Fuels and Fire Behavior Modeling Using Remotely Sensed Data on the San Francisco Peaks, Arizona

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A Thesis

Submitted in Partial Fulfillment

of the Requirements for the Degree of

Master of Science

in Forestry

Northern Arizona University

December 2005

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ABSTRACT

FUELS AND FIRE BEHAVIOR MODELING USING REMOTELY SENSED DATA ON THE SAN FRANCISCO PEAKS, ARIZONA

Joseph Edward Crouse

Multi-date Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite imagery was classified to develop data layers for a portion of the San Francisco Peaks in northern Arizona. The data layers were developed to be used as inputs to fire simulation models. Pair-wise comparisons of all mapped layers showed that only four layers were statistically different. Kappa analysis showed that twenty-four of the thirty-nine classified layers were statistically better than chance.

Crown fire activity was modeled using the FlamMap fire simulation program. Simulations were run using 10, 40, and 70 km/hr wind speeds. Area of active crown fire increased by 221% between the 10 and 70 km/hr wind speed scenarios. At the landscape-level, mean patch size of active crown fire increased over 700% from the 10 to 70 km/hr wind speed scenarios and the number of patches decreased by 60% between 10 and 70 km/hr wind speed scenarios. At the class-level, active crown fire mean patch size increased slightly in all five forest types (aspen, bristlecone pine, mixed conifer, ponderosa pine, and spruce-fir) with increasing wind speed. The number of patches increased, at the class-level, between the 10 and 40 km/hr wind speed scenarios but tended to decrease between the 40 and 70 km/hr wind speed scenarios. An Erosion Index model to identify areas that had a high potential for erosion was created using slope,

coarse woody debris (1000 hour sound and rotten fuels), and heat/area layers created in 10, 40, and 70 km/hr wind speed simulations, as inputs.

ACKKNOWLEDGEMENTS

This research was funded by the USDA Forest Service Rocky Mountain Research Station and USDI Bureau of Land Management.

A huge thank you to Dr. Peter Fulé for giving me the opportunity to conduct this research and for being supportive of all my work with the ERI; to Dr. Margaret Moore for encouraging me throughout this project and for hiring me to work on the Woolsey project, and to Dr. G. Lennis Berlin for sharing his extensive knowledge of remote sensing with me and for being a mentor for nearly 20 years.

None of this would have been possible without the extensive help from the staff and students, past and present, with the ERI. Thanks to all that carried bags of rebar, jugs of water, field gear, and everything else we needed to conduct the fieldwork. We did an incredible amount of work and had a great time doing it. Special thanks go out to those, particularly Allison Cooke, David Huffman, Robin Long, JP Roccaforte, and Judy Springer, that have been extremely supportive throughout the entire process.

Finally, a special thank you to my wife Susan and our children, Ryan, Aaron, Jonathan, and Kelsey. They have supported me throughout this endeavor and I couldn't have done it without them. Thanks to Susan for putting up with 21 years of my fieldwork.

TABLE OF CONTENTS

List of Tables

List of Figures

PREFACE

This thesis was written in manuscript form. Because of this there is some redundancy between the literature review and the two manuscript chapters.

CHAPTER ONE

INTRODUCTION

Land use management decisions on fire exclusion and livestock grazing in ponderosa pine-dominated sites in the Southwest have resulted in increases in tree density, canopy cover, vertical fuel connectivity, and fuel loadings. These increases have led to the potential for more severe and larger wildfires (Covington and Moore 1994, Swetnam et al. 1999). Beginning by the early 1950s, it was recognized that overgrazing and fire suppression had led to dense forest conditions and excessive fuels and that the "fire hazard has increased tremendously and is continuing to increase" (Weaver 1951). Mixed conifer and spruce-fir forests have also experienced changes in tree densities.

The occurrence of larger and more intense fires requires that more land managers become familiar with fire and the variables that determine its behavior. Pyne et al. (1996) discussed the concept of the "fire environment" (Countryman 1972) where topography, fuel, weather and the fire itself are interactive variables that make up the fire environment. The interaction of these variables determines the characteristics and behavior of a fire. Vegetation, woody, and forest floor fuels are the only components of the fire environment that can be manipulated by landuse managers. Fires of the scale and severity of the ~200,000 ha Rodeo-Chediski fire that occurred in eastern Arizona in 2002 are unprecedented and show that the development of methods to accurately estimate fuels has become essential.

The site for the research presented in this thesis is the San Francisco Peaks. The Peaks are made up of a number of peaks, one of which, Humphreys Peak, is the tallest mountain in Arizona. The Peaks are an important ecological and cultural resource. The steep elevational gradient of the Peaks allows for a unique opportunity to work within nearly all forest floor fuel conditions found in the Southwest. They also serve as a source of drinking water for the surrounding area, provide recreational opportunities, offer solitude in the Kachina Peaks Wilderness, serve as a refugia for species that once occurred over much of the Southwest (Mitton et al. 2000), and hold a spiritual significance for Native American tribes across the Colorado Plateau.

Cocke (2005) found that a moderate increase in mixed conifer tree density had occurred at this study site. Spruce-fir tree density increases, while lower than that of ponderosa pine and mixed conifer, also occurred. Similar findings have been reported in ponderosa pine, mixed conifer, and spruce-fir forest type in Grand Canyon National Park, Arizona, by White and Vankat (1993) and Fulé et al. (2003). These studies concluded that fires in the ponderosa pine and mixed conifer forest types are likely to be larger in extent than past fires and will burn with a higher severity.

Fire has played a natural role in maintaining the ecological balance on the Peaks. Dieterich (1980) and Heinlein (2005) found mean fire return intervals of roughly five years or less in studies conducted in the ponderosa pine and mixed conifer zones on the San Francisco Peaks. It is logical to consider that these fires may have burned up into the higher elevation spruce-fir and bristlecone pine forest types on occasion. Spruce-fir forests usually burn with stand-replacing intensities (Taylor and Fonda 1990, Aplet et al. 1998) and the topography of the Peaks would make such a fire particularly difficult to contain. Photographs from the early 1900s show large burned areas on the Peaks. Stands of aspen on the Peaks indicate that large-scale disturbances, likely due to fire, have occurred. The Pumpkin fire, ignited by lightning in 2000, burned approximately 6,000 ha on Kendrick Peak. This 3,100 m peak is located approximately 18 km northwest of the San Francisco Peaks and has the same forest types. Heavy fuel loading and low fuel moisture, due to drought conditions, contributed to high fire severity.

Fires have not occurred in the high elevation forests of the Peaks for one or more centuries. The Leroux fire of 2001 began in the ponderosa pine forest type and quickly burned out once it reached the aspen dominated mid-elevation forests. Near average moisture levels likely prevented it from reaching the higher elevations (Cocke 2005). This extended fire-free period coupled with high productivity has resulted in the spruce-fir forest type having the greatest amount of large woody fuels and forest floor fuels. During extended periods of drought, fires may be expected to carry through the spruce-fir forest type with its high tree density and heavy accumulation of fuels.

The question of what role fire should currently play on the Peaks is complicated by the Federal Wilderness designation of much of the area. The Wilderness Act of 1964 states that wilderness should have minimal impacts of human activities but it also states that it be “managed so as to preserve its natural conditions”. Ecological and social concerns must be considered before re-introducing fire to the Peaks. Issues related to smoke and the potential for fire to cross prescribed fire boundaries are risks that land managers must consider (van Wagtendonk 1995). Prescribed natural fires have been used in other wilderness areas (Parsons 2000) and because of access issues may be the most appropriate method of fire reintroduction (Miller 2003).

My objectives in this study were: 1) to directly assign species, canopy cover, and fuel class labels to the Peaks landscape through the use of a supervised classification, 2) to evaluate the effectiveness of a multi-temporal dataset, with finer spatial resolution than Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data, to develop overstory vegetation, and both dead woody and forest floor fuel layers, 3) to create the required inputs (elevation, slope, aspect, fuel model and canopy cover) as well as the optional layers of duff loading and coarse woody debris that would allow me to model fire behavior using the FlamMap model (Finney in preparation), 4) to use FlamMap to simulate active crown fire behavior and heat/area at low, moderate, and high wind speeds, 5) to analyze the change in the number of patches and mean patch sizes under low, moderate, and high wind speeds, and 6) to develop a model to identify areas with a high potential for erosion following a wildfire.

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CHAPTER TWO

LITERATURE REVIEW

Introduction

A century of fire suppression and livestock grazing in the Southwest has resulted in a buildup of forest floor fuels and increased tree densities. These conditions have led to larger and more intense wildfires (Covington and Moore 1994, Swetnam et al. 1999). Fire behavior modeling is now widely used to address priority areas for forest thinning and fuels treatments.

This review addresses previous vegetation and fuels mapping projects using remotely sensed data and the development of fire behavior modeling inputs. I will also review fire behavior simulation research and landscape metrics used to analyze fire behavior simulation outputs. Finally, issues related to fire management in wilderness areas will be reviewed.

Vegetation Mapping Using Satellite Imagery

Satellite imagery, especially Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper Plus (ETM+) data, has been extensively used to map and monitor vegetation (Franklin 1986, Moore and Bauer 1990, Fiorella and Ripple 1993, Congalton et al. 1993, Cohen et al. 1995, He et al. 1998, Keane et al. 2000). Sensors with greater spatial resolution than that offered by MSS, TM or ETM+ have also been used in vegetation studies (Golden 1991, Henry and Hope 1998, Giakoumakis et al. 2002, Lennartz and Congalton 2004). The French SPOT satellites, with the High-Resolution Visible (HRV) sensor, have a panchromatic band with 10 m spatial resolution and multispectral bands with 20 m spatial resolution. Golden (1991) compared vegetation classification results from the TM and HRV sensors for a ponderosa pine and pinyon-juniper dominated area in northern Arizona and found that the TM derived classification was more accurate than the SPOT derived classification. He concluded that the greater spectral resolution was the key factor in the increased classification accuracy. Lennartz and Congalton (2004) used 4 m IKONOS imagery to classify and map forest types in the northeastern United States. They found that while the increased spatial resolution provided a greater amount of informational detail, the in-class variability was also increased. The increased variability, along with an insufficient number of accuracy assessment reference sites, led to poorer than expected classification accuracy.

Forest Fuels Mapping

There have been studies that have investigated the correlation of fuel loadings with forest stand variables but they have had mixed success. Ffolliott et al. (1968, 1976) attempted to predict forest floor fuels in the northern Rocky Mountains using stand age, crown closure as predicted by basal area, and potential insolation. They concluded that basal area was the only variable that significantly predicted forest floor fuel loadings. Sackett

(1979) looked at estimating dead fuel loadings in ponderosa pine and mixed conifer forest types using basal area and other stand variables but concluded that there were no reliable statistical relationships. Sackett attributed his findings to the wide range of fuel loading that can be expected to exist within and between stands of both ponderosa pine and mixed conifer. Harrington (1986) found a statistical relationship between forest floor depth and fuel loading on four ponderosa pine sites in southern Arizona. However, the variability between sites, due to climate, soils, stand disturbances, stand characteristics, biomass production rates, and needle deposition rates, does not allow for a single regression model to be used across all ponderosa pine stands. Fulé (1990) developed forest floor depth and bulk density prediction models for ponderosa pine dominated forests on the North Rim of Grand Canyon National Park. The models were compared to models developed by Ffolliott (1968, 1976), Harrington (1986), and Eakle and Wagle (1979) and were found to predict within the mid-range of values of these studies. The high variability of the data resulted in no predictive models for litter and all size classes of woody fuels.

Studies have also been conducted to investigate relationships between site variables and fuel loadings as well as between the different fuel size classes. No significant relationship was found between site variables (aspect, elevation, slope) and fuel loadings by Brown and See (1981) in a study conducted in the northern Rocky Mountains. They reported that fuel size class loadings could not be predicted with loadings from another size class. Brown and Bevins (1986) also found no association between the various fuel size classes. Both studies concluded that high variation in fuels between and within stands made predicting fuel loadings difficult.

The mapping of fuels has been the focus of numerous research projects e.g., Burgan et al. 1998, Bertolette and Spotsky 1999, Keane et al. 2000, Giakoumakis et al. 2002, Riano et al. 2002, Miller et al. 2003, and van Wagtendonk and Root 2003. These projects have used various forms of remotely sensed data ranging from USGS Digital Orthophoto Quarter Quads (DOQQs) with 1 m spatial resolution (Bertolette and Spotsky 1999) to imaging spectrometer data with 20 m spatial resolution (Roberts et al. 1999) to Advanced Very High Resolution Radiometer (AVHRR) data with 1 km spatial resolution (Burgan et al. 1998). Landsat TM and ETM+ data have been extensively used for wildland fuels mapping (Keane et al. 2000, Giakoumakis et al. 2002, Riano et al. 2002, Miller et al. 2003, van Wagtendonk and Root 2003) because of the high availability and temporal resolution of the data. Falkowski et al. (2005) investigated the utility of ASTER satellite data for modeling fuel models.

Roberts et al. (1999) used Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data to map vegetation species of a chaparral dominated area in southern California. The fuels layer was derived by “cross-walking” from the species map. AVIRIS data contains 228 spectrally unique bands. The high degree of spectral resolution allowed them to map vegetation, both overstory trees and shrubs, green live biomass, the ratio of live to dead canopies, and live fuel moisture. Hyperspectral data such as AVRIS requires that the spectral properties of the mapped vegetation species are known. Spectral libraries that can be used to identify the band(s) sensitive to the features of interest exist for some vegetation species but not for all. In these cases, a handheld radiometer would be needed to determine the reflectance of the vegetation of interest. For this AVIRIS study, over 6,000 field spectra were collected. The authors discussed accuracy assessment challenges associated with hyperspectral data but did not provide any accuracy numbers. Bertolette and Spotsky (1999) developed fire model inputs for a portion of the North Rim of the Grand Canyon, Grand Canyon National Park, Arizona, from USGS Digital Orthophoto Quarter Quadrangles. Homogeneous areas were delineated based on image tonal differences and vegetation density. Over 400 vegetation polygons were delineated and then field visited. Data collected during the field visit were used to label each polygon. An accuracy assessment of the resulting vegetation map was not conducted but it was compared to a 1968 vegetation classification (Warren et al. 1982). Landsat Multispectral Scanner, Thematic Mapper and Enhanced Thematic Mapper Plus data have been extensively used for wildland fuels mapping because of the high availability and temporal resolution of the data. Burgan and Shasby (1984) used Landsat Multispectral Scanner and digital topographic data to develop a fuel model classification on a 400 square-mile area in western Montana. Their fuel model coverage had a 1 acre minimum mapping area and in conjunction with topographic and weather data, was intended to model “broad-area” fire potential.

Keane et al. (2001) discussed four methods that have been used to map fuels. They termed the four methods as: (1) field reconnaissance, (2) direct remote sensing, (3) indirect remote sensing and, (4) biophysical modeling. Each method has its advantages and disadvantages. The first method described is field reconnaissance. In this method, existing maps or aerial photographs are used to delineate fuel types while actually in the field. The major disadvantage to this method is the high cost of mapping large areas. Verbyla (1995) described direct remote sensing as assigning fuel characteristics to an image classification output. Direct remote sensing is the assignment of fuel characteristics to the outputs of image classification or photo interpretation (Verbyla 1995). This approach is an attempt to directly classify fuels rather than mapping vegetation and assigning fuels labels based on forest type. This is a simple approach that minimizes possible errors because of the limited number of steps involved. The main disadvantage is that fuels are often not visible through the forest canopy. The image classifications will often be driven by vegetation characteristics rather than fuel characteristics.

The indirect approach uses vegetation characteristics to assign fuel types. Fuel characteristics are not directly mapped but rather are determined through forest types that are more easily mapped using remotely sensed data. However, forest type is not necessarily the best surrogate for fuels (Miller et al. 2003) so the addition of topographic layers and/or multi-date data sets are sometimes used in an effort to improve classification accuracy.

The use of multi-temporal datasets has been investigated in vegetation and fuels mapping studies. These studies combined two or more dates of Landsat TM imagery into one dataset. Riano et al. (2002) used a May and July combination to develop fuel type maps for an area in central Spain. The addition of a texture band, Landsat band 6 (thermal), and topographic variables, were also investigated to determine how they affected classification accuracy. The accuracy of their fuel type map increased from 57.8% to 67.3% when using the multi-temporal dataset while the greatest accuracy (82.8%) was achieved using both dates of imagery, the texture and thermal band, and the topographic variables.

