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**NATIVE FIRE REGIME AS A REFERENCE FOR ESTABLISHING
MANAGEMENT PRACTICES**

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of
Philosophy in the Department of Biology in the College of Sciences
at the University of Central Florida Orlando, Florida

Fall Term
2009

Major Professor: John F. Weishampel

ABSTRACT

Our understanding of natural fire regimes in human-dominated landscapes is limited. Fire regimes operating in the pyrogenic ecosystems of Florida have been altered by fire suppression and fuel fragmentation. This is especially true of North Merritt Island, Florida, where human impacts have led to an incomplete knowledge of current fire regimes. We know that growing season fires frequently occurred within general return intervals and that many native terrestrial species require fire to remain viable. A 20-year plus period of fire suppression caused structural and compositional changes to vegetation/fuels that led to catastrophic fires and the decline of native species populations such as the Florida Scrub-Jay. Fire has been reintroduced as a means to reduce fuels and maintain habitat requirements for native species. Scientific studies have documented the effects and benefits of prescribed burning on KSC/MINWR habitat/fuels structure. The necessity for fire to maintain vegetation/fuels structure and composition on the landscape is clear so fire is being applied to the landscape despite our imperfect knowledge of the native fire regime. It is imperative for the survival of many native species that fire managers be able to mimic the results of the native fire regime. Fire regime research is difficult in shrublands, and using dendrochronologic techniques are often not possible in flatwoods communities. I therefore used a process of remote sensing, GIS mapping, and spatial modeling to quantify lightning fire ignition properties, the current managed fire regime, and the natural fire regime.

Chapter one develops a new remote sensing technique to accurately map burned areas in Florida scrub and pine flatwoods dominated communities on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force

Station, Florida. At the center of this technique is a newly developed separation index (*SI*) that was used to evaluate each individual satellite image band for its power to discriminate unburned and burned areas. Burned areas were classified and found to be highly accurate in relation to empirical fire records. This chapter addressed a number of issues relevant to the classification of burned areas including: the effect of geographic extent of remote sensing data on classification, determining the best bands for classification, and cleaning classification results by using GIS masking. It also serves as the first published effort to map fire scars in the Florida scrub and flatwoods vegetative communities of the southeastern U.S. using image processing techniques.

Chapter two quantified a managed fire regime on John F. Kennedy Space Center, Florida and surrounding federal properties by mapping all fires between 1983 to 2005 using the image processing technique developed in chapter one, time series satellite imagery, and GIS techniques. The goals were to: (1) determine if an image processing technique designed for individual fire scar mapping could be applied to an image time series for mapping a managed fire regime in a rapid re-growth pyrogenic system; (2) develop a method for labeling mapped fire scar confidence knowing that a formal accuracy analysis was not possible; and (3) compare results of the managed fire regime with regional information on natural fire regimes to look for similarities/differences that might help optimize management for persistence of native fire-dependent species. The area burned by managed fire peaked when the drought index was low and was reduced when the drought index was high. This contrasts with the expectations regarding the natural fire regime of this region.

Chapter three quantified the natural lightning ignition regime on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. Lightning is the natural ignition source in Florida, substantiating the need

for understanding lightning fire incidence. Sixteen years of lightning data (1986-2003, excluding 1987 and 2002 due to missing data) from the NASA Cloud to Ground Lightning Surveillance System and fire ignition records were used to quantify the relationship between lightning incidence and fire ignition. Precipitation influenced the efficiency of lightning ignitions, particularly July precipitation. Negative polarity strikes caused the majority of ignitions. Pine flatwoods was ignited more frequently than expected given equal chance of ignition among landcover types. About half (51%) of detected fires were instantaneous ignitions and the other 49% were delayed an average of two days. Summer lightning ignitions were dominant, especially during July, with only one winter lightning ignition.

Chapter four used an existing fire regime model (HFire) to simulate the natural fire regime (prior to European settlement) on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. A sensitivity analysis was performed to establish which parameters were most important and the range of variation surrounding empirically derived model information from the same model. A mosaic pattern of small fires dominated this fire regime with extremely large fires occurring during dry La Nina periods. Dead fuel moisture and wind speed had the largest influence on model outcome. The majority of variability was found to be in the largest fires.

The research presenter here provides a comprehensive perspective on current and historic fire regimes that may be useful for optimizing land management on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida and throughout the southeastern United States. Native fire dependent species are suffering from many changes imposed from human alteration. The success of conservation efforts protecting native fire dependent species hinge on my factors. Two of the

largest factors are first protecting native habitat and then secondly managing that protected habitat to mimic natural maintenance processes for suitable structure and composition which may favor their demography. This study focuses on developing techniques necessary for producing information that can aid the optimization of fire management on these properties and within the southeastern United States, but may be useful in other fire maintained ecosystems globally.

I dedicate this achievement to my family, especially to my beautiful wife Lorene and my boys Parker and Braeden, who have supported and nourished me throughout this long journey. To my many friends who have stimulated and encouraged me. To my constant companion dyslexia, which has continually humbled me and taught me that there is much to work for in life.

ACKNOWLEDGMENTS

This research was conducted under NASA contract NAS10-12180. We thank Denise DeLaPascua Thaller, Steven Brisbin, Kelly Gorman, and Burton Summerfield for their help and support. I would like to thank my committee John Weishampel, Pedro Quintana-Ascencio, Reed Noss, and Frank Davis for their guidance and support. I would also like to thank Ross Hinkle for his belief in me and his support over the years. I cannot thank Carlton Hall enough for his uncompromising support. I owe a huge debt of gratitude to Paul Schmalzer who has always taken time to help me and provided me with countless stimulating intellectual discussions, shaping my work. To Frederick Adrian at Merritt Island National Wildlife Refuge who has made this effort possible by lending his experience, data and knowledge so unselfishly. I need to thank Max Moritz and especially Seth Peterson for help with the HFire model. To my many colleagues within the Ecological Program at Kennedy Space Center, especially Tammy Foster, Eric Stolen, Danny Hunt, and John Drese who have been very kind and generous supporting me. I also would like to thank Guofan Shao and Fred Johnson and the U.S.G.S. for support acquiring satellite imagery for this study. I would also like to thank the Merritt Island National Wildlife Refuge and the 45th Space Wing Weather Squadron for their support.

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INTRODUCTION

Returning the effects of natural fire processes to conservation landscapes with altered fire regimes is of great importance. Fire plays an important role determining vegetation composition, structure, and pattern (Bond and Van Wilgen 1996). Many species have evolved, adapted and become dependent on natural fire regimes (Noss and Cooperrider 1994, Whelan 1995, Bond and Van Wilgen 1996). The influence of individual fire events over longer periods of time are collectively known as a fire regime. The natural fire regime of a region is defined by its fire type, fire intensity, fire size, return interval, seasonality, and spatial pattern (Christensen 1985, Agee 1993). Urbanization combined with other human factors have altered natural fire regimes through such influences as fuel removal, fuel alteration, fuel fragmentation, and fire exclusion or suppression (Bond and Van Wilgen 1996). Alteration of ecosystem structure and composition has contributed to the decline of many species populations (e.g., Menges and Hawkes 1998, Breininger and Carter 2003, Quintana-Ascencio et al. 2003, Webb and Shine 2008).

Many conservation areas suffer from these same human influences altering the natural fire regime. For example, many conservation areas have been subject to fire suppression directly or indirectly; the areas themselves are relatively small limiting natural fire dynamics, or they have some degree of fuel fragmentation limiting the spread and extent of fires (Noss and Cooperrider 1994, Duncan and Schmalzer 2004).

Fires that occur from lightning ignitions or arson in many conservation areas are controlled or suppressed to protect harvestable natural resources, human structures, or human lives. In areas where fire has been largely absent, prescribed fire may be used. Managed fire is used to reduce fuels to safe levels; it is used to maintain fuel/vegetation/habitat composition and

structure (e.g., Adrian and Farinetti 1995). Few conservation areas have good fire history information or a complete record of the natural fire regime for that area or region. This reference information is useful as a background for restoration and management decisions guiding fire management (Beckage et al. 2005).

As desirable as it may be, it may be difficult or impossible to return to the natural fire regime in most conservation areas. In fact, trying to return directly to natural fire regimes may be harmful for some ecosystems and the species presently inhabiting them (Whelan 1995, Veblen et al. 2000, Heinlein et al. 2005). In other very large conservation areas letting nature take over and allowing naturally ignited fires to burn may be the best policy (Baker 1992). Most conservation areas require a fire management policy, and many require direct fire management to sustain native biodiversity. This is especially important in pyrogenic communities hosting habitat specialists that require fire to either maintain habitat conditions or demographic processes. Fire management policy may be best constructed and implemented with knowledge of the historic fire regime within that region. Our ability to return to natural fire regimes may be limited, but we must learn to closely mimic the results of native fire regime processes to maintain vegetation structure and composition.

The best way to help conservationists and land managers to achieve this goal may be to quantify as much as possible about the current and natural fire regime of an area. Many studies have successfully reconstructed fire histories and elements of fire regimes. The majority of these studies have used dendrochronologic techniques (Swetnam et al. 1999, Veblen et al. 2000, Heyerdahl et al. 2001, Stephens 2001, Heinlein et al. 2005). These techniques work very well in areas that have an even spatial distribution of suitable long lived tree species that scar during fire and are not killed by the event. Other studies have successfully used stratigraphic techniques to

reconstruct fire histories (Clark 1990, Carcaillet et al. 2001, Lynch et al. 2004). Stratigraphic techniques work well for fire frequency reconstructions and may be less suitable for spatial reconstruction. Mapping fire histories using remote sensing techniques have also been successful (Minnich 1983, Johnson et al. 1990, Weir et al. 2000). This technique works best in areas with relatively slow growing vegetation where fire scar boundaries remain visible from remotely sensed imagery for some duration after the fire event. Recorded fire records are also a good source of historic fire regime information but are limited to areas with good recorded history (Keeley et al. 1999, Cleland et al. 2004).

Reconstruction of fire regimes and fire histories in shrub systems are especially difficult. Typically they do not have an even spatial distribution of trees that are suitable for dendrochronologic techniques. Fast growing shrub systems present additional challenges, making fire scar boundaries transient and difficult to map using remote sensing techniques. Pyrogenic systems in Florida may present the ultimate challenge for fire regime reconstruction. The vegetation recovers very quickly after fire (Schmalzer and Hinkle 1992a) and the pyrogenic ecosystems with trees such as pine flatwoods systems are not suitable for dendrochronological tree scar dating because the trees either do not scar or are completely killed by fire. The trees thick bark protect them from scarring during low intensity fires but are often killed during high intensity fire events as the canopies are consumed and top killed. Stratigraphic techniques are suboptimal for fire interval delineation and in some systems can only determine the length of time that fire has been an active force on the landscape (Shepherd 2002).

Computer modeling has become a viable option for simulating fire regimes as modeling capabilities have advanced simultaneously with computer technology. Two main types of models have evolved, with the first being fire event simulation models and the second being

landscape fire succession models. Fire event simulation models are generally used to predict individual fire event behavior. Landscape fire succession models incorporate vegetation succession making these models capable of simulating long-duration ecosystem dynamics. There are at least 45 landscape fire succession models in use today (Keane et al. 2004). These models have been created for different purposes in a diverse range of ecosystems. The majority of these models have been used to investigate long duration landcover dynamics, of which fire is a major influence (Ratz 1995, Noble and Gitay 1996, Klenner et al. 2000, Kurz et al. 2000, Groeneveld et al. 2002, Mouillot et al. 2002, Chew et al. 2004). Fewer of these models have been designed specifically to simulate fire regimes. Many of the landscape fire succession models require statistical information derived from empirical fire regime data as input, making them unsuitable for reconstructing natural fire regimes (Li 2000). They may be used for answering a different type of question, such as addressing landscape dynamics under a known fire regime.

Computer simulations have been successfully used to reconstruct elements of both natural and human influenced fire regimes. The regional fire regime simulation model (REFIRES) was created to simulate prehistoric and modern fire regimes of the coastal California chaparral ecosystems (Davis and Burrows 1994). Application of the model produced a map of simulated fire history, fire size distribution, fire recurrence interval, final patch size, and age distributions. The SEM-LAND model was created to simulate the fire regime of forests in west-central Alberta, Canada (Li 2000). The fire cycle, known as the average period required to burn a cumulative area equivalent to the entire area under investigation, was modeled. This modeling effort also produced a time since fire distribution and forest age map. Fire pattern was inferred by using the forest age mosaic map. The SEM-LAND model was also used to simulate the fire

regime of central Saskatchewan (Li et al. 2005). The model was used to model the fire cycle, mean fire size, fire number per year, and mean forest age. The DISPATCH model was used to simulate pre-EuroAmerican settlement and post-settlement fire regimes in the Boundary Waters Canoe Area, Minnesota (Baker 1992). Application of this model indicates that settlement has caused smaller, less frequent fires relative to the pre-EuroAmerican period. Fire suppression after settlement caused even smaller and less frequent fires and brought about an increase in mean landscape age, an increase in richness and diversity of the landscape, and a decline in mean patch size (Baker 1999).

Quantifying potential fire ignition and actual natural ignition rate is also important for a complete understanding of any fire regime and its influence on ecosystem dynamics and biodiversity. Several studies have documented lightning occurrence and its relationship to fire regimes. Lightning and human fire frequency, size, and seasonality were studied in a Brazilian savannah for purposes of comparing natural and managed fire regimes (Ramos-Neto and Pivello 2000). The study concluded that the managed fire regime was not taking advantage of the beneficial effects of the natural fire regime and was likely reducing biodiversity. A lightning study conducted in the central cordillera area of Canada revealed very different lightning strike effectiveness in relative spatial proximity on either side of the continental divide (Weirzchowski et al. 2002). This study found that on average it took over 14,000 lightning strikes to start a fire in Alberta vs. fewer than 50 strikes in British Columbia. This study found that lightning fire incidence was greatly different in many of the protected areas and this information had important fire management implications. A lightning study conducted in Finland found a lightning fire density gradient decreasing from south to north in that country (Larjavaara et al. 2005). The

authors stressed that this variability suggested that different management approaches are needed to support natural forest structures, processes, and biodiversity in different parts of the country.

This research used a combination of remote sensing, GIS, and modeling techniques to document the current and historic natural fire regime for Kennedy Space Center (KSC), Merritt Island National Wildlife Refuge (MINWR), Canaveral National Seashore (CNS), and Cape Canaveral Air Force Station (CCAFS), Florida. It 1) developed a processing routine using multispectral satellite imagery to classify burned areas in the fast growing flatwoods and oak scrub terrestrial communities. It then 2) developed a fire history for the past 20 years of fire management, using the previously developed classification technique and a time series of multispectral satellite imagery. Next 3) it used the NASA/USAF Cloud-to-Ground Lightning Surveillance System (CGLSS) data and MINWR fire incidence records to quantify the relationship between lightning activity and fire ignition for the past 20 years. It then 4) used an existing fire regime vegetation succession model (HFire) to simulate elements of the natural fire regime on KSC/MINWR/CNS/CCAFS. This work will facilitate an understanding of the difference between the current managed fire regime and the natural fire regime while helping to optimize land management actions for persistence of native fire dependent species. There are many fire dependent species of special concern on these properties (e.g., Florida Scrub-Jay, eastern indigo snake, the eastern gopher tortoise, drysand pinweed, giant orchid). Adaptive fire management is being implemented on these properties in an effort to improve fire management, and the information from this work will provide direct input into this process. The information will also benefit fire managers throughout the southeastern United States, and many of the novel techniques developed here will transfer to delineating fire regimes globally.

DEVELOPMENT OF AN IMAGE PROCESSING TECHNIQUE FOR CLASSIFYING FIRE SCARS IN A FIRE ADAPTED ECOSYSTEM IN EAST-CENTRAL FLORIDA

Published as: Shao, G., and B.W. Duncan. 2007. Effects of band combinations and GIS masking on fire-scar mapping at local scales in East-Central Florida, USA. *Canadian Journal of Remote Sensing* 33:250-259. Used with the permission of the Canadian Aeronautics and Space Institute.

Introduction

Fire is an important ecological factor maintaining vegetation in East-Central Florida (Abrahamson and Hartnet, 1990; Myers, 1990; Duncan and Schmalzer, 2004). The historic natural fire regime of this region consisted of frequent spring and summer fires ignited by lightning (Duncan and Schmalzer, 2004). The fire regime of an area is defined by fire type (ground vs. crown), intensity, size, return interval, seasonality, and spatial pattern. Native vegetation and many animal populations of this region are dependent on this fire regime (Stout, 2001). An example of a fire dependent species in this region is the Florida Scrub-Jay (*Aphelocoma coerulescens*). The Florida Scrub-Jay is a threatened species that nests in oak scrub vegetation which resprouts after fire (Bowman and Woolfenden, 2002). Florida Scrub-Jay demography has been observed to peak in oak scrub habitat with optimum structure (120-170 cm tall scrub with scattered sand openings and little to no overstory) maintained by fire (Breininger and Carter, 2003). The recovery rate of oak scrub is highly variable and can take as few as 4 years or as many as 12 years to reach 120 cm tall after a fire occurs. If there is no fire for 15

years or greater, the oak scrub vegetation structure will change from shrubs to a closed canopy forest, becoming unsuitable for most native fire dependent species (Schmalzer 2003).

The National Aeronautics and Space Administration (NASA) began acquiring land in early 1962 on Merritt Island, along the east coast of central Florida, where the John F. Kennedy Space Center (KSC) is located (Figure 1). A 57,000 ha area is managed primarily by the U.S. Fish and Wildlife Service as the Merritt Island National Wildlife Refuge (MINWR). After NASA acquired the land, fire suppression went into effect on KSC until 1981. Fire suppression activity in the area combined with other anthropogenic influences (vegetation removal by facilities, roads, citrus farming, etc.) has altered vegetation structure, composition, and pattern on the landscape reducing habitat for many plant and animal species. For example, the Florida Scrub-Jay population has experienced a dramatic decline throughout KSC/MINWR (Breininger et al., 1996). Restoration of the native vegetation structure using prescribed fire began in 1981 and then in 1992 mechanical treatment techniques were added and have become the major focus for natural resource management at KSC/MINWR (Schmalzer and Hinkle, 1992; Duncan et al., 1999; Duncan and Schmalzer, 2004). Breininger et al. (2002) suggested that understanding spatial variations in fire frequencies among vegetation types is important for sustaining suitable habitat structure for specialized plants and animals. Vegetation at KSC/MINWR has been frequently burned (annually within selected FMUs) by prescribed fires since 1981. Documented fire records exist of all fires on KSC/MINWR, including fire date, fire management units (FMUs), and estimated area burned, but no detailed fire scar-pattern maps or area information are available. Optimization of fire management on KSC/MINWR for fire dependent native species requires that accurate spatial fire history records exist, including time since last burn and fire frequency information.

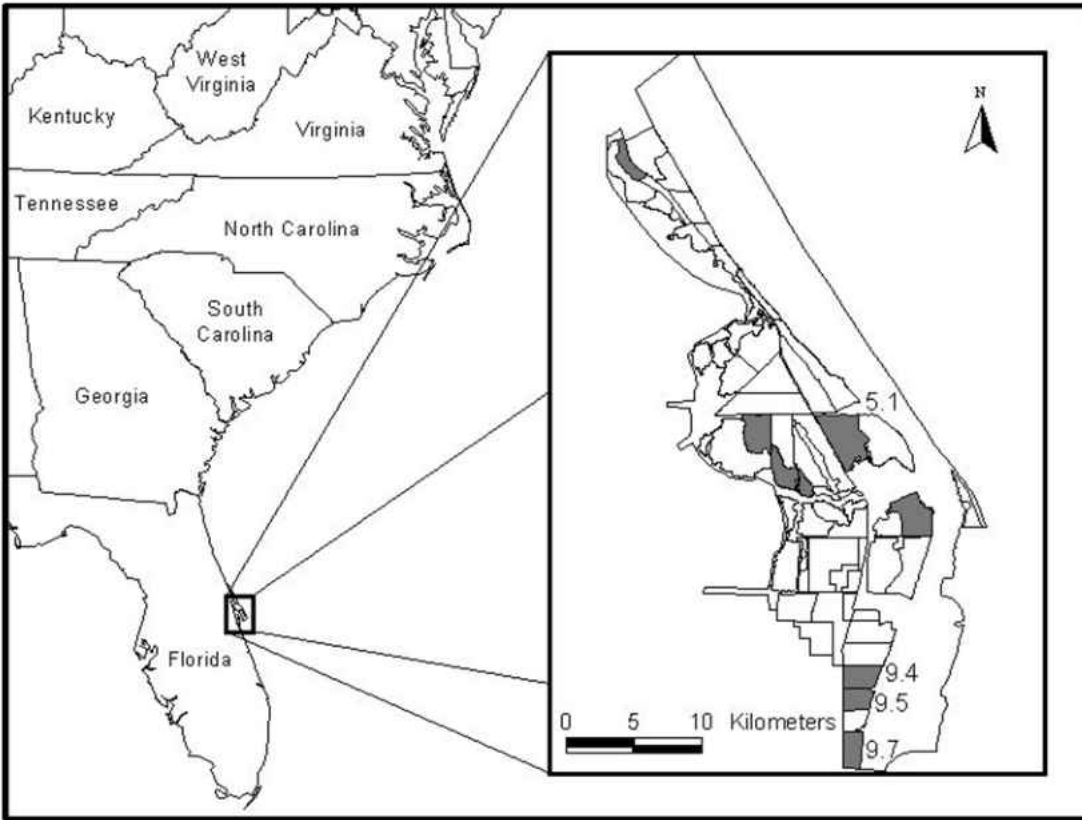


Figure 1. The location of NASA Kennedy Space Center (KSC) and Merritt Island National Wildlife Refuge (MINWR) in East-Central Florida, USA. Relevant fire management units (FMU) are indicated. The shaded eight FMUs were burned in 1986-1987 and were used for masking; the labeled four FMUs were used for band selection and accuracy assessment.

During the past two decades remote sensing has been used to identify and map fire scars in natural vegetation all around the world (Boyd and Danson, 2005). However, the remote sensing techniques used depend on the scale required for mapping. Eva and Bambin (1998) suggest that the most reliable strategy for estimating the extent of fire scars is through use of a multisensor approach in which estimates of burned area acquired from low-spatial-resolution data are calibrated with high-spatial-resolution data. Pre 2000, the main low-resolution sensor employed in continental to global-scale fire-scar detection was the Advanced Very High

Resolution Radiometer (AVHRR) on board the NOAA polar-orbiting platforms (Fuller, 2000; Maggi and Stroppiana, 2002). Recently, additional low-spatial-resolution remote sensing data from SPOT and MODIS are available for fire-scar mapping (e.g., Amiro and Chen, 2003; Tansey et al., 2004; Csiszar et al., 2005). These sensors have multiple spectral bands but only a subset of these bands (and/or newly transformed bands), are used for fire-scar mapping. A study by Boschetti et al. (2004) that involved a comparison of three fire-scar datasets derived from low-resolution data showed major disagreements in terms of areal estimates. This suggests that fire-scar mapping using low resolution remote sensing data needs further improvement.

Landsat data have been broadly employed for fire-scar mapping at both regional and local scales (e.g., Ranson et al., 2003; Hudak and Brockett, 2004; Mitri and Gitas, 2004; Pu and Gong, 2004). However, how to use data characterized by low spectral resolution and what wavelengths (bands) are best for mapping fire scars requires further study. Pereira and Setzer (1993) found that Thematic Mapper (TM) channel 4 was the best for identifying fire scars, followed by channel 5, 3, and 7. Pu and Gong (2004) suggested that TM bands 4 and 7, the Normalized Difference Vegetation Index (NDVI) derived from TM4 and TM7, and the NDVI derived from TM bands 4 and 3, provided the best discrimination between burned scars and areas of unburned vegetation. Hudak and Brockett (2004) compared the Tasseled Cap (TC) and Principal Components (PC) Transformations for mapping fire scars and found that PC helped differentiate the spectral signal of fire scars in each image. Patterson and Yool (1998) pointed out that bands transformed using the TC transformation resulted in a 17% higher overall classification accuracy than bands produced for the PC transform. Past studies, either at small or large scales, suggest that the usefulness of individual bands for fire-scar mapping depends on the data source (sensor), fire intensity, fire extent, and vegetation types. Less research has focused on

studying the effects of varying geographic extents of remote sensing data on band selection and classification accuracy. In previous studies, classification accuracy has been used to evaluate how useful individual bands are for mapping fire scars (e.g., Pu and Gong, 2004); however, it is time consuming to perform classification experiments with every possible band combination from multi-spectral imagery.

Remotely sensed data are often integrated with geographic information systems (GIS), as part of the fire scar mapping process (Chuvieco and Congalton, 1989). A GIS can be used to provide various ancillary data to enhance and validate image data classification (Sunar and Ozkan, 2001). High-quality remote sensing data are most frequently available in spring, relative to other seasons at KSC/MINWR. This is because spring is the driest season in this region and is typified by relatively long periods of cloud-free skies without storms.

The purpose of this paper is to compare various masking/classification options using Landsat TM data in concert with FMUs linked with existing KSC/MINWR fire records. As an initial effort in mapping fire scars for fire-adapted vegetation in East-Central Florida, a classification experiment was conducted to provide information on a number of relevant issues related to the mapping and classification of fire scars using remotely sensed data. These include:

- the effect of masking (pre and post-classification) on classification accuracy, and
- detection of the best and optimum number of bands (or derived bands) for classification.

The results from studying these issues will not only be useful for fire scar mapping world wide but will be especially important for future fire mapping efforts in Florida and the southeast U.S. where reliable methods for mapping fires at this landscape scale (1:24,000-1:50,000) are not available.

Methods

The data used for conducting the classification experiment included GIS data layers of the KSC boundary, fire management units, historical fire records associated with FMUs, and Landsat5 TM data, Path 16 and Row 40, acquired on April 21, 1987. The TM data set was rectified in State Plane coordinates in meters to make it spatially compatible with the GIS data layers. For safe management of fires, KSC/MINWR has been divided up into 61 FMUs. These FMUs are of different size/shape and are separated by non-flammable fire lines so that managed fires can be contained within selected areas. The FMUs are named using a numbering system with the first digit being a regional designator and the second digit after the decimal being a subunit within that region. Some of the units are further subdivided using letter designators such as A,B,C, etc. Based on the historical fire records, eight FMUs were partially burned with controlled fires between October 1986 and April 1987 (Fig. 1). Fire scars at only four FMUs were previously digitized and those at FMU9.4 were published (Breininger et al., 2002). Fire scar data for FMU9.4 were used for sorting and selecting individual bands, while those for the other three FMUs (5.1, 9.5, 9.7) were used to compute classification accuracy (Fig. 2). To maximize classification accuracy, two different masking routines were tested and described.

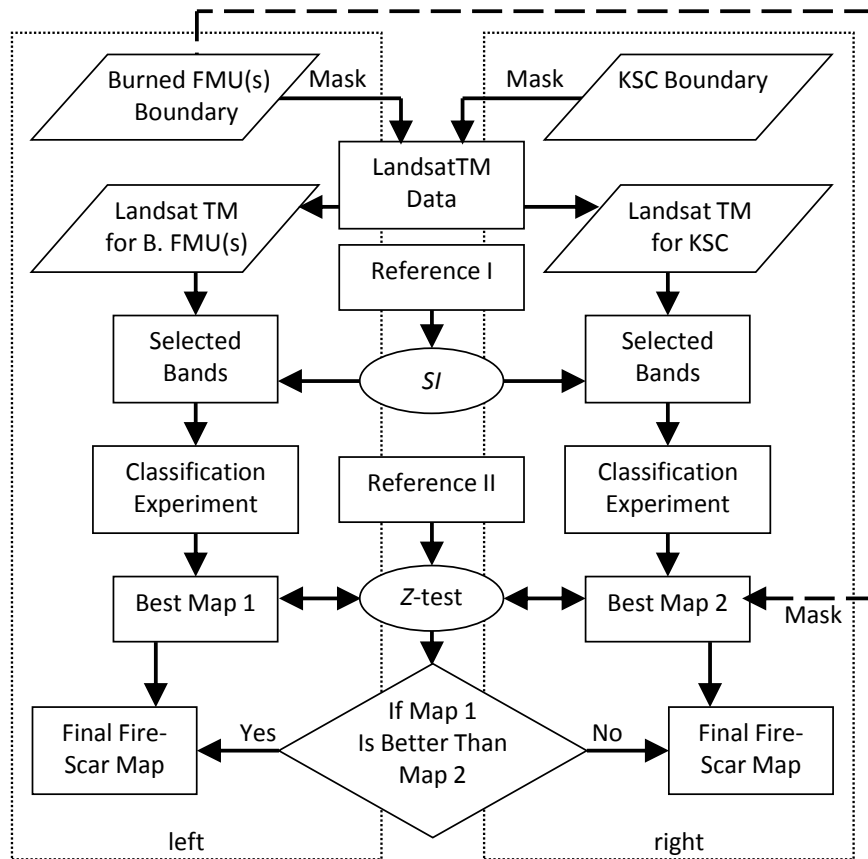


Figure 2. A work flow diagram of stepwise image processing for mapping fire scars at KSC/MINWR with Landsat TM data.

Geographic Extent Determination by GIS Masking

The rectified TM data set was masked with the KSC/MINWR boundary (Fig. 2: right) and with eight burned FMUs (Fig. 2: left), respectively. The resultant image data sets are called KSC TM data and Burned-FMU data. The Normalized Difference Vegetation Index (NDVI) between TM bands 4 and 3, PC Transformation, and TC Transformation were computed from

KSC TM data and Burned-FMU data, respectively. Rather than stretch to 8 bits, the original values of the transformed bands were used for classification.

To determine the association of how much information is in each TM band and each principal component, the correlation of each TM band k with each PC p was computed using the following formula (Jensen 2004):

$$R_{kp} = \frac{a_{kp} \times \sqrt{\lambda_p}}{\sqrt{Var_k}} \quad (1)$$

where, a_{kp} is the eigenvector for bank k and component p , $\lambda_p = p$ th eigenvalue, and Var_k is variance of band k in the covariance matrix.

Band Selection

To evaluate the potential of every band to separate burned and unburned areas, the overlap area of histograms between burned and unburned area was used. The new transformed bands and the original TM bands were overlaid with FMU9.4 fire scar data. FMU9.4 was the only one used here so the others (5.1, 9.6, and 9.7) would be available later for accuracy assessment. Histograms of pixels values for each band were computed for burned and unburned areas (Fig. 3). To avoid bias caused by the land cover type with larger area, the overlay area was divided by the area of a smaller land cover type. A simple index is calculated as follows:

$$SI_{i,j} = 1 - \frac{A_{i,j}}{\text{Min}(A_i, A_j)} \quad (2)$$

where, $SI_{i,j}$ is separation index between cover types i and j ($0 \leq SI_{i,j} \leq 1$), $A_{i,j}$ is the overlap area between cover types i and j , A_i or A_j is area for cover type i or j , and Min represents the minimum function (using a smaller number between A_i and A_j).

