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Using Spatial Analysis to Evaluate Fire Activity in a Pine Rockland Ecosystem, Big Pine Key, Florida, USA

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Using Spatial Analysis to Evaluate Fire Activity in a Pine Rockland Ecosystem, Big Pine Key, Florida, USA

A Dissertation Presented for the
Doctor of Philosophy
Degree
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Lauren Ashley Stachowiak
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Dedication

I would like to dedicate this dissertation to my mother, a woman I sincerely love and admire, and someone who has stood by me throughout my life. Without you, mom, I would not be where I am today.

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Many people have influenced me throughout my PhD, but I would like to first thank my advisor, Dr. Henri D. Grissino-Mayer, for his continued assistance and direction as I matriculated through the program. I was first introduced to Dr. Grissino-Mayer in spring of 2008 while an undergraduate student conducting climate research via tree-ring analyses. I diverted to another discipline for my Master's degree, but I reconnected with tree rings and the Laboratory of Tree-Ring Science during the Fall of 2011 when I pursued acceptance into the PhD program at the University of Tennessee. His commitment to his students, integrity to advanced research, and his extensive credentials and experience in the field of dendrochronology ultimately convinced me a degree from UTK was the right choice. While I have been a student at UTK, Dr. Grissino-Mayer has made a tireless effort to ensure I was nominated for various department and university awards and recognitions. Furthermore, he made it a priority for me to gain as much field and laboratory experience as possible, through various field work trips all over the country, and he has helped me, and other graduate students in his lab, enhance our CVs through quality publications in tree-ring science journals. Finally, when the time came to look for career opportunities, Dr. Grissino-Mayer was an extremely valuable source of guidance and expertise, which helped me successfully navigate the job market and secure employment after graduation.

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My dissertation research was funded in part via two primary funding sources, without which my field trips to the Florida Keys would not have been possible. Specifically, these sources include a seed grant from the Initiative for Quaternary Paleoclimate Research (IQPR), directed by Dr. Sally Horn, and funding from the Stewart K. McCroskey Fund in the Department of Geography at UTK. In the summer of 2012, before I arrived at UTK, Drs. Grissino-Mayer and Horn conducted preliminary field work in the National Key Deer Refuge on Big Pine Key to investigate the potential for fire history research. Without this preliminary research, and the seed grant from the IQPR to further investigate fire activity in the area, my research project would not have solidified into a working dissertation. The financial assistance from the Stewart K. McCroskey Fund allowed me to take an additional graduate student with me into the field. I am grateful for the support given to me from both of these two funding organizations.

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Abstract

Pine rocklands are fire-prone ecosystems with limited spatial extent, and have experienced reduced area in the previous decades through habitat conversion and urbanization. The purpose of this dissertation research was to evaluate the historical range of variability of fire activity and spatial patterns of fires in a pine rockland ecosystem in the National Key Deer Refuge (NKDR) on Big Pine Key in the Lower Florida Keys. To investigate the temporal and spatial patterns in fire activity, I (1) evaluated the temporal patterns for fires in my study area in the NKDR, (2) analyzed differences in standard fire history metrics since the advent of land management in the 1950s, (3) mapped the spatial extents of fires that scarred > 25% of the recording trees, (4) investigated how regression relationships fire activity and microtopographic parameters changed with aggregated scale, and (5) calculated global and local indications of spatial autocorrelation in the geographic fire-scar data.

The 2011 fire was no more severe than other historic fires in the dataset, and was within a range of expectations for severe fires in the area. The relationships between fire activity and microtopography peaked at approximately 50 m (residual topography $p < 0.05$; curvature $p < 0.10$). Finally, spatial autocorrelation analyses found statistically significant ($p < 0.01$) clustering in the fire-scar data network across the study area, and significant low-clustering ($p < 0.05$) at the at smaller scales. Recent lack of fire return intervals consistent with pre-management periods confirms the influence that people have had on fire in this ecosystem, and the presence of the neighborhood adjacent to the study area in the south may have dampened fire activity in that area.

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Chapter 1

Introduction

1.1 Purpose for the Research

Human disturbances are having a detrimental impact on natural fire activity, especially in ecosystems that have highly dynamic disturbance regimes. A natural fire for this dissertation represents one that ignites and initiates without human intervention, such as arson or prescribed fires, and is completely non-anthropogenic. A severe wildfire, determined by U.S. Fish and Wildlife officials post-fire based on factors such as intensity during the fire, amount of biomass consumed, and forest damage, occurred in the pine rocklands in the National Key Deer Refuge (NKDR) on Big Pine Key in September of 2011. Given the severe nature of the 2011 fire, my goal for this dissertation was to evaluate fire from both a temporal, and spatial, perspective within the NKDR. Specifically, I evaluated the historical range of variability of fire activity and spatial patterns of historic fires in a pine rockland ecosystem using dendrochronology and a Geographic Information System (GIS). Fire is a major disturbance to affect a pine rockland, and plants such as the dominant canopy species, South Florida slash pine (*Pinus elliottii* var. *densa* Little & K.W. Dorman; referred to in the following pages as slash pine), require fire to perpetuate and survive.

Fire in the subtropics follows a basic ecological principle of fire regimes dominated by high-frequency but low-intensity fires, which often counters public opinion of fire (*i.e.* all fires are high-intensity conflagrations and therefore bad for the environment). My research area is located at a wildland-urban interface (WUI) where fires are actively suppressed with occasional but methodical use of prescribed burns. The highly prevalent and contentious relationship between local citizens and wildlife officials regarding controlled burning is primarily due to strong community aversion to fire in the refuge and near neighborhoods. Public opinion that fires occur relatively infrequently was addressed by my research using dendrochronology and GIS as a means to evaluate historical range of variability and fire frequency in the NKDR. In periods of prolonged fire absence, a shift in the pine rockland ecosystem toward more fire-intolerant hardwood species occurs (Alexander & Dickson, 1972). Therefore, a better understanding of fire in pine rockland ecosystems is important for their continued survival. Important habitat for endangered species, such as the Key deer (*Odocoileus virginianus clavium* Barbour & G.M. Allen) and Big Pine partridge pea (*Chamaecrista lineata* var. *keyensis* (Pennell) H.S. Irwin & Barneby), would be lost.

The Blue Hole Burn in September of 2011 provided a unique opportunity to investigate fire regimes in the south Florida Keys due to the extensive removal of underbrush, which made scouting and collecting fire-scar data possible. The high-intensity fire created major local and regional distress over the health of the forest and the safety of people and their dwellings. The maps of historic fire surfaces, and quantitative data on the nature of fire activity throughout the pine rocklands, were beneficial outcomes of the research that followed this fire. My research will provide the U.S. Fish and Wildlife Service stationed on the Keys with the most current scientific information for effective prescribed burning procedures, and the potential for predictive fire risk modeling.

Quantitative measures of fire activity can provide land managers with essential tools for protecting the pine rockland ecosystem while implementing safety protocols for the local community. The application of dendrochronology to fire science in the subtropics is a newly developing opportunity for research. Demand has grown considerably for reconstructions of fire history from tree-ring based fire-scar analyses in subtropical regions, such as the Florida Keys. Additionally, fire history research in the southeastern U.S. is becoming a popular research avenue as we learn more about the important role of fire in pine rockland ecosystems. My research incorporated all of these factors related to dendrochronology into a comprehensive and spatially-explicit GIS, which allowed me to evaluate fire activity from a new perspective.

My dissertation was designed and centered around two general and overarching objectives. The first was to precisely determine the pre-management (1956 and earlier) fire regime of pine rocklands on Big Pine Key, as compared to a post-management fire regime (1957–2014), using a systematic grid-based sampling method. This experimental design was constructed in such a way to generate continuous surfaces of fire activity across geographic space and through time at an annual resolution. The second general objective was to statistically assess the spatial relationship between fire and environmental variables, and within the fire-scar data to assess spatial autocorrelation from both global and local perspectives. To accomplish both of my goals, I geo-located and collected fire-scar cross sections from 94 trees (Figure 1.1) within a network of seven plots to accurately capture the spatial and temporal patterns of fire activity.

While pine rocklands in the southern U.S. may have a small geographic range, restricted to southern Florida and the Keys, physical and biological similarities between the rocklands and adjacent ecosystems make this study area perfect for constructing preliminary fire analysis models for geographic locations with low local relief. Furthermore, the rocklands

Figure 1.1 An example of a snag, both before (a) and after (b) a cross section was removed from the trunk. The scars (c) are found along the basal margin of the snag, preserved as lobe growth during the recovery process. BH1008 is the sample ID, indicating Blue Hole plot 1, tree 8.

are endangered and thus this dissertation research aimed to provide information that land managers could use to supplement the ecologically-sound and research-driven fire management plan already in place. A better understanding of fire in this ecosystem will lead to better understandings of fire activity in the greater ecoregion as a whole into the future.

1.2 Study Area

The fieldwork for this project was conducted entirely within the burned perimeter (approximately 48.5 total hectares) of the NKDR on Big Pine Key in the south Florida Keys (Figure 1.2). The area has low overall local relief (< 1.5 m) with karst limestone bedrock and extensive dissolution holes spread throughout the landscape. Well-developed soil is not found in this landscape, only a thin covering of organic matter, and many areas have exposed bedrock, particularly locations with greater distance from large or well-developed dissolution holes. Digital elevation models developed from LiDAR satellite data found local relief in some areas varied by as little as one m (Sah *et al*., 2006). Within the burned area, the ecosystem consists of pine rockland, but along the edges, primarily to the west of the NKDR, the pine rocklands transition to hardwood hammocks. The bordering hardwood hammocks create an environment that is less conducive to fire compared to the adjacent pine rocklands because the vegetation is less flammable.

The Lower Florida Keys lie within a climatically-active region between the Gulf of Mexico and the Atlantic Ocean. The northeast tradewinds provide a continuous flow of air

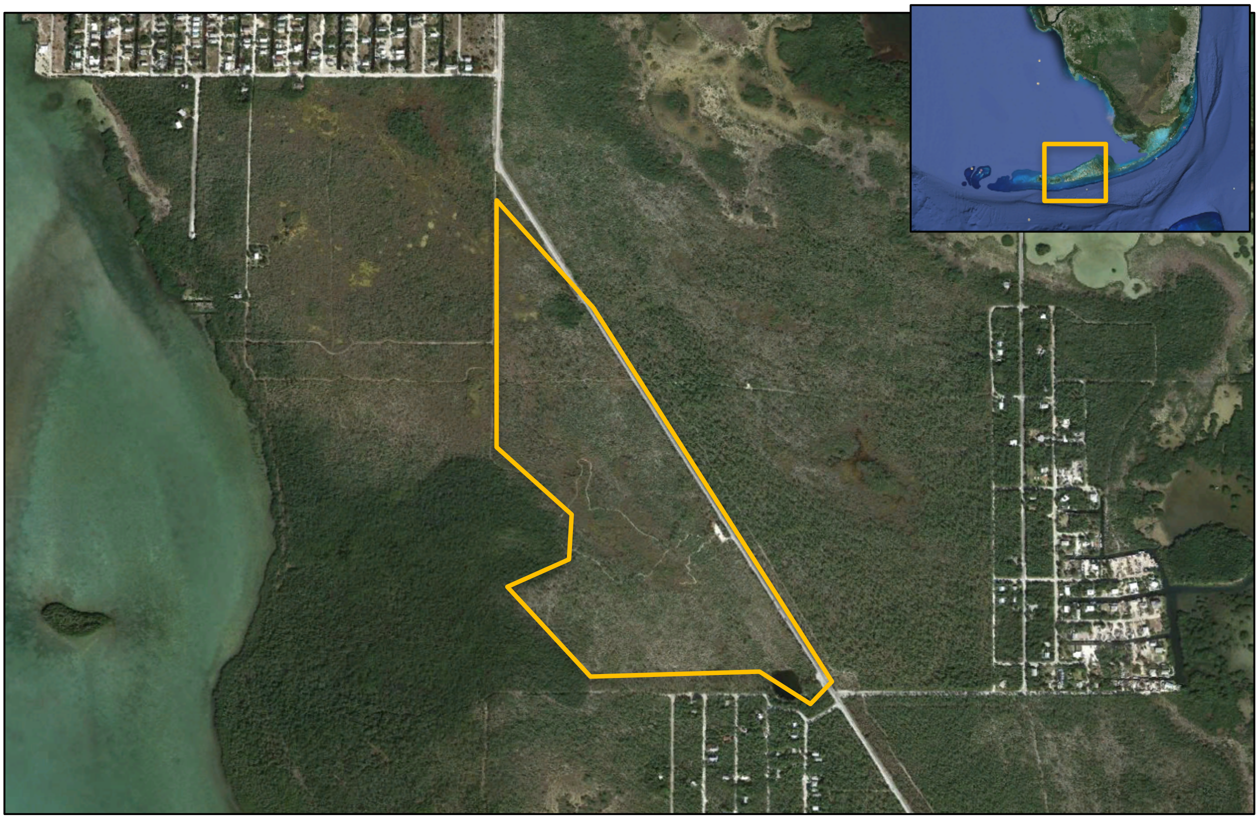

Figure 1.2. Big Pine Key study area. The 2011 Blue Hole Burn perimeter is in yellow. The inset (upper right) delineates Big Pine Key within the Lower Florida Key island chain. Source image provided by ArcGlobe 10.2.2.

across the lowland areas, and the interactions between land and air masses create a maritime tropical climate (Hela, 1952). The region also experiences an active tropical storm and hurricane season, but the Keys receive less annual precipitation on average compared with areas in southern mainland Florida, such the Everglades (Karl *et al*., 1983; Bergh & Wisby, 1996). Many disturbance events, such as fires, hurricanes/tropical storms, and thunderstorms, occur concurrently on an annual basis for pine rockland ecosystems. The repercussions of these disturbance events (particularly fire) directly influences the canopy vegetation of the Keys, and herbaceous species and endangered local wildlife, such as Key Deer (*Odocoileus virginianus clavium*).

The canopy species in the pine rockland ecosystem is the slash pine and the understory consists primarily of species that respond quickly to wildfires through rapid re-sprouting. Under low fire activity, or given enough time post-fire disturbance, regrowth in the understory layer is extensive, with a mixture of palms and low shrub species (Figure 1.3). The understory is dense (Sah *et al*., 2004; Sah *et al*., 2006), and common taxa in this shrubby layer include buttonbush (*Cephalanthus occidentalis* L.), poisonwood (*Metopium toxiferum* (L.) Krug & Urb.), and locustberry (*Byrsonima lucida* (Mill.) DC.). Herbaceous species found in the ground layer include Big Pine partridge pea (*Chamaecrista lineata* var. *keyensis* (Pennell) H.S. Irwin & Barneby), an endangered herbaceous plant dependent on regular occurrence of fire, and

Figure 1.3 Professor Henri D. Grissino-Mayer cuts a slash pine in the NKDWR with a chainsaw. Notice the thick underbrush just three years after the 2011 Blue Hole fire. The slash pines (background) are the tallest woody species in the rocklands. The ones shown here were not damaged in the fire.

sand flax (*Linum arenicola* (Small) H.J.P. Winkl.), and Florida white-top (*Rhynchospora floridensis* (Britton ex Small) H. Pfeiff.) (Table 1.1) (Wunderlin, 1982).

Geographically, the pine rocklands one of the most spatially-threatened ecosystems in Florida (Doren *et al*., 1993). The pine rocklands on the Keys are endangered, primarily due to the advent of fire-suppression, increases in human populations on the Keys, and a pervasive and disruptive transportation infrastructure (Noss *et al*., 1995; Bergh & Wisby, 1996). Larger land area specifically on Big Pine Key provides more expansive contiguous sections of rocklands, and could expose the rocklands to greater instances of lightning strikes and increases the chance of a lightning-caused fire (Bergh & Wisby, 1996). In general, when fires are regularly present pine rocklands persist over hardwood hammocks (Alexander and Dickson, 1972; Snyder *et al*., 1990; Bergh & Wisby, 1996).

1.3 Dendrochronology and Slash Pines in the Subtropics

1.3.1 Fire History Research

Previous research has established the importance of fire history reconstructions using tree rings and fire scars in the southeastern U.S. (Guyette & Spetich, 2003; McEwan *et al*., 2007), in many areas of the American Southwest (Baisan & Swetnam, 1990; Beaty & Taylor, 2007; Schoennagel *et al*., 2007), and beyond (Heyerdahl *et al*., 2002). Fires sweep through an area and leave their mark on trees, either by killing them and leaving charred remains, or by damaging

Table 1.1 List of most common herbaceous and woody plant species in all three layers of the canopy. The canopy species is slash pine and it has no competition for the canopy layer (Wunderlin, 1982).

Species Name	**Common Name**	**Forest Level**
Pinus elliottii var. *densa*	slash pine	Canopy
Byrsonima lucida	locust-berry	Understory
Cassia chapmanii	Bahama senna	Understory
Coccothrinax argentata	silver thatch palm	Understory
Conocarpus erectus	buttonwood	Understory
Crossopetalum ilicifolium	ground-holly	Understory
Eugenia rhombea	red stopper	Understory
Metopium toxiferum	poisonwood	Understory
Morinda royoc	mouse pineapple	Understory
Myrica cerifera	wax-myrtle	Understory
Pithecellobium guadalupense	blackbead	Understory
Psidium longipes	long-stalked stopper	Understory
Serenoa repens	saw palmetto	Understory
Thrinax radiata	thatch palm	Understory
Acacia pinatorium	pine acacia	Groundlayer
Eragrostis elliottii	Elliott's love grass	Groundlayer
Ernodea littoralis	golden-creeper	Groundlayer
Rhynchospora spp.	white-topped sedge	Groundlayer
Smilax havanensis	greenbriar	Groundlayer

them, with the tree developing the scar post-fire (Smith and Sutherland, 1999). The evidence left by a fire that scars trees provides researchers with a wealth of information, including flame height, temperature (intensity) of the fire, spatial extent of the burn, fire frequency, and fire seasonality. However, some trees may not be scarred in a given fire event if the fire was not intense enough to damage the tree and create a fire scar (Speer, 2010).

Traditionally, dendrochronology has been restricted to biogeographic regions where trees undergo a distinct growth period/dormancy period cycle. The seasonality of climate in these regions, especially in the middle and higher latitudes, allows for the formation of annual rings. With time, a tree that develops annual ring boundaries becomes a standing recorder of biological and ecosystem history of that location (Fritts, 1976; Stahle, 1999; Speer, 2010). Part of the physical history of the area includes occurrence of fire, which is recorded in fire scars along the basal area of the tree trunk. Repeated scars can form distinctive shapes on the tree trunk known as “catfaces,” from which we can extract a partial (from a living tree) or complete (from a dead tree) section from the trunk with a chain saw. We can then date the tree rings on these sections with annual accuracy using standard dendrochronological techniques.

1.3.2 Dendrochronological Status of Slash Pine

South Florida slash pine is a subtropical pine species whose extent reaches from lower central Florida through the Florida Keys (Landers & Boyer, 1999; Harley *et al*., 2012b). Slash pine is the dominant canopy species in southern pine rocklands, and the species is found specifically in the United States in the Lower Florida Keys, Everglades National Park, and Big Cypress National Preserve (Snyder *et al*., 1990; Doren *et al*., 1993; Harley, 2012). Mature slash pine trees grow to a maximum of 45 m in height and < 1 m diameter at breast height, and live to approximately 150 years of age. Given the dynamic nature of the ecosystems, disturbances such as fire, hurricanes, and saltwater incursions inhibited slash pines from regularly maturing past 150 years, although older trees have been found (Harley *et al*., 2012a).

Slash pines are considered a foundation species in the pine rockland environment (Menges & Deyrup, 2001). Slash pines have developed specific biophysical characteristics that allow the species to tolerate fires in a range of intensities as long as flame height and temperature do not exceed the critical threshold for mortality. Once the tree passes the seedling stage, fire-resistance increases as the fire adaptations of the tree, such as heat-resistant bark (Menges & Deyrup, 2001), become stronger and more well-developed (Heyward, 1939). The viability of seed is less than one year, thus adult pines have no seed bank capability in the event of a canopy-replacing fire. Seed can be stored for many years under optimal environmental conditions, but given the lack of a well-developed soil layer, pines must produce new seed every year to regenerate.

1.4 GIS and Spatial Analyses

Geospatial analyses in physical geography combine information from the biophysical environment with applied modeling techniques to accurately represent real-world phenomena. To holistically evaluate fire activity of an area, a suite of GIS tools is necessary because no single method or tool exists to answer all questions. Additionally, no single route or methodology exists to evaluate fire activity of an area because no universal solution is viable in all kinds of ecosystem analysis (Rollins *et al*., 2004), especially for locations that are dynamic, constantly changing, and influenced by the human community. Many different tools and methods exist to answer the questions for my dissertation; thus I have chosen my methods carefully and have defended them throughout the dissertation. Commonly researchers will incorporate field-collected data with recently-acquired, high-resolution (5 m or less) LiDAR imagery, along with various fuel characteristics, to capture important environmental relationships of the burned area. Ultimately, the combinations of biophysical data allow scientists to build surfaces of fire activity and assess spatial patterns of historic fire better than would be possible with a less holistic dataset.

Methods for converting GPS-located tree and fire-scar point data into fire activity surfaces incorporate various types of spatial interpolation (Keane *et al*., 2001; Rollins *et al*., 2004). Specifically, Inverse Distance Weighted (IDW) and spline interpolations can be used to generate surfaces with fire-scar representation at increasing distances from a fire-scarred tree. Fire-scarred cross sections are collected in the field and dated using standard dendrochronological techniques of wood processing, measuring, and crossdating (Stokes & Smiley, 1968; Grissino-Mayer, 2001a). These cross sections are also tagged with GPS locations (Garmin GPSmap 62s, variable error rate +/- 4 m), which makes the dataset inherently spatial, but also provides fire-scar counts per tree, which gives an additional layer of depth to the dataset. Finally, interpolated surfaces can then be generated from point shapefile data (*i.e.* GPS-tagged trees) to create idealized landscapes of historic fire activity.

Areas of historically low to high fire activity can be modeled based on frequency and spatiotemporal density of past fires. Filters can be applied to the fire history data and interpolated surfaces can be generated for years with high fire extent (*e.g.* > 10% or > 25% trees scarred in a given year) to show how the fire "looked" spatially in that year. The final surfaces are composed of cells (sometimes referred to as pixels) and record historic fire frequency across a continuous landscape. The technique of interpolating fire activity across a landscape is fairly new and literature is sparse, but by choosing the appropriate interpolation technique we ensured the surfaces will accurately represent fire activity.

A large suite of environmental predictor variables exist that could be included in an effective model of fire activity. Topography is the primary static or unchanging predictor variable for fire activity, while dynamic variables such as rate of spread and wind direction are also used if available (Rothermel, 1972; Finney, 1998, 2003). Outside of a geomorphic event such as a landslide, topographic variables, including slope, aspect, or elevation do not change significantly through time. However, variables such as wind speed or direction can vary significantly through time, thus they are considered here as dynamic. Additionally, in traditional fire risk modeling, soil moisture and heterogeneous fuel loading, if the data are available, are used to enhance model results. However, pine rockland ecosystems in the Florida Keys have homogeneous groundlayer fuel loads and soil characteristics, with little to no soil cover or surface hydrology. Considering pine rocklands are flat, microtopography derivatives were isolated as the primary variables of interest in our site. Lastly, by using topographic variables only, the techniques for relating fire to the physical landscape can be applied elsewhere, outside of pine rocklands, where biological characteristics will begin to vary. The models were not built using variables only found in pine rocklands, which would have precluded or inhibited future research using these same techniques in other locales.

Many fire risk models exist to calculate surfaces of fire activity, with some surfaces representing real-time activity if data are available while the fire is burning. One such model is LANDIS (Mladenoff *et al*., 1996), which models fire spread in broadleaf and conifer forests. Another model is BEHAVE (Andrews, 1986), which creates object-oriented and discrete event simulations for higher relief areas. A third model is FARSITE (Finney, 1998), which uses a wave propagation approach to operationally model fire spread. Keane *et al*. (2004) created a comprehensive resource for the various developed fire spread models, which provides information on the geographic areas and forest types, in which these models can be used by future researchers for best results. I introduce these models to show that fire activity analyses, for both historic and current fires, exist in literature and in practice. However, the common models listed above and those outlined by Keane *et al*. (2004) demonstrate the importance of high local relief in fire risk and spread modeling, and these fire activity assessments are ill-suited for areas of low total relief such as locations found in the Florida Keys.

1.5 Methods Overview

My research design incorporates fire-scar and tree-ring data to analyze changes in fire activity through time, establish relationships between fire activity and microtopography, and calculate presence/absence of spatial autocorrelation in fire activity in the NKDR. The grid centroid locations in the Blue Hole Burn area were provided by the U.S. Fish and Wildlife Service and are spaced 250 m apart along constant parallels of latitude. The grid network covered the entirety of Big Pine Key, but I selected seven adjacent locations within the Blue Hole Burn boundary in which to sample my slash pines. Each plot, when characterized with LiDAR data, encompassed numerous cells, each 1 m^2. The contiguous network of cells translated to a large (approximately 8.5 ha), spatially-explicit sampling design, and ensured no location in the site was missed when scouting trees. By "spatially-explicit" sampling design, I mean a continuous network of cells, which collectively cover the entire study area, and which prevent a mosaicked collection method whereby certain areas of the study area are overlooked when sampling slash pines. Furthermore, the experimental design allowed me to definitively evaluate how fire activity changes with changes in spatial scale. For example, fire activity of a single cell (*e.g.* 1 x 1 m resolution) can be compared to fire activity of aggregated resolution (*e.g.* 3 x 3 m, 10 x 10 m, and upwards). Additionally, I was able to calculate global and local indicators of spatial autocorrelation in my fire-scar data, to delineate locations of clustering or dispersion.

In each of the seven plots, my research team and I conducted reconnaissance for an optimal subset of 30 fire-scarred trees. From this 30-tree subset, we chose the 10–15 best trees from which to collect cross sections. For the sample tree criteria, I define "best" as those trees with old-growth forms, indicating old age and therefore increased sample depth back through time (Schulman, 1937; Speer, 2010), and those with high numbers of preserved scars for a more extensive temporal record of fire. I was not able to scout exactly 30 fire-scarred trees in every plot because every plot did not have 30 fire-scarred trees, thus more than 10–15 were collected from some plots and less from others. In some instances, more trees were collected from a given plot to fill in any geographic gaps in data caused by plots with less than 10–15 trees.

1.5.1 Dendrochronological Methods

The cross sections collected from each tree were brought back to the laboratory for processing. I sanded the cross-section samples to an ultra-fine polish using progressively finer sand paper to distinguish earlywood and latewood boundaries and cell structure of each ring (Stokes & Smiley, 1968; Orvis & Grissino-Mayer, 2002). Ring boundaries, particularly between earlywood and latewood cells within the ring, were particularly hard to define for the slash pine species. This difficulty led me to rely on WinDendro™ version 2014b (release date June 9, 2015; Regent Instruments Inc.) software with a high-resolution digital scanner to record images with an average dot-per-square inch (dpi) density of 2000 or greater. Due to memory storage constraints, some samples of larger size (greater DBH) required a lower dpi to ensure the entire sample could be scanned and analyzed.

Fire scars were corroborated with fire history records already established for the area to achieve correct fire chronology development (Harley *et al*., 2011). Placement of the fire scar within the ring determined the calendar year of each fire, and the estimated season when the fire occurred during the growing season of that year based on position of the fire scar within the annual ring (Grissino-Mayer, 2001b). A select few fires occurred in the dormant season between the latewood of one year and the earlywood of the next calendar year. Most fires occurred later in the growing season, before dormancy, where small amounts of latewood cells could be seen after the scar. Major fire years were filtered into two classes, specifically > 10% of samples scarred and > 25% scarred for a particular year. For example, if a fire scar was present in the 1850 calendar year for > 25% of the samples, then this indicated a year with a large, site-wide fire. Finally, I split the temporal record into pre- and post-management periods and conducted a standard comparison analyses to test for changes in fire regime through time.

1.5.2 GIS Methods

I used the fire dates of the larger (> 25% scarred) fires to create a continuous spatiotemporal surface of fire across the entire landscape using ArcGIS 10.2. For each major fire year, I generated spatially-explicit surfaces of historic fire activity through the use of two separate spatial interpolation techniques, specifically Inverse Distance Weighted (IDW) and tension splining. Spatial extent of fire activity was evaluated for changes since the pre-settlement and fire suppression periods. Once evaluated using this grid-based approach, I could clearly see the spatial structure of fire activity through time. I was able to address questions regarding locations of patchy fire activity, spatial extents of larger fires, and where different sections of the study area burned in different fire years, which causes the reduction of fuel loads.

The historic fire activity data were assessed for spatial autocorrelation from both the global and local perspectives. I calculated global autocorrelation statistics (Moran's I and Getis-Ord G) on the fire-scar count data per tree for evidence of clustering or dispersion. Clustering of high and low fire activity indicates clear spatial patterns of fire activity which can be used in future analyses for predictive risk assessment or modeling. In addition to the global indicators of spatial autocorrelation, I also calculated local metrics, including Anselin's Local Moran's *I*, Getis-Ord Gi*, and Ripley's K. Each of these metrics evaluated clustering and dispersion from the spatial scale of "neighborhoods" in the data. For example, Ripley's K breaks the study area into increasing bands of distance around a fire-scarred tree of interest and evaluates fire-scar counts on neighboring trees in those bands. If the trees possess similar fire-scar counts, localized clustering of data is present.

I analyzed the relationships between fire activity and microtopography in the NKDR through a suite of linear regressions at aggregated scales. Each of the four primary microtopography variables of interest were derived from the original 1 m LiDAR elevation model. The predictor variables include: elevation, slope in degrees, residual topography (peaks and depressions), and curvature (2^{nd} derivative of slope). A single regression was conducted for each scale of interest, specifically 1 x 1 (no scaling), 3 x 3, 10 x 10, 50 x 50, and 100 x 100 (all scalar windows in m). I compared the model outputs of each of the five linear regressions to assess changes in the predictor-response variable relationship with aggregations in scale. The purpose of aggregating the data to coarser resolution was to determine the presence, if any, of strengthening or dampening of relationships with decreasing resolution.

1.6 Motivation for the Research

Pine rocklands are flat, and spatial homogeneity in environmental parameters normally included as predictor variables in fire activity models makes robust modeling of fire activity in this area difficult. This dissertation research was designed to evaluate fire activity particular to pine rocklands and ecosystems with similar characteristics, specifically those with little to no relief, and generally homogenous fuel characteristics. Therefore, this research investigated spatiotemporal patterns of fire activity using a spatially-explicit research design in an ecosystem that, to the best of my knowledge, has received no attention from fire modelers.

Current public resistance to use fire as a tool for ecosystem protection and conservation stems largely from two fears: destroying remaining portions of this ecosystem, and destroying numerous exurban structures that are heavily concentrated around the refuge. A prime example was the frustration and disappointment expressed by the local community after the September 15, 2011 Blue Hole Burn. This wildfire started as a prescribed burn that escaped prescription due to unforeseen weather patterns. The 2011 burn landscape was fairly contiguous representing a mosaic of effects that resulted from low, moderate, and high severity fire. Along the eastern edge of the burn bordering a primary island thoroughfare, however, the fire burned at a much higher intensity and more plants were consumed. Local community upheaval for the wildfire reinforced the need for more efficient planning and more effective responses to either planned or unplanned fire activity along the WUI. My dissertation provides information on historic fire regimes across a large swath of pine rockland along this WUI and may help in the development of predictive risk models to locate areas of high-low future fire risk. Furthermore, given the likelihood of increased populations, coupled with continued stress on the rocklands given observed sea level rises and general habitat loss, the need to better understand these fragile and spatially-unique ecosystems is strong.

1.7 Dissertation Research Objectives

1. Conduct a standard fire history reconstruction for our study site within the NKDR (Chapter 2);
2. Place the 2011 Blue Hole Burn fire in the NKDR within the historical range of variability for fire activity derived from the fire-scar and tree-ring record (Chapter 2);
3. Generate surfaces of major historical fire years to spatially display historic fire activity in the NKDR (Chapter 2);
4. Isolate specific topographical variables that display statistically significant relationships with historic fire activity (Chapter 3);
5. Determine if relationships between fire activity and microtopography fluctuate with changes in scale (Chapter 3);
6. Evaluate global spatial patterns of fire activity for the study area (Chapter 4);
7. Evaluate local spatial patterns of fire activity for the study area (Chapter 4).

1.8 Dissertation Organization

My dissertation consists of five chapters, three of which are individual manuscripts prepared for submission to peer-reviewed journals. The final chapter of my dissertation discussed broad results to holistically discuss and conclude the study. The second chapter of my dissertation focused on calculating standard fire regime metrics for Big Pine Key, but also investigated the spatial extents of large historic fires through the use of spatial interpolations. I discussed how I created fire frequency surfaces from the GPS point data and number of fire scars, and the interpolation techniques used and comparisons between methods to establish the best possible surface creation method. For the first part of Chapter 2, I focused on the study area as a whole, and calculated current fire activity metrics, which I then used to compare with historical activity and assessed changes post-1950 (the start of fire suppression practices and land management in the NKDR).

In Chapter 3, I investigated the statistical relationship between fire activity and topographical variables derived from 1 m LiDAR data. Essentially, the terrain data were deconstructed into various metrics of surface roughness, and then regressed onto the fire frequency data through the use of various GIS techniques. Each tool I used to combine the raster data (LiDAR) with the point shapefile data (GPS-located trees) is described in detail, and with necessary calibration parameters, in the methods section of Chapter 3. I performed standard linear regressions at increasing scales to evaluate changes, if any, that exist in the relationship between fire activity and microtopography with decreasing resolution (aggregated cell windows).

In Chapter 4, I evaluate the spatial structure of the fire-scar data, specifically those that pass certain filter or cut-off percentages. I conducted two separate investigations into clustering and dispersion, first at the global (*i.e.* study-area-wide) scale, and the second from a localized perspective. I chose Moran's *I* and Getis-Ord G as my global indicators of spatial autocorrelation, and Anselin's Local Moran's *I*, Getis-Ord Gi*, and Ripley's K as my three local indicators. I outlined the details of each operation, including calibration and specification parameters, in the methods section in Chapter 4. The purpose of using both global and local indicators was to assess clustering and dispersion from two perspectives because it is possible that localized clustering/dispersion is overlooked in global analyses.