A hybrid unsupervised/supervised classification approach was used by Miller et al. (2003) to classify a pair of Landsat TM images to map fuels within vegetation type structural stage classes. The overall classification accuracy was 54%. An overall classification accuracy of 84% was achieved for a map with fuel classes within vegetation types collapsed into single classes.

The applicability of vegetation indices has also been investigated. Van Wagtendonk and Root (2003) used normalized difference vegetation index (NDVI) values from a sequence of six Landsat TM scenes, acquired from May through November, to map fuel models of Yosemite National Park in California. Fuel models are representations of fuel loadings and, in conjunction with topographic and weather data, can be used to estimate fire behavior. They hypothesized that seasonal changes in plant phenology would allow them to distinguish fuel models. They concluded that a temporal sequence of NDVI values proved adequate to determine fuel model types. The overall classification accuracy was 54.3%. They found that for both short-needled and long-needled conifers, the NDVI values were greatest in June and July. Short needled conifers with a heavy fuel component exhibited highest NDVI values in September.

The final approach discussed by Keane et al. (2001) uses environmental gradients and biophysical modeling to map fuels. This method can be used to describe environmental variables that can be used to predict fuels. This method requires an extensive amount of field data, statistical analysis, and extensive modeling. Keane et al. (1998, 2000) used a biophysical modeling approach for mapping fuels in the northern Rocky Mountains and on the Gila National Forest located in southwest New Mexico. This approach analyzed variables that influence vegetation and fuels characteristics. These variables included slope, aspect, elevation, climate, and site disturbance. The above projects produced what Keane et al. (1998, 2000) described as a "vegetation triplet" made up of classifications of biophysical setting, species composition, and vertical stand structure. Fuels categories were then assigned to various combinations of the vegetation triplet. This approach required an extensive amount of field data, complicated modeling, and intensive statistical analysis (Keane et al. 2001). Falkowsik et al. (2005) used the vegetation triplet approach to model crown fuels and fuel models for an area in northern Idaho.

Accuracy Assessment

Accuracy assessment is the comparison of a map resulting from a satellite image classification, for example, to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. Accuracy assessment indicates the effectiveness of the methods used to produce the map and also determines the usefulness of the map as a tool for land management decisions and studies (Congalton and Green 1999).

The most common method used to represent the accuracy of a satellite classification is an error matrix (Congalton et al. 1983). An error matrix is a square array of numbers which express the number of pixels assigned to a particular land cover class relative to the actual land cover as identified in the field or from aerial photographs. Generally, the columns represent the reference data and the rows represent the map data (Story and Congalton 1986). An error matrix can also be described as a way to compare the map labels of a certain area with reference data for the same area. An error matrix is an effective way to represent map accuracy because individual class accuracies as well as users and producers map accuracy is shown (Verbyla 1995). User's accuracy (commission errors) describes how often the map label corresponds with the actual forest type on the ground. Producer's accuracy (omission errors) describes how often the actual forest type on the ground is labeled as such on the map (Congalton and Green 1999). Story and Congalton (1986) described user's accuracy as being calculated by dividing the number of correctly classified samples of a particular class by the total number of samples that were classified in that same class. They described producer's accuracy as being calculated by dividing the number of correctly classified samples of a particular class by the total number of reference samples of the same class. The result, in percentage form, indicates the probability that a reference sample will be classified correctly.

Much has been written about selecting the appropriate number of samples to be able to perform a statistically valid analysis (Congalton and Green 1999, Curran and Williamson 1986, Tortora 1978, van Genderen et al. 1977). Congalton and Green (1999) compared the use of equations based on the binomial distribution versus the multinomial distribution. There tends to be little agreement on the "correct" method to use. Binomial equations, as presented by van Genderan et al. (1977), provided a statistically sound method of determining the required sample size to compute overall map accuracy or overall individual class accuracy. To achieve an overall accuracy of 90%, the USGS standard for map accuracy, approximately 30 samples per class are necessary. Wilkie and Finn (1996) presented a different method that determines that 144 samples are required for an accuracy of 90%.

Congalton and Green (1999) suggested that the binomial method is not appropriate if an error matrix will be used. They stated that for an error matrix with n classes, for a given class there is one correct answer and (n-1) incorrect answers and that a sufficient number of samples must be acquired to be able to represent the confusion. They further suggested that equations based on the multinomial distribution are appropriate to use when an error matrix will be used. The multinomial equation presented by Tortora (1978) and Congalton and Green (1999) calculated that roughly 80 samples per class are required.

There are five commonly used sampling schemes for collecting reference data: simple random sampling, stratified random sampling, systematic sampling, cluster sampling, and stratified systematic unaligned sampling (Congalton and Green 1999). Stratified random sampling has been accepted as being the most appropriate in studies using remotely sensed data (van Genderen et al. 1977). The main advantage of this sampling method is that all the land forest types or classes, regardless of the class area, will be sampled.

Fire Behavior and Landscape Fire Succession Models

Fire behavior analysis has been an important component of forest research for many years. Originally, fire behavior was studied to provide land managers with a basis for determining fire suppression crew size and fire suppression strategies (Fons 1946). More recently, fire behavior analysis has been done to test the effectiveness of fuels treatments (Stratton 2004, Scott and Reinhardt 2001).

Common fire behavior models include FARSITE (Finney 1998), FlamMap (Finney in preparation), and Nexus (Scott and Reinhardt 2001). FARSITE is a deterministic model (Stratton 2004) that simulates the spatial and temporal spread of fire. Inputs include aspect, elevation, slope, fuels, and weather. Outputs can be in tabular, vector, and raster formats. FlamMap requires many of the same inputs as FARSITE but is a hazard model, not modeling the spatial and temporal spread of fire. Each pixel is treated independently from those around it. Fire behavior (surface fire, passive crown fire, or active crown fire) is determined for each pixel. Outputs are in tabular format. Nexus is a deterministic model of surface fire behavior and is also useful for assessing fuel hazards. Crown fire transition and crown fire spread is also modeled (Scott and Reinhardt 2001).

Fulé et al. (2001) used the Nexus model to analyze the effectiveness in three thinning treatments in a ponderosa pine ecosystem in northern Arizona. All three treatments were successful in reducing crown fire activity. In a study conducted in a pinyon pine and juniper ecosystem southern Utah, Stratton (2004) reported reductions in crown fire activity, fire intensity and flame length, and fire size when modeling for fuel treatment effects using FARSITE and FlamMap. The latter study identified the underprediction of crown fire by FlamMap.

Fuels treatments are an important management tool but may not be enough to prevent active crown fire during periods of extreme fire weather. Bessie and Johnson (1995) used Rothermel's (1972) surface fire intensity model and Van Wagner's (1977) crown fire initiation model to predict surface fire intensity and crown fire initiation in a Canadian subalpine forest. They found that at extreme weather conditions, the importance of fuel loading decreases as crown fire initiation thresholds are met.

Landscape fire effects and succession models are used by land management agencies to provide additional information to guide management activities. Models are useful for identifying areas where research is needed (Keane et al. 1990). First-order fire effects (Reinhardt et al. 2001) such as vegetation mortality, the amount of fuels consumed, and smoke production can be effectively modeled. The modeling of second-order fire effects such as erosion and vegetation succession gives land managers the ability to determine where ecosystem rehabilitation activities should be conducted.

Landscape Metrics

Landscape metrics provide ecologists with ways to quantify landscape pattern and the influence it has on ecological processes (Turner et al. 2001). The various landscape metrics give researchers ways to analyze landscape structure and function, both of which are major areas of analysis in landscape ecology (Toth 1988). A patch is an important concept in landscape ecology that can be defined as “an area differing in appearance from its surroundings” (Forman and Godron 1986). Patch variables such as size, shape, and number are used to define landscape structure (Forman and Godron 1986).

Patches are heavily influenced by the grain size and extent of the data, and by the classification scheme used to derive the patch (Turner et al. 2001). Studies have been conducted to investigate the effects of changing scale on landscape parameters (Turner et al. 1989, Benson and MacKenzie 1995, Wu 2004). These studies concluded that most landscape parameters were affected by changes in grain size.

Fire Management in Wilderness Areas

The question of what role fire should currently play in wilderness areas is complicated by the Federal Wilderness designation of much of the area. The Wilderness Act of 1964 states that wilderness should have minimal impacts of human activities but it also states that it be “managed so as to preserve its natural conditions”. Ecological and social concerns must be considered before re-introducing fire to any wilderness area. Issues related to smoke and the potential for fire to cross prescribed fire boundaries are risks that land managers must consider (van Wagtendonk 1995). Prescribed natural fires have been used in other wilderness areas (Parsons 2000) and because of access issues may be the most appropriate method of fire reintroduction (Miller 2003).

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CHAPTER THREE

FUELS MAPPING ON THE SAN FRANCISCO PEAKS, ARIZONA, USING HIGH RESOLUTION SATELLITE IMAGERY

Abstract

Multi-date Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite imagery was classified to develop data layers for a portion of the San Francisco Peaks in northern Arizona. The data layers were developed to be used as inputs to fire simulation models. The following data layers were produced: overstory tree species, canopy cover, fuel model, 1h, 10h, 100h timelag fuels, coarse woody debris, and forest floor (duff and litter) fuels. Overall accuracy of the species layers ranged from 41% for the 2002-2003 composite image to 47% for the 2003 image. Accuracy for the canopy cover layers ranged from 33% for the 2003 image to 45% for the 2002-2003 composite image. The 1h, 10h, and 100h fuels layers developed from the 2003 image had the highest overall accuracies. The coarse woody debris layers (1000h fuels) developed from the 2003 image were the most accurate across all years. Average duff and average litter layers created from the 2003 image and the 2002-2003 composite image had the greatest accuracies. Pair-wise comparisons of all mapped layers showed that only four layers were statistically different. Kappa analysis showed that twenty-four of the thirty-nine classified layers were statistically better than chance.

Keywords: Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER); fire; fire behavior modeling; remote sensing; accuracy assessment

Introduction

The widespread use of fire behavior simulation programs among land managers, such as FARSITE (Finney 1998), requires the development of detailed and accurate data layers. The most efficient way to create the required inputs over large areas is through the classification of remotely sensed data such as aerial photos or satellite imagery. Fuel mapping projects use various forms of remotely sensed data ranging from Advanced Very High Resolution Radiometer (AVHRR) data with 1 km spatial resolution (Burgan et al. 1998), to imaging spectrometer data with 20 m spatial resolution (Roberts et al. 1999), to USGS Digital Orthophoto Quarter Quads (DOQQs) with 1 m spatial resolution (Bertolette and Spotsky 1999).

Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) are used extensively for wildland fuels and fuel model mapping because of the high availability and temporal resolution of the data. In an early study, Burgan and Shasby (1984) used MSS and digital topographic data to map fuel models on a 1000 km^2 area in western Montana. The Burgan and Shasby (1984) fuel model coverage had a 0.4 ha minimum mapping area and was intended to model "broad-area" fire potential. Standard fuel models were described by Anderson (1982). Variables used to determine fuel models include loading, fuel bed depth, moisture of extinction, and the ratio of surface area to volume (Pyne et al. 1996). Fuel models are representations of fuel loadings and, in conjunction with topographic and weather data, can be used to estimate fire behavior. They are described in terms of both expected fire behavior and vegetation (Anderson 1982).

The use of multi-temporal datasets and the addition of texture bands, computed from one of the visible bands, have been investigated in vegetation and fuels mapping studies. Riano et al. (2002) used a May and July combination to develop fuel type maps for an area in central Spain. The addition of a texture band, TM band 6 (thermal), and topographic variables, were also investigated to determine how they affected classification accuracy. Image texture is useful because spatial pattern, or texture, is often a dominant characteristic of vegetation stands (Woodcock et al. 1994). Coburn and Roberts (2004) stated that incorporating a texture band is important when using higher spatial resolution imagery. Ryherd and Woodcock (1996) found that adding a texture band can improve image classification accuracy in areas with local variance. The accuracy of the Riano et al. (2002) fuel type map increased with the multi-temporal dataset while the greatest accuracy was achieved using both dates of imagery, the texture and thermal band, and the topographic variables. Miller et al. (2003) found that topographic variables did not significantly differentiate between fuel classes in a southern Arizona oak/pine and mixed conifer forest.

The NDVI has proven effective for measuring vegetation cover (Jensen 1996). It is calculated as the difference in reflectance between the near infrared and visible red bands divided by the sum of the two bands. The NDVI is sensitive to green biomass cover because actively photosynthesizing vegetation has greater reflection in the near infrared band. Early or late season vegetation has greater reflection in the red band (Hardy and Burgan 1999). Van Wagtendonk and Root (2003) used normalized difference vegetation index (NDVI) values from a sequence of six TM scenes, acquired from May through November, to map fuel models of Yosemite National Park in California. They hypothesized that seasonal changes in plant phenology would allow them to distinguish fuel models. They concluded that a temporal sequence of NDVI values proved adequate to determine fuel model types.

Various approaches to fuels mapping were reviewed by Keane et al. (2001). They concluded that none of the approaches was best. The direct mapping approach is an attempt to directly classify fuels rather than mapping vegetation and assigning fuels labels based on vegetation type (Keane et al. 2001). Verbyla (1995) defined the direct mapping approach as assigning fuel characteristics to an image classification output. Direct mapping does not imply that features such as forest floor fuels are being detected by the satellite sensor. This method is relatively simple but it is difficult to distinguish canopy fuels from forest floor fuels (Keane et al. 2001). With the indirect mapping approach, fuel characteristics are not directly mapped but rather are determined through vegetation types that are more easily mapped using remotely sensed data (Keane et al. 2001). However, vegetation type is not necessarily the best surrogate for fuels (Miller et al. 2003), fuels are not always correlated with vegetation (Keane et al. 2001) and fuels are highly variable across a landscape (Brown and See 1981). These issues have been addressed, in certain studies, with the addition of topographic layers and/or multi-date data sets of higher resolution (such as ASTER) in an effort to improve classification accuracy. Falkowski et al. (2005) developed fuel model, crown closure, and crown bulk density layers using the biophysical modeling approach described by Keane et al. (2001). An objective of the study was to test the utility of ASTER imagery for creating fuels layers. Only the bands (green, red, near-infrared) with 15 m spatial resolution were used.

My objectives in this study were: 1) to directly assign species, canopy cover, and fuel class labels to a landscape through satellite image classification, 2) to evaluate the accuracy of the ASTER multi-temporal dataset, with finer spatial resolution than Landsat TM and ETM+ data, in developing overstory vegetation and fuel layers (both woody and forest floor), and 3) to create the required inputs (elevation, slope, aspect, fuel model and canopy cover) as well as the optional layers of duff loading and coarse woody debris that would allow me to model fire behavior.

Methods

Study Area

The 5,000 hectare area chosen for this study was located almost entirely within the Kachina Peaks Wilderness Area on the south side of the San Francisco Peaks (Figure 3.1). The steep elevational gradient of the site provided a unique opportunity to work within nearly all of the forest fuel conditions found in the Southwest within a small geographic area. Forest types included ponderosa pine, mixed conifer, spruce-fir, and sub-alpine. The ponderosa pine (*Pinus ponderosa*) type occurred at the lowest elevations of the study area and was found up to elevations of 2,500 m. The mixed conifer type, which included limber pine (*Pinus flexilis)*, Douglas-fir (*Pseudotsuga menziesii*), ponderosa pine, and aspen (*Populus tremuloides*), ranged from 2,500 m to 3,000 m. The spruce-fir type generally occurred between 3,000 m and 3,500 m and included Engelmann spruce (*Picea engelmannii*), corkbark fir (*Abies lasiocarpa* var. *arizonica*), and bristlecone pine (*Pinus aristata).* The subalpine forest type was found from 3,100 m to 3,600 m. Bristlecone pine was the dominant tree species in this zone. Elevations range from 2,440 m to 3,560 m.

