FIRE RISK ASSESSMENT OF THE WESTERN PORTION OF THE CENTRAL HARDWOODS FOREST REGION

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by

MICHAEL C. STAMBAUGH

Dr. Richard P. Guyette, Dissertation Supervisor

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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled:

FIRE RISK ASSESSMENT OF THE WESTERN PORTION OF THE CENTRAL HARDWOODS FOREST REGION

presented by Michael C. Stambaugh

a candidate for the degree of Doctor of Philosophy in Forestry, and hereby certify that, in their opinion, it is worthy of acceptance.

Dr. Richard Guyette

Dr. Anthony Lupo

Dr. Daniel Dey

Dr. Hong He

Dr. C Mark Cowell

DEDICATION

For Amy, Silvia, and Philip

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FIRE RISK ASSESSMENT OF THE WESTERN PORTION OF THE CENTRAL HARDWOODS FOREST REGION

Michael Charles Stambaugh Dr. Richard Guyette, Dissertation Supervisor

ABSTRACT

This study examined how fire risk, a combination of fuels conditions and fire probabilities, varied across a large portion of Missouri, Illinois, and Indiana. Case studies were conducted to evaluate the fuel loading variability in Missouri Ozark forests, determine the temporal variability in fuel accumulation rates, and quantify the role of topographic roughness in fire regimes. Using knowledge gained from these case studies two regional scale studies were conducted describing 1) variability in fuel loading and hazard and, 2) fire probabilities. For the fuel hazard study a stepwise multiple linear regression model ($r^2 = 0.36$) predicted litter depth from five parameters: residence time (number of months since leaf fall (November)), topographic roughness index, elevation, precipitation, and slope exposure. Model estimates of litter depth were weighted with litter moisture content to produce maps of litter hazard index. Maps displayed spatial changes in litter hazard for different drought conditions. Overall, litter hazard appeared to be relatively homogeneous throughout the study area with greatest levels attained in southeastern Missouri. Month of year and drought condition are likely the most important parameters concerning fuel hazard. For the fire probability study a large set of fire occurrence records (>12,000) for the period 1986 to 2008 were used to develop a predictive model of fire probability. CART and logistic regression analysis were used to

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identify variables related to ignition frequency and to model the spatial variability in fire occurrence probabilities. Eight model parameters were used in a predictive model that showed fire probabilities to be substantially greater in the southern Ozark Highlands compared to the northern Ozarks and most of Illinois and Indiana. Finally, fire probabilities were combined with fuel hazard indices to generate fire risk indices. Fire risk pertained to the risk of forests burning and indices were designed so that increased fire frequency (i.e., fire probabilities) and severities (i.e., fuel hazard) represented increased fire risk. Fire risk indices closely resembled fire probabilities and gave increased weights to both exposed slopes and increased drought conditions. Areas of highest fire risk were identified as being primarily located on Mark Twain National Forest lands. The model appears to have captured much of the variability associated with known cultural patterns related to fires.

CHAPTER 1

PREFACE

In 2000, in response to a landmark wildfire season, the U.S. Secretaries of Agriculture and the Interior drafted a report titled "Managing the impact of wildfires on communities and the environment" otherwise known as the National Fire Plan (NFP). Soon after, Congress passed Public Law 106-291¹ which enacted the NFP by allocating over 425 million dollars for fire preparedness, suppression operations, research, emergency rehabilitation and hazardous fuels reduction. Since the plan's initiation hundreds of research projects have been undertaken through the support of the NFP with the objectives to of understanding, managing, and living with wildland fire. This study represents one such research project.

The NFP website² states: "Though wildland fires play an integral role in many forest and rangeland ecosystems, decades of efforts directed at extinguishing every fire that burned on public lands have disrupted the natural fire regimes that once existed. Moreover, as more and more communities develop and grow in areas that are adjacent to fire-prone lands in what is known as the "wildland / urban interface", wildland fires pose increasing

¹ Department of the Interior and related agencies appropriations Act of 2001" (PL 106-291, October 11,

^{2000).} Available from: GPO Access (National Archives and Records Administration),

http://www.gpoaccess.gov/plaws/106publ.html; accessed: 11/02/08.

² http://www.forestsandrangelands.gov/NFP/overview.shtml; accessed: 11/02/08.

threats to people and their property." The overall intent of this research is to address these issues for a large portion of the Central Hardwoods forest region.

The threat of wildland fires varies across the United States based on each fire regimes characteristics such as topography, climate, ignitions, fuels and the resulting fire behavior. Compared to much of the western U.S., wildfires in the Central Hardwoods Forest Region currently pose very low risk. Since the last half of the 20th century wildfires have rarely threatened lives and were rarely forest stand replacement events-information with which to put the results here into a national perspective. During very dry climate conditions (e.g., Dust Bowl drought, 1952-54, 1980) fire risk could is significantly elevated to be comparable to western or southeastern (i.e., Florida, Georgia).

Based on historical records it is evident that potential exists for a much more active fire regime with respect to fire severity, fire sizes, and fire risk. Furthermore, a half century of fire suppression has led to significant changes in the fire environment included an unprecedented fire frequency (i.e., lack of fire) and fuels conditions. Few large scale comprehensive studies have addressed this issue. Some of the central questions include:

- What are the current conditions of fire ignitions and fuel loading?
- What conditions represent increased fire risk?
- Where and when do conditions of increased fire risk occur?

The overall research objectives were to 1) characterize the overall spatial and temporal variability of fuels and ignitions, and 2) assess fire risk to forestlands based on fuel conditions and fire probabilities. In five chapters I have described various aspects of the

regional fire regime, including a fire risk assessment that will hopefully be useful to researchers, land managers, and communities with fire interests.

Chapter descriptions

Chapter 2. Little information is available concerning fire risk in the eastern United States. This chapter describes the general approach to the fire risk assessment which was divided into two modules: ignition potential and fire hazard. I describe the fuel sampling design and methods and report on the variability in fuels in the Ozark region by time-lag fuels classes. Comparisons between ecological subsection units showed fuel loading is homogeneous across the region. Regression equations were made describing the changes in litter moisture contents by aspect during increasing drought conditions. In addition, changes in 1000-hour fuel moisture content due to drought conditions were described.

Chapter 3. Characterizations of surface fuels should consider both the spatial and temporal variability. This chapter describes a study conducted to estimate the temporal variability in litter that is controlled by accumulation and decomposition. Three methods were used to estimate the litter accumulation coefficient for the Ozark region. One of the methods used a temporally and spatially diverse set of new and previously published litter loading data were used. All methods suggested a seventy-five percent of total litter accumulation occurs within 4 years and one-hundred percent within 13 years.

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Chapter 4. Variability in a landscape surface likely imparts significant influence on fire (behavior, spread rates, potential sizes), however few metrics have been developed or tested. This chapter describes a method for measuring topographic roughness using an index. Topographic roughness index was shown to be a significant historic control on fire frequency in the Ozark region prior to EuroAmerican settlement (in Chapter 5 it is shown that topographic roughness continues to be an important control on the modern fire occurrence frequency). Thirty fire scar history sites were used to verify that as topographic roughness increased the frequency of fire decreased and other studies have shown its influence outside of the study region (Guyette et al. 2006).

Chapter 5. Few characterizations of regional surface fuels loading have been made, particularly with actual fuels data. This chapter describes the variability in fuels across the study region that includes large portions of Missouri, Illinois, and Indiana. About 1500 fuel plots were sampled on public lands. Attempts were made to develop predictive models of each fuel class (i.e., litter depth, 1-hour, 10-hour 100-hour, 1000-hour) from social, biological, and geographic variables. Only litter depth was successfully modeled ($r^2 = 0.36$). Significant variables were: litter residence time, topographic roughness roughness index, elevation, slope, and precipitation. Residence time contributed the most explanatory power. Monthly litter loading predictions were combined with moisture contents to develop a litter hazard index that was then mapped for the study area.

Chapter 6. A large set of fire occurrence records (> 16,000) for the period 1986 to 2007 were used to develop a predictive model of fire occurrence probability and assess fire

risk. CART and logistic regression analysis were used to identify variables associated with fires and to model the spatial variability in fire probabilities. Fire probabilities were combined with previously developed fuel hazard indices to generate fire risk indices. Fire risk pertained to the risk of forests burning and indices were designed so that increased fire frequency (i.e., fire probabilities) and severities (i.e., fuel hazard) represented increased fire risk. The model appears to have captured much of the spatial variability observed in the modern fire locations.

In summary, this research identified the conditions and areas of highest fire probability and risk. Overall, fire risk was greater in Missouri than in Illinois and Indiana. Within Missouri, Mark Twain national forest lands were associated with the greatest fire risk. Areas of the Salem-Potosi and Cassville districts had the highest risk. Drought appeared to a critical factor in determining the variability in risk as it is related to both ignitions and fuel hazard.

CHAPTER 2

FOREST FUELS AND LANDSCAPE-LEVEL FIRE RISK ASSESSMENT OF THE OZARK HIGHLANDS, MISSOURI

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Abstract

In this paper we describe a fire risk assessment of the Ozark Highlands. Fire risk is rated using information on ignition potential and fuel hazard. Fuel loading, a component of the fire hazard module, is weakly predicted ($r^2 = 0.19$) by site- and landscape-level attributes. Fuel loading does not significantly differ among Ozark ecological landtypes. Drought and exposure are related to fuel moisture content. Drought is particularly important to the Ozark fire regime and fire risk as it is related to both ignitions and fuels.

INTRODUCTION

In recent decades much attention has centered on the occurrence of wildfires and the concomitant changes in vegetation, climate, and human population. Despite over 15,000 fires occurring annually in the Central Hardwoods Region (National Fire Occurrence Database 2001), little work has been done to assess fire risk. The high number of fire events and relatively low level of concern supports the widely recognized fact that the region's fire risk is much lower than that of western states. Although unrealized, extreme drought conditions enhance the potential for high fire risk in the Central Hardwoods. The importance of fire risk information lies in understanding its spatial and temporal variability, knowledge that can be used for a variety of purposes. Managers can prioritize areas for fuel reduction treatment and integrate fire risk information to improve protection and response to fires (Winter and Fried 2001). Forest harvesting schedules can be planned and optimized to reduce fuel hazard (Englin and others 2000).

Ozark fire regime

For over 400 years the fire regime of the Ozark Highlands has been influenced by humans (Guyette and Dey 2000, Guyette and Spetich 2003). The historic frequency of burning was largely a result of changing human population and culture (Guyette and others 2002). Today, human ignitions represent over 98 percent of the total ignitions (1980-2003; Missouri Department of Conservation fire data) and their number is highly correlated to drought. Arson is the largest cause of human ignitions. Year to year changes in number of acres burned are correlated (r = 0.61) between state lands and the Mark Twain National Forest suggesting a larger scale influence on fire occurrence (data: Westin 1992, National Fire Occurrence Database 2001, USFS Missouri fire records unpublished data). Previous studies have characterized the dynamics of surface fires and vegetation in the Ozarks (Jenkins 1997, Batek and others 1999, Kolaks 2004, Nigh 2004). Mean fire size in the Ozark Highlands is about 31 acres and 54,502 acres burn annually on average (1939-2003: Missouri Department of Conservation data, Westin 1992). Before European settlement, 250,000 acre fires were estimated to have occurred at least once per century in the Current River watershed (Guyette and Kabrick 2002)-an area that represents about 8 percent of the Missouri Ozark Highlands. Even larger fires occurred during extreme drought years (e.g., 1780 (Guyette and others 2002)). Due primarily to fire suppression, average annual fire size in Missouri has decreased exponentially from about 100 acres to 15 acres during the period 1939 to 2001.

Fire risk model

A fire risk model is being developed from current and historic fire records to provide information for fire preparedness and prevention (USDA and others 2002). Fire risk is defined as the probability of a fire of a specified severity happening during a given period, in a given area (Preisler and others 2004). Fire risk assessments provide a means for quantifying fire risk and prioritizing fire management activities on multiple spatial scales (Haight and others 2004). Multiple approaches have been taken to assess fire risk including theory-based functions (Prestemon and others 2002), analysis of satellite imagery (Maselli and others 2003), and landscape simulation models (Shang and others 2004). For the Ozarks, a large set of landscape-level data makes possible an index modeling approach for fire risk assessment. Fire risk indices are used to classify a landscape into incremental levels (e.g., low to high). The model is based on two modules: ignition potential and fuel hazard (Figure 2.1). Ignition potential is rated using data on human population, topographic roughness, roads, and suppression potential. Similarly, fuel hazard is estimated from data on fuel loading, fuel moisture, vegetation, precipitation, land-use, and multiple topographic features. In our model, fuel loading is based on a region-wide collection of fuels data, which is unlike many models that do not include empirical fuel loading data. In this paper, we describe results of the Ozark Highland region-wide fuel measurements. Fuel data and relationships will be used in the development of the fuel hazard module for the assessment of fire risk. The objective of this paper is to describe the regional fuel variability and discuss its relevance and use in fire risk assessment.

METHODS

Fuel loading

Utilizing ESRI[®] ArcGIS[™] v 9.1 (ESRI 2005), ecological subsections (Nigh and Schroeder 2002) were identified within the Ozark Highlands section of Missouri (Figure 2.1). One hundred fifty-nine fuel transect locations were randomly placed within 17 subsections. The number of transects per subsection was weighted by subsection area. Transect locations were moved to the nearest forested public property ownership within the same subsection. Ownerships included state conservation areas, national forest lands, and state and county parks. Transects consisted of multiple fuel loading plots using methods described by Brown (1974) with modification. Transects were randomly located within forested areas. Transect bearings were randomly chosen from a predetermined bearing range that ensured crossing landforms and that varied in location, topography, and vegetation. Three to ten fuel plots were sampled per transect depending on forested area and landform. A total of 1,030 fuel loading plots were sampled across the region, and their locations were recorded by a GPS and entered into a GIS. Data were collected from July 2004 through June 2005, a period of highly variable drought conditions.

Fuels were tallied and measured in four size classes (0.0-0.25 inch (1-hour), 0.26-1.0 inch (10-hour), 1.01-3.0 inch (100-hour), and > 3 inch (1000-hour)). No differentiation was made between solid and rotten 1000-hour fuels. Fuel loading constants, specific gravities, and squared average-quadratic-mean diameters are unavailable for most tree species in the Central Hardwoods Region. Thus, constants for fuel calculations were derived from several sources (Brown 1974, Adams and Owens 2001) including field measurements of fuels. At each plot we collected data on species composition, elevation, slope, aspect, slope shape and position, basal area, percent ground cover (leaves, needles, herbaceous plants, bare soil), estimate of down dead wood, number of snags > 3 inches dbh, small diameter stem density, moisture content of 1000-hour fuel, and evidence of past fire. Moisture content of 1000-hour fuels was measured with a Protimeter[®] hand-held moisture meter on stems at least 3 inches in diameter and 1 foot above the forest

floor. Additional GIS data were spatially joined to the plot data. These data included elevation, precipitation, topographic roughness (Guyette and Dey 2000), land-use, vegetation, and geographic coordinates (decimal degrees, UTM, Zone 15N). Spatial trends in litter loading were examined using ArcGISTM.

Fuel loading data were summarized by ecological subsection and tested for normality using the Shapiro-Wilk test (SAS/STAT 2002). Fuel loading data were modeled for the purpose of predicting region-wide fuel variation. Combinations of fuel variables were developed from the original litter and time-lag class fuel data, and a model was constructed describing fuel variation using multiple regression. We chose the simplest model whose relevance could be verified both statistically and biologically.

Litter and moisture

In mixed hardwood forests of the Ozark Highlands, much of the energy released during fires results from combustion of litter (i.e. leaves, needles, twigs,) and 1-hour fuels (Kolaks 2004). For this reason, emphasis is placed on the litter layer for the purpose of evaluating risk and understanding landscape variation in litter loading. We measured litter depth (cm) at 3 points at each fuel loading plot (n = 3,090). In a separate experiment we measured litter loading using randomly placed 0.5 m² clip plots located in the Current River Hills (Guyette and others 2003, 112 plots) and Outer Ozark Border subsections (51 plots). Litter collection was completed within a two day period so that sampling time and date had minimal effect on moisture content. Litter was placed in sealed plastic bags, weighed at field moisture content, and then dried at 60° C until weight became constant.

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Percent moisture content was calculated by dividing the weight of water in the litter by the oven-dried weight of the litter and then multiplying by 100. Repeated collections (September 2004, March 2005, June 2005) were made at clip plots located in the Outer Ozark Border for the purpose of understanding within year temporal changes in loading and moisture. Regression analysis was used to develop equations that relate litter loading and moisture content to landscape variables. Both litter and 1000-hour fuel moisture contents were correlated against monthly divisional Palmer Drought Severity Index data (Palmer 1965, NCDC 1994). As drought conditions increase, it is hypothesized that the differentiation in litter moisture by solar exposure is lessened.

RESULTS AND DISCUSSION

Fuel loading

Total fuel loading averaged 4.5 tons per acre and ranged from 0.1 to 70.3 for all Ozark plots (Table 2.1). Mean 1-hour and mean 10-hour fuel loading were similar among all Ozark subsections. Trend analysis indicated a small decrease in 1-hour and 10-hour fuel loading along a north to south Ozark gradient, and geographic location was a significant variable in predicting total fuel loading (see below). None of the fuel time-lag classes were normally distributed (p<0.0001)(Figure 2.2, 2.3). High variability existed in 1000-hour fuel loading with the majority of plots having no 1000-hour fuels and 51 plots having over 15 tons per acre. The majority of plots with high 1000-hour fuel loading (>15 tons per acre) had usual levels of tree mortality; however, many of the highest

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loadings (e.g., > 50 tons per acre) resulted from forest management activities and windthrow disturbance. Fuel loadings between time-lag classes are correlated because larger fuels are typically connected to and provide smaller fuels. Multiple regression analysis of landscape variables on plot fuel loading resulted in a four variable model ($r^2 = 0.19$, p<0.0001, all variables and intercept significant, p<0.0001):

 $FUEL = -417.33 + (1.76^{*}10^{-5})^{*}tri + 0.08^{*}elev + 0.07^{*}ba - (5.48^{*}10^{-12})geo$

where:

- FUEL = litter depth (cm)*(log(tons of 1-hour fuel)+log(tons of 10-hour fuel)+log(tons of 100-hour fuel)
- tri = an index of topographic roughness (Guyette and Dey 2000)
- elev = elevation in meters
- ba = basal area
- geo = (-1* y UTM coordinate)*(x UTM coordinate)

Although significant, the fuel model explains a low percentage of fuel variation, suggesting that little regional variability in fuel loading exists. In a separate study within the Current River Hills subsection no significant differences were found in fuel loading between forest types (Personal communication. Keith Grabner. 2005. Community ecologist, USGS Columbia Environmental Research Station, 4200 New Haven Rd, Columbia, MO 65201). Model variables, spatial fuel loading trends, and fuel statistics support that both large- and small-scale factors influence fuel variation within the Ozark Highlands.

Litter and moisture

Decomposition causes total forest litter depth to decrease between litter fall events. However, our measurements of litter loading showed erratic changes in litter depths between the three collection dates likely due to the high spatial variability in litter within small extents (e.g., 3 meters) and the movement of litter by wind (e.g., leaves). Fifty-nine percent of the plots decreased in litter loading from September 2004 (pre-leaf fall) to March 2005 (post-leaf fall) and 61 percent increased from March 2005 to June 2005. Maximum litter loading occurred when basal area was approximately 150 square feet per acre and decreased as basal areas deviated both above and below this stand density.

Percent moisture content (PMC) of litter was a function of solar exposure. Differences in PMC were greatest when conditions were slightly wet (PDSI = 1.0 - 1.99). The equation describing PMC of litter during incipient wet (0.5 - 0.99) conditions is:

PMC =
$$63.2 - 18.4$$
*(exposure)(r²=0.43, p<0.01);

where: exposure = COS(3.1415/180*(180-aspect))+1. During wetter conditions no relationship existed between PMC and solar exposure, and during drier conditions the differentiation in PMC is lessened (Figure 2.4). During mild droughts (PDSI = -1.95) PMCs, regardless of exposure (i.e., aspect), became nearly equal or "undifferentiated

dry". This is similarly true during extreme wet conditions when PMCs are "undifferentiated wet" by exposure. Assessment of the equation's predictive ability in modeling the spatial patterns in PMC during various PDSI conditions would be valuable, however requires additional collections during wet and dry extremes.

Drought has been an important component of the Ozark fire regime for centuries, even during the recent period (1940 to present) of fire suppression. Drought influences multiple components of the Ozark fire regime including the number of acres burned, average fire size, fire severity (percent trees scarred), and number of arson fires (Guyette and others in press). Understanding the effects of drought on ignition potential and fuel hazard would be valuable, particularly for the assessment of fire risk.

Both fire hazard and ignition potential can be better understood from the conditions of litter. For hazard, litter is the key fuel type facilitating surface fire propagation. Even during rare crown fire events, fires are initiated from surface fires that burn litter. Likewise, litter is likely the primary material for initial ignitions regardless of fire cause. As drought increases, the area for potential ignitions is increased because more area of the landscape contains dry fuels. During droughts (PDSI < 0) moisture contents of 1000-hour fuels were at levels below the common fuel moisture prescription range (e.g., 17-20 percent) (Figure 2.5) which indicates conditions of increased fire danger.

CONCLUSIONS

Information about fire regimes in deciduous forests is needed in order to adequately assess fire risk. Although wildfires rarely threaten lives and homes in the Ozarks and Central Hardwoods region, the potential exists and is increased during droughts. During drought and dry weather, "undifferentiated dry" litter and low moisture content of 1000-hour fuels increase fuel hazard and ignition potential. Forests of greatest fuel loading are those of high elevation, greatest basal area, and highest topographic roughness that occur in the southeast portion of the Ozark Highlands region.