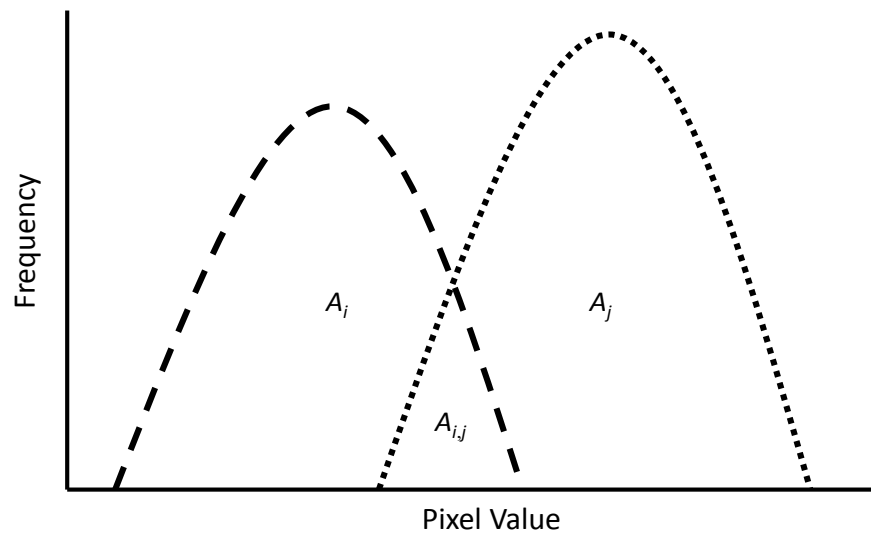


Figure 3. An illustration of the overlap of two histograms. Type i (dashed line) and j (dot line) can represent burned and unburned cover types. $A_{i,j}$ represents the overlap areas between burned and unburned cover types. A_i or A_j represents area for burned or unburned cover types.

The higher the $SI_{i,j}$ value, the more discriminative power the band has to separate the two cover types. All the bands with $SI_{i,j}$ value greater than 0.1 were accepted for classification. Bands with SI values > 0.5 were called the most suitable bands and were stacked into a single image.

Classification and Assessment

For each TM data set, original TM data, NDVI, selected PC bands, selected TC bands, the total of these bands, and the most suitable bands were used independently for classification. The unsupervised classification algorithm ISODATA was employed. The number of spectral classes was 20, the number of iterations was 20, and the convergence threshold was 0.99 for all the classifications with different band combinations. The 20 spectral classes were then manually recoded into two information classes, burned and unburned to form the classified fire-scar maps. For each classification, an error matrix table was formed by overlaying the classification map with the digitized map from FMUs 5.1, 9.6, and 9.7. There were a total of 17,800 pixels in the three FMUs. Producer's accuracy and user's accuracy for burned-area cover type were computed. The mean accuracy value between producer's and user's accuracy was computed for each classification. Fire-scar maps created with different bands were quantitatively compared with a Z-test based on the error matrix tables (Congalton and Green, 1999). All the image data analyses were performed with Erdas Imagine (www.leica.com).

Post-Classification Cleaning

Following each classification with the KSC TM data set, the fire-scar maps were masked with a GIS data layer of the eight burned FMUs (Fig. 2). This masking process, called post-classification cleaning, took advantage of the MINWR fire records and masked out any unburned FMUs. This step removed commission errors outside burned FMUs and assured a noise-free fire-scar map. When the Burned-FMU TM data set was used for classification, no further masking

was needed for the fire-scar maps from the Burned-FMU data. This was because the FMUs already represented the finest masking unit in this study.

Results

Geographic Extent

KSC TM data: Among all the 15 bands, including 7 original TM, 1 NDVI, 4 PC, and 3 TC bands, the bands with *SI* values > 0.5 were PC4, TM4, TC2, and NDVI (Fig. 4). The first four PC bands had *SI* values higher than 0.1. Among the four PC bands, PC4 had the highest *SI* value (Fig. 4b). The eigenvalues for the four PCs were 8538.5, 696.1, 118.8, and 45.5, respectively (Table 1). They contained 99.9% of the total data variance. The PC1 seemed correlated with every TM band, PC2 correlated with only the near- and middle-infrared bands, and other PCs not correlated with any TM bands (Table 1).

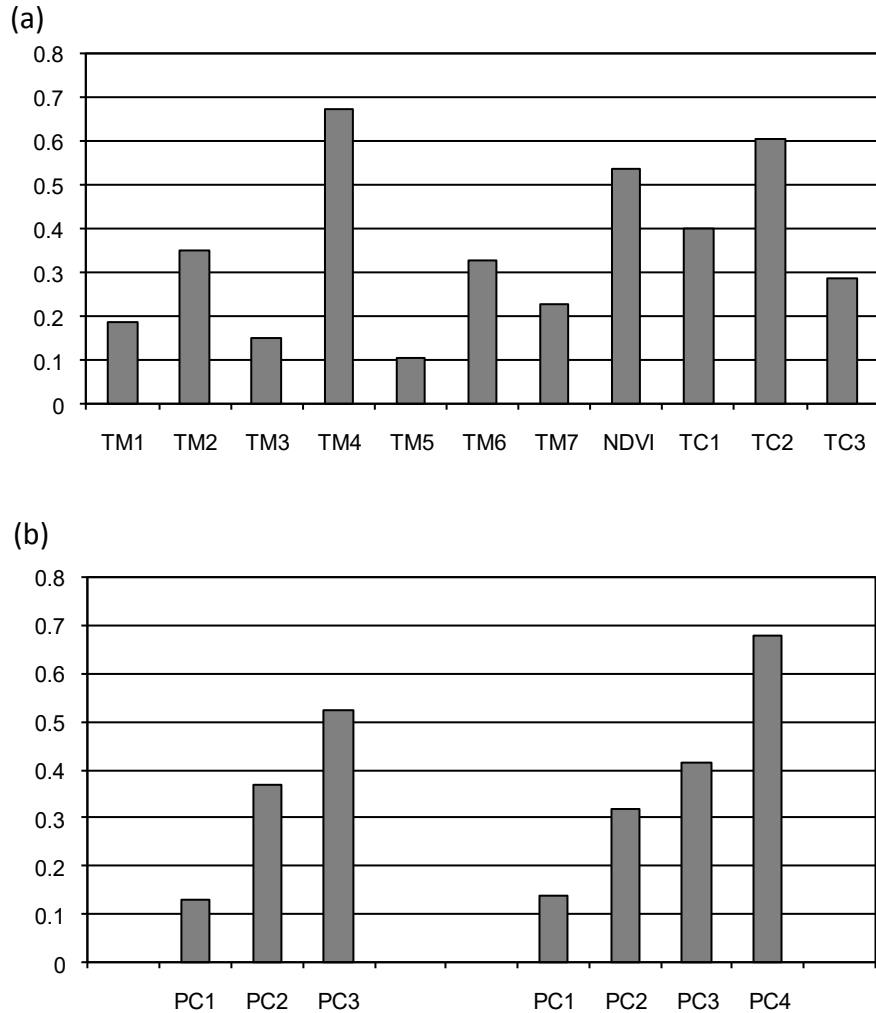


Figure 4. A comparison of SI values: (a) 7 original TM, 1 NDVI, and 3 TC bands common to both FMU9.4 and KSC/MINWR area and (b) 3 PC bands for FMU9.4 and 4 PC bands for KSC/MINWR area.

Burned-FMU data: Among all the 14 bands, including 7 original TM, 1 NDVI, 3 PC, and 3 TC bands, the bands with *SI* values > 0.5 were TM4, TC2, NDVI, and PC3 (Fig. 4). The first three PC bands had *SI* values greater than 0.1. Among the three PC bands, PC3 had the highest *SI* value (Fig. 4b). The eigenvalues for the three PCs were 585.4, 365.4, and 26.2, respectively

(Table 2). They contained 96.6% of the total data variance. The PC1 seemed correlated with every TM band except for the thermal-infrared band, PC2 correlated with only the near-, middle-, and thermal-infrared bands, PC3 correlated with the visible bands, PC4 correlated with the thermal-infrared band and other PCs not correlated with any TM bands (Table 2).

Table 1: The relationship of the original TM bands to the PCs from the KSC TM data set.

Original TM Bands	Principal Components						
	1	2	3	4	5	6	7
1	0.8110	-0.1257	0.0680	-0.0475	0.0178	-0.0014	-0.0037
2	0.9825	-0.0789	0.1254	-0.1076	-0.0040	0.0020	0.0329
3	0.9675	0.0356	0.2179	-0.0948	-0.0772	0.0150	-0.0090
4	0.8812	0.4070	-0.2135	-0.1100	-0.0037	-0.0104	-0.0012
5	0.8320	0.5447	0.0783	0.0653	0.0120	0.0232	0.0005
6	0.9712	-0.1434	-0.0569	0.0507	-0.0056	0.0000	0.0006
7	0.7828	0.5412	0.2659	0.1223	-0.0092	-0.0924	0.0005
Eigenvalues	8538.5	696.1	118.8	45.5	3.7	2.6	0.5

Table 2: The relationship of the original TM bands to the PCs from the Burned-FMU TM data set.

Original TM Bands	Principal Components						
	1	2	3	4	5	6	7
1	0.8167	-0.1424	-0.5228	0.1527	-0.0200	-0.1309	0.0184
2	0.8592	0.1993	-0.4135	0.1279	-0.0488	0.0536	-0.1757
3	0.8767	-0.1209	-0.4290	0.0542	-0.1108	0.1246	0.0504
4	0.5314	0.8338	0.0474	0.1240	0.0279	0.0023	0.0035
5	0.9795	-0.1474	0.0848	-0.0961	-0.0493	-0.0075	-0.0013
6	-0.0100	-0.8712	0.1688	0.4436	-0.0979	-0.0012	-0.0008
7	0.7108	-0.6831	-0.0056	0.0468	0.1526	0.0124	0.0010
Eigenvalues	585.4	363.4	26.2	25.7	6.3	1.4	0.6

Band Selection

TM4 had the highest *SI* value among the 7 original TM bands, followed by TM2, TM6, and TM7 (Fig. 4a). TM1, TM3, and TM5 had the lowest *SI* values. NDVI's *SI* value was lower than TM4's *SI* value but higher than other TM bands' *SI* values. Among TC bands, TC2, a greenness band, had the highest *SI* value, which was even higher than NDVI's *SI* value. TC1 (brightness) and TC3 (wetness) were less capable than TC2 at separating burned and unburned vegetation.

Classification Accuracy

When the KSC TM data set was used for classification, the mean of producer's and user's accuracies for the burned cover class was 96.5% for the four most suitable bands (PC4, TM4, TC2, and NDVI), which was higher than that for 3 TC bands (94.3%), original 7 TM bands (93.9%), 4 PC bands (93.2%), NDVI (93.2%), and all 15 bands (91.6%) (Fig. 5a). When the lower value between producer's and user's accuracy was used for comparisons, the differences in classification accuracy among the six classifications were even greater: 95.8% for the four most suitable bands, 93.0% for the original 7 TM bands, 92.2% for the 4 PC bands, 90.8% for the 3 TC bands, and 90.6% for the 15 bands. The Z-test suggests that the classification map created with the four most suitable bands was significantly more accurate than those created with any of the other band combinations at a 99% confidence level (Table 3). The maps created with 7 TM, 4 PC, and 3 TC bands had significantly higher accuracy than those created with NDVI alone and all 15 bands.

Table 3: Z-values based on error matrix tables between different classification maps created with spectral bands derived from KSC TM data set.

	NDVI	4 PC Bands	3 TC Bands	All 15 Bands	4 most suitable bands
7 TM Bands	7.21*	1.08	2.02	8.86*	15.03*
NDVI		6.24*	5.12*	1.39	21.88*
4 PC Bands			0.98	16.38*	7.87*
3 TC Bands				6.67*	16.73*
All 15 Bands					24.15*

Note: sign * indicates significant difference at a 99% confidence level.

When the Burned-FMU TM data set was used for classification, the original 7 TM bands, 1 NDVI band, 3 PC bands, 3 TC bands, all 14 bands, and the four most suitable bands (TM4, TC2, NDVI, and PC3) resulted in mean accuracy ranging from 91.2 to 93.8% for the burned cover type (Fig. 5b). Band NDVI alone resulted in the lowest mean accuracy. If the lower value between producer's and user's accuracy was used for comparison, the classification with the four most suitable bands had a relatively higher accuracy, which was 93.7%, better than classifications with other bands, whose lower values of producer's and user's accuracy were 92.2, 92.1, 91.2, 91.1, and 89.4% for the original 7 TM, 3 PC, 3 TC, NDVI, and all 14 bands, respectively. By comparing Z-values at a 99% confidence level, all the six classification maps were grouped into three accuracy levels: the highest accuracy group contained maps created with 7 TM, 3 PC, and the four most suitable bands; the lowest accuracy group contained maps created with NDVI and all 14 bands; the map created with 3 TC bands was in the middle (Table 4).

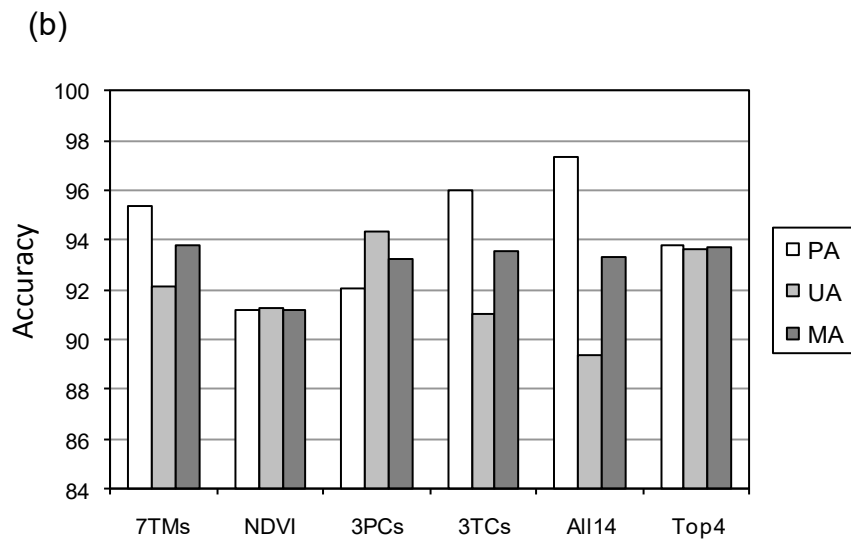
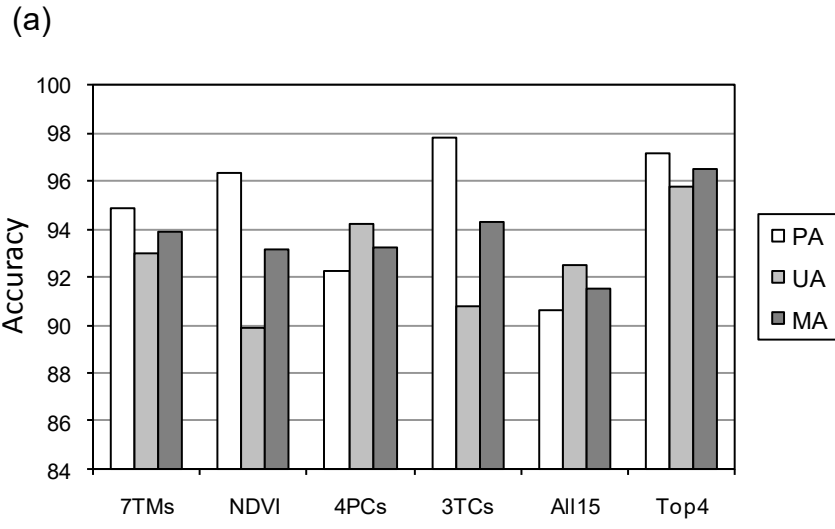


Figure 5. A comparison in classification accuracy among different band combinations derived from the KSC TM data set (a) and the Burned-FMU TM Data set (b). PA is producer's accuracy, UA is user's accuracy, and MA is the mean of producer's and user's accuracy.

Table 4: Z-values based on error matrix tables between different maps created with spectral bands derived from Burned-FMU TM data set.

	NDVI	3 PC Bands	3 TC Bands	All 14 Bands	4 most suitable bands
7 TM Bands	9.13*	0.78	2.72*	6.66*	1.85
NDVI		10.09*	6.33*	2.26	11.10*
3 PC Bands			3.54*	7.54*	1.11
3 TC Bands				3.94*	4.59*
All 14 Bands					8.54*

Note: sign * indicates significant difference at a 99% confidence level.

When all the accuracy statistics were considered, the classifications with both TM data sets had a similar trend in classification accuracy: the four most suitable bands resulted in the best maps while NDVI and the stack of all the bands resulted in the worst classifications; the fire-scar maps created with the four most suitable bands had low variation between producer's and user's accuracy; both fire-scar maps created with the original 7 TM, 3 PC, or 3 TC bands had similar combinations of producer's and user's accuracy. The classification with the KSC TM data set was generally superior to the classification with the Burned-FMU TM data set. The Z-value between the two maps created with the four most suitable bands derived from image data for KSC and burned FMUs was 15.83, much higher than the critical Z-value of 2.58 at a 99% confidence level.

Post-Classification Cleaning

Because the four most suitable bands derived from the KSC TM data set resulted in higher classification accuracy than those derived from the Burned-FMU TM data set, the procedure described with the right-hand column of Fig. 2 was the better choice. In this case, the

four most suitable bands derived from the KSC TM data set were chosen for final classification. The immediate result of image data classification with the four most suitable bands contained information about old fire scars and misclassification noise in other FMUs. To reduce noise in the fire-scar map, the resultant classification map was masked with a GIS data layer of the eight burned FMUs (Fig. 6).

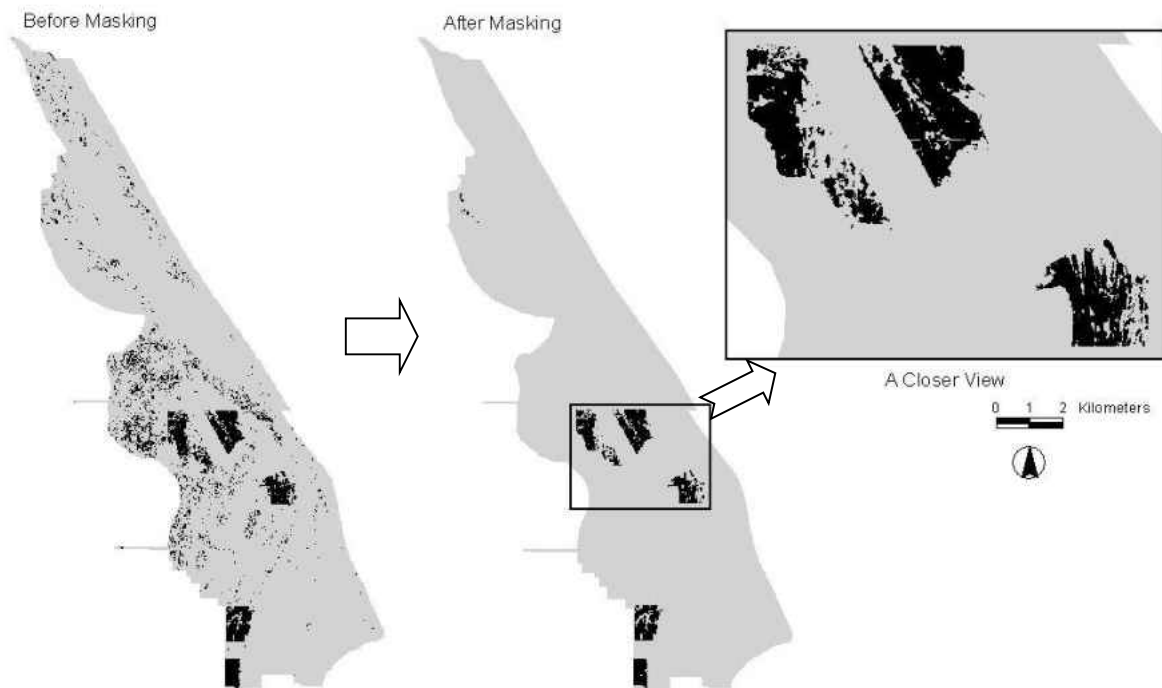


Figure 6. The reduction of classification noise through GIS masking. A comparison of before and after GIS masking with fire scars shown in black. Fire scars were classified using PC4, TM4, TC2, and NDVI derived from the KSC TM data set.

Discussion

Effects of Geographic Extent

In addition to the significant increase in classification accuracy by using the four most suitable bands for both TM data sets, there was another slight increase in classification accuracy when masked with the burned FMUs (Fig. 5). This may have to do with the fact that burned FMUs were so small in area that the local variability of the TM data could not represent the global variability of typical cover classes. A difference in geographic extent of the TM data also affects transformed PC bands. From this point of view, geographic extent of remote sensing data cannot be overlooked in image data classification.

The most effective PC bands for fire-scar mapping were not those with the highest or lowest eigenvalues. In other words, the PC band with a relatively low eigenvalue was powerful in discriminating burned from unburned areas. This is because fire scars were local phenomena and spectral variance between burned and unburned cover types in the study area accounted for a small fraction of the total data variance and did not enter the earlier components. The covariance matrix used to generate PCs is a global variability measure of the original image segment, and local variability may appear in a later component (Richards, 1986). This was exactly what happened when mapping fire scars with PC bands in this study. Due to the differences in geographic extent between the FMU and KSC TM data sets, the PCs that capture the variance between burned and unburned areas did not necessarily stay in the same order. The geographic extent of remote sensing data and its influence on band selection and classification accuracy may

explain the band selection variation of past studies, as they were conducted at different spatial scales.

During the process of assigning or recoding every spectral class into an information class, pixel responses inside and outside of burned FMUs could be visually compared to each other if the KSC TM data set was used. Such a recoding procedure is more reliable than being restricted to the burned FMUs only. This was another reason why the KSC TM data set resulted in higher classification accuracy than Burned-FMU TM.

Band Selection

Fire scars in the fire-adapted vegetation at KSC/MINWR are relatively small in terms of geographic extent but their spatial variation determines habitat suitability for the Florida Scrub-Jay (Breininger et al., 1998). Time since fire influences vegetation height and the pattern of fire determines the mosaic pattern of vegetation heights, influencing Florida Scrub-Jay demography (Breininger and Carter 2003). Minor vegetation changes can alter habitat conditions for threatened and endangered animals and plants (Schmalzer, 2003). The sensitive nature of the habitat demands a high standard for mapping fire scars at KSC/MINWR. We chose to use Landsat TM data because they are available since the mid 1980s and have suitable spatial and spectral resolution. We examined several groups of spectral bands to obtain the optimal classification. This was a different approach from fire-scar mapping with NDVI alone (e.g., Salvador, 2000) or with all the PC bands (e.g., Hudak and Brockett, 2004). Our experiment suggests that too few (e.g., NDVI alone) or too many bands (e.g., total 14 or 15 bands) were not optimal for mapping fire scars at KSC/MINWR.

Comparing individual bands and their capabilities for identifying fire scars was an effective approach for band selection (e.g., Pereira and Setzer, 1993; Pu and Gong, 2004). Classification accuracy has been used for evaluating individual bands, but image data classification is a time-consuming process. Unlike other statistical methods of feature selection, such as Transformed-Divergence (Jensen, 2004), which are used to measure how close two signatures are for different band combinations in supervised classification, the separation index or *SI* in this study is a non-parametric measure for exclusively examining how effective each individual band is for separating two classes. In discriminating burned and unburned areas, the *SI* proved convenient and dependable for band comparisons. Our results suggest that bands with high *SI* values, when combined, can result in relatively high classification accuracy. This quantitative method may have a general applicability for mapping fire scars with remotely sensed data.

It is not surprising that TM4, NDVI, and TC2 are capable of separating burned and unburned areas, because they all reflect the greenness of land surface. Although these three bands are correlated, they do not completely represent each other. Because the selected PC bands were not correlated with TM4 (Table 1&2), their roles in increasing classification accuracy may be more important than any other individual green bands.

Classification Assessment

A number of accuracy statistics or measures can be derived from error matrices (Congalton and Green, 1999) but each has unique implications (Foody, 2002). The mean accuracy in this study has a similar meaning to the Individual Classification Success Index

proposed by Koukoulas and Blackburn (2001). Normally the difference between user's and producer's accuracy for a cover type has a close relationship with the area to be estimated for that type (Shao et al., 2003). Classifications with the same mean accuracy but with a large difference between user's and producer's accuracy, have different implications in terms of area estimation accuracy for a given cover type. Because the Z-test uses all the numbers of an error matrix, it indirectly considers the variations of user's and producer's accuracy. For example, the fire-scar map created with 3 TC bands derived from the Burned-FMU TM data set was significantly different from different maps created with other band combinations, though its mean accuracy value was close to those of the other maps (Fig. 5a). An ideal fire-scar map should have high mean accuracy but low difference between user's and producer's accuracy. That explains how the fire-scar map based on the four most suitable bands derived from the Burned-FMU TM data set was superior to other maps in the FMU masking experiment (Fig. 5a). The fire-scar map based on the four most suitable bands derived from the KSC TM data set was indeed the best choice because it had the highest mean accuracy and relatively low difference between user's accuracy and producer's accuracy (Fig. 5b). Since both the fire-scar maps based on the four most suitable bands were better than those based on other bands, the combination of the most suitable bands seemed reliable in enhancing the accuracy of the fire-scar mapping even if they were correlated.

Summary and Conclusions

Both band combination and the geographic extent of remote sensing data affects the quality of fire-scar maps produced. Therefore, a reliable image processing procedure for

mapping fire scars at KSC must include four steps. Step one was to mask the TM data with the KSC boundary data layer. The resultant TM data set contains information beyond burned areas. Step two was to use the separation index (*SI*) to evaluate each individual band for its potential capability in discriminating unburned and burned areas. By comparing and sorting all the bands of interest, it was possible to select reliable bands for image data classification. Step three was to compare classifications with selected band groups derived from Landsat TM data. This helped determine the best band combinations for discriminating unburned and burned areas. Step four was to clean the classification map by masking it with the burned FMUs GIS layer. This removed all the noise outside the burned FMUs and beyond the fire-detection period, resulting in an accurate fire-scar map.

There are many options for fire-scar mapping with geospatial data. Specific mapping techniques depend not only sensor type, but also on vegetation type and fire properties (Eva and Lambin, 1998; Boyd and Danson, 2005). The comparison of various classification options in this study not only led to a reliable approach to detect detailed fire scars within the rapidly growing vegetation of this region, but also highlighted four general concerns: (1) the geographic extent of remote sensing data used for classification affects discriminative power of individual bands generated from the data and, therefore, cannot be overlooked for classification; (2) many spectral bands can be derived from remote sensing data but only a limited number of bands can lead to satisfactory results for a specific classification purpose; eigenvalues should not solely be relied on for PC band selections; (3) a classification based on too few or too many bands is a poor choice, while an optimum band combination depends on the discriminative capability of the individual bands, but not on the correlations among the bands; and (4) GIS masking is an effective method of cleaning fire-scar maps. The mask-GIS data layers can be obtained from

ground records or with coarser-resolution remote sensing data. Administrative regions, natural watersheds, or management units can be used as mask data.

This remote sensing technique will support both historic and future fire scar mapping work on KSC/MINWR as well as other locations in the southeastern United States and fire dependent systems world wide. The technique will be applied to annual Thematic Mapper imagery derived from the historic Landsat archive dating back to the early 1980's. It will also be relied upon for future fire scar mapping on KSC/MINWR. Fires in this region typically form complex mosaic patterns with enclaves of unburned fuels throughout the burned area, requiring inordinate amounts of effort to map by field survey. This remote sensing technique will provide a means to map future fire scars in an efficient and consistent manner.

This technique is most readily transferable to areas with some existing fire records documenting the date and general location of past fires. Geographic masking can be accomplished using many types of spatial tessellation maps such as FMUs (as performed here), watershed, property boundaries, or other mappable units. Future work may strive to increase available information by documenting fire intensities and mixed pixel contributions by burned/unburned fractions.

DELINEATING A MANAGED FIRE REGIME AND EXPLORING ITS RELATIONSHIP TO THE NATURAL FIRE REGIME IN EAST CENTRAL FLORIDA, USA; A REMOTE SENSING AND GIS APPROACH

Published as: Duncan, B.W., G. Shao, and F.W. Adrian. 2009. Delineating a Managed Fire Regime and Exploring its Relationship to the Natural Fire Regime in East Central Florida, USA: A Remote Sensing and GIS Approach. *Forest Ecology and Management* 258:132-145.

Introduction

The behavior of many individual fire events summed over years is collectively known as a fire regime and is defined by fire type, intensity/severity, size, return interval, seasonality, and spatial pattern (Christensen, 1985; Agee, 1993). Natural fire regimes have been altered by humans and no longer maintain many fire-dependent ecosystems around the globe. Human influences such as fuel removal, fuel fragmentation, fire suppression, and increased fire frequencies are among the principle factors altering natural fire regimes (Leach and Givnish, 1996; Cochrane, 2003; Duncan and Schmalzer, 2004; Heinlein et al., 2005). Many ecosystems are suffering from altered fire regimes (Olson and Platt, 1995; Allen et al., 2002; Odion et al., 2004), and as a result have allowed fire sensitive exotic species to thrive (Brooks et al., 2004). Fire management is now necessary as a synthetic forcing to approximate natural fire regimes (Noss and Cooperrider, 1994).

The ability of land managers to mimic natural fire regimes may be essential to sustain diverse assemblages of native fire-adapted species. Monitoring of managed fire regimes is thus important to evaluate management goals, provide information necessary for adaptive management, and compare to natural fire regimes. Remote sensing techniques are suitable for

fire monitoring in many open or crowning fire-maintained systems (Minnich, 1983; Salvador et al., 2000; Russell-Smith et al., 2003; Bowman et al., 2004; Fisher et al., 2006). Relatively new satellite fire monitoring tools such as MODIS Fire, TRMM VIRS, and ATSR-2 are superb for recent (post - 1995) fire history mapping at coarse scales (Csiszar et al., 2005; Bradley and Millington, 2006). For longer fire histories, especially when fine detail pattern information is necessary, mapping fire scars from a time series of high resolution imagery is preferred (Fuller, 2000; Bowman et al., 2003).

A managed fire regime has been in place on Kennedy Space Center (KSC)/Merritt Island National Wildlife Refuge (MINWR) since 1981. This managed fire regime includes prescribed and natural lightning fires, all of which are ultimately controlled. Text records have been maintained documenting the cause, size, and general management unit location of every known fire on these properties. Detailed fire boundary information is missing from these records and is necessary to aid effective habitat management of native fire maintained species. This pyrogenic system is home to many fire-dependent native species that have been in decline in the southeastern United States due to habitat destruction and fire regime alteration. One such species is the Florida Scrub-Jay (*Aphelocoma coerulescens* Bosc.), which is dependent on fine scale burn patterns for optimum demographic performance (Breininger et al., 2006).

In this paper our goal was to answer the following three questions: 1) Could an image processing technique developed for mapping individual fire scars (Shao and Duncan, 2007) be applied to an image time series to map/describe a managed fire regime, within a rapid re-growth pyrogenic system on KSC/MINWR and surrounding federal properties of east central Florida, USA? 2) Could we develop a method for determining the level of confidence with which each fire scar was mapped, because the historic nature of this fire regime reconstruction would inhibit

our ability to conduct a formal accuracy assessment of our maps? 3) Could we compare the results of this managed fire regime with expected spatio-temporal patterns of the natural fire regime from other published studies to assess differences and help improve fire management benefiting native fire dependent species?