Weather data from 1909 – 2001, collected at the Fort Valley weather station (www.wrcc.dri.edu), located in the ponderosa pine zone five km southwest of the study site, were summarized. Mean January temperatures were 5.2º C maximum and -12.3ºC minimum. Mean July temperatures were 26.7º C and 7.1º C minimum. Mean annual precipitation was 56.9 cm. Contemporary weather data are not available for the study area in all zones; however, a series of weather stations was established in the study area in 1916 (Pearson 1920a). Weather stations were located in the following forest types: ponderosa pine, Douglas-fir, limber pine, Engelmann spruce, and subalpine. Pearson (1920a) used data collected from these stations to determine climate factors that influenced the distribution of forest types. Data collected at these stations in 1917 and 1918 show annual average temperatures that range from 5.8º C in ponderosa pine, 5.4º C in Douglas-fir, 3.1º C in Engelmann spruce, and -0.05º C in the subalpine type. Annual precipitation was 61.7 cm in the ponderosa pine type and 102.1 cm in the alpine type (Pearson 1920a).

Remotely Sensed Data

I chose ASTER imagery for this project because of its relatively high spatial resolution and low cost. ASTER has an extensive archive of available images, making it an attractive option for projects that require a quick turnaround. The TERRA satellite, which houses the ASTER sensor, was launched in 1999 and is part of NASA's Earth Observing System (http://asterweb.jpl.nasa.gov/). ASTER collects data in 14 spectral bands ranging from the visible to the thermal infrared portion of the electromagnetic spectrum. The two visible bands (0.60µm-0.62µm and 0.63µm-0.69µm) and the near infrared band (0.78µm-0.86µm) have a 15 m spatial resolution. The mid-infrared bands have a 30 m resolution and the thermal bands have a 90 m spatial resolution. Each ASTER scene covers an area of 60 km x 60 km. ASTER scenes (ID SC:AST_L1B.003:2006460439 and ID SC:AST_L1B.003:2019598738) from 2 April 2002 and 21 October 2003 were purchased from the USGS EROS Data Center, Sioux Falls, South Dakota.

Ancillary data consisted of a digital elevation model (DEM) of the study area. The DEM was resampled, using the nearest neighbor method, from 10 m to 15 m to match the spatial resolution of the ASTER data. Slope and aspect layers were developed from the DEM to assist with identifying errors in the classified layers.

Image Preprocessing

ASTER bands 1 (green), 2 (red), and 3 (near-infrared) from each scene were imported into ERDAS Imagine (Leica 2004). In keeping with the goal of using higher resolution imagery, only the bands with 15 m spatial resolution were used. Each scene was geometrically corrected prior to classification. A hybrid approach using both an image-to-map rectification and an image-to-image registration (Jensen 1996) was used to rectify each scene to the UTM Zone 12 projection and NAD 27 datum using USGS 7.5 minute Digital Raster Graphic (DRG) files and the resampled DEM. A second-order transformation was used (Jensen 1996) due to the high degree of topographic relief within the study area. Root mean square errors were 7.5 m for the 2002 image and 7.3 m for the 2003 image. The raw digital number (DN) values of the rectified images were then converted to at-satellite reflectance using methods described in Markham and Barker (1986) and Huang et al. (2002a). Solar irradiance values used for the conversion were taken from Thome et al. (2001). The conversion to at-satellite reflectance largely reduces the problems associated with atmospheric effects (Huang et al. 2002b). Conventional atmospheric correction methods can have undesirable effects that are not easily noticeable (Cohen et al. 2001) and the lack of agreement on appropriate methods has resulted in there being no universally applicable models (Riano et al. 2003). An unsupervised classification was then performed to identify non-forest and burned areas within the imagery. These areas were masked from the imagery to reduce the amount of spectral variation within the imagery. Normalized difference vegetation index (NDVI) layers were created from each date of imagery.

A texture band, using a 3x3 pixel window, was created from band 2 (red) (Ryherd and Woodcock 1996). The green, red, near infrared, NDVI, and texture bands from both the 2002 and 2003 ASTER datasets were combined into a single dataset. All classifications were run using this combined dataset.

Field Data

One hundred thirty-five permanent plots, based on the National Park Service's Fire Monitoring protocol (Reeberg 1995), were established during the 2000–2003 field seasons (Figure 3.1). Forest closures due to drought and wildfires, adverse weather conditions, and the overall steepness of the terrain prevented completion of the plots in one or two field seasons.

The plot centers were 300 m apart, in the north-south direction, and 300 m or 600 m in the east-west direction (Figure 3.1). Each 0.1 ha (20 x 50 m) plot was oriented with the 50 m sides uphill-downhill to maximize sampling of variability along the elevational gradient. All overstory trees were tagged on the uphill side and tree measurements collected included species, diameter at breast height (dbh), canopy base height and total height. Pole trees (2.5-15 cm dbh) were measured on a 250 m^2 subplot. Seedling (<2.5 cm dbh) trees were tallied by species, condition, and height class on a 50 m^2 subplot. Tree canopy cover was measured by vertical projection every 30 cm (Ganey and Block

1994) along the two 50 m plot edges. Slope and aspect were recorded for all plots. Plot elevations were taken from a digital elevation model. Stand structure and site characteristics are shown in Table 3.1.

Woody debris was measured on four 15.2 m planar transects (Brown 1974) that originated from each 10 m point from the centerline (long axis) of the plot. Woody debris was recorded by timelag classes (Anderson 1982). Litter and duff depth measurements were taken every 1.5 m along each transect. Downed dead woody fuel consists of dead twigs, branches, stems, and boles of trees and shrubs that had fallen and lie on or near the ground (Brown and See 1981) and were classified into four diameter size classes: 0-0.6 cm diameter (1h), 0.6-2.5 cm (10h), 2.6-7.5 cm (100h), and 7.6 cm and greater (1000h) (Anderson 1982). The largest size class is divided into solid and rotten components because they differ in bulk density and exhibit different fire behavior.

Image Classification

All supervised classifications were run using training sites developed from the data on the 135 permanent plots. Training sites are areas on the ground used to represent a particular forest type or structural stage category (Lachowski et al. 1995). The training sites were digitized on the ASTER imagery to create a supervised training site signature file. Each training site polygon had at least 10 pixels including the pixel or pixels that corresponded with each plot center.

Three supervised classifications were conducted. Classifications were run on the 2002 imagery bands, the 2003 imagery bands, and on the combined image data layers. Visual analysis of each classified output showed confusion between the different forest types. For example, ponderosa pine and bristlecone pine pixels occurred well outside their elevational limits. There was also confusion between bristlecone pine and mixed conifer, between ponderosa pine and aspen, and between bristlecone pine and aspen. I developed a model that incorporated the elevation, slope and aspect files, to assist in the identification and correction of misclassed pixels based on the topographic limits of each forest type. The nonforest layer was mosaiced over each final layer. This kept the nonforest consistent throughout all layers and helped avoid the issue of incongruent layers as discussed by Keane et al. (2000).

I assigned classification labels for each of the eleven fuel layers (Table 3.2), as well as classification labels for the species and canopy cover layers, to each of the training sites. Each fuel layer was recoded to three classes that were determined by dividing the range of data into three equal intervals. Fuel model layers for each image were developed through an indirect mapping approach using the species and canopy cover layers and criteria outlined by Anderson (1982). Species labels were based on an 'importance value' (Taylor 2000) calculated as the sum of the relative frequency (percent tree stems) and relative density (percent basal area) for each species. Canopy cover was recoded to four classes of 11-25%, 26- 40%, 41-70%, and 71-100% to meet the input requirement of the fire behavior model.

Accuracy Assessment

I carried out an accuracy assessment with an independent set of reference plots. Accuracy assessment indicates the effectiveness of the methods used to produce the map and also determines the usefulness of the map as a tool for land management decisions and studies (Congalton and Green 1999).

A considerable amount has been written about selecting the appropriate number of reference sites to be able to perform a statistically valid accuracy assessment. There tends to be little agreement on the "correct" method to use. Congalton and Green (1999) compared the use of equations based on the binomial distribution versus the multinomial distribution. They suggested that the binomial method is not appropriate if an error matrix will be used to present the results, but that equations based on the multinomial distribution are appropriate. The multinomial equation presented by Tortora (1978) and Congalton and Green (1999) calculates that roughly 80 samples per class are required. However, practical considerations often determine the sample size selection (Congalton and Green 1999). Difficulty reaching portions of the study area and unpredictable weather made it necessary to use an approach that provided both a statistically sound method for selecting the appropriate sample size and one that could be realistically accomplished (van Genderen 1977, Congalton and Green 1999). I used thirty reference sites per class as the target for this project. A total of 146 reference sites were completed. While 30 reference sites per vegetation class was my goal, weather conditions and access problems prevented the completion of thirty reference sites in the aspen and spruce-fir forest types. Twenty reference sites were completed in each of these forest types. In addition, some forest types ended up with greater than thirty sites because of misclassifications in the preliminary vegetation classification.

I combined the stratified random sampling and systematic sampling methods to establish reference sites. A 500 meter point grid was created and overlaid on the preliminary vegetation classification. Every fifth point was selected and the forest type that corresponded to each point was noted. Queries were run to determine which of the forest types were represented with 30 points. Forest types with fewer than 30 points were supplemented with purposively selected reference sites.

Each reference site was comprised of three sub-plots with plots located 30 m apart. The central plot was located in the field using a handheld GPS unit. The east and west plots were located using a 50 m tape measure. The distance was corrected for slope. The three variable plots per site were used to reduce potential registration errors between the reference site coverage and the classified layers. Congalton and Green (1993) identified registration error as a factor that contributes to confusion between the classified data and the reference data.

A variable radius plot was established at each sub-plot center. A 0.9 or 1.6 BAF prism was used, depending on the tree density, so that 5 to 12 trees were sampled at each point (Avery and Burkhart 1994). Species and diameter at breast height (dbh) were recorded for each tree. A randomly located 36 m canopy cover transect was established from plot center. A sighting tube was used at each meter mark to determine whether overstory vegetation occurred above the point. Canopy cover was calculated as the percentage of points with overhead vegetation (Ganey and Block 1994). A 15.2 m fuels transect was randomly located from plot center of the middle plot. Fuels measurements were completed using the same methods used for the training sites. Data from each of the three reference plot subplots were combined and used to calculate importance values for each species present (Taylor 2000). Species class labels were determined using these importance values just as was done for the plots that were used for training sites.

The most commonly used method to represent the accuracy of a classification developed from satellite imagery is an error matrix (Congalton et al. 1983, Congalton and Green 1993). An error matrix is a square array of numbers where the columns represent the reference site data and the rows represent the satellite imagery classification data (Story and Congalton 1986). Kappa analysis is a measure of classification accuracy (Cohen 1960, Landis and Koch 1977, Congalton 2001). This analysis produces a KHAT statistic that can be used to test if a classification is significantly better than one produced by randomly assigning labels. The KHAT statistic is also used to compare two classification error matrices to determine if they are statistically significantly different.

Error matrices and KHAT statistics were computed for each of the classified layers derived from the 2002, 2003, and combined date datasets. Landis and Koch (1977) categorized KHAT values as follows: < 0 indicates poor agreement, 0 – 20% indicates slight agreement, 21 – 40% shows fair agreement, 41 – 60% indicates moderate agreement, 61 – 80% indicates substantial agreement, and 81 – 100% shows almost perfect agreement. Rosenfield and Fitzpatrick-Lins (1986) did not follow the Landis and Koch (1977) categories. They simply stated that positive KHAT values indicate greater than chance agreement. Accuracy assessment of the fuel model, canopy cover, and eleven fuels layers was also done by forest type to determine if these could be mapped more precisely in a particular forest type.

Results

Field Data

The bristlecone pine forest type had the least amount of both woody and forest floor fuels. With one exception, the ponderosa pine type had the next least amount of woody fuels and had less forest floor fuels than two of the five forest types. The spruce-fir type had roughly twice as much 1000h fuels than the type with the least amount and also had the greatest amount of forest floor fuels. All forest types had fuel categories that were significantly skewed to the right (Table 3.2). There was little variation in the area covered by each of the eleven mapped fuels categories between the three image combination classifications. The 2002 and the 2002-2003 classifications had the greatest area of fuels (3,332 ha) while the 2003 classification had only slightly less with 3,314 ha (Appendix 1).

Species and Canopy Cover Classification

The total forested area, and area by species, varied little between the three classifications. Aspen was classified as the dominant species in all three time periods and made up approximately 25% of the study area in each of the three classifications. Spruce-fir was classified as the least dominant species on all three classifications and made up roughly 10% of the study area in each of the classifications. The classified area of the other species did not remain constant across the three classifications. Total area classified as forested differed by only 14 ha between the three classifications (Table 3.3). Seasonal variation in vegetation phenology with the early spring and early fall ASTER images account for the differences in the species classifications from the three image combinations.

Canopy cover area on all three time periods was greatest in the 41%-70% class. The total area for this class varied by approximately 50 ha between the three classifications. Canopy cover was consistently lowest by area in the 11%-25% class. Mean canopy cover was greatest in mixed conifer and lowest in bristlecone pine (Table 3.1).
It varied considerably, between the three classifications, by approximately 200 ha (Table 3.4).

Accuracy Assessment

Overall accuracies and KHAT values for all layers are presented in Table 3.5. For all mapped layers the classification for species was consistent with an overall accuracy ranging from 41-47%. The fuel model layers derived from each of the three image combinations were the most accurate. Three of the fourteen layers (fuel model, wood 1-100, and average duff) derived from the 2002 image had the highest accuracy. Three layers (species, 100h, and wood 1000) created from the 2003 image and two layers (canopy cover and 1000h rotten) from the 2002-2003 image combination had the highest accuracies. Woody fuels had the greatest average overall accuracy on the 2003 classification but woody fuel layers developed from all three images had relatively consistent overall accuracies ranging from 34-47%. While the forest floor fuels layers derived from the 2002-2003 image had the highest overall accuracy (40-55%) again, these layers were consistent with all image combinations. The species, canopy cover, and fuel model layers had similar accuracies on all three images combinations but had a slightly greater overall accuracy with the 2002-2003 image. Four of the fourteen layers (species, canopy cover, fuel model, and 10h) created from the 2002 image were statistically better than chance (Congalton and Green 1999). Six of the fourteen layers (species, fuel model, 1h, 10h, wood total, and average litter) derived from the 2003 image were statistically better than chance and six of the fourteen layers (species, canopy cover, fuel model, 1h, 10h, and average forest floor) created using the 2002-2003 image composite were statistically better than chance. The 2002-2003 image had the greatest number of layers that had “slight” and “fair” agreement (Landis and Koch 1977) with the reference data used in the accuracy assessment process. The only classified layers that were significantly different from each other between the three image combinations (Congalton and Green 1999) were the canopy cover layers created from the 2002 image and 2002-2003 image composite (Z=2.69 p-value = 0.00) (Table 3.6).

Analyzed by forest type, accuracy results for all layers are shown in Appendices 2, 3, and 4. Aspen consistently had the highest woody fuel overall accuracy, as high as 75% for the 10-h fuels, and forest floor fuel accuracies as high as 74% on all three classifications. Spruce-fir consistently had the lowest woody fuel overall accuracies, as low as 21% for

100h fuels, of all forest types and had the lowest forest floor fuel overall accuracies, as low as 17%, for two of the three classifications. Mixed conifer and spruce-fir each had species layers overall accuracies that were considerably lower than the other forest types with all three image combinations. The average forest floor layers created from the 2002 and 2002-2003 datasets where the only layers significantly different from one another (Z=2.00 p-value = 0.02) (Appendix 5). Three of the 2002 data layers (bristlecone average duff and average forest floor and spruce-fir canopy cover) were statistically better than chance, four of the 2003 data layers (aspen 1h and mixed conifer canopy cover, wood 1000, and average litter) were statistically better than chance, and six (aspen 1h and average forest floor, mixed conifer canopy cover and average forest floor, and spruce-fir wood 1000 and wood total) of the 2002-2003 data layers were statistically better than chance. Bristlecone pine, mixed conifer, and spruce-fir had the fewest layers that have "poor" agreement (Landis and Koch 1977) with the reference data. Bristlecone pine had the most layers that have "slight" agreement with the reference data. Bristlecone pine, mixed conifer, and spruce-fir, had layers with "fair" agreement.

Discussion

Providing land managers with methods to assess fuel loadings and forest stand conditions would assist them with the data necessary to make well informed fire management decisions. These types of data are difficult to obtain, so they are often not collected in remote and difficult to access areas such as the San Francisco Peaks. Satellite imagery is appropriate for developing fuel type maps over large landscapes and has been used extensively (Keane et al. 2000, Riano et al. 2002, van Wagtendonk and Root 2003).