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Missouri Ozark Highlands ecological sub	
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Summary of fuel loadi	002).
Table 2.1. S	Schroeder 2

		Fuel		FL	Fuel loading (tons per acre	ce)	
Ozark Ecological Subsections	Subsection code	transects, (plots)	1-hour	10-hour	100-hour	1000-hour	TOTAL
					mean, s.d., (range)		
Springfield Flain	021	19 (115)	0.1, 0.1, (0-0.6)	0.3, 0.1, (0-0.7)	1.1, 1.2, (0-8.8)	2.9, 6.2, (0-36.9)	4.4, 6.4, (0.1-36.8)
Elk River Hills	023	2 (14)	0.1, 0.1, (0-0.4)	0.3, 0.1,(0.1-0.5)	1.5, 0.7, (0.4-2.8)	4.5, 5.1, (0-15.6)	6.4, 5.7, (1.1-18.8)
White River Hills	024	17 (112)	0.1, 0.1, (0-0.4)	0.3, 0.2, (0-1.0)	1.2, 1.0, (0-4.9)	2.3, 4.7, (0-25.4)	4.0, 5.1, (0.2-31.0)
Central Plateau	025	26 (158)	0.1, 0.1, (0-0.3)	0.2, 0.2, (0-1.3)	1.1, 0.8, (0-6.2)	3.5, 7.2, (0-51.2)	5.0, 7.4, (0.1-53.4)
Osage River Hills	026	14 (94)	0.1, 0.1, (0-0.4)	0.2, 0.2, (0-1.5)	1.1, 1.2, (0-8.8)	7.6, 8.0, (0-68.9)	3.7, 8.3, (0.1-70.3)
Gasconade River Hills	027	11 (68)	0.1, 0.1, (0-0.4)	0.2, 0.1, (0-0.6)	0.8, 0.8, (0-4.2)	3.1, 5.8, (0-26.0)	4.2, 5.6, (0.1-27.1)
Meramec River Hills	028	8 (53)	0.1, 0.1, (0-0.3)	0.3, 0.1, (0-0.5)	1.1, 1.0, (0-6.2)	4.0, 6.5, (0-30.8)	5.4, 6.5, (0.3-32.6)
Current River Hills	620	15 (112)	0.1, 0.1, (0-0.4)	0.3, 0.2, (0-1.5)	1.3, 0.9, (0-6.2)	4.1, 6.1, (0-29.3)	5.8, 6.6, (0.3-31.8)
St. Francious Knobs and Basins	0210	6 (37)	0.1, 0.1, (0-0.2)	0.2, 0.1, (0-0.4)	0.9, 0.6, (0-2.9)	1.7, 2.9, (0-12.7)	2.8, 3.2, (0.1-15.9)
Prairie Ozark Border	0211	5 (31)	0.1, 0.1, (0-0.4)	0.3, 0.2, (0-1.1)	0.8, 0.6, (0-2.2)		3.8, 6.8, (0.2-38.0)
Outer Ozark Border	0212	16 (106)	0.1, 0.1, (0-0.4)	0.3, 0.2, (0-0.9)	1.1, 0.7, (0-3.3)	4.3, 8.2, (0-44.9)	5.8, 8.4, (0.1-47.1)
Inner Ozark Border	0213	11 (73)	0.1, 0.1, (0-0.3)	0.2, 0.2, (0-0.9)	0.7, 0.7, (0-4.0)	1.8, 3.6, (0-24.4)	2.9, 4.0, (0.1-28.7)
Black River Ozark Border	0214	7 (46)	0.1, 0.1, (0-0.3)	0.2, 0.1, (0-0.5)	0.8, 0.6, (0-3.0)	2.1, 4.1, (0-23.6)	3.2, 4.3, (0.1-24.9)
Missouri R. Alluvial Plain	0215	1 (5)	0.2, 0.1, (0.1-0.3)	0.3, 0.1,(0.2-0.4)	1.6, 0.7, (0.7–2.6)	15.1, 13.4, (0-36.4)	17.1, 13.5, (1.1-37.6)
Mississippi R. Alluvial Plain	0216	1 (6)	0.1, 0.04, (0.1-0.2)	0.2, 0.1, (0.1-0.3)	0.5, 0.4, (0-1.1)	1.0, 2.2, (0-5.9)	1.8, 2.1, (0.3-6.5)
All (Ozark Highlands Section)		159 (1030)	0.1, 0.1, (0-0.6)	0.3, 0.2, (0-1.5)	1.0, 0.9, (0-8.8)	3.1, 6.5, (0-68.9)	4.5, 6.7, (0-70.3)

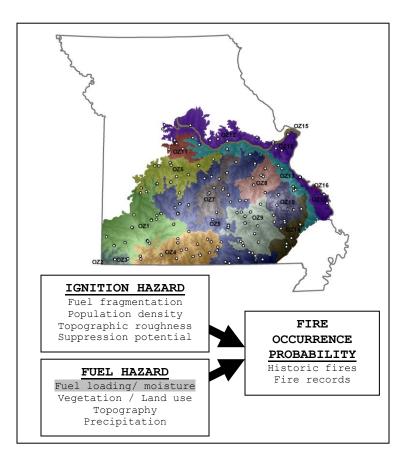


Figure 2.1. (top) The Ozark Highlands section of Missouri with 16 ecological subsections. Subsections names are given in Table 1. Small circles are locations of fuel loading plots (n = 1030). (bottom) Conceptual model showing integration of fuel loading and moisture data into the fuel hazard module of the fire risk assessment model.

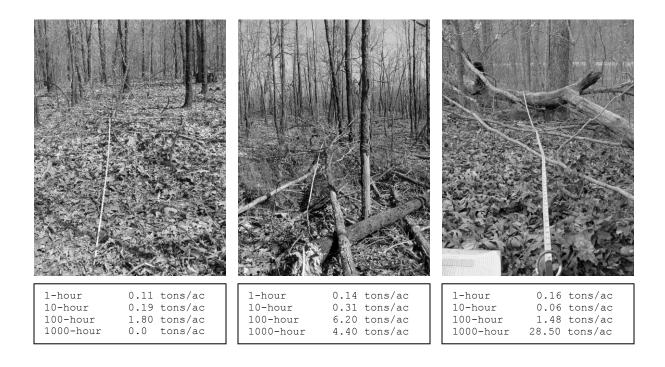


Figure 2.2. Three examples of fuel loading illustrating the physical variability of the four time-lag fuel classes.

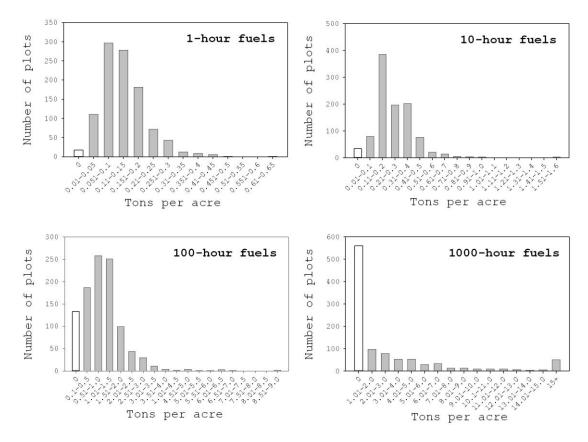


Figure 2.3. Histograms of the four fuel time-lag classes. Scales of x- and y-axes differ between graphs.

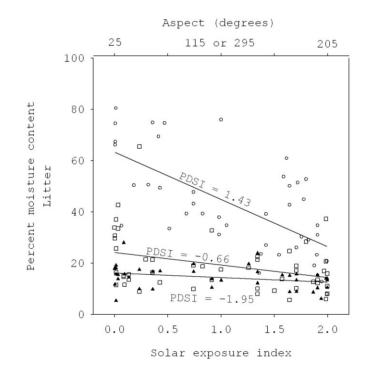


Figure 2.4. The relationship between percent moisture content of litter and solar exposure index for three Palmer Drought Severity Index (PDSI) values. Solar exposure variable is significant in all models ($p \le 0.05$).

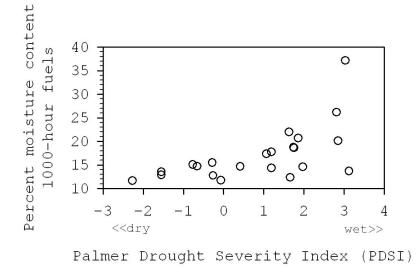


Figure 2.5. The relationship between 1000-hour fuel moisture and Palmer Drought Severity Indices. Data were collected throughout the Missouri Ozark Highlands during the period July 2004 to July 2005.

CHAPTER 3

UNDERSTANDING OZARK FOREST LITTER VARIABILITY THROUGH A SYNTHESIS OF ACCUMULATION RATES AND FIRE EVENTS

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Abstract

Measuring the success of fuels management is improved by understanding rates of litter accumulation and decay in relation to disturbance events. Despite the broad ecological importance of litter, little is known about the parameters of accumulation and decay rates in Ozark forests. Previously published estimates were used to derive accumulation rates and combined litter measurements, model estimates, and fire scar history data were used to derive a decay constant (k = 0.38). We used accumulation equations to demonstrate temporal changes in litter loading. For example, after a fire event that consumes nearly 100 percent of the litter, about 50 percent of the litter accumulation equilibrium is reached within 2 years, 75 percent within 4 years, and the equilibrium (99 percent accumulation) after approximately 12 years. These results can be used to determine the appropriate prescribed burning intervals for a desired fire severity. For example, fire history data show that the percentage of trees scarred, a surrogate for fire severity, is

influenced by the length of historic fire intervals (i.e., amount of litter accumulated). This information will be incorporated into regional fire risk assessments and can be used as a basic knowledge of litter dynamics for both fire management planning and forest ecosystem understanding.

INTRODUCTION

The Ozark Highlands lacks a general synthesis of the rate of litter accumulation and temporal variability of litter following fire events. Information on the temporal variability of fuels is needed by fire and forest managers in order to measure the success of management activities. In addition, information on litter accumulation is critical for modeling and monitoring of fuel loading and fire effects. This information is regionally specific and depends on the balance between rates of litter accumulation and decomposition (Olson 1963). Litter accumulation rates are controlled by vegetation type, decomposition rate, ecosystem productivity, and their interrelationships. Litter accumulation rates can be difficult to predict because of the high variability imposed by changes in species, tissues, vertical structure of vegetation, elevation, site, and time of year (Gosz and others 1972). Litter decays by leaching, physical weathering, faunal activities, and microbial consumption. Microbial consumption is the primary mode of decay and it is a process controlled by physical and chemical litter properties and climatic conditions (Meentemeyer 1978, McClaugherty and others 1985). Meentemeyer (1978) presented a general equation for predicting average annual decomposition rates (k) from actual evapotranspiration (AET) and leaf lignin contents.

In order to provide general information for the Ozark region we synthesized data from existing studies and produced a model for predicting litter accumulation. In this paper we 1) provide a regionally averaged fuel accumulation equation for use in estimating fuel loading and 2) describe the long-term variation in Ozark fuel loading with fire history data. The objectives of the paper are to develop a quantitative relationship between litter

amounts and time, and use this relationship to examine the effects of fire management on the accumulation and decay of litter.

METHODS

Ozark Litter Accumulation and Decay Estimates

Estimates of litter accumulation and decay parameters were derived from four sources: 1) previous published studies, 2) actual litter loading measurements, 3) empirical litter relationships, and 4) analysis of historic fire intervals and tree scarring.

Previous Studies

In a study in the northern Ozarks, Kucera (1959) ranked litter from oaks (*Quercus alba*, *Q. rubra*, *Q. marilandica*) as being most resistant to decay, followed by sugar maple (*Acer saccharum*), shagbark hickory (*Carya ovata*), and American elm (*Ulmus americana*). At the same location, Rochow (1974) estimated a litter decomposition rate (*k*) of 0.35 for oak-dominated forest. More recently, Ryu and others (2004) arrived at a similar estimate for a larger portion of the Missouri Ozarks using an ecosystem productivity model (PnET-II) (Aber and others 1995).

Litter Loading Measurements

Missouri Ozark region litter loading data was gathered for many forested sites and time periods (Table 3.1). Litter was collected using clip plot methods, dried to a constant weight, and reported on a dry-weight basis. In addition, we gathered associated data, including collection date (pre- and post-burn), dates of fires, number of previous fires, and physical plot attributes (slope, aspect, vegetation type, overstory basal area, and stand density). Variability in litter sample weights likely occurred due to collection by different investigators, years of collection, and forest conditions. When possible, we only used measurements that excluded the zone of highly decomposed material commonly called the humus or duff layer. We estimated the litter decomposition rate (k) using the equation developed by Olson (1963), where the annual production of litter is divided by the standing crop litter. The mass of annual litter production was estimated using mean litter loading values collected one year after burning. Estimates of the average standing crop (steady-state level) of litter were derived from litter masses that had accumulated for >20 years and were based on multiple measurements taken from many Ozark sites (Table 3.1).

Empirical Litter Relationships

We also estimated litter decomposition rates using Meentemeyer's (1978) general equation, which incorporates lignin contents and actual evapotranspiration (AET). Average litter lignin content for the important Ozark tree species was derived from previously published studies. Tree species included black oak (*Q. velutina*), scarlet oak (*Q. coccinea*), white oak (*Q. alba*), post oak (*Q. stellata*), and shortleaf pine (*Pinus echinata*) (Table 3.2). No lignin contents were obtained for hickories (*Carya* spp.). Though there is likely high variability in decomposition rates due to variability among sites, climatic conditions (for example AET), and numerous vegetation assemblages, we utilized a multi-species average of lignin contents for the region since our aim is to develop a better general understanding of litter dynamics in the Ozarks. We obtained AET estimates for the Ozark Highlands region from the Global Hydrologic Archive and Analysis System (GHAAS). Data were 0.5 degree gridded average annual AET estimates given in millimeters per year (Vörösmarty and others 1998). We averaged long-term grid means for the Ozark region to get a mean regional AET value.

Historic Fire Intervals

Historic fire intervals were derived from four previously constructed published and unpublished fire scar history studies in the Ozarks. Study sites were located in Shannon County, Missouri and included Stegall Mountain (Guyette and Cutter 1997), Mill Hollow, MOFEP Site 3, and MOFEP Site 4 (Guyette and Dey 1997). Methods for sample collection, tree-ring crossdating, and fire scar dating can be found in several published studies (Guyette and others 2003, Stambaugh and others 2005). Site level fire scar chronologies were input to FHX2 software (Grissino-Mayer 2001) where fire intervals were calculated for each fire at each site as the number of years between fire events. Fire intervals were paired with the percentage of trees scarred in the fire year that ended each interval. The percentage of trees scarred was calculated as the number of sample trees scarred in a given year divided by the number of recorder sample trees in the same year. All data were pooled into a single dataset with 111 paired observations of fire intervals and percentage of trees scarred. Due to the changing characteristics of the anthropogenic fire regime (Guyette and others 2002), we only used data from the period A.D. 1700 to 1850 in the analysis. This period was selected because it is well replicated (9-20 recorder trees at any given year) at all sites and because there exists high variation in the length of fire intervals. We used non-linear regression (exponential equation) to describe the variability in the percentage of trees scarred is related to fuel accumulation. Based on this assumption, an exponential function should approximate the litter accumulation rate and the exponential term of the regression model would be an estimate of litter decomposition rate (k).

Temporal Litter Variability Model

The mass loss of litter as a function of time is generally expressed as an exponential decay model (Bärlocher 2005, Olson 1963). The temporal litter variability for Ozark forests was described using an exponential decay function:

$$\mathbf{X}_{\mathbf{t}} = \mathbf{X}_0 * e^{-k\mathbf{t}},$$

where X_t is the amount of litter remaining after time t, X_0 is the initial quantity of litter, and t is time of accumulation. The estimated rate of litter decomposition (k = 0.38) was a mean derived from four different procedures (Table 3.3). The mean standing crop of litter (4.57 tons/acre, see results below) was used to define maximum mass accumulation. We used the exponential decay function to describe the rate of accumulation of litter and the time required to reach maximum litter accumulation. Additionally, the equation was applied to historic fire event data from four Ozark fire scar history sites (Stegall Mountain, Mill Hollow, MOFEP Site 3, MOFEP Site 4) in order to reconstruct past temporal variability in litter loading. Using fire scar chronologies, the model was initiated at the first year of record. Fire event years were used to reset the litter accumulation model to zero. Accumulation following fire events assumed 100 percent fuel consumption and a constant weight of annual litterfall.

RESULTS

Ozark Litter Accumulation and Decay Estimates

Litter Loading Measurements

The mean mass of annual litter production was 2.11 tons/acre (n = 6, s.d. = 0.47) or 0.77 tonnes/hectare. The mean standing crop of litter was 4.57 tons/acre (n = 24, s.d. = 1.22) or 1.68 tonnes/hectare. Based on the ratio of mean annual production of litter to the mean standing crop, the estimated litter decomposition rate (k) was 0.46.

Empirical Litter Relationships

Average percent lignin contents of litter for the important Ozark overstory forest tree species (Table 3.2) was 22.63%. AET values ranged from 675 to 760 mm/yr and the mean was 712 mm/yr. Based on Meentemeyer's (1978) equation the estimated litter decomposition rate (k) ranged from 0.59 to 0.69.

Historic Fire Intervals

The relationship between the percentage of trees scarred in a fire event and the preceding fire interval (years since last fire) was established using the non-linear equation:

percent trees scarred =
$$13.8 + 7.72$$
 (ln[fire interval]),

where the fire interval is years since last fire event (model $r^2 = 0.21$, intercept and variables significant p<0.0001, n = 111). Although the fire-free interval model explained only about one-fifth of the variance, the model and variables were highly significant. The form of the equation resulted in an exponential term (litter decomposition rate (*k*)) of 0.34.

Temporal Litter Variability Model

The temporal litter variability for Ozark forests was described using an exponential decay equation and is presented in terms of percent accumulation (eq. 1) and mass accumulation (eq. 2).

Percent accumulation = $100 - (100e^{-0.38t})$ (eq. 1), Mass accumulation = $4.57 - (4.57e^{-0.38t})$ (eq. 2),

where t is the years of litter accumulation. The equation predicts that litter accumulates to 25 percent, 50 percent, and 75 percent of maximum accumulation at approximately 1 year, 2 years, and 4 years, respectively (Fig. 3.1). An equilibrium accumulation (99 percent) is reached at approximately 12 years. In terms of mass accumulation, roughly one ton of litter per acre is accumulated per year up to 3 years post-fire (Fig. 3.1).

The litter accumulation function showed important differences in litter accumulation with burning frequency (Fig. 3.2). For example, annual burning allows a maximum of 32 percent of the total litter to accumulate. A burning frequency of 5 years allows a maximum of 85 percent of the total litter to accumulate, while a burning frequency of 10 years allows a maximum of 97 percent of the total litter to accumulate. In terms of litter loading, the difference between annual and 5- year burning frequency is over two times greater than the difference between 5-year and 10-year burning frequencies.

The effects of variable burning frequencies were further exhibited by a reconstruction of long-term Ozark litter loading (Fig. 3.3). The long-term variation in historic fuel

loading is striking and a result of frequent anthropogenic ignitions. Prior to EuroAmerican settlement (pre-1800), fuel loading was both spatially (between sites) and temporally variable. Comparisons between sites show that Stegall Mountain has undergone conditions of continuous burning and rapid fuel replenishment. Mill Hollow and MOFEP Sites 3 and 4 underwent prolonged frequent fires (1-3 years) that lasted most of the 19th century and had a long-term effect on minimizing fuel loading. Mean fuel loading of the four sites was 2.91 tons/acre prior to 1800 and 1.45 tons/acre from 1800-1900. Since about 1930 to 1940, the effects of fire suppression has resulted in maximum litter loading and lowered temporal litter variability. An exception is Stegall Mountain, where prescribed burning management has been in practice since about 1980.

DISCUSSION

Fire suppression policies of the past 75+ years have altered Ozark forest ecosystems, often in ways that are not fully understood at this point in time. From fire scar studies, we know that much of the Ozarks landscape burned relatively frequently (8-15 years) for at least 200 years prior to Euro-American settlement. The natural communities that developed during that time are now changing, and restoration efforts often include the reintroduction of fire, despite a lack of quantitative information on how fire might behave under the conditions resulting from years of fire suppression. One of the many ways in which fire suppression has affected Ozark forests is by altering the nature of fuels at the forest floor, though there has not previously been a way to quantify these changes. In this paper, we present a litter accumulation model specific to the Ozark region, which we

hope will improve our general understanding of the temporal variability in litter accumulation and our ability to manage fuels effectively in the Ozarks. The litter accumulation equations provide managers and scientists with a standard of expected fuel loading, the potential effects of different burning frequencies on fuel accumulation and loading, and estimates of the historic variability in fuel loading at four Ozark sites.

Estimates of temporal changes in fuel depend primarily on the litter decomposition rate (k) and level of maximum litter accumulation. The best estimates of litter decay and accumulation in the Ozarks were based on litter loading measurements and the historic fire record. We chose not to include the value of k derived from mean annual AET and lignin contents as the estimate was extremely high (k = 0.64). Though litter decomposition rates differ from year to year due to changing conditions (for example climate, species, forest density), we felt that the value was a gross overestimate and outside of a plausible range of rates (Ryu and others 2004). The increased rate of decomposition of mixed-species litter (Gartner and Cardon 2004) was unaccounted for, and may be one important reason why Meentemeyer's equation yielded a decay constant much higher than other estimates.

The rapid accumulation of litter following disturbance events likely leads to large differences in burn coverage and fire behavior between fire frequencies of 1, 2, and 3 years. To illustrate this point Behave Plus 3.0.1, fire behavior prediction software, was used to estimate the different fire rates of spread and flame lengths between fuel accumulation rates at 1, 2, and 3 years (Table 3.4). All else equal, fires occurring at 10-year intervals versus 20-year or longer intervals may not differ significantly in behavior or severity (percent trees scarred) because the level of litter accumulation is similar

(Table 3.4). One important factor in surface fire behavior is litter moisture content which can be highly variable by aspect and drought condition (Stambaugh and others, in press). Litter profiles can also be highly variable with dry litter on the surface covering a relatively moist "mat" of partially decomposed but identifiable leaves of the previous few growing seasons (Crosby 1961, Loomis 1975). Furthermore, although fuel loading following 10 and 20 years of accumulation may be marginal, important differences in the development and conditions of the underlying litter profile likely exist.

In addition to the quantification of accumulation and decay rates, the reconstruction of long-term litter loading under different fire regimes provides a unique perspective for fuels management. Although difficult to substantiate, frequent burning during the 19th century may have altered the nature of Ozark fuels by increasing herbaceous and grass vegetation, possibly leading to even lower fuel loading (for example tons/acre) than reconstructed (Fig. 3.3). Frequent and long-term burning likely led to a transition in the dominant litter type from forest leaf litter to herbaceous grass and forb litter, which possibly resulted in increased decomposition rates and decreased total litter loading. In the southeastern Missouri Ozarks, Godsey (1988) found that both annual and periodic and annual burning of an oak-hickory forest after 36 years resulted in an increased abundance of grasses, forbs, and legumes that only comprised about 0.02 tons/acre. Additionally, Hector and others (2000) discussed the differences in decomposition between plant functional groups (legumes, grasses, herbs) and showed increasing decomposition rates with decreasing litter carbon to nitrogen ratios. The conditions conducive to high litter loading potential are most likely found where forest floors are dominated by leaf litter and have been subject to fire suppression for more than 12 years.

Much of the forested area of Missouri has had no fire disturbance since the mid-20th century, which has resulted in relatively high litter loading and reduced variability in litter loading compared to the previous 200+ years.

The accumulation of organic litter on forest floors has implications for many processes which involve soils, litter invertebrates, floral diversity, hydrology, and carbon cycling. Furthermore, the effects of historically frequent fire and reduced litter, as well as current and future effects, are poorly understood. Several studies have commented on the slow recovery of endophage populations and activity following burning (Crossley and others 1998). Auten (1934) and Meier (1974) found that burned Ozark sites had significant reduction in water infiltration compared to unburned sites. Studying the same Ozark experimental burn plots, Scowcroft (1965) speculated that prolonged, frequent burning eventually led to decreased soil productivity. Frequent fire also results in decreased fuel connectivity, particularly as canopy trees are killed and inputs of litter are reduced (Miller and Urban 2000). These represent only a few of the myriad of ways that frequent fire may impact forest processes, and highlight the value of continued research into the dynamics of fire frequency and severity and the subsequent impact on organic litter accumulation.

Prescribed burning management is faced with multiple challenges in the Ozark region. Few studies have been conducted to investigate the effects of fire on multiple ecosystem components. Meanwhile, previously fire-maintained communities and species are decreasing in area and abundance, and require fire disturbance to persist. Even with relatively general information about litter decay and accumulation, decisions about forest management and prescribed burning activities are better informed. For example,

successful regeneration of shortleaf pine, a species of restoration concern in the Ozarks, could be greatly enhanced through better understanding of the rate of litter accumulation, which often precludes seedling establishment. Also, burning prescriptions for areas being managed for multiple resources can be tailored to achieve an optimal level of fuel loading and desired fire behavior.

Though based on regionally specific data from the Ozarks, the litter accumulation and decay estimates presented here are generalized and do not take into account interannual variability due to variable fire effects (for example partial litter consumption), climate, litter production, litter chemistry, and other influencing factors. Despite these limitations, the approach to understanding long-term litter variability is new and applicable to other locations. Many improvements to this approach are attainable, including: the incorporation of variability in fuel accumulation and decomposition between leaf fall events; taking changing climate into account; addressing differences in species and vegetation densities; and, addressing differences in modern and historic fire conditions (for example fuel consumption, fire severity). The estimates and equations provide a context for fuels management under current conditions, facilitate a new understanding of historic fire regimes, and provide the foundation for a more refined understanding of the fuel-fire interaction.

