over large areas.

In fall of 2003 I was given my first Landsat TM scene of the Gila National Forest. Scars from fires in years preceding the image acquisition were visible in the image. It quickly dawned on me that a new type of fire atlas derived from satellite imagery (rather than paper maps of fire extent) could provide not just perimeters, but also information about the ecological effects of those fires. The idea of a “burn severity atlas” developed rapidly from there. Others, including Nate Benson and Carl Key of the National Park Service, had already begun pursuing this idea and had recently begun the National Monitoring Trends in Burn Severity Program (MTBS), which attempts to map all major fires in United States since 1984.

Despite the abundance of satellite data now available from Landsat and other spaceborne sensors, a legacy of fire exclusion has left surprisingly few landscapes in the United States where fires have burned often enough and over large enough areas that studying burn severity patterns within a 20-year period makes any sense. In the southwestern US, the Gila Aldo Leopold Wilderness Complex (the Gila) is arguably the best. The area is large and remote with little residential development near the wilderness and National Forest boundaries. Elevations in the Gila range from 1400 to 3300 meters, supporting diverse vegetation groups ranging from grass and shrublands at the lowest elevations to spruce-fir forests at the highest elevations. Soils in the Gila are regionally simple but locally complex. The Gila National Forest, experiences frequent fires and has one of the most active Wildland Fire Use programs nationwide during the last 20 years. Under the program, lightning-ignited fires have been managed to burn with minimal suppression. The Rincon Mountains, Grand Canyon and other areas in southwestern US have active WFU programs. However, these areas are much smaller than the Gila. I’ve compared time series of Landsat images from the Gila NF and the Grand Canyon. Dozens of fires greater than 10,000 hectares (some as large as 50,000 ha) have burned in the Gila in the last twenty years. Of the approximately 50 fires that have burned in the Grand Canyon during the last 20 years, the largest fire is less than 10,000 hectares. This rich history of fires in the Gila, many of which have burned over periods of weeks and months during the natural fire season have created a truly unique

natural experiment. Although the accuracy is unknown, the fire perimeters derived from satellite imagery are almost certainly more accurate than perimeters derived from traditional atlases, and reflect interactions of fire with vegetation, climate, weather and topography.

Wildland Fire Use in the Gila has by most accounts been incredibly successful. Hundreds of thousands of hectares have burned since the program was implemented. Despite the overall success of this program, management of fire in the Gila sometimes clashes with other resource values. The Gila hosts several federally listed endangered species including the Gila trout (*Onchorynchis gilidae*). Four genetically distinct species of Gila trout live in streams in the Gila River and its tributaries and nowhere else on earth. Each species is replicated such that a genetic reservoir exists in case a severe disturbance like fire eradicates one population. In the last 20 years, several fires have caused post-fire debris flows that have wiped out some populations, and millions of dollars have been spent on emergency fish evacuations or on repopulation of streams where fish have been removed by fire. Despite the overall success of the Wildland Fire Use program in the Gila NF, important questions remain about how best to continue active burning while preserving and protecting endangered species like the Gila trout. In the longer term, we are wise to ask to what extent fire-induced habitat modifications (e.g. debris flows, woody debris accumulation) were an important component of the long-term survival of the Gila trout. Where populations were connected and able to repopulate, fires would likely not have threatened the long-term survival of Gila trout. Today, however, we are forced to deal with the short-term implications of fire on Gila trout. Where are severe fires likely to occur? Are populations of Gila trout large enough and their habitat connected enough to survive some amount of fire-induced ash and debris flow associated with fire? How can we best protect remaining populations of these fish while continuing to allow fires to play their natural role? Answering these questions is critical to the long-term viability of the Gila trout as well as the success of a continuing Wildland Fire Use program on the Gila National Forest.

My dissertation is composed of 5 chapters, broadly aimed at describing where on the landscape and under what climatic conditions severe fires are likely to occur. Each chapter

has been prepared as a manuscript intended for a specific journal. Therefore, the reader may find some formatting differences among the different chapters.

Chapter 2 is a synthesis and review of remote sensing techniques for assessing post-fire effects. The idea for the chapter came from Dr. Alistair Smith and Penny Morgan, who along with Leigh Lentile and I, synthesized the research and wrote this manuscript. It has already been published in the International Journal of Wildland Fire with Penny Morgan, Mike Falkowski, Pete Robichaud, Andrew Hudak, Nate Benson, Paul Gessler and Sarah Lewis as additional co-authors.

The Landsat TM 5 sensor may be nearing the end of its life and has already long outlived its projected lifetime while a defective Landsat TM 7 sensor has limited utility for precise remote sensing analysis. Alternative data sources may be sought in the future that can supplement or replace Landsat. In chapter 3 of my dissertation I use four satellite sensors (Quickbird, ASTER, Landsat and MODIS) to infer burn severity on a portion of the Dry Lakes Fire that burned in New Mexico in 2003. This manuscript has now been submitted to the International Journal of Wildland Fire with Penny Morgan, Alistair Smith and Lee Vierling as co-authors.

In Chapter 4 of my dissertation, I describe twenty-year temporal patterns of burn severity and their relationship to snow pack and precipitation on the Gila NF. This study is now published in the journal Geophysical Research Letters with Penny Morgan, Michael Crimmins, Kirk Steinhorst and Alistair Smith as co-authors.

Chapter 5 is a follow-up study to chapter 4 and reflects my attempt to find a mechanism to support my conclusions from chapter 4. Here, I use a time series of Advanced Very High Resolution Radiometer data (AVHRR) to infer vegetation green-up patterns from 1989-2005. I then use multivariate statistical analyses to demonstrate the statistical relationships between patterns of vegetation green-up preceding and during the fire season (April-July) and the precipitation metrics described in Chapter 4. The AVHRR data used in this study are also significantly correlated with fire severity patterns in this study area. This is the first time that

relationships between annual and seasonal patterns of vegetation productivity have been directly linked to fire activity.

In chapter 6, I focus on the topographic and vegetation controls on burn severity within the Gila NF. Using variables derived from a Digital Elevation Model (DEM) and a Potential Vegetation Type (PVT) data layer developed specifically for the Gila NF by Keane et al. (2001), I describe the patterns of severe fire occurrence with respect to topography. I then use a machine-learning algorithm called Random Forests to predict severe fire occurrence from the same topographic variables. The findings from this chapter will be combined with work by hydrologists at the Rocky Mountain Research Station in Boise to develop a risk assessment map for Gila trout on the Gila NF. The resulting products will be integrated into a decision support tool that fire managers and wildlife biologists could use to make decisions about how to manage fires on the Gila NF.

In the final chapter, I summarize the key findings from this work. I outline ongoing and future research that will follow from the work presented in this dissertation.

The work presented here describes new patterns and processes relevant to the science and management of wildland fire. This is the first time that temporal trends in burn severity have been evaluated for so many different fires, highlighting several important climate variables that influence the occurrence of severe fire in this study area. Of potentially broad significance is the finding that alternative mechanisms besides warming spring temperatures and early snowmelt described by Westerling et al. (2006) may be partly responsible for the recent increase in fire activity in the southwestern US. The novel use of time series of AVHRR data highlights some of the mechanisms that, interacting with those climate variables influence the potential for severe fire occurrence. The strong patterns of burn severity relative to topography and vegetation described in chapter 6 compliment these findings, demonstrating the underlying “bottom up” influence of landscape and vegetation patterns that interact with climate to modulate fire extent and severity in this study area.

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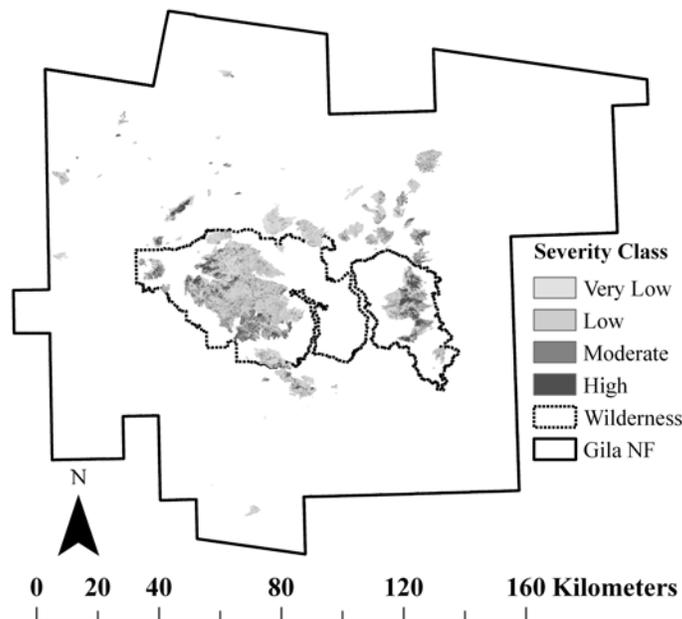


Figure 1. Gila National Forest with the Gila Aldo Leopold Wilderness Complex (dotted line) and burn severity data for all fires from 1984-2004.

CHAPTER 2

Remote Sensing Techniques to Assess Active Fire Characteristics and Post-fire Effects

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Abstract

Space and airborne sensors have been used to map area burned, assess characteristics of active fires and characterize post-fire ecological effects. Confusion about fire intensity, fire severity, burn severity, and related terms can result in the potential misuse of the inferred information by land managers and remote sensing practitioners who require unambiguous remote sensing products for fire management. The objective of this paper is to provide a comprehensive review of current and potential remote sensing methods used to assess fire behavior and effects and ecological responses to fire. We clarify the terminology to facilitate development and interpretation of comprehensible and defensible remote-sensing products, present the potential and limitations of a variety of approaches for remotely measuring active fires and their post-fire ecological effects, and discuss challenges and future directions of fire-related remote sensing research.

Extra Keywords: fire intensity, fire severity, burn severity, ecological change, fire perimeters, fire atlas, burned area, radiative energy, NBR, FRP, NDVI

1. Introduction

Fire is an important ecosystem process that significantly impacts terrestrial, aquatic and atmospheric systems throughout the world. Over the past few decades, wildfires have received significant attention because of the wide range of ecological, economic, social and political values at stake. Additionally, fires impact a wide range of spatial and temporal scales, and stakeholders are only beginning to understand relationships between pattern, process and potential restorative measures.

At the local scale, fire can stimulate soil microbial processes (Wells *et al.* 1979; Borchers and Perry 1990; Poth *et al.* 1999; Wan *et al.* 2001; Choromanska and DeLuca 2002), promote seed germination, seed production, and sprouting (Lyon and Stickney 1976; Lamont *et al.* 1983; Hungerford and Babbitt 1987; Anderson and Romme 1991; Perez and Moreno 1998), and combust vegetation, ultimately altering the structure and composition of both soils and vegetation (Ryan and Noste 1985; Wyant *et al.* 1986; Ryan and Reinhardt 1988; McHugh and Kolb 2003).

At the regional scale, fires may also affect the quantity and quality of water yield (Minshall *et al.* 2001; Spencer *et al.* 2003), accelerate erosion and sedimentation (Scott and Van Wyk 1990; Robichaud *et al.* 2000; Ice *et al.* 2004) and result in a myriad of beneficial, neutral or detrimental consequences for aquatic systems (Gresswell 1999; Vieira *et al.* 2004). Wildfires are potentially hazardous to human life and property (Bradshaw 1988; Beebe and Omi 1993; Cohen and Butler 1998; Cohen 2000), and the economic costs of fire management and suppression in the United States have over the past two decades been among the highest on record. Departure from the historical frequency, timing, extent and severity of some fires, particularly in the dry forests, has led to significant ecological and policy changes (Delasalla *et al.* 2004). Fire is also important in the creation and maintenance of landscape structure, composition, function and ecological integrity (Covington and Moore 1994; Morgan *et al.* 2001), and can influence the rates and processes of ecological succession and encroachment. At local to regional scales, criteria pollutants (e.g. ozone, carbon monoxide, nitrogen dioxide,

sulphur dioxide, and particulate matter) emitted by fires impact air quality (Hardy *et al.* 2001) and raise concern about risks to human health (Brauer 1999).

At the global scale, fire emissions have direct and significant impacts on atmospheric and biogeochemical cycles and the Earth's radiative budget (Crutzen and Andreae 1990; McNaughton *et al.* 1998; Andreae and Merlet 2001; Smith *et al.* 2005a). The influence of fire spans a wide range of temporal and spatial scales, and the interpretation of causal factors, fire effects and ecosystem response is a challenge to both research and management.

These issues of scale and more practically, the size and inaccessible nature of many wildfires, make remotely sensed data an important and widely applied resource for fire science and management (Hardy *et al.* 1999). Space and airborne sensors have been used to assess environmental conditions before and during fires and to detect changes in post-fire spectral response (Table 1). Remotely sensed data have been used to detect active fires (Roy *et al.* 1999; Ichoku *et al.* 2003), map fire extents at local (Parsons 2003; Holden *et al.* 2005), regional (Eva and Lambin 1998; Smith *et al.* 2002) and continental (Scholes *et al.* 1996) scales; estimate surface and crown fuel loading (Nelson *et al.* 1998; Means *et al.* 1999; Lefsky *et al.* 2002; Falkowski *et al.* 2005); assess active fire behavior (Kaufman *et al.* 1998; Wooster *et al.* 2003; Smith and Wooster 2005; Dennison *et al.* 2006, in press); examine post-fire vegetation response (Turner *et al.* 1994; White *et al.* 1996; Diaz-Delgado *et al.* 2003); and identify areas where natural recovery may prove to be problematic (Bobbe *et al.* 2001; Ruiz-Gallardo *et al.* 2004). Multi-temporal remote sensing techniques have been effectively employed to assess and monitor landscape change in a rapid and cost effective manner. Remotely sensed data give researchers a means to quantify patterns of variation in space and time. The utility of these data depends on the scale of application. Coarse-scale maps of fire regimes based largely on remotely sensed biophysical data have been used for planning and prioritizing fuels treatments at regional and national levels, but may have limited local applicability (Loveland *et al.* 1991; Morgan *et al.* 1996; Hardy *et al.* 1999; Morgan *et al.* 2001). Higher spatial-resolution remote sensing of spectral patterns before, during and after wildfire may facilitate prediction of areas likely to burn or experience uncharacteristic effects

when they burn, and assist with strategic decisions about fuels management before fires occur, suppression as fires burn, and post-fire rehabilitation efforts.

Since the mid 1980s, numerous remote sensing techniques have been developed to assess how 'severe', in terms of ecological change, a fire is on both local and regional ecosystems. Early studies inferred fire-caused vegetation change from spectral changes measured by the satellite sensor, while more recent studies have sought to relate ecological measures to fire-induced physical changes on the land surface (e.g., Milne 1986; Jakubauskas *et al.* 1990; White *et al.* 1996). When vegetation is burned there is, at the spatial resolution of most satellite sensors (pixel size > 30m), a drastic reduction in visible to near-infrared surface reflectance [i.e. 0.4 – 1.3 μm] associated with the charring and removal of vegetation (Eva and Lambin 1998; Trigg and Flasse 2000). At finer spatial resolutions (pixel size < 5m), the combustion of large quantities of wood (or other fuels) can in some cases lead to an increase in surface reflectance due to the deposition of white ash (Landmann 2003; Smith and Hudak 2005; Smith *et al.* 2005b; Roy and Landmann 2005). This is typically accompanied by a rise in short wave infrared reflectance [i.e. 1.6 – 2.5 μm] and brightness temperatures, which is attributed to the combined effects of increased soil exposure, increased radiation absorption by charred vegetation, and decreased evapotranspiration relative to the pre-fire green vegetation (Chuvienco and Congalton 1988; Eva and Lambin 1998*a,b*; Stroppiana *et al.* 2003; Smith *et al.* 2005b). The degree of post-fire change may vary depending on vegetation type, annual differences in growing season weather, and overall time since fire. For this reason, stratification among vegetation types, comparison of images with similar vegetation phenology, and image differencing techniques including pre-, immediate-post, and one-year post-fire images have been recommended to assess fire effects and ecological change (White *et al.* 1996; Cocke *et al.* 2005; Hudak *et al.* 2005). Further fire effects such as canopy mortality, ground charring and changes in soil color can be readily detected, provided sensors have adequate spatial and spectral resolution (Pereira and Setzer 1993; White *et al.* 1996).

The observation of broad spectral changes due to burning has led to the use of a variety of spectral indices (combinations of different sensor bands), including the Normalized Burn Ratio (NBR), the difference in the Normalized Burn Ratio between pre- and post-fire images

(dNBR) and the Normalized Difference Vegetation Index (NDVI). NBR and dNBR are widely used to infer fire severity from remotely sensed data (Key and Benson 2002; Key and Benson 2005; van Wagtenonk *et al.* 2004; Smith *et al.* 2005b; Cocker *et al.* 2005; Roy *et al.* 2006) and are commonly used to produce maps for Burned Area Emergency Response (BAER) teams (Parsons 2003). Other recent remote sensing research has focused upon the development of techniques used to remotely infer fire behavior and fuel combusted through the assessment of thermal infrared imagery (Kaufman *et al.* 1998; Wooster 2002; Riggan *et al.* 2004; Smith and Wooster 2005; Wooster *et al.* 2005; Roberts *et al.* 2005; Zhukov *et al.* 2006).

The objective of this paper is to review current and potential remote sensing tools and techniques that can quantify and monitor fire-related processes that cause change in soil and vegetation. For information on the remote sensing of fuels and fire hazards, see Keane *et al.* (2001), Hardy (2005), and Tian *et al.* (2005). In this paper, we clarify the terminology to facilitate development and interpretation of comprehensible and defensible remote-sensing products, present the potential and limitations of a variety of approaches for remotely measuring active fires and their post-fire ecological effects, describe field assessment of surface change, and discuss management implications and future directions of fire-related remote sensing research.

2. Fire and Fire Effects Terminology

The terms fire intensity, fire severity and burn severity are three descriptors that exist on a temporal continuum associated with pre-fire conditions, active fire characteristics, and post-fire ecosystem response (DeBano *et al.* 1998; Jain *et al.* 2004).

Although remotely sensed imagery has been used to assess each of these descriptors, there remains a need to clarify linkages between remotely sensed measurements and the physical or ecological processes that each measure infers. Additionally, overlapping and inconsistent use of fire terminology has created a need to spell out the ecological meanings and implications of each term. For instance, the term “severity” is frequently used to describe the

magnitude of ecological change caused by fire. In the remote sensing literature, severity has been related to vegetation consumption (Conard *et al.* 2002; Miller and Yool 2002; Kasischke and Bruhwiler 2003; Zhang *et al.* 2003), white ash production (Landmann 2003; Smith and Hudak 2005), changes in surface reflectance (White *et al.* 1996; Key and Benson 2002; Smith *et al.* 2005b), alteration of soil properties (Ketterings and Bigham 2000; Lewis *et al.* 2006); and long-term post-fire vegetation mortality and recovery (Patterson and Yool 1998). In some cases, fire descriptors of intensity and severity are used interchangeably within the same document (e.g., White *et al.* 1996; Diaz-Delgado *et al.* 2003; Landmann 2003), and exactly what is being measured is often unclear or largely inferential. More often, however, severity is used very generally, without reference to a specific process (soil, hydrologic, vegetation) or vegetation strata (understory, overstory). In particular, the terms fire severity and burn severity are often confused and used interchangeably in both the ecological and remote sensing literature. Although this confusion has been highlighted by recent studies (e.g., Hardy 2005; Smith *et al.* 2005b), clarification of the different fire descriptors is needed.

One of the sources of confusion arises due to where on the temporal gradient the fire severity and burn severity terms lie. Fire severity is usually associated with immediate post-fire measures (e.g. vegetation consumption, vegetation mortality, soil alteration), while burn severity relates to the amount of time necessary to return to pre-fire levels or function. For example, in grassland ecosystems fires typically consume large portions of aboveground biomass, which would be indicative of high fire severity. However, in these ecosystems grasses and forbs typically rejuvenate quickly, indicating low burn severity. It is apparent that although fire severity may refer to short-term effects more directly related to fire intensity, the overlap between fire severity and burn severity is inevitable. We will clarify each term and then propose adoption of more precise and descriptive terminology.

2.1 Fire Descriptors

Fire intensity is a description of fire behavior quantified by the temperature of, and heat released by, the flaming front of a fire (Whelan 1995; Neary *et al.* 1999; Morgan *et al.* 2001).

Fire intensity is measured by two factors: the rate of spread, calculated by the number of meters burned per second, and energy flux, the amount of kilowatts a fire generates per meter burned. Physical attributes used to quantify fire intensity include temperature, flame length duration and the emission of pyrogenic gases. Fire intensity and rate of spread are partly controlled by factors such as vegetation type (forests, shrubs, herbaceous plants), vegetation moisture content, weather (wind speed, atmospheric stability, and humidity) and topography (DeBano *et al.* 1998). Fire intensity can be measured by measuring kinetic temperature (via thermocouples), via thermal remote sensing systems, or by inferring observations of flame length and fire spread rate (Key and Benson 2002; Smith *et al.* 2005b; Dennison *et al.* 2006). Fire intensity is typically reported in kilojoules per second per meter.

Fire severity integrates active fire characteristics and immediate post-fire effects on the local environment. Even though the fire intensity often influences fire severity (Key and Benson 2002; van Wagendonk *et al.* 2004), these phenomena are not always correlated (Hartford and Frandsen 1992; Neary *et al.* 1999; Miller and Yool 2002; Smith *et al.* 2005b). Fire severity differs from fire intensity by its focus on how much of the duff, logs, and other dense organic matter on the soil surface burns (Parsons 2003; Ice *et al.* 2004). Fire behavior may be simultaneously influenced by several factors, resulting in high vertical and horizontal spatial heterogeneity of fire effects and subsequent ecological responses. Fire duration, which determines the amount of heat transferred to the soil and the amount of aboveground vegetation consumed, often has a greater impact on fire severity than the fire intensity (Neary *et al.* 1999). In turn, the nature of the fuels available for burning and fire duration determine the energy produced by the fire and are the contributing forces for many ecosystem fire effects (DeBano *et al.* 1998). For example, a high-intensity, fast-moving fire transfers less heat into the soil (i.e., most of the energy is dissipated horizontally and vertically via radiation or convection) than a low-intensity slow-moving (or smouldering) fire, and therefore leaves belowground process largely intact.. A high intensity fire of the former type may actually benefit the ecosystem by increasing the amount of available nutrients (Neary *et al.* 1999), and as such would be correctly described as low fire severity. In contrast, a low-intensity slow-moving fire impacts above- and below-ground plant components, killing a majority of the

vegetation, and therefore might have a more immediate impact on ecosystem health, and as such would be correctly described as high fire severity.

Burn severity incorporates both short and long-term post-fire effects on the local and regional environment. Burn severity is defined by the degree to which an ecosystem has changed due to the fire (Morgan *et al.* 2001; Key and Benson 2002; National Wildfire Coordinating Group 2005). Vegetation influences burn severity as biomass production often exceeds decomposition and some plants are specifically adapted to the characteristics of fires that commonly burn in these systems (Key 2005) (Fig. 1). Several aspects of burn severity can be quantified, but burn severity cannot be expressed as a single quantitative measure that relates to all resource impacts (DeBano *et al.* 1998; Robichaud *et al.* 2000). Relative magnitudes of burn severity are often expressed in terms of post-fire appearance of vegetation, litter, and soil. However, it is easier to measure what remains following fire than it is to know what was there before the fire. Although the physical manifestations of burn severity vary continuously, for practicality burn severity is often broadly defined and partitioned into discrete classes ranging from low (less severe) to high (more severe). Burn severity is typically assessed after a fire by measuring soil characteristics (char depth, organic matter loss, altered infiltration, and color) (Ryan and Noste 1985; DeBano *et al.* 1998; Neary *et al.* 1999) and aboveground vegetation consumption, mortality, scorch and recovery (Morgan *et al.* 2001). Burn severity serves as a baseline with which other data layers may be integrated.

Severe burns have long lasting ecological effects because they alter belowground processes (hydrologic, biogeochemical, microbial), which are essential to the health and sustainability of aboveground systems (Neary *et al.* 1999). Long-term ecological changes can potentially result from severe fires that remove aboveground overstory vegetation, even if impacts to belowground processes are minimal. Post-fire weather conditions can also influence severity, in particular when looking at vegetation change through time in relation to severity (Key 2005). Remotely sensed measures of burn severity may reflect inter-annual phenological change of vegetation, as well as the interaction of longer-term climate patterns such as drought. Image acquisition date, in relation to time of field data collection and time since fire, may be more important than type of imagery or index used to compare severity

measures. Hudak *et al.* (2004) attributed low correlations between field and remotely sensed measures of burn severity to post-fire wind and precipitation events that may have transported ash and soil off-site following fire in chaparral systems in southern California.

Burn severity is not a direct measure, but a judgement that changes based on the context. It is likely that severity may vary depending on the issue or resource being addressed (e.g., vegetation mortality, soil erosion, soil nutrition etc.), leading Jain *et al.* (2004) to propose abandoning the categorical descriptions of low, moderate, and high severity, commonly used in the ecological and remote sensing literature. Burn severity classifications are often driven by objectives. For example, burn severity mapping is an important part of the analysis of US Burned Area Emergency Response (BAER) teams including emergency treatment specifications and identification of potential deleterious effects. Burn severity mapping is used in post-fire project planning and monitoring, by researchers exploring relationships between pre-, during, and post-fire characteristics and response, and, in some cases, as evidence in legal debates. Considerable confusion surrounds definitions and interpretations of burn severity. However, these terms are useful descriptors that are deeply entrenched in the nomenclature of fire managers and rehabilitation teams to describe post-wildfire effects in the United States. Thus wholesale abandonment is neither possible at this stage, nor advisable given the diverse array of users employing these descriptors.

In the fire-behavior and fire-effects modelling communities, the terms **first-order** and **second-order fire effects** are often used, although these terms do not directly correspond to the descriptors of fire intensity, fire severity and burn severity. **First-order fire effects** include the direct and immediate fire effects on the environmental parameter of interest. First-order fire effects such as plant injury and death, fuel consumption and smoke production are the direct result of the combustion process and, as such, are best described as active fire characteristics. **Second-order fire effects** result from the indirect effects of fire and other post-fire interactions such as weather and, as such, are best described as post-fire effects. Some important second-order fire effects are smoke dispersion, erosion, and vegetation succession which may be evident immediately to many decades after a fire (Reinhardt *et al.* 2001). To non-fire modelers this jargon can be confusing as these terms do not implicitly

describe a temporal dimension, but rather suggest relative degrees of severity within a given parameter (e.g. degrees or ‘orders’ of soil char or biomass combustion within an area).

Therefore, to assist in separating the different remote sensing studies that have been described as quantifying fire intensity, fire severity, and burn severity, this paper will henceforth refer to these fire descriptors as either ‘**active fire characteristics**’ or ‘**post-fire effects**’. The active fire characteristics include ‘immediate’ variables that can only be measured during the fire’s combustion (whether flaming or smoldering), while post-fire effects include short and long-term effects that impact the environment following the passage of the fire. Following a brief description of the available satellite sensor systems, this paper will provide a review of how remotely sensed imagery has been used to monitor and evaluate these fire descriptors.

2.2 Remote Sensing Instruments and Platforms

Many different sensor platforms and instruments have been used to remotely map and monitor active fire characteristics and post-fire effects (Table 1) In terms of the remote sensing of active fire characteristics and post-fire effects, we can divide the available sensor systems into passive/active and then further into aerial/satellite sensors. The most commonly used type of active sensor being used to evaluate fire-related information is light detection and ranging (Lidar) systems. These provide information on the elevation (and thus relative height) of a surface by measuring the time taken for a pulse of laser light to journey between an sensor and a surface. Lidar systems are predominately aerial-based and have widely used to characterize individual-tree and stand-level canopy structure (e.g., Means *et al.* 1999, 2000; Lefksy *et al.* 1999, 2005; Falkowski *et al.* 2006; Hudak *et al.* 2006), with limited studies directly evaluating fire fuels information (Seielstad and Queen 2003).

The majority of remote sensing systems that have been used to infer active and post-fire characteristics have been passive sensors measuring the reflection or emission of electromagnetic radiation from surfaces. Multispectral airborne and satellite sensors use radiometers that are sensitive to narrow bandwidths (bands) of the electromagnetic spectrum. For example, the Landsat Thematic Mapper (TM) sensor has 6 bands that span visible to mid-infrared wavelengths, and a thermal band that is sensitive to the surface brightness

temperature. Like many satellite sensors, the Landsat TM bandwidths were selected in part to maximize sensitivity to the dominant factors controlling the spectral reflectance properties of green vegetation.

The application of aerial or satellite sensors depends greatly on the intended application. The data quality issues of most satellite sensor imagery are widely known and several software packages exist that can assist in their analysis. In contrast, aerial systems add a level of complexity with most images needing “fixes” to correct for the pitch, roll, and yaw of the aircraft. The advantages of aerial acquisitions are that imagery with very high spatial resolutions (<0.5m per pixel) can be acquired. More importantly, aerial systems have the potential to allow a ‘rapid response’ system to be implemented. Given flight clearance, most aerial systems can fly on demand and thus characterize specific fire-related processes in a timely manner. There is a clear ‘trade-off’ when comparing aerial and sensor acquisitions. Although the user is restricted by the imagery having both a specific pixel size and the sensor flying at specific times of day (and night), the sensor will always acquire the data even when aerial acquisitions are not permitted.