Accuracy Assessment

ASTER imagery, "trained" with the permanent plot data, was used to map species, canopy cover, fuel models and both woody and forest floor fuels, over a wide range of vegetation and fuel types, using both a direct and indirect mapping approach (Keane et al. 2001). Overall accuracies are similar to other fuel mapping studies that used satellite imagery and a more complicated biophysical modeling approach. I have reported accuracy assessment results that allow for assessment by other researchers of our mapped layers. Interpreting the usefulness of many fuels and fuel model layers from other projects, derived from remotely sensed data, is sometimes difficult because of inconsistencies on how accuracies are reported, or the accuracies are not reported at all.

Keane et al. (2000), using Landsat TM imagery, reported an overall accuracy of 36% and an overall KHAT value of 45% for their forest type layer, which is analogous to my species layer. Their overall accuracy was slightly lower than what I achieved but their KHAT value was larger. For their fuel model layer they reported an overall accuracy of 35% and a KHAT value of 24%, which were both considerably less than what I achieved. While accuracy was reported for individual classes, individual class KHAT values were not reported. This makes it impossible to determine which of the individual layers could be mapped better than by random chance. They also reported large increases in accuracies after fuzzy logic was applied. Fuzzy logic recognizes that the transition between mapped classes is seldom clear-cut and that at class extremes, an item may actually belong to two classes (Gopal and Woodcock 1994, Congalton and Green 1999).

Falkowski et al. (2005), using ASTER imagery, achieved an overall accuracy of 72% and a KHAT value of 63% for their cover type map. Their fuel model classification had an overall accuracy of 62% and a KHAT value of 54%. The higher accuracies of their data layers indicate that the biophysical mapping approach (Keane et al. 2001) may be a more suitable mapping method when using ASTER data.

Riano et al. (2002) reported overall accuracies of 58% to 67% and KHAT values of 51% and 61% when evaluating the effectiveness of using a single date of Landsat TM imagery compared to using an image comprised of multiple dates of Landsat TM imagery for mapping fuel types. This layer is similar to our fuel model layer and their methodology is comparable to the methods I employed. Their accuracies are slightly lower than ours while their reported overall KHAT value is quite high. Similar to Keane et al. (2000), KHAT values for individual classes were not reported so a detailed assessment by outside users of their mapping project is not possible. Another fuel model mapping project using multi-date imagery (van Wagtendonk and Root 2003) reported the overall accuracy (54.3%) and KHAT (39%) value. KHAT values for individual mapped classes were not reported. My project benefited from the use of a multi-date image. The 2002-2003 image I used did not have a large effect on overall accuracies but it did produce more layers that were significantly better than random.

Sources of Classification Error

Variability in species and canopy cover image classification accuracy in our study can be attributed to a number of factors. For example, aspen trees were not fully leafed out in the 2002 image, acquired in early April, well before the start of the growing season. In the 2003 image, acquired in late October, the absence of leaves on the aspen trees was visually evident. Van Wagtendonk and Root (2003) used NDVI values calculated from TM scenes acquired in May, June, July, September, October, and November. They found that for both short-needled and long-needled conifers, the NDVI values were greatest in June and July, though they did find that short needled conifers with a heavy fuel component exhibited highest NDVI values in September. This indicated that fuels layers may be more accurately mapped at the end of, and perhaps at the beginning of, the growing season. Fuels in the aspen forest type may very likely be more accurately mapped with "leaf-off" images.

The relatively small increase in accuracy when using the 2002-2003 image was again likely due to neither of the images having been acquired during the middle of the growing season. The canopy cover variation, especially with aspen, can also be attributed to the dates of the imagery. Canopy cover on the permanent plots was measured during the summer field season (May through August) when the aspen trees were leafed out. These canopy cover data were used to "train" the April and October images to produce the canopy cover layers. As with the training data, data on the reference plots were collected during the summer months when the trees were fully leafed out. The discrepancies on the image dates, along with the data collection on the permanent and reference plots limited to the summer months due to logistics and weather made it extremely difficult to develop an accurate canopy cover layer, especially for the aspen forest type.

The majority of the fuel layers have relatively high overall accuracies but surprisingly low KHAT values. Variability in fuels can also be attributed to inconsistent data collection methods, and with forest floor fuels, in the interpretation of what constitutes litter and duff (Brown and Bevins 1986). I do not feel that data collector variability is a large factor in this study because our findings were consistent with other studies. The dead woody fuels distribution on our plots is highly skewed to the right. This was consistent with what is reported by Brown and See (1981) and Brown and Bevins (1986). The majority of the fuels being in one size class made it very likely that they will be classified correctly and that the classification was only marginally better than random. Dead woody fuel loading and forest floor fuels were also consistent with other studies. The range of fuels in the ponderosa pine type fall within the range of variability that Harrington (1986) found in various ponderosa pine sites throughout Arizona. Pearson (1920b) in his work on the Peaks noted that "…in the Douglas-fir and Engelmann spruce types (analogous to our mixed conifer and spruce-fir types, respectively) the surface foot contains an appreciable amount of organic matter." He goes on to state that the amount of organic matter becomes "less conspicuous as the alpine type (our bristlecone pine, or subalpine, type) is approached." Brown and Bevins (1986) reported that subalpine trees tend to retain their branches due to the lack of natural pruning. This variability of fuels in ponderosa pine and higher elevation forests across the Southwest and the fact that all

Southwest forest fuel types are represented on the San Francisco Peaks and that this variability was shown by the low KHAT values to be difficult to detect, suggests that mapping fuels using our methods would likely result in similar low accuracies.

Conclusions and Management Implications

The vegetation and fuel conditions of the San Francisco Peaks and the frequent low-severity fire regimes (ponderosa pine), mixed-severity fire regimes (ponderosa pine, Douglas-fir, limber pine) and infrequent high-severity fire regimes (Engelmann spruce and subalpine fir) are representative of mountainous areas throughout the Southwest. Heavy fuel loadings combined with the threat of extended drought conditions may make it necessary for land managers to allow naturally ignited fires to burn when conditions allow. The shift of more mesic forest types, such as spruce-fir, described by Cocke (2005), toward lower elevations further emphasizes the importance of the reintroduction of fire. Knowledge of fuel loadings and forest composition will assist in these difficult decisions.

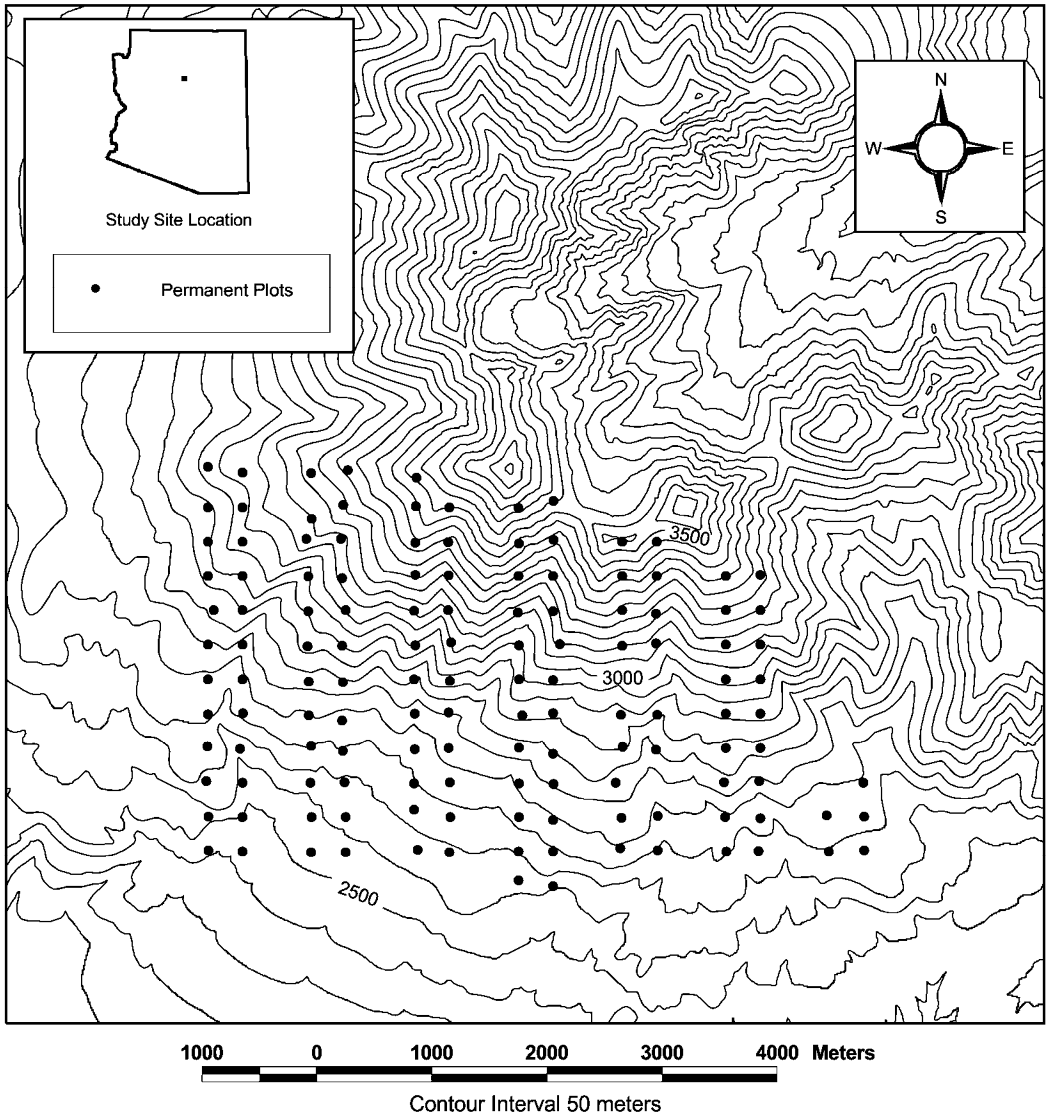

Figure 3.1. Elevational gradient with 135 permanent plots on the San Francisco Peaks, northern Arizona.

Table 3.1 Stand structure and study site characteristics taken from the permanent plot data. These data were used to develop the supervised training site signature file. This file was used to classify the three ASTER image combinations.

		Canopy Cover (%)	Trees/ha	Basal Area (m2/ha)	Aspect°	Elevation (m)	Slope (%)
Aspen	Mean (SE)	63 (3)	513.4 (41.1)	42.4 (2.3)	195 (7)	2865 (24)	30 (2)
N=42	Range	16 - 97	100.6 - 1277.3	8.8 - 74.9	106 - 275	2565 - 3208	0 - 57
Bristlecone	Mean (SE)	39 (4)	344.1 (29.6)	44.9 (4.7)	171 (7)	3292 (33)	53 (2)
N = 23	Range	0 - 75	70.6 - 651.1	4.8 - 99.6	120 - 260	3053 - 3069	35 - 66
Mixed conifer	Mean (SE)	64 (4)	426.2 (33.0)	43.0 (4.1)	186 (11)	2780 (23)	31 (2)
N = 30	Range	19 - 97	41.9 - 743.9	6.9 - 100.4	35 - 360	2531 - 3077	13 - 66
Ponderosa	Mean (SE)	49 (3)	396 (51.9)	32.4 (2.8)	189 (5)	2606 (14)	16 (1)
N = 30	Range	19 - 84	50.3 - 988.3	2.6 - 60.1	132 - 244	2458 - 2781	6 - 42
Spruce-fir	Mean (SE)	58 (5)	492.8 (44.5)	56.0 (3.9)	228 (13)	3195 (41)	41 (3)
N = 10	Range	28 - 72	260.3 - 683.3	36.3 - 73.1	123 - 280	2942 - 3390	17 - 50

Table 3.2 Fuels summary statistics, from the 135 permanent plots, by forest type. Positive skewness values indicate data skewed to the right. Skewness is considered significant if the absolute value is >2. Woody fuels in Mg/ha.

		1h	10h	100h	1+10+100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Aspen	N = 42											
	Mean (SE)	0.2 (0.03)	1.6 (0.2)	6.5 (0.6)	8.3 (0.8)	41.1 (6.2)	44.9 (13.0)	85.9 (16.5)	94.2 (16.6)	1.1 (0.1)	2.6 (0.2)	3.7 (0.2)
	Range	0 - 1.0	0 - 5.2	0 - 23.1	0 - 27.8	0 - 163.9	0 - 435.3	0 - 576.7	0.9 - 587.7	0.1 - 2.2	0.3 - 5.5	0.8 - 6.3
	Skewness	1.8	1	1.4	1.4	1.5	3.4	2.9	2.9	0.5	0.1	-0.2
Bristlecone	N = 23											
	Mean (SE)	0.4 (.06)	1.0 (0.2)	3.0 (0.7)	4.4 (0.9)	26.9 (7.2)	30.8 (14.6)	57.7 (19.3)	62.0 (19.5)	0.7 (0.1)	1.8 (0.3)	2.5 (0.3)
	Range	0.02 - 1.1	0 - 2.6	0 - 14.0	0.02 - 17.0	0 - 166.3	0 - 286.4	0 - 363.1	0.02 - 372.7	0.1 - 3.5	0.1 - 5.1	0.2 - 5.6
	Skewness	0.6	0.5	1.9	1.6	3.2	3	2.7	2.7	3.3	1	0.5
Mixed conifer	N = 30											
	Mean (SE)	0.3 (0.04)	2.8 (0.5)	7.4 (1.0)	10.5 (1.4)	32.2 (6.4)	29.6 (6.4)	61.9 (12.8)	72.3 (13.2)	1.2 (0.1)	3.8 (0.3)	5.0 (0.4)
	Range	0.1 - 1.0	0 - 13.5	0 - 20.4	0.1 - 29.0	0 - 234.3	0 - 104.5	0 - 338.8	0.1 - 352.0	0.2 - 3.3	0.1 - 8.0	0.2 - 9.8
	Skewness	1.4	2.2	0.6	0.8	2.7	1	2.3	2.1	1.4	-0.2	-0.2
Ponderosa	N = 30											
	Mean (SE)	0.2 (0.04)	1.5 (0.3)	3.0 (0.5)	4.7 (0.7)	28.0 (16.3)	36.8 (17.1)	64.9 (25.1)	69.6 (25.0)	1.6 (0.2)	2.5 (0.3)	4.1 (0.4)
	Range	0 - 1.2	0 - 5.8	0 - 12.9	0 - 19.3	0 - 487.7	0 494.8	0 - 532.0	0 - 533.0	0.6 - 3.6	0.4 - 6.0	1.1 - 8.8
	Skewness	2.1	1.4	1.7	2	5	4.5	3	3	0.9	0.9	0.6
Spruce-fir	N = 10											
	Mean (SE)	0.6 (0.1)	2.3 (0.8)	4.9 (1.0)	7.8 (1.6)	55.5 (24.3)	68.7 (38.8)	124.1 (50.9)	131.9 (52.0)	1.1 (0.2)	4.3 (0.8)	5.4 (0.8)
	Range	0.2 - 1.0	0.3 - 9.1	0 - 10.0	0.7 - 18.4	0.9 - 262.4	0 - 405.3	19.2 - 489.4	23.3 - 507.8	0 - 2.7	0.8 - 8.7	1.6 - 10.0
	Skewness	0.1	2.4	0.1	0.9	2.6	2.8	1.7	1.7	1.3	0.6	0.6

* 1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

Table 3.3 Total area (ha) and percent cover by forest type as classified by the three image combinations.

	2002	%	2003	%	2002 - 2003	%
Aspen	854	27	772	25	819	26
Bristlecone	726	23	711	23	686	22
Mixed conifer	793	25	615	20	790	25
Ponderosa	527	17	698	22	605	19
Spruce-fir	253	8	341	11	245	8
Total Area	3152		3138		3145	

Table 3.4 Total area (ha) of canopy cover classes as classified by the three image combinations.

Classes (%)	2002	2003	2002+2003
1 - 25	324	119	291
26 - 40	397	636	428
41 - 70	1447	1498	1472
71 - 100	915	819	893

Table 3.5 Accuracy assessment results for all three image combinations. Layers significantly better than random are shown in bold. Alpha is 0.05. Woody fuels in Mg/ha.