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Table 3.1. Data on oven dry-weights of litter from 35 Ozark Highlands sites. Forest structure codes and site information are given at the bottom of the table.

			Basal				
	Forest		area	Years	Litter	Litter	
Site	structure	n	(ft ² /ac)	accumulation	(tons/ac)	(tonnes/ha)	Source
Knob Noster S.P.	1	5	80	2	3.02	1.11	authors
HaHa Tonka S.P.	1	5	58	2	3.12	1.14	authors
Meremac S.P.	1	7	108	3	2.50	0.92	authors
Taum Sauk Mnt S.P.	1	7	52	2	2.90	1.06	authors
Bennett Spring S.P.	1	4	66	1	2.56	0.94	authors
USFS - Mark Twain	1	7	51	1	2.71	0.99	authors
University Forest A1	1	2	55	1	2.18	0.80	authors
Baskett WMA A1	2	9	na	1	1.56	0.57	Rochow 1974
Stegall Mtn.	1	3	38	2	2.76	1.01	authors
Chilton Creek 2003	1	26	na	1	2.00	0.73	Hartman 2004
Chilton Creek 1998	1	26	na	>20	3.40	1.25	Hartman 2004
University Forest B1	1	na	na	1	1.64	0.60	Scowcroft 1965
University Forest B2	2	na	na	>20	5.45	2.00	Scowcroft 1965
University Forest C1	2	na	na	>20	3.88	1.42	Meier 1974
University Forest D1	2	na	na	>20	6.10	2.23	Paulsell 1957
Jerktail Mtn.1	2	18	96	>20	5.77	2.12	authors
Jerktail Mtn. 2	2	6	67	>20	4.17	1.53	authors
Powder Mill 1	2	10	82	>20	4.97	1.83	authors
Powder Mill 2	2	6	93	>20	4.00	1.47	authors
Akers1	2	14	99	>20	3.49	1.28	authors
Akers2	2	10	86	>20	3.88	1.42	authors
Alley Spring	2	6	93	>20	3.76	1.38	authors
Bay Creek 1	2	6	90	>20	3.84	1.41	authors
Bay Creek 2	2	6	73	>20	4.13	1.52	authors
Black River 1	2	15	na	>20	3.02	1.11	Kolaks 2004
Black River 2	2	15	na	>20	3.19	1.17	Kolaks 2004
Black River 3	2	15	na	>23	2.92	1.07	Kolaks 2004
Coot Mtn.	2	6	103	>20	3.23	1.19	authors
Williams Mtn.	2	6	90	>20	6.53	2.40	authors
Wildcat Mtn.	2	8	93	>20	4.29	1.57	authors
Baskett WMA B1	2	102	129	>20	6.52	2.39	authors
Goose Bay Hollow	2	8	110	>20	5.44	2.00	authors
Dent & Iron Co.'s ^a	2	na	na	>20	6.60	2.42	Loomis 1975
Sinkin Exp. Forest 1 ^a	2	na	na	>20	6.20	2.28	Loomis 1965
Sinkin Exp. Forest 2 ^b	2	na	30	>20	5.00	1.84	Crosby and Loomis 1968
Mean maximum accum	ulation (>20) years	accumulat	ion)	4.57	1.68	

forest structure: 1 = savanna/woodland, 2 = forest

na = not available

^a contains organic matter

^b shortleaf pine plantation

Table 3.2. Lignin contents of important Ozark forest species.

Species	Lignin Conte (%)	Source
Quercus velutina	25.70	Marten and Aber 1997, Aber (online data)
Quercus coccinea	18.70	Washburn and Arthur 2003
Pinus echinata ^a	25.50	Washburn and Arthur 2003
Quercus rubra ^b	23.43	Marten and Aber 1997
Quercus rubra and Quercus alba	23.48	Marten and Aber 1997
Mean	23.36	

^a samples include *Pinus rigida* litter ^b samples include *Acer rubrum* litter

Method	k	Source
Litter loading measurements	0.46	this paper
Climate/leaf lignin model	0.64*	this paper
Historic fire intervals	0.34	this paper
Litter loading measurements	0.35	Rochow 1974
Climate/leaf lignin model	0.35	Ryu and others 2004
Mean	0.38	

Table 3.3. Litter decomposition rates (k) from the Missouri Ozark Highlands.

*not used to calculate mean

Table 3.4. Behave Plus prediction of fire behavior using litter accumulation rates from this study. Behave Plus was run using fuel model 9 and 1 hour fuel loading was adjusted according to accumulation rates.	
Table 3.4. Behave Plus pre Plus was run using fuel mo	

Litter Accumulation	Midflame	Slope	1hr	10hr	Rate	Flame
Rate	Windspeed	(%)	% Moisture	% Moisture	of Spread	Length
	(udu)		Content	Content	(chains/hr)	(ft)
1 yr (25% max)	10	5	5	L	24.8	3.3
2 yr (50% max)	10	5	5	L	29.4	4.5
(65% max)	10	5	5	L	30.1	4.9
r (97% max)	10	5	5	7	29.5	5.3
20 yr (100% max)	10	5	5	7	29.6	5.3

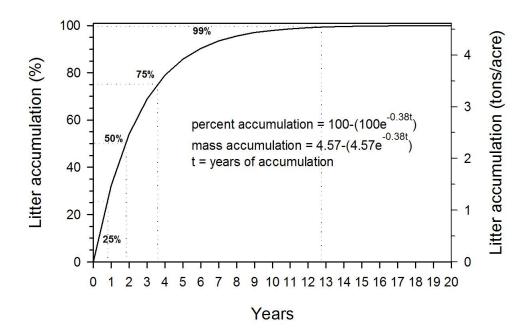


Figure 3.1. Plot illustrating a litter accumulation function in terms of percent of maximum and mass for forests of the Ozark Highlands, Missouri. The decomposition constant (k) was based on the mean from multiple sources and methods (Table 3.3).

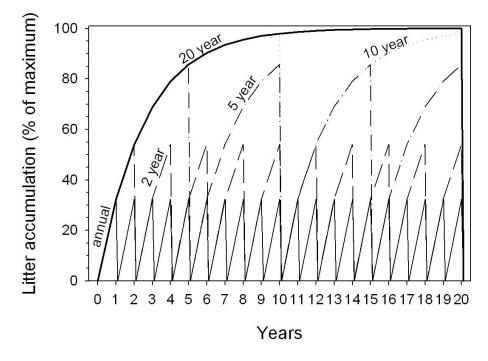


Figure 3.2. Litter accumulation dynamics with litter removed by fire (or other means) at different but regular intervals. Given here are litter accumulation patterns for annual fire intervals (solid fine line), 2-year fire intervals (short dashed line), 5-year fire intervals (dot dashed line), and a single 20-year interval (solid bold line).

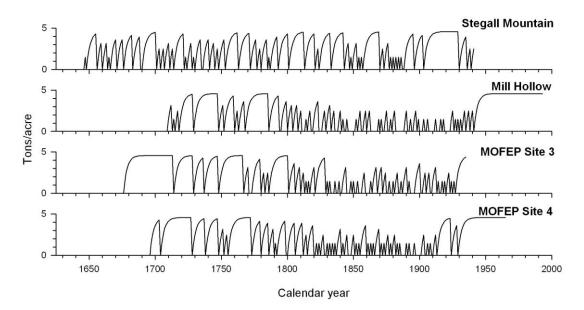


Figure 3.3. Litter loading reconstructions for four forest sites in the Ozark Highlands, Missouri. Reconstructions are based on fire scar history data and a litter mass accumulation function (Fig. 3.1). Site reconstructions begin and end at different calendar years based on the period of fire scar chronology records.

CHAPTER 4

PREDICTING SPATIO-TEMPORAL VARIABILITY IN FIRE RETURN INTERVALS USING A TOPOGRAPHIC ROUGHNESS INDEX

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Abstract

The shapes of landscapes are fundamental to ecosystem processes at various spatial scales. Topographic roughness index (TRI) is a measure of variability in the landscape surface and a proxy of the potential of disturbances to propagate across the earth's surface, such as a wildland fire burning across a landscape. We describe the significance of TRI, present methods for calculation, and demonstrate the utility of the index in a fire frequency prediction model. The model was used to show how the relationships between topography, fire, and humans changed during the period of AD 1620 to 1850 for a study area (5,180 km²) in Missouri, USA. The model predicted historic mean fire return intervals from TRI and two human population variables. The model explained 46% of the variation in mean fire return intervals and demonstrated that topographic roughness was most important in controlling fire frequency during the period AD 1620 to 1780 when human population density was lowest (< 0.35 humans/km²). Due to increases in human population, mean fire return intervals were shortened by up to one-fourth of their

original length and the landscape became more homogeneous with respect to fire frequency despite topographic roughness. The use of TRIs in wildland fire research aid in quantifying and visualizing topographic variability and could be applicable to multiple scales and ecosystem processes.

INTRODUCTION

The influence of earth's surface features on terrestrial ecosystems can be described on an array of spatial scales. From planetary to continental scales, surface roughness influences many of the key abiotic components that define ecosystems: the location of general circulation features (Hansen and Sutera, 1995), temperature variability (Kang et al., 2002) and rainfall and runoff patterns (Robinson, 1996; Head et al., 1999). At the scale of climatic regions and ecosystems (i.e., mesoscales), landforms or surface features aid in understanding the conditions controlling ecosystem patterns (Swanson et al., 1988; Bailey, 1996) such as spatial distribution of vegetation or the lateral migration of a stream channel. At a smaller scale, surface roughness has been used to describe disturbances of soil surfaces (Romkens et al., 2002), plant success (Freeman et al., 1993), and geomorphological processes (Rogers and Zuber, 1997). At microscopic scales, surface roughness aids in understanding microbiological properties such as surface adherence and surface area (Yamakawa et al., 2003).

Topographic roughness is the amount of land surface variability of a particular area and is a proxy for describing the potential of terrestrial propagation. Many studies have emphasized the importance of surface features to ecosystem processes. Surface roughness causes patterning in ecosystems by regulating the distribution of organisms and rates of processes (Swanson et al., 1988; Turner, 1989). Sanson et al. (1995) and Downes et al. (2000) showed a positive relationship between rock surface roughness and organic biomass concentrations in streams. Jenness (2000) and Guyette and Kabrick (2002) demonstrated the association between surface roughness and wildlife populations. The

importance of topographic features to forest disturbance processes (e.g., windthrow, fire) has been well documented (Wright and Bailey, 1982; Foster and Boose, 1992; Finnigan and Brunet, 1995; Whelan, 1995; Knapp, 1997; Rogers and Zuber, 1997). Variability in topography likely controls many ecosystem processes, particularly those that occur on the earth's surface like wildland fire (Grimm, 1984; Kobziar and McBride, 2006). Because the physical shape of the land surface is relatively constant for long periods of time (e.g., millennia), surface roughness is a constant in models that characterize long-term processes such as historic disturbance frequencies (Swanson et al., 1988; Kulakowski and Veblen, 2002).

While previous mesoscale studies have focused on the influence of topography on ecosystem processes, few have attempted to quantify or model topographic variability. Quantifying the variability in topography (i.e., slope degree, shape, aspect, and position) allows for comparison of different landscapes and illuminates their degree of heterogeneity. Through the use of GIS, these comparisons are relatively easily made and serve to enhance our basic understanding of its potential influence on ecosystem processes. For wildland fire, this understanding can aid in predicting spatial variability in fire behavior, wildfire risk, and long-term fire frequency. For example, spatial variability in fire frequency is influenced by factors that control fire spread and behavior, such as fuels and wind, which are in turn heavily influenced by the degree of topographic variability. On a site of low topographic variability, low frictional drag of wind over the land surface (Yoshino, 1975) promotes rapid spread, combustion, and homogenous fire coverage. On a site of high topographic variability, slower winds (Gloyne, 1967), reduced

fuel continuity, and greater variability in fuel moisture have a mitigating effect on fire spread and intensity.

There are several other important factors to consider when estimating the effects of surface roughness on long-term fire frequency such as changes in ignitions. Most empirical evidence that relates topography to fire frequency is derived from 19th and 20th century data- a period when fire frequency was strongly influenced by changes in human population, land use, and culture throughout North America (Veblen and Lorenz, 1986; Guyette et al., 2002; Weisberg and Swanson, 2003). The relationship between topography and fire has been modified as growing human populations have impacted the number of ignitions, altered native vegetation, disrupted fuel continuity, and suppressed fires. In considering these interactions among fire environment variables, it is necessary for models predicting long-term fire frequency to consider past differences in both the environment and human influences.

Application of surface roughness measures

Measures of surface roughness aid in identifying ecological relationships (Swanson et al., 1988; Guyette and Kabrick, 2002) and determining the spatial scales at which they are appropriately applied (Turner et al., 2001). Many ecological processes and relationships are scale dependent (Goodchild and Quattrochi, 1997); therefore, identification of scale dependency in ecological variables is necessary for determining the appropriate resolution at which to analyze and identify ecological relationships. Topography (i.e., angle, shape, aspect) at a landscape scale (e.g., $> 10 \text{ km}^2$) can be highly

variable and computationally difficult to quantify. Topographic variability must be measured at a resolution appropriate to the ecosystem property of interest. For example, the influence of topography on surface fire propagation is likely most appropriately measured at a resolution that sufficiently detects changes in slope and aspect that are important to fire behavior and propagation. Topographic roughness can be estimated using many materials and techniques including fractal geometry (Davies and Hall, 1999), laser altimetry (Plaut et al., 2001), photoclinometry (Beyer and McEwen, 2001), elevational transects (Bulmer et al., 1999), variograms of DEMs (Helfenstein and Veverka, 1998), ratios of digital surface areas and measuring scales (Jenness, 2000), directional counts of contour lines intersected, and chain set measurements (Merrill et al., 2001). Because topographic roughness is multiscalar, values increase with finer scale resolution. Depending on materials and techniques, inconsistencies in estimates of surface areas (when scale and calculation methods are held constant) may or may not occur (Chang and Tsai, 1991; Lam and De Cola, 1993; Jenness, 2004). Varying the scale at which the topography is measured provides the opportunity for exploring the influence of topographic roughness on multiple ecosystem processes. For example, at very fine scales, topographic roughness may represent a measure of soil erodibility, and at coarser scales, a measure of soil structural factors that affect wind or water erodibility (Merill et al., 2001). Similarly, for wildland fire, topographic roughness represents a fire behavior variable at fine scales and a fire size or burn patchiness variable at coarse scales.

The ability to reconstruct the spatio-temporal variability of historic fire frequency has importance spanning biological research, natural resource management, urban planning, and policy development. Since fire is a disturbance type that cannot be separated from

the landscape surface fuels, a detailed analysis and characterization of surface features is logical for understanding its movement potential – even for canopy fires. Considering the complex temporal changes in key fire environment variables (ignitions, fuels, and weather) (Butler et al., 1994; Pyne, 1996), topography is one of few that is static from historic to modern time periods. Previously, fire history research has emphasized the temporal presence and absence of fire at a particular site. Recently, studies have used networks of fire histories to advance our spatio-temporal understanding of historic fire regimes (McKenzie et al., 2000; Morgan et al., 2001; Hessl et al., 2006). Archived fire history data (e.g., International Multiproxy Paleofire Database, National Oceanic and Atmospheric Administration) are improving the ability to study these dimensions of historic fire regimes across large geographic regions (Guyette et al., 2006b; Kitzberger et al., 2007). Topographic roughness indices may be useful measures for linking fire history data from geographically disjunct locations. Improving our knowledge of historic fire frequency is needed because of its contributions for understanding long-term developmental processes of ecosystems, developing objectives and targets for prescribed burning, assessing fire risk, and measuring deviations of current fire regimes from their historic conditions.

In this paper we propose an index of topographic roughness as an important metric for characterizing topographic influence on long-term surface fire frequency. Although previous studies have utilized the index (Guyette and Dey, 2000; Guyette et al., 2002; Guyette and Spetich, 2003; Guyette et al., 2006a; Guyette et al., 2006b) a complete description of the methods and rationale have not been previously analyzed. Here we describe detailed methods for calculating a topographic roughness index. We surmise

that topography is an important control on surface fire frequency and that spatial patterning of fire is imparted on the landscape via topographic roughness. Based on a spatial model of long-term surface fire frequency we attempt to demonstrate the utility of the topographic roughness index and show its changing influence in the fire regime relationship along with human population density using a network of fire history sites across a large landscape (5180 km²).

METHODS

Topographic roughness indices

TRI is a surface area ratio of the land surface to a flat surface within a given extent. We developed a TRI using three area units: 1) a planimetric surface area, 2) a variable surface area, and 3) an area of interest (Fig. 4.1).

Planimetric surface area

The planimetric surface area (*Area* $_P$) consists of the extent of the landscape surface, or neighborhood, considered for generating the TRI. In this study, the planimetric area was a single, flat, circular and horizontal surface. The planimetric area represents the largest area that appears sufficient for capturing the influence of topographic roughness on the predicted variable. For example, the size of the planimetric area appropriate for determining the influence of topographic roughness on fire frequency is determined by the distance that encircles topographic changes that are important to fire behavior and propagation.

Variable surface area

The variable surface area (*Area* $_V$) has the same shape and perimeter as the planimetric area (Fig. 4.1). The area of its 3-dimensional surface is calculated from small cell units (e.g., digital elevation model (DEM)). Cell slope (radians) and a trigonometric conversion using the Pythagorean Theorem are used to determine the 3-dimensional surface area of each cell. The sum of cell surface areas within the entire extent is the variable surface area (*Area* $_V$).

Area of interest

The area of interest (*Area*₁) is the location for which TRI is calculated. The cells of the area of interest are excluded from both the planimetric and variable surface area calculations so to be independent of its neighborhood TRI value (Fig. 4.1).

Indices calculation (TRI)

The ratio of the variable surface area to the planimetric surface area is the topographic roughness index (TRI) for the area of interest. Topographic roughness index (TRI) is given as:

$$TRI = (Area_V - Area_I) / (Area_P - Area_I);$$
(1)

Increasing TRI values represent increasing topographic roughness. Theoretically, TRI values (using materials and methods described here) could range from 1.0 (perfectly flat) to over 800 (89 degree slope cells). TRI values for earth's landforms are typically much lower with values in the Midwestern U.S. rarely exceeding 1.08.

Study Area

The study area is a 5,180 km² square portion of the Current River watershed (37°15'N, 91°30'W) located in the Current River Hills ecological subsection (Nigh and Schroeder, 2002) of the Ozark Highlands ecoregion in southeast Missouri, USA. This portion of the Ozark Highlands is characterized as an ancient uplifted plateau that has been dissected by long-term erosion processes (Fig. 4.2). High, minimally dissected interfluves give way to rolling to rugged hills, through river breaks with bench and cliff topography. Pre-EuroAmerican settlement vegetation included open post oak and shortleaf pine savannas on the highest, least dissected lands, shortleaf pine woodlands on dissected plains, oak-pine woodlands and mixed oak forests on hills and river breaks, and mixed mesic forests along rivers and adjacent slopes (Nelson, 1997; Batek et al., 1999). General Land Office survey notes describe presettlement vegetation structure as having a greater surface area of glade, savanna, and woodland communities than presently exists and historic maintenance of these open canopy community structures is primarily attributed to historic

fire disturbances of anthropogenic ignition (Batek et al. 1999; Dey, 2002; Guyette et al., 2002). Lightning ignitions are uncommon in the region, accounting for about 1% of fire occurrences over the last 30 years (Westin, 1992; Missouri Department of Conservation, unpublished fire data; Yang et al., 2007). The potential for lightning ignitions is low because storms with lightning are typically accompanied by rain and occur primarily during the growing season when humidity is relatively high and vegetation flammability is low. Schroeder and Buck (1970) classified the Ozarks in a region of the U.S. where the lowest number of lightning caused fires occur (<1 lightning fire per 400,000 ha per year). In comparison, humans have caused an

average of 105 fires per year per 400,000 ha in the Ozark Highlands region of southern Missouri from 1970 to 1989 (Westin, 1992).

Designing the topographic roughness index

Topographic roughness indices were calculated for the purpose of predicting the spatiotemporal variability in fire frequency. Using ArcView v.3.2 and ArcInfo GIS software (ESRI, 2000a; ESRI, 2000b) and a 30 m grid cell digital elevation model (DEM) of the study area, the surface area of a circular 2.7 km radius planimetric surface area neighborhood was identified using the FOCALSUM command. We chose a 2.7 km radius neighborhood because 1) 2.7 km is larger than multiple slope length (valley to ridgetop) distances (i.e., large enough to cause variability in fire behavior and size due to changes in topography), 2) the distance minimized overlapping of neighborhoods between fire history sites allowing observations in the fire frequency model to be spatially independent (see section 2.4), 3) iterations of correlations between different TRI neighborhood sizes and mean fire intervals showed using a 2.7 km radius circle resulted in the highest correlations for the earliest time period (pre-1780) when human influences were assumed to be least (Fig. 4.3).

The area of the earth circumscribed by the planimetric surface was calculated from a 30 m cell grid DEM. Cells were included when the cell center fell within the boundary of the circular planimetric surface. We used the same 30 m grid in calculating the variable surface area. We assumed the DEM resolution was high enough to capture changes in slope. After excluding the area of interest, the variable surface area was divided by the planimetric surface area to generate the TRI. We excluded a one-cell area of interest, located at the center of both the planimetric and variable surface areas (Fig. 4.1), from our calculations, although other designs may also be suitable (see section 4.5). We chose to center the neighborhood on the area of interest because we had little information (e.g., shape, size, or directionality of unsuppressed historic fires) or justification for positioning the area in an otherwise specified distance or direction from the center. Edge calculation errors caused by the planimetric area overlapping the square study area boundaries were avoided by calculating TRIs for an area larger than the study area and then clipping the grid data to the study area boundary. Accuracy of index calculations was verified by 1) multiple calculation attempts providing repeated results and 2) comparing TRIs to directional counts of contour lines crossed (tally of number of contours crossed in 4 cardinal directions) using 7.5 minute USGS topographic maps of the study area.

Historic Fire Frequency Model

Fire History Data

The fire history of the study area spans the past 400 years with fires occurring somewhere nearly every year through the period 1700 to 1955 (Fig. 4.2). Fire frequency has changed through time according to human population, culture, and land use (Guyette et al. 2002). Historic mean fire interval data were derived from thirty-one previously documented fire scar history sites (Guyette and Cutter, 1997; Guyette and Kabrick, 2002; Guyette et al., 2002). Three additional sites (ALY, PUL, BPA, Fig. 4.2) (Stambaugh et al., 2005) were used for model verification. For each fire history site, we determined the mean fire intervals for four time periods of interest using composite fire intervals (Fig. 4.2). Site mean fire intervals were determined for the periods AD 1620 to 1700, 1701 to 1780, 1781 to 1820, and 1821 to 1850. Periods were defined based on length and changes in human settlement and land use (Guyette et al., 2002). Fire intervals that spanned more than one time period were assigned to the period containing the majority of the interval. Later periods (post- AD 1850) were excluded because at higher population densities the landscape was saturated with human ignitions (Fig. 4.2) (Guyette et al., 2002), and fuel conditions and fragmentation replaced topography as important determinants of fire frequency (Guyette and Dey, 2000).