Background/Study Site

The United States federal government began acquiring land in the 1950s on Cape Canaveral and in 1962 on north Merritt Island, along the east coast of central Florida. KSC covers 57,000 ha of land, which is primarily managed by the U.S. Fish and Wildlife Service as the Merritt Island National Wildlife Refuge with a smaller portion managed by the National Park Service as the Canaveral National Seashore (CNS). Cape Canaveral Air Force Station (CCAFS) is 6,475 ha and occupies the Cape Canaveral barrier island (Figure 7). After the federal government acquired the land, fires were suppressed until 1981, at which point catastrophic wildfires (due to fuel build up) became a safety and operations problem on KSC/MINWR. The first fire management plan for KSC/MINWR was developed in 1981 to reduce dangerous fuel levels and prevent future fuel build up (Lee et al., 1981; Adrian et al., 1983). The realization that natural communities were becoming degraded and concern for wildlife species led to fire being used as a tool for restoring and maintaining natural communities on KSC/MINWR (Schmalzer et al., 1994).

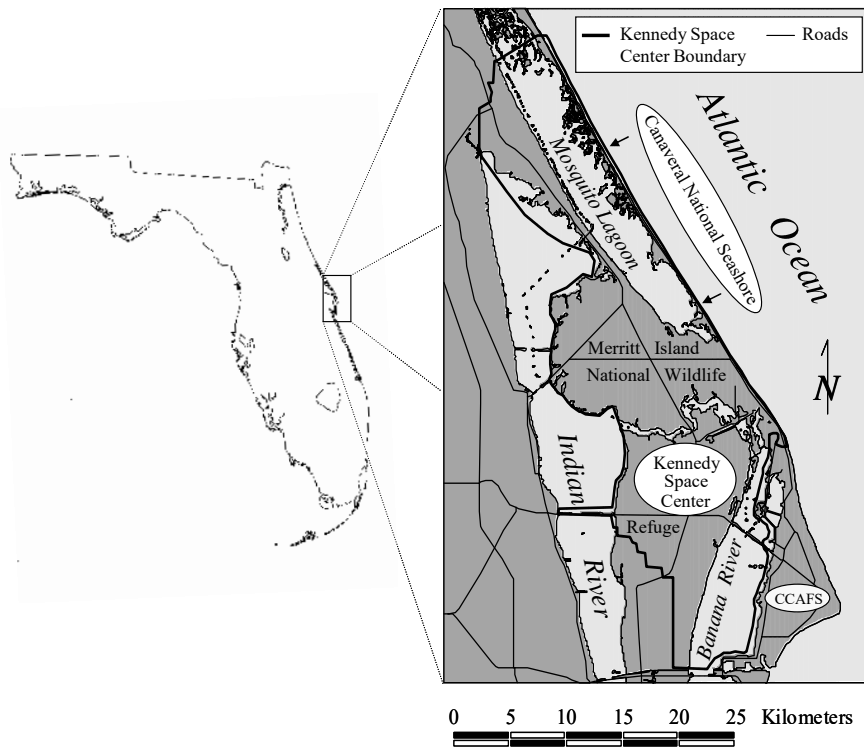


Figure 7. The geographic locations of Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station.

When referring to these properties collectively we will use the first letter from each location and shorten the name from KSC/MINWR/CNS/CCAFA to KMCC. KMCC occupies a barrier island complex covered with a diverse assemblage of fire-adapted terrestrial vegetative communities. Upland xeric sites are dominated by oak scrub vegetation (*Quercus* spp.), while mesic sites are dominated by flatwoods (e.g., saw palmetto (*Serenoa repens* (W. Bartram) Small), staggbrush (*Lyonia* Nutt. spp.), holly (*Ilex* L. sp.), and an overstory of slash pine (*Pinus elliotii* Engelm.)) (Schmalzer and Hinkle, 1992a; Schmalzer and Hinkle, 1992b). Because the landscape is comprised of relict dunes forming ridge-swale topography, there are interleaving swale marshes and hammocks on hydric soils between the xeric ridges. The swales are

dominated by cordgrass (*Spartina bakeri* Merr.) and bluestem (*Andropogon* L. spp.), while the hardwood hammocks are dominated by live oak (*Quercus virginiana* Mill.) and laurel oak (*Quercus laurifolia* Michx.) and have a structure that is much less flammable than surrounding communities. Coastal strand occurs just inland of the coastal dunes and is a shrub community with saw palmetto, sea grape (*Coccoloba uvifera* L.), wax myrtle (*Myrica cerifera* L.) being dominant (Schmalzer et al., 1999). An extensive network of industrial infrastructure and facilities supporting launch operations are present.

Many of KMCC's species of special concern are directly dependent on habitat structures maintained by fire. This is the case for the Florida Scrub-Jay; it is listed as a federally threatened species and is considered an indicator of suitable habitat conditions for many other species. Suitable Scrub-Jay habitat includes areas with sandy openings, sufficient scrub oak cover, little or no tree cover, and shrub heights of 1 to 2 meters (Woolfenden and Fitzpatrick, 1984; Breininger et al., 1995; Duncan et al., 1999). KMCC is one of the three remaining population cores for the Florida Scrub-Jay (Stith et al., 1996).

On these federal properties, arson fire is generally not part of the contemporary fire regime. This is because much of the area within this study is inside secured boundaries restricting human ignitions to prescribed fires only. In contrast, arson and escaped incendiary fires are now a major component of many contemporary fire regimes in the southeastern United States (Genton et al., 2006). For this reason, the federal properties in this study are ideal for studying a managed fire regime because it is not confounded by unplanned anthropogenic wildfire.

Methods

Burn scar classification

A time series of multispectral satellite imagery was used to map fire scars (burned areas identifiable on imagery by bare ground and dark charcoal/ash appearance). The image data consists of multiple bands collected in the visible and infrared spectral wavelengths that are used for classification and discriminative purposes. Two images a year were used to maximize the number of fire scars mapped, due to the rapid vegetation growth rates following disturbance on KMCC (Schmalzer and Hinkle, 1992b; Schmalzer, 2003). A total of 40 satellite scenes (pre-processed with geometric and radiometric correction) were used dating from 1984 to 2005, 39 were Landsat Thematic Mapper (TM) images and 1 was a SPOT image needed to fill a gap in TM availability (Table 5). Using the first image from 1984, we were able to map some of the fires that occurred in 1983. Because there was only one SPOT image we employed a conventional unsupervised classification (Jensen 2005) on the original bands and used the MINWR fire records to select the best classified image. The image processing technique that was used to classify fire scars in each individual Landsat TM scene was more rigorous and followed Shao and Duncan (2007). This source should be consulted for details on the technique, including accuracy assessment information.

Table 5. Multispectral satellite imagery used to map fires on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Landsat Thematic Mapper (TM) scenes are path 16, row 40 with less than 10 percent cloud cover and pre-processed to level 1T (geometric and radiometric correction). A single Satellite Pour l’Observation de la Terre (SPOT) scene was used to fill a gap in landsat coverage with the K/J designation 536/280 and pre-processed to level 2A (geometric and radiometric correction).

Image Date (YYYY MM DD)	Image Type	Satellite #	Image Date (YYYY MM DD)	Image Type	Satellite #
1984 05 14	TM	5	1995 12 07	TM	5
1984 11 06	TM	5	1996 03 12	TM	5
1985 01 09	TM	5	1996 12 09	TM	5
1985 05 17	TM	5	1997 01 26	TM	5
1986 04 02	TM	5	1997 06 19	TM	5
1986 08 24	TM	5	1998 03 02	TM	5
1987 04 21	TM	5	1998 07 24	TM	5
1987 12 01	TM	5	1998 12 31	TM	5
1988 04 07	TM	5	1999 01 16	TM	5
1988 12 19	TM	5	1999 09 05	TM	5
1989 04 26	TM	5	2000 01 11	TM	7
1989 11 20	TM	5	2000 04 05	SPOT	4
1990 10 06	TM	5	2001 04 01	TM	5
1991 08 06	TM	5	2001 08 25	TM	7
1992 05 04	TM	5	2002 02 17	TM	5
1993 01 31	TM	5	2002 04 22	TM	5
1993 07 10	TM	5	2003 01 19	TM	7
1994 05 26	TM	5	2003 05 27	TM	7
1994 11 02	TM	5	2004 05 05	TM	5
1995 03 26	TM	5	2005 0 305	TM	5

This classification routine consists of the following general steps:

(1) Each satellite scene was rectified to State Plane NAD83 Meters to be compatible with existing spatial data and so it could be clipped to the geographic boundaries of the federal properties (See Shao and Duncan 2007 for complete discussion of the influence of geographic area on classification results);

(2) A nonparametric separation index (SI) was used to select the best bands for classifying burned areas. The ideal bands have burned and unburned areas separated by their spectral signature, making them unique and easy to classify, hence the separation index. For each band, histograms of pixel spectral values were computed for burned and unburned areas as derived by visual interpretation and MINWR fire records. Areas were derived by knowing the image pixel size (e.g., Landsat TM is 30 meter) and frequency from the histograms. To avoid bias caused by the burned or unburned cover type with larger area, the overlap area was divided by the area of the smaller cover type. SI is calculated as follows:

$$SI_{i,j} = 1 - \frac{A_{i,j}}{\text{Min}(A_i, A_j)} \quad (3)$$

where, $SI_{i,j}$ is separation index between cover types i and j ($0 \leq SI_{i,j} \leq 1$), $A_{i,j}$ is the overlap area between cover types i and j , A_i or A_j is area for cover type i or j , and Min represents the minimum function (smaller number between A_i and A_j).

The higher the $SI_{i,j}$ value, the more discriminative power the band has to separate the two cover types. All the bands with an $SI_{i,j}$ value greater than 0.1 were accepted for classification. Bands with SI values > 0.5 were designated the most suitable bands. One TM band (TM4 – near infrared), and three transformed bands (Normalized Difference Vegetation Index, Principal Component 4, and Tasseled Cap 2) (Jensen, 2005) were collectively used for classifying burned from unburned areas;

(3) The unsupervised classification algorithm ISODATA was employed because it is a consistent and repeatable classification method suitable for use on an image time series. The

number of spectral classes was 20, the number of iterations was 20, and the convergence threshold was 0.99 for all the classifications with different band combinations. The 20 spectral classes were then manually recoded into two information classes, burned and unburned, to form the classified fire-scar maps; and,

(4) Following each classification, the fire-scar maps were masked with a GIS data layer of the burned fire management units (FMUs). This masking process, called post-classification cleaning, took advantage of the MINWR fire records and masked out any unburned FMUs. This step removed commission errors outside burned FMUs and helped produce a high quality fire-scar map.

GIS database

After the fire scar maps were visually inspected and identified problems were rectified, the final thematic maps were converted from ERDAS Imagine (Leica Geosystems 2008) into ArcGIS GRID format (ESRI 2008), and then to a vector format. Attribute information such as burn date, FMU, type of burn (prescribed vs. natural), and age (time since last burn), were added to the fire scar maps. Because MINWR maintained a database containing both natural and prescribed fires on KMCC since 1977, it was possible to assess and label fire boundary confidence by comparing visual evidence of burn scars on the satellite images and the classified burn scars with the MINWR fire records. If there was agreement between all forms of evidence, the burn scar was labeled with a high confidence value, and if not, the burn scar was labeled with a lower value of confidence. The confidence value (CV) ranged from 1 to 4 and was also added to the fire scar maps (Figure 8). A CV of 1 indicates low confidence in fire scar boundaries with

a value of 3 or 4 indicating high confidence in mapped fire boundaries. This is a similar application of classifying landcover confidence (Liu et al., 2004), but modified for application to mapping fire scars. Results are presented with confidence level information, allowing the selection of mapped features based on the confidence in which the fire scars were mapped. The confidence values are important because they provide a means for documenting mapped feature quality despite the inability to conduct a formal accuracy analysis due to the historic nature of this study.

The time difference between each fire date and the date of the closest image acquired after that fire (used to map that fire scar) was recorded in months and called the delta burn date. This was done for each recorded fire using the MINWR fire database and combined with the confidence item information. We wanted to know how fast the rapidly growing vegetation in this region takes to obscure fire scars, indicating how many images are required per year to map high quality (high confidence) fire scar boundaries. Insight into this question could be gained by exploring how the mapped confidence decreased with increased time since burn (delta burn date). In addition, each fire scar was categorized into one of three dominant landcover types (wetland, flatwoods, or scrub) to determine how re-growth rates of each landcover type influences the ability to map high quality fire scar boundaries.

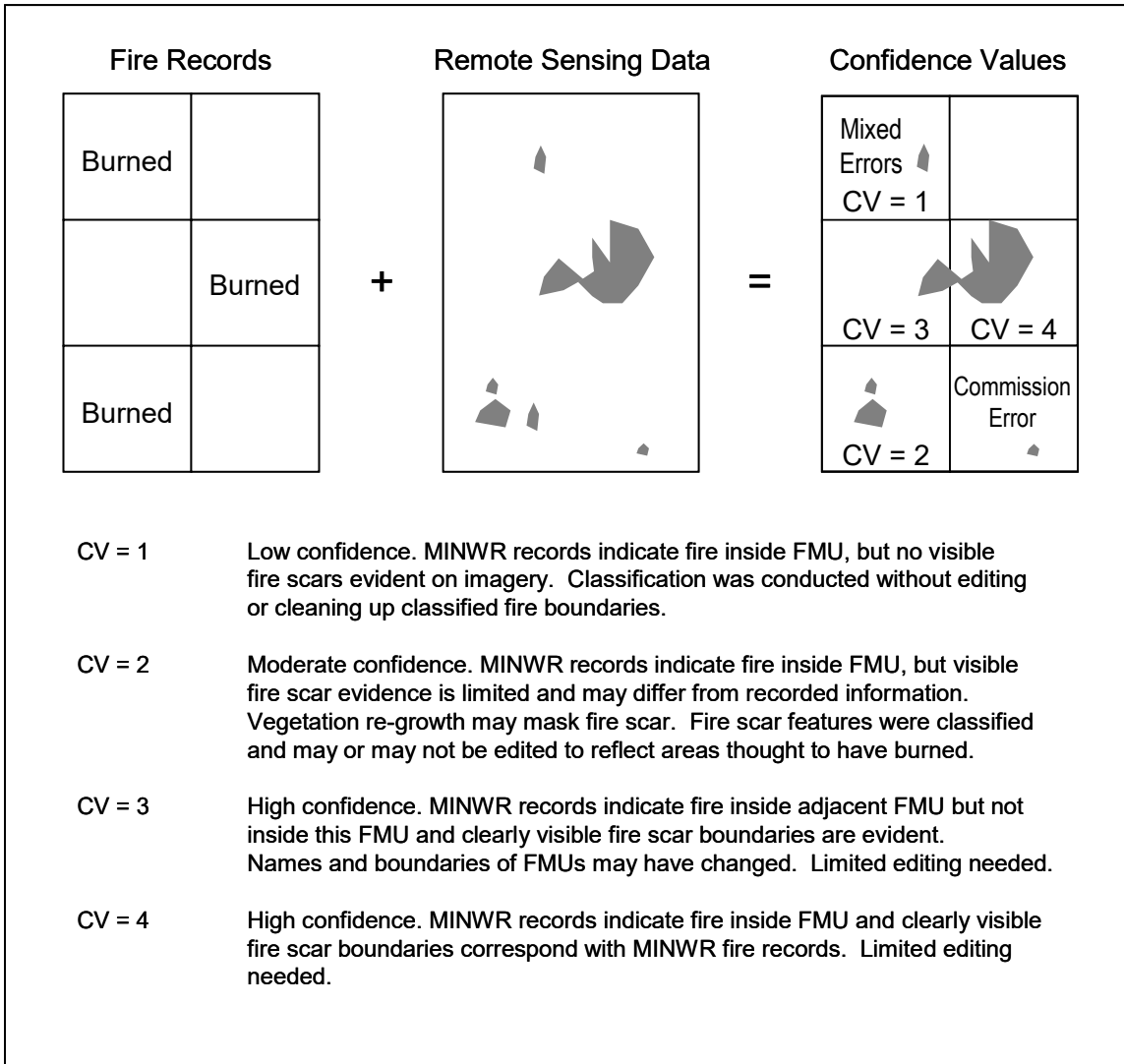


Figure 8. The process of determining and labeling fire boundary confidence values (CV). The diagram on the left symbolizes the fire records kept by Merritt Island National Wildlife Refuge (MINWR). The diagram in the middle represents fire scars mapped from satellite imagery. The diagram on the right shows how the information is used to label mapped confidence values.

Landscape age, landscape fire frequency, and dominant burn season maps were created in the GIS. An Arc Macro Language program was written to combine all of the individual fire boundary maps into a single GIS data file. Burn date attribute information was exported to Microsoft Access (Microsoft 2008) for each burn polygon (record) in the database. The season of burn was tallied and then the attribute information was appended back to the GIS database where a map showing the dominant burn season (most frequently burned season) for each area was produced. Seasons were defined so that the months of December, January, and February comprised Winter, the months of March, April, and May comprised Spring, the months of June, July, and August comprised Summer, and the months of September, October, and November comprised Fall.

To analyze the relationship between annual fire area and drought variation, burn area by year, month, season, and drought data were organized in Microsoft Excel (Microsoft 2008). Statistical analysis was performed in the statistical software package, SPSS (SPSS Version 12.0 2008). The drought information used was the cumulative severity index (CSI) or Keetch-Byram Drought Index (Keetch and Byram, 1988). These data were recorded by MINWR personnel for 1995 to 2004, excluding 1996. The CSI is a cumulative algorithm for estimating fire potential from meteorological inputs such as daily maximum temperature, daily total precipitation and mean annual precipitation. The CSI daily values were averaged by month for statistical analysis.

Results

Mapped confidence and fire boundary degradation

The delta burn date values were the smallest for wetlands and largest for scrub landcover types (Table 6). This trend was the same for the delta burn dates with CVs of 3 and 4. There were 24 fire scars labeled with a confidence greater than 3 and a delta burn date period greater than six months (these were the largest delta burn dates and had the highest confidence values). All except one of these fires were growing season fires indicating that growing season fire scars may have a longer residency time on the landscape making them easier to map using remote sensing. The growing season varies for each species but the core growing season for dominants in this system is from April through early October.

Table 6. Delta burn date statistics for fire scars mapped between 1983 and 2005 on KMCC, Florida. Delta burn date is the time difference in months between a fire and the next image in time series (after that fire) used to map the burn scar. Confidence values of a) 1 through 4 and b) 3 through 4.

(a)

Cover type	Mean	Median	Minimum	Maximum
Wetlands	3.0	2.0	1	11
Flatwoods	3.7	3.0	1	10
Scrub	4.0	3.0	1	10

(b)

Cover type	Mean	Median	Minimum	Maximum
Wetlands	2.3	2.0	1	6
Flatwoods	3.9	4.0	1	10
Scrub	4.0	3.0	1	10

Seasonality/Area/Size managed fire regime elements

A total of 54,175 ha were mapped as burned between 1983 and 2005. Of that total, 48,601 ha were mapped as burned with a $CV > 1$. Only 10 percent of the mapped burn area had a $CV = 1$. The amount of area burned peaked in 2003 for all confidence values and peaked in 1997 for $CV > 1$, with reduced amounts of burned area in 1999 and 1990, respectively (Figure 9). Area burned peaked in the month of November with the lowest amount in October (total can be found by taking the average multiplied by number of years = 21) (Figure 10). Annual variability in monthly area burned was generally low, with variability being greatest in November, the month with the highest average and total burn area. Area burned reached a maximum in the winter season and a minimum in the spring for all CVs and a minimum in the summer for $CV > 1$ (Figure 11). Annual variability in season burned is very low with uniformly small standard error bars.

The CSI values for each year were highly variable (Figure 12, A-I). The monthly mean for all years indicated that the CSI peaked in May and reached a low in October (Figure 12, J). April is typically the start of the spring dry period (Mailander 1990) so we investigated the relationship between April drought index and area burned. Total area burned and CSI for April of each year (1995, 1997-2004) were normally distributed (Shapiro-Wilk test, $P = 0.598$, $P = 0.719$) and negatively correlated ($r = -0.693$, $P < 0.038$).

Areal extents for single fires had a mean of 198 ha, a median of 112 ha, a minimum of 0.73 ha, and a maximum of 1,324 ha for all CVs. For CVs > 1 , the mean was 209 ha, the median was 126 ha, the minimum was 1.26 ha, and the maximum was the same at 1,324 ha.

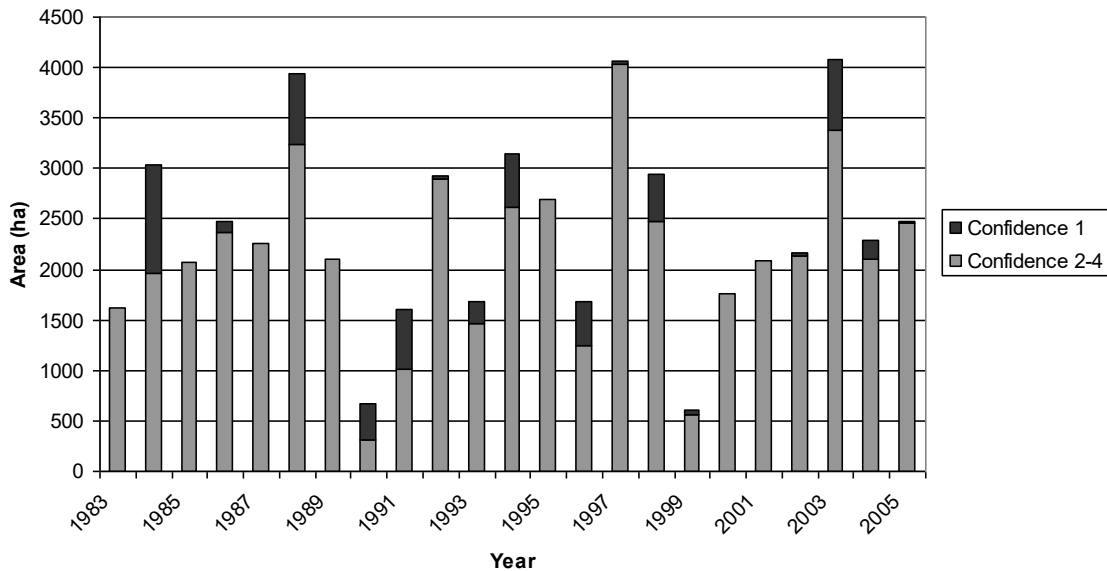


Figure 9. Mapped burn scar area by year for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Areas were summarized by confidence values 1 and 2 through 4.

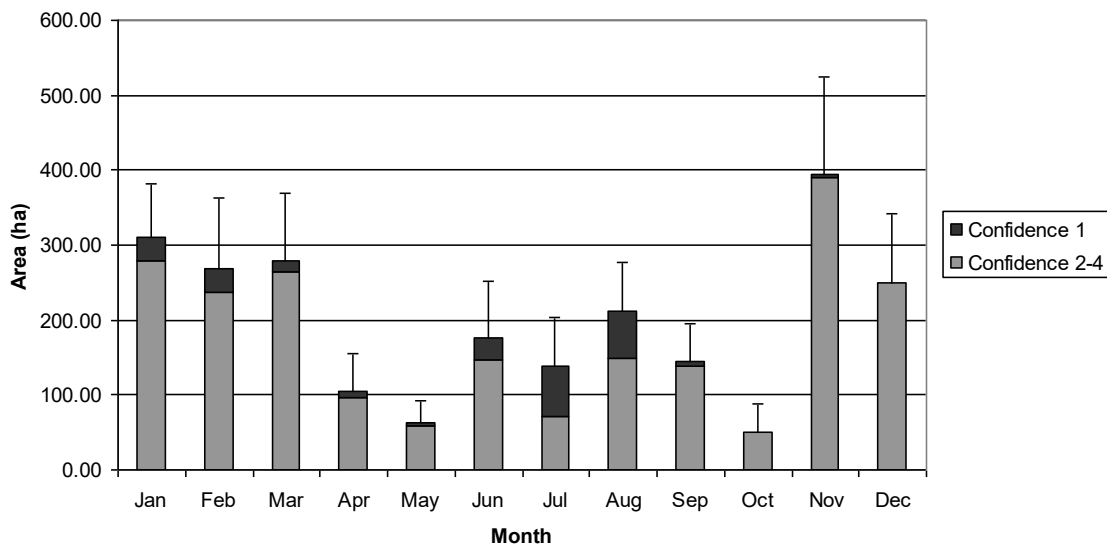


Figure 10. Annual average burn area by month for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Winter was comprised of Dec., Jan., and Feb.; Spring was Mar., Apr., May; Summer was Jun., Jul., Aug.; and Fall was Sep., Oct., Nov. Areas were summarized by confidence values 1 and 2 through 4 for the period of 1984-2004. Error bars represent standard error for confidence values 1 through 4.

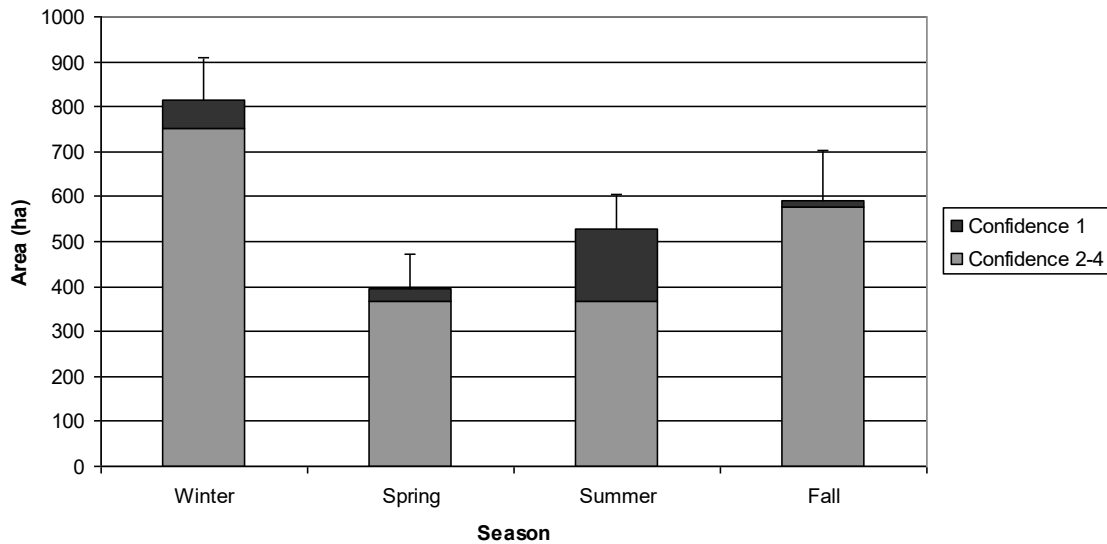


Figure 11. Annual average burn area by season for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Winter was comprised of Dec., Jan., and Feb.; Spring was Mar., Apr., May; Summer was Jun., Jul., Aug.; and Fall was Sep., Oct., Nov. Areas were summarized by confidence values 1 and 2 through 4 for the period of 1984-2004. Error bars represent standard error for confidence values 1 through 4.

Frequency/Return interval managed fire regime element

The mean fire frequency was 12 fires per year (274 total fires/23 years), the minimum was four fires per year, and the maximum was 24 fires per year for all confidence values. For CVs > 1, the mean fire frequency was 10 per year (233 total fires/23 years), the minimum fire frequency was one per year, and the maximum was 19 per year. Fire frequency peaked in 1997 and the low was in 1990 for years with a complete burn record (Figure 13).

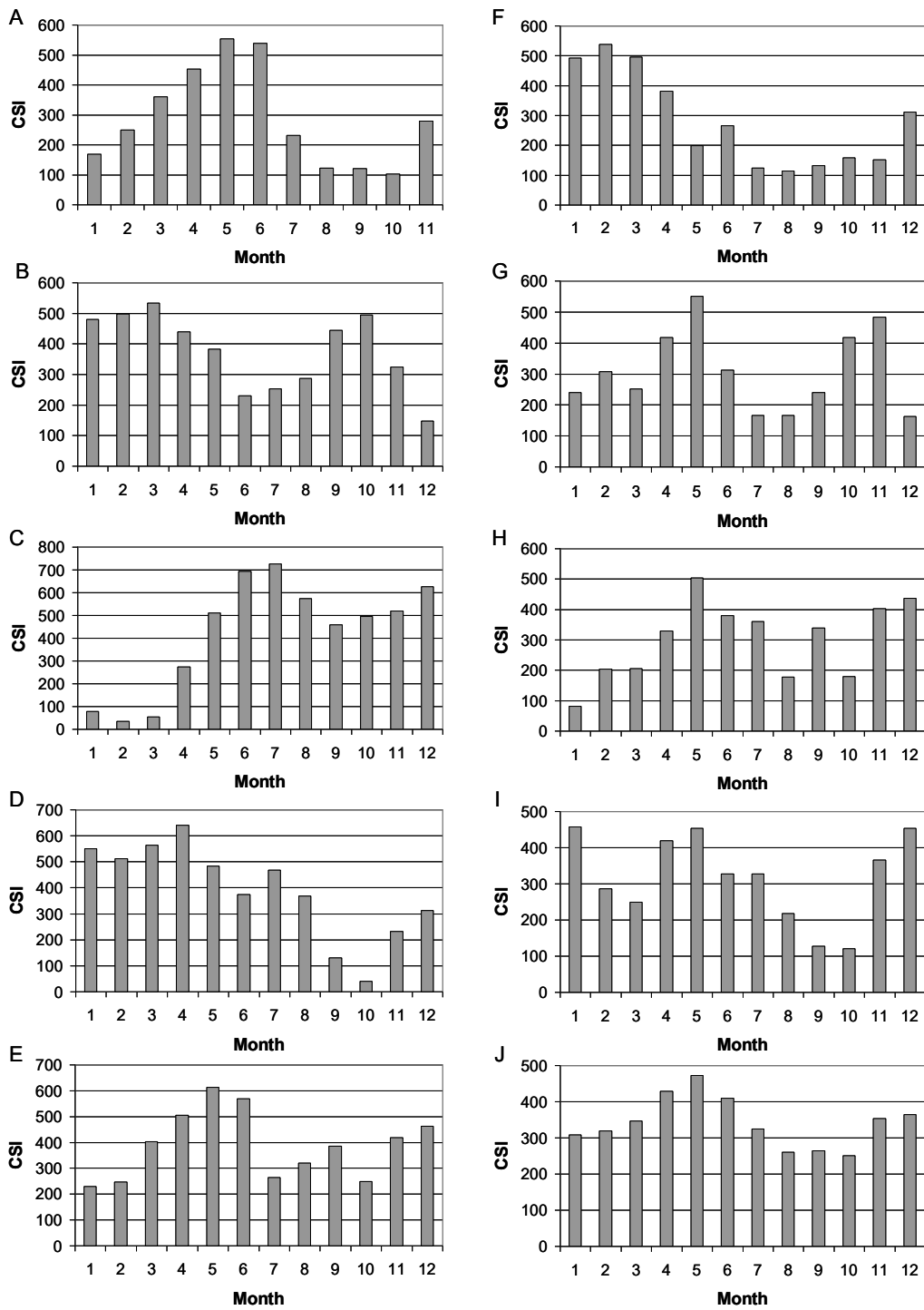


Figure 12. Cumulative Severity Index (CSI) drought data presented by monthly average. Drought index for A) 1995, B) 1997, C) 1998, D) 1999, E) 2000, F) 2001, G) 2002, H) 2003, I) 2004, and J) monthly average for all years.

