ABSTRACT OF A DISSERTATION

Characterizing Alaskan Wildfire Regimes through Remotely Sensed Data: Assessments of Large Area Pattern and Trend

Crystal A. Kolden

May 2010

Submitted to the faculty of Clark University, Worcester, Massachusetts, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Geography

And accepted on the recommendation of

John Rogan, Ph.D.
Chief Instructor
Wildfires are an integral disturbance component of dynamic ecological communities, but for humans to thrive in wildfire-prone regions, they must mitigate wildfire risks to human infrastructure and ecosystem services. Boreal forest and tundra ecotypes have co-evolved with wildfire disturbances, but the nature of fire effects on the landscape boreal regions is poorly understood due to sparse human settlement. The most extensive work thus far covers Alaska, where five decades of research have focused primarily on localized wildfire as a catalyst for succession in the boreal forest. This dissertation explores wildfire regimes at a regional scale in the Alaskan interior through remotely sensed data. It uses an exploratory approach to identify spatial patterns and temporal trends in remotely-sensed wildfire activity, determines the relative influence of climate and vegetation on those trends, and describes the importance of understanding these trends to increase the accuracy of global emissions models.

The first paper examines novel approaches for representing ground-observed one-year post-wildfire impacts in concurrently-acquired remotely sensed data from two sensors. High correlation ranges between spectral indices and wildfire consumption of above-ground vegetation were found, and several bi-temporal indices were significantly correlated to ground observations of fire effects.

The second paper examines three assumptions held about wildfire regimes in the Alaskan interior boreal forest: that larger fires burn more severely than smaller fires, that wildfires burning during anomalously warmer and drier conditions burn at higher severity,
and that more recent wildfires have burned more severely as compared to wildfires in the 1980s and 1990s. Findings refute previously stated assumptions. Fires that were smaller and burned under cooler, wetter conditions burned more severely than fires that were ultimately larger and burned under hotter and drier conditions.

The third paper explores the role of climate and vegetation composition on fire regimes in the Alaskan interior boreal forest. An analysis of vegetation burned from 2002-2008 indicated that there are likely multiple fire regimes in interior Alaska, instead of the single boreal forest regime that has often been described. Together, the three manuscripts identify methods for and avenues for further quantification and characterization of fire regimes in Alaskan landscapes.
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INTRODUCTION

In 2007 the U.S. Environmental Protection Agency (EPA) characterized wildfires in the conterminous U.S. (CONUS) as being “managed;” the mechanisms of ecosystem disturbance by fire and the ability of humans to control this disturbance were understood and executable (EPA 2007). Alaskan wildfires, however, were characterized as unmanaged and unmanageable by the EPA, which considers Alaskan wildfires to be truly “wild.” During the largest fire years in Alaska (e.g., 2004), annual burned area in the state has exceeded that burned in CONUS, with several historic fires exceeding 100,000 ha. Despite the size, duration, and intensity of Alaskan wildfires, fire regimes in the state are poorly understood, particularly when compared to the vast body of scientific literature covering fire regimes in CONUS ecotypes. This is largely a function of the rural and inaccessible nature of the state, its low population density, and a lack of merchantable timber in the boreal forest. Boreal fire regimes in both Alaska and across the high latitudes, however, have become critically important to an emerging global concern; climate change and the role of carbon cycling.

Boreal ecosystems harbor an estimated one-third of global terrestrial carbon stocks (Apps et al. 1993; Kasischke 2000), primarily as soil organic matter. Estimates of greenhouse gas (GHG) emissions from wildfires in boreal forests vary widely due to differing assumptions about fire characteristics and effects (Kasischke et al. 2005), but are widely estimated to increase over the next century in accordance with projected warming trends in boreal regions (IPCC 2007; Amiro et al. 2009). French et al. (2004) noted that the greatest uncertainty in estimating boreal wildfire emissions lies in quantifying the
heterogeneity of surface organic layer burning as there is considerable spatial variability in both the biomass available (depth and density) and the volume of fire consumption. Hence, the bulk of wildfire research in boreal ecosystems over the last two decades has been characterized by ground observations of fire consumption of soil carbon at fine spatial scales (reviewed in Chapin et al. 2006; French et al. 2008). Most of this research has focused on black spruce (Picea mariana) forest and peatlands; the primary ecotypes comprising the boreal carbon sink (Kasischke 2000). In Alaska, the work has been focused geographically in the vicinity of Fairbanks and at the Long-Term Ecological Research (LTER) site at Bonanza Creek (Chapin et al. 2006).