2002

	Species	Canopy Cover	Fuel Model	1h	10h	100h	1000hs*	1000hr*	Wood1-100	Wood 1000	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Forest Floor (cm)
Overall Accuracy	**0.44**	**0.38**	**0.72**	0.38	**0.62**	0.36	0.42	0.38	0.47	0.4	0.39	0.47	0.43	0.45
KHAT	**0.3**	**0.15**	**0.34**	0.07	**0.22**	0.03	0.06	0.06	0.05	0.09	0.07	0.02	0.07	0.08
Variance	**0.003**	**0.003**	**0.006**	0.004	**0.007**	0.005	0.005	0.009	0.004	0.003	0.004	0.006	0.004	0.004
Z Score	**5.51**	**2.71**	**4.23**	1.14	**2.58**	0.36	0.87	0.65	0.77	1.54	1.13	0.21	1.08	1.25
P-value	**0**	**0**	**0**	0.13	**0**	0.36	0.19	0.26	0.22	0.06	0.13	0.42	0.14	0.11

2003

	Species	Canopy Cover	Fuel Model	1h	10h	100h	1000hs*	1000hr*	Wood1-100	Wood 1000	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Forest Floor (cm)
Overall Accuracy	**0.47**	0.33	**0.71**	**0.47**	**0.62**	0.4	0.45	0.3	0.42	0.42	**0.43**	**0.55**	0.4	0.39
KHAT	**0.34**	0.09	**0.37**	**0.16**	**0.23**	0.097	0.12	-0.06	-0.01	0.12	**0.14**	**0.17**	0.06	0.07
Variance	**0.002**	0.002	**0.004**	**0.005**	**0.007**	0.006	0.004	0.012	0.003	0.003	**0.003**	**0.005**	0.003	0.003
Z Score	**6.38**	1.8	**5.42**	**2.22**	**2.63**	1.24	1.81	-0.56	-0.19	2.02	**2.3**	**2.32**	0.97	1.16
P-value	**0**	0.04	**0**	**0.01**	**0**	0.11	0.04	0.71	0.58	0.02	**0.01**	**0.01**	0.17	0.12

2002+2003

	Species	Canopy Cover	Fuel Model	1h	10h	100h	1000hs*	1000hr*	Wood1-100	Wood 1000	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Forest Floor (cm)
Overall Accuracy	**0.41**	**0.45**	**0.7**	**0.47**	**0.61**	0.36	0.45	0.4	0.43	0.35	0.34	0.55	0.4	**0.45**
KHAT	**0.26**	**0.28**	**0.3**	**0.19**	**0.2**	0.04	0.14	0.09	0.04	0.07	0.06	0.15	0.08	**0.15**
Variance	**0.002**	**0.003**	**0.005**	**0.004**	**0.007**	0.005	0.004	0.007	0.004	0.003	0.003	0.005	0.003	**0.004**
Z Score	**4.87**	**5.17**	**3.96**	**2.89**	**2.26**	0.59	2.08	0.99	0.64	1.25	0.98	1.94	1.3	**2.33**
P-value	**0**	**0**	**0**	**0**	**0.01**	0.28	0.02	0.16	0.26	0.11	0.16	0.03	0.09	**0.01**

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

Table 3.6 Pair-wise comparisons of all mapped layers. Z statistic and (p-value) are shown. Layers that are significantly different are shown in bold. Alpha is 0.05. na = Z statistic could not be calculated because one or more KHAT values were negative or zero.

Layers Compared	Species	Canopy Cover	Fuel Model	1h	10h	100h	1000hs*
2002 & 2003	0.57 (0.29)	0.88 (0.20)	0.03 (0.38)	0.95 (0.17)	0.08 (0.47)	0.67 (0.25)	0.63 (0.26)
2002 & 2002+2003	0.57 (0.29)	1.68 (0.05)	0.38 (0.35)	1.34 (0.09)	0.17 (0.43)	0.10 (0.46)	0.84 (0.20)
2003 & 2002+2003	0.26 (0.10)	**2.69 (0.00)**	0.74 (0.23)	0.32 (0.38)	0.25 (0.40)	0.57 (0.28)	0.22 (0.41)

Layers Compared	1000hr*	Wood1-100	Wood 1000	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Forest Floor (cm)
2002 & 2003	na	na	0.39 (0.35)	0.84 (0.20)	1.43 (0.08)	0.12 (0.45)	0.12 (0.45)
2002 & 2002+2003	0.24 (0.41)	0.11 (0.46)	0.26 (0.40)	0.12 (0.45)	1.24 (0.11)	0.12 (0.45)	0.78 (0.22)
2003 & 2002+2003	na	na	0.65 (0.26)	1.03 (0.15)	0.20 (0.42)	0.26 (0.40)	0.96 (0.17)

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

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CHAPTER FOUR

FIRE BEHAVIOR MODELING

Abstract

Crown fire activity was modeled using the FlamMap fire simulation program. Area of active crown fire increased by 190% between the 10 and 40 km/hr wind speed scenarios, by an additional 10% between the 40 and 70 km/hr wind speed scenarios, and by 221% between the 10 and 70 km/hr wind speed scenarios. At the landscape-level, mean patch size of active crown fire increased over 700% from the 10 to 70 km/hr wind speed scenarios and the number of patches decreased by 60% between 10 and 70 km/hr wind speed scenarios. At the class-level, active crown fire mean patch size increased slightly in all five forest types (aspen, bristlecone pine, mixed conifer, ponderosa pine, and spruce-fir) with increasing wind speed. For all classes, the number of patches increased, at the class-level, between the 10 and 40 km/hr wind speed scenarios but tended to decrease between the 40 and 70 km/hr wind speed scenarios. Heat/area increased with greater wind speeds at both the landscape and class-levels. An Erosion Index model used to identify areas that had a high potential for erosion was created using slope, coarse woody debris (1000 hour sound and rotten fuels), and heat/area layers created in 10, 40, and 70 km/hr wind speed simulations, as inputs. Area of high erosion potential increased by 83% between the 10 and 70 km/hr wind speed scenarios.

Keywords: erosion; fire behavior modeling; fuels; landscape; patch size; watershed

Introduction

The San Francisco Peaks represent, over the elevational gradient, forest structure and fuels conditions that occur through the Southwest. Additionally, much of the Peaks is within a federally designated wilderness, the City of Flagstaff has municipal water wells [illegible] the Peaks, and a major watershed (Rio de Flag), that has in the past flooded the Flagstaff area, has its origins on the south side of the Peaks (Leao 2005). The base of the Peaks is being encroached upon, particularly on the south side, by neighborhoods and scattered private residences. The urban-wildland interface has become a source of concern for land managers throughout the Southwest (Marzoff and Bradley 2003). Years of fire suppression have led to an increased connectivity of surface fuels that has the potential to support fires outside the historical range of variability in size and severity (Miller and Urban 2000). Wildfire could, especially under drought conditions, quickly move into the Flagstaff city limits and, conversely, residential fires could quickly move onto the Peaks. This latter scenario is more likely due to the prevailing southwest to northeast wind direction. The 450 ha Leroux fire, which occurred on the south side of the Peaks in 2001, made Flagstaff residents very aware of the fire threat.

Fire behavior models allow land managers to simulate fire behavior conditions in areas that have been undergone fuel reduction treatments (Scott 1998, Fulé et al. 2001), in areas adjacent to population centers (Stratton 2004) and in roadless and wilderness areas where decades of fire suppression has led to high fuel loadings (Fulé et al. 2004). Common fire behavior models include FARSITE (Finney 1998), FlamMap (Finney in preparation), and Nexus (Scott and Reinhardt 2001). FARSITE is a deterministic model that simulates the spatial and temporal spread of fire (Stratton 2004). Inputs include aspect, elevation, slope, fuels, and weather. Outputs can be in tabular, vector, and raster formats. FlamMap requires many of the same inputs as FARSITE but is a hazard model, not modeling the spatial and temporal spread of fire. Each pixel is treated independently from those around it. Fire behavior (surface fire, passive crown fire, or active crown fire) is determined for each pixel. Outputs are in tabular format. Nexus is a deterministic model of surface fire behavior, also useful for assessing fuel hazards. Crown fire transition and crown fire spread is also modeled (Scott and Reinhardt 2001). FlamMap was chosen for this project because the addition of the topographic inputs was deemed better suited to simulating fire behavior in the steep terrain of the study area.

Landscape metrics provide ecologists with ways to quantify landscape pattern and the influence it has on ecological processes (Turner et al. 2001). A patch is an important concept in landscape ecology that can be defined as “an area differing in appearance from its surroundings” (Forman and Godron 1986). White and Pickett (1985) stated that a patch “implies a relatively discrete spatial pattern” and (Turner et al. 2001) note that patches are heavily influenced by the grain size and extent of the data and by the classification scheme used to derive the patch.

Agee (2002) stated that patch size of burned areas in eastside Oregon and Washington forest types with frequent low-severity fire regimes, such as ponderosa pine, tended to be small, ranging from 0.02 to 0.35 ha. Patch size in mixed-severity fire regimes had larger patches ranging from 2.5 to 250 ha. The Douglas-fir, aspen, and limber pine types on the

Peaks fall within this regime. High-severity fire regimes, such as the spruce-fir type on the Peaks, had considerably larger patches (Agee 2002). This mosaic of patch sizes is difficult for land managers to mimic through traditional forest thinning and prescribed fire. Allowing wildfires to burn under normal weather conditions or to allow wider use of management-ignited prescribed fire (Parsons 2000) may be the most practical ways to return this mosaic to the landscape.

Large increases in soil erosion rates after wildfires were reported by Morris and Moses (1987). Areas with severe erosion need to be addressed so that rehabilitation can be done to minimize damage to watershed function (Neary et al. 2000). There has been a corresponding increase in post-fire erosion control activities with the increase in the size and severity of wildfires (Robichaud 2005). This increase in post-fire erosion control is also crucial because the population living in the urban-wildland interface has also increased (Robichaud 2005).

My objectives in this study were: 1) to use FlamMap to simulate active crown fire behavior and heat/area at low, moderate, and high wind speeds, 2) to analyze the change in the number of patches and mean patch sizes under low, moderate, and high wind speeds, 3) to develop an Erosion Index model to identify areas with a high potential for erosion following a wildfire, and 4) draw implications for management of the Peaks and similar southwestern landscapes.

Methods

Study Area

The 5,000 hectare area chosen for this study was located almost entirely within the Kachina Peaks Wilderness Area on the south side of the San Francisco Peaks. The steep elevational gradient of the site provided an opportunity to work within nearly all of the forest floor fuel conditions found in the Southwest within a compact geographic area. Forest types (Figure 4.1) included ponderosa pine, mixed conifer, spruce-fir, and subalpine. The ponderosa pine (*Pinus ponderosa*) type occurred at the lowest elevations of the study area and was found up to elevations of 2,500 m. The mixed conifer type, which included limber pine (*Pinus flexilis)*, Douglas-fir (*Pseudotsuga menziesii*), ponderosa pine, and aspen (*Populus tremuloides*), ranged from 2,500 m to 3,000 m. The spruce-fir type generally occurred between 3,000 m and 3,500 m and included Engelmann spruce (*Picea engelmannii*), subalpine fir (*Abies lasiocarpa*), and bristlecone pine (*Pinus aristata var. arizonica).* The subalpine forest type was found from 3,100 m to 3,600 m. Bristlecone pine was the dominant tree species in this zone. Elevations range from 2,440 m to 3,560 m.

Weather data from 1909 – 2001, collected at the Fort Valley weather station (www.wrcc.dri.edu), located five km southwest of the study site, were summarized. Mean January temperatures were 5.2º C maximum and -12.3ºC minimum. Mean July temperatures were 26.7º C and 7.1º C minimum. Mean annual precipitation was 56.9 cm.

A series of weather stations were established in the study area in 1916 (Pearson 1920a). Weather stations were located in the following forest types: ponderosa pine, Douglas-fir, limber pine, Engelmann spruce, and subalpine. Pearson (1920a) used data collected from these stations to determine climate factors that influenced the distribution of forest types. Data collected at these stations in 1917 and 1918 show temperatures that range from 5.8º C in ponderosa pine, 5.4º C in Douglas-fir, 3.1º C in Engelmann spruce, and -0.05º C in the subalpine type. Annual precipitation was 102.1 cm in the subalpine type and 61.7 cm in the ponderosa pine type (Pearson 1920a).

Field Data

One hundred thirty-five permanent plots, based on the National Park Service's Fire Monitoring protocol (Reeberg 1995), were established during the 2000–2003 field seasons. Forest closures due to drought and wildfires, adverse weather conditions, and the overall steepness of the terrain prevented the completion of the plots in one or two field seasons.

The plot centers were 300 m apart, in the north-south direction, and 300 m or 600 m in the east-west direction. Each 0.1 ha (20 x 50 m) plot was oriented with the 50 m sides uphill-downhill to maximize sampling of variability along the elevational gradient. All overstory trees were tagged on the uphill side and tree measurements collected included species, diameter at breast height (dbh), canopy base height and total height. Pole trees (2.5-15 cm dbh) were measured on a 250 m^2 subplot. Seedling (<2.5 cm dbh) trees were tallied by species, condition, and height class on a 50 m^2 subplot. Tree canopy cover was measured by vertical projection every 30 cm (Ganey and Block 1994) along the two 50 m plot edges. Slope and aspect were recorded for all plots. Plot elevations were taken from a digital elevation model.

Woody debris was measured on four 15.2 m planar transects (Brown 1974) that originated from each 10 m point from the centerline (long axis) of the plot. Woody debris was recorded by timelag classes (Anderson 1982). Litter and duff depth measurements were taken every 1.5 m along each transect. Downed dead woody fuel consists of dead twigs, branches, stems, and boles of trees and shrubs that had fallen and lie on or near the ground (Brown and See 1981) and were classified into four diameter size classes of 0.1-0.5, 0.6-2.5 cm, 2.6-7.5 cm, and 7.6 cm and greater (Anderson 1982). The largest size class is divided into solid and rotten components because these exhibit different fire behavior. The fuels size classes were also characterized by moisture timelag classes.

Development of Fire Model Inputs

Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite imagery was used, in conjunction with the permanent plot data, to develop overstory tree species, canopy cover, fuel model, and both woody fuels and forest floor fuels layers. A fuel model is a stylized and simplified description of fuels, described in terms of fire behavior and vegetation type, that are used in fire simulation and behavior models (Pyne 1996). A discussion of the image classification process is discussed in Chapter 3 of this thesis.

A suite of data layers are necessary as inputs for FlamMap (Finney in preparation). Required data layers include elevation, slope, aspect, fuel model, and canopy cover. Optional data layers are stand height, canopy base height, and canopy bulk density. The three topographic layers were derived from a digital elevation model (DEM). The spatial resolution of the DEM was resampled from 10 m to 15 m to match the spatial resolution of the ASTER dataset.

Fuel models (Anderson 1982) were assigned as follows: aspen was model 8, aspen-mixed conifer stands were model 10, bristlecone pine was model 8, mixed conifer was model 10, and spruce-fir was model 10. Fuel moisture values, representing the 90th and 97th percentiles of low fuel moistures were used in all FlamMap simulations. These were calculated from 30 years of weather data from the Coconino National Forest (Fulé et al. 2001).

Canopy bulk density is an optional theme in the FlamMap program. It was not used in this study. In the absence of a canopy bulk density layer, average stand height and canopy bulk density can be used. The lowest quintile was used to categorize canopy base height to better represent actual stand conditions (Fulé et al. 2002).

Wind speeds of 10 through 70 km/hr, in 10 km/hr increments, were used. This range of wind speeds represents realistic wind speeds that occur during the fire season (Fulé et al. 2001). A range of wind speeds is necessary to quantify the influence of wind speed on active crown fire behavior. High wind speeds were found to have a stronger influence than fuel loadings on crown fire activity in high elevation forests (Bessie and Johnson 1995). Low, moderate, and high wind speeds of 10, 40, and 70 km/hr were used for heat/area, mean patch size, and number of patches simulations. Wind azimuth was held constant at 225° because of the prevailing southwest-to-northeast wind direction.

A foliar moisture content of 100% was used in the simulation process. I chose to use 100% foliar moisture content due to the diversity of forest types. Agee et al. (2002) found foliar moisture content values of 80-90% for ponderosa pine and Douglas-fir and 100-120% for subalpine fir.

Simulations were conducted using each wind speed to model heat/area and crown fire activity. Each FlamMap output was saved as an ASCII file and then converted to raster files. The Patch Analyst (version 3.0) extension for Arcview 3.3 (ESRI, Redlands, CA.) was used to calculate area (ha), mean patch size (ha), and number of patches for both the heat/area and crown fire FlamMap outputs. Calculations were run on both the landscape-level and class-level. The above landscape metrics were also computed for heat/area and crown fire activity in each forest type.