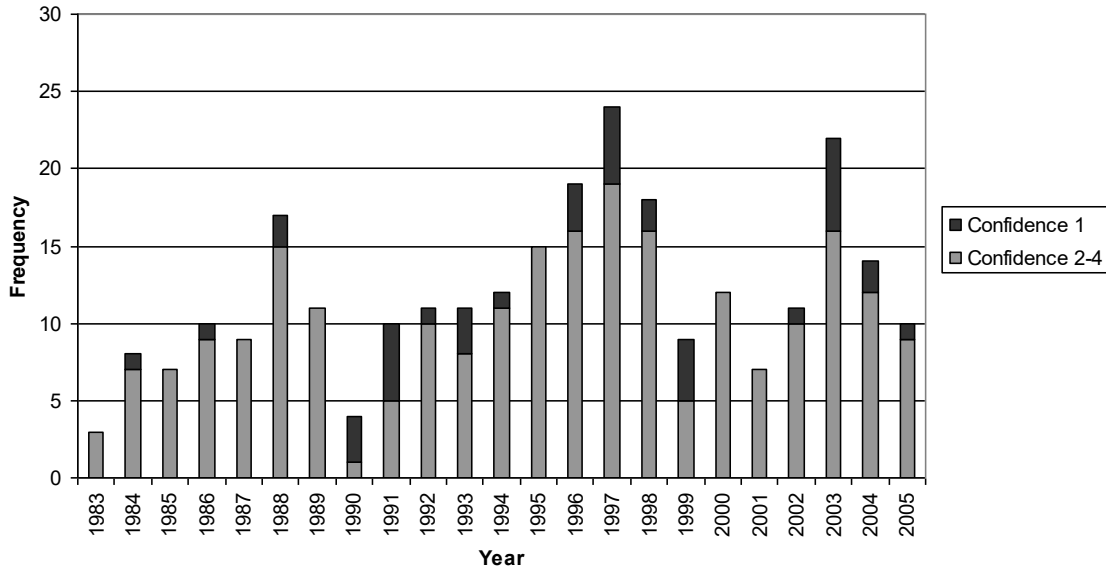


Figure 13. Mapped burn frequency by year for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Frequencies were summarized by confidence values 1 and 2 through 4.

The fire cycle is defined as the amount of time needed to burn an area equal to the study site, in this case, 27,500 ha (area of open water excluded). The fire cycle (fire rotation) at KSC/MINWR, excluding CCAFS and CNS, was 12 years for all CVs and 13 years for CVs > 1. Because the fire cycle is measured in years, the initial year (1983) of study was excluded from the calculation, because the available satellite imagery did not allow mapping of all fires for that year. The calculation started with 1984 and each annual burn total was added until the flammable area of the study site (27,500 ha) was reached, the number of years added became the fire cycle. The fire cycle was very similar to the return interval of 11.5 years for all confidence values and 13 years for CVs > 1. The return interval is calculated by dividing the upland

flammable area (27,500 ha) by the average area burned each year (2,393 ha). The same calculation was followed for CVs > 1 (2,120 ha).

Spatial pattern managed fire regime element

The landscape mosaic maps cover 21,528 ha for all CVs and 20,659 ha for CVs > 1. We present the confidence maps 2 through 4 in this paper because they represent areas that we are certain burned. Recent burn categories are prevalent on the age class mosaic map and tend to occur in large blocky polygons due to the burns being conducted in management units with linear boundaries (Figure 14). The age mosaic map has a mean polygon size of 2.65 ha, a minimum of 0.002 ha, and a maximum of 887 ha. The majority of the burned area is in the young age classes (Figure 14, histogram inset). The age mosaic map also makes it evident that fire has been excluded from much of CNS and the majority of CCAFS.

Fire frequency was manifested in much finer scale patterns than the age mosaic map and there is a single fire frequency hot spot that burned seven or eight times (Figure 15). The frequency mosaic map is a combination of the 233 fires that occurred between 1983 and 2005 with CVs > 1. This map has a mean polygon size 0.90 ha, a minimum of 0.002 ha, and a maximum of 222 ha. The majority of area on this landscape belongs to the low frequency categories (Figure 15, histogram inset). Winter season burns were prominent (Figure 16). The multiple burn season category covered the largest area, with the smallest being the spring season (Figure 16, histogram inset).

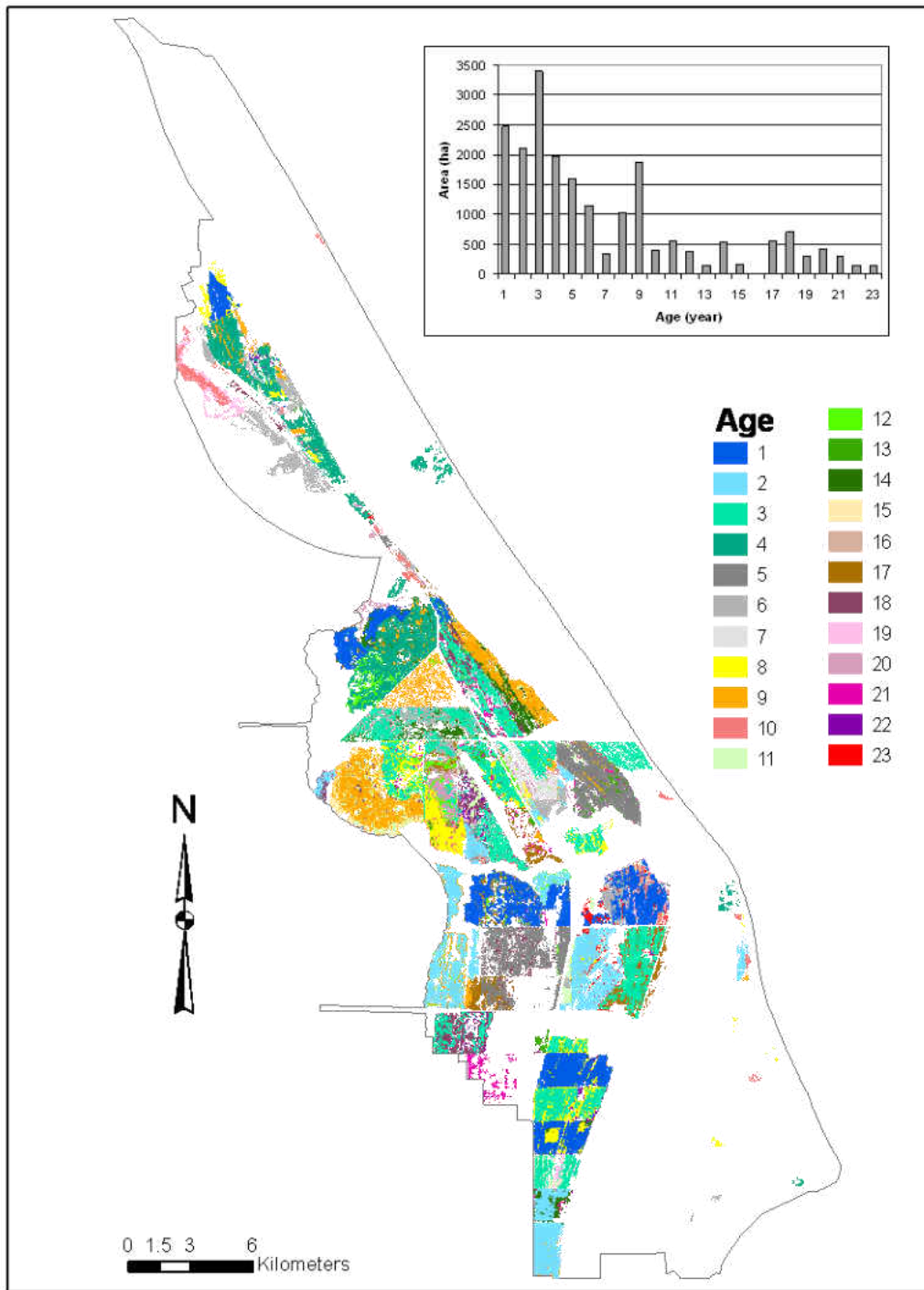


Figure 14. Landscape age mosaic map and associated area (inset) for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Age is the time since last burn, initialized from 2006, the year the mapping was complete. Areas shown are for confidence values greater than one.

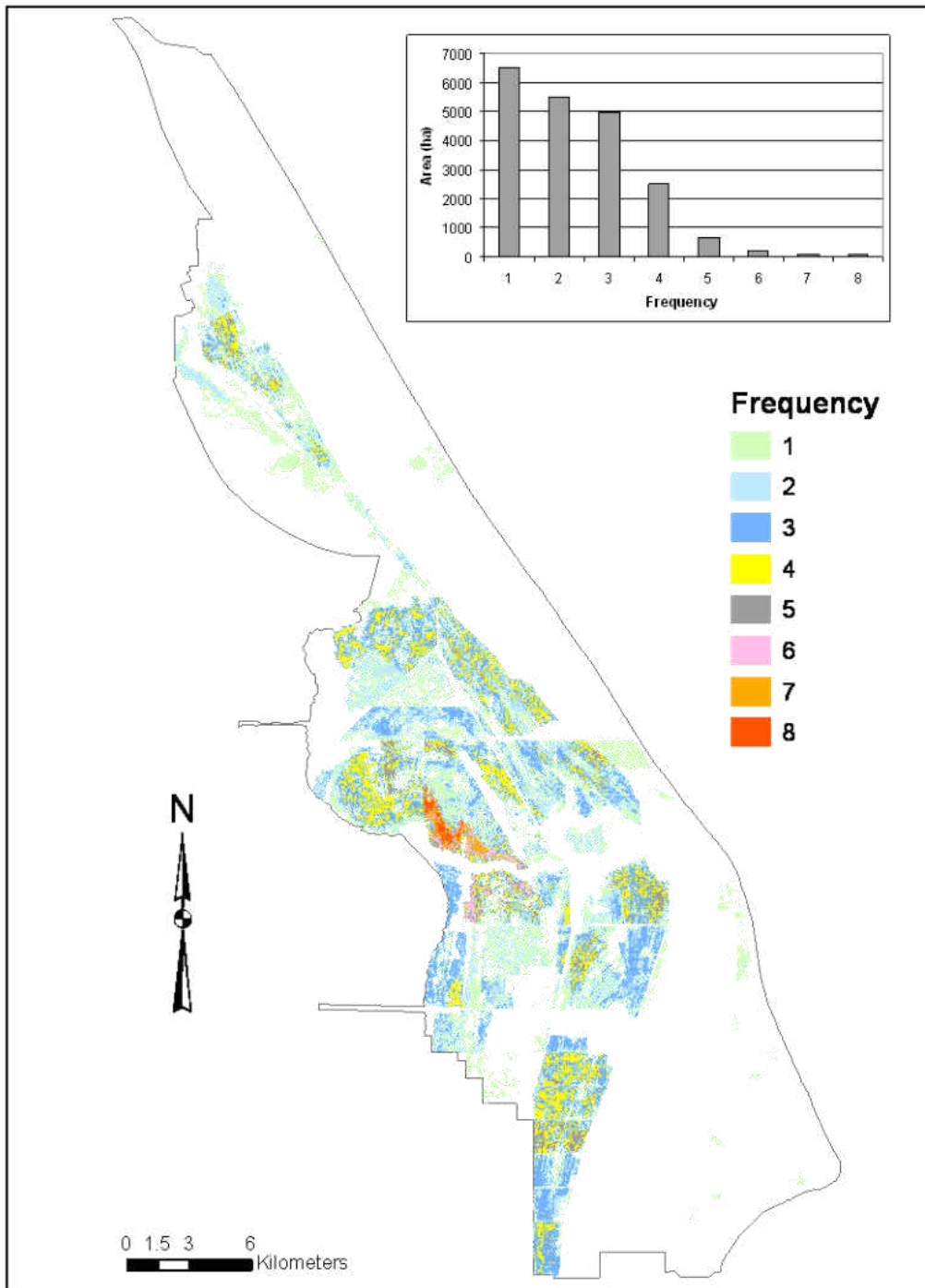


Figure 15. Fire frequency map and associated area (inset) for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Frequencies derived by overlaying all mapped fires with a confidence value greater than one and summing the number of times each area burned.

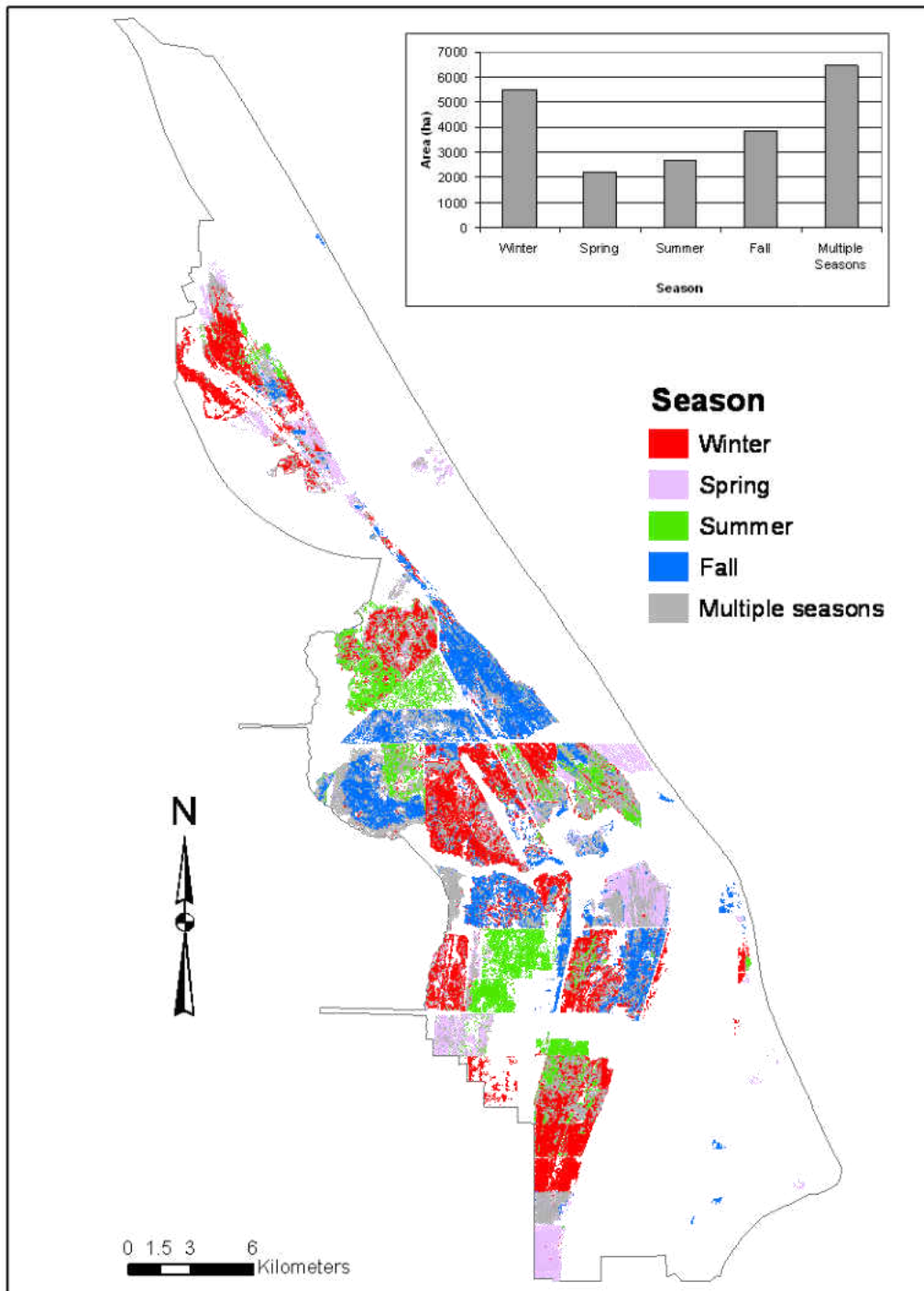


Figure 16. Dominant burn season map and associated area (inset) for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station. Areas shown are for confidence values greater than one.

Discussion

Mapped confidence and fire boundary degradation

Due to the rapid vegetation growth rates, we did not know how many images would be needed annually to guarantee that we could map every fire that occurred in our study. Experience dictated that one a year would not be suitable to map accurate boundaries so we acquired two (one spring and one fall) each year. Because the time gap between images was not always exactly six months apart (some were longer), it allowed us to explore the limits of our classification technique to delineate high confidence fire scar boundaries after time intervals exceeding six months following fire. The confidence values helped provide guidance on mapping quality (high confidence) fire scar boundaries and their degradation with time since burn. We tested the outer limits of detectability, for example, using our first image in the series, we tried to map fires as far back into 1983 as possible and lost the ability to detect any fire scars occurring eleven months prior to the date of image acquisition. Getting the optimum number of images in series is important so that an ideal balance can be created between reducing imagery costs, minimizing classification effort, and maximizing the quality of fire regime reconstruction. If our primary objective was to map fire scars in marshes, than we would need a higher number of annual images, likely a minimum of three. We conclude that for general mapping of fire scars, two images a year spaced about six months apart, acquired in the spring and fall is reasonable in relation to the tradeoffs discussed above. The number of images may be dependent on the time of year also, for example, to map marsh fire scars it might be necessary to have images every two months during the growing season but further apart during other times of the

year. More study may be required to truly optimize the number of images in this system or any other.

Using the confidence information, we determined that the most persistent fire scars were left by growing season fires. These fires had the largest delta burn dates and this may signify that growing season fires take a longer time to reestablish vegetative cover following disturbance. This makes sense as the large flush of leaves occur at the beginning of the growing season (generally late March) prior to most of these fires and then the plants are dormant in fall/winter.

Comparison of managed and natural fire regimes

Seasonality/Area/Size fire regime elements

Current theory derived from empirical evidence holds that most burning under the natural fire regime occurred during the early growing season (April-June) in this region (Slocum et al., 2003; Platt et al., 2006). Large fires would occur at this time of year because fuels were dry, ground water levels were low, and lightning frequencies were relatively high simultaneously. The April-June period is the maximum in the mean rain-free interval and minimum in mean ground water level for this region (Mailander, 1990; Schmalzer and Hinkle, 1990; Platt et al., 2006). Limited convective storm activity begins during this time, providing lightning activity but not yet depositing large quantities of rainfall. These factors created ideal conditions for large, extreme fire events during late spring/early summer in this region. This was particularly

true during La Niña periods that magnified dry early growing season periods (Harrison and Meindl, 2001; Beckage et al., 2005).

The largest fire recorded in this present study was 1,324 ha during the La Niña period in June of 1998 ignited by lightning. This fire would have burned a much larger area if it were not controlled. This fire burned across many fire lines and consumed nearly all fuels in its path before it was brought under control (Breininger et al., 2002). Fire modeling shows that large, extensive fires likely occurred across this landscape before fragmentation was prevalent (Duncan and Schmalzer, 2004).

The negative correlation of April CSI and total acreage burned indicates that under the managed fire regime the opposite of the natural system is occurring with the largest acreages burning when April CSI values are low. April is typically the first month of the dry season, and if April is extremely dry, this will limit prescribed burning until appreciable rain occurs. During periods of drought (high CSI), area burned declines and during wet periods (low CSI) area burned increases. Under the managed fire regime, November is also the month of maximum area burned annually, and winter is the season that most area is burned.

The influence of burn season has been investigated in some of the fire adapted communities of the southeast and these results have implications for survival of many fire dependent species in this ecosystem (Hiers et al., 2000; Liu et al., 2005; Brewer, 2006). Generally, burn season has a larger influence on the abundance of seeding species than resprouting species in this region. Burn season influences flowering and hence seed generation of wiregrass (*Aristida stricta* Michx.), an important foundational species supporting fire in the understory of longleaf pine and flatwoods communities (Outcalt, 1994; Mulligan and Kirkman,

2002). Burn season was found to have little effect on post-fire recovery of resprouting Florida scrub species in the flatwoods communities on KSC/MINWR (Foster and Schmalzer, 2003).

The influence of burn season is clearly important depending on the ecosystem and the species within them. Fire is not the only seasonal natural phenomenon influencing ecosystem structure. Fires followed by flooding produce unfavorable conditions for pine and palm establishment (Platt et al., 2006). Fire intensity is also an important factor that influences the pattern of shrub abundance (Thaxton and Platt, 2006). We mapped fire presence/absence in this study, but it may be possible to map fire severity from Landsat TM data as it has been achieved in other ecosystems (Patterson and Yool, 1998; van Wagendonk et al., 2004; Duffy et al., 2007; Stow et al., 2007; Wimberly and Reilly, 2007).

The annual area burned and fire frequency (Figures 9 and 13) show a cyclical nature by rising and falling within an 8 to 10 year pattern. When El Niño and southern oscillation (ENSO) events are superimposed on these it appears that there may be a relationship between them (Figure 17). Area burned and fire frequencies from managed fires tended to increase during or immediately after El Niño events and declined during or immediately after La Niña events. The variability in lag time between the onset of sea surface temperature changes, climatic response and fire management action made determining the specific relationship between ENSO events and area burned difficult for the relatively short duration of this study.

The combination of drought and lightning determines the seasonality of the natural fire regime in this region (Beckage *et al.* 2005; Slocum *et al.* 2007). The variability of the CSI data suggests that the availability of a natural ignition source (lightning) is the timing mechanism and the key to the seasonality of the natural fire regime. The highest mean CSI is reached in May and the lowest value is reached in October. This result backs the findings in the literature. The

variability found in the individual years however, suggests that because drought values can be high during just about any month within any given year, the critical factor is lightning availability, creating a coincidence of both. The CSI drought index considers rainfall, temperature, and ultimately soil moisture (Keetch and Byram, 1988), so when CSI values approach 600 it is very likely that a fire will ignite given an ignition source. The CSI data for 1998 has both the lowest and highest CSI values of any year in this study. This year was known for its rapid turn around from El Niño to La Niña and the outbreak of wildfires during the summer of this year due to the drought and “dry” lightning strikes (Pye et al., 2002).

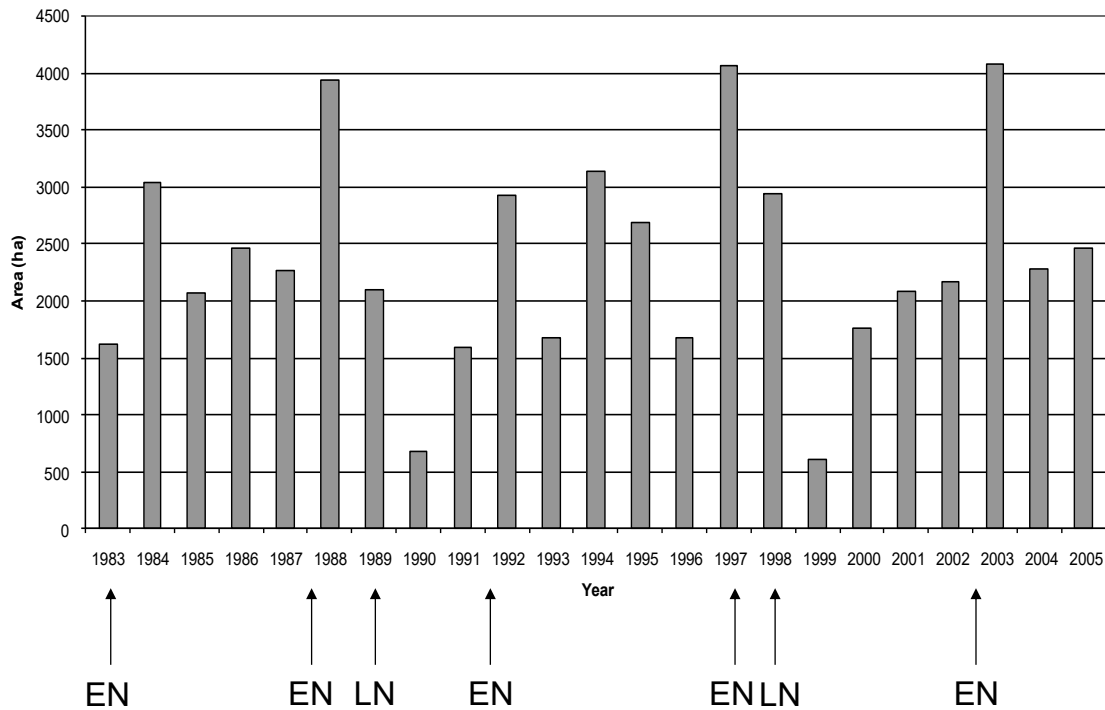


Figure 17. Burned area by year with El Niño Southern oscillation events superimposed. El Niño events are indicated by EN and La Niña events are indicated by LN. Areas shown are for all confidence values.

Frequency/Return interval fire regime element

The fire return interval and fire cycle indicate relatively frequent managed fire. Estimated fire return interval ranges in Florida for mesic flatwoods are from 1 to 8 years and 8 to 25 years for scrubby flatwoods (FNAI & DNR 1990). These communities are dominant in our study area, supporting our fire cycle and return interval values. Fire return interval information can be used to compare the difference between and within systems for both natural and contemporary fire regimes (Odion and Hanson, 2008), but it is important to get dependable return interval values into the literature to facilitate comparison.

Spatial pattern fire regime element

Burn pattern is also important and is influenced by season (Slocum et al., 2007). Fuel connectivity is higher during the early growing season, particularly during La Niña (Beckage et al., 2005) when it is relatively hot and dry, leading to extensive hot fires. Naturally ignited late growing season fires tend to be patchy and small relative to fires during the spring drought. This is the period of highest rain fall, and fuels are generally saturated and do not burn as readily. High hydroperiod marshes are full of water at this time and influence burn pattern in the coastal ridge-swale topography present at KMCC.

The potential exists for a positive feedback cycle to occur between invasive exotic species and an altered fire regime (Vitousek, 1990; Brooks et al., 2004). Once exotics are present, it is possible that they gain an advantage over native species through an altered fire regime. With the decline of native foundational species which historically supported natural fire

regimes a negative feedback cycle is created or reinforced (Leach and Givnish, 1996; Outcalt et al., 1999; Schmalzer and Adrian, 2001). Burn season and fire frequency are important elements of any fire regime that may influence which species are successful. The dominant burn season map is useful to look for potential species selection bias that may be introduced by a managed fire regime based on burn season and frequency. This dominant burn season map is most useful when the link between fire frequency, fire season, and species demography are known.

The landscape age map has the majority of its area in the young age classes as new fire scars over burn the old ones (Figure 14, histogram inset). There is a spike in area that is 9 years old, having not burned since 1997. There are many small areas that have not been burned for longer time periods. These are modern fire refugia and the reason for their resistance to burning should be investigated. Many of these areas may have made a transition to a less flammable fuel/landcover type, which is often the case with a long fire absence (Duncan et al., 1999). The lack of fire in the federal properties surrounding KSC/MINWR makes it appear that they are behind schedule with prescribed burning activities.

The age map shows the latest fire scar over the top of existing burns and reveals a much coarser pattern than the frequency map, shaped by FMU boundaries and fire breaks. The actual physical height structure/stature evident from the fuels/vegetation on the landscape will primarily resemble the pattern of the last fire scar or most recent fire scars. Comparing the Figure 14 histogram inset and Figure 9, it becomes evident that significant over burning of an area (new fire) generally does not take place for about seven years. This makes the pattern of each individual fire important (because it will persist for years) when considering native fire-dependent species and their habitat needs. The Florida Scrub-Jay is one such species that is

dependent on a particular habitat structure maintained by fire (Breininger and Carter, 2003; Breininger et al., 2006).

General considerations of mapping a managed fire regime

Managed fire regimes operate under restrictions in addition to the natural controls that governed natural fire. Stringent permitting requirements must be met to receive a burn permit. Primary among them are wind speed, wind direction, relative humidity, drought index, smoke dispersion, and impacts of smoke on roads and surrounding cities. In addition, conducting prescribed burns on KMCC has its own set of restrictions (Adrian, 2006). The spaceport has clean room facilities housing expensive payloads being readied for launch into space. Managers in charge of the many spaceport operations often have input into the burn schedule. These restrictions combined with crew and equipment requirements influence the date, location, and size of the prescribed burns that take place.

One of the requirements of controlling fires within a geographic area is the presence of non-flammable fire breaks. This includes roads (dirt or paved) that are just about completely void of fuels or fire lines cleared to mineral soils. The result is that burns often have very geometric shapes. This is very evident particularly in the age and dominant season of burn maps where burn boundaries are made up of straight lines. Natural fire boundaries would likely follow natural ecotone boundaries bordering less flammable fuels such as high hydroperiod marshes, water bodies, or less flammable fuels such as closed canopy hammocks or Florida scrub fuels (Myers, 1990). These fire ecotone interactions would rarely leave straight burn boundaries. Fire refugia may also have been created and maintained by the combination of the predominant wind

pattern and these natural fire breaks. Human made fire lines are now largely responsible for the burn patterns found on the landscape and are a contributing factor leading to the low annual burn area variability.

The age classes found on the landscape age map were initialized from the year of 2006. This was the year that the remote sensing of the fire scars was carried out and all of the GIS maps were created. These age classes will be updated when recent imagery is available to map the latest fires and update the database. We attempted to map every fire that occurred within the study site boundaries during the study period. Although many small fires did get mapped, some very small fires that occur in the MINWR fire records were not visible on the imagery and did not get mapped.

The classification algorithm performs best in the upland xeric communities (Shao and Duncan, 2007) and has some difficulty in hydric systems, where dark soils and standing water may be confused for burn scars. Safe-guards were instituted to minimize classification errors. Post-classification cleaning or masking was the first safe-guard, the next was to edit out features that consistently did not change with time on previous years imagery (known wetland features) and then lastly, using the confidence values. The confidence value allows the user to remove any fire scar that might have questionable boundaries from consideration. The irony is that the actual number of fires mapped and area mapped as burned may be closer to reality when confidence values of 1 are included. For this reason the normality and correlation statistics were performed on the full data set including all confidence values.

Conclusion

This study used remote sensing and GIS techniques to map and describe a managed fire regime on KMCC in east central Florida, USA. Our image processing technique (developed for mapping individual fire scars) was applied to an image time series for successfully mapping and describing a managed fire regime. We developed a system for labeling mapped confidence for each delineated fire scar and demonstrated its utility. This information was used for preferentially selecting fire scars to include or exclude from analysis. It was also used for studying the degradation of fire scar boundaries with time since burn. This information can be used for aiding the selection of a suitable number of images in time series, helping maximize information capture for fire regime mapping projects.

We were able to make comparisons between a managed fire regime and recorded information on natural fire regimes in the southeastern USA. The managed fire regime reacts and functions very differently during wet and dry meteorological periods compared to natural fire regimes of this region. There is an opposing reaction to these meteorological periods, during wet conditions; most area was burned under the managed fire regime and a minimum amount of area would burn under the natural fire regime. The opposite occurred during dry periods; little area burned under the managed fire regime and a maximum would burn under the natural fire regime. April precipitation was an effective predictor for this relationship.