Human population density estimates were derived from previously published estimates of population in the study area (see list in Guyette et al., 2002). We attempted to include a human population density variable in the model because of its previously documented importance in studies of historic eastern U.S. fire (Altobellis, 1993; Dey and Guyette, 2000; Hicks, 2000; Guyette et al., 2003b; Torretti, 2003; Delcourt and Delcourt, 2004; Lafon et al., 2005; Guyette et al., 2006b). We used the natural log of population density based on the assumption that the relationship between population density and fire frequency is not linear, but likely asymptotic where at some level of human population density the subsequent increase has no influence on increasing the fire frequency. In addition a digital river distance (km) was interpolated from previously measured distances for the Current and Jacks Fork Rivers (National Park Service, 1999), with river distance values increasing in an upstream direction. River distance was as an interactive variable with human population density to reflect the decreasing abundance of humans with watershed reach. The current population density of humans in the study area decreases with river distance and, based on historic Native American sites, historical towns and farms (1812 to 1860) (Guyette et al., 2002) and the area of agriculturally productive bottomland, we assumed that the relative distribution of humans in the study area is similar to that during the study time period.

Modeling approach

We developed a fire frequency model of the time period 1620-1850 when the number of fires was limited by number of ignitions. Because the historic fire frequency was highly dependent upon human ignitions (Guyette et al., 2002), we correlated topographic roughness indices to mean fire return intervals for four time periods (AD 1620 to 1700, 1701 to 1780, 1781 to 1820, and 1821 to 1850) during an era of increasing but low human population density. Choice of independent variables considered in the regression was based on documentation of human and land use history of the Ozark Highlands (Rafferty, 1985; Stevens, 1991). The dependent variable, mean fire return interval, was defined as the average time (yrs) between subsequent fires occurring at the fire history sites (approximately 1 km² areas) (Baker, 1989; Grissino-Mayer, 1999). We conducted a multiple regression analysis using SAS software (SAS Institute, 1990) and the PROC REG (ordinary least squares) command. We predicted mean fire return intervals of the 31 fire history sites from the topographic roughness index, human population density and river distance variables. Fire history data did not cover all time periods resulting in 97 of a possible 124 periods used in the analysis. Fire history site data were included in the analysis for each time period.

Spatial coordinates of fire history sites were used to locate the corresponding topographic roughness index, human population density, and river distance values to be used in the regression analysis. Because many cells (e.g., n = 850) covered each fire history site, an average fire history site topographic roughness index value was used in the regression equation. For the final model we chose a single equation based on model

diagnostics and verification results (Table 4.1). We wanted a single model that could explain the variability in fire through multiple time periods and topographies.

Model diagnostics included 1) data bootstrapping to ensure model stability and 2) confirming that a principal components model did not improve the amount of variance explained. Model verification included an accuracy assessment using actual and predicted mean fire intervals for three additional fire history sites. A sensitivity analysis was conducted over the range of TRI values. Since TRI and population were an interactive variable, changes in population were capable of determining the rate at which TRI affected the predicted MFIs. Therefore, we determined the influence of TRI in MFI over a range of human population densities. The utility of the TRI was compared to other topographic variables (see descriptions in Table 4.2) by substituting them in the regression model and comparing model r-square values. In addition we compared correlations between MFIs and each topographic variable for each of the time periods of interest. The model equation was spatially mapped by applying regression coefficients to surface variables. Maps of predicted mean fire return intervals were produced for the four time periods of interest. We classified mean fire interval predictions into equal interval classes (except for annual burning (predictions ≤ 1.0) and 1.1 - 3.6 yr intervals) in order to describe changes in shapes, locations, and areas of fire intervals within the study area and to describe spatial changes in intervals between time periods.

RESULTS

Topographic Roughness Index

The TRIs of the Current River study area ranged from 1.000 to 1.044. TRIs were normally distributed with a modal TRI value range of 1.014 to 1.019. TRI values and the locations of areas of high (rough) and low (smooth) index values were consistent with those identified using directional counts of contour lines on topographic maps. Topographic roughness index values > 1.034 represented less than 5% of the study landscape. The most topographically rough areas (> 1.025) were located ~ 2 km Euclidean distance from the two major river channels (i.e., Current or Jacks Fork Rivers). The spatial variation in TRI values was greatest in the breaks region between plains and the highly dissected valleys of the Current River (Fig. 4.4). Excluding the high plains landscapes, located on much of the periphery of the study site, TRIs of the three highest elevations showed they were not necessarily the roughest (TRIs < 1.023, Fig. 4.4). Locations of high TRIs (e.g., > 1.034) were small and localized (e.g., $< 100 \text{ km}^2$), whereas the sites of topographic roughness < 1.009 tended to be larger contiguous areas $(e.g., > 500 \text{ km}^2)$ located in the periphery of the study area consisting of upland plains. Topographically smooth areas included within larger topographically rougher regions were typically small in size (e.g., $< 1 \text{ km}^2$) and few (< 40).

A multiple regression analysis of fire history data was conducted on topographic roughness indices, human population density, and river distance. In this case two interaction variables incorporating population density were significant in predicting mean fire intervals (MFIs). We estimated the mean fire return intervals (MFI) of each 30 m cell as:

$MFI = -0.485 - 238(TRI*POP) - 0.000735(POP*RD^{2}) + 241(POP)$

$$(\text{model } r^2 = 0.46, P < 0.0001) \qquad (2)$$

where *TRI* denotes the topographic roughness index, *POP* signifies the natural log of human population density, and *RD* is river distance.

All variables included in the model were significant (p < 0.01) (Table 4.1). The linear model form provided a tendency for model predictions to become negative, particularly at low population densities and river distances. Correlation analyses (Table 4.2) show that TRI and MFIs were most strongly correlated in the earliest period when human population density was the lowest and that TRI consistently provided higher correlations compared to other topographic measures. Model sensitivity analysis illuminated the non-linear relationship between the interactive variable TRI*POP and predicted MFI (Fig. 4.5). As human population increases, the rate at which TRI increases MFIs is lessened. Model verification using data from three additional fire history sites showed actual and

predicted MFIs differed relatively widely, with the model generally predicting longer MFIs than were reconstructed using tree-ring dated fire scars (Table 4.1) (Fig. 4.6).

Periods: AD 1620 to 1700, AD 1701 to 1780

Generally, the mean fire return interval prediction surface was similar in pattern to the topographic roughness surface, particularly for the roughest locations; however the correlation between mean fire intervals and TRI decreases as human population density increases. Mean fire return intervals ranged from 1 to 39.0 yr. The range of predicted mean fire return intervals was greater for the periods prior to 1781 (i.e., 1620 to 1700, 1701 to 1780) than for the latter two periods (Fig. 4.4). The modal mean fire return interval was 3.7 to 8.7 vr and covered approximately 1200 km^2 of the study area. The highest fire frequencies (1 to 3.7 yr) occurred in areas where TRI values were less than 1.019 (e.g., dissected plains). The surface area of mean fire return interval classes decreased with interval length. Shape and juxtaposition of interval classes were highly influenced by the variability of topographic roughness. Mean fire return intervals followed the trend of shorter mean fire return intervals in the downstream Current River region (Fig. 4.4, southeast ¹/₄ of map) and longer intervals in the upstream Current River stream reaches. Mean fire return interval classes > 23.8 years were located in the upper one half of the study area and only represented in these time periods. The juxtaposition of the area covered by mean fire return interval classes from 1701 to 1780 was not noticeably different than during the 1620 to 1700 period (Fig. 4.5), despite the fact that

human population density, although low (e.g. $.04 \text{ humans / } \text{km}^2$), increased by approximately three times from 1620 to 1780.

Period: 1781 to 1820

The size and shape of mean fire return interval classes changed considerably throughout the study site between the periods 1701 to 1780 and 1781 to 1820. Some resemblance between the shape and juxtaposition of mean fire return intervals classes and the topographic roughness surface were evident and topographic roughness values of approximately 1.02 or less tended to burn most frequent (1 to 3.7 yr). The range of mean fire return intervals decreased from the previous time period to 1 to 23.8 yr, and 1 to 3.6 yr intervals covered only a small area (approximately 200 km²). Surface area enclosed by mean fire return interval classes decreased by an average of 516 km² (\pm 156 km² SD) per interval class increase and over half of the study area (~3700 km²) burned at a frequency of 8.7 yr or less. The shortest mean fire return intervals tended to be located in the eastern- and southern-most portions (e.g., plains) of our study area while longer intervals (i.e., > 13.8 yr) were located almost exclusively in upper-most reaches of the Current River (Fig. 4.4, northwest ¼ of map).

Period: 1821 to 1850

Only three different mean fire return interval classes were represented in the study area during this time period emphasizing the increasing homogeneity of frequent burning.

The shapes and the juxtaposition of mean fire return interval classes continued to resemble the topographic roughness surface from previous time periods. Mean fire return intervals further decreased across the study area (i.e., from 1781 to 1820 and 1821 to 1850). Frequent burning (1 to 3.6 yr) characterized approximately 70% (3640 km²) of the study area and 3.7 to 8.7 yr intervals occurred on 29% (1525 km²). Only a small area (~14 km²) located on the upper-most portion of the Current River had a fire frequency of ≥ 13.9 yr.

DISCUSSION

Fire history model

TRIs aid in describing the spatial changes in topography, both quantitatively and visually. Inclusion of TRIs in fire history models has significantly increased our ability to predict and understand spatio-temporal variability in fire frequencies within the study area. Even beyond the study area TRIs show promise in understanding historic variability in fire frequency (Guyette et al., 2006a). Knowledge of TRIs can be extremely useful in field investigations (Guyette et al., 2003b), both in targeting geographic locations with specific historic fire frequencies and identifying the likely locations of unique natural communities and species based on the disturbance frequency. Although intuitive, a proxy for the limitation of fire or other surface propagated processes by surface roughness has not been previously included in a fire history prediction model. The use of TRIs is new for landscape fire research and as methods of generating TRIs are further developed, its

predictive ability in models could enhance our understanding of historic fires and future wildfire potential (Haydon et al., 2000).

This fire frequency model is unique because it was developed from a large fire history data set in a relatively small spatial extent. Although we feel the model accurately portrays the spatio-temporal variability in fire frequency there still remain inconsistencies and errors in the model predictions and maps. Model verification showed over-prediction of mean fire intervals, particularly in the earliest time period, and many sources of error are possible. Considering the high importance of anthropogenic ignitions, better information on the spatial variability in human populations is needed, however likely impossible to confidently reconstruct at finer resolutions. Many changes in the design of TRI are possible and could further improve its predictive ability and application to other regions. In fact, the multiple input surfaces and ability to vary their designs (e.g., areas, shapes, and positions) is likely an important advantage over using conventional slope, elevation, and aspect metrics. Although TRI showed only slightly greater predictive ability over slope measures, its correlations with MFIs were consistently greater suggesting it could be a better metric of the topographic control on fire frequency.

Index considerations

From a defined propagation type and known spatial scale, surface input components of topographic roughness indices may be designed to more specifically portray the surface area relevant to a species or disturbance type. Topographic roughness indices aim to convert landscape surface data into a process oriented spatial data set. The planimetric

area need not be level, but is appropriately tilted to be a plane parallel with the regional landform (e.g., the angle of repose of mountain range, the acute angle (i.e., gradient) of the Great Plains, USA). Because many types of surface propagations have an expected shape or direction of movement, (e.g., fire-ellipse (Perry, 1998; Pyne et al., 1996), surface winds-linear (Coutts and Grace, 1995), caribou migration-linear (Bergman et al., 2000)), incorporation of the propagation direction can be considered in the analysis of topographic influence. To integrate directional propagation shape or direction, the planimetric area could be designed to incorporate the areas of topography that are most relevant (i.e., most likely to be propagated over) and exclude those that are not. Knowledge about fire direction or dispersal rate may be justification to accentuate the planimetric area length-to-width ratio or shape for the purpose of more closely mimicking surface propagation potential.

The appropriate cell size of the variable surface area is represented by the smallest likely scale relative to the variable or process of interest. For example, in cases where the behavior of a wildland fire varies with topography (i.e., landform features characterized over distances of 30 to 150 m such as slope and aspect), it is necessary to calculate the topographic roughness at similar or finer scales (e.g., 10 to 30 m cells). Size and scale of the variable surface area cells influence the range of TRI values. Underestimation of the scale unit will result in a higher resolution of information than is needed to accurately predict the independent variable.

If characteristics of the ecological process (e.g., rate, direction) are known, the area of interest may be designed to take on a more appropriate size, shape, or position within the planimetric and variable surface areas. Although not required, *a priori* information can

be used in determining the best design for calculating and representing the ecological process. The TRI value is a unique value for each area of interest be it a cell (e.g., fire ignition point, bird nest location) or area of cells (e.g., wildfire burn area, bird territory).

Enhancing regional fire understanding

One of the most important results of this study is the evidence for high variability in fire frequencies within a small extent and prior to major Euro-American influence. Evidence of humans changing fire frequency and mitigating the effects of topographic roughness is not unique to the study area, but can be viewed worldwide (Andreae, 1991; Laurance, 1998). Humans are considered the primary ignition source in the world (Pyne, 1982) and increases in human population are likely to increase the total ignition potential. The density of humans needed to overcome the influence of topographic roughness is a complex relationship between landform, vegetation and fuels, climate, and culture. The timing and rate of change in the relationship between topographic roughness and fire frequency caused by changing human populations or cultures are important to consider when describing the dynamics of historic fire regimes. Although intuitive, data from a larger network of fire history sites throughout the Central U.S. region suggest that fewer humans are needed to keep topographically smooth surfaces at a state of pyrosaturation (i.e., a stage in a fire regime when fuels are burned as soon as they accumulate enough to carry a fire (Guyette and Dey, 2000)) compared to topographically rough surfaces. This relationship between humans, fire, and the landscape surface has important implications, particularly to connecting ecosystems and societies. For our study area at low human

population densities (e.g., < 0.35 humans/km², prior to 1850) fire frequency decreased with topographic roughness (Fig. 4.5). As human population densities increased this relationship weakened. The model results suggest that as human population density (ignitions) increases the control of topographic roughness on the spatial heterogeneity of fire frequency is diminished. Although not included in this analysis, after approximately AD 1850, the relationship between TRI and mean fire return intervals in the study area became negatively related (Guyette et al. 2002) because inhabitants frequently burned forests to "improve" land for grazing despite their being located in topographically rough locations.

Topographic roughness index likely has wide application in landscape research efforts that include topography as a potential influence or variable in ecosystem modeling. Understanding the shape, behavior, and history of landscapes is fundamental in understanding ecosystem processes at various temporal and spatial scales (Swanson et al., 1988). Perhaps the widest use of topographic roughness is in delineating landscape classification boundaries of ecological units for entire states and countries (Cleland et al., 1997; Nigh and Schroeder, 2002). TRI is also applicable to studies of various surface feature processes that provide long-term perspectives of the dynamics of abiotic and biotic ecosystem components (Guyette and Kabrick, 2002; Head et al., 1999). Topographic roughness index's application and correlation to various plant and animal abundances suggests that an important interaction exists between surface features, species, and disturbance. The importance of topographic roughness likely differs with propagation type such as those with direct surface contact (e.g., surface fires, walking organisms, water movement) to those with indirect contact (e.g., flying organisms, wind).

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fire interval model results and prediction verification.	al fire history sites not included in model develop
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Mean fire interval	addition
Table 4.1. M	data from three a

	Mear	Mean Fire Interval Model	Model		
(A) Regression results					
Calibration period	и	r^2	F-value	prob. > F	Coeff. Variation
1620-1850	67	0.461	26.52	0.0001	83.48
(B) Regression coefficients					
Predictor		В	$SE^* \ of B$	^a p level	
Intercept		-0.485	1.994	0.808	
TOPO*POP		-237.97	67.874	0.0007*	
$POP * RD^2$		-0.000735	0.000138	<0.0001*	
POP		241.289	69.512	0.0008^{*}	
(C) Verification results					
		Actu	Actual (Predicted) Mean Fire Intervals (yrs)	ean Fire Interva	ls (yrs)
Fire History Site	TRI	1620-1700	1701-1780	1781-1820	1821-1850
Alley Spring (ALY)	1.030	na (26.0)	13 (25.0)	3.3 (13.2)	3.3 (6.0)
Pultite Ridge (PUL)	1.028	na (27.1)	10 (25.9)	3.3 (13.6)	2.1 (6.3)
Big Spring Pines Nat. Area (BPA)	1.025	na (9.8)	16 (9.4)	3.6 (4.9)	1.4(2.0)

 $^a\,$ p level is the statistical significance of the independent variable's t value. * Significant at the p = 0.01 level. SE = standard error; MFI = mean fire interval

Table 4.2. Model performance and comparison of the topographic roughness index (TRI) with
other topographic variables. All models were attempted including variables 'rivermile' and
'population density'.

			Pea	Pearson correlations (r) with MFI	ons (r) with N	1FI
Topographic variables	Description	MFI model r ²	1620-1700 n = 12	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	I78I-820 n = 28	I82I-850 n = 28
Topographic Roughness Index (TRI)	a designed surface area ratio, 2.7 km neighborhood	0.461	0.556 p = 0.060	0.402 p = 0.042	0.102 p = 0.607	0.202 p = 0.302
Slopesum	sum of slope degrees, 2.7 km neighborhood	0.459	0.362 p = 0.247	0.345 p = 0.084	0.069 p = 0.726	0.167 p = 0.395
Slopemean	mean of slope degrees, 2.7 km neighborhood	0.459	0.363 p = 0.246	0.345 p = 0.084	0.07 p = 0.722	0.169 p = 0.390
Elevation (sum)	sum of elevations (m), 2.7 km neighborhood	0.419	-0.298 p = 0.347	0.173 p = 0.397	0.362 p = 0.058	0.178 p = 0.364

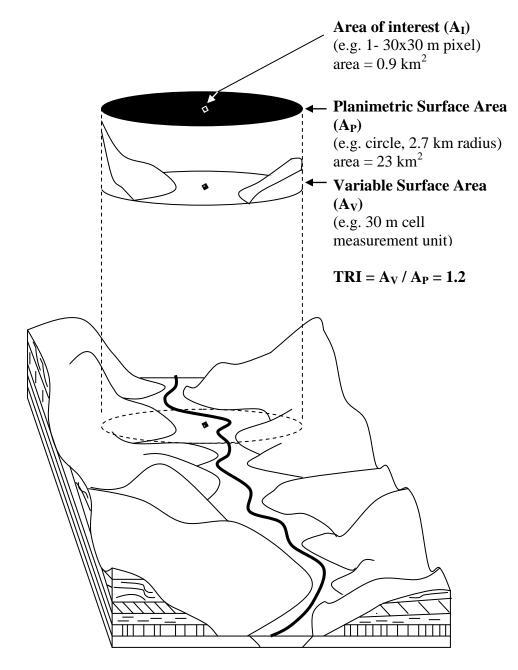
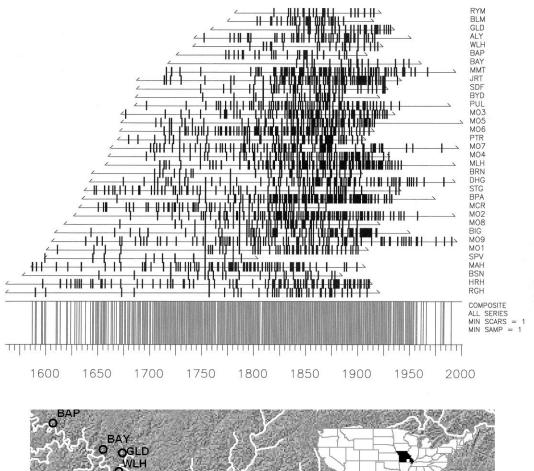


Figure 4.1. Topographic roughness index is a metric that has many implications and uses. The illustration above shows how the topographic roughness index is calculated by measuring the circumscribed region of a given dimension and shape with a large planimetric surface ($Area_P$) and a variable surface ($Area_V$). The variable surface area is divided by the planimetric surface area to obtain the topographic roughness index. The area of interest ($Area_I$) is excluded from the both the planimetric and variable surface area measurements. The topographic roughness index value is assigned to the area of interest.



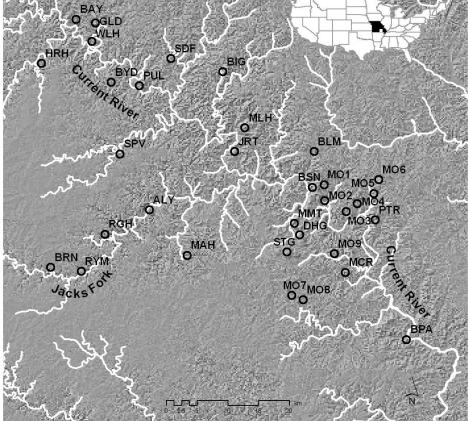


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Figure 4.2. (Top) The landscape surface of the study area (37°15'N, 91°30'W) located in southeastern portion of Missouri, USA (white box of U.S inset). Surface is a 30 m cell digital elevation model depicting the variability in the surface of the study site and the resolution at which topographic roughness was calculated. Black circles represent locations of the fire history sites used to calibrate and verify the fire return interval model. Three letter codes correspond to fire history diagram below. (Bottom) Composite fire history diagram showing model data. Three letter codes represent fire history sites. The horizontal bars depict the period of fire history data for each site and vertical tick marks represent a fire event at the site. All fire events for the study area are shown at the bottom of the diagram. Three sites (ALY, BPA, PUL) were used in model verification.

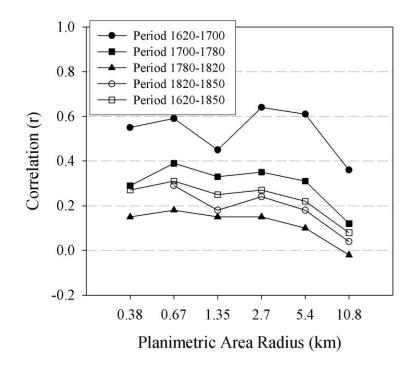


Figure 4.3. Correlations between mean fire intervals and topographic roughness are shown using multiple sizes of planimetric areas for five historic time periods. Our fire history model utilized topographic roughness indices generated using a planimetric area with a 2.7 km radius. The choice of size was based on correlation values, the spatial variability in the landscape surface, and the distance between fire history sites.

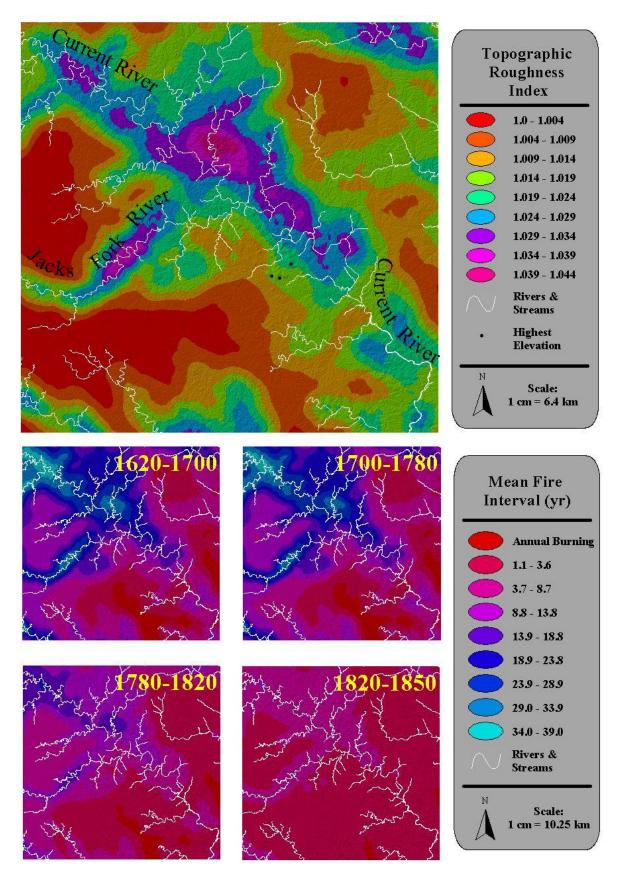


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Figure 4.4. Study area illustrations show the spatial distribution of topographic roughness index values (top, large panel) and predicted mean fire return intervals for four historic periods (bottom, small panels). Topographic roughness is displayed using nine equal interval classes with the brightness of classes representing a hill shade function. The accuracy of the generated topographic roughness surface values and their geographic location was verified by visually comparing roughness values to directional counts of topographic lines using 7.5 minute United States Geological Survey maps for various locations in the study area. The model used to predict historic mean fire return intervals included topographic roughness index, human population density and human population density dispersal by river distance. The final model was calibrated using 31 fire history sites and explained 46% of the variation in historic mean fire return intervals. White lines (stream locations) are used for reference and comparison.