An Erosion Index model was created to model potential post wildfire soil erosion. A coarse woody debris (1000 hour sound and rotten fuels) layer was integrated with the active crown fire layer, each heat/area layer, and the slope layer to identify areas of low, moderate, and high erosion potential. Model parameters used were slopes ≥ 10%, coarse woody debris > 0 and heat/area 223,385 KJ/m^2 for the 10 km/hr scenario, 227,584 KJ/m^2 for the 40 km/hr scenario, and 237,393 KJ/m^2 for the 70 km/hr scenario.

Results

Crown Fire Activity

Active crown fire increased across the study area from roughly 650 ha (13% of study area) at a wind speed of 10 km/hr to nearly 2,000 ha (40% of study area) at a wind speed of 70 km/hr (Figure 4.2). The greatest single increase in active crown fire area occurred at a wind speed of 20 km/hr, nearly doubling from what FlamMap simulated for a wind speed of 10 km/hr. Increases in crown fire area of roughly 300 ha occurred between the 20 to 40 km/hr wind speeds. Modest increases in active crown fire area, of approximately 50 ha, were modeled between the 50 to 70 km/hr wind speeds. Conversely, passive crown fire dramatically decreased from 765 ha (15% of study area) at a wind speed of 10 km/hr to less than a hectare at 70 km/hr. The largest decrease, 95%, occurred between the 40 and 50 km/hr wind speeds.

When analyzed by species (Figure 4.3), the area of active crown fire consistently increased throughout the 10 to 40 km/hr wind speed range. For all species, FlamMap modeled a sharp decrease in active crown fire area at the 50 km/hr wind speed. Active crown fire area again increased in the 60 and 70 km/hr wind speed scenarios. Passive crown fire area consistently decreased, with all species, from the lowest to the highest wind speeds.

Heat/area

Increases in average heat/unit area occurred at increasing wind speeds (Figure 4.4). Heat/area, at all wind speeds, was greatest in the spruce-fir class (Figure 4.5). There was little difference between heat/are values in the 10 and 40 km/hr wind speed classes. The mixed conifer forest type had the second highest values and had greater variation between the 10 and 40 km/hr wind speed classes. The ponderosa and aspen classes exhibited similar heat/area values at the 70 km/hr wind speed class. Aspen had higher values in the 10 and 40 km/hr wind speed classes. The bristlecone pine class had very little variation between the three wind speed classes.

Mean Patch Size and Number of Patches and Erosion Index

In areas of active crown fire, the number of crownfire patches decreased as wind speed increased from 10 to 40 to 70 km/hr. Mean patch size increased by nearly a factor of ten between the 10 and 70 km/hr wind speed classes (Table 4.1).

The number of patches in the aspen class dramatically increased between the 10 and 70 km/hr wind speed classes while the mean patch size increase was very small (Table 4.2). The bristlecone pine class had a small increase between the 10 and 40 km/hr wind speed classes while the number of patches in the 70 km/hr wind speed class decreased slightly from the number of patches in the 40 km/hr wind speed class. Mean patch size increased very slightly in the bristlecone pine class. The number of patches increased between the 10 and 40 km/hr wind speed classes in the mixed conifer class. Similar to the bristlecone pine type, the number of patches was lower in the 70 km/hr wind speed class than in the 40 km/hr wind speed class and the increase mean patch size was relatively small. There was an increase in the number of patches between the 10 and 40 km/hr wind speed classes in the ponderosa class. As in the bristlecone pine and mixed conifer classes, the number of patches decreased in the 70 km/hr wind speed class. The increase in mean patch size was greater in the ponderosa pine class than in the other four forest types. There were slight increases in both the number of patches and mean patch size in the spruce-fir forest type. Areas of modeled high erosion potential varied slightly between the 10 (41 ha), 40 (65 ha), and 70 (75 ha) km/hr wind speed classes (Figure 4.6).

Discussion

Active Crown Fire Behavior

Active crown fire increased in overall area and in patch size with increases in wind speed. Other studies, in various forest types, have had similar results. Stratton (2004) reported increases in area consumed by both passive and active crown fire in a pinyon-juniper (*Pinus edulis/Juniperus spp*.) ecosystem, in southern Utah, when using 95th percentile weather conditions. Bessie and Johnson (1995) concluded that in subalpine forests located in the southern Canadian Rocky Mountains, weather, in particular wind, played a more important role in crown fire activity than did fuels. Similarly, Fulé et al. (2001) found, in a study conducted in a ponderosa pine ecosystem of northern Arizona, that 72 km/hr wind speeds would lead to crown fire initiation in areas that did not support crown fires at slower wind speeds.

It is very likely that FlamMap underestimates the actual area of active crown fire. As previously discussed, FlamMap treats each pixel independently from those around it. FlamMap requires that the criteria for a surface fire and then for a passive crown fire are met before a pixel can have an active crown fire value. The progression from surface to active crown fire is not possible, within FlamMap, if the canopy base height values are too great. Canopy base height is the variable used in FlamMap that has the greatest influence on the progression from a surface fire to an active crown fire. Active crown fire behavior, under the extreme conditions simulated in the model, would almost certainly spread to adjacent pixels regardless of canopy base height. The canopy base height layer I used for the FlamMap simulations was created using the training site data as described in Chapter 3 of this thesis. No accuracy assessment of this layer was performed but the accuracy is likely to be quite low as this is a forest structure variable that is difficult to detect with traditional remote sensing sensors. Stratton (2004) addressed the FlamMap issue of active crown fire underestimation by combining the passive and active crown fire categories. This combination of fire behavior categories would have added little area to the active crown fire class in this study because of the small area modeled as passive crown fire.

My model simulations indicate that patch number and mean patch size increase as fire severity increases. Henry and Yool (2002) and Romme (1982) found that the number of patches decreases after long fire-free periods. Mean patch size increases as the landscape becomes more homogeneous. Forests with a frequent fire regime often have a mosaic of stand ages, densities, and species composition due to the variation in fire severity across a landscape (Romme 1982).

Topography has been shown to have significant effects on fire behavior (Kushla and Ripple 1997). The varied topography of the Peaks would almost certainly lead to a mosaic of burned and unburned patches, as reflected in the model results. The Leroux fire, which burned under normal weather conditions, created a mosaic of unburned, moderately burned, and severely burned patches (Cocke 2005). Under extreme weather conditions though, topography has a decreased influence on fire behavior (Kushla and Ripple 1997). Bessie and Johnson (1995) and Turner and Romme (1994) also found that in extreme weather conditions, the importance of fuel loading decreases as the conditions necessary to attain crown fire are met. Weather is more closely associated with fire behavior than are fuels and analysis by Bessie and Johnson (1995) found that weather explained 83% of the variance in fire intensity.

Fire Effects

Invasive plant species often thrive in areas that were created by high severity fire. These species will often be the dominant post-fire plant community (Romme et al. 2003). The various conifer species in the study area respond differently to fire. Ponderosa pine has a high fire resistance, the mixed conifer species in the study area (Douglas-fir and limber pine) have a high fire resistance, and the spruce-fir species (Engelmann spruce and subalpine fir) have a low fire resistance. Bristlecone pine, located in the highest points in the study area, have a moderate resistance to fire. Aspen, found throughout nearly the entire study area, has a very low resistance to fire. Although many of these species have a high resistance to low and moderate severity fires, high-severity fire areas may have little conifer regeneration due to high seed mortality (Romme et al. 2003). Buds and branch cambium must survive a fire in order for a tree to survive (Miller 2000). The long needles on ponderosa pine and limber pine help to shield the buds and this can increase bud survival at a 20% lower height than that where foliage is killed (Ryan 1990).

Second-order fire effects, such as erosion and changes in vegetation composition, are indirect post-fire effects that occur from just hours up to decades after a fire (Reinhardt et al. 2001). Erosion is a second-order fire effect of particular importance to the study area. The removal of forest floor litter, which acts to slow water runoff and allow for water infiltration, accelerates the erosion process (Morris and Moses 1987). Post-fire sediment amounts can be extreme in areas of steep terrain, particularly in areas that also experience high intensity thunderstorms. Average slope in the study area is roughly 35%. The runoff from both snow and the summer monsoons provide the perfect combination for large amounts of sediment to be washed down-slope. Removal of topsoil is detrimental to vegetation recovery, leads to flooding, and severely eroded drainages (Miller et al. 2003).

Leao (2005) modeled post-fire flooding on the Rio de Flag watershed, covering much of my study area, showing that peak discharge could increase two to nearly seven times the historical 100 year discharge. Debano et al. (1998) found that in areas of steep terrain that experience heavy summer monsoon precipitation, such as the Peaks, discharge can increase up to 9,600%.

Identifying areas that have high erosion potential is important to identify high risk areas that need to be considered for some type of fuels treatment. High risk areas are typically areas that have experienced a recent high-severity fire as low and moderate-severity fires do not have similar erosion and runoff impacts (Cipra et al. 2003). The Erosion Index Model created in this study was used to high identify high risk areas. I feel that the model underestimated the high risk area. The steep slopes and relatively high coarse woody debris level throughout much of the study area would seem to suggest that the potential for severe runoff would be greater.

Model Limitations

The FlamMap model has limitations that need to be understood before management decisions are made based on the model outputs. The criteria for active crown fire initiation is such a limitation. Agee (1996) found that the parameters in the Van Wagner (1977) crown fire initiation model, utilized in FlamMap, seemed more sensitive to canopy base height than to foliar moisture content. My simulations confirmed this. All models are also scale dependent (Benson and MacKenzie 1995, Turner et al. 2001) and results will differ depending on what scale is used. The accuracy of the data layers used as inputs needs to be taken into consideration. The FlamMap outputs are not necessarily accurate estimates of active crown fire, but they do allow for reasonable comparisons of potential active crown fire activity in relative terms (Fulé et al. 2004).

Conclusions and Management Implications

Over a century of fire suppression has resulted in unnatural forest conditions and large, severe wildfires (Covington and Moore 1994, Swetnam et al. 1999). The size and frequency of crown fires have increased. Crown fires in the 1940s to the 1970s averaged from 100 to 3,000 acres with fewer than ten fires per decade. During the 1990s, crown fire size increased to 2,000 to 7,000 acres and averaged twenty-six fires per decade (Mast 2003). The potential for crown fire activity can be greatly reduced, but not necessarily eliminated, through management of surface fuels or by raising the canopy base height (Agee 1996).

The question of what role fire should currently play on the Peaks is complicated by the Federal Wilderness designation of much of the area. The Wilderness Act of 1964 states that wilderness should have minimal impacts from human activities but it also states that it be "managed so as to preserve its natural conditions." Wilderness is managed for both naturalness and wildness (Cole 2001). Naturalness in wilderness describes conditions that are largely unaffected by humans and the wildness of wilderness refers to it being untrammeled and unmanipulated by humans (Parsons et al. 2003).

It is difficult to manage for both naturalness and wildness. Over a century of fire suppression may make it necessary to use human ignited prescribed fires and mechanical fuels reduction techniques to return areas to a more natural state. These types of fuel treatments completely go against the idea of an area untouched by humans (Parsons et al.

2003). The decision to manage wilderness for wildness or naturalness may be one of the main wilderness management issues of the 21st century (Cole 2001).

Prescribed fire, both human ignited and wildland use fires, has been used, but very few of the designated wilderness areas outside of Alaska have approved fire plans. Budget limitations, interagency boundaries and cooperation, and air quality concerns are some of the reasons that there has been little progress in wilderness fuels management (Parsons et al. 2003).

The reintroduction of fire to the San Francisco Peaks may be the only management alternative available. The steep terrain of the Peaks would make any mechanical treatments too impractical. Wildland use fires have been used in other wilderness areas (Parsons 2000) and because of access issues may be the most appropriate method of fire reintroduction (Miller 2003). Ecological and social concerns must be considered before reintroducing fire to the Peaks. Issues related to smoke and the potential for fire to cross prescribed fire boundaries are risks that land managers must consider (van Wagtendonk 1995). These issues must be addressed because of the ecological and social impacts of a catastrophic wildfire and the potential resulting erosion and flooding.

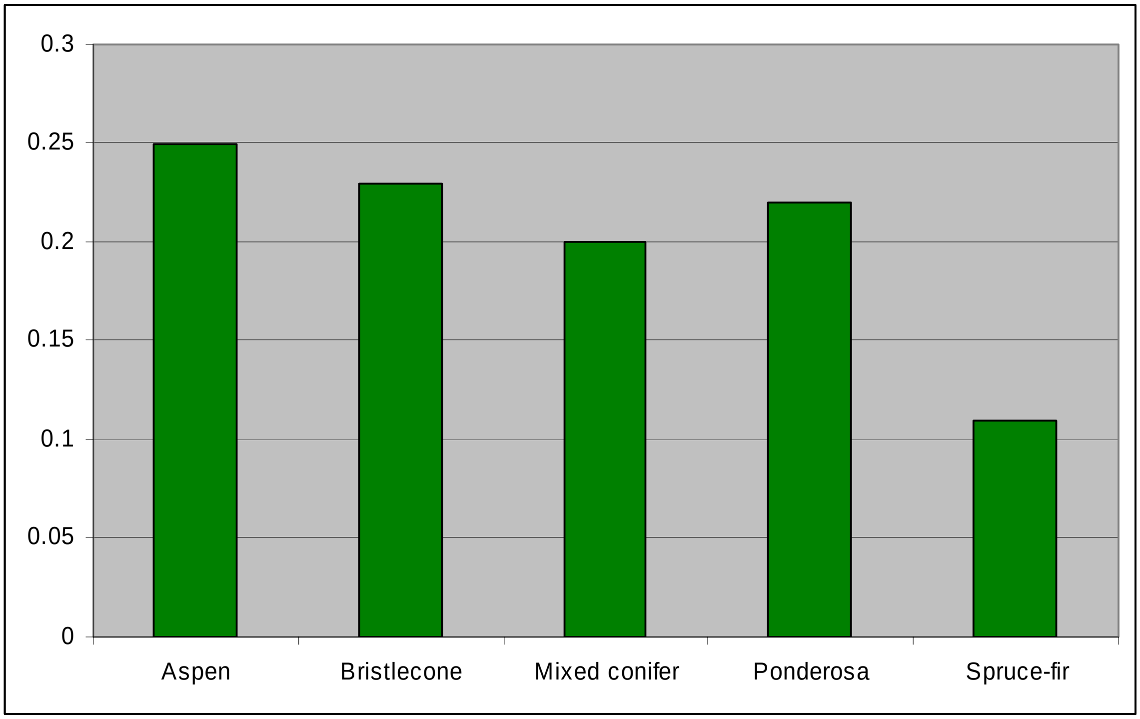

Figure 4.1 Percent of landscape by forest type.

