EFFECT OF FIRE SIZE AND SEVERITY ON SUBSEQUENT FIRES USING DIFFERENCED NORMALIZED BURN RATIOS IN PINE DOMINATED FLATWOOD FORESTS IN FLORIDA

By

SPARKLE LEIGH MALONE

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LIST OF ABBREVIATIONS

AIC	Akaike's information criterion
BIC	Bayesian information criterion
dNBR	differenced Normalized Burn Ratio
MTBS	Monitoring trends in burn severity
NBR	Normalized burn ratio
NRCS	Natural Resource Conservation Service
NRMSC	Northern Rocky Mountain Science Center
PDSI	Palmer drought severity index
TSLF	Time since last fire
USFS	United States Forest Service
USGS	United States Geological Survey
WUI	Wildland urban interface

Abstract of Thesis Presented to the Graduate School
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By

Sparkle Malone

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Chair: Christina Staudhammer
Cochair: Leda Kobziar

Florida forests naturally experienced frequent low intensity fires, yet fire exclusion polices have altered the forest structure. The Osceola National Forest in north Florida has experienced high wildfire occurrence for a number of years. Vegetation communities within the Osceola are fire dependent and require regular burning for ecosystem health. Although prescribed fire has been used to reduce wildfire risk and maintain ecosystem integrity across much of the forest, managers are still working to reintroduce fire to long-unburned units. The objective of this study is to use differenced Normalized Burn Ratio (dNBR) to evaluate the relationships between previous fire severity, size, and historical frequency to inform prioritization and timing of future fire use. Based on remotely-sensed Landsat imagery, dNBR analysis captures spectral features over a time interval, and indicates the degree of change that is due to fire. This analysis has shown that fires in areas burned 5 or more years prior exhibited a higher probability of experiencing moderate-high severity fire and have a higher probability of increasing in severity level in subsequent fires. Areas that have not experienced fire in 10 years are indistinguishable from areas that have never burned. Using dNBR as a

method of analyzing past fire severity is a useful tool for managers to determine the lasting effects of prior fire severity. The analysis has further provided an effective method of determining fire frequencies necessary to maintain the optimum level of wildfire protection.

CHAPTER 1
INTRODUCTION TO FIRE IN THE SOUTHEASTERN UNITED STATES

Introduction

Fuel is any combustible material that is used to maintain fire. Without regular fire, fuel loads in forested ecosystems grow to dangerous levels increasing the risk of catastrophic wildfire. In systems where fire is a natural component, fuel management is important for ecosystem health. Wildfire risk is not only affected by fuel, the increase in population in the wildland urban interface (WUI) is also of great importance. Anthropogenic influences are a major source of wildfire ignitions. Land managers are currently working to reduce fuel accumulation in efforts to reduce the risk of catastrophic wildfires but sensitive areas within WUI create additional problems. Land managers are challenged with protecting surrounding land in a way that contributes to their management goals.

The focus of this project is on a forest wide burn severity analysis in a north central Florida forest using differenced Normalized Burn Ratios (dNBR) for fires that occurred between 1998 and 2008. This analysis is important for the evaluation of past fire history and the effects it can have on subsequent fires. This study provides valuable information regarding appropriate fire regimes to keep fuel loads low enough to mitigate the effects of wildfires. This method of fire assessment using remote sensing techniques can easily be modified to evaluate past fire effects for any land manager to impart site specific statistics to their land management practices. The main objectives of this study are:

1. Determine how past fire size and severity level effect subsequent fire behavior?
2. Identify the relationship between fire size and the proportion of area burned at high severity?

Suppression in Pine Flatwoods

Pine flatwoods are successional communities with southern mixed hardwoods, mixed hardwoods, or bay heads as the climax community (Monk 1968). Without regular disturbance, this fire maintained community shifts to one of the 3 climax communities. Soil moisture and fertility determine which climax community is attained (Monk 1968). Historically, fires were ignited by Indian hunting parties to corral game, by naval store operators to reduce wildfire risk, by cattle owners to encourage grass growth, and by lightning (Heyward 1939). Pine flatwoods burned at a frequency of every 1-15 years (Maliakal et al. 2000). In the 1920s fire suppression began in the region (Frost 1993). Long-term fire exclusion altered stand structure permitting hardwood species to occupy pine flatwood forest at high densities (Gilliam et al. 1999; Heyward 1939). The lack of disturbance created conditions outside the evolutionary history of species adapted to this disturbance regime giving species adapted to less frequent disturbance the advantage (Maliakal et al. 2000).

Pyrogenic species survive fire by either sprouting to regenerate or are able to withstand repeated burning by maintaining features that allow the plant to survive fires (Abrahamson 1984). Pine species have evolved to have thick bark and high crowns (Waldrop et al.1992) while other species re-sprout or seed (Abrahamson et al. 1996). The majority of non-coniferous woody species re-sprout from underground reserves rather that re-seeding (Abrahamson et al. 1996). Changes in vegetation following

extended periods of suppression leads to more intense, patchier, and less frequent fires which may require more extreme conditions to burn (Maliakal et al. 2000).

Fire as a Forest Management tool

One of the most effective tools for fuel management in the southeastern United States is prescribed burning (Davis et al. 1963). The purpose of using prescribed fire as a management tool is to reduce fuel accumulations to levels that minimize damage from wildfire and wildfire occurrence (Davis et al. 1963), improve wildlife habitat, reintroduce fire to pyrogenic communities and, conserve biodiversity (Outcalt et al. 2004). Fire management in Florida is largely dictated by urban encroachment, forest fragmentation, and the challenges associated with smoke management (Wolcott et al. 2007). As long as fuel loads are kept below 5 years, using fire to reduce the occurrence of catastrophic wildfires is a profitable investment (Davis et al. 1963). Past research has shown that wildfires could be kept small and damage limited with regular use of prescribed fire. Regular prescribed burning keeps fuel accumulations on the forest floor and in the understory within tolerable levels (Outcalt et al. 2004).

The amount of time that has passed after fire can greatly affect wildfire behavior and effects. Davis et al. (1963) found the wildfire occurrence rate for areas on the Osceola that contained fuel loads 3 years and older were higher than lower fuel loads. Large fires were also found to be restricted by roughs 5 years and greater (Davis et al. 1963). As fires moved into younger roughs, intensity level was reduced to a degree where suppression was possible (Davis et al. 1963). Outcalt et al. (2004) also found a significant relationship between time since last fire and fire intensity. As time increased, fire intensity also increased (Outcalt et al. 2004). Fuel accumulations of 3 years or less

support fewer fires, lower fire intensities, and lower annual burned acreage (Davis et al. 1963).

Prescribed burns are implemented under optimal circumstances where conditions are suitable for vegetation consumption but not at levels to cause fire to become unmanageable. Favorable conditions are characterized by cool weather, relatively constant winds, dry litter, and wet soil (Davis et al. 1963). During prescribed burns wet areas burn lightly if at all. Understory fuel is partially consumed with little consumption of the duff layer (Outcalt et al. 2004). Therefore, wet areas (cypress ponds) generally carry very heavy fuel volumes. During extended drought periods, these areas (cypress ponds) dry up making them capable of very large very intense wildfires (Davis et al. 1963).

Mortality is a major issue in prescribed fire management. Prescribed fire is used to reduce the effects of catastrophic wildfire where a higher amount of mortality is likely to result. Outcalt et al. (2004) found prescribed fire to be efficient in reducing mortality levels and timber loss. Tree mortality was 64% in previously unburned areas and 17% in areas burned within the last 3 years (Outcalt et al. 2004). Outcalt et al. (2004) also found that relative moisture levels of an area influenced tree mortality. Mortality was significantly higher on wetter sites, likely due to high fuel loads. It was also shown that during extreme drought conditions, mortality was significantly higher on sites where fires had been absent for 5 or more years.

The most favorable timing of prescribed fire depends on management objectives and site characteristics. Flatwoods are generally burned either during winter (dormant

season) or summer burns (growing season). Vegetation and fuel consumption differs significantly between the two.

Winter, in north central Florida, is typically a dry season with most precipitation coming from periodic cold fronts. Ambient temperatures are lower reducing the total amount of heat transferred to surrounding vegetation during fire, resulting in less damage to plant tissues. Prescribed fires following fronts are manageable and allow the upper layers of litter to carry fire while lower layers are unavailable. This time of year, grasses and other fine fuels are avialible to burn while deciduous hardwoods have their food reserves below ground and are prepared to sprout back following fire. Dormant season burning affects the size, cover, and vigor of hardwoods but is not effective at reducing abundance.

Early spring is typically a season marked by thunderstorm development and lightning ignitions. Hydric communities are most likely available to burn during this time yet the prolonged time between precipitation events, make this season less desirable for most management objectives. Spring fires are useful for stimulating seed, raising insect populations, and increasing the quality of browse to boost food availability for wildlife.

Although summer is the hottest season, it is also the wettest. The increase in temperature causes fires to be more intense and more likely to cause damage to plants. This is also the season of thunderstorms. Unstable atmospheres associated with such events bring lighting, unpredictable wind speeds and direction that can complicate prescribed burning. Burns during this season must be carefully monitored. Summer fires reduce hardwood vigor allowing grasses and forbs to increase in abundance.

Fire Severity

Fire severity is a measure of ecological and physical change attributed to fire (Agee 1993; Hardy 2005). It is influenced by both abiotic and biotic factors. Abiotic determinants include weather, moisture, time of day, sunlight incidence, and slope (Oliveras et al. 2009). Vegetation attributes such as species, tree size, succession stage, and pathogens are among the many factors influencing fire severity (Cocke et al. 2005). The variability in landscape and weather conditions during a fire are the cause of heterogeneous burn patterns (Cocke et al. 2005). Major differences in severity are also associated with the location of the fire perimeter (Oliveras et al. 2009). Head fires burn with greater flame lengths and intensity than backing fires. Head fires move in the same direction as the wind while backing fires move against the wind. Consequently, we would expect to see greater severity in areas burned by heading fires than in areas burned by backing fires.

Low severity burns are characterized by lightly burned areas where only fine fuels are consumed with minor scorching of trees in the understory (Wagtendonk et al. 2004). Areas of moderate severity retain some fuels on the forest floor and have crown scorching in mid-large trees with mortality of small trees (Wagtendonk et al. 2004). High severity zones are generally composed of complete combustion of all litter, duff and small logs, mortality of small-med trees, and consumption of large tree crowns (Wagtendonk et al. 2004). Unburned and low burn areas serve as seed sources for more severely burned sections (Cocke et al. 2005).

Severity is important to monitor as its effects on exotic species establishment, soil responses, and regeneration can be significant. Large fires may remove existing plant biomass, providing ideal habitat for exotic species (Kuezi et al. 2008). Responses

in soil condition following fire can range from affirmative nutrient availability to loss of nutrients, soil micro-organisms, and changes in physical structure of the soil (Busse et al. 2005). The degree of canopy degeneration due to cambium and crown scorch can severely impact the ability to re-sprout or seed. Combined with the biophysical condition, plant recovery following a severe fire can prove nearly impossible for remnant vegetation (White et al.1996).

The same fire behavior can result in very different severity effects in over and understory vegetation, as well as in soil conditions (Wagtendonk et al. 2004). Burn severity effects aren't always evident directly following fire. Therefore, a fire severity analysis will help managers anticipate the short and long term effects of severity level, and how to better predict areas of potential high severity. The burn severity analysis will further improve our understanding of why and where fires burn severely.

Measuring Fire Severity with DNBRs

Fire severity can be effectively measured through remote sensing techniques. A differenced Normalized Burn Ratio (dNBR) captures the spectral response, over a time interval, and indicates the degree of change that is due to fire (Wagtendonk et al. 2004; Miller et al. 2006). The mapping methodology was initially developed and tested by the USGS Northern Rocky Mountain Science Center (NRMSC). Multi-temporal image differencing was employed to enhance contrast and detection of changes from pre- and post-fire images using Landsat Thematic Mapper (TM) bands 4 and 7 (Wagtendonk et al. 2004). Normalized Burn Ratios (NBR) were designed to enhance the bands' response to fire by normalizing their difference to compensate for variations in the overall brightness of the scene (Wagtendonk et al. 2004). The use of shortwave infrared bands was found to have the highest accuracy (Cocke et al. 2005). Employed

as a radiometric index, dNBRs are directly related to burn severity (Wagtendonk et al. 2004) and as long as the fire is within the resolution range of the satellite sensor, 30m, it is detectable (White et al. 1996).

Sensitivity to vegetation and soil moisture, changes in canopy cover, biomass removal, and soil chemical composition allow dNBRs to define different levels of burn severity. Fire effects on soil, litter, and vegetation impact the spectral response of the post-fire image (White et al. 1996 and Cocke et al. 2005). The degree of change between the two images determines the extent to which fire has affected the area of interest (White et al.1996). An increase in dNBR corresponds to an increase in severity level. Unburned areas have values near zero, signifying little to no change between the pre- and post-fire image (Wagtendonk et al. 2004). High severity areas have higher DNBRs due to greater vegetation die off (Kuezi et al. 2008). In order to model the fire severity accurately it is important to pair the pre- and post-fire images by phenology and moisture levels (Wagtendonk et al. 2004). Timing of acquisition can impact dNBRs if there is a significant difference in vegetation and moisture levels due to phenology, not fire (Wagtendonk et al. 2004).

Important to consider when using dNBRs is the chance that values are being influenced by events other than fire. Turner et al. (1994) used dNBRs in Yellowstone National Park and discovered bias in particular severity classes due to pine beetle infestation (White et al. 1996). Jakubauskas et al. (1990) found that burn severity is detected differently among conifers, deciduous trees, and shrubs due to re-vegetation patterns. In addition, drought stress and vegetation re-growth makes it difficult to discern low severity and unburned areas (Cocke et al. 2005). The highest accuracy is

achieved in detecting high severity burns (Cocke et al. 2005). More severely burned areas have a much greater difference in vegetation cover changing the radiation budget in the post fire image by a greater degree (White et al. 1996).

DNBR is used within the United States to appraise fire severity following major fires (Wagtendonk et al. 2004; Godwin 2008). Image differencing is one of the most accurate methods of detecting the level of change caused by fire (Cocke et al. 2005). It can accurately detect burn severity in a way that is repeatable. Beyond any other band combinations, NBRs emphasize the effects of fire. Other methods that use bands in the visible part of the spectrum introduce atmospheric interference from dust and smoke (Cocke et al. 2005). And, indices derived from near infrared and mid-infrared reflectance are not sensitive enough to remotely sense water stress (Wagtendonk et al. 2004).

Studies using dNBRs have been in efforts to calibrate severity levels (Cocke et al. 2005; Hoy et al. 2008), compare severity levels of a previous fires to a subsequent fires (Collins et al. 2009; Allen et al. 2008;), interpret the effects of fuel management on severity (Safford et al. 2009), and to monitor changes in vegetation over time (White 1996; Kuenzi et al. 2008) and topographical variations (Holden 2009; Oliveras et al. 2009). Currently in the United States there is a multi agency project, Monitoring Trends in Burn Severity (MTBS), using dNBRs to map burn severity and perimeters of large fires. This project uses data from 1984 – 2010 to identify national trends in burn severity in efforts to determine the effectiveness of the National Fire Plan and Healthy Forest Restoration Act.

Study Site

The Osceola National Forest is located in the northeastern portion of the state of Florida (Latitude: 30.34371, Longitude: -82.47322) about 40 miles west of the city of Jacksonville (Figure 1-1). The forest consists of pine flatwoods and areas of cypress and bay swamps. Pine flatwoods have an overstory of pines on low, flat, sandy, acidic soils with an understory of herbaceous plants and grasses. This community is fire dependent and requires regular burning for pine germination and maintenance of plant and animal communities. The lack of fire for prolonged periods will increase broad leaf woody vegetation and reduce herbaceous plant cover and eventually reduce pine germination. The main communities found within flatwoods on the Osceola are Longleaf (*Pinus palustris*) wiregrass (*Aristida beyrichiana*), and slash pine (*Pinus elliotti*) –gallberry (*Illex glabra*) -palmetto. In the low lying wet areas scattered throughout the forest are cypress (*Taxodium spp*) ponds.

Fire management of the forest consist of a prescribe burn fire frequency of 2-5 years for most managed compartments with areas that have never been an active part of their prescribed fire program. Fire frequencies are determined based on current forest type and the desired future condition of the forest. The largest struggle fire managers' face on this forest is burning large acreages every year given few days that are within specified prescribed fire weather conditions. Forest managers must also deal with smoke management issues associated with being near a major urban area, an interstate highway, and an airport.

Conclusion

Fire management in the southeast plays a crucial role in maintaining ecosystem health and protecting private and public land. Evaluating fire severity for 11 years of

fire data for the Osceola National Forest has the potential to provide very important information regarding fire frequencies necessary to reduce wildfire risk and the effects of previous fires on subsequent fires. The analysis aims to identify the effects of fire frequency, the time since last fire, and the severity level of past fires on fire behavior using inexpensive remote sensing techniques. This information can then be used to identify areas that should be a high priority for prescribed burning and areas that may require immediate attention if threatened by wildfire.

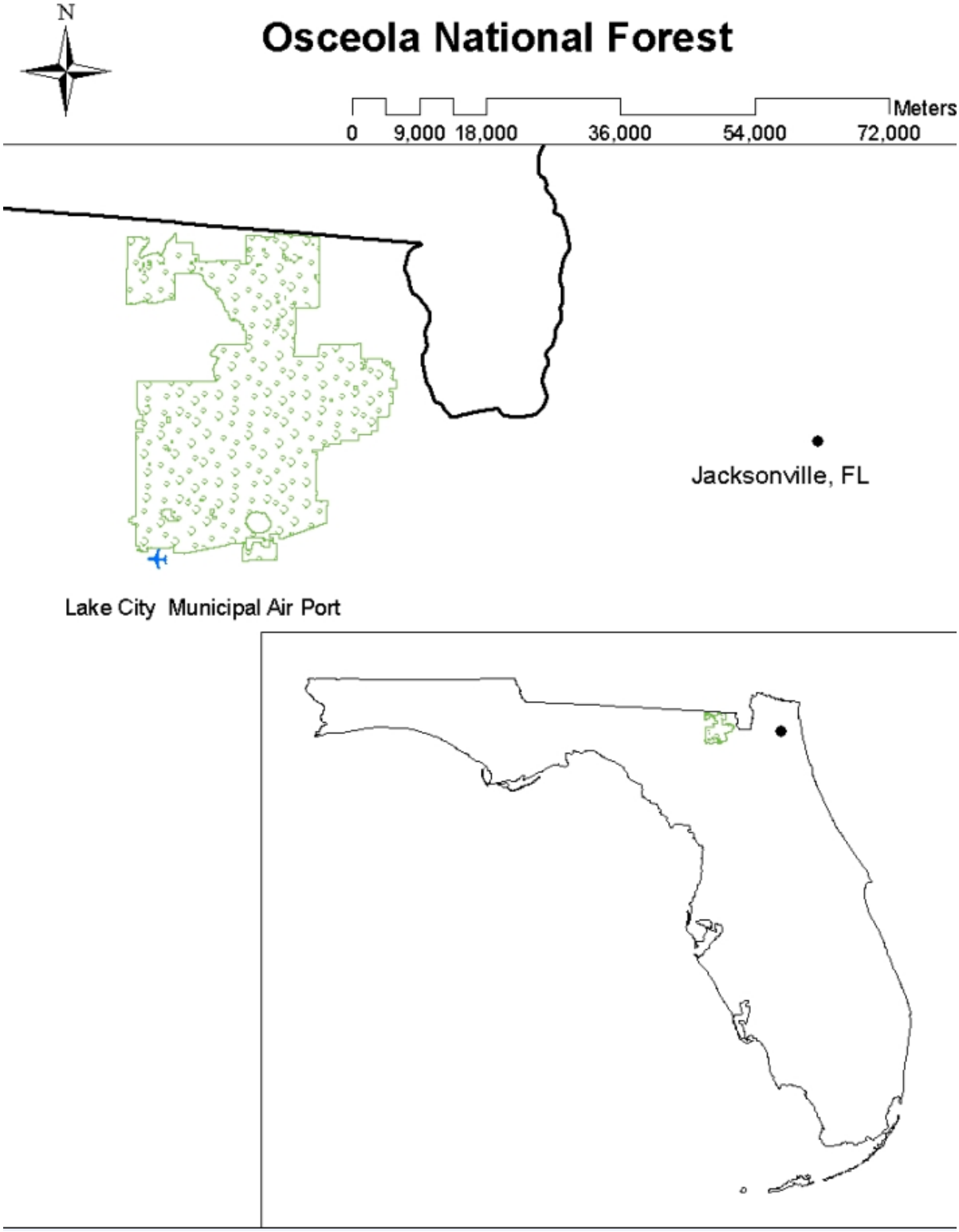


Figure 1-1. Osceola National Forest in North Florida.

CHAPTER 2
EFFECTS OF FIRE FREQUENCY, SIZE, AND TIME BETWEEN FIRE EVENTS IN NORTH FLORIDA FLATWOODS

Introduction

Prescribed fire is an important management tool in the south eastern United States. In pyrogenic communities that require regular burning for ecosystem health, forest managers are working to implement prescribed fire in place of natural wildfire cycles. Florida forest naturally experienced frequent low intensity fires yet high population, forest fragmentation, and dwindling budgets make prescribed fire management increasingly difficult. Sensitive areas (around major highways and roads, airports, and communities) reduce the amount of prescribed burning that can be done safely. Land managers are faced with decisions on how to implement prescribed fire in a manner that meets their management objectives and reduces the risk of catastrophic wildfire.

At present, land manager objectives include: reduced fuel accumulation to levels that minimize damage from wildfire (Davis et al. 1963), improved wildlife habitat, and the conservation of biodiversity (Outcalt et al. 2004). Timing of burning, fire frequency necessary to meet objectives, and the effects of fire are of major concern to land managers. Managers could greatly benefit from a quantifiable method of evaluating fire effects that is site specific. This study aims to develop a spatially explicit fire history for the Osceola National Forest that can be used to determine past fire effects and future implications.

Forested communities are in a constant state of change. They are continuously recovering from some sort of disturbance. The state of the community is a function of the frequency of disturbance, the time between disturbance events, and the severity of

the disturbance. The main source of disturbance associated with the species composition and abundance of pine flatwoods forests is fire.

In pyrogenic communities the frequency, intensity, and the amount of time between disturbances dictate community composition and further impacts the vegetative response to fire. Pyrogenic species promote and are able to support the spread of fire through the community. Without fire, pyrogenic communities become invaded with fire sensitive species reducing the communities' flammability. Fire sensitive species affect the way fire spreads through this community. These species don't facilitate fire as well as pyrogenic communities and may promote dangerous fire behavior if fuel loads are high.

Measuring Fire Severity

Fire severity is a measure of ecological and physical change attributed to fire (Agee 1993; Hardy 2005). Severity is influenced by weather, moisture, time of day, sunlight incidence, slope (Oliveras et al. 2009), species, tree size, succession stage, and pathogens (Cocke et al. 2005). Landscape variability and differences in micro-climate contribute to heterogeneous burn patterns and hence patchy severity (Cocke et al. 2005). Major variations in severity are also associated with the location of the fire perimeter (Oliveras et al. 2009). Head fires burn with greater flame lengths and intensity than backing fires. As a result, we would expect to see greater severity in areas burned by a head fires than in areas burned by backing fires.

Severity levels are characterized by the amount of fuel consumed, fire effects on residual vegetation, mortality, and changes in moisture levels. Low severity burns are characterized by lightly burned areas where only fine fuels are consumed with minor scorching of trees in the understory (Wagtendonk et al. 2004). Areas of moderate

severity retain some fuels on the forest floor and have crown scorching in mid-large trees with mortality of small trees (Wagtendonk et al. 2004). High severity zones have a high degree of combustion of litter, duff and small logs, mortality of small-med trees, and consumption of large tree crown foliage (Wagtendonk et al. 2004).

The same fire behavior can result in very different severity effects in over- and understory vegetation (Wagtendonk et al. 2004). Large, high severity fires have the potential to remove existing plant biomass, providing ideal habitat for exotic species (Kuezi et al. 2008). Responses in soil condition can range from affirmative nutrient availability to loss of nutrients, soil micro-organisms, and changes in physical structure of the soil (Busse et al. 2005). The degree of canopy degeneration due to cambium and crown scorch can severely impact the ability to re-sprout or seed. Plant recovery following a severe fire can prove nearly impossible for remnant vegetation (White et al.1996). Therefore, severity is important to monitor as its effects on exotic species establishment, soil responses, and regeneration can be significant.

To identify the effects of fire, remote sensing techniques can be utilized to model changes that are due to fire. Techniques have been developed to measure the amount of change to a system caused by fire. Normalized Burn Ratios (NBR) were designed to enhance the response of Landsat Thematic Mapper (TM) bands 4 and 7 to fire (Wagtendonk et al. 2004)(1). Multi-temporal image differencing is then employed to enhance contrast and detection of changes from pre- and post-fire images (Wagtendonk et al. 2004).

$$NBR = \frac{B_4 - B_7}{(B_4 + B_7)}$$

$$dNBR = NBR_{pre\_fire} - NBR_{post\_fire} \quad (1)$$

Differenced Normalized Burn Ratios determine the level of severity a 30 meter by 30 meter unit of landscape experienced due to a fire event by measuring the amount of change between a pre and post fire image (2). Employed as a radiometric index, dNBRs are directly related to burn severity (Cocke et al. 2005; Hoy et al. 2008; Godwin 2008; Allen et al. 2008, Wagtendonk et al. 2004). Fires within the resolution range of the satellite sensor, 30 meter, can be detected (White et al.1996).

Previous studies have used dNBRs to identify and monitor the effects of fire. Studies have used dNBRs to calibrate severity levels to specific forest types (Cocke et al. 2005; Hoy et al. 2008; Godwin 2008; Allen et al. 2008), compare severity levels between fire events (Collins et al. 2009; Allen et al. 2008;), interpret the effects of fuel management techniques on severity levels (Safford et al. 2009; Finney et al. 2005; Safford et al. 2009; Wimberly et al. 2009), and to monitor changes in vegetation over time (White 1996; Kuenzi et al. 2008) and topographical variations (Holden 2009; Oliveras et al. 2009; Duffy et al. 2007). There have also been efforts to relate remotely sensed severity to biophysical attributes and processes. Boer et al. (2008) used dNBRs to define severity as a change in leaf area index (LAI) in a pre and post fire image. Currently, there is a multi agency project, Monitoring Trends in Burn Severity (MTBS), using dNBRs to map burn severity and the perimeters of large wildfires for the entire United States. MTBS is using data from 1984-2010 to identify national trends in burn severity to determine the effectiveness of the National Fire Plan and Healthy Forest Restoration Act. Duffy et al. (2007) analyzed the relationship between the area burned

by wildfire and remotely sensed severity level. This study used NBRs for 24 wildfires in Alaska. The study found that the average burn severity increased with the natural logarithm of the area of the wildfire. Larger fires were more likely to contain areas that were more severely burned than smaller fires. Epting et al. (2005) evaluated the usefulness of 13 remotely sensed indices of burn severity to find that NBR and dNBR were the most accurate (Escuin et al. 2009), exhibiting high accuracy when compared with field based severity indices in forested areas. To our knowledge, no other study has used dNBRs to model how fire severity from previous fire affects subsequent fire over time. The Osceola National Forest in North Florida presents a unique opportunity to conduct such an analysis. Landsat imagery enables an investigation into the effectiveness of the Osceola's prescribed burning program for reducing wildfire severity, and lends insight into the complex interplay between fire severity, fuels recovery rates, time between fires, and subsequent fire severity.

Detecting burn severity for fires on the Osceola National Forest is in efforts to anticipate the short and long term effects of severity level and the effects of time intervals between fire events, and to predict areas of potential high severity. The burn severity analysis will further improve our understanding of why and where fires burn severely. The following questions fuel this investigation:

- 1. How does past fire size and severity level affect subsequent fire behavior?
- 2. Is there a relationship between the size of fires and the proportion of area burned at high severity?

We hypothesize that fires with a high severity level will have a negative effect on the severity level of fires occurring within three years. High severity fires are expected to have a lower severity level in subsequent fires as long as the second fire is within three

years. Vegetation recovery is not expected to reach pre-fire conditions within this time frame. We also hypothesize that larger fires will have a higher probability of experiencing high severity.

Study Site

On the Osceola National Forest, thousands of acres are burned every year to reduce fuel levels and manipulate succession stages. The Osceola is Located in north central Florida (Latitude: 30.34371, Longitude: -82.47322) 40 miles outside the city of Jacksonville. The Osceola consist of pine flatwoods with an overstory of pines on low, flat, sandy, acidic soils; pine flatwoods have an understory of herbaceous plants, grasses, palmetto, and woody species. This community is fire dependent and requires regular burning for ecosystem health. The main communities found within flatwoods on the Osceola are longleaf pine (*Pinus palustris*) -wiregrass (*Aristida beyrichiana*) and slash pine (*Pinus elliotti*) -gallberry (*Illex glabra*) -saw palmetto (*Serenoa repens*). Fire management on the Osceola and much of Florida is largely dictated by urban encroachment, forest fragmentation, and the challenges associated with smoke management (Wolcott et al. 2007; Duncan et al. 2004). These anthropogenic influences have reduced fire sizes and recurrence, increasing fuel connectivity and load (Duncan et al. 2004).

Prescribed burns are implemented under conditions that are suitable for vegetation consumption, yet not at levels to cause fire to become unmanageable. Favorable conditions are characterized by cool weather, consistent winds, dry litter, and wet soil (Davis et al. 1963). Prescribed fires are performed under conditions that promote low severity fire though variability in the landscape and weather conditions can cause higher severity levels. Hydric areas burn lightly if at all during prescribed burns.

Understory fuel is partially consumed with little consumption of the duff layer (Outcalt et al. 2004). Therefore, wet areas generally carry very heavy fuel volumes and during extended drought periods, these areas dry up making them capable of very large, very intense wildfires (Davis et al. 1963; Maliakal et al. 2000). The season of prescribed fire is determined by management objectives and site characteristics. Flatwoods are generally burned either during winter (dormant season) or early summer (growing season).

Methods

Data

DNBRs were developed for each fire event greater than 1ac on the Osceola National Forest. Severity levels were defined based on general severity classes provided by the United States Geological Survey (USGS). Severity classes were reclassified and merged into 4 main levels; unburned cells, low severity cells, moderate severity, and high severity (Table 2-1). To test the hypotheses, two datasets were developed, a time and fire size dataset. The time analysis dataset consisted of consecutive fire events (prescribed and wildfire), that were then separated into time intervals to indicate the time between fire events. To control for the number of times a pixel burned between fire events, pixels had to be unburned previous to the first fire and remain unburned until the second fire. For each pixel the following information was included in the data set: severity level of fire event 1, severity level of fire event 2, community type (hydric or mesic), forest type (pine, hardwood, and pine/hardwood), and Palmer drought severity index (PDSI) for the year before each event and the year of each event.

PDSI, developed in the 1965 by Wayne Palmer, is the most effective way of determining long-term drought (NOAA 2009). This method compares weather conditions to determine if they are abnormally dry or abnormally wet compared to historical weather data. The palmer index is based on the supply-and-demand concept of the water balance equation, taking into account more than just the precipitation deficit at specific locations. The index uses temperature, rain fall information, and the local available water content of the soil to determine dryness that is standardized to local climate. Standardization allows the index to be compared against different locations and time periods. PDSI uses 0 as normal and negative numbers (-1 to -6) to indicate drought (Table 2-2). Moderate drought is a -2, severe -3, and extreme drought is -4. To reflect excess rain the index uses positive numbers. A major advantage of this index is that it is standardized to local climate and can be applied to any part of the United States.

The fire size dataset was comprised of the 115 wildfires that occurred and were recorded on the Osceola National Forest from 1998-2008. Fires had to be at least 1 acre to be included in the dataset. For each fire the portion of cells burned in each severity class, the size in acres, season of fire, Forest Service forest type classification (Figure 2-1), soil drainage class (Figure 2-2), and PDSI values for the year of and before the fire event were recorded.

Model Development

Logistic regression techniques were utilized to model the probability of experiencing a high severity fire (model 1), the probability of increasing in severity level (model 2), the probability of burning (model 3), and the probability of decreasing in severity (model 4) for the time dataset. Logistic regression can be used to measure

binary responses by describing the relationship between one or more independent variables and the binary response.

$$y_i = \begin{cases} 1 \; success \\ 0 \; failure \end{cases}$$

3

Responses are coded as [0, 1] to [-∞, ∞] and y_i is a realization of a random variable Y_i that can take on the values of 0 and 1 with probabilities π_i and 1- π_i (3). The distribution of Y_i is a Bernoulli distribution with the mean (4) and variance (5) depending on the underlying probability π_i.

$$E(Y_i) = \pi_i$$

4

$$var(Y_i) = \pi_i \, (1 - \pi_i)$$

5

To make the probability π_i a linear function of a vector of observed covariates $\boldsymbol{x}_i$ the probability is transformed to remove the range restrictions (**6**).

$$\text{logit}\,(\pi_i) = \log \frac{\pi_i}{1 - \pi_i} = \boldsymbol{x}'_i \beta$$

6

Logits map probabilities from [0, 1] to [-∞, ∞]. Negative logits represent probabilities below ½ and positive logits represent probabilities above ½. Solving for the probability of success requires exponentiating the logit and calculating the odds of success (**7**).

$$\pi_i = \frac{\exp(\boldsymbol{x}'_i \beta)}{1 + \exp(\boldsymbol{x}'_i \beta)}$$

7

Maximum likelihood methods were used for parameter estimation. With this approach, parameters are estimated iteratively until parameters that maximize the log of

the likelihood are obtained. Goodness of fit statistics, Akaike's information criterion (AIC) and Bayesian information criterion (BIC), were used to compare competing models. AIC is a statistic that is used to rank different models based on how close fitted values are to true values (8) (Littell et al. 2006).

$$\mathrm{AIC} = 2k - 2\mathrm{In}(L) \tag{8}$$

Where: k is the number of parameters in the statistical model and L is the maximized value of the likelihood function for the estimated model (8). Like AIC, BIC was used to rank models with a different numbers of parameters to avoid increasing the likelihood by over-fitting the model (Littell et al. 2006).

$$\mathrm{BIC} = -2 * \mathrm{In}(L) + k\,\mathrm{Ln}(n) \tag{9}$$

Where: n is the sample size. Unexplained variation in the dependent variable and the number of covariates increases the BIC and AIC values (9). For both AIC and BIC, the lowest score indicates the best model.

The ratio of the Pearson chi-square to its degrees of freedom is used to determine if the model displays lack of fit. Values closer to 1 indicate that the model fits the data well (Littell et al. 2006). To address the assumption of independence among observations, a generalized linear mixed model was used using the SAS procedure PROC GLIMMIX. Correlation among responses is incorporated into the model by adding random components to the linear predictor. To account for the correlation among responses, random residuals were modeled.