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Chapter 2

Spatiotemporal Fire History Reconstruction and Historical Range of Variability Analysis for Pine Rocklands on Big Pine Key, Florida USA

This chapter includes sections from Chapter 1 that were modified to fit within the introduction, literature review, and site description segments to follow. The use of "we" or "our" in this chapter refers to the many people who assisted in the field and laboratory to make this research project successful. Details on specific individual involvement can be found in the Acknowledgements section at the end of this chapter. This research was funded in part by a seed grant from the Initiative for Quaternary Paleoenvironmental Research. I am first author, and my contributions to this project include experimental design, data collection and analyses, and manuscript completion. This chapter will be submitted to the journal *Dendrochronologia* for publication.

Abstract

Fire disturbance is an important process in ecosystems for maintaining habitat and vegetation. Fire regimes of many forest and rockland ecosystems follow a fire regime of high-frequency and low-intensity fires, which curtails fuel load accumulation and preserves fire-tolerant plant species composition. In 2011, a fire escaped prescription in the pine rocklands on Big Pine Key in the Lower Florida Keys, and burned near a residential area causing community upheaval regarding what is "natural" for fires in the area. The goal of our project was to determine the natural fire regimes of the area and to evaluate spatial relationships of major fires. Our study area in the National Key Deer Refuge is a pine rockland and the dominant canopy species is South Florida slash pine (*Pinus elliottii* var. *densa*). We reconstructed the fire regimes for both pre- (1911–1956) and post-management (1957–2014) periods, and evaluated fire history metrics for two levels of fire burn percentages (> 10% and > 25%). We used a GIS to spatially analyze the fire activity patterns for each of the 21 major fire years (> 25%). We visually assessed the spatial relationships between large fires of different years. Fire return intervals were statistically different for both time periods ($p < 0.01$), but were statistically the same for both > 10% and > 25% fires ($p > 0.10$). Composite fire interval results show that fires burned approximately once every 3 years. Furthermore, we found that fires burned in different spatial arrangements for each of the major fire years, and in different locations across the study area. Spatial representations of major fire years could distinguish fire scars from separate trees, all with the same seasonality placement (*e.g.* latewood), which resulted from separate fires. Our analyses conclude that the 2011 fire statistically fell within the expected historical range of fire variability for pine rockland ecosystems. Lastly, we are able to display that fire frequency has decreased in the post-management era.

Key words: dendrochronology, fire history, slash pines, GIS, spatial analyses

2.1 Introduction

Globally, pine rocklands are a spatially-limited ecosystem, occurring in the United States only in the southern portions of Florida (Snyder & Robertson, 1990; Noss *et al.*, 1995; Sah *et al.*, 2004; Harley *et al.*, 2011). The Lower Florida Keys, and specifically Big Pine Key, have a mixture of these subtropical pine rocklands and hardwood hammocks that create a unique mosaic across the landscape. The pine rocklands are dominated in the canopy layer by the South Florida slash pine (*Pinus elliottii* var. *densa* Little & K.W. Dorman; hereafter slash pine), with a mixture of palm and herbaceous species in the subcanopy (Table 2.1). With the effects of natural disturbances (*e.g.* hurricanes, insect outbreaks, and sea-level rise) and anthropogenic influences (*e.g.* urbanization and fire suppression), the already naturally-limited rocklands have experienced endangering losses in the subtropical U.S. (Abrahamson, 1984; Frost *et al.*, 1986; Doren *et al.*, 1993; Ross *et al.*, 1994; Platt *et al.*, 2000; Menges & Deyrup, 2001; Ross *et al.*, 2008; Harley *et al.*, 2011). Without regular occurrence of fire in pine rocklands, the ecosystem experiences a distinct shift in vegetation, from a pine rockland composition (slash pine dominated with an open canopy) to a tropical forest composed of various hardwood species with high tree density (Alexander & Dickson, 1972; Snyder *et al.*, 1990).

Fire is a natural disturbance in many ecosystems, particularly important for maintaining the overall health and productivity of plant communities (Ahlgren & Ahlgren, 1960; Taylor, 1973; Wagner, 1978; Noble & Slatyer, 1980; Mutch *et al.*, 1993; Sah *et al.*, 2004; Liu *et al.*, 2005; Possley *et al.*, 2008; Stevens & Beckage, 2009). Fire is a common ecosystem process in the American Southwest (Baisan & Swetnam, 1990; Grissino-Mayer, 1999; Grissino-Mayer &

Table 2.1 List of common plant species found in the pine rockland ecosystem. The canopy species is slash pine, and it has no competition for the canopy layer (Wunderlin, 1982).

Species Name	**Common Name**	**Forest Level**
Pinus elliottii var. *densa*	slash pine	Canopy
Byrsonima lucida	locust-berry	Understory
Cassia chapmanii	Bahama senna	Understory
Coccothrinax argentata	silver thatch palm	Understory
Conocarpus erectus	buttonwood	Understory
Crossopetalum ilicifolium	ground-holly	Understory
Eugenia rhombea	red stopper	Understory
Metopium toxiferum	poisonwood	Understory
Morinda royoc	mouse pineapple	Understory
Myrica cerifera	wax-myrtle	Understory
Pithecellobium guadalupense	blackbead	Understory
Psidium longipes	long-stalked stopper	Understory
Serenoa repens	saw palmetto	Understory
Thrinax radiata	thatch palm	Understory
Acacia pinatorium	pine acacia	Groundlayer
Eragrostis elliottii	Elliott's love grass	Groundlayer
Ernodea littoralis	golden-creeper	Groundlayer
Rhynchospora spp.	white-topped sedge	Groundlayer
Smilax havanensis	greenbriar	Groundlayer

Swetnam, 2000; Stephens *et al*., 2003; Covington & Moore, 2008), and in ecosystems across the globe (Larson, 1996; Lindbladh *et al.*, 2003; Drobyshev & Niklasson, 2003; Gavin *et al.*, 2003; Horn & Kappelle, 2009; Niklasson *et al.*, 2010). The public often associate sites in the western U.S. (such as Colorado or southern California) as those that experience more frequent and more severe fire activity, but do not understand the need for fire in forests of the eastern U.S. and locations such as the Florida Keys. Additionally, not all forest communities experience fire the same way, or as frequently, but fire can vary in frequency, severity, and intensity (Snyder, 1991; Swetnam, 1993; Grissino-Mayer & Swetnam, 2000; Kipfmueller & Baker, 2000; Harley *et al.*, 2011).

In the southeastern and subtropical regions of the U.S., low severity, high frequency fires were most common until ca. 1950 (Chapman, 1926; Van Lear & Waldrop, 1989; Frost, 1998; Swetnam *et al.*, 1999; Harley *et al.*, 2013; Grissino-Mayer, 2016). These lower severity fires rarely left the understory, burning fuels that had accumulated on the forest floor (Van Lear & Waldrop, 1989; Keeley, 2008). However, larger more ecologically severe forest fires can still occur (Heilman *et al.*, 1998; Jenkins *et al.*, 2011; Grissino-Mayer, 2016). Fire is particularly important for pine rockland ecosystem health and preservation because it prevents the conversion of pine rocklands into hardwood hammocks (Chapman, 1932; Snyder *et al.*, 1990; Snyder, 1991). The woody and herbaceous plant species in the rocklands are specifically adapted to regular occurrence of low severity fires. For example, pine trees must have approximately 18 mm or more of phloem and bark thickness to survive most fires (Hare, 1965; Hengst & Dawson, 1994; Pinard & Huffman, 1997). The endangered Big Pine partridge pea

(*Chamaecrista lineata* var. *keyensis* (Pennell) H.S. Irwin & Barneby) is a rare endemic species found only in select rocklands in the subtropics, and without regular fire it is out-competed for resources with other species (Liu & Koptur, 2003; Liu & Menges, 2005; Slapcinsky *et al.*, 2010; Maschinski *et al.*, 2011).

Plant species in ecosystems such as the pine rocklands depend on fire regimes with specific ranges of variability both in terms of severity and frequency. The typical fire return interval for lower severity fires in southern Florida and pine rocklands is one fire every 2 to 10 years, or about 1 to 2 times per decade (Harper, 1927; Taylor, 1981; Platt *et al.*, 2002; Liu *et al.*, 2005), which allows for ecosystem recovery after fire, but also prevents hardwood invasion after long absences of fire. Taylor (1981) stated that fires during the pre-European settlement period in the Everglades were predominantly caused by lightning during the wet season (June–October) as a result of increased thunderstorm activity. For Big Pine Key, fires were used during the earlier portion of the 1900s to promote quality habitat for Key Deer and for hunting purposes (Albritton, 2009). The U.S. Fish and Wildlife Service ignites prescribed fires during periods of drier weather conditions within the June–October window (Doren *et al.*, 1993; Platt *et al.*, 2002).

Our study specifically is concerned with the Blue Hole Burn, a high-intensity fire that took place in the National Key Deer Refuge on Big Pine Key in the Lower Florida Keys in September of 2011. The Blue Hole Burn was initially a prescribed fire ignited by the U.S. Fish and Wildlife Service, and planned to cover ca. four ha. An unexpected weather pattern changed the trajectory of the burn front and the fire grew in size to consume approximately 40 ha. The burn site (Figure 2.1) is located directly adjacent to and west of Key Deer Boulevard which runs northwest to southeast on Big Pine Key. The burn perimeter extended approximately 750 m due west of Key Deer Boulevard and directly north of the Blue Hole neighborhood. The fire reached the slash pine canopy through the subcanopy, completely consuming fuel loads near Key Deer Boulevard (Chad Anderson USFWS, *personal communication*). Fire intensity and severity decreased in the northwestern sections due to freshwater marshes and dissolution holes with standing water. The level of community dissatisfaction, particularly from citizens owning property that bordered the burned perimeter, was severe and appears to be long lasting. The distress that community members felt was primarily for the perceived devastation to the health of the forest ecosystem, which further perpetuated the stigma of wildfires as being "unnatural." Our primary goal in this study was to evaluate fire activity using the fire-scar record found in slash pine trees to accurately place the 2011 fire within the historical range of variability for fires in the area.

We can place contemporary fires either outside or within the historical range of variability (Morgan *et al*., 1994). By determining the extent of this fire relative to other major fires of the area, we can provide factual basis for comparison, as opposed to those driven by media or personal opinion. By reconstructing the activity of fire for periods before human settlement and influence on an ecosystem (Frost, 1998), quantifiable comparisons between fires that occur today and those that occurred in the past can be evaluated. Furthermore, fire history reconstructions that incorporate dendrochronological techniques provide higher

Figure 2.1 The 2011 Blue Hole burn is shown by the yellow polygon (left). Big Pine Key is highlighted by the yellow rectangle (lower inset). The location of Big Pine Key in the Florida Keys island chain is shown by the yellow rectangle (upper inset). Source for imagery is ArcGlobe 10.2.2.

temporal detail and accuracy and for longer expanses of time into the past than historical records (McEwan *et al.*, 2007; Sherrif & Veblen, 2007). Essentially, researchers can use tree rings to evaluate statistical patterns in fire activity through time by analyzing metrics such as frequency, variability, and spatial extents of fires in the past (Brown *et al.*, 1999; Gutsell *et al.*, 2001; Veblen, 2003).

Our study examined spatial patterns of fire on Big Pine Key using a Geographic Information System (GIS). Often in GIS research, datasets are packaged or collected in different forms, thus making data conversions and basic manipulations necessary for future analyses. Data can be of either vector or raster form, which requires the user to convert one dataset into the form of another for analyses. Data conversions are often needed in cases of GPS-located items (*e.g.* trees, point shapefiles) being used in conjunction with surface data (*e.g.* LiDAR digital elevation models, cell-based raster layers).

The purpose of this research was to reconstruct the history of fire for our study area and conduct analyses to quantify the historical range of variability, both temporally and spatially. The research questions that guided our project were: (1) What are the fire regime metrics for the entire timespan of the data set (historical and contemporary)? (2) Has fire frequency significantly changed from pre-management periods (before 1957) after the establishment of the NKDR in 1957? And if so, to what degree has fire frequency changed (*i.e.* become more or less frequent)? (3) What were the spatial characteristics of major historical fires in terms of extent and patterns of fire activity interspersed with areas of less or no fire activity? (4) How does the 2011 Blue Hole burn compare in terms of spatial burn patterns and percent severity with other major historical fires in our study area? We chose our research questions to capture information about the fire history on Big Pine Key from both a temporal and spatial perspective. By including this spatial perspective, we can investigate fire activity on the landscape in a non-conventional and unique way to complement the traditional analysis of fire activity through time.

2.2 Methods

2.2.1 Big Pine Key Study Area

Our study site was located within the National Key Deer Refuge (established in 1957) on Big Pine Key (24.70° N, 81.37° W) in the Lower Florida Keys. Pine rocklands have a dense understory (Figure 2.2) that consists of numerous herbaceious species of herb and shrubs such as silver thatch palm (*Coccothrinax argentata* (Jacq.) L.H. Bailey), buttonwood (*Conocarpus erectus* L.), and pine acacia (*Acacia pinetorum* F.J. Herm.). Slash pines are the dominant species in the canopy, and are the species we used in our fire history analyses because they produce annual rings (Harley *et al.*, 2011), and can record fire events below a fatal intensity threshold. Big Pine Key has a tropical savanna climate, with distinct wet summers and dry winter seasons. The mean annual precipitation for the area is approximately 980 mm, with approximately 80% of rainfall occurring from thunderstorms between June to October (NOAA, 2010).

Groundlayer characteristics of pine rocklands are unique because soil development is limited. Rocklands in general are topographically flat, which distinguishes fire reconstructions from those in the high-relief areas of the western and eastern U.S. The lack of

Figure 2.2 An example of the canopy and subcanopy of the study site. This area did not experience significant burning in the 2011 Blue Hole burn. Notice the thick understory and living slash pine canopy.

significantly-developed soil layer causes large expanses of exposed limestone bedrock (Miami and Key Largo varieties) (Hoffmeister & Multer, 1968). These groundlayer characteristics likely create a unique pattern of fire spread due to low relief and spotty fuel loads compared to areas with a higher topographic relief, well-defined soils, and contiguous fuels.

2.2.2 Field Methods

We collected our samples in the southern half of the 2011 Blue Hole Burn perimeter away from the freshwater marshes. We used a gridded network of plot-center locations set up previously by the U.S. Fish and Wildlife Service with each centroid spaced 250 m apart (Figure 2.3). This sampling design allowed us to create a continuous surface of collection locations across seven plots to ensure that no potential fire-scarred slash pine was overlooked, and to create a cohesive network of collection points across the burned landscape.

Our experimental design used a stratified, pseudo-systematic sampling method to guarantee we collected similar numbers of samples per plot. We also wanted to ensure that the best samples were collected per plot, thus we scouted through the seven plots and targeted the 30 best trees in each plot. Considering we targeted the best trees, our experimental design is not completely systematic, but it was necessary to target the best trees for our fire history reconstructions to ensure that most, if not all, past fires were captured in the tree-ring record (van Horne & Fulé, 2006).

Slash pine trees were carefully inspected and then flagged for collection based on total number of visible fire scars present along the basal margin of the tree (Figure 2.4). Our sampling design began by locating 30 fire-scarred trees per plot, but we soon realized the need to

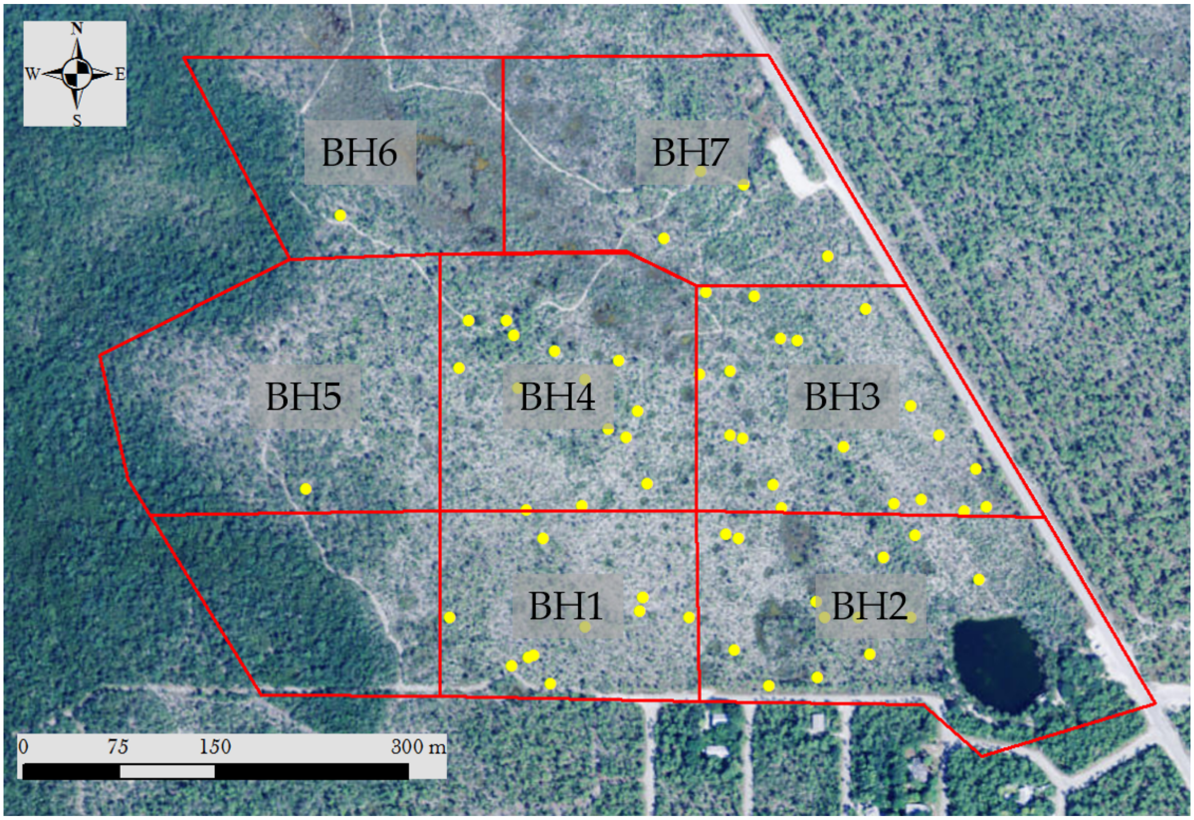


Figure 2.3 Sampling grid with tree locations in yellow. Key Deer Boulevard is the road in the eastern section of the image, Blue Hole pond is in the lower right. Source of image is ArcGlobe 10.2.2.

Figure 2.4 Catface (left) and its fire-scarred cross section (right) for sample BH1008.

constrain the number of collectible samples. Some plots had more than 30 optimal trees, while others had less than 30 trees. We recorded precise locations with a hand-held Garmin GPSmap 62s (variable error rate +/- 4 m), counted the number of fire scars present, and recorded standard tree descriptions, such as tree height and crown condition. Within each plot, we then collected cross-sections from what we considered the 10–15 best trees, focusing primarily on those trees with the highest scar counts, the best preservation, and considerable age based on established physical characteristics that denote older individuals (Schulman, 1937; Speer, 2010). For plots where more than 10–15 optimal trees were found, we collected additional samples to supplement data from plots without enough optimal trees (94 total trees collected). For plots 5 and 6, slash pine tree density decreased, which limited the western extent of the study area in terms of sampling.

We labeled each cross section we collected with the plot ID and tree number (*e.g.* BH1001 = Blue Hole Burn plot 1, tree 1), so that each sample could be traced back to the original GPS location in the field. For trees with large scarred surfaces, we collected sections of the basal margin at different heights above the ground (*e.g.* sample ID would be BH1001a and BH1001b, with increasing letter placement closer to the ground surface). Such collecting of multiple samples per tree is preferred because trees do not always record every fire across the entire length of the cat face (Arno & Sneck, 1977). Rather, some fires only scar a portion of a cat face. Each cross section was protected with plastic wrap to ensure no pieces were lost in transport, and dried in the woodshop for further processing.

2.2.3 Laboratory Methods

In the laboratory, the samples were first flat-surfaced with a band saw to remove chainsaw grooves, and then progressively sanded with increasingly finer sandpaper grit beginning with ANSI 100-grit (125–149 μm) and ending with ANSI 400-grit (20.6–23.6 μm) to ensure the best clarity in cellular structure and ring boundaries (Stokes & Smiley, 1968; Orvis & Grissino-Mayer, 2002). We then scanned each sample using an EPSON 10000XL flat-bed scanner at a minimum of 2000 dpi to create an image record of each sample, and to analyze ring boundaries and fire scars at high resolution. We used skeleton plotting to match fire scars in our samples with those in the fire chronology created for Boneyard Ridge on Big Pine Key (Harley *et al.*, 2013). We also used the Harley *et al.* (2011) chronology and the list method (Yamaguchi, 1991) to visually crossdate the tree rings in our samples. The list method uses narrow rings as marker years by which we can accurately date fire scars. The use of skeleton plots and the list method together allowed evaluation of dead material (*e.g.* stumps, snags, or remnant wood), where the calendar years for the outer rings were not known (Stokes & Smiley, 1968). For the few samples that were collected from living trees, the outer rings were known (last ring was 2014), thus we used the anchored samples to bolster comparison between our fire scars and those in the established fire chronology.

Each dated fire-scarred sample was entered into a data file in FHX (Fire History Exchange) format (Grissino-Mayer, 2001), and then analyzed using FHAES (Fire History Analysis and Exploration) software (version 2.0, released November 2015 (open source); Brewer *et al.*, 2015) and FHX2 fire analysis software (Grissino-Mayer, 2001). We calculated composite fire history metrics, including mean fire interval and Weibull median probability interval (Grissino-Mayer, 1995, 1999), for both total temporal length and pre-/post-management segments. We considered the pre-management era to be before ca. 1957 because the NKDR was established in 1957 (Williams, 1991), and our study area was completely within the NKDR boundary. We applied a threshold filter to our fire-scar dataset at two levels (> 10% and > 25%), to determine if return intervals and the spatial patterns of fire activity changed for larger fires (Swetnam, 1990; Swetnam & Baisan, 1996; Grissino-Mayer, 1999, 2001). For the composite, filter classes, and temporal change (pre-/post-1957) statistics, we used a total sample depth threshold cut off of ten trees and a recorder sample threshold of three trees. The temporal analysis data were normalized in FHX2, and we conducted a Student's t-test on the normalized data to evaluate statistical changes in fire return intervals pre-/post-management.

2.2.4 Spatial Analyses

The data for our project was packaged as GPS-located point shapefiles that need to be converted to a 3D surface of fire activity for interpretation. Data estimation for discrete locations without specifically collected data is usually accounted for in GIS analyses by using spatial interpolation techniques. This process is similar to interpolation through points on a graph, but with a z-coordinate included, whereby data are estimated based on data values of nearby locations (Naoum & Tsanis, 2003). Various forms of interpolation exist to generate 2D and 3D surfaces from point data (Cressie, 1991), but not all are appropriate for all uses. Ultimately, choices on interpolation method are left to the researcher based on specific need and appropriateness for methods (Englund, 1990; Genton and Furrer, 1998). Researchers have evaluated different interpolation techniques, with thin plate (splining), Inverse Distance Weighted (IDW), and kriging (*e.g.* ordinary least squares) being the dominant methods (Englund, 1990; Genton and Furrer, 1998).

We used the Spatial Analyst toolset of ArcMap (version 10.3.1 of ArcGIS for Desktop, released May 2015; ESRI ™ (non-open source)) to generate 1 m cellular resolution maps of major historic fires in our study area. Each tree collectively became the point shapefile we used as the foundation for our modeled fire surfaces. With increasing distances from each fire-scarred tree, the interpolation model must estimate fire activity. For larger regionally expansive study areas, estimation between points becomes less robust because more locations without anchored points must be estimated. However, our study area is small and less than 30 hectares, and our sampling design ensured appropriate coverage of points per plot across the surface. We point out that we can only be 100% certain that fire occurred wherever a fire-scarred tree is precisely located. Surfaces generated from our models represented estimates for locations wherever fire-scarred trees were absent, and actual values for wherever trees were present. Nevertheless, our maps still show basic representations of historic fire at high accuracy in relation to the small spatial extent of our study area.

We used two separate interpolation methods to provide estimates of historic fire activity in locations without actual recorded fire-scarred trees: Inverse Distance Weighted (IDW) and a tension-based spline to convert the point shapefiles of major fires (> 10% and > 25% burned) to raster surfaces. The surfaces are constructed of 1 m raster cells, which collectively compose the seven plots in our study area. Each plot is composed of numerous contiguous cells that cover the entire study area. Given the high resolution (*i.e.* 1 m) of our surfaces, only a single tree was ever present in any given cell, which precluded the model from generating erroneous fire scar estimates for instances of higher tree densities. Each of the two interpolated surfaces for each fire year did not need to be standardized to generate surfaces of similar range because the point shapefile dataset for fire years is binary (*i.e.* 1 = fire in that year, 0 = no fire in that year), thus the output rasters all vary around the 0/1 range. Once each major fire surface was created, we spatially compared the two different interpolation surfaces to identify specific cells of differences, if any, in interpolation results.

We used the raster calculator tool to locate individual cells of difference between the two interpolation methods for our discrepancy analysis. Each of our interpolated surfaces per major fire year represent the same geographic location in our study area, thus each 1 m cell from the IDW surface has a complement in the spline surface, which allowed us to compare any two cells for a given location for discrepancies in cell value. We evaluated each surface and searched for any two cells representing the same location with considerable difference in value, which we considered as above 0.5. We chose the 0.5 discrepancy limit to reflect the 0/1 range of cell values in the dataset; thus a difference of 0.5 would be more than half the cell value range between no fire (0) and fire (1). We flagged fire years if the two interpolated surfaces had more than 25% of the cells with differences greater than 0.5. For example, if the fire in year X produced two different interpolated surfaces with the number of different cells exceeding 25% of the total cells, then the spatial pattern for that particular fire interpolation methods can produce considerably different surfaces. We chose the difference cut off of 0.5, and the 25% cell threshold, to be conservative when averaging the two surfaces in later steps. We wished to ensure that our two interpolation methods did not produce vastly different surfaces, and that averaging them in future steps was appropriate. Lastly, our reasoning for the interpolation checks was to confirm that our interpolation method was not giving an unusual result based on the specific technique or the spatial distribution of the data.

The Inverse Distance Weighted (IDW) interpolation technique required an input shapefile dataset. For our project, the point shapefile was trees in an individual fire year that exceeded a burn percentage (> 25%). We calculated burned percentages first in FHAES, and then recorded the years that exceeded the burn thresholds. The trees reporting fire scars in major burn years were uploaded into the IDW interpolation tool as the starting shapefile. We chose to use a power decay of 2, which calculated a smooth exponential decay from a starting value of 1 (fire positively burned at this cell location in the given fire year) to 0 (no fire occurred at all in this cell location for the given fire year). The range of values for the output raster did not exceed the range for the input values and preserved natural variance. The IDW tool generated a smooth 1 m cellular resolution surface of estimated fire activity for each major fire year.

We chose the spline interpolation technique because it prevents artificially inflated surface features from the point data. Trees with fire scars in major burn years were uploaded into the IDW interpolation tool as the starting shapefile. Similar to the IDW technique, we used the > 25% threshold for years determined in FHAES and FHX2 as the input data for the splines. We customized the spline operation by using the tension option for surface production, which generated a slightly rougher surface than the IDW, but it allowed for tighter conformity to our tree locations. Finally, we used 12 nearest-neighbor points for each individual tree location for best estimation, which allowed the tool to "look" in the general neighborhood of each tree location for scar information from nearby trees, thus producing stronger estimations. The spline operation produced an estimated fire activity surface with an output cell size of 1 m cellular resolution.

We overlaid the two interpolated surfaces for each major fire year on each other and used map algebra and raster calculator to average each fire surface. After each interpolation method, we had created two fire activity surfaces for each of the major fire years, which were then combined into a single estimated surface for fire activity using raster calculator. The final interpolated surface for each fire year had cells with values in the 0/1 range. We were confident in the accuracy of our surfaces based on our thorough interpolation checks, which minimized method bias.

2.3 Results

2.3.1 Fire History

From the 94 sampled trees, we successfully dated 63 fire-scarred slash pine samples to annual resolution to evaluate fire history at our site. Dating of some samples was unsuccessful because of various factors, including heavily-decayed wood, prevalence of extensive beetle galleries that obscured ring boundaries and scars, low ring counts (*e.g.* samples with less than approximately 50 rings), or lack of overlap with the established dated chronology. We dated 385 fire scars across all years in the dataset, which spanned from 1783 to 2014 (Figure 2.5). From the 63 samples (Table 2.2) and 385 recorded fire scars, we distinguished 55 separate fire events (Figure 2.5). Fires were dated back to 1783, but sample depth did not reach above 10 trees until 1890. The composite mean fire return interval (MFI) for the Blue Hole Burn site (1890–2014; n = 63) was 3.03 years with a standard deviation of 1.49 years. The Weibull median probability interval (WMPI) was slightly shorter at 2.91 years with a standard deviation of 1.46 years (Table 2.3). The range of return intervals for all fires was between 1 and 7 years.

We found 27 fire events that scarred > 10% of our samples, and 20 fire events that scarred > 25% of our samples (Table 2.4). The average percent scarred in the > 10% group was 40% and the average percent scarred in the > 25% group was 48%. For the > 25% group, the 2011 fire (74% of samples scarred) was within the normal quartile range and was not classified as an outlier (Figure 2.6). The 1911 and 1918 fires (100% of samples scarred for each) were the only classified outliers in either group (Figure 2.6). The MFI for the > 10% group was 3.57 years with a standard deviation 1.85 years, and the WMPI was 3.40 years with a standard deviation of 1.80 years (Table 2.3). The range for the > 10% group was 1 and 8 years. The MFI for the > 25% group was 4.76 years with a standard deviation of 3.43, and the WMPI was 4.23 years with a standard deviation of 3.15 years (Table 2.3). The range for the > 25% group was 1 and 14 years.

We further analyzed the fire history of our site by dividing the temporal record into two parts: 1890–1956 and 1957–2014 to represent the beginning of federal management by the U.S. Fish and Wildlife Service on Big Pine Key. Using the > 25% threshold to isolate temporal changes in major fires, we found 14 fire events for the 1911–1956 group, and 8 fire

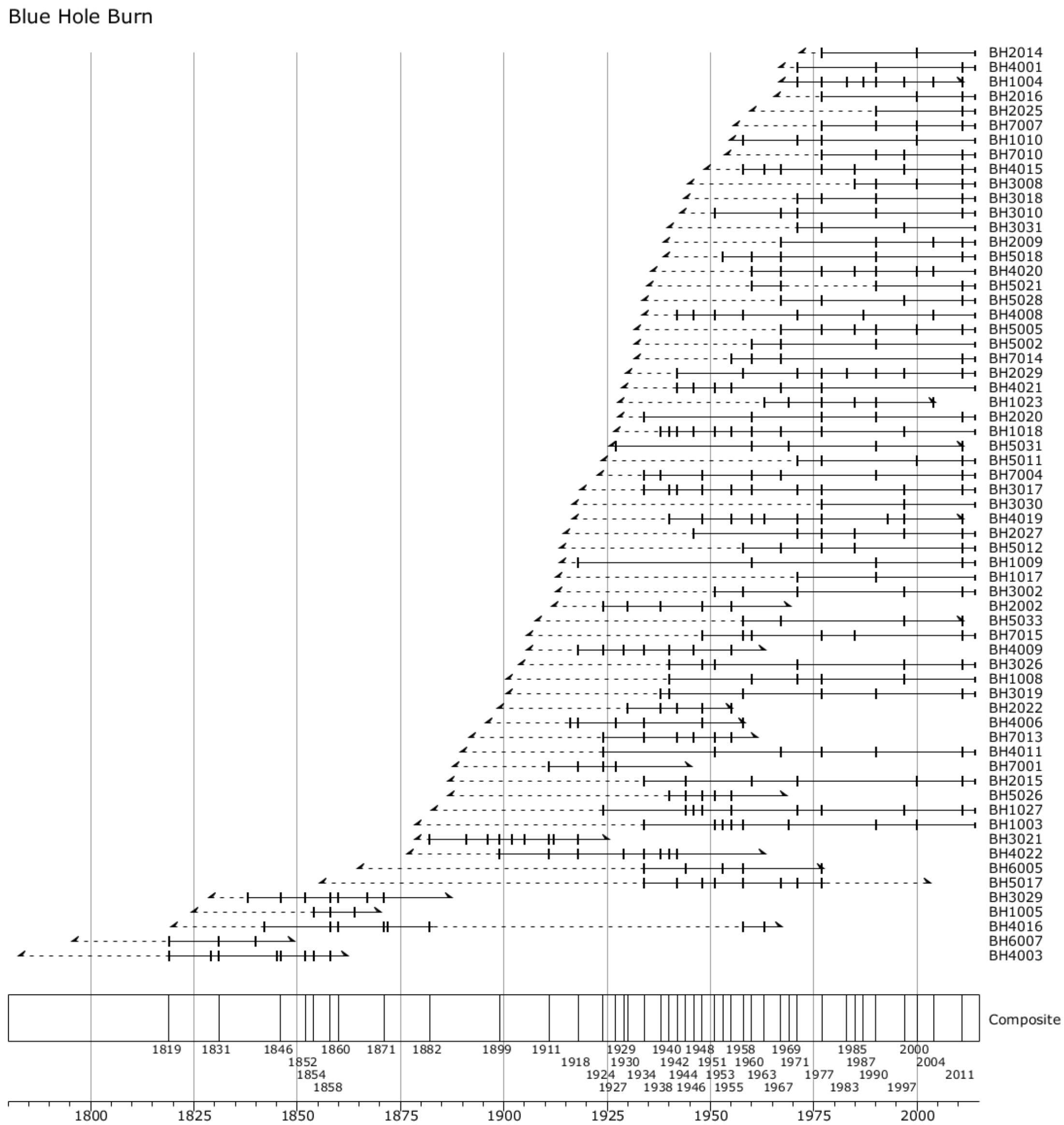


Figure 2.5 Fire history of the Blue Hole burn study site (n = 63 samples). Horizontal lines represent trees. Vertical tick marks along each horizontal line represent fire events recorded by that tree. The dashed lines indicate years that are not recorder years, the solid line represents recorder years, and arrows at the end of each horizontal line indicate first and last year for each tree. The composite bar shows fire years when the number of fires was two or greater.

Table 2.2 List of all collected slash pine samples with GPS locations, number of scars per sample, recorder years, and condition when collected.