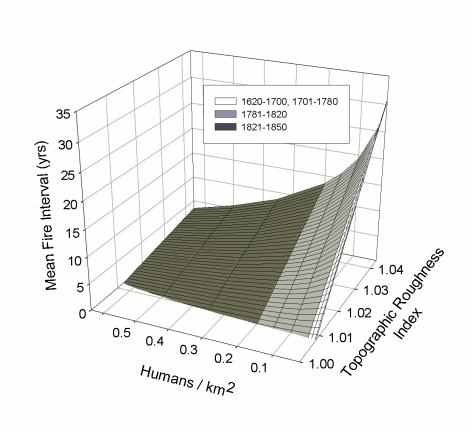


Figure 4.5. Sensitivity analysis of the effects of changing the topographic roughness index (TRI) on mean fire return interval. In the model equation TRI is an interactive variable with population density (POP), therefore the rate at which TRI affects predicted MFIs depends on POP. Dashed lines delineate the range of population densities for different time periods used in the model.

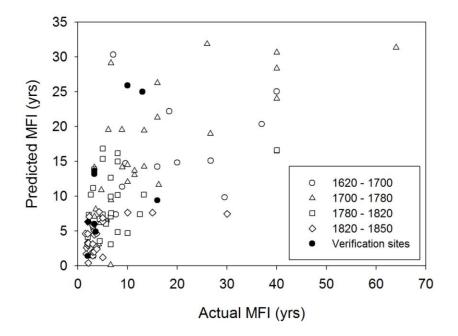


Figure 4.6. Scatterplot of actual vs. predicted mean fire intervals by time period. Verification sites were not used in the model development.

CHAPTER 5

SPATIAL PATTERNING OF FUEL LOADING AND FINE-FUEL HAZARD IN THE WESTERN CENTRAL HARDWOODS FOREST REGION

Abstract

Information about changes in fuel hazard is essential to assessing overall fire risk. Currently there is little information concerning the landscape-scale and regional-scale variation in fuels across large regions, particularly in the eastern United States. I describe the spatial variability in fuel loading across a large portion of the western central hardwoods forest region. In addition I developed maps of monthly litter hazard index from litter depth and litter moisture content-drought relationships. First, a regional litter depth prediction model was empirically derived from data collected on 1,446 fuel plots located throughout the Missouri Ozark and Illinois and Indiana Interior Lowland Plateau ecoregions. A stepwise multiple linear regression model ($r^2 = 0.36$) predicted litter depth from five parameters: residence time (number of months since leaf fall (November)), topographic roughness index, elevation, precipitation, and slope exposure. In a separate study, fine-fuel moisture content equations were developed that described changes in litter moisture content by aspect and drought conditions. Model estimates of litter depth were weighted with litter moisture content to produce maps of litter hazard index. Maps displayed spatial changes in litter hazard for different drought conditions. Overall, litter hazard appeared to be relatively homogeneous throughout the study area with greatest

levels attained in southeastern Missouri. Month of year and drought condition are likely the most important parameters concerning fuel hazard. In the future, litter hazard indices could be paired with ignition information in order to rate the fire risk of the study region.

INTRODUCTION

Forest fuels management is a global fire issue (Canadian Wildland Fire Strategy Project Management Team 2006, Gould 2006, Xanthopoulos et al. 2006), particularly in the United States (Andrews et al. 2006). Currently there is a rapidly growing body of information describing site-level forest fuel loading in United States, but in the eastern U.S. few characterizations of landscape- to regional-scale fuel variability have been made. The first attempt at mapping large-scale fuels patterns in the eastern U.S. was by Chojnacky et al. (2004) and since then other summaries at various scales and extents have been made (Fan et al. 2005, Graham and McCarthy 2006, Waldrop and others 2006, Woodall et al. 2007). Recently forest coarse and fine woody debris has been attributed to Köppen's climatic regions (Kotteck et al. 2006), however only weak correlations exist with temperature and precipitation (Woodall and Liknes 2008).

Within the Central Hardwoods forest region and Ozark Highlands in particular, fuels information is available regarding fuel loading (Crosby 1961, Shifley et al. 1997, Kolaks et al. 2003, Stambaugh et al. 2006, Stambaugh et al. 2007), fire behavior and fire effects (Grabner 1996, 2001, Kolaks et al. 2003, Shang and others 2004, Hartman 2004, Stambaugh et al. 2007, Stevenson 2007, D. Swanson unpublished data), and fire risk (Shang et al. 2004, He et al. 2004, Stambaugh et al. 2007). Despite having increasing information from different sites a broad-scale synthesis is needed (Woodall 2003) and would aid in identifying spatial and/or temporal patterns in the fuel (fire) environment. This information has the potential to advance our understanding of current fire issues

such as fuel hazard and fire risk, smoke emissions management, and the general role of fire in oak forest ecosystems.

For surface fire regimes of eastern deciduous forests litter is the most important fuel layer for continuous fire propagation and estimating fire behavior. Much of the energy released (i.e., fire intensity) from fires results from flame combustion of fine fuels such as litter (i.e. undecomposed leaves, needles, leaf stems) and 1-hour (i.e., twigs < 0.25 inches in diameter) fuels (Kolaks 2004). Following fire events it is estimated that Ozark forests can reaccumulate seventy-five percent of their total litter load within four years and, consequently, this period coincides with rapidly changing fire spread rates and flame lengths (Stambaugh et al. 2006). Measurements of hardwood litter have been commonly reported as depths. Relating litter depth to loading can be difficult because litter bulk densities can be highly variable (Ottmar and Andreu 2007) and due to many factors such as litter type, litter age, and repeated compression and expansion of the litter layer. Intuitively, variability in litter depths and bulk densities are likely strongly influenced by time of year (time since leaf fall, compaction) and the rate of litter accumulation relative to decomposition (Crosby and Loomis 1974).

For the purpose of developing a fire hazard index I analyzed a spatially extensive fuel loading data set from throughout the western portion of the Central Hardwoods forest region. In this paper I 1) describe the regional variability in fuel loading, 2) identify the mechanisms and model the patterns of regional temporal and spatial variation in litter loading and 3) present mapped results of the estimated spatial variability in litter fuel hazard during varying drought conditions.

METHODS

Study area

The study area is a large continuous landscape comprising the southern portions of the states of Missouri, Illinois, and Indiana (Fig. 5.1). The study area boundaries are delineated by the Ozark Highlands and Interior Lowland Plateau ecoregions (Bailey 1998, Nigh and Schroeder 2003). Within the study region are large contiguous areas of forest including three national forests. All three states have significant forested areas managed by state and federal agencies and private landowners. Annual precipitation varies from about 92 cm in the northwestern portion of the study area to 138 cm in the southeastern portion of the study area (Daly et al. 2004).

Annual growing period and days are relatively consistent with leaf and stem growth initiating in approximately late-March to early April and continuing until approximately early to mid-September. Leaffall timing is variable and highly dependent on timing of the first dormant season freeze event. Leaffall is a gradual process consisting initially of small inputs that increase to a primary leaffall period typically occurring in mid-October to early-November and lasting a few weeks. Coincident with leaffall can be an increased input of other fine fuels (< 3 inches diameter) (Pallardy unpublished data, other paper looking for) while input of larger fuels is probably more consistent throughout the year and dependent on disturbance events and mortality rates.

Fuel data collection

Fuels data were collected during the period of June 2004 to January 2006. Fuels data were collected exclusively from forests in the study area; therefore the results may not pertain to the fuel loading within other regions or land use types (e.g., agricultural lands, grasslands, and urban areas). Ownerships included state lands, national forest lands, and state and county parks. Fuels data were collected at plots located along transects that crossed multiple topographic positions. Transects were randomly placed in public ownerships within the study region utilizing a random point generator and ESRI® ArcGIS[™] v 9.1 (ESRI 2005) (Fig 5.1.) Transect bearings were randomly chosen from a predetermined bearing range ensuring that they crossed landforms and varied in location, topography, and vegetation. Fuel plots were taken at seventy-five meter intervals along transects. Fuel plots consisted of nested planar intersect transects using guidelines developed by Brown (1974) with modification. Modifications were 1) solid and rotten 1000-hour fuels were undifferentiated and 2) no fuels were removed from plots. Three to ten fuel plots were sampled along each transect depending on the size of forested area and variability in landforms. A total of 158 transects (1030 plots) were sampled in Missouri, 36 transects (205 plots) in Illinois, and 34 transects (211 plots) in Indiana (Fig. 5.1). A total of 228 transects (1446 plots) were sampled across the study region with their locations GPSed and transferred to a GIS.

Brown's (1974) fuel plot methodology was designed to record fuels in four size classes: (0.0-0.25 inch (1-hour), 0.26-1.0 inch (10-hour), 1.01-3.0 inch (100-hour), and > 3 inch (1000-hour)). Reasons for separating fuels into larger fuel size classes include: increased fuel sizes may decrease in abundance and increased fuel sizes likely correspond to increased longevity on the ground. Fuel loading constants are needed to adjust fuel weights based on their slope, specific gravity, and mean size class diameters. Few studies have been conducted that describe fuel constants for tree species in the Central Hardwoods Region. I derived fuel loading constants from several sources including other published studies (Brown 1974, Adams and Owens 2001) and field measurements of fuels characteristics (e.g., quadratic mean diameters, specific gravity). In addition to fuels measurements other field data were collected plots including forest tree species composition in the plot (coded using forest service forest type codes), elevation, slope, aspect, slope shape and position, basal area, percent ground cover (leaves, needles, herbaceous plants, bare soil), number of standing snags > 3 inches dbh, small diameter tree stem density, moisture content of 1000-hour fuels, and information on evidence of past fire. Mean litter depth (cm) was recorded at each fuel plot based on 12 measurement points. Other spatial data were joined to the plot data using GIS including: elevation, mean annual precipitation, mean maximum temperature (Daly et al. 2004), topographic roughness index (Stambaugh and Guyette 2008), land-cover (Homer et al. 2007), and geographic coordinates.

Fuel loading

Fuels were described by converting counts of fuel intercepts and fuel sizes into tons per acre using equations described in Brown (1974). Summary statistics of fuel loading were generated by state and for all states combined. Fuels were described by time-lag classes and provided state-level and region wide summaries. Frequency distributions of fuel loading by time-lag class by state were compared in order to judge whether major differences occurred between states. Spatial trends in fuel loading were examined using ArcGIS[™] (ESRI 2005). From this examination maps were made displaying regional fuel loading which were then used to identify region-wide patterns in fuel loading.

Fuel loading models

The purpose of the modeling exercise was to determine if variation in fuels could be explained from plot characteristics. I attempted to develop a relatively simple model whose relevance could be verified both statistically and biologically. Individual fuel layers and combinations of fuel layers were analyzed by combining the litter depth and time-lag class fuel loading data. Fuel plot data were excluded from the analysis when there was evidence of recent fire and when plot litter was dominated by eastern redcedar (Juniperus virginiana). Fire can cause fuels to be significantly altered (reduced or accumulated) and eastern redcedar fuels can have significantly different fuel characteristics (Stambaugh, unpublished data). Multiple regression analysis (SAS/ STAT 2002) was used to 1) analyze fuel relationships with ecological and social variables (Table 5.1) and 2) develop fuel models- a similar approach as Chojnacky et al. (2004) and Reich et al. (2004). Month of fuel collection was used as a predictor variable by assigning months integers representing months since November (i.e., leaffall). Parameters were allowed in the model at the significance level of p < 0.01. Bootstrap methods were used (100 iterations, with replacement) to assess the appropriate predictor

variables and model stability. A final model was chosen based on the bootstrap results (i.e., model stability and r^2). Model validation was achieved by regressing actual fuel loading values against predicted values for an unused portion of the dataset (n = 551).

Fine-fuel hazard index

A fine-fuel hazard index was developed for the purpose of describing changes in litter loading and moisture content during different months and drought conditions. Fine-fuel hazard index was calculated from the product of the litter depth model estimates and the inverse of litter moisture contents so that more and drier litter would be represented by increasing index values. I assumed that higher litter amounts represented either increased litter loading or a litter layer with low bulk density, which we assumed equaled higher fire hazard. Similarly, I assumed lowered litter moisture contents equaled higher fire hazard due to the increased potential for ignitions and increased rate of chemical reactions and combustion.

Maps depicting fuel hazard during drought extremes are likely of low utility because during extreme drought all locations can burn, and during extreme wet conditions all locations are of low concern. For this reason, maps depicting litter hazard during the transition from one extreme to the other are likely to be most useful for understanding and depicting spatial differences in litter hazard. Litter moisture contents were described around moderate drought and wet conditions. Litter moisture contents can be described using aspect and the Palmer Drought Severity Index (Palmer 1965). I used previously developed relationships that described litter moisture content by aspect during three

levels of drought (moderately wet, PDSI = 1.43; near normal, PDSI = -0.66; moderately wet, PDSI = 1.95) (Stambaugh et al. 2007). Monthly maps of changing fuel hazard were created to display the regional variability due to changing month of year (i.e., time since leaffall) and how it likely changes due to drought condition.

RESULTS

Fuel loading

Fuel loading tended to be very similar throughout the study region (Table 5.2, Fig. 5.2). State fuel loading means for small diameter fuels (i.e., 1- and 10-hour) were nearly identical. Overall, mean woody fuel (1- to 1000-hour class) loading was slightly higher for Indiana and Missouri than for Illinois – a difference primarily due to larger fuels (i.e., 100- and 1000-hour). Mean woody fuel loading was 4.37 tons per acre for the entire study region (Table 5.2). Mean woody fuel loading was two times higher in Indiana and Missouri than Illinois. Missouri showed slightly greater variability in woody fuel loading across all time-lag classes. Missouri had the highest recorded woody fuel loading (68.4 tons per acre) followed by Indiana (55.2 tons per acre) and Illinois (33.4 tons per acre) (Table 5.2).

Fuel loading frequency distributions showed that fuel sizes were typically positively skewed towards smaller fuels (Figure 5.2). Distribution shapes were nearly identical between the three states even though different numbers of plots and locations were sampled. Smaller fuels (1- and 10-hour) tended to be more normally distributed while

larger fuels (100- and 1000-hour) appeared to decrease with size (Figure 5.2). For data from all states combined, mean fuel loading increased by 2 to 3 times with each increase in fuel class. The number of plots with no fuels (i.e., tons per acre = 0) increased with fuel size class. The majority of plots had no fuels in the 1000-hour class.

Mapped fuel loadings showed several spatial patterns (Figure 5.3). Fuel loading in Missouri and Indiana had the highest variability. One-hour fuel loading was highest in southern Missouri and lowest in Illinois (north of the Shawnee Hills). Spatial variability in 10-hour fuels appeared similar across all states. One-hundred hour fuels were least along the western portion of the study region and in Illinois. One-thousand hour fuel loading was greatest in southeastern Missouri and in the unglaciated portion of southcentral Indiana. Although some fuel plots in Illinois showed 1000-hour fuel loading variability similar to Missouri and Indiana, many plots had less than average fuel loadings for this fuel size class.

Fuel loading models

Only analyses based on litter depth produced a statistically significant and biologically relevant predictive model. Model attempts to predict time-lag class fuels (1- hour to 1000-hour fuels) from ecological, plot, and social parameters (Table 5.1) showed no predictive ability. Litter depth was significantly correlated to woody fuel loading, however this correlation decreased with increasing time-lag class fuel size. Fuel loading of time-lag class fuels did not appear to be related to month of year.

The final litter depth model ($r^2 = 0.36$) predicted litter depth from five parameters: residence time (number of months since leaf fall (November)), topographic roughness index, elevation, precipitation, and slope exposure (Table 5.3, Fig. 5.4)). The variable 'residence time' had the greatest explanatory power (partial $r^2 = 0.22$), while slope and precipitation had the least. The model suggested that the factors related to increased litter are topographically rough terrain, higher elevations, steeper slopes and increased precipitation. Bootstrap results showed that model prediction was relatively stable with model r^2 varying from 0.31 to 0.40 (Fig. 5.4).

Maps depicting the spatial pattern of litter depth varied greatly depending on month of year (Fig. 5.5). Within a growing year, the model predicts that litter depths can vary by up to 3.5 cm in any location. Overall, the Missouri southern Ozarks and unglaciated portions of Indiana had the greatest areas of increased litter depths. Unglaciated regions, particularly in Illinois, showed the lowest litter depths as did large river corridors. The general spatial pattern of litter loading variability appeared to be consistent throughout the year with all areas decreasing in litter depth (Fig. 5.5).

Litter hazard index

Regionally, litter hazard indices were highest during mild dry conditions than incipient wet conditions (Fig. 5.6). In addition, hazard was greatest in November than for March and July. During mild dry conditions, the spatial pattern in fuel hazard was not significantly changed during different months of the year. However, during incipient wet conditions, changes in month had a greater effect on changing the fuel hazard. Changes

in fuel hazard between incipient wet and mild dry conditions were greater for the month of July than for November or March. From reviewing the hazard maps (Fig. 5.6) the model suggests that incipient wet conditions in July represent the lowest hazard while mild dry conditions in November represent the highest hazard. Areas of greatest fuel hazard were those that occurred during mild drought conditions during November, and were located in areas of southwestern Missouri (Fig. 5.7).

DISCUSSION

Compared to other eastern U.S. landscape fuel models the litter loading model shows similar explanatory power. Chojnacky et al. (2004) explained 30 percent of the variance in litter across the eastern U.S. Precipitation was the only model parameter in common with the litter model. In addition, they found geographic coordinates to be significant which I did not. The relatively low predictability of the litter depth model is likely an accurate depiction of the low degree of "patterning" in litter depth. A second explanation for the low model predictability is not that litter is somewhat variable and randomly distributed across the region, but the opposite; that is litter loading throughout the region is homogeneous¹.

The litter depth model estimates and maps should be considered a temporal "snapshot" generated from regional trends that vary with site specific factors such as time since local small- and large-scale disturbances and changes in forest density and species through succession. Within a growing year, the model predicts that litter depths can vary by up to 3.5 cm at any particular site. During any given month, the model predicts that litter depth

¹ It is important to restate that litter depths were plot-level means with plots consisting of 50 foot transects.

can vary by up to 4.7 cm within the study area. In terms of litter depth, the model predicts that greatest fuel depths occur throughout the central Ozark Highlands region in Missouri and in the unglaciated portions of Indiana (Fig. 5.5). Overall, the highest litter depths were in the southwest portion of the study area and decreased to the northeast. Generally, Chojnacky et al. (2004) found the same patterns in litter loading including counties in the central Missouri Ozark Highlands having the highest loading. From this similarity it is suggested that the litter depth map presented here reflects patterning in actual loading.

One of the seeming weaknesses of this study is that litter is reported in depths and not weights. Due to time and support, it was operationally not possible for this study to collect meaningful (i.e., dried, replicated) litter weights from the 1,446 plots in the study region. It is difficult to convert litter depths to loadings using bulk densities due to the many factors influencing the litter layer (Ottmar and Andreu 2007). Despite these limitations, I feel that litter depths are an excellent indicator of fuel hazard for two reasons: 1) increased litter depths equate to higher fuel hazard because there is more fuel available to support the combustion reaction and, 2) should increased litter depths due to expansion, then increased litter depths still equate to increased fuel hazard because an expanded ("fluffier") litter layer can dry more rapidly and within the litter layer is more oxygen promoting a faster rate of combustion.

Increases in litter hazard indices were represented by increased litter depths and decreased litter moisture contents. From reviewing the litter hazard maps (Fig. 5.6) the model suggested that incipient wet conditions in July represent the lowest hazard while mild dry conditions in November represent the highest hazard. Although the results are

intuitive it is important to verify that the model is predicting conditions that are biologically accurate. Areas of high fuel hazard appeared to be more strongly linked to drought conditions than month of year. For example, the highest fuel hazard area (located in southeastern Missouri) (Fig. 5.6) does not appear to diminish as month of year is altered. Here it appears that drought condition is the dominant factor. Although drought is known to be an important determinant of ignitions, less is known about its relationship to fuels, particularly in creating coarse scale patterning in litter hazard.

One of the most important results was that time since leaffall was an important control on litter depth. Regression analyses suggested its influence is greater than that of topography or climate. I am not aware of any large scale fuel modeling efforts that have included time since leaffall as a model parameter, but fuel case studies have indicated the importance of leaffall events to litter depth and mass. In Kentucky, Lyons et al. (2006) found that leaffall after a prescribed burn that significantly reduced fuels (up to 10-hour class fuels) resulted in litter levels equal to pretreatment levels. In Ozark forests, litter reaches maximum accumulation levels after approximately 12 years with 75 percent accumulation occurring within four years (Stambaugh et al. 2006). Understanding of the rates of accumulation and decomposition will likely prove significant when identifying large-scale patterns of leaf litter loading (Chojnacky et al. 2004), while other factors such as slope, stand age and basal area may have much less importance (Woodall et al. 2007).

Many factors could be responsible for the high degree of unexplained variance in the litter model. For example, differences in species and physical and chemical leaf composition substantially alters litter characteristics (Kucera 1957, Mellilo et al. 1985). Oak leaves have higher lignin composition than maples and elms, which can cause them

to persist longer in the leaf layer. Leaf curling, particularly in oaks, can give the leaf layer greater vertical structure and aeration while other species such as elms and maples lie flat and have less mass. Following leaffall events, litter depths decrease due to decomposition, but also due to compaction. Variability in litter depth can be caused by differences in leaf compaction that occurs from precipitation that varies among climatic regions. Compared to rain, when precipitation is in the form of snow, the above-layer weight can be increased and compaction duration lengthened. When snow covers and compacts litter the decomposition may be slowed, causing delays in litter decay. In contrast, studies monitoring soil respiration suggest litter decomposition is continued despite snow cover and that snow cover may enhance litter decomposition as it provides a thermal barrier from ambient temperatures promoting the microbial activities responsible for decomposition (K. Hosman, personal communication). Litter decomposition may be associated with other factors as well such as species composition and mixes (Hansen 1999, Gartner and Cardon 2004), soil nutrient dynamics (McClaugherty et al. 1985, Washburn and Arthur 2003, Demchik and Sharpe 2004), climate (Aerts 1997), and regional differences in litter response following disturbance (Blair and Crossley 1988).

Patterning in larger fuels

Fuel hazards may be even greater than predicted once the woody fuel loadings are considered. Overall, loadings found for 1- through 1000-hour fuels were comparable to those reported for other similar hardwood forest types across the eastern U.S. (Woodall et al. 2007). Unfortunately, development of a model predicting woody fuel loadings has

proven unsuccessful and woody fuels were not utilized in the fuel hazard assessment. In an analysis of eastern U.S., Chojnacky et al. (2004) similarly showed that models of woody fuel loading consistently had lower explanatory power compared to models estimating litter. Temporally, woody fuel input can be sporadic or constant (Rochow 1974). Although leaffall events can correspond with small twigfall, the degree of this input suggests being lower and less predictable. For larger fuels (i.e., 10- to 1000-hour), field and sampling experience indicated that these fuels are best described as randomly distributed- both temporally and spatially. This was particularly the case at a site-level scale where adjacent fuel plots could have dramatically different woody fuel loading, particularly for larger fuels (e.g., 100- and 1000-hour). At very broad scales, increased patterning may exist and be associated with climate divisions, however, estimates of coarse-scale woody fuel loading based on climate parameters are weak (Woodall and Liknes 2008).