Raster data is spatially correlated due to the adjacency of pixels. Although it would have been more effective to model the spatial correlation directly, without the aid

of a super computer this option is infeasible. The GLIMMIX procedure can also make use of several predictor variables that may be either numerical or categorical (Littell et al. 2006).

In this analysis we evaluated the probability of experiencing (1) moderate to high severity, (2) increased severity level, (3) burning, and (4) decreased severity between the first fire and the second fire at different time intervals. Variables used in the 4 models include: the severity level of the first fire event (unburned, low severity, moderate severity, and high severity), the time interval between fires (1-2, 3-4, 5-6, 7-8 and 9-10 years) (Table 2-3), the type of fire in the second fire event (wild or prescribed), and the PDSI for the year before and the year of each fire. The logit of the probability was modeled as

$$logit\left(\pi_{ijkl}\right) = \eta + \alpha_i + \beta_j + \gamma_k + \tau_1 X_{ijkl} + \tau_2 X_{ijkl} + \tau_3 X_{ijkl} + \tau_4 X_{ijkl} + \varepsilon_{ijkl} \quad \textbf{10}$$

where: η is the intercept, α_i (for i =1, 2, 3, 4) is the net effect of the *i*th severity level for the first fire, β_j (for j = 1, 2, 3, 4, 5) is the net effect of the *j*th time intervals between fire events, γ_k (for k= 1,2) is the effect of the type of fire, τ_1 is the effect of PDSI for the year prior to fire 1, τ_2 is the PDSI for the year of fire 1, τ_3 is the PDSI for the year before fire 2, τ_4 is the PDSI for the year of fire 2 and ε_{ijk} is the random error (10). Final model covariates were indicated by parameters that were significant based on the Wald chi-square statistic and the model with the lowest AIC and BIC value. Interactions between all parameters were also considered. Non- significant parameters were removed from the full model one at a time. To test for differences among categorical levels, least square means were produced and differences were tested.

Logistic regression was also used to examine the probability of burning at high severity for each fire size class for the fire size data set. Variables used in this model include: season of fire (winter, spring, summer, and fall), soil drainage class (1-9), Forest type (pine, hardwood, pine/hardwood, and hardwood/pine), and PDSI for the year before and the year of each fire (Table 2-4). Model selection was determined by goodness of fit statistics AIC and BIC. A backward selection method was used to determine the final model; first all parameters were included within the model, and then parameters were removed one by one based on the Wald chi square statistic.

Results

Data

The time data set is composed of 484,715 pixels. The majority of these pixels burned as prescribed fires in the second fire (341,143). Over all years for fire 2, there were higher percentages of cells experiencing low severity (40%), and high severity (~10%) (Figure 2-1). The proportion of cells burned in each severity class is shown by time (Figure 2-2, Figure 2-3, Figure 2-4, Figure 2-5, Figure 2-6). In fire 1 there was also a higher percentage of cells experiencing low severity (51%), while ~4% experienced high severity. The largest difference between the fires is the portion of cells in the low severity category, a 10% increase between fire 1 and fire 2, and the difference in cells in the high severity category,-5.6%. The major difference between the distributions of cells among severity levels is that unburned cells in fire 1 moved to a higher severity level.

Burned pixels were not evenly distributed over time. To reduce the amount of variation between years, categories were created (Table 2-3). Fires with 5-6 years

between events had the highest percentage of cells that burned at high severity in the second fire, with 53% for wild fires and 24.9% for prescribed fires burning at high severity (Figure 2-4). Time interval 3-4 years and 7-8 years had the highest portion of cells remaining unburned in the second fire event; ~70.8% and 49.4% remained unburned 3-4 years and 7-8 years after wildfire, respectively 51.4% and 81.6% remained unburned 3-4 years and 7-8 years after prescribed fires, respectively (Figure 2-3, Figure 2-5). In the second fire, wildfires had a much larger portion of the cells in the unburned and high severity category, 44% and 17%, respectively, versus prescribed fires. Overall, there was very little change in the proportion of pixels burned in each severity class between fire 1 and fire 2 ignoring time between events. Until time between fires reaches 5-6 years, prescribed fires decease in severity in the second fire more than they increase in severity. After 5-6 years more cells increased in severity than cells decreased in severity. Wildfires had a higher portion of the pixels decrease in severity over all time intervals except time interval 5-6 years where 77% of the cells increased in severity between the first and second fire.

Probability Modeling

Probability of experiencing moderate to high severity during a fire

Severity level **(**α_i) at the first fire, time intervals between the first and second fire (β_j), type of fire (γ_k), and the interaction between severity level and time interval$(\alpha\beta)_{ij}$, were significant predictors of the probability of experiencing high severity fire (11).

$$logit\left(\pi_{ijkl}\right) = \eta + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + \varepsilon_{ijkl}$$

11

The effects of PDSI were not significant parameters. The overall model was significant and the parameters were significant based on the Wald chi-square statistic (Table 2-5). Moderate and high severity levels were merged for this analysis to avoid convergence issues associated with low counts in the high severity category. The ratio of the Pearson chi-square statistic to its degrees of freedom is approximately 1 indicating good fit of the model to the data.

The probability of experiencing a moderate to high severity fire was higher for wildfires than prescribed fires. Overall, the probability of burning at a moderate to high severity class was low for all severity classes in fire 1 for prescribed fires (Figure 2-9). The probability of moderate to high severity was high for wildfires when the time interval was 5-6 years between fires (Figure 2-10). Areas with moderate and high severity in the first fire had the highest probability of high severity fire for both wild and prescribed fires (Figure 2-10, Figure 2-9). At 1-2 years between fire events, the probability of moderate to high severity fire was the lowest (Figure 2-9). The highest probability by time interval was at 5-6 years between fires, followed by 7-8, then 9-10 years. For wildfires, 3-4 and 7-10 years between events yielded very low (<1%) probability of moderate to high severity (Figure 2-10). Time interval 5-6 years had very high (>70%) probabilities of moderate to high severity for wildfire (Figure 2-10).

Probability of increasing in severity in subsequent fires

Model 2 estimates the probability of severity level increasing from the first fire to the second fire.

$$logit\left(\pi_{ijkl}\right) = \eta + \alpha_i + \beta_j + \gamma_k + \tau_1 X_{ijkl} + \tau_2 X_{ijkl} + \tau_3 X_{ijkl} + \tau_4 X_{ijkl} + \varepsilon_{ijkl} \quad \textbf{12}$$

The model includes the effects of severity level at fire 1 (α_i), time interval between fire events (β_j), fire type (γ_k), and PDSI value for the year prior to and the year of each fire (τ_1,τ_2,τ_3, and τ_4) for the kth measurement in the ith severity level and the jth time interval (12). The overall model was significant and the 8 parameters were significant based on their Wald chi-square statistics (Table 2-6). The ratio of the Pearson chi-square statistic to its degrees of freedom was close to 1(0.99), indicating good model fit to the data.

The probability of increasing in severity was modeled for all events where fire could increase (where the severity level in fire 1 was less than 4). As expected, the model shows that the probability of increasing in severity was highest for unburned cells, then low severity pixels and lowest for medium severity over all time intervals (Figure 2-11,Figure 2-12, Figure 2-13). For all severity levels the probability of increasing in severity was highest at 5-6 and 9-10 years between fire events (Figure 2-12, Figure 2-13). The probability of increasing in severity level was higher for wildfires than for prescribed fires and showed the same decreasing trend with increased severity both fire types. Time Interval 7-8 years was surprisingly low for both wild and prescribed fires.

Probability of burning during a fire

Model 3 examines the probability of burning (13).

$$logit\left(\pi_{ijkl}\right) = \eta + \alpha_i + \beta_j + \gamma_k + \tau_1 X_{ijkl} + \tau_2 X_{ijkl} + \tau_3 X_{ijkl} + \varepsilon_{ijkl} \quad \textbf{13}$$

The severity level of fire 1(α_i), time interval (β_j), fire type, and PDSI for the year prior to fire 1 and 2 and the PDSI for the year of fire 1 (τ_1,τ_2, and $\tau_3$respectively) were all

included within the final model(13). The model was significant and all parameters were significant based on their Wald chi-square statistics (Table 2-7). The ratio of the Pearson chi-square statistic to its degrees of freedom was close to 1(1.02) indicating good fit of the model to the data.

The probability of burning was approximately the same for each severity class (Figure 2-15, Figure 2-16). Areas that had been burned by prescribed fires had a higher probability of burning than areas that had been burned by wildfires for all time intervals and severity levels (Figure 2-15). Over time, the probability of burning peaked (~80-90% depending on severity level) at 5-6 years and, was the lowest for 1-2 and 7-8 years between fires.

Probability of decreasing in severity in subsequent fires

Model 4 predicts the probability of fire severity decreasing in the second fire (14).

$$logit\left(\pi_{ijkl}\right) = \eta + \alpha_i + \beta_j + \gamma_k + \tau_1 X_{ijkl} + \tau_2 X_{ijkl} + \tau_3 X_{ijkl} + (\alpha\gamma)_{ik} + \varepsilon_{ijkl} \quad \textbf{14}$$

The severity level of the first fire (**α_i**), time interval between fire1 and fire 2 (β_j), fire type (γ_k), PDSI value for the year prior to and the year of both fire 1 and fire 2 (τ_1,τ_2,τ_3, and τ_4), and the interaction between severity level and fire type were kept in the final model (14). The model was significant and the parameters were significant based on their Wald chi-square statistic (Table 2-8). The ratio of the Pearson chi-square statistic to its degrees of freedom was close to 1(1.03) indicating good model fit.

The probability of decreasing fire severity was modeled for all severity classes except unburned. Over all time intervals and severity levels, the probability of decreasing was lower for wildfires than for prescribed fires except at the low severity

level (Figure 2-17). At the low severity level, the probability of fire severity level decreasing for wildfires was the lowest and the probability increased with increased severity level. Both wild and prescribed fires show a reduced probability of decreasing fire severity level when fires were 5-6 years apart. The probability of decreasing fire severity level increased as the severity level increased for both fire types (Figure 2-18, Figure 2-19).

Fire size analysis

A useful model could not be found for the probability of burning at high severity using the fire size dataset. Fire size class was not a significant indicator of the probability of experiencing a high severity fire. The data indicated that larger fires had a higher portion of their pixels in the high severity size class so it was expected that larger fires would have a higher probability of experiencing high severity fire. The best model of the probability of high severity fire based on goodness of fit statistics included only fire size class yet the model yielded no significant relationship between fire size and the probability of experiencing high severity. The model parameters were not significant based on their Wald chi-square statistics (Table 2-9). The ratio of the Pearson chi-square statistic to its degrees of freedom was equal to 1 indicating good model fit.

Discussion

Probability of Experiencing Moderate to High Severity During a Fire

The probability of experiencing high severity fire has important implications for fire effects and the degree to which wildfires are being mitigated. Based on the severity level of the first fire event and time between events, this also has the capacity to identify target intervals between fires. The probability of experiencing moderate to high severity in the second fire was highest for time interval 5-6 years for all severity levels of the first

fire and both fire types (Figure 2-10). This indicates that by this point, vegetation has reached pre-fire conditions regardless of the severity level it burned at in the first fire. Davis et al. (1963) collected ground data from 380 fires in Florida and Georgia from 1955 to 1958 to evaluate prescribe fire effectiveness in reducing fire size and intensity. This analysis found that fuel loads must be less than 5 years to adequately reduce the occurrence of catastrophic wildfire on the Osceola National Forest. Vegetation is able to recover quickly due to fast growing and re-sprouting species further fueled by an increase in nutrient availability as a result of fire. Lemon (1949) found that the maximum amount of litter is approached at 5 years and, by 8 years vegetation returned to pre-burn status. This study used permanent plots on the Alapaha Experimental Range (Georgia) to monitor changes in vegetation following prescribed fire. At 1-2 years between fires, wildfires have a higher probability of moderate to high severity fire compared to longer time intervals where the probability is nearly 0. Factors beyond the length of time between fire events may be the cause for the relationship between short time intervals and the probability of moderate to high severity for wildfires. Weather conditions and errors associated with the amount of biomass present in the pre-fire image may be affecting this. We would expect the probability of moderate to high severity fire to increase as the time interval increased yet, the lack of an increase over time suggests that vegetation that isn't burning as often on the Osceola National Forest remains unburned (Maliakal et al. 2000). This may be explained by the change in flammability associated with natural succession in the pine flatwoods forest type. In long-unburned stands, vegetation composition is shifting away from flammable saw palmetto /gallberry complex with pine overstory towards less flammable, higher

moisture-content, hardwood dominance. Previously unburned cells likely remained unburned in subsequent fires due to fuel that was not available to burn and a combination of weather conditions.

As expected, the probability of high severity fire is higher for wildfires than for prescribed fires. Prescribed fires are performed under optimal conditions where the chance of mortality of fire-adapted species such as longleaf and slash pine, saw palmetto and gallberry, is small. In contrast, most wildfires greater than 1 ac in size occurred during optimal fire spread conditions, with high winds, lower relative humidities, and dry fuels. Regardless of the severity class of the first fire, the probability of moderate to high severity in the second fire was low for prescribed fires (<30%). This suggests one of two things: either that regardless of the severity of the prescribed burn, it is mitigating severity in subsequent fires; or the areas that are prescribed burned are repeatedly prescribed burned, so that the second fire is typically of lower severity.

The moderate and high severity class had the highest probability of moderate to high severity for both fire types (prescribed and wildfires). Within this dataset, areas that have a history of burning at a moderate to high severity often continue the trend regardless of the amount of time since the last fire event or the type of fire. This can be due to a number of effects such as the type of fuel at the site, delayed mortality inflating the severity signal over time, or the continued burning resulting in reduced vegetation vigor, which appears via the dNBR analysis to be higher severity. This may then result in a bias in the high severity class towards areas with less vegetation and ground fuels. The reduction in fuel may promote more complete consumption resulting in an increase in severity.

Variations in the landscape may also be a major cause for unexpected relationships regarding time intervals between fire events. In hydric areas, if fuel availability is reduced due to high moisture contents, distortions in the relationship between time interval between fires and the probability of moderate to high severity may occur. Even though these areas burned lightly in previous fires and time intervals were long, the probability of moderate to high severity fire was still low. Variations in the landscape adds additional variation to fire effects, prescribed fire planning, and fire suppression efforts. In the future, adding depth to water table, dominant understory vegetation, and dominant overstory vegetation may help to sort out unexpected relationships between fire effects and time.

Probability of Increasing in Severity

The model predicting the probability of fires increasing in severity gave similar results to the previous model (probability of experiencing high severity) for both fire types. The probability of increasing in severity was higher for wildfire than for prescribed fire. As expected, the probability of increasing in severity was the highest for unburned cells and increased as the time interval increased (Figure 2-12) for all time intervals except 3-4 and 7-8 years where the probability of increasing was close to 0. Most prescribed fires on the Osceola are maintained at a 3-4year cycle. Therefore, most fires that occur at this time interval were prescribed fires. Fires occurring with 7-8 years between events consistently had a lower than expected probability of having higher severity over all severity levels. Vegetation that has remained unburned for 7-8 years, in this dataset, may not be available to burn as readily as vegetation with time between events <6 years due to fuel moisture content and changes in species composition.

Without fire, fire-adapted species are replaced by broadleaf woody species that don't facilitate the spread of fire as well as fire adapted species.

The time interval 5-6 years was identified once again, this time as being associated with the highest probability of increasing fire severity, followed very closely by 9-10 years. This time interval (5-6 years) may be the point at which vegetation has recovered from previous fire events to a degree where the next fire event has enough fuel available to burn and at increased severity levels. Lavoie et al. (2010) found that living biomass recovered within 3 years of a fire event and predicted that fuel loads would return to pre-fire conditions by 5-8 years in a similar pine flatwoods forest also in North Florida. This suggest that time between fire events should not exceed 4 years. Land managers should consider fire return intervals that are between 1-4 years in pine flatwoods to mitigate moderate to high severity fire and increasing severity levels in subsequent fires.

Probability of Burning

The probability of burning followed the same trend for each severity class and was highest for the time interval 5-6 years for both wild and prescribed fires. The probability of burning was low when fires were 1-2 years apart and increased with time interval. Short time intervals between fires affect the way fire spreads due to the lack of continuous combustible material to maintain fire spread. Once again 7-8 years between fires had a lower probability of burning than expected indicating vegetation that had been burning at this interval has reduced availability. The probability of burning was higher for prescribed fires than for wildfires. Prescribed fires are performed under conditions and in areas that facilitate understory vegetation and litter consumption

whereas wildfires often result in incomplete patchy burning of the under and over story species due to rapid changes in climatic conditions and vegetation availability.

Probability of Decreasing in Severity

As severity levels increased, the probability of subsequent fires decreasing in severity level increased. At all severity levels the probability of decreasing in severity was lowest for fires occurring 5-6 years apart followed by 9-10 years apart. By 5-6 years between fires we would expect fuel levels to recover to a point where wildfire risk is high and past fires no longer have an effect on subsequent fires. This model supports the hypothesis that fires with moderate to high severity levels have a negative effect on severity level of fires occurring within 3 years. Land managers should consider 1-4 year fire frequencies for pine flatwoods to reduce the risk of moderate to high severity prescribed and wildfires. This evidence strongly suggests that beyond a five year interval, severity will be higher than what the majority of management objectives seek.

Areas previously burned by low severity fire had a high probability of remaining unburned in the next fire event if they were burned in a wildfire. This relationship indicates that during a wildfire, land that previously burned at a low severity level may have had vegetation that was unavailable to burn during the subsequent fire. Because the land previously burned at a low severity level, there should be enough vegetation there to carry higher severity fires should conditions be suitable. For moderate and high severity levels first fires, the probability of decreasing severity was higher for prescribed fires. So, areas that previously burned at moderate and high severity levels had a higher probability of decreasing in severity level if they were prescribed burned.

Conclusion

Fire history for the Osceola National Forest was effectively modeled to determine past trends in fire effects and future implications of fire management decisions. The models also provide valuable information regarding the influence of severity level and time between events for both prescribed and wildfires. The data shows that vegetation on this forest recovers quickly following fire and that fuel loads reach levels where they are available to burn within 1 year and are at pre-fire conditions by 5 years. The data also identifies areas that are within fire perimeters and are consistently remaining unburned. Likely hydric communities, land that has gone unburned for 7-8 years showed signs that the fuel just wasn't available to carry high severity fire from 1998-2008. Hydric communities may require extreme drought condition to reduce moisture levels.

All four models identified the time interval 5-6 years as a point where the effects of previous fires had little to no effect on subsequent fires. At this point, the probability of high severity fire, increasing severity level in subsequent fire, and the likelihood of burning at all is highest. This is also a point where the probability of decreasing severity in subsequent fires was lowest. These findings indicate that time between fires should be kept below 5 years. Results from this work are supported by other studies suggesting that the use of remote sensing techniques sufficiently represent relationships between time since last fire and the severity level of past fire events on subsequent fire behavior.

The relationship involving time between fire events and fire severity are influenced by variations in the landscape. Fire effects are influenced by the type of vegetation and the availability of that vegetation. Land managers must consider vegetation recovery

and availability differences by both forest and community types to determine the risk of the high severity fire. Although hydric communities are often unavailable to burn, fuel loads in these communities are high and must be managed. Land managers may consider other alternatives to mitigate high fuel loads in hydric communities.

Although previous studies have found a relationship between fire size and high severity (Duffy et al 2007) a useful model could not be found for the probability of high severity fire using the fire size dataset. The data indicated that larger fires had a higher portion of area in the high severity size class yet this relationship was not significant. Out of 115 wildfires included within this dataset, few fires were large. Most fires were less than 50 ac in size (93 fires). Although large fires had a higher portion of their cells in high the high severity class, the vast majority of the area was burned by moderate and low severity fire. A larger dataset may be required to capture the relationship between fire size and high severity.

Errors introduced by severity level classification may also influence the models. General severity level classifications were used and further generalized from seven levels to four. In the future, severity levels should be calibrated to pine flatwood forest of the southeastern U.S for the best results. Also, delineation of fire perimeters is not exact and may introduce error into the unburned and low severity levels.

Table 2-1. Severity class descriptions for the time analysis and fire size datasets.

Severity Class	Description	Reclassified Severity Classes
1	Unburned within a fire perimeter (DNBR -100 - 99)	1 Unburned within a fire perimeter (DNBR 100 - 99)
3	Enhanced Regrowth/Low Severity (DNBR -500 - -101, 100 - 269)	2 Low Severity (DNBR -500 - -101, 100 - 269)
4	Low-Med Severity (DNBR 270 - 439)	3 Med Severity (DNBR 270 - 439)
5	Med-High Severity (DNBR 440 - 659)	4 High Severity (DNBR 440 - 1300)
6	High Severity (DNBR 660 - 1300)	

Table 2-2. Palmer Drought Severity Index values and descriptions

Palmer Drought Severity Index	
4.0 or more	exceptionally wet
3.0 to 3.99	very wet
2.0 to 2.99	moderately wet
1.0 to 1.99	slightly wet
0.5 to 0.99	incipient wet spell
0.49 to -0.49	near normal
-0.5 to -0.99	incipient dry spell
-1.0 to -1.99	mild drought
-2.0 to -2.99	moderate drought
-3.0 to -3.99	severe drought
-4.0 or less	extreme drought

Table 2-3. Time interval classification for time analysis dataset.

Time Interval (years)	Code	Observations
1-2	1	115,273
3-4	2	136,254
5-6	3	131,409
7-8	4	79,886
9-10	5	21,893

Table 2-4. Covariate classifications for fire size model.

Variable	Class	Code
Fire Size Class	1-15ac	1
	16-50ac	2
	50- 150ac	3
	150-500ac	4
	>500ac	5
Season	Spring	1
	Summer	2
	Fall	3
	Winter	4
Forest Type	Pine	1
	Hardwood	2
	Pine Hardwood	3
	Hardwood Pine	4
Soil Drainage	Somewhat poorly drained	1
	Somewhat- poorly drained	2
	Somewhat-very poorly drained	3
	Poorly Drained	4
	Poorly- very poorly drained	5
	very poorly drained	6
	standing water- poorly drained	7

Table 2-5. Parameter estimates and their respective standard errors and p-values for the model predicting the probability of high severity fire.

Parameter	Categories	Estimate	Std. Error	P-value
Intercept		-3.8923	0.06453	<0.0001
Severity of fire 1	Unburned	-0.1251	0.01703	<0.0001
	Low	-0.4520	0.01716	<0.0001
	Med-High	0	.	.
Time between fires	1-2 years	-1.7801	0.1018	<0.0001
	3-4 years	-0.5907	0.07174	<0.0001
	5-6 years	3.0129	0.06509	<0.0001
	7-8 years	1.4293	0.06713	<0.0001
	9-10 years	0	.	.
Type of fire	Wildfires	-3.0456	0.5039	<0.0001
	Prescribed Fires	0	.	.
Time between fires* Type of Fire	1-2 years- Wildfire	6.6121	0.5102	0.0034
	1-2 years- Prescribed	0	.	.
	3-4 years- Wildfire	2.2647	0.5190	<0.0001
	3-4 years- Prescribed	0	.	.
	5-6 years- Wildfire	4.3310	0.5040	<0.0001
	5-6 years- Prescribed	0	.	.
	7-8 years- Wildfire	0.2111	0.5137	0.6812
	7-8 years- Prescribed	0	.	.
	9-10 years- Wildfire	0	.	
	9-10 years- Prescribed	0	.	
Residual		0.9981	.	.

Table 2-6. Parameter estimates and their respective standard errors and p-values for the model predicting the probability of increased severity in the second fire.

Parameter	Categories	Estimate	Std. Error	P-value
Intercept		-1.3176	0.02894	<0.0001
Severity of fire 1	Unburned	3.2190	0.01976	<0.0001
	Low	0.9239	0.01917	<0.0001
	Med	0	.	.
Time between fires	1-2 years	-1.9621	0.02665	<0.0001
	3-4 years	-1.1353	0.01973	<0.0001
	5-6 years	-0.1612	0.02780	<0.0001
	7-8 years	-1.8658	0.02556	<0.0001
	9-10 years	0	.	.
Type of Fire	Wildfires	0.1889	0.009466	<0.0001
	Prescribed Fires	0	.	.
PDSI (year before Fire 1)		-0.04698	0.007130	<0.0001
PDSI (year of Fire 1)		0.09065	0.005490	<0.0001
PDSI (year before Fire 2)		0.4761	0.005154	<0.0001
Residual		0.9879	.	.

Table 2-7. Parameter estimates and their respective standard errors and p-values for the model predicting the probability of burning.

Parameter	Categories	Estimate	Std. Error	P-value
Intercept		2.2829	0.02519	<0.0001
Severity of fire 1	Unburned	-0.8139	0.01715	<0.0001
	Low	-0.6254	0.01654	<0.0001
	Med	-0.5244	0.01985	<0.0001
	High	0	.	.
Time between fires	1-2 years	-0.8888	0.01790	<0.0001
	3-4 years	-0.8372	0.01525	<0.0001
	5-6 years	0.6326	0.02318	<0.0001
	7-8 years	-1.0399	0.01969	<0.0001
	9-10 years	0	.	.
Type of Fire	Wildfires	-0.4576	0.007613	<0.0001
	Prescribed fires	0	.	.
PDSI (year before Fire 1)		-0.2168	0.005665	<0.0001
PDSI (year of Fire 1)		0.2542	0.004379	<0.0001
PDSI (year before Fire 2)		0.2874	0.003676	<0.0001
Residual		1.0249	.	.

Table 2-8. Parameter estimates and their respective standard errors and p-values for the model predicting probability of decreased severity in the second fire.

Parameter	Categories	Estimate	Std. Error	P-value
Intercept		2.0265	0.03806	<0.0001
Severity of fire 1	Low	-3.6857	0.02957	<0.0001
	Medium	-1.5663	0.03233	<0.0001
	High	0	.	.
Time between fires	1-2 years	0.6019	0.02928	<0.0001
	3-4 years	0.7416	0.02167	<0.0001
	5-6 years	-0.7121	0.03419	<0.0001
	7-8 years	0.6949	0.02871	<0.0001
	9-10 years	0	.	.
Type of Fire	Wildfires	-1.9317	0.04718	<0.0001
	Prescribed Fires	0	.	.
PDSI (year before Fire 1)		0.6048	0.009813	<0.0001
PDSI (year of Fire 1)		-0.4611	0.007046	<0.0001
PDSI (year before Fire 2)		-0.2332	0.006323	<0.0001
PDSI (year of Fire 2)		0.01577	0.003421	<0.0001
Severity of fire 1* Type of Fire	Low-Wildfire	2.2143	0.04818	<0.0001
	Low- Prescribed	0	.	.
	Medium- Wildfire	1.2070	0.05505	<0.0001
	Medium- Prescribed	0	.	.
	High – Wildfire	0	.	<0.0001
	High - Prescribed	0	.	.
Residual		1.0264	.	.

Table 2-9. Parameter estimates and their respective standard errors and p-values for model predicting the probability of high severity fire by fire size class.

Parameter	Categories	Estimate	Std. Error	P-value
Intercept		-1.9994	0.09005	<0.0001
Fire size class	1	-1.2949	2.8899	0.6550
	2	-0.2208	1.2268	0.8575
	3	-0.2040	1.2681	0.8725
	4	-0.8258	0.4992	0.1009
	5	0	.	.

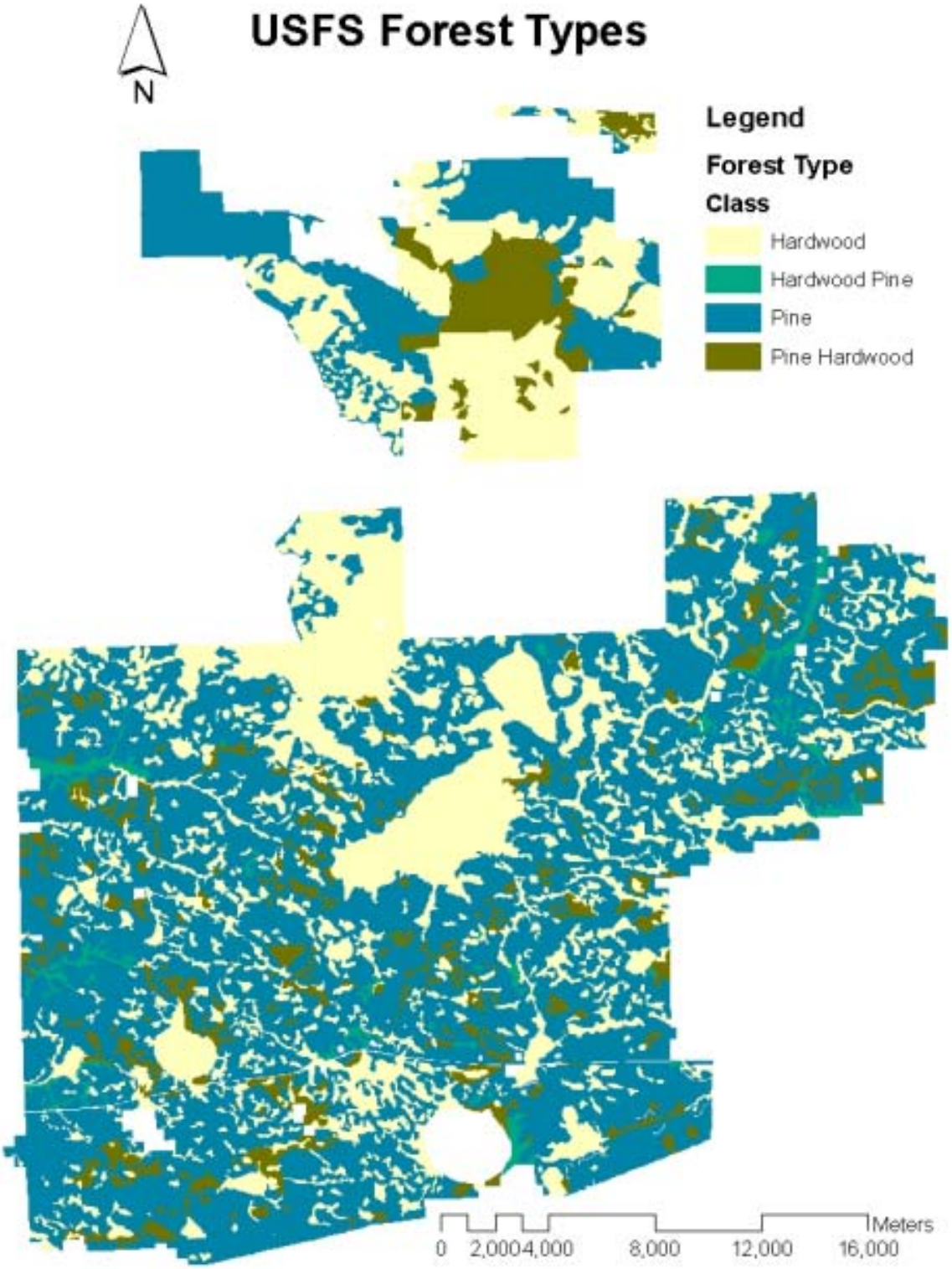


Figure 2-1. USFS forest type classifications.

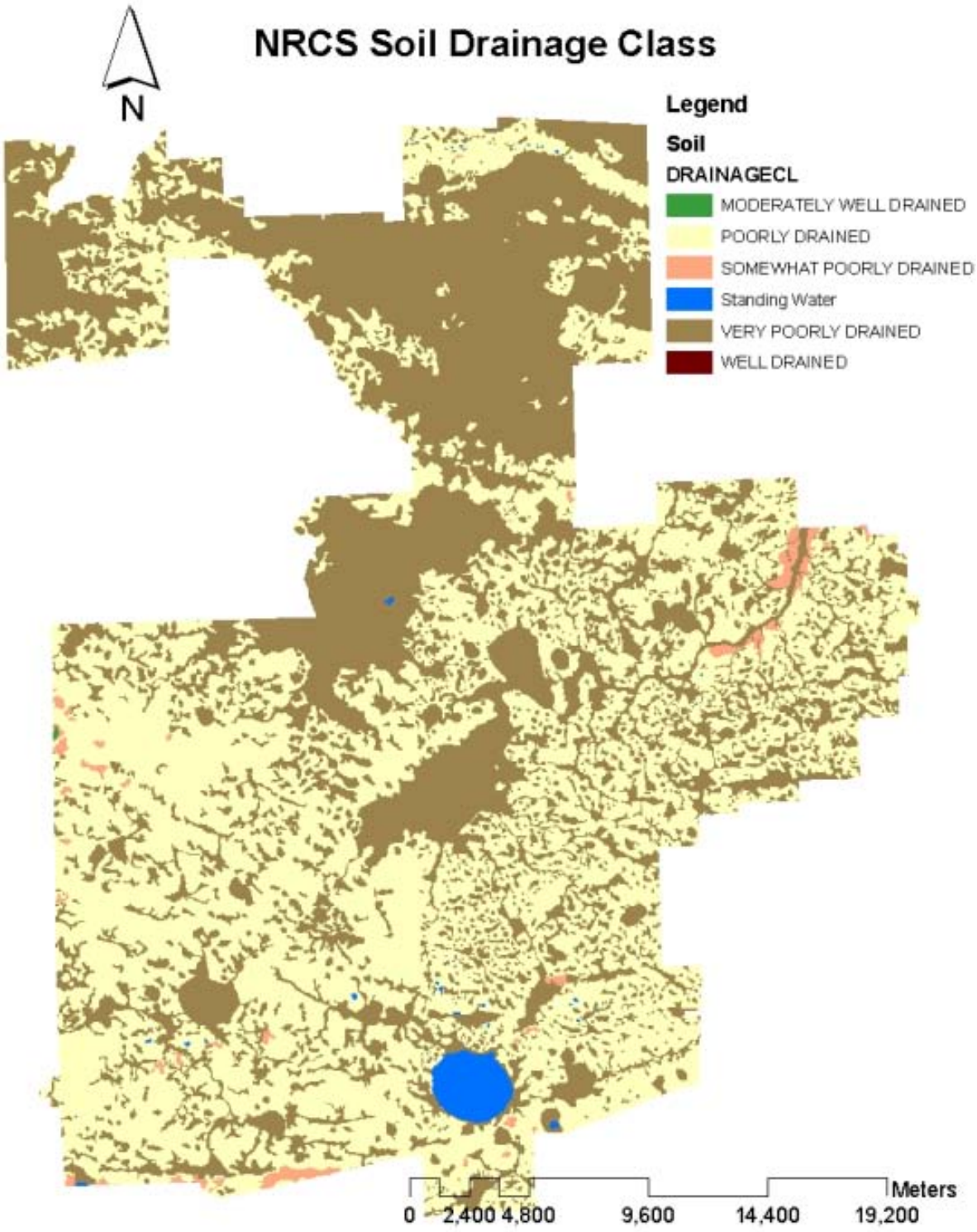


Figure 2-2. NRCS soil drainage class classification.