Sample ID	Lat. (N)	Long. (W)	No. of Scars	Recorder Years	Condition
BH1003	24.7059	81.38435	8	1934–2014	living
BH1004	24.70588	81.38439	8	1967–2004	snag
BH1005	24.7061	81.38395	3	1854–1870	stump
BH1008	24.70631	81.38351	5	1940–2014	stump
BH1009	24.70631	81.38351	4	1918–2014	stump
BH1010	24.70621	81.38353	5	1955–2014	living
BH1017	24.70582	81.38452	2	1971–2014	living
BH1018	24.7057	81.38422	10	1937–2014	living
BH1023	24.70616	81.385	6	1963–2004	snag
BH1027	24.70692	81.38441	9	1924–1955, 1977–2014	living
BH2002	24.70575	81.38216	5	1924–1955	snag
BH2009	24.70591	81.38175	4	1967–2014	living
BH2014	24.70617	81.38184	2	1977–2014	living
BH2015	24.70617	81.3821	6	1934–2014	living
BH2016	24.70628	81.38217	3	1977, 2000–2014	snag
BH2020	24.70569	81.38253	5	1934, 1960–2014	snag
BH2022	24.70594	81.3828	5	1930–1955	snag
BH2025	24.70617	81.38315	2	1990–2014	living
BH2027	24.70675	81.38287	6	1944–2014	snag
BH2029	24.70672	81.38277	8	1942–2014	living
BH3002	24.70834	81.38179	5	1951–2014	snag
BH3008	24.70812	81.38232	4	1985–2014	snag
BH3010	24.70813	81.38245	5	1951–2014	snag
BH3017	24.70745	81.38284	10	1934–2014	snag
BH3018	24.7079	81.38284	4	1971–2014	snag
BH3019	24.70788	81.38307	6	1938–2014	snag
BH3021	24.70762	81.38355	8	1882–1918	snag
BH3026	24.70743	81.38274	6	1940–2014	snag
BH3029	24.7071	81.3825	7	1838–1887	snag

Table 2.2 Continued.

Sample ID	Lat. (N)	Long. (W)	No. of Scars	Recorder Years	Condition
BH3030	24.70694	81.38244	2	1977–2014	snag
BH3031	24.70737	81.38196	3	1971–2014	living
BH4001	24.70672	81.38428	3	1971–2014	living
BH4003	24.70695	81.38398	8	1819–1862	snag
BH4006	24.70711	81.38348	6	1916–1958	snag
BH4008	24.70743	81.38364	7	1942–2004	snag
BH4009	24.70749	81.38378	7	1918–1924, 1934, 1940–1955	snag
BH4011	24.70784	81.38396	6	1924, 1951, 1967, 1990–2014	snag
BH4015	24.70778	81.38448	7	1958–2014	snag
BH4016	24.70792	81.38493	8	1842–1967	snag
BH4019	24.70825	81.38486	10	1940–2011	stump
BH4020	24.70825	81.38457	7	1960–2014	living
BH4021	24.70815	81.38451	6	1942–2014	living
BH4022	24.70804	81.38419	8	1899–1942	snag
BH5002	24.70617	81.38144	3	1960–2014	snag
BH5005	24.70659	81.38165	6	1967, 1977, 1985, 1990–2014	snag
BH5011	24.70697	81.38157	4	1971–2011	living
BH5012	24.707	81.38136	5	1958–2014	snag
BH5017	24.70766	81.38144	8	1934–1977	snag
BH5018	24.70745	81.38122	5	1953–2014	snag
BH5021	24.70722	81.38094	4	1960–1967, 1990–2014	snag
BH5026	24.70692	81.38103	5	1940–1968	snag
BH5028	24.70695	81.38086	4	1967–1977, 1997–2014	living
BH5031	24.70675	81.38141	4	1927–1990	snag
BH5033	24.70644	81.38091	4	1958–2011	snag
BH6005	24.70706	81.38611	5	1934–1977	snag
BH6007	24.70899	81.38585	3	1819–1846	stump
BH7001	24.70871	81.38209	4	1911–1945	snag
BH7004	24.70843	81.38265	7	1934–2014	snag
BH7007	24.70846	81.38303	4	1977–2014	remnant
BH7010	24.70883	81.38335	4	1977, 1990–2014	snag
BH7013	24.70797	81.3837	6	1924–1955	snag
BH7014	24.70931	81.38307	4	1955–2014	stump
BH7015	24.70921	81.38274	6	1948–2014	stump

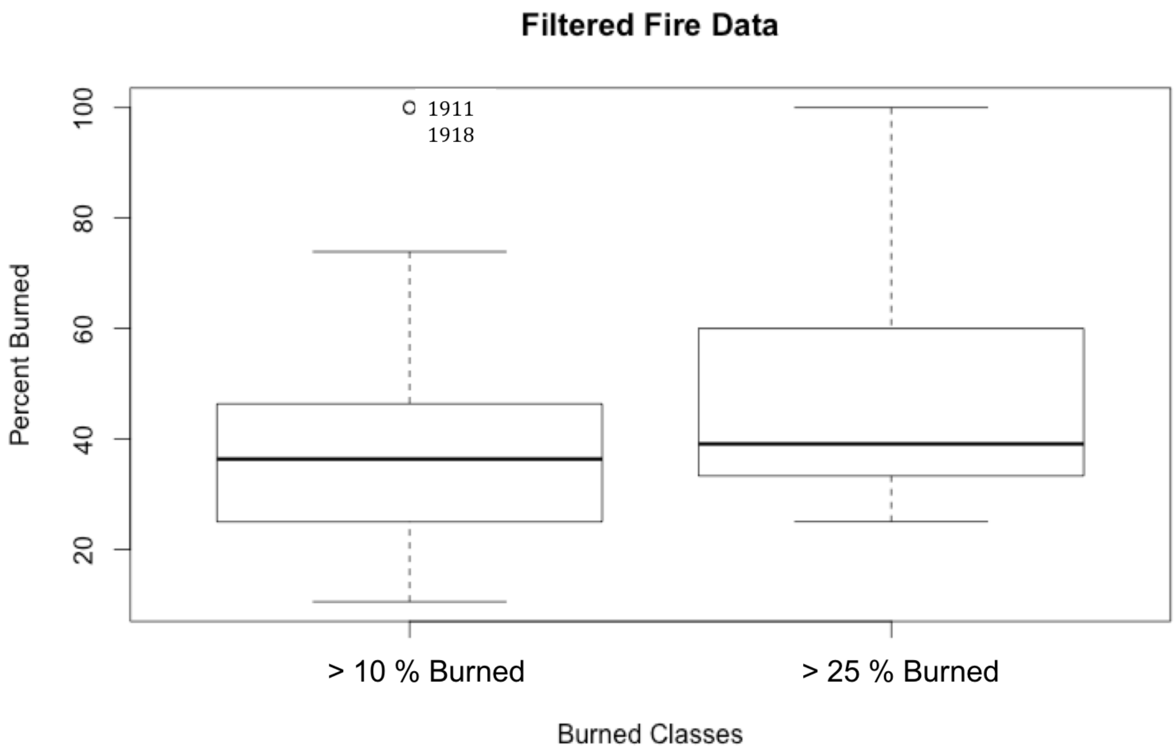
Table 2.3 Fire history statistics for the Blue Hole Burn site for by all fire years, those years when > 10% of samples scarred, and those when > 25% of samples scarred. Values are in years.

Blue Hole Burn (n = 63)	**MFI**[1]	**SD**[2]	**WFF**[3]	**WMPI**[4]	**WSD**[5]	**Range**
All	3.03	1.49	0.34	2.91	1.46	1−7
> 10 % (n = 27)	3.57	1.85	0.29	3.40	1.80	1−8
> 25 % (n = 20)	4.76	3.43	1.00	4.23	3.15	1−14

[1] mean fire interval (MFI)
[2] mean fire interval standard deviation (SD)
[3] Weibull fire frequency (WFF)
[4] Weibull median probability interval (WMPI)
[5] Weibull standard deviation (WSD)

Table 2.4 Fire Years (> 10% and > 25%). Sample depth was at least 10 trees, and the minimum recording depth was three trees.