These findings are important because establishing sound fire management practices to mimic the influence of natural fire regimes is increasingly important in the fire-maintained and fire-adapted communities around the world. If fire management is not properly and carefully executed, entire populations of rare species can be at serious risk for survival (Odion and Tyler,

2002). Mimicking natural processes that once effectively maintained diverse assemblages of biodiversity is a very challenging proposition, especially considering imposed anthropogenic influences. The uncertainties surrounding effective fire management make monitoring necessary. Monitoring fire management programs in relation to demography of native species will allow us to learn from successes and failures. Rigorous, scientifically-based adaptive management strategies are being developed to help streamline management efforts in complex systems such as the one studied here. Being able to quantify current fire regimes is an important part of improving future fire management to support native fire-dependent species. This paper is a step toward this goal by developing techniques for confidently delineating fire scars in rapid growth scrub systems, allowing the documentation of a managed fire regime. The results here are particularly relevant in east central Florida and the Southeastern U.S., but the techniques may be applicable to any pyrogenic system world wide.

ISOLATING THE LIGHTNING IGNITION REGIME FROM A CONTEMPORARY BACKGROUND FIRE REGIME IN EAST CENTRAL FLORIDA, USA

Submitted as: Duncan, B.W., F.W. Adrian and E.D. Stolen. 2009. Isolating the Lightning Ignition Regime from the Contemporary Background Fire Regime in East Central Florida, USA. Submitted Canadian Journal of Forest Research.

Introduction

The fire regime of an area is defined by its fire type, intensity (severity), size, return interval, seasonality, and spatial pattern (Christensen 1985). While fires start naturally through lightning or volcanic activity, anthropogenic ignitions such as arson and escaped incendiary fires heavily influence many fire regimes globally (Bond and van Wilgen 1996; Vigilante et al. 2004; Genton et al. 2006; Syphard et al. 2007). Changes in ignition source over time combined with fire suppression and fuel fragmentation have altered most fire regimes. Many contemporary fire regimes now only partially resemble those typical of the past. This is the case in the southeastern United States, particularly Florida, it incurs one of the highest rates of lightning incidence in North America (Orville and Huffines 2001; Murphy and Holle 2005). The natural fire regime in Florida, defined here as the fire regime prior to European settlement, was comprised of frequent, lightning-ignited fires (Abrahamson and Hartnett 1990; Brewer 2006; Slocum et al. 2007). Various native species (e.g., the Florida Scrub-Jay (*Aphelocoma coerulescens*), Highlands scrub hypericum (*Hypericum cumulicola*)) adapted and became dependent on this fire regime and are struggling with declining populations under contemporary fire regimes (Quintana-Ascencio et al. 1998; Breininger et al. 2006; Menges et al. 2006).

Fire management programs are now trying to reverse anthropogenic influences to either reduce dangerous fuel levels or to restore habitat for native fire-dependent species. To restore and maintain habitat for native fire-dependent species, it is necessary to have sound, scientifically based information detailing the natural fire regime. In most areas it may not be possible to return to a “natural fire regime”, but it is possible for land managers to mimic some of the processes and resulting patterns. The relationship between cloud to ground lightning and fire ignition is a fundamental component of the natural fire regime, which must be quantified so that fire/land managers can approximate natural system conditions and behaviors.

Lightning research in Florida has contributed significantly to our current knowledge of this natural force. Many research studies that documented electrical properties of lightning were conducted in Florida (Livingston and Krider 1978; Beasley et al. 1983; Shindo and Uman 1989; Rakov and Huffines 2003). Additional lightning research focusing on lightning climatology (e.g., (Hodanish et al. 1997; Mitchener and Parker 2005) and predictive modeling (e.g., (Reap 1994; Shafer and Fuelberg 2006) has also occurred in Florida.

The majority of the studies detailing the relationship between cloud to ground lightning and fire ignition have taken place in the boreal forest (Flannigan and Wotton 1991; Nash and Johnson 1996; Wierzchowski et al. 2002; Larjavaara et al. 2004; Larjavaara et al. 2005; Krawchuk et al. 2006; Kilinc and Beringer 2007) or other regions outside of the southeastern United States (Minnich et al. 1993; Petersen and Drewa 2006). Surprisingly, there have not been any lightning fire ignition studies published in the literature that link the characteristics of cloud to ground lightning and fire ignition in Florida. However, one study details the spatial patterns of fire by different means of ignition, including lightning, for Florida’s St. Johns River Water Management District (Genton et al. 2006). Another documented that negative polarity cloud to

ground lightning strikes initiated more fires than positive polarity lightning (Mitchener and Parker 2005).

Our goal was to separate the lightning ignition component from the contemporary background anthropogenic fire regime to define the natural fire ignition regime for Kennedy Space Center (KSC), Merritt Island National Wildlife Refuge (MINWR), Canaveral National Seashore (CNS), and Cape Canaveral Air Force Station (CCAFS), Florida. The managed contemporary fire regime on these properties has been delineated and described in a separate study, for details please refer to Duncan et al. (2009). The lightning fire ignition regime we delineated in this study includes the lightning ignition frequency, lightning ignition seasonality, lightning ignited fire size, spatial lightning and ignition densities, and properties of lightning that ignite fires. The influence of precipitation on lightning ignition efficiency and fire size was also investigated. We wanted to delineate the natural fire ignition regime while referencing existing knowledge generated from previous studies to help improve opportunities for land managers to mimic natural fire processes, ultimately benefiting native fire dependent species. Florida, like other fire adapted regions of the world, has many conservation areas designed to protect native species but a limited amount of scientifically sound information on which land managers can base fire management decisions. Our results will help fill a current information gap and allow the parameterization of future modeling efforts which may predict optimum management strategies for maintaining conservation areas. This study will be directly applicable on these federal properties, throughout Florida, the southeast United States, and will serve as an example of how to isolate and quantify the natural ignition component from contemporary fire regimes world wide.

Methods

Study site and background information

KSC is 57,000 ha and is primarily managed by the U.S. Fish and Wildlife Service as the MINWR with a smaller portion managed by the National Park Service as CNS(Figure 18). CCAFS is 6,475 ha and occupies the Cape Canaveral barrier island. Because these properties overlap to some degree and we are studying all of the federally owned area, we will use the first letter from each location and shorten the name from KSC/MINWR/CNS/CCAFS to KMCC. KMCC forms a barrier island complex covered with a diverse assemblage of fire-adapted terrestrial vegetative communities. Coastal strand occurs just inland of the coastal dunes and is a shrub community with saw palmetto (*Serenoa repens*), sea grape (*Coccoloba uvifera*), wax myrtle (*Myrica cerifera*) and other species being dominant. Coastal scrub occurs on neutral to alkaline sandy soils; a shrub form of live oak (*Quercus virginiana*) is the dominant species along with saw palmetto. Inland, upland xeric sites are dominated by oak scrub vegetation (*Quercus* spp.), while mesic sites are dominated by flatwoods (e.g., palmetto, staggerbrush (*Lyonia* spp.), holly (*Ilex* sp.), and an overstory of slash pine (*Pinus elliottii*). Because the landscape is comprised of relict dunes forming ridge swale topography, there are interleaving swale marshes and hammocks on hydric soils between the xeric ridges. The swales are dominated by sand cordgrass (*Spartina bakeri*) and bluestem (*Andropogon* spp.), while the hardwood hammocks are dominated by live oak (*Quercus virginiana*) and laurel oak (*Quercus laurifolia*) and have a structure that is much less flammable than surrounding communities. Salt marsh borders these barrier islands and is dominated by sand cordgrass grading into saw palmetto and the flatwoods

community on higher elevations. These communities are dominated by species that resprout following fire (Schmalzer 2003). Maps showing the distribution of these landcover types can be found in Duncan et al. (2004).

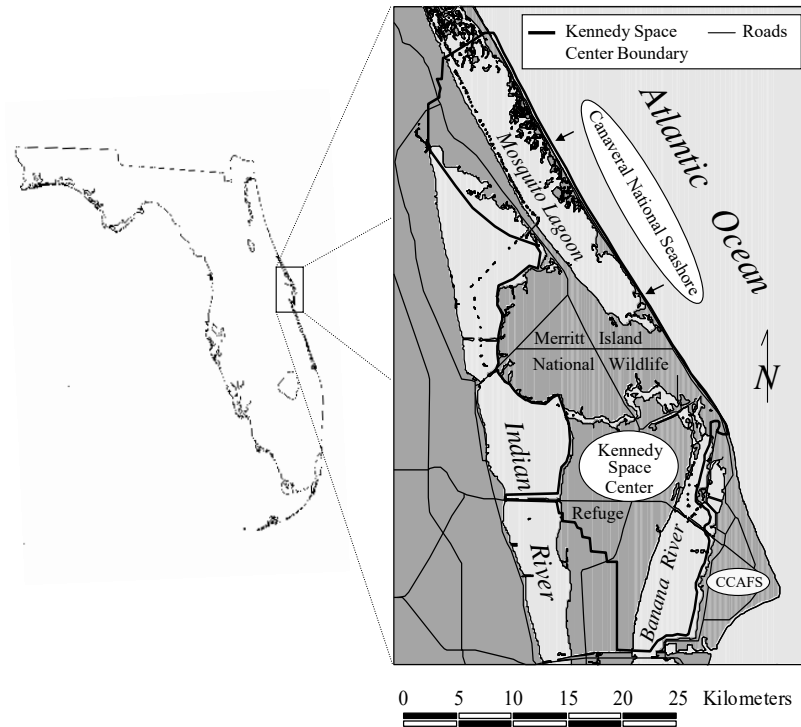


Figure 18. The geographic locations of Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

The growing season varies for each species, but the core growing season for dominants in this central Florida system is from April through early October. Early and late growing season are also used to describe periods in time that cross seasonal boundaries and tend to differ in humidity and precipitation. Early growing season is relatively dry and refers to the time period

of April through the start of the wet convective storm season, which typically starts in late June or early July. Late growing season refers to the time period when the wet convective storm season begins (either mid to late June or as late as mid July in dry periods) and then ends in September or early October with the completion of the convective storm season.

Native Americans used fire in this region to thin vegetation and to increase forage, which would attract prey for hunting. Not that much is known about their fire practices but it is believed that they did not greatly alter the natural fire regime through suppression. It is thought that they actually supplemented the natural fire frequencies across central Florida (Davison and Bratton 1986; Duncan et al. 1999).

Cloud to Ground Lightning Surveillance System

The Cloud to Ground Lightning Surveillance System (CGLSS) records the geographic location of cloud to ground lightning strikes surrounding the KMCC region. The system is comprised of a sensor network located throughout east central Florida and a position analyzer located on CCAFS where the data are maintained and stored via computer. The system has a detection rate of 98% and positional accuracy of 350 meters at 95% confidence (Roeder et al. 2005). The CGLSS records date, time, strength/polarity, and location for each lightning strike. CGLSS data were mapped using ArcGIS software via the geographic coordinates, with all other data recorded as attribute information. Cloud to ground lightning locations outside of the federal property boundaries of KMCC were excluded from the data set.

Fire records

A fire database containing fire name, date, location, type, cause, and size exists for all fires on KMCC and is maintained by the MINWR personnel. These data have been collected since 1977. Included in this database is a type of fire referred to as a “natural out”. A natural out is a fire that was ignited by lightning, went undetected while burning, and then went out on its own. These fires were recorded by periodic visual observation from helicopter surveys. Helicopter surveys were suspended in 2000 due to funding constraints. Each fire location is recorded in the township, range, section system with the management unit of the fire also being recorded. The township and range information for all lightning ignited fires were converted into latitude and longitude by recording the center coordinate of the corresponding section in ArcGIS. The mapped accuracy of fire centers are, at worst, 0.8 km from the true position.

Lightning GIS

The CGLSS and fire data for 1986 through 2003, excluding 1987 and 2002 due to missing CGLSS data, were overlaid and analyzed in a GIS. Data were collected for distance, normalized signal strength, polarity, and number of return strokes for nearest lightning strike to actual fire locations by date. Normalized signal strength (NSTR) is the estimated peak current of the return stroke recorded in kilo-amperes (ka) and is normalized for the inferred distance to the return stroke. Included in the NSTR value is the polarity indicated by a plus or minus sign. Cloud to ground lightning density within 1 and 2 km from each actual fire was also recorded. In the cases where there were no lightning strikes recorded for the same date of a recorded fire,

previous days' lightning strikes were overlaid until a reasonable match could be recorded. This delay in ignition is known as holdover time (Wotton and Martell 2005).

Lightning incidence, ignition frequency and landcover

Fire occurrence has been shown to vary among landcover types so a chi-squared analysis was performed to determine if ignition and lightning frequencies occurred more or less than expected for each landcover class. Landcover is used to refer to a specific category of vegetation, and fuels are used to refer to the structure of vegetation that is available for consumption by fire within or between landcover types. A 1990 landcover map was used because it represented landcover at a central time during this study and because it also represented overstory structure within its classification system, pine overstory structure is an important factor determining flammability in this system (Duncan et al. 1999; Duncan et al. 2004). For details about the landcover types and their mapped distributions, see Duncan et al. 2004. The null hypothesis for the chi-squared analysis was no relationship between landcover category and frequency of fire/strikes. To explore the strength of these relationships (effect size) simultaneous binomial confidence intervals (Neu et al. 1974; Byers et al. 1984) were used to compare occurrence frequency of both fire and lightning strikes versus landcover type availability. The technique calculates a set of simultaneous confidence intervals using a Bonferroni correction to adjust individual alpha levels for multiple comparisons. This is useful to determine if the expected proportion of occurrence (lightning ignition type and strike type category) falls within or outside the interval. If outside the interval, we conclude that the expected and actual are significantly different.

Precipitation and ignition frequency

Precipitation controls many important variables influencing fire ignition. We used both correlation analysis and regression techniques to learn more about the relationship between precipitation and lightning fire ignitions. The data consisted of the ratio of the number of strikes to the number of ignitions for each month of the study. The natural log of the response variable was used to better meet the assumptions of the linear regression model.

Lightning properties and fire ignition

The characteristics of lightning strikes that ignite fires have been shown to vary; so we used several techniques to investigate their relationship. Pearson correlation analysis was performed to investigate the relationship between the number of lightning strikes and the number of fires. It was also used to investigate the relationship between precipitation and the number of lightning fires. A log-linear analysis was performed to determine if the number of return strokes (multiplicity) were different between lightning strikes that ignited fires and those that did not. A null hypothesis stating that there was no difference was used. The log-linear technique was selected for this test because it is suited to count data with an error term following a Poisson distribution. A Wilcoxon Rank Sum test was used to look for differences between the NSTR values of lightning strikes that started fire and those that did not. The null hypothesis was that there was no difference between strike NSTR for cloud to ground lightning strikes that started fires and those that did not start fires.

Results

Lightning and lightning fire ignitions

Lightning characteristics

The CGLSS recorded 110,300 lightning strikes on these federal properties. The annual mean was (6,892), median was (6,705), the minimum number for any year was 3,647 strikes in 1988, and the maximum was 10,648 in 1990. The number of cloud to ground lightning strikes have risen and fallen through the duration of this study indicating the potential for a larger, cyclical trend (Figure 19). The majority of the cloud to ground lightning strikes, 101,678 (91.5%), were negatively charged; 8,619 (8.5%), were positively charged. The spatial density of lightning strikes averaged across all years was highest on the west side of the federal property decreasing to the east (Figure 20).

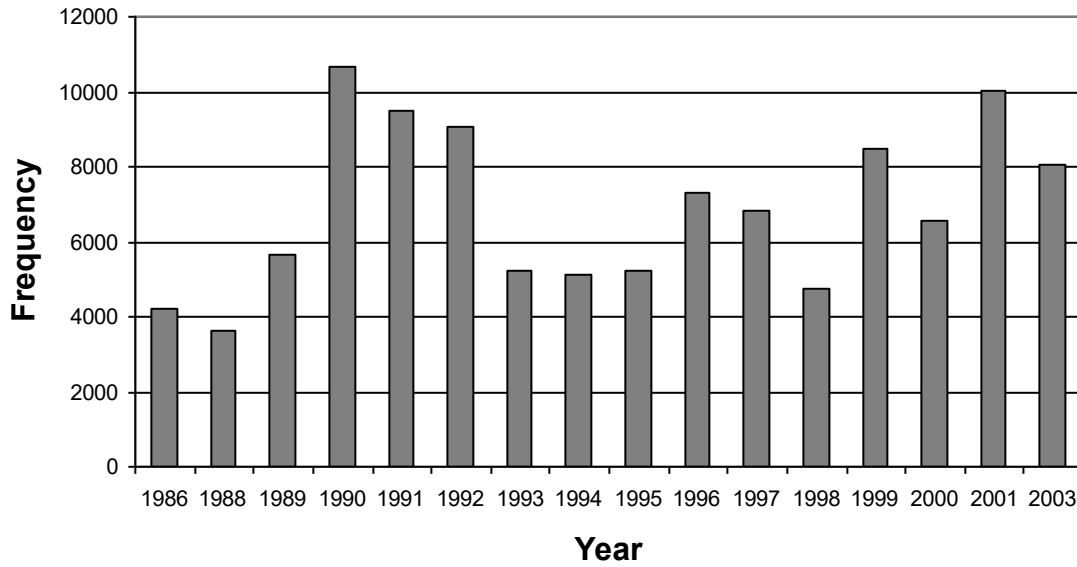


Figure 19. Cloud to ground lightning frequency by year on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

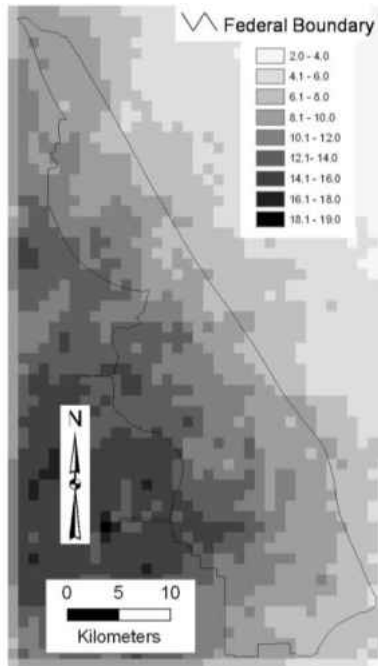


Figure 20. Average lightning density/ km^2 for 1986 through 2003 excluding 1987 and 2002 on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

Lightning fire characteristics

There were 230 fires ignited by lightning within the boundaries of these federal properties for the years that correspond to the CGLSS data. The annual mean was 14 and median was 12. The minimum number of ignitions in a year was two occurring in 1995 and 1996; the maximum was 39 occurring in 1992. The number of lightning ignitions again displayed a rising and falling trend (Figure 21). Out of the 230 fires, 40 were natural outs, accounting for about 17% of the total. The recorded size of the natural outs was small. The mean was 0.08 ha, median was 0.04 ha, the minimum was 0.04 ha, and the maximum was 0.8 ha. The mean size of extinguished fires was 16 ha, the median was 0.2 ha, the minimum was 0.04 ha, and the maximum was 1,012 ha. The minimum area reported for all fires was 0.04 ha (0.1 ac). Moderately high ignition densities occurred at the north end of the study site with the highest densities in the southwestern portion (Figure 22). Average lightning strike densities were 2.5 strikes per km² per day and 9 strikes per km² per day within a 1 km and a 2 km radius of each lightning ignition, respectively.

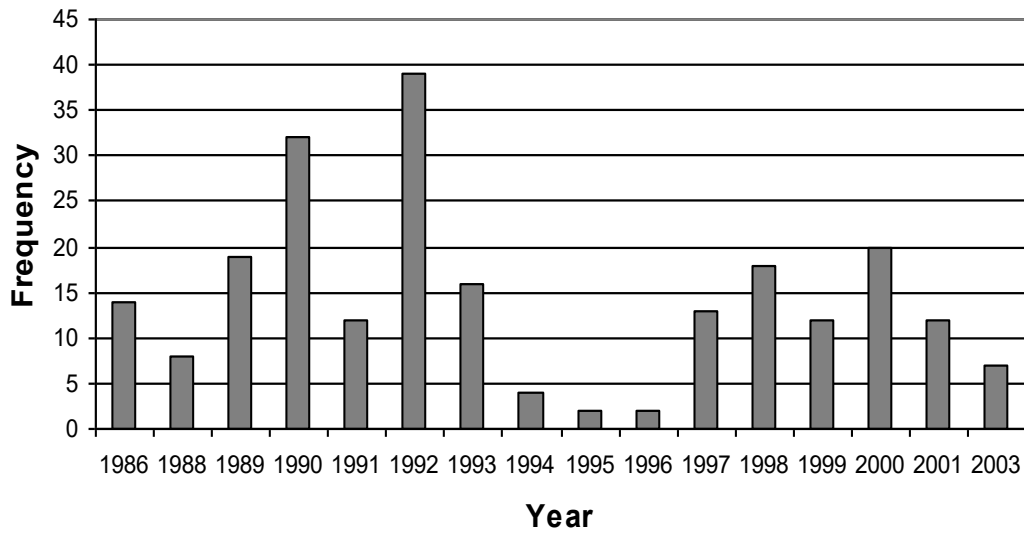


Figure 21. Ignition frequency by year on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

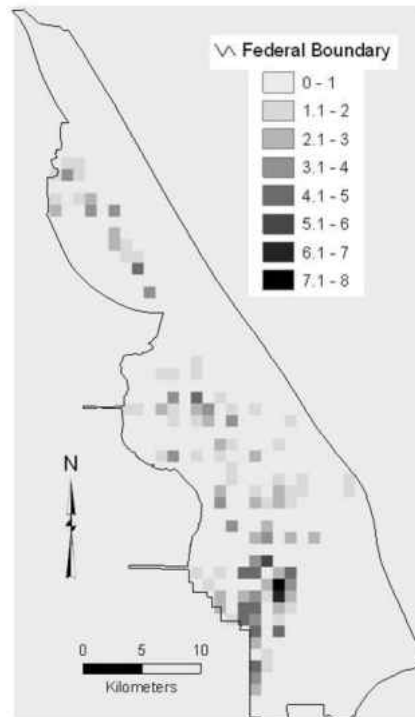


Figure 22. Lightning ignition density/km² for 1986 through 2003 excluding 1987 and 2002 on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

Lightning fire frequency and season

The lightning ignition frequencies were concentrated during the summer months (Figure 23). The month of July had the greatest number of ignitions with 94, and the only winter month with any ignitions was January, with one fire. By season, winter (Dec, Jan, Feb) had one ignition, spring (Mar, Apr, May) had 27 ignitions, summer (Jun, Jul, Aug) had 189, and fall (Sep, Oct, Nov) had 13 ignitions. Natural outs were concentrated during the month of July with 28 (70%) (Figure 23). Seasonally, winter had one natural out, spring had one, summer had 33, and fall had five. Holdover ignition times reveal an almost even distribution of instantaneous and delayed ignitions 118 (51%) to 112 (49%), respectively. The maximum ignition delay was 23 days, and the average was two days.

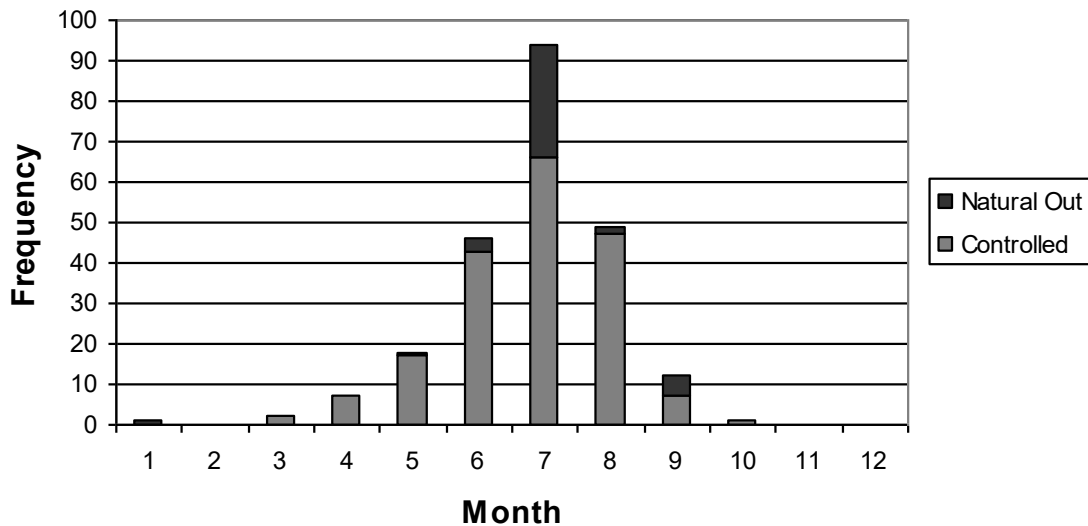


Figure 23. Lightning fire frequency by month on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. Frequencies were summarized for fires that were detected/controlled and undetected fires that extinguished themselves (natural outs).

Precipitation and lightning fire frequency

The annual number of lightning ignitions and July precipitation were normally distributed (Shapiro-Wilk test, $P = 0.132$, $P = 0.276$) and negatively correlated ($r = -0.719$, $P = 0.002$).

Summer time precipitation variability is highest during the early summer season (Table 1). The month of June had the smallest and greatest precipitation total of the summer months, while early July is dryer than late July. Regressing the natural log of the strike to ignition ratio vs. precipitation revealed that lightning ignition efficiency declines with increasing precipitation (Figure 24). Residuals from this model met statistical assumptions and had an $R^2 = 0.37$, indicating a structural relationship in the data.

Table 7. Precipitation amounts (cm) for different time periods during the Summer on Kennedy Space Center/Merritt Island National Wildlife Refuge/Canaveral National Seashore/Cape Canaveral Air Force Station from 1986 to 2003 excluding 1987 and 2002.

Time period	Min	Max	Median	Mean	Var.	Std dev.
June	1.52	30.23	17.54	17.07	73.87	8.59
July	2.95	28.96	11.34	12.16	53.46	7.31
Aug	4.27	25.96	13.75	14.62	46.58	6.83
July1-15	0.00	11.96	5.35	5.47	13.25	3.64
July16-31	0.20	19.69	5.79	6.70	29.45	5.43
June-July15	7.95	39.01	19.20	22.54	104.91	10.24
July16-Aug	8.41	43.87	20.84	21.32	67.23	8.20

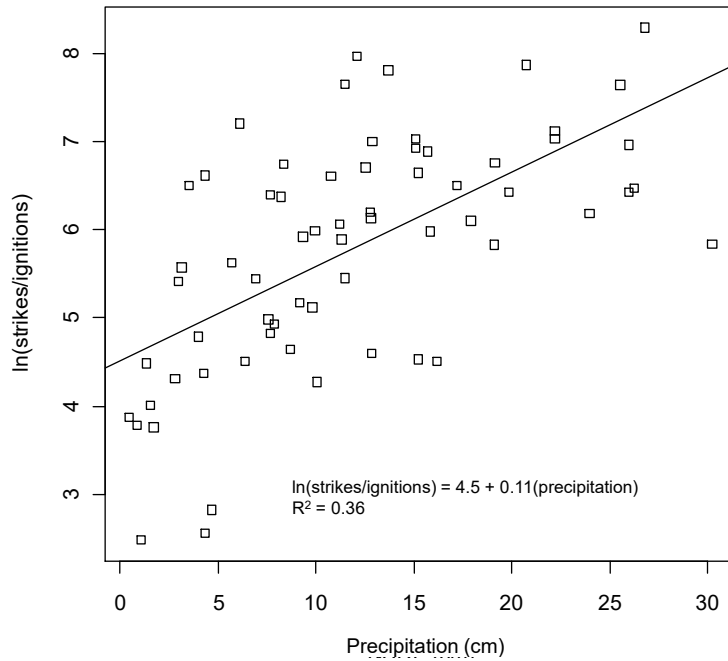


Figure 24. Regression plot displaying the relationship between the natural log of the strike to ignition ratio and precipitation on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

Strike to ignition ratios

The ratio of cloud to ground lightning strikes to ignitions for each year varied with a mean of 881, a median of 491, a minimum of 233 in 1992, and maximum of 3,647 in 1996. There were a few years that had an inordinately large ratio of strikes to ignitions (Figure 25). These same years had above average precipitation (Figure 26). The monthly ratio of cloud to ground strikes had a mean of 812, a median of 536, a minimum in July of 309, and a maximum in October of 2,153 (Figure 27). The annual number of cloud to ground lightning strikes and the number of actual ignitions were normally distributed (Shapiro-Wilk test, $P = 0.488$, $P = 0.083$) and not significantly correlated ($r = 0.398$, $P = 0.126$).

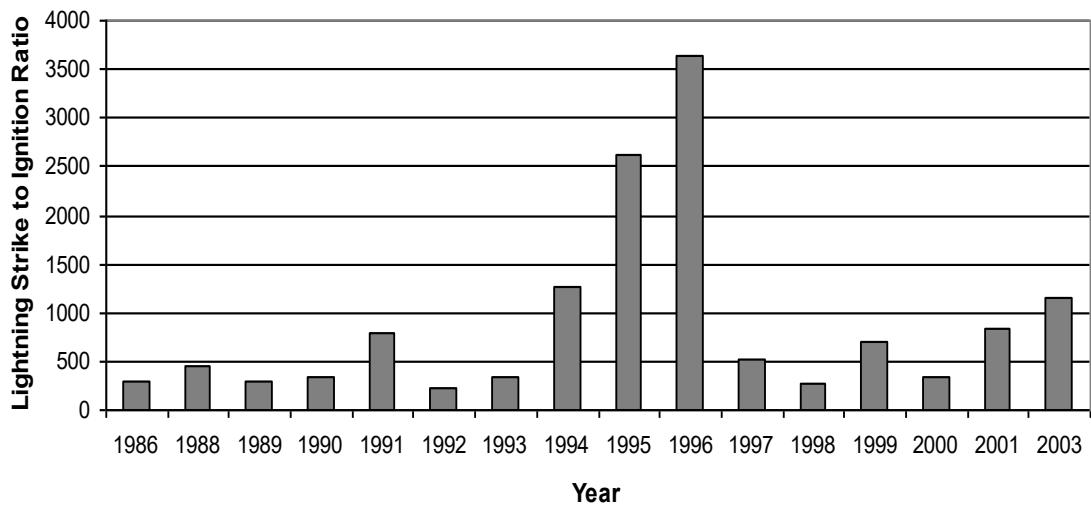


Figure 25. Annual lightning strike to ignition ratio for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. The lightning strike to ignition ratio is derived by dividing the total number of cloud to ground lightning strikes by the total number of ignitions for each year.