There is considerable need to further characterize boreal wildfire regimes, both to increase the accuracy of global GHG emissions estimates and to address the potentially changing impacts of wildfires on local and regional concerns such as infrastructure, air quality, wildlife, tourism, resource extraction industries, and ecosystem services. Fire histories have been reconstructed for some boreal regions to estimate fire frequency and return intervals (French et al. 1995; Murphy et al. 2000; Kasischke et al. 2002), and a limited number of individual wildfires have been assessed to estimate within-fire heterogeneity of ecological fire effects (French et al. 2008). Records of area burned in North American boreal forests over the last six decades indicate a significant increase in wildfire activity (Kasischke et al. 2002; Flannigan et al. 2005; Kasischke and Turetsky 2006), but the drivers behind this increase and its subsequent effects on boreal ecosystems remain unknown.
In 2004 and 2005, a combined 4.6 million ha burned in Alaska, the first and third-largest fire seasons recorded since the Alaska Fire Service began keeping records in the 1940s. In 2007, a record large wildfire burned on Alaska’s North Slope tundra, a portion of the state that has recorded less than 25 mostly smaller wildfires in the last half-century. These events, occurring during the then-warmest Alaskan summers on record, sparked considerable interest in the impacts of climate change on wildfire regimes. Duffy et al. (2005) assessed temporal trends in area burned by Alaskan wildfires associated with climatological conditions and found greater area burned to be associated with increasing growing-season temperatures, while Duffy et al. (2007) examined spatial heterogeneity of wildfire effects in the Alaskan interior using a limited, non-representative dataset and concluded that larger fires burn more severely. This sequence of events and results has led to concerns that Alaska, like other regions of the U.S. (Holden et al. 2005; Miller et al. 2008), will continue to experience larger and more severe wildfires as a response to projected warming over the 21st century (Kasischke and Turetsky 2006; Balshi et al. 2009a; Flanigan et al. 2009), and that these wildfires will convert the boreal carbon sink to a carbon source (Balshi et al. 2009b). To better understand the pathways by which this conversion could occur, however, a more detailed understanding of boreal fire regimes and their historical range of variability at a regional scale is needed. This dissertation explores three key existing knowledge gaps in Alaskan wildfire regimes by utilizing a regional scale approach through the lens of remotely sensed data.

Assumptions about remote sensing of wildfires
Given the challenges of collecting ground observations across vast and relatively inaccessible boreal regions, it is not surprising that remotely sensed data are considered a valuable resource for studying high-latitude components of earth systems, including wildfire regimes (French et al. 1995; Stow et al. 2004; Wulder et al. 2009). To-date, however, there has been considerable debate over the accuracy with which remotely sensed data and derived indices capture surface metrics of interest. Specifically, research findings thus far have indicated that while spectral indices measuring vegetation change are often indicative of overall fire effects, and particularly removal of healthy, photosynthetic vegetation (Epting et al. 2005; Allen and Sorbel 2008), accurately quantifying the volume and depth of soil organic matter consumed by wildfires in Alaska is not feasible from multispectral reflectance data (French et al. 2008; Hoy et al. 2008; Murphy et al. 2008). These studies, however, have all focused the utility of remote sensing for measuring local fire effects, not regional-scale fire patterns.

Two primary approaches are used in characterizing fire regimes, based on concepts of ecological hierarchy theory (O’Neill et al. 1986). A “bottom-up” approach utilizes Discriminate Data Analysis (DDA) to generalize spatially explicit, localized observations across larger areas (e.g., predicting fire return intervals for a forest based on individual tree ring cores and abiotic predictor variables). A “top-down” approach uses Exploratory Data Analysis (EDA) to identify patterns and downscale them (e.g., identifying patterns of land cover change and reconstructing causal factors). Remotely sensing is widely employed in the both approaches, but each approach (or scale) bears a different assumption about source data. DDA assumes the field observations to be representative of ecological
phenomena, and places the burden of responsibility on coarser-scale data (i.e. remotely sensed data) to reflect that observation. This assumption characterizes burn-severity mapping to-date, where ground observations of fire effects measured on Composite Burn Index (CBI) plots (Key and Benson 2006) comprise the ground observations. This approach also sets up spectral indices as the straw man in burn severity accuracy assessments, as there are numerous factors that confound a post-fire spectral scene and introduce sources of error (Rogan and Miller 2006).

In contrast, EDA assumes that a significant pattern found at a coarser scale is meaningful ecologically, and seeks to identify the finer-scale components and causes of that pattern assuming that the pattern itself is an observed phenomenon. This approach has been widely applied to forest disturbance more generally (Wulder and Franklin 2006), and has been utilized to explore patterns of fire effects by both Holden et al. (2005) in New Mexico, and Miller et al. (2008) in California, although in both cases the investigators began by correlating ground observations to spectral indices. Since it makes no assumptions about a fine-scale ecological phenomenon of interest, and only looks for patterns, this approach does not depend on random sampling, replication, and appropriate stratification of ground observations.

**Research Objectives and Organization of the Dissertation**

This research employs both DDA and EDA methods to address three key knowledge gaps in Alaskan fire regimes:

1) How can we monitor wildfire effects in the Arctic tundra; an ecologically fragile region that is projected to experience significant increases in fire frequency and extent but has historically few wildfires?
2) Have wildfire effects become more severe over the last few decades in response to larger wildfires that burn during warmer and drier conditions?

3) How are wildfire effects spatiotemporally heterogeneous in the Alaskan interior with regard to vegetation and climatic influences?

These questions are addressed in three research articles; briefly described here.

Article 1

The first article utilizes DDA to test methodologies for classifying wildfire effects on the Arctic tundra of Alaska’s North Slope. Tundra ecosystems in Alaska are widespread, but relatively fire-free compared to the boreal forest. They also tend to be the most remote ecosystems from population centers, occurring along the western (Bering tundra), northern (Arctic tundra), and high-altitude (Alpine tundra) fringes of Alaska. Despite the lack of historical fires in tundra ecosystems, recent large fire events in 2002 on the Bering tundra and 2007 on the Arctic tundra have led to investigations of the potential for increasing fire activity as Alaska’s climate warms (Higuera et al. 2008). This paper identifies methods for monitoring fire activity through assessment of spectral indices as univariate predictors of ground-observed burn severity metrics.