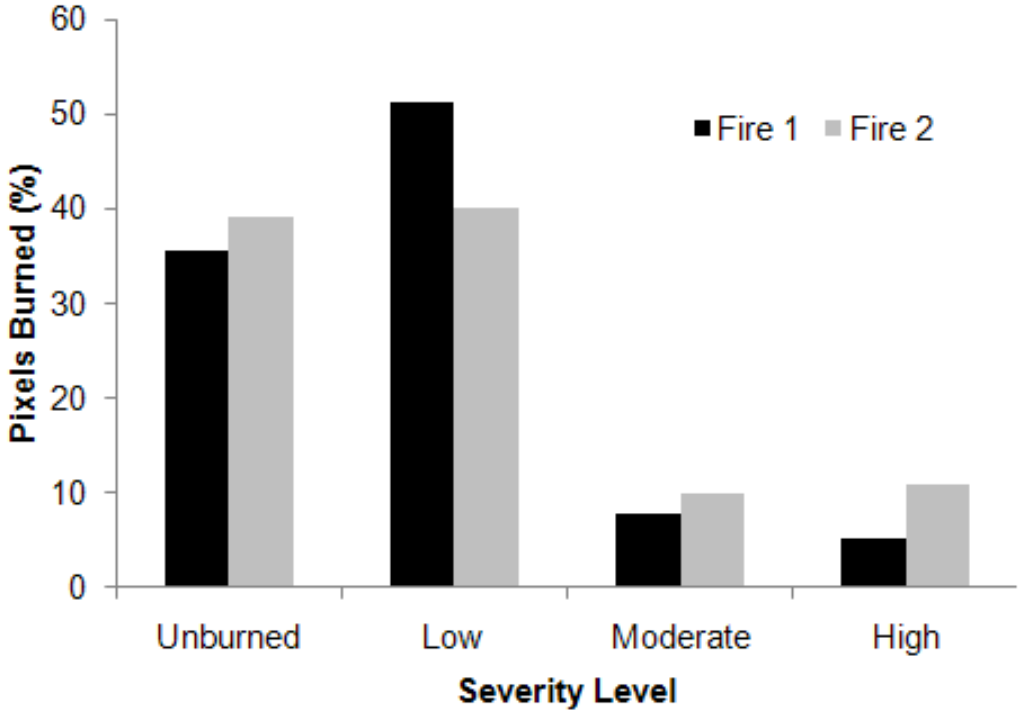
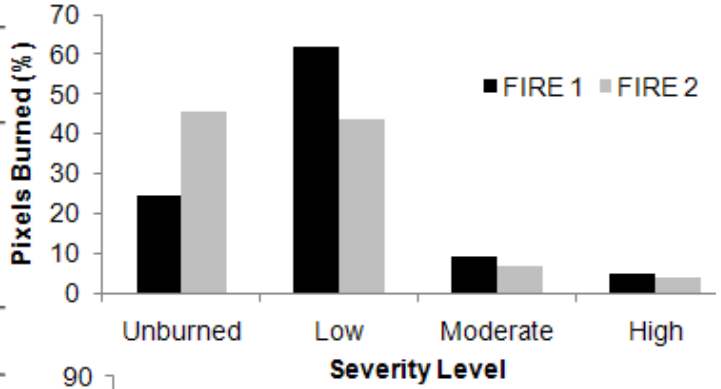
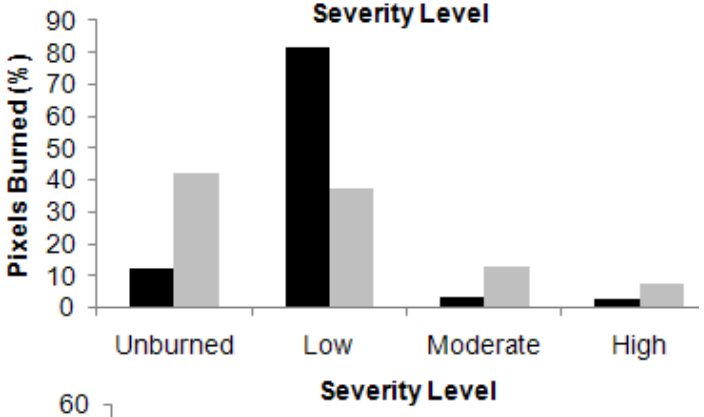


Figure 2-1. Portion of pixels burned in each severity level in fire 1 and fire 2.

1-2 YEARS BETWEEN FIRES (Wild/ Prescribed) N=115273					
	FIRE 2				
FIRE 1	**1**	**2**	**3**	**4**	**Percentage**
1	13.27	10.59	0.46	0.14	24.46
2	26.62	27.69	4.73	2.80	61.85
3	3.32	3.89	1.63	0.08	8.92
4	2.22	1.56	0.10	0.89	4.77
Percentage	45.44	43.73	6.91	3.91	



1-2 YEARS BETWEEN FIRES (Wild) N=56351					
	FIRE 2				
FIRE 1	**1**	**2**	**3**	**4**	**Percentage**
1	8.35	3.17	0.68	0.23	12.43
2	33.35	33.77	8.95	5.57	81.63
3	0.18	0.19	3.04	0.10	3.50
4	0.19	0.35	0.08	1.82	2.44
Percentage	42.06	37.47	12.74	7.72	



1-2 YEARS BETWEEN FIRES (Prescribed) N=58922					
	FIRE 2				
FIRE 1	**1**	**2**	**3**	**4**	**Percentage**
1	17.97	17.69	0.25	0.05	35.97
2	20.19	21.88	0.70	0.15	42.92
3	6.33	7.43	0.27	0.07	14.10
4	4.17	2.72	0.11	0.01	7.01
Percentage	48.67	49.72	1.34	0.27	

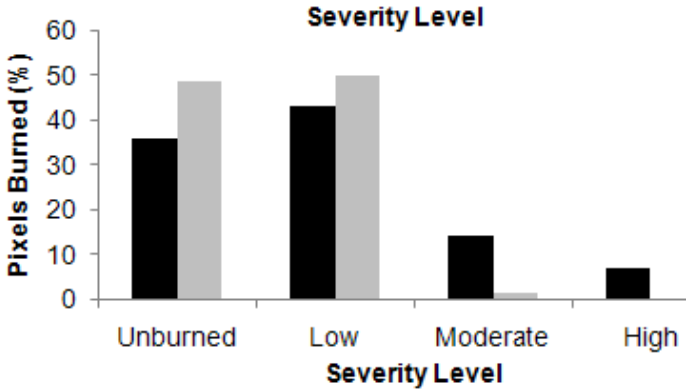
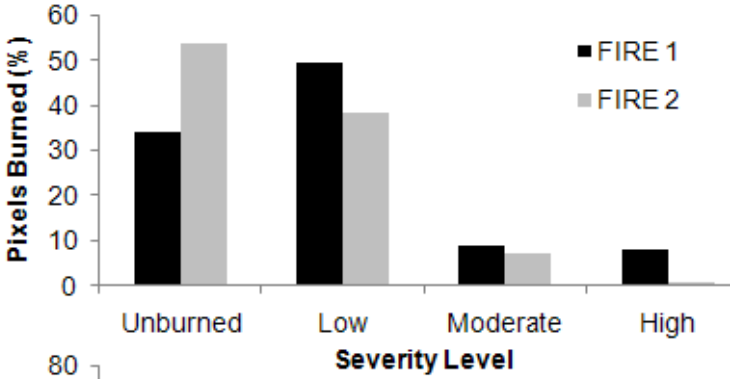
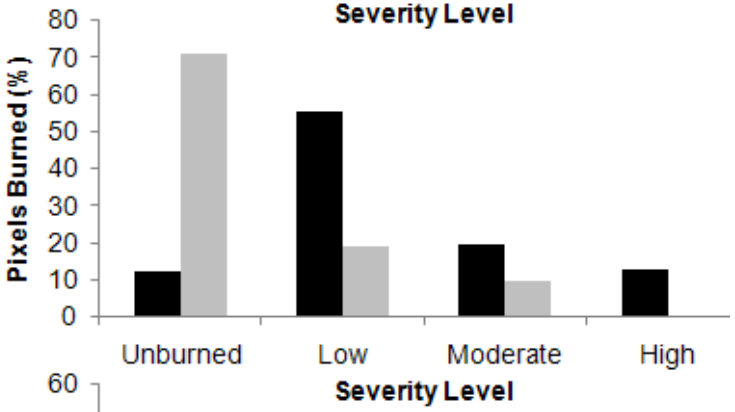


Figure 2-2. Distribution of pixels among severity classes with 1-2 years between fire events separated by type of fire and the probability of moving from one severity class to the next.

3-4 YEARS BETWEEN FIRES (Wild/Prescribed) N=136254					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	18.75	13.76	1.30	0.21	34.02
2	26.71	20.01	2.33	0.29	49.34
3	5.30	2.35	0.88	0.12	8.64
4	3.09	2.30	2.40	0.20	8.00
Percentage	53.85	38.42	6.91	0.81	



3-4 YEARS BETWEEN FIRES (Wild/Prescribed) N=17086					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	9.02	2.08	0.79	0.33	12.23
2	39.42	9.61	6.43	0.07	55.53
3	13.58	4.31	1.81	0.00	19.71
4	8.85	3.13	0.56	0.00	12.54
Percentage	70.88	19.13	9.59	0.40	



3-4 YEARS BETWEEN FIRES (Wild/Prescribed) N=119168					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	20.15	15.43	1.37	0.19	37.15
2	24.89	21.50	1.75	0.32	48.45
3	4.11	2.07	0.75	0.13	7.06
4	2.27	2.18	2.66	0.23	7.34
Percentage	51.41	41.19	6.53	0.87	

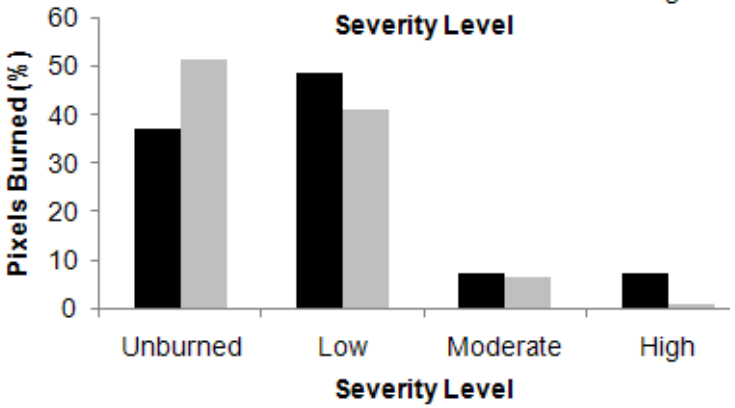


Figure 2-3. Distribution of pixels among severity classes with 3-4 years between fire events separated by type of fire and the probability of moving from one severity class to the next.

5-6 YEARS BETWEEN FIRES (Wild/Prescribed) N=131409					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	4.69	17.10	5.70	16.02	43.50
2	6.39	16.75	6.15	13.12	42.40
3	0.41	3.15	1.83	2.66	8.06
4	0.24	2.84	1.76	1.20	6.04
Percentage	11.73	39.83	15.44	33.00	

5-6 YEARS BETWEEN FIRES (Wild) N=37712					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	2.23	10.25	6.77	25.91	45.16
2	4.03	14.02	7.81	24.05	49.91
3	0.04	0.90	0.63	2.51	4.08
4	0.00	0.15	0.10	0.60	0.85
Percentage	6.30	25.32	15.30	53.07	

5-6 YEARS BETWEEN FIRES (Prescribed) N=93697					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	5.68	19.85	5.27	12.03	42.83
2	7.34	17.84	5.48	8.72	39.38
3	0.56	4.05	2.31	2.73	9.66
4	0.33	3.92	2.43	1.45	8.13
Percentage	13.91	45.67	15.49	24.93	

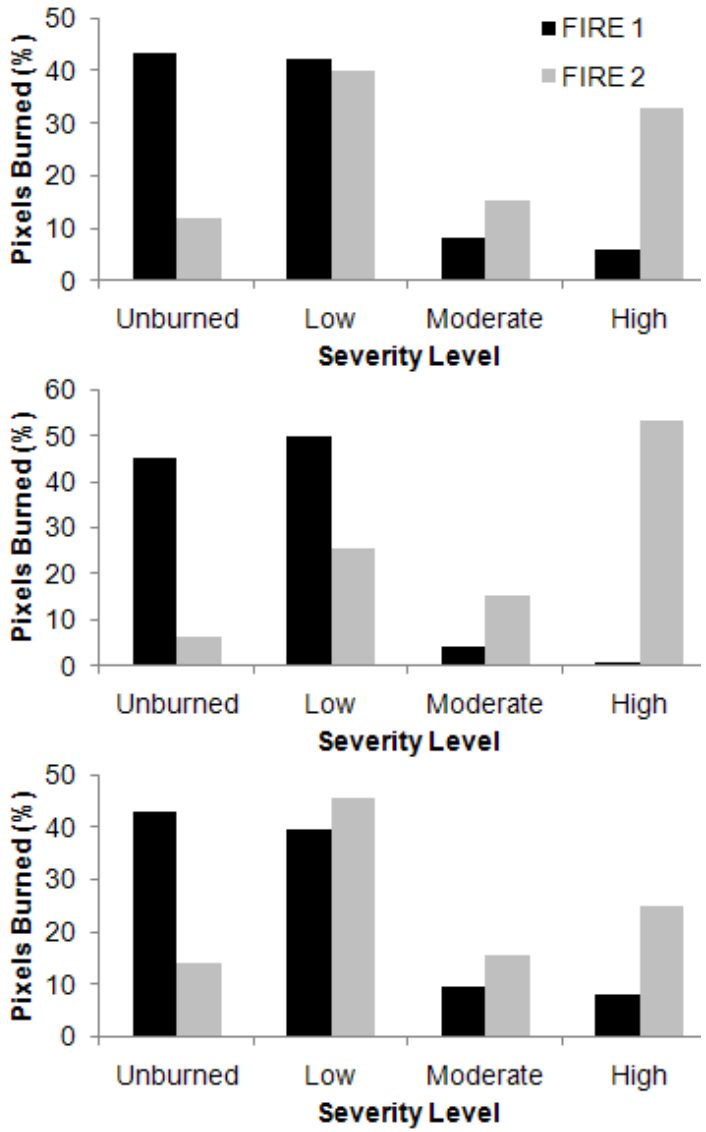


Figure 2-4. Distribution of pixels among severity classes with 5-6 years between fire events separated by type of fire and the probability of moving from one severity class to the next.

7-8 YEARS BETWEEN FIRES (Wild/Prescribed) N=79886					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	22.23	12.74	4.02	2.06	41.04
2	23.59	22.53	4.49	1.84	52.45
3	2.90	1.83	0.49	0.15	5.37
4	0.68	0.23	0.16	0.08	1.14
Percentage	49.40	37.33	9.15	4.13	

7-8 YEARS BETWEEN FIRES (Wild) N=26522					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	39.98	3.85	0.87	0.18	44.88
2	32.06	10.66	1.19	0.21	44.12
3	7.62	1.33	0.04	0.00	8.99
4	1.95	0.06	0.00	0.00	2.01
Percentage	81.60	15.90	2.11	0.39	

7-8 YEARS BETWEEN FIRES (Prescribed) N=53364					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	13.41	17.15	5.58	3.00	39.14
2	19.38	28.44	6.13	2.64	56.59
3	0.55	2.08	0.71	0.23	3.57
4	0.05	0.31	0.23	0.11	0.70
Percentage	33.39	47.98	12.65	5.98	

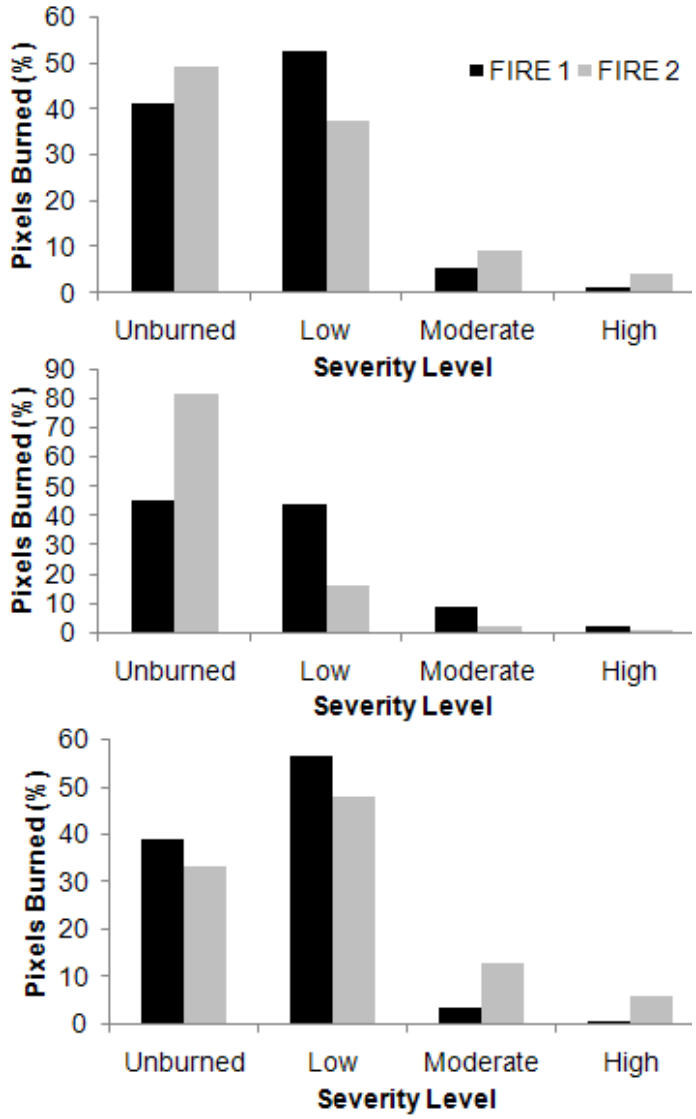


Figure 2-5. Distribution of pixels among severity classes with 7-8 years between fire events separated by type of fire and the probability of moving from one severity class to the next.

9-10 YEARS BETWEEN FIRES (Wild/Prescribed) N=21893					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	15.32	17.24	5.64	0.70	38.89
2	25.70	25.57	6.95	0.39	58.60
3	1.01	0.69	0.28	0.03	2.01
4	0.25	0.23	0.00	0.01	0.49
Percentage	42.28	43.72	12.88	1.13	

9-10 YEARS BETWEEN FIRES (Wild) N=5901					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	12.37	6.81	2.93	0.03	22.15
2	45.38	22.50	7.68	0.03	75.60
3	2.12	0.08	0.03	0.00	2.24
4	0.02	0.00	0.00	0.00	0.02
Percentage	59.89	29.40	10.64	0.07	

9-10 YEARS BETWEEN FIRES (Prescribed) N=15992					
	FIRE 2				
FIRE 1	1	2	3	4	Percentage
1	16.40	21.09	6.64	0.94	45.07
2	18.44	26.69	6.68	0.52	52.33
3	0.60	0.91	0.38	0.04	1.93
4	0.34	0.31	0.01	0.01	0.67
Percentage	35.78	49.00	13.70	1.52	

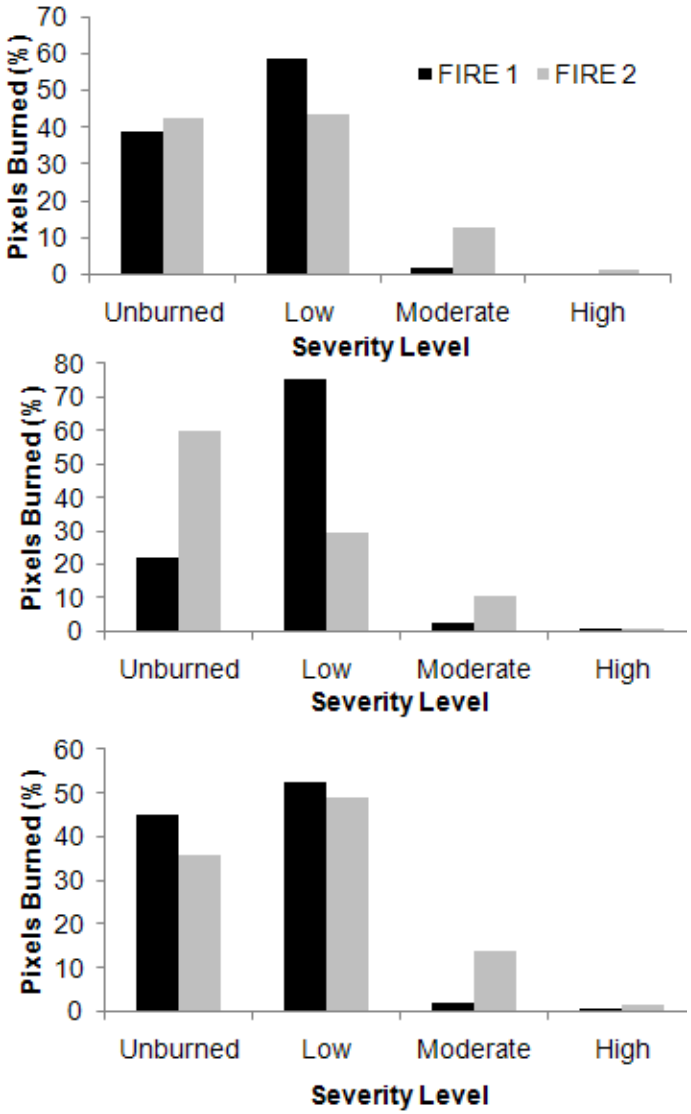


Figure 2-6. Distribution of pixels among severity classes with 9-10 years between fire events separated by type of fire and the probability of moving from one severity class to the next.

Wild/ Prescribed Fires

Time Interval	INCREASE (%)	DECREASE (%)
1-2	18.81	37.72
3-4	18.01	42.16
5-6	60.74	14.79
7-8	25.29	29.38
9-10	30.95	27.88

Wildfires

Time Interval	INCREASE (%)	DECREASE (%)
1-2	18.69	34.33
3-4	9.70	69.86
5-6	77.30	5.23
7-8	6.30	43.02
9-10	17.49	47.60

Prescribed Fires

Time Interval	INCREASE (%)	DECREASE (%)
1-2	18.92	40.95
3-4	19.20	38.18
5-6	54.08	18.64
7-8	34.73	22.60
9-10	35.91	20.60

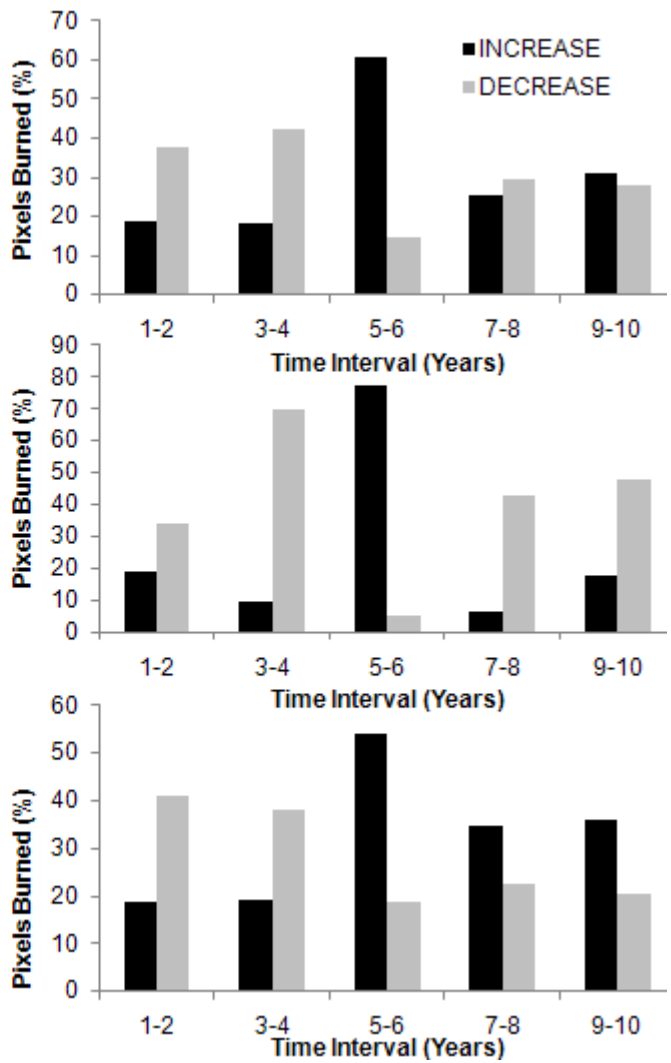


Figure 2-7. Percentage of pixels increasing and decreasing in severity level by time and type of fire.

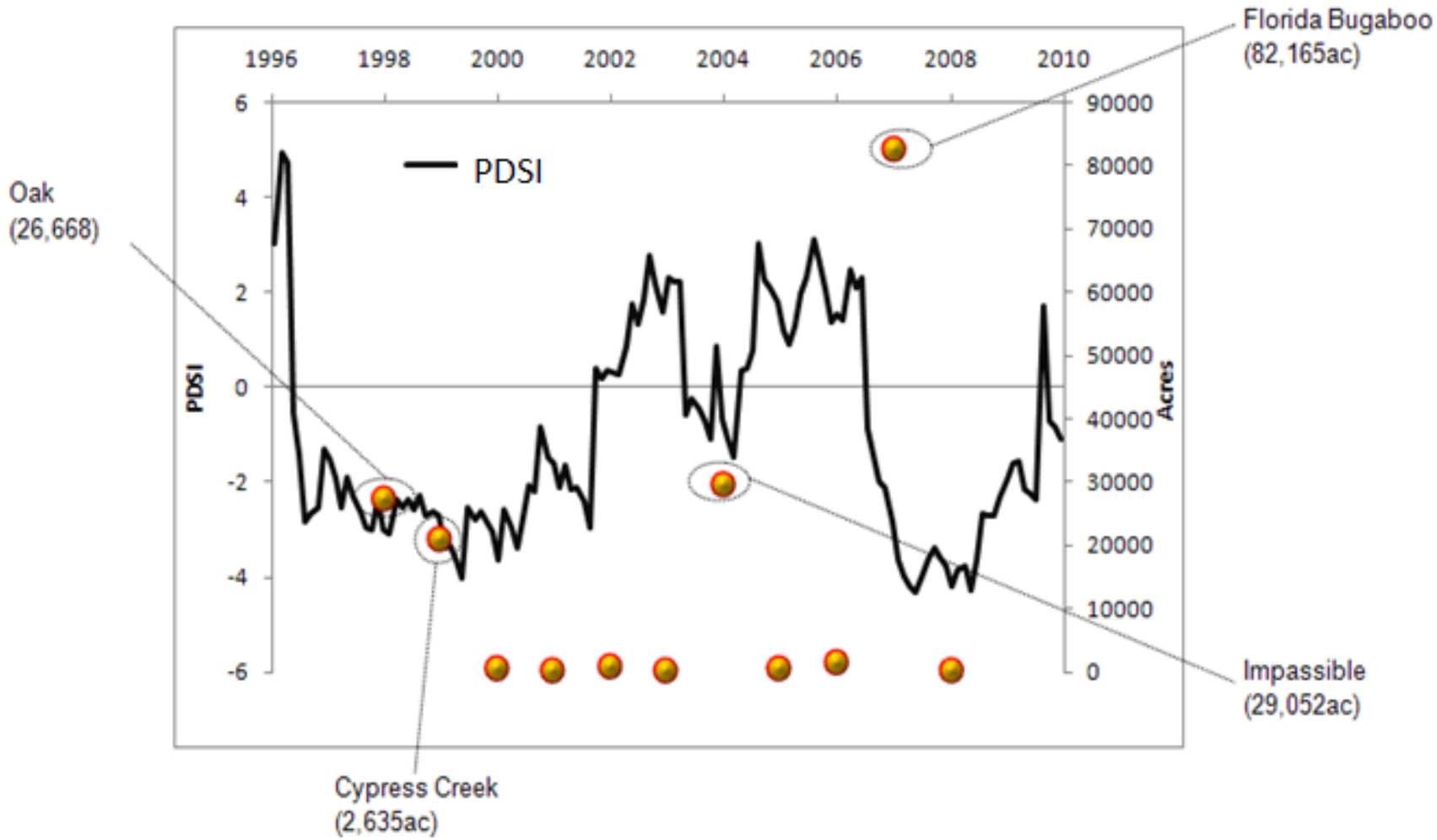


Figure 2-3. Fire size compared with Palmer drought severity index between 1996 and 2010. This suggests large fire events are associated with prolonged droughts.

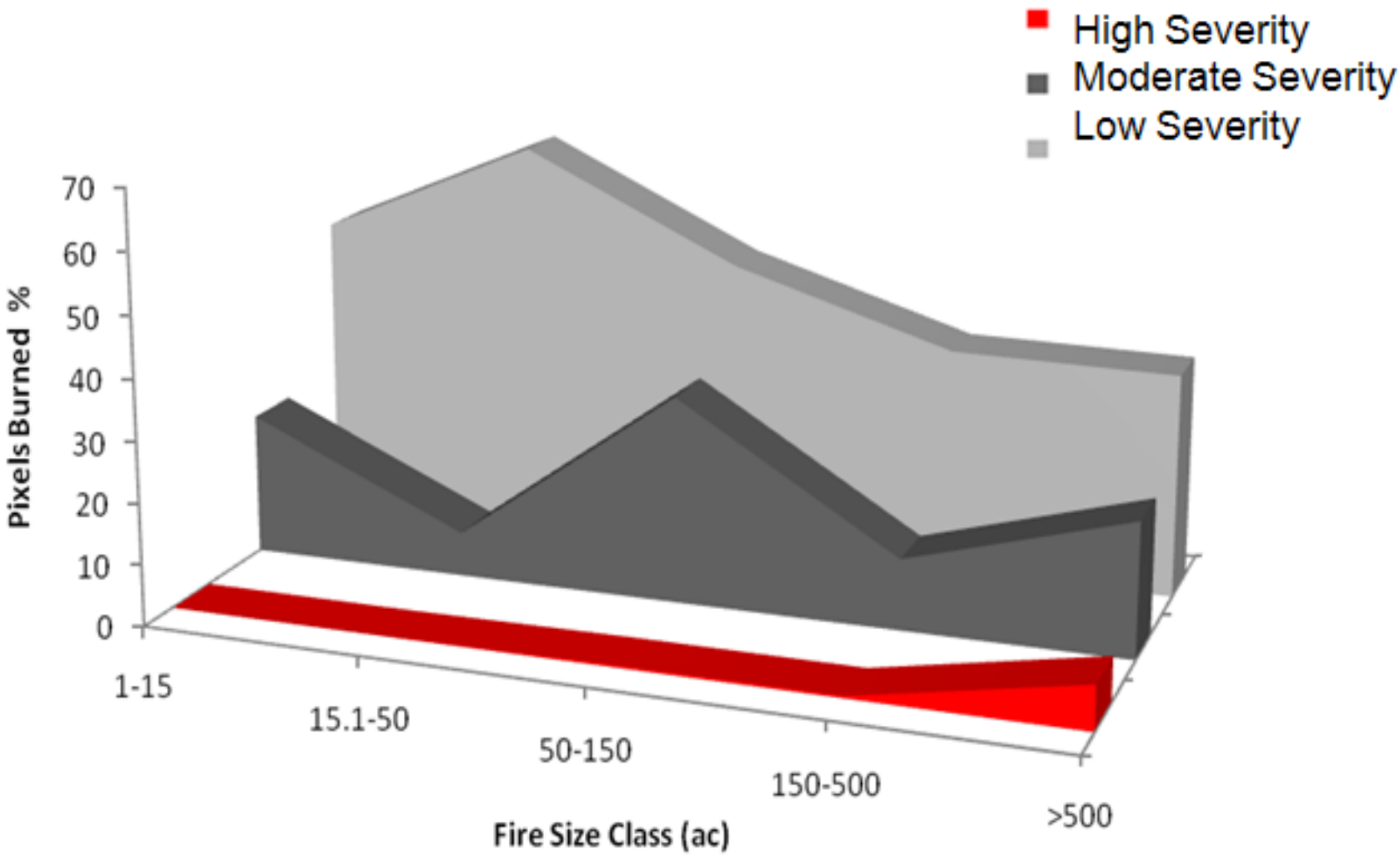


Figure 2-4. Percentage of pixels burned at each severity class by fire size class. Larger fires have a higher portion of their cells in the high severity class.

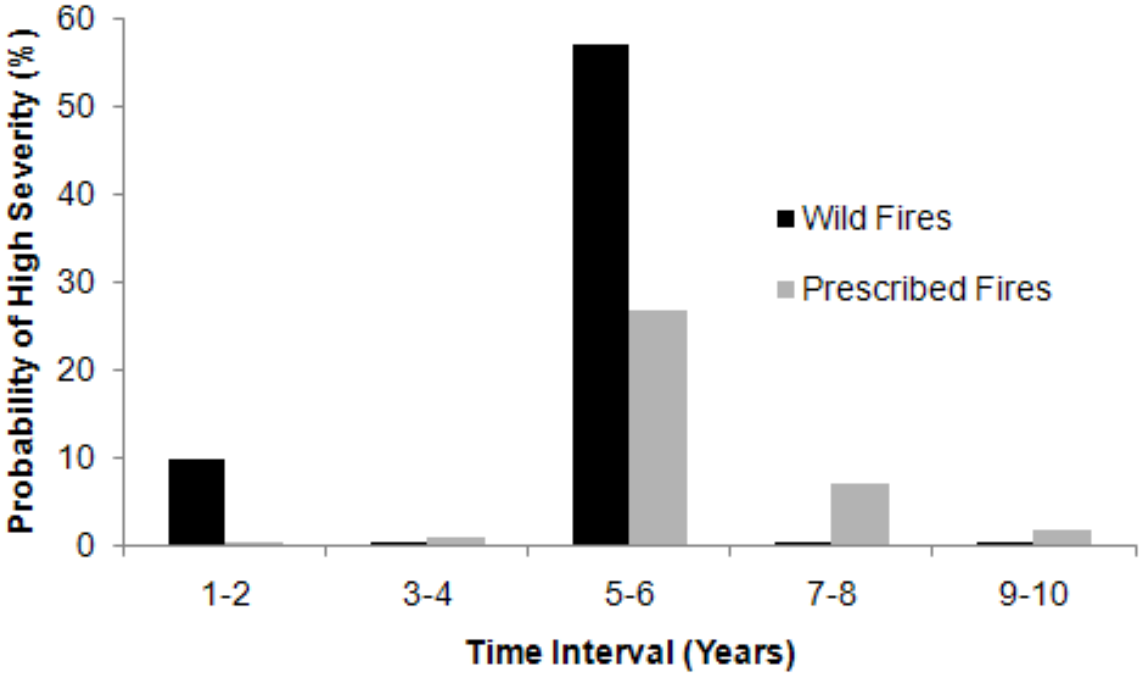


Figure 2-8. Probability of experiencing high severity in fire 2 by time interval and fire type.