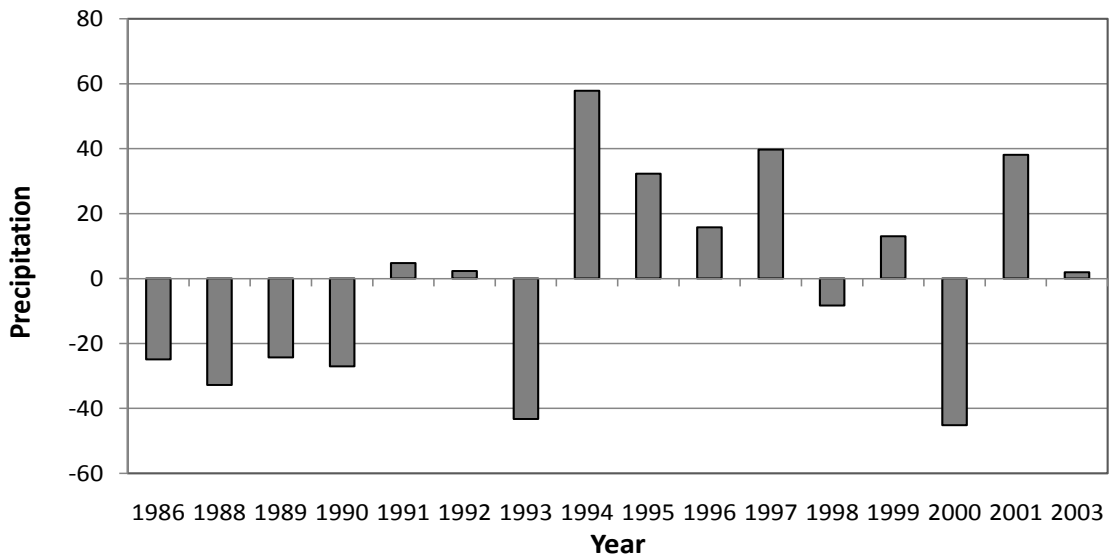


Figure 26. Precipitation, above and below the mean as measured at the National Atmospheric Deposition Program collection site on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. The mean precipitation value for the years from 1986 through 2003 excluding 1987 and 2002 is 127.9, all values are in centimeters.

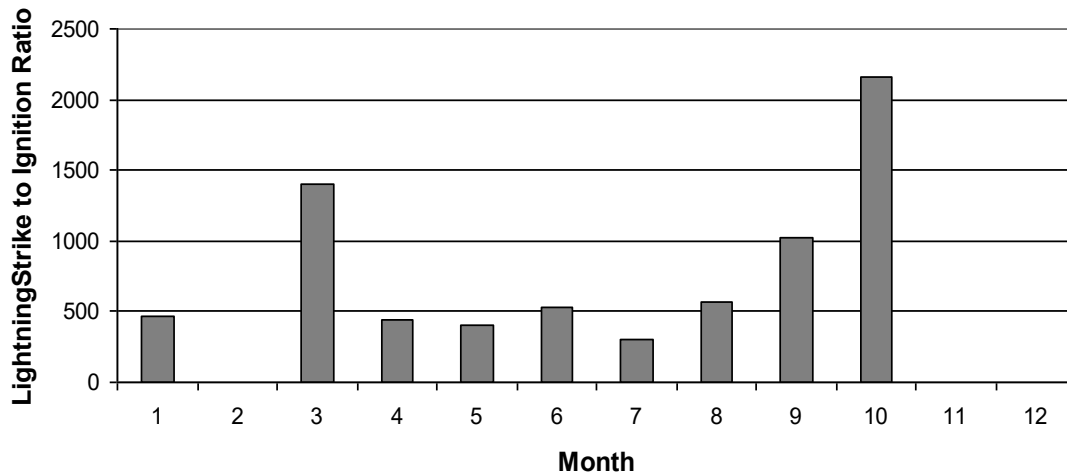


Figure 27. Monthly lightning strike to ignition ratio for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. The lightning strike to ignition ratio is derived by dividing the total number of cloud to ground lightning strikes by the total number of ignitions for each month. There were no ignitions during February, November and December.

Fire size and season

Fire size was typically small, with 220 fires smaller than 12 ha and only ten larger in size. During the fall, winter, and spring most lightning fires were small (Table 8). A few lightning fires accounted for the majority of total area burned by lightning ignition (Figure 28). The majority of the large fires occurred early in the summer season. There were three very large lightning fires during this study. The first of these fires occurred on July 6th of 1992 with a size of 486 ha, the second and third occurred on June 21st 1998 with sizes of 643 ha and 1,012 ha, respectively.

Table 8. Fire size statistics by season on Kennedy Space Center/Merritt Island National Wildlife Refuge/Canaveral National Seashore/Cape Canaveral Air Force Station. The seasons are comprised of the months designated in parenthesis. The summer season is split in half and divided into early and late summer with the largest fires occurring during the early summer. Areas are in hectares and 0.04 ha is the minimum recorded fire size.

Season	Frequency	Min. Size	Max Size	Mean	Median
Winter (12,1,2)	1	0.04	0.04	0.04	0.04
Spring (3,4,5)	27	0.04	12.14	2.23	0.20
Summer (6,7,8)	189	0.04	1,011.74	15.22	0.08
Fall (9,10,11)	13	0.04	10.12	1.58	0.04
Early Summer (6/1-7/15)	95	0.04	1,011.74	24.93	0.04
Late Summer (7/16-8/31)	94	0.04	218.54	5.71	0.12

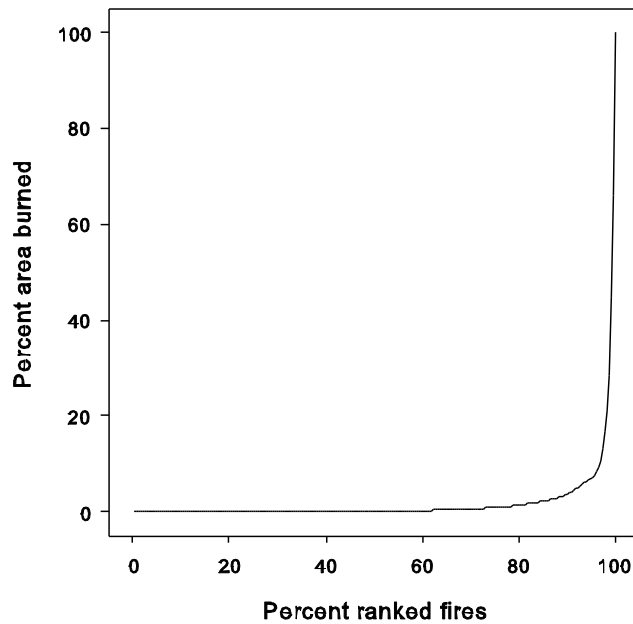


Figure 28. The proportion of ranked fires (small to large) and the proportion of area burned by lightning fires on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. A few large fires accounted for the majority of area burned by lightning fires.

Lightning fire incidence and landcover type

The chi-squared test indicated significant differences between actual ignition and expected ignition ($X^2 = 329.6$, $df = 12$, $P < 0.00001$), and between actual lightning strike frequency and expected frequency in the different landcover classes ($X^2 = 1235.8$, $df = 12$, $P < 0.00001$). The simultaneous interval confidence method indicated that there was slightly more fire ignitions in the disturbed uplands and forested wetlands than expected given their area (Table 9). There were significantly fewer fire ignitions in the water category, and slightly fewer in the 'other' category (including the landcover types sand/barren, mangrove, and coastal strand) confirming the technique performed properly. The lightning strike proportions and the type availability were very tightly bunched with the largest separations (significant differences) occurring in the flatwoods, water, forested wetlands and other landcover types. The occurrence of fire in the flatwoods landcover type occurred much more frequently than would be expected given equal chance of ignition among landcover types.

Lightning properties and fire ignition

Comparing the nearest cloud to ground lightning strike and ignition location indicated that 215 (93%) of the ignitions were caused by negatively charged lightning strikes and 15 (7%) were caused by positively charged lightning. Negative polarity lightning was dominant during all seasons with 83% of all strikes being negatively charged in winter, 88% in spring, 93% in summer, and 90% during fall. The multiplicity (number of strokes per flash), had a average of 2.4, a median of 2.0, minimum of one, and a maximum of 14, for strikes that initiated fires. The

number of return strokes from lightning strikes that started fires and those that did not were significantly different ($F = 4.27, P = 0.0387$). Normalized signal strength was also significantly different for lightning strikes that started fire and for those that did not ($W = 5935327, P = 0.0026$). The NSTR values were lower (more negative) for non-fire igniting lightning strikes.

Table 9. Proportions of landcover type, cloud to ground lightning strikes and lightning ignited fires occurring on Kennedy Space Center, Merritt Island National Wildlife refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. Confidence intervals are given for lightning strikes and lightning ignited fires, showing if they differed significantly from that expected based on proportion of each landcover type. Proportions in bold have 95% confidence intervals above, and those underlined are below, the proportions of landcover type.

Landcover	p(Landcover)	p(Strokes)	CI (95%)	p(Fires)	CI (95%)
Urban	0.050	0.049	(0.048, 0.050)	0.067	(0.047, 0.088)
Agriculture	0.012	0.015	(0.014, 0.015)	0.032	(0.018, 0.046)
Flatwoods	0.080	0.090	(0.089, 0.092)	0.301	(0.264, 0.339)
Scrub	0.101	<u>0.096</u>	(0.095, 0.097)	0.112	(0.086, 0.138)
Hammock	0.068	0.076	(0.075, 0.077)	0.089	(0.066, 0.113)
Disturbed uplands	0.021	0.022	(0.021, 0.022)	0.045	(0.028, 0.062)
Water	0.387	<u>0.363</u>	(0.361, 0.365)	<u>0.067</u>	(0.047, 0.088)
Forested wetlands	0.039	0.045	(0.044, 0.046)	0.093	(0.069, 0.117)
Freshwater marsh	0.057	0.067	(0.066, 0.068)	0.058	(0.039, 0.077)
Saltwater marsh	0.073	0.078	(0.076, 0.079)	0.067	(0.047, 0.088)
Disturbed marsh	0.019	0.022	(0.021, 0.022)	0.026	(0.013, 0.038)
Spoil	0.027	0.028	(0.027, 0.028)	0.022	(0.010, 0.034)
Other	0.065	<u>0.050</u>	(0.049, 0.051)	<u>0.019</u>	(0.008, 0.030)

Discussion

Strike to ignition ratios and precipitation

Fewer lightning strikes are needed to ignite fires during dry, rain-free periods. For the central Florida landscape, this was most pronounced in July. The years of 1994, 1995, and 1996 required many more strikes than average (881) to ignite a single fire. The precipitation records on Merritt Island indicate that these years were all above average and are the only consecutive years during this study with above average precipitation. The year of 1997 was also an above average year for precipitation but fewer than the average lightning strikes were needed to ignite a single fire. This year was an El Niño year and the majority of its precipitation fell during November and December. Until November, 1997 was actually fairly dry with Palmer Hydrologic Drought Index values consistently in the -1 to -2 range, indicating dry conditions (the index ranges from -6 to +6, dry to wet, respectively). This explains why there was a drop in the lightning strike to ignition ratio for 1997. These findings were supported by the regression between precipitation and the strike to ignition ratio as well as the negative correlation between the number of ignitions and July precipitation. Generally, when it has rained, more strikes are required to ignite fires and especially when July is dry, fewer strikes are needed to ignite fires and when July is wet, it takes more lightning strikes to ignite fires. July rainfall is particularly important because it corresponds with the peak in lightning incidence. This trend is clearly visible in the monthly strike to ignition ratio data. The fewest strikes are required to ignite fires in July just after the annual dry period, and the maximum number of strikes is required to ignite fires in October after the summer wet season (Mailander 1990).

Fire size, season and precipitation

The majority of lightning fires occurred during the wet season and they were small, supporting the conclusion that most fires in this natural system were small. Natural out fires greatly contributed to this trend. The resources necessary to document natural out fires are significant and generally out of reach for most organizations. As a result recording of small fires, particularly natural out fires, are usually lacking in many empirical data sets (Nash and Johnson 1996; Cui and Perera 2008). Natural out fires were documented for 14 of the 16 years in this study before suspension of funding for helicopter support. Natural out fires were all smaller than 0.8 ha (2 acres), and the overwhelming majority occurred during the wet and humid growing season. Presumably the wet, humid conditions at this time of year controlled the size of these fires and they went undetected. In light of the delayed (hold over) ignitions, it is reasonable to assume that not all of these fires would have stayed small. Some of these small fires may have started and burned until conditions became unfavorable, entered a smoldering state, and then reignited when conditions became favorable, ultimately growing to be larger fires. Most of the fires (83%) in this study were controlled. Of the fires that were controlled, the mean size was 16 ha, with a median of 0.2 ha, indicating that fire suppression was successful at controlling most fires before they became large and that many natural fires would have at least been 16 ha in size or larger. There were three very large lightning fires that contributed most of the area burned, and all of these fires were during the first half of the growing season. The two largest fires occurred during the very dry La Niña period of 1998. During the early growing season, dry periods are intermixed with wet periods creating a large amount of precipitation variation when compared

with the late growing season. The amount of actual precipitation is very comparable between early and late growing season but the later part is more consistently wet, limiting favorable conditions for large fires. It is during these dry early season periods that the large fires occurred. The month of June had the least and greatest amount of rain during the duration of this study. The number of lightning strikes required to ignite a fire is at a minimum during the month of July and increases until peaking in October, just after the maximum of September rainfall (Mailander 1990).

There was a large size discrepancy between the fires that commonly occurred (under wet and average meteorological conditions) and those that occurred during the less frequent drought periods. Evidence suggests that natural, large fires occurred in Florida during the drought periods in the early growing season (Brenner 1991; Beckage et al. 2005). El Niño Southern Oscillation patterns are strongly linked to this trend, and the most extreme fires likely occurred during these climatic events (Brenner 1991; Beckage and Platt 2003; Beckage et al. 2003), as indicated in this study. The majority of the fires in this study were controlled, and they ranged from small to medium in size. This is because they occurred under average meteorological conditions making them relatively easy to control, as opposed to the ones during drought periods that were difficult to control, hence their large size. Evidence for the medium-sized fires (under 400 ha) is limited because fire suppression and control appear to be most effective in this size class. The smallest fires (natural outs) are not influenced by suppression efforts and the largest fires burn under extreme meteorological conditions when control efforts are less effective. Under the natural fire regime, large fires would have been infrequent relative to small and medium fires. These frequent, small and medium-sized fires would have created a mosaic of different aged fuels on the natural landscape. This mosaic of fuels would have greatly influenced

flammability and propensity to burn (Myers 1990; Breininger et al 2002), ultimately influencing fire patterns through a feedback of fuels ready to carry fire based on structure, referred to as self organization (Cui and Perera 2008). These burn patterns would have created a complex physical arrangement of vegetation influencing habitat quality for fire dependent species, such as the Florida Scrub-Jay (Breininger and Carter 2003). The Florida Scrub-Jays demography peaks in habitat with sand openings and oak scrub heights of approximately 120 cm (Breininger et al. 2006). These are very specific conditions that do not persist on the landscape without frequent fire (Schmalzer 2003). For these conditions to persist through time, there must be a rotation of vegetation into this structure on the landscape.

Lightning fire incidence and landcover type

Areas with the highest lightning incidence did not correspond directly to areas with the highest ignition incidence. The southwestern side of the federal properties has the highest average lightning density and therefore the greatest overall ignition potential. The greatest ignition density however is found where there is a convergence of highly flammable landcover and relatively high lightning incidence. Areas of high ignition density in the north and the highest density in the southwest corner of the study area correspond to areas comprised of pine flatwoods landcover. The pine flatwoods landcover type displayed significantly higher than expected ignition incidence. In general the difference between the amount of actual lightning strikes per landcover category and expected is very small. The confidence intervals are tight because the lightning strike sample size is extremely large. The largest differences are in the water and the other categories (less strikes than expected), with flatwoods, hammocks, and

freshwater marsh (more strikes than expected) following in that order. There are slightly more lightning strikes in each of the flatwoods, hammocks, and freshwater marsh categories, but in the actual ignitions, flatwoods is the only one of these three categories to have a greatly larger amount of actual ignitions. This finding may be supportive of earlier studies (Mitchener and Parker 2005), who found that lightning density was not the dominant factor determining fire ignition within national forests of the southeastern United States. Pine fuel types in general have been found to be highly susceptible to lightning ignition (Latham and Schlieter 1989), while flatwoods flammability has long been noted due to its pine overstory and flammable understory (Myers 1990; Duncan et al. 1999).

Lightning properties and fire ignition

Negative polarity lightning strikes overwhelmingly started fires in this study. This differs from early studies asserting that lightning with long continuing current (LCC) started fires and because positive strikes have a higher probability of LCC, positive strikes had greater ignition potential (Fuquay et al. 1972; Flannigan and Wotton 1991). More information is now available suggesting that negative lightning polarity is an important ignition source igniting fires in many ecosystems (e.g., Flannigan and Wotton 1991; Orville and Silver 1997; Larjavaara et al. 2005; Mitchener and Parker 2005). Lightning polarity varies geographically and seasonally in North America (Orville and Silver 1997). Negative polarity lightning is the dominant polarity in the southeast. In this study, negative polarity is dominant even during the winter season, and the annual background polarity values are similar to the ignition proportions for both positive and negative polarities. Thus lightning ignitions are occurring with the same proportions as available

lightning polarity. Also, lightning strikes initiating fires are negatively polarized, but they do not possess a large negative magnitude. Negative strike multiplicity has been shown to be the highest in the southeast, United States (Orville 1994). Multiplicity has been linked with ignition probabilities (Flannigan and Wotton 1991; Larjavaara et al. 2005). Different results have been found however. Flannigan and Wotton (1991) found that the average negative multiplicity was a very important predictor and correlated with lightning ignition, while Larjavaara et al. (2005) showed that higher multiplicity decreased ignition probability. Multiplicity values that ignited fires in this study were significantly lower than background values.

General considerations and management implications

A caveat of this study is that fuel fragmentation by roads, buildings, agriculture, and exotic species has influenced the flammability of the landscape in this study. The influence of fuel fragmentation on fire spread and fire size was modeled in this landscape, it was found to reduce both (Duncan and Schmalzer 2004). The removal of fuels and the replacement of flammable native fuels by less flammable exotic species potentially influenced both the number of fire starts and the rate of fire spread, affecting fire size.

Fire managers wanting to mimic the results of the natural fire regime to benefit native fire dependent species will benefit from the information generated by this study. A primary example is the current managed fire regime burns the maximum area in November (Duncan et al. 2009) and this study shows that there was not a single lightning ignition for the duration of this study, during November. The influence of fire season could have a profound impact on demography of some species (Outcalt 1994) and as an example, should be considered by fire managers. The

number, timing, size, and location of natural fires are all important references for fire managers attempting to mimic the natural fire regimes in fire maintained systems worldwide.

Conclusion

This empirical study used lightning data from the CGLSS and fire ignition records to quantify the relationship between lightning incidence and fire ignitions for 16 years on KMCC. The study clearly indicated the natural seasonality of fire in this fire adapted system with the largest frequency of lightning ignition (82%) occurring in the summer and the smallest frequency (0.4 %) during the winter. A few large early growing season fires accounted for the majority of the area burned with the largest fires occurring during the 1998 La Niña drought. The frequent small fires occurred in the late growing season under moist, humid conditions. Rainfall was an important factor determining the efficiency of lightning fire starts, with fewer ignitions during years with high July precipitation. The spring and early summer period required the fewest lightning strikes to ignite fires. The pine flatwoods landcover type was ignited more frequently than expected by chance. Fire ignitions were predominantly caused by negative polarity lightning strikes that were in proportion to background values with low return stroke multiplicities.

This study isolated the natural lightning ignition regime component from the background managed fire regime including prescribed and lightning ignitions (see Duncan et al. 2009 for description and details of the contemporary managed fire regime) to answer many long standing questions about the relationship between cloud to ground lightning and fire ignition in this region. We know that the natural fire regime maintained the native flora and fauna and

mimicking it is an important step to sustaining viable populations of native species in fire dependent systems. If fire management is not properly and carefully executed, entire populations of rare species can be at serious risk for survival (Odion and Tyler 2002). This study is directly relevant for existing fire management programs on these properties and throughout the southeast United States, it will help parameterize models used to optimize future fire management (e.g., define ignition frequency, density location and seasonality needed as inputs to fire regime models), and will add additional information to the growing number of studies quantifying the environmental factors driving lightning fire initiation.

SIMULATING THE NATURAL FIRE REGIME ON A BARRIER ISLAND COMPLEX ALONG THE CENTRAL EAST COAST OF FLORIDA

Introduction

The fire regime of a region is defined by its fire type, fire intensity, fire size, return interval, seasonality, and spatial pattern (Christensen 1985, Agee 1993). Humans have altered fire regimes by suppressing fires, shifting fire seasonality, fragmenting fuels, propagating non-native fuels, and permitting unnaturally high fuel loads. Understanding how anthropogenic influences have altered fire regimes is important when attempting to manage conservation areas for the survival of native fire-dependent species. A reference outlining the natural fire regime is useful to foster an understanding of the environment that native fire-dependent species have adapted to and coexisted in. Fire has been an active force on global ecosystems for millions of years (Bond and Wilgen 1996). A thorough knowledge of the difference between the natural fire regime and contemporary fire regimes is essential to effectively and efficiently manage habitat for fire-dependent species. Many fire-dependent species populations are declining in their native ecosystems with fire regime alteration being a large contributing factor (e.g., Noss and Cooperrider 1994, Breininger and Carter 2003, Quintana-Ascencio et al. 2003, Webb and Shine 2008).

Florida is dominated by fire-adapted vegetative communities that have seen their composition and structure modified by fire regime alteration (Myers and Ewel 1990, Duncan et al. 1999). The dominant terrestrial communities are pine flatwoods, dry prairies, Florida scrub, and high pine (Abrahamson and Hartnett 1990, Myers and Ewel 1990). These vegetation

communities do not lend themselves to recording and preserving past fire history and present many problems for natural fire regime reconstructions. The prevailing regeneration strategy in the understory of these communities is through re-sprouting after being top killed by frequent fire. The relatively short lived sand pine with thin bark (*Pinus clausa*) are easily killed by moderate to intense fires. The longer lived slash pines (*P. elliotii* var. *elliottii*, *P. elliotii* var. *densa*) and longleaf pine (*P. palustris*) with their thick protective bark generally do not scar from low and moderate intensity fires but are killed by intense fire. This generally limits the utility of dendrochronologic techniques for historic fire regime reconstruction. With the convergence of particular circumstances, it is possible to use dendrochronology to reconstruct historic fire regimes in Florida (Huffman 2004). However, that study was conducted on a protected barrier island where past turpentine operations had stripped the protective bark from the pines allowing fires to scar the trees and facilitated fire scar dating. Stratigraphic varve dating has been used in Florida but has had limited success reconstructing historic fire dates (Shepherd 2002). Remote sensing techniques have been used for reconstructing fire histories but are limited to recent time periods (Duncan et al. 2009a).

Computer simulation is an alternative that has shown promise for reconstructing historic fire regimes in many ecosystems outside of Florida (Baker 1992, Davis and Burrows 1994, Li 2000). There are at least 45 landscape fire succession models in use today (Keane et al. 2004). A few of the models have been successfully applied in shrubland systems that also share attributes of the Florida ecosystems and lack a natural record of fire history. The regional fire regime simulation model (REFIRES) was created to simulate prehistoric and modern fire regimes of the coastal California chaparral ecosystems (Davis and Burrows 1994). The HFire simulation model has also been applied in the California chaparral ecosystem (Morais 2001,

Peterson et al. 2009). Both applications generated fire regime information such as maps of fire history, fire size distribution, fire recurrence interval, final patch size, and age distributions.

The cluster of federal properties known as Kennedy Space Center (KSC), Merritt Island National Wildlife Refuge (MINWR), Canaveral National Seashore (CNS), and Cape Canaveral Air Force Station (CCAFS) in Florida is the largest conservation area on the Atlantic coast of Florida. These properties have fire management programs that actively conduct prescribed burns to reduce/maintain fuel loads and to manage habitat for native fire-dependent species (Adrian and Farinetti 1995). The goal of this work is to apply the HFire model (Morias 2001) to simulate the natural fire regime (prior to European alteration) on KSC/MINWR/CNS/CCAFS. The model was parameterized with empirical information from previous studies and meteorological data. A sensitivity analysis was performed to determine the importance of each parameter and to establish a range of variation surrounding the empirical model. This approach offers an opportunity to apply an advanced fire regime model built on the best current fire simulation algorithms to estimate the natural fire regime in dynamic, fire-adapted ecosystem and provide a possible range of variation surrounding that estimate.

Study Site and Background

The United States federal government began acquiring land in the 1950s on Cape Canaveral and in 1962 on north Merritt Island, along the east coast of central Florida. KSC covers 57,000 ha of land and waters, which is primarily managed by the U.S. Fish and Wildlife Service as the Merritt Island National Wildlife Refuge with a smaller portion managed by the National Park Service as the Canaveral National Seashore (CNS). Cape Canaveral Air Force

Station (CCAFS) is 6,475 ha and occupies the Cape Canaveral barrier island (Figure 29). When referring to these properties collectively we will use the first letter from each location and shorten the name from KSC/MINWR/CNS/CCAFS to KMCC.

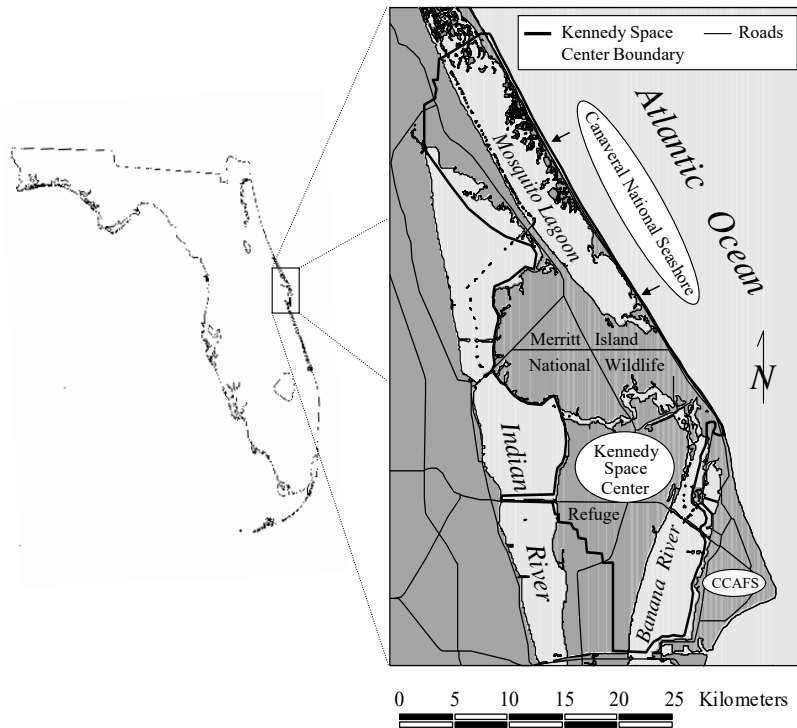


Figure 29. The geographic locations of Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

KMCC occupies a barrier island complex covered with a diverse assemblage of fire-adapted terrestrial vegetative communities. Upland xeric sites are dominated by oak scrub vegetation (*Quercus* spp.), while mesic sites are dominated by flatwoods (e.g., saw palmetto (*Serenoa repens* (W. Bartram) Small), stagebrush (*Lyonia* Nutt. spp.), holly (*Ilex* L. spp.), and an overstory of slash pine (*Pinus elliotii* Engelm.)) (Schmalzer and Hinkle, 1992a; Schmalzer and Hinkle, 1992b). Because the landscape is comprised of relict dunes forming ridge-swale topography, there are interleaving swale marshes and hammocks on hydric soils between the

xeric ridges. The swales are dominated by cordgrass (*Spartina bakeri* Merr.) and bluestem (*Andropogon* L. spp.), while the hardwood hammocks are dominated by live oak (*Quercus virginiana* Mill.) and laurel oak (*Quercus laurifolia* Michx.) and have a structure that is much less flammable than surrounding communities. Coastal strand occurs just inland of the coastal dunes and is a shrub community with saw palmetto, sea grape (*Coccoloba uvifera* L.), and wax myrtle (*Myrica cerifera* L.) being dominant (Schmalzer et al., 1999).

Methods

HFire (Highly Optimized Tolerance Fire Spread Model) is a spatially explicit raster-based model that can be used as a single event model or to simulate fire regimes over long time periods. The model is based on the Rothermel fire spread equations (Rothermel 1972) and can use standard (Anderson 1982, Scott and Burgan 2005) or custom fuel models. This model uses adaptive time steps and finite fractional distance techniques to solve the problem of distorted fire shapes using traditional raster fire spread models (Morais 2001, Peterson et al. 2009). This model was used because it can be parameterized for Florida vegetation communities, is based on the robust Rothermel equations, it is computationally efficient, provides spatial output, and has been found to be reasonably accurate when simulating historic fire events (Peterson et al. 2009).

Configuration files are used to operate HFire for simulating fire regimes (Table 10). Parameterizing is accomplished through these files and run in a command window on a PC to execute each simulation. The parameters for the empirical HFire model run are shown in the fourth column of Table 10. The spatial resolution for the modeling was 30 meters. This resolution was consistent with previous fire regime mapping work on these properties (Duncan et

al 2009a) and is reasonable tradeoff between spatial detail and computing efficiency. Spatial resolution larger than 30 meters would reduce computation time but would have generalized the ridge-swale topography, misrepresenting the distribution of fuels on the KMCC landscape. To create a natural fuels map devoid of anthropogenic features (roads, railways, buildings, agricultural fields, etc.), these features were removed from a 1920 landcover map (Duncan et al. 2004) by using soils maps and soils vegetation relationships (Duncan et al. 2000). Each landcover type was converted to one of 13 standard fire behavior models (Anderson 1982) with swale marshes assigned to the short grass fire behavior model 1. The tall grass model 3 could have been used in these marshes, as *Spartina bakeri* is prominent in many of these marshes. The problem with using the tall grass model is that it can cause unrealistically fast rates of fire spread in these marshes (Duncan and Schmalzer 2004). Oak scrub was assigned to the chaparral model 4 and pine flatwoods was assigned to the southern rough fuel model 7. Hammocks and wetlands hardwoods were assigned to the fire behavior model number 8. Specific fuel load information allowing the model to predict fire behavior was input through a sub file. The elevation grid was given a uniform value of three meters and the slope and aspect grids were given values of zero. This barrier island landscape has very slight topographic relief of one to two meters. This small relief influences the distribution of fuels, which influences fire behavior. Despite the zero values in the slope and aspect grids, the most important aspects of topography are incorporated into the modeling through the fuels grid. Rather than starting with uniform fire history of zero age, the output from a previous model run of 300 years was used to help reduce initial modeling conditions.

Table 10. HFire Configuration file parameters.

Variable	Entry Type	Units/Format	Empirical
Start date	User defined	Yr/mo/day/hour	2000/3/1/0
End date	User defined	Yr/mo/day/hour	2500/10/31/0
Simulation Time step	User defined	Seconds	3600
Ignition frequency	User defined	Number/yr	14
Random seed	User defined	Number	1260624655
Fire extinction thresholds	User defined	Hour/spread rate (m/s)	3/.05
Extreme fire weather frequency	User defined	Number/yr	0.8
Ellipse adjustment factor	User defined	Real number	0.66
Wind speed adjustment factor	User defined	type	BHP
Failed ignition cell threshold	User defined	Number	1
Fuel models	File	Number	1,4,7,8
Vegetation regeneration	File	Number	File
Wind direction (hourly)*	File	degrees	File
Wind speed (hourly)*	File	Km/hr or mile/hr	File
Dead 10hr fuel moisture (hourly)*	File	Percent	File
Live fuel moisture (hourly)*	File	Percent	File
Elevation (30 m)	Spatial file	Meters	File
Slope (30 m)	Spatial file	Degrees	File
Aspect (30 m)	Spatial file	Degrees	File
Fire history (30 m)	Spatial file	Age/years	File
Export	Output files	.txt, .asc, .png, etc.	Files

* Parameterization needed for regular and extreme weather conditions

Vegetation regeneration with time since fire information was gathered by utilizing twenty five years of vegetation monitoring data (Schmalzer 2003) combined with expert opinion on specific transitions for each fuel type. Ignition frequency was derived from a previous study (Duncan et al. 2009b) delineated the lightning ignition regime on KMCC. Fires were simulated for March through October because natural winter fires rarely occur (Duncan et al. 2009b). The HFire model was originally written to simulate fire in the chaparral ecosystem of California, which experiences extreme fire weather known as Santa Anna events. The model accommodates these extreme fire weather events, which here have been utilized to represent La Niña events that occur in Florida. La Niña events take place during the ENSO cycle in Florida on a roughly seven year rotation. ENSO cycles greatly influence fire dynamics in Florida with wet El Niño

events reducing area burned and dry La Niña events enhancing area burned (Brenner 1991, Harrison and Meindl 2001, Goodrick and Hanley 2009). In the central Florida region, extreme fire years have occurred in the fire record on a rotation of 23 plus or minus 5 years (Davison and Bratton 1986). This corresponds to about every third or fourth La Niña event being extreme, such as the 1998 year. An extreme fire event frequency of 0.8 events a year, averaged one extreme fire year every 23 years, mimicking the empirical records.