The Anaktuvuk River Fire burned 103,000 ha in 2007, in an area where subsequent sediment cores have revealed no previous evidence of wildfire going back 5,000 years BP (P. Higuera, personal communication, November 2009). Given recent indications that shrub cover and volume are increasing on the North Slope (Sturm et al. 2005), and findings from Higuera et al. (2009) that increased shrub cover in the paleorecord resulted in
increased fire frequency during the Holocene, it is likely that wildfire activity will increase on the Arctic tundra, necessitating reproducible methods for monitoring fire impacts. The research objectives of this paper were:

- To identify which ground observations of burn severity and fire impacts were represented by spectral indices derived from satellite imagery
- To determine which spectral indices provided the most accurate representation of ground observations
- To assess the utility of downscaled MODIS data for burn severity monitoring compared to high-resolution Landsat data

Article 2

The second article utilizes EDA to test three widely-held assumptions about wildfire and climate change as they apply to Alaska boreal forest fire regimes. Work in California by Miller et al. (2008) verified their hypotheses that larger wildfires burn at higher severity, that there is an increasing trend in burn severity over the last 25 years, and that warmer climatic conditions have produced higher severity fires. These same hypotheses have been made in Alaska (Kasischke et al. 2002; Kasischke and Turetsky 2006), but are untested to-date with a spatiotemporally representative sample of fires. This paper tests these three hypotheses using a multi-faceted approach.

One of the challenges of identifying trends in, modeling, and predicting burn severity is that wildfire impacts occur along a continuous gradient, but the bulk of previous research in burn severity mapping and measurement has focused on classification into three or more categories of fire impacts (i.e., Low, Moderate, High). Classification has also tended to use subjective methods for delineating class thresholds that have little to no
ecological meaning. This paper presents a new approach to analyzing burn severity data derived from the most commonly used spectral index, the differenced Normalized Burn Ratio (dNBR) (Key and Benson 2006), that is based on maintaining dNBR as a continuous representation of fire effects, and classifying dNBR using statistical thresholds developed from a regional, spatiotemporally representative burn severity atlas. The primary objectives of this article were:

• To develop methods for assessing burn severity that maintain a continuous representation of fire impacts and use objectives, statistical methods of classification;

• To explore trends in fire impacts as characterized by the dNBR over a multidecadal period utilizing a representative subsample fire atlas; and

• To test the hypotheses that larger fires, more recent fires, and fires burning under warmer and drier conditions have burned more severely in Alaska boreal forest.

**Article 3**

The third article utilizes EDA to explore the relationships between fire activity, climate, and vegetation in Alaskan interior boreal forest. Carbon emissions models depend on accurate fire regime attributes (e.g., mean frequency, range of severity, percent and type of vegetation consumed) to estimate both historic carbon emissions for a given year and future emissions based on projected climate change (Balshi et al. 2009b). In the circumpolar boreal forest, however, this information is lacking, leading modelers to utilize incomplete historical fire perimeter data. Regional emissions estimates to-date in Alaska have assumed that the primary land cover types burning are spruce forest and bogs, and that consumption is homogenous both spatially across a fire and temporally on an interannual basis. This paper tests these assumptions by identifying the spatiotemporal
variability of vegetation burning, how climate impacts that variability, and the subsequent variability of fire impacts as characterized by remotely sensed data.

One of the primary challenges to characterizing fire regimes in Alaska has been the lack of a high resolution, validated land cover map that allows for stratification of the primary ecotypes. The National Land Cover Database (NLCD) was extended to Alaska in 2001, and allows for the stratification of ecological processes, such as fires, by ecotype.

The primary objectives of this paper were:

- To explore the interannual variability of the composition of vegetation burned and compare it to the landscape composition;
- To determine the significant impacts of climatological conditions on the composition of vegetation burned; and
- To explore the interannual variability of spatially heterogeneous fire impacts, stratified by land cover type.

Together, these three articles aim to provide fundamental insights into Alaskan fire regimes and test methodologies for reproducible, standardized assessment of fire impacts both in the region and elsewhere.

References


Chapter 1

Mapping wildfire burn severity in the Arctic tundra: novel approaches for an extreme environment