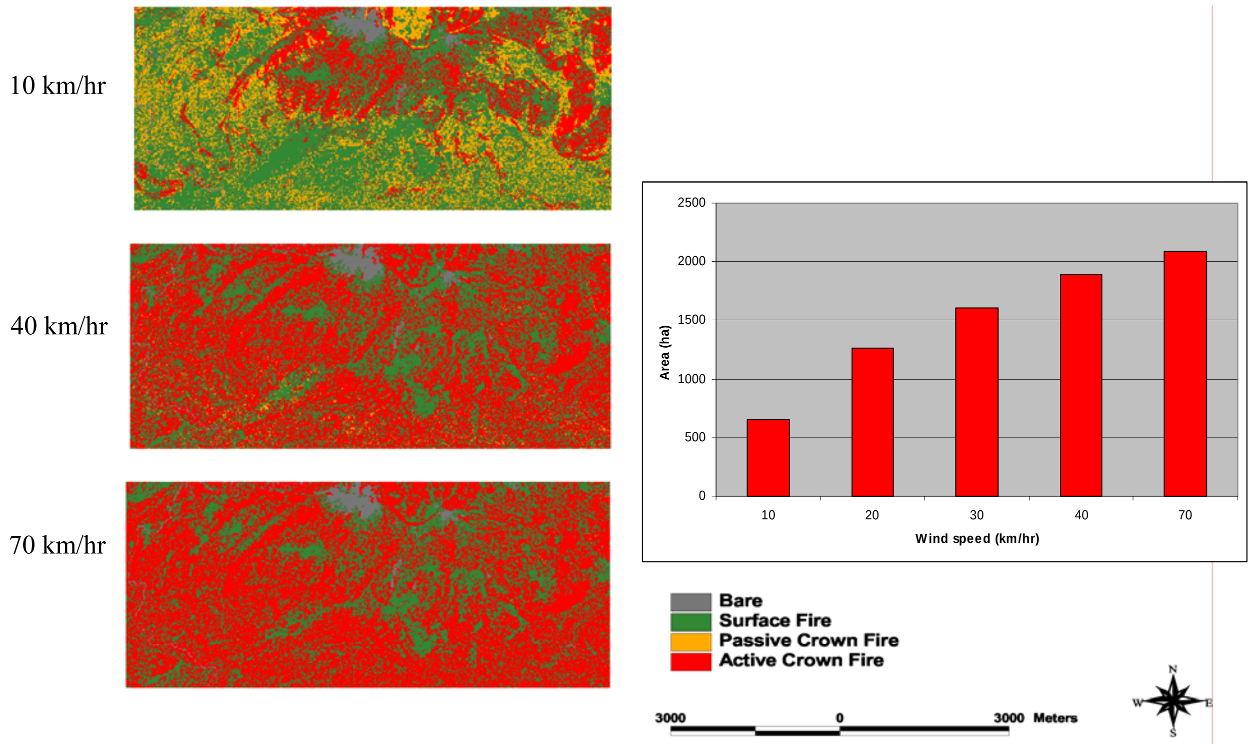

Figure 4.2 Fire behavior classes under low (10 km/hr), moderate (40 km/hr), and high (70 km/hr) wind conditions. Bar graph shows area of the active crown fire class under wind conditions from 10-40 and 70 km/hr to more clearly identify the active crown fire threshold.

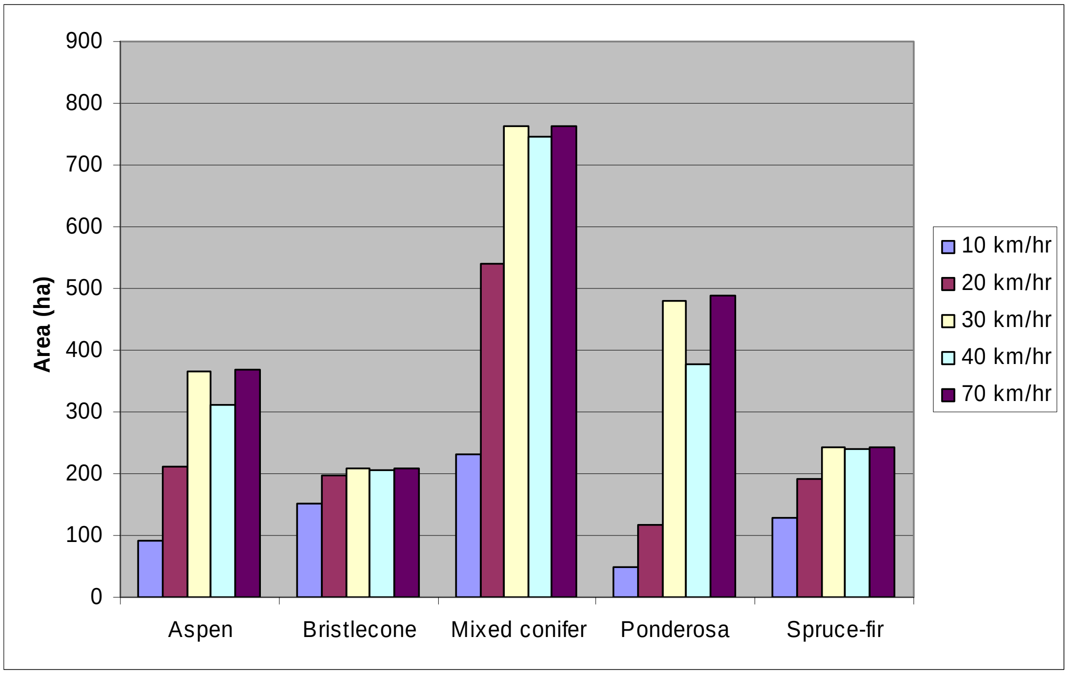

Figure 4.3 Area of active crown fire in the five forest types under low, moderate, and high wind conditions.

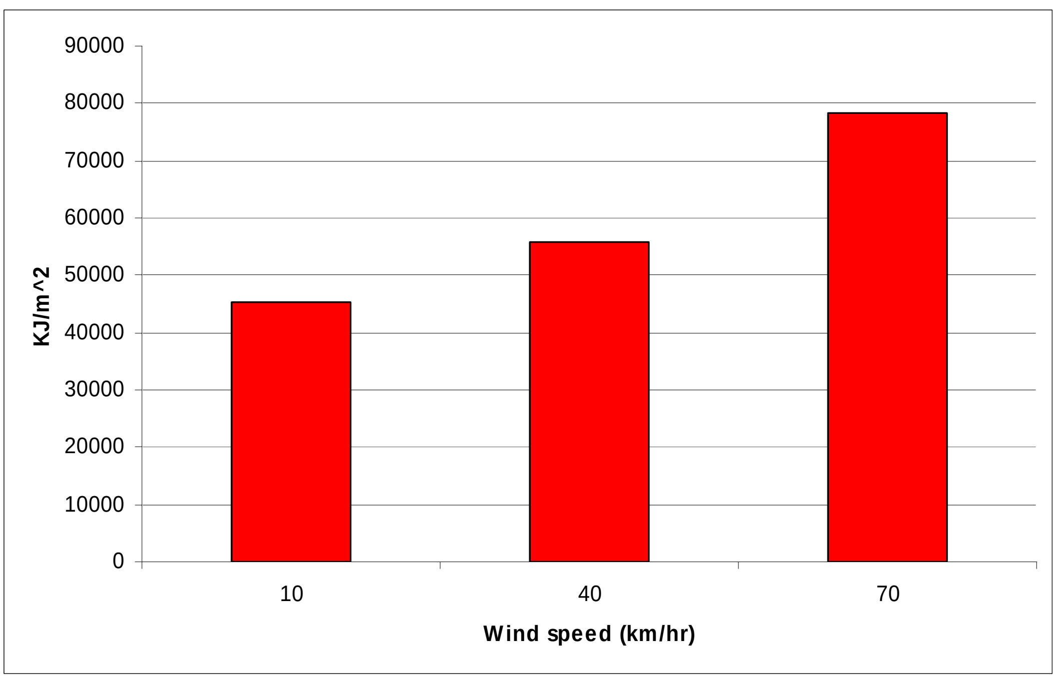

Figure 4.4 Heat/area under active crown fire conditions and low, moderate, and high wind conditions.

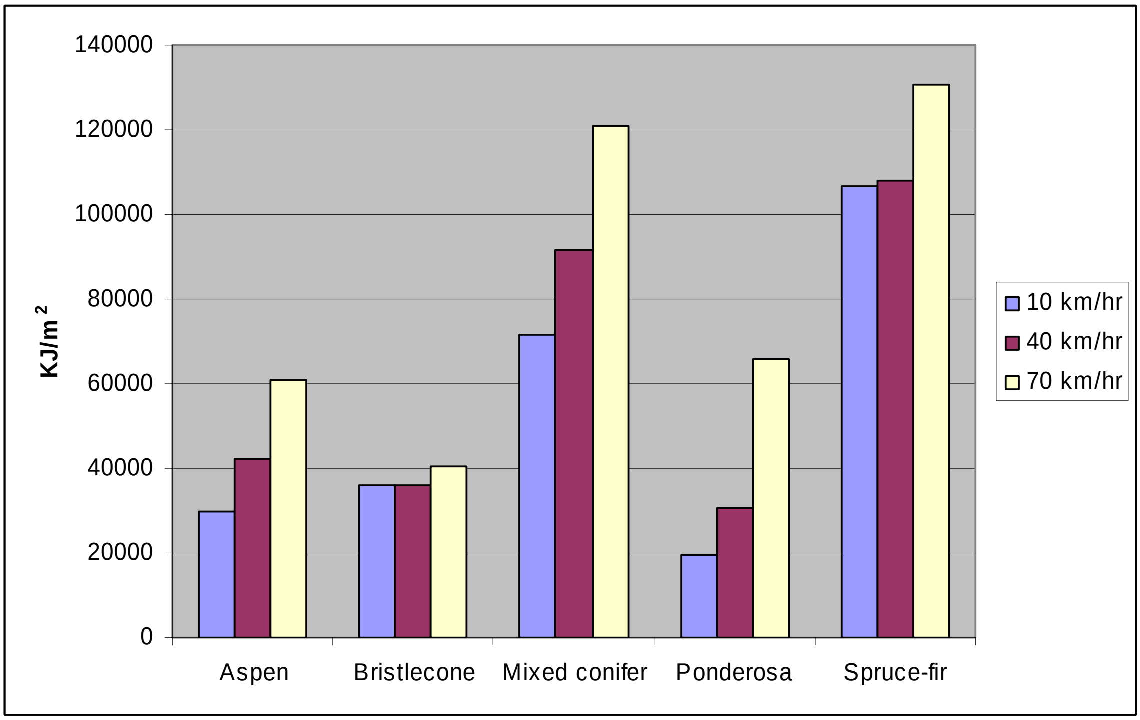

Figure 4.5 Heat/area under active crown fire conditions and low, moderate, and high wind conditions for the five forest types.

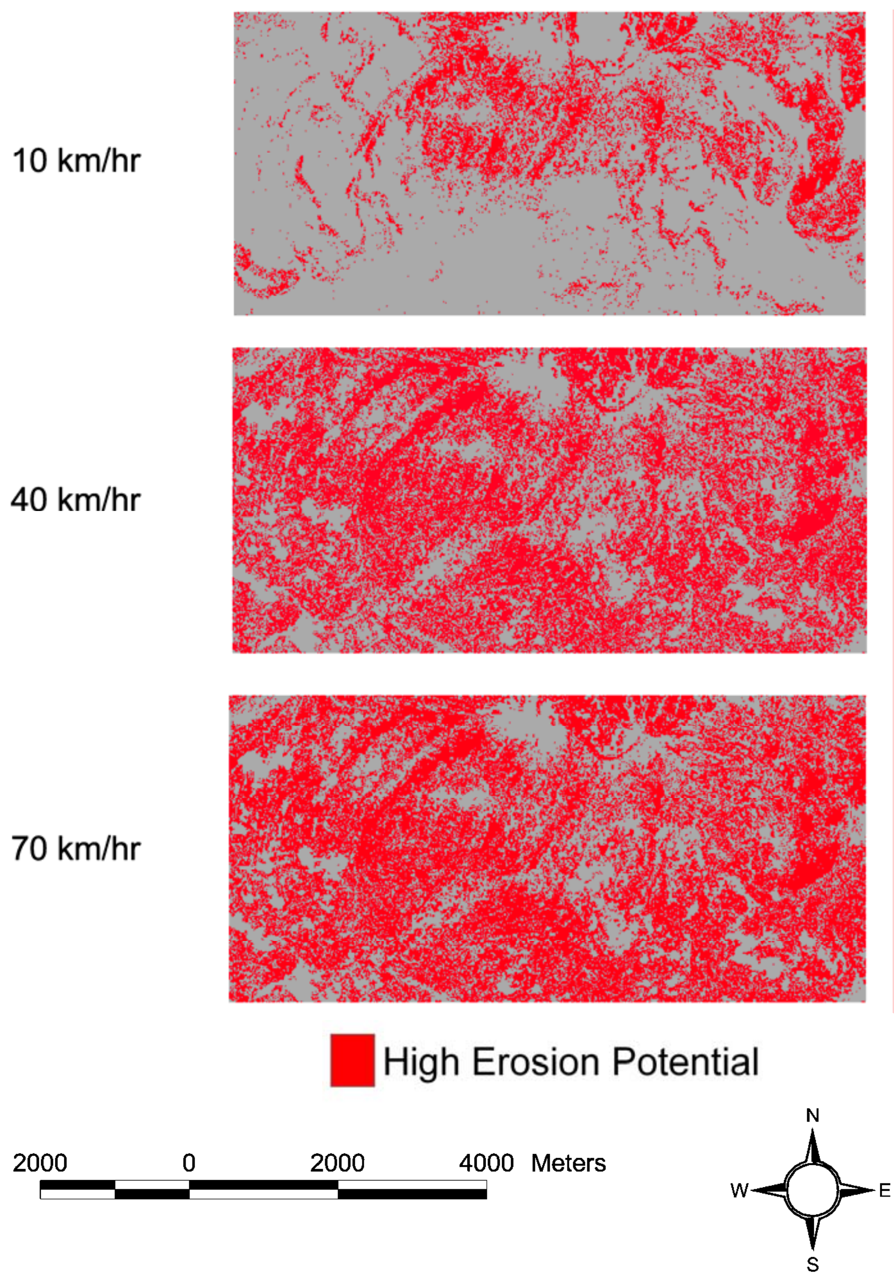

Figure 4.6 Areas of high erosion potential under active crown fire conditions and low, moderate, and high wind conditions. Model parameters used were slopes ≥ 10%, coarse woody debris > 0 and heat/area 223,385 KJ/m^2 for the 10 km/hr scenario, 227,584 KJ/m^2 for the 40 km/hr scenario, and 237,393 KJ/m^2 for the 70 km/hr scenario.

Table 4.1 Number of patches and mean patch size, in areas of active crown fire, at low, moderate, and high wind speeds at the landscape-level.

Wind Speed (km/hr)	Number of Patches	Mean Patch Size (ha)
10	2020	0.32
20	3167	0.4
30	1895	0.85
40	1080	1.75
70	811	2.58

Table 4.2 Number of patches, and mean patch size, in areas of active crown fire, at low, moderate, and high wind speeds for the five forest types.

	Wind Speed (km/hr)	Number of Patches	Mean Patch Size (ha)
Aspen	10	1596	0.06
	20	3727	0.06
	30	4584	0.08
	40	4373	0.07
	70	4591	0.08
Bristlecone	10	1059	0.14
	20	1379	0.14
	30	1358	0.15
	40	1369	0.15
	70	1358	0.15
Mixed conifer	10	1213	0.19
	20	3541	0.15
	30	3127	0.24
	40	3254	0.23
	70	3127	0.24
Ponderosa	10	983	0.05
	20	1906	0.06
	30	2342	0.2
	40	2786	0.14
	70	2309	0.21
Spruce-fir	10	608	0.21
	20	992	0.19
	30	933	0.26
	40	946	0.25
	70	933	0.26

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Appendix 1

Area (ha) and percent (%) of landscape woody and forest floor fuel types for the three image combinations. Woody fuels in Mg/ha.

Fuels Class	1h	10h	100h	1+10+100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
2002											
1	2388 (72)	2992 (90)	2083 (62)	2357 (71)	2276 (68)	1765 (53)	1731 (52)	1956 (59)	2136 (64)	1939 (58)	1884 (57)
2	635 (19)	102 (3)	580 (17)	744 (22)	486 (15)	521 (16)	945 (28)	1013 (30)	901 (27)	1256 (38)	1305 (39)
3	210 (6)	50 (1)	110 (3)	147 (4)	107 (3)	173 (5)	283 (8)	324 (10)	256 (8)	112 (3)	117 (4)
No Fuels	100 (3)	189 (6)	560 (17)	85 (3)	463 (14)	873 (26)	374 (11)	39 (1)	39 (1)	26 (1)	25 (1)
Total	3332	3332	3332	3332	3332	3332	3332	3332	3332	3332	3332
2003											
1	2296 (69)	2903 (88)	2444 (74)	2369 (71)	2128 (64)	1910 (58)	1705 (51)	1782 (54)	2036 (61)	1790 (54)	1382 (42)
2	630 (19)	154 (5)	529 (16)	713 (22)	740 (22)	505 (15)	1084 (33)	1082 (33)	855 (26)	1249 (38)	1479 (45)
3	276 (8)	117 (4)	93 (3)	160 (5)	126 (4)	176 (5)	303 (9)	403 (12)	344 (10)	249 (8)	428 (13)
No Fuels	111 (3)	139 (4)	248 (7)	73 (2)	319 (10)	723 (22)	222 (7)	46 (1)	79 (2)	26 (1)	26 (1)
Total	3314	3314	3314	3314	3314	3314	3314	3314	3314	3314	3314
2002-2003											
1	2432 (73)	2999 (90)	2182 (65)	2345 (70)	2151 (65)	1707 (51)	1652 (50)	1818 (55)	2164 (65)	1799 (54)	1478 (44)
2	586 (18)	121 (4)	611 (18)	797 (24)	600 (18)	560 (17)	1010 (30)	1093 (33)	871 (26)	1360 (41)	1512 (45)
3	189 (6)	46 (1)	61 (2)	99 (3)	110 (3)	190 (6)	313 (9)	379 (11)	259 (8)	148 (4)	317 (10)
No Fuels	125 (4)	167 (5)	478 (14)	92 (3)	471 (14)	875 (26)	358 (11)	42 (1)	37 (1)	26 (1)	26 (1)
Total	3332	3332	3332	3332	3332	3332	3332	3332	3332	3332	3332

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

Appendix 2

Accuracy assessment results, by forest type, for layers created with the 2002 dataset. Layers significantly better than random are shown in bold. Woody fuels in Mg/ha.