3. Remote Assessment of Active Fire Characteristics

Numerous measures have been applied to describe active fire characteristics within both the remote sensing and fire ecology literature (Table 2). The remote assessment of active fire characteristics can, however, be grouped into two main application branches:

- (i) The detection of actively burning areas using a combination of optical and thermal imagery, and
- (ii) The use of thermal imagery (airborne and satellite) to estimate the energy radiated from the fire as it burns.

3.1 Detecting and Counting Active Fires

The accurate identification of fire events has been recognized by international research organizations, such as the International Geosphere and Biosphere program (IGBP), to be crucial in the development of a broader understanding of how fire extent and frequency impact global environmental processes (Giglio *et al.* 1999; Ichoku *et al.* 2003). Actively burning fires can be detected using thermal infrared bands (3.6 – 12 μm range) from coarse spatial resolution sensors such as the Advanced Very High Resolution Radiometer (AVHRR), the Along Track Scanning Radiometer (ATSR), or the Moderate Resolution Imaging Spectroradiometer (MODIS). Thermal emissive power from fires is orders of magnitude more intense than from the surrounding background. Such high contrast allows active fires to be reliably detected even when the fire covers small fractions (for example $< 0.01\%$, or 1 ha of a 1 km^2 area) of the pixel (Robinson 1991). Numerous algorithms for active fire detection have been developed (e.g. Kaufman *et al.* 1990; Justice *et al.* 1993, 1996; Flasse and Ceccato 1996; Pozo *et al.* 1997; Fraser *et al.* 2000; Seielstad *et al.* 2002; Dennison *et al.* 2006, *in press*) and prior reviews of several of these methods have been presented by Li *et al.* (2001) and Ichoku *et al.* (2003).

Broad-scale fire effects have been inferred from active fire images (Pozo *et al.* 1997; Roy *et al.* 1999; Fraser *et al.* 2000; Li *et al.* 2000*a, b*). Pozo *et al.* (1997) applied a technique in southeastern Spain in which the total area burned was calculated by measuring the total number of active fire pixels over the period of a fire event. A major limitation of such methods is that they only identify pixels containing active fires when the satellite passed overhead. The limited temporal coverage of most satellite sensors, (e.g., Landsat 5 acquisitions occur about once every 16 days) likely results in major errors of omission, which are magnified by the effects of cloud cover (Pereira and Setzer 1996; Fraser *et al.* 2000). Such limitations have been addressed by incorporating active fire pixel detection techniques with methods employing spectral indices to detect the area burned in either neighboring pixels or the same pixels days after the active fire (Roy *et al.* 1999; Barbosa *et al.* 1999*a, b*; Fraser *et al.* 2000). Fraser *et al.* (2000) developed the automated Hotspot And NDVI Differencing Synergy (HANDS) technique for use in boreal forest environments. The HANDS technique combined the simple active-fire pixel method with a post-fire burned area mapping technique utilizing presumed post-fire decrease in surface near-infrared reflectance.

The relationship between burned areas from HANDS and Landsat TM has also been reported over a wide range of boreal fires in Canada (Fraser *et al.* 2004). Although these hotspot-based techniques have been widely applied to data acquired from the mid-infrared channel (3.55-3.93 μm) of the AVHRR sensor (Kaufman *et al.* 1990; Justice *et al.* 1996; Randriambelo *et al.* 1998; Fraser *et al.* 2000), the availability of more thermal channels from the MODIS sensor increases the potential for such techniques (Kaufman *et al.* 1998; Justice *et al.* 2002). An added advantage of MODIS is that it is now available on two satellites allowing 2-4 daily (night and day) image acquisitions. Considerable research is ongoing to develop applications of the freely-available MODIS products for detecting active fires and burned area.

3.2 Estimating the Energy Radiated by a Fire

The energy produced by a fire is lost to the environment through a combination of conduction, convection and radiation (Kaufman *et al.* 1998a). Thermal infrared remote sensing research has focused on inferring information from the radiative component, as the convective and conductive components are difficult to directly quantify. The earliest research and development into using remote sensing to analyze the energy radiated by fires was performed in the late 1960s by the Fire Lab in Missoula, where a US Department of Defence sensor was modified and tested for fire detection (Wilson *et al.* 1971). Subsequent research has demonstrated that thermal infrared remote sensing data can provide a useful measure of the rate of energy released from fire, termed the fire radiative power (FRP) (Kaufman *et al.* 1998a; Wooster 2002; Wooster *et al.* 2003, 2005; Butler *et al.* 2004; Riggan *et al.* 2004; Ichoku and Kaufman 2005; Roberts *et al.* 2005; Smith and Wooster 2005). Simply stated, this method relies on the assumption that the amount of energy produced by combusting a quantity of mass X is half that emitted by burning a quantity of the same material of mass $2X$. Assuming that the proportions of energy emitted as conductive, convective and radiative are constant, the measure of the radiative energy released from burning biomass is indicative of the biomass combusted. If the combustion efficiency of the biomass is known, (as established through burn experiments), then the biomass burned to produce a measured quantity of heat can be calculated (Wooster 2002; Wooster *et al.* 2005).

FRP has been derived from spectral measurements made by the MODIS sensor, and is directly related to the rate of fuel combusted (Kaufman *et al.* 1998; Wooster *et al.* 2003). FRP for a given fire pixel from the MODIS 3.9 μm band is defined as (Wooster *et al.* 2003):

$$\text{FRP} = A_{\text{samp}} [1.89 \times 10^7 (L_{\text{MIR},f} - L_{\text{MIR},\text{bg}})] * 10^{-3} \quad (1)$$

where FRP is in kW; $L_{\text{MIR},f}$ and $L_{\text{MIR},\text{bg}}$ denote the radiance recorded in the MODIS MIR channel ($\text{W}/\text{m}^2/\text{sr}/\mu\text{m}$) at the fire and background ‘non-fire’ pixels, respectively; A_{samp} is the MODIS ground sample area at the relevant scan angle of the observation. The middle infrared region of the electromagnetic spectrum is particularly suited to the FRP method, since the radiative energy component as given by the Planck function for temperatures consistent with wildfires (i.e. 1000-2000 K) is approximately ten times greater than the emittance of the Earth’s ambient surface in this wavelength region (Wooster *et al.* 2005).

The integration of FRP over the lifetime of the fire provides a means to calculate the Fire Radiative Energy (FRE), which is the total energy radiated by the fire (i.e., the area under the FRP with time curve). FRE has been experimentally demonstrated to be directly proportional to the total amount of fuel combusted (Kaufman *et al.* 1996; Wooster 2002; Wooster *et al.* 2005; Roberts *et al.* 2005). The underlying assumption of the FRP method is that if sufficient observations are made during the fire, it should be possible to well-characterize the FRP with time curve (e.g., see Roberts *et al.* 2005). Remote instantaneous measures of FRP can be produced using the MODIS ‘active fire product’. Apart from this product (i.e., MOD14), other sensor systems are being evaluated to characterize both FRP and FRE measures from wildfires. Wooster *et al.* (2003) used the Bi-directional InfraRed Detection (BIRD) sensor to measure FRE from Australian fires; Roberts *et al.* (2005) measured FRP with the Spinning Enhanced Visible and Infrared Imager (SEVIRI); and Wooster *et al.* (2005) used 4 km spatial-resolution GOES-8 imagery to detect MIR fire pixels. Although, MODIS affords a temporal resolution of >2 images per day, via both the TERRA and AQUA satellites, this

temporal sampling interval is only sufficient for a ‘snap-shot’ estimate of FRP. In contrast, research with both aerial systems (e.g. Riggan *et al.* 2004) and the geo-stationary SEVIRI satellite sensor (Roberts *et al.* 2005) have allowed near-continuous FRP measurements.

FRP data from MODIS were recently used to compare energy radiated from boreal forest fires in Russia and in North America (Wooster and Zhang 2004). The Russian fires radiated considerably less energy and subsequently emitted fewer emissions than American fires, owing in part to a difference in dominant fire type. Fires in Russian boreal forests are typically driven by surface fuels and burn less fuel per unit area, in contrast with the more intense crown fires that burn more fuel per unit area in North America. Mottram *et al.* (2005) supported these findings, by demonstrating that the observed FRP differences were not due to associated sensor effects. In a further application of FRP, Smith and Wooster (2005) in a study in African savannas, demonstrated that the FRP of backing fires was an order of magnitude lower than that observed in heading fires; a finding consistent with field measures of fire line intensity (Trollope *et al.* 1996). Therefore, FRP could potentially be used to remotely discern the fire type that burned an area. Additionally, as the conductive component of the energy might be expected to impact post-fire processes, more research is needed to understand the relationships between FRP and impacts on soil, forest floor, and vegetation recovery.

4. Remote Assessment of Post-Fire Effects

The assessment of short and long-term fire effects on local, regional and global processes has been conducted using a wide range of in-situ and remote methods (Table 3). The application of remotely sensed imagery to monitor and assess the impacts of fire on local and regional environments can be broadly divided into:

- (i) Burned area and perimeter methods, and
- (ii) Methods that assess a surface change (cover, fuel, etc.) caused by the fire

4.1 Burned Areas, Fire Perimeters, and Spatial Heterogeneity

The simplest and most common remote measure of post-fire effects is a map of the area burned. The raster nature of digital imagery naturally lends itself to burn area mapping. A fire perimeter map is a vector representation of the burn area boundary that can be rendered digitally from remotely sensed imagery or by moving along the burn area boundary on the ground with a global positioning system (GPS). Reliance on overhead imagery is increasing as it offers a birds-eye view of burned areas and therefore has a decided advantage over field fire perimeter maps, which often fail to capture the heterogeneity and patchiness of fires and fire effects. Yet field fire perimeter maps will remain important not only for validation purposes, but when the atmosphere is too cloudy or smoky (a problem minimized using infrared imagery) to obtain useable imagery, and when the remotely sensed data is not available when needed. “Real-time” data acquisition, however useful to map burned areas, is commonly constrained by logistical and economic factors. More thorough reviews of the comparatively large body of burn area mapping via remote sensing literature have already been accomplished (e.g., Barbosa *et al.* 1999b; Pereira 2003), so here we will only note a few key research papers and previous reviews.

Remote assessment of burned areas has been conducted using a wide variety of aerial and satellite sensors. Since the 1980s, the majority of techniques have been developed for data acquired from the Advanced Very High Resolution Radiometer (AVHRR) sensor, and as such were restricted to a limited number of reflectance and thermal bands (Flannigan and Vonder Harr 1986; Kaufman *et al.* 1990; Setzer and Periera 1991; Kasichke and French 1995; Fernandez *et al.* 1997; Razafimpanilo *et al.* 1997; Randriambelo *et al.* 1998; Barbosa *et al.* 1999; Fraser *et al.* 2000; Fuller and Falk 2001; Al-Rawi *et al.* 2001; Nielsen *et al.* 2002). Although data from the AVHRR sensor is restricted by a relatively large pixel size (i.e., 1.1 km) global data have been obtained from a series of different satellites for over twenty years, and importantly, these data can be obtained at no cost. These data have enabled the long-term monitoring of large-scale fires in remote and isolated areas (e.g. African savannas and boreal regions). In more recent years, other sensors have been developed that provide a greater selection of bands.

These sensors, which have also been used to evaluate burned area, include the Advanced Long Track Scanning Radiometer (Eva and Lambin 1998a; Smith *et al.* 2002), MODIS (Roy *et al.* 2005), SPOT-VEGETATION (Stroppiana *et al.* 2002; Silva *et al.* 2003; Zhang *et al.* 2003), and Landsat (Salvador *et al.* 2000; Russell-Smith *et al.* 2003; Holden *et al.* 2005). Several regional scale products also exist that apply tailor-made algorithms to various satellite sensors (i.e., GBA2000, GLOBSCAR, The MODIS burned area product, etc.). Essentially, until recently (e.g. MODIS on TERRA and AQUA), there was not a space-based system design specifically to “look” at terrestrial earth. Previous to MODIS, most other sensor systems (e.g. AVHRR - an atmospheric mission), were opportunistic exploitations of band ratios for terrestrial products (e.g. NDVI).

The vast majority of satellite-based burned area mapping studies use information on differences in spectral or thermal properties of a land surface before and after a fire (e.g. Eva and Lambin 1998a, b; Barbosa *et al.* 1999; Fraser *et al.* 2000; Fuller and Falk 2001; Nielsen *et al.* 2002). Novel spectral indices including the Burned Area Index (Chuvieco *et al.* 2002), a thermal variation of the Global Environmental Monitoring Index (Pereira 1999); different thermal variations of the VI-3 index (Barbosa *et al.* 1999); thermally enhanced variations of common indices (Holden *et al.* 2005); and the Mid-infrared Bispectral Index (Trigg and Flasse 2001) have recently been developed and tested. A limited number of studies have also investigated the utility of principal components analysis (Richards and Jia 1999; Garcia-Haro *et al.* 2001; Hudak and Brockett 2004), texture analysis (Smith *et al.* 2002; Hann *et al.* 2003), spectral mixture analysis (Cochrane and Souza 1998; Sa *et al.* 2003), and neural networks (Al-Rawi *et al.* 2001). Although most studies do compare a suite of several methods within their particular study areas (e.g. Pereira 1999; Chuvieco *et al.* 2002; Holden *et al.* 2005), there still exists a need to assess how such methods work over the wide range of fire-affected environments.

Remotely sensed data have been used to retrospectively produce fire history, frequency and perimeter information (Chuvieco and Congalton 1988; Salvador *et al.* 2000; Hudak and Brockett 2004, Holden *et al.* 2005), although the data availability can limit such approaches. Such data are of immediate use to land managers in the United States as a potential surrogate

for fire perimeter data, ‘digital fire polygon histories’ or ‘fire atlases’, which are typically collated after the fire (sometimes weeks, months or years later) using a combination of paper records, aerial photographs, and local experience (Morgan *et al.* 2001). Land management agencies in the United States including the National Park Service (NPS) and the United States Forest Service (USFS) have begun developing atlases of burned area (or fire atlases) from satellite imagery, field maps, and aerial photographs as part of fire management efforts. As yet, no standardized protocol has been developed for building digital fire perimeter layers, which may lead to questionable quality, accuracy and reproducibility of atlases developed from these data sources (Morgan *et al.* 2001).

Fire atlases provide perspectives on the location and spatial distribution of fires on the landscape. Limitations include the relative lack of details on the spatial variation within fires, as well as the changes in mapping standards, methods, and recording over time (Morgan *et al.* 2001). The overall accuracy is largely unknown. Remote sensing has great potential to supplement existing information on fire regimes by enabling researchers to acquire data at broad spatial scales, in areas where fire atlases do not exist, and in previously inaccessible areas. However, only ~30 years of satellite images and ~70 years of aerial photographs are available now, and many people want to characterize fire regimes over much longer time intervals including those less influenced by land use.

High to moderate spatial resolution (pixel sizes between 1 and 30 m) satellite sensors, such as IKONOS, SPOT, and Landsat, enable the assessment of the degree of heterogeneity within large and remote fires. Turner *et al.* (1994) used Landsat TM imagery to explore the effects of fire on landscape heterogeneity following the 1988 Yellowstone fires. Smaller patches (< 1250 ha) were often more heterogeneous in fire effects, whereas larger patches were more homogenous in effects (Turner *et al.* 1994). The heterogeneity of fire effects in patches of various size, shape, and distance from living vegetation differentially impact species and influence successional trajectories (Pickett and White 1985; Turner *et al.* 1999). The fine-grained pattern of living and dead vegetation in patches ranging from square meters to thousands of hectares has major implications for recovery processes. Fire effects on soil and vegetation recovery rates may vary according to the specific interactions between fire

behavior and available fuels (Ryan and Noste 1985; Agee 1993; Turner and Romme 1994; DeBano *et al.* 1998). Remote sensing has great potential for studying fine-scale heterogeneity in fire effects across large areas immediately, during, and following fires; such studies could help us understand the causes and consequences of spatial variability in active fire and fire effects.

Remotely-sensed estimates of post-fire heterogeneity and spatial arrangement of burned patches have also been used to explore causal relationships (Rollins *et al.* 2001; Ruis-Gallardo *et al.* 2004), to document rates of recovery (Turner *et al.* 1994; Lentile 2004) and to prioritize areas for fuels reduction (Hardy *et al.* 1998; Hardy *et al.* 1999) and post-fire rehabilitation (Parsons 2003). Variation in fire effects due to weather, topography, and vegetation type and structure occurs even within large fires (Eberhard and Woodward 1987; Turner *et al.* 1994), and heterogeneous or “mixed” effects occur at some scale in all fires. Remotely sensed data allow researchers to conduct multi-scale and spatially explicit analyses of fires relative to topography, pre-fire vegetation structure or composition, and land use. Rollins *et al.* (2001) found that the area burned in 20th century fires in the Gila/Aldo Leopold Wilderness Complex (New Mexico) and the Selway-Bitterroot Wilderness areas (Idaho and Montana) was influenced by elevation, drought, and land use. Lentile (2004) found that pre-fire vegetation as influenced by stand history and abiotic gradients was the best predictor of post-fire effects and subsequent vegetation recovery in ponderosa pine forests of the South Dakota Black Hills. Turner *et al.* (1997) found significant effects of burn severity on most biotic responses including seedling density and cover following the Yellowstone fires. However, geographic location, particularly as it related to broad-scale patterns of serotiny in lodgepole pine (*Pinus contorta*), was the most important variable influencing forest reestablishment and pathways of succession (Turner *et al.* 1997). Post-fire tree regeneration is dependent on adequate seed dispersal and favorable microsite conditions, which are in turn related to competitive interactions at fine scales and landscape position (i.e., elevation, slope and aspect) at broad scales (Turner *et al.* 1994; Chappell and Agee 1996; Turner *et al.* 1997). Identification of factors influencing vegetation dynamics at multiple spatial scales will improve our understanding of how post-fire environmental heterogeneity relates to fuel accumulations and burn severity patterns in forested landscapes.

4.2 Remote Assessment of Surface Change

The analysis of post-fire effects from satellite imagery is not a new concept. Hall *et al.* (1980) classified multi-temporal Landsat MSS data of tundra fires in northwestern Alaska into light, moderate and severe fires as defined by the abundance of live post-fire vegetation. Over the next twenty years, others assessed the correlation of satellite data with different ground-based inferences of fire severity relating to vegetation consumption (Milne 1986; Miller and Yool 2002) and mortality (Patterson and Yool 1998).

Although the majority of remote assessments of post-fire effects have employed moderate spatial-resolution imagery from the Landsat sensor (30 m) (e.g. Fiorella and Ripple 1993; Turner *et al.* 1994; Viedma *et al.* 1997), other sensors such as SPOT XS (Henry and Hope 1998) and AVIRIS (Riaño *et al.* 2002) have also been used. Furthermore, the use of temporal series (Kushla and Ripple 1998; Henry and Hope 1998; Diaz-Delgado *et al.* 2003) and transformations (Henry and Yool 2002) are widespread. A wide range of remote sensing approaches have been applied across a diversity of fire regimes and environments including temperate coniferous stands in Oregon (Fiorella and Ripple 1993), chaparral vegetation in California (Henry and Hope 1998; Riaño *et al.* 2002), forested shrublands of southern Spain (Viedma *et al.* 1997), and coniferous forests of Yellowstone National Park (Turner *et al.* 1994).

The NDVI has been widely used to assess post-fire vegetation regrowth. This is appropriate as long as direct change in green vegetation cover is the main ecological process being measured. Several studies have applied NDVI and similar spectral indices to remotely assess post-fire effects (Fiorella and Ripple 1993; Henry and Hope 1998; Diaz-Delgado *et al.* 2003).

Significant developments in the spectral analysis of post-fire effects were made by Ekstrand (1994), who used field data, aerial photographs, and Landsat bands 4 and 5 to assess the degree of defoliation in Norway spruce stands in Sweden following fire. White *et al.* (1996) used field data, post-fire aerial photographs, and Landsat data within a variety of vegetation

types in the Flathead National Forest and Glacier National Park, Montana to compare remotely-sensed measures of severity. However these techniques in general do not relate actual spectral reflectance or brightness temperature collected in-situ to changes in radiance or thermal emittance as measured by the satellite sensor. In contrast, the development of two spectral indices, namely the mid-infrared bispectral index (MIRBI) for burned savanna surface assessment (Trigg and Flasse 2001) and the normalized burn ratio (NBR) (Equation 2) for ‘burn severity’ assessment of forested regions (Key and Benson 2002; Brewer *et al.* 2005), incorporate information of the spectral changes at the surface to infer post-fire effects.

$$\text{NBR} = (\rho_4 - \rho_7) / (\rho_4 + \rho_7) \quad (2)$$

Where, ρ_4 and ρ_7 are the surface spectral reflectances as measured in bands 4 (0.76 - 0.90 μm) and 7 (2.08 - 2.35 μm) of the Landsat Enhanced Thematic Mapper (ETM+) sensor.

Through collection of the spectral reflectance of pre- and post-fire surfaces, both of these methods incorporate the observed decrease in spectral reflectance in the visible-mid infrared region with a corresponding increase in mid-infrared (2.2 μm) reflectance. Although MIRBI was developed purely for burned area assessment, NBR and dNBR are widely being used to assess landscape-scale post-fire effects in the USA (Key and Benson 2002; van Wagtendonk *et al.* 2004; Brewer *et al.* 2005; Cocke *et al.* 2005) and in southern African savannas (e.g., Smith *et al.* 2005b; Roy *et al.* 2005). The band ratio that is now commonly referred to as NBR was initially developed and used by Lopez-Garcia and Caselles (1991) using ratios of Landsat bands 4 and 7 to map burned areas in Spain. In addition to measuring burned area, NBR is used to infer the degree of post-fire ecological change.

Van Wagtendonk *et al.* (2004) used the AVIRIS airborne hyperspectral sensor (a spectral instrument with 224 bands over the visible to mid-infrared range) to demonstrate that the largest spectral decrease in visible-near infrared reflectance between pre- and post-fire occurred at AVIRIS bands 47 (0.788 μm) and 60 (0.913 μm), while the largest spectral increase at mid-infrared wavelengths occurred at AVIRIS band 210 (2.370 μm). This research suggested that an improved NBR index could be used if imagery is available with these

wavelengths. In a similar fashion, Smith *et al.* (2005b) used ground-based spectroradiometer data in southern African savannahs to evaluate which Landsat spectral band ratios could best characterize fire severity, as defined by the duration of the fire at a point. Smith *et al.* (2005) demonstrated that simple ratios of the blue, green, or red bands with the Landsat SWIR (band 7) band each outperformed NBR. Therefore, NBR may not be the optimal remote indicator of post-fire effects, particularly in grasslands and shrublands. Further research to evaluate other approaches is warranted.

Others have sought to develop spectrally-derived post-fire effect metrics based upon the spectral reflectance of post-fire surfaces. The spectral reflectance of such surfaces can provide important insights into the degree of combustion completeness within the fire (McNaughton *et al.* 1998; Landmann 2003). Incomplete combustion produces residual carbon residue termed char or black ash (Robinson 1991; Trigg and Flasse 2000, Smith *et al.* 2005a), while complete combustion produces incombustible mineral residue termed white ash (Landmann 2003; Smith *et al.* 2005b). The quantity of white mineral ash produced per unit area could therefore be considered a measure of fuel consumption (Landmann 2003; Smith and Hudak 2005; Roy and Landmann 2005).

As stated earlier, in most environments and fire regimes, fires occur when the vegetation is either senesced or green and burning results in a net decrease in visible and near-infrared reflectance due to deposition of black char onto the surface (Robinson 1991; Eva and Lambin 1998a). This assumption is not always valid as complete combustion of large woody debris or large quantities of other fuels can produce patches of white mineral ash (i.e., silica), which is highly reflective (i.e., > 50%) between 0.3 and 2.5 μm (Landmann 2003; Smith *et al.* 2005b; Smith and Hudak 2005; Roy and Landmann 2005). In savannas, the post-fire surface reflectance typically decreases initially (< 20 minutes) as black ash replaces green vegetation, then increases when fires of long duration produce increasing quantities of white ash (Smith *et al.* 2005b; Roy and Landmann 2005). Smith *et al.* (2005b) demonstrated that in order for remotely sensed imagery to detect the spatial density of common white ash patches produced in woodland savanna fires, imagery with pixel sizes less than 5 m are needed and as such Landsat or imagery of similar spatial resolution (i.e., 15 to 60 m) are not suitable. The utility

of such a fine spatial resolution (i.e., 1-5 m) to detect patches of grey ash (which is simply a mixture of black and white ash) may be suitable in forested environments, where due to higher fuel loads the potential white ash patch density might be more significant (Smith *et al.* 2005; Smith and Hudak 2005). Therefore, in addition to remote sensing producing coarse-scale measures of area burned, very high spatial resolution imagery can potentially allow the remote assessment of more localized post-fire effects such as soil water repellency and vegetation mortality.

5. Field Assessment of Active Fire and Post-Fire Effects

The assessment of active fire and post-fire effects using remotely sensed data relies on a thorough understanding of what precise measure or process is being recorded on the ground. There are few, if any, consistent, quantifiable indicators of active and post-fire effects that are linked to remotely sensed data. Even ground-based indicators of fire effects are largely qualitative. Most studies have not incorporated scales of spatial variability in fire effects, thus limiting inferences that can be drawn from remotely sensed imagery. A lack of spatial context limits the confidence that can be placed in data of a particular resolution. Remote sensing has the potential to greatly increase the amount of information available to research and managers; however, it is still challenging to adequately characterize enough ground reference locations across the full range of variability in fire effects. Traditional study designs are typically too coarse to account for the varying scales of spatial complexity of fire effects. Field sampling to verify and characterize remotely sensed data must include sampling across the full range of variability in topography and vegetation structure and composition, in a time frame that will allow comparison between data sets. Quantification of the spatial variability of active and post-fire effects will provide a better understanding of the relevant scales at which research questions can be addressed with remotely sensed data and facilitate more effective and accurate application and interpretation of these data.

5.1 Field Measures of Active Fire Effects

Field measures of active fire characteristics have traditionally included in-situ measures such

as fire line intensity, flame length, and rate of spread of the fire front (Byram 1959; Albini 1976; Alexander 1982; Trollope and Potgieter 1985; Trollope *et al.* 1996), while more recent techniques have involved monitoring the temperature generated by the fire through the use of thermal infrared cameras (e.g. Riggan *et al.* 2004), spectroradiometers (Wooster 2002), heat sensitive crayons and paints (Hely *et al.* 2003*a, b*), and thermocouples (Stronach and McNaughton 1989; Stocks *et al.* 1996; Ventura *et al.* 1998; Molina and Llinares 2001; Smith *et al.* 2005*b*). In addition to instruments estimating fire thermal characteristics, other active fire characteristics can include assessment of trace gases within smoke plumes (Yokelson *et al.* 1996, 2003), which have important implications for regional air quality (Hardy *et al.* 2001), and in-situ assessment of fuel combusted (Trollope *et al.* 1996; Smith *et al.* 2005*a*).

The assessment of such parameters ideally requires unfettered access and timely (i.e., rapid response) measurements, both of which are often impractical during wildfires due to safety concerns. Remote locations of many fires make accessibility difficult. The application of remotely sensed optical and thermal imagery over large fires is a very important and necessary tool from the standpoint of both researchers and land resource managers.

5.2 Field Measures of Post-fire Effects

Field-based measures of fire effects have included an assessment of the change in soil color (Wells *et al.* 1979; Ryan and Noste 1985; DeBano *et al.* 1998; Neary *et al.* 1999); soil infiltration and hydrophobicity (DeBano 1981; Neary *et al.* 2004; Lewis *et al.* 2006); change in vegetation char and ash cover (Landmann 2003; Smith 2004); and amount of canopy scorch (Ryan and Reinhardt 1988; McHugh and Kolb 2003), tree scarring (Barrett *et al.* 1997; Grissino-Meyer and Swetnam 2000; Lentile *et al.* 2005), and organic fuel consumption (Lenihan *et al.* 1988). In an attempt to integrate a variety of these different post-fire effect measures, Key and Benson (2005) developed the ground-based Composite Burn Index (CBI). The CBI is based on a visual assessment of the quantity of fuel consumed, the degree of soil charring and the degree of vegetation rejuvenation (van Wagtenonk *et al.* 2004). CBI was designed as a field-based validation of the post-fire NBR spectral index. Fire effects on 30 m

x 30 m sample plots in five strata (soils, understory vegetation, mid-canopy, overstory, and dominant overstory vegetation) are evaluated individually and later combined for an overall plot-level burn severity value. The CBI method is rapid but very subjective.

6. Management Use of Remote Sensing Fire Effects Products

Remote sensing has the potential to provide data to address pre-, active, and post-fire characteristics over broad spatial scales and remote areas. However, the utility of such data is determined by temporal availability, spectral and spatial resolution of data, ground-truthing, and accurate interpretation at appropriate scales. Additionally integral to the advancement of remote sensing science is the quantification of variables that relate reflected or emitted radiation to ground and canopy combustion processes.