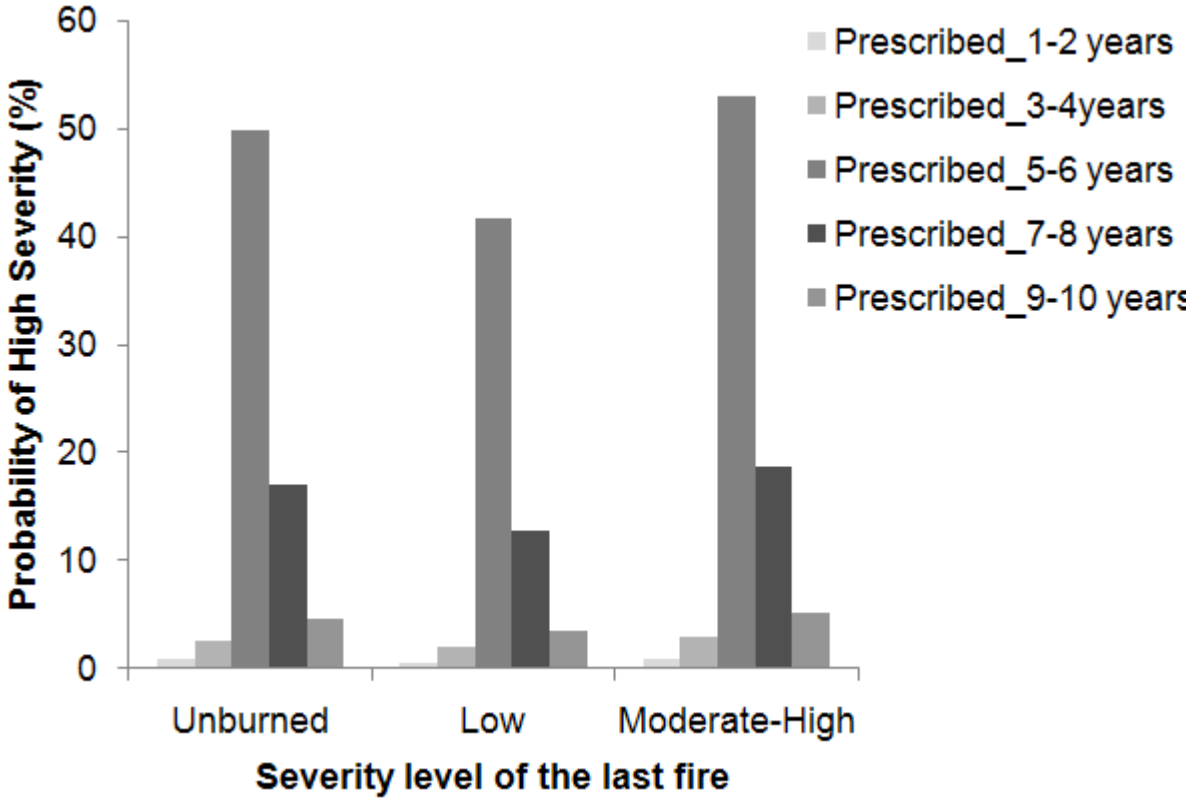


Figure 2-9. Probability of experiencing high severity in fire 2 by severity level of fire 1 and time interval for prescribed fires.

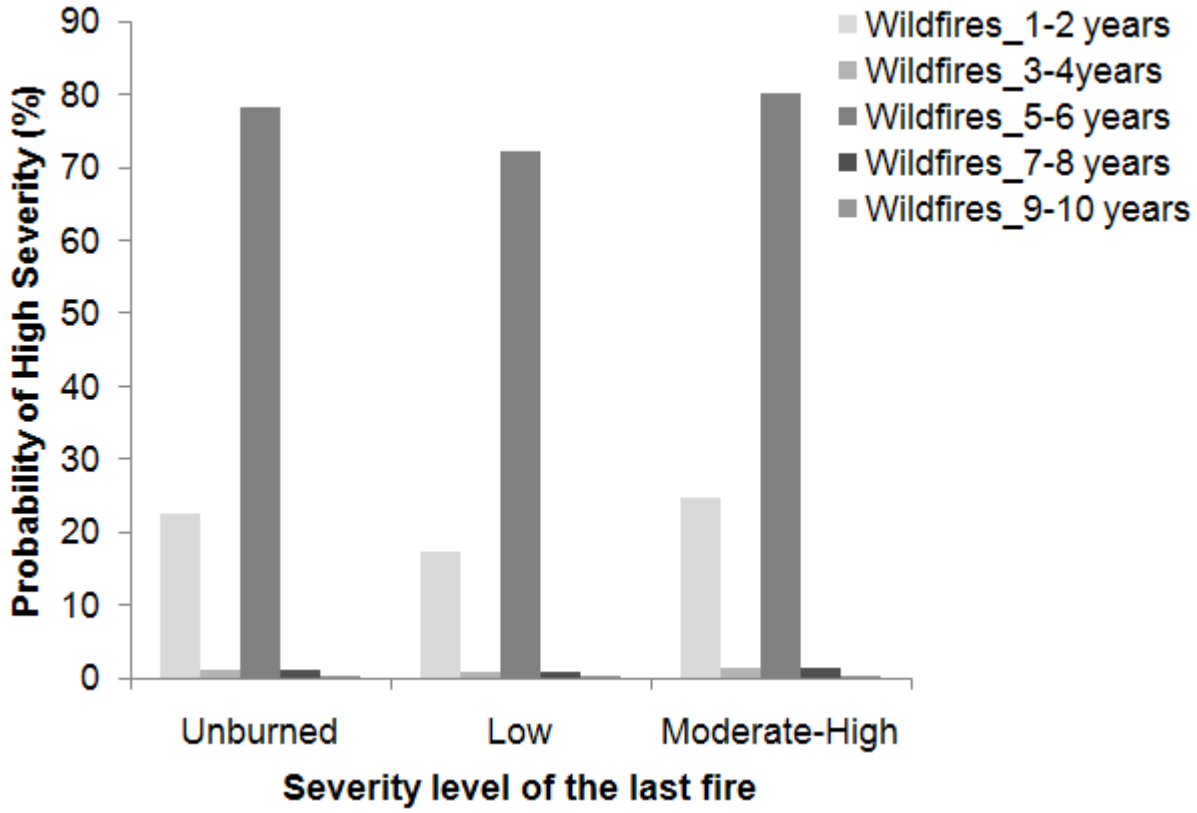


Figure 2-10. Probability of experiencing high severity in fire 2 by severity level of fire 1 and time interval for wildfires.

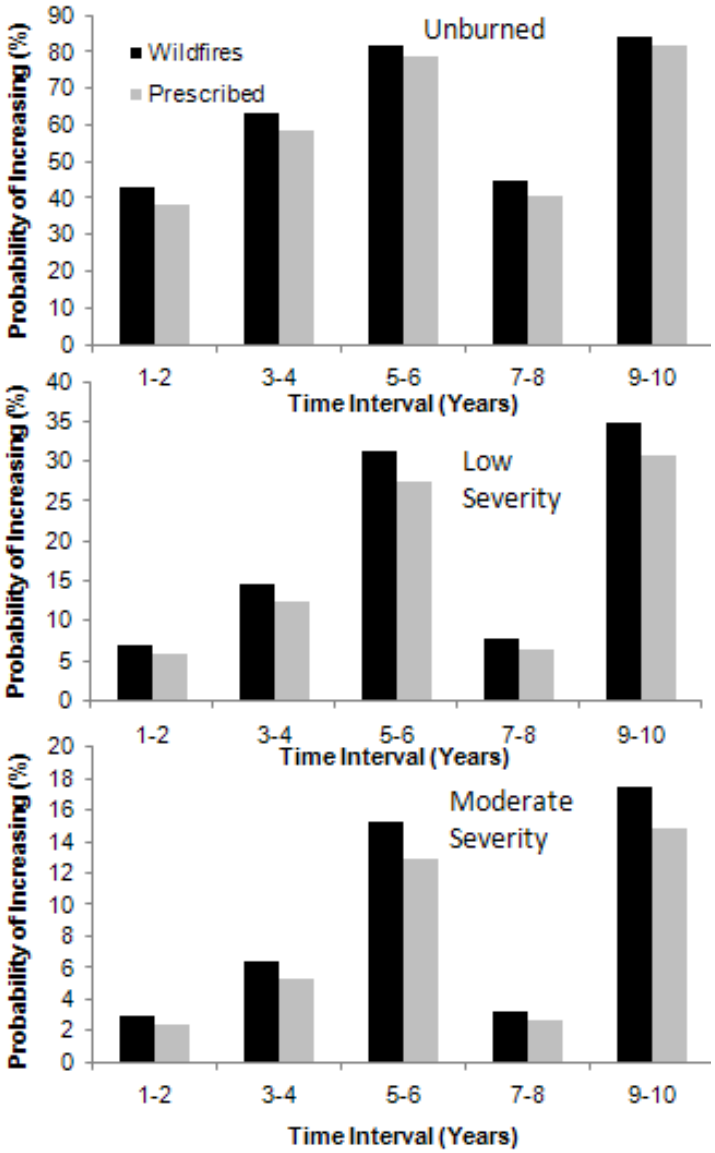


Figure 2-11. Probability of increasing fire severity by time interval and fire type.

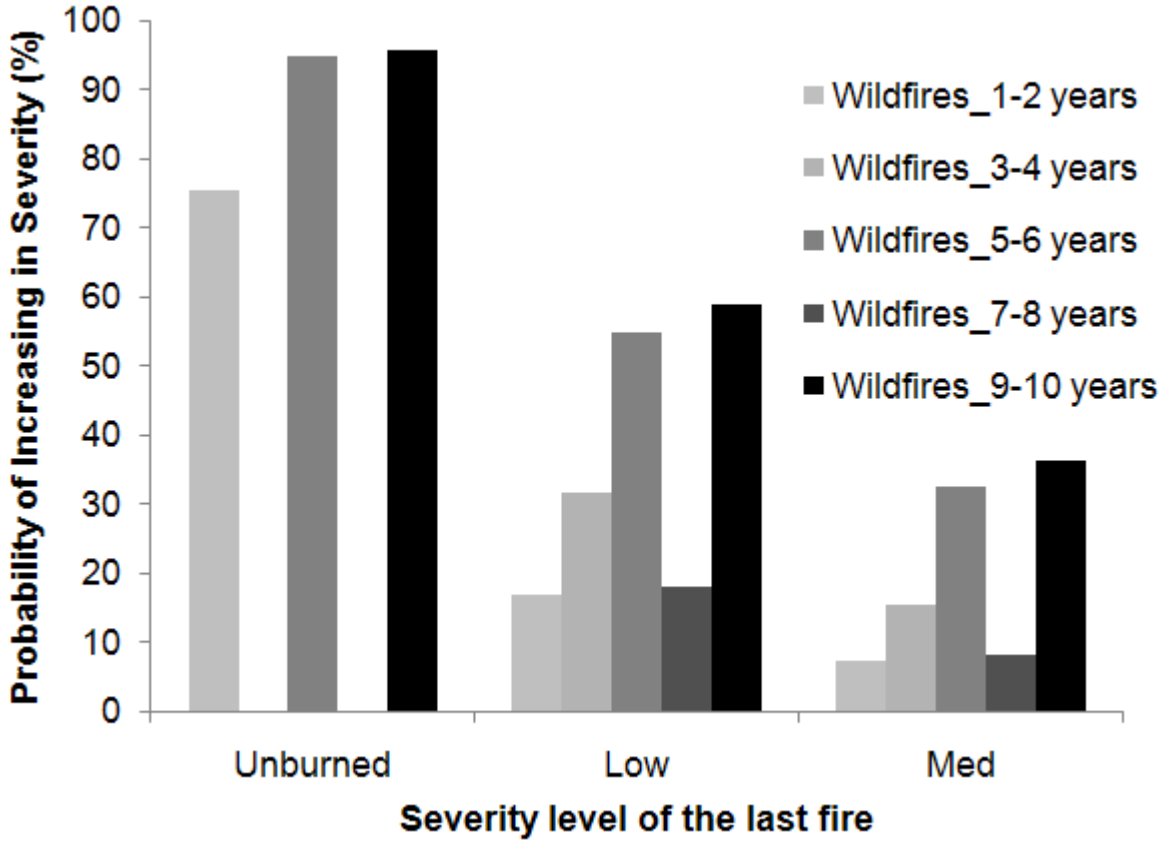


Figure 2-12. Probability of increasing fire severity by severity level of the last fire and time between fires for wildfires.

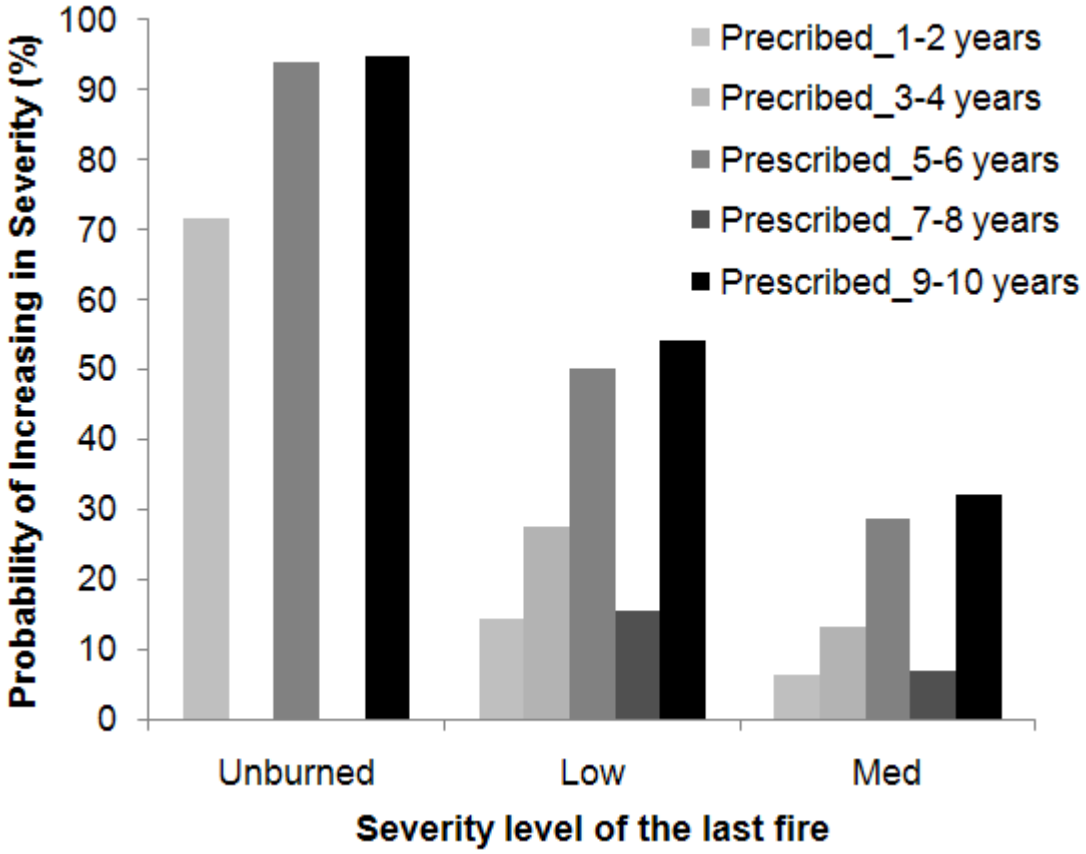


Figure 2-13. Probability of increasing fire severity by severity level of the last fire and time between fires for prescribed fires.

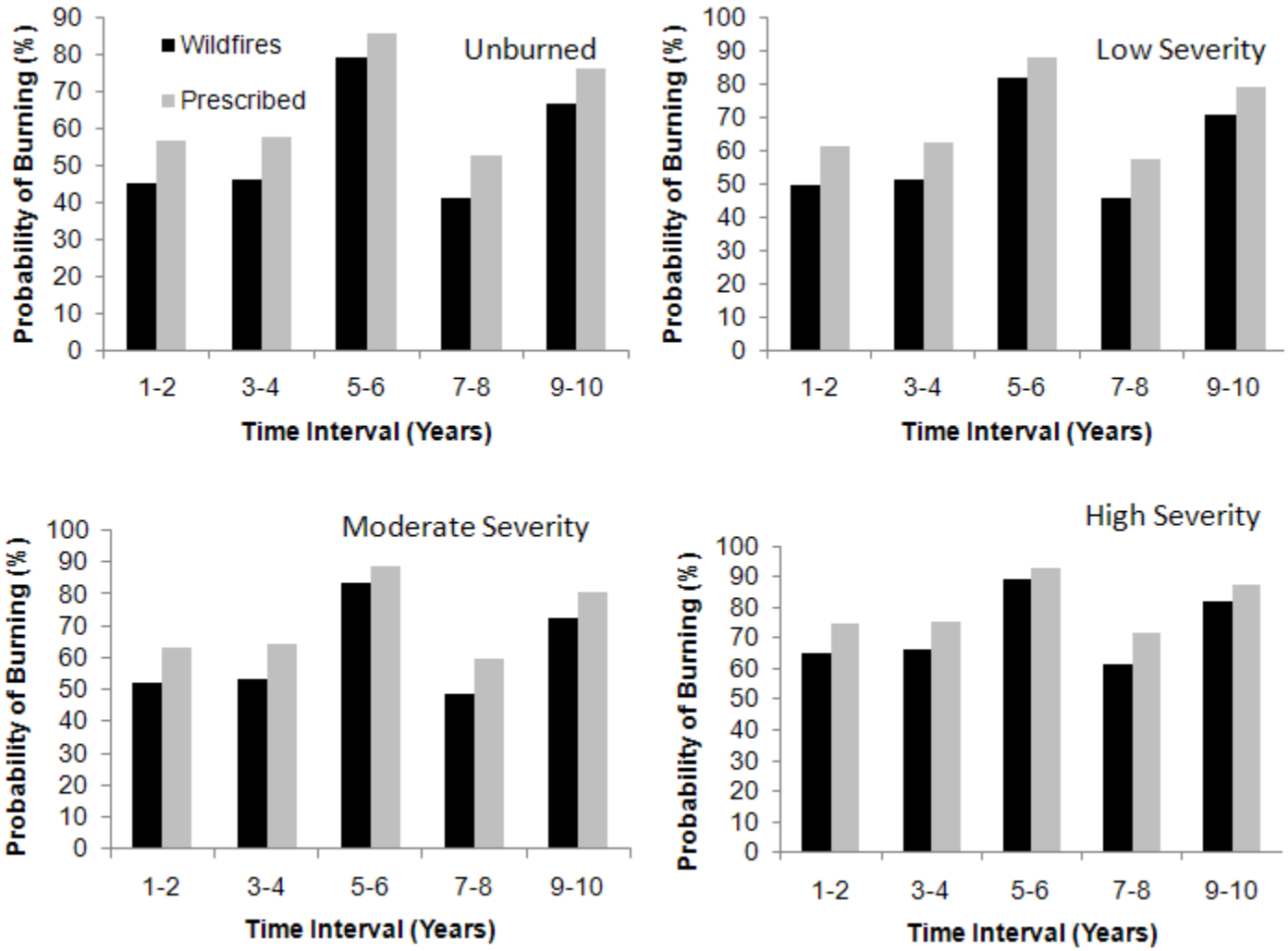


Figure 2-14. Probability of burning by time interval, fire type, and fire severity level.

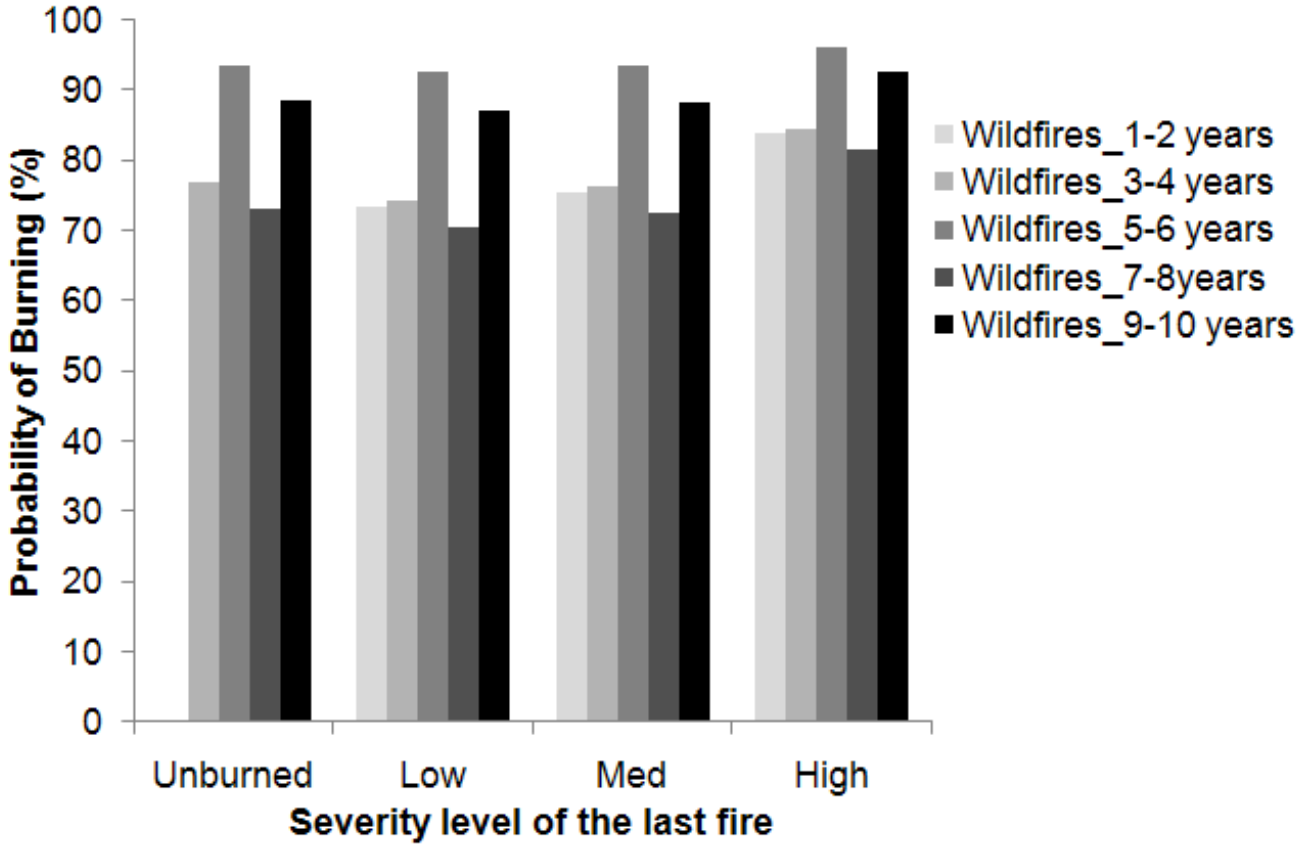


Figure 2-15. Probability of burning by fire severity level and time interval for wildfires.

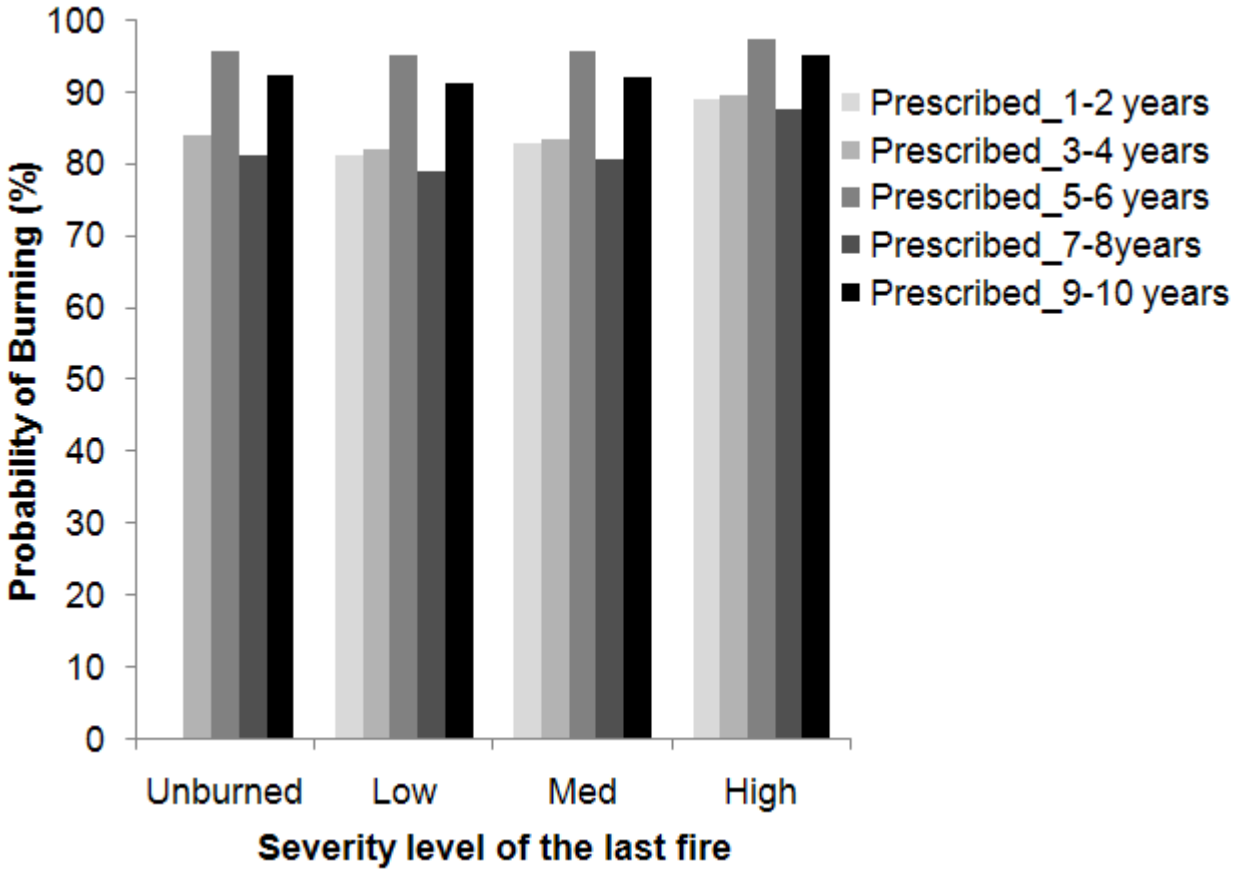


Figure 2-16. Probability of burning by fire severity level and time interval for prescribed fires.

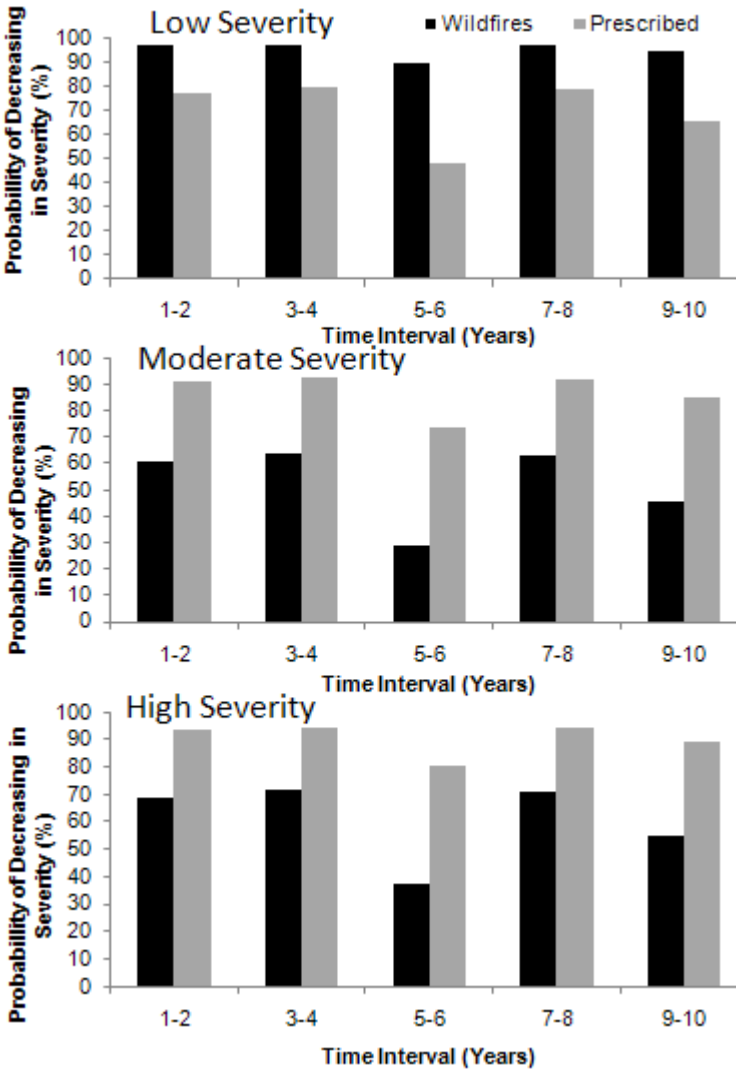


Figure 2-17. Probability of decreasing in severity level by time interval and severity level of fire 1.

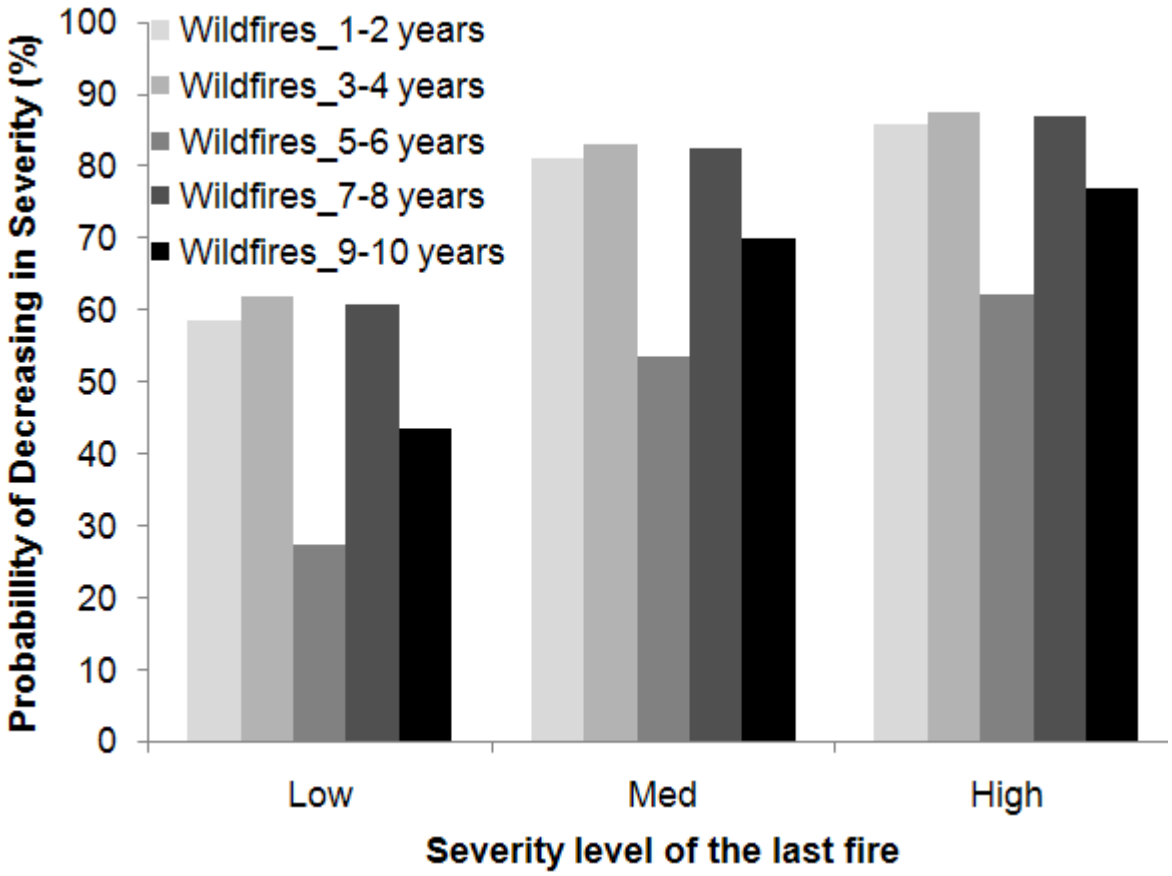


Figure 2-18. Probability of decreasing in severity by severity level of fire 1 and time interval for wildfires.

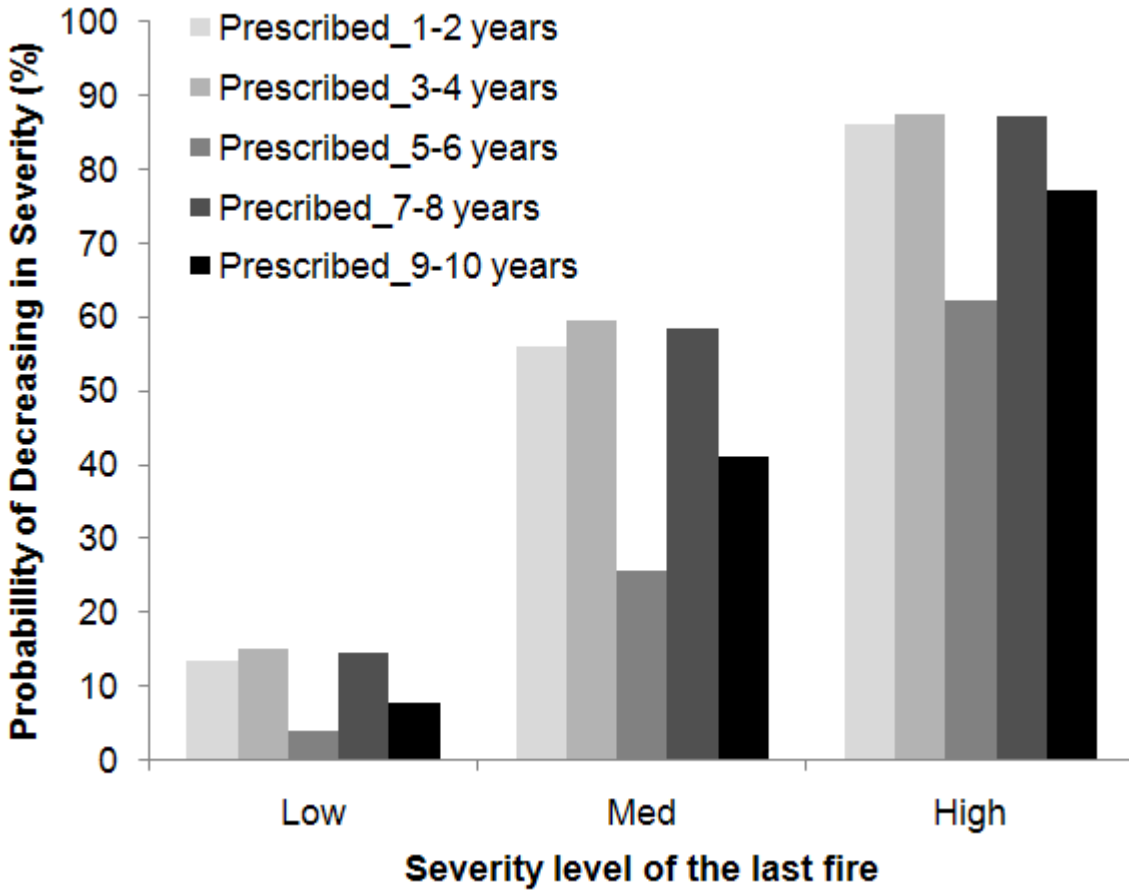


Figure 2-19. Probability of decreasing in severity by severity level of fire 1 and time interval for prescribed fires.