> 10% Scarred				> 25% Scarred			
Year	**Recording Depth**	**Fire Events**	**Percentage**	**Year**	**Recording Depth**	**Fire Events**	**Percentage**
1911	3	3	100	1911	3	3	100
1918	6	6	100	1918	6	6	100
1924	10	6	60	1924	10	6	60
1927	10	3	30	1927	10	3	30
1929	10	2	20	1934	18	11	61
1930	11	2	18	1938	20	6	30
1934	18	11	61	1940	24	9	38
1938	20	6	30	1942	27	9	33
1940	24	9	38	1946	27	7	26
1942	27	9	33	1948	28	11	39
1944	27	4	15	1951	30	11	37
1946	27	7	26	1955	33	12	36
1948	28	11	39	1958	36	14	39
1951	30	11	37	1960	38	15	39
1955	33	12	36	1967	40	17	43
1958	36	14	39	1971	41	19	46
1960	38	15	39	1977	46	30	65
1963	38	4	11	1990	47	24	51
1967	40	17	43	1997	47	16	34
1971	41	19	46	2011	46	34	74
1977	46	30	65		**AVERAGE**		**48%**
1985	45	8	18				
1990	47	24	51				
1997	47	16	34				
2000	47	10	21				
2004	47	5	11				
2011	46	34	74				
	AVERAGE		**40%**				




```
 1 | 11588
 2 | 016
 3 | 0034678999
 4 | 36
 5 | 1
 6 | 015
 7 | 4
 8 |
 9 |
10 | 00
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 2 | 6
 3 | 0034678999
 4 | 36
 5 | 1
 6 | 015
 7 | 4
 8 |
 9 |
10 | 00
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Figure 2.6 Box plot (top) displaying quartile ranges of the > 10% scarred group (n = 27) and the > 25% scarred group (n = 20). The 1911 and 1918 fires are captured as outliers only in the > 10% group. Stem and leaf plot (bottom) displays individual data points for the > 10% group (left) and the > 25% group (right).

events for the 1957–2014 group. The MFI for the earlier group was 3.38 years with a standard deviation of 1.71 years, and a WMPI of 3.25 years with a standard deviation of 1.63 years. The range of fire intervals for the earlier group was 1 and 7 years (Table 2.5). The MFI for the later group was 7.57 years with a standard deviation of 4.43 years, and a WMPI of 7.14 years with a standard deviation of 4.06 years. The range of fire intervals for the later group was 2 and 14 years (Table 2.5). We conducted a Student's t-test on the normalized data for the different periods and found a statistically significant difference ($t=3.1925$; $p < 0.01$) between the pre- and post-management fire regimes. This finding suggests a shift in fire regime, with fires occurring more frequently before 1957 in the pre-management period than after 1957 in the post-management period.

2.3.2 Spatial Representation of Large Fires

We classified major fires as those that scarred > 25% of the trees, with a sample depth of at least 10 trees and at least 3 recorder trees. The discrepancy results for the interpolated surfaces represent the number of cells with difference values above 0.5 for a given location given the two different interpolation methods out of the total number of cells for the study area (Table 2.6). A difference > 0.5 represents a result based on the interpolation method and not necessarily from fire activity. The only two fire years to surpass the defined threshold (more than 25% of the total cells have a value > 0.5) in the discrepancy analysis were 1977 and 1997.

The spatial patterns of past fires in the NKDR distinctly vary from year to year (Figures 2.7–2.11). Beginning with the 2011 fire, we found a distinct delineation in the fire activity that

Table 2.5 Fire history statistics for the Blue Hole Burn site for pre- and post-management periods. Values are in years for the > 25% scarred group. Statistical comparisons were conducted on the normalized data (via FHX2) for both groups.

Period	MFI[1]	SD[2]	WFF[3]	WMPI[4]	WSD[5]	Range
1911–1956 (n = 14)	3.38*	1.71	0.31	3.25	1.63	1–7
1957–2014 (n = 8)	7.57*	4.43	0.14	7.14	4.06	2–14

[1] mean fire interval (MFI)
[2] mean fire interval standard deviation (SD)
[3] Weibull fire frequency (WFF)
[4] Weibull median probability interval (WMPI)
[5] Weibull standard deviation (WSD)
* statistically significance difference ($p < 0.01$)

Table 2.6 Interpolation discrepancies for each fire year.

Interpolation Discrepancies	
Fire Year	**Percentage***
1911	4.3
1918	4.3
1924	7.1
1927	3.2
1934	12.8
1938	3.2
1940	10.9
1942	12.3
1946	13.6
1948	9.9
1951	19.4
1955	14.5
1958	24.7
1960	16.5
1967	20.4
1971	15.7
1977	84.8
1990	20.8
1997	39.5
2011	10.1

* Percentages of cells of difference (cell values > 0.5) between the two interpolation methods.

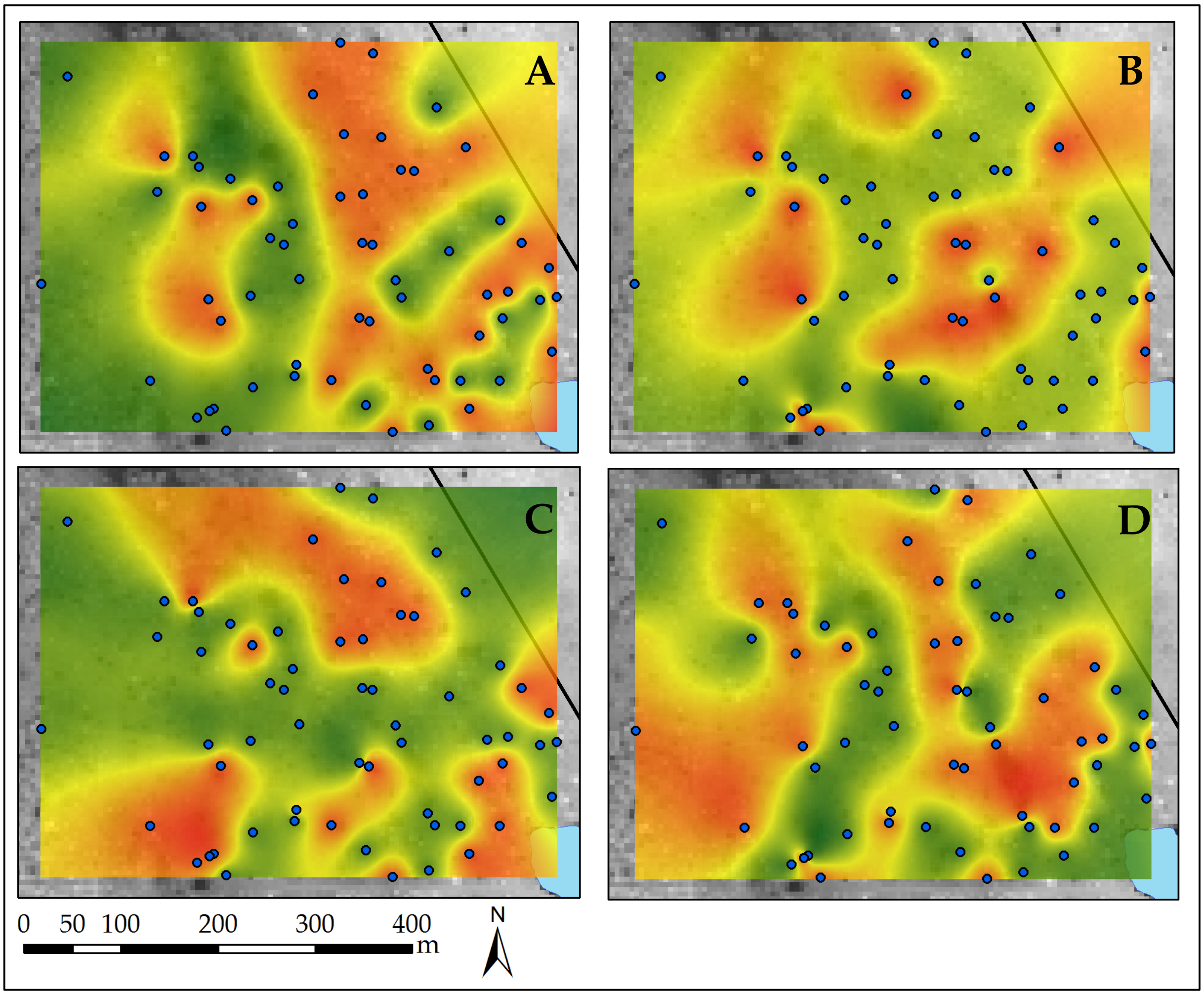

Figure 2.7 The 2011 fire (A), 1997 fire (B), 1990 fire (C), and 1977 fire (D). Key Deer Boulevard is the diagonal black line in the eastern section of each image, and Blue Hole pond is in the lower right of each image. Each surface has a color scheme that represents areas of fire activity (shades of red) and areas of no fire activity (shades of green).

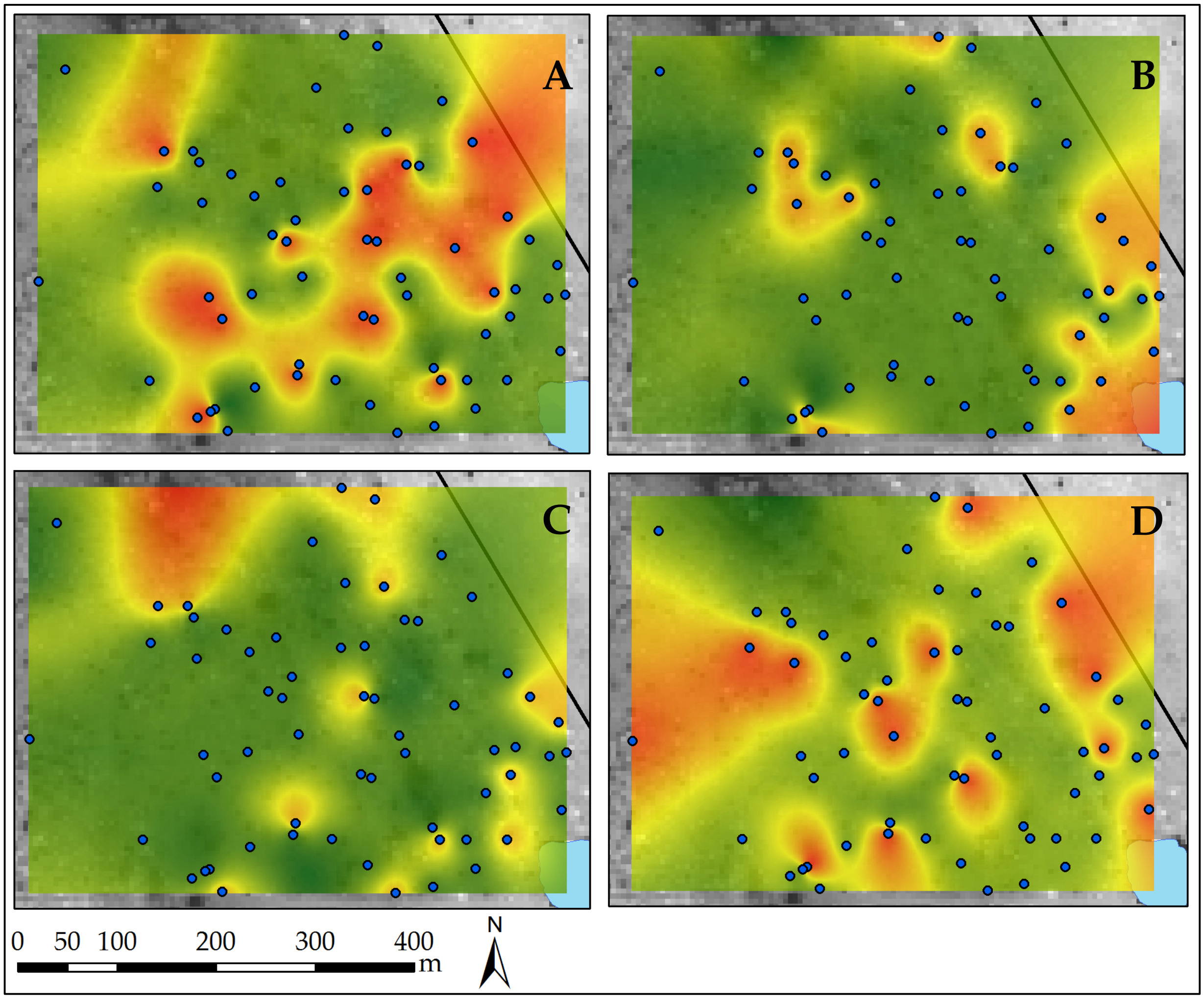

Figure 2.8 The 1971 fire (A), 1967 fire (B), 1960 fire (C), and 1958 fire (D). Key Deer Boulevard is the diagonal black line in the eastern section of each image, and Blue Hole pond is in the lower right of each image. Each surface has a color scheme that represents areas of fire activity (shades of red) and areas of no fire activity (shades of green).

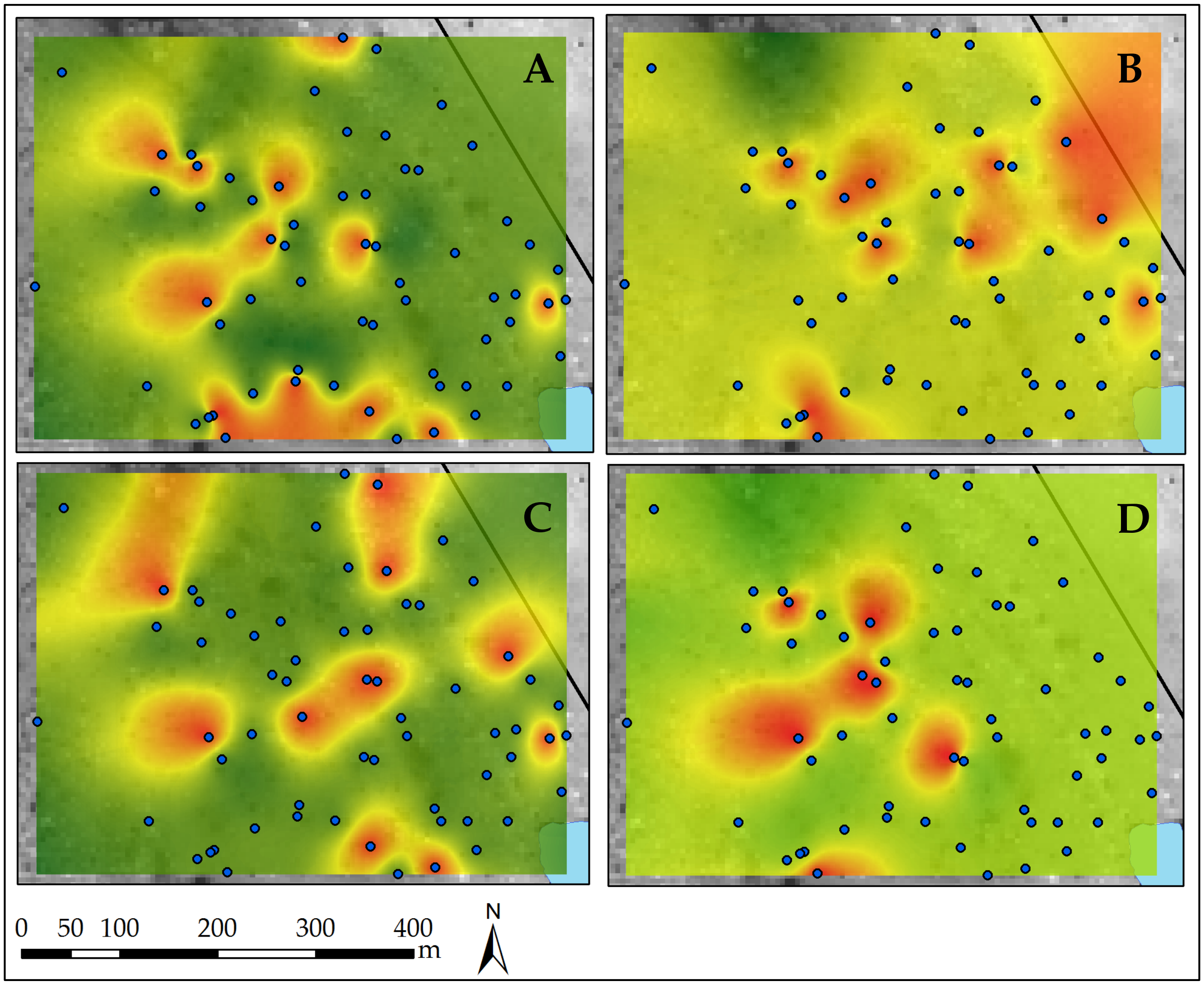

Figure 2.9 The 1955 fire (A), 1951 fire (B), 1948 fire (C), and 1946 fire (D). Key Deer Boulevard is the diagonal black line in the eastern section of each image, and Blue Hole pond is in the lower right of each image. Each surface has a color scheme that represents areas of fire activity (shades of red) and areas of no fire activity (shades of green).

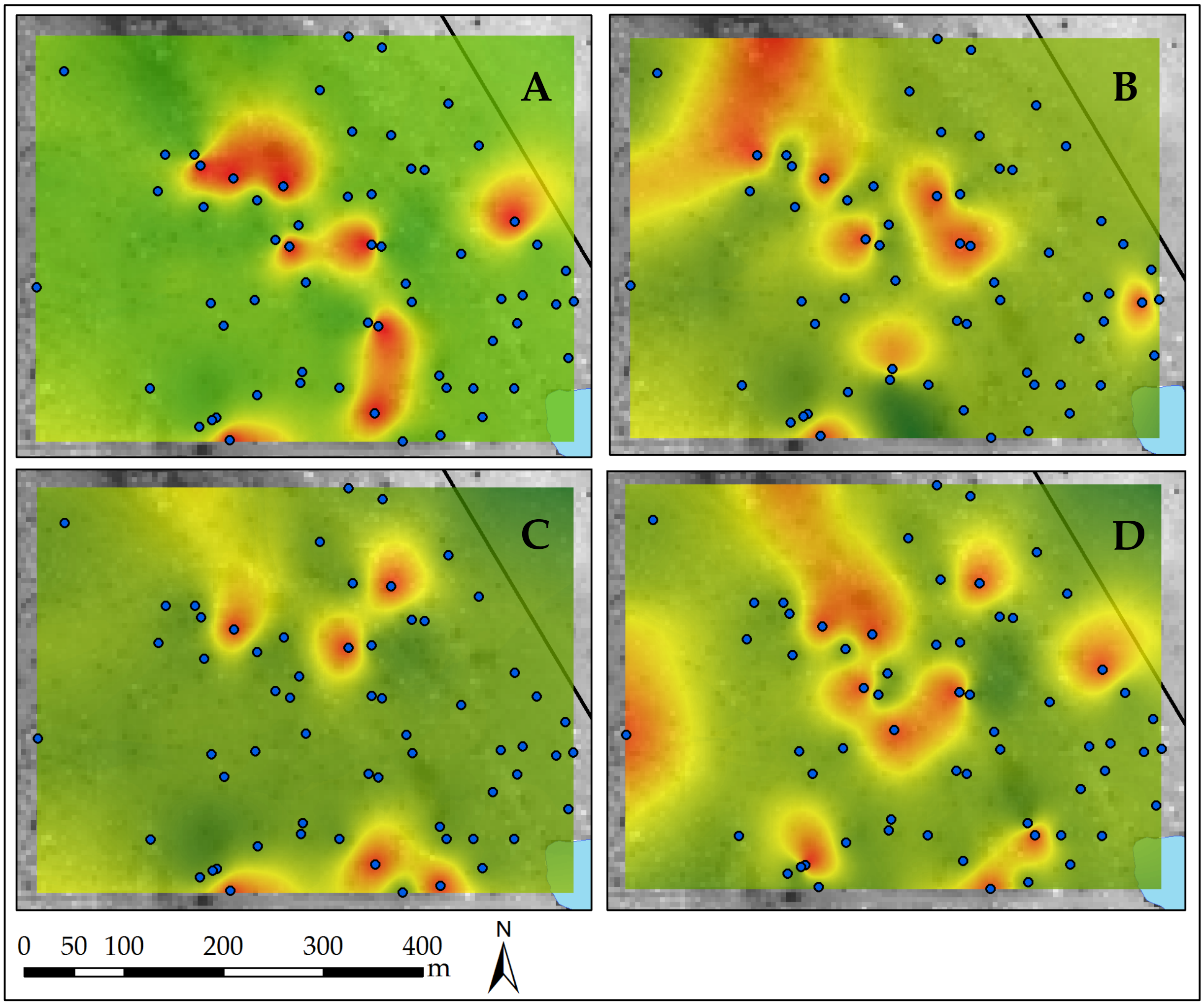

Figure 2.10 The 1942 fire (A), 1940 fire (B), 1938 fire (C), and 1934 fire (D). Key Deer Boulevard is the diagonal black line in the eastern section of each image, and Blue Hole pond is in the lower right of each image. Each surface has a color scheme that represents areas of fire activity (shades of red) and areas of no fire activity (shades of green).

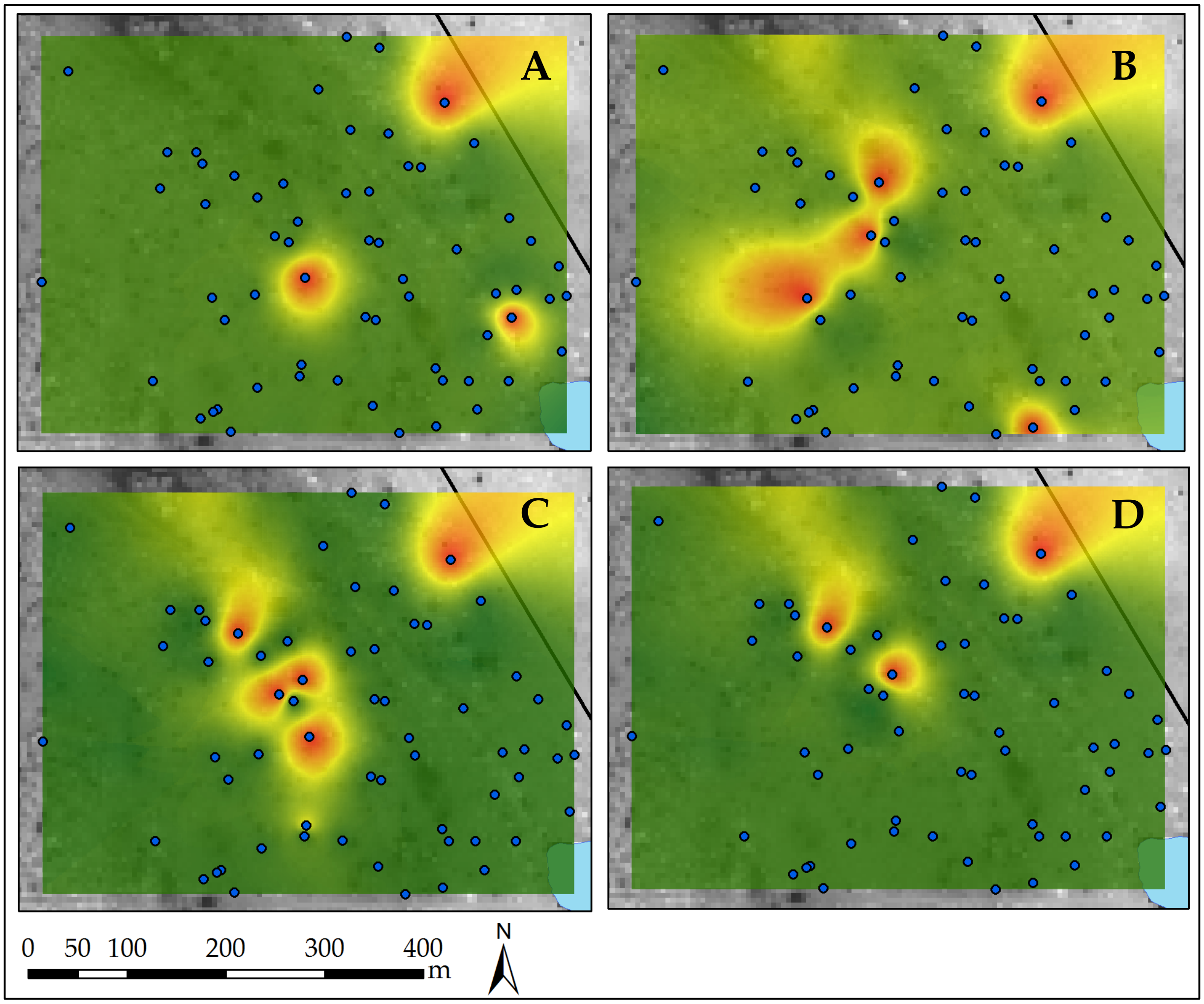

Figure 2.11 The 1927 fire (A), 1924 fire (B), 1918 fire (C), and 1911 fire (D). Key Deer Boulevard is the diagonal black line in the eastern section of each image, and Blue Hole pond is in the lower right of each image. Each surface has a color scheme that represents areas of fire activity (shades of red) and areas of no fire activity (shades of green).

ran north-south. The majority of fire-scarred trees were located on the eastern border of the study area adjacent to Key Deer Boulevard (Figure 2.7A). The next largest fire occurred in 1977, with only four fewer trees scarred than the 2011 fire (34 samples in 2011, 30 samples in 1977). The spatial pattern of the 1977 fire suggests a less clustered spread, with more burned areas near the Blue Hole pond in the southeast corner of the study area and near the hardwood hammocks along the western border (Figure 2.7D). The 1997 fire spread across the majority of the study area, focusing in the east and east-central regions, and overlapping with those areas burned in the 2011 fire (Figure 2.7B). The 1990 fire was also large, with 24 trees scarred and patterns of fire activity to the north-central, southwest, and southeast portions of the study area (Figure 2.7C). The 1958 fire was the largest fire near the pre-management period, and one that was also comparable in size and pattern to the 1977 and 2011 fires (Figure 2.8D).

Some years with temporally-clustered fires tended to show that areas burned in one fire year were fire free in other years. For example, the 1971 and 1967 fires complement each other in terms of fire extents, with the central area burning in 1971 (Figure 2.8A) and the southeastern portion burning in 1967 (Figures 2.8B). We found that for certain fire years, such as 1960, the interpolated surface depicted patchy fire activity where individual trees recorded fire amongs other trees that did not record fire (Figure 2.8C). The 1955 fire scarred more trees in the west and west-central sections of the study area (Figure 2.9A), while the 1951 fire burned closer to Key Deer Boulevard, with smaller burned areas located in the central and southern sections (Figures 2.9B).

Fires that occurred in the pre-management era also suggest specific spatial patterns in fire activity. Several fire years occurred during the 1940s at a rate of one fire almost every two years. The 1948 fire surface displays a distinct patchy pattern of fire-scarred trees, with patchy fires through the study area (Figure 2.9C). The 1946 fire was clustered almost exclusively in the central and south-central section of the study area, with no trees near Key Deer Boulevard recording a fire (Figure 2.9D). The 1942 fire was centrally-focused with only a single tree recording a fire near Key Deer Boulevard (Figure 2.10A). The 1940 fire had fire-scarred trees spread across the majority of the study area, with some clustered in the north-central section (Figure 2.10B). The 1938 fire was patchy with three fire-scarred trees located in the north-central section and three located along the southern border of the study area (Figure 2.10C). The 1934 fire displayed relatively the same spatial patterns as larger fires, despite having only 11 trees recording a fire scar in that year (Figure 2.10D). Finally, the 1927, 1924, 1918, and 1911 fires were the earliest fire years we interpolated and all four had patchy surfaces due to lower sample depth and number of fire-scarred trees compared to more contemporary fires (Figures 2.11A-D).

2.4 Discussion

2.4.1 Fire History

Our MFI and WMPI results corroborate results from previous research in pine rocklands, which found return intervals between 2 and 10 years (Harper, 1927; Taylor, 1981; Snyder *et al.*, 1990; Platt *et al.*, 2002; Liu *et al.*, 2005; Harley *et al.*, 2013). Harley *et al.* (2012) found WMPI values between six and nine years from an area of pine rockland on the eastern side of

Key Deer Boulevard, and a site on No Name Key (adjacent to Big Pine Key). Short MFI and WMPI values indicate a higher frequency of forest fires, which translates to lower intensity and lower severity fires. We can not say that high-intensity fires did not occur in our study area, but the presence of fire scars back to 1819 indicates that high-intensity, stand-replacing fires are unlikely to have occurred or seldom occur in this ecosystem. This frequency-severity relationship is primarily due to fuel loading because available fuel loads to support larger and more severe fires decrease as fire frequencies increase (Miller & Urban, 2000; Schoennagel *et al.*, 2004). Overall, our MFI and WMPI values are within the expected range of fire occurrence intervals for this type of ecosystem (Harper, 1927; Taylor, 1981; Platt *et al.*, 2002; Liu *et al.*, 2005; Harley *et al.*, 2013).

Our results demonstrate that the 2011 Blue Hole Burn was within the historical range of variability for fire activity on Big Pine Key. While it was the largest fire (trees scarred = 34) in our dataset, the next largest fire in 1977 had nearly the same number of samples scarred (trees scarred = 30), and both showed a broad spatial extent of fire-scarred trees across the study area. The percentage of samples scarred based on sample depth was also similar, with approximately 74% scarred in 2011 and 65% scarred in 1977. Furthermore, our quartile analysis showed that for the > 25% group (n = 20), the 2011 fire was not a statistical outlier, meaning that within all burn percentages per fire year for that filter class, the 2011 fire was not outside of the normal quartile range. Our results show that this particular fire did not burn a statistically higher percentage of trees than other major fires in our study area on Big Pine Key. Furthermore, other large historic fires, such as those that occurred in 1977, 1990, 1958, and 1934, all display spatial extents across the study area similar in extent to the 2011 fire.

Prescribed burning practices on Big Pine Key have been incorporated into U.S. Fish and Wildlife Service ecosystem management since ca. 1960, and within the NKDR officially since ca. 1980. The extent and overall intensity have varied with each prescribed fire, but all have been ignited for the purpose of reducing understory density and preventing hardwood hammock encroachment (Bergh & Wisby, 1996). The 1977 fire (second largest fire in our dataset) was a prescribed fire ignited on October 25th that burned approximately 40 ha of land on both the west and east side of Key Deer Boulevard near Blue Hole Pond (Bergh & Wisby, 1996). The 1990 fire (third largest fire in our dataset) was also a prescribed fire and was ignited on September 11th, burning approximately 40 ha (Bergh & Wisby, 1996). A precipitation event prior to the 1977 burn date increased moisture availability in the defined burn perimeter, thus preventing the 1977 prescribed burn from reaching full intensity as expected. The 1990 fire perimeter stopped south of the Jack Watson Nature Trail (northern border of our study area) and north of 6th Street (southern border of our study area), with the most destruction to the east and adjacent to Key Deer Boulevard. According to Bergy and Wisby (1996), approximately 90–95% of the understory was consumed in this fire. The two largest and most severe fires to occur before the 2011 burn were just as spatially extensive, and the 1990 fire burned comparable amounts of understory vegetation. Historical records on prescribed burning on Big Pine Key add further evidence that the 2011 Blue Hole Burn was within the natural range of variability for fires in the area (Bergh & Wisby, 1996).

Other fires that occurred on Big Pine Key near or within the now established NKDR give further insights and corroborate our interpretations of fire activity based on the tree-ring record, and to verify the fire surfaces we generated in our analyses. For example, the 1985 fire was caused by lightning and started on September 5th, buring approximately 25 ha (Bergh & Wisby, 1996). The burn perimeter for this fire began to the northwest of our study area, but extended to our northwestern border (Bergh & Wisby, 1996). Records indicate that the border of this fire is an approximation because it ignited in a remote corner of the refuge with limited road access. The 1985 fire likley extended south of Jack Watson Nature Trail and into our study because eight of our trees were scarred in the latewood for the 1985 ring. Lastly, the spatial extents of both the 1977 and 1990 fires, as outlined by Bergh and Wisby (1996), overlap with those defined in our interpolated fire surfaces.

The statistical analyses on the fire regime metrics for pre-management (1911–1956) and post-management (1957–2014) periods found a significant statistical difference in fire frequency between these periods. This result is not surprising considering many fire history analyses find that the MFI and WMPI for earlier fire periods are shorter than for later periods due to the prevalance of fire suppression measures and changes in land-use practices in more recent decades. The settlement history of Big Pine Key gives further insights into why fire frequency decreased during the post-management period, specifically in regard to changes in land use and fire suppression practices.

The settlement and management history of Big Pine Key offers some insight into potential causes for the change in fire frequency through time. Currently, Big Pine Key is a

Census Designated Place, with a population of approximately 5,000 people (U.S. Census Bureau, 2010), but people have settled Big Pine Key since before 1900 (Simpson, 1982). Total population was low in the early 1900s, with a total of 17 people by 1910 (Simpson, 1982; Albritton, 2009), and did not increase to an appreciable number until the mid-1900s (Simpson, 1982). Most property on Big Pine Key before ca. 1950 was owned by railroad companies, with little subdivision and neighborhood development (Simpson, 1982; Albritton, 2009). Therefore, even though Euro-American settlers were present on the island as far back as the 19th century, the island was only very sparsely populated until the mid-20th century when sufficient transportation infrastructure was available from mainland Florida (Albritton, 2009). Furthermore, the increase in fire frequency through the 1920s to the 1940s can be explained through repeated slash and burn management, and hunting practices to flush Key Deer (Simpson, 1982). From 1957 to ca. 1980, fire was actively suppressed on Big Pine Key until U.S. Fish and Wildlife Service management initiated prescribed burning that continues into the 21st century (Chad Anderson, *personal communication*). These prescribed burning management strategies help to preserve the natural fire regime of the area, and by extension the flora and fauna that depend on frequent, low-intensity fires.

2.4.2 Spatial Representation of Fire

Our study is the first conducted in subtropical pine rocklands to analyze and evaluate fire activity via a spatially-explicit experimental design using interpolated surfaces. The results from our study show that fires do not have the same spatial patterns, regardless of percentage of trees scarred, from one fire year to another. Furthermore, the 2011 Blue Hole Burn fell within the historical range of variability both temporally and spatially. For example, we demonstrated that several other fires, specifically 1990 and 1977, were just as expansive and scarred similar numbers of slash pine trees. Our results offer complementary evidence to the historical records of prescribed burning on Big Pine Key and within the NKDR, and establish that the 2011 burn was not unique. Additionally, when comparing surfaces of fire activity in subsequent years (*e.g.* 1967 and 1971), we found that areas that burn in one year are fire-free in the next succeeding fire years, adding further insight into the natural rhythms of fire activity in pine rocklands.

Certain fire years, such as 1960 and 1948, displayed interesting patterns of fire activity on a per-tree basis rather than a cohesive region of trees across the study area. The surfaces were patchy, with fire-scarred trees for a given fire year interspersed in regions of low to no fire activity for that year. This patchy fire activity on a landscape suggests the possibility of multiple fires occurring in a single season, an observation not readily apparent when simply evaluating fire scars within the tree-ring record. For example, if 20 trees contained a scar in the latewood of any particular year, a plausible assumption would be that one large fire occurred in that year. However, with spatial interpolations of fire activity, the locations of each scarred tree on the surface could give an indication of multiple fires if the landscape displays a patchy fire pattern.

In a single fire hypothesis, one would expect to find spatial patterns of widespread fires consistent with a naturally spreading fire, not a landscape of isolated hot spots. If the fire surface is patchy a multi-fire season is possible, but canopy fires could cause fire to spread in a non-uniform pattern (*i.e.* non-continuous fire area). Additionally, select trees could have been scarred from embers ignited in distant or non-adjacent areas, creating the appearance of a patchy fire pattern. Unfortunately, detailed historical records for these older fires do not exist, particularly for fire years before the establishment of the NKDR, thus, we cannot definitively say that for fire years with patchy patterns, such as the 1948 fire surface, multiple fires occurred for that year. However, spatial interpolations of fire can enhance the historical narrative of previously unknown fires that conventional dendrochronological methods might overlook by elucidating how the fire(s) potentially burned, or if more than one fire occurred in a given season.

Finally, our method of using an average of two interpolation methods was verified in our discrepancy analysis. Only two of the 20 major fires (> 25% burned) produced interpolated surfaces with more than 25% of the cells varying by a degree larger than 0.5. The values for each individual cell ranged from 0–1 (*i.e.* 0 = no fire, 1 = fire), making a difference value of 0.5 more than half the potential range of fire activity. For example, if one cell from the spline interpolation had a value of 0.25 (*i.e.* low end of fire activity spectrum), while the same cell had a value of 0.80 (*i.e.* high end of fire activity spectrum) from the IDW interpolation, then the choice of method is causing the fire result and that cell is not necessarily representative of the true fire activity. This particular cell would have been tagged in our discrepancy analysis as exceeding the difference threshold, and if more than 25% of the cells between the two interpolation methods were more than 0.5 different, we determined that the fire surface as influenced by the interpolation method. However, this does not mean the averaged fire surface (average value per cell from the IDW and splining) is necessarily spatially inaccurate, rather that intricate (*i.e.* finer scale) details in the surface should be examined with caution.

The two fire years that surpassed the 25% difference threshold were 1997 and 1977. These particular fires had intricate burn conditions, creating patterns of fire activity that would likely generate less smooth surfaces. In other words, we found that the likelihood of differences in interpolated values at the individual cell level was elevated in years with numerous dispersed fire-scarred trees compared to fires with either less samples scarred, or those that tended to cluster in one location. We emphasize that any interpolation induces some level of error, and likelihood of error in an interpolated surface is compounded if an inappropriate interpolation method is used. However, our discrepancy analysis results show that we chose two appropriate methods (*i.e.* IDW and tension splining) based on the level of consistency between surfaces for each major fire year. Aside from the 1997 and 1977 fire, the average difference percentage among major fire years was less than 13%, meaning that for all other major fire years the two interpolation methods generated fire surfaces with less than 13% of the total cells having a difference value of more than 0.5. We chose these specific thresholds to be conservative in our surface generation techniques and to provide a quantitative basis as to how each method produces different results in an effort to remove any bias in our methods.

2.5 Conclusions

One of the two primary conclusions is that the 2011 Blue Hole Burn, while large and severe, was not an anomaly outside the historical range of variability for fires in the NKDR. This prescribed fire was heavily vilified by the media and community, and was considered a severe burn well outside the range for what is considered a "normal fire" for the area. Our study demonstrated that, using both statistical analyses and spatial representations, the 2011 fire was not a singularity, but in fact a large fire similar to other major fires in the past. The results from our study provide the U.S. Fish and Wildlife Service with important background on fire activity that justifies the use of prescribed fires as effective management practices and for promoting overall ecosystem health. Essentially, the so-called "massive" 2011 fire occurred within expectations of a large fire on Big Pine Key.

Additionally, our results show that MFI values were statistically different for the pre- and post-management eras. Fire frequency decreased after the mid-1900s, with the institution of the NKDR, the loss fire for hunting Key deer, and the stoppage of any slash and burn land management that was in effect. In an age where effective fire suppression takes precedence over fires ignited by lightening, our results indicate fires occur with less frequency than this ecosystem has seen in approximately 50 years. In fact, the fire years with the three largest extents, after settlement increased through the 1920s, occurred in the past 40 years, potentially indicating an increase in fire size due to a decrease in fire frequency. Our results show that a persistent lack of sufficient fire moving forward could increase the likelihood of even more ecologically-severe fires occurring in the near future on Big Pine Key.

We would also like to address here the idea of a "natural" fire as one that is completely without human influence. The prevalence of human impacts on the environment, even before European settlement, has created ecosystems today that still reflect those changes, such as those seen in fire activity. People were starting fires for land and resource management practices before Europeans settled the Florida Keys, thus we would like to present a caveat to our "pre-management" conditional era. We consider "pre-management" to be before 1957 with the establishment of the NKDR, however people were managing the land via fire, just not officially through prescribed burning practices. The argument could be made that human influence on fire activity in the early to mid 1900s was land management, but we would like to stress that fires started in that period were for the purpose of flushing game, not to preserve the native fire regime. Finally, we acknowledge that people have been impacting fire activity on Big Pine Key, and that the ecosystem has experienced various fire activity regimes throughout time, thus a "natural" fire may have various interpretations.

The second primary conclusion reached was the ability to detect spatial patterns of fire (*e.g.* patchy) that temporal analysis may not necessarily reveal. If a fire scar exists in a given calendar year for many different samples, we can tell the seasonality of the fire by placement in the annual ring itself. If each of the scars is in the latewood for each sample, it is conventionally assumed to be the same fire, unless historical records exist that show two fires for a given season. If, in fact, this collection of scars all in the latewood for any particular year is representative of two fires in that season, it is not as apparent via direct wood analysis. However, by spatially representing fire years via a continuous surface, we can begin to differentiate patterns in fire activity not obvious from the tree-ring record. This multi-fire per season scenario was likely seen in fire years 1960 and 1948 where spotting was present in the fire surface that did not follow conventional activity and spread. In other words, fire rarely sweeps across a surface and catches single trees at a time, which is what a single-fire theory for these surfaces would contend. These surfaces instead show that likely two (more than two in a given season for a single year is rare) fires occurred in 1948 and again in 1960 that would otherwise not have been seen in non-spatially represented fire scar data. Overall, our study offers an alternative and complementing technique for traditional dendrochronological methods for analyzing fire history of an area in the subtropics and beyond.

The results of our study are informative in numerous ways, including providing a definitive description of the range of historical variabililty for fire activity and visual representations of historic fires in the NKDR. The fire return intervals for our study area match expected intervals for subtropical locations in the southeastern U.S., and the 2011 fire fits within the severity boundaries delineated by previous major fires in the NKDR. We also found that fire frequency changed pre- and post-management, and became less frequent after approximately the late 1950s. The spatial patterns of the major historic fires give indications of potential rotational fire activity, where fire free areas in one fire become fire active areas in a later fire. Overall, our results give insight into the fire activity of the NKDR that was otherwise unknown.

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Chapter 3

Effects of Microtopography on Fire Activity Across Different Scales in a Pine Rockland Ecosystem, Big Pine Key, Florida, USA

Parts of the introduction, literature review, and site descriptions were adapted from Chapter 1 of this dissertation. The use of "we" in this chapter refers to the many people who assisted in the field and laboratory to make this study possible. Details on specific individual involvement can be found in the Acknowledgements section at the end of this chapter. This research was funded in part by a seed grant from the Initiative for Quaternary Paleoenvironmental Research. I was first author, and my contributions to this research were leading and developing the experimental design, data collection, GIS and statistical analyses, and writing the manuscript. This chapter will be submitted to the journal *Landscape Ecology* for publication.

Abstract

A lack of fire history reconstructions and applied dendrochronology using GIS exists for subtropical ecosystems in the Lower US, particularly in low-relief areas. We combined a Geographic Information System (GIS) and spatial statistics to investigate the relationship between fire occurrence, susceptibility, and surface roughness characteristics in a pine rockland ecosystem dominated by south Florida slash pine (*Pinus elliottii* var. *densa* Little & K.W. Dorman), a fire-tolerant species. We calculated surface roughness parameters (elevation, slope, curvature, and residual topography after a 3 x 3 smoothing window was applied) from a 1 m resolution LiDAR digital elevation model (DEM). The GIS data analysis was completed in ArcGIS 10.2, and the statistical analyses were conducted in NCSS and RStudio using the R programming language. We used hierarchical and non-hierarchical clustering analyses on the surface roughness dataset to assess structure of the microtopography across the landscape to determine potential explanations for weak relationships between fire activity and surface roughness. We used five different scaling windows (1 m, 3 m, 10 m, 50 m, and 100 m) to evaluate fire occurrence and surface roughness relationships with increasing aggregation. Multiple linear regression results indicated a weak but significant relationship between certain surface roughness parameters and fire activity with changes in scale. Overall, the model R^2 values for each scale was low throughout, but peaked at the 50 m window aggregation, with a value of 0.19. The structure of the microtopography dataset is different than that of the fire-scar data, which we determined accounts for the low model success at each scale, even at the optimal 50 m aggregated window. We conclude that collection density of slash pines in this ecosystem is optimal at the 50 m resolution, and that capturing more data at finer resolutions did not provide more explanative power. The techniques we proposed in this chapter can be used to investigate microtopography as it relates to fire susceptibility wherever fire history analyses are being conducted. We have linked, quantitatively, how various microtopography parameters can influence fire regimes of an area, which can be beneficial for future studies throughout the southeastern U.S.. Furthermore, we suggest that a larger and more expansive sampling design be employed for future analyses to cover a larger spatial area.

Keywords: dendrochronology, *Pinus elliottii*, pine rocklands, hierarchical and non-hierarchical clustering, discriminant analysis.

3.1 Introduction

3.1.1 Pine Rocklands

Pine rocklands in the Florida Keys and select locations in southern Florida (such as the Everglades) are topographically flat with a lower groundlayer fuel compared to other subtropical ecosystems such as hardwood hammocks. Pine rocklands have small geographic ranges and are often bordered by urbanized areas, particularly in the Florida Keys (Snyder *et al.* 1990; Noss *et al.* 1995; Sah *et al.* 2004). The surface of pine rocklands typically has little to no soil development, and many areas exhibit exposed limestone bedrock of two potential varieties: Miami and Key Largo (Hoffmeister & Multer, 1968). Both bedrock types are highly porous and the Key Largo limestone is fossiliferous (Ross *et al.*, 1992). Dissolution holes are common for these types of bedrock, especially in areas of humid, subtropical climates like the Florida Keys.