6.1 ‘Severity Classifications’ and Implications for Recovery

The occurrence of areas with similar fire environments, behaviors, and effects have led to the use of ‘severity classes’ within both the ecological and remote sensing literature (Ryan and Noste 1985; DeBano *et al.* 1998; Patterson and Yool 1998; Robichaud *et al.* 2000; Isaev *et al.* 2002; Diaz-Delgado *et al.* 2003). Yet there is considerable variation in low, moderate, and high severity classifications across regions and vegetation types (Fig. 1). Additionally, such burn severity classes have been inconsistently characterized in the remote sensing literature (Table 4). Many studies have relied on Ryan and Noste’s (1985) field characterization of post-fire effects and consistent visual assessment of ground and canopy fire effects (White *et al.* 1996; Ruiz-Gallardo *et al.* 2004). This classification provided a physical description for assessing the heat impact on overstory and understory vegetation, fuels, litter and soils. This model has been particularly useful to classify remotely sensed data because the discriminating features are detectable from satellite data (White *et al.* 1996). However in forested environments, remotely-sensed burn severity maps are often highly correlated with fire effects on overstory vegetation and exhibit low correlations with ground and soil variables where the vegetation occludes the ground (Patterson and Yool 1998; Hudak *et al.*

2004). Satellite imagery integrates changes in all parts of the forest, illuminating areas of low canopy closure, thus field assessment is necessary to verify which parts of the soil and vegetation strata are affected (White *et al.* 1996; Hudak *et al.* 2004; Cocke *et al.* 2005; Epting *et al.* 2005).

The degree of post-fire change typically increases with increasing vegetation mortality and proportion of charred soil and vegetation, and is linked with long duration of soil heating. For example, high burn severity classes are attributed to areas with high quantities of reddened soil and charred fuels and vegetation, but high burn severity may differentially impact ecosystem function depending on the pre-fire environment and vegetation types. For example, high burn severity resulting in increased water repellency may be common in California chaparral systems, yet rare in Alaska black spruce (*Picea mariana*) forests due to major differences in pre-fire soil and forest floor conditions, vegetation characteristics, and the relative occurrence of hydrophobic conditions (Fig. 1). Fires of all sizes will have some very localized effects that could be classified as high severity, and heterogeneous mosaics of fire effects occur at some scale in all fires (Fig. 2). The scale and homogeneity of fire effects is important ecologically. Often larger fires and large patches within fires are dominated by high severity components (Turner *et al.* 1994; Graham 2003). Hudak *et al.* (2004) suggested that high severity fires resulted in more spatially homogeneous fire effects on soil and vegetation than moderate or especially low severity fires, while Turner *et al.* (1994) found that large burns (~ 500-3700 ha) tended to have a greater percentage of crown fire and smaller percentages of light surface burns. Such severely burned areas may be more vulnerable to invasive species and soil erosion and may not return to pre-fire conditions for extended time periods. Patch size and the spatial mosaic of severity exert a strong influence on vegetation and nutrient recovery. Extensive areas of high burn severity may have fewer resprouting individuals or surviving trees to provide seeds (Turner *et al.* 1999). Unburned or lightly burned patches within high severity regions may provide seed sources to increase rates of plant recovery. The post-fire environment may change greatly within one year, some aspects of which may be predictable while others may be more driven by local and regional weather. Thus, depending on the timing and extensiveness of the field data collection effort, it is possible, for example via geostatistical kriging techniques, to infer ecological processes

from remotely sensed landscape patterns of fire effects and use this information to guide post-fire planning decisions.

6.2 Current Applications of Remote Sensing Fire Effects Products

The USFS Remote Sensing Applications Center (RSAC) and the USGS EROS Data Center (EDC) provide satellite imagery and image-derived products for managing and monitoring wildfires. RSAC produces Burned Area Reflectance Classification (BARC) maps for use by Burned Area Emergency Response (BAER) teams to identify social, ecological and economic values at risk. BARC products are based on dNBR values or, if pre-fire imagery is unavailable, then NBR values, from satellite imagery such as Landsat TM, Landsat Enhanced Thematic Mapper Plus (ETM+), SPOT, Multispectral (SPOT-Xi), and MODIS.

BARC maps are made as soon as possible during a significant wildfire event. These preliminary maps of post-fire condition are assessed and modified by BAER teams to aid in planning and implementing erosion mitigation in severely burned areas. BARC maps measure satellite reflectance and may be used by BAER teams to develop burn severity maps. BAER teams are assigned to measure and map severity based on ground and soil characteristics rather than canopy vegetation (Miller and Yool 2002; Parsons and Orlemann 2002; Lewis *et al.* 2006). However dNBR and NBR correlate more highly to vegetation attributes, especially those of dense upper canopy layers, rather than ground and soil attributes (Hudak *et al.* 2004).

Post-fire maps may substantially vary depending on when and how burn severity is assessed and for what objectives (Fig. 3). In many cases, managers have abandoned traditional sketch maps based on ground and helicopter surveys and have become dependent on the Landsat sensor and its associated BARC products to provide short-term decision support. There are varying levels of confidence associated with remote sensing products, and even very experienced managers need better initial ground validation and longer-term monitoring protocols to build confidence in these products. In a comparison of field validations of BARC maps, Bobbe *et al.* (2003) found the dNBR to be no more accurate than NBR for

indicating immediate post-fire effects. Some BAER teams have opted to use a combination of available imagery, existing GIS-based maps of topography and pre-fire forest condition, and local knowledge to guide post-fire assessments (Fig. 3). Severity assessments often fail to specifically identify whether vegetation, soil, or erosion potential was low, moderate or high, but have nonetheless been used to guide management activities such as post-fire timber harvest and reforestation activities. Often those other management activities would be better served with dNBR-based assessments using post-fire images taken one or two years post-fire accompanied by extensive ground-truthing (Cocke *et al.* 2005).

Determining the scale appropriate for management decisions may help to streamline approaches to post-fire rehabilitation. For example, it is often assumed that high burn severity classes are positively correlated with increasing soil water repellency (Doerr *et al.* 2000). Many studies have shown that pre-fire soil texture, the amount and depth of litter cover, soil water, soil organic matter, and the temperature and residence time of the fire all affect the degree of soil modification during fires and the resulting soil water repellency (Giovannini and Lucchesi 1997; Doerr *et al.* 2000; Wondzell and King 2003). Laes *et al.* (2004) attempted to use airborne high spatial/spectral resolution (4 m / 224 bands) hyperspectral imagery to identify surface water repellent soils over the Hayman fire in the summer of 2002. Hyperspectral imagery may have the potential to indirectly detect soil water repellency via detection of an ash signal in the soil (Lewis *et al.* 2006). Further study is needed to learn whether such high spatial and/or spectral resolution is needed to capture soil microsite heterogeneity, or if the resolution of 20 m SPOT-XI (4 bands) or 30-m Landsat-TM (6 bands) imagery may be adequate for BAER teams to identify large areas at risk for erosion, sedimentation, and landslide events. The acquisition of high spatial/spectral resolution data is comparatively expensive and logistically challenging, particularly if accomplished via aircraft in an active fire zone. Rapid and defensible delineation of large, severely burned areas with high potential for erosion could reduce the time necessary for BAER teams to conduct evaluations, improve recommendations for treatment, and decrease the amount of money spent on rehabilitation projects.

Remote sensors have the potential to be used for carbon budget investigations (Conard *et al.* 2000). Fires release carbon that is stored in trees, shrubs, and herbaceous vegetation, litter, duff, and even the soil if the fire is intense and long-lasting. Vegetation recovery draws carbon back in from the atmosphere. The dNBR technique is currently being applied by researchers around Yosemite National Park, CA to estimate fire-use emissions and monitor air quality. Other management applications of the dNBR include production of GIS-based fuel layers in Glacier National Park, MT and Grand Teton National Park, WY, as well as identification of extreme fire risk zones and propensity for post-fire erosion and landslides around the Salmon-Challis National Forest in Idaho. For more information, see <http://www.nrmssc.usgs.gov/research/ndbr.htm> and <http://giscenter.isu.edu/research/>

7.0 Future Directions of Fire-Related Remote Sensing Research

The influence of fire spans a wide range of temporal and spatial scales, and the interpretation of causal factors, fire effects, and ecological responses is a challenge to both research and management. As outlined in this review, current fire effects terminology is used inconsistently. However, simply classifying remotely sensed measures as either active or post-fire characteristics is difficult as the effects of fires vary temporally and with topography and vegetation, and multiple current and new sources of remote sensing data continue to accrue. Challenges remain in how to infer active and post-fire characteristics using remotely sensed data.

Challenges

Landscape-level ecological effects of fires are not well understood.

Predicting where on the landscape fires are likely to cause severe short and long-term ecological effects and understanding why these effects vary are central questions in fire science and management. Remote sensing can help us to characterize the fuels, vegetation, topography, fire effects and weather before, during and after fires. Doing so is critical to understanding which factors and which interactions between them are most important in

influencing immediate and long-term fire effects at local, regional and global scales. For instance, low spatial resolution imagery (i.e., 0.25 – 1 km² pixel size) can provide coarse-scale maps of area burned; while high spatial resolution imagery (i.e., 1 – 5 m² pixel size) can help provide information on the fine-scale spatial heterogeneity of post-fire effects (e.g., patches of white ash or soil char). In chapter 6 of this dissertation, I use topographic variables derived from a digital elevation model to predict the occurrence of severely burned areas inferred from Landsat satellite imagery in the Gila National Forest. For remotely measuring fuel combusted within a fire, an upper constraint can be produced by multiplying the mean fuel load with the broad measure of area burned, while detailed imagery can provide information on fine-scale patchiness that is not resolved in the coarse-resolution imagery. The accuracy of estimates of biomass burned will likely be improved by incorporating data from higher spatial resolution imagery.

Studies linking active fire characteristics, post-fire effects and pre-fire stand conditions are limited.

Direct measurement of fire behavior is difficult. More work is needed in this area to understand the dynamics of these three tightly interrelated factors. We need to expand remotely sensed systems that characterize real-time energy transfer, and, when possible, avoid attribution of retrospective causality. Mechanistic models based on an understanding of how energy transfer translates to fire effects and post-fire recovery is needed. For example, direct measurement of forest floor consumption and surface to canopy fire transition is of crucial value to forest managers for fire management planning. We lack data that connect current stand and vegetation condition to fire behavior and ecological response. In particular, we need improved techniques to detect post-fire effects on the surface where residual canopy density is high or where fire consumes only litter (Patterson and Yool 1998; Holden *et al.* 2005). In these fires, the integration of ground-based and remote measures of active and post-fire effects is especially important.

Remote sensing and field assessments are poorly integrated.

The NBR and NDVI indices have been widely used to measure fire-induced vegetation loss. However, these indices and others should be tested against field data (e.g., canopy scorch, tree mortality, ground char, fuels consumption, ash cover, etc.) across a variety of vegetation biomes and fire regimes to determine where they are most useful and what they actually measure in terms of post-fire ecological effects. For example, further studies comparing these indices to field data, such as CBI, could help us understand whether values of post-fire ecological change arise from fire effects on canopy, understory vegetation, or soil. Thoughtful combinations of field and remotely sensed data collection, interpretation, and analysis and appropriate application is important to increase confidence in the ability of remote sensing to address many applied questions and to streamline associated costs.

Need to improve analysis at differing spatial and temporal scales.

Incorporation of different data sources to refine remotely sensed measures of active fire and post-fire ecological measures would take advantage of the spatial and spectral resolution of different satellite sensors. There is a wide range of potential uses of different sensors and the appropriate technique and image data sources may depend on the objective of the study. For example, sensor requirements to assess post-fire re-sprouting of chaparral shrubs are likely different than those of managers trying to assess watershed-level erosion potential following wildfire near homes in southern California. While Landsat TM and ETM data are most commonly used to assess post-fire ecological effects in North America, application of alternative sensors (ASTER, MODIS, Quickbird, IKONOS, airborne hyperspectral sensors) with varying spectral, spatial, and temporal resolutions warrants further investigation. For example, once ASTER data are available for an area, post-fire tasking of the ASTER TERRA satellite sensor with higher spatial resolution than Landsat in the NIR wavelength bands could provide better information about post-fire effects. Furthermore, in comparison with the single short wave infrared (SWIR) band of Landsat that is used in NBR (i.e., Landsat band 7), the ASTER sensor has five SWIR bands. These alternative SWIR bands (or alternative NBR variants) may vary in their effectiveness with soil type and other factors. Many units of the National Park Service (NPS) have purchased high spatial resolution Quickbird or IKONOS imagery as part of their inventory and monitoring efforts. These sensors may also

provide better information on the potential for fine-scale slope failure, regeneration capacity of vegetation post-burn, and the longer-term effects of fire on ecological integrity. In chapter 3 of this dissertation, I use pre and post-fire Quickbird and ASTER satellite images to assess burn severity on the 2003 Dry Lakes Fire in New Mexico. Additional research is needed to explore the potential value of airborne sensors that can be continuously tasked to study temporal, as well as high spatial and spectral variations.

Traditional remote sensing platforms are limited to 2-dimensional data.

The predominant availability of only 2-D satellite sensor data limits inferences about crown height, crown base height, and crown bulk density, all of which influence fire behavior, fire intensity and hence both fire and burn severity. The availability of light detection and ranging (lidar) systems, and their ability to accurately measure vegetation height, should facilitate studies that incorporate information from both two and three-dimensional datasets to improve estimates of post-fire effects and pre-fire fuel conditions. Lidar has particular potential for assessing crown bulk density, described as the foliage biomass divided by the crown volume, because it does not saturate at high biomass levels (Drake *et al.* 2002; Riaño *et al.* 2003). Crown bulk density has been regarded as one of the most critical variables for modeling crown fire behavior (Scott 1999), since where trees are dense, fire easily spreads from one tree to the other. Lidar is able to detect subtle differences in vertical structure (recording accuracy of 5-15 cm, Baltsavias 1999). Pre-fire lidar can provide a 3-dimensional canopy fuels measurement that can be used to describe crown volume and structure. As such, lidar may allow the development of an improved metric for use in crown fire models, instead of the current reliance of models on crown bulk density. Some researchers have integrated multi-spectral and structural (i.e., Lidar) data to model canopy fuels (Hudak et al. 2002).

Recommendations

Scientists and managers use remote sensing to map, understand and predict the ecological effects of fire. Much has been learned; challenges remain. Our recommendations for increased effectiveness follow.

Use terminology consistently

Jain *et al.* (2004) recommend that researchers simply report what they are actually measuring (be clear about level of inference in methods), identify the temporal and spatial scale that is being referenced, avoid categorical description (low, moderate, and high unless defined with range of observations), and define all terminology (active vs. post-fire effects). We agree. Such an approach should enable scientists to communicate more effectively and managers who juggle a variety of resource objectives to make more informed decisions about where within the fire disturbance continuum to concentrate prevention, suppression, or mitigation efforts (Jain *et al.* 2004). If there is a need to categorize or group different measures, then we advocate limited use of the expressions fire intensity, fire severity and burn severity (due to, in many instances, to their clear overlap on the temporal gradient). Instead we propose that various processes associated with fire intensity and severity be evaluated purely in terms of either active fire characteristics or post-fire effects. As adopted within this review, active fire characteristics would be concerned with all timely measurements ‘during’ the fire (e.g. information on the heat generated by the fire, the fire duration, the immediate combustion of the biomass, and other ecosystem changes induced by the fire process), which could include the flaming, smouldering, or residual combustion stages. These are the direct, first-order fire effects (Reinhardt *et al.* 1997; Reinhardt *et al.* 2001). In contrast, post-fire effects would involve all measurements acquired after the fire has passed (e.g., soil charring, nutrient changes, surface spectral changes, vegetation response, etc). These are the indirect, second-order fire effects (Reinhardt *et al.* 1997; Reinhardt *et al.* 2001).

Quantify and validate metrics of post-fire effects

There are no consistent indicators or classifications of post-fire effects (Morgan *et al.* 2001; Ryan 2002). Those that exist are largely qualitative and plot-based. Quantitative indicators of post-fire effects are needed that encompass fire effects on both the overstory and the soil surface (Morgan *et al.* 2001). These indicators must be useful across a broad range of site conditions, readily mapped remotely or in the field and remotely, and linked to conditions representing pre-fire (e.g. fuels and forest structure), during fires (fire behavior, fuel

consumption and soil heating) and post-fire (vegetation response, soil erosion potential, and invasive species risk). A new generation of tools is needed to support strategic fire management before (fuels management), during (fire management), and after (rehabilitation) wildfires.

With increased reliance on remote sensing, field validation data becomes even more important, but where and how the field data are collected (e.g., plot size, stratification) must be adapted to the spatial resolution of the sensor and the wide range of conditions represented in the imagery. However logical it may seem that higher spatial resolution will likely better represent the fine-scale heterogeneity found in most fires, this has not been proven.

The remote sensing measure should be validated for each application environment by comparing it to equivalent surface processes or properties. For instance, concern has appropriately been raised about the widespread application of spectral index-based methods without establishing the validity and mechanistic relations between post-fire effects and such spectral indices across a variety of environmental conditions (Roy *et al.* 2005; Smith *et al.* 2005b). For example, the NDVI index applied to satellite imagery effectively provides a measure of the greenness of each pixel. In the case of post-fire assessment, an equivalent surface measure would include an average measure of green vegetation cover within a corresponding area of interest on the ground. Likewise if a change in NDVI is used to assess differences between pre- and post-fire environments, an equivalent surface measure could be the change in green vegetation cover before and following the fire. A mid-scale assessment such as that obtained from an airborne sensor could provide a better quantitative understanding of pattern and process relationships.

Validation of dNBR should be conducted in a wide range of environments to ensure that the adopted range of dNBR values, as cited by Key and Benson (2002) and commonly used in post-fire assessment studies, are valid for those environment, or that a process be recommended for local calibration. The authors of the dNBR technique never intended the burn severity class break values developed for fires in Glacier National Park, MT (i.e., the location of the original dNBR study) to be universal thresholds (cf. Key and Benson 2005).

Importantly, the seven levels of dNBR proposed by Key and Benson (2002) are only valid in other environments if the changes in the surface properties that occur in the environment of interest are similar to those observed within Glacier National Park. When considering the wide variation of different fuel conditions and fire regimes, this is unlikely. The solution is to follow the original methodology used by Key and Benson (2002). For each environment of interest make local field measurements of the CBI over a range of post-fire conditions. The CBI methods are described in FIREMON (Lutes et al 2006). Then, correlate the dNBR for the same locations with the CBI values measured in the field, and use that relationship to identify the thresholds between burn severity classes (e.g. Key and Benson 2002; van Wagtendonk *et al.* 2004; Cocke *et al.* 2005)., Rather than then using the Glacier National Park dNBR ranges to classify the satellite imagery, the CBI field measure could be used to set locally meaningful dNBR ranges by providing for each separate environment of interest the dNBR ranges associated with fixed ranges of CBI values (e.g., Epting *et al.* 2005). Using the same thresholds of dNBR between severity classes in all environments avoids the assumption of the same relative degree of post-fire ecological change. The intent of the CBI was to be sufficiently robust to accommodate most vegetation communities. The CBI may require some minor refinements in some communities, but these refinements remain within the conceptual framework of the CBI (cf. Key and Benson 2005). For example, in Alaska, tundra tussocks dominated by sedges, grasses, low shrubs and mosses are treated as heavy fuel. For each environment this recalibration should be conducted at a consistent and available spatial scale (e.g., the 30-m scale of the Landsat TM sensor) as van Wagdentonk *et al.* (2004) illustrated that the relationship between CBI and dNBR for a single environment is dependent on the spatial scale of the remote sensing instrument. This variation of post-inferred fire effects with satellite sensor pixel size has further been highlighted by Key (2005).

Synthesize knowledge about fire patterns over time and space

The causes and consequences of spatial variability in fire effects is one of the largely unexplored frontiers of information. Research needs include a better understanding of how post-fire effects and spatial variability are related to the pre-fire fuels and topography, pre-

fire climate and active fire weather, vegetation structure and composition, and land use. Recognizing this need, a multi-agency project, Monitoring Trends in Burn Severity (MTBS), sponsored by the Wildland Fire Leadership Council, has been tasked to generate burn severity data, maps, and reports for all large historical and current fires 1984 (<http://www.nps.gov/applications/digest>). These data will provide a baseline for monitoring the recovery of burned landscapes and a framework to address highly relevant fire and other natural resource management questions. Knowledge relating to when and where various fuel treatments and fire suppression efforts are likely to be effective will greatly assist managers in prioritizing and making strategic decisions.

Link remotely sensed measures to the fire process.

Mechanistically linking surface processes to imagery is the goal of remote sensing science. As such the characteristics and scale of both the patterns and the inferred processes must be clearly defined. Remote sensing data may represent many interacting processes. For example, processes such as soil water infiltration may be spatially variable at fine spatial scales (e.g., sub-meter and sub-surface), whereas the imagery used to view the process may be too coarse to detect sub-pixel variation of the process. The methodological approach must be transparent, repeatable, and robust if we are to compare results from one geographical area to another or among sensors. Additionally, it is challenging to deal with fine-scale pattern when assigning an overall severity class to a pixel, stand (Fig. 1), or landscape (Fig. 2-3).

One such approach is to measure the fraction of a specific cover type present within an area at both the field plot and satellite pixel scales. A traditional field interpretation of severity was the assessment of “green, brown, and black” as indicators of low, moderate, high severity. This simplistic protocol has a direct parallel to the remote sensing method of spectral mixture analysis (SMA), which can allow the measurement of the fractional cover within each separate pixel (Drake and White 1991; Wessman *et al.* 1997; Drake *et al.* 1999; Vafeidis and Drake 2005). SMA can be applied to commonly available multispectral satellite imagery. Moderate spatial-resolution satellite sensors, such as Landsat (30-m pixel size), however, are

not of adequate spatial resolution to accurately capture the fine-scale soil char or white-ash fractions or their distribution patterns across the landscape (Smith *et al.* 2005; Smith and Hudak, 2005). Therefore, we propose that SMA research only be used to evaluate the fractional cover of unburned (green), scorched (brown), bare soil, and charred (black) vegetation; as these measures are analogous to the traditional field ‘severity’ indicators. Evaluation of such fractions provide a link between what we can interpret from satellite imagery and what effects have occurred on the ground. Further, as fractions are inherently scalable, SMA allows a truly mechanistic link between field and remote sensing measures.

Until we can understand underlying processes and link them directly to remotely sensed measures, we are doomed to developing empirical relationships for many different environments. Fire effects are often “symptoms” of the impact to an underlying process which has been affected by fire. Many fire effects are driven by the heat pulse below the soil surface and subsequent impacts on belowground processes, in particular nutrient cycling and soil water infiltration. Understanding how post-fire effects relate to pre-fire conditions (forest structure and fuels) and fire behavior will facilitate the development of improved tools for predicting and mapping the degree of ecosystem changed induced by the fire process (e.g., heat penetrating soil, consumption of organic materials, change in soil color). This information can lead to improved understanding of the role of fire in creating conditions that drive sustainable ecosystem processes, structures, and functions, and in turn to quantitative measures that will improve the utility and interpretability of remote sensing assessments.

Develop and test novel remote sensing methods

Few remote sensing research studies have actually collected spectral reflectance and thermal information from pre- and post-fire surfaces. Although such data has been collected in African savannas (e.g., Trigg and Flasse 2000; Landmann 2003; Smith *et al.* 2005b) and in early NBR research in North America (e.g., Key and Benson 2002), a lack of post-fire spectral data exists over the multitude of other fire regimes. This lack of data is problematic as several remote sensing methods rely on recalibration within each new application environment. Failure to collect these needed data could result in use of methods that are not

calibrated for a given biome. Further to the lack of site-dependent spectral data, the majority of current studies assessing the extent of area burned or the degree of ecological change with Landsat TM data do not use all the data provided to them by the sensor. Namely, thermal infrared is commonly discarded, but can provide useful hindsight into the cover of exposed soils and the lack of evapotranspiration (from the removal of vegetation).

Improve estimates of local and regional fire emissions.

Currently fire emission estimates for use in global change research generally rely on the parameterization of a simple model, in which the total biomass combusted (and gases emitted) are calculated through the multiplication of the area burned by the pre-fire fuel load, and by the proportion of fuel combusted within the fire (Kashiscke and Bruhwiler 2003; Smith *et al.* 2005a). Such an approach relies on localized information of the fuel and fire conditions extrapolated over the extent of area burned. Within the global change community this approach is known to exhibit considerable uncertainties (Andreae and Merlet 2001; Kashiscke and Bruhwiler 2003; French *et al.* 2004), and only the area burned is particularly suited to measurement via satellite sensors. In some studies the proportion of fuel combusted over very large areas (e.g., Russian boreal forests) has been produced through ‘educated guesses’ of the likely distribution of fires to consume fixed percentages of the fuel load (e.g., Conard *et al.* 2002; Zhang *et al.* 2004), which in part might explain the significant discrepancy in carbon emissions estimates between Siberia and North America (Wooster and Zhang 2004). Clearly, emission estimates produced using such approaches are not ideal, but to date this has been ‘the best tool available for the task’. This review has highlighted other research efforts, such as the use of the FRP methodology (e.g. Wooster *et al.* 2003; Ichoku and Kaufman 2005; Roberts *et al.* 2005; Smith and Wooster 2005), which might allow (provided sufficient temporal resolution is available) improvements to the above model.

Work with managers to determine the scale of operations and thus, appropriate sensors (and resolutions) to address applied questions

The limitations to remote sensing and associated barriers to more widespread use may include costs, user acceptability, and technical problems. The benefits (expediency, coverage, and reliability of results) must outweigh the technical and logistical costs (costs of equipment, human training and field data collection). Users must overcome the technology curve associated with the acquisition and processing of large remotely-sensed datasets. In some cases, there are time constraints to the use of remotely sensed data. Fire managers need timely and often real-time answers, not loads of data to process. Researchers can help develop protocols for processing data, and can partner with managers to provide data and interpretations, but their efforts must be sufficiently timely and completed without interfering with the operations of the fire command. Managers are tasked to focus on fuels treatment and fire management in the Wildland Urban Interface, but they may know relatively little about the effectiveness of management activities there. Researchers need to develop remote sensing products and tools that can address questions that are directly applicable to these highly visible and vulnerable areas. Managers also need standardized procedures for updating vegetation and fuels maps as fires occur, monitoring the effects of post-fire rehabilitation treatments, and modelling post-fire succession. End users must have a firm understanding of the consequences of data use, yet have high confidence in data and products. Users must also accept that there are inherent problems with satellites and aircrafts, such as time intervals between images, clouds obscuring the imagery, topographic relief, surface variations existing at a scale that the imagery is unable to detect, etc.

8. Conclusions

When combined with field data, remote sensing can be very helpful in mapping and analyzing both active fire characteristics and post-fire effects. Unfortunately, the inconsistent use of fire descriptors, including fire intensity, fire severity and burn severity, confuse measurement and interpretation of field and remotely sensed fire effects. The use of qualitative terms such as fire and burn severity has limited utility given the highly variable nature of fire behavior and subsequent effects and the dynamic aspect of post-fire recovery. Fire is a stochastic, spatially complex process that is influenced by a multitude of interacting factors, making generalizations from one fire to the next difficult (Morgan *et al.* 2001) unless

we understand the underlying processes. Using consistent terminology is an important step in developing a better understanding of the causes and consequences of spatial variability of fire effects.

Remote sensing has great potential for scientists and managers seeking to map, understand, predict and assess the ecological effects of fires. In addition to these current applications, remote sensing has great potential for detecting and quantifying local and regional fire emissions to improve estimates of fire emissions for use in studies of both air quality and global climate change. Atmospheric emissions from fire increasingly limit the use of prescribed fire, especially near urban areas, which are often in need of burning as part of restoration and fuels reduction treatments. Global climate change research has focused attention on carbon storage, release and sequestration. Remotely sensed data are useful for quantifying carbon released by fire, and potentially for estimating increases in vegetation growth and carbon sequestration post-fire. Remote sensing has made great strides in terms of providing data to address operational and applied research questions, beyond the scope and feasibility that ground-based studies can provide.