CHAPTER 3
PREDICTING FIRE SEVERITY IN PINE FLATWOODS USING DIFFERENCED NORMALIZED BURN RATIOS TO RECORD FIRE EVENTS

Introduction

Fire severity can be measured using remote sensing techniques to monitor changes in fire regimes over time and to map fire history. Fire severity is a measure of ecological and physical change attributed to fire (Agee 1993; Hardy 2005) and is influenced by both biotic and abiotic factors. Severity is altered by weather, moisture, time of day, sunlight incidence (Oliveras et al. 2009), species, tree size, succession stage, and pathogens (Cocke et al. 2005). Severity is important to monitor as it can have a significant effect on exotic species establishment, soil responses, regeneration, and ecosystem health.

Measuring Fire Severity

Normalized burn ratios (NBR) use short wave inferred bands, from Landsat Thematic Mapper (TM) bands 4 and 7 (Wagtendonk et al. 2004), to detect the severity level of a burned area (1). At this spectrum, differences in reflectance due to fire induced changes in soil moisture, canopy cover, biomass, and soil chemical composition is captured and compared to pre-fire conditions to determine the level of change or severity that occurred as a result of the fire event.

$$NBR = \frac{B_4 - B_7}{(B_4 + B_7)} \qquad 1$$

Difference normalized burn ratios (dNBR) capture the degree of change that can be attributed to fire by using a pre- and post- fire image (2).

$$dNBR = NBR_{pre\_fire} - NBR_{post\_fire}$$

The mapping methodology was originally developed and tested by the USGS Northern Rocky Mountain Science Center (NRMSC). Employed as a radiometric index, dNBRs are directly related to burn severity (Wagtendonk et al. 2004) and, as long as the fire is within the resolution range of the satellite sensor, 30m, it is detectable (White et al.1996). Combined with existing information about fire locations and perimeters, fire histories can be mapped to monitor trends in severity over time, frequency of fire, and time since last fire on a pixel level. This detailed dataset can then be used to make inferences about future fires.

Using remote sensing data to determine specific and effective return intervals can have serious implications for land managers. Currently land managers are using indiscriminate frequencies that range anywhere from 1-10 years between fire events for pine flatwoods management. Depending on site characteristics, frequencies may require modification for more or less productive sites. With a detailed fire history, land managers can identify areas that require immediate attention to both mitigate the risk of wildfire and prevent successional change.

Previous studies have used dNBRs to calibrate severity levels to specific forest types (Cocke et al. 2005; Hoy et al. 2008; Godwin 2008), compare severity levels between fire events (Collins et al. 2009; Allen et al. 2008;), interpret the effects of fuel management techniques on severity levels (Safford et al. 2009), and to monitor changes in vegetation over time (White 1996; Kuenzi et al. 2008) and topographical variations (Holden 2009; Oliveras et al. 2009). In the United States there is currently a multi agency project, Monitoring Trends in Burn Severity (MTBS), which is using dNBRs to map burn severity and the perimeters of large wildfires in the entire United States.

MTBS is using data from 1984–2010 to identify national trends in burn severity to determine the effectiveness of the National Fire Plan and Healthy Forest Restoration Act. As of now, no other study has used dNBRs to model the fire history of an entire forest. This study uses all prescribed and documented wildfires (greater than 1 ac) to create a complete fire history for the entire Osceola National Forest using dNBRs for each fire event.

The objective of this analysis is to determine the risk of high severity prescribed fire and the probability of moderate to high severity wildfires using data from 1998-2008. The probability high severity prescribed fire is important for monitoring fire effects and how these effects meet management objectives. Prescribed burns are implemented under optimal circumstances where conditions are suitable for vegetation consumption but not at levels to cause fire to become unmanageable and cause high mortality of overstory species. Optimally, prescribed fires should cause low levels of mortality in overstory species and understory fuel should be partially consumed with little consumption of the duff layer (Outcalt et al. 2004). High severity fires are characterized by complete combustion of most of the litter layer, duff and small logs, with mortality of small-med trees, and consumption of large tree crowns (Wagtendonk et al. 2004). During prescribed fires, land managers aim for low-moderate severity fire.

Considering wildfires, fire behavior that causes moderate to high severity levels may cause extensive challenges in suppression efforts and high mortality rates. Therefore, a model predicting the probability of moderate to high severity fire would be appropriate as low severity wildfires would be preferred from a suppression and salvage stand point. We hypothesize that the number of times a pixel burns will

influence its probability of burning, at high severity for prescribed fires and moderate-high severity for wildfires, if burned within 5 years and we also expect mesic communities to have a higher probability of burning at high severity than hydric communities for prescribed fires and the opposite for wildfires.

Study Site

The Osceola National forest located in north central Florida (Latitude: 30.34371, Longitude: -82.47322) about 40 miles west of the city of Jacksonville (Figure 1-1). The majority of the forest is pine flatwoods with scattered areas of cypress and bay swamps. With an overstory of pines on low, flat, sandy, acidic soils; pine flatwoods have an understory of herbaceous plants, grasses, palmetto, and woody species. Flatwoods communities are fire dependent and require regular burning for regeneration of fire-adapted species and ecosystem health. On the Osceola National Forest, communities include Longleaf pine (*Pinus palustris*) -wiregrass (*Aristida beyrichiana*), and slash pine (*Pinus elliotti*) -gallberry (*Illex glabra*) -saw palmetto (*Serenoa repens*). Cypress ponds (*Taxodium spp*) are found scattered throughout the forest in low lying wet areas. In this fire maintained community the lack of fire for prolonged periods will increase broad leaf woody vegetation and reduce herbaceous plant cover and eventually reduce pine germination. Fire suppression would cause significant changes in species composition that would then lead to changes in ecological processes within this system.

Fire management on the Osceola National forest is quite active. The majority of the forest is prescribed burned at a frequency of every 2-5 years. There are also sensitive areas within the forest that are not currently and actively managed by fire. Fire regimes are determined on a compartment level based on the current forest type and the desired future condition of the compartment. On this forest, fire managers are faced

with burning large acreages annually with few days that are within prescribed fire weather conditions. Sensitive areas near the forest like Lake City Municipal Airport, I-10, and the City of Jacksonville, provide addition constraints for fire managers.

Methods

Image Analysis

Landsat 7 ETM imagery was provided by the United States Geological Survey (USGS). The USGS provided geometrically and radiometerically corrected NBRs. Geometric corrections involved removing distortions from imagery caused by the sensor geometry. The geocorrection process consisted of two steps: (1) rectification, and (2) resampling. Geo-rectification was performed in order to relate pixels to their exact ground location and resampling determined the pixel values. Radiometric corrections involved the removal of atmospheric noise to accurately represent ground conditions. In this process the pixel values were modified to account for noise produced by atmospheric interference, sun-sensor geometry, and the sensor itself.

Following geometric and radiometric corrections, pixel values were in digital numbers. Digital numbers are a measure of at-satellite radiance. Finally, digital numbers are converted to at-satellite reflectance. NBRs were derived from a ratio of bands 4 and 7 (1) that has been corrected to at-satellite reflectance and range from ~-1000 to 1000. Pre-processed NBRs were provided by the USGS Global Visualization Viewer (http://glovis.usgs.gov).

Data

A fire history dataset was created using the dNBRs for each fire event (prescribed and wildfires). DNBRs were created for each event using images closest to the date of the fire event. General severity levels provided by the United States Geological Survey

(USGS) were reclassified to 4 severity levels; unburned, low severity, moderate severity, and high severity (Table 2-1). To account for variation due to phenology and surface moisture conditions in the pre- and post- fire images, the mean value of unchanged pixels were subtracted from the dNBR (Collins et al. 2009). DNBRs were then clipped using fire perimeter shape files provided by the U.S. Forest Service. Next, fires were merged to create an image that represented fire events for each year (Appendix A, Table 3-1). The layers created for each year were finally used to calculate model covariates. (1) Time since last fire is the number of years since last fire (Figure 3-1). (2) Frequency is the number of times a pixel has burned within the dataset (Figure 3-2). (3) Latest severity level is the severity level of the last fire event (Figure 3-3). These three layers were then compiled to create a fire history for each individual pixel. Calculations were made using ArcGIS software.

Forest type and community type were obtained from the Florida Geographic Data Library (http://www.fgdl.org/metadataexplorer/explorer.jsp). The forest type layer was developed by the University of Florida Geoplan Center (Figure 3-4). Vegetative communities were distinguished based on Davis (1967). Swamps, marshes and other areas classified by the National Hydraulic Dataset as having standing water were classified as hydric and the rest of the forest was classified as mesic based on soil and forest types (Figure 3-5).

Model Development

Logistic regression was utilized to determine the probability of burning at a high severity for prescribed fires and moderate-high severity for wild fires, on a pixel level, in 2008. Logistic regression is used to measure binary responses by describing the

relationship between one or more independent variables and the binary response (Littel et al. 2006). Responses are coded as 0 or 1:

$$y_i = \begin{cases} 1 \; success \\ 0 \; failure \end{cases} \tag{3}$$

Where y_i is a realization of a random variable Y_i that can take on the values of 0 and 1 with probabilities π_i and 1- π_i (3). The distribution of Y_i is a Bernoulli distribution with the mean (4) and variance (5) depending on the underlying probability π_i.

$$E(Y_i) = \pi_i \tag{4}$$

$$var(Y_i) = \pi_i \, (1 - \pi_i) \tag{5}$$

To make the probability, π_i , a linear function of a vector of observed covariates ($\boldsymbol{x_i}$) π_i, the probability is transformed to remove range restrictions (**6**).

$$\text{logit}\,(\pi_i) = \log \frac{\pi_i}{1 - \pi_i} = \boldsymbol{x}'_i \beta \tag{6}$$

Logits map probabilities from range [0, 1] to [-∞, ∞]. Negative logits represent probabilities below ½ and positive logits represent probabilities above ½. Solving for the probability of success requires exponentiating the logit and calculating the odds of success (7).

$$\pi_i = \frac{\exp(\boldsymbol{x}'_i \beta)}{1 + \exp(\boldsymbol{x}'_i \beta)} \tag{7}$$

Maximum likelihood methods were used for parameter estimation. With this approach, parameters were estimated iteratively until parameters that maximized the

log of the likelihood were obtained. Goodness of fit statistics, Akaike's information criterion (AIC) and Bayesian information criterion (BIC), were used to compare competing models. AIC is a statistic used for model selection that ranks different models based on how close fitted values are to true values (8) (Littell et al. 2006).

$$\mathrm{AIC} = 2k - 2\mathrm{In}(L) \tag{8}$$

Where: k is the number of parameters in the statistical model and L is the maximized value of the likelihood function for the estimated model (8). Like AIC, BIC was used to rank models with a different numbers of parameters to avoid increasing the likelihood by over fitting the model (Littell et al. 2006).

$$\mathrm{BIC} = -2 * \mathrm{In}(L) + k\,\mathrm{Ln}(n) \tag{9}$$

Where: n is the sample size (9). Unexplained variation in the dependent variable and the number of covariates increases the AIC and BIC values. For both AIC and BIC, the lowest score indicates the best model.

The ratio of the Pearson chi-square to its degrees of freedom is used to determine if the model displays lack of fit. Values closer to 1 indicate that the model fits the data well (Littell et al. 2006). To address the assumption of independence among observations, a generalized linear mixed model was used using the SAS procedure PROC GLIMMIX (Littell et al. 2006). Correlation among responses is incorporated into the model by adding random components to the linear predictor. To account for the correlation among responses, random residuals were modeled. Raster data is spatially correlated due the adjacency of pixels. Although it would have been more effective to model the spatial correlation directly, without the aid of a super computer this option is

infeasible. The GLIMMIX procedure can also make use of several predictor variables that may be either numerical or categorical.

In this analysis we evaluated the probability of experiencing high severity and moderate to high severity based on the history of fire for prescribed and wild fires. Covariates included frequency of fire, time since last fire, severity level of the latest fire (categorical), forest type (categorical) and, community type (categorical) (Table 3-2). Frequency of fire is the number of times a fire occurred within the data frame. Time since last fire is the number of years that passed since the last fire event. The latest severity level is the severity level of the last fire event. Forest types are classified as pine flatwoods, longleaf pine / xeric oaks, fresh water marshes and swamp forest; and community types are classified as hydric or mesic.

A backward selection method was used to determine the appropriate covariates for the final model. The Wald chi-square statistic was used to identify significant covariates. Final model selection was also determined based on significant parameters and the model with the lowest AIC and BIC value. Interactions between all parameters were also considered. Non-significant parameters were removed from the full model one at a time. To test for differences among categorical levels least square means were produced and differences were tested.

Data used to create the logistic model included the years 1998-2006 for prescribed fires and 1998-2007 for wildfires. Fire history was developed for pixels using data up to 2005. This data was used to predict the probability of prescribed fires burning at a high severity level in year 2006. Fire history from 1998-2006 were used to model the probability of wildfires burning at a moderate-high severity in 2007. These models were

then used to predict the probability of experiencing a high severity prescribed fire and the probability of experiencing a moderate-high severity wildfire in 2008.

Spatial Model

The models, probability of high severity prescribed fire and moderate to high severity wildfire, were recreated spatially using parameter estimates from logistic regression and ArcGIS spatial analyst extension. Layers were created for each parameter and calculations were made using the spatial analyst/ raster calculator. The spatial model was used to show the probability of high severity prescribed fire and the probability of moderate-high severity wildfire in 2008.

Results

Probability of High Severity Prescribed Fire

Severity level of the last fire γ_i, frequency of fire X_{1ij}, time since last fire X_{2ij}, and the interaction between frequency and time since last fire were significant parameters in the model for prescribed fires (10).

$$\text{logit}(\pi_{ij}) = \eta + \gamma_i + \alpha_1 X_{1ij} + \alpha_2 X_{2ij} + \alpha_3 X_{1ij} X_{2ij} + \varepsilon_{ij} \qquad \textbf{10}$$

The model was significant and the parameters were significant based on their Wald chi-square statistics (Table 3-3). The ratio of the Pearson chi-square statistic to its degrees of freedom was approximately 1 indicating good model fit.

Time since last fire showed a positive relationship with the probability of high severity; as the time interval increased the probability of high severity fire also increased (Figure 3-6, Figure 3-7, Figure 3-8). The effect of the severity level of the last fire varied by severity level; unburned, moderate, and high severity levels in the last fire increased the probability of high severity in the subsequent fire and low severity level in the last

fire reduced the probability of high severity in the subsequent fire. Unburned areas had a very high probability (>80%) of experiencing high severity fires regardless of the amount of time that had passed since the last fire event (Figure 3-8). Areas that had experienced low and high severity in the last fire had a low probability of experiencing high severity in subsequent fire, followed by areas that experienced a moderate severity level which approached a 50% probability at 7-9 years since the last fire. Frequency of fire also had a positive relationship with the probability of high severity fire. As frequency of fire increased, the probability of experiencing high severity subsequent fire also increased (Figure 3-6).

Probability of Moderate to High Severity Wildfire

The model for the probability of experiencing a moderate to high severity wildfire incorporated frequency of fire X_{1ij}, time since last fire X_{2ij}, and the interaction between the two (11).

$$\text{logit}(\pi_{ij}) = \eta + \alpha_1 X_{1ij} + \alpha_2 X_{2ij} + \alpha_3 X_{1ij} X_{2ij} + \varepsilon_{ij} \quad \textbf{11}$$

The model was significant and the parameters were significant based on their Wald chi-square statistics (Table 3-4). The ratio of the Pearson chi-square statistic to its degrees of freedom was approximately 1 indicating good model fit. As the time since last fire increased, the probability of moderate-high severity fire also increased (Figure 3-9). The increased probability over time since last fire varied by the number of fires that occurred since 1998. Areas that had never experienced fire had a much higher probability than previously burned areas. As the frequency of fire increased, the probability decreased (Figure 3-10).

Spatial Models

The spatial models identified areas that had increased probability of burning at a high severity based on fire history for prescribed fire (Figure 3-11, Figure 3-12), and identified the probability of moderate to high severity for wildfires. Areas with probabilities greater than 95% are highlighted as areas we would expect to burn severely if a fire event were to occur.

The High severity model (for prescribed fires) identified areas that burned often, as targets for high severity. Probabilities range from 35-99% for the entire forest. A small portion of the forest had a probability greater than 95% (6.2%), while most of the forest had a probability of high severity greater than 50% (84%). Although forest type was not a significant predictor of high severity fire, the model indicated that mesic communities had a small portion of the area with a probability greater than 95% (6.3%) (Figure 3-13). Hydric communities had a higher portion of area (45%) with a probability of high severity greater than 95%. A small percentage of the prescribed fires in 2008 actually burned at a high severity level (2.4%) (Figure 3-14) and these areas were often found to have a probability of high severity that was at least 95%.

In the 2008 fire season there were very few wildfires greater than 1 ac that occurred on the Osceola National forest. The model Identified areas that had not burned or had burned only once from 1998-2007 as having a higher probability of burning at a moderate-high severity level. Most of the forest had a probability less than 15% (Figure 3-16). The probability of burning at a moderate to high severity level was quite low for the entire dataset (<20%). Although forest and community types were not significant predictors of moderate to high severity, the model indicated that hydric communities had a probability less than 1% for most areas (Figure 3-17). Mesic

communities had a higher probability (below 5%) for the majority of the area. Of the four forest types, fresh water marshes had the highest probability of moderate-high severity (>15%) (Figure 3-18).

Discussion

Probability of High Severity Prescribed Fire

The model predicting the probability of high severity for prescribed fires yielded important information regarding the relationship between time between fire events, the severity level of previous fires, and the frequency of fire. As time since last fire increased, the probability of experiencing a high severity fire also increased. Previous studies conducted on the Osceola National Forest, found that as time between fire events increased, fire intensity also increased causing greater tree mortality following fires (Outcalt et al. 2004). Vegetation recovery and fuel loads increase with time since the last disturbance event. So, as the time since the last fire increases there is also an increase in the amount of fuel and an increase in vertical structure of fuel. As fuel and vertical structure increases, so should the probability of burning at a high severity level due to the increase in combustible material. Increases in vertical structure also provide ladder fuels that increase the chance of ground fires moving into tree crowns.

Areas previously burned by low severity fire had a lower probability of high severity prescribed fire just as areas with high and moderate severity levels had a higher probability of high severity fire. This indicates that fuel availability may be influencing the amount of change caused by fire more than previous fires. Low severity fires may be the result of fuel availability and not fuel accumulation. Areas with high and moderate severity levels that have high probabilities of experiencing high severity at short return intervals suggest that vegetation on these sites quickly recovered from fire

events and were able to burn severely again. Alternatively this may reflect a bias in the high severity class. If these areas burned severely then there is likely less vegetation to burn during subsequent events. If this vegetation is consumed during a fire it would take less fuel consumption to cause a large amount of change between pre- and post-fire images. This effect increases subsequent fire severity level and increases severity level with increased fire frequencies. This phenomenon would explain the unexpected relationship between frequency and the probability of high severity as well as the high probability associated with prescribed fires versus wild fires.

Hydric communities had a higher probability of high severity prescribed fire then mesic communities. This may be explained by the conditions chosen to perform prescribed fires under. In stands that have been burned multiple times in the past, land managers may choose weather conditions that are more risky to execute prescribed fires. And, even though hydric areas are usually unavailable during prescribed fires, when they are avialible they may burn at a high severity level.

Probability of Moderate to High Severity Wildfire

Predicting the probability of moderate to high severity wildfires yielded information unlike the prescribed fire model. Time since last fire had the same increasing relationship, yet fire frequency had a decreasing relationship in this model. The relationship between frequency and the probability of moderate to high severity wildfire is what we would expect; as the number of times an area burned increased, we would expect there to be a reduced chance of experiencing higher severity levels because fuel loads were reduced. Increased frequency also reduces the vigor in vegetation recovery so that with each fire, vegetation re-growth declines.

Forest and community types were not significant indicators of high and moderate to high severity fire. During prescribed fires we might expect similar fire effects (low severity) in the different forest and community types as areas are burned under optimal conditions. Yet, during wildfires we expect hydric communities to burn more severely if the vegetation is avialible to burn due to high fuel loads especially during prolonged drought periods (Outcalt et al. 2004). Within this dataset, few hydric communities burned severely indicating that fuel was not avialible to burn during wildfires. We would also expect that forest types would influence severity levels. The lack of significance may be due to Osceola National Forest being composed mostly of pine flatwood and mesic forest.

Spatial Models

The spatial models were effective in identifying, spatially, where you would expect to observe high severity fire in the event a prescribed fire occurred and moderate to high severity in the event a wildfire occurred. The prescribed fire model identified areas that have a history of burning often as being at an increased risk of high severity fire. Areas that have not burned in 10 years also had an elevated risk of high severity fire. Most of the area burned in 2008 was burned by prescribed fire at moderate (45%) and low (18%) severity levels. Sections of prescribed fires that actually burned at high severity had probabilities of high severity greater than 50% and most of the area had probability greater than 95%. This suggests that the model adequately identified areas that were at a high risk of high severity fire based on its ability to recover from previous fire, the effects of the last fire event, and the amount of time between events.

The wildfire model had low probabilities of moderate-high severity for the entire forest for 2008. Areas that had not been burned were identified as having increased

risk of moderate to high severity fire. A single wildfire occurred on the Osceola in 2008 (less than 5 acres) and this wildfire had no areas of moderate or high severity.

Conclusion

Remote sensing techniques were successfully used to model fire history for the Osceola National Forest to determine the risk of experiencing high and moderate severity fire in the event of a fire. The models identified areas that require attention in order to reduce the risk of high and moderate to high severity fire. The prescribed fire model identified areas that burn often as having an elevated risk of high severity. This relationship between fire frequencies and high severity implied that either the vegetation with high frequencies was at the highest risk due largely to fast recovery time for prescribed fires or that there was a bias in the high severity class for areas with less vegetation. Forests that can burn on short time intervals need to as a response to the short time period required for fuel loads and live vegetation to return to pre-fire conditions. Yet, continued burning would also reduce the amount of vegetation available for subsequent fires and this reduction could be causing a bias in the high severity class.

Conditions suitable for prescribed fire are determined by climatic factors and fuel loads, and are increasingly influenced by burned acreage quotas set by regional or federal management. Forest managers are under pressure to burn as many acres as possible each year. They may be willing to burn areas with high fire frequencies under more risky weather conditions due to reduced fuel loads and short time since last fire. Fire effects in these areas may then end up being more severe than in areas that are burned under less extreme fire weather conditions.

Smoke sensitive areas are at an elevated risk for high severity and moderate to high severity. These areas are dangerous to burn due to the risk of disrupting transportation, reducing air quality, or damaging property. Conditions suitable to burn sensitive areas occur rarely often increasing the amount of time between fire events. Parts of the Osceola just north of the airport and that surround Interstate 10 have a probability of high severity that ranges from 50-75% for prescribed fires. During wildfires, the risk is elevated compared to probabilities for the rest of the forest (10-19%). Both models identify these areas as being at an elevated risk requiring significant suppression efforts in the event of fire.

The relationship between frequency and the probability of high severity may also be due to error introduced by differences in biomass. Additional research to address the amount of biomass in relation to dNBR values is necessary to determine if areas with lower biomass have a higher probability of high severity due to the smaller amount of vegetation necessary to cause a significant change in pre- and post- fire images. It may also be useful to look at the effects of delayed mortality in areas with short fire return intervals to identify if this would cause further bias in the high severity class.

Overall, the probability of moderate to high severity (for wildfires) is less than what we would expect. The low probability may be caused by how wildfires are mapped. Wildfire perimeters are mapped using Landsat imagery based on ocular estimates of where fires occurred. The perimeters are not exact so wildfires tend to have a high amount of unburned and low severity pixels. Also, most wildfires within this dataset are less than 50 acres. Wildfire size is determined by both suppression efforts and fuel availability. Therefore, smaller wildfires indicate that wildfires were not often exhibiting

fire behavior that would likely cause high severity fire effects. There were few wildfires (Oak Fire 1998, Impassible 2004, and the Bugaboo 2007) that were large in size and that required great suppression efforts assisted by weather conditions for suppression. Larger fires had higher portions of moderate and high severity than smaller fires (not significantly larger). So, for the entire dataset, very few areas burned at high severity during wildfires (excluding the impassible fire of 2004) and there was not a very large increase in the area burned by moderate severity for larger fires. Biases introduced by perimeter estimates and the greater amount of smaller wildfires are the likely cause for the low probability of experiencing moderate to high severity.

Table 3-1. Number of pixels in each severity class by year.

Year	Severity			
	High	Moderate	Low	Unburned
1998	9720	18442	214519	106581
1999	5946	18791	111048	149600
2000	6404	1785	4961	7996
2001	56	180	372	505
2002	1	50	42680	71144
2003	1	27	179	72
2004	119570	58799	127579	31298
2005	3668	13045	63549	43737
2006	22283	23283	25804	9565
2007	120	7182	26136	69340
2008	2757	40332	17183	2757

Table 3-2. Covariates for the model measuring the probability of high severity prescribed fire and moderate to high severity wildfire.

Forest Type	Community Type	Frequency	Time since Last Fire	Last Severity Level
Pine flatwoods Longleaf/ xeric oaks Fresh water marshes Swamp forest	Hydric Mesic	The Number of times a pixel burned at a severity level greater than 1	Number of years since last fire event where pixel burns at a severity level greater than 1	Severity level of the last fire event

Table 3-3. Parameter estimates and their respective standard errors and p-values for the model predicting the probability of high severity prescribed fire.

Parameter		Estimate	Std. Error	P-value
Intercept		-3.0979	0.3210	<0.0001
Frequency of Fire		1.9709	0.1899	<0.0001
Time Since Last Fire		0.09361	0.02556	0.003
Severity Level of the last Fire	Unburned	1.5268	0.1458	<0.0001
	Low Severity	-0.5854	0.07704	<0.0001
	Medium Severity	0.3493	0.08290	<0.0001
	High Severity	0	.	.
Residual		1.009	.	.

Table 3-4. Parameter Estimates and their respective standard errors and p-values for model predicting the probability of Moderate to High severity wildfire.

Parameter	Estimate	Std. Error	P-value
Intercept	-3.2121	0.1391	<0.0001
Frequency of Fire	-1.5005	0.1302	<0.0001
Time Since Last Fire	-0.1470	0.01383	<0.001
Frequency * Time Since Last Fire	0.2194	0.01404	<0.001
Residual	0.9975	.	.

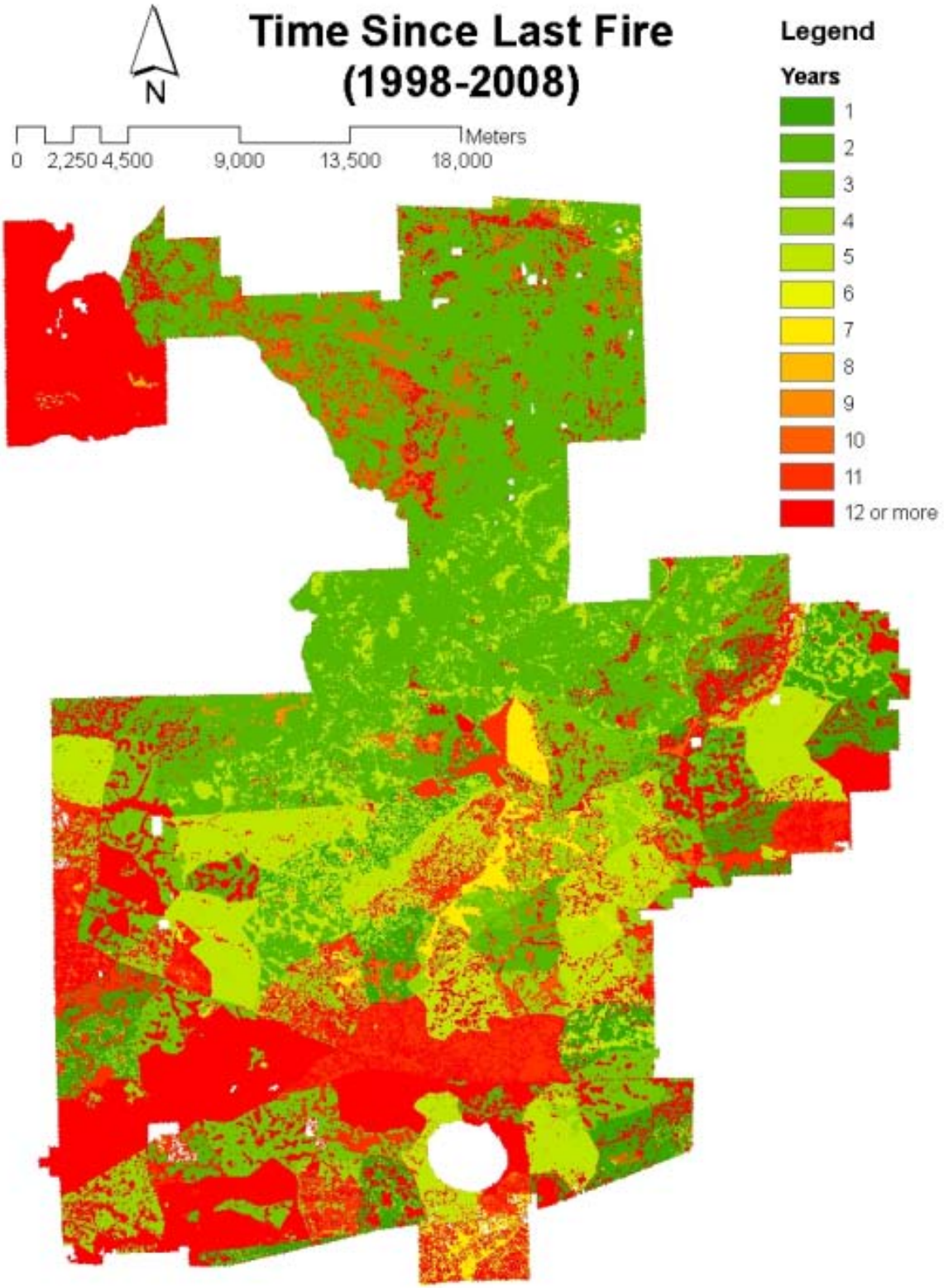


Figure 3-1. Time since last fire for the Osceola National Forest (1998-2008)

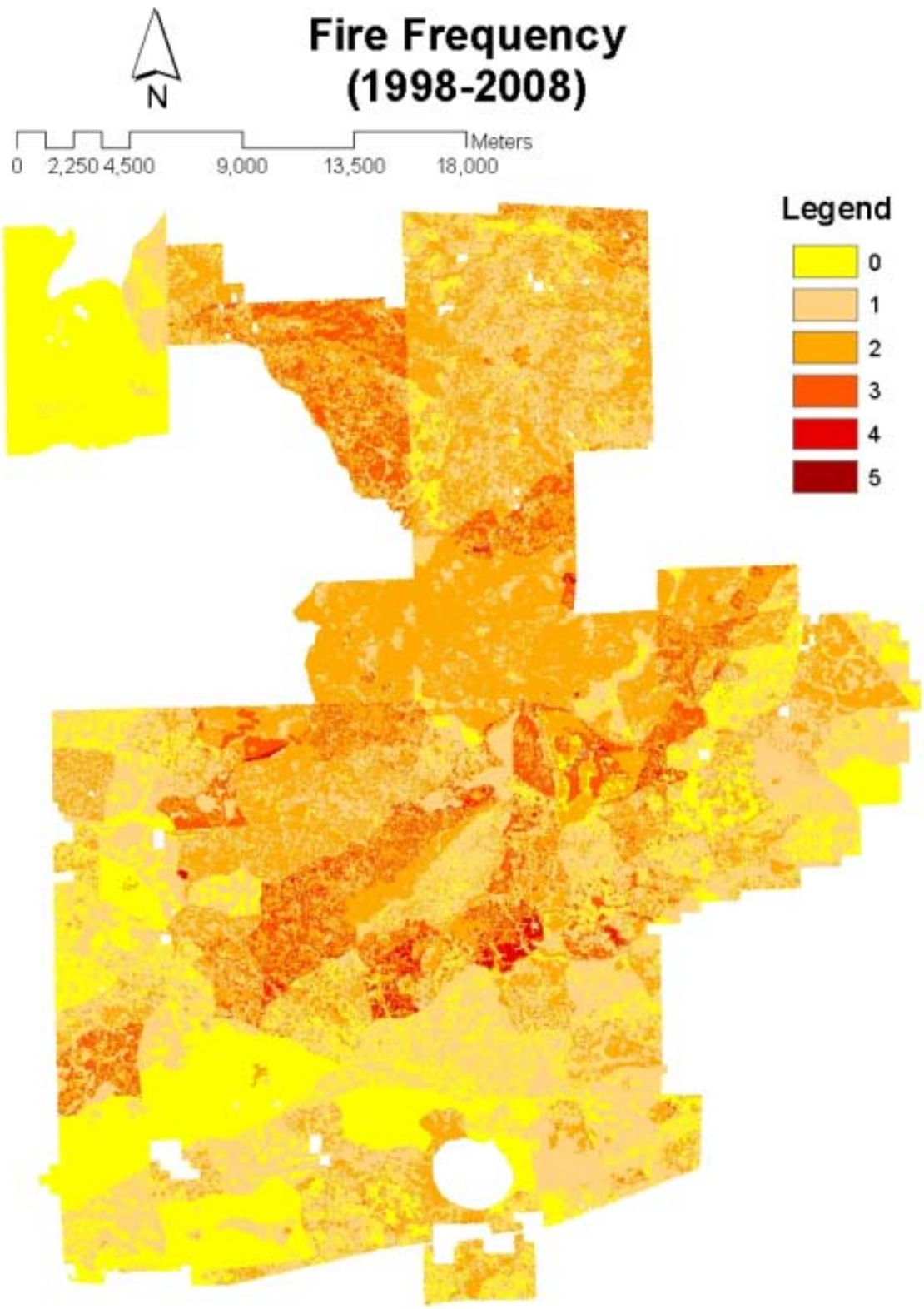


Figure 3-2. Fire frequency from 1998-2008 for the Osceola National Forest.