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Abstract

Wildfires are historically infrequent in the Arctic tundra, but are projected to increase with climate warming. Fire effects on tundra ecosystems are poorly understood and difficult to quantify in a remote region where harsh environmental conditions during a short growing season limit ground data collection. Remote sensing has been widely utilized to characterize wildfire regimes, but considerable disagreement exists over how accurately the most widely used spectral index (the differenced Normalized Burn Ratio) represents wildfire severity, particularly in boreal ecotypes. Here, remotely sensed data are assessed as a means to quantify wildfire burn severity in the Arctic tundra. The 2007 Anaktuvuk River Fire burned 103,000 ha on Alaska’s North Slope as the largest tundra wildfire ever recorded. Data from Landsat Thematic Mapper (TM) and Moderate-resolution Imaging Spectroradiometer (MODIS) were processed to single date and bi-temporal spectral indices, and correlated to metrics of burn severity observed on Composite Burn Index plots. Spectral indices were strongly correlated to ground data that quantified above-ground vegetation consumption and overall site severity, but poorly correlated to metrics of organic soil horizon consumption. Bi-temporal spectral indices that reflected a loss in green vegetation produced the highest correlations to overall measures of observed burn severity. There was no significant difference between spectral indices derived from Landsat data and those derived from MODIS data downsampled using a technique
developed by Gao et al. (2006). These results indicate that Landsat and MODIS-derived indices effectively represent changes in vegetation associated with wildfire, but that estimates of soil carbon consumption are not represented by these indices. They show that widely-used indices, such as dNBR, provide a reasonable alternative to ground data collection for analysis of some wildfire effects in arctic ecosystems. Finally, they indicate that the historic Anaktuvuk River Fire of 2007 burned predominantly at moderate to high severity.

Key Words: tundra, burn severity, dNBR, wildfire, Landsat, MODIS

1. Introduction

Wildfires are historically rare in the Arctic tundra (Wein, 1976) but new evidence of more frequent fires during Holocene warm periods suggests wildfire activity may increase significantly due to relatively rapid climate change and its effects (Higuera et al., 2008). Observed warming trends over the past 50 years have impacted the high-latitudes (>60°) more rapidly than elsewhere on Earth (Serreze et al., 2000; IPCC 2001; Hinzman et al., 2005), fostering concerns over the fate of fragile ecosystems and endangered species in those regions (e.g., O’Neill et al., 2008; Durner et al., 2009), and the one-third of global terrestrial carbon stocks that are sequestered in boreal biomes (Apps et al., 1993; Kasischke, 2000).

Across the North American arctic, surface air temperature increased 1.09 degrees C per decade (± 0.22 degrees) from 1981-2000 (Cosimo, 2006). In Alaska, this warming
trend is attributed to the advance of spring snowmelt (by 9.1 days per decade for the Arctic coastal plain, referred to as the ‘North Slope’) (Chapin et al., 2005), an observed six percent increase in tall shrub cover across the North Slope over the last 50 years, which lowers surface albedo (Chapin et al., 2005; Sturm et al., 2005), and an observed (but not quantified) treeline advance into the Alaskan tundra (Lloyd et al., 2003). The feedbacks produced by these observed changes, including increasing wildfire activity, thawing permafrost, and further shrub expansion, are expected to amplify general warming trends and changes in the tundra environment (Chapin et al., 2005; Hinzman et al., 2005).

Only 20 wildfires had been recorded prior to 2007 on Alaska’s North Slope, and wildfire effects on the tundra there have not previously been assessed (but see Jones et al., 2009). In 2007, four wildfires occurred in the region, including the largest tundra fire ever recorded, the 103,000 ha Anaktuvuk River Fire. This event provided dramatic evidence supporting the hypothesis of increased wildfire activity resulting from climate change (Jones et al., 2009). Alaska land managers concerned with fire effects on wildlife conservation efforts, carbon sequestration, and natural resource management have concurrently expressed a need for reproducible methods to monitor wildfire impacts in remote regions (Allen and Sorbel, 2008; Murphy et al., 2008), where growing seasons span less than four months and ground data collection in roadless areas is challenging and expensive (Bogdanov et al., 2005).

Remotely sensed data have been widely utilized to characterize wildfire regimes in ecotopes with characteristics similar to tussock tundra. For example, fire histories have been mapped using remotely sensed data in grasslands dominated by tussock-building
species (Curry, 1996; Allan, 1993; Russell-Smith and Yates, 2007), but fire effects in
tussock-grasslands have not been quantified from spaceborne imagery (Allan, 2003). In
boreal forests and peatlands, remotely sensed data have been used to quantify fire
frequency and return intervals (Kasischke et al., 2002; Balzter et al., 2005; Kasischke and
Turetsky, 2006), fire impacts on vegetation (Epting et al., 2005; Hoy et al., 2008; Wulder
et al., 2009), and uncertainties in carbon models such as pre-fire carbon stocks and volume
of organic soil consumed (Kasischke et al., 1995; Michalek et al., 2001; Kasischke et al.,
2005). In Alaska, recent efforts have focused on utilizing remotely sensed data to map
various fire effects metrics in black spruce (*Picea mariana*) forests (Epting et al., 2005;
Hudak et al., 2007; Hoy et al. 2008; Kasischke et al., 2008, Murphy et al.; 2008), but have
largely ignored tundra wildfires, since most (94 percent) of area burned in Alaska during
the historic period was spruce-dominated boreal forest (AFS, 2009).

The objective of this study was to assess remotely sensed spectral indices from two
distinct platforms to characterize the record 2007 Anaktuvuk River wildfire that occurred
on the North Slope of Alaska. Landsat Thematic Mapper (TM) and Enhanced Thematic
Mapper-Plus (ETM+) platforms have been the most commonly utilized sensors for
monitoring wildfire effects worldwide, owing to their relatively fine spatial resolution, but
Landsat data acquisition in the Arctic is limited by a short (2-4 months) growing season
(Stow et al., 2004) and 93 to 100 percent cloud cover during the growing season months of
June, July and August (Intrieri et al., 2002). The Moderate resolution Imaging
Spectroradiometer (MODIS) sensor is widely used to monitor fire occurrence and fire
effects due to its daily temporal resolution (Kaufman et al., 2003) and recent efforts have
produced data fusion techniques that downsampled 500 m MODIS data to the native spatial resolution of Landsat (30 m) (Gao et al., 2006, Hansen et al., 2008, Potapov et al., 2008, Hilker et al., 2009). The goals of this study were to: 1) correlate ground observations of fire effects on vegetation and soil to a suite of spectral indices to identify the most appropriate index for characterizing wildfire effects in arctic tundra; and 2) assess MODIS as an alternative to Landsat TM/ETM+ for mapping and monitoring wildfire characteristics in a data-poor region.