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Aspen	Overall Accuracy	0.45	0.35	0.75	0.55	0.7	0.45	0.45	0.31	0.56	0.3	0.3	0.4	0.6	0.58
	KHAT		0.1		0.24	0.28	0	-0.05	-0.16	0.33	0.02	0.02	-0.08	0.18	0.11
	Variance		0.021		0.034	0.059	0.049	0.055	0.404	0.029	0.039	0.039	0.066	0.053	0.059
	Z Score		0.71		1.29	1.13	0	-0.24	-0.79	1.9	0.11	0.11	-0.3	0.76	0.44
	P-value		0.24		0.1	0.13	0.5	0.6	0.78	0.03	0.46	0.46	0.62	0.23	0.33

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Bristlecone	Overall Accuracy	0.53	0.37	0.83	0.43	0.61	0.37	0.45	0.43	0.48	0.4	0.37	0.47	**0.6**	**0.67**
	KHAT		0.12		0.18	0.28	-0.01	0.09	0.1	-0.01	0.11	0.11	0.06	**0.36**	**0.46**
	Variance		0.013		0.021	0.041	0.045	0.028	0.022	0.128	0.018	0.026	0.03	**0.02**	**0.016**
	Z Score		1.08		1.26	1.37	-0.03	0.53	0.65	-0.02	0.8	0.69	0.34	**2.51**	**3.64**
	P-value		0.14		0.1	0.09	0.51	0.3	0.26	0.51	0.21	0.25	0.37	**0**	**0**

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Mixed-conifer	Overall Accuracy	0.21	0.42	0.85	0.37	0.63	0.42	0.47	0.5	0.45	0.42	0.37	0.42	0.45	0.39
	KHAT		0.18	-0.08	0	0.31	0.08	0.05	0.12	-0.03	0.12	0.03	0.09	0.17	0.1
	Variance		0.013	0.001	0.017	0.027	0.015	0.021	0.202	0.1	0.014	0.015	0.022	0.021	0.024
	Z Score		1.57	-2.01	0	1.85	0.67	0.31	0.81	-0.08	1.03	0.27	0.58	1.14	0.62
	P-value		0.06	0.98	0.5	0.03	0.25	0.38	0.21	0.53	0.15	0.39	0.28	0.13	0.27

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Ponderosa	Overall Accuracy	0.44	0.28	0.88	0.32	0.62	0.31	0.51	0.49	0.29	0.39	0.45	0.46	0.33	0.44
	KHAT		-0.02	0	-0.14	0.11	0.01	0.04	0.12	-0.06	0.01	0.09	-0.11	-0.17	-0.07
	Variance		0.012	0.235	0.034	0.034	0.027	0.021	0.037	0.068	0.025	0.026	0.01	0.018	0.02
	Z Score		-0.18	0	-0.73	0.57	0.05	0.25	0.6	-0.21	0.06	0.56	-1.05	-1.26	-0.49
	P-value		0.57	0.5	0.77	0.28	0.48	0.4	0.27	0.58	0.48	0.29	0.85	0.9	0.69

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Spruce-fir	Overall Accuracy	0.42	**0.58**	0.88	0.32	0.58	0.21	0.53	0.33	0.47	0.5	0.53	0.68	0.16	0.17
	KHAT		**0.39**	-0.06	0.07	0.04	-0.16	0.11	-0.14	0.23	0.16	0.2		-0.16	-0.22
	Variance		**0.024**	0.001	0.028	0.06	0.014	0.039	0.028	0.061	0.028	0.039		0.065	0.087
	Z Score		**2.52**	-1.42	0.42	0.15	-1.32	0.53	-0.81	0.92	0.93	0.98		-0.63	-0.75
	P-value		**0.01**	0.92	0.34	0.44	0.91	0.3	0.79	0.18	0.18	0.16		0.74	0.77

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

Appendix 3

Accuracy assessment results, by forest type, for layers created with the 2003 dataset. Layers significantly better than random are shown in bold. Woody fuels in Mg/ha.

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Aspen	Overall Accuracy	0.65	0.2	0.8	**0.65**	0.75	0.45	0.5	0.37	0.47	0.35	0.45	0.5	0.5	0.56
	KHAT		-0.04		**0.38**	0.4	0.04	0.05	0.03	-0.01	0.08	0.18	0.04	0.03	0.06
	Variance		0.016		**0.038**	0.048	0.036	0.046	0.046	0.05	0.04	0.032	0.047	0.045	0.055
	Z Score		-0.33		**1.97**	1.84	0.19	0.22	0.16	-0.03	0.42	0.99	0.2	0.14	0.27
	P-value		0.63		**0.02**	0.03	0.43	0.41	0.44	0.51	0.34	0.16	0.42	0.45	0.39

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Bristlecone	Overall Accuracy	0.47	0.33	0.83	0.47	0.53	0.34	0.39	0.5	0.37	0.47	0.43	0.5	0.4	0.3
	KHAT		0.12		0.19	0.17	0.04	0.04	0.23	-0.15	0.2	0.19	0.1	0.07	-0.04
	Variance		0.013		0.027	0.04	0.055	0.031	0.023	0.162	0.023	0.027	0.019	0.017	0.012
	Z Score		1.06		1.18	0.83	0.16	0.22	1.49	-0.37	1.29	1.15	0.72	0.54	-0.35
	P-value		0.14		0.12	0.2	0.44	0.41	0.07	0.65	0.1	0.12	0.23	0.29	0.64

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Mixed-conifer	Overall Accuracy	0.18	**0.45**	0.79	0.5	0.57	0.47	0.42	0.37	0.31	**0.5**	0.47	0.61	0.39	0.39
	KHAT		**0.26**	-0.06	0.16	0.15	0.16	0.05	0	-0.05	**0.26**	0.23	0.29	0.15	0.13
	Variance		**0.01**	0.08	0.018	0.04	0.018	0.014	0.014	0.11	**0.015**	0.014	0.017	0.018	0.017
	Z Score		**2.51**	-0.22	1.19	0.75	1.2	0.38	-0.38	-0.14	**2.08**	1.87	2.18	1.13	1.03
	P-value		**0.01**	0.58	0.12	0.23	0.12	0.35	0.52	0.56	**0.02**	0.03	0.01	0.13	0.16

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Ponderosa	Overall Accuracy	0.56	0.23	0.64	0.36	0.69	0.41	0.49	0.51	0.29	0.39	0.42	0.51	0.36	0.41
	KHAT		-0.07	-0.21	-0.07	0.24	0.13	-0.01	0.15	-0.1	-0.03	0.03	0.18	-0.21	0.07
	Variance		0.008	0.03	0.03	0.034	0.029	0.015	0.038	0.045	0.023	0.026	0.018	0.012	0.03
	Z Score		-0.77	-1.17	-0.37	1.31	0.78	-0.12	0.76	-0.45	-0.18	0.17	1.31	-1.87	0.39
	P-value		0.78	0.88	0.65	0.1	0.22	0.55	0.22	0.67	0.57	0.43	0.1	0.97	0.35

		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Spruce-fir	Overall Accuracy	0.32	0.42	0.88	0.42	0.72	0.32	0.28	0.59	0.26	0.47	0.47	0.63	0.37	0.39
	KHAT		0.12	-0.06	0.21	0.22	-0.1	-0.37	0.28	0.01	0.08	0.12		0.12	0.09
	Variance		0.023	0.0019	0.033	0.091	0.06	0.018	0.04	0.08	0.033	0.037		0.028	0.031
	Z Score		0.77	-1.42	1.16	0.74	-0.42	-1.72	1.41	0.05	0.43	0.62		0.73	0.51
	P-value		0.22	0.92	0.12	0.23	0.66	1	0.08	0.48	0.34	0.27		0.23	0.3

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

Appendix 4

Accuracy assessment results, by forest type, for layers created with the 2002+2003 dataset. Layers significantly better than random are shown in bold. Woody fuels in Mg/ha.

	Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Overall Accuracy	0.65	0.2	0.8	**0.7**	0.75	0.35	0.4	0.42	0.44	0.25	0.25	0.6	0.55	**0.74**
KHAT		-0.09		**0.47**	0.38	-0.03	-0.06	-0.04	0.02	-0.13	-0.13	0.11	0.1	**0.45**
Variance		0.013		**0.03**	0.048	0.032	0.043	0.047	0.047	0.051	0.051	0.039	0.055	**0.044**
Z Score		-0.75		**2.7**	1.72	-0.18	-0.3	-0.18	0.08	-0.57	-0.57	0.56	0.45	**2.15**
P-value		0.77		**0**	0.04	0.57	0.62	0.57	0.47	0.71	0.71	0.29	0.33	**0.02**

	Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Overall Accuracy	0.47	0.07	0.83	0.47	0.54	0.33	0.45	0.47	0.63	0.37	0.3	0.67	0.47	0.4
KHAT		-0.25		0.22	0.19	0.01	0.15	0.21	0.05	0.1	0.05	0.27	0.2	0.09
Variance		0.005		0.025	0.045	0.044	0.026	0.017	0.102	0.014	0.02	0.02	0.019	0.018
Z Score		-3.45		1.39	0.91	0.07	0.9	1.57	0.17	0.84	0.34	1.86	1.44	0.68
P-value		1		0.08	0.18	0.47	0.18	0.05	0.43	0.2	0.37	0.03	0.08	0.25

	Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Overall Accuracy	0.18	**0.47**	0.92	0.5	0.63	0.45	0.5	0.5	0.56	0.34	0.34	0.39	0.45	**0.53**
KHAT		**0.27**	0.46	0.15	0.28	0.11	0.18	0.21	0.14	0.07	0.07	0.07	0.2	**0.31**
Variance		**0.011**	0.105	0.019	0.031	0.017	0.017	0.015	0.077	0.013	0.013	0.024	0.015	**0.015**
Z Score		**2.51**	1.41	1.11	1.56	0.84	1.35	1.68	0.52	0.59	0.58	0.44	1.57	**2.52**
P-value		**0.01**	0.08	0.13	0.06	0.2	0.09	0.05	0.3	0.28	0.28	0.33	0.06	**0.01**

	Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Overall Accuracy	0.51	0.39	0.69	0.38	0.59	0.28	0.44	0.38	0.41	0.31	0.35	0.54	0.33	0.33
KHAT		0.15	0.13	-0.05	0.05	-0.03	-0.09	0.02	0.08	-0.02	0.03	0.15	-0.09	-0.04
Variance		0.012	0.106	0.022	0.033	0.034	0.02	0.027	0.041	0.023	0.023	0.018	0.017	0.032
Z Score		1.32	0.4	-0.35	0.25	-0.14	-0.63	0.13	0.39	-0.12	0.19	1.14	-0.66	-0.22
P-value		0.09	0.34	0.64	0.4	0.56	0.73	0.45	0.35	0.55	0.42	0.13	0.74	0.59

	Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
Overall Accuracy	0.32	0.47	0.89	0.42	0.67	0.37	0.33	0.5	0.32	**0.65**	**0.65**	0.68	0.21	0.33
KHAT		0.16	-0.06	0.21	0.19	0.04	-0.18	0.19	0.06	**0.43**	**0.42**		-0.08	0.03
Variance		0.031	0.001	0.03	0.09	0.025	0.016	0.032	0.074	**0.026**	**0.028**		0.035	0.045
Z Score		0.9	-1.42	1.18	0.62	0.24	-1.4	1.03	0.21	**2.67**	**2.46**		-0.42	0.15
P-value		0.19	0.92	0.12	0.27	0.41	0.92	0.15	0.42	**0**	**0.01**		0.66	0.44

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.

Appendix 5

Pair-wise comparisons of all mapped layers by forest type. Z statistic and (p-value) are shown. Layers significantly different are shown in bold. Alpha is 0.05. na = Z statistic could not be calculated because one or more KHAT values were negative or zero. Woody fuels in Mg/ha.

Layers Compared		Species	Canopy Cover	Fuel Model	1h	10h	100h	Wood1-100h	1000hs*	1000hr*	1000h s+r	Wood Total	Ave. Litter (cm)	Ave. Duff (cm)	Ave. Litter+Duff (cm)
2002 & 2003	Aspen	na	na	na	0.52 (0.30)	0.36 (0.35)	na	na	na	na	0.21 (0.42)	0.60 (0.27)	na	0.48 (0.32)	0.14 (0.44)
	Bristlecone	na	0.01 (0.49)	na	0.05 (0.42)	0.39 (0.35)	na	0.21 (0.42)	0.61 (0.27)	na	0.444 (0.328)	0.35 (0.36)	0.18 (0.43)	1.50 (0.07)	na
	Mixed-conifer	na	0.53 (0.30)	na	na	0.62 (0.27)	0.44 (0.33)	0.00 (0.50)	na	na	0.82 (0.21)	1.17 (0.12)	1.01 (0.16)	0.10 (0.46)	0.15 (0.44)
	Ponderosa	na	na	na	na	0.50 (0.31)	0.51 (0.31)	na	0.11 (0.46)	na	na	0.26 (0.40)	na	na	na
	Spruce-fir	na	1.25 (0.11)	na	0.20 (0.42)	0.46 (0.32)	na	na	na	0.59 (0.28)	0.32 (0.37)	0.29 (0.39)	na	na	na
2002 & 2002+2003	Aspen	na	na	na	0.91 (0.18)	0.31 (0.38)	na	na	na	1.12 (0.13)	na	na	na	0.24 (0.40)	1.06 (0.14)
	Bristlecone	na	na	na	0.19 (0.43)	0.31 (0.38)	na	0.26 (0.40)	0.56 (0.29)	na	0.055 (0.477)	0.28 (0.39)	0.94 (0.17)	0.81 (0.21)	**2.00 (0.02)**
	Mixed-conifer	na	0.58 (0.28)	na	na	0.12 (0.45)	0.17 (0.43)	0.67 (0.25)	0.19 (0.42)	na	0.30 (0.38)	0.24 (0.41)	0.09 (0.46)	0.16 (0.44)	1.06 (0.14)
	Ponderosa	na	na	na	na	0.23 (0.41)	na	na	0.39 (0.35)	na	na	0.27 (0.39)	na	na	na
	Spruce-fir	na	0.98 (0.16)	na	0.58 (0.28)	0.39 (0.35)	na	na	na	0.46 (0.32)	1.16 (0.12)	0.85 (0.20)	na	na	na
2003 & 2002+2003	Aspen	na	na	na	0.35 (0.36)	0.06 (0.47)	na	na	na	na	na	na	0.24 (0.41)	0.22 (0.41)	1.24 (0.11)
	Bristlecone	na	na	na	0.13 (0.45)	0.07 (0.47)	.10 (0.46)	0.46 (0.32)	0.10 (0.46)	na	0.519 (0.301)	0.65 (0.26)	0.86 (0.19)	0.69 (0.25)	na
	Mixed-conifer	na	0.07 (0.42)	na	na	0.49 (0.31)	0.27 (0.39)	0.74 (0.23)	na	na	1.13 (0.13)	0.97 (0.17)	1.09 (0.14)	0.28 (0.39)	1.01 (0.16)
	Ponderosa	na	na	na	na	0.73 (0.23)	na	na	0.51 (0.31)	na	na	0.00 (0.50)	0.15 (0.44)	na	na
	Spruce-fir	na	0.17 (0.43)	na	0.75 (0.23)	0.07 (0.47)	na	na	0.34 (0.37)	0.13 (0.45)	1.44 (0.07)	1.18 (0.12)	na	na	0.22 (0.41)

*1000hs indicates 1000h solid fuels and 1000hr indicates 1000h rotten fuels.