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Table 1. Remote Sensing Systems Relevant to Fire Detection and Monitoring

Sensor Acronym + Additional Web Resources	Temporal Resolution	Spatial Resolution (km)	VIS-NIR Bands (μm)	TIR Bands (μm)
AATSR ¹ Website: http://www.le.ac.uk/ph/research/eos/aatsr/	2 days	1.00	0.56, 0.66, 0.86 1.6	3.7, 11, 12
ALI ² Website: http://eo1.gsfc.nasa.gov/Technology/ALHome1.htm	16 days	0.010-0.09	0.44, 0.48, 0.56 0.64, 0.79, 0.87 1.25, 1.65, 2.23	-
ASTER ³ Website: http://asterweb.jpl.nasa.gov/	16 days	0.015-0.09	0.56, 0.66, 0.82 1.65, 2.17, 2.21 2.26, 2.33, 2.34	8.3, 8.65, 9.1 10.6, 11.3
ATSR ⁴ http://www.atsr.rl.ac.uk/	3 days	1.00	0.55, 0.67, 0.87 1.6	3.7, 10.8, 12
AVHRR ⁵ http://www.nesdis.noaa.gov/	4 daily	1.10	0.63, 0.91, 1.61	3.74, 11, 12
HSRS ⁶ http://www.itc.nl/research/products/sensordb/getsen.aspx?name=HSRS		0.37		3.8, 8.9
Hyperion http://eo1.gsfc.nasa.gov/technology/hyperion.html	16 days	0.03	[424 Bands: 0.38-2.5 μm]	
IKONOS http://www.spaceimaging.com/	3 days	0.001-0.004	0.48, 0.55, 0.67 0.81	
IRS ⁷ -1A,B IRS ⁷ -1B,C http://www.isro.org/	22 days 24 days	0.036-0.072 0.023-0.188	0.55, 0.65, 0.83	
Landsat 5,7 http://landsat.gsfc.nasa.gov/	16 days	0.015-0.09	0.48, 0.56, 0.66 0.85, 1.65, 2.17	11.5
MODIS ⁸ http://modis.gsfc.nasa.gov/	4 daily	0.25-1.0	19 bands	16 bands
QuickBIRD http://directory.eoportal.org/pres_QUICKBIRD2.html	1-5 days	0.001-0.004	0.48, 0.56, 0.66 0.83	
VEGETATION http://www.spot-vegetation.com/	1 daily	1.15	0.55, 0.65, 0.84 1.62	

¹Advanced Along Track Scanning Radiometer ² Advanced Land Imager ³ Advanced Spaceborne Thermal Emission and Reflection Radiometer ⁴ Along Track Scanning Radiometer ⁵ Advanced Very High Resolution Radiometer ⁶ Hot Spot Recognition Sensor System ⁷ Indian Remote Sensing ⁸ Moderate Resolution Imaging Spectroradiometer

Table 2 Selected Examples of Field and Remote Measures of Active Fire Characteristics

Characteristic Description	Type of Measure	Example Reference(s)
Flame length and height	Heat sensitive objects Direct observation Video	Hely <i>et al.</i> (2003) Stocks <i>et al.</i> (1996)
Fire duration	Thermocouples	McNaughton <i>et al.</i> (1998) Smith <i>et al.</i> (2005b)
Fire temperature	Heat sensitive paint or ceramics Thermocouples TIR ¹ cameras and imagery	Hely <i>et al.</i> (2003) McNaughton <i>et al.</i> (1998) Riggan <i>et al.</i> (2004)
Integrated temperature with time	Thermocouples	McNaughton <i>et al.</i> (1998) Smith <i>et al.</i> (2005b)
Rate of Spread	Thermocouples Visual records/stop watches Video	Smith <i>et al.</i> (2005b) Stocks <i>et al.</i> (1996)
Direct pyrogenic emissions	Gas analyzers Fourier transform IR ² spectroscopy	Andreae <i>et al.</i> (1996) Yokelson <i>et al.</i> (2003) Yokelson <i>et al.</i> (1996)
Fuel Combusted	Forest fuel and duff combustion In-situ fire fuel sampling Change in laser profiling data Fire radiative power/energy	Ottmar and Sandberg (2003) Smith <i>et al.</i> (2005a) n/a Kaufman <i>et al.</i> (1998) Wooster (2002)
Fire energy output	Fire line intensity Fire radiative power/energy	Byram (1959) Trollope <i>et al.</i> (1996) Smith and Wooster (2005) Kaufman <i>et al.</i> (1998) Wooster <i>et al.</i> (2003, 2005) Roberts <i>et al.</i> (2005)

¹ Thermal Infrared² Infrared

Table 3. Selected Examples of Field and Remote Measures of Post-Fire Effects

Characteristic Description	How Measured	Example References
Char and Ash cover	In-situ measurements Aerial photographs VIS-MIR ¹ sensor imagery	Smith <i>et al.</i> (2005b) Smith and Hudak (2005) Landmann (2003)
Surface Temperature Changes	In-situ measurements Thermal Infrared imagery	Trigg and Flasse (2000) Kaufman <i>et al.</i> (1998)
Surface Reflectance Changes	In-situ measurements VIS-MIR sensor imagery	Trigg and Flasse (2000) Fuller and Falk (2001)
Area Burned and Fire Perimeters	In-Situ records VIS-MIR sensor imagery	Eva and Lambin (1998a) Pereira (1999)
Vegetation Consumption	Field VIS-MIR sensor imagery	Lenihan <i>et al.</i> (1988); Cocke <i>et al.</i> (2005) Hall (1980); Miller and Yool (2002)
Vegetation Mortality	Field VIS-MIR sensor imagery	Wyant <i>et al.</i> (1986); Cocke <i>et al.</i> (2005) Patterson and Yool (2002)
Vegetation Recovery	Field Changes in multi-date imagery	Lyon and Stickney (1976); Anderson and Romme (1991); Turner <i>et al.</i> (1997); Lentile (2004) Henry and Hope (1998); Diaz-Delgado <i>et al.</i> (2003)
Canopy Scorch	Field	Ryan and Reinhardt (1988); McHugh and Kolb (2003)
Soil Charring	In-situ measurements Hyperspectral Imagery	DeBano <i>et al.</i> 1979; Lewis <i>et al.</i> (2006) Laes <i>et al.</i> (2004)
Soil Water Repellency	In-situ measurements Hyperspectral Imagery	Lewis <i>et al.</i> (2006); Doerr <i>et al.</i> (2000)
Atmospheric Chemistry Changes	Atmospheric Sounders	Spichtinger <i>et al.</i> (2001)

¹visible, mid-infrared

Table 4. Selected Examples of Approaches that Remotely Assess Degree of Post-fire Change

Approach to Divide Classes of Post-fire Effects	# of Classes	Reference(s)
Number fine branches remaining on woody plants	7	Diaz-Delgado <i>et al.</i> (2003)
Complete and partial stand mortality	2	Isaev <i>et al.</i> (2002)
Weighted carbon storage in different fuel components	3	Zhang <i>et al.</i> (2003) Conard <i>et al.</i> (2002) Conard and Ivanova (1997)
USFS fire classification rules (c.f Cotrell 1989) - degree of canopy and soil organic matter consumption	4	Patterson and Yool (1998)
Fuel consumption and proportion of grey ash endmember	2	Landmann (2003)

Low



Moderate



High



CA

MT

AK

Figure 1. Low, moderate, and high 'burn severity' sites in Californian chaparral, Montanan mixed-conifer forests, and Alaskan black spruce forests. Burn severity classified via consistent visual assessment of ground and canopy fire effects.

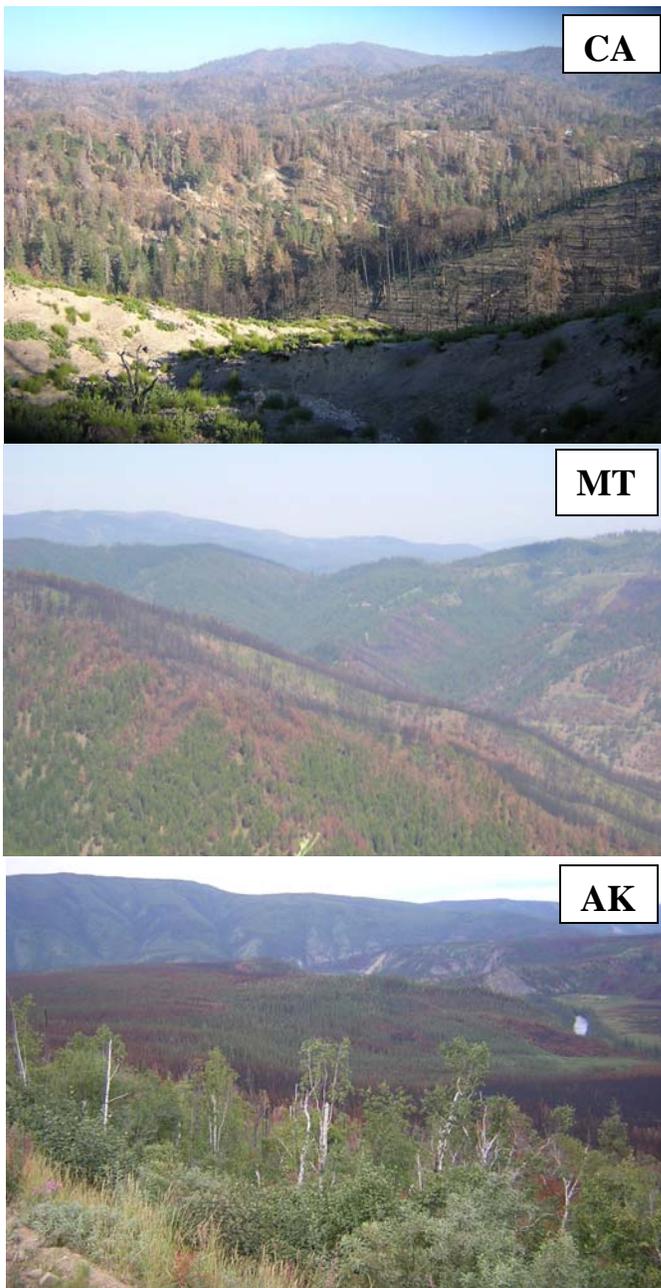


Figure 2. Landscape scale heterogeneity following fires.

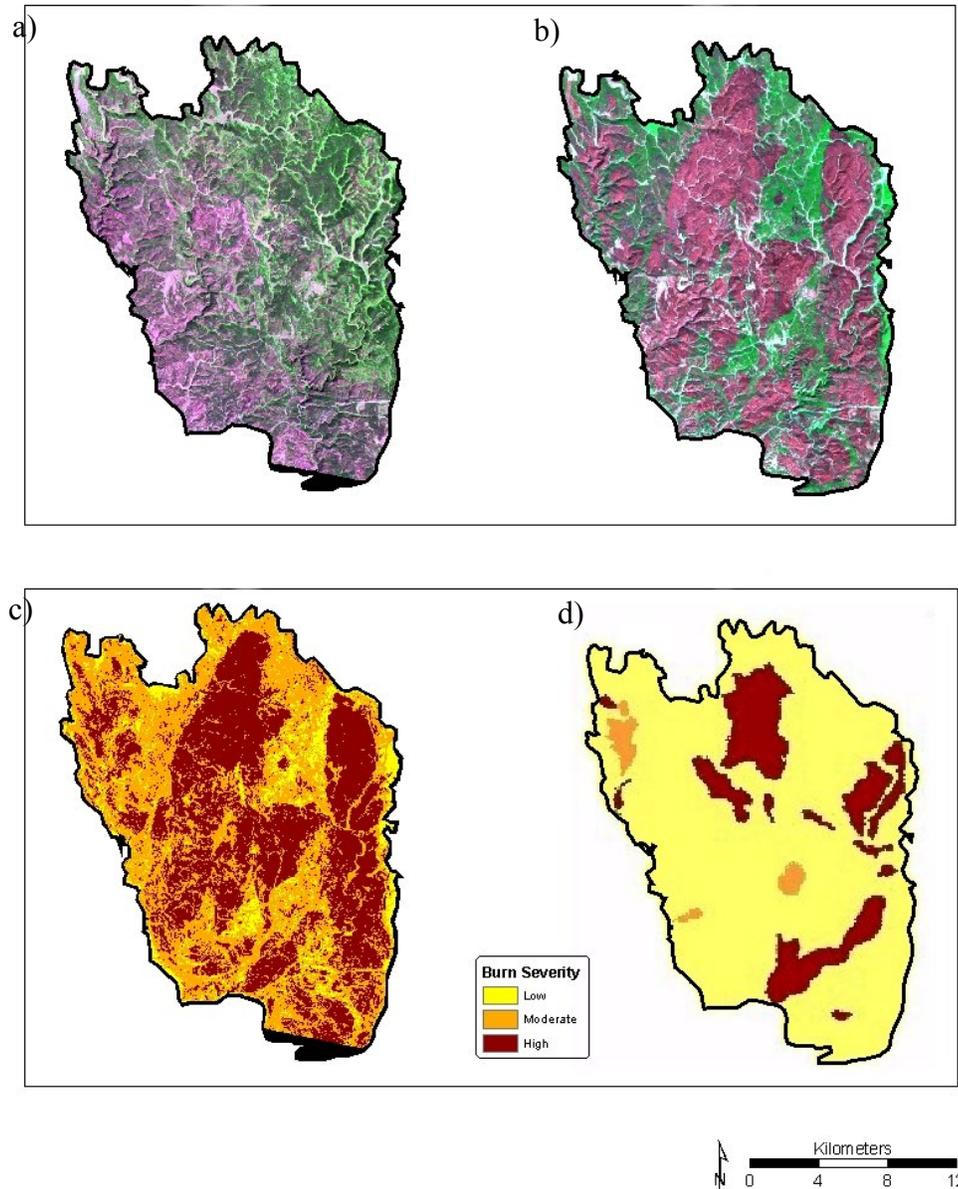


Figure 3 a) Pre-fire Landsat 7 image (7-4-3 false-color composite) acquired on August 18, 1999; b) Post-fire Landsat image 7 image (7-4-3 false-color composite) acquired on Sept. 14, 2000; c) Burn severity map produced for the Jasper fire in the South Dakota Black Hills from images in a and b according to dNBR methods (Key and Benson 2005); d) Burn severity map produced by the BAER team for the Jasper fire using a single date post-fire Landsat image and GIS-based maps of topography and pre-fire forest condition.

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CHAPTER 3

Beyond Landsat: An Assessment of Four Satellite Sensors for Detecting Burn Severity in Ponderosa Pine Forests of the Gila Wilderness, NM, USA.

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Abstract

Methods of remotely measuring burn severity are needed to evaluate the ecological and environmental impacts of large, remote wildland fires. The uncertain future of the Landsat program highlights the need to evaluate alternative sensors for characterizing post-fire effects. We compared pre- and post-burn imagery from four satellite sensors with varying spatial-resolutions: Quickbird Multi-spectral, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Landsat Thematic Mapper (TM), and the Moderate Resolution Imaging Spectroradiometer (MODIS), using a subset of the 2003 Dry Lakes Fire in the Gila Wilderness, NM. Where spectrally feasible, burn severity was evaluated using the differenced Enhanced Vegetation Index (dEVI), differenced Normalized Difference Vegetation Index (dNDVI) and the differenced Normalized Burn Ratio (dNBR). We use 55 Composite Burn Index (CBI) plots to assess burn severity on the ground. Both the dEVI derived from Quickbird and the ASTER-derived dNBR showed similar or slightly improved correlations over the dNBR derived from Landsat TM data ($r^2 = 0.82, 0.84, \text{ and } 0.78$, respectively). The relatively coarse resolution MODIS-derived NDVI image was weakly correlated with ground data ($r^2 = 0.38$). Our results suggest that moderately high-resolution satellite sensors like Quickbird and ASTER have potential for providing accurate information about burn severity. Future research should further develop stronger links between higher resolution satellite data and burn severity across a range of environments.

Keywords: ASTER, Quickbird, Landsat, MODIS, Fire, Burn Severity

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Introduction

Recent large fires in the western United States have highlighted the need to better understand the consequences and extent of severe fire events. Because fires are large and often occur in remote areas, air and space-borne sensors are needed to measure both active fire behavior and post-fire effects. Because fire patterns are inherently spatially heterogeneous (Morgan *et al.* 2001), remote assessments of this heterogeneity can aid in the understanding of post-fire ecological trends and restoration priorities.

A variety of remote sensing techniques have been developed to assess post-fire ecological change across a range of environments. See Lentile *et al.* (2006) for a comprehensive review. Methods such as the normalized burn ratio (NBR) and the Normalized Difference Vegetation Index (NDVI) have been widely applied to Landsat TM imagery and ground-based spectral reflectance data to infer burn severity (Benson and Key 1999; Key and Benson 2005, to be published; Roy, Yin *et al.* 2005; Smith, Wooster *et al.* 2005a; Van Wagtenonk, Root *et al.* 2004). Forest structural characteristics that influence post-fire effects vary at scales finer than 30 m and satellite sensors with higher spatial resolution (i.e. < 30x30 m pixel sizes) have potential for increasing the accuracy and precision of such remotely sensed estimates. Van Wagtenonk *et al.* (2004) evaluated NBR derived from both Landsat and AVIRIS imagery, but did not investigate spatial scaling issues. Several commercially available satellite sensors have yet to be evaluated for their ability to infer post-fire ecological effects. Such an assessment would inform the future selection of satellite sensors for assessing the broad-scale impacts of fires on the environment.

Landsat TM and Enhanced TM (ETM+) imagery is frequently used to evaluate the effects of fire on the environment (Lewis, Wu *et al.* 2006; Miller and Yool 2002). (See table 4 for Landsat TM sensor specifications). However, given the recent failure of the Landsat 5 sensor and the malfunction in the Landsat 7 sensor, alternative data sources will likely be sought in the future. Data from a variety of satellite sensors are now readily available at little or no cost. The MODIS sensor (Justice 1998), mounted on both the AQUA and TERRA satellites, has 16 available bands in the visible (VIS) to short-wave infrared (SWIR) and may acquire up to 4 images of a given site per day. With relatively large pixel sizes (250 m) in the VIS

and near infrared (NIR) and even larger pixels in the SWIR (i.e. 500-1000m) compared to the 30 m resolution of Landsat TM, MODIS cannot be expected to capture the moderate- or fine-scale variations of post-fire ecological effects given the heterogeneity of most fires.

However, given its low cost, relatively simple processing, high temporal resolution, and wide use in numerous broad-scale fire effects studies (Roy, Yin *et al.* 2005; Smith, Wooster *et al.* 2005b), MODIS data merit evaluation for their potential applicability to understanding fire effects across the landscape.

The ASTER sensor is also housed aboard NASA's TERRA satellite (see sensor specifications in Table 2). The ASTER sensor has been used to investigate a wide variety of scientific issues including measurement of canopy fuel biomass (Falkowski, Gessler *et al.* 2005), moisture content (Toomey and Vierling, 2005) and geological mapping (Rowan and Mars 2003), in addition to several applications highlighted in a recent special issue of the journal *Remote Sensing of Environment* (Gillespie, Abrams *et al.* 2005). ASTER exhibits a moderately high spatial resolution in the VIS and NIR wavelengths (15 m), with 30-m pixels available in the six SWIR bands (Table 2). Relative to Landsat TM imagery, the ASTER sensor therefore has potential for improved measurement of post-fire ecological effects.

The Quickbird sensor, owned and operated by Digital Globe Inc. (Longmont, CO), features the highest spatial resolution of any civilian satellite-borne sensor, with 0.6 m and 2.4 m panchromatic and multispectral pixel sizes, respectively (Table 3). While Quickbird imagery is relatively expensive (\$28 to 54/km²), the fine-scale resolution of this sensor might allow ecologically meaningful assessment of post-fire effects over large spatial extents while retaining great spatial detail. Researchers are currently investigating the ability of the Quickbird sensor to detect post-fire exotic weed invasions (Hudak, pers. comm.) and to differentiate between understory and overstory post-fire effects. Furthermore, the Quickbird sensor may be manually pointed from the ground and at additional expense can be given priority tasking, therefore enabling some flexibility with respect to its image acquisition frequency during and after wildfire.

The objective of this case study is to assess the utility of the four aforementioned satellite sensors (Quickbird, ASTER, Landsat, and MODIS) to derive information relating to burn severity for the Dry Lakes fire that burned mixed conifer forests and woodlands in New Mexico in 2003. We hope to provide information that will assist scientists and managers tasked with mapping burn severity to select and analyze satellite sensor data.

Methods

Study Area and Landcover Data

Gila Wilderness

The study area was located in the northern portion of the 230,800 ha Gila Wilderness, New Mexico (Figure 1) and is described in detail by Holden et al. (2005). The mean elevation is 2500 m and this region is very dry, receiving on average 34 cm of rain annually (Sheppard, Comrie *et al.* 2002). The Gila Wilderness was grazed extensively until the 1950's but has never been logged. Lightning ignited several fires in the wilderness in June 2003, which formed what was later called the Dry Lakes Fire Complex (DLF). The Dry Lakes fire was managed under Wildland Fire Use (WFU), a program implemented by the Gila National Forest in 1975 that allows naturally ignited fires to burn where no human lives or structures are threatened and resources are available to suppress the fire in the event it spreads beyond a pre-defined boundary. More than 49,000 ha had burned by the time rains extinguished the fire in early August, the largest recorded wildfire in New Mexico. Previously acquired Quickbird imagery (13 May 2003) and a matching post-fire scene that coincided with a portion of the Dry Lakes fire (19 May 2004) delineated the spatial extent of our work, and allowed us to study a 2,600-ha area of the fire in mid-elevation (2500 m) ponderosa pine forests in the north-central portion of the Gila Wilderness.

Image Processing and Analysis

Multi-temporal satellite imagery from Quickbird (multi-spectral product), ASTER, Landsat TM, and MODIS were acquired for a 26 km² portion of the DLF (Figure 1). Because our analyses were restricted to the extent of the Quickbird imagery, all other imagery was subset to match these data in order to enable comparative analysis.

Quickbird scenes (standard processing levels) were converted from at-sensor radiance to reflectance using equations provided by the Landsat imagery users guide (LPSO 1998) and adapted for IKONOS imagery following Fleming (2003). Because Quickbird band spectral response functions are nearly identical to the IKONOS imagery (Rangaswamy 2003), mean solar exoatmospheric irradiances (ESUN) values from Fleming (2003) were used to process the Quickbird imagery. The 2003 pre-fire Quickbird scene was georegistered to a digital orthophotoquad (DOQ) using image-to-image registration in ENVI 4.0 software (RSI, Boulder, CO; RMSE = 0.56 pixels). The post-fire 2004 scene was then georeferenced to the 2003 Quickbird scene. Concerns about topographic influence on the accuracy of georectification were minor, due to the relatively flat mesa tops that characterize this study area.

Pre- and post-fire ASTER level 1B images (16 May 2003 and 19 June 2004) were imported into the ERDAS Imagine (Leica 2004) image processing software. The 2003 image was georeferenced to a digital orthophotoquad (DOQ). The 2004 image was then georeferenced to the 2003 image. Both images were then converted to top-of-atmosphere reflectance. The ASTER images were converted to at-sensor reflectance using ESUN values calculated by convolving the ASTER spectral response functions with the Exoatmospheric Solar Irradiance (Table 2).

Pre and post-fire Landsat TM scenes (15 June 2002 and 20 June 2004) were processed by the EROS data center (Sioux Falls, SD) as part of the national Monitoring Trends in Burn Severity (MTBS) project. Both scenes were terrain corrected and converted to at-sensor reflectance (by convolving the spectral response functions with exoatmospheric solar irradiance (ESUN) values (LPSO 1998).

Pre- and post-fire MODIS scenes (13 June 2003 and 19 June 2004) were imported into ENVI 4.0 software and georeferenced using the sensor-specific MODIS reprojection tool (<http://edcdaac.usgs.gov/landdaac/tools/modis/index.asp>). The MODIS data were then converted into at-sensor radiance using the gain and offset parameters within the MODIS

header file. Because images from each sensor were retrospective and our study area is in a remote, dry, high-elevation environment, we did not perform any atmospheric correction.

Several spectral indices were calculated for each satellite sensor and then differenced between pre- and post-fire scenes to detect fire-caused changes in vegetation (Table 5). The Normalized difference vegetation index (NDVI) (Rouse, Haas *et al.* 1974) and enhanced vegetation index (EVI) (Chen, Vierling *et al.* 2004; Huete, Didan *et al.* 2002; Miura, Huete *et al.* 2001) were calculated for Quickbird and Landsat imagery to facilitate direct comparisons among sensors. The EVI could not be calculated with the ASTER sensor because it does not detect blue wavelength radiation. We chose not to calculate the EVI or NBR using MODIS data because the required rescaling to 500-m resolution would provide too coarse a scale to be useful for burn severity mapping.

The Normalized Burn Ratio and differenced Normalized Burn Ratio (dNBR) (Key and Benson 1999) were calculated for the Landsat and ASTER imagery. Separate NBR images were created for the ASTER images using each of the six SWIR bands (Table 2). Differenced NBR (dNBR) images were then created for both the Landsat and ASTER data products by subtracting post-fire NBR image from the NBR for the pre-fire image and multiplying by 1000.

Field Data Collection

Burn severity was measured on the ground in May and June 2004 (1-year post-fire) using the Composite Burn Index (CBI) (Key and Benson 2002). We sampled 55 CBI plots randomly located within homogeneous (> 150 x 150 m) patches of unburned, low, moderate, moderate-high and high severity areas of the Dry Lakes Fire. Plot sampling was stratified using a 23 October 2003 post-fire Landsat TM NBR image. The CBI is a relatively rapid method of measuring post-fire effects, and includes soil, understory and overstory strata. Several characteristics are measured or estimated within each stratum and then combined to give an overall CBI score from 0 to 3 (unburned to severely burned). Despite the qualitative nature of several CBI measures, some measures (e.g. crown scorch, torch) are measurable and repeatable. Others, like fuel consumption, depend on the observer. Having spent the previous

summer collecting forest structure and fuel data in the areas described in this study, we felt it appropriate to include these measures.

Data Analysis

We compared the severity detection capabilities of each sensor with 55 CBI plots using linear regression techniques. Severity estimates from the Quickbird dEVI and dNDVI image were calculated for the center pixel, and the mean of 3x3, 6x6 (approximate size of 1 ASTER pixel) and 12x12 (approximate size of 1 Landsat pixel) pixel groups. Standard errors were calculated for 12x12 pixel groups in order to represent the variability among pixels within each plot. Severity estimates for each ASTER dNBR image were calculated for a single (15x15m) pixel. Regression plots of CBI and imagery data were clearly non-linear. We fit second order polynomial functions, selected because of the non-linear appearance of the data, to the data and calculated regression coefficients and coefficients of determination (R^2) values.

Results and Discussion

Coefficients of determination among vegetation indices and CBI data are presented in Table 1. The EVI derived from means of 12x12 pixel groups from Quickbird imagery explained a high degree of CBI plot data variance ($R^2 = 0.82$, Figure 2) and outperformed the NDVI ($R^2 = 0.76$, Figure 3). There was substantial variation among pixels within a 12x12 pixel group, yet the coefficients of determination remained high ($R^2=0.68$) between CBI and Quickbird EVI data even when the area of analysis was decreased by 75%, from 12x12 to 6x6 pixels in size (Figures 2 and 3).

The dNDVI was weakly but significantly correlated between ASTER imagery and CBI plot data ($R^2 = 0.55$, Table 1). The ASTER-derived dNBR was well correlated with CBI data, (Figure 4). There was slight variability (R^2 values ranged from 0.75 to 0.84) in the performance of dNBR indices derived from the six ASTER SWIR bands, with band 9 showing the strongest correlation with CBI data (Figure 4).

Both the ASTER-derived dNBR and Quickbird-derived dEVI performed slightly better than dNBR derived from Landsat TM data based on correlations with ground data ($R^2 = 0.84$, 0.82 ; 0.78 respectively, Table 1). This result bodes well for the future use of these sensors for measuring post-fire ecological effects, now that the future of the Landsat program is in question.

The improved correlation between Quickbird severity estimates and CBI data with aggregation to larger spatial scales suggests that shadow effects, variability in vegetation structure (open vs. closed canopy) and variability in post-fire ecological effects at small spatial scales may influence the effectiveness of this fine spatial resolution sensor. Because our study design did not incorporate this spatial variability into our plot sampling, we are unable to meaningfully evaluate the potential causes of variation between pixels. Once the Quickbird data were aggregated to a 6x6 pixel size, the heterogeneity seemed to match well with the heterogeneity captured by the CBI plot data, as evidenced by a 0.68 coefficient of determination. When the remote sensing scale of analysis was at the level of 3x3 or a single pixel of Quickbird data, the correlations were much lower (Figure 2).

The dEVI performed slightly better than the dNDVI for the Quickbird imagery, but dEVI performed poorly when calculated using Landsat data (R^2 with CBI = 0.03, Table 1). This suggests that corrections for canopy background effects in the dEVI may help account in some way for the within-pixel variability of the Quickbird data. In addition, correlations between Quickbird-derived dEVI and ground data were clearly linear. Previous studies have shown that the EVI is sensitive to within-canopy shading (Chen et al. 2004; Chen et al. 2005). While our data are inconclusive, the relationship between the dEVI and ground-based measures, as well as other spectral indices, warrants further study.

Relationships between Landsat dNBR and CBI fire severity measures in this (figure 5) and in previous studies were all non-linear (Cocke, Fule *et al.* 2005; Van Wagtenonk, Root *et al.* 2004). With the exception of the dEVI derived from Quickbird imagery, we observed the same non-linear relationship between severity estimates from each sensor and CBI data. There are several possible explanations for this apparent relationship. One is that beyond

some threshold level of severity (e.g. the majority of tree canopies consumed), the concomitant changes in surface spectral radiance may limit the sensitivity of spectral vegetation indices used to discriminate among levels of fire-caused ecological effects. For example, where fires are “moderately severe” in ponderosa pine forests, a fire may scorch (heat-induced leaf death) all overstory trees without actually consuming the needles. Because the photosynthetically active tissue in tree crowns is lost beyond this level of severity, post-fire spectral data may not indicate such differences, despite the ecologically meaningful role scorched needles play in reducing post-fire erosion (Pannkuk and Robichaud 2003). Another possible explanation is that one year post-fire vegetation response might vary depending on the condition of the vegetation before the fire, and subsequent post-fire response. Rapid green-up of understory vegetation one year post-fire in an area that burned “severely” according to satellite imagery and CBI plot data might contribute to variation in correlations between ground and imagery data. Alternatively, Miller and Thode (2007) suggest that the dNBR may be sensitive to differences in post-fire soil characteristics while the CBI reaches a maximum once all aboveground vegetation has been removed, resulting in variable dNBR values at maximum CBI plot values of 3.0.