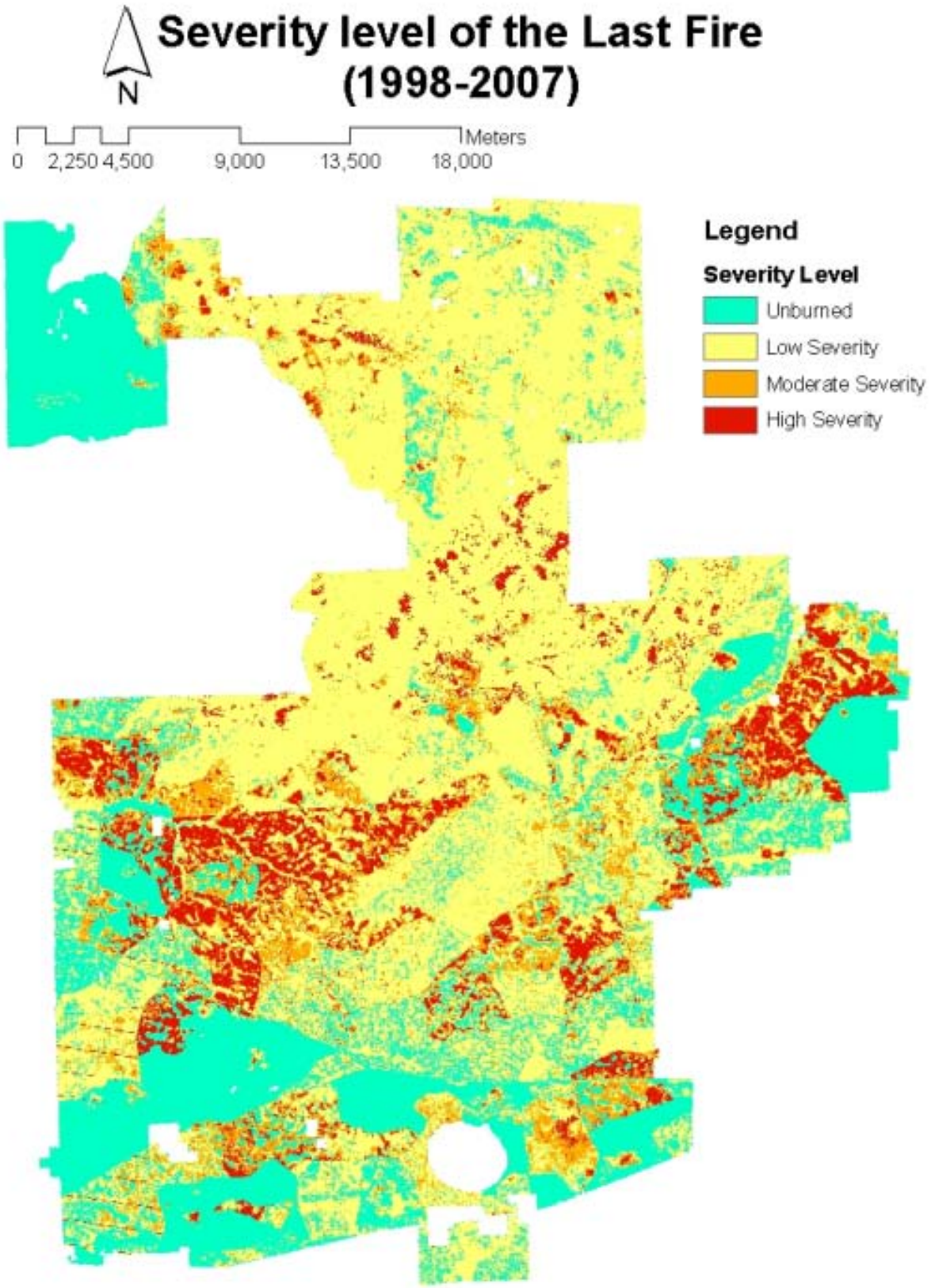


Figure 3-3. Severity level of the last fire event (1998-2007).

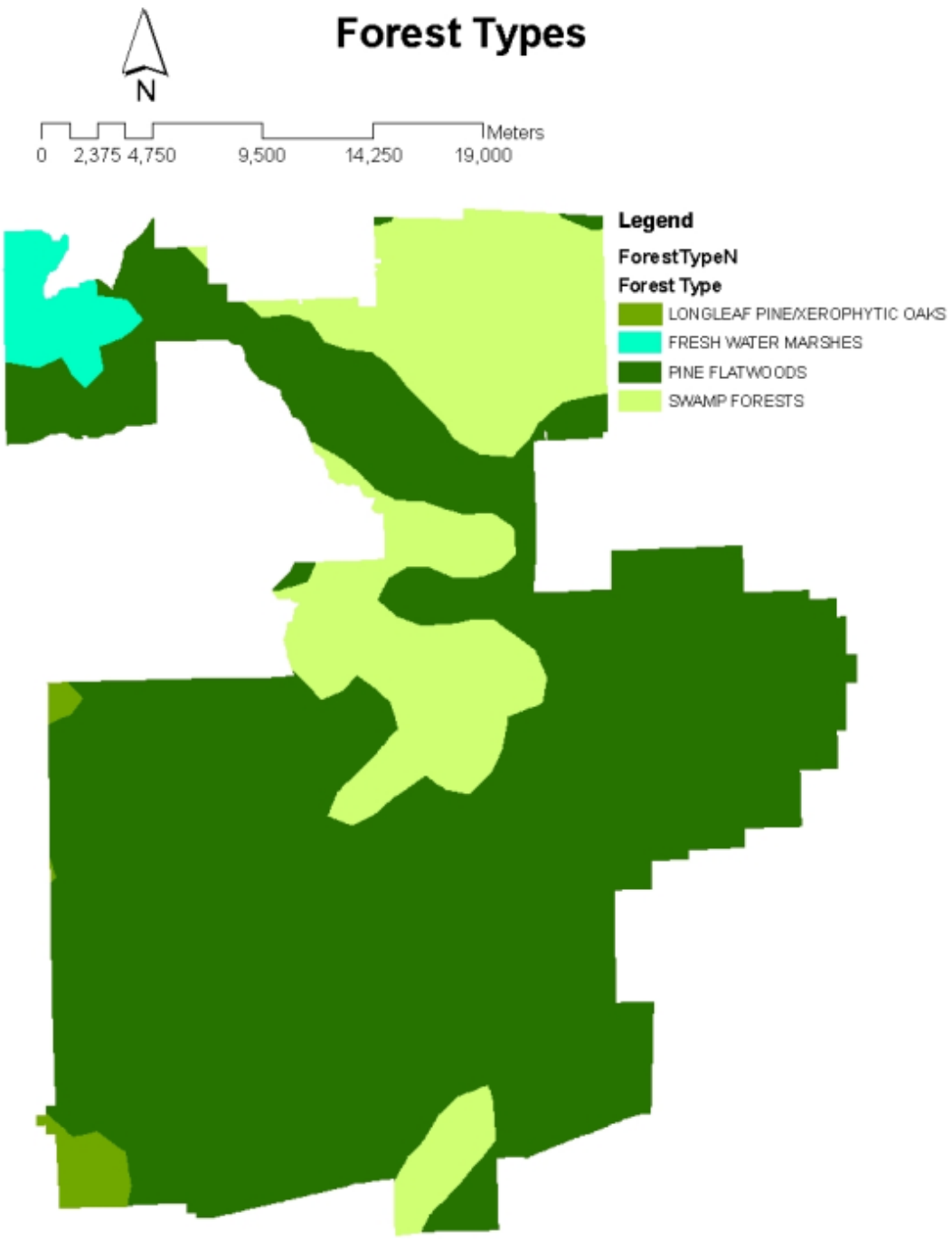


Figure 3-4. Florida Geographic Database Library Map of forest types for the Osceola National Forest.

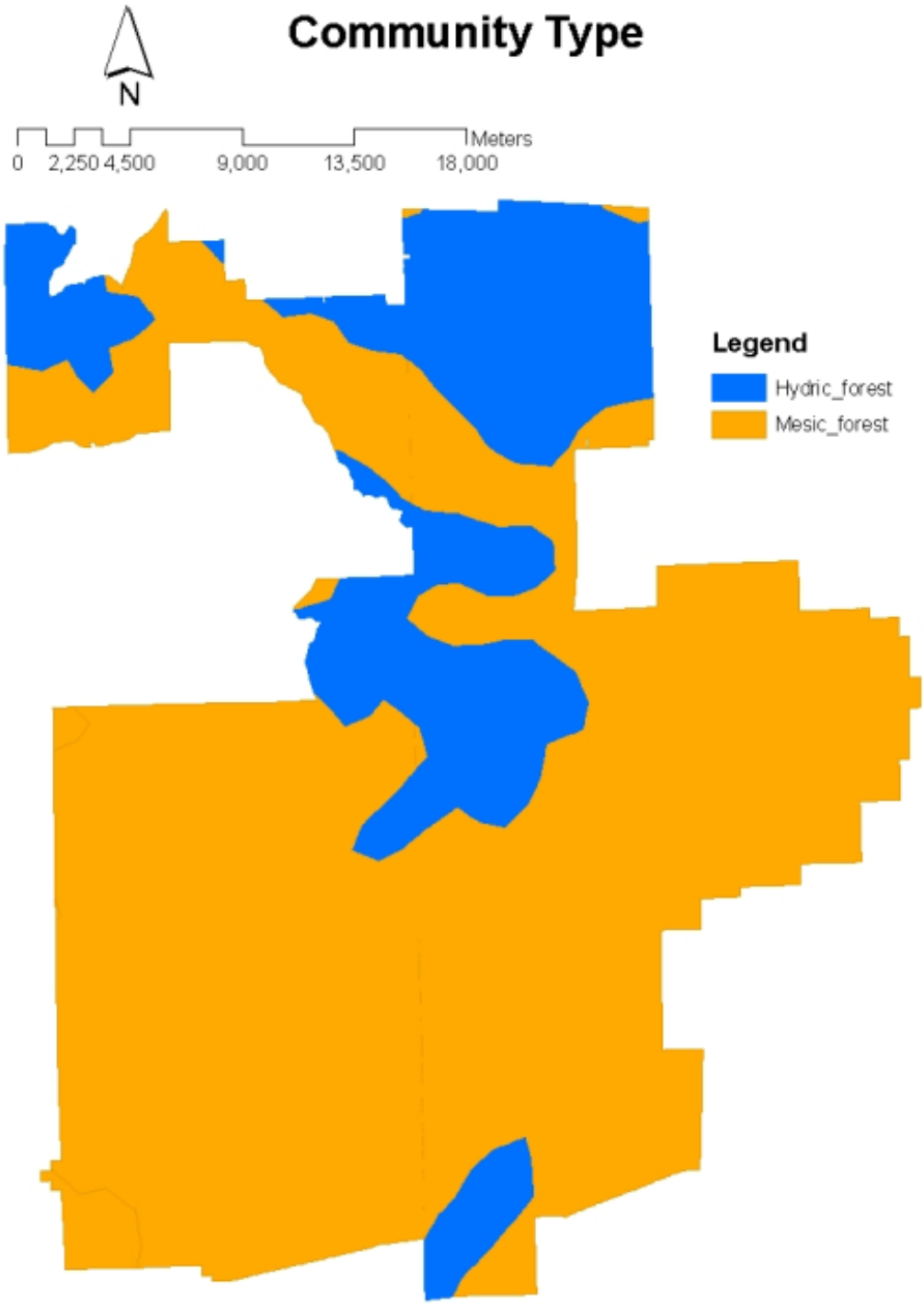


Figure 3-5. Map of the community types, hydric and mesic, for the Osceola National Forest.

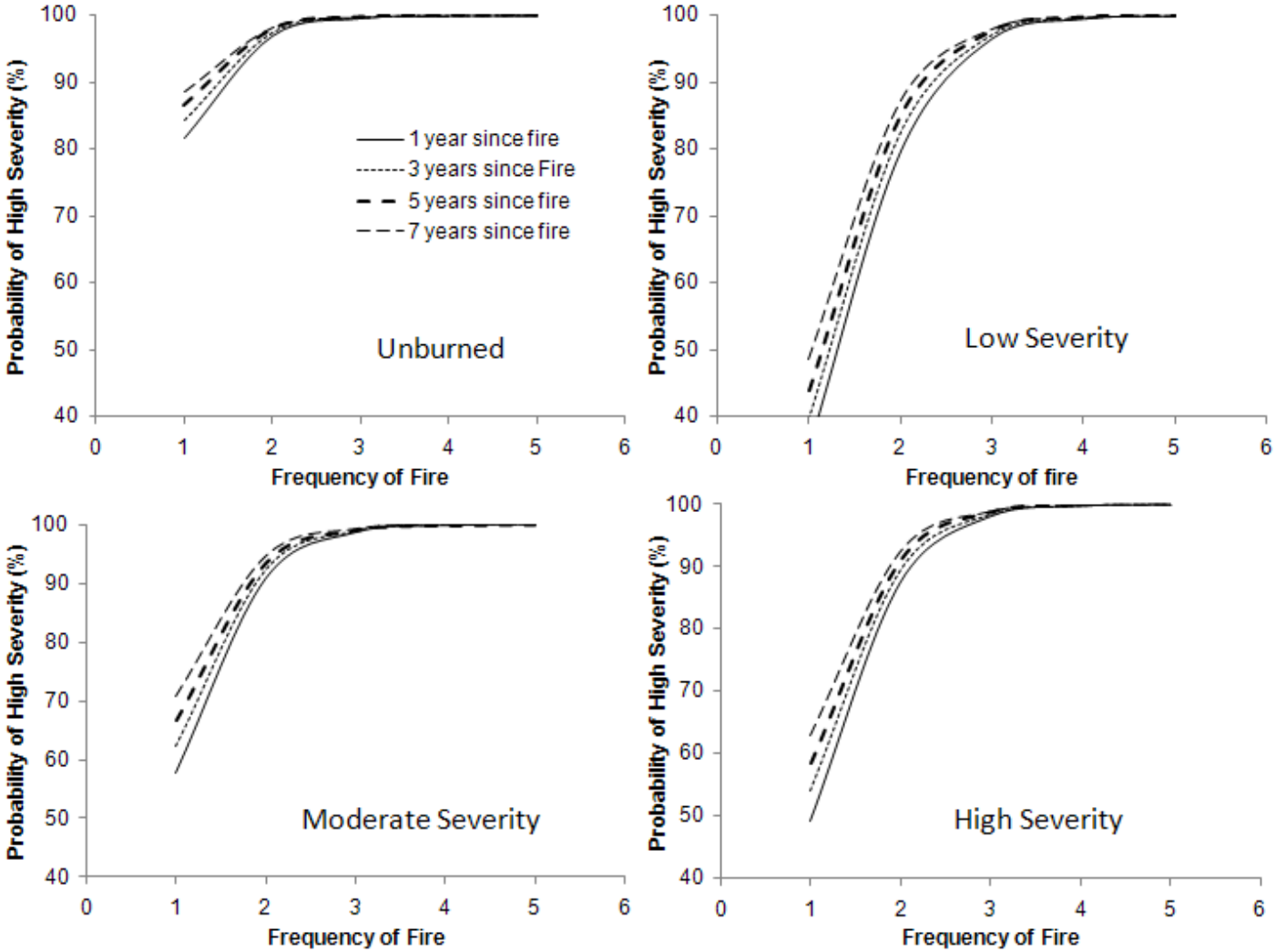


Figure 3-6. Relationship between the probability of high severity prescribed fire, frequency of fire, and time since last fire.

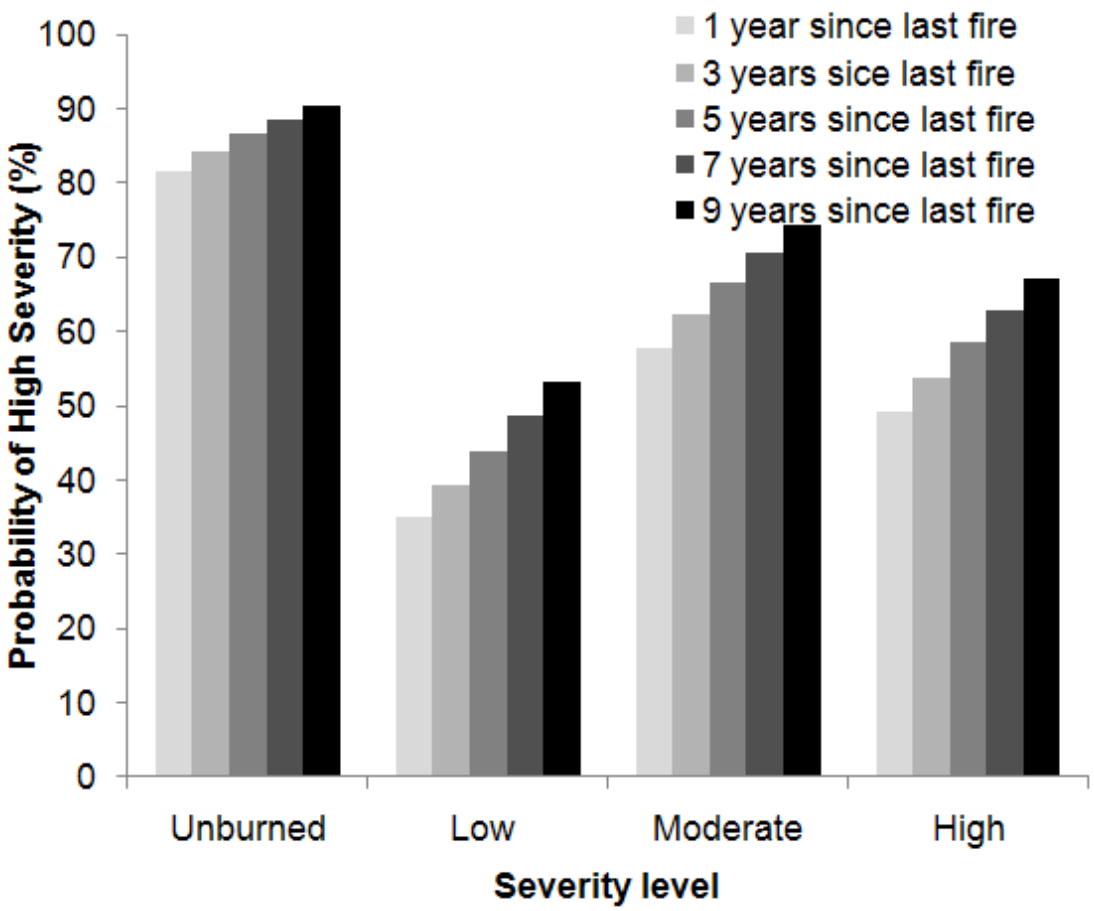


Figure 3-7. Relationship between the probability of high severity prescribed fire, the severity level of the last fire event, and time since last fire.

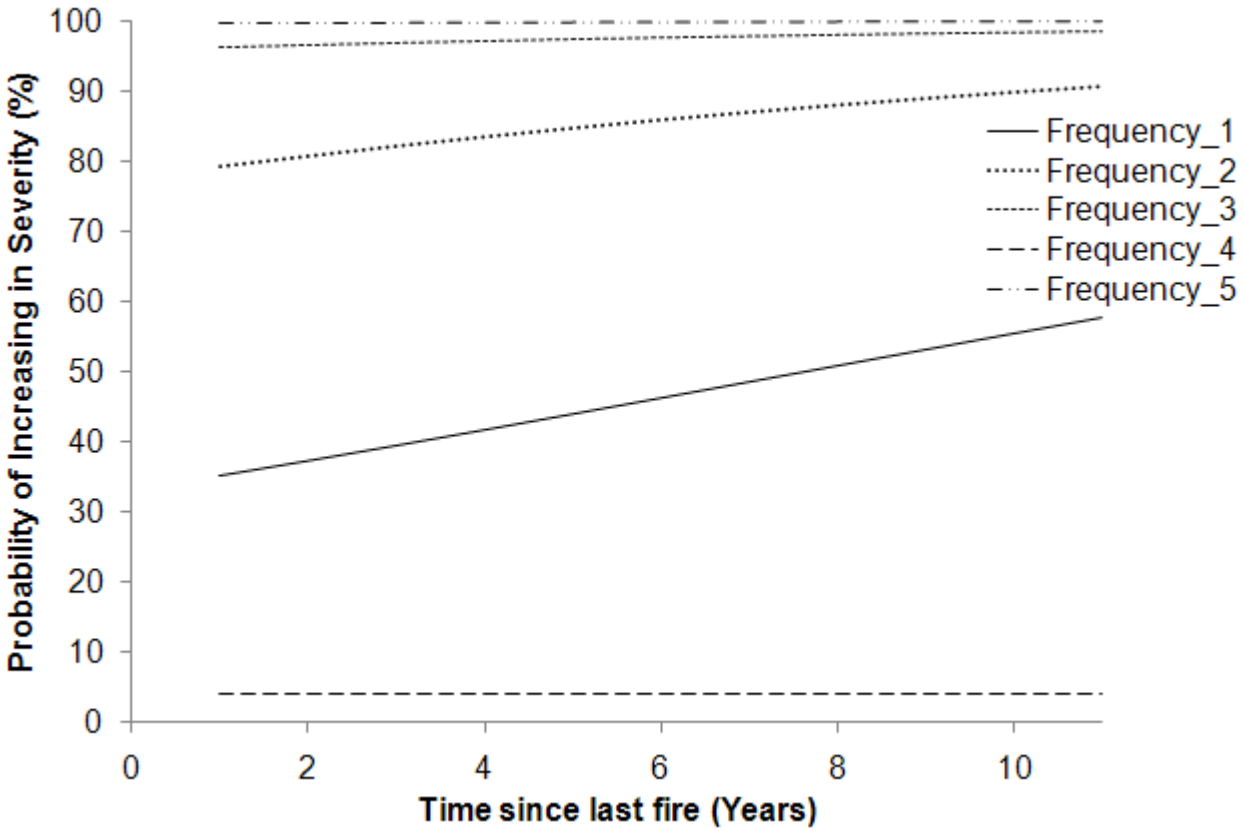


Figure 3-8. Relationship between the probability of high severity prescribed fire, frequency of fire, and time since last fire.

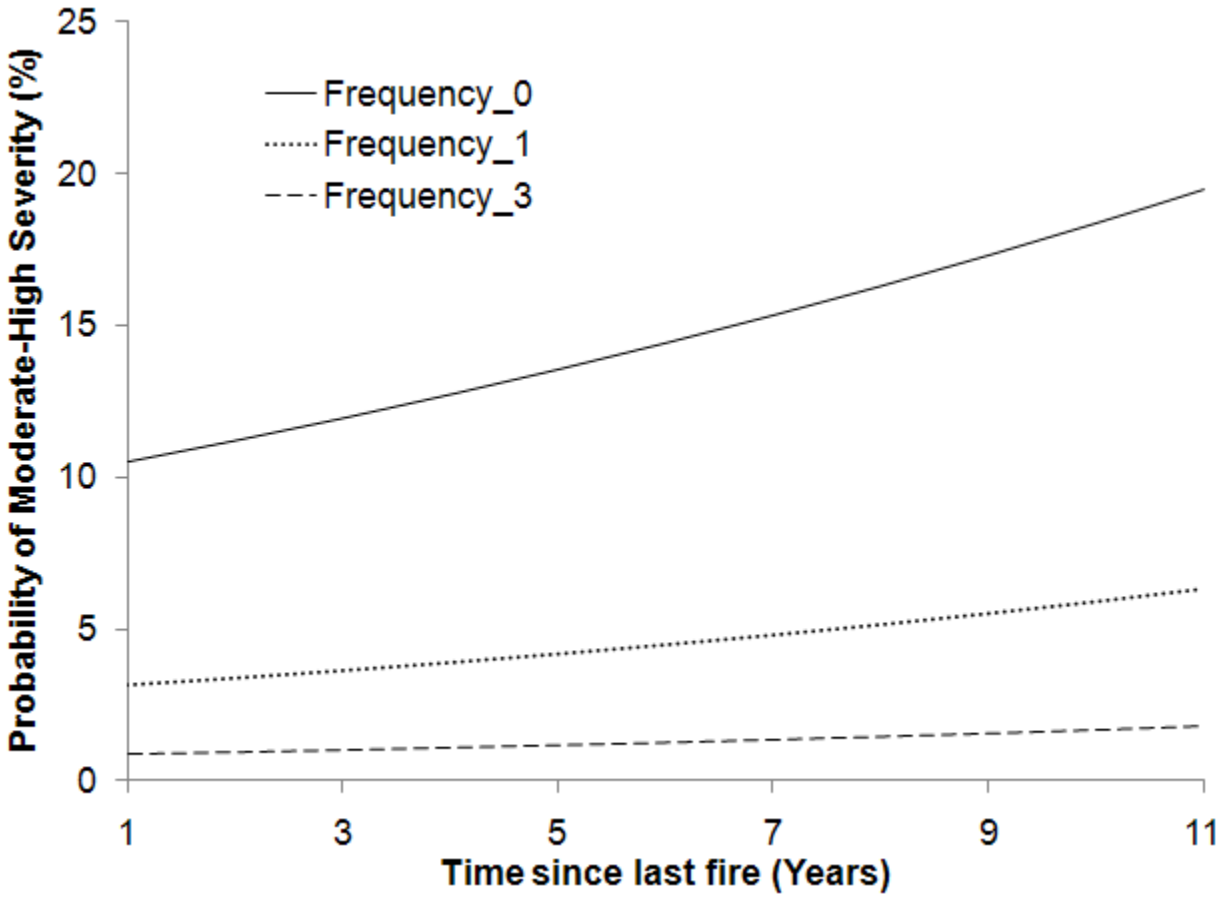


Figure 3-9. Relationship between the probability of moderate to high severity wildfire, frequency of fire, and time since last fire.

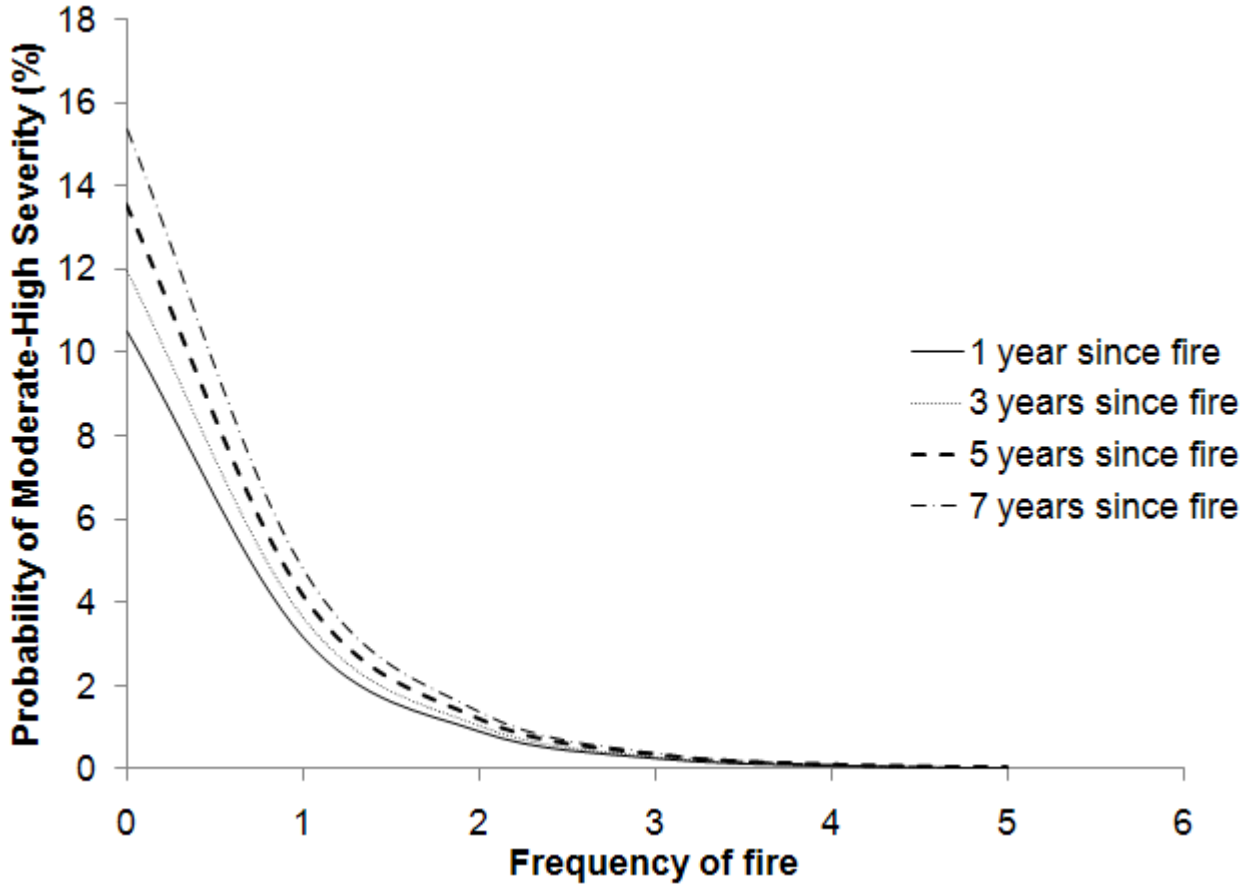


Figure 3-10. Relationship between the probability of moderate to high severity wildfire, fire frequency, and time since last fire.

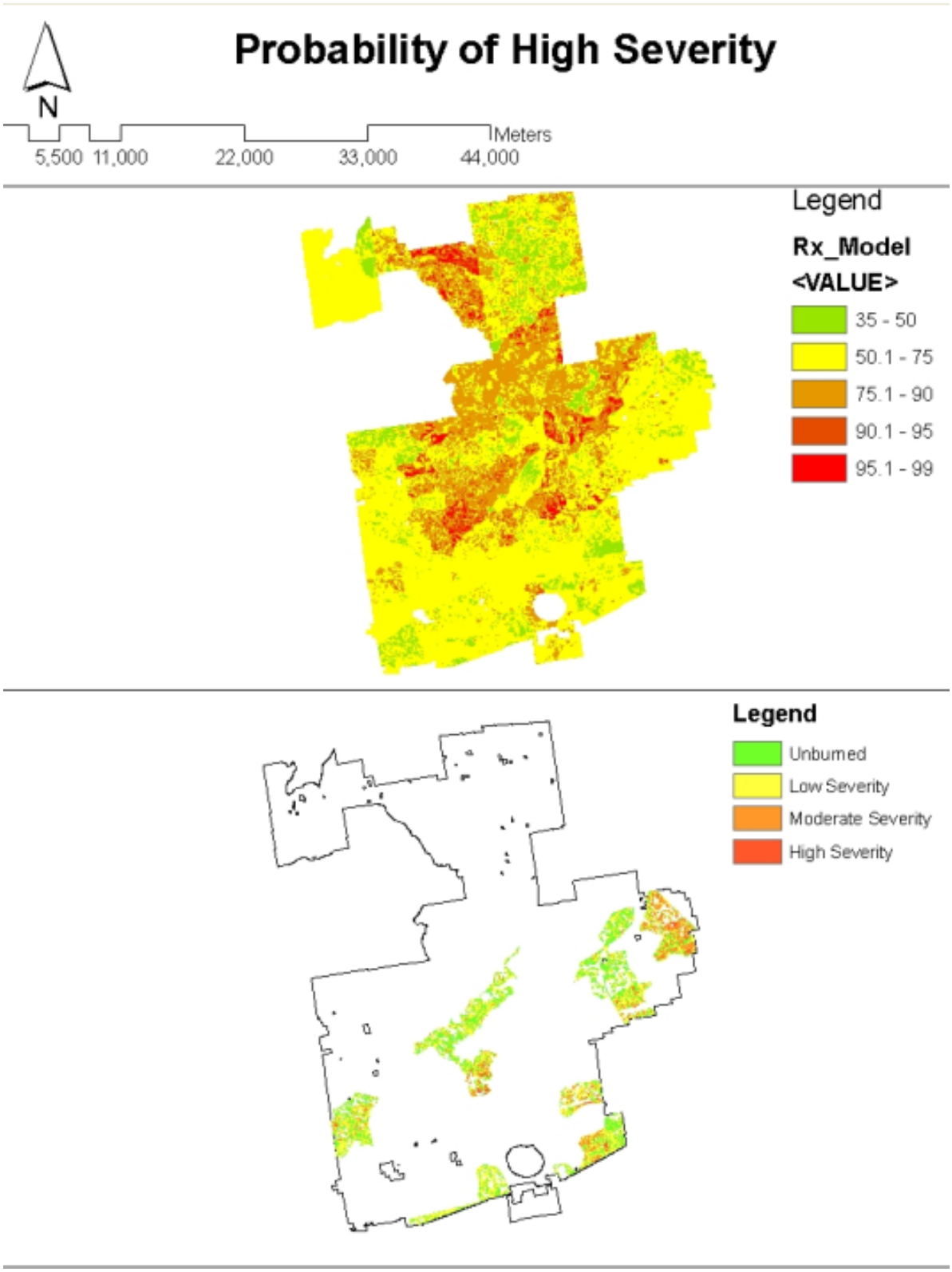


Figure 3-11. Probability of high severity prescribed fire versus observed severity levels for 2008 prescribed fires.