The fire extinction thresholds of 3 hours and 0.05 m/s were used. If a fire did not spread outside of a single cell in three hours or the rate of spread was less than 0.05m/s for an hour the fire was extinguished by the model. A failed ignition threshold of 1 cell was used. If a fire grew to larger than one cell it could only be classified as a successful ignition and fire. The ellipse adjustment factor was set at 0.66 because that value was found to be the most realistic in relation to modeling historic fires (Peterson et al. 2009). The meteorological inputs were taken from the network of weather station on KSC. A wind speed adjustment factor is applied to wind speeds collected high on towers to adjust them to represent speeds at mid flame heights (usually eye-level). This saved time reducing the effort it takes to calculate and enter the winds at mid flame heights initially. Fuel moistures were taken from data recorded by MINWR personnel and other unpublished fuel moisture data collected on KMCC (Duncan and Schmalzer 2004).

Ten model runs were conducted with the empirical parameter settings and different random seed numbers. These runs were averaged and are referred to as the composite empirical run, which have a standard error associated with each measure. The mean of the ten means, the median of the ten medians, the minimum of the ten minimums, and the maximum of the ten maximums will be presented.

A sensitivity analysis was performed to determine the importance of each input variable and to establish the range of variability from the empirical model run. Each model input was varied both positively and negatively by ten percent. The random number seed was held constant for all sensitivity model runs forcing the HFire model to be deterministic, isolating the influence of each input variable one at a time. The first empirical model run used the same random seed number as the other sensitivity analysis runs. This run is labeled empirical and was used to represent the empirical model outcome in the sensitivity analysis.

The FRAGSTATS program (McGarigal and Marks 1995) was used to quantify the spatial pattern of age polygons predicted by each model run. A subset of landscape metrics were selected to represent the spatial distribution of polygons on the landscape. Each of these metrics were selected based on their relevance to quantifying spatial pattern of burn age and their ease of interpretation.

Results

The composite empirical simulation predicted that the mean fire size was 152 ha (standard error of 1.59), the median was 0.09 ha (standard error of 0.08), the minimum was 0.09 ha (standard error of < 0.0001), and the maximum size was 9,153 ha (standard error of 403.6) for the five hundred years of simulation. The composite annual mean fire area was 2,043 ha (standard error of 20.8), the median was 1,518 ha (standard error of 27.1), the minimum was 0.18 ha (standard error of 0.53), and maximum was 15,060 ha (standard error of 527.5). The largest fires overall and annually were recorded during La Niña events. The amount of annual area burned followed a rising and falling cyclical pattern (Figure 30) with significant negative

autocorrelation at one (r = -0.161, p < 0.001) and eight years (r = -0.101, p < .0006) and positive autocorrelation at 11 years (r = 0.101, p 0.003) (Figure 31). The majority of the fires predicted to burn in this system were very small (Figure 32).

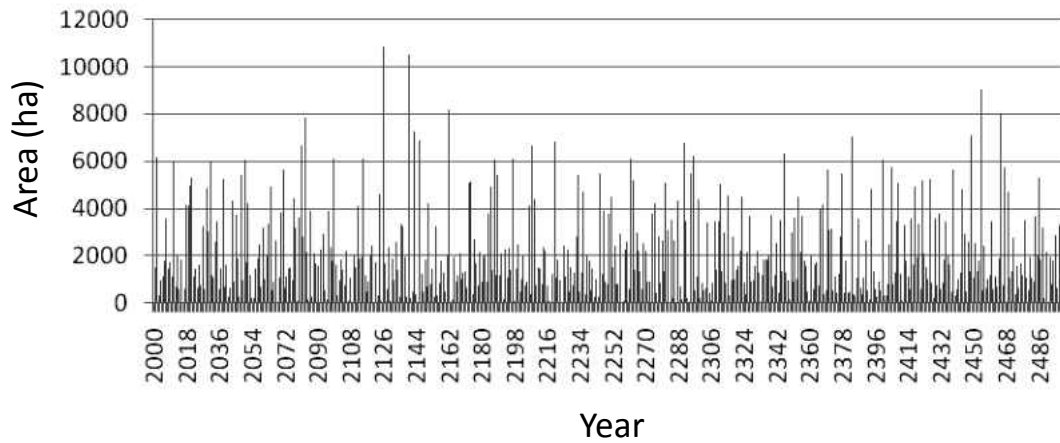


Figure 30. Time series of annual area burned for the empirical HFire model run on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

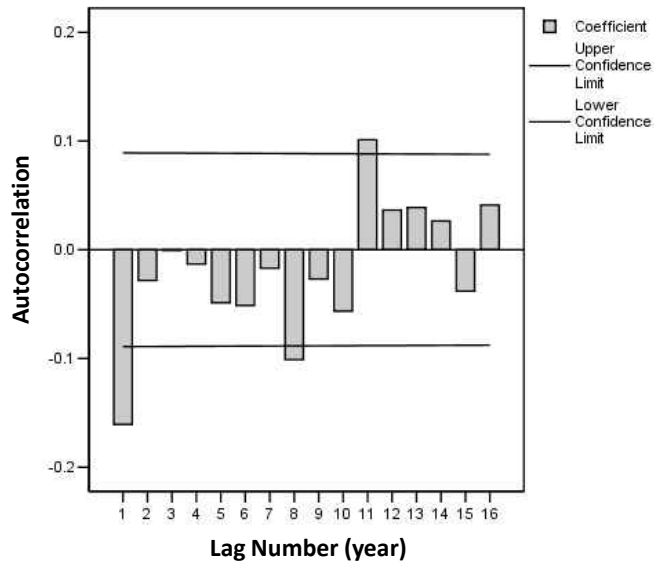


Figure 31. Autocorrelation coefficient and 95% confidence limit values for the annual area time series generated using the HFire model on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

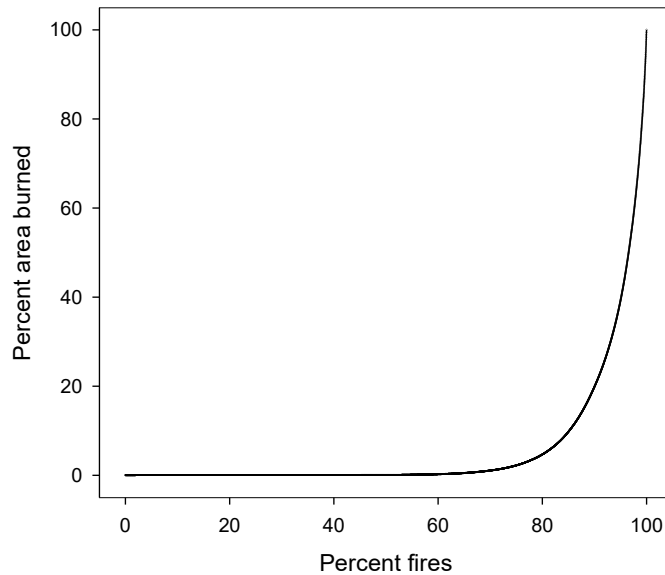


Figure 32. The proportion of ranked fires (small to large) and the proportion of area burned during the empirical HFire model simulation on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

The model started an average of 6,726 fires (standard error of 33.4) over 500 years. Many of those fires (average of 3,417, standard error 18.1) or 51% failed to spread and ended up classified as failed ignitions. The composite mean of annual fires was 13.8, the median was 13.9, the minimum was 2.0, and the maximum was 29.0. The annual fire frequency increased and decreased through time (Figure 33) but did not display a cyclical pattern or any significant autocorrelation.

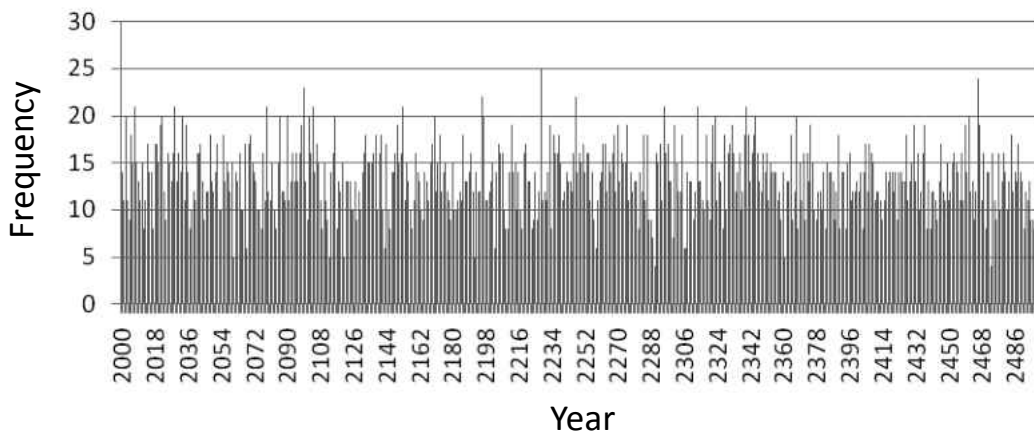


Figure 33. Time series of annual fire frequency for the empirical HFire model run on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

The fire cycle is the number of years it takes to burn area equivalent to the study sites burnable area. The composite mean fire cycle was 14.4 years, the median was 14.2 years, the minimum was 7 years and the maximum was 21 years. The return interval was calculated by

dividing the burnable area (29,541 ha) by the annual average fire size (2,043 ha), resulting in a return interval of 14.4 years.

The landscape age map displays a mosaic pattern of different age areas (Figure 34). The landscape age pattern is dominated by smooth curved boundaries with the only straight edges cause by the federal land boundaries. The empirical model run had 1,079 different age patches on it. The largest patch constituted 32 percent of the study area (largest patch index), a mean patch area of 64 ha, and 189 different age patches (patch richness). The area distribution by age class is skewed with most of the burned area being younger than 50 years old (Figure 35). The composite empirical average area distribution by mapped age class shows a distribution that is also skewed to the younger ages and peaks in the eight to ten age class (Figure 36). The standard error is the greatest in the two year age class and least in the 301 to 500 year age class.

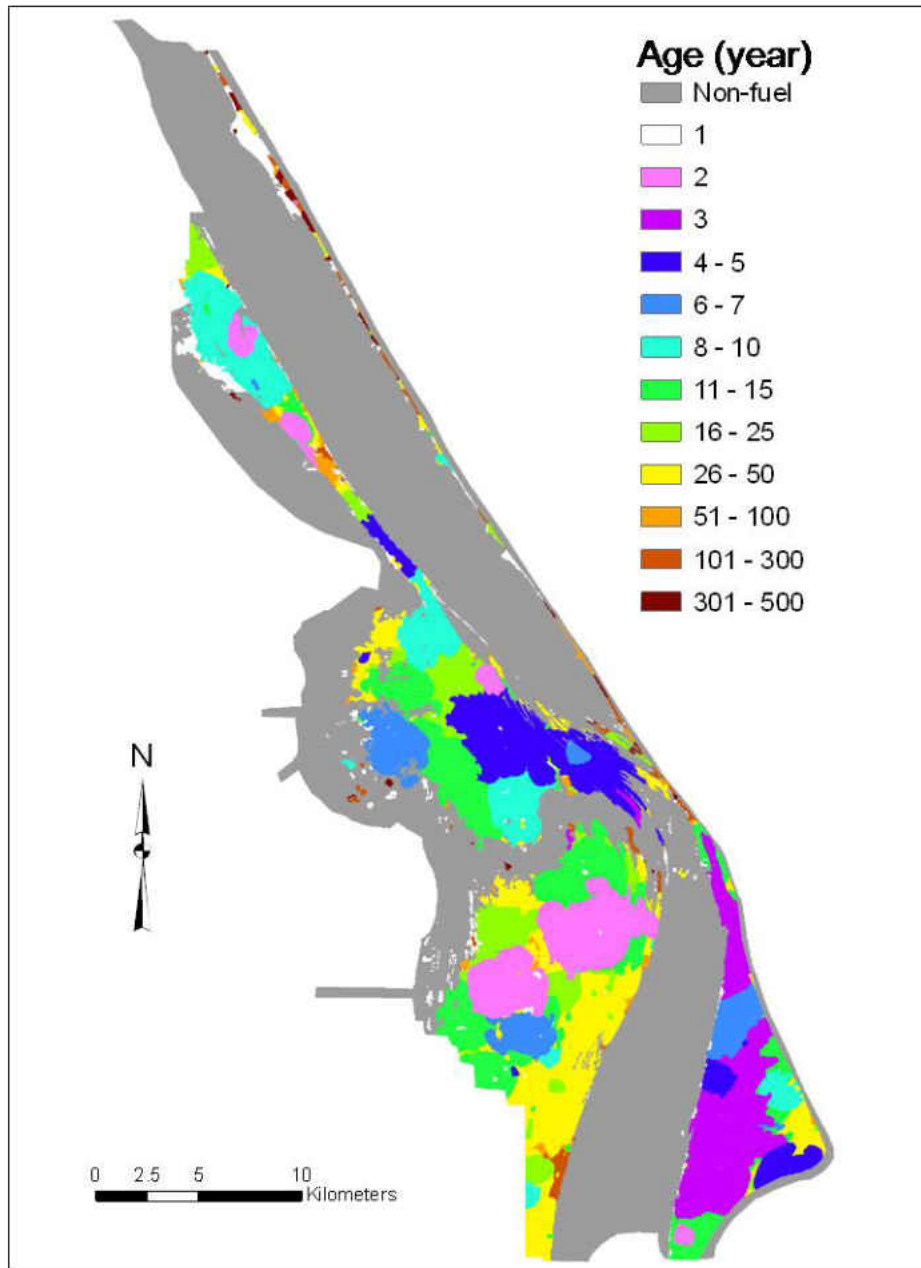


Figure 34. Landscape age map produced by the empirical HFire simulation for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

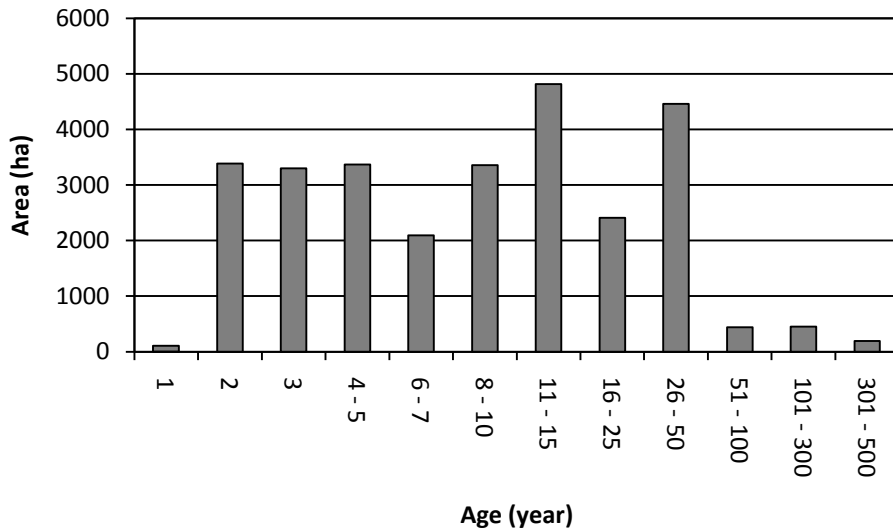


Figure 35. Frequency distribution of area by age class for the empirical HFire simulation on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. This distribution represents the age categories from the empirical map in Figure 34.

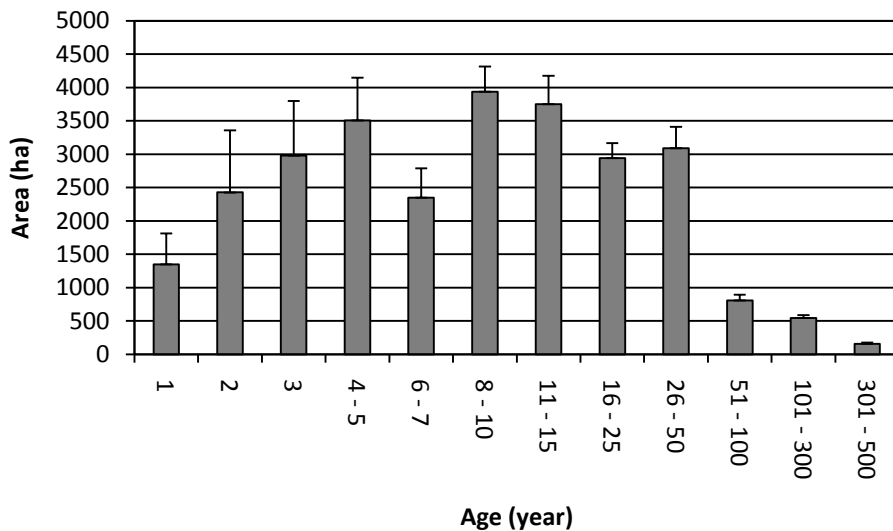


Figure 36. Frequency distribution of the average composite empirical area by age class. Distribution was generated by averaging the ten empirical HFire model runs. Error bars represent standard error for each age class.

Sensitivity Analysis and the Natural Range of Variability

The sensitivity analysis revealed that there were six inputs that had a large influence on the output of the HFire model (Figure 37). The combination of regular and La Niña dead fuels and regular and La Niña wind speeds appeared to influence the outcome the most, particularly in the medium sized fires. Differencing the six most sensitive parameters and the empirical area burned results revealed that the combination of regular and La Niña dead fuels and regular and La Niña wind speeds again produced the largest differences from the empirical run (Figure 38). The most interesting result however, is that the greatest differences are in the largest fires and not in the medium sized fires. The largest magnitude effects of varying the inputs positively ten percent were in the combination of the regular and La Niña wind speed (increase of 7.5%) and the regular and La Niña dead fuel moisture content (decrease of 6.2%). The largest magnitude effects of varying the inputs negatively ten percent were in the combination of regular and La Niña dead fuel moistures (increase of 5.1%) and dead fuel moistures (increase of 5.1%). The largest combined difference was the regular and La Niña wind speed of 12.3%, regular and La Niña dead fuel moistures of 11.3%, and dead fuel moistures of 10.5%.

The landscape metrics that were selected to diagnose the age structure predicted by the HFire model revealed a wide range of values (Table 11). The number of patches and the mean landscape patch area were normally distributed (Shapiro-Wilk test, $P = 0.253$, $P = 0.178$) and negatively correlated ($r = -0.99$, $P < 0.001$), while the number of patches and patch richness were normally distributed (Shapiro-Wilk test, $P = 0.647$) and positively correlated ($r = 0.94$, $P < 0.001$).

There was a wide range of fire sizes that may serve as an indication of the potential range of variability in this system (Table 12). The mean total fire size for all 500 year simulations was 988,625 ha, the median was 1,021,100 ha, the minimum was 519,993 ha, and maximum was 1,292,625 ha. The difference between the minimum and maximum value is 40%. There was also a large range of variation in the maximum individual fire sizes with a mean of 7,731 ha, a median of 7,630 ha, a minimum of 5,289 ha, and a maximum of 10,320 ha. The difference between the minimum and maximum was 51%. Total fire frequencies displayed a bit tighter distribution with a mean of 6,740, a median of 6,751, a minimum of 6,300, and maximum of 7,178. This was only a difference of 12% between minimum and maximum fire frequencies.

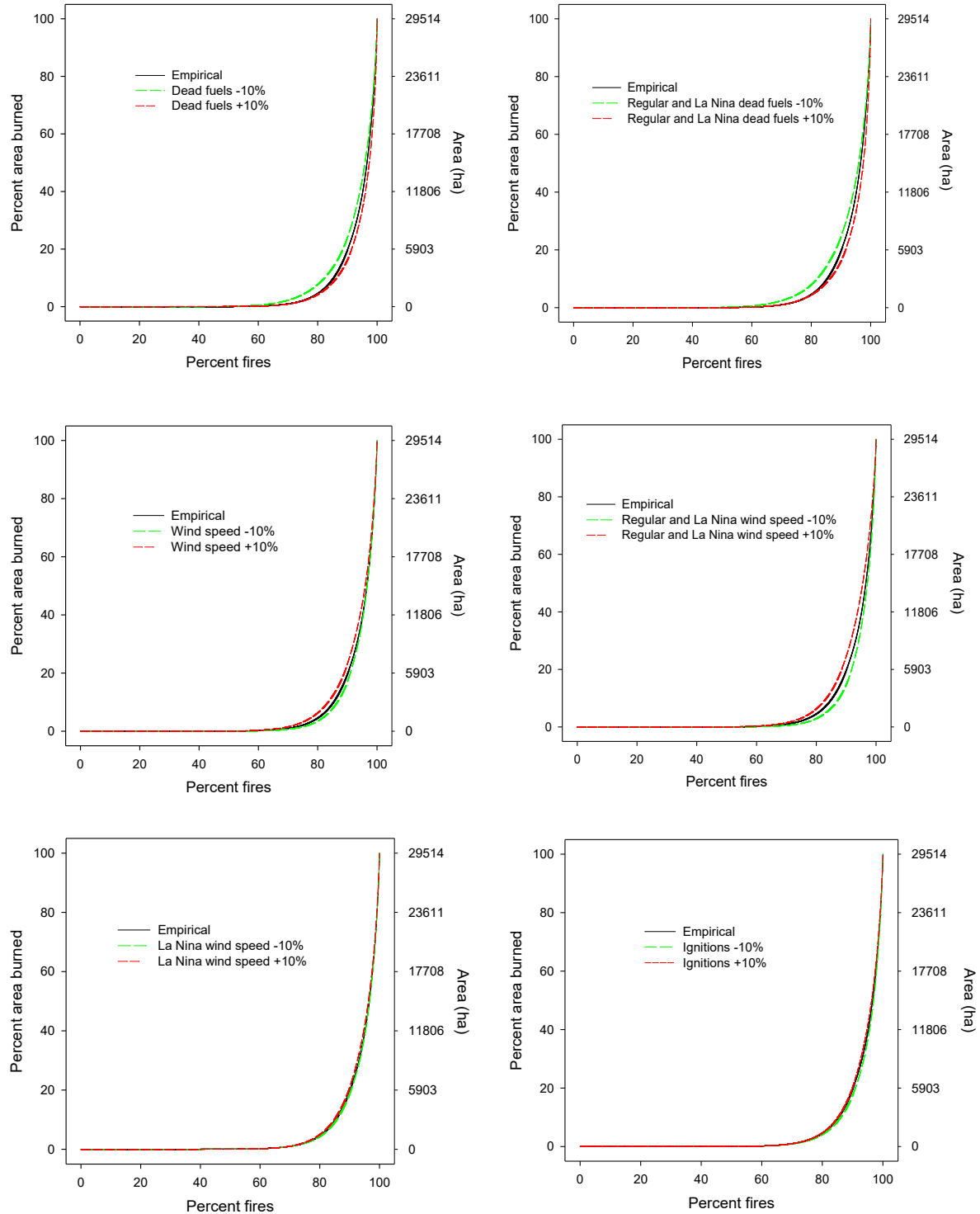


Figure 37. HFire model sensitivity analysis results, comparing the six largest magnitude differences from the empirically parameterized model run. Random seed number was held constant for all sensitivity simulations isolating the influence of input parameter variation.

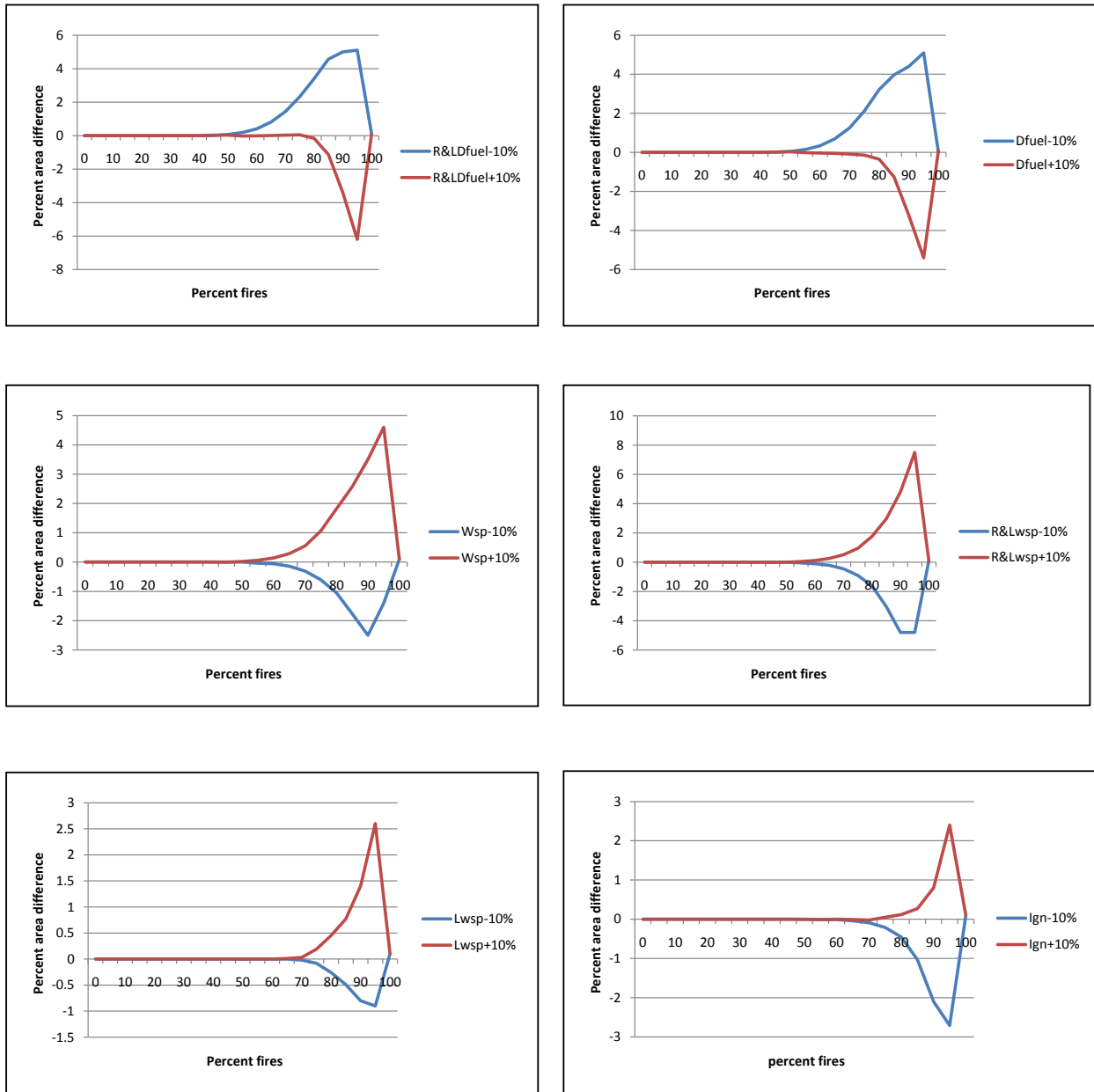


Figure 38. The Difference between the sensitivity analysis runs and the empirical model runs. The empirical model run is the horizontal line in the middle. The six model runs displaying the largest differences are shown. The random seed number was held constant for all sensitivity analysis simulations to isolate the influence of input parameter variation. Abbreviations are: R&LDfuel = regular and La Niña dead fuel, Dfuel = regular dead fuel, Wsp = wind speed, R&Lwsp = regular and La Niña wind speed, Lwsp = La Niña wind speed, and Ign = ignition frequency.

Table 11. Select landscape metrics for the large magnitude sensitivity analysis model runs on KMCC. Abbreviations are: NP = number of patches, LPI = largest patch index, TE = Total edge, AM = area mean, PR = patch richness, dfm = dead fuel moisture, and wsp = wind speed.

Model Run	NP	LPI	TE	AM	PR
Empirical	1079	32	1,361,400	64	189
Dead fuel Moisture -10%	1631	58	1,954,170	42	281
Dead fuel Moisture +10%	1626	60	1,919,550	43	308
Reg. & La Nina dfm -10%	1429	30	1,885,110	48	256
Reg. & La Nina dfm +10%	1595	31	1,985,910	43	276
Wind speed -10%	1331	31	1,826,730	52	215
Wind speed +10%	1095	61	1,672,500	63	189
Reg. & La Nina wsp-10%	1394	31	1,795,890	50	202
Reg. & la Nina wsp+10%	965	60	1,593,930	72	152

The full range of spatial variability was revealed by using the large magnitude sensitivity analysis runs and the FRAGSTATS program (Table 13). The relationship of the empirical model run (Table 4) can be compared to the distribution of landscape metric values from all runs (Table 11). The number of patches, largest patch index, total edge, and patch richness for the empirical run was below the mean near the low end of the range; however, the area mean and perimeter area mean were above the overall mean and near the maximum value for those metrics. There was a difference of 41% between the smallest and largest number of patches, a difference of 51% in the largest patch index, a difference of 42% in the area mean, and a difference of 51% for patch richness.

Table 12. Maximum fire area and total burn frequency values for HFire model output on Kennedy Space Center/Merritt Island National Wildlife Refuge/Canaveral National Seashore/Cape Canaveral Air Force Station, Florida . Empirical 2 through empirical 10 have unique random seed numbers, all other runs have the same random seed numbers to facilitate comparison within the sensitivity analysis.

Model Run	Total Burned Area (ha)	Max. Individual Fire Area (ha)	Total Burn Frequency
Empirical	1032291	5866	6730
Empirical 2	1068640	5865	6756
Empirical 3	1040307	7720	6491
Empirical 4	1017558	6519	6826
Empirical 5	970863	5289	6684
Empirical 6	983539	7817	6721
Empirical 7	1022562	9153	6631
Empirical 8	1015630	7540	6758
Empirical 9	1066885	8092	6838
Empirical 10	1019247	8724	6826
Ellipse adjustment factor -10%	1062584	6539	6679
Ellipse adjustment factor +10%	986404	7413	6755
Reg. & La Niña dead fuel moist. -10%	788712	9543	6811
Reg. & La Niña dead fuel moist. +10%	519993	9593	6934
Reg. & La Niña wind speed -10%	918390	8944	6740
Reg. & La Niña wind speed +10%	1292625	7528	6659
Dead fuel moisture -10%	761110	7237	6821
Dead fuel moisture +10%	540205	8838	6863
La Niña dead fuel. moisture -10%	1058339	8558	6748
La Niña dead fuel. moisture +10%	1067532	10016	6610
La Niña wind speed -10%	1076376	9168	6689
La Niña wind speed +10%	1053048	5664	6773
Wind speed -10%	897010	6189	6754
Wind speed +10%	1275102	7294	6674
La Niña Annual frequency -10%	990491	7960	6757
La Niña Annual frequency +10%	1050416	6450	6736
Annual Ignition -10%	1019639	10320	6300
Annual Ignition +10%	1086017	6633	7178

Table 13. The landscape metrics range of variability for all sensitivity analysis HFire model runs. Abbreviations are: NP = number of patches, LPI = largest patch index, TE = total edge, AM = area mean, PR = patch richness.