Many models of woody fuels include broad forest characteristics such as stand age or disturbance as an important control of loading variability (Pregitzer and Euskirchen 2004). Assuming many of the forests that were sampled were second growth regenerated from early 20th-century logging or earlier (this appeared to be the case), greater variability in fuel loading may be expected as greater successional ages are attained (Ryu et al. 2004). In the study region, variability in fuels is commonly affected by disturbances at various spatial scales. It seems plausible that increased disturbance severity could result in increased patterning of larger fuels such as from a local scale single tree fall event to a meso-scale ice storm event to a severe tornado event. In southwestern Missouri, ice storms during the past 3 years have dramatically increased

fuel loading². A broad pattern seemed to exist in larger fuels manifested by relatively low fuel loading in the northern areas of Illinois (Fig. 5.3) - a highly agricultural landscape. Interestingly, the region tended to show lowered fuel loading for all time-lag classes except for the 10-hour fuels. Currently, it is not clear why this pattern existed. An association to agricultural lands does not appear to be a consistent attribute of areas with lowered fuel loading. Decreasing the extent of analyses could reveal evidence of significant differences in woody fuels at smaller scales or be able to identify areas of past disturbances. One comparison of fuel loading between Missouri ecological landtype associations did not reveal significant differences in woody fuel loading (Stambaugh et al. 2007).

CONCLUSION

Within the study region litter is the most important fuel layer in terms of fire hazard because without successful fire propagation, fire hazard is irrelevant. Although fire hazards do not exclusively pertain to the litter layer, understanding the litter layer is likely most important. Woody fuels may be less relevant because they appear to be somewhat randomly distributed across the study region and show a potential to change frequently both spatially and temporally. Overall, the litter hazard model is the critical fuel base on top of which site level information of ephemeral woody loading and condition can be overlain.

 $^{^{2}}$ Maps of woody fuel loading included in this study (Fig. 5.3) were generated from measurements prior to this event.

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rameters used in multiple regression analysis to predict litter depths across the western	Central Hardwood forest study area.
Table 5.1. Parameters used	portion of the Central Hardy

	Description	Units	Source
Ecological variables			
TRI	Topographic roughness, surface area ratio	Indices	Stambaugh and Guyette 2007
Precip	Mean annual precipitation	30-yr avg., cm	PRISM data; Daly et al. 2004
Landcov	Landcover type	categorical	National Land Cover Database
Mmaxt	Mean maximum temperature	30-yr avg, °C	PRISM data; Daly et al. 2004
Elev	Elevation	Ē	National Elevation Database
Slope	Slope	degrees	National Elevation Database
Spp_comp	Species composition	categorical	
Plot variables			
Plot number	Sequence of plot sampled	#	plot data
Transect number	Sequence of transect sampled	#	plot data
X Coordinate	Geographic coodinates of plot	UTM	GIS
Y Coodinate	Geographic coodinates of plot	UTM	GIS
Residence time	Months since leaf fall (October)	#	plot data
Social variables			
State	State name	categorical; 3 classes	US Census Bureau
Road_dens	Road density	km/km ²	US Census Bureau

Table 5.2. Woody fuel loading summaries for the entire western central hardwoods forest region study area and for individual states.

Fuel loading (Missouri, Illinois, Indiana)

	1-hour	10 hour	100 hour	1000 hour	Total
Count	1446	1446	1446	1446	1446
Min	0.00	0.00	0.00	0.00	0.00
Max	0.62	1.52	8.86	67.10	68.40
Mean	0.12	0.25	0.97	3.03	4.37
St. Dev.	0.07	0.16	0.85	6.41	6.65
Skewness	1.39	1.91	2.39	4.10	3.86
Kurtosis	6.94	11.69	14.74	25.31	22.95
1st Quart.	0.07	0.13	0.37	0.00	1.00
Median	0.01	0.25	0.75	0.00	2.10
3rd Quart.	0.16	0.31	1.27	3.30	4.80

Fuel loading (Missouri)

	1-hour	10 hour	100 hour	1000 hour	Total
Count	1030	1030	1030	1030	1030
Min	0.00	0.00	0.00	0.00	0.00
Max	0.62	1.52	8.86	67.12	68.44
Mean	0.13	0.25	1.02	3.16	4.56
St. Dev.	0.08	0.16	0.91	6.53	6.82
Skewness	1.33	2.13	2.44	3.97	3.71
Kurtosis	6.45	12.99	14.46	24.11	21.56
1st Quart.	0.07	0.13	0.37	0.00	1.04
Median	0.12	0.25	0.75	0.00	2.21
3rd Quart.	0.16	0.31	1.47	3.59	5.23

Fuel loading (Illinois)

	1-hour	10 hour	100 hour	1000 hour	Total
Count	205	205	205	205	205
Min	0.02	0.00	0.00	0.00	0.10
Max	0.30	0.68	2.60	32.70	33.40
Mean	0.11	0.24	0.76	1.66	2.77
St. Dev.	0.05	0.13	0.56	4.20	4.33
Skewness	0.79	0.85	0.70	4.41	4.28
Kurtosis	3.79	3.69	3.21	25.52	24.06
1st Quart.	0.07	0.13	0.37	0.00	0.80
Median	0.09	0.25	0.73	0.00	1.40
3rd Quart.	0.14	0.31	1.11	1.80	3.13

Fuel loading (Indiana)

	1-hour	10 hour	100 hour	1000 hour	Total
Count	211	211	211	211	211
Min	0.00	0.00	0.00	0.00	0.19
Max	0.25	0.87	4.73	54.11	55.15
Mean	0.10	0.26	0.92	3.72	5.00
St. Dev.	0.05	0.15	0.74	7.39	7.43
Skewness	0.68	1.02	1.52	3.94	3.84
Kurtosis	3.26	4.51	7.13	22.47	21.69
1st Quart.	0.07	0.13	0.37	0.00	1.13
Median	0.09	0.25	0.75	1.33	2.71
3rd Quart.	0.14	0.33	1.15	4.14	5.61

Table 5.3. Parameter estimates for a multiple regression model predicting litter depths in the western Central Hardwoods forest region.

(A) Regression results

Model	п	r^2	F value	p level
	557	0.363	63.03	<.0001
(B) Regression coefficients				
Parameter	В	SE of B	^b p level	partial r ²
Intercept	-29.127	7.802	0.0002	
residence time	-0.743	0.059	<.0001	0.223
topographic roughness	29.109	7.880	0.0002	0.070
elevation	0.004	0.0006	<.0001	0.042
slope	0.031	0.008	0.0002	0.017
precipitation	0.003	0.0008	0.0037	0.009

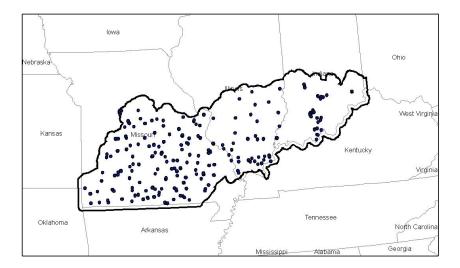


Figure 5.1. Study area (bold line) consists of southern portions of Missouri, Illinois, and Indiana. Black dots represent the location of transects (n = 153) along which multiple fuel loading plots (n = 1445) were sampled.

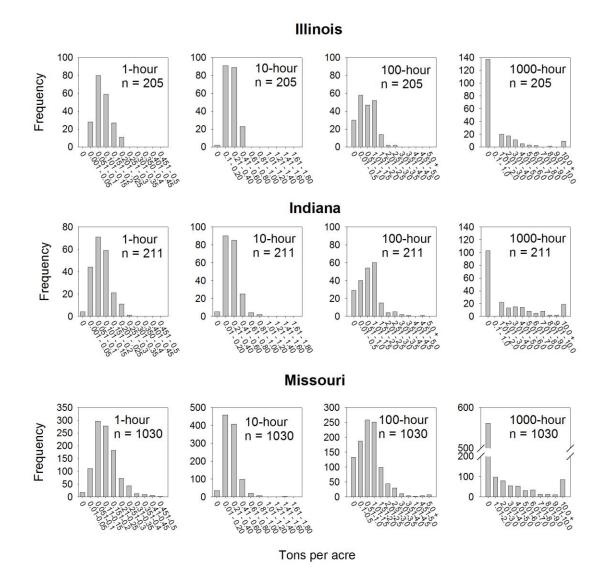


Figure 5.2. Frequency distributions of tons per acre of fuels in four time-lag classes for Illinois, Indiana, and Missouri.

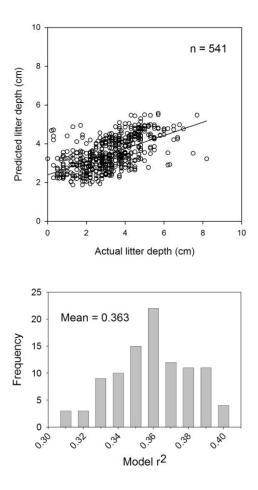


Figure 5.3. (Top) Scatterplot of actual versus predicted litter depths generated from the multiple regression model (Table 5.2). (Bottom) Bar plot of bootstrap results of the model r-square for 100 iterations.

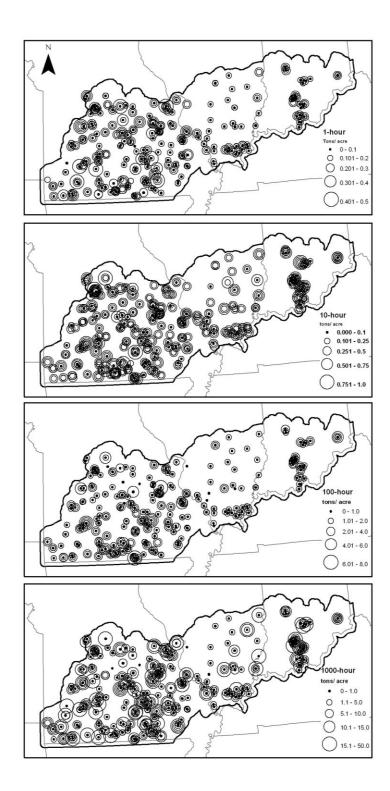


Figure 5.4. Spatial pattern of fuel loading for the four time-lag fuel classes. Circle size corresponds to increased fuel loading (see legend).

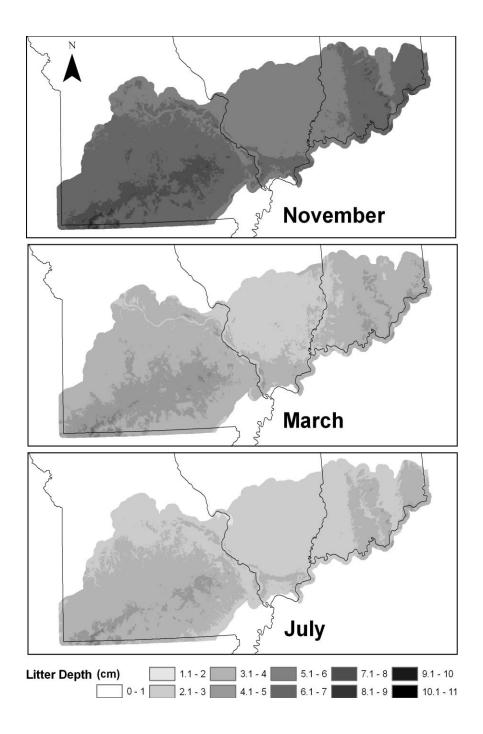
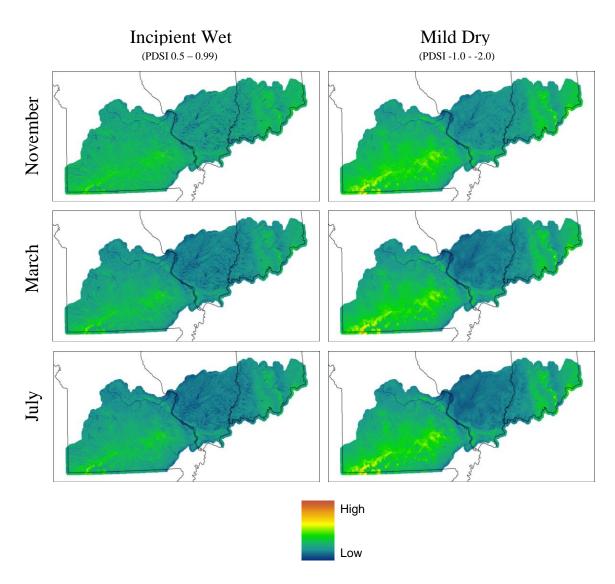


Figure 5.5. Maps of modeled fuel loading for three equally spaced months during the year. Maps decrease in regional litter depth according to residence time (i.e., months since leaffall).



Fuel Hazard

Figure 5.6. Maps of fuel hazard index for three equally spaced months during incipient wet and moderately dry conditions.

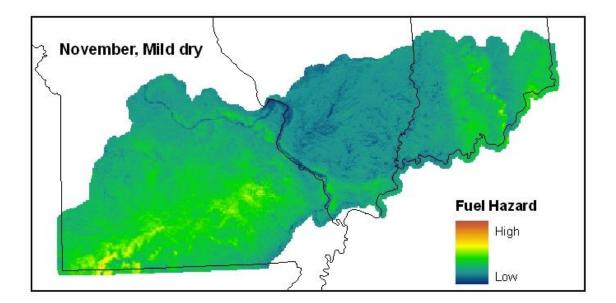


Figure 5.7. Enlargement of fuel hazard index map for November during moderate dry drought conditions. This scenario represents the highest regional fuel hazard for this drought condition. Fuel hazard would further increase with increased drought, however less pattern complexity is likely as fuel become homogeneously dry regardless of aspect.

CHAPTER 6

SPATIAL-TEMPORAL VARIABILITY OF MODERN WILDFIRE IGNITION PATTERNS AND FIRE RISK IN THE WESTERN PORTION OF THE CENTRAL HARDWOODS

Abstract

Little work has been done to characterize ignition patterns and fire risk across large regions of the eastern United States. In the Central Hardwoods, the modern role of fire is spatially heterogeneous, temporally variable and somewhat small compared to its past. The objectives of this study were 1) to develop a model predicting ignition probabilities for a large region of Missouri, Indiana, and Illinois from ecological and anthropogenic variables and 2) to combine ignition probabilities with previously developed fuel hazard indices to rate the landscape in terms of fire risk. A large set of fire occurrence records (> 16,000) for the period 1986 to 2007 was used to develop a predictive model of fire occurrence probability and assess fire risk. CART and logistic regression analysis were used to identify variables associated with fires and to model the spatial variability in fire probabilities. Eight parameters were used in a predictive model that showed fire probabilities to be substantially greater in the southern Ozark Highlands compared to the northern Ozarks and most of Illinois and Indiana. Fire probabilities were combined with previously developed fuel hazard indices to generate fire risk indices. Fire risk pertained to the risk of forests burning and indices were designed so that increased fire frequency

(i.e., fire probabilities) and severities (i.e., fuel hazard) represented increased fire risk. Patterns of fire risk indices closely resembled that of fire probabilities and gave increased weights to both exposed slopes and increased drought conditions. Areas of highest fire risk were identified as being associated with government lands, particularly Mark Twain National Forest lands. The model captured much of the spatial variability observed in the modern fire locations; however it poorly characterized the variability associated with known cultural patterns related to fires.

INTRODUCTION

Characterizations of fire regimes commonly include identification of ignitions and their underlying influences. The major drivers of ignitions can be highly variable and dependent upon geographic location and time period. Patterns of fires are reflected through broad-scale influences such as climatic patterns and fine-scale determinants such as land ownership or road density. Temporally ignitions can be influenced over long time scales that include gradient shifts in wet and dry periods (Hessl et al. 2004, Brown 2006) or abrupt passages of dry lightning storms that initiate hundreds of new fire starts (Bartlein et al. 2008). Factors influencing both spatial and temporal ignition patterns are scale dependent, therefore the size of the study area and scale of the analysis must be considered when determining the factors important to ignitions.

Historic information can provide an important perspective on current fire regime conditions and aid in defining fire influences. In terms of ignition sources, the central U.S. region, particularly the Ozark Highlands and Interior Lowland Plateau, has a very low frequency of natural ignitions compared to anthropogenic ignitions (Schroeder and Buck 1970, Westin 1992). Prior to widespread EuroAmerican settlement, human populations and cultures and their movements imparted distinct vegetation and ignition patterns on the landscape through their use of fire (Batek 1999, Guyette et al. 2002, Guyette et al. 2004, Ruffner and Groninger 2004). Recent studies suggest the degree of human influence on eastern U.S. historic fire regimes may have been previously underestimated (Delcourt and Delcourt 2004, Guyette et al. 2006a, Abrams and Nowacki 2008).

Fires in the western portion of Central Hardwoods

Throughout the Central Hardwoods region fire scar history studies characterizing the period AD 1600 to present strongly implicate humans as a primary ignition source. Many studies from a diversity of states have shown a common temporal progression in fire occurrences that is characterized by a consistent burning frequency prior to EuroAmerican settlement, increased burning frequency during the transition from Native American and EuroAmerican occupation, followed by dramatic decreases in fires with the end of free range grazing and development of state and federal fire programs. Variation from this progression occurred when landscapes were already in open structure (i.e. didn't require burning to promote grazing) such as in prairies and savannas (Guyette et al. 2003, Dey et al. 2004). Since the mid-20th century land acquisitions, development, and statewide policies (e.g., Clarke-McNary Act, closing of open range) have been effective at reducing fires. In Missouri, this period saw the enlargement of fire protection districts and their numbers correspond to an approximately 10-fold reduction in fire events. From about 1952 to 1990, Westin (1992) showed the number of acres burned in Missouri (private and state lands) steadily trended downward as the number of acres protected increased. From 1997 to 2006 the average number of fires per year was 2,641 and average number of acres burned was 47,442 (rural fire department data from state and private lands; source: George Hartmann, Missouri Department of Conservation). Within this ten year period there was a sustained increase in both fires and acres burned beginning in 2000.

As a result of European settlement, modernization, and fire suppression, significant changes in forest communities have occurred throughout the region. In general, the cessation of widespread burning has resulted in widespread increases in forested areas and decreases in floristic diversity (Beilmann and Brenner 1951a, b, Nowacki and Abrams 2008). The likely immense amount of smoke emissions associated with historic frequent fires has been forgotten. Equally significant, the role of fire in lifestyles (e.g., heating, cooking) was substituted by other technologies (Pyne 1982, 2007). In terms of climate, the relationship between drought and fire occurrences seems to have changed and been muted, but not lost.

Drought is an important factor influencing fires worldwide. Historically, temperature and precipitation, the key components to drought, imparted a continental pattern on fire frequency (Swetnam and Baisan 1996, Brown 2006, Guyette et al. 2006a). For the Ozark Highlands, it is estimated that up to 50 percent of the region could have burned in a single year during extreme drought conditions (Guyette et al. 2006b, McMurry et al. 2006). Regional studies of fire history in Missouri and Arkansas have shown drought in the year of fire is important compared to drought in lagged years (Stambaugh and Guyette 2006). Drought is linked to fire such that with increased drought larger areas of the landscape have the potential to burn and the combustion reaction is more readily achieved.

Since EuroAmerican settlement, the role of drought influencing fire has become somewhat masked. Examples of this masking effect include frequent ignitions (circa 1830-1900) occurring regardless of drought condition (Dey et al. 2004) and increasingly effective fire suppression precluding ignitions and large fires regardless of drought (circa 1955 to present) (Westin 1992). During the modern period (post-1940), drought was

significantly correlated to acres burned in Missouri, and the number of arson fires shows an increase with drought (Westin 1992). This suggests that in the future the frequency of fires and the influence of climate (e.g., drought) could be highly dependent on human fire use and ignitions.

Humans are possibly the "keystone species" to the Central Hardwoods fire regime (McClain and Elzinga 1994, Bonnicksen et al. 2000, Guyette et al. 2006a). If true, this link has critical implications for understanding pre-EuroAmerican contact (e.g., Mississippian era) fire frequencies, interpreting "natural" fire regimes, and plotting and justifying the course for future fire management. Humans are both innately drawn to fire and domestically prohibited from fire. In Missouri, these actions seem to be manifested in the modern fire period by numbers of arson fires increasing with drought while numbers of fires caused from debris burning decrease. In terms of arson fires, a person's cultural tradition, feelings toward government and access to lands are important factors influencing their frequency and location (Jenkins 1997, Yang et al. 2008, Brosofske 2007).

The objectives of this study were 1) to develop a model predicting ignition probabilities and 2) to combine ignition probabilities with previously developed fuel hazard indices to rate the landscape in terms of fire risk.

METHODS

From a large dataset of fire ignitions I predicted the probability of fire across the landscape using ecological and anthropogenic variables. I included many data

characterizations to make the logic, data structure, and model development process as transparent as possible. Additionally, conducted multiple analyses and comparisons to challenge the validity of the model parameters, the accuracy of the model estimates, and the fire-environment-human relationships posed. The final construction of fire indices and maps combined fire probabilities with fuel hazard indices to rate the study area landscape into low to high fire risk classes.

Study area

The study area is a large continuous landscape with an approximate area of 190,000 km², comprising the southern portions of the states of Missouri, Illinois, and Indiana. Within these states, the study area is delineated by the Ozark Highlands and Interior Lowland Plateau ecoregions (Bailey 1998, Nigh and Schroeder 2003). Within the study area are approximately 116,000 km² of forested land. Approximately 11 percent of the area is publicly owned comprising three national forests, 11 national wildlife refuges, 1,552 state management areas and numerous other smaller public land ownerships. In addition about $30,000 \text{ km}^2$ are agricultural lands of pasture and row crops that are primarily privately owned.

The climate of the study area is broadly characterized as humid continental. Variability in El Niño/Southern Oscillation (ENSO), a 4-7 year oscillation, is the most pronounced short-term general circulation feature influencing moisture regimes. Annual precipitation varies from about 92 cm in the northwestern portion of the study area to 138 cm in the southeastern portion (Daly et al. 2004). Annual mean maximum temperature ranges from

about 15.5 to 22.5 degrees Celsius. Elevations range from 80 to 540 meters a.s.l. with the highest elevations located in the Ozarks of Missouri and the lowest in the valleys of major rivers. Major riverways (e.g., Mississippi River, Missouri River, Wabash River) border and bisect the study area. These rivers and their associated landforms are associated with physiographic and cultural differences that likely influence fire occurrence. Major metropolitan areas (St. Louis (MO), Louisville (KY), and Indianapolis (IN)) lie on the periphery of the study area.