2. Wildfire in the Arctic tundra

Wildfires are a primary ecological disturbance in boreal ecosystems (Wein and MacLean, 1983; Kasischke and Stocks, 2000; Chapin et al., 2006) but wildfire impacts on wildlife habitat, vegetative trajectories and carbon cycles are poorly understood in the Arctic tundra due to their historical infrequency and a lack of empirical research studies (Wein, 1976; Jones et al., 2009). The Alaska Fire Service (2009) recorded only 24 wildfires on the North Slope region from 1950-2008), with the fires burning a mean area of 6240 ha, but a median area of only 115 ha (i.e., an anomalous 103,000 ha wildfire in 2007 skewed the mean value). The fire return interval for the region is very roughly estimated at 50 to 10,000 years (Racine et al., 1987; Murphy and Witten, 2008). Historic North Slope fire frequency is unknown since only large fires (>400 ha) were recorded prior to 1989 (AFS, 2009), but mean fire frequency was 144 years (± 90) during the early Holocene between 10,000 and 14,000 years BP (Higuera et al., 2008) and at two sites in the
Anaktuvuk River Fire, there is no evidence of wildfires to 5,000 years BP (P. Higuera, personal communication, November 2009).

Previous research on tundra wildfire impacts focused solely on a spate of 1977 and 2002 wildfires on the western coastal plain and in the Noatak River watershed (Racine et al., 1987, 2004; Liljedahl, et al., 2007), an area known as the Bering tundra. The Bering tundra is climatically distinct from the North Slope in that it receives two to three times as much annual precipitation, is an average of 5 to 10°C warmer than the North Slope, and is subject to a different synoptic pattern more conducive to lightning during fire season (Shulski and Wendler, 2007; Murphy and Witten, 2008; WRCC, 2009). These distinctions suggest that while Bering tundra wildfire research can inform hypotheses about Arctic tundra wildfires, there are likely key differences in fire regimes between the two regions. Studies specific to Arctic tundra wildfires are needed to identify these differences and understand their effects on the Arctic ecosystem.

2.1 Remote sensing of fire effects

Wildfire severity mapping has been addressed widely by the wildland fire and remote sensing research communities, with recent efforts focused on defining ‘burn severity’ (Key, 2006, Diaz-Delgado et al., 2003; Lentile et al., 2006; French et al., 2008), measuring fire effects on ecosystems (Robichaud et al., 2000; Michalek et al., 2000; Bobbe et al., 2001; Thode, 2005; Key and Benson, 2006) and developing methods and indices for delineating fire severity from remotely sensed data (Jakubauskas, 1990; Lopez and Casilles, 1991; White et al., 1996; Rogan and Yool, 2001; Rogan and Franklin, 2001; van
Wagtendonk et al., 2004; Holden et al., 2005; Miller and Thode, 2007). Previous research has quantified a range of burn severity metrics; including aboveground vegetation consumption, belowground soil consumption, canopy consumption, and a measure of comprehensive fire impacts known as the Composite Burn Index (CBI) (Robichaud et al., 2001; Key and Benson, 2006; Lentile et al., 2006; Miller and Thode, 2007; Keeley, 2009). French et al. (2008) specifically suggest that soil carbon consumption depth define burn severity for the Alaska boreal forest, and note that future researchers should carefully define burn severity specific to their study. Building on these previous efforts, Keeley (2009) more generally defines burn severity as the consumption of organic matter both above and below ground by fire, and specifically notes that the spectral indices (i.e., dNBR) used to measure fire impacts in remotely sensed imagery should not be defined as or confused with burn severity.