The dominant canopy species is slash pine (*Pinus elliottii* var. *densa* Little & K.W. Dorman; hereafter referred to as slash pine), with various palm species and West Indian hardwoods such as poisonwood (*Metopium toxiferum* (L.) Krug & Urb.) found in the subcanopy. In areas of more frequent burning, the understory layer is sparse and can be traversed easily, but the understory becomes very dense without fire. The groundlayer is composed of various herbs such as Big Pine partridge pea (*Chamaecrista lineata* var. *keyensis* (Pennell) H.S. Irwin & Barneby, which is an endangered species that relies on regular fire activity to survive), Florida white-top (*Rhynchospora floridensis* (Britton ex Small) H. Pfeiff), and sand flax (*Linum arenicola* (Small) H.J.P. Winkl) (Table 3.1). All species in this ecosystem, from the groundlayer to the canopy, rely on fire to varying degrees for success and survival in pine rocklands.

Table 3.1. List of common plant species found in pine rockland ecosystems (Wunderlin, 1982).

Species Name	**Common Name**	**Forest Level**
Pinus elliottii var. *densa*	slash pine	Canopy
Byrsonima lucida	locust-berry	Understory
Cassia chapmanii	Bahama senna	Understory
Coccothrinax argentata	silver thatch palm	Understory
Conocarpus erectus	buttonwood	Understory
Crossopetalum ilicifolium	ground-holly	Understory
Eugenia rhombea	red stopper	Understory
Metopium toxiferum	poisonwood	Understory
Morinda royoc	mouse pineapple	Understory
Myrica cerifera	wax-myrtle	Understory
Pithecellobium guadalupense	blackbead	Understory
Psidium longipes	long-stalked stopper	Understory
Serenoa repens	saw palmetto	Understory
Thrinax radiata	thatch palm	Understory
Acacia pinatorium	pine acacia	Groundlayer
Eragrostis elliottii	Elliott's love grass	Groundlayer
Ernodea littoralis	golden-creeper	Groundlayer
Rhynchospora spp.	white-topped sedge	Groundlayer
Smilax havanensis	greenbriar	Groundlayer

In our study, we used dendrochronology to detect information about the surrounding environment of the ecosystem into the distant past. Each ring of a tree represents a single calendar year, and the patterns in ring widths can provide growth activity for as long as the tree was photosynthesizing (Fritts, 1976; Speer, 2010). Most dendrochronological studies have been historically limited to the temperate regions, where trees experience distinct seasonality and therefore grow clear rings. However, previous research has shown that tropical and subtropical tree species can produce well-defined rings (Martin & Fahey, 2006; Zuidema, 2006; Harley *et al.*, 2011; Ferrero *et al.*, 2014).

A paucity of fire history reconstructions and applied dendrochronology using GIS exists for subtropical ecosystems in the Lower US, particularly in low-relief areas. Research in the Florida Keys on slash pine has shown this tree species produces annual rings (Harley *et al.*, 2011), allowing dendrochronologists to use the pine rocklands to investigate fire activity through time. Furthermore, a need exists for a greater knowledge base of fire in the subtropics because rising sea levels will cause urbanized areas to encroach on natural ecosystems with property loss. Dendrochronology can help scientists and land managers develop a better understanding between natural, spatiotemporal fire activity and research-driven management practices for these endangered pine rocklands.

3.1.2 Topography and Fire Activity Analyses

Spatial patterns of fire preserved in the tree-ring record can provide insights on possible topographic factors that influence fire activity. Variability in the landscape can greatly influence the action of fire through time. Stambaugh and Guyette (2008) found that topographic roughness indices were able to explain 46% of the variance in the fire return intervals from forests in Missouri. Patterns inherent in landscape structure translate to patterns in other factors that directly influence fire activity, such as build-up of biomass and fuel loadings or concentrations of stream networks (Downes *et al.*, 2000). Positive relationships often exist between surface roughness and fire activity (up to a certain roughness threshold), because of the positive influence surface roughness has on other environmental variables, such as increased slope generally increases fuel loading to a certain threshold (Wright & Bailey, 1982; Downes *et al.*, 2000; Dickson *et al.*, 2006). Surface roughness can express a variety of physical characteristics of the landscape depending on which geomorphological elements need to be highlighted, such as elevation, slope, curvature, or aspect. Depending on the research project, surface roughness could include biotic factors such as canopy or shrub height, but when discussing the physical landscape biotic variables are not considered.

In high-relief locations, elevation, slope, and aspect directly influence fire activity to an appreciable and visible degree, but the relationship is not as clear in low-relief locales. Given the low-relief nature of the pine rocklands, potential relationships between fire activity and topography may be challenging to establish, but are needed to evaluate fire as a disturbance mechanism. Low overall variation in surface roughness makes relying on topography for fire modeling difficult because, even in topographically-homogenous landscapes, surface roughness may still exact a small influence on fire activity (Cardille *et al.*, 2001; Preisler *et al.*, 2004). Dickson *et al.* (2006) found that probability of fire occurrence increased with increasing surface roughness (using a slope-derived metric). Thus, removing topography from the risk prediction because of low variability is not appropriate. For this project, we analyzed the relationship between fire occurrence and low levels of surface roughness through changes in scale (increased window size).

Relationships between predictor-response variables, particularly those in dynamic systems such as pine rockland, may not stay consistent across scale. The modifiable areal unit problem (MAUP) states that correlations between variables can change when considering aggregated versus individual data (Openshaw, 1984; Fotheringham *et al.*, 2000; Dark & Bram, 2007). For MAUP and spatial data, the scale of operations is important when evaluating model results and processes, such as fire, may not produce the same correlations with predictor variables across different scales. Thus, analyzing the relationship between fire activity and microtopographic parameters, such as slope or curvature, from a single spatial scale is insufficient to capture the holistic nature of the relationship. Systematically aggregating the microtopographic data to coarser resolution will illuminate the true relationship between the predictor-response variables.

3.1.3 Data Structure Analyses with Clustering Methods

Clustering of datasets into natural groups allows researchers to evaluate variance structure. Various statistical clustering methods exist to explore structure. We have chosen to use both hierarchical and non-hierarchical clustering approaches to prevent bias. A clustering analysis, regardless of type, classifies observations in a dataset into specific groups (Ward, 1963; Cormack 1971; Anderberg, 1973; Bailey, 1974; Everett 1974; Blashfield, 1976). The agglomerative hierarchical methods (*e.g.* Ward's Minimum Variance) calculate a variance-covariance matrix (dispersion matrix), which measures similarity/dissimilarity and allows for the formation of clusters (Jain *et al.*, 1999). Variations among hierarchical clustering methods are focused primarily on the formation of the dispersion matrix, with little differences elsewhere (Johnson, 1967; Lance & Williams, 1967).

The Ward's Minimum Variance (WMV) hierarchical clustering method combines observations in a dataset to minimize within-group variance (Ward, 1963; Blashfield, 1976). Each group formed with WMV has been optimized to have the lowest possible variance as defined through the dispersion matrix. While a bias exists in this method to produce nearly uniform spherical clusters (Cormack, 1971), for our purposes we needed only baseline grouping, not perfectly defined individual cluster shapes. By using WMV, we generated our clusters through an iterative process that adds successive observations to clusters of ever-increasing size, until all observations in the dataset were classified. Our aim for this project was not to create a new clustering method specific for pine rocklands, but to use established clustering methods to evaluate baseline variance structure in the topographic dataset. Thus, we have supplemented our hierarchical method with a non-hierarchical fuzzy clustering approach.

Fuzzy clustering is a non-hierarchical approach for classifying observations in a dataset based on maximum membership probabilities per cluster (Ruspini, 1969; Bezdek, 1981; Dave, 1992; Jain *et al.*, 1999). This method is different from hierarchical clustering in that each observation technically belongs, to some degree, to each cluster in the dataset with varying degrees of membership for each. The final cluster membership is set for each observation based on the maximum probability membership for all clusters, which represents a hard clustering solution (Jain *et al.*, 1999; de Carvalho, 2007; Miyamoto *et al*., 2008). Each observation is grouped into a specific cluster based on the highest probability of membership, until all observations have been placed. For example, if one tree has a membership probability of 0.25 for cluster 1, 0.25 for cluster 2, and 0.50 for cluster 3 (in a 3 cluster system), it will be placed in cluster 3. Fuzzy clustering provides more flexibility in input data structure, while providing robust grouping results to outliers and weakly-variable datasets, such as the topographic data from the NKDR.

3.1.4 Research Objectives

Fires occur in a non-random fashion (Brillinger, 2003; Preisler *et al.*, 2004), thus predicting patterns in fire activity through the use of non-random datasets, such as topography, could be beneficial to land management. Establishing relationships between historic fire activity and topography on Big Pine Key will facilitate more accurate fire risk predictions as a multiscalar process. The research objectives for this project were to (1) isolate specific topographical variables that display statistically significant relationships with historic fire activity, (2) determine if those relationships change with increases in scale (aggregated cellular resolution), and (3) evaluate the surface roughness parameters for natural clustering.

3.2 Methods

3.2.1 Big Pine Key Study Area

Big Pine Key, Florida, USA (24.6°N, 81.3°W) is the largest island in the Florida Key island chain, and it supports the largest contiguous pine rockland. The data for this project included the GPS-located fire-scarred slash pine trees collected from the Blue Hole burn site in the NKDR located on Big Pine Key. The burned area was approximately 48.5 hectares adjacent to Key Deer Boulevard in the north central section of the island, and the study site was in the southern extent of the burn perimeter (Figure 3.1). Karst limestone is exposed throughout the area, with little to no soil development, except near wetter areas. Dissolution holes are dispersed across the rocklands, averaging in size from 0.2–5 m in diameter. Larger holes tend to hold more water, which in combination with greater limestone erosion, have more soil development and groundlayer vegetation. These wetter areas create small wetland complexes, one of which is expansive in the north central section of the burned area. The climate of the Lower Florida Keys is tropical savanna, and the region lies within a climatically-active region in the Gulf of Mexico. Tropical savanna climate types are characterized by hot-wet summers, and cool-dry winters, with upwards of 70% of the total rain (approximately 980 mm) occurring between May and November (NOAA (CLIM60) 2010; Harley *et al.* 2011).

The study area is bordered by mixes of neighborhoods and hardwood hammocks. The hardwood hammocks are located to the west of the burned area and are composed of species intolerant of regular fire. Lack of regular fire in the pine rocklands through fire suppression has allowed encroachment of the hardwoods into the rocklands, especially in areas of higher moisture availability. To the north and south of the burned area are neighborhoods, with the southern border labeled as a wildland-urban interface (WUI). The eastern border is Key Deer Boulevard, which acted as a firebreak in the 2011 Blue Hole burn. Some areas experienced a

Figure 3.1 The 2011 Blue Hole burn is shown by the yellow polygon (left). Big Pine Key is highlighted by the yellow rectangle (lower inset). The location of Big Pine Key in the Florida Keys island chain is shown by the yellow rectangle (upper inset). Source for imagery is ArcGlobe 10.2.2.

lower intensity fire, which meant less destruction and the continued survival of a well-developed subcanopy layer (Figure 3.2).

3.2.2 Experimental Design

Traditional dendrochronological sampling methods for fire history analyses follow a targeted sampling approach for fire-scarred trees. For this study, we created a gridded network of cells overlain across the burned area using plot center locations (spaced 250 meters apart) provided by the U.S. Fish and Wildlife Service (USFWS), which created a contiguous plot network (Figure 3.3). We used a stratified pseudo-systematic sampling design, whereby the 30 best trees were targeted in each plot. A total of seven plots were explored, and certain plots did not have 30 optimal samples, while others had more than 30. In total, we successfully dated and included cross sections from 63 trees in this study. No even distribution of trees was found across all plots or cells. Given the 1m resolution of the LiDAR, multiple trees per cell was rare. We envisioned our sampling design of a contiguous plot network to collect tree-ring and fire-scar data across a surface, rather than disjointedly targeting trees across the burned area, which would have created a mosaicked design. Thus, in the field we collected trees that followed the plot network, although an even number of trees per plot was not found.

3.2.3 Laboratory Methods

Each sample was labeled in the field with a specific plot ID and tree number (*e.g.* BH1001 = Blue Hole burn plot 1, tree 1). If a particular scarred tree had a large catface (term for scarred surface along basal margin of burned tree; Figure 3.4), we took sections at different

Figure 3.2 An example of the canopy and subcanopy of the study site. This area did not experience significant burning in the 2011 Blue Hole burn. Notice the thick understory and living slash pine canopy.

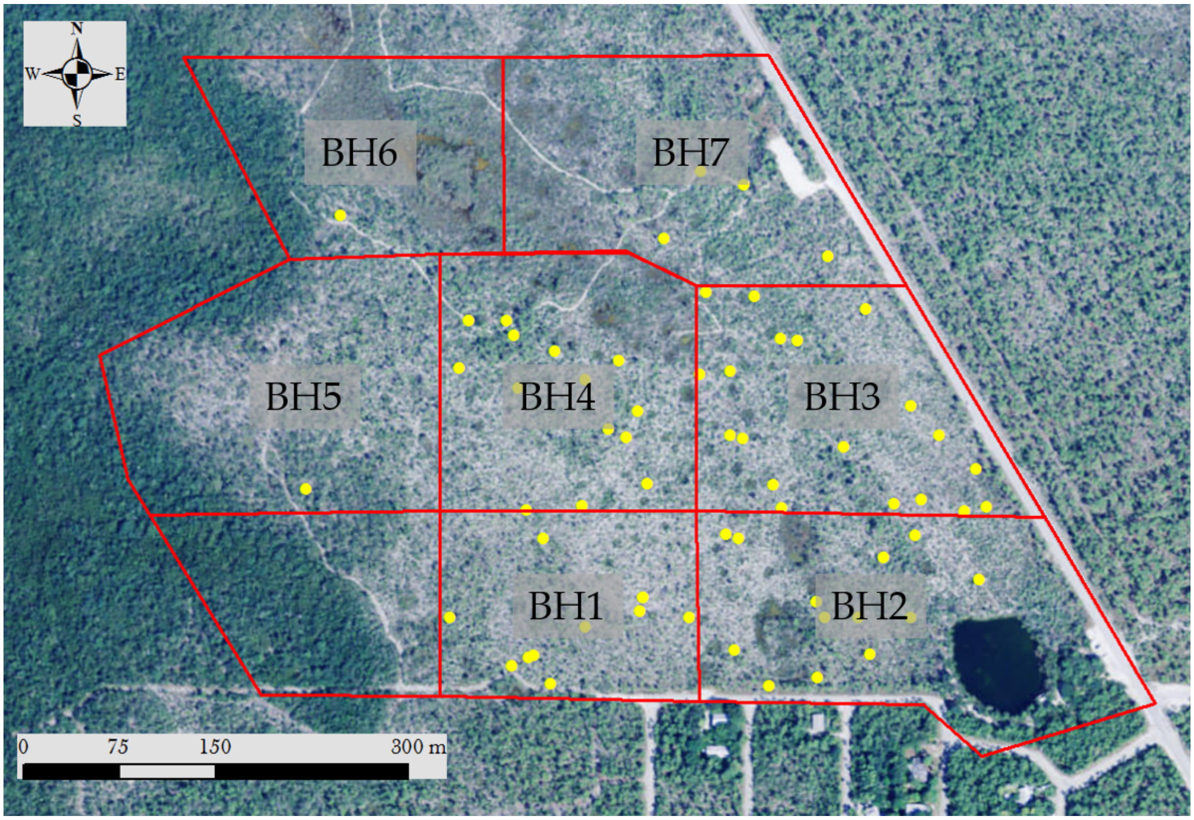

Figure 3.3 Sampling grid with tree locations in yellow. Key Deer Boulevard is the road in the eastern section of the image, Blue Hole pond is in the lower right. Source of image is ArcGlobe 10.2.2.

Figure 3.4 Catface (left) and its fire-scarred cross section (right) for sample BH1008.

heights above ground (*e.g.* sample ID would be BH1001a and BH1001b for top and bottom, respectively). The cross sections were secured and protected with plastic wrap, dried in the storage room, and then processed in the woodshop. Once the wood was dry, we sanded each sample using increasingly finer-grit sandpaper to generate a polished finish on the measuring surface. Standard sanding methods were used (Stokes & Smiley, 1968; Orvis & Grissino-Mayer, 2002), starting with ANSI 100-grit (125–149 μm) and progressing to ANSI 400-grit (20.6–23.6 μm) to ensure optimal cellular structure could be seen on the surface of interest.

All cross sections were scanned using a high-resolution EPSON 10000XL scanner at a minimum of 2000 dpi for ring boundary preservation. We scanned the samples to preserve a digital archive of the slash pine trees for future research, but to also produce high-quality visual imagery of ring boundaries during visual crossdating in the WinDENDRO ™ version 2014b (release date June 9, 2015; Regent Instruments Inc.). Per standard practice, we used skeleton plotting in conjunction with a known and established fire chronology (Harley *et al.*, 2011) to find frequency patterns between fire years and dated fire scars from the Blue Hole burn site. For samples that were living when collected, the outer ring years were known, and dating of fire scars was straightforward. For samples that were snags, remnant stumps, or downed logs when collected, the outer year was not known and skeleton plotting was required to date those samples (Stokes & Smiley, 1968).

3.2.4 GIS Methods

We used two primary datasets in the geographical analyses for this project. Specifically, the GPS-located tree and fire scar data were stored as a point shapefile in ArcMap 10.2.2, and the topographical data were all derived from a single 1 m resolution LiDAR elevation model (DEM) (Figure 3.5). The topographic parameters used in this project were: elevation (meters), slope (degrees; range 0–90), curvature (1/100 z-units), and residual (meters) topography. The DEM was uploaded to ArcMap 10.2.2 software (ESRI) and processed using the Spatial Analyst (extensions package) toolbox. The GPS point shapefile was processed using basic Attribute Table calculations and the Analysis toolbox.

Each microtopography parameter was in a raster grid form (standard DEM file type), and we first calculated each from the LiDAR data, and then converted each final surface to a compatible format with the GPS point shapefile. No calculations were required for elevation, as the LiDAR dataset is a digital representation of elevation. We calculated slope from the DEM to define values for rate of change in the z-axis for each cell using the following algorithm:

(Eq. 3.1) $$Degrees\ Slope = Tan\left(\sqrt{\left(\left[\frac{\Delta z}{\Delta x}\right]^2 + \left[\frac{\Delta z}{\Delta y}\right]^2\right)}\right) \times \frac{180}{\pi}$$

Curvature was the third microtopographic parameter extracted from the LiDAR DEM for this project, and can be thought of as the slope of the slope. The Curvature tool in the Spatial Analyst toolbox calculates the second derivative of the DEM for each cell in the grid, and assigns a new value to each cell based on steepest descent. The fourth-order polynomial applied to the DEM is:

(Eq. 3.2) $$Curvature = Ax^2y^2 + Bx^2y + Cxy^2 + Dx^2 + Ey^2 + Fxy + Gx + Hy + I$$

where *E* is the cell of interest, and *A* through *I* are the surrounding cells in the 3x3 window (*A* in upper left and clockwise through *I* around *E*). We calculated overall curvature, profile

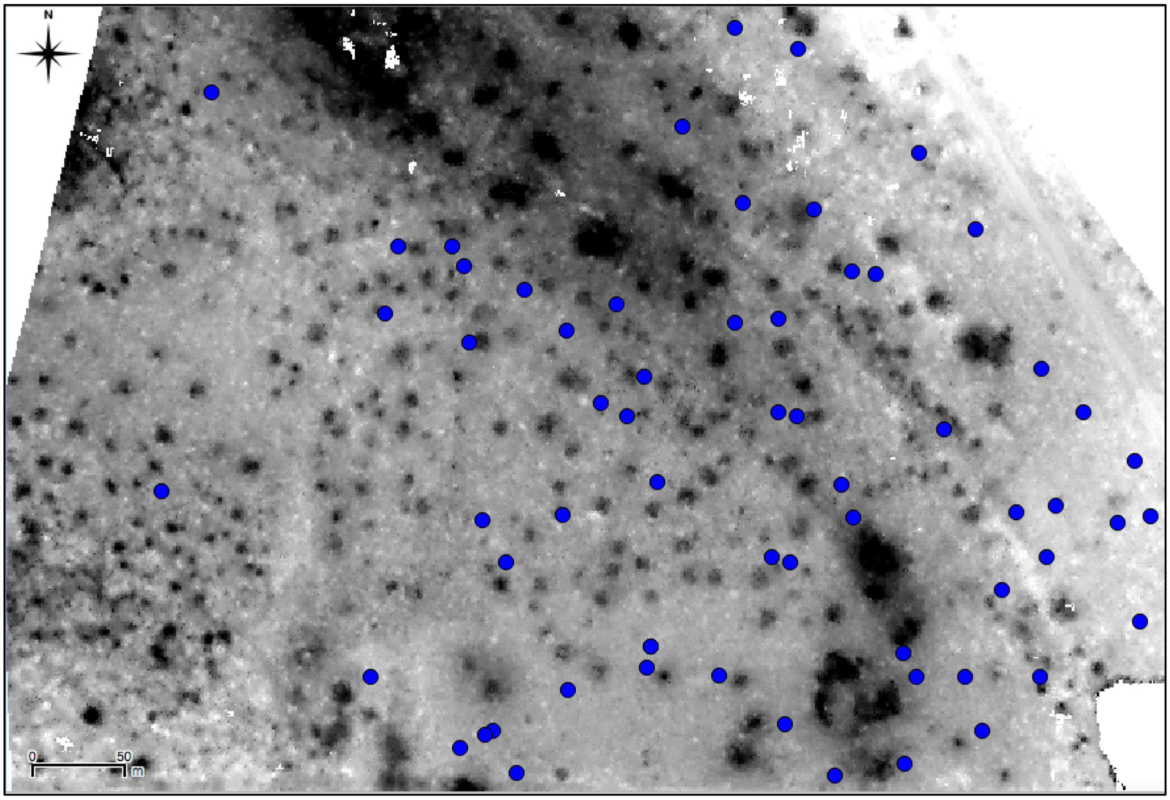

Figure 3.5 A zoomed in look at the GPS-located sample trees overlain on the 1 meter LiDAR elevation model. The Blue Hole pond is located in the lower right corner.

curvature (curvature of the direction of maximum slope), and planar curvature (curvature perpendicular to the direction of maximum slope).

Residual topography represents residual elevation after a 3 x 3 smoothing spline was applied to the LiDAR DEM. This topographic metric isolates specific locations of peaks and depressions in the landscape. We used the Focal Statistics tool in the Neighborhood toolset in the Spatial Analyst toolbox, with the "mean" operation as our operational smoothing method. The tool shifted a 3 x 3 cell window across the DEM grid and calculated average elevation for that window, and assigned the average to the center cell in the 3 x 3 window (cell-of-interest). The output raster was a smoothed DEM, which was then subtracted from the original DEM to achieve residual topography.

Once each of the new microtopography raster grids was calculated, we converted them to point shapefiles to be compatible with the GPS tree data. Centroid locations for every cell in each of the microtopographic grids were extracted using the raster conversion macro in ArcMap 10.2, whereby each point was attributed with characteristics of the parent cell. For example, we transformed the slope degree raster to a shapefile of several hundred centroid points, all with an attribute table for corresponding slope of the original cell. Batch spatial joining the generated a single point shapefile where each centroid point was attributed with each of the microtopographic parameters from the parent raster layers. Finally, we joined the microtopographic points to the target GPS tree points to create a final dataset of points. The spatial joining looked at the 12 nearest centroid locations to each GPS-located tree and attributed the average surface parameter to the attribute table of that tree. The final attribute table included fire scar counts, elevation, degrees slope, curvature, and residual topography for each of the 63 GPS-located trees.

To assess potential changes in the relationships between fire activity and microtopography, we conducted this analysis at varying levels of cellular resolution using the following scaling windows: No Scale (original raster layers), 3 x 3 window, 10 x 10 window, 50 x 50 window, and 100 x 100 window. The 3 x 3 window is a standard smoothing window for raster data layers and focuses only on the immediate eight-cell neighborhood of a cell-of-interest. We used increasingly large smoothing windows to find a critical cellular resolution to capture the highest possible statistical significance between the model variables. Focal statistical smoothing operations were conducted on the derived surface rasters, rather than directly on the original DEM to preserve as much landscape variance as possible in each successive window size. For each scale aggregation, we generated point shapefiles via raster conversion, when we then joined with the GPS tree data. In total, we created five final datasets (each representing increasing cellular aggregation) via our GIS model and used in statistical analyses of relationships between fire activity and surface roughness parameters.

3.2.5 Statistical Methods

The datasets derived from the dendrochronological and GIS methods were analyzed for statistical relationships between fire activity and microtopography. First, we conducted a robust and unrotated Principal Component Analysis (PCA) on the dataset to evaluate explained variance between microtopography and fire activity. A PCA linearizes the combinations of variables to find the variance structure of the dataset. We then ran the PCAs on the non-scaled data only, as a measure of overall ability of the microtopography to explain variance in the scar frequency.

We used a varimax rotation to orthogonally optimize cumulative explained variance. The varimax rotation eigenvalues were not used in further steps, but rather were used to evaluate optimal explained variance possibilities given the microtopography dataset. We retained those principal components from the robust and unrotated PCA with eigenvectors above the standard 1.0 Kaiser threshold for the clustering and discriminant analyses in later steps. We ran hierarchical multivariate analyses on normalized PC scores rather than raw data to ensure that we captured the greatest possible variance for enhanced predictive power.

We next ran linear models in R to assess relationships between microtopographic parameters and fire activity. The multiple regressions included the fire-scar data for the dependent (response; left-hand side of the equation) variable, and the microtopography data for the independent (predictor; right-hand side of the equation) variables. The coefficients for each predictor variable were analyzed based on individual value (positive or negative), and statistical significance, which is indicated by the p values for each coefficient. Those specific predictor variables with significant coefficients were determined to be of higher influence to fire-scar susceptibility and activity than those without appropriate significance ($p < 0.05$). We ran multiple linear regressions for each of the five scaling windows, to assess statistical significance between the response and predictor variables at each scale. The multiple regression model after variable subset selection took the following form:

(Eq. 3.3) $$Y_{Scars} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_{3....}$$

We next evaluated the natural clusters in the dataset using both hierarchical and fuzzy clustering methods to provide further insights on the variance structure of the microtopography. We conducted the clustering analyses due to the low overall model fits of each multiple regression across scales. Furthermore, we wished to demonstrate the potential for the fire activity and microtopography relationship to change with increasing scale, including changes to the clustering structure of the microtopography data.

Those factors calculated from the original PCA, with eigenvectors above the 1.0 Kaiser threshold, were retained for the clustering analyses. We normalized the factor scores for each observation from the robust and unrotated PCA based on the following equation, and then used as input data for the clustering algorithms:

(Eq. 3.4) $$Factor_{normalized} = \left(Factor_{raw} \times \sqrt{eigenvector}\right)$$

where the eigenvector is the unique value for each of the initial PCs. These scores are the ones that are normalized and used in subsequent steps.

The hierarchical and fuzzy clustering were conducted in NCSS using pre-constructed algorithms for each operation. We did not undertake the clustering methods at each scale, rather clustering was used to show overall structure in the microtopography dataset. Having already found the optimal scale in the multiple regressions, the purpose of the clustering was to show potential discrepancies in clusters based purely on microtopographic data. The natural clusters present in the surface roughness data may not follow natural clusters in the scar frequency.

The hierarchical clustering analysis we used was Ward's Minimum Variance using a Euclidean distance measure between cluster centroids and a cluster distance cutoff of 50 (this value is unique to each dataset and must be iteratively chosen). We collected the cluster IDs for each clustering operation and then used as inputs for a discriminant analysis to validate each cluster group. We validated our analyses using a linear discriminant function with the predicted clusters and the original microtopography variables. The classification matrix was then evaluated for classification error rates.

3.3 Results

3.3.1 Principal Component Analyses

The eigenvectors for the robust PCA revealed that 77.8% of the cumulative variance could be explained by the first two principal components. The third PC was close to the 1.0 threshold at 0.918. The scree plot shows a distinct elbow (clear decay in eigenvalues in decreasing value; ideal elbows take the form of exponential decays) after the third PC, indicating no additional PCs should be considered (Table 3.2).

The varimax rotation calculated a linearized combination of the microtopography variables, but then also orthogonally rotated the dimensions 90 degrees. The first four PCs were above the 1.0 Kaiser threshold in the varimax PCA, with a total explained variance of 98.42% (if all four PCs are considered). A distinct elbow in the scree plot was not obvious, and overall interpretation of the varimax rotation is limited (Table 3.3). In general, this rotation showed the

Table 3.2 Eigenvalues and explained variance percentages for the regular, unrotated PCA.

<table>
<tr><th colspan="5">Eigenvalues</th></tr>
<tr><th>No.</th><th>Eigenvalue</th><th>Ind. Percent</th><th>Cumulative Percent</th><th>Scree Plot</th></tr>
<tr><td>1</td><td>3.552968</td><td>59.22</td><td>59.22</td><td>| | | | | | | | | | | |</td></tr>
<tr><td>2</td><td>1.114867</td><td>18.58</td><td>77.8</td><td>| | | |</td></tr>
<tr><td>3</td><td>0.918339</td><td>15.31</td><td>93.1</td><td>| | | |</td></tr>
<tr><td>4</td><td>0.333299</td><td>5.55</td><td>98.66</td><td>| |</td></tr>
<tr><td>5</td><td>0.080527</td><td>1.34</td><td>100</td><td>|</td></tr>
</table>

Table 3.3 Eigenvalues and explained variance percentages for the varimax rotated PCA.

Eigenvalues				
No.	**Eigenvalue**	**Ind. Percent**	**Cumul. Percent**	**Scree Plot**
1	2.536161	42.27	42.27	||||||||||
2	1.008692	16.81	59.08	||||
3	1.010491	16.84	75.92	||||
4	1.350033	22.5	98.42	|||||
5	0.094623	1.58	100	|

potential for distinct orthogonality in the data structure, but provided little in the way of interpretation or predictive power.

3.3.2 Multiple Regression

3.3.2.1 No Scaling

The linear model with no scaling produced an R^2 value of 0.06846, which translates to approximately 6.8% of explained variance in the fire activity data captured with microtopographic factors as predictor variables. No coefficients for any microtopography parameter were significant ($p > 0.05$), and the closest to significance was profile curvature ($p = 0.25$) (Table 3.4). The residual plot did not indicate patterns or striping in the model residuals, and the Normal Q-Q plot indicated a fairly continuous relationship with changes in number of fire scars (Figure 3.6). Adjusted R^2 was negative. The F-statistic was also low at 0.8377 with 57 degrees of freedom (p-value = 0.5285). All of these results indicate that, at this scale, the model was poorly fit with low explained variance power, and none of the parameters were significant.

We aggregated window sizes between the "no-scaling" class to the 100 x 100 class, but have only reported results here for a select few "snapshots" across the range of window sizes. An upward trend was found in model fit and coefficient significance values with increasing window size until approximately the 50 m window size, with decreasing significance following 50 m to the 100 m window maximum. Therefore, we selected and reported only four window sizes succeeding the "no-scaling" class.

Table 3.4 Multiple Regression with No Scaling. Coefficients are listed for each parameter, with only the intercept significant. ($p < 0.05$). Planar curvature was a singularity (NA).

Regression Coefficients -- No Scaling				
Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6.44196	1.90718	3.378	0.00132
Elevation	–1.56279	2.3727	–0.659	0.51277
Slope Degrees	0.08916	0.22285	0.4	0.69059
Residual	21.12523	42.32223	0.499	0.61959
Curvature	–0.08649	0.126	–0.686	0.49524
Profile Curvature	0.16476	0.14221	1.159	0.25146
Planar Curvature	NA	NA	NA	NA

Residual Std. Error: 2.052 on 57 DFs
Multiple R-squared: 0.06846
Adj. R-squared: -0.01326
F-statistic: 0.8377, **p value:** 0.5285

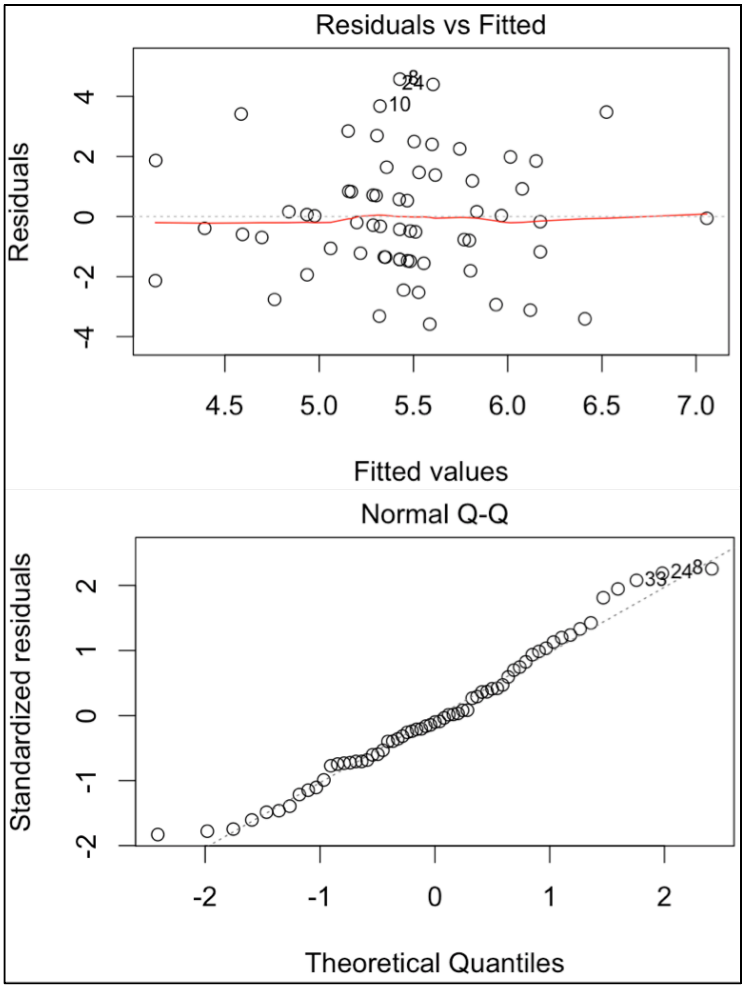

Figure 3.6 No Scaling: These two diagnostic plots, Residuals vs. Fitted (top) and Normal Q-Q (bottom), show no patterns in the residuals or significant changes in the relationship with changes in the response variable.

3.3.2.2 Aggregate 3 x 3 Cell Window

The linear model with the 3 x 3 aggregated cell window produced an R^2 value of 0.1098, which means this model could explain roughly 10.9% of the variance in the fire activity. This R^2 value was an improvement from the previous model fit for no scaling, but it was still low. No coefficients for any of the microtopography parameters were significant ($p < 0.05$) (Table 3.5). The p-value for elevation dropped, indicating increasing statistical significance, but it was still above the 0.05 alpha threshold ($p = 0.23345$). The residual and Normal Q-Q plots did not show any specific trends of merit (Figure 3.7). The adjusted R^2 value was 0.03177, which indicated a reduction penalty in model fit due to higher numbers of parameters. The F-statistic was low at 1.407 on 57 degrees of freedom and with a p-value of 0.2356. Again, all of these results for the 3 x 3 scale aggregate indicated low explained variance power and poor model fit.

3.3.2.3 Aggregate 10 x 10 Cell Window