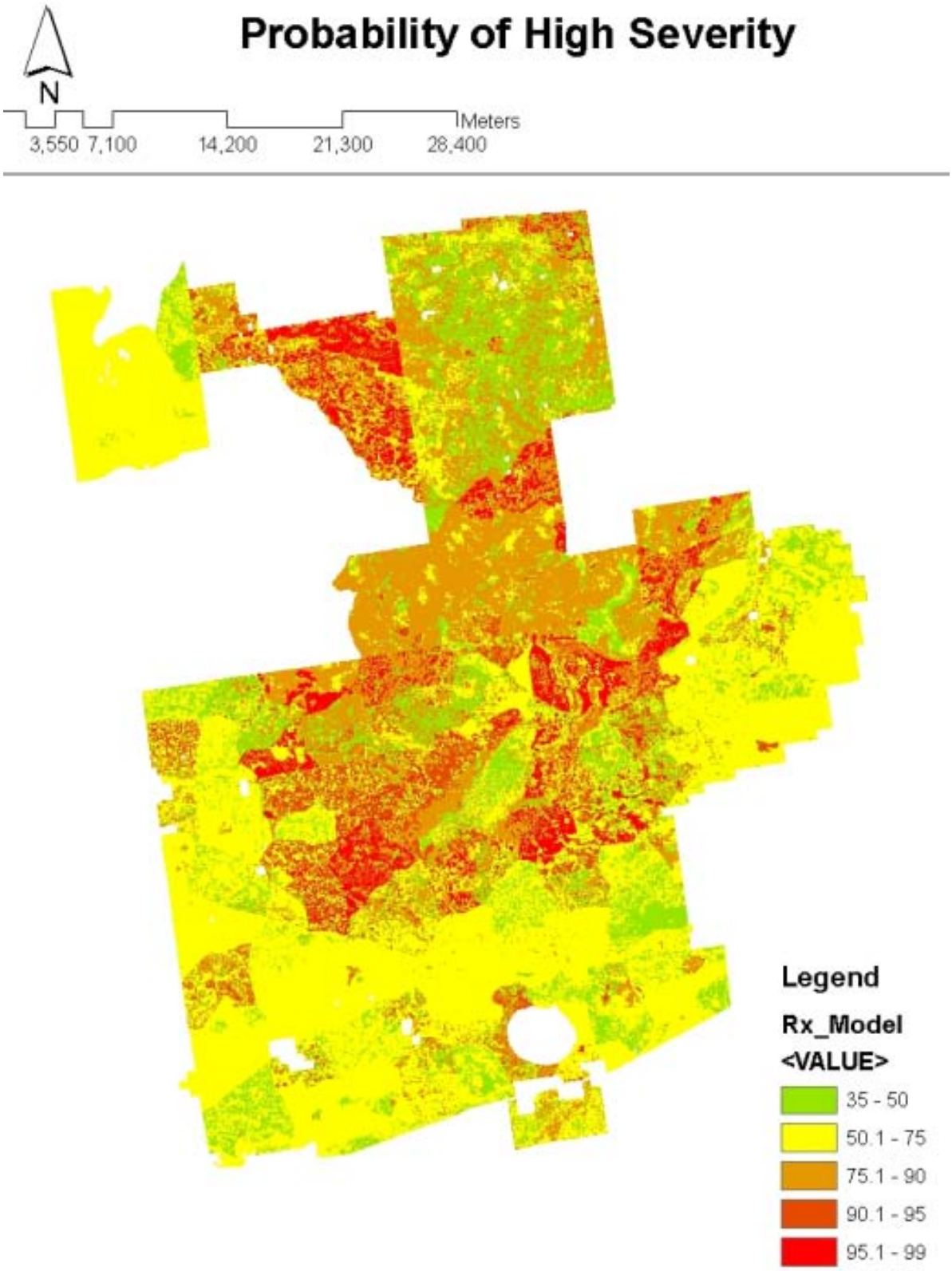


Figure 3-12. The probability of high severity prescribed fire in 2008.

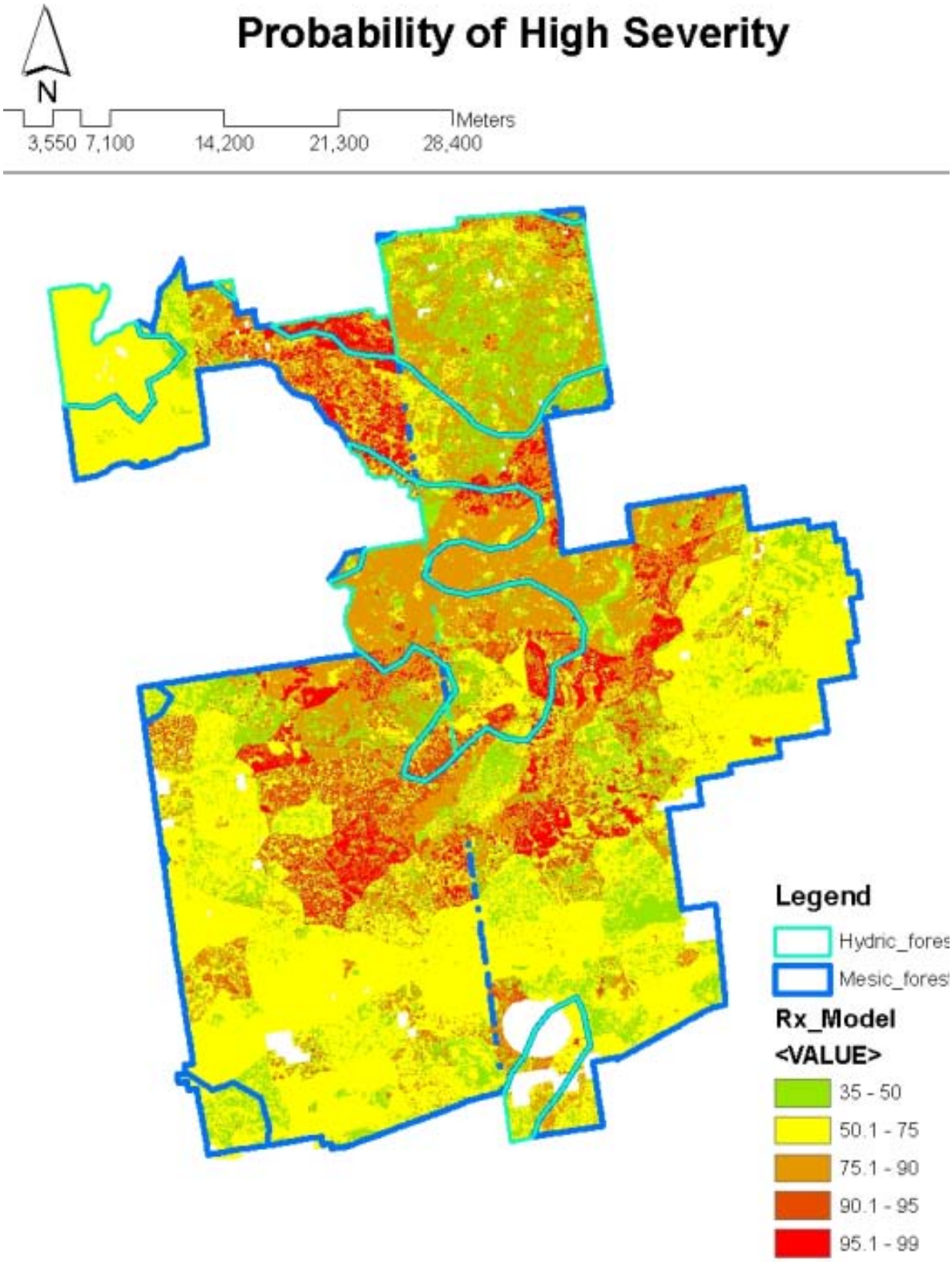


Figure 3-13. The probability of high severity prescribed fire in 2008 by community type.

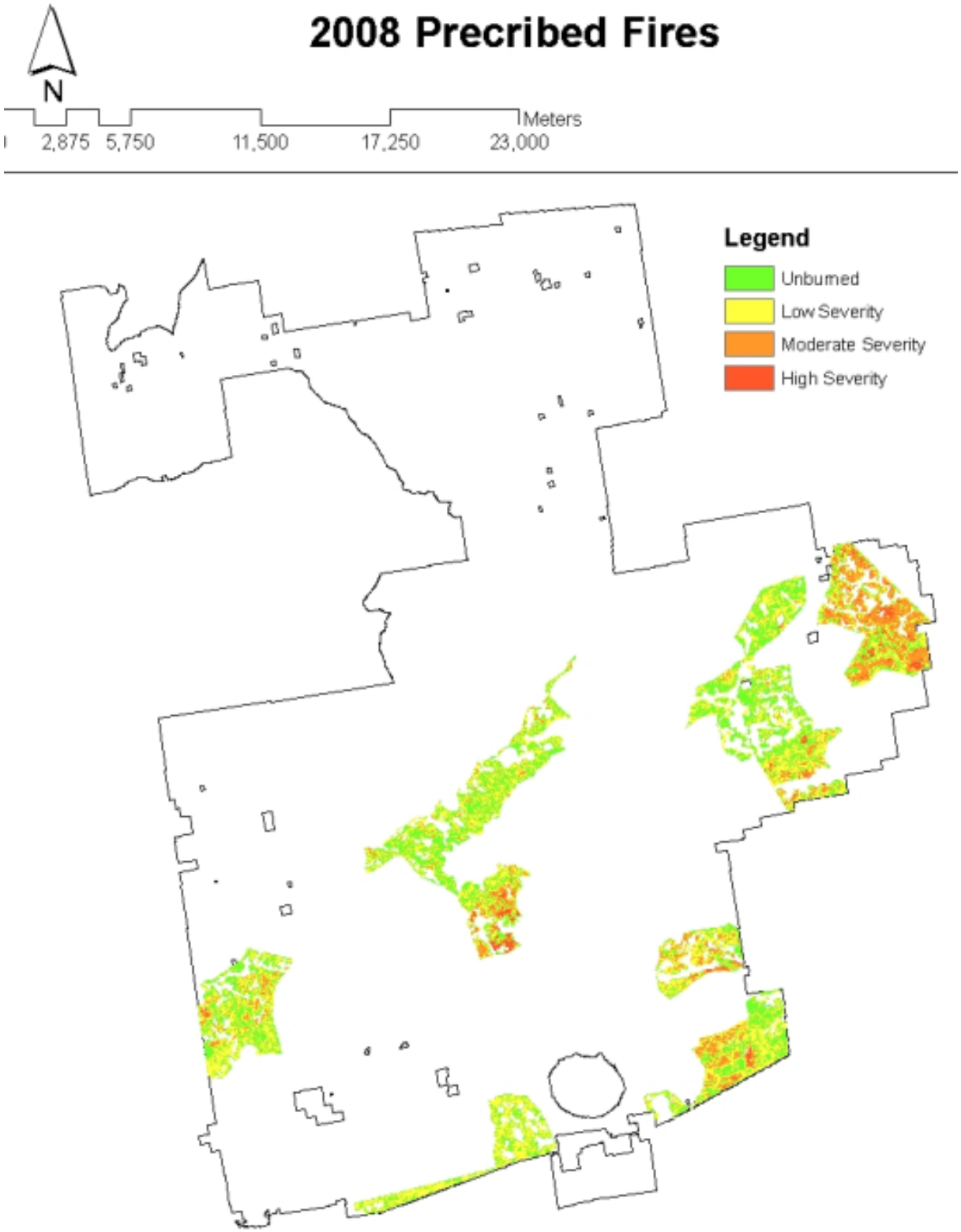


Figure 3-14. Severity levels of 2008 prescribed fires on the Osceola National forest.

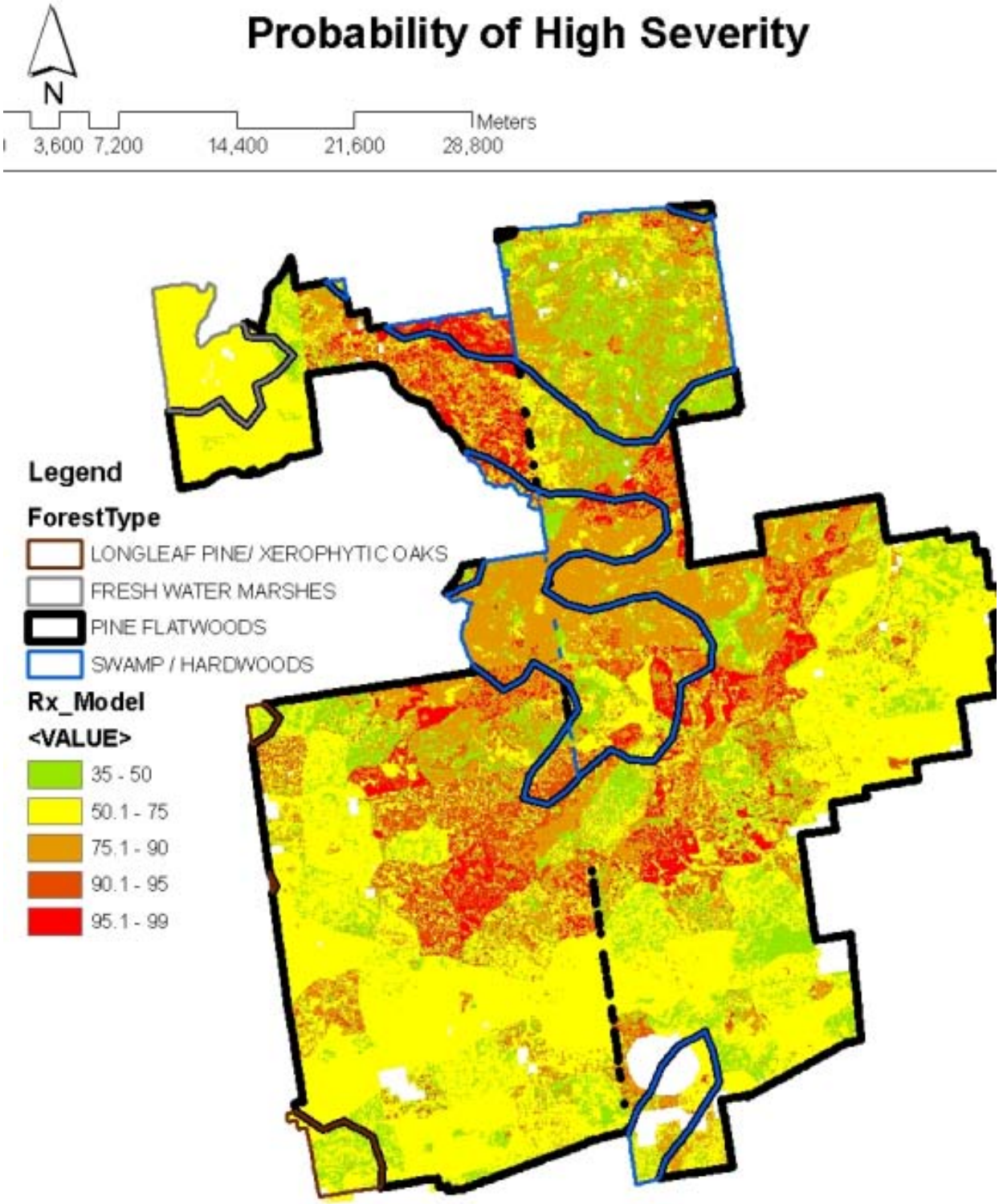


Figure 3-15. The probability of high severity prescribed fire in 2008 by forest type.

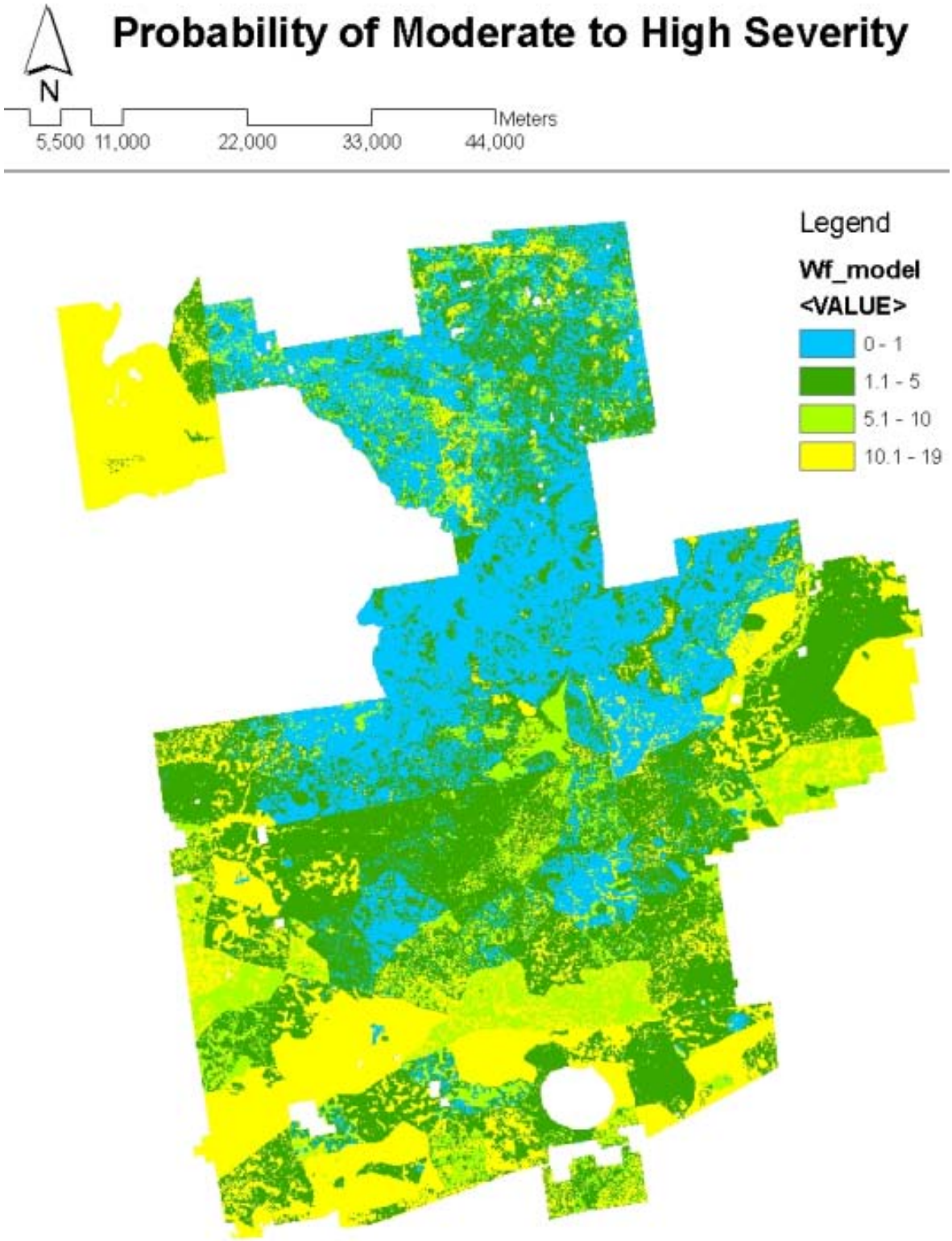


Figure 3-16. The probability of moderate to high severity fire for 2008.

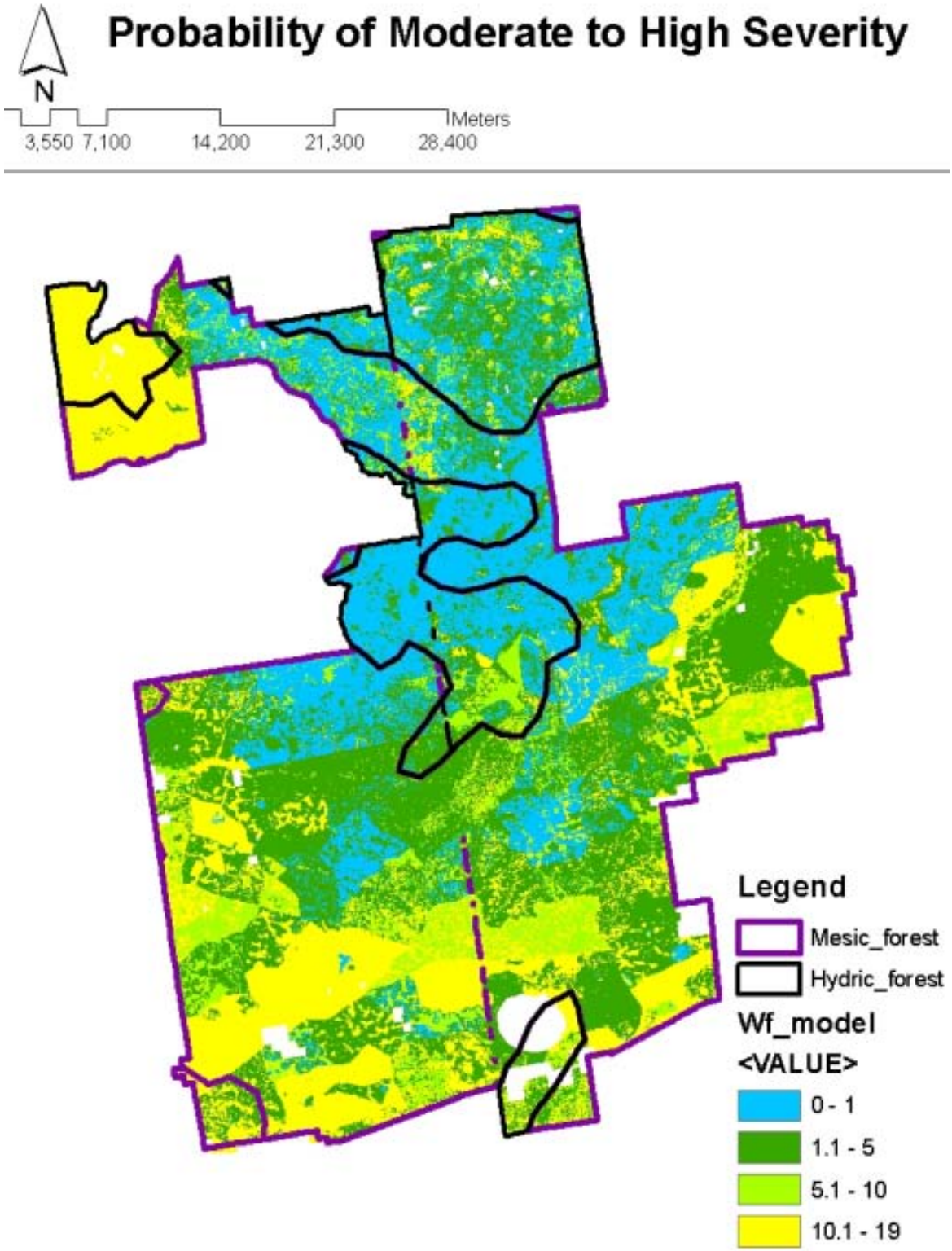


Figure 3-17. The probability of moderate to high severity wildfire for 2008 by community type.

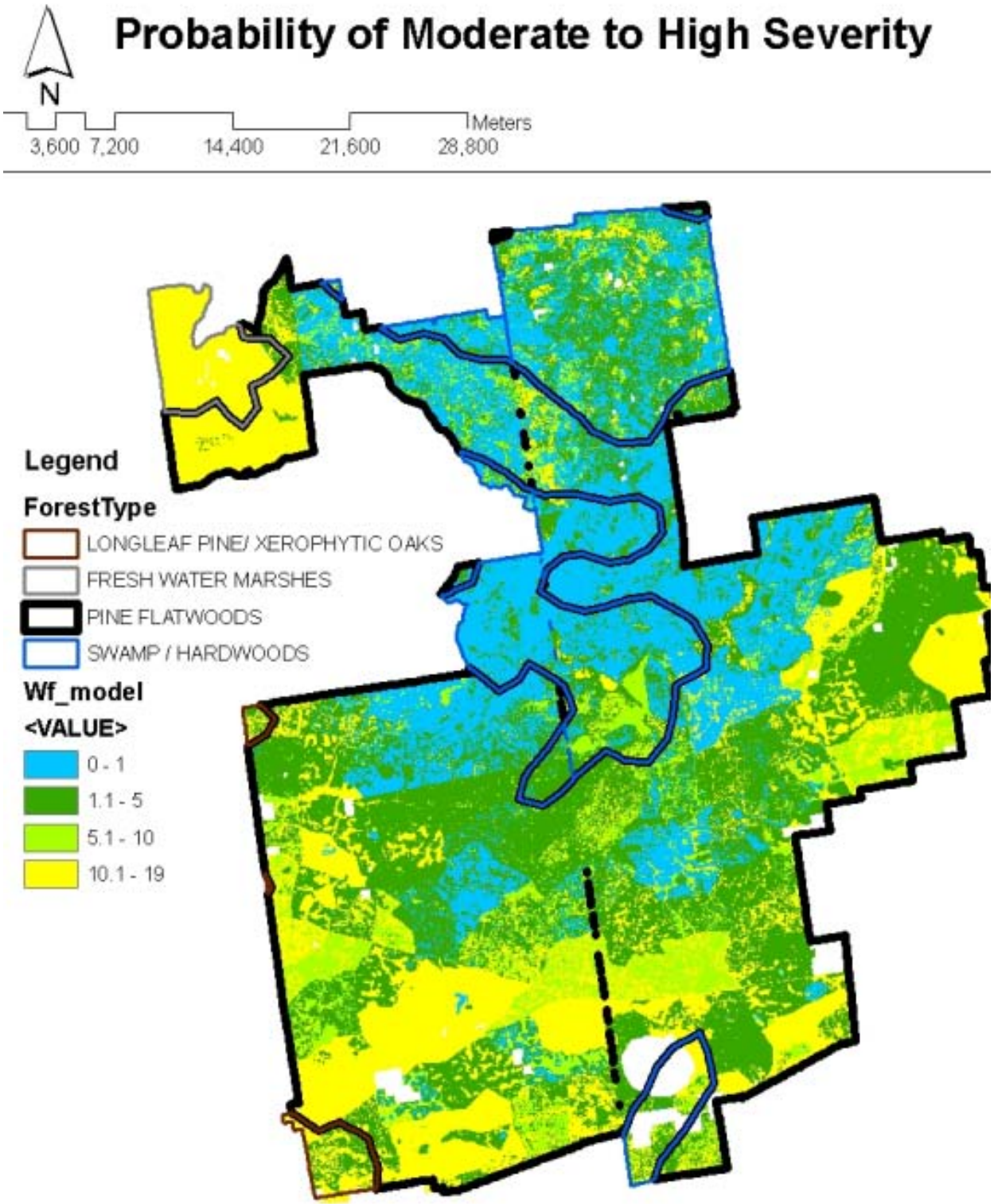


Figure 3-18. The probability of moderate to high severity wildfire in 2008 by forest type.

CHAPTER 4
CONCLUSION

Remote sensing techniques used to model fires on the Osceola National forest has provided valuable information regarding fire severity, the effect of time between burns and the risks incurred by management decisions. Fuels on the Osceola National Forest have fast recover times as evident by the relationship between frequency and the probability of high severity. Forest land that burns more frequent also burns at a higher severity. This indicates that fuels are able to regenerate at a rate to support higher severity fires in short time periods.

The analysis has provided valuable information regarding the influence of severity level and time between events. Models identified the time interval 5-6 years as a point where the effects of previous fires had little to no effect on subsequent fires. At this point, the probability of high severity fire, increasing severity level in subsequent fire, and burning in successive fire is highest. This is also a point where the probability of decreasing severity in subsequent fires was lowest. It has also become evident that effects of previous fires have little to no influence on subsequent fires past 5-6 years. Therefore fire frequencies larger than this will not adequately mitigate wildfire risk in pine flatwoods.

Variations in the landscape influence the relationship between time between fire events and fire severity. Fire effects are influenced by the type of vegetation and the availability of that vegetation. Land managers must consider vegetation recovery and availability differences by both forest and community types to determine the risk of the high severity fire. Hydric areas have exhibited a lack of fire activity during wildfires, implying that these areas have not been available to burn often. This raises the risk of

experiencing high severity fire during prolonged drought periods. When these high fuel loads become available to burn they will likely burn quite severely (Maliakal et al. 2000). To incorporate this into the model it may be useful to add a weighted overlay to identify hydric communities and further weight them by time since last fire during prolonged drought conditions. Land managers should also consider other options to treat heavy fuel loads in these areas; including mechanical treatments.

To increase model performance it may be effective to include more meteorological attributes into the models. This would allow the models to take into account weather effects that may further identify areas that are at highest risk of experiencing high severity. Spatial autocorrelation of fire severity and other model covariates should also be incorporated into the models to account for variations in space.

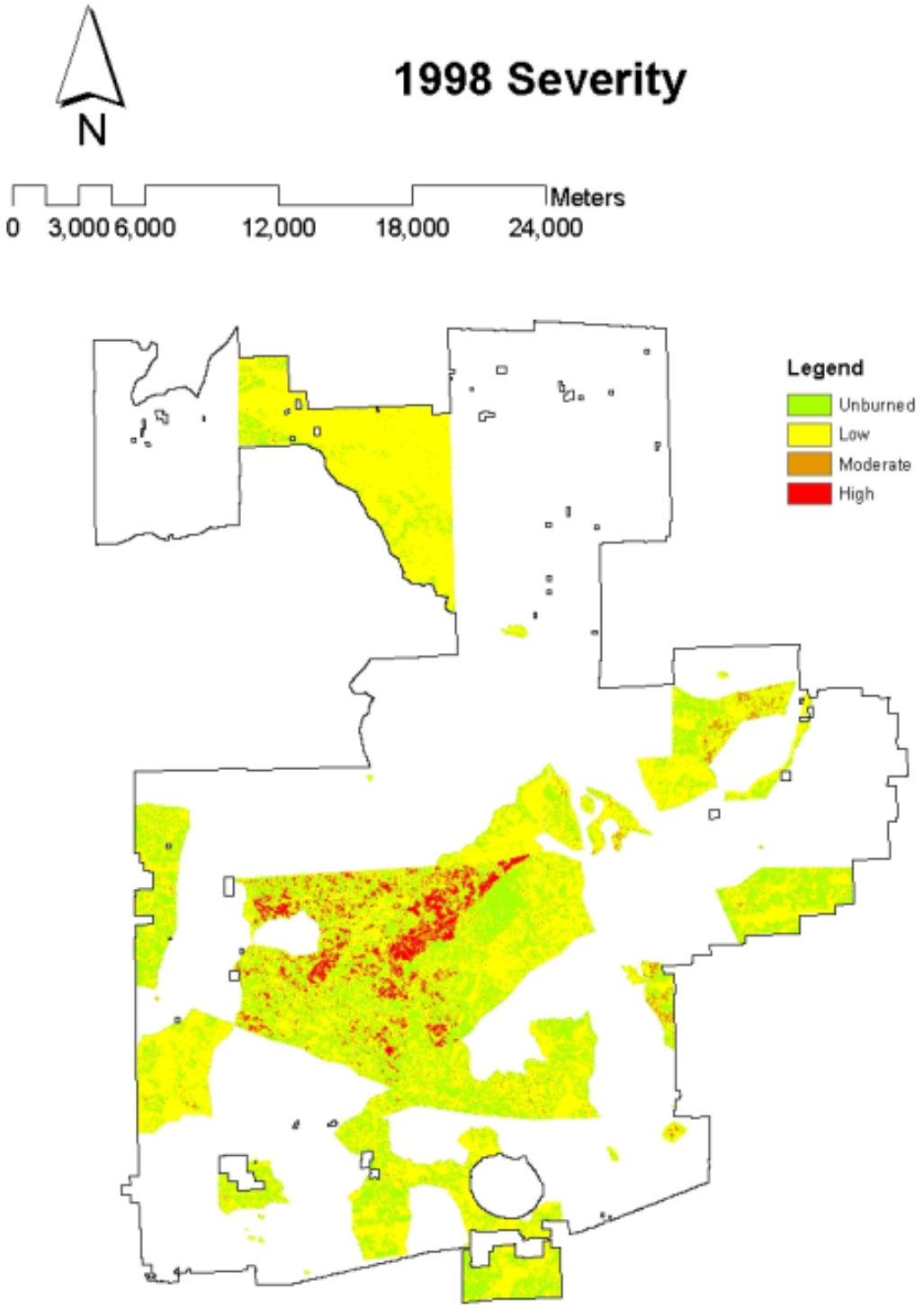


Figure A-1. Severity levels of fire events for the 1998 fire season.

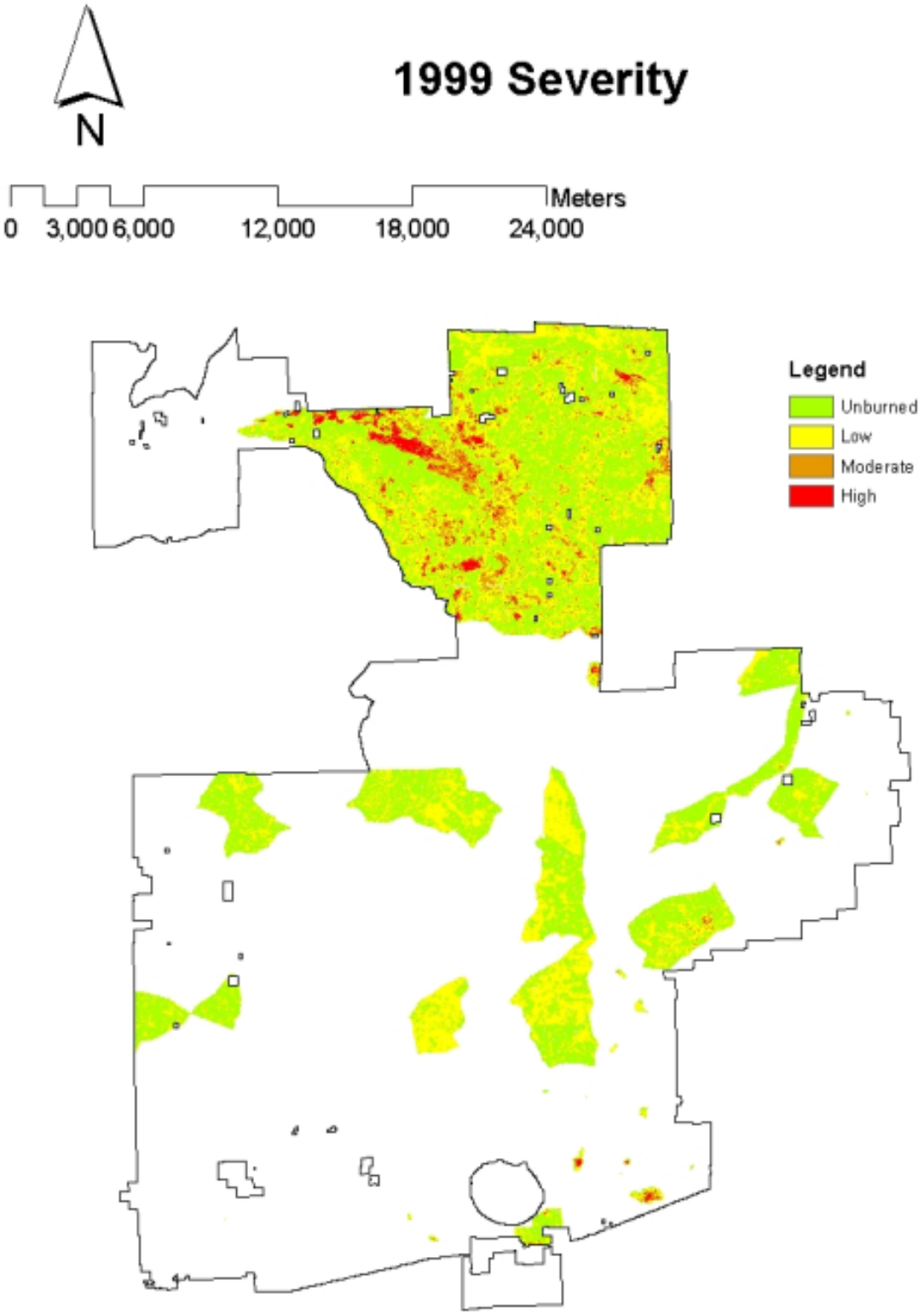


Figure A-2. Severity levels of fire events for the 1999 fire season.