The ASTER sensor proved effective for deriving burn severity. While each of the six dNBR images correlated relatively well with the CBI data, Band 9 performed slightly better. Van Wagtenonk and Key (2004) identify AVIRIS channel 210 (2.37 μm) as showing the greatest positive response in areas that burned severely. While this channel lies just beyond the range of the Landsat TM band 7, it corresponds to the ASTER band 9 (2.36-2.43 μm). The slightly improved performance of the ASTER band 9 and its correspondence with the AVIRIS channel suggests that the ASTER data may indeed improve estimates of severity in some situations.

The MODIS-derived dNDVI did not correlate well with ground data ($R^2=0.38$, Figure 6). This was expected given the relatively poor spatial resolution of this sensor. Because the Gila Wilderness has remained unlogged and portions of our study area burned several times in the 20th century, much of this fire was likely less severe than other wildfires burning in the Southwestern US. In addition, the small size of our study area (2600 ha) may have limited

the usefulness of the MODIS data. Nelson et al. (in press) found that 500-m MODIS data performed poorly relative to Landsat, but improved with fire size and where fires were predominantly in vegetation that typically burns with high severity fires. While MODIS data are clearly useless in situations where relatively fine-scale information is needed, they might still be useful for mapping coarse-scale post-fire ecological effects across large fire events.

Measuring fire-induced vegetation change in ponderosa pine forests poses special challenges, particularly where fires burn on the ground without significantly altering the canopy of the largest trees, those that occupy dominant and codominant positions in the forest canopy (Holden, Smith *et al.* 2005). Fires could theoretically burn slowly below the canopy, altering soil properties and causing severe ecological changes that would go undetected by sensors that integrate vegetation-dominated change into a single signal. Very high-resolution sensors such as Quickbird (and perhaps IKONOS, due to its similar spectral and spatial characteristics) may be able differentiate between understory and overstory effects. However, the high cost of such data may limit its widespread application in post-fire severity analyses. Creative partnerships and cooperative agreements between private and public organizations are necessary to ensure the affordability of these commercial data for future operational use.

The timing of image selection when dealing with issues of vegetation change and recovery are also particularly important for ecosystems in this region of the world. Annual precipitation often displays a bimodal distribution in the southwestern US, with snow and rain falling in the winter and summer, and monsoon storms bringing additional rain in the late summer and early fall. The quantity and extent of snow and rainfall are highly variable in both seasons, and likely influence the amount of understory vegetation growth each year. Therefore, depending on the year, peak vegetation green-up could occur in either the late spring or fall. Because post-fire vegetation recovery is an important factor associated with burn severity, reflecting both damage to vegetation and soils, the timing of image acquisition and field data collection may influence the perceived post-fire vegetation recovery. Due to this and other factors, the results presented in this case study should be treated as a first step

towards understanding the relationship between burn severity and spectral reflectance as measured at a variety of spatial scales in conifer-dominated landscapes.

Conclusions

Relatively new satellite sensors like ASTER, Quickbird and IKONOS clearly have potential for mapping burn severity using remote sensing. The low cost and improved spectral and spatial resolution of the ASTER sensor over Landsat TM data warrant further testing at other post-fire sites, particularly where effects of fire on soil properties and varying soil types are of interest. Very high resolution Quickbird data were well correlated with ground-based estimates of burn severity and may have potential for improving assessments of burn severity, despite the lack of available mid-infrared bands. The non-linear trends in relationships between CBI measures and sensor-derived severity estimates suggest that spatial scaling may be an issue when relating CBI data to remotely sensed data, and warrants further study. In contrast to other indices, the EVI derived from Quickbird imagery showed a linear relationship to ground data. The MODIS sensor poorly predicted burn severity, probably due to its poor spatial resolution. These results indicate that several alternative data sources may be useful for inferring burn severity in this era of limited data availability from the Landsat family of sensors.

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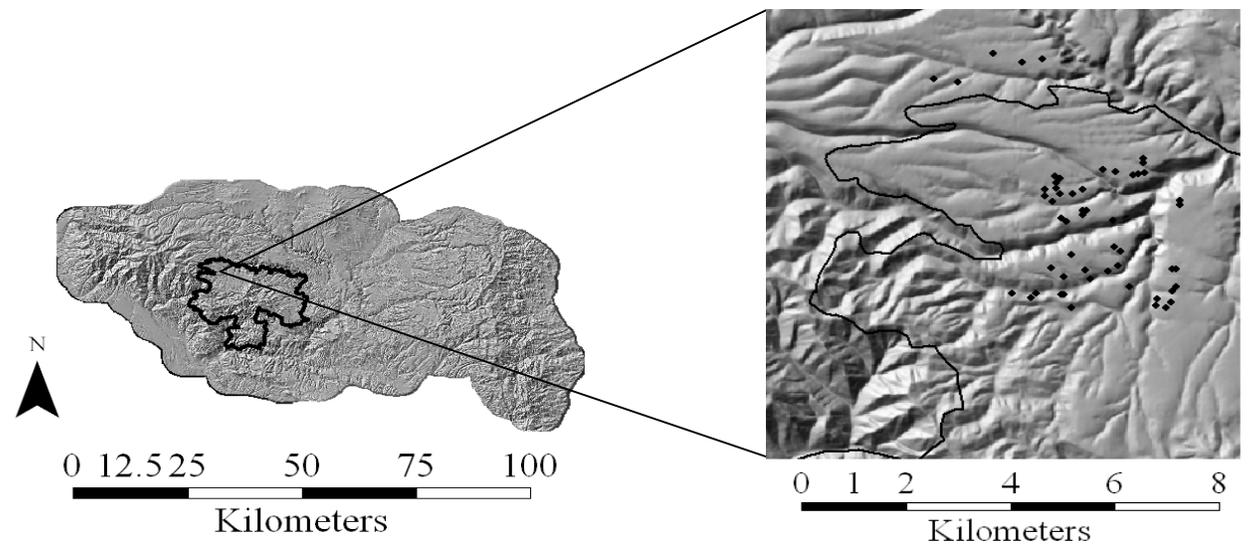


Figure 1. Dry Lakes Fire Complex perimeter (48,800 ha) within the Gila Aldo Leopold Wilderness Area, New Mexico (Left) and the 2600 ha-ha area used for analyses. Plot locations are indicated by dots.

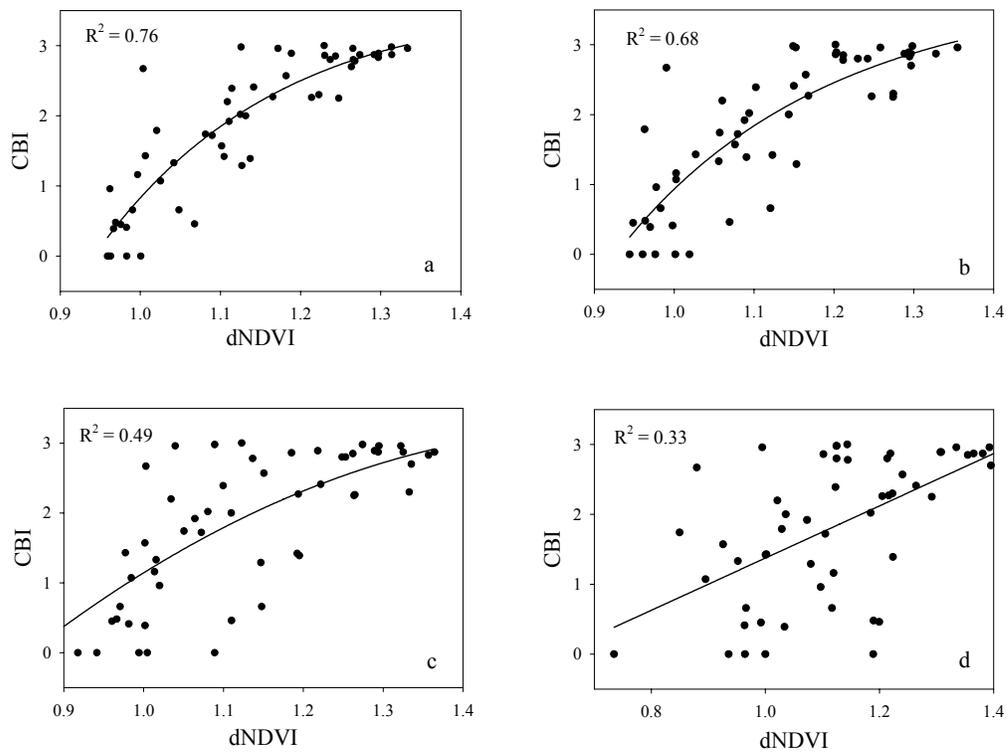


Figure 2. Quickbird dNDVI values for the mean of a 12x12 pixel area (a), for the mean of a 6x6 pixel area (b), the mean of a 3x3 pixel area (c), and a single pixel (d) correlated with CBI plot data

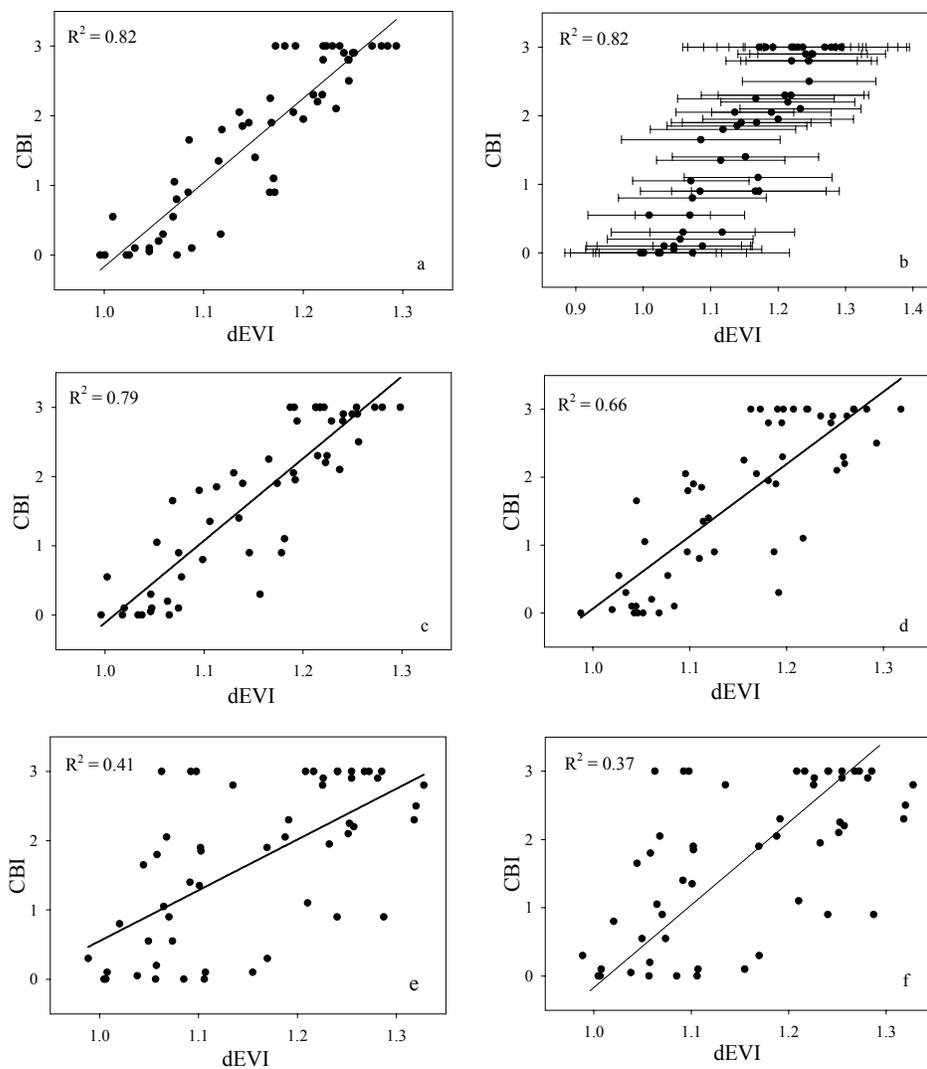


Figure 3. Quickbird dEVI values for (a) 12x12 pixel mean, (b) 12x12 pixel mean ± 1 standard deviation, (c) 9x9 pixel mean, (d) 6x6 pixel mean, (e) 3x3 pixel mean, and (f) single pixel correlated with CBI plot data.

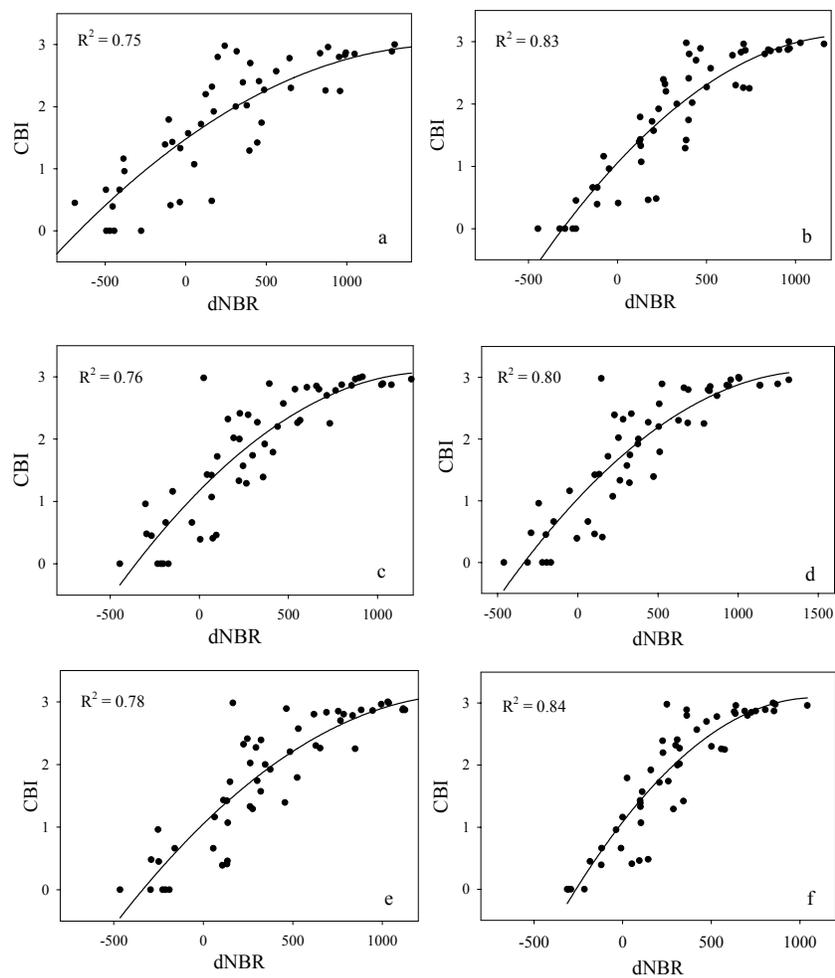


Figure 4. ASTER dNBR values for each of six SWIR bands correlated with CBI plot data: (a) SWIR band 4, (b) SWIR band 5, (c) SWIR band 6, (d) SWIR band 7, (e) SWIR band 8, and (f) SWIR band 9.

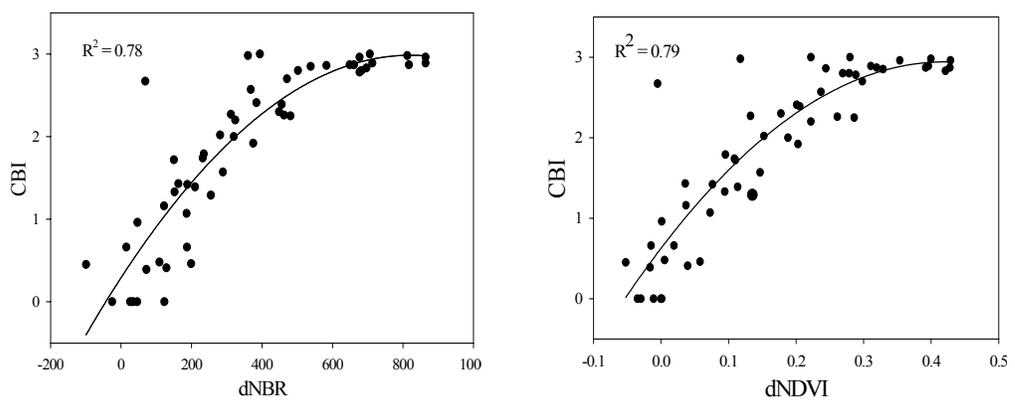


Figure 5. Landsat TM-derived dNBR (left) and dNDVI (right) correlated with CBI data.

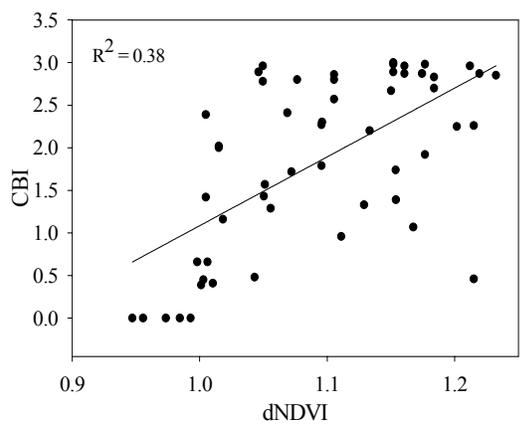


Figure 6. MODIS 250-m NDVI correlated with CBI data

Table 1. Coefficients of determination (R^2 values) between satellite-derived indices and CBI data. ASTER band numbers represent the SWIR bands used to calculate the dNBR and dEVI.

Sensor	Spectral Index	Spatial Resolution	R^2
Quickbird	dNDVI	2.4 m	0.76
Quickbird	dEVI	2.4 m	0.82
ASTER (B9)	dNDVI	15 m	0.55
ASTER (B9)	dNBR	15 m	0.84
Landsat TM	dNBR	30 m	0.78
Landsat TM	dNDVI	30 m	0.79
Landsat TM	dEVI	30 m	0.03
MODIS	dNDVI	30 m	0.38

Table 2. ASTER sensor bands, band wavelengths and ESUN Values. A guide outlining the production of the ASTER ESUN values is available online at:
<http://www.cnrhome.uidaho.edu/default.aspx?pid=85984>

ASTER Band	Wavelength (nm)	Resolution	ESUN
VNIR_Band 1	0.52-0.60	15m	1845.99
VNIR_Band 2	0.63-0.69	15m	1555.74
VNIR_Band 3N	0.76-0.86	15m	1119.47
SWIR Band 3B	0.76-0.86	30m	Not typically used
SWIR Band 4	1.60-1.70	30m	231.25
SWIR Band 5	2.145-2.185	30m	79.81
SWIR Band 6	2.185-2.225	30m	74.99
SWIR Band 7	2.235-2.285	30m	68.66
SWIR Band 8	2.295-2.365	30m	59.74
SWIR Band 9	2.36-2.43	30m	56.92

Table 3. Quickbird Multispectral sensor characteristics.

Sensor Band	Wavelength (um)	Resolution	ESUN
VNIR_(blue)	0.45-0.52	2.4m	1939.4
VNIR_(green)	0.52-0.60	2.4m	1847.4
VNIR_(red)	0.63-0.69	2.4m	1536.4
NIR	0.76-0.90	2.4m	1147.8

Table 4. Landsat sensor bands characteristics.

Landsat Band	Wavelength (um)	Resolution	ESUN
VNIR_Band 1	0.45-0.52	30m	1845.99
VNIR_Band 2	0.52-0.60	30m	1555.74
VNIR_Band 3	0.76-0.90	30m	1119.47
SWIR Band 4	1.60-1.70	30m	231.25
SWIR Band 5	1.55-1.75	30m	79.81
SWIR Band 6	10.4-12.5	30m	74.99

Table 5. Spectral indices and the equations used to calculate each index.

Method	Equation	Reference
NDVI	$\frac{\rho(\lambda_{NIR}) - \rho(\lambda_{red})}{\rho(\lambda_{NIR}) + \rho(\lambda_{red})}$	Rouse et al. (1974)
NBR	$\frac{\rho(\lambda_{NIR}) - \rho(\lambda_{SWIR})}{\rho(\lambda_{NIR}) + \rho(\lambda_{SWIR})}$	Key and Benson (2002)
EVI*	$G \frac{\rho(\lambda_{NIR}) - \rho(\lambda_{red})}{\rho(\lambda_{NIR}) + C_1 \rho(\lambda_{red}) - C_2 (\lambda_{blue}) + L}$	Muira et al. (2001)

*Values of $G = 2.5$, $L = 1$, $C_1 = 6$ and $C_2 = 7.5$ suggested by Huete et al. (1997) were used in this study, where G is a gain factor, C_1 and C_2 are aerosol adjustment factors and L is a canopy background adjustment factor.

CHAPTER 4

Fire Season Precipitation Variability Influences Fire Extent and Severity in a Large Southwestern Wilderness Area, USA

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Abstract

Despite a widely noted increase in the severity of recent western wildfires, this trend has never been quantified. A twenty-year series of Landsat TM satellite imagery for all forest fires on the 1.4 million ha Gila National Forest suggests that an increases in area burned and area burned severely from 1984-2004 are well correlated with timing and intensity of rain events during the fire season. Winter precipitation was marginally correlated with burn severity, but only in high-elevation forest types. These results suggest the importance of within-season precipitation over snow pack in modulating recent wildfire size and severity in mid-elevation southwestern forests.

Introduction

Wildfires burned more than 3.9 million hectares in the United States in 2006, the largest area since records began in 1960, highlighting a recent trend toward increasing fire activity in the western US (www.nifc.gov). Despite a widely perceived increase in the severity (generally defined as the magnitude of ecological change caused by a fire) of fires in the western US, actual burn severity trends and their association with regional and global climate patterns remain unknown. Understanding the causes and consequences of severe fires is particularly important in the southwestern US, where disruption of natural fire cycles in dry forests and land use change have altered their structure and resulting fire behavior and effects [Allen, *et al.*, 2002; Covington, 2000]. Severe, stand-replacing fires may lead to high post-fire erosion [Cannon and Reneau, 2000], alter ecosystem function and are difficult to manage or suppress [Pyne, *et al.*, 1996].

Numerous studies have described general relationships between regional climate patterns and historical fire extent in the western US. Dendroecological studies of surface fire regimes in dry pine forests in the northern Rocky Mountains and the southwestern US have noted that small fires occur during regionally wet years [Heyerdahl, *et al.*, 2002; Schoennagel, *et al.*, 2004]. However, historically, wet winters and springs followed by dry years may have increased fine fuel production necessary to carry large fires [Swetnam and Betancourt, 1998; Swetnam and Betancourt, 1990]. More recently, fire occurrence databases have been used to establish links among early, warm spring temperatures, timing of snow melt and the recent increase in fire activity in the western US [Westerling, *et al.*, 2006].

In the southwestern United States, weather patterns vary widely across annual and multi-decadal time scales and strongly influence the southwestern US fire season. Multi-year to interdecadal regional drought have been shown to be associated with the El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) from the 1900's to present [McCabe and Dettinger, 1999; McCabe, *et al.*, 2004]. Based on these historical patterns, climatologists predict that alignment of the negative (La Niña) phase of the ENSO and a positive phase of the PDO may create a prolonged period of intense drought in the southwestern US [McCabe, *et al.*, 2004]. Climate models predict increasing aridity across the

southwestern US as global climate warming alters patterns of the North American monsoon [Seager, *et al.*, 2007]. Both of these studies highlight serious implications for fire activity in the Southwestern US. However, we lack a thorough understanding of the role of natural climate variability as well as the potential role of current and future climate change on fire activity in this region.

Here, we present the first temporal analysis of satellite-derived trends in burn severity for 114 fires and 195,600 ha burned within 1.4 million ha encompassing the Gila Aldo Leopold Wilderness Complex and surrounding National Forest. This un-logged wilderness area has been ungrazed for the last 60 years and is an ideal area in which to study fire patterns, where many large, naturally ignited fires have been allowed to burn with a minimum of management or suppression activities. The term burn severity has been used to describe a variety of post-fire ecological effects, and can therefore be misleading [Lentile, *et al.*, 2006]. We define severity specifically as the magnitude of change in overstory vegetation measured one year after a fire relative to the pre-burn conditions.

This unique data set provides spatially explicit information about fire perimeters and the post-fire ecological effects within burned areas. Importantly, this data can be combined with archives of seasonal weather patterns to understand linkages between intra-annual climate and fire. We compared annual area burned and area burned within each severity class with snow pack and precipitation metrics from a snow pack telemetry (SNOTEL) site and a daily surface climate station located within the Gila National Forest. Three measures of April-July 15th precipitation were extracted from daily climate data: The total number of days without precipitation (TNR), the maximum consecutive days without precipitation (MNR) and the cumulative precipitation (PCP), and three, six and twelve month instrumental Palmer Drought Severity Index data [Cook, *et al.*, 2004].

Methods

A time series (1984-2004) of summer Landsat 5 Thematic Mapper (TM) satellite images were used to create burn severity maps for all fires greater than 40 ha on the Gila National Forest, NM (Figure 1). Hundreds of fires have burned as wildland fire use (WFU) fires in the

Gila Aldo Leopold Wilderness Complex, New Mexico (GALWC) and surrounding National Forest since the program was implemented there in 1974. Pre and post-fire satellite images for 114 fires (total area burned = 195,600 ha) were processed using the Relative Differenced Normalized Burn Ratio [Miller and Thode, in press]. The RdNBR is a variant of the Differenced Normalized Burn Ratio [Key and Benson, 2006], devised to improve performance in open vegetation types by dividing the dNBR by a pre-fire NBR value. Perimeters of each fire were manually digitized using both the RDNBR index image and the reflectance-corrected Landsat images.

109 ground-based Composite Burn Index (CBI) plots [Key and Benson, 2006] were collected in 2004 on the 2003 Dry Lakes Fire Complex in the Gila Wilderness. The CBI is a measure that combines 27 ocular estimates, including overstory and understory vegetation consumption, scorch and fuel consumption. We refined our final CBI estimates for each plot by removing several measures (e.g. change in soil color) that were too subjective to be accurately estimated post-fire. Correlations between ground plots and the RDNBR image of that fire were used to define severity thresholds for all fires from 1984-2004 on the Gila National Forest. RDNBR index images for each fire were classified into 4 classes (very low, low, moderate and high severity), which were used in subsequent analyses. A classification of “severe” was assigned to areas where 75% or more of overstory vegetation was removed.

Instrumental Palmer Drought Severity Index (PDSI) data [Cook, *et al.*, 2004] and historical precipitation data from the Gila Hot Springs climate station (Elevation 1768 m; central to areas where most fires have occurred) were obtained from the National Climate Data Center (www.ncdc.noaa.gov). Daily precipitation data from each station were used to calculate the total number of days without rain (TNR), the maximum consecutive number of days without rain (MNR) and total precipitation (PCP) from 1st April to 15th July from 1984-2004. Snow water equivalent data from February-April (SWE) were obtained from the Lookout Mountain snow pack telemetry (SNOTEL) site located within the Gila National Forest.

Data Analysis

Multiple analysis of variance (MANOVA) was used to evaluate the influence of climate variables on total area burned in each burn severity class. Area burned as very low, low, moderate and high severity was calculated from classified burn severity maps for all fires by year. Residuals of burn severity data were normally distributed. Area burned in each severity class was treated as a multivariate response variable. TNR, MNR, PCP, SWE and three month, six month and annual instrumental Palmer Drought Severity Index data were used as independent variables. Potential Vegetation Type (PVT), defined as the dominant vegetation expected at a site after long periods without any disturbance, was included as an independent variable [Keane, *et al.*, 2001]. Akaike Information Criteria (AIC) methods were used to select statistical models that best explained variation in area burned in each severity class [Akaike, 1974]. Canonical analysis was used to evaluate the relationship between the original dependent variables and the canonical variates.

Results

Total area burned and total area burned severely increase over the 20-year period for which imagery are available (figure 2). This trend is best explained by variability in the frequency and intensity of springtime rain events (figure 3). Area severely burned each year is well correlated with TNR and MNR, which together explain 63% of the variability. Linear models of area severely burned within individual Potential Vegetation Types (PVT) show that SWE is only a marginally significant predictor in upper elevation spruce-fir forest types ($p = 0.055$) and mixed conifer forest types ($p = 0.062$) but not in lower elevation Douglas-fir, ponderosa pine, and Pinyon-juniper vegetation types.

Discussion and Conclusions

Variability in timing and intensity of precipitation (days without rain and maximum consecutive days without rain) during the fire season in the southwestern US strongly influences the extent and severity of fires across the Gila NF. Canonical analysis reveals that while the significance of TNR, (a measure that describes the overall dryness of the spring and early summer fire season) is related to area burned in all severity classes (including the very low and low burn severity classes which contain more than 90% of the area burned), MNR is

related mainly to area burned severely. This intuitive result suggests that longer rain-free periods may increase the likelihood that a fire will burn as a high severity crown fire, a reflection of increasingly dry live and dead fuels.