Fire ignition data acquisition and processing

Many data sources were considered and reviewed prior to the development of a regional fire database (Table 6.1). An initial requirement of data was that the final dataset be represented with consistent data reporting methods over the entire study area. Overall, only MODIS fire detection data (satellite detections) (Csiszar et al. 2005) were deemed consistent across the study area; however these data were relatively few and only available for years 2000 to present. Because MODIS data alone did not contribute to understanding the spatial patterns in fires I considered the next best dataset for the region, the National Fire Occurrence Data (NFOD)¹. Comparisons of the spatial distributions of MODIS and NFOD fires suggested that NFOD were likely spatially incomplete and limited to a county-level summarization because of the absence of records on non-federal and state lands in Illinois and Indiana. In Missouri, however, the opportunity for generating a reliable spatial dataset was greatest based on the availability of many more fire records (up to 10 times), data with potentially higher spatial resolution despite

¹ http://ww.fs.fed.us/fire/fuelman/fireloc.htm

landownership, and the availability of multiple spatial datasets. Because of the data constraints in Illinois and Indiana the fire probability model was developed in Missouri and then applied to the entire study area. Characteristics of fires from each of the states were similar, thus justifying the assumption that Missouri fire relationships are applicable to Illinois and Indiana (Figure 6.1, 6.2)

Multiple spatial datasets of fires were available from Missouri (Table 6.2), however only the NFOD were consistently available across the entire region. Some of these datasets represented overlapping time periods and had replicated fire records. For example, from state fire records (rural fire departments (RFDs)) I developed a separate section level spatial dataset of fire occurrences. Comparisons of these fire records with NFOD showed that these data had the same source with the majority of the records duplicated. State fire records that did not duplicate information on a fire were added to the NFOD. The final fire dataset spanned the period 1986 to 2007 (except for years 1998, 1999) and consisted of state data, NFOD, and MODIS data sources. These data constituted 16,218 records with a spatial resolution of a legal section (approx. 1 mi^2). Approximately 12,140 records contained detailed fire event information including month, hour of response and containment, acres, and cause. I assumed that no within year changes occurred that affected the overall spatial fire pattern by reviewing maps of monthly fire locations (Figure 6.3). Because of the large size of the dataset, data were sorted for possible errors and missing values. Approximately 200 observations were removed because of the presence of zero values that were likely generated from GIS zonal statistic or spatial join operations of points on the margins of the study area.

A polygon coverage of the actual Missouri Public Land Survey (PLS) System was obtained from the Missouri Spatial Data Information Service (MSDIS)² and fire records were joined to PLS polygons. A map of section-level annual fire occurrence probability was developed by dividing the number of fires in a section by the total number of fires divided by 20 (number of years of records). Sections whose majority area was represented as water were removed from the dataset (n = 740). In addition, cells that were smaller or larger than typical 1 square mile sections were removed. These were represented by land grants and sections located on the northern edges of townships whose areas varied because of correcting for surveyor error and earth curvature effects. Sections without fires were selected (n = 29,555) and converted to centroids. All PLS centroids were assigned a binary code (fire = 1, no fire = 0), and sections with multiple fires received multiple records. The final dataset contained 45,398 records.

Ecological variables

GIS layers of many fire-related ecological variables (Table 6.3) were obtained for the purpose of modeling fire probabilities. These independent variables consisted of raster and polygon data describing topography (elevation, slope, topographic roughness), climate (precipitation and temperature), and vegetation (land cover, ecological classification). Raster data were of varying resolution and if necessary were resampled to a common 30 m cell size. Raster data were summarized for all PLS sections using the zonal statistic command in ArcGIS (ESRI, Inc.) and polygon data were assigned to

² http://www.msdis.missouri.edu

sections using a spatial join routine. Section-level zonal statistics of PLS polygons included mean, maximum, minimum, median, and majority of records.

Elevation data were DEMS obtained from the U.S. Geological Survey's seamless data distribution system (SDDS³). National Land Cover Data, also obtained from the SDDS, were separated into forest (Anderson Level I, classes 41, 42, and 43) and agriculture lands (Anderson Level I, classes 81, 82) (Anderson et al. 1976). Percentages of sections in these classes were calculated by dividing the area of each class by the area of the PLS section. Ecological subsections were classed as being part of the inner Ozarks (e.g., Current River Hills, Springfield Plateau) or not (e.g., outer Ozark border, Mississippi Alluvial Plain) using Missouri's ecological classification system (Nigh and Schroeder 2002). Topographic roughness indices were calculated using a 2.7 km radius neighborhood – a distance shown to most highly correlate with historic fire frequency (see methods in Chapter 4).

Anthropogenic variables

Because the regional fire regime is strongly related to anthropogenic ignitions, I obtained a large set of GIS data characterizing human demographics and fire response (Table 6.3). The majority of variables (37 of 40) were obtained from the US Census Bureau's TIGER[®] data⁴ for the 2000 Census period. I chose this reporting year as opposed to 1990 because it occurred at the middle of my fire record reporting period. Census block

³ http://seamless.usgs.gov/website/Seamless/

⁴ http://www.census.gov/geo/www/tiger/

polygons were summarized to PLS sections using Hawth Tools⁵ extension and the polygon to polygon routine, which allows for summary calculations using area weighted means. Once summarized, census data were then joined to the PLS sections. Locations of TIGER roads were also obtained for the study area. Road densities were calculated using the line density routine and reported as km of roads per km². Locations of rural fire departments responding to Missouri wildland fires were obtained from the MDC. From these point data a raster data set representing distance to fire department was created using the distance to point tool in the ArcGIS 9.2 toolbox and then the raster values were summarized by PLS section.

Public land ownership boundaries were obtained from many different GIS data services and clearinghouses. For Missouri, Mark Twain National Forest (MTNF), Missouri Department of Natural Resources (state parks), and MDC boundaries were obtained from MSDIS while National Park Service boundaries utilized agency GIS records. For Illinois, boundaries for state conservation areas, state forests, state parks, and state fish and wildlife areas were obtained from the Illinois Natural Resource Geospatial Data Clearinghouse⁶. Shawnee National Forest boundaries were obtained from agency GIS records. Hoosier National Forest and state management areas boundaries were obtained from IndianaMap⁷. For the entire study region, National wildlife refuge boundaries were obtained for the Great Lakes – Big Rivers Region (Region 3)⁸. Boundaries were not obtainable for state natural areas; however some are contained within already existing boundary files (e.g., conservation areas). General locations of all areas in the GIS were

⁵ http://www.spatialecology.com/index.php

⁶ http://www.isgs.uiuc.edu/nsdihome/

⁷ http://www.in.gov/igic/projects/indianamap/index.html

⁸ http://www.fws.gov/data/NWRdata.htm

verified through comparisons to publicly available maps. Percentages of government land were calculated by determining the area of government land in each PLS section and dividing by the section area.

Data Analysis

The distribution of fire ignition points within Missouri was estimated using the Kfunction (Ripley's K) - a cumulative density function that uses the second-moment (i.e., the variance of all point-to-point distances in a closed plane) to evaluate two-dimensional distribution patterns (Ripley 1976, Yang 2005). The K-function describes the spatial point-pattern in terms of randomness or regularity. K-function was described using the Multi-Distance Spatial Cluster Analysis ArcGIS script. Edge effects were mitigated using Ripley's edge correction formula and effects of study area shape were mitigated by using a minimum enclosing rectangle. The script calculates a confidence interval using the k-function for a random point distribution. Nine permutations were used to calculate confidence intervals, which were determined from the K values that deviated above and below the expected K by the greatest amount. In addition to the K function, I explored fire point distributions by mapping the fire probabilities, calculating the kernel density of fire probabilities, and viewing the semivariogram of fire probabilities. Fire probabilities were calculated as the number of fires per section divided by the total number of fires divided by the total number of years of record. Kernel densities were calculated for fire probabilities based on an arbitrary 5 cell (i.e., 8.05 kilometers (5 miles)) search radius from PLS section centroids.

I used classification and regression tree (CART) analysis and logistic regression to determine the important variables for predicting fire occurrences probabilities. These methods complement each other in that CART analysis can be used to hierarchically identify important predictor variables, while logistic regression can identify independent variables that can be used to develop predictive equations. Recently, two studies (Brosofske et al. 2007, Yang et al. 2008) also used these methods to assess fire occurrences on the MTNF under the assumption that together the methods aid in providing a more robust set of predictor variables and relevant statistical model. Brosofske et al. (2007) reviewed why each nonparametric technique is strengthened by the other and the limitations of CART analysis alone as a predictive mapping tool.

Because the dependent data were binary (i.e., 0 = no fire, 1 = fire), I used classification analysis (i.e., CART) to create trees describing the relationship between fire ignitions and independent variables. Classifications were made using the statistical program R (Hornik 2008), a free software environment for statistical computing and graphics, and utilized the recursive partitioning and regression trees (RPART) statistical package. In general, classification analysis calculates candidate splits for each independent variable, saves the split of each variable that represents the smallest deviance, and then utilizes the variable split (and split level) that has the smallest deviance for the splitting node. All ecological and anthropogenic variables were considered in the CART analysis. CART analysis was conducted on the entire dataset (n = 45,398) and sub-sets consisting of fires of different fire size classes. CART analyses for varying fire size classes used the same fire-size classes as Brosofske et al. (2007) for purposes of comparison. Fire-size classes were: all fires (n = 16,128), all fires > 0.4 ha (1 acre, n = 10,728), all fires > 4 ha (10 acres, n =

4,008), all fires > 16 ha (40 acres, n = 1,554), and all fires > 40 ha (100 acres, n = 507). "No fire" observations equal to the number of fire observations in each class were randomly obtained from the total "no fire" data pool. Classification trees were controlled by requiring 10 observations to exist in a node in order for a split to be considered, a minimum of 5 observations in any terminal node, splits to decrease the overall lack of fit by a complexity factor (cf) of 0.001, a maximum depth of four nodes not counting the root node.

I used logistic regression for developing a predictive model of fire probability. The dependent variable was a binary (no fire, fire) classification of PLS sections. Independent variables were the ecological and anthropogenic PLS section characteristics (Table 6.3). Prior to analysis, I examined Spearman rank correlations among predictor variables and eliminated independent variables from the initial set based on correlations above 0.6 between candidate variables (Table 6.3). In addition, I examined the distributions of the independent variables and, if possible, explored the utility of data transformations during model development. Variance inflation factors (VIFs) were determined for the final model parameters by substituting the dependent variable for a continuous arbitrary variable and using the PROC REG command in SAS (SAS Stat 2002). All parameters in the final model had a VIF less than 2.6 indicating minimal collinearity among predictors.

Logistic regression was implemented using the PROC LOGISTIC procedure in SAS with a descending option (i.e., probability of fire event as opposed to non-fire event).

The logistic model took the form:

Logit (P) =
$$\log[P / 1 - P]$$

= $\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$ (1)

Where P is the probability that a fire occurs, α is the intercept, and β_n are slope parameters associated with the independent variables X_i (Hosmer and Lemeshow 2000). The probabilities can be quantitatively expressed in terms of the independent variables by:

$$P = \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n) / 1 + \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)$$
(2)

Variables entered and were kept in the model if their probabilities were $P \le 0.05$. Criteria for judging models included model r-square and max-rescaled r-square, model and variable significance (Wald chi-square tests), model parsimony, and judgments about the biological relevance of model parameters and their signs. In addition, models were judged using the receiver operating characteristic (ROC) attempting to develop a model with a minimum c statistic (i.e., area under the ROC curve) of 0.70 (a "reasonable" discriminatory level, Pearce and Ferrier [2000]). Model variable validation and model stability were judged by observing changes in model parameters, their signs, and model receiver operating characteristic through 100 bootstrap iterations using 5,000 observations. Fire probability predictions were compared to the original point pattern and results of Brosofske et al. (2007) and Yang et al. (2008).

The fire probability model was validated by comparing rotation intervals calculated using model estimated fire probabilities (1986-2007) to those generated from fire records from different time periods. Rotation intervals were calculated from fire probabilities as:

$$(A_C/\overline{X}_{F)}/P) \quad (3)$$

Where A_C is the area of the probability cell (e.g., 640 acres), \overline{X}_F is the regional mean fire size (e.g., 30 acres), and *P* is the annual fire probability. Mean, maximum, and minimum fire rotation intervals were compared to those generated for the MTNF, the Missouri Ozark Highlands region, and Missouri fire districts (Westin 1992).

Fire probability and risk maps

Fire probabilities were mapped by applying the logistic regression model to the GIS layers. A 1 square mile grid was created for the entire study region to avoid problems associated with differing PLS section sizes and their arrangements. Model parameters were recalculated for this new grid prior to mapping the logistic equation. Risk maps were generated for the purpose of rating locations considering both ignitions and fuels information. Fire risk indices are meant to represent the risk to forestlands burning whereby more fires (i.e., increased fire probability) and more severe fires (i.e., increased fire hazard) represent increased fire risk. Fire risk indices were calculated as the product of ignition probabilities and fuel hazard indices (see Chapter 5, Figure 5.6). Since fuel hazard indices were developed for 30 m cells, I resampled the final ignition probability

prediction grid to 30 m prior to calculating fire risk indices. I displayed risk indices for November, March, and July; three equally spaced months that represent the highest fall season fire occurrence, highest spring season fire occurrence, and low summer season fire occurrence (Figure 6.3). Maps of fire risk were calculated using the fuel hazard maps that were created for two Palmer Drought Severity Index (PDSI) conditions; incipient wet (PDSI = 0.5 to 0.99) and moderately dry (PDSI = -1.0 to -2.0). I assumed that wetter conditions would represent overall low risk and drier conditions would represent overall high risk based on the results from Chapter 5.

RESULTS

Many characteristics of fire events appeared to be similar between the study area states. For example, the number of fires per month showed spring season fires tended to be most common followed by fall season fires (Figure 6.1). Fires most commonly occurred between 11 am and 3 pm (Figure 6.2). The majority of fires were represented from relatively smooth as opposed to rough terrain, at relatively low road densities, and within a range of similar elevations. The majority of fires from all states were less than 10 acres in size. The number of fires per year was perhaps the most dissimilar fire event characteristic between states.

The distribution of fires within Missouri was estimated using the *K*-function (Ripley's K) and showed fires were significantly clustered within a distance of 20 km (Figure 6.4). Based on the semivariogram of fire probabilities it appeared that no spatial autocorrelation structure existed. Maps of the point kernel density showed highest density of points occurred in the vicinity of Camden and Laclede counties of Missouri (i.e., Lake of the Ozarks). Several other locations also showed high point densities and were associated with national forest lands.

The majority of classification trees split first on precipitation (PRECIP) at about 106 cm (41.7 in) (Figure 6.5). Percent area in forest (PERCFOREST) was consistently the next splitting factor and was most important for fires > 40 ha (100 ac). Splits occurred when percent forest was near 50 percent. All classification trees indicated that higher elevations (ELEV) were associated with fire occurrences with all splits occurring between about 210 and 260 meters (Figure 6.5). Area of Mark Twain National Forest (MTNF_m2) was present in trees of fires > 4 ha (> 10 ac) with all trees indicating increased area of Mark Twain National Forest was associated with fire. For anthropogenic variables only road density (RD_DENS) and median age of males (MED_AGE_M) appeared in classification trees, both of which were higher order splits and found in trees of fires > 16 ha (> 40 acres).

Overall the variables identified through logistic regression were the same as those identified from CART analysis. The final logistic model contained eight ecological and anthropogenic parameters (Table 6.4). All variables were significant based on Wald chisquare tests. The area under the ROC curve was 0.727 and can be considered as indicating adequate discriminatory ability. Bootstrapping the data did not change the final model variable set nor variable signs, however occasionally the number of vacant homes (VACANT) entered the model. Model validation used comparisons of rotation intervals estimated using the fire probability model and those generated from fire records. For the MTNF, model predicted fire rotation intervals were longer than those generated

using older agency fire records and data in Brosofske et al. 2007 (Table 6.5). Similarly, fire rotation intervals predicted for the larger Ozark Highlands (and sub-regions) were compared to those generated from several smaller state fire districts. Overall, rotation intervals were longer than documented for several Ozark districts, except for the Bootheel district where estimated rotation intervals appeared to be comparable to those generated from fire records (Table 6.5). Other comparisons for moderate drought years suggest that rotation intervals could be shortened by one-third or more during prolonged drought conditions (Table 6.5).

Fire probability and risk

Predicted fire probabilities ranged from 0.00049 to 0.042 per square mile per year. The majority of the study area was represented by low probabilities (< 0.001). Predictions of fire probabilities indicated that areas of the inner Missouri Ozarks, particularly in the vicinity of large areas of government lands, had the highest fire probabilities (Figure 6.7). In terms of Missouri, transitioning from interior Ozark locations to outer Ozark locations generally represented decreasing fire probabilities. Larger river valleys were generally associated with lower fire probabilities such as the Missouri, Mississippi, and Wabash Rivers. This may not be the case for lands along the Ohio River as large areas on the southern borders of Indiana and Illinois showed relatively higher risk compared to more northern locations in the same states. In Illinois, higher fire probabilities were concentrated in the vicinity of the Shawnee Hills and Shawnee National Forest. In

Indiana, a more patchy pattern of areas of higher fire risk were observed that were strongly associated with the more heavily forested government lands.

Fire risk indices represented both fire probabilities and fuel hazard. Risk indices ranged from $1.6E^{-6}$ to 0.02. Overall, Missouri had the greatest fire risk compared to Illinois and Indiana (Figure 6.8). Similar to fire probabilities, the highest risk indices were located in the interior of the Ozark Highlands and lowest risk indices occurred throughout Illinois, Indiana, and northern and eastern portions of Missouri. In Missouri, the pattern of indices showed to generally decrease along a line corresponding to Interstate 44 – a direct route from St. Louis to Springfield, Missouri.

Incipient wet conditions represented lower overall risk compared to mild drought conditions (Figure 6.8). Of the three months considered November showed to have the highest fire risk followed by March then July. Some cells showed to go relatively unchanged particularly those that were heavily forested and located on government lands. During incipient wet conditions risk was extremely low across the entire study area. Increased drought conditions and fuel hazard caused risk indices to increase and accentuated risk differences, particularly in the Ozarks. Although more area of increased fire risk occurred during drought the general spatial pattern in fire risk was still similar to that of incipient wet conditions (Figure 6.8). During mild drought conditions greatest risk occurred in November followed by March and July. Throughout all months the southeastern portion of Missouri appeared to have the greatest area of high risk. In particular, the region between the Salem-Potosi and Eleven Point districts of the Mark Twain National Forest had the highest risk as did many areas along a line from Summersville to Branson, Missouri (Figure 6.8).

DISCUSSION

One of the most significant findings of this study was the identification of several variables that are important for understanding the distribution of modern wildfire occurrences. When considering the role of temperature and precipitation, though found to be important, these variables should be carefully interpreted with regard to their influence on fire occurrence. For example, precipitation can be both positively related to fire in hot-fuel limited environments and negatively associated with fire in cool-wet environments (Westerling et al. 2003, Guyette et al. 2006a). In hot-fuel limited environments increased periods of precipitation may promote fire through increases in fuel production. In cool-wet environments increased precipitation may prohibit fire by limiting ignition potential through fuel moisture. It was somewhat surprising that precipitation was a significant predictor variable of fire probability because it has not been previously regarded as a major influence of fire within the study area. Although regression and CART analysis identified precipitation as an important predictor variable of fire probability, the results may contradict each other. Regression analysis suggested a negative relationship between precipitation and fire probability while partitioning (i.e., CART analysis) suggested a positive association. More specifically, CART analysis suggested that a threshold in precipitation of about 106 cm is important in determining the occurrence of fires. This precipitation isohyet coincides with a rapid transition in fire point densities (and modeled probabilities and risk) that occurs in the northern portion of the study area in Missouri roughly following the Missouri River. Interestingly, this

isohyet also roughly defines 1) the ecotone between the eastern deciduous forest and prairie lands connected to the much drier and smoother Great Plains and 2) the transition into communities of German settlement origin to the north to Scotch-Irish in the Ozarks interior (Gerlach 1986)⁹. Although not fully known, precipitation may be a surrogate for a closely related characteristic such as the prairie-forest border, changes in culture, or land use.

Overall, the predicted pattern of fire probabilities was accurately portrayed from the fire point data. Verification was that patterns of fire point data (Figure 6.5) and fire probabilities (Figure 6.7) were similar. One major concern in model development was that a model developed from Missouri data may not accurately portray the fire probability patterns of Illinois and Indiana. In comparing the fire probability pattern to the distribution and density of MODIS detected fires (2000-2007), it appears that the predicted pattern of low fire probabilities throughout large portions of these states is observable in MODIS data. Furthermore, although data are somewhat limited in numbers of observations, the pattern of increased density of fires on government lands is also observable. In Missouri, this is particularly the case in the vicinity of Lead Mine CA, Drury-Mincy CA, and portions of the MTNF. In Missouri, Yang et al. (2008) also found national forest lands, including private inholdings, had increased fire probabilities. Public lands burn more frequently than private lands across large portions of the U.S. (Zhai et al. 2004). It is not clear whether or not this pattern is holds in Illinois and Indiana. MODIS

⁹ Although not shown, the density of fires (2001 to present) immediately to the west of the study area (i.e., in the Great Plains) is much higher. If this increased density be related to drier conditions in prairielands then much higher fire probabilities would be expected for western Missouri during drier conditions.

fire detection data from these states show that relatively few fires have occurred on national forest lands between 2000 and 2007. Certainly, one counterpoint to using MODIS data to describe current fire patterns is that the detections do not discriminate between wildfires and prescribed fires, although the relevance of this point is debatable. Certainly public lands commonly have higher numbers of wildfires in many regions. Brosofske et al. (2007) stated that arson fires constituted 73 percent of all fires between 1986 and 2002, and other portions of Missouri (e.g., vicinity of Lead Mine CA) have very high arson rates (Westin 1992). With regard to wildfires and prescribed fires, the mechanisms influencing the fire probability model may not differ and many of the variables related to the probability of wildfires are likely related to prescribed fires as well. Furthermore, although prescribed fires are controlled, they can result in a wildfire and wildfire response.

Fires were negatively associated with population density – a relationship widely found across the eastern United States (Zhai et al. 2003, Yang et al. 2008). One important broad factor not accounted for by the fire probability model was the cultural influence on fire distributions. In the study area, the area of highest fire density (i.e., Camden and Laclede Counties, Missouri; Figure 6.5) were not well predicted by the fire probability model (Figure 6.7). In this area a cultural burning legacy continues that is considered both a tradition and arson. Jenkins (1997) translated the practice of burning in this region through "interviews with locals". In short, these interviews confirmed the presence and longevity of a cultural fire tradition and described annual burning, a resistance to stop burning, needs for grazing lands, and historic fire feuds. Westin (1992) described this region (Lake Ozark and Clinton districts) as the only one in Missouri where arson caused

fires exceeded that of other causes (period: 1970-1989). Some land managers have suggested that the occurrence of these fires will subside once the elders occupying the region die. These fire traditions are attributed to the traditions of the Scotch-Irish descendents whose fire practices were the most pronounced (in terms of high fire frequency) in the historical record (Guyette et al. 2002). Maps showing the distribution of the origins of settlers in Missouri (Gerlach 1986) depict a large population of Scotch-Irish descendents overlaying nearly the identical area that contains the modern cluster of fires in the Lake Ozark vicinity. Although Gerlach's settlement origin map could be used to improve the predictability of the fire probability model, comparable maps were not available for Illinois or Indiana. In speculation, perhaps the increased burning in the southern Illinois' Shawnee Hills could also be related to cultural identities as much of the region was settled by immigrants from Appalachia who included immigrants from Scotland and Ireland (Meyer 1976).

Although human-fire cultural traditions and perceptions of government agencies are difficult to quantify and predict, the limitation of access has been studied and is perhaps better understood in the study area. On the MTNF, both Yang et al. (2008) and Brosofske et al. (2007) found modern ignitions were highly dependent on roads. Yang et al. (2008) stated that burn probabilities increased up to a few hundred meters from roads after which it decreased gradually. These relationships commonly occur within a range of specific conditions (Wilson 1979) such as non-urban roads, but roads with adequate access and escape (Zhai et al. 2003, Brosofske et al. 2007, Maingi and Henry 2007, Yang et al. 2008). The density of roads and their speed limits are limited by topographic roughness (Guyette and Stambaugh 2008, Stambaugh unpublished data). Although

topographic roughness was attempted as a variable in the logistic model the variable mean slope showed to be a better predictor and was used instead. From Chapter 3, mean slope and topographic roughness showed to be near equal predictors of historic fire frequency despite having different overall methods of calculation and meaning. The fire prediction model suggested that slope was negatively associated with fire probability – a relationship that was common to other studies in the region (Yang et al. 2008), but may not hold in other regions (Dickson et al. 2006).