No spectral index or ratio (e.g., Normalized Differenced Vegetation Index) derived from remotely sensed data has been shown to consistently and accurately capture burn severity across all ecotypes. This is due to the many different definitions of ecological burn severity (Lentile et al., 2006; French et al., 2008; Keeley, 2009), the heterogeneous mosaic of fire impacts at finer resolution than the remotely sensed data (Kokaly et al., 2007), and the inadequacy of a linear spectral index for capturing non-linear ecological changes on the ground (Roy et al., 2006). In Alaska, classification accuracy in remote sensing of ecological phenomena is further reduced by errors in geometric registration (Verbyla and Boles, 2000), a growing season of less than four months (Stow et al., 2004), increased topographic shadowing due to steep terrain and low sun angles (Verbyla et al., 2008), and
Landsat data gaps prior to the construction of a receiving station in 2005 (French et al., 2008). An additional challenge specific to burn severity mapping is that the advancement of growing season can vary by several weeks, (Markon, 2001; Stow et al., 2004) and vegetation regeneration can occur within days after a fire and before post-fire imagery can be acquired (French et al., 2008; Allen and Sorbel, 2008). More complex burn severity mapping approaches that utilize pixel fractions (i.e. Rogan and Franklin, 2001) or incorporation of additional information such as fraction of cover (De Santis and Chuvieco, 2009) have produced more accurate burn severity maps than those derived from linear indices alone. However, linear spectral indices continue to be the most desirable to land managers due to their reproducibility and low processing requirements (Zhu et al., 2006; Murphy et al., 2008). As such, the differenced Normalized Burn Ratio (dNBR), a ratio index utilizing differenced near-infrared and short-wave infrared Landsat-derived spectra, was selected for development of a national burn severity atlas in the U.S. (Eidenshink et al., 2007). To date, the dNBR is the only spectral reflectance index that has been assessed for its ability to reflect ground observations of wildfire burn severity in the tundra, and was only tested for representation of a composite measure of burn severity, the CBI (Allen and Sorbel, 2008), with moderately good correlation ($R^2_{adj} = 0.81$). Other spectral mapping methods and indices have not yet been tested in the Alaskan tundra, but are assessed here.

3. Data and Methods

3.1 Study Area
In 2007, the 103,000 ha Anaktuvuk River Fire burned across the arctic tundra on Alaska’s North Slope. The fire burned in Brooks Range foothills, a region that is dominated by cold winters (-25 C mean high in January), cool summers (20 C mean high in July), and 14 cm average annual precipitation. The lightning-ignited fire was discovered on July 16, and burned for an estimated three months. The greatest rate of fire spread occurred during a three-week period in early September during an anomalous late-season drought (Jones et al., 2009). During the peak burning period, annual herbaceous vegetation had already senesced, and temperatures were 5-10 degrees C above normal (Jones et al., 2009).

The burned area was confined by the Itkillik River to the east and the Anaktuvuk and Nanushuk Rivers to the west between 84 and 520 m elevation (Figure 1). More than eighty percent of the fire burned in vegetation identified by the National Land Cover Database (NLCD) as dwarf scrub, more commonly referred to as ‘tussock tundra’ due to the dominance of the grasses that form tussocks and low shrubs (Viereck et al., 1992), while seventeen percent was scrub/shrub, and three percent sedge/herbaceous. The dominant vegetation types include willow (*Salix* spp.), Labrador tea (*Ledum palustre*), blueberry (*Vaccinium* spp.), and birch (*Betula nana*) that grow as shrubs, and sedges (*Carex* spp.) and cottongrass (*Eriophorum* spp.) that form thick, dense tussocks capable of spanning over a meter in diameter. A variety of forbs, lichens and mosses carpet the surface between the tussocks and rapidly colonize any bare soil. The uplands of the tundra region are covered by tussock-building grasses that are rhizomatous and can regenerate within weeks after burning (Allen and Sorbel, 2008), while shrubs regenerate to pre-fire
levels within 10-25 years (Racine et al., 2004). Lichen species, which are critical winter forage for the Central Arctic Caribou Herd in this region, can take up to 120 years to recover from wildfire, although reestablishment is dependent upon climate variability (Jandt and Myers, 2000). The depth of soil consumption by wildfire also determines post-fire vegetation recovery, as the Arctic tundra is underlain by continuous permafrost insulated by the thick organic soils and experiences a prolonged thaw following wildfire events (Jones et al., 2009).

*The Anaktuvuk River Fire Scene Model*

Strahler et al. (1986) describe the utility of developing a scene model for analysis of remotely sensed data. Due to frequent cloud cover on the North Slope from 2002 to 2007, the Anaktuvuk River Fire scene model is partly defined by available cloud-free Landsat scenes and consists of three dates: pre-fire at peak phenology (July 2001), post-fire before peak phenology and plant regeneration (June 2008), and post-fire after regeneration but at peak phenology (July 2008). The pre-fire scene consisted of low lying herbaceous material (including grass tussocks) on less productive sites or continuous dwarf shrub canopy less than two meters in height on more productive sites (Figure 2a). Bare soil is not a component of the pre-fire scene in this ecotype, as an organic horizon of decomposing biomass covers the mineral soil. The June post-fire scene (Figure 2b) corresponds with the best available 2008 Landsat image, and was acquired one year after the fire but before the 2008 green-up began due to a colder-than-normal June in 2008 (WRCC 2009). Observations prior to and during field data acquisition indicate that the scene included
standing water, burned and saturated char and soil surfaces that were still black and small patches (sub-meter to several meters in area) of unburned or only partially-consumed non-photosynthetic vegetation (NPV), consisting primarily of grasses from prior growing seasons. The organic horizon was consumed in a spatially variable pattern up to a meter in depth (Jandt, 2008).

In the July post-fire scene, tussock regeneration had occurred on some sites, adding photosynthetic vegetation (PV) to the scene. On lower severity sites, the fire consumed less than 20% of the tussock basal area, and unburned mosses interspersed scorched herbaceous cover (Figure 2c). On moderate severity sites, most of the surface was charred, minimal litter was present, the organic duff layer had been irregularly consumed in patches, and the fire had burned 20% to 60% of the tussock basal area, leaving irregular remnants (Figure 2d). On higher severity sites, more than 60 percent of the tussock basal area had been consumed, leaving columnar “stumps” and deep duff consumption. These sites comprised mostly of char, but some tussock grasses regenerated by early July (Figure 2e). At a few sites, all organic material had been consumed to mineral soil, which had oxidized to a reddish color (Figure 2f).