While snow-pack is a significant variable in statistical models, univariate analysis of extent and severity within the individual vegetation types reveal that snow pack in this study only marginally influences fire extent and severity in upper elevation (Spruce-fir and Mixed conifer) forest types but lacks significance in other forest types. SNOTEL station data shows that snow rarely persists after March below 2600 m, where most fires in this area have occurred, suggesting that burning in mid-elevation ponderosa pine and pinyon-juniper vegetation types during the last 20 years occurred independently of winter precipitation. This is most likely due to the climatologically warm and dry conditions that persist across the region each spring [Sheppard, *et al.*, 2002]. Winter precipitation patterns across the Southwest are known to be influenced by the El Niño -Southern Oscillation with the cold phase (La Niña) favoring drier-than-average conditions while the warm phase (El Niño) favors wetter-than-average conditions [Sheppard, *et al.*, 2002]. Several dry winters associated with La Niña events followed by increased burning in spruce-fir and mixed-conifer forest types are observed within the study period, but the overall relationship between winter precipitation and fire extent and severity is very weak.

The causes and consequences of stand-replacing wildfires have been the subject of intense scientific and political debate. Such high severity fires were thought to have been relatively uncommon historically in ponderosa pine forests of the southwestern US, which cover 29% of the area burned during the 20 years included in this study. Land management and climatic trends have both been proposed to explain the recent increase in fire severity in the western United States [Running, 2006; Westerling, *et al.*, 2006]. Our results suggest that an alternative mechanism to early snowmelt may play a role in the observed trend toward larger more severe fires in ponderosa pine forests of the southwestern US. Our analysis of fire season precipitation patterns shows increasingly dry springs during last 20 years, including an increase in the total and consecutive number of days without rain, which provide longer periods of weather favorable for fire activity. Whether this variability is associated with

trends in the Pacific Decadal Observation (PDO) [Mantua, *et al.*, 1997], Pacific and Atlantic SST teleconnections, or shifting precipitation patterns associated with global climate warming [Seager, *et al.*, 2007] is unclear. However, precipitation records from the last century show similar increases in spring precipitation variability during past dry periods, suggesting that the localized variability in precipitation observed here might be a cyclical phenomenon related to regional and global climate patterns. Controls on transitional springtime and early summer precipitation patterns in this region require further study.

I speculate that the recent trends in fire activity described in our study reflect the changes that fire regime have undergone across much of the southwestern US. Prior to suppression and exclusion, fires burned synchronously across extensive areas of the Southwest. Given consecutive years of regionally widespread fire activity, lack of fine fuels would have become the primary factor limiting fire spread. While the importance of antecedent climate on fine fuel production and fire activity will vary by vegetation type, dry pine forests in the Southwest today are generally not fuel limited. With tens of millions of acres unburned for decades, fine fuels are abundant. Some dense forests with thick layers of needles and duff no longer maintain grassy understories and hence do not produce abundant fine fuels in response to wet antecedent conditions. Only dry fuels and ignition are necessary for fires to burn under these conditions. Given these changes, it seems likely that precipitation rather than fine fuels and biomass production now influence fire activity in dry pine forests in the Southwestern US. Further research to evaluate to which the degree to which patterns in spring season dryness observed during the last 20 years can be observed in the tree ring record and fire-scar chronologies may provide additional insights on this relationship. Similar analyses of burn severity time series data for other large wilderness areas will elucidate the extent to which recent climate warming versus natural climatic variability may be influencing recent burn severity in the western US.

Acknowledgements

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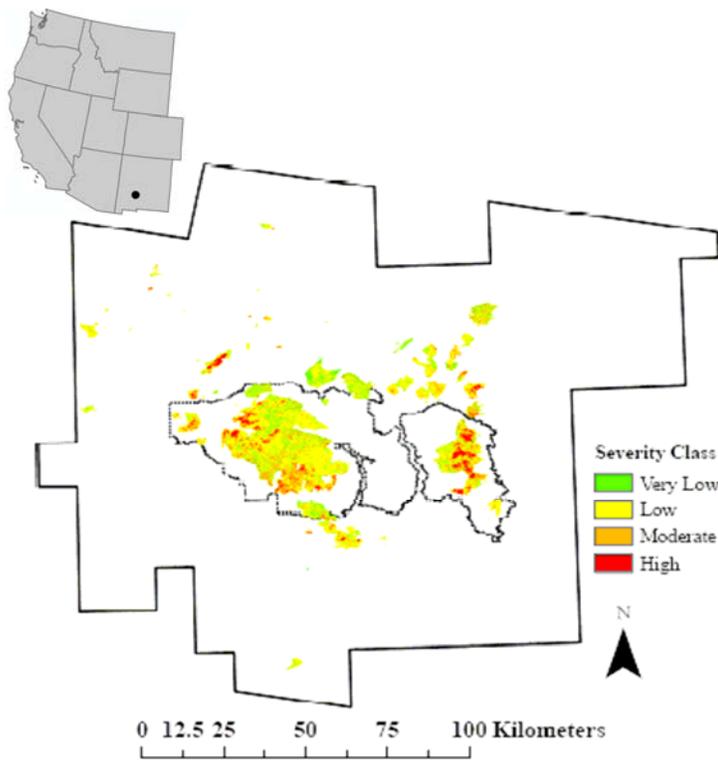


Figure 1. Burn severity atlas of 114 fires and 195,600 ha burned (1984-2004) on the Gila National Forest. Outer perimeter delineates the Gila NF boundary, inner perimeter the Gila and Aldo Leopold wilderness complex.

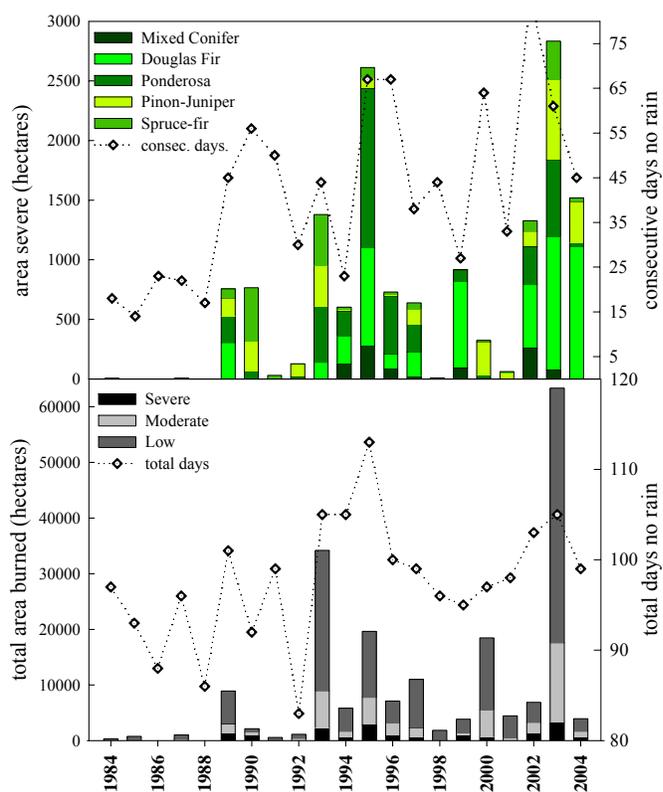


Figure 2. Annual area burned as severe grouped by Potential Vegetation Type (upper graph) and total area burned in all severity classes (lower graph). The dotted lines represents the maximum number of consecutive rain-free days and the total rain free days from April-July 15th.

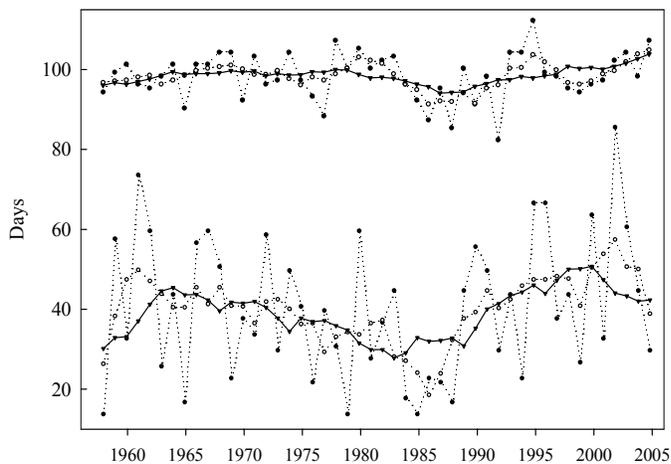


Figure 3. Annual, 5 and 10 year running average maximum number of consecutive days without rain (bottom line) and total number of days without rain (top line) from April-July 15th for Gila Hot Springs (1958-2005).

CHAPTER 5

Fire Season Precipitation Variability and Green-Up (1989-2005) Across a Vegetation Gradient in the Gila Wilderness, New Mexico, USA

Zachary A. Holden and Penelope Morgan

Abstract

I compared annual patterns of spring green-up from 1989-2005 inferred from 1-km² AVHRR Normalized Difference Vegetation Index (NDVI) data with spring precipitation metrics that are correlated with patterns of fire extent and severity in the Gila Wilderness, NM. For each of the 17 years, I extracted three different NDVI values (17 April, 29 May, and 9 July) corresponding to the peak fire season in the Southwest for five sites that varied by vegetation type and 20th-century fire frequency. Annual NDVI values were significantly correlated with snow water equivalent (SWE), maximum consecutive days without rain from 1 April to 15 July (MNR) and total April-June precipitation (PCP) (canonical correlation = 0.80 – 0.88). In the three sites dominated by ponderosa pine, spring NDVI was strongly correlated with SWE, PCP and MNR, with most of the strength of that relationship driven by MNR. In spruce-fir forests, only SWE and MNR were significant model variables, with SWE strongly correlated with 17 April NDVI, likely reflecting delayed green-up due to persistent snow pack at higher elevations. Annual area burned by burn severity class inferred from Landsat-derived Relative differenced Normalized Burn Ratio (RdNBR) was also significantly correlated with these same NDVI variables (canonical correlation = 0.57). Two principal components explain 89% of variability in NDVI. Principal component scores were well correlated with both SWE and MNR, supporting the canonical analysis results. The first principal component, which describes spring and early summer productivity was negatively correlated with both February and May maximum average temperatures, suggesting that warm spring temperatures could influence vegetation productivity by increasing evapotranspiration and soil water loss rates that would could intensify fire activity preceding the arrival of summer monsoon rains. I conclude that that precipitation patterns drive vegetation productivity and drying, thus influencing burn severity, and thus support the results of our previous study (Holden et al. 2007 and chapter four of this dissertation)

suggesting that fire season precipitation patterns are an important driver of fire extent and severity in mid-elevation ponderosa pine forests in this study area.

Introduction

Temporal patterns of precipitation and topography determine the occurrence of species and plant communities globally (Holridge 1947, Whittaker and Niering 1975). Precipitation limits vegetation productivity in semi-arid ecosystems and interacts with temperature, solar radiation and wind to regulate moisture content in leaf litter and dead woody biomass, or fuels. The amount of fuel available to burn is, in turn, a major factor in determining fire rate of spread and intensity (Rothermel 1972). Thus, global and regional climate entrain the weather patterns that, interacting with topography and vegetation, largely determine fire behavior and as a consequence, post-fire ecological effects.

Our knowledge of historical fire occurrence comes mainly from tree rings and historical fire perimeter data or “fire atlases”. Patterns of fire occurrence across the western United States derived from extensive fire scar records have been linked to oscillations in Atlantic and Pacific sea surface temperatures (Kitzberger et al. 2007). In the southwestern US, years with widespread fire were dry year and followed wet years, a pattern that was associated with the El Niño Southern Oscillation (Swetnam and Betancourt 1990). However, these patterns explain only about 30-35% of the year-to-year variation in fire occurrence (Swetnam and Betancourt 1990). Fire atlases, while shorter in temporal depth, provide spatially explicit information about fire extent during the last century (Rollins et al. 2001). These data sets have been used to identify climate drivers associated with regionally synchronous fire years in the US Northern Rockies (Morgan et al. in press). Fire atlases of fire extent and severity inferred from differenced Normalized Burn Ratio have been used to assess fire patterns relative to precipitation (Holden et al. 2007).

The number and size of fires in the western US has increased in recent decades, a trend that has been attributed to warm springs, longer fire seasons, and land management (Westerling et al. 2006), and perhaps to human-induced climate change (Running 2006). In the southwestern United States, the increased size and severity of recent forest fires has been attributed to both recent drought and changes in the stand structure and fuel loading resulting from land use change and fire exclusion (Covington 2000). In a recent analysis of twenty-year satellite-derived fire extent and severity patterns in the Gila National Forest, we

observed a strong relationship of total area burned and area burned severely with patterns of precipitation during the fire season (Holden et al. 2007; Chapter four of this dissertation), suggesting that in addition to inter-annual variation in spring temperatures, within-season precipitation influences fire activity in the Southwest. Our objective was to explore patterns of vegetation productivity across the growing season as inferred from low-spatial resolution (1 km) Advanced Very High Resolution Radiometer (AVHRR) data. We hypothesized that patterns of spring precipitation analyzed in our earlier study would be reflected in the patterns of spring and early summer green-up inferred from time series of NDVI data, and that these could support our inferences about the mechanisms linking fire activity to precipitation.

Methods

Study Area

Data for this study are remotely sampled from within the 230,208-ha Gila Wilderness area, New Mexico within the Gila National Forest (Figure 1). I chose wilderness sites for our analysis because they are less influenced by logging, grazing, and fire suppression than sites outside designated wilderness areas. I wanted to avoid sampling in areas where stand-replacing fires might alter green-up patterns. Approximately 60% of the wilderness area burned during this time period restricted sampling to only a few areas and making randomized pixel selection difficult. I selected AVHRR pixel groups from within unburned areas of pure Spruce-fir, ponderosa pine/Douglas-fir and pinyon-juniper Potential Vegetation Types (PVT). The number of pixels sampled at each site varied depending on the amount of contiguous unburned area available a given PVT. PVT is a classification of biophysical settings named for the vegetation expected at a site after long periods without disturbance (Keane et al. 2000, Keane et al. 2001). Ponderosa-pine/Douglas-fir sites included three mesa tops within the Gila Wilderness that vary by 20th-century fire history and stand structure (Table 1). The open ponderosa pine site (denoted open PIPO in figure 2) is known to have burned at least once during the mid-century (1946) and then again in 1993 and 2003. I consider this site a reference area (Stephens and Fulé 2005) with tree densities approaching those of pre-Euro-American settlement forests. The moderate density site (denoted Mod. Open PIPO in figure 2) burned in 1979 and 1993, and it has a moderately open stand

structure. I hypothesized that the understory vegetation in areas with relatively open tree canopies would be more detectable via a two-dimensional satellite sensor and would respond noticeably to minor precipitation events, and that this would be reflected in the NDVI response. A third area (denoted Dense PIPO in figure 2) is unburned since at least 1900 and has a dense overstory structure and very little understory vegetation. Abolt (1996) described fire histories of upper-elevation forests in the Gila Wilderness; she found 300-year old Douglas-fir and spruce trees with no signs of recent fire. Our field sampling within this site in 2004 confirmed the absence of recent fires. I analyzed time (1984-2004) series of Landsat TM satellite images and visually confirmed that neither the spruce-fir nor the pinyon-juniper sites burned during the time period of this analysis. Average tree density and 20th century fire occurrence for all five sampled sites are listed in table 1.

Satellite Imagery Data

Data for this study comes from a 1989-2005 1-km² AVHRR Normalized Difference Vegetation Index (NDVI) time series (Eidenshink 1992). Annual AVHRR series are comprised of 26 bi-weekly image composites. Image selection for composites and smoothing to reduce noise associated with cloud cover and sensor noise are described in detail by Swets et al (1999). The NDVI is calculated as a ratio of the difference and sum of AVHRR channel 1 (0.58-0.68 μm) and channel 2 (0.725-1.10 μm) and is sensitive to both structural (e.g. leaf area) and physiochemical (e.g. chlorophyll content) characteristics of vegetation (Penuelas et al. 1994). At coarse scales, the NDVI has been described as a measure of gross photosynthesis (Goetz et al. 2005). AVHRR and similar data sets have been used to link NDVI and precipitation patterns (Wang et al. 2003), drought-induced declines in vegetation cover (Brashears et al. 2005) and variable response of non-native vegetation to precipitation (Bradley and Mustard 2005).

Data Analysis

I selected NDVI at three dates chosen to reflect the green-up patterns during the period of peak fire activity in our study area (Figure 2). I sought to select dates for analysis of NDVI that captured variation in spring green-up patterns in as few variables as possible, thus avoiding multi-colinearity and model over fitting. Initially, I selected maximum spring peaks

and troughs of NDVI. However, during wet years, there were no distinct spring peaks in NDVI. Instead, I chose three NDVI values using fixed dates (17 April, 29 May, and 9 July) that approximately captured the time period within which most fires have occurred during the time period of the study (data not shown). I selected 9 July to represent late spring conditions preceding the summer monsoon, with 17 April and 29 May dates selected to capture the general pattern of green-up during the spring. The significant autocorrelation between consecutive NDVI dates is strong enough ($r^2 > 0.70$) that these fixed dates should approximately capture the overall pattern during the fire season.

Snow Water Equivalent data (SWE) was obtained from the Lookout Mountain SNOTEL station (Elevation 2560 meters). Precipitation and temperature variables used in our analysis were calculated using daily weather recorded at the Gila Hot Springs climate station (Elevation 1738 meters) (www.ncdc.noaa.gov). These included the maximum consecutive rain-free days (MNR) and total days (TNR) without rain from 1 April to 15 July, annual precipitation and average monthly maximum and minimum temperatures. Both stations are centrally located to our study sites (Figure 1). Additional predictor variables included in multivariate models included the Keetch-Byram Drought Index (Keetch and Byram 1968) and the Energy Release Component (ERC) (Cohen and Deming 1985) which were calculated from Remote Automated Weather Station data (RAWS), also from the Gila Hot Springs station. These metrics are part of the National Fire Danger Rating System and are commonly used to infer fuel moisture for predicting fire behavior. PVT was used as a stratifying variable.

Multivariate analysis of variance (MANOVA) was used to test for significant relationships between NDVI (3 dates for each of 17 years) and predictor variables. Akaike Information Criteria (AIC) methods were used to select significant model variables (Akaike 1974). The AIC penalizes models for including additional variables and hence helps avoid over-fitting. I performed separate statistical analyses within each individual vegetation type in order to understand the relative contribution of each predictor variable. I then used canonical analysis to further explore the relationships. Canonical analysis searches for linear relationships between two sets of variables (Johnson and Wichern 2002) and describes the strength of that

relationship in terms of a canonical correlation value that approximates a correlation coefficient. In what is termed “canonical structure analysis”, the relationships between the canonical variates and the individual variables used for analysis can be further broken down and used to interpret which individual dependent and independent variables explain most of the variation observed.

I also applied Principal Components Analysis (PCA) across the 26 NDVI dates across the 17 years. This reduced the data to two principal components (PCs) that captured 89% of the variability in the AVHRR time series. Correlation analysis was then used to identify relationships between each PC and the temperature and precipitation variables described above.

Once I observed a significant relationship between the NDVI and predictor variables, it was logical to revisit our data on fire extent by burn severity class for this area (Holden et al. 2007) in order to validate the link between burn severity and climate-driven vegetation patterns. Area burned by severity class for all fires on the Gila NF from 1989-2004 was used as response variables. As I have described elsewhere (Holden et al. 2007; chapter four of this dissertation), I used relative differenced Normalized Burn Ratio (Miller and Thode 2007) calculated from multi-temporal Landsat-derived images for all fires greater than approximately 40 ha to infer annual area burned in each of four burn severity classes: very low, low moderate and high burn severity with “severe” defined as having greater than 75% overstory tree canopy volume loss one year post-fire and a Composite Burn Index value greater than 2.2 (Holden *et al.* 2007).

Results

Spring NDVI was strongly correlated with precipitation metrics across all vegetation types with canonical correlations ranging from 0.80 at the pinyon-juniper site to 0.88 at the unburned ponderosa pine site (Table 1). SWE, PCP, MNR and PVT are significant predictors of NDVI (Table 2). Green-up within the spruce-fir forest type is best explained by SWE, and the strength of that correlation is due primarily to early (17 April) NDVI (Table 3). In the three ponderosa pine sites, variability in NDVI patterns is driven mainly by MNR and

secondarily by SWE and PCP. NDVI on 9 July was significantly correlated with the average June Energy Release Component ($R^2 = 0.43$). Declines in NDVI prior to the arrival of monsoon rains are strongly related to the length of the rain-free period (MNR) (Table 3). The MNR was also well correlated with the ERC ($R^2 = 0.53$). Burn severity is significantly correlated with NDVI at all three fire-season dates analyzed (Canonical correlation = 0.57). Burn severity is most highly correlated with the 29 May and 9 July NDVI (Table 5).

PCA yielded two significant principal components that explained 89% of the variability in the annual AVHRRR green-up patterns. I interpreted the first principal component as spring and summer productivity. It was positively correlated with February SWE, negatively correlated with February maximum average temperatures and negatively correlated with maximum rain-free days from April-June (table 6). This first principal component was also well correlated with May maximum average temperatures. The second principal component, which I interpret as seasonal dryness, was well correlated with annual precipitation, the Palmer Drought Severity Index, KBDI and ERC (Table 6).

Discussion

Our study suggests that patterns of precipitation timing and intensity during the spring and early summer, when most wildfires in this region occur, strongly influence vegetation green-up patterns in mid-elevation forests. SWE, total precipitation from April to June and the consecutive number of rain-free days from 1 April to 15 July explain 64 to 77% of the variability in NDVI during the April to July fire season (Table 1). The decline in NDVI that is often observed prior to the onset of summer monsoon rains suggests that water stress during this typically dry period causes a decline in vegetation productivity. Whether the loss of greenness is a result of senescing understory vegetation, needle loss or a decline in photosynthetic activity is unknown. Regardless, the drying of surface fuels and increased surface fuel loadings associated with such a decline, in the absence of wetting rains, would indirectly influence potential fire activity.

PCA results are similar to the canonical analysis results described above. The first principal component, which explains 79% of the variation in annual NDVI patterns, is well correlated

with both SWE and MNR, and it is negatively correlated with February maximum average temperatures, supporting the conclusions of Westerling et al. (2006) suggesting that warm springs and early snowmelt lengthens the fire season. However, the first principal component is also significantly correlated with May maximum temperatures. This result suggests that warm spring temperatures during a period when snow has already melted may also influence fire activity in the Southwest by increasing evapotranspiration and fuel drying rates that would in turn decrease live fuel moistures and intensify fire activity preceding the arrival of summer monsoon rains.

Past studies of climate-fire linkages in the southwestern US have tended to emphasize the importance of interannual variation in moisture. Regionally extensive fires occurred when dry years followed wet winters (Swetnam and Betancourt 1990). Increasing fire activity during the last 34 years in the western US has been attributed to warm springs, although this relationship was much weaker in the southwestern US than the northern Rockies (Westerling et al. 2006). Our results suggest that weather patterns within the fire season strongly influence fire activity in our study area. Certainly, in warm springs, there is less snow and it disappears earlier, and so fuel drying starts early. Saturated, large diameter logs can become extremely dry within 60 days at 26 degrees C and 15% relative humidity (data predicted from equations in (Cohen and Deming 1985) (data not shown here). While lack of snow will compound the effects of dry springs, if there is a long enough period without rain after the snow is gone, vegetation and logs will be dry enough to fuel fires.

Precipitation during the spring and early summer could also directly influence fire activity by slowing the rate of spread of actively burning fires. Even minor precipitation events would bring increased relative humidity, lower air temperatures and cloud cover that would reduce the fire intensity and rate of spread. The maximum number of days without rain (MNR) is also an indicator of when monsoon rains arrive. A rain-free period that extends into July would indicate the delayed arrival of summer storms. These storms are often intense and bring large amounts of precipitation that that would likely diminish or even extinguish actively burning fires. A delay in their arrival would allow fires to continue burning in an already dry period, likely with increased intensity. I note that while NDVI is correlated with

annual burn severity (canonical correlation = 0.57; table 5) the relationship between precipitation and NDVI is much stronger (canonical correlation = 0.80-0.88) with as much as 77% of the variability in NDVI explained by snow and precipitation patterns. The relative strength in the relationship between these variables supports the idea that precipitation patterns, and in particular the MNR, may influence fire patterns directly by slowing or extinguishing actively burning fires.

Vegetation green-up is often bimodal in the Southwest (Figure 2), reflecting bimodal precipitation (Sheppard et al. 2002). During the 17-year AVHRR time series, seven years show a pattern of rapid green-up in the early spring followed by a period of slowed growth or decline leading up to onset of summer monsoon storms that typically begin during the first week of July. However, green-up patterns vary considerably between years. During very wet years like 1992 (Figure 2) patterns of green-up become uni-modal, with no significant decline in productivity or senescence prior to the arrival of the summer monsoon. While fall is generally considered to be the peak green period in the Southwest, several of the 17 years, e.g. 1991 in figure 2, had peak green-up in the spring exceeding the fall. These patterns highlight the considerable variability in precipitation patterns in the Southwest during this 17-year record.

MNR is a strong predictor variable of fire season NDVI in the pinyon-juniper, open and moderately open ponderosa pine sites (table 3), supporting our working hypothesis that open-canopy forests with abundant understory vegetation are more strongly coupled to (and hence more strongly correlated statistically) with precipitation patterns. This pattern suggests that the understory vegetation component at these sites, which are likely to fluctuate more within the season, may be responding to spring and early summer water stress, or that this is simply more detectable in open than in closed-canopy sites. In a concurrent study using stable oxygen isotope data extracted from tree rings at these sites, understory vegetation influenced the water sources used by ponderosa pine trees, with trees in open forests using deeper water than the closed-canopy, unburned sites (Heward et al. in preparation). It is impossible to test specific hypotheses on the dynamic competitive interactions between the understory and overstory vegetation components retrospectively and at the coarse resolution used in this

analysis. However, it is interesting to speculate as to the reason for the observed differences between these sites. One possibility is that dense forest stands with overall higher NDVI values are less resilient to stress than open stands or they respond more strongly to water stress than trees in more open sites. Increased canopy interception in closed-canopy sites might limit or slow the acquisition of water after a long dry period in the spring.

Alternatively, increased investment in surface roots at sites where little understory vegetation is present to compete for surface water could result in surface root mortality during a dry period that would be followed by a subsequent loss in foliar biomass, once soil moisture is regained. I can't rule out the possibility that this weak statistical pattern is simply an artifact of sensor variations, or that spatial extent of individual precipitation events varies across our study sites and is reflected in minor differences in green-up patterns between sites.

While there is considerable uncertainty in the future climate in the southwestern US climate, most atmospheric circulation models predict regional drying associated with global climate change (Seager et al. 2007). Recent studies have shown rapid and sudden vegetation loss in response to drought in the Southwest (Breshears et al. 2005), supporting the theory of thresholds in vegetation-climate systems. Systems approaching limits to those thresholds, like chaotic and complex systems, would be sensitive to minor perturbations. As such, I suggest that it may be important to separate and understand seasonal components of the Southwest climate system. Although the spring has typically been ignored in Southwest because it is generally dry, during this 17-year period we see years with as much as 15 cm and as little as 1 cm of rain falling from April to June. This spring and early summer period could very well act as a tipping point or trigger, whereby significant ecological changes are fomented by series of cumulative stressors, for example fires following dry warm winters coupled with dry springs.

Study Limitations

Coarse-scale AVHRR data are useful for inferring coarse scale green up patterns. However, sensor malfunction and sensor degradation over the lifetime of these sensors likely introduce errors at certain dates and years. Efforts to eliminate cloud contamination (Swets et al 1999) and relatively clear skies in the Southwest should minimize cloud effects. The local scale of this analysis limits the inferences I can draw about the influence of precipitation and

snowpack to our study area. Finally, I used weather data from two stations located at different elevations and relative locations to our sample sites. I used SNOTEL station data in order to capture the influence of snowpack on green up but also on reflectance patterns caused by snow albedo effects. Gila Hot Springs station data was used because we were interested in validating the maximum rain-free interval metric used in our previous study (Holden et al. 2007; Chapter four of this dissertation). However, analysis of the same rain-free interval metric extracted from the Lookout Mountain SNOTEL site showed weaker ($r^2 = 0.32$), but still significant relationships with the AVHRR data.

Conclusions

Our study shows strong relationships between patterns of spring and early summer green-up inferred from AVHRR time series data and precipitation patterns during that same period. This relationship demonstrates an important potential link between precipitation patterns, their influence on green-up patterns preceding and during the fire season, and the resulting fire activity for this study area. It is still unclear to what extent the patterns we have observed in the Gila NF are a localized rather than regional phenomenon. However, these results support the conclusion that recent increases in the size and severity of fires in our study area and perhaps the Southwest are driven by seasonal climate patterns, in particular dry periods in the spring corresponding to periods when fire activity is usually at its peak. In the future, we plan to evaluate these patterns at multiple sites across this area of the US.