For purposes of comparing results, many of the methods used in this study closely resembled those of studies conducted within MTNF boundaries by Brosofske et al. (2007) and Yang (2005), hereafter abbreviated Brosofske and Yang. One important point is that Yang's study was conducted at a finer resolution while Brosofske, similar to this study, utilized PLS sections as the base cell and data summary resolution. With respect to the discriminatory ability of the model (i.e., area under the ROC curve), the model presented here was nearly identical to Brosofske's. Despite this study characterizing ignitions across a much larger region, many of the results and model parameters are similar between all of the studies. Both this study and Brosofske's and Yang's studies found road density and elevation to be significant variables. Brosofske also found precipitation and percent forest area as important variables with temperature being important only for fires ≥ 16 ha. Similar to this study, Yang found fire points to be more clustered than random distributed. Both this model and Brosofske's identified the Salem-Potosi and Doniphan-Eleven Point Ranger Districts as having relatively higher fire probabilities than other MTNF districts. One major addition of this study is that the results show that the study areas of Brosofske and Yang represent some of the highest

areas of fire density within the three state study region used here. It is unclear how this translates to the applicability of their models outside of MTNF boundaries; however the model presented here suggests that areas between MTNF Districts commonly have lowered fire probabilities.

Fire risk assessment

Fire risk pertained to the risk of forests burning and indices were designed so that increased fire frequency (i.e., fire probabilities) and fuel hazard represented increased fire risk. The scenarios of changing fire risk for different months and drought conditions exemplified that distinctly different levels of fire risk occur throughout the study area (Figure 6.8). Within a given square mile and drought condition, the increases in fire risk were related to monthly changes in fine fuels. It is important to review that the loading of coarse fuels (1 to 1000-hour) were not included in the fuel loading model because of the lack of defining a spatial pattern. Although unaccounted for in the risk indices, coarse fuels likely serve to further accentuate the fire risk map due to their lag in moisture retention. For example, during wet conditions larger fuels maintain higher moisture contents and are less flammable than litter. As drier conditions ensue, coarse fuels become increasingly flammable and serve to increase fire severity and duration. Findings of He et al. (2004) using simulations of fuels and ignitions support this notion. Their maps of fine- and coarse fuel loadings support that both the distribution of coarse fuels can be highly heterogeneous and fire risk can be assumed to increase with increased coarse fuel loading.

The logistic regression model showed that probability of fire increased with percentage of land owned by government agencies. When fuel hazard was considered, this resulted in the MTNF having the highest fire risk, particularly the Salem-Potosi District and the southwestern portion of the Cassville District. The highest fire risk indices in the entire study area were located in the area around the southwestern portion of the Cassville District. In general, national wildlife refuges were associated with areas of low fire risk. The refuges with greatest fire risk were the southernmost portions of Crab Orchard NWR (Illinois) and Big Oaks NWR (Indiana). In Missouri, state lands with high fire risk were located primarily within the Current River Hills (e.g., Sunklands CA, Peck Ranch CA) and other specific areas to the north (e.g., Indian Trail CA, Ketcherside Mountain CA) and southwest (e.g., Caney Mountain CA, Pilot Knob CA, Roaring River SP). In Illinois, relatively higher risk was associated within the vicinity of Shawnee National Forest lands, particularly in the vicinity of the La Rue-Pine Hills (Clear Springs and Bald Knob Wilderness Areas) and Bell Smith Springs (Bay Creek Wilderness). On the Hoosier National Forest, the area around Seton Knob on the Little Blue River had the highest fire risk. Other locations in Indiana with relatively high risk were the Harrison-Crawford and Clark State Forests.

CONCLUSION

This study outlines the conditions and describes the areas of fire occurrences and fire risk throughout the major forest regions of Missouri, Illinois, and Indiana. For many reasons described above, Missouri has a much greater proportion of fires and higher risk than the other states. The need to address these fire issues comes and goes as fire seasons are more and less active. The patterns of ignitions have been spatially consistent and observable through independent sources. Perhaps the most important and least predictable factor influencing fire risk is drought. From paleoclimate records, the full range of drought variability (and likely fire risk) has not been realized for decades. With the information here, organizations are better equipped to prepare for increased fire risk such as may be experienced when drought conditions become extreme or persistent. For national forests, risk mitigation may include fire danger campaigns and tactical suppression readiness in areas identified as having high fire risk. On private lands within areas of high fire risk, this may translate to creating a defensible space for wildfire protection. For rural communities, this may translate to increased fire education and outreach programs such as is supported by organizations such as Firewise Communities¹⁰.

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¹⁰ http://www.firewise.org/usa/index.htm

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Table 6.1. Fire record data by state and source for the western Central Hardwoods region study area.

area
study
for
data
record
of fire
Summary

State*	Source	Level	Spatial precision	Period	Records (n)
	National Fire Occurrence	federal lands	GPS	1986-1996	2526
	National Fire Occurrence	non-federal lands	GPS	1989-1997	9896
	National Fire Occurrence	county	centroid	1990-1997	6807
	Missouri Dept. of Conservation	RFD (non-federal)	section level / none	1990-2003	30942
	Missouri Dept. of Conservation	RFD (non-federal)	section level	1990-2003	8356
MO	Missouri Dept. of Conservation, Westin 1992	RFD (non-federal)	fire district / state	1939-1991	~190420
	USFS, Mark Twain National Forest	federal lands	GPS	1970-1995	6538
	National Fire Occurrence	federal lands	GPS	1986-1996	338
	National Fire Occurrence	county	centroid	1987-1996	187
	USFS, Shawnee National Forest	federal lands	GPS	1995-2005	217
	National Fire Occurrence	federal lands	GPS	1986-1996	107
	National Fire Occurrence	county	centroid	1986-1996	7663
	USFS, Hoosier National Forest	federal lands	GPS	1995-2004	324

Table 6.2. Monthly wildfire data by state and for all states from the National Fire
Occurrence database (1986-1996). Records are separated into two reporting
categories; reports from state agencies (state) and federal agencies (federal).

	I	Illinois		h	ndiana			Miss	ouri		All S	tates	
	state	federal	%	state	federal	%	state	%	federal	%	state	federal	%
Jan	na	20	5.9	na	2	1.8	24	0.2	129	5.1	24	151	5.0
Feb	na	39	11.5	na	8	7.3	1941	19.7	353	13.9	1941	400	13.4
Mar	na	91	26.8	na	31	28.4	3787	38.5	916	36.0	3787	1038	34.7
Apr	na	51	15.0	na	25	22.9	1805	18.4	479	18.8	1805	555	18.5
May	na	14	4.1	na	8	7.3	267	2.7	116	4.6	267	138	4.6
Jun	na	14	4.1	na	5	4.6	66	0.7	52	2.0	66	71	2.4
Jul	na	11	3.2	na	5	4.6	323	3.3	41	1.6	323	57	1.9
Aug	na	5	1.5	na	4	3.7	305	3.1	35	1.4	305	44	1.5
Sep	na	5	1.5	na	1	0.9	170	1.7	18	0.7	170	24	0.8
Oct	na	17	5.0	na	7	6.4	376	3.8	109	4.3	376	133	4.4
Nov	na	58	17.1	na	13	11.9	480	4.9	217	8.5	480	288	9.6
Dec	na	15	4.4	na	0	0.0	284	2.9	78	3.1	284	93	3.1
Sum		340			109		9828		2543		9828	2992	

Table 6.3. Independent variables used in CART and Logistic regression analyses to determine important model parameters and predict fire probabilities.

		Description	Units	Source
Eco	ological variables			
	SLOPE	Slope (mean, max, majority)	degrees	USGS
	TRI*	Topographic roughness index (mean, max, min)	indices	Stambaugh and Guyette 2008
	PRECIP	Mean annual precipitation	centimeters	PRISM
	MMAXTEMP	Mean maximimum temperature	degrees C	PRISM
	PERCAGRIC	Percentage agricultual land	percent	NLCD
	PERCFOREST	Percentage forest land	percent	NLCD
	ELEV	Elevation (mean, median, majority)	meters	USGS
	ECS	Ecological sections	binary	Nigh and Schroeder 2002
An	thropogenic variable	S		
	POPDENS	Population density	humans/km ²	US Census Bureau
	WHITE*	Residents of white ethnicity	number/km ²	US Census Bureau
	BLACK	Residents of black ethnicity	number/km ²	US Census Bureau
	AMERI_ES	Residents of American eskimo ethnicity	number/km ²	US Census Bureau
	ASIAN	Residents of Asian ethnicity	number/km ²	US Census Bureau
	HAWN_PI	Residents of Haw aiian ethnicity	number/km ²	US Census Bureau
	OTHER	Residents of other ethnicity	number/km ²	US Census Bureau
	MULT_RACE	Residents of multiple ethnic race	number/km ²	US Census Bureau
	HISPANIC	Residents of hispanic ethnicity	number/km ²	US Census Bureau
	MALES*	Residents	number/km ²	US Census Bureau
	FEMALES*	Residents	number/km ²	US Census Bureau
	AGE_UNDER5*	Residents under age of 5	number/km ²	US Census Bureau
	AGE_5_17*	Residents betw een ages 5 and 17	number/km ²	US Census Bureau
	AGE_18_21*	Residents betw een ages 18 and 21	number/km ²	US Census Bureau
	AGE_22_29*	Residents betw een ages 22 and 29	number/km ²	US Census Bureau
	AGE 30 39*	Residents betw een ages 30 and 39	number/km ²	US Census Bureau
	AGE_40_49*	Residents betw een ages 40 and 49	number/km ²	US Census Bureau
	AGE_50_64*	Residents betw een ages 50 and 64	number/km ²	US Census Bureau
	AGE_65_UP*	Residents betw een ages 65 and above	number/km ²	US Census Bureau
	MED_AGE	Median age	years	US Census Bureau
	MED_AGE_M*	Median age of males	number/km ²	US Census Bureau
	MED_AGE_F*	Median age of females	number/km ²	US Census Bureau
	HOUSEHOLDS*	Houses occupied	number/km ²	US Census Bureau
	AVE_HH_SZ	Average persons per household	number/km ²	US Census Bureau
	HSEHLD_1_M*	Houses with 1 male	number/km ²	US Census Bureau
	HSEHLD_1_F*	Houses with 1 female	number/km ²	US Census Bureau
	MARHHD_CHD*	Houses with married couple and child	number/km ²	US Census Bureau
	MARHHD_NO_C*	Houses with married couple, no child	number/km ²	US Census Bureau
	MHH CHILD	Houses with only father and child	number/km ²	US Census Bureau
	FHH_CHILD	Houses with only mother and child	number/km ²	US Census Bureau
	FAMILIES*	Houses occupied by families	number/km ²	US Census Bureau
	AVE_FAM_SZ*	Average family size	number	US Census Bureau
	HSE_UNITS*	Housing units	number	US Census Bureau
	VACANT	Number of vacant homes	number/km ²	US Census Bureau
	OWNER_OCC*	Number of houses occupied by ow ner	number/km ²	US Census Bureau
	RENTER_OCC*	Number of houses occupied by owner Number of houses occupied by renter	number/km ²	US Census Bureau
	RD_DENS	Road density (min, max, mean)	km/km2	US Census Bureau
	DIST_TO_FD	Distance to rural fire department (mean, max)	km	MDC
	MTNF_m2	Area of Mark Tw ain NF	m2	MTNF
	MDC_m2	Area of Missouri Department of Conservation	m2	MDC
		Area or missouri Department or Conservation	112	

Parameter ^{a,b}	Estimate	SE	Pr > ChiSq
Intercept	-19.21550	0.43810	<.0001
PRECIP	-0.00832	0.00315	0.0083
RD_DENS	0.21990	0.01700	<.0001
ELEV	0.00701	0.00016	<.0001
POPDENS	-0.04870	0.01110	<.0034
MMAXT	0.84120	0.02870	<.0001
SLOPE	-0.04390	0.00554	<.0001
PERCFOREST	0.01840	0.00058	<.0001
PERCGOVTLAND	0.00163	0.00056	<.0033
c ^c	0.727		
^a Soo Tablo 6.2 for paramoto	r descriptions		

Table 6.4. Parameter estimates for the logistic equation predicting fire occurrence in square mile sections of the study area in Missouri.

^a See Table 6.3 for parameter descriptions

^b probabilities based on Wald chi-square test

^c Area under the ROC curve

Table 6.5. Comparisons of rotation intervals generated from the fire probability model and federal, state, and historical fire records.

	Rotation intervals (yrs)				
	mean	min	max	Source	
Mark Twain National Forest					
Predicted (1986-2007) ¹	743	506	9275	fire probability model	
Fire records (1970-1985)	468	231	1454	MTNF	
Fire records (1986-2002)	220	na	na	Brosofske et al. 2007	
Missouri Ozark Highlands					
Predicted (1986-2007) ¹	2133	506	21333	fire probability model	
Fire records $(1952)^2$	na	42	na	Westin 1992	
Fire records $(1980)^2$	na	182	na	Westin 1992	
Fire history (1700-1820) ³	na	4	na	Guyette 1995	
Missouri Forest Districts (1970-1989)					
Fire records (Bootheel)	1176	375	24809	Westin 1992	
Fire records (Lake Ozark)	95	57	419	Westin 1992	
Fire records (Clearwater)	444	165	3152	Westin 1992	
Fire records (Eminence)	289	125	3156	Westin 1992	

¹assumed a mean fire size of 12 hectares (30 acres)

²mild drought conditions, considered a relatively active fire year

³based on fire scarred trees from Current River watershed

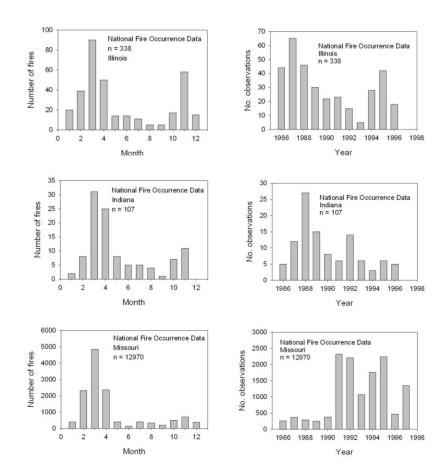


Figure 6.1. Histograms of fires by month (left graphs) and fires by year (right graphs) for each state in the study area.

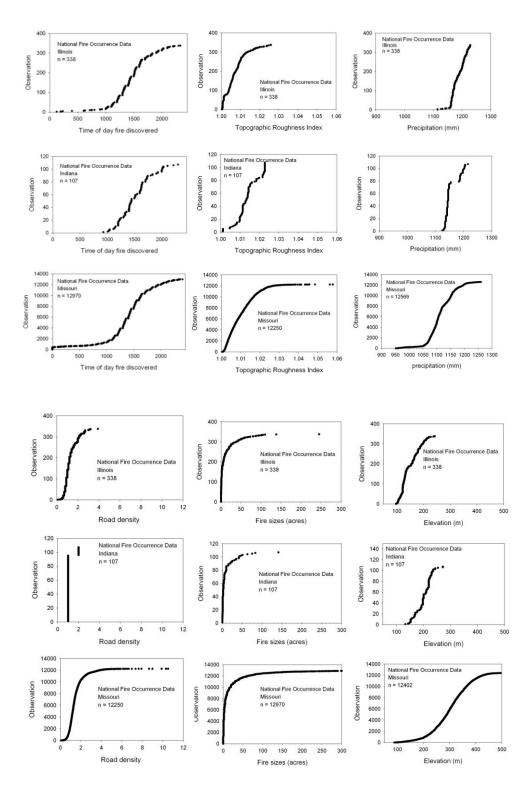


Figure 6.2. Six sets of cumulative distributions of fires displaying the betweenstate similarities with regards to various fire characteristics (source: National Fire Occurrence Data).

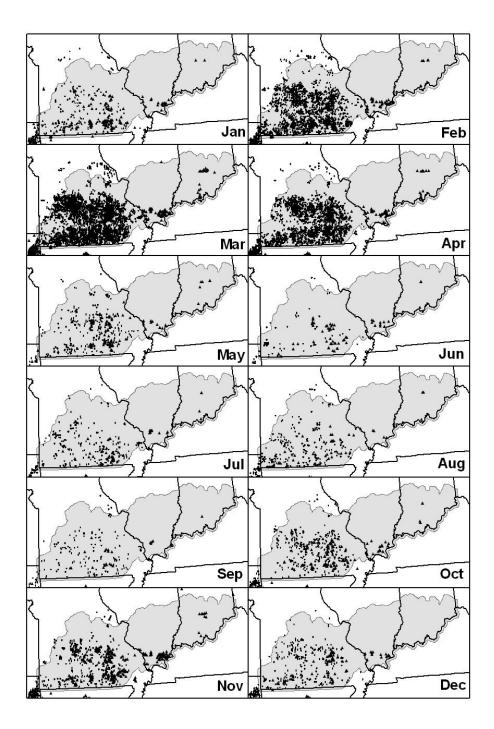
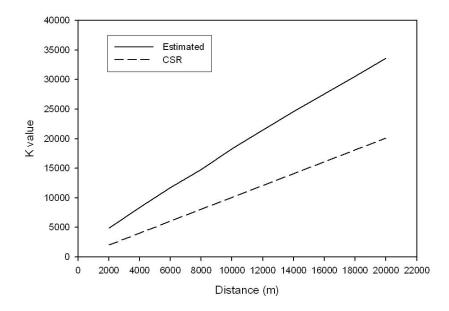
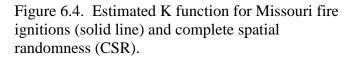


Figure 6.3. Monthly fire locations for the study area (grey) (source: National Fire Occurrence Data). Only limited data are represented for Illinois and Indiana (see Table 6.1 and 6.2).





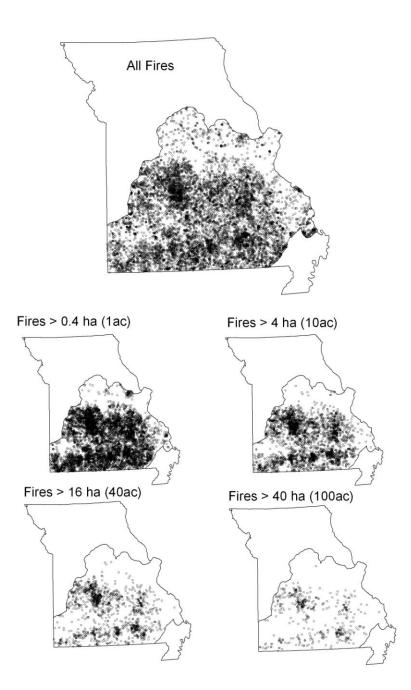


Figure 6.5. Locations of fires by fire size classes for the 20 year period (1986-2007, missing 1998 and 1999). The figure of all fires represents the data used in the CART analysis (see Figure 6.6) and the development of the fire probability model.

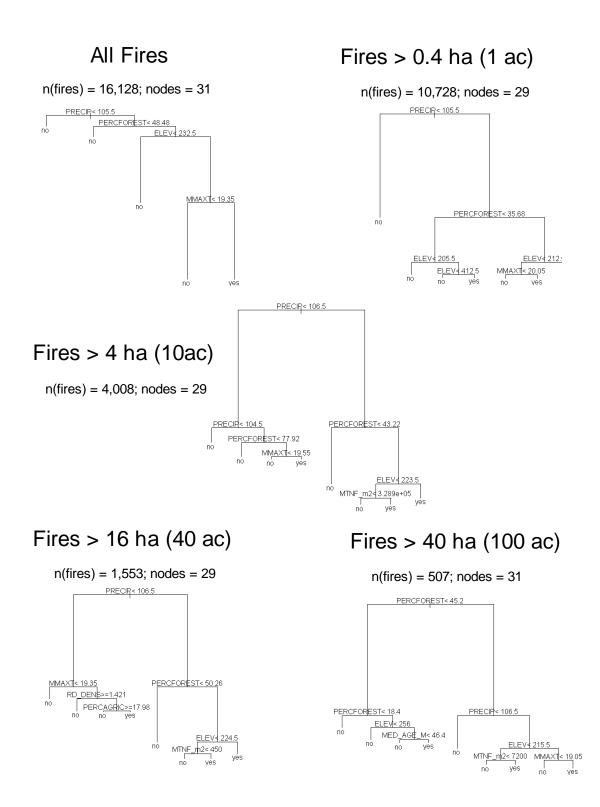
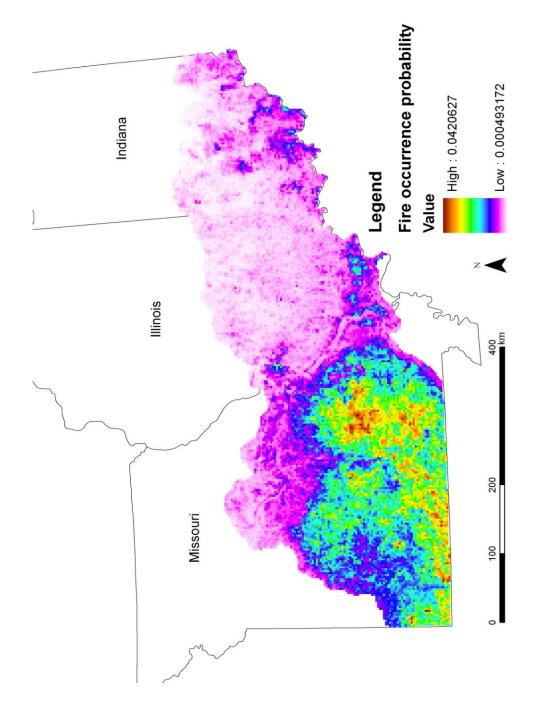
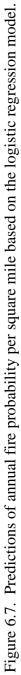


Figure 6.6. Classification trees for Missouri fires of 5 fire size classes (see Table 6.3 for variable explanations and methods for tree truncation rules).





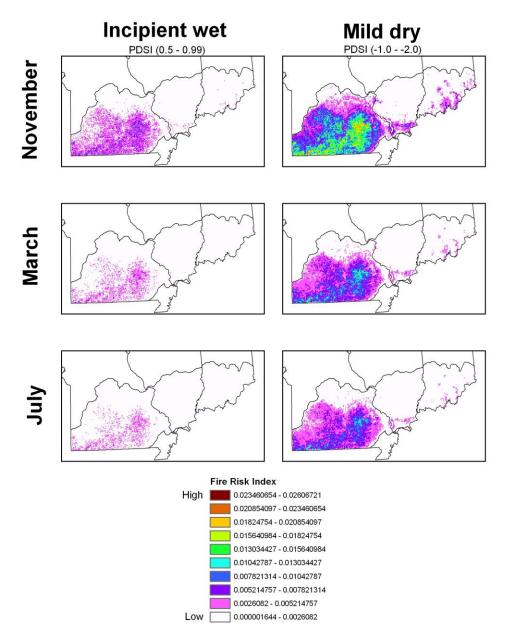


Figure 6.8. Fire risk indices (dimensionless) based on fire probabilities and changes in fuel hazard indices by month and drought conditions. Drought conditions are represented by the Palmer Drought Severity Index (PDSI) (see Chapter 5 for description of fuel hazard).

VITA

Michael Stambaugh was born November 13, 1973 in Rolla, Missouri, USA. He earned both a B.S. (1996) and M.S. (2001) degree in Forestry from the University of Missouri-Columbia.