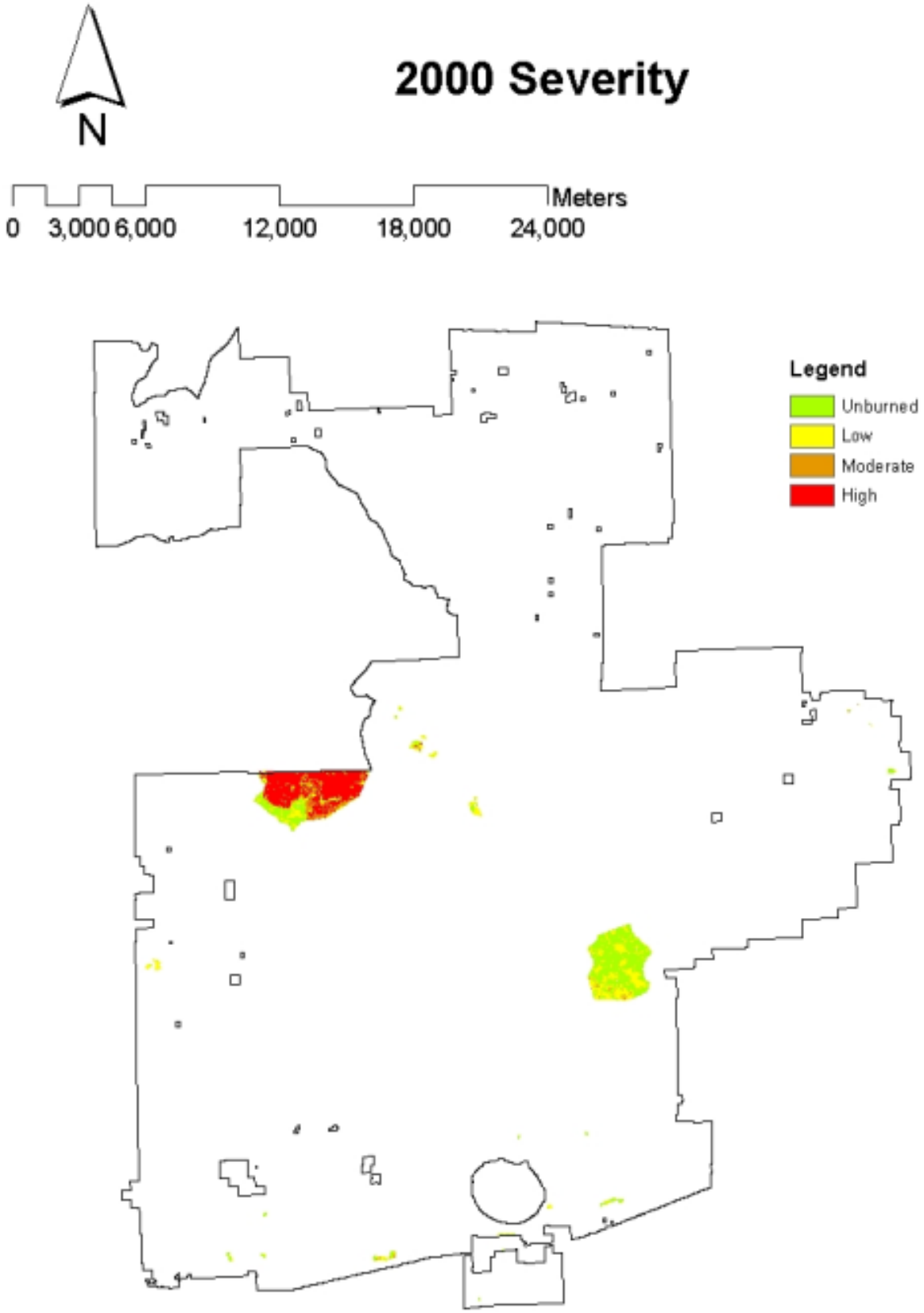


Figure A-3. Severity levels of fire events for the 2000 fire season.

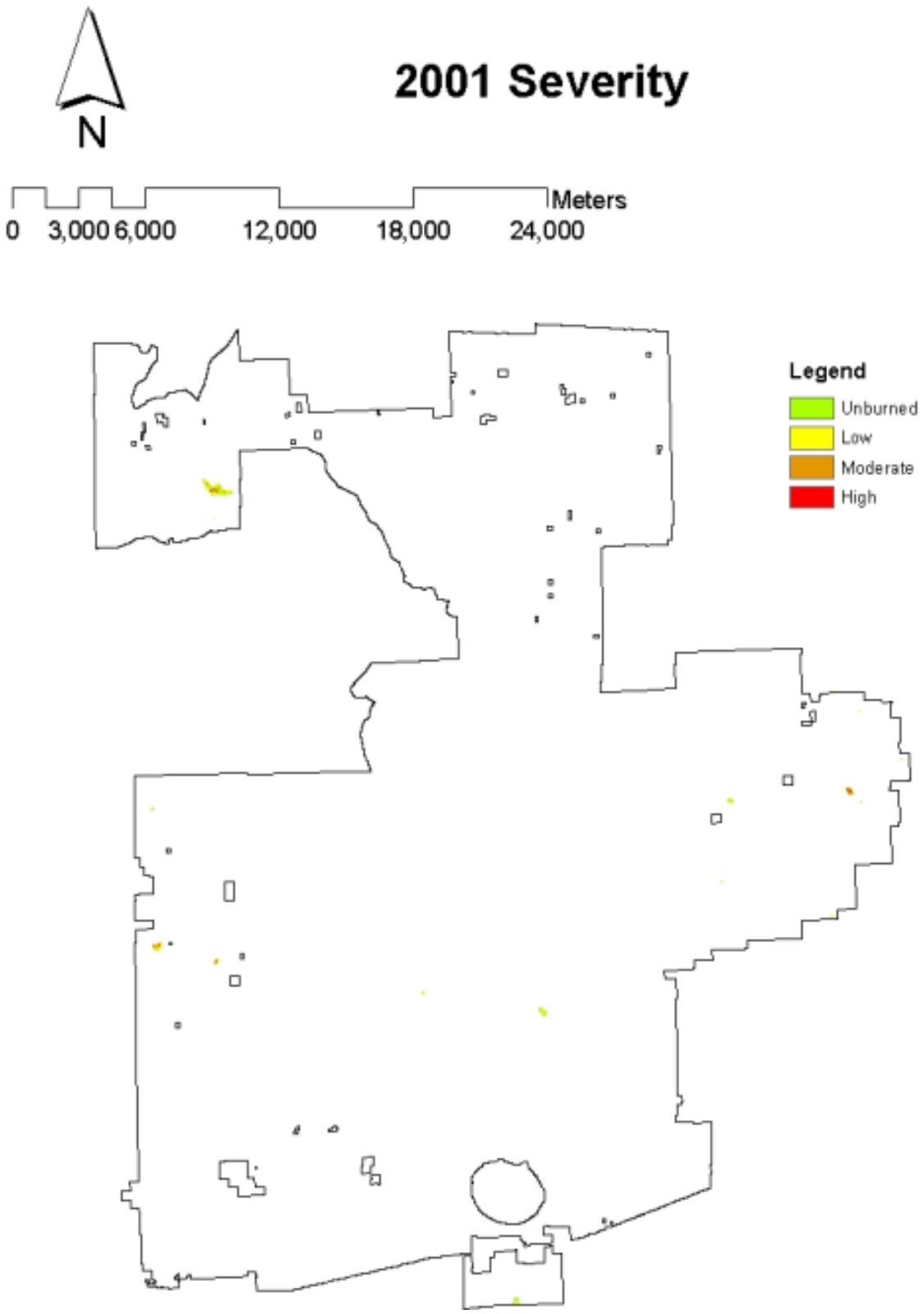


Figure A-4. Severity levels of fire events for the 2001 fire season.

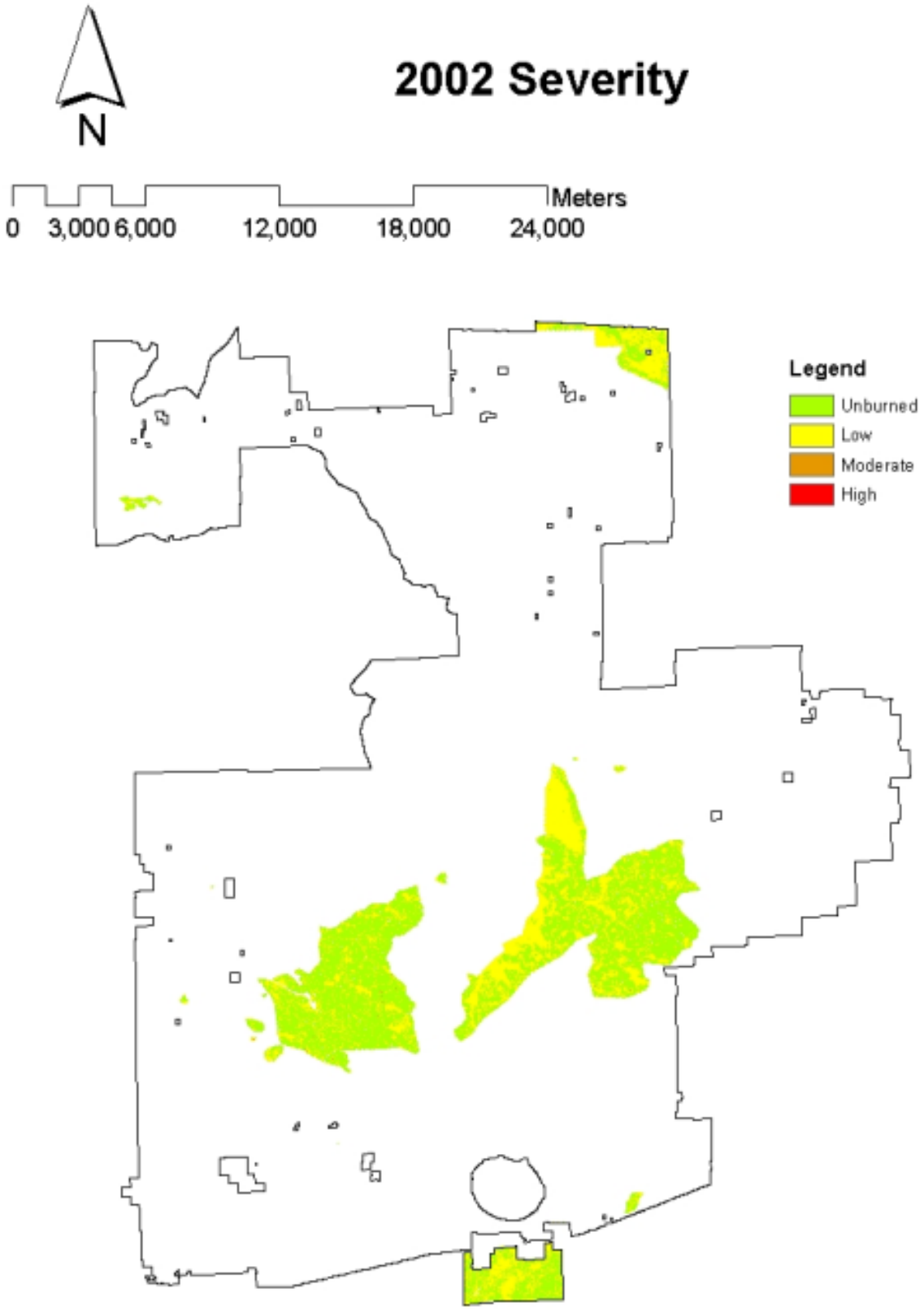


Figure A-5. Severity levels of fire events for the 2002 fire season.

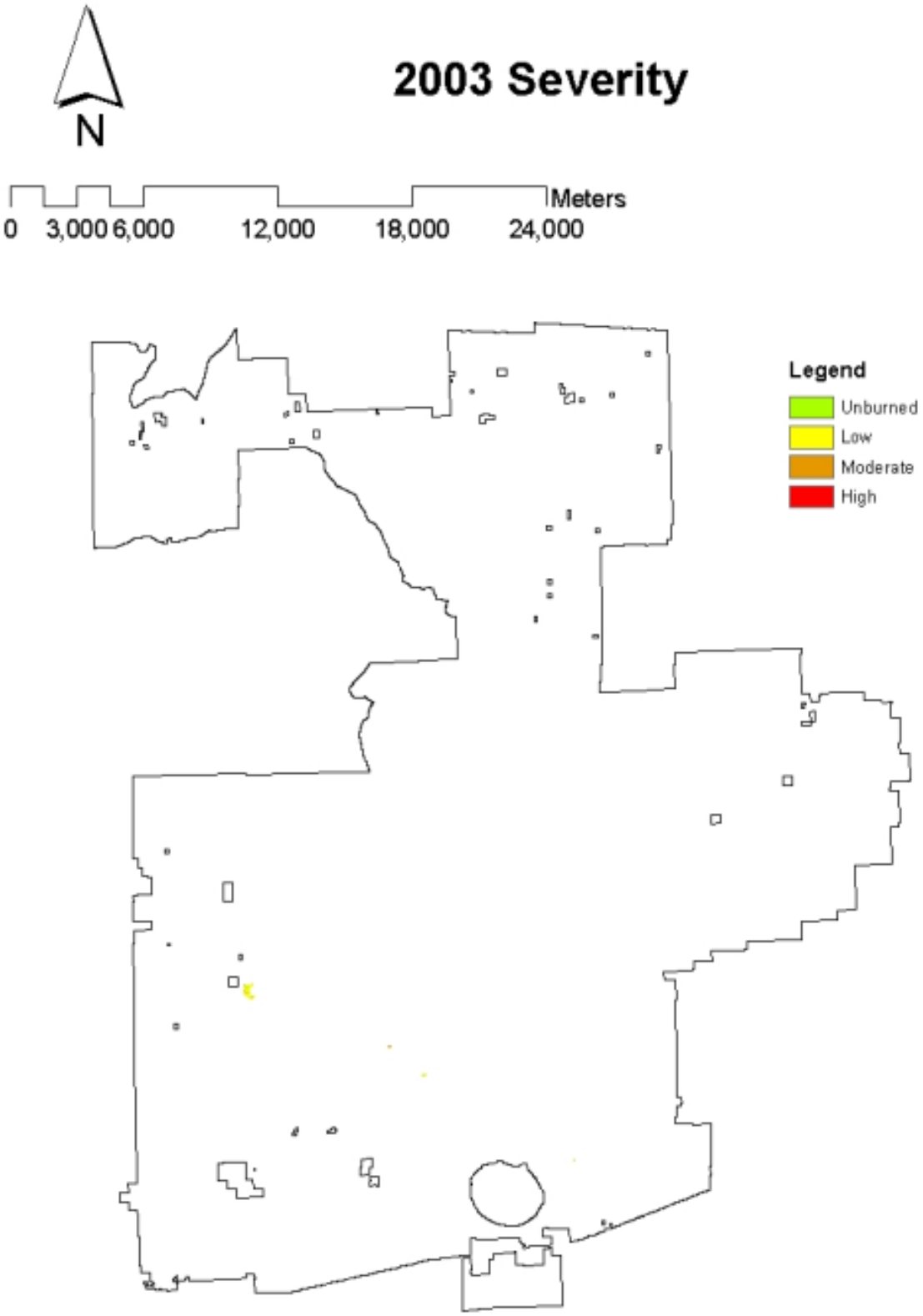


Figure A-6. Severity levels of fire events for the 2003 fire season.

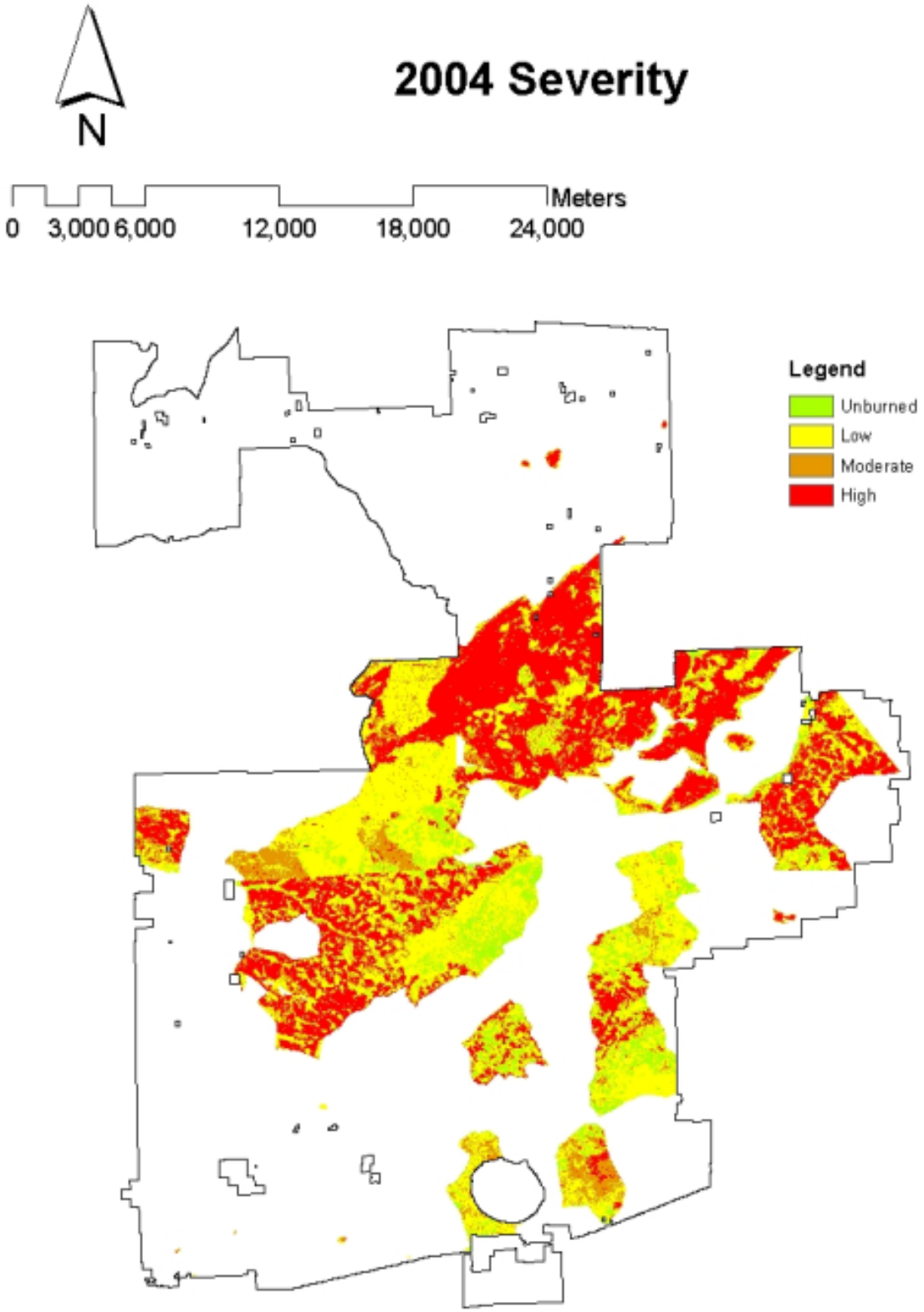


Figure A-7. Severity levels of fire events for the 2004 fire season.

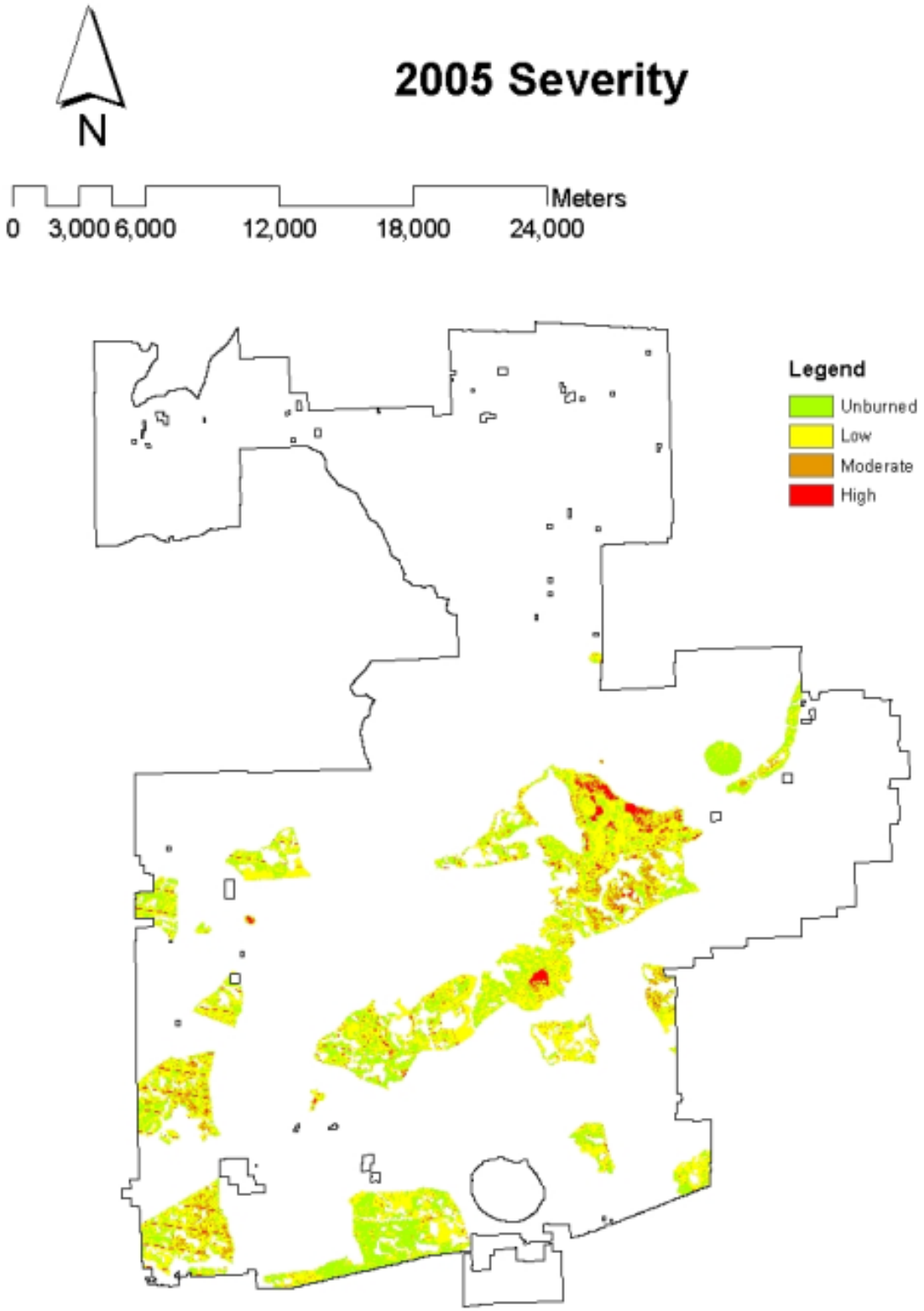


Figure A-8. Severity levels of fire events for the 2005 fire season.

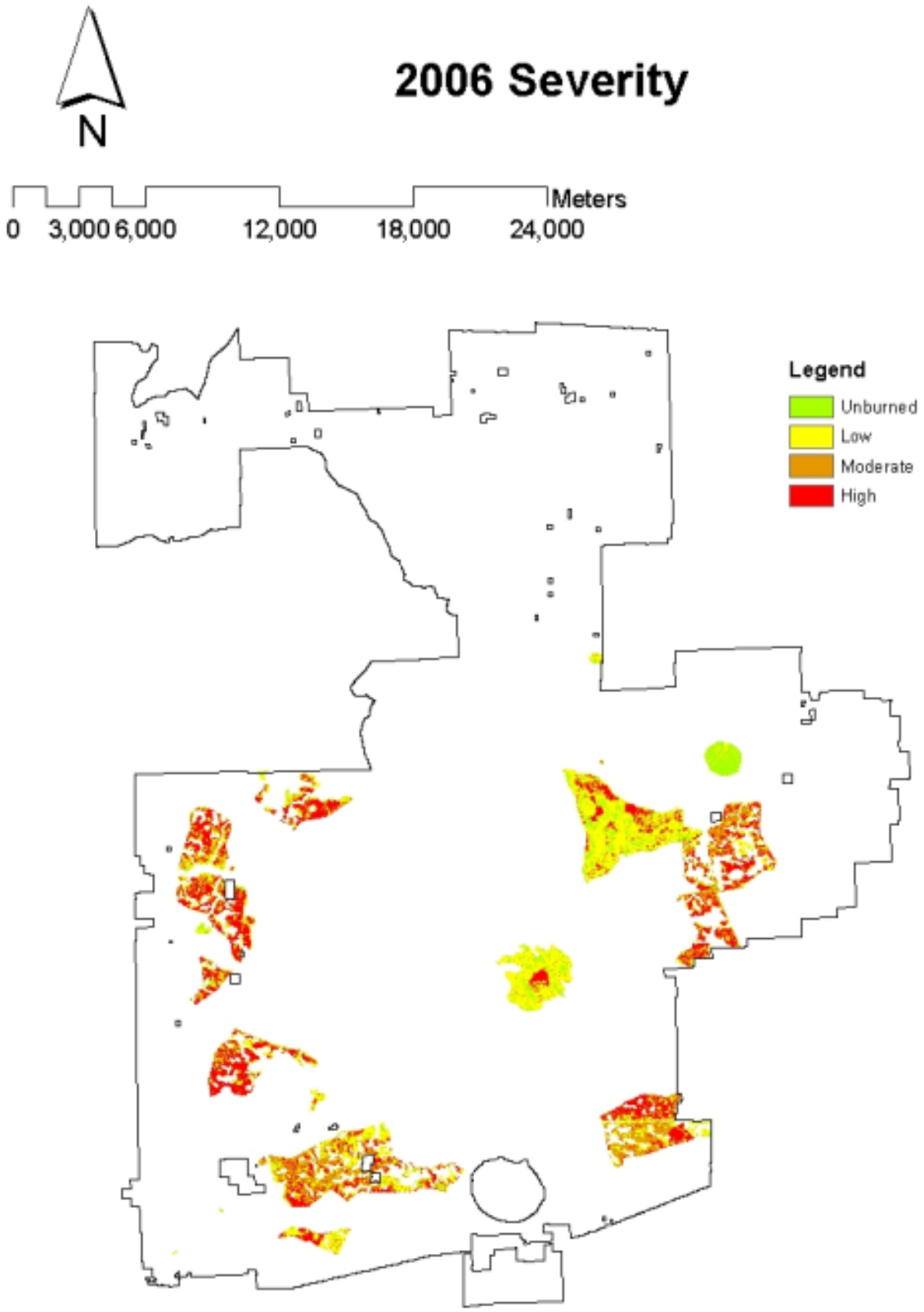


Figure A-9. Severity levels of fire events for the 2006 fire season.

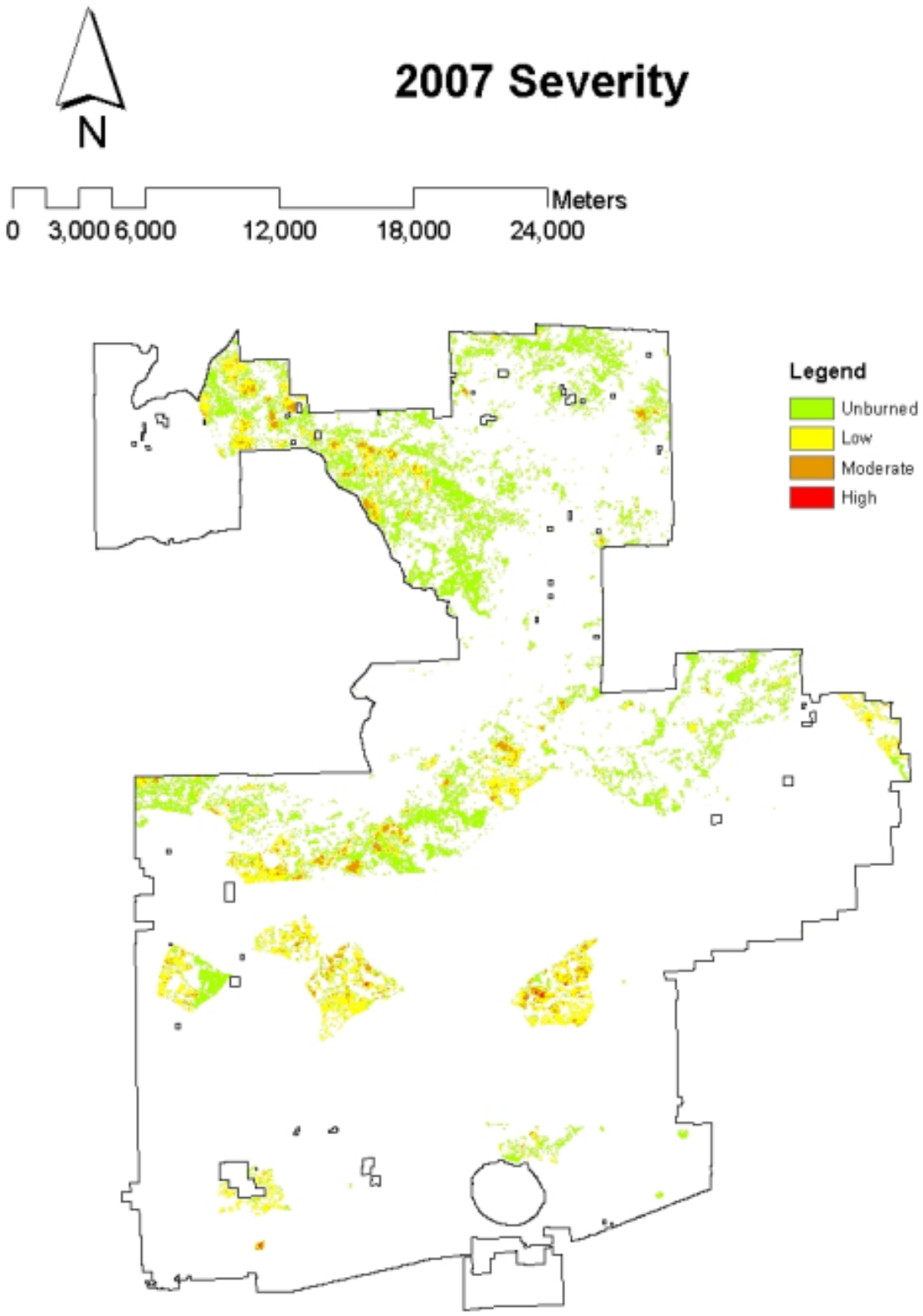


Figure A-10. Severity levels of fire events for the 2007 fire season.

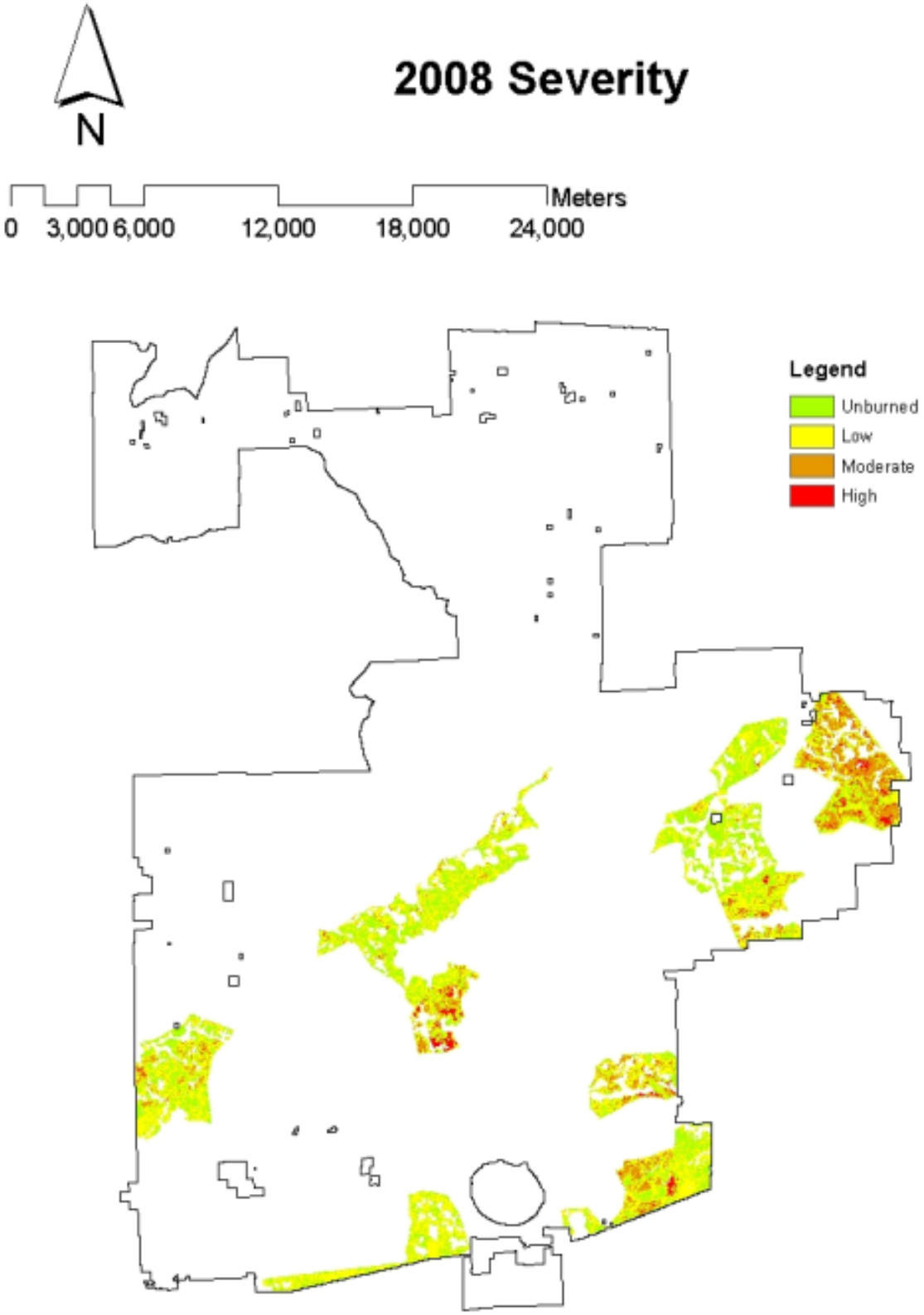


Figure A-11. Severity levels of fire events for the 2008 fire season.

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BIOGRAPHICAL SKETCH

Sparkle Leigh Malone was born in the spring of 1985, in Chicago, Illinois to Rita and Rodney Malone. She grew up in Miami, Florida, after her family moved from Chicago to Miami when she was an infant. Sparkle graduated from Dr. Michael Krop Senior High School in 2003. Her college career began in 2005 at Florida Agricultural and Mechanical University in Tallahassee, FL. Her major area of study was agronomy. In 2007 she transferred into the University of Florida's School of Forest Resources and Conservation by way of the 1890s scholars program. Here, Sparkle majored in forestry with a specialization in informatics. She obtained a Bachelor of Science from the university in the spring of 2009 and a master's degree in the summer of 2010.