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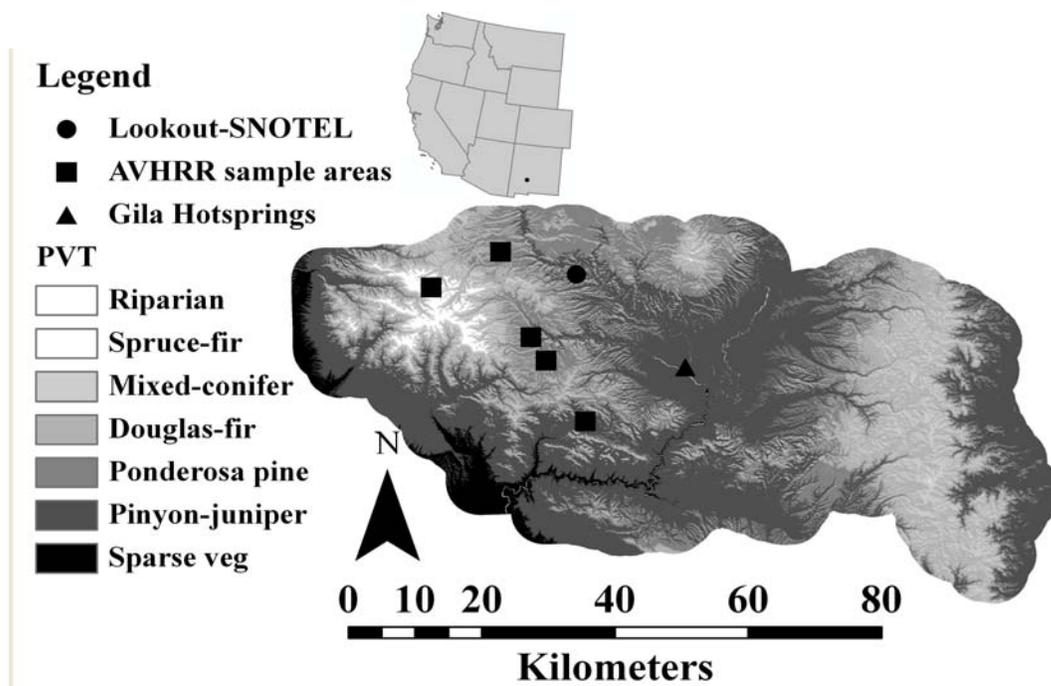


Figure 1. Gila Aldo Leopold Wilderness Complex stratified by Potential Vegetation Type (PVT). AVHRR sample locations are denoted by squares. Weather information was drawn from the Lookout SNOTEL station and from the weather records from Gila Hot Springs.

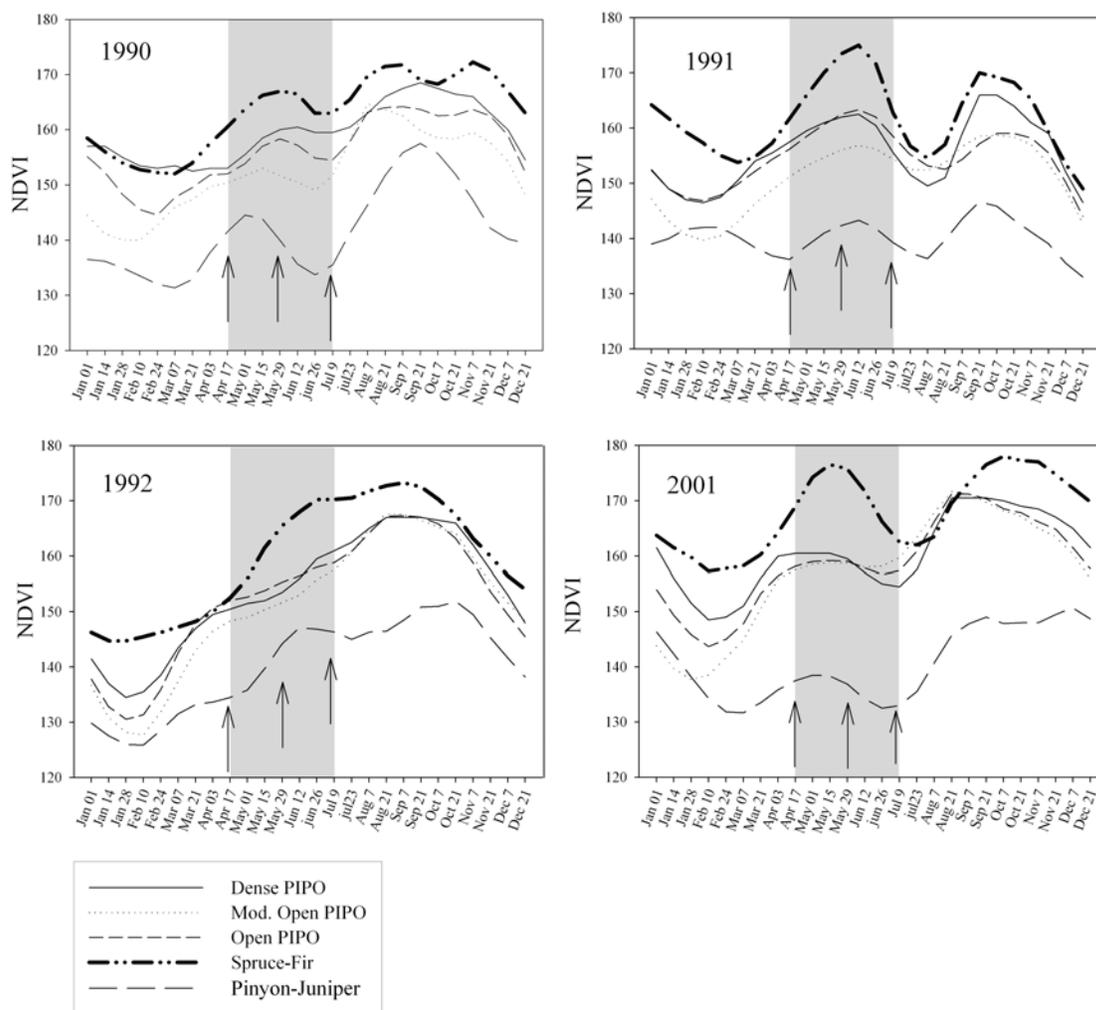


Figure 2. NDVI derived from AVHRR satellite imagery for four different years, selected to represent some of the dominant green-up patterns observed in the 17-year time series. Vertical lines indicate the dates used in analysis. Shading denotes the period of peak fire activity in this study area. Arrows indicate NDVI dates used in statistical analyses.

Table 1. Correlation between NDVI and precipitation for 17 years (1989-2005) for five different sites, each characterized by different vegetation types.

Study Area	1 st Canonical Correlate	Squared Canonical Correlate	# 1-km ² AVHRR Pixels	Fire occurrence	Avg (1 SD) trees/ha
Pinyon Juniper	0.80	0.64	6	unburned	NA
Open PIPO	0.80	0.64	6	1946;1993;2003	170 (75)
Mod. Open PIPO	0.84	0.71	6	1979;1985;1993	400 (270)
Dense PIPO	0.88	0.77	2	unburned	600 (400)
Spruce-fir	0.85	0.73	4	unburned	1100 (NA)

Table 2. AIC for selected MANOVA models.

MODEL	AIC	Δ AIC
Y ~ SWE + PCP + MNR	1251	357
Y ~ SWE + VEG	933	39
Y ~ ERC + KB + VEG	929	35
Y ~ SWE + PCP + VEG	911	17
Y ~ SWE + PCP + MNR + VEG	894	0

Table 3. Canonical structure results by vegetation type, showing the relative correlations between the first canonical weight and the original model variables. Larger values indicate stronger relative strength in overall relationships between groups of response and predictor variables. SWE is the strongest predictor in the spruce-fir forest type. MNR is the strongest predictor variable in all open canopy sites.

	Pinyon- Juniper	Open PIPO	Mod. Open PIPO	Dense PIPO	Spruce-fir
17 April	0.49	0.28	0.38	0.02	0.86
29 May	0.99	0.96	0.37	0.93	0.24
9 July	0.50	0.69	0.56	0.77	0.39
SWE	0.80	0.41	0.45	0.47	0.97
PCP	0.27	0.29	0.73	0.36	0.38
MNR	-0.82	-0.75	-0.88	-0.64	-0.53

Table 4. Multivariate model results with annual area burned within 4 burn severity classes with site as a stratifying variable and NDVI variables as predictor variables.

Variable	Df	Pillai	approx F	num Df	den Df	Pr(>F)
PVT	6	0.41	1.96	24	408	0.0048
17 April	1	0.09	2.46	4	99	0.049
29 May	1	0.31	11.20	4	99	<0.0001
9 July	1	0.14	4.10	4	99	0.0043

Table 5. Canonical analysis results for NDVI metrics and annual area burned within four burn severity classes. One canonical variate was statistically significant (shown in bold). Canonical structures describe the influence of the original variable on the overall correlation between the two sets of variables.

Canonical Analysis	1 st Can.Var.	2 nd Can. Var.
Canonical Correlation	0.57	0.38
Sq. Can. Correlation	0.32	0.15
Canonical Structures		
17 April	0.26	0.48
29 May	-0.78	0.14
9 July	-0.77	0.63
Very low severity	0.10	0.86
Low severity	0.56	0.69
Moderate severity	0.59	0.78
High severity	0.35	0.80

Table 6. Correlations (R^2) between principal component scores and statistically significant ($p < 0.05$) precipitation and temperature variables. The proportion of variance explained by each principal component is shown in parentheses.

	PC1 (79%)	PC2 (10%)
SWE in Feb.	0.59	-
SWE in Mar.	0.47	
Feb. Max. Temp.	0.39	
Annual Precipitation		0.39
MNR	-0.42	
6-month PDSI		-0.32
KBDI (June avg)		0.46
ERC (June avg.)		0.44
May Max. Temp.	-0.40	

CHAPTER 6

Twenty-Year (1984-2004) Severe Fire Occurrence Across Vegetation and Topographic Gradients in a Large Southwestern US Wilderness Area

Zachary A. Holden, Penelope Morgan

Abstract

Using a burn severity atlas derived from multi-temporal Landsat TM satellite imagery and differenced Relative Normalized Burn Ratio (RdNBR) images, we describe patterns of severe fire occurrence for 20 years (1984-2004) with respect to Potential Vegetation Type (PVT) and topography (elevation, aspect, slope, solar radiation, heat load index and wetness). In 20 years, 11% (152,874 ha) of the 1.4 million-ha Gila National Forest burned, and 10% of that burned severely (>75% of tree canopy removed), mainly in upper elevation mixed-conifer and spruce-fir forest PVTs. When all PVTs were analyzed together, severe fire occurred more frequently at higher elevations and on north-facing, steep slopes. Based upon regression Tree analyses within drier pinyon-juniper, ponderosa pine and Douglas-fir PVTs, severe fire occurrence was associated with north-facing slopes, higher wetness index and lower heat load index values. We suggest that moisture limitations on productivity in the southwestern US interact with topography to influence vegetation density and fuel production that in turn influence burn severity. Within higher-elevation spruce-fir forest types, where the season for burning is often short due to persistent snow pack and cool temperatures, severe fire was more common at locally warmer, drier sites with higher heat load index values and drier aspects. Using the Random Forest algorithm with 14 topographic predictor variables, we predict the occurrence of severely burned pixels with a classification error rate of 17.3% and 38.3% for RdNBR grids classified as severe vs. not severe (two classes) or as low, moderate and high severity (three classes), respectively. In this area, there are strong bottom up (topographic) controls on severe fire occurrence. The strong predictability of burn severity based on topographic variables demonstrates the strength of vegetation-topography coupling in this semi-arid wilderness area. This analysis approach has potential as a tool for identifying potential areas for fuels treatment designed to alter fire severity.

Introduction

As a keystone disturbance process, fire influences local, regional and global processes (Agee 1993). In recent decades, fires have burned millions of hectares in the western US and cost billions of dollars to contain and suppress (www.nifc.gov), likely reflecting both a legacy of fire exclusion and climate (Westerling et al. 2006). While it is widely believed that recent fires are increasingly severe, and the severity of some individual fires have been well documented (Odion et al. 2004, Lentile et al. 2006b), we lack understanding of the patterns of burn severity from many fires across gradients of vegetation and topography through time. The term “burn severity” can describe a variety of post-fire effects (Lentile et al. 2006a). Throughout this study, I refer to burn severity as the changes in overstory vegetation from pre-fire to one year post-fire. Severe, stand-replacing fires are difficult to suppress, and they can be ecologically significant when they lead to debris flows (Cannon and Reneau 2000), accelerated soil erosion (Pannkuk and Robichaud 2003) and changes in dominant vegetation type post-fire (Savage and Mast 2005). In this study, I sought to understand where severe fires are likely to occur across the landscape and how patterns of burn severity vary with vegetation and topography, two of the biophysical drivers of fire regimes. Accurately assessing post-fire ecological effects and predicting where severe fires are likely to occur has great relevance to resource managers tasked with reducing surface and canopy fuel loads through thinning, fuel reduction and prescribed burning.

Topography, vegetation and climate interact in complex ways to influence fire extent and fire frequency across a range of spatial scales (Stephens 2001, Rollins et al. 2002), but we lack understanding of their interacting influence on fire severity. Paleoecological data suggest that fire extent and vegetation types have varied with past climate variability (Whitlock et al. 2003), and Pierce et al. (2005) linked Holocene warming to severe, stand-replacing fires in dry pine forests in Idaho. Decades of fire exclusion have altered stand structure and surface fuels loads, likely contributing to fire regime changes in forests that once burned frequently (Covington and Moore 1994, Moore et al. 2004). While much is known about historical trends in fire frequency, spatial patterns of burn severity over time are poorly understood (see further discussion in recent review of burn severity by Lentile et al. (2006a) and Chapter 2 of this dissertation).

Several authors have recently evaluated relationships between severe fire, vegetation and topography for individual large fire events. Odion et al. (2004) described patterns of severe fire occurrence within a large fire in central Oregon. Lentile et al. (2006b) used hundreds of field measurements and remote sensing to evaluate the relative influence of stand structure and topography on severe fire occurrence within the 2000 Jasper Fire in the Black Hills of South Dakota. Alexander et al. (2006) examined the occurrence of severely burned areas within two fires in northern California and southern Oregon. Rogan and Yool (2001) used satellite imagery to map burn severity for two fires in the southwestern US. Lentile et al. (Submitted), Lewis et al. (2008), and Hudak et al. (2008) analyzed the vegetation response and soil effects of burn severity in the field and from multiple remote sensing tools from eight fires in Alaska, California and Montana. No single study has encompassed burn severity from many fires at once burning over decades. The objective of this study was to evaluate 20 years of satellite-derived burn severity patterns with respect to topography and Potential Vegetation Type (PVT) across the Gila National Forest (Gila NF). Most of the fires (90 of 114 fires and more than 80% of the area burned) I analyze occurred within the Gila Aldo Leopold Wilderness Complex (GALWC), under near natural conditions. Within the wilderness, naturally ignited fires are often managed under the Wildland Fire Use program adopted there in 1974. Pioneering fire management efforts in the GALWC have made it a model for wilderness fire management in the United States (Burke 2004). I take advantage of this rich history of large fires that burn during the natural fire season and with relatively little influence of roads, grazing, and logging to examine broad-scale patterns of severe fire occurrence and their association with vegetation and topography.

Methods

Study Area

My research focused on the 1.4 million-ha Gila National Forest in New Mexico, USA (Figure 1). This area encompasses diverse landforms and topography. Many of the fires included in this study burned in the central and northern portion of the Gila Wilderness, where extensive stands of ponderosa pine and mesic ponderosa pine-Douglas-fir forests grow on broad, flat mesas. These forests transition into mixed-conifer and spruce-fir forests to the

north, where the Mogollon Mountains rise to an elevation of 3200 meters. Steep, rugged terrain dominates the Diablo and Pinos Altos ranges to the south. Precipitation in our study area is bimodal, occurring mainly in the winter, and following a typically dry period in the spring, as monsoon rain storms that begin, on average, in the first week of July (Sheppard et al. 2002). Lighting is frequent at mid and upper elevations in our study area (Rollins 2001).

Burn Severity Atlas Construction and Analysis

A digital burn severity atlas including all fires > 40 ha in area that occurred 1984-2004 was created for the Gila National Forest using pre and post-fire Landsat images provided by the Monitoring Trends in Burn Severity (MTBS) project (<http://fsgeodata.fs.fed.us/mtbs/>). All images were terrain corrected and converted to reflectance following protocols developed as part the MTBS program. Pre- and post-fire spring scenes (15 May – 15 July) in the Gila NF were processed using the Relative Differenced Normalized Burn Ratio (RdNBR) (Miller and Thode 2007). The RdNBR is a variant of the dNBR, a spectral index first developed by Lopez Garcia et al. (1991) to map burned areas and then later used by Key and Benson (2002) to assess post-fire effects. Relative to dNBR, the RdNBR showed stronger and more linear correlations with field data from our study and is appropriate given the prevalence of open-canopy vegetation in our study area.

Each fire was manually digitized on-screen using a combination of images. Digital fire perimeter databases (also called a fire atlas or a digital polygon fire history (Gibson 2006), produced by the GIS analyst on the Gila National Forest were used to identify names and dates of major fires. Landsat bands 7:4:1 color composite and RdNBR images created for each fire were then used to verify the location of fires documented in the fire perimeter database and to locate additional smaller fires visible on the imagery but not in the fire perimeter databases. The resulting perimeters were then used to subset the RdNBR for each fire in the ARCTIC GIS software package (v. 9.2; ESRI, Inc. 2005). More than 40,000 hectares burned for a second or third time during the time period of our study. Inclusion of recently reburned areas could confound our overall interpretation of burn severity patterns. Therefore, I excluded these data from this analysis by assigning those cells the RdNBR value

of the first fire occurrence. Burn severity patterns within reburned areas are potentially of great interest and will be presented in a separate manuscript.

Field Data Collection

Burn severity on the ground was measured using 30-m diameter CBI (composite burn index) plots (www.frames.nbi.gov) collected between 20 May 2004 and 20 July 2004. Within the 2003 Dry Lakes Fire perimeter, 109 sampling points were randomly located and stratified by burn severity using a 23 October 2003 post-fire Landsat TM-derived Normalized Burn Ratio (NBR) image. Applying the CBI in the field post-fire requires an ocular assessment of the degree of change in soil and vegetation strata as a result of the fire. While this required judgment, I was confident in our estimates after spending three months collecting fuels, understory vegetation and forest structure data within the burned area the previous year. The CBI is a useful tool for rapidly assessing post-fire change and relating that change to reflected radiation detected by a satellite sensor. I removed two CBI measures from final CBI estimates (change in species composition, change in soil color) because they were difficult to objectively quantify in the field. I also removed estimates of medium and large-diameter fuel consumption and bole char height because we felt they were unlikely to be detectable by the Landsat sensor. These estimates were collected in the field but removed from the final CBI values that were used to validate our satellite imagery. Comparison of scatter plots using both the full and modified CBI values showed that the removal of these variables had little overall effect on the final CBI measure (data not shown).

Burn severity images for each fire were classified into 4 severity classes (unchanged, low, moderate, high), with breakpoints for each severity class defined based on CBI data. Post-fire ecological effects occur along a continuum, making classifications of burn severity data somewhat arbitrary. However, doing so simplifies data analysis and interpretation. I classified “severe” pixels as burned areas where more than 75% of prefire overstory tree foliage volume was black or red post-fire, corresponding to a CBI value of 2.2 ($RdNBR = 665$). Scatter plots of $RdNBR$ and the CBI stratified by PVT showed no patterns of separation. Therefore, the same threshold was applied across all vegetation types. I selected this slightly conservative threshold to account for delayed tree mortality expected several

years post-fire (Harrington 1990). Because we lack field data on burn severity for previous fires, CBI data from this one 2003 fire were used to set thresholds for all burns in the 20-year record. However, based upon our comparison of pre- and post-fire high resolution digital aerial photographs we suggest that for three fires through time (1993; 1996; 1997), fire-created canopy openings in ponderosa pine, Douglas-fir and mixed-conifer forests are mapped with a high degree of accuracy when this threshold is applied to earlier fires (data not shown).

Data Analysis

We used fifteen different predictor variables in all analyses. PVT is a classification of biophysical setting named for the vegetation that would occur at a site after long periods without disturbance. We used a PVT classification developed by Keane et al. (2000) for the Gila National Forest based on extensive ground validation. Fourteen predictor variables were derived from a 30-meter digital elevation model (Table 1). These included slope and aspect, elevation, Heat Load Index (McCune and Keon 2002), solar radiation, Compound Topographic Index (Moore et al. 1993), elevation relief ratio (ERR) and roughness (ROUGH) indices calculated with 3 x 3 and 15 x 15 pixel window sizes. Grids describing hill slope position (HSP) and cross-slope and down-slope curvature (PROCRV; PLNCRV) were also included. All variables were classified using equal interval breaks for Bayesian conditional probabilities. An unclassified cosine-transformed slope and aspect grid (SAT; McCune 2002) was used in regression tree and Random Forest models. Solar radiation (total direct and diffuse from April-July) was derived using slope, aspect and elevation grids in the Solar Analyst Extension for ArcView 3.3 (ESRI, Inc. 2002).

We used three methods to analyze patterns of severe fire occurrence with respect to vegetation and topography. First, relationships between single predictor variables and severe fire occurrence were graphed and assessed using Bayesian conditional probabilities in the Bayes extension for Arcview 3.3 (ESRI Inc. 2002) (Aspinall 1992, 2000). Conditional probabilities quantify the likelihood of severe fire occurring with respect to each predictor variable given the proportion of that variable within the total area burned. I calculated

conditional probabilities for eight classified topographic variables individually using a binary (severe vs. other burned) grid of total burned area as the response.

Second, I used Classification and Regression Tree analyses (CART) (Breiman et al. 1984) to explore the relationships between burn severity, vegetation and topography. Classification and regression trees search for splits among groups of predictor variables that minimize residual error at each node or split (Breiman et al. 1984). This analysis method is suited to classified and continuous variables and large data sets, requires no assumptions about data independence, and is robust to the spatial autocorrelation inherent in both the response and predictor variables. We used continuous (i.e. unclassified) RdNBR data for all fires as a response variable and Potential Vegetation Type (PVT) as a vegetation layer (Keane et al. 2000).

I used a variant of Classification and Regression Trees called Random Forests (Breiman 2002) to assess the ability of landscape variables to predict severe fire occurrence (Breiman 2002). Random Forests implements a bootstrapping procedure whereby approximately 60% of the data are used in a classification tree with the remaining data used as a validation data set (termed the “out of box sample”). The Random Forest algorithm creates bootstrapped samples of thousands of classification trees. Binary splits at each node of the trees are bootstrapped as well, with random sets of predictor variables used in different combinations to select strong variable splits. This method is computationally very intensive, but has yielded robust predictions across a variety of applications (Prasad et al. 2006, Rehfeldt et al. 2006). The random selection of variables eliminates problems associated with co-linearity and spatial autocorrelation that plague other statistical modeling techniques. We applied the Random Forest algorithm using RdNBR data classified into two classes (severely burned vs. other) and into three classes (low, moderate and high burn severity classes). We used fifteen topographic variable derived from a 30 m digital Elevation Model (Table 1). We ran Random Forest for all PVTs combined, with PVT as a predictor variable and then for individual PVTs. The low proportion of severe compared to other severity class pixels within the drier PVT’s initially led to slight over-prediction. To account for this bias, we used a stratified random sampling routine to select more balanced proportions of each severity class. Model

outputs were compared using varying numbers of output trees. The models appeared to stabilize after 1000 trees, and final trees models were run with 2000 trees, and four variables evaluated at each split within each tree.

Results

The RdNBR was a good predictor of CBI field measurements ($r^2 = 0.78$; Figure 2). In contrast with other studies that have used the dNBR to predict CBI values, (e.g. (Van Wagendonk et al. 2004, Alexander et al. 2006) relationships between the CBI and RdNBR were linear. Of the 1.4 million-ha Gila National Forest, 152,874 (about 11%) burned 1984-2004, and 10% of the burned area was burned severely (Table 2). The percentage of area burned with low, moderate and high severity varied among vegetation types (Table 2). The upper elevation spruce-fir and mixed-conifer forests PVTs had the highest proportion of the area burned severely (Table 2). Severely burned areas occurred disproportionately on north- and northeast-facing slopes (azimuth 315-360 and 0-90°), on steep slopes (>16%), and where solar radiation values were low to moderate (99 to 113 kWh/m²) (Figure 3a-d) and at high elevations (Figure 3g). Severe fire was more common where heat load (HLI) was either very low or very high (Figure 3f). Severe fire was also associated with low CTI values and high slope position values (Figure 3e and 3h), likely reflecting the tendency for severe fire to occur at the crest of hills.

Within the pinyon-juniper PVT severe fire occurs more frequently on north-facing aspects, with low heat load index and solar radiation values and in areas with high CTI values (Figure 4). Within the ponderosa pine and Douglas-fir PVT, severe fires were also more likely to occur at cooler, wetter sites (Figure 5). However, slope was a dominant splitting variable within these vegetation types, reflecting the large amount of area burned on flat mesas in the north-central part of the wilderness. Within spruce-fir and mixed conifer PVTs, severe fire occurred at high elevations and on dry, south-facing aspects (Figures 6 and 7).

Classification accuracy of Random Forest models on all PVTs combined was 82% and 62% for two and three burn severity classes, respectively (Table 3). With the exception of the

spruce-fir PVT, classification accuracy decreased slightly across a gradient from dry (Pinyon-Juniper) to wet (mixed-conifer) PVT's (Table 3).

Discussion

Burn severity and topography influence site productivity and vegetation occurrence (Whitaker and Niering 1975). Forest ecosystem productivity in the southwestern US is primarily water-limited (Chapin et al. 2002), and topographic factors like elevation, slope aspect and compound topographic index (CTI) influence biomass production and fuel accumulation rates (Whitaker and Niering 1975). Even slight increases in effective moisture can lead to significant changes in vegetation structure. For example, Douglas-fir encroaches on slightly north-facing slopes and ponderosa pine establishes at mesic sites within areas dominated by pinyon and juniper. This pattern appears to shift in upper elevation mixed-conifer and spruce-fir forest types, where increased solar insolation and heat load index values, factors that would increase evapotranspiration and drying of surface fuels, are associated with increasing burn severity. This general pattern is supported by Random Forest model results. Classification accuracies are highest for dry vegetation types and decrease across a gradient from dry to moist sites. Classification accuracy then increases significantly within the highest elevation spruce-fir forests.

Winter precipitation combined with the timing and intensity of precipitation events during the fire season influences green-up patterns in our study area, with the length of the dry period preceding summer monsoon rains influencing fire occurrence, presumably by affecting vegetation productivity and stress (Holden et. al in preparation). Combined with temperature, relative humidity and the timing and intensity of monsoon rains, these precipitation variables should largely determine fuel moistures and the length of the burning window during the fire season, which in turn influences fire extent and severity (Holden et al. 2007). The length of this window is shorter at higher elevations, where snow pack delays early season green-up. Within the drier PVTs at lower elevation, spring precipitation patterns influence the peak and subsequent decline of green-up preceding monsoon rainstorms (Holden et al. in preparation). We speculate that these patterns are reflected in the patterns of severe fire occurrence in this landscape. At lower elevations, dry PVTs have a long window

within which burning is possible. At locally wet and more productive sites, higher vegetation density and fuel accumulation means that the effects of fire will be more severe (greater change pre- to post-fire). Given the relatively short burn window within high elevation, mesic vegetation types, extremely cool, wet areas (e.g. those at high elevation, north-facing slopes) may not have experienced ignition when conditions were favorable for burning during this study period. In contrast, fuels on dry and relatively warm south-facing slopes within these cool sites will dry earlier and thus be ready for burning should ignition occur.

The strength of the relationships between severe fire occurrence and topographic variables presumably also reflect the influence of topography on fire behavior. Slope aspect position influences the type of vegetation that will occur on a site as well as drying rates of live and dead fuel moistures, directly influencing fire intensity when fire occurs. Slope steepness is known to directly influence fire rate of spread (Rothermel 1972). Other topographic features like landform curvature and topographic complexity (described by variables like the Elevation Relief Ratio (ERR) and topographic Roughness (ROUGH)) may exert more subtle influences on fire behavior by influencing microclimate, wind patterns or the length of wind-driven fire runs. They also reflect soil development and water holding capacity.

Taken together, these results and our analyses of climate and vegetation green up patterns support the theory of hierarchical controls on fire regimes (Heyerdahl et al. 2001). The strong relationship between topography and burn severity reflects the “bottom up” control of burn severity occurrence and the tight coupling of climate, topography and vegetation in this semi-arid region, where moisture limits vegetation production. The limited human influence on the fuels and vegetation in the majority of fires that burned within the wilderness have allowed these fire-vegetation-topography interactions to play out for decades. Random Forest predictions decrease in their classification accuracy from dry to moist vegetation types (table 3), which suggests that vegetation-topographic coupling and its influence on fire behavior breaks down in wetter vegetation types. Fires were suppressed aggressively for many years, even within the Gila Wilderness. As elsewhere, however, the effects of fire exclusion are less significant in terms of altering fire regimes in wet, less frequently burned sites than in drier, frequently burned forests (Brown 2004, Noss et al. 2006). We hypothesize that the

relative amount of change in vegetation accumulation within drier vegetation types in the absence of recent fires would have been greater in dry forests than in upper elevation PVTs, where historically, fires were less frequent (Abolt 1996).