The linear model with the 10 x 10 aggregated cell window produced an R^2 value of 0.1487, indicating the model could explain approximately 14.8% of the observed variance in fire activity (scar frequency). Curvature was significant at the 0.05 alpha level and showed a negative relationship with fire activity. Both profile curvature and residual microtopography were significant at the 0.10 alpha level, with profile curvature displaying a negative relationship with fire activity while residual topography had a positive relationship (Table 3.6). The residual plot did not indicate a pattern in the model residuals, but the Normal Q-Q plot did indicate a change in the relationship depending on the scar counts (Figure 3.8). The model fitted the data

Table 3.5 Multiple Regression results with 3 x 3 window size. Coefficients are listed for each parameter, with only the intercept significant. ($p < 0.05$). Planar curvature was a singularity (NA).

Regression Coefficients -- 3 x 3 Window

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	7.1787	1.9202	3.739	0.000431
Elevation	–2.7589	2.2909	–1.204	0.23345
Slope Degrees	0.2187	0.3618	0.605	0.547863
Residual	–270.3389	317.0326	–0.853	0.397385
Curvature	0.7006	0.9221	0.76	0.450517
Profile Curvature	0.5693	0.3626	1.57	0.121917
Planar Curvature	NA	NA	NA	NA

Residual Std. Error: 2.006 on 57 DFs
Multiple R-squared: 0.1098
Adj. R-squared: 0.03177
F-statistic: 1.407, **p value:** 0.2356

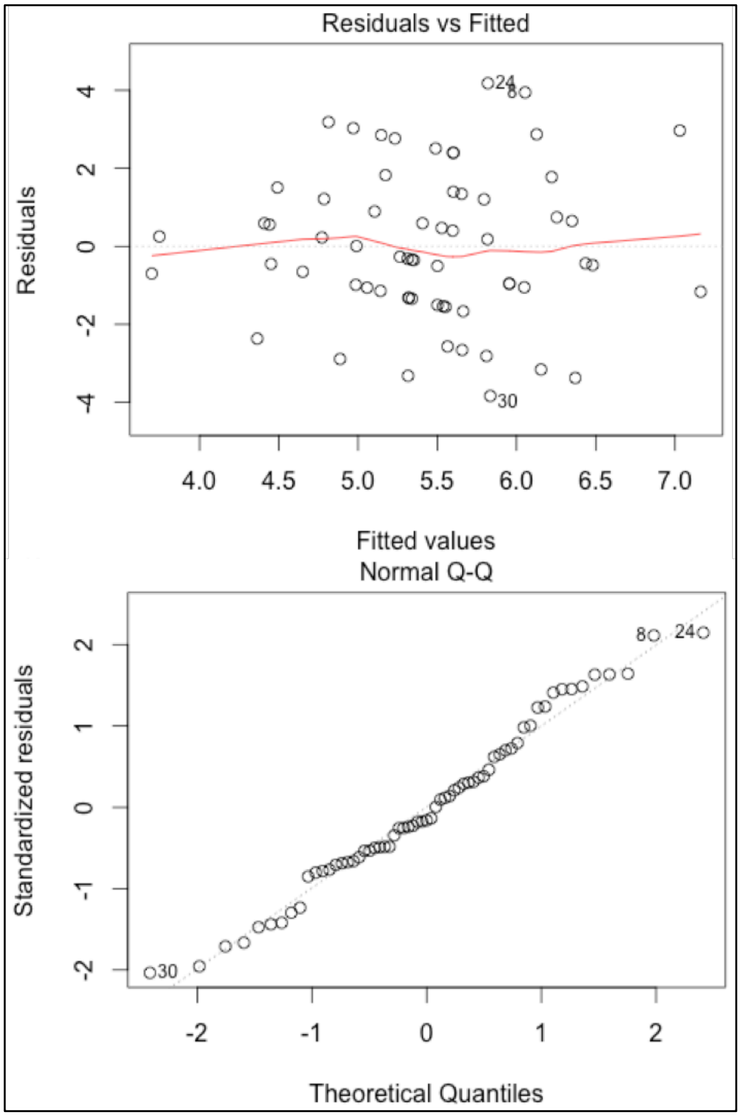

Figure 3.7 Aggregated 3 x 3 Scale: The Residual vs. Fitted (top) and the Normal Q-Q (bottom) show a lack of patterns in the residuals and a consistent relationship between the response and predictor variables for the model.

Table 3.6 Multiple Regression results with 10 x 10 window. Coefficients are listed for each parameter, and Curvature is significant ($p < 0.05$). Residual and Planar Curvature are not significant ($p > 0.05$).

Regression Coefficients -- 10 x 10 Window				
Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	7.3435	2.1829	3.364	0.00139
Elevation	–3.0713	2.4472	–1.255	0.21469
Slope Degrees	0.1958	0.4746	0.413	0.68142
Residual	4883.6985	2736.1911	1.785	0.0797
Curvature	–31.3969	13.0987	–2.397	0.01989*
Profile Curvature	14.3451	8.7752	1.635	0.10771
Planar Curvature	–15.1376	8.7764	–1.725	0.09008
Residual Std. Error: 1.979 on 56 DFs				
Multiple R-squared: 0.1487				
Adj. R-squared: 0.05746				
F-statistic: 1.63, **p value:** 0.156				

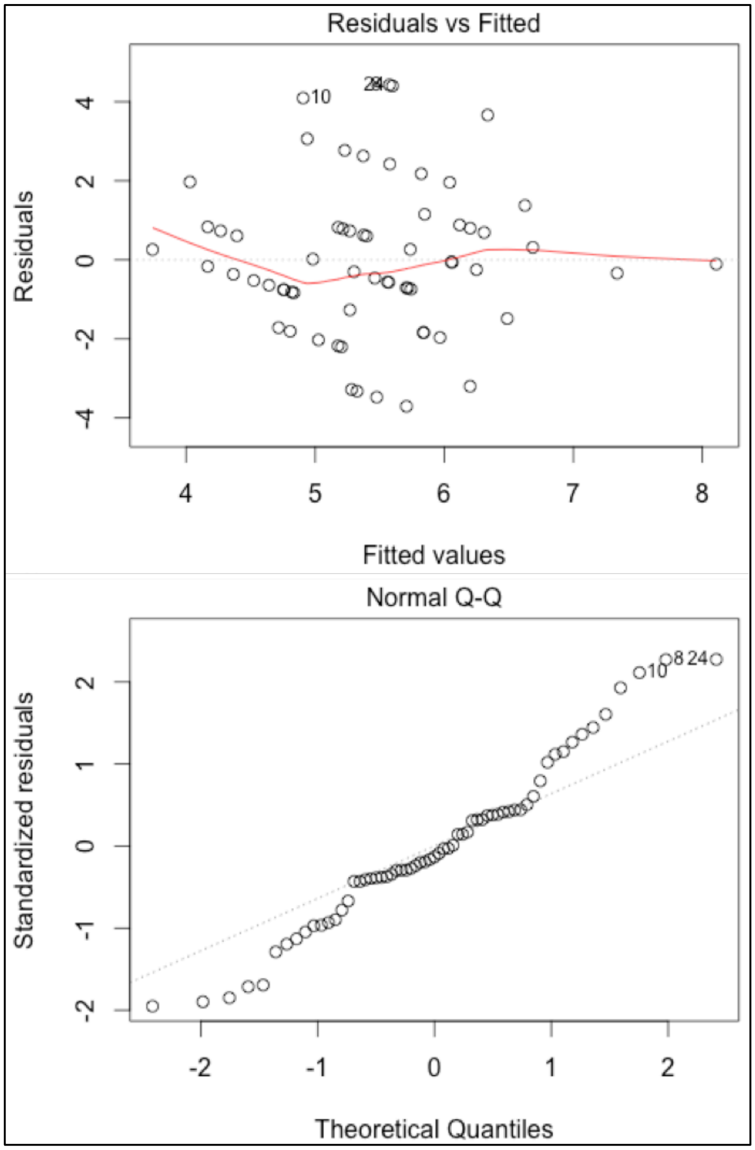

Figure 3.8 Aggregated 10 x 10 Scale: The Residual vs. Fitted (top) and the Normal QQ (bottom) indicate slight patterns or trends in the residuals and a breakdown of the relationship between the scar frequency and surface roughness parameters at the tails of the response distribution.

less at the tails of the scar frequency distribution. The adjusted R^2 value was 0.05746, still indicating a decrease in model fit with increases in parameter loadings. The F-statistic was 1.63 with 56 degrees of freedom and the p-value was 0.156. The scalar representation of the microtopography indicated a low level of significance between the predictor variables and fire activity, particularly with curvature and its two derivatives.

3.3.2.4 Aggregate 50 x 50 Cell Window

The linear model for the 50 x 50 aggregated cell window produced an R^2 value of 0.1971, which means the linear model at this scale could capture almost 20% of the variance observed in the fire scar data per tree. At this scale, each of the three curvature metrics dropped back out of significance. However, residual topography became the strongest parameter of any of the previous models ($p < 0.05$). Curvature was not significant ($p > 0.05$), although the p-value was less than for the 10 x 10 aggregated cell window (Table 3.7). The residual and Normal Q-Q diagnostic plots indicated no distinctive pattern in the model residuals and a consistent relationship between the dependent and predictor variables throughout the scar frequency distribution (Figure 3.9). The adjusted R^2 value was 0.111. The F-statistic was 2.291 on 56 degrees of freedom with a p-value that was statistically significant ($p < 0.05$). This scale produced the highest statistical significance of any of the five scaling windows.

3.3.2.5 Aggregate 100 x 100 Cell Window

The linear model for the 100 x 100 aggregated cell window produced an R^2 value of 0.1338, which indicated a model that could explain approximately 13.3% of the observed variance in scar frequency. Residual topography was still significant ($p < 0.05$), but none of the

Table 3.7 Multiple Regression results for 50 x 50 window. Coefficients are listed for each parameter, and Residual is significant ($p < 0.05$).

Regression Coefficients -- 50 x 50 Window				
Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	6.4600	2.793	2.313	0.0244
Elevation	–0.7889	2.404	–0.328	0.7441
Slope Degrees	–0.4871	0.9095	–0.536	0.5944
Residual	–6.81E+04	2.93E+04	–2.33	0.0235*
Curvature	225.4	129.5	1.74	0.0873
Profile Curvature	–3.821	81.1	–0.047	0.9626
Planar Curvature	–2.468	81.59	–0.03	0.976

Residual Std. Error: 1.922 on 56 DFs
Multiple R-squared: 0.1971
Adj. R-squared: 0.111
F-statistic: 2.291, **p value:** 0.04777

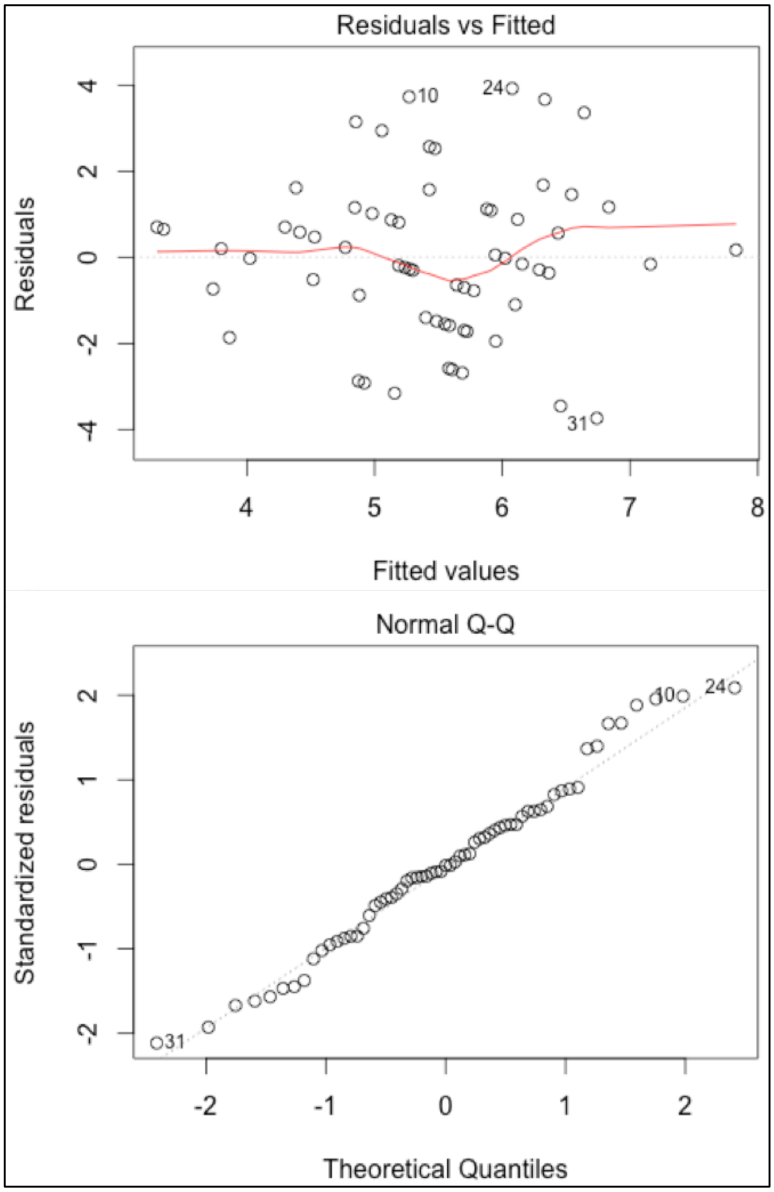

Figure 3.9 Aggregated 50 x 50 Scale: The Residual vs. Fitted (top) shows a slight indication of striping in the residuals. The Normal Q-Q (bottom) shows a fairly continuous relationship across the response distribution.

other microtopography parameters were close to statistical significance (Table 3.8). The residual plot showed the presence of patterns in the residuals, further emphasizing poor overall model fit, but the Normal Q-Q diagnostic plot indicated a fairly consistent relationship between scar frequency and the predictor variables for the length of the scar frequency distribution (Figure 3.10). The adjusted R^2 value was 0.04096, which demonstrated a strong penalty for the number of predictor variables in this model. The F-statistic was 1.441 on 56 degrees of freedom with a p-value of 0.2154. The adjusted R^2 value and the F-statistic clearly showed a decrease in model fit with the step up in aggregated cell window from the previous size.

3.3.3 Hierarchical Clustering and Discriminant Analysis

The Ward's Minimum Variance hierarchical clustering algorithm found four natural clusters in the microtopographic dataset. The dendrogram displayed the break down of each observation into one of the four clusters (Figure 3.11). The linear discriminant analysis validated the clustering with a classification matrix on actual versus predicted cluster values based on the original dataset (not the adjusted factor scores) and found a remarkably high classification rate. The validation analysis achieved a 100% classification rate, with 63 out of 63 observations correctly categorized (Table 3.9). The plot of the first two canonical scores for each observation showed a clear and linear clustering of each group with no overlap in distance or group membership (Figure 3.12).

Table 3.8 Multiple Regression results for 100 x 100 window. Coefficients are listed for each parameter, and Residual is significant ($p < 0.05$).

Regression Coefficients -- 100 x 100 Window				
Parameter	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.0252	4.1933	1.198	0.2358
Elevation	–0.4941	2.9663	–0.167	0.8683
Slope Degrees	0.1455	1.4701	0.099	0.9215
Residual	3.12E+04	1.52E+04	2.053	0.0447*
Curvature	29.8853	230.0041	0.13	0.8971
Profile Curvature	–149.2425	225.9281	–0.661	0.5116
Planar Curvature	141.8709	227.1657	0.625	0.5348

Residual Std. Error: 1.996 on 56 DFs
Multiple R-squared: 0.1338
Adj. R-squared: 0.04096
F-statistic: 1.441, **p value:** 0.2154

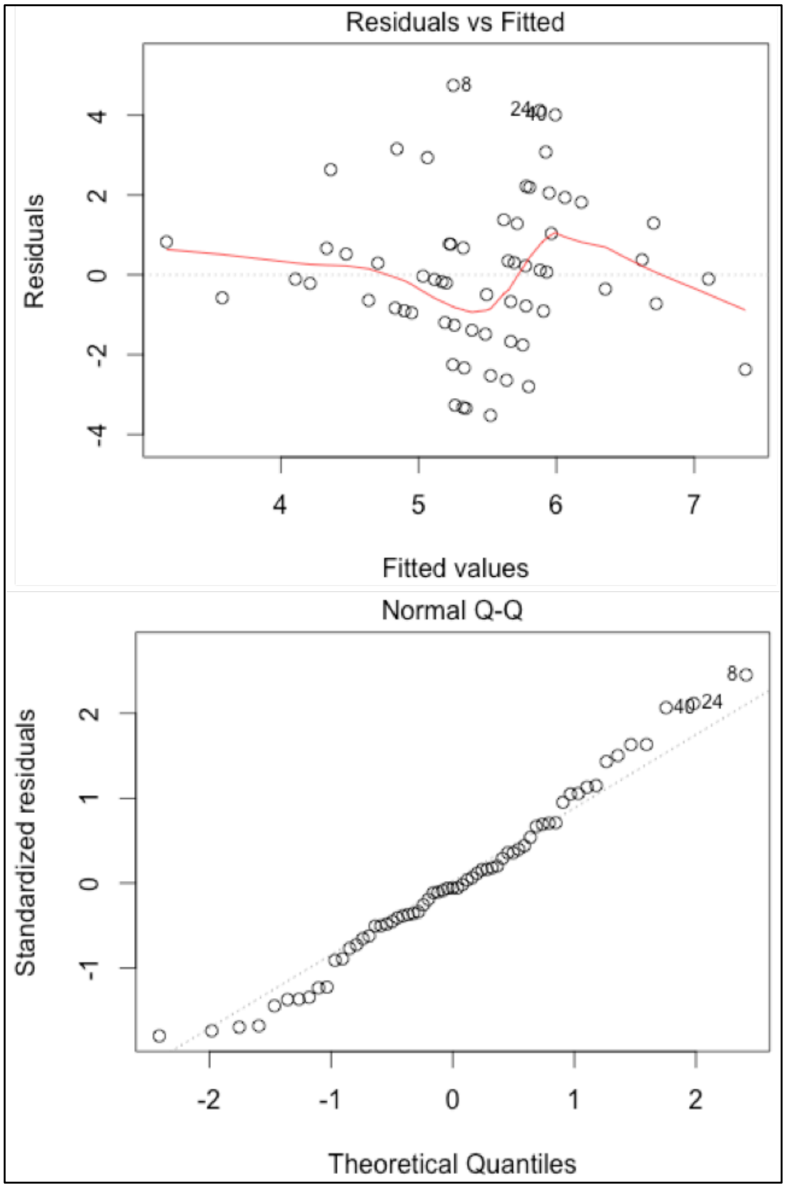

Figure 3.10 Aggregated 100 x 100 Scale: The Residual vs. Fitted (top) shows a clear indication of patterns in the residuals with slight striping and a clustering of points in the center. The Normal Q-Q (bottom) shows a continuous relationship across the response distribution, with slight shifts along the tails.

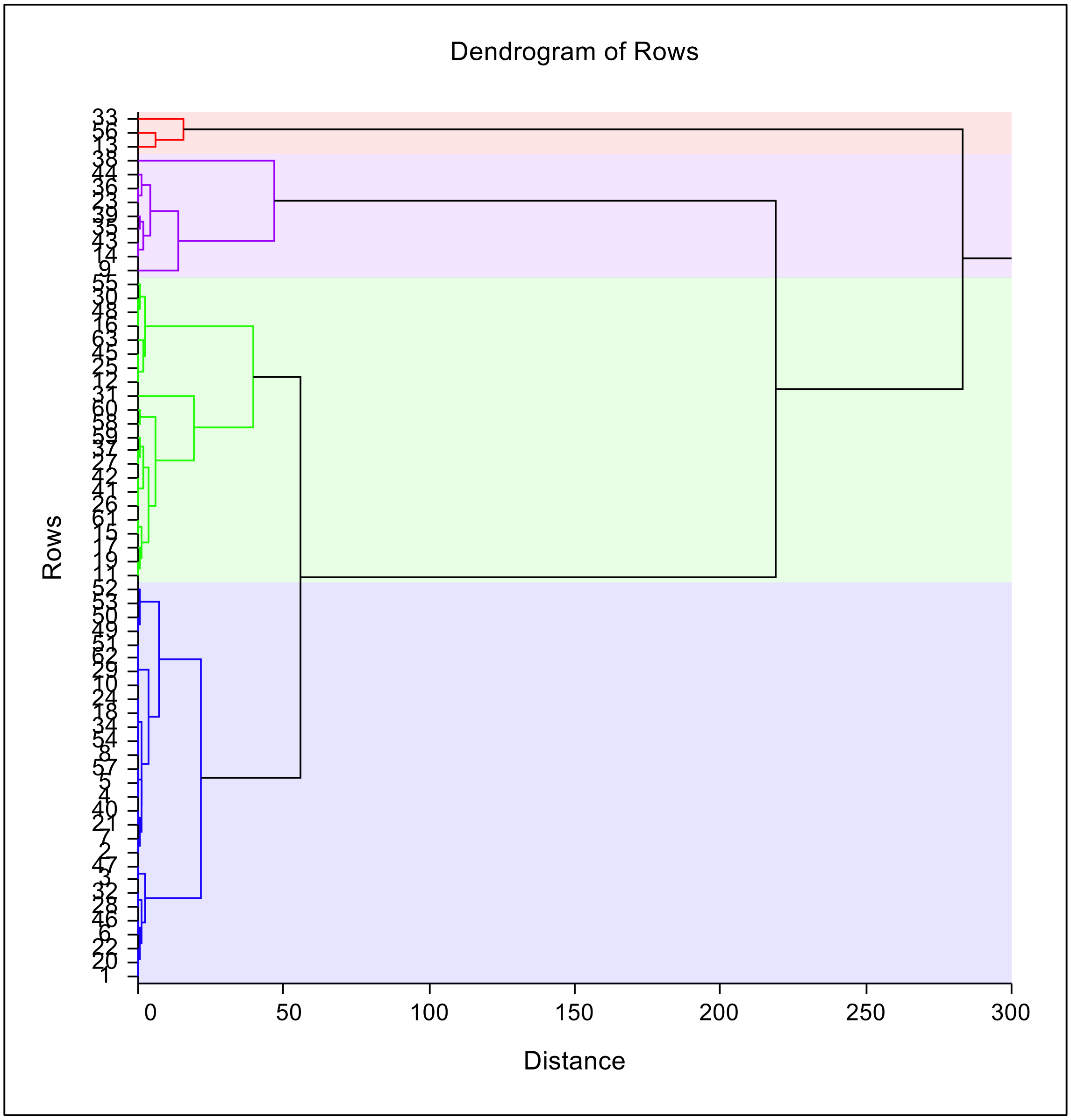

Figure 3.11 The dendrogram (classification tree) for the Ward's Minimum Variance hierarchical clustering operation. The tree shows four clusters in the microtopography dataset. The y-axis is "Distance" which is Euclidean graph distance and measures the distance between cluster centroids. The range of values is dataset dependent and arbitrary outside of the dendrogram.

Table 3.9 Classification Matrix for Linear Discriminant on Ward's Clustering. Hit ratio on the diagonal is 63/63 (100%) successful.

Classification Contingency Table

	Predicted				
Actual	**1**	**2**	**3**	**4**	**Total**
1	3	0	0	0	3
2	0	29	0	0	29
3	0	0	22	0	22
4	0	0	0	9	9
Total	3	29	22	9	63

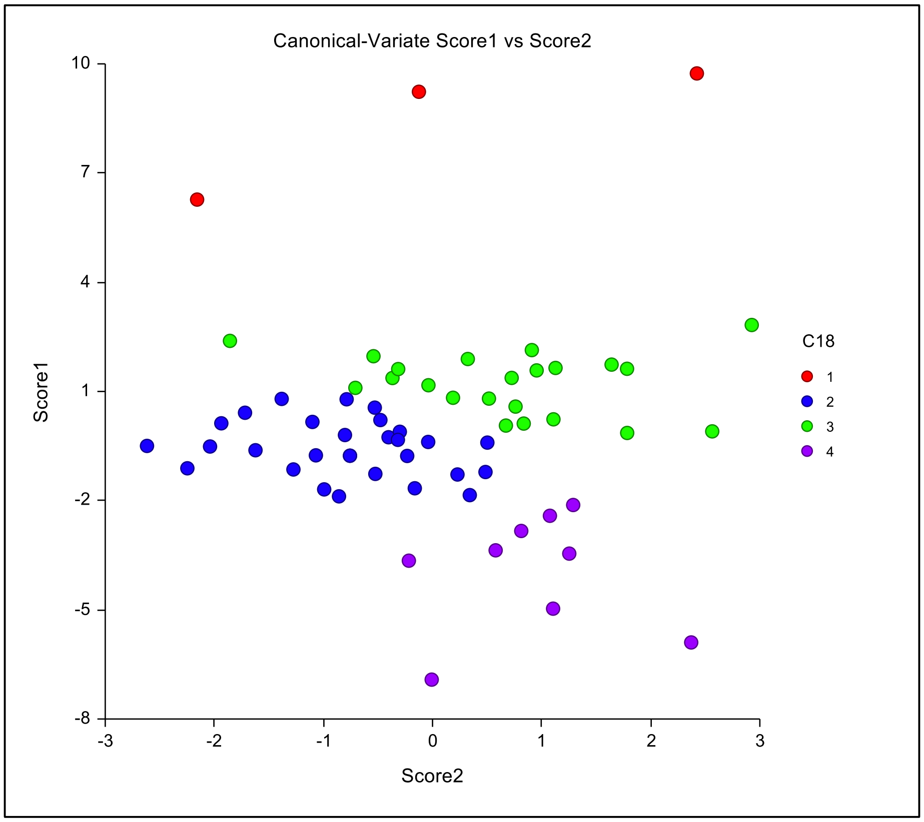

Figure 3.12 Discriminant validation analyses of the clustering results from the Ward's Minimum Variance operation that shows clear linear separation between clusters. C18 is the plot reference code for Cluster ID. The plot also shows that cluster 1 is likely composed of outliers.

3.3.4 Fuzzy Clustering and Discriminant Analysis

The fuzzy clustering algorithm found five natural clusters based on maximum cluster membership probabilities. No dendrogram for the fuzzy clustering algorithm is produced because each observation technically belongs in all five clusters in varying degrees of membership. Final cluster membership was given to the cluster for each observation with the highest probability. The discriminant analysis validation achieved a strong classification rate of 84% with 53 out of 63 observations correctly categorized (Table 3.10). The majority of the misclassification was found when predicting observations for group 1 from actual groups of 2, 4, and 5. This misclassification was likely the result of the fuzzifier value, which diluted hard cluster boundaries as it was increased. The plot of the first two canonical scores for each observation displayed a tighter cluster formation, with some observations overlapping into the Euclidean space of more than one cluster (Figure 3.13).

3.3.5 Variable Profiles by Cluster

3.3.5.1 Ward's Minimum Variance Clustering

Given the different grouping patterns for each clustering algorithm, we thought it appropriate to profile each cluster based on each of the microtopography parameters. Additionally, we also captured scar frequency per cluster to evaluate any discrepancies between the surface roughness groups and the natural breaks in scar frequency. First, the group size for the Ward's method varied depending on the cluster, and the second and third clusters had the bulk of observations (Table 3.11). We found little correlation between scar frequency and cluster, with the span of scar counts ranging from 2 to 10 per observation per cluster.

Table 3.10 Classification Matrix for Discriminant Analysis on Fuzzy clustering. The hit ratio on the diagonal is 53/63 (84.1%) successful.

Classification Contingency Table						
			Predicted			
Actual	**1**	**2**	**3**	**4**	**5**	**Total**
1	11	1	0	1	0	13
2	1	12	0	0	0	13
3	0	0	9	0	0	9
4	2	0	0	15	0	17
5	4	1	0	0	6	11
Total	18	14	9	16	6	63

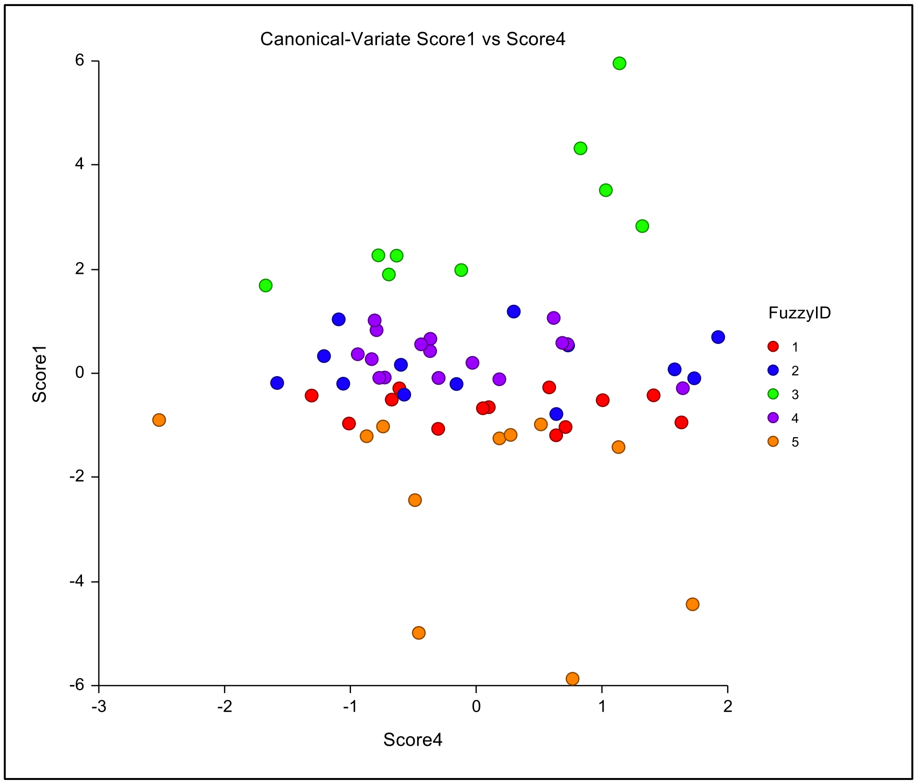

Figure 3.13 This plot comes from the discriminant validation analyses for the fuzzy clustering operation. While there is no dendrogram for fuzzy clustering, notice that this clustering algorithm found five clusters. The separation between clusters is less distinct than the Ward's. Clusters 3 (green) and 5 (orange) have the greatest separating distance.

Table 3.11 Profiles for each variable per cluster for the Ward's operation. The units for each variable are: Elevation (m), slope (degree), residual (m), curvature (1/100 z-units).

Cluster No. 1					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	3	4.333333	3.21455	2	8
Elevation	3	0.64	0.1039279	0.545	0.751
Slope Degree	3	3.344808	2.53319	1.187114	6.13401
Residual	3	–0.05888889	0.009311501	–0.06711113	–0.04877776
Curvature	3	–29.50415	5.527683	–34.947	–23.89537
Planar Curvature	3	–15.15623	3.280531	–18.73789	–12.29737
Profile Curvature	3	14.34792	5.349959	10.93221	20.51355
Cluster No. 2					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	29	5.448276	2.338898	2	10
Elevation	29	0.8174483	0.1025996	0.6760001	1.027
Slope Degrees	29	0.9702234	0.576658	0.2937818	2.442944
Residual	29	0.000704979	0.008357438	–0.01455557	0.01655555
Curvature	29	1.71319	3.380822	–3.38517	10.65336
Planar Curvature	29	1.171231	2.582443	–3.316357	7.957017
Profile Curvature	29	–0.5419594	2.369373	–4.13587	7.073473
Cluster No. 3					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	22	5.227273	1.571527	2	8
Elevation	22	0.6713637	0.09675574	0.504	0.8340001
Slope Degrees	22	2.00969	1.423798	0.2181676	6.662285
Residual	22	–0.002388886	0.01088407	–0.02888888	0.01955557
Curvature	22	–2.14515	4.330394	–9.458576	5.675161
Planar Curvature	22	–1.380502	2.597111	–7.940751	4.191057
Profile Curvature	22	0.7646486	3.511084	–6.158318	5.747957
Cluster No. 4					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	9	6.333333	1.581139	3	8
Elevation	9	0.7602223	0.09264689	0.654	0.9350001
Slope Degrees	9	1.54062	1.308504	0.4610262	4.47498
Residual	9	0.03845681	0.01516376	0.02500004	0.06622225
Curvature	9	17.25778	9.150015	9.159905	37.63522
Planar Curvature	9	8.355434	5.317347	0.796519	18.77987
Profile Curvature	9	–8.902342	4.399221	–18.85535	–3.609197

We found no natural breaks or clustering in the scar frequency data. Finally, the curvature parameters were the only variables that showed strong differences among groups. The first cluster had values significantly higher than the other three clusters, which combined with the low group size (n = 3) potentially indicated this cluster was composed of outliers. The canonical scores plot of Factor 1 vs. Factor 2 reinforced the group separation.

3.3.5.2 Fuzzy Clustering

The variable profiles for the fuzzy clustering algorithm were much more even compared to the Ward's clustering (Table 3.12). The results of this algorithm clustered into groups of similar sizes: the maximum group size was 17 and the smallest was nine. Additionally, the cluster centroids were closer to each other and several observations overlapped onto adjacent group territory. However, what is most striking is that even though fuzzy clustering allowed for more ambiguous group boundaries, each of the clusters displayed the same distribution for scar frequency, with each group ranging from approximately two to ten scars.

3.4 Discussion

By using a grid-based experimental design for our collection method we were able to evaluate relationships between fire activity and surface roughness variables across scales and from a spatially-explicit perspective. A targeted approach, when viewed at the study area scale, generates information from a more mosaicked perspective, with bundles of samples in certain areas, or with individual trees spread across larger spatial expanses. The targeted sampling

Table 3.12 Profiles for each variable per cluster for the Fuzzy operation. The units for each variable are the same as for Ward's.

Cluster No. 1					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	13	5.615385	2.292686	2	10
Elevation	13	0.8407693	0.1279565	0.6210001	1.027
Slope Degrees	13	0.9484664	0.6065021	0.3456899	2.369017
Residual	13	–0.006427343	0.004498944	–0.01455557	–0.00022221
Curvature	13	–1.42453	1.152811	–3.38517	0.3982511
Planar Curvature	13	–0.2856596	2.639122	–3.316357	7.471724
Profile Curvature	13	1.138871	2.325054	–1.991285	7.073473
Cluster No. 2					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	13	5.307693	1.548366	3	8
Elevation	13	0.6423077	0.08143852	0.504	0.8050001
Slope Degrees	13	2.584115	1.536106	0.7059707	6.662285
Residual	13	0.003888887	0.008239594	–0.01155555	0.01955557
Curvature	13	0.7429034	2.738651	–4.480378	5.675161
Planar Curvature	13	–0.1224634	2.175051	–3.683865	4.191057
Profile Curvature	13	–0.8653667	3.56348	–6.158318	4.6429
Cluster No. 3					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	9	6.333333	1.581139	3	8
Elevation	9	0.7602223	0.09264689	0.654	0.9350001
Slope Degrees	9	1.54062	1.308504	0.4610262	4.47498
Residual	9	0.03845681	0.01516376	0.02500004	0.06622225
Curvature	9	17.25778	9.150015	9.159905	37.63522
Planar Curvature	9	8.355434	5.317347	0.796519	18.77987
Profile Curvature	9	–8.902342	4.399221	–18.85535	–3.609197

Table 3.12 Continued

Cluster No. 4					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	17	5.352941	2.370158	2	10
Elevation	17	0.7880589	0.08481999	0.6760001	1.005
Slope Degrees	17	0.9791147	0.5537753	0.2937818	2.442944
Residual	17	0.005934634	0.006129527	–0.00377786	0.01655555
Curvature	17	3.912284	2.567701	1.194783	10.65336
Planar Curvature	17	2.159291	1.993019	–0.7507116	7.957017
Profile Curvature	17	–1.752994	1.419846	–4.13587	0.4318731
Cluster No. 5					
Variables	**Count**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Scars	11	4.818182	2.088932	2	8
Elevation	11	0.7017273	0.1085855	0.518	0.8340001
Slope Degrees	11	1.801415	1.621702	0.2181676	6.13401
Residual	11	–0.02515151	0.02282723	–0.06711113	–0.00655556
Curvature	11	–13.06099	10.91377	–34.947	–4.878641
Planar Curvature	11	–6.661489	5.900776	–18.73789	–1.466599
Profile Curvature	11	6.399503	5.774524	1.364916	20.51355

approach does not provide the observer with any information between the sampling locations, which creates a disjointed landscape interpretation. Our method was the scientific equivalent of placing a continuous "sheet" across the pine rockland landscape, whereby any location on the sheet had information on the nearest fire scar activity. This kind of experimental design allowed for the investigation of changes in response-predictor variable relationships with increasing and decreasing scale. Trees were targeted within the plot network based primarily on scar criteria, but we made sure to collect as even a distribution of trees across each of the seven plots as possible.

The results from the scaled multiple regressions indicate a clear scalar presence in the relationship between fire activity and surface roughness. Even though the changes in R^2 value for each of the five models were small, we found a clear increase in value to the 50 x 50 cell window and then a sharp decline in R^2 value at the 100 x 100 cell window. Furthermore, given the 50 x 50 scale was the only model with a significant F-statistic ($p < 0.05$), we can infer that scale influences the relationship between the response and predictor variables. Considering slash pine trees are the single woody species in the rockland to produce fire scars and they are spread approximately 25–30 meters apart, it follows that the surface roughness parameters are best suited at that scale. Additionally, closer clustered slash pines could feasibly create micro-soil environments with increased moisture and humidity, which would dampen the relationship between fire activity and microtopography.

While patterns in fire activity can be classified at different scales, a minimum threshold exists below which fire activity cannot be captured. In this study we found that the least compatible relationships between historic fire activity and the microtopographic surface roughness parameters existed at the finest cellular resolution (1 m). These results are to be expected considering the high resolution of the original digital elevation model. The finest-scale models in the analyses are not detecting relationships between fire activity and microtopography, but rather the natural stochasticity and perturbations in the dataset. Essentially, we determined that, at finer scales, the noise in the predictor variables dilutes any weak relationship that may exist between fire activity and the various surface roughness parameters. More fire-scarred slash pine samples across a larger geographic area would be needed to make a firm conclusion on coarser scale processes.

Scaling affects the relationships between environmental variables, and information regarding the optimal spatial resolution of an experimental design is highly valuable. For our study, we were able to show that, for this landscape and given these surface roughness parameters, future research need only collect data at a cell resolution of approximately 50 meters. Collecting data at any finer of a resolution will not add anything to the results because no relationships are found at fine scales. Only with aggregated scale do we begin to see statistically significant relationships. Furthermore, collecting fire-scarred slash pines across an approximately 50 m sampling spread will remove small fluctuations in fire scar counts, amplify the statistical signal, and dampen the stochastic noise. Some trees may have more or less scarring based on factors outside of topographic influence. For example, closer proximity to the road would likely lead to fewer trees with more scars due to immediate extinguishing of fire or removal of trees that appear damaged for safety and aesthetic purposes.

The results of the clustering analyses show that natural clustering of the topographic data did not follow natural clustering or breaks in the scar frequency data. Grouping structure inherent to the topographic data was not influenced by natural structure in the fire-scar data. We found that fire-scar counts for each observation varied independently of microtopography. For example, trees with low scar counts (1s, 2s, and 3s) were equally likely to be found in areas of high or low elevation, slope degree, curvature, or residual topography. In the same example, trees with high scar counts (8s, 9s, and 10s) were equally likely to be found in areas of high or low elevation, slope degree, curvature, or residual topography. A tree with a low (high) scar count was not automatically found in an area of low (high) elevation, slope degree, curvature, or residual topographic cell.

The discrepancies between natural clustering of the two datasets are potentially due to two factors: (1) differences in the distributions of each dataset, and (2) patterns in topographic fluctuations of low-relief areas occurs at larger scales than fire activity in those areas. To address the first, scar frequency follows a Poisson-like distribution while the microtopographic parameters are much more Gaussian. Furthermore, the cross validation of each clustering algorithm (*i.e.* Ward's Minimum Variance or Fuzzy) showed remarkably high classification rates, indicating a stronger clustering signal among the variables. To address the second, a larger expansive sampling design (now that we have established precedence for collecting trees spaced farther apart) could strengthen the relationship between the fire activity and surface roughness.

3.5 Conclusions

Future research will investigate potential environmental variables to add to the model that would improve overall model fit and predictive power. Such variables could include interactions between those surface roughness parameters already in the model, or new variables entirely, such as distance to the nearest dissolution hole or estimated soil coverage. These new variables could also be calculated from the LiDAR DEM, but some will need to be collected in the field, which will require future fieldwork on Big Pine Key. However, two things should be noted about our current spatial models, and those with a potentially improved suite of predictor variables: (1) even using only DEM-derived surface roughness parameters, our models were able to detect and explain approximately 20% of the variance (R^2 value of 0.19) in fire activity, and (2) including more variables may not improve model fit. The possibility exists that, for reasons not explained by our current model, fire activity in these low-relief locations is more stochastic than fire activity in the high-relief regions of the western and southwestern US. Therefore, even with the best environmental variables added to the model, there could only be a marginal increase in the R^2 value.

Avenues for better data selection include isolating variables from a statistical perspective, rather than a physical or environmental perspective. Given what we know about the distribution of the scar frequency data, it might be beneficial to select variables that also have a similar Poisson distribution. A potential variable of interest could be density of dissolution holes within “x” meters of a fire scarred slash pine tree. This kind of data set would be heavily skewed to low values (*e.g.* 0s, 1s, 2s, or 3s), with a weak tail at high values, which is similar to the fire scar distribution. In general, there is room for future work in the NKDR, and we have isolated several avenues for additional research questions for future projects.

The foundational outcome of our study is the application of our modeling and techniques to isolate potential areas where trees are most susceptible to fire. The techniques we used were not new methods, but rather established methods used in innovative ways for dendrochronological and fire history research. We have provided a quantifiable means to isolate areas where the landscape, and therefore the trees, are most susceptible to fire and scarring. Future fire history studies in locales across the southeastern U.S. can take advantage of methods proposed in this study to ask questions such as: "Where on the landscape are fires most likely to occur?" Our findings are important because, historically, fire history research has taken the form of choosing a study area and then investigating *if* the location is suitable for fire history analyses.

By using the techniques described in our study, the research design can automatically include an investigation into the topographic features of the landscape to see if susceptibility of fire is high enough to pursue further research in an area. Conventionally, land managers, forestry officials, and those invested in fire disturbance research have targeted potential field sites via means such as: south-southwest facing slopes, historically high fuel loads, or even predominant tree species. These techniques, while valid, are not quantifiable means to specifically isolate areas of high-likelihood of scarring. This study will allow future fire history research to be more targeted, focused, and prepared before actual sampling begins.

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Chapter 4

Evidence of Spatial Autocorrelation in Fire Activity in Pine Rocklands on Big Pine Key, Florida, USA

This chapter includes sections from the introduction, literature review, and site descriptions from Chapter 1 of this dissertation. The use of "we" or "our" in this chapter refers to the many people who assisted in the field and laboratory to make this study possible. Details on specific individual involvement can be found in the Acknowledgements section at the end of this chapter. This research was funded in part by a seed grant from the Initiative for Quaternary Paleoenvironmental Research. I was first author, and my contributions to this research were leading and developing the experimental design, data collection, GIS and statistical analyses, and writing the manuscript. This chapter will be submitted to the journal *Dendrochronologia* for publication.

Abstract

Fire is an important disturbance process in forested ecosystems, including southern pine rocklands, where many plant species show adaptations for fire survival. Pine rocklands are a globally-limited ecosystem, found only in the subtropical portions of the U.S., and select locations elsewhere. The dominant canopy species of pine rocklands is the south Florida slash pine (*Pinus elliottii* var. *densa*), which has been previously used in fire activity analysis because it forms annual rings and fire scars along the basal margin of the stem. The activity of fire in pine rocklands has been evaluated in previous studies from the perspective of changes in activity through time. Our study area was in the National Key Deer Refuge on Big Pine Key, in the Lower Florida Keys. The goal of our project was to evaluate spatial associations in fire activity, via the fire-scar and tree-ring record, through the use of global (study-area-wide) and local (neighborhood) indicators. We built our GIS to incorporate five difference metrics of spatial association and autocorrelation, including: Moran's *I*, Getis-Ord G, Anselin's Local Moran's *I* (ALMI), Getis-Ord Gi*, and Ripley's K. We found a statistically significant clustering pattern in fire-scar activity among trees in our data set using the Moran's *I*, with an index value of 0.278 and z-score of 2.585 ($p < 0.01$), while no significant high-low clustering was found with the Getis-Ord G. Statistically significant clusters of trees with low fire-scar counts exist with the ALMI and Gi* local analyses in the south-central location of our study area, and near a subdivision to the south. Ripley's K results indicated a peak in clustering significance at approximately 50–65 m, with a lack of significant clustering at closer distances. We propose that the cluster of trees with low fire-scar counts is due to the proximity to the subdivision, and therefore lack of prescribed burning and quick extinguishing of lightning-caused fires by local officials. The results of our research can be used in future analyses of predictive fire risk modeling by matching variables found in the area of the low-valued cluster to areas outside of our study area.

Key words: dendrochronology, spatial statistics, slash pine, GIS, fire activity

4.1 Introduction

The Lower Florida Keys are home to pine rocklands, which are globally-limited ecosystems located exclusively in subtropical regions of the United States (Noss *et al.*, 1995). The largest spatial extent of pine rockland vegetation in the Florida Keys is found on Big Pine Key, in Monroe County, approximately midway between mainland Florida and Key West. Areas of pine rocklands are interspersed with hardwood hammock on Big Pine Key, but these two vegetation types are composed of different plant species and have different canopy characteristics. The understory layer of pine rockland consists of various palm and shrubby herbaceous species (Sah *et al.*, 2004) (Table 4.1), but the canopy is open with slash pine (*Pinus elliottii* var. *densa* Little & K.W. Dorman; hereafter slash pine) as the sole dominant canopy species (Gunderson, 1994; Landers & Boyer, 1999; Menges & Deyrup, 2001). The hardwood hammocks have a more diverse and dense assemblage of West Indian hardwoods, with species including gumbo limbo (*Bursera simaruba* (L.) Sarg.), cocoplum (*Chrysobalanus icaco* L.), and Jamaican dogwood (*Piscidia piscipula* (L.) Sarg.) (Chad Anderson, *personal communication*). Additionally, herbaceous species in the pine rocklands, such as the Big Pine partridge pea (*Chamaecrista lineata* var. *keyensis* (Pennell) H.S. Irwin & Barneby) and wedge sandmat (*Chamaesyce deltoidea* subsp. *serpyllum* (Small) D.G. Burch), are adapted to frequent fires, whereas plant species in hardwood hammocks are fire-intolerant (Ross *et al.*, 2008; Slapcinsky *et al.*, 2010).

Table 4.1 List of common plant species found in pine rocklands. The canopy species is slash pine (top row), and it has no competition for the canopy layer (Wunderlin, 1982).

Species Name	**Common Name**	**Forest Level**
Pinus elliottii var. *densa*	slash pine	Canopy
Byrsonima lucida	locust-berry	Understory
Cassia chapmanii	Bahama senna	Understory
Coccothrinax argentata	silver thatch palm	Understory
Conocarpus erectus	buttonwood	Understory
Crossopetalum ilicifolium	ground-holly	Understory
Eugenia rhombea	red stopper	Understory
Metopium toxiferum	poisonwood	Understory
Morinda royoc	mouse pineapple	Understory
Myrica cerifera	wax-myrtle	Understory
Pithecellobium guadalupense	blackbead	Understory
Psidium longipes	long-stalked stopper	Understory
Serenoa repens	saw palmetto	Understory
Thrinax radiata	thatch palm	Understory
Acacia pinatorium	pine acacia	Groundlayer
Eragrostis elliottii	Elliott's love grass	Groundlayer
Ernodea littoralis	golden-creeper	Groundlayer
Rhynchospora spp.	white-topped sedge	Groundlayer
Smilax havanensis	greenbriar	Groundlayer