3.2 Data

Field Data

The Bureau of Land Management established seventeen permanent transects in the area burned by the Anaktuvuk River Fire and two transects in the smaller (740 ha), nearby Kuparuk River fire burned area during the first week of July 2007. The latter two plots
were established to ensure that lower severity plots were included in the CBI data (Jandt, 2008). The permanent transects included nineteen CBI plots (see Key and Benson, 2006) that were sampled using the modified protocol for Alaskan tundra described in Allen and Sorbel (2008), with twenty-two total metrics of burn severity for each plot in four categories: pre-fire conditions (10 metrics), post-fire substrate characteristics (4 metrics), post-fire surface vegetation characteristics (4 metrics), and total measures of burn severity (4 metrics) (Table 1).

_Satellite data_

Few relatively cloud-free Landsat scenes were available for the region during the overlap of peak solar elevation angle and peak phenology (i.e., mid-June to mid-July). A pre-fire image was acquired for World Reference System 2 (WRS-2) path 74, row 11 on July 14, 2001 by the Landsat-7 ETM+ sensor. The June post-fire image was acquired for WRS-2 path 75, row 11 on June 14, 2008 by the Landsat-5 TM sensor. Data were pre-processed to 30 m resolution by USGS EROS data center to Level 1T, including geometric, terrain, and radiometric correction to top of the atmosphere reflectance (USGS 2009). Each image was corrected for atmospheric scattering using dark object subtraction (Chavez, 1996), and converted to at-surface reflectance (Chander and Markham, 2003).

MOD09A1 8-day 500 m at-surface reflectance data (Vermote and Kotchenova, 2008) were acquired contemporaneous to the two Landsat acquisition dates, and for additional dates in July 2007 and 2008 to represent the optimal anniversary-date sun angle and peak phenology as described by Key (2006) (Table 2). MODIS data were
downsampled to 30 m Landsat spatial resolution using a technique developed by Gao et al. (2006) called the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM). The technique uses a Landsat scene and a concurrent MODIS scene to develop a series of spatial relationships between the coarse and finer resolution data, and projects those relationships onto a MODIS scene for a date when no Landsat scene exists in order to downsample the MODIS to finer scale (deemed ‘downsampled MODIS scenes’ hereafter). Quirino et al. (2008) demonstrated the applicability of STARFM for deriving finer scale Normalized Differenced vegetation Index (NDVI) products, but the method has not yet been assessed for burn severity mapping.

Two single date (post-fire) and three bi-temporal (pre-fire minus post-fire) sets of spectral indices were calculated from the Landsat and downsampled MODIS data (Table 2). Both single (post-fire) and bi-temporal spectral indices were calculated from the reflectance data, as several previous Alaska burn severity studies have found single-date indices to produce stronger correlations to ground observations than bi-temporal indices (Epting et al., 2005; Hudak et al., 2006; Hoy et al., 2008). The single-date indices were calculated from the June Landsat data and the downsampled July 3, 2008 MOD09A1 data (using the June 14, 2008 Landsat and June and July MOD09A1 as inputs to STARFM). Landsat-Landsat (LL) bi-temporal spectral indices utilized the 2001 and 2008 Landsat data as the pre- and post-fire images, respectively. The Landsat-MODIS combination (LM) utilized downsampled MOD09A1 data from June 10, 2007 (STARFM: 7/14/2001 Landsat-concurrent MOD09A1) for the pre-fire image and the July 14, 2008 Landsat data for the post-fire image. The MODIS-MODIS (MM) combination utilized downsampled

For both of the single (post-fire) dates, 22 spectral metrics were produced as predictor variables (Table 3). These include the six reflectance bands of Landsat, with band center wavelengths of 0.485 (B1), 0.560 (B2), 0.660 (B3), 0.830 (B4), 1.65 (B5), and 2.215µm (B7); the first three principal components (PC); the Normalized Burn Ratio (NBR) (B4 - B7 / B4 + B7); the Normalized Differenced Water Index (NDWI) (B4 – B5)/(B4 +B5); and two SWIR/NIR band ratios (B7/B5 and B7/B4). Three vegetation indices were calculated, including NDVI (B4 – B3)/( B4 + B3); the Soil-Adjusted Vegetation Index (SAVI), which adds a soil adjustment factor of 0.5 to the denominator in NDVI to reduce the influence of soil reflectance (Huete, 1988); and the Enhanced Vegetation Index (EVI) (Huete et al., 2002). Two methods that delineate individual scene components were also employed: linear spectral mixture analysis (SMA), and the Kauth-Thomas brightness (KTB), greenness (KTG) and wetness (KTW) transformation using coefficients from Mather (1989) and Huang et al. (2001) for TM and ETM+ data, respectively.