Patterns of severe fire occurrence inferred from only twenty years of data should be interpreted cautiously. We have not accounted for the influence of vegetation structure, which influences burn severity here (Holden 2005). Although some of the fire years included in this study were very wet (e.g. 1984-1987) and others were very dry (e.g. 2002), we can't assume that these data encompass the range of possible fire-vegetation interactions. We also note the potential significance of fire origin and direction of travel in this wilderness area. For example, because most WFU fires during the last 20 years have started in central portions of the Gila Wilderness and spread to the north, many north-facing slopes experienced backing fires. We observed in the field many north-facing slopes at mid-elevations dominated by ponderosa pine and Douglas-fir forest types that had experienced surface fires at least once during the last 20 years, despite relatively dense stands and young understory Douglas-fir tree encroachment. When these north-facing slopes finally experienced a fire that began outside the wilderness and spread to the south, many of them burned as stand-replacing fires (Holden, personal observation). We can't rule out the possibility that wind direction and other aspects of weather and fuels not evaluated here may also be responsible for the fire severity patterns observed within mixed-conifer and spruce-fir forest types.

Implications for Management

One impetus for this analysis was concern about the impacts of fires in the Gila on endangered Gila trout populations (*Oncorhynchus gilae*). Debris flows following fires in 1995, 2002 and 2003 severely impacted or extirpated several local populations (Probst and Monzingo, personal communication). The predictive capabilities of landscape and topographic variables alone, without data on pre-fire surface fuel loading and forest structure, and without during-fire weather, was 83% overall, and slightly higher within individual PVT's. Using imputation techniques, we will use the Random Forest model results to predict the probability of severe fire occurrence in unburned areas and identify areas with high

probabilities of burning severely. The resulting prediction map will be combined with analysis of debris flow and fish extinction probability models and then incorporated into a decision support model in order to predict and map risks of fish extinction. This product could then be integrated into the fire management decision-making process.

Much of fuels management is focused on altering fire severity via mechanical treatments and prescribed burning. Current interest in the influence of past treatments on the behavior and severity of recent fires reflects the uncertainty about their effectiveness. It is unclear how broadly the results from our study extend to other areas of the Southwest, and it is likely that other land uses like logging and grazing will have altered the vegetation-topography interactions in some places, confounding the resulting burn severity patterns where subsequent fires have occurred. Further evaluation of burn severity-topography interactions across a range of environments and vegetation types will be necessary to understand how these patterns vary across space and varying land use histories. Interpreting burn severity from satellite data, for hundreds of fires across a range of environments and climatic conditions will greatly enhance our understanding of why and where fires burn severely. Such analyses will help us to strategically target fuels and fire management. They may also help us better understand the climate and weather conditions under which fire management options like Wildland Fire Use may or may not be appropriate.

Understanding the complex interactions among fire, vegetation, topography, climate, and land use is critical to predicting how fire regimes will change in response to climate and future land use (Morgan et al. 2001). Our current understanding of burn severity as an aspect of fire regimes is mainly theoretical or based on anecdotal evidence and case studies from a few fires. This study is the first to evaluate these patterns across multiple fires over multiple years. Through the Monitoring Trends in Burn Severity (MTBS) project (<http://fsgeodata.fs.fed.us/mtbs>), data similar to ours will be available nationwide for thousands of fires. The data will be immensely valuable for understanding burn severity to complement our growing understanding of how fire extent and occurrence are linked to climate.

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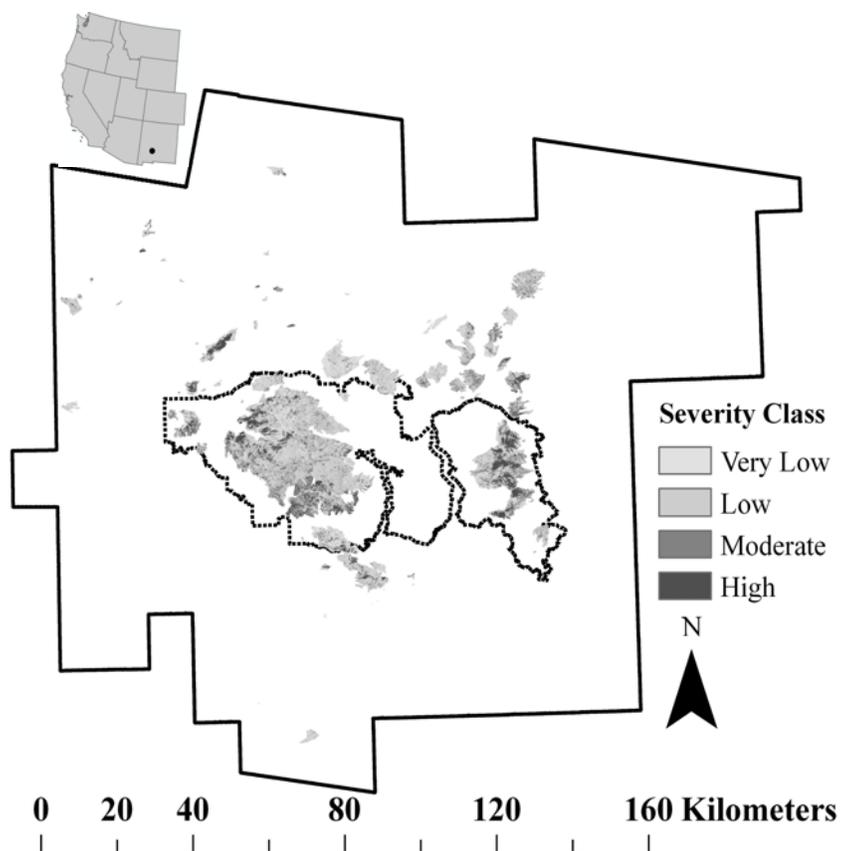


Figure 1. Burn severity atlases (1984-2004) for the 1.4 million-ha Gila National Forest in New Mexico. Fires varied in burn severity (shaded polygons, 114 fires burned 152,800 ha). as interpreted from Landsat satellite imagery using the Relative differenced Normalized Burn Ratio (RdNBR). Solid dark line is the Gila NF boundary. Dotted inner line denotes the Gila and Aldo Leopold Wilderness Complex boundary.

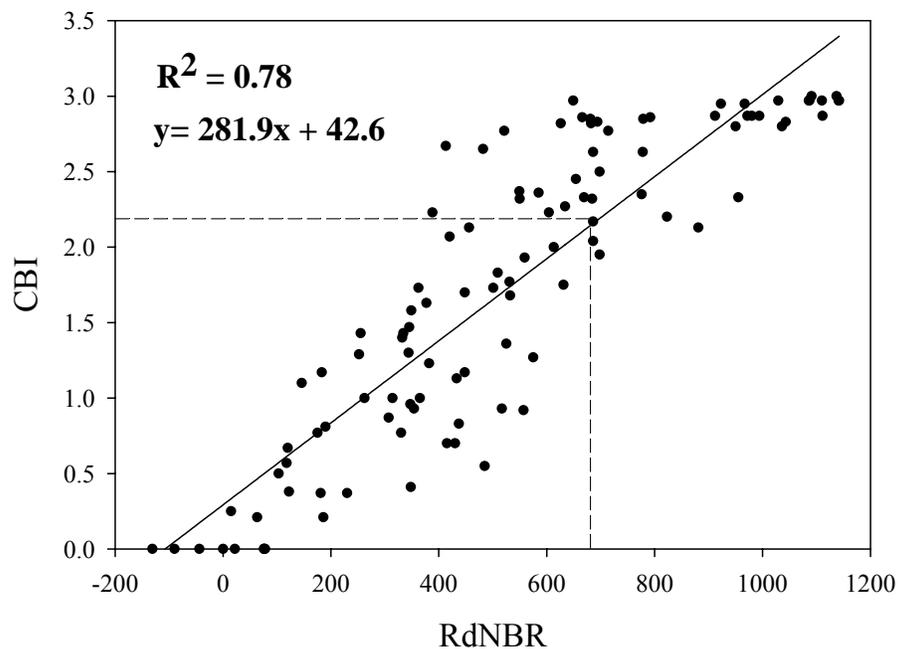


Figure 2. Modified Composite Burn Index (CBI) from 109 field plots vs. the differenced Relative Normalized Burn Ratio (RdNBR) collected on the 2003 Dry Lakes Fire, New Mexico. Data were collected between 20 May 2004 and 20 July 2004, 1 year after the 2003 fire. Dashed lines show threshold between “moderate” and “severe” burn severity classes ($CBI = 2.2$; $RdNBR = 665$).

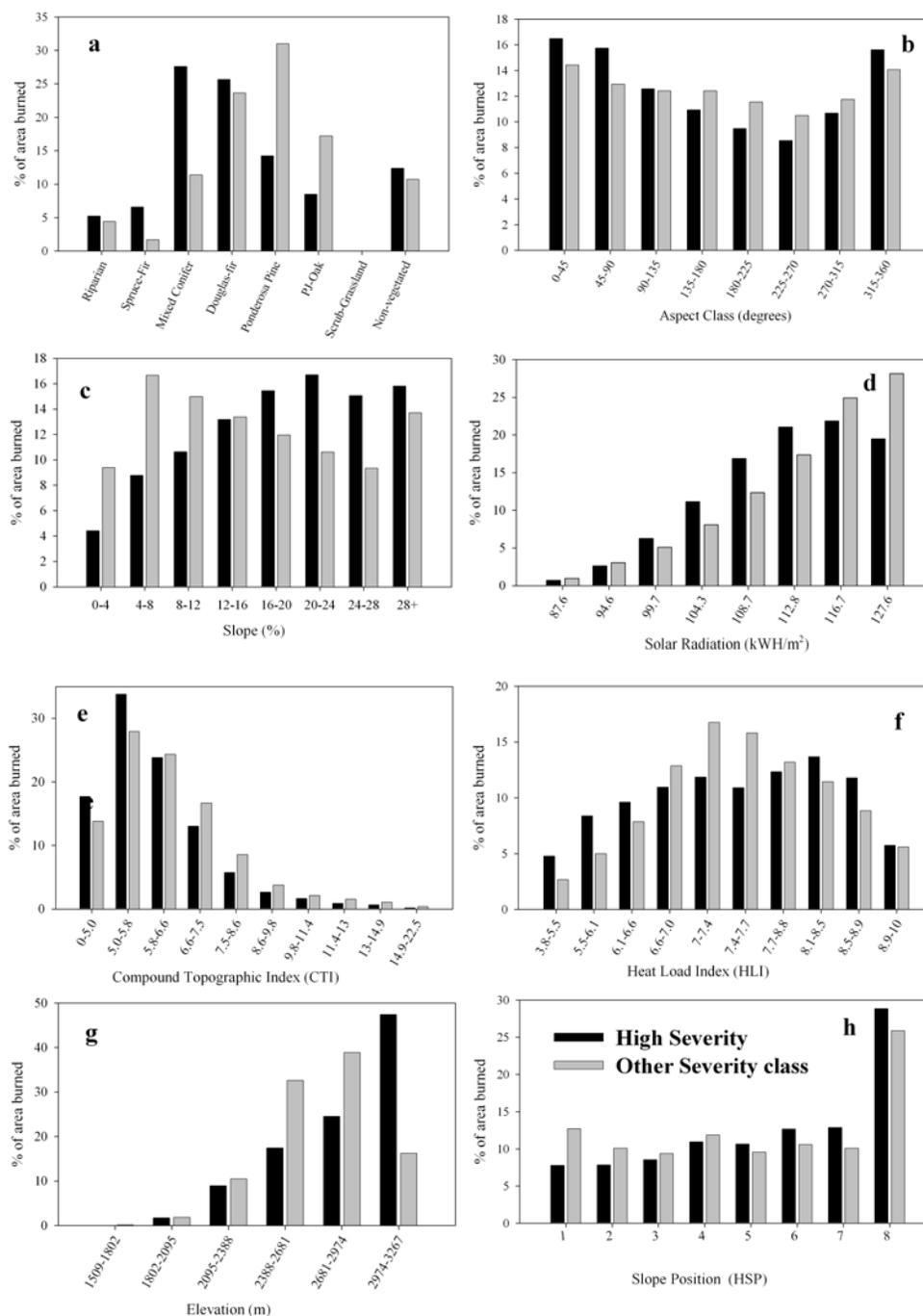


Figure 3. Bayesian conditional probability of severe fire occurrence for (a) Potential Vegetation Type (b) aspect class (c) slope class (d) cumulative April-June solar radiation class (e) Compound Topographic Index class (f) Heat Load Index class (g) Elevation class and (h) slope position class. Black bars indicate percentage of total area burned within a class that was classified severe. Grey bars show percentage of area in all other burn severity classes. Black bars higher than grey bars for an individual class indicate a higher proportion of severe fire occurring in that class relative to the total area that was burned.

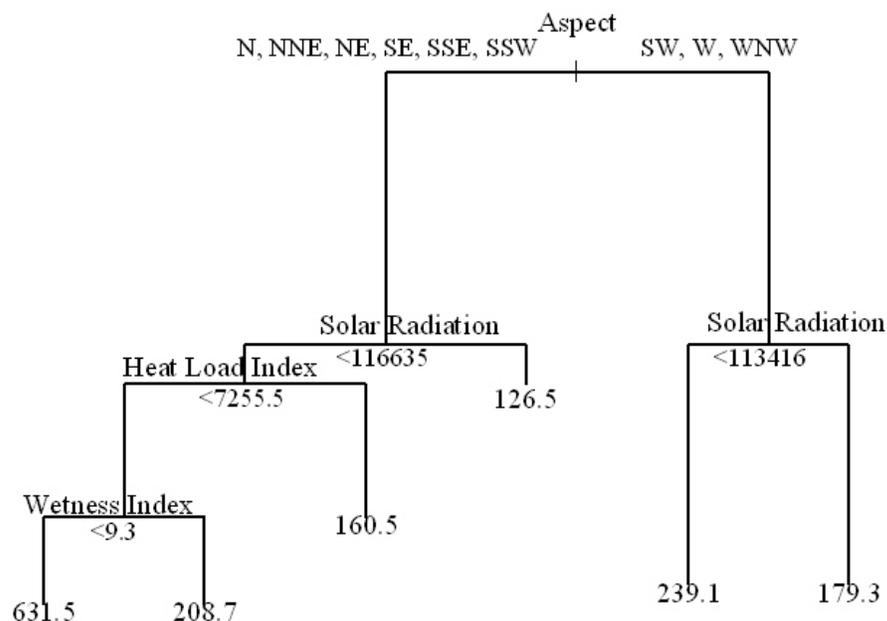


Figure 4. Regression tree showing severe fire occurrence within the pinyon-juniper Potential Vegetation Type. Terminal node values are average unclassified RdNBR values. Variables to the left of each split are “less than” the indicated value and those to the right “greater than” that value.

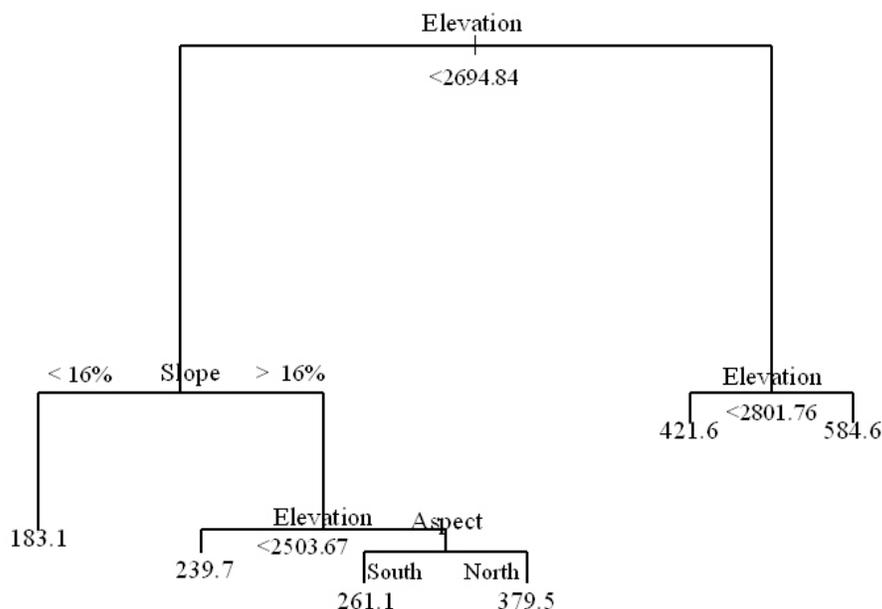


Figure 5. Regression tree showing severe fire occurrence within the combined ponderosa pine and Douglas-fir Potential Vegetation Types. Terminal node values are average unclassified RdNBR values. Variables to the left of each split are “less than” the indicated value and those to the right “greater than” that value.

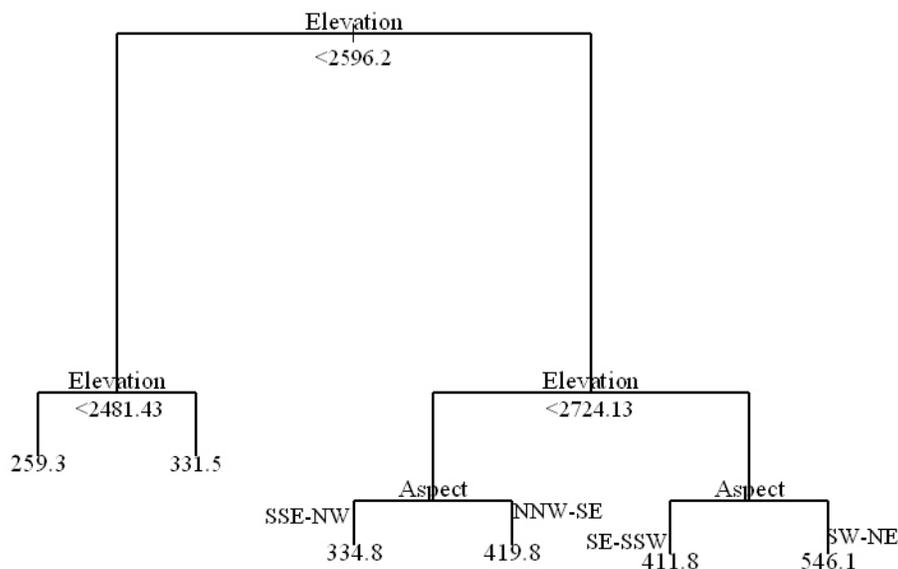


Figure 6. Regression tree of burn severity within the Mixed-conifer Potential Vegetation Type. Terminal node values are average unclassified RdNBR values. Variables to the left of each split are “less than” the indicated value and those to the right “greater than” that value.

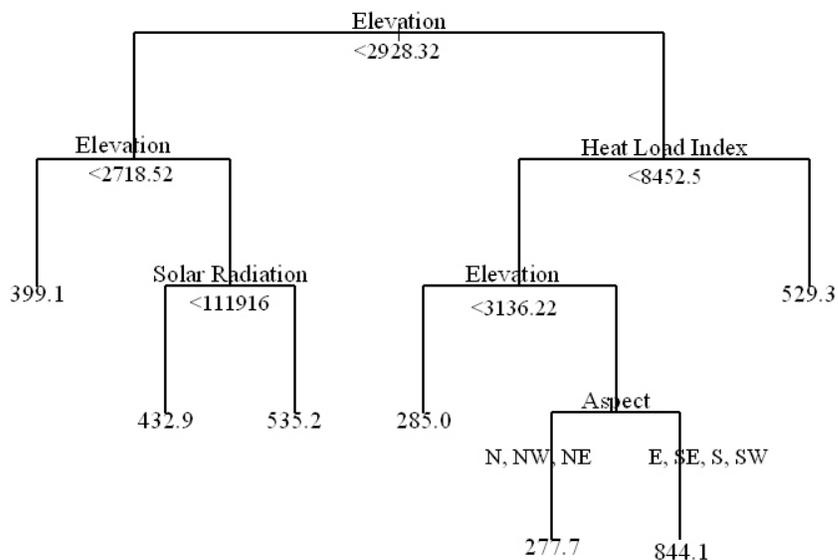


Figure 7. Regression tree showing severe fire occurrence within the spruce-fir Potential Vegetation Type. Terminal node values are average unclassified RdNBR values. Variables to the left of each split are “less than” the indicated value and those to the right “greater than” that value.

Table 1. Predictor variables included in Random Forest models.

Variable	Description	Reference
PVT	Potential Vegetation Type	Keane 2001
ELEV	Elevation (meters)	
SAT	Transformed slope/aspect	Stage 1976
CTI	Compound Topographic Index	Moore et al. 1993
HLI	Heat Load Index	McCune and Keon 2002
SLPPOST	Relative Slope Position	Unknown
SOLAR	Solar Radiation (April-July)	Fu and Rich 1999
PLNCRV	Down-slope curvature	Pike and Wilson 1971
PROCRV	Cross-slope curvature	Pike and Wilson 1971
DISS3	Modified dissection coefficient (3x3)	Pike and Wilson 1971
ROUGH15	Topographic Roughness (3x3)	Riley 1999
ROUGH27	Topographic Roughness (15x15)	Riley 1999
ERR3	Elevation Relief Ratio (3x3)	Evans 1972
ERR15	Elevation Relief Ratio (15x15)	Evans 1972
HSP	Hierarchical Slope Position	Unknown

Table 2. Area burned by burn severity class (RdNBR) within each Potential Vegetation Type (PVT) on the Gila NF (1984-2004). Only fires >40 ha in size are included. Percentages are of the area burned within each PVT. Of the 1.4 million ha on the Gila National Forest, 11% (152,874 ha) burned at least once within the PVTs listed.

PVT	% of PVT		Low	%	Moderate	%	High	%	Area burned (ha)
	in Study	Area							
Sparse veg.	10	1030	62	4540	27	1809	11	16609	
Pinyon-juniper	39	18856	75	4937	20	1242	5	25034	
Ponderosa pine	19	33412	74	9467	21	2085	5	44965	
Douglas-fir	7	24223	67	8417	23	3757	10	36397	
Mixed-conifer	4	10917	55	4774	24	4043	20	19733	
Spruce-Fir	1	1625	49	705	21	962	29	3292	
Riparian	1	3388	50	2692	39	764	11	6844	
Area burned		102,680	67	35,532	23	14,661	10	152,874	

Table 3. Classification error rates and important predictor variables from Random Forest for all PVTs and each PVT analyzed separately using a 2-class (high vs. other burn severity) and 3-class (low, moderate, high severity) RdNBR grid. See Table 1 for abbreviations.

PVT	Classification Error		Important variables
	Severity classification		
	2 Class	3 Class	
All PVTs	17.3%	38.3%	ELEV, SAT, ROUGH27, HSP
Spruce-fir	11.8%	23.7%	ELEV, HSP, ERR15, ROUGH27
Mixed-conifer	21.8%	39.7%	ELEV ROUGH27, HSP, SAT
Douglas-fir	19.9%	38.3%	ELEV ROUGH27, HSP, SAT
Ponderosa pine	18.7%	36.3%	ELEV, ROUGH27, HSP, SAT
Pinyon-juniper	16.9%	34.3%	ELEV, HLI, ROUGH27, HSP

CHAPTER 7

CONCLUSIONS

The broad aim of this dissertation was to identify where on the landscape and under what climatic conditions fires are likely to burn severely on the Gila National Forest. Analysis of twenty-year temporal and spatial burn severity patterns yielded new insights into factors influencing burn severity in this study area. To address the question of where on the landscape fires are likely to burn severely, I used fourteen topographic indices derived from a 30-meter digital elevation model to predict the occurrence of severe fire relative to topography. In the first study to evaluate burn severity patterns across many fires from multiple years, I found that vegetation, topography and burn severity appear to be tightly coupled within this largely wilderness-dominated study area. Severe fires were more likely to occur at locally wet and cool sites, such as north-facing slopes and where solar radiation is low. These results suggest that in the semi-arid southwestern US, where water limits vegetation productivity and hence fuel production, topography exerts a strong “bottom up” control on burn severity. Topography alone predicts more than 80% of the variability in severe fire occurrence, without information about fuels or forest structure.

Using the Random Forest model developed in chapter 6 of this dissertation, I will use imputation techniques to assign severe fire probabilities to 30-meter grid cells across the Gila National Forest. Colleagues will then integrate this severe fire prediction layer into a decision support system tool designed to assess the risks to fish of post-fire erosion and debris flow. The output from this model will be used to produce a risk assessment map for managers on the Gila National Forest. We anticipate that this will be a product that fire managers and wildlife biologists will find useful in making decisions about how to manage fires (e.g. whether to allow them to burn as WFU fires, whether to suppress all or part of the fires, or whether to do prescribed burning under conditions that would limit future fire severity). The predictability of severe fire occurrence based on topography must be tested in more areas across a range of vegetation types. However, our analysis approach using the Random Forest algorithm could prove to be a useful tool with which to identify areas for treatment (e.g.

thinning and prescribed burning) in order to reduce the intensity and severity of future wildfires.

To address the question of when (in terms of climate) severe fires are likely to occur, I used data from a snow pack telemetry (SNOTEL) site and a local climate station to examine how climate variables have influenced fire extent and fire severity during this 20-year period. This is the first study to evaluate links between climate, weather and satellite-derived burn severity patterns. Based upon my results, I suggest that both snowpack and precipitation variability during the fire season influence fire extent and fire severity. Historical fire patterns have been linked to antecedent (winter) precipitation driven largely by the El Nino Southern Oscillation (ENSO). While it is clear that overall dryness will increase fire season severity, this study is the first to show that even short, dry windows occurring during a typically warm, dry period in the region can be sufficient to increase fire severity.

Analysis of relationships between annual precipitation patterns and area burned within four fire severity classes described in chapter four of this dissertation showed a strong relationship between severe fire activity and the length of rain-free-periods from April to July, a period of peak fire activity in the southwestern US. I explored the significance of this rain-free period as a potential ecological and climatic variable using a 17-year AVHRR NDVI time-series. Patterns of vegetation productivity across the growing season often show a bi-modal pattern, with a distinct decline in productivity in late spring and early summer. I hypothesized that this decline would at least partially be explained by the length of rain free periods. Several analysis methods showed strong relationships between annual NDVI patterns and the length of rain free-periods from April to July, supporting the results of chapter four and suggesting that the length of dry periods in the spring influences both live and dead fuel moistures and hence the likelihood of severe fire.

The analyses presented in this dissertation contribute new knowledge to our understanding of fire-climate relationships in the southwestern US, and raise questions about current and historical climate patterns in the region. Recent studies have implicated both warm springs (Westerling et al. 2006) and natural sea surface temperature oscillations (Kitzberger et

al. 2007) as drivers of recent and historical fire activity in the western US. Spring in the Southwest is a period of transition from Pacific ocean-dominated winter climate patterns to summer monsoon patterns influenced by the tropical cyclonic activity in the Gulf of Mexico (Sheppard et al. 2002). This raises an important question: is the length of spring dry periods a distinct climatic feature linked with oceanic or atmospheric patterns, or is it simply an artifact of regional drought in the Southwest? My hypothesis is that springtime dry periods described in our study may be one mechanism driving periods of increased historical fire activity in the Southwest. I believe it is possible to reconstruct spring dryness using dendroecological techniques. In the future, I hope to evaluate whether false ring formation in ponderosa pine trees correspond to years where we observe long rain-free periods as well as decreases in AVHRR-derived NDVI prior to the arrival of monsoon rains. Reconstructions of spring dry periods and comparisons with historical fire scar databases may provide new insights into historical controls on fire activity in the Southwest. Further, the sub-regional variability in the Southwest has been largely ignored in scientific research. Sub-regional analyses of precipitation, AVHRR green-up patterns and fire severity in different areas of the Southwest will help us to understand the relative importance of natural climate variability and global climate change on precipitation in the Southwest, and this has tremendous implications for fire extent and severity.

The goal of this dissertation was to identify the climate and topographic drivers of burn severity over a twenty-year period in a large southwestern wilderness area. The local scale of this analysis limits our ability to draw inferences to other areas of the southwestern US. However, my findings raise interesting questions about the causes and consequences of recent trends in fire severity in the western US and should therefore be examined elsewhere. While there is currently a strong consensus that climate change is occurring, surprisingly little is known about the climate and topographic factors that influence severe fire occurrence in the western United States. In ongoing work that is based, in part, on my dissertation, I and a team of research scientists are using databases assembled by the Monitoring Trends in Burn Severity Project, we have begun analyzing climate-burn severity relationships across the interior western US. These analyses will tell us the extent which the patterns described in this dissertation are local rather than regional phenomenon, and are likely to yield new insights

into the current increasing trends in fire activity that have been observed across the western US. Similarly, we lack knowledge about burn severity patterns relative to vegetation and topography for most areas of the US and the world. Fire ecology as a science will benefit from further exploration of burn severity patterns relative to vegetation type. Predicting burn severity occurrence also has great relevance to how we manage fire in the future. With plant species ranges predicted to shift with climate change, important decisions have to be made about when to let fires burn and where to apply thinning and prescribed burning treatments in order to mitigate wildfire effects. The research presented in this dissertation contributes new knowledge and applications that may ultimately help in making those decisions.

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