From a broader perspective, the importance of fire is not unique to pine rocklands, but extends to many different ecosystems that depend on fire for overall health and productivity (Taylor, 1973, 1981; Wagner, 1978; Nobel & Slatyer, 1980; Sah *et al.*, 2004; Possley *et al.*, 2008; Stevens & Beckage, 2009). Numerous studies suggest that fire has played a major part in shaping forest ecosystems across North America (Shumway *et al.*, 2001; Stephens *et al.*, 2003; Covington & Moore, 2008; Iverson *et al.*, 2008), and globally (Larson, 1996; Lindbladh *et al.*, 2003; Drobyshev & Niklasson, 2003; Gavin *et al.*, 2003; Niklasson *et al.*, 2010). In fact, fire is so crucial to forest successional pathways that many conifer species have serotinous cones (Beaufait, 1960; Johnson & Gutsell, 1993; Verkaik & Espelta, 2006), while other plants have extensive underground biomass storage (Abrahamson, 1984; Neary *et al.*, 1999; Bond & Midgley, 2001), both of which are traits plants have evolved that enhance survival in fires.

Pine rocklands are composed of species adapted to fire and most species, including the slash pine, depend on frequent fires to maintain dominance (Snyder & Robertson, 1990; Sah *et al.*, 2006). The presence of fire in pine rocklands ensures the success of the herbaceous groundlayer through fuel reductions in the mid-canopy, and also the prevention of hardwood hammock encroachment (Snyder & Robertson, 1990; Snyder, 1991; Sah *et al.*, 2006). The absence of fire over a minimum timespan of approximately 50 years will allow a full transition from pine rockland to hardwood hammock (Alexander & Dickson, 1972). Studies from across the U.S. have found that historically fires were low severity and occurred with high frequency (Frost, 1998; Swetnam *et al.*, 1999; Harley *et al.* 2013; Grissino-Mayer, 2016). Fires burn in pine rocklands at a rate of approximately 1 to 2 fires per decade, with some lower severity fires occurring at higher frequency (Harper, 1927; Taylor, 1981; Platt *et al.*, 2002; Liu *et al.*, 2005; Harley *et al.*, 2013). This higher frequency fire regime maintained low fuel loads, prevented canopy damage from larger fires, and ensured competitive advantage and survival for fire-tolerant species, such as slash pine (Liu *et al.*, 2005; Maschinski *et al.*, 2011).

Specific adaptations in slash pine allow for survival of individual trees in fires of higher severity and intensity. Once the tree passes seedling stage, fire-resistance increases as external defenses become stronger and well-developed (Heyward, 1939). Due in part to a thin soil layer and changes in seed viability throughout the year, no accumulated seed bank exists for slash pine past a single year in pine rocklands. However, slash pines exhibit resilient defense strategies, such as thick, heat-resistant bark (Menges & Deyrup 2001), and faster juvenile development to reach resistance maturity faster than similar southern pines (Brown & Smith, 2000). Ultimately, their more southerly distribution, proximity to coastline, and fire-resistance promote slash pine as the dominant canopy species in pine rocklands (Snyder & Robertson, 1990).

Slash pines record fire occurrence in the surrounding habitat in the form of a fire scar, which is a lobe of growth tissue that marks the temporal placement of a fire event within a ring as the tree heals (Arno & Sneck, 1977; McBride, 1983). Fire scars can be used in tree-ring analysis for fire history reconstructions because they record the calendar year and season in which a fire occurred (Grissino-Mayer, 1995, 1999). Physical evidence evaluated post-fire left on the tree, and in the vicinity, provides information on fire metrics such as flame height, temperature of the fire, spatial extent of the fire, and intensity-recurrence relationships (Speer, 2010).

Researchers have previously established the importance of fire activity analysis using tree rings in the southeastern U.S. (Guyette & Spetich 2003; McEwan *et al*. 2007), many areas of the southwest (Baisan & Swetnam 1990; Grissino-Mayer & Swetnam, 2000; Beaty *et al.* 2007; Schoennagel *et al.* 2007), and the Pacific Northwest (Heyerdahl *et al.* 2002). Work has also been done that incorporates conventional fire history analysis with spatial statistics to assess experimental design strategies for more effective reconstructions (van Horne & Fulé, 2006). Additionally, by incorporating the spatial dimension into fire activity data, scientists have been able to relate locations of fire-scarred trees to environmental parameters, such as topography, and thereby evaluate relationships between the biotic and abiotic factors of a habitat (Wright & Bailey, 1982; Downes *et al*., 2000; Dickson *et al*., 2006; Stambaugh & Guyette, 2008). Finally, the use of global (study-area-wide) and localized (neighborhood) measures of clustering and dispersions using fire-scarred trees can give insight into the spatial patterns of fire activity in a study area (Franklin, *et al*., 1985; Getis & Franklin, 1987; Donnegan & Rebertus, 1999; Mast & Wolf, 2004; Youngblood *et al*., 2004; Wolf, 2005).

Measures of spatial autocorrelation, such as Moran's *I* and Getis-Ord G, are indications of correlations between similarly located observations (*e.g.* fire-scarred trees) in a dataset (Moran, 1948, 1950; Cliff & Ord, 1973; Burridge, 1980; Cliff & Ord, 1981; King, 1981; Getis & Ord, 1992; Tiefelsdorf & Boots, 1995; Li *et al*., 2007). Correlation between geographically located points in a dataset can be based on any variable of interest, such as fire activity, which is the variable attribute we used for this study. By building a basic spatial weights matrix for individual points, or fire-scarred trees in a dataset, geographic relationships between points based on their locations can be determined (Getis & Aldstadt, 2004). The null hypothesis for metrics such as Moran's *I* and Getis-Ord G states that the data are independent of each other (*i.e.* no correlation based on geographic location) (Li *et al.*, 2007). Distance is the most common spatial characteristic that is incorporated into an analysis of clustering or dispersion, and can be calculated using a GIS.

Global Moran's *I* tests randomness in a dataset (to be rejected if clustering or dispersion is found), whereas Getis-Ord G evaluates specific clustering of points with either high or low values (Moran, 1950; Getis & Ord, 1992; Getis & Aldstadt, 2004). Both of these statistics can be incorporated into a GIS to assess spatial patterns in attributes of interest, such as patterns in fire-scar counts on trees (Griffith, 1993; Anselin, 1995). Positive z-score values for Moran's *I* autocorrelation indicate points of similarity are clustered together in space, whereas negative values indicate dispersion of similar points. A value of zero indicates perfect randomness. For Getis-Ord G, positive z-score values indicate clustering of high values (*e.g.* trees with high fire-scar counts), while a negative score indicates clustering of low values (*e.g.* trees with low fire-scar counts). A value of zero indicates perfect randomness, with no high-low clustering. Both the Moran's *I* and Getis-Ord G statistics are useful for fire activity analyses because they assess stochasticity in fire-scar data in reference to geographic location, which can determine metrics of clustering or dispersion of data within a study area.

Spatial statistical analyses that break down a study area into smaller units of focus provide both a localized evaluation of association, and indications of clustering or dispersion amongst subsets of the data (Openshaw, 1993; Anselin, 1995). These localized or subsetted indicators of spatial association and autocorrelation include metrics such as Anselin's Local Moran's *I*, Getis-Ord Gi*, and Ripley's K. Both Anselin's Local Moran's *I* and the Gi* are localized versions of the corresponding global indicators and assess spatial autocorrelation from the perspective of non-stationarity (*i.e.* the data changes across space) (Getis & Ord, 1992; Anselin, 1995; Ord & Getis, 1995). Ripley's K is a mixture of global and local pattern analysis, and considers all points in a dataset, but evaluates patterns based on neighborhoods (Ripley, 1977, 1978; Diggle, 1983; Rossi *et al.*, 1992; Haase, 1995; Franklin, 2010). If the neighborhood is the size of the study area, Ripley's K "acts" like a global indicator of spatial autocorrelation, but it can evaluate localized patterns if the neighborhood window is adjusted for different sizes (Franklin, 2010).

We evaluated spatial structure of fire activity in a pine rockland from the perspective of spatial dependence among features in our fire-scar dataset. More specifically, we investigated how, and to what extent, fire-scarred trees related to neighbors across space in our study area. Our research questions include: (1) Are fire-scarred trees with similar fire-scar counts (*i.e.* indication of similar fire activity) located at closer distances to each other than trees with dissimilar fire scar counts? (2) To what extent is the fire activity heterogeneous across our study area in the National Key Deer Refuge? Do localized areas of similar fire activity exist? Our questions were prompted to assess potential statistical relationships within our fire-scarred tree network from both global and local spatial indicators of autocorrelation.

4.2 Methods

4.2.1 Big Pine Key Study Area

The fieldwork for this project was conducted within the 2011 Blue Hole Burn area (approx. 48.5 ha) of the National Key Deer Refuge (NKDR) on Big Pine Key, Florida (24.70° N, 81.37° W) (Figure 4.1). The NKDR was established in 1957 (Bergh & Wisby, 1996) and is composed primarily in pine rocklands with areas of interspersed hardwood hammock. The sole canopy species of pine rockland is South Florida slash pine (*Pinus elliottii* var. *densa* Little & K.W. Dorman; hereafter slash pine), and the canopy is open with the majority of sunlight reaching the subcanopy (Figure 4.2). Slash pine forms annual rings (Harley *et al.*, 2011) and scars whenever fire sweeps through the area at an intensity high enough to wound the tree, but low enough to avoid tree fatality (McBride, 1983; Myers, 1985). A variety of species make up the groundlayer and subcanopy, such as silver thatch palm (*Coccothrinax argentata* (Jacq.) L.H. Bailey), buttonwood (*Conocarpus erectus* L.), poisonwood (*Metopium toxiferum* (L.) Krug & Urb.), and pine acacia (*Acacia pinetorum* F.J. Herm.).

Pine rockland ecosystems are found in the subtropical locations in the U.S., and select locations in the tropics, and experiences a maritime climate due to proximity to coastlines. The area has low overall relief with exposed karst limestone bedrock and extensive networks of dissolution holes spread throughout the landscape, and a poorly-developed, thin soil layer (Hoffmeister & Multer, 1968; Bergh & Wisby, 1996). Two varieties of limestone exist in rocklands, Miami and Key Largo (Hoffmeister & Multer, 1968). Digital terrain models developed from LiDAR survey data found local relief varied by as little as 1 m in some

Figure 4.1 The 2011 Blue Hole burn is shown by the yellow polygon (left). Big Pine Key is highlighted by the yellow rectangle (lower inset). The location of Big Pine Key in the Florida Keys island chain is shown by the yellow rectangle (upper inset). Source for imagery is ArcGlobe 10.2.2.

Figure 4.2 An example of the canopy and subcanopy of the study site. This area did not experience significant burning in the 2011 Blue Hole burn. Notice the thick understory and living slash pine canopy.

locations, with a total relief of less than 10 m (Sah *et al.* 2006). The climate is classified as tropical savanna, and Big Pine Key experiences wet summers (primarily via thunderstorm activity) and dry winters (Hanson & Maul, 1993; NOAA, 2010). Approximately 70% of total annual precipitation (980 mm) occurs between May and November (Ross *et al.*, 1994; NOAA, 2010; Harley *et al.*, 2011). The region experiences an active hurricane/tropical storm season in the growing season, although the Keys receive less total precipitation than the southern region of mainland Florida (Hela, 1952; Karl *et al*., 1983; Bergh & Wisby, 1996).

4.2.2 Field Methods

We used fire scars from fire-scarred slash pines to analyze the spatial patterns of fire activity from a spatially-explicit perspective. We collected our samples from the section of the 2011 Blue Hole Burn nearest to Blue Hole pond and the southern region of the NKDR (Figure 4.3). The grid locations we used in our study were previously established by the U.S. Fish and Wildlife Service, spaced 250 m apart along constant parallels of latitude. We used this gridded network of point locations as centroid locations for each our seven plots to create a contiguous plot network (Figure 4.3). The data were converted to a surface of pixels or cells so that each plot was composed of numerous contiguous cells, and thus the entire study area was delineated for our statistical analyses into a cell surface.

The experimental design for our project was constructed in such a way to ensure all areas were scouted and inspected, and that the best possible fire-scarred trees were collected. Additionally, we wanted a dataset that was an accurate representation of fire activity, via fire-

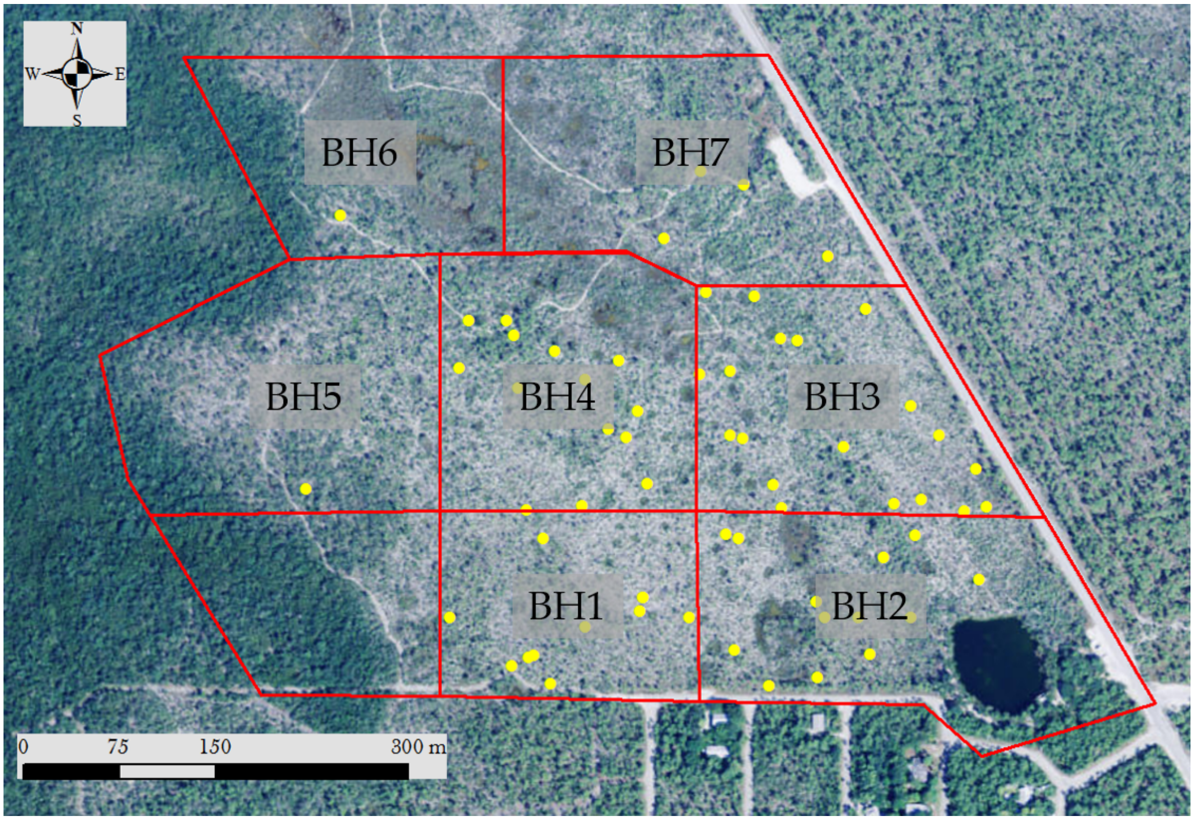

Figure 4.3 Sampling grid with collected tree locations in yellow. Key Deer Boulevard is the road in the eastern section of the image, Blue Hole pond is in the lower right, and Watson Hammock is the closed canopy woodland on the western edge of the study area.

scarred slash pine trees, across the burned landscape, and not just select points or locations with geographic gaps in data throughout (*i.e.* a purely targeted sampling design without a plot network). We used a stratified, pseudo-systematic sampling method to collect similar numbers of samples whenever possible among each of the seven plots. We chose our samples from each plot in a non-random fashion, thus our design is not completely systematic. However, a targeted collection approach was necessary within our stratified design to ensure as many past fires were captured from the available tree-ring record in our study area as possible (van Horne & Fulé, 2006). The associated bias with a targeted approach is a non-random collection of samples, which can impose a selection bias to the analyses and representation of results. However, a targeted approach is necessary at certain steps in a sample collection for tree-ring research because it ensures the best possible fire-scarred trees are collected.

We conducted reconnaissance to find optimal possible slash pines from which to collect cross sections. We defined "optimal" as those trees with the highest visible scar counts, lack of apparent or excessive decay (*e.g.* presence of bark, absence of observable beetle galleries), and trees that displayed classic indicators of older age (Schulman, 1937; Grissino-Mayer, 1995; Speer, 2010). We limited our sampling design to a maximum of 30 samples per plot for 210 potential samples to prevent an over-burdening collection. Furthermore, some plots had more than 30 optimal, fire-scarred trees, while others had less than 30 trees. The purpose of the sampling design, plot layout, and collection strategies was to ensure as many slash pine trees were sampled as possible, over as widespread an area as possible.

From the initial scouting of the 30 optimal trees, we then selected what we considered the best 10–15 trees from which to collect cross sections. Each cross section was labeled with a plot ID and tree number (*e.g.* BH1008 represented Blue Hole Burn, plot 1, tree 8) (Figure 4.4), and tagged with a GPS location (recorded on a Garmin GPSmap 62s) so that each individual tree had a physical representation traced back in the field. Our goal was to collect all fire scars present on each of our best trees, thus for larger trees the catface had to be collected in sections (*e.g.* BH1008a and BH1008b represented Blue Hole Burn, plot 1, tree 8, section a and b, respectively). To guarantee that all fire scars were collected from a larger catface, sections were necessary because not every fire scar is found along the entire length of the basal margin. A total of 93 cross sections were collected from our Blue Hole Burn study area (Table 4.2).

4.2.3 Laboratory Methods

The samples collected in the field were brought back to the laboratory, then flat-surfaced using a standing band saw to remove roughness on the ring surface from the chainsaw. Once the chainsaw grooves were removed from each sample, we progressively sanded the samples with sandpaper, starting at ANSI 100-grit (125–149 μm) and finishing with ANSI 400-grit (20.6–23.6 μm). By polishing each sample with increasingly finer grit sandpaper, we achieved high clarity in ring structure and the best possible definition of the fire scars (Stokes & Smiley, 1968; Orvis & Grissino-Mayer, 2002).

4.2.4 Statistical Methods

We calculated two separate variations in metrics for spatial autocorrelation, specifically global and local indicators. To begin with the global metrics, we used a Global Moran's *I* and a

Figure 4.4 Catface (left) and its fire-scarred cross section (right) for sample BH1008.

Table 4.2 Sample list.

ID	Lat. (N)	Long. (W)	Scars
BH1001	24.70603	81.38417	0
BH1002	24.70567	81.38407	2
BH1003	24.7059	81.38435	8
BH1004	24.70588	81.38439	8
BH1005	24.7061	81.38395	3
BH1006	24.70608	81.38387	1
BH1007	24.7061	81.38372	0
BH1008	24.70631	81.38351	5
BH1009	24.70631	81.38351	4
BH1010	24.70621	81.38353	5
BH1011	24.706	81.3838	0
BH1012	24.70625	81.3839	0
BH1013	24.70637	81.38384	1
BH1014	24.70648	81.38387	1
BH1015	24.70649	81.38392	3
BH1016	24.70587	81.38436	4
BH1017	24.70582	81.38452	2
BH1018	24.7057	81.38422	10
BH1023	24.70616	81.385	6
BH1024	24.70646	81.38513	1
BH1026	24.70743	81.38496	4
BH1027	24.70692	81.38441	9
BH2001	24.70577	81.38212	7
BH2002	24.70575	81.38216	5
BH2009	24.70591	81.38175	4
BH2014	24.70617	81.38184	2
BH2015	24.70617	81.3821	6
BH2016	24.70628	81.38217	3
BH2020	24.70569	81.38253	5
BH2022	24.70594	81.3828	5
BH2025	24.70617	81.38315	2
BH2027	24.70675	81.38287	6
BH2029	24.70672	81.38277	8
BH3002	24.70834	81.38179	5

Table 4.2 Continued.

ID	Lat. (N)	Long. (W)	Scars
BH3010	24.70813	81.38245	5
BH3011	24.70791	81.38266	3
BH3014	24.70765	81.38256	3
BH3015	24.70768	81.38268	3
BH3017	24.70745	81.38284	10
BH3018	24.7079	81.38284	4
BH3019	24.70788	81.38307	6
BH3021	24.70762	81.38355	8
BH3022	24.70735	81.38338	6
BH3026	24.70743	81.38274	6
BH3028	24.70698	81.38212	3
BH3029	24.7071	81.3825	7
BH3030	24.70694	81.38244	2
BH3031	24.70737	81.38196	3
BH3032	24.70782	81.38188	5
BH4001	24.70672	81.38428	3
BH4003	24.70695	81.38398	8
BH4006	24.70711	81.38348	6
BH4007	24.70718	81.38354	3
BH4008	24.70743	81.38364	7
BH4009	24.70749	81.38378	7
BH4011	24.70784	81.38396	6
BH4015	24.70778	81.38448	7
BH4016	24.70792	81.38493	8
BH4019	24.70825	81.38486	0
BH4020	24.70825	81.38457	7
BH4021	24.70815	81.38451	6
BH4022	24.70804	81.38419	8
BH5002	24.70617	81.38144	0
BH5005	24.70659	81.38165	6
BH5011	24.70697	81.38157	4
BH5012	24.707	81.38136	5
BH5017	24.70766	81.38144	8
BH5018	24.70745	81.38122	5

Table 4.2 Continued.

ID	Lat. (N)	Long. (W)	Scars
BH5023	24.70734	81.38118	4
BH5026	24.70692	81.38103	5
BH5028	24.70695	81.38086	4
BH5031	24.70675	81.38141	4
BH5033	24.70644	81.38091	4
BH6001	24.70648	81.38562	3
BH6002	24.70663	81.38562	3
BH6005	24.70706	81.38611	5
BH6006	24.70767	81.38608	4
BH6007	24.70899	81.38585	3
BH6008	24.70874	81.38564	4
BH6012	24.70713	81.38558	8
BH6013	24.70668	81.38525	10
BH7001	24.70871	81.38209	4
BH7004	24.70843	81.38265	7
BH7007	24.70846	81.38303	4
BH7009	24.70833	81.38332	6
BH7010	24.70883	81.38335	4
BH7013	24.70797	81.3837	6
BH7014	24.70931	81.38307	4
BH7015	24.70921	81.38274	6

high-low clustering metric named Getis-Ord G. Each of these two indicators assess overall or study-area-wide spatial patterns in specific attributes (*i.e.* fire-scar counts per tree), with Moran's *I* measuring similarity between attribute values based on feature locations, while Getis-Ord G measures instances of clustering in high-low attribute values for features. We calculated Anselin's Local Moran's I, Getis-Ord G_i*, and Ripley's K to measure local patterns in spatial autocorrelation.

All five of these metrics work under the same basic principle of correlation across space, but the local indicators are used to calculate patterns in attribute values for features at a finer scale and under the assumption the data are non-stationary (*i.e.* feature attributes trend or change across space). We use the term "feature" in the following methods to represent individual trees, and each of the five indicators is a calculation for each tree in our dataset to determine presence/absence and extent of spatial autocorrelation. In a point shapefile, which is a GIS data layer composed of point locations, an individual feature is represented by a single point on a map (*e.g.* a fire-scarred tree in our study). We use the term "attribute" in the following methods to represent fire-scar counts per tree, and each tree in our dataset will have a value for the number of fire scars. We used each of these five correlation metrics to determine if trees of similar fire-scar counts are found in similar or dissimilar locations.

Global Moran's *I* evaluates correlation between attributes of each feature in a dataset based on the individual location of each feature, and the relative location of the feature in respect to other features in the dataset. The null hypothesis (H_0) of this statistic is that the dataset is completely random with no correlation in attribute values among points in the dataset. The formula to calculate Moran's *I* is:

(Eq. 4.1)
$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2}$$

where z_i is deviation of fire-scar counts for tree *i* from the mean for fire-scar counts in the dataset, *n* is the number of fire-scarred trees, $w_{i,j}$ is the spatial weight between tree *i* and tree *j*, and S_0 is the aggregate of spatial weights (Goodchild, 1986; Getis & Ord, 1992). We used the Euclidean Distance parameter in the Moran's *I* tool for our distance method because we wished to capture straight line distances, deemed paths "as the crow flies," between each of the fire-scarred trees in our dataset. We did not use row-standardization for our spatial weights because our sampling design minimized aggregation bias, defined as clustering of trees based on collection location rather than an evenly distributed sample network. Finally, we used the Inverse Distance conceptualization for our feature relationships because we wanted neighboring trees to have a higher impact and larger influence on the target feature than trees farther away. In other words, when we analyzed our spatial correlations between trees in our dataset, we did not want to limit the analyses by imposing a fixed distance (*e.g.* "look" for trees within 50 m), rather we wanted the tool to calculate the spatial scale of the relationships based on the geographic spread of the points in our dataset. The output result for this tool was a z-score and p value to accept or reject the H_0.

Getis-Ord G evaluates specific clustering of high or low attribute values for features, based on individual feature locations relative to other features in the dataset. The H_0 for G is the same as for Moran's *I*, however the interpretation of the z-score is different. High z-scores for G indicate clustering of high attribute values, and low z-scores indicate clustering of low attribute values. The equation for G is:

(Eg. 4.2) $$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j}, when\ j \neq i$$

where x_i and x_j are the fire-scar counts for their corresponding trees *i* and *j*, and $w_{i,j}$ is the spatial weight matrix between tree *i* and tree *j* (Getis & Ord, 1992). To keep the parameters of the calculation for the G metric the same as those for Moran's *I*, we used the Inverse Distance as our spatial relationship conceptualization and Euclidean Distance for our distance calculation method. We also did not standardize our spatial weights ($w_{i,j}$). The output result for this tool was a z-score and a p value to accept or reject the H_0.

Anselin's Local Moran's *I* (ALMI) evaluates attribute correlation between features in a dataset from a localized perspective. In other words, ALMI calculates clustering of high values, low values, and spatial outliers by "looking" at neighboring subsets of data surrounding the target feature, or tree of interest, processing one individual fire-scarred tree at a time, and identifying the presence, if any, of localized concentrations of trees of similar fire-scar counts. The sum of ALMI values for each fire-scarred tree is proportional to the global Moran's *I* indicator, thus lack of strong clustering observed with a global Moran's *I* will likely mean weaker clustering of values at the local scale, although the ability to capture slight clustering is still possible (Anselin, 1995). The H_0 for ALMI is no local spatial association or autocorrelation. The formula for ALMI is:

(Eq. 4.3)
$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j} (x_j - \bar{X})$$

where x_i is the fire-scar count for tree *i*, X-bar is the mean for fire-scar counts, and $w_{i,j}$ is the spatial weight matrix between tree *i* and tree *j* (Anselin, 1995). Additionally, the denominator of the first term, which represents the variance for all locations, is calculated by:

(Eq. 4.4)
$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} (x_i - \bar{X})^2}{n-1}$$

where *n* is the total number of fire-scarred trees. Finally, we parameterized the ALMI operation with the same configurations as for the Moran's *I* and Getis-Ord G to be consistent with the global indicators.

The output result for the ALMI tool is a newly-classified shapefile of fire-scarred trees for our study with the following attributes for each individual fire-scarred tree: local Moran's *I*, z-score, p value, and a categorization for cluster-outlier type. The categorization classes for cluster-outlier type list statistically significant ($p < 0.05$) cluster types: HH (feature value is high and is surrounded by other high-valued features), LL (feature value is low and is surrounded by other low-valued features), outlier HL (feature value is high and is surrounded by low-valued features), and outlier LH (feature value is low and is surrounded by high-valued features). A positive z-score ($p < 0.05$) indicates a clustering pattern in the dataset, whereas a negative z-score ($p < 0.05$) indicates a dispersion pattern. A z-score near zero indicates randomness in spatial association. These results are useful in indicating localized areas on a map of hot/cold spots and label exactly which points fall into the cluster, and the relationships among other points in the neighborhood (Anselin, 1995).

Getis-Ord Gi* evaluates a dataset for statistically significant hot or cold clustered locations from the perspective of neighborhoods. Logistically, this local indicator is similar to the ALMI metric, but the difference is how the z-scores for Gi* are interpreted: positive z-scores indicate clusters of high values and negative z-scores indicate clusters of low values. The H_0 for Gi* states that no high-low clustering exists in the dataset, and the formula is:

(Eq. 4.5)
$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

where x_j is the fire-scar counts for tree *j*, *n* is the total number of fire-scarred trees, and $w_{i,j}$ is the spatial weight between tree *i* tree *j*. The output for the Gi* analysis is a new shapefile of points, and each feature (*i.e.* fire-scarred tree) is assigned a z-score and p value, and a confidence level. These three new attributes for each tree isolate areas of statistically high-valued clusters, areas of statistically low-valued clusters, and non-significant locations.

Ripley's K evaluates clustering or dispersion similar to ALMI, and from a range of distances and neighborhoods of increasing size. The tool isolates an individual tree and computes distance "bands" or "buffers" into which other nearby trees are located. Calculations for clustering or dispersion occur at increasing distances from the starting feature until all features in the dataset are incorporated. By evaluating spatial association based on increasing distances from the target feature, Ripley's K builds a dataset for clustering/dispersion across the study area to pinpoint specifically a distance at which clustering or dispersion becomes clear or apparent. The formula for this operation is:

(Eq. 4.6)
$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} k_{i,j}}{\pi n(n-1)}}$$

where *d* is the distance parameter, *n* is total number of trees, *A* is the total area of all the features (calculated from the spatial extent, or spread, of the tree locations), and $k_{i,j}$ is a weight term. This weight term will be one when the distance between tree *i* and tree *j* is less than *d*; otherwise this value is zero. We ran this operation with 99 permutations to generate a 99% confidence envelop for the observed clustering or dispersion. The output of the Ripley's K analysis is a dataset of observed values, expected values, an upper confidence boundary, and a lower confidence boundary. Observed values that fall above the upper confidence boundary are considered statistically ($p < 0.01$) clustered, and those that fall below the lower confidence boundary are considered statistically ($p < 0.01$) dispersed. Anything in-between is considered random across space.

Each of our spatial association and autocorrelation indicators provides a quantitative analysis of fire activity relationships among fire-scarred trees in our dataset. The global indicators, specifically Moran's *I* and Getis-Ord G, assess statistically significant clustering or dispersion patterns across our entire study area, which allows us to isolate any potential patterns in fire activity from a "global" scale. The local indicators, specifically Anselin's Local Moran's *I*, Getis-Ord Gi*, and Ripley's K, evaluate statistically significant clustering or dispersion in fire activity on a localized scale, or within neighborhoods and distance bands. We chose to incorporate both types of indicators in our analyses of spatial association to evaluate fire activity from all possible scales.

4.3 Results

We found statistically significant clustering in our global Moran's *I* analysis. The index (*I*) was 0.278 and the z-score was 2.584 ($p < 0.01$), indicating a clustered relationship in fire activity (Table 4.3). A distribution of z-scores placed our value in the highest significance bracket for "clustered" data (Figure 4.5). Given our calculated z-score ($p < 0.01$), less than a 1% likelihood exists that our results are the consequence of pure chance, and not from inherent clustering in our fire-scar data across space. The Moran's *I* results clearly indicate strong clustering of trees with similar fire-scar values in our study area on Big Pine Key.

We found no statistically significant relationships in high or low clustering in our dataset for the Getis-Ord G global indicator. This indicator evaluates clustering from a high or low perspective, rather than clustering or dispersion as in Moran's *I*. The index metric (G) was 0.002 and the z-score for our results was –0.496 ($p > 0.01$), indicating a random distribution of trees with high or low fire-scar counts (Table 4.3). A distribution of z-scores placed our value in the center bracket confirming a random distribution of trees with high or low values (Figure 4.6). These results do not mean that no clustering was found, rather that no clear clusters or patches of high/low fire activity across space exist in our data. In regard to specific clustering of high-low fire-scar counts, the pattern we found in our data is not significantly different than a random distribution.

Table 4.3 Global Indicators of Spatial Autocorrelation

Global Indicators of Spatial Autocorrelation		
	Moran's *I*	**Getis-Ord G**
z-score	2.584	–0.496
p value	0.009	0.619
Metric Value	0.278	0.002

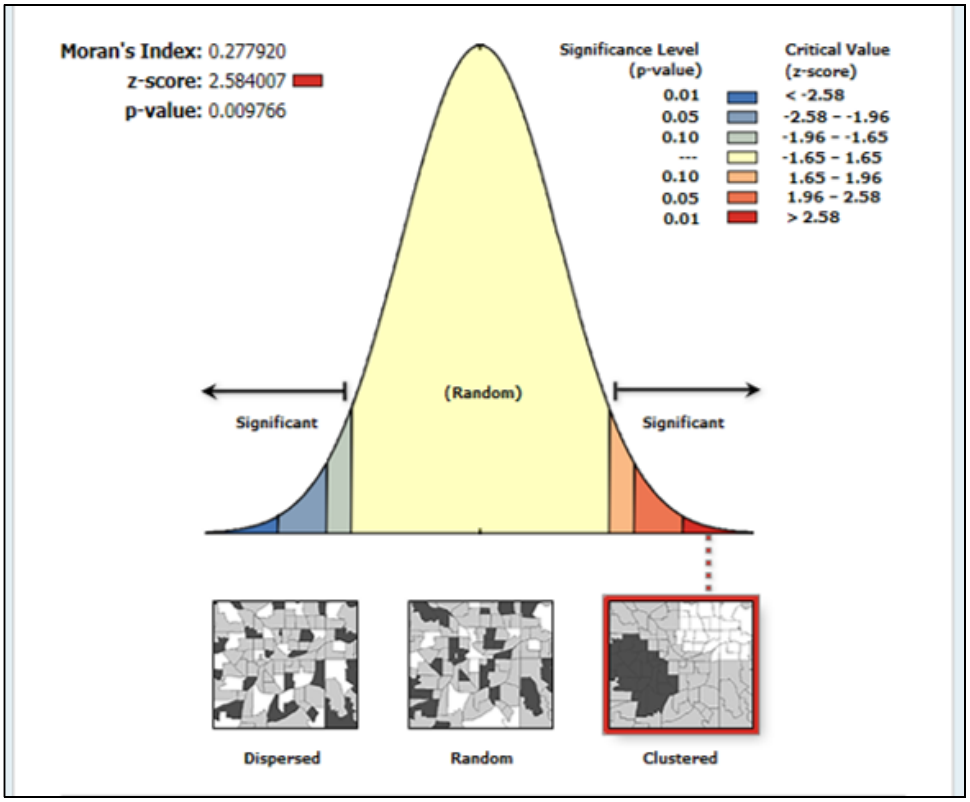