Statistic	NP	LPI	TE	AM	PR
Mean	1349	44	1777243	53	230
Median	1394	32	1826730	50	215
Minimum	965	30	1361400	42	152
Maximum	1631	61	1985910	72	308

Discussion

Fire size

The model predicted the majority of fires to be small. The cumulative fire size distribution generated by the model is very similar to an empirically derived distribution for this site (Duncan et al. 2009b). The modeled distribution has a higher percentage of medium sized fires presumably due to a lack of fire suppression efforts. Fire suppression is most effective within the medium size fires because the small fires are mostly undetected (Duncan et al 2009b), and the large fires burn under extreme meteorological conditions, making fires difficult to control or suppress in the contemporary managed fire regime. The largest individual fire was 9,153 ha in size, which is much larger than both the largest lightning fire (1,012 ha) and human ignited fire (1,324 ha) that were previously documented (Duncan et al. 2009a, Duncan et al. 2009b). The largest individual fire in this study was from a La Niña year. All the largest lightning fires on record for this site have burned during past La Niña events (Duncan et al. 2009b). The smallest fires 0.09 ha were very similar in size to the other studies at 0.04 ha. This

information indicates that the predicted natural fire sizes were wide ranging and more variable than under the managed fire regime.

Grouping the fires in annual blocks reveals much the same pattern. The largest area burned annually was recorded during a La Niña year. The 15,060 ha maximum was much larger than the annual total recorded for the managed fire regime of 4,078 ha (Duncan et al. 2009a). The minimum burned annually within the managed fire regime was 603 ha. As with the individual fire sizes, the predicted range of annually grouped fire size is much greater.

Previous studies suggest that the largest fires in Florida occur during La Niña events (Brenner 1991, Beckage et al. 2003, Duncan et al. 2009a and b). There is empirical evidence, however, that large fires do repeatedly occur during the spring dry periods (Beckage et al 2005, Duncan et al. 2009b). The model supports this because there were many very large fires that occurred during non-La Niña years.

The time series of annual area burned predicted a cyclical pattern with fire area being the most dissimilar (negative autocorrelation) for ten years and then switching to be similar (positive autocorrelation) at eleven years. There are two likely factors combining to create this pattern, fuel loadings and climate variability. The pattern is the most dissimilar in the first year following fire likely due to lack of fuels supporting fire. For the next ten years the pattern of dissimilarity continues with a peak in the dissimilarity at eight years. This may be climate driven with the ENSO cycle being around 7 years. The pattern switches to being one of similarity at eleven years and then generally repeats itself. As an example of this pattern, if the cycle starts during a year with lots of area burned then the point at which there is the smallest area burned is the following year (not much fuel left to burn) and then next, around eight years followed at eleven years by another year with a large amount of area burned. The model is predicting this

cycle which has a resemblance to the ENSO cycle at roughly an interval of 7 years that has been shown to influence area burned in Florida and the southeast (Brenner 1991, Beckage et al. 2003). The eighth year could be explained by being a wet El Niño year followed by a dry La Niña year at the eleventh year. The model also hinted at a longer time interval of roughly 325 years where there would be years with inordinately large area burned. Because the model was only run for 500 years, it is difficult to determine if this would be predicted as a cyclical reoccurring pattern. We know that there are long term climatic cycles that may also influence fire cycles (Goodrick and Hanley 2009). The model would have to be run for a longer time period and include more meteorological data to investigate longer period trends.

Frequency

The HFire model builds a Poisson distribution around the mean fire frequency that is user entered through the configuration file. For this reason, the mean (13.8 ignitions per year) was very similar to the mean from the empirical study (14 ignitions per year), the minimum was exactly the same for empirical and modeled at two, but the maximum (29) was smaller than the maximum empirical (39) ignition frequency value (Duncan et al. 2009b). The range in modeled ignition frequency values was less than was observed in the empirical study. Because the number of fires influences the distribution of fire on the landscape, the model was possibly underestimating both predicted area burned and the spatial pattern of fire.

Seasonality

The season and month that these large fires took place can be tracked but this information is of limited use. The model does not solicit information on the seasonal/monthly distribution of ignition and then the model randomly samples the meteorological data by time. The distribution of fires by season and month were plotted but showed little useful information. For these reasons, a year is the minimum temporal unit that should be quantified using this version of the fire regime model.

Spatial Pattern

Smooth curved boundaries dominated the pattern of age classes on the landscape. The managed fire regime pattern on this same landscape has prominent straight edges from the human-made fire management unit boundaries and fire breaks. The prominent fuel break crossing Merritt Island in an east-west direction is Banana Creek. This fuel break restricted fire spread across the center and widest part of the Merritt Island.

Most of the burned area was in the young age categories. The single empirical map and its age distribution (Figure 35) differed from the averaged composite empirical area by age class distribution (Figure 36) in a couple of ways. The first is that the single distribution peaked in the eleven to fifteen year age class and the composite empirical average distribution peaked in the eight to ten year age class. The single distribution had very little area in the one year age class while the composite empirical average distribution had more area routinely in that category.

Another important difference was that the single distribution had the second highest amount of area in the 26 to 50 year age class when on average it was the fourth from the largest class by area. The composite average distribution resembled a normal arrangement more than the single distribution. An interesting similarity was that both distributions dipped with less area in the six to seven year age category. Another similarity was that the area burned tapers off after 51 years of age. The single empirical run peaks in the eleven to fifteen year category with the fire cycle and return interval values also falling in this year range. After 15 years there was significant over burning (cycling of burn area) on the landscape with some areas taking longer (generally up to 50 years) to burn again. The eleven to fifteen year category is the second greatest area category in the composite average distribution with the amount of area declining from this point.

There was a mosaic of over a thousand different age patches on the landscape comprised of 189 different age patches at the end of the empirical model run. These may be conservative estimates because the model predicts the spread of a uniform burn pattern propagating from a single ignition point. Enclaves or islands of unburned fuels may not be realistically represented by this process. Spot fires that are secondary ignitions started by hot embers drifting aloft from an existing fire are common in this system (Duncan and Schmalzer 2004), and are not represented by the model. The remote sensing process of mapping fires for the managed fire regime revealed a much finer/detailed pattern of both fire boundaries and within boundary pattern (Duncan et al. 2009a). The absence of enclaves and spot fires undoubtedly influence the final pattern on the landscape.

Sensitivity Analysis and the Natural Range of Variability

The sensitivity analysis revealed that there were several parameters that were more influential than others. Wind speed and dead fuel moisture consistently produced the largest magnitude differences. The single largest difference in fire area was less than the ten percent input variation in each parameter during the sensitivity analysis. This revealed that the model is driven by a combination of parameters cooperatively. Wind speed had a direct effect on modeled fire area with increased wind speeds resulting in larger area burned. Dead fuel moistures had an inverse effect on the model outcome as reducing fuel moisture, increased burned area. Although having a small effect on area burned, a positive increase in the number of ignitions also increased the amount of area burned. Perhaps the lack of major influence was due to this system being dominated by small fires. The number of ignitions would likely have a larger influence in systems with larger fires.

The sensitivity analysis revealed that the positive and negative adjusted parameters had different responses when differenced from the empirical result (Figure 38). The positively increased parameters all had spiked shaped distributions with abrupt run ups to the largest percent difference and an even more abrupt descent back to the empirical value at 100%. This distribution indicates that the larger the fire, the larger the increase in area burned. The negatively adjusted parameters generally displayed a more gradual run up and return to 100%. In some cases the peak was gradual and reached an asymptote at lower fire sizes than the positively adjusted parameters of the same type. In this case as fire size increased, the effect of the negative parameter did not increase at the same rate, lessening its influence at the larger fire

sizes. The negatively adjusted parameters generally have a larger influence on the moderately large fires and may influence the largest fires less.

By using all of the sensitivity analysis model runs, the model predicted that there was an inverse relationship between the number of patches and the mean fire size on the landscape. It also indicated a direct relationship between patch richness (number of age classes) and patch number. Ecologically this means that spatial landscape pattern, specifically patch richness and mean fire size vary through time, both seasonally, with wet and dry seasons (small and large fires respectively) and on a longer time frame, with climatic variations such as El Niño and La Niña (small and large fires respectively).

The sensitivity analysis information combined with the information generated by multiple empirical model runs indicated that the majority of variability were in the large, extreme values. There was less variation in the minimum values than in the maximum values. For this reason, I concentrate my discussion of variability on the large extreme values.

The range of fire size variation indicated that some very large fires are expected to occur on these federal properties. The model indicates that the largest fires would be of greatest size if there were fewer fires. An explanation for this may be that over many years, fewer fires on the landscape would reduce the discontinuity between fuels capable of carrying fire, creating a more even-aged fuel bed. With more fires, a fuel mosaic is created with a patchwork of different age/fuel loadings. The younger areas have less fuel and may not burn as well, acting as a fuel break. The total burned area show the cumulative effect of altering each input parameter. Increasing fuel moisture just a little can have a large impact over time just as increasing wind speed for both regular and La Niña periods can dramatically increase the amount of area burned over a long time period. As expected, the burn frequency was the lowest for the run having the

fewest ignitions and the greatest the run having the greatest number of ignitions. There is not much difference between the two ignition frequency extremes; in fact, when divided out by the total number of years in the simulation it is only about two ignitions per year.

The landscape metrics for the large magnitude sensitivity analysis runs summarized the spatial distribution of age classes on the landscape (Table 11 and Table 13). The empirical model results are generally at the lower end of the range of variability. Reducing fuel moisture increased the number of landscape patches to the highest number in the study and caused the smallest patch area mean. The model suggests that there is a negative relationship between the two. The smallest landscape patch (largest patch index) value was caused by reducing regular and La Niña fuel moisture, reinforcing the previous finding. Increasing the wind speed caused there to be the fewest patches, the largest landscape patch mean area, and smallest patch richness. The model suggests that the higher winds cause fires to spread and become larger than would otherwise occur, reducing the number of different age patches on the landscape. This is reinforced by the largest patch index, because the largest value was caused by increasing the wind speed. The highest patch richness was caused by increasing fuel moisture values. The model predicts that higher fuel moistures cause increased resistance to burn; so more patches of different ages are ultimately left unburned.

General observations and model limitations

The Banana Creek feature running in an east-west direction limited individual fire sizes. Fire sizes would undoubtedly be larger if this non-flammable feature was not on this landscape. A Monte Carlo model structure may be necessary to accurately quantify the true range of

variation. It is likely that the approach used here covered the major variability but an even larger number of simulations exploring all possible parameter value combinations would help make certain that all subtleties were covered. The standard errors derived by averaging the empirically parameterized runs were generally small indicating, that the predicted stochastic range of variation for the empirical run was limited and generally captured in the modeling structure used here.

The HFire model was designed to model fires in the chaparral system. The vegetation regeneration/succession routine in this model is restricted to 30 years post-fire. In a chaparral system fuel accumulation may cease to differ significantly after this time frame but the flammability will increase. In the southeast and especially on KMCC within the oak scrub community, flammability can actually decrease with time since fire. Long fire suppression periods can cause the structure of oak scrub to become xeric hammock reducing flammability (Schmalzer and Hinkle 1992b, Duncan et al. 1999). This is less critical for simulations under natural conditions but could be important for simulations on the contemporary landscape. The model currently does well to predict fire size, return interval, and spatial distribution of ages on the landscape. If seasonal and monthly trends could be predicted, this would add to the utility of the model. This would likely require more input data but could extend the models usefulness to predicting all elements of a fire regime.

It may also be useful to allow specific distribution values to be input through the parameter files. Currently the mean is the only value entered. The full distribution of values may be available in some locations, and the model should take advantage of that information. As an example in this experiment, minimum and maximum ignition frequencies are available but not utilized. The result is that the model output may not be as informative and realistic as

possible. The absolute effect of this was not explored in this study but would be useful to explore in the future.

Conclusion

Fire regime modeling can be useful in the absence of a traditional means of reconstructing fire regimes such as dendrochronology. The raster based HFire model represents the latest in fire regime models, it improves efficiency and accuracy from previous models, it is based on the robust Rothermel equations, and it is currently being benchmarked and evaluated by the United States Forest Service (Peterson et al. 2009). The Hfire fire regime model does well to predict fire size, return intervals, and spatial distributions of age classes. Other fire regime elements such as intensity and seasonality are not directly supported by this model.

The model was parameterized primarily using empirically-derived values from studies conducted on these federal properties. The model predicted that the natural fire regime was dominated by a mosaic of quickly recycling small fires, with fewer medium and large fires on the landscape. Large fires were common during La Niña ENSO events but also occurred during regular weather conditions. The largest difference from the empirical-derived output values obtained from varying input parameters by ten percent in the sensitivity analysis was 7.5%. Total ranges of variability were from 13% to 55% for fire sizes and landscape metrics. The empirical run was at the lower end of the range of variability indicating that potential variation is greatest at the large value extremes.

The information generated in this study may be directly useful to land managers who have an interest in mimicking the natural fire regime for purposes of managing habitat for native

fire dependent species. There are gaps in the information but together with empirical findings from other studies the results can be extremely informative. Many of the findings in this study reinforce results gathered by empirical means and others may be new and warrant further study. This study represents only one of many steps in a quest to quantify the natural fire regime in a region that has been shaped and maintained by fire. Mimicking aspects, or the results of the natural fire regime and adapting them on the contemporary landscape within the boundaries of conservation areas may be one of the best hopes for conserving many native fire-dependent species in this region. This will take more study including empirical and modeling as well as innovative land management to apply the critical information.

GENERAL DISCUSSION/SUMMARY/CONCLUSION

Major Differences between the managed fire regime and natural fire regime

Seasonality

Seasonality of the managed and natural fire regimes are very different. The managed fire regime behaved inversely to the natural fire regime in relation to meteorological moisture conditions (Duncan et al. 2009a). Large areas typically burn in Florida during spring droughts and dry La Niña periods (Brenner 1991, Slocum et al. 2003). Under the managed fire regime, burned area declined during drought periods and increased during wet periods.

The majority of area burned under the managed fire regime is during the winter season and during the month of November. There was only one winter lightning ignition during the 16 year natural ignition study and none during the month of November. The peak in lightning ignition was during the summer season specifically during the month of July. The current HFire model is not parameterized to predict seasonal and monthly differences in fire during simulations. Annual differences are the finest temporal unit that can practically be predicted using the current version of the model.

Fire size/area

All the evidence in this research point to the natural fire regime being dominated by many very frequent small fires (Table 14). These small fires occur particularly during the moist, late growing season. The empirical studies indicated that the largest fires occurred during the

spring droughts, particularly the La Niña droughts. The HFire model results indicate that it is also possible for large fires to occur during non-La Niña periods. The modeled fire sizes display a wider range of fire size than the managed fire size. This is particularly true of the largest fire sizes between the managed and modeled natural fire regimes. The maximum fire size is estimated to be four times the size of the managed fire size.

Table 14. Comparison of fire regime fire sizes for Kennedy Space Center/Merritt Island National Wildlife Refuge/Canaveral National Seashore/Cape Canaveral Air Force Station, Florida.

Fire regime	Mean	Median	Minimum	Maximum
Managed fire regime	198	112	0.73	1,324
Lightning fire regime	13	0.08	0.04	1,012
Simulated natural fire regime	153	0.09	0.09	5,865

Both the lightning ignition regime and the modeled natural fire regime have fire size distributions that are largely made up of small fires (Table 14). The managed fire regime does not have the same distribution structure of fire size because there are fewer very small fires and the largest fires are not as large. The fire size distribution structure is very similar for the lightning fire regime and the simulated natural fire regime (Figure 39). The main difference between them is in the medium sized fires. This difference would have to be attributed to fire suppression efforts. The smallest fires, many of which go undetected and go out on their own (natural outs) will stay small regardless, while large fires generally burn under severe conditions

and there is little that can be done to control/extinguish them. Fire control and suppression efforts are therefore most effective for medium sized fires and this is displayed in the difference between these curves.

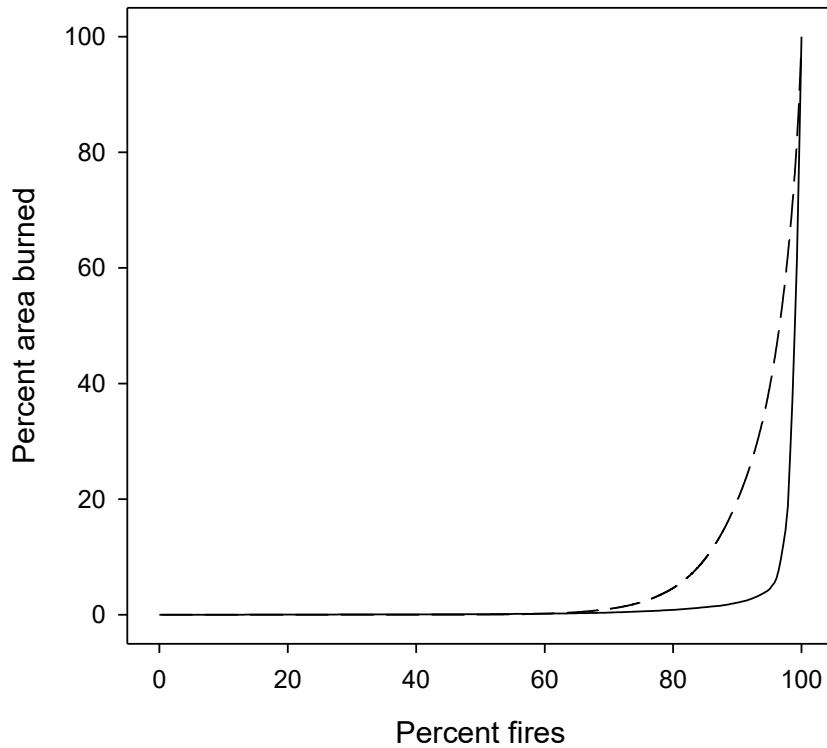


Figure 39. Comparison of cumulative fire size distributions from the lightning ignition regime (solid line) and the modeled natural fire regime (dashed line) for Kennedy Space Center/Merritt Island National Wildlife Refuge/Canaveral National Seashore/Cape Canaveral Air Force Station, Florida.

Fire frequency/Return Interval

The fire cycle and fire return interval numbers are very similar for both the managed fire regime and the modeled fire regime. The entire range of values is between 11.5 and 14 years. There is a difference however. The fire size distribution for the modeled natural fire regime is primarily made up of very small fires but roughly every 11 years there is a large fire event. It would take a very long time for the fire cycle to be completed with all of these small fires but less frequent very large fires help close the fire cycle in roughly two years more than the managed fire regime. The managed fire regime has a smaller range of fire sizes with more medium sized fires that add up consistently, quickly closing the fire cycle.

Spatial pattern

There is a striking difference between the age patterns left on the landscape by the different fire regimes. The age pattern from the managed fire regime is comprised of evenly sized geometric areas, the result of fire management unit boundaries and fire breaks. The pattern left from the modeled natural fire regime is a mosaic of different sized, mostly round shapes. The remote sensing classification processes also contributes a detailed internal pattern that the modeled age patches do not possess. Because not all areas burned inside the fire boundary, the remote sensing method is able to map out the unburned internal areas. The model estimates the fire spread and the outer patch boundary. The model does not estimate and represent the internal complexity that may occur within those boundaries.

The dominant burn season map revealed areas that were primarily burned during different seasons. There are areas that have mostly burned during the winter. Based on the lightning ignition regime, the likelihood of areas repeatedly burning during the winter season are remote under the natural fire regime.

Management implications

To mimic the natural fire regime there are some points that should be made in light of the information made available by these studies. The lightning ignition regime study indicates that there should be an average of 14 ignitions per year with some years having fewer and some more. The annual range was between 2 to 39 per year. There is a large difference between the season of burn in the managed fire regime and the natural lightning driven fire regime. A shift in burn season would need to be accomplished to mimic the natural fire regime on these properties. Chapter two discusses some of the implications of the influence of different fire seasons on native seeding and sprouting species. Essentially, resprouting species appear to be affected little by the winter fire regime (Foster and Schmalzer 2003), while seeding species such as wiregrass have been shown to be affected (Outcalt 1994, Mulligan and Kirkman 2002). Wiregrass is an important foundational species with its fine fuel characteristics that help carry fire in longleaf pine and flatwoods communities. With prolonged winter fire, species like wiregrass will likely decline. Wiregrass vegetatively sprouts following fire during any season but flowers and seeds during growing season fires (Maliakal et al. 2000). Wiregrass is not currently a dominant component of the vegetative composition of the communities found on these sites (personal communication with Paul Schmalzer). The problem is that these properties were subject to a

long period of fire suppression (Duncan et al. 1999). We don't know what the historical composition of this landscape truly was, and there are no areas that have burned under a natural fire regime that can be used as control for this information. Visual evidence does support the notion that wiregrass sprouting/vigor does increase following growing season fire in some flatwoods sites on these properties.

Late growing season fires were generally smaller than early growing season fires. Each year there is a switch from the dry, early growing season into the wet, late growing season. The spring months of April and May are typically dry and that is when the majority of the large fires occur in Florida (Slocum et al. 2007). The month of June has high variability in precipitation; June can either be very wet or very dry. If June is wet, then there is a shift to smaller fire sizes in June, and if not, then the shift occurs later in July. The data suggest that this shift in fire size consistently occurs after the middle of July, as July is consistently wet with less variability. To mimic the natural fire regime, large fires would be conducted during the early growing season and small fires would generally take place in the late growing season after the middle of July.

There should be far more small fires in this system than large ones. There may be several ways to achieve small fires. The first is to follow the natural fire regime and take advantage of moisture conditions to keep fires small or put fire lines in to break up larger fire units. The pattern of fire breaks may also be important. The managed fire regime displayed a very geometric pattern on the landscape. It is unclear that the pattern of fire breaks matter much. It has been noted in the past that aerial predators can take advantage of straight edges (Duncan et al. 1995). Future curved fire breaks can be put in to break up the blocky pattern. With modern machinery temporary fire breaks may also be an option.

Growing season fire scars were present on the landscape for a longer duration than non-growing season fires. This may be an important subtlety when considering how to restore and maintain open mineral, sand openings. Mineral sand openings are a prominent landscape feature that Florida scrub species depend on (Woolfenden and Fitzpatrick 1984, Quintana-Ascencio et al. 1998, Breininger and Carter 2003, Menges et al. 2006) and land managers are concerned with maintaining. Mineral sand openings may be present on the landscape for longer duration if growing season fires are used.

Pine aforestation has become a problem with alteration of native fire regimes in Florida and on these federal properties (Duncan et al. 1999). Growing season fire followed by submersion produce unfavorable conditions limiting recruitment of pine trees and palm trees (Platt et al. 2006, Menges and Marks 2008).

The pine flatwoods community was ignited by lightning fire much more frequently than other types. Fires probably started in this community and then spread into other adjacent types such as Florida scrub (Myers 1990, Breininger et al. 2002). When considering subdividing fire management units to create smaller fires this detail must be taken into account.

Exotic species have also had an influence on landscape flammability. Exotics can both increase (Lippincott 2000) and decrease flammability on a landscape, having important ramifications for fuel continuity and fire spread (Duncan and Schmalzer 2004).

New/reinforcing science information

The work presented in this document was most specifically conducted to aid the management of fuels and habitat for the goal of sustaining native fire dependent species in

Florida. In addition there are many innovative developments and new scientific information within this work that has the potential to advance fire science. The image processing technique developed a non-parametric separability index that is different from popular statistical feature selection routines such as transformed divergence and Jeffreys-Matusita distance techniques (Shao and Duncan 2007). These traditional techniques rely on training data from each class within each image band being normally distributed (Jensen 2005). The separability index is very simple and cuts the effort substantially to select bands which maximize classification accuracy. Conceptually, the separability index uses area under the curve to look for the bands which best separate burned from unburned image signatures. It is very simple, the band that has the smallest overlap area (common area) between burned and unburned has the highest separability index value (closest to one) and is the best for classifying burned from unburned (Figure 40). This is because the image signatures are the most distinct making burned and unburned areas easy to classify.

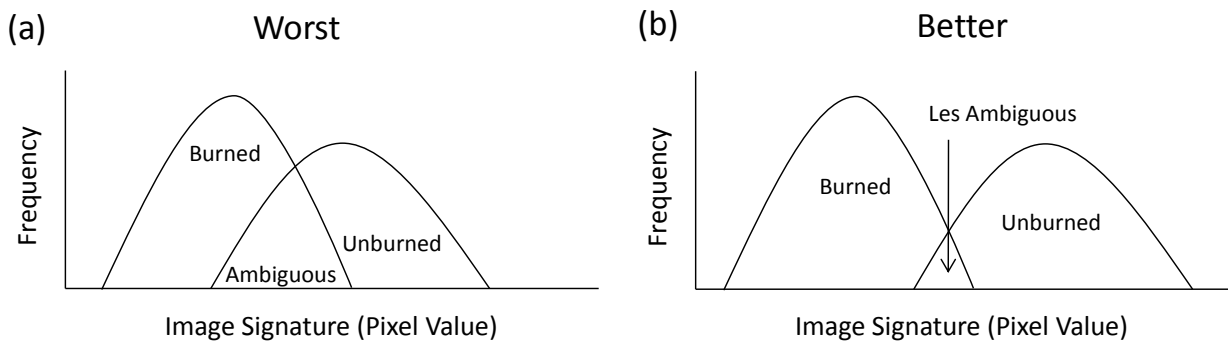


Figure 40. Conceptual diagram of the separability index for (a) when burned and unburned areas are ambiguous and overly each other in image signature space and (b) when there is less ambiguity between burned and unburned image signatures.

This method of sorting and selecting the best bands for classifying fire scars may be used for classifying any spatial feature on any landscape. Because the Separability Index is so easy to use and is distribution free, it would not be surprising to see it widely used in favor of the traditional methods.

Geographic information systems have been used in spatial science since the 1980's. New methods are still being devised to take advantage of its benefits, this study is no different. In chapter two a system was developed to label the confidence for which historic fire boundaries were mapped. This approach is an outgrowth of a technique used to classify the quality of mapped landcover information (Liu et al. 2004). The conceptual underpinnings remained the same but we adapted the concept for use in fire scar mapping. The technique assigns a confidence value to each mapped fire scar so the user can include or exclude it from consideration in any application. The confidence values is derived base on the cross validation of empirical fire records with remotely sensed information. This technique has ramifications far beyond its original application because it provides a means to assign a quality label to mapped historic features. It was used in this study to quantify fire boundary degradation with time since fire. It has another use that may be very significant and is yet unexplored. Generally the quality of mapped historic features *post hoc* is unknown. Because a classic accuracy assessment can generally not be conducted on historic maps, this confidence technique provides a second option for quantifying the quality of historic mapped features that would otherwise not exist.

There were two other techniques used in this study that took advantage of the capabilities of GIS technology that are innovative and may be useful for other studies. The first is tracking the spatial cumulative frequency on the landscape. Each fire was given a count item and then

summed to produce a final frequency map. A similar coding was used to track season of burn information to track spatial bias in season of burn patterns on the landscape.

There was much lightning fire ignition information generated that may not directly benefit land managers concerned with managing habitat for conservation of fire-dependent species. This information included lightning polarity, lightning multiplicity, the abundance of natural outs, the abundance of hold-over ignitions, and the ignition to lightning strike ratio. This information directly helps quantify the lightning ignition regime in this region providing useful reference information to those who study aspects of lightning meteorology here and elsewhere.

Model limitations/improvement and future analysis

Season of burn is a fire regime element. The current version of the HFire model is not parameterized for simulation of seasonal influences on the fire regime. A monthly distribution of ignition probability could be included in future versions of the model. The meteorological and fuels inputs can already support a more detailed seasonal ignition regime because the data are entered by year, month, day, and hour. For sites with empirical information regarding the specific temporal distribution of ignition, this would allow a more robust fire regime simulation. The empirical information that now exists for these federal properties gives insight into this problem. As a good example, the cumulative severity index data showed that droughts can occur during all seasons. This indicates that there are many times when fuel conditions would be right to carry extreme fire. The timing of dry fuels with an ignition source is the key to the natural fire regime. Fuels may be able to carry fire at many times during a given year but the probability of an ignition is only high during the growing season. With the HFire model, we witnessed that the

largest fires occurred during non-La Nina years. Empirical data throughout Florida, including the empirical set here, suggests that this is unlikely. Without the proper parameterization in HFire, we do not know for sure if it is possible for the largest fires to occur during non-La Nina years? Empirical evidence suggests not, so further research is needed.

Another useful addition would be the ability to assign ignition probabilities to fuel types. The empirical information showed that pine flatwoods was ignited more than other types. This would add the ability to make the simulations more realistic and explore the spatial patterns that may have been present under the natural fire regime.

The vegetation regeneration routine is not optimum for the ecosystems here on these properties. The Hfire model allows for only 30 years of vegetation succession. Oak scrub will convert to xeric hammock with absence of fire. Xeric hammock is much less flammable because of its mature treelike structure that creates a moist understory environment. This transition often takes longer than 30 years and so do many other secessional transitions that can occur with long fire free periods. The model was developed for the chaparral system and after 30 years the fuel buildup is more or less complete. As we have pointed out this is not the case in Florida and for the HFire model to be universal, a longer successional routine is necessary.

A burn frequency map would also be a nice addition so that the patterns of fire frequency can be tracked through time. Fire intensity information would also be a welcome addition to model output.

Considerations of Managing Fire on the Space Port, Florida

As discussed in Chapter two there are many restrictions limiting the management of fire in this system. There are the common permitting restrictions such as safety for all personnel involved in fire operations and the general public. Visibility on roads from smoke is an example of the types of safety permitting requirements. The infrastructure of Space Port operations imposes an entirely unique set of restrictions. There are fuel farms and fuel storage facilities, along with clean rooms that frequently have multi-billion dollar satellites inside of them being readied for launch into space. Facility managers in charge of facilities such as these are generally not willing to allow fires if there is the slightest chance that it may threaten their operations. When prescribed fire is being discussed on the Space Port, conflict resolution skills are necessary. These restrictions combined with weather requirements make scheduling prescribed fires challenging.

A chain of communication has been established on the space port. This is in an effort to minimize the chance that prescribed fires will be restricted for any reason, other than a legitimate significant hazard to space launch mission. More work is needed by all stake-holders to work out a system that will maximize opportunities to conduct fire on these important conservation properties.

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Title: Delineating a managed fire regime and exploring its relationship to the natural fire regime in East Central Florida, USA: A remote sensing and GIS approach
Author: Brean W. Duncan, Guofan Shao and Frederic W. Adrian
Publication: Forest Ecology and Management
Publisher: Elsevier
Date: 15 June 2009

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Volume number	258
Issue number	2
Pages	14
Type of Use	Thesis / Dissertation
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Format	Both print and electronic
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Expected publication date	Oct 2009
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