Figure 4.5 The z-score distribution for the Moran's *I* results. The index value calculated for the fire-scar data is in the most significant bracket on the positive tail of the z distribution, indicating clustering ($p < 0.01$). We generated the distribution in ArcMap 2.2.1.

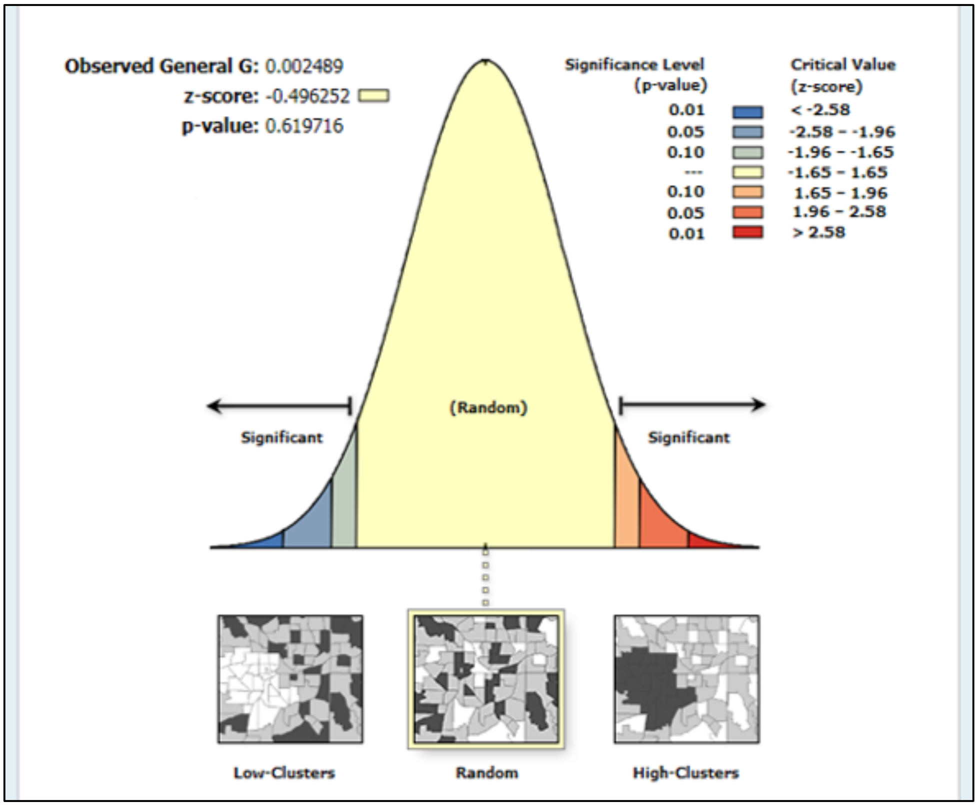

Figure 4.6 The z-score distribution for the Getis-Ord G results. The index value is within the significance bands for high-low clustering, and is classified as random (p > 0.01). We generated the distribution in ArcMap 2.2.1.

The Anselin's Local Moran's *I* (ALMI) analysis revealed several areas of local spatial association among fire-scarred trees in our dataset. The output of this analysis is not a single distribution, as in the global indicators, but rather a new map, with individual trees tagged based on their significance classification. A small group of fire-scarred trees with low fire-scar counts would be tagged with LL (and vice versa for a group of trees with high fire-scar counts). The map we created displayed a single patch or cluster of eight trees in the south-central section of our study area with low fire scar counts (Figure 4.7). We did not capture a low-valued cluster in the Getis-Ord G calculation because ALMI is a local indicator, rather than a global indicator, thus the cluster was "diluted" when using a global scale spatial autocorrelation analysis. Finally, a single cluster of trees with high fire-scar counts was located in the center of our study area, with three trees tagged with HH (*i.e.* high fire-scar counts surrounded by other data points of high value) (Figure 4.7). The results of the ALMI analysis were crucial to delineating and isolating local, or finer scale areas, in our dataset of high or low fire activity.

The results of the Getis-Ord Gi* analysis corroborated results from the ALMI and found statistically significant localized clusters of fire-scarred trees. The output for this analysis is similar to ALMI, without a single z-score distribution, but a z-score attributed to each fire-scarred tree. The result is a map of z-scores indicating high or low clustering of trees of similar fire-scar counts. A single cluster of trees with lower fire-scar counts was isolated in the south-central section of our field site, approximately 50 m north of the southern border and the adjacent neighborhood (Figure 4.8). This low-valued cluster was not found with the Getis-Ord G analysis because Gi* is a local indicator and does not calculate clusters based on all points in

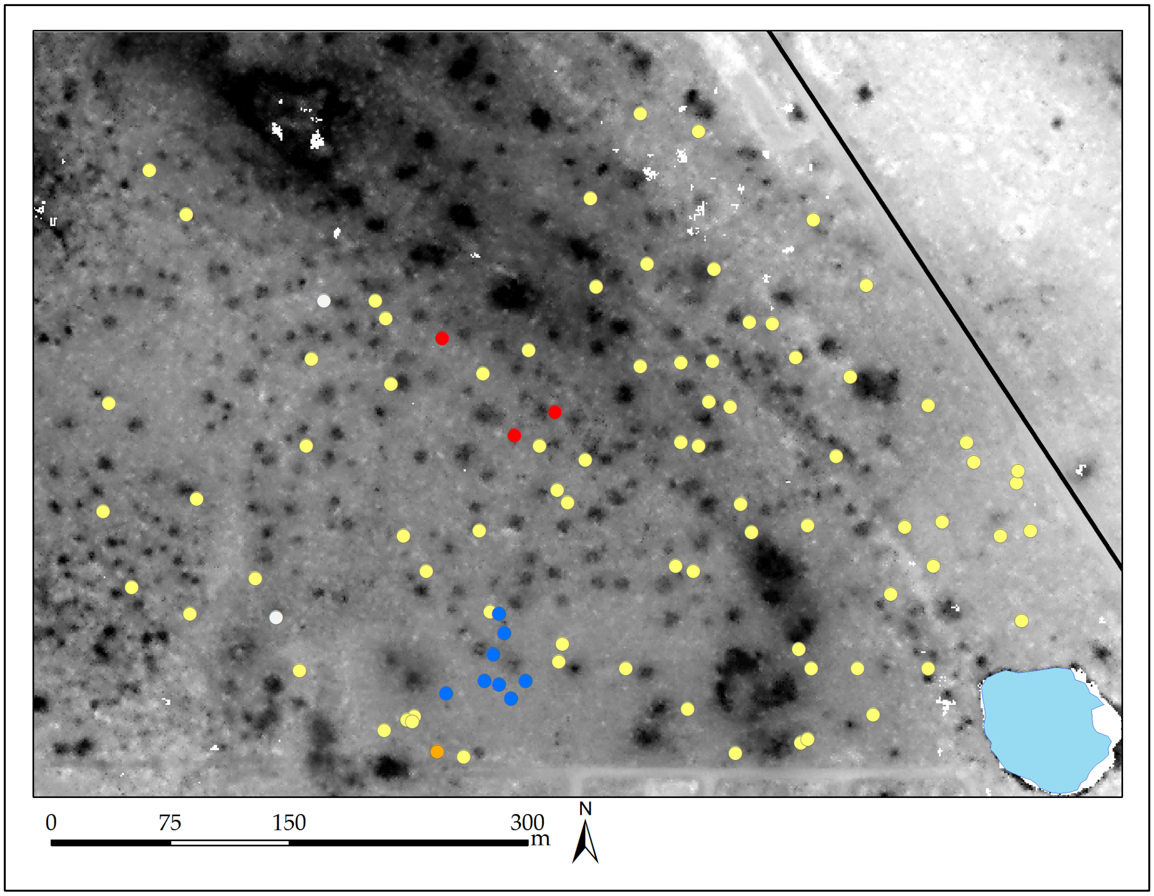

Figure 4.7 The Anselin's Local Moran's *I* results. Each point is a fire-scarred tree tagged with a color representing localized significance of clustering. Yellow indicates no statistically significant indication of clustering, orange indicates a tree with a high fire-scar count surrounded by trees of lower scar counts (HL), red indicates trees with high fire-scar counts in an area of similarly high fire-scar counts (HH), and blue indicates trees of low fire-scar count surrounded by trees of similarly low counts (LL).

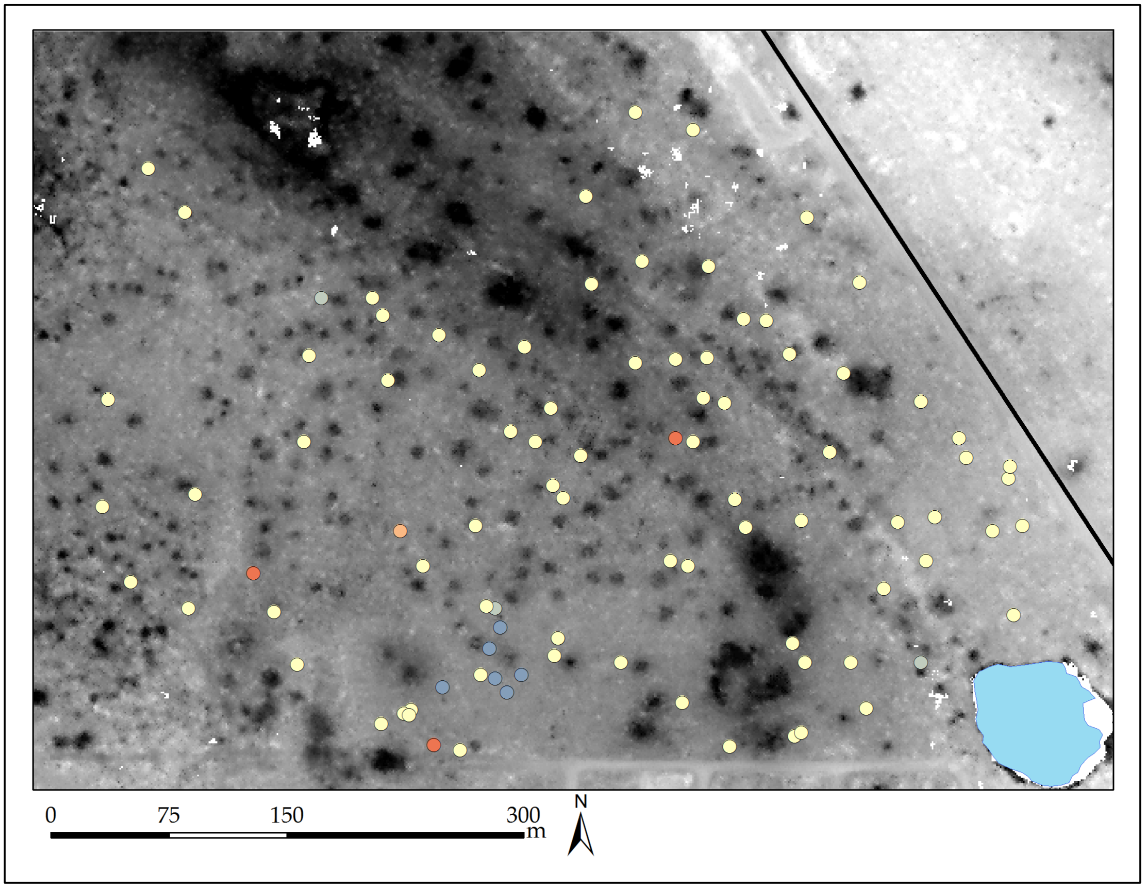

Figure 4.8 The Getis-Ord Gi* results. Each point is a fire-scarred tree tagged with a color representing localized significance of clustering. Yellow indicates no evidence of significant clustering, shades of red indicate areas of clustering in trees with higher fire-scar counts (darker red means higher fire-scar count values), and shades of blue indicate areas of clustering in trees with lower fire-scar counts (darker blue means lower fire-scar count values).

the dataset, thereby enhancing power to isolate smaller scale autocorrelation. Finally, Gi* did not find the same cluster of high-valued trees as in ALMI, but three isolated trees with high fire-scar counts were found dispersed across the central and south-central sections of the study area (Figure 4.8). The results of the Gi* were beneficial because we were able to capture localized clustering not found in the global indicator analyses.

Finally, the Ripley's K analysis used bands of increasing distance around each individual fire-scarred tree to find an optimal distance, if possible, where clustering peaked. The operation calculated clustering and dispersion over a total distance of 100 m (10 distance bands). We found that clustering was most significant ($p < 0.01$) at approximately 50–65 m (Figure 4.9). The observed data surpassed the upper significance threshold representing clustered data at approximately 40 m, and did not fall below the threshold at greater distances. The observed data never fell below the lower significance threshold representing dispersed data (Figure 4.9). The results of our Ripley's K analysis were valuable because they "looked" at spatial autocorrelation and association from a localized perspective, but also allowed for increasing distance. We were able to slightly expand on our local analysis by incorporating a variable neighborhood, or localized area that increases but does not approach global size.

4.4 Discussion

The spatial analysis of fire activity can give insights into how fire spreads in an ecosystem. Given what we know about fire activity as it trends or changes with scale (*e.g.* aggregating data from fine to coarse resolution), information on spatial association or

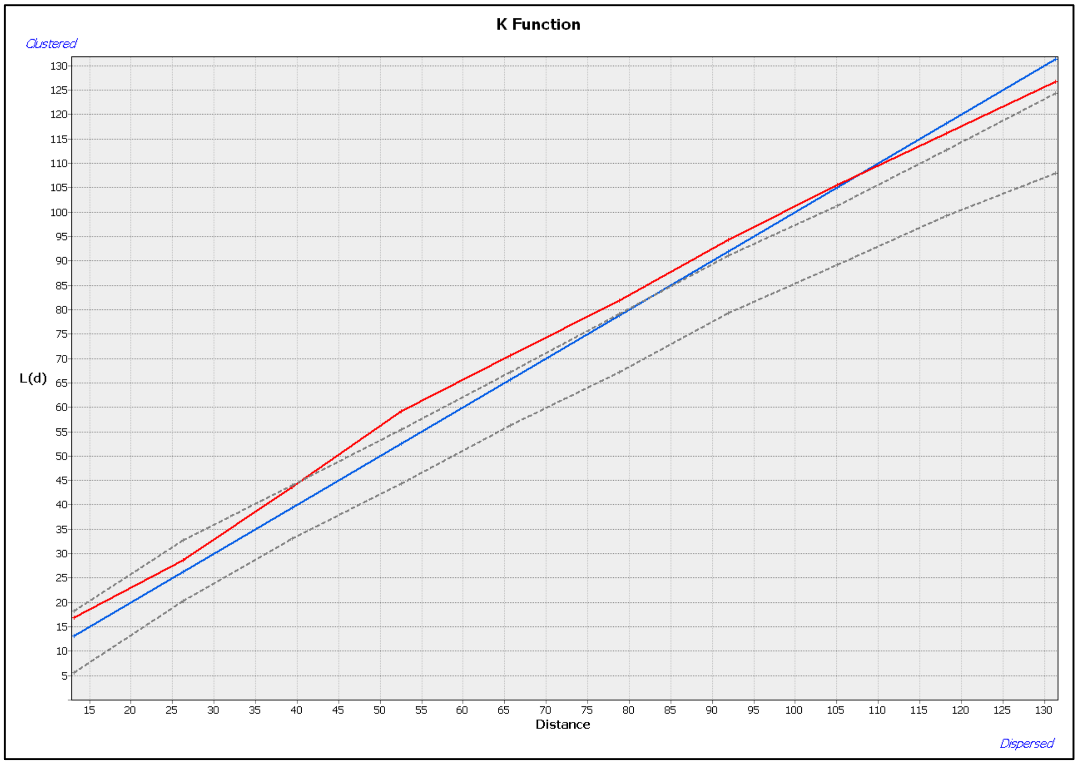

Figure 4.9 Ripley's K results based on bands of increasing distance away from each individual fire-scarred tree. The red line is the observed data, the blue line is the expected data, and the grey dashed lines are the 99% confidence envelope. Distance is measure in meters.

autocorrelation of fire activity isolates potential hot or cold spots, and general patterns in clustering or dispersion in fire-scar data across space. Our analyses tackled the idea of spatial association within our fire-scarred tree network from both the global and local, or neighborhood, perspective and helped delineate areas of high or low past fire activity.

The analysis of the global indicators of spatial association revelared statistically significant clustering of fire activity across the study area but no statistically significant clusters of trees with specifically high or low numbers of fire scars. The results from the Moran's *I* and Getis-Ord G analyses may seem counterintuitive because the former found a strong, statistically significant result while the latter found almost a purely random result. While the H_0 for each metric is similar (*i.e.* both assuming complete randomness in the spatial association), the interpretations of the z-scores for each are different. A high-valued z-score in Moran's *I* suggests highly-clustered data, whereas a high z-score for G translates to clustering of high-valued data points only. Therefore, a lack of trees with distinctly high or distinctly low numbers of fire scars would translate to a high p-value and z-score of approximately zero for G, whereas simple clustering in a dataset would translate to a low p-value and high z-score for *I*. Dispersion is not the opposite of clustering in G as it is in *I*, which could then allow for a statistically significant result for *I* with no significant result for G.

Specific high or low clustering in a dataset is harder to detect mathematically when the spatial extent of the dataset, or the total areal coverage, is low, particularly when the sample size is also small. Given our smaller study area, variations in fire-scar counts by tree becomes easily diluted in a global analysis of spatial association. The spatial association "landscape" in a global analysis requires a higher density of points, and more variation among points, to capture clusters of high or low values in fire-scar counts. If the total range in fire-scar counts is low, isolated locations or clusters of high-low values are harder for Getis-Ord to detect. Therefore, our results of the Getis-Ord operation should be taken with caution because they only indicate a lack of clustering within our study area. If we were to extend the spatial extent of our study area to include more trees from a broader geographic range, the potential for high-low clustering could increase.

We complemented our global indicator analyses of spatial association with three separate analyses at the local scale. The results of our Anselin's Local Moran's *I* (ALMI) and Getis-Ord Gi* both isolated a single area in the southern section of our study area as containing trees with statistically significant low numbers of fire scars. We propose two separate lines of reasoning for this low-valued cluster, including: proximity to the southern border and neighborhoods, and location in relation to Blue Hole pond. The localized cluster of trees with low fire-scar counts for ALMI and Gi* is approximately 50–60 m due north of 6th street, which is a perpendicular road that marks the southern extent of our study area. We propose that these trees have historically experienced lower fire activity because the neighborhood to the south has acted as a "fire lookout" for any fire that may have ignited and initiated in that area. The higher density of people and visual proximity to this area of our study area allows citizens living in that community to spot a fire earlier and report it to U.S. Fish and Wildlife Service officials or the local fire department. Additionally, prescribed fires scheduled in the NKDR would not be ignited that close to a neighborhood, both for aesthetic and safety reasons. All of these barriers to fire activity in this location are potential reasons for the low-value cluster found by ALMI and Gi*.

The second potential reason we propose for the low-valued cluster in the south-central section of our study area is its relative proximity to Blue Hole pond. The Blue Hole pond area has generally lower relief, and the ground surface is closer to the water table. The area directly in between the low-valued cluster and Blue Hole Pond contains some of the lowest elevations in our study area, potentially causing a micro-environment with a shallower depth to the water table and increased fuel moisture and therefore less fire activity (Renkin & Despain, 1992; Dennison & Moritz, 2009; Krawchuk & Moritz, 2011). Additionally, the groundlayer of this area was particularly barren, with the majority of the ground surface composed of exposed limestone bedrock and scarce surface debris. Therefore, fuel loading in this area is lower, which would translate to lower fire activity because of general fuel breaks and lower fuel availability (Agee *et al.*, 2000; Schoennagel *et al.*, 2004).

The results of the Ripley's K analysis provide a more in-depth analyses of local spatial association of fire activity because the distance band around each targeted tree is variable. We used 10 distance bands, totaling to 100 m, to evaluate clustering or dispersion around each individual tree with increasing neighborhood size. Interestingly, the peak in clustering in our fire-scarred tree dataset approximately matched the aggregated scale results for best relationship between fire activity and microtopography in our regression analyses. We suggest that fire activity in this ecosystem clusters to the highest, most statistically significant degree at approximately 50–60 m distances. At finer scales, fire activity was found to be generally random (within the 99% confidence envelope), and no clustering of higher significance was found at coarser scales. These results also corroborate our global Moran's *I* analyses, which found statistically significant clustering across the study area.

Two caveats must be mentioned for the global and local indicators of spatial association and autocorrelation. Each method is influenced by study area size and locations of sampled data because space is an inherent feature in both global and local indicators. We collected slash pine samples from a pre-designed plot network, rather than a targeted approach in the field, to mitigate sampling bias across space, and prevent erroneous clustering results based on locations of sampled trees. If the samples were collected in a clustered pattern, then spatial associations among trees would be biased due to sampling design rather than fire-scar counts. We collected trees from across the study area to prevent selection bias resulting from a targeted sampling approach, and to ensure that any clustering or dispersion observed in our analyses was due to actual fire activity. The second caveat to spatial association analyses, and local indicators in particular, is that the resulting statistics assume normal data distributions. However, we are confident in our analyses because our fire-scar data, while not perfectly Gaussian, is relatively normal. A slight skew to lower fire-scar counts does exist in our data, but we do not believe that it generated erroneous results.

Our analyses and results in this study indicate patterns of fire activity, captured via the fire-scar and tree-ring record, at both global and local scales. At the global scale, our Moran's *I* analysis found statistically significant ($p < 0.01$) clustering of fire-scar data across our study area, although no statistically significant high or low clustering was found in our Getis-Ord analysis ($p > 0.01$). We found a statistically significant ($p < 0.01$) localized cluster of trees with low fire-scar counts in both the ALMI and Gi* analyses. This cluster of trees was near the southern extent of our study area, within approximately 50 m of an adjacent neighborhood, and near locations of lower elevation. Finally, our Ripley's K results indicate a peak in clustering significance at a scale of 50–65 m, which supports results found in our scalar analysis in a previous chapter.

4.5 Conclusion

Our research provides a more robust and comprehensive understanding of fire activity, which can be used to bolster efforts to protect and conserve the pine rocklands. Quantitative measures of spatial association and patterns of fire activity from both a global and local perspective can pinpoint locations of potential fire "hot-spots" or "cold-spots." Through our spatial analyses in this project, we showed specific areas of clustering in past fire activity, and define a potential scalar threshold for clustering across the study area. Our research is the first in this ecoregion to approach an investigation of fire activity from the perspective of a contiguous network of plots, rather than a mosaicked targeted approach, which was crucial to our ability to provide such spatially-explicit results for a contiguous area within the the NKDR on Big Pine Key.

The implications of our research extend beyond the scope of our project and into the realm of predictive risk modeling. While we did not focus on predicting specific fire risk in this study, our results provide precise spatial locations of clustered fire activity, and indications of the nature of fire activity in the ecosystem through ALMI, Gi*, and Ripley's K. Specifically, we were able to quantitatively define an area along a wildland-urban interface and the adjacent community to the south of our study area that has historically experienced lower fire activity. These results allow for investigations into any potential predictor variables responsible for lower fire activity that match the environment of the lower-valued cluster, which can be extrapolated across our landscape and used to predict other areas of potentially lower fire. For example, a future analysis could take the fuel load and moisture characteristics, and distance to neighborhoods, found in the location of clustered lower fire activity from our results and isolate other locales beyond our study area that match those same characteristics to predict potential fire risk. Considering fire is not a purely stochastic process and is based on a suite of potential environmental and human-related variables, we can take the distinguishing characteristics of the south-central location in our study area and find other similar locations elsewhere. Finally, future analyses could expand the spatial extent of our study area to collect a broader spatial range of fire-scarred trees, and potentially isolate areas of high-low fire activity.

Fire in southern pine rocklands is critical to the conservation of this geographically-limited ecosystem. The analyses we conducted for this research provide scientists and land managers with the spatial and quantitative data required to describe how fire should "act" in this area, and surrounding locations with similar environmental characteristics. The results of this project, and future research conducted in the area, will ensure not only the continued survival of these pine rocklands, but also the safety of people living along the borders.

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Chapter 5

Conclusions

5.1 Summary of Dissertation Research

Fire is a disturbance phenomenon in pine rocklands in the subtropical U.S. The purpose of this dissertation research was to assess fire activity in pine rocklands in the National Key Deer Refuge on Big Pine Key from both a temporal and spatial perspective. Specifically, the this dissertation followed the 2011 Blue Hole Burn, which was a prescribed fire that escaped prescription and became a severe wildfire. By assessing fire data from a holistic temporal and spatial perspective, I was able to quantitatively evaluate fire activity in this ecosystem. These rocklands have experienced marked decline in the past century, and they are at risk for further range loss and impacts from anthropogenic habitat changes as the islands and surrounding locations become increasingly populated. Increased urbanization and development near the NKDR increases the potential for interaction between people and lightning-caused fires in this ecosystems, such as what occurred in September of 2011.

The 2011 Blue Hole Burn was a high-intensity, crown fire in the southern section of the NKDR that burned approximately 48 ha near the Blue Hole quarry adjacent to Key Deer Boulevard. This particular wildfire inspired considerable response from local community members and Big Pine Key citizens because it was viewed as a horrible and costly mistake by the U.S. Fish and Wildlife Service. The fire was considered by citizens to have been too severe or extensive to be within the historical range of variability for a pine rockland. Furthermore, and the likely more dominant reaction from citizens, was in regard to the resulting charred landscape which was viewed as uninhabitable for the endangered Key deer.

Considering how poorly the 2011 wildfire was perceived by the general public, the goal of my dissertation was set to quantitatively establish exactly how fires have acted in the past within the fire perimeter. Specifically, I wanted to establish how fire return intervals may have changed with increased population and ecosystem management, and what spatial extents can be expected for a large (> 10% and > 25% scarred) fires. Additionally, I evaluated the breadth and strength of relationships between fire activity and the surrounding microtopographic landscape through regressions at varying scales. The goal of these regressions was to (1) determine what relationships, if any, existed between fire frequencies per tree and surrounding microtopographic features, and (2) assess how, if at all, those relationships changed with aggregated scale (*i.e.* increases in cell window size). Finally, I tested various metrics of local and global spatial autocorrelation to locate statistically significant indications of clustering or dispersion in the fire-scar data. The purpose of the spatial autocorrelation analyses was to determine (1) the presence or absence, and extent, of correlation in fire-scar counts among fire-scarred trees from a global (*i.e.* study area) perspective, and (2) determine if localized subsets or neighborhoods of data exhibited spatial autocorrelation in fire-scar counts. Holistically, each chapter in my dissertation builds upon the next to evaluate fire activity in the NKDR from both a temporal and spatial perspective.

5.1.1 Temporal Analysis of Fire Activity

In regard to temporal patterns in fire activity, I evaluated the historical range of variability for fire activity in pine rocklands within a section of the NKDR that burned in the 2011 Blue Hole Burn. Specifically, I investigated how, and to what extent, fire activity changed after management practices began in the NKDR in the late 1950s. A statistically significant difference existed in my dataset for mean fire interval (MFI) between the pre- and post-management periods, with post-management fires occurring less often than in the previous period. The frequency of fires decreased after the mid-1900s with the loss of slash and burn land management which was first institutionalized in the late 1800s for development of the railroad. Furthermore, when the NKDR was established in 1957, fires set for hunting Key deer were prohibited, which caused the frequency of smaller fires to decrease as well.

In addition to the standard fire history analyses, I also investigated the spatial extents of large fires (> 25%) in the NKDR. For those fires that were highlighted in the temporal analysis as having scarred > 25% of the recording trees for that year, I built a GIS that interpolated among the fire-scarred trees to generate a surface of past fire activity. The interpolation results complement the temporal range of variability analysis and confirm that the 2011 fire was no more spatially extensive than other large fires in the dataset, such as the 1990 and 1977 fires. Additionally, the 1990 and 1977 fires were also prescribed by the U.S. Fish and Wildlife Service on Big Pine Key, and both scarred comparable amounts of trees over a similar spatial area. When the results from the temporal and spatial analyses were combined, I provided quantitative evidence against the 2011 fire being a uniquely large and extensive fire.

5.1.2 Scalar Analysis of Fire Activity

After analyzing the fire history of my study area in the NKDR, I evaluated relationships between fire activity via the fire-scar record and the surrounding microtopography in my scalar analysis. I conducted a suite of linear regressions, using fire-scar data as the response variable and four primary microtopography parameters (elevation, slope, residual topography, and curvature) as the predictor variables at increasing aggregations. I began my regression using no scaling (1 m x 1 m), and increased the window size to 100 m x 100 m. The predictor-response relationships at each of these different scales were weak at each scalar increase, but each model found increasing statistically significant variables with increasing window size. The peak in model and variable significance was with the 50 m x 50 m model with a statistically significant model R^2, and significant residual and curvature model variables. I used two different clustering analyses to verify that my model results were due to inconsistencies in variance structure between the predictor and response variables, and not poor model calibration.

While the specific results for my dissertation may be anti-climatic in regard to the regression modeling, the true power of this study comes in the applicability of these regression techniques in different locations across the southeastern U.S. and elsewhere. Future fire history analyses can use the GIS techniques from this study to isolate areas on the landscape where fires are more likely to occur. Areas of higher local relief, and more heterogeneity in environmental features, for example in vegetation composition, surface hydrology, and the presence or absence of a developed soil layer, may be able to overcome the dominant stochasticity in my models and generate more robust results. Historically, fire history research has taken a more exploratory approach, whereby potential locations are first scouted and vetted for fire activity, and in some cases rejected after numerous hours of work. The techniques I used in my research would allow others to approach sampling and cross-section collections from a more-informed perspective by first isolating areas in the landscape that have a higher likelihood of having fire-scarred trees.

5.1.3 Spatial Autocorrelation Analysis of Fire Activity

After establishing relationships between fire activity and microtopography at various scales, I analyzed relationships within the fire-scar data in regard to spatial autocorrelation. Specifically, I calculated two levels of spatial autocorrelation: (1) global indicators that incorporate the whole dataset and give a study-area-wide evaluation of clustering or dispersion, and (2) local indicators that break the study area into localized neighborhoods. The global Moran's *I* was statistically significant for clustering across the study area meaning that fire-scarred trees in the NKDR of similar fire-scar counts tend to be located at closer distances. I was not able to identify specific clustering of trees with high or low scar count numbers. The results of the local analyses indicate a small cluster of trees with low fire-scar counts directly adjacent to the bordering neighborhood marking the southern extent of the study area. I propose that this pocket of low fire activity is the result of no prescribed burning because of the proximity to the neighborhood, and people acting as fire lookouts if a lightning-caused fire were to ever start.

Spatial autocorrelation analyses also provide insight into the structure of fire across an area, which can be used similarly to the regression techniques and extrapolated outside of the study area. The implications of this research extend into the realm of habitat modeling along wildland-urban interfaces, where people and communities may have both direct and indirect influence on the natural rhythms of nearby habitats. For example, abiotic and biotic characteristics of the pine rocklands surrounding the localized cluster of low fire activity can be isolated and then used to delineate areas without fire-scar data that may also experience low fire activity. Lastly, by tackling local indicators of spatial autocorrelation from three different metrics, I was able to find a spatial window that displayed a peak in clustering significance. The Ripley's K analysis found a window of approximately 50–65 m where clustering in fire-scar data peaked in significance. This window matches the aggregation window from the scalar analyses and indicates fire activity in this pine rockland operates within that window.

5.2 Future Work

5.2.1 Sampling Design Expansion

The sampling design for this project was sufficient to protect the robustness of the spatial statistics in the analyses of this dissertation, but an augmented sampling design would be beneficial to future work on Big Pine Key. Although the extent of my study area was appropriate and sufficient for the analyses I conducted, a broader spatial extent would be ideal. Specifically, future work should expand the plots into the northern regions of the 2011 burned area, and if possible into areas that did not experience the 2011 fire. While a higher density of collected samples may not necessarily improve statistical results, primarily because the landscape has low local relief, a larger study area may allow for detection of stronger relationships among model variables. However, the contiguous nature of the plot design, where each plot is adjacent to its neighbor, must be preserved to ensure the ability to generate fire surfaces across the study area. Lastly, my study area was within a single pine rockland on a single island in the lower Florida Keys, thus future work may benefit from expanding the study area to a pine rockland outside of the NKDR.

My second recommendation for the sampling design relates to which specific trees are collected and recorded in the dataset. For this research I was interested in capturing as many fire scars as possible from an optimally-designed subset of fire-scarred trees. In the future, I suggest that all trees are at least recorded, if not necessarily sampled for fire history analysis. Clustering analyses and regression modeling for data that historically display Poisson distributions (such as fire-scar counts) rely on zero count data just the same as data of higher values. My regression models may have demonstrated higher significance if trees without fire scars were also included, and with the spatial autocorrelation analyses. Of course in hindsight and given another field season trees without fire scars would be GPS-located and included in the dataset, but they were absent in the analyses for this dissertation.

5.2.2 Predictive Risk Modeling

Predictive risk modeling is the natural next step for research to expand on the work in this dissertation. Results from the regression analyses, and the global and local metrics of spatial autocorrelation, indicate the potential for delineating areas of high-low fire risk. Preliminary results not included in this dissertation have shown that risk surfaces can be generated, although they are tempered by low variability in the current dataset. Expansion of the sampling design to include a larger geographic area, or another pine rockland in a different location, will help bolster predictive fire risk modeling for this habitat type. Additionally, data should be collected on dissolution holes, specifically in regard to locations dispersed throughout the study area and the influence they have on fire spread. Finally, even though the rocklands are flat with minimally-variable groundlayer characteristics, other data such as time-since-last-hurricane or depth-to-groundwater would provide another layer of information for regression modeling.

Quantitatively delineating areas of high-low fire activity is beneficial in predictive modeling of fire risk and research on risk assessment from a wildland-urban interface perspective. How people view fire, from either a negative or positive vantage point, is extremely important when evaluating the holistic nature of fire risk. Future work investigating fire risk on Big Pine Key and within the NKDR should include research on public perception of personal fire risk to develop a framework by which people become a part of the analysis. Personal perception of risk may not directly be a "data point" in a predictive risk model or regression, but I believe the information is valuable (*e.g.* through a public survey) and should be included in research dealing with land management. For example, a person with a "high perceived risk of wildfire" may maintain a heavily-manicured property with complete removal of shrubs or vines attached to the main housing structure. Conversely, a private citizen without any perception of individual fire risk may maintain a house covered in thick vines. These may seem like overly simple pieces of data, but risk perception as it relates to personal behavior could be another layer of data in a fire risk assessment for an area.

VITA

Lauren A. Stachowiak earned a Bachelor of Science degree in Geography and Biology with concentrations in physical geography, field ecology, and GIS from the University of Wisconsin at Whitewater in the spring of 2010. She earned a Master of Environmental Science degree with concentrations in environmental biology and GIS from the University of Pennsylvania in the spring of 2012. Her thesis investigated the influence of bedrock lithology and forest type on stream densities in Puerto Rico. She earned a Doctor of Philosophy degree in Geography, with a PhD minor in computational science and statistical modeling from The University of Tennessee in the spring of 2016. She was awarded the J. Wallace and Katie Dean Graduate Fellowship her first year as a doctoral student, and worked as a Graduate Teaching Associate and Graduate Research Associate in the Department of Geography. Lauren accepted a position as an assistant professor in the Department of Geography at Eastern Washington University, and she will be moving to Washington upon graduation.