SMA was utilized to calculate the fraction of each pixel covered by char (CHAR), photosynthetic vegetation (PV), and non-photosynthetic vegetation (NPV). In both forested and non-forested ecotypes where components of a burn severity scene occur at sub-pixel resolution, SMA has been shown as a more robust method for enhancing change than traditional approaches such as pixel-based vegetation indices or tasseled cap transforms.
(Rogan and Franklin, 2001; Rogan et al., 2002; Hudak et al., 2007). The SMA technique utilizes spectral angle mapping to calculate the fraction of each “pure” endmember present in a given pixel via disaggregating distinct spectral reflectance signatures (Roberts et al., 1998). This study follows Hudak et al. (2007) in using three endmembers to represent the primary components of the scene: PV, NPV, and CHAR.

To derive reference endmember spectra, the EVI index and the KTG transform were used to identify exemplary photosynthetic pixels, the B7/B5 and a B5/B4 ratio image were utilized to define areas of high NPV, an image summing reflectance across bands was used to delineate CHAR, and a principal components analysis was performed to further refine homogenous target areas for training polygons. A pixel purification technique using a Mahalanobis distance typicality threshold was used to remove pixels and reduce training polygon variance, and a mean reflectance signature calculated for each polygon. Library spectra were used to further thin candidates and derive a mean-reflectance spectral signature for the three endmembers, and each single-date pre- and post-fire image was spectrally unmixed into fraction images of PV, NPV, and CHAR.

Eighteen bi-temporal differenced (denoted by ‘d’) indices were calculated for each of the three sensor pairs, (LL, LM, and MM) (Table 3) to assess pre-fire to post-fire change. These included the two ratio images (dB7/B4 and dB7/B5); the three tasseled cap images (dKTG, dKTB, and dKTW); the three SMA fractions (dPV, dNPV, and dCHAR), the NBR (dNBR); the NDWI (dNWDI); and the three vegetation indices (dNDVI, dEVI, and dSAVI). To assess the influence of variably dense pre-fire vegetation on burn severity mapping in many ecotypes, a relativized version (denoted by ‘R’) was calculated for five
of the differenced indices (RdNBR, RdNDWI, RdNDVI, RdEVI, and RdSAVI) (Miller and Thode, 2007).

Methods

On each of the 19 CBI plots established after the Anaktuvuk River Fire, 22 ground metrics of burn severity were measured (Table 1). Regression was performed between these ground metrics and the 40 spectral indices, with correlation coefficients of determination ($R^2$) and significance values ($p$) calculated for each of the 880 indicator/index combinations (22x40) for the 19 points in each regression combination. The distribution of all correlation coefficients for each indicator of burn severity was examined in a box-plot across both single-date (18 spectral indices each for June and July 2008) and all three bi-temporal image pairs (22 spectral indices each for LL, LM, and MM) for 108 total correlation coefficients per box plot. The distribution of all correlation coefficients for each spectral index was also examined in a box plot. A Wilcox rank sum hypothesis test was utilized to identify significant differences between correlation distributions at the 95 percent confidence level. Individual metric pairs were further examined to determine if low, moderate and high classes of burn severity were spectrally separable.

To determine if STARFM-projected data from MODIS were significantly different from the Landsat data for the purpose of assessing burn severity, three criteria were examined. First, coefficients of determination ($R^2$) were calculated between each set of LL, LM, and MM bi-temporal spectral indices to determine consistency of indices. Second, a
paired t-test was utilized to determine if there were significant differences between the CBI-Landsat index and the CBI-MODIS index correlations. Third, to determine if utilizing MODIS data reduces the potential error associated with interannually variable phenology (different green-up dates each year), the unburned areas were compared between the three image pairs. A 15x15 neighborhood variance filter (450 m to be nearest the size of the original 500 m MODIS pixel) was used to identify the most homogenous unburned regions in the three most highly correlated bitemporal spectral indices for each image pair (LL, LM, and MM). A t-test was used to determine if the most homogenous unburned areas were significantly different, as it was hypothesized that the MM image pair would display less interannual phenological variability than the LL pair due to more optimal anniversary date imagery acquired only one year apart in the MM pair.

3. Results

3.1 Relationships between CBI metrics and spectral indices

CBI metrics measuring post-fire conditions were strongly correlated to spectral indices, while CBI estimates of pre-fire conditions were poorly correlated to spectral indices (Figure 3). The Percent of Foliage Altered measurement exhibited the highest correlations to spectral indices (mean $R^2 = 0.59$, max $R^2 = 0.94$, SD = 0.29), while the Exposed Mineral Soil metric produced the lowest for the post-fire metrics (mean $R^2 = 0.31$, max $R^2 = 0.61$, SD = 0.17). The summary burn severity metrics exhibited strong correlations with spectral indices (Figure 4), although this is partially an artifact of the low number of CBI plots established. For example, while the Percent Burned metric (percent of
area burned within a 30 m radius of the plot center) produced the highest correlations to the spectral indices (mean $R^2 = 0.59$, max $R^2 = 0.95$, SD = 0.29), this is largely due this metric representing a dichotomy between burned and unburned, rather than a continuous gradient of burn severity (Figure 5). The Surface summary metric (mean $R^2 = 0.56$, max $R^2 = 0.87$, SD = 0.28) showed a significantly higher correlation to spectral indices than the Substrate metric (mean $R^2 = 0.49$, max $R^2 = 0.81$, SD = 0.26), but there was no significant difference between the Surface and CBI metrics, or the Substrate and CBI metrics.

Both the bi-temporal and the single-date spectral indices showed a wide range of correlation with the 12 post-fire CBI metrics, and both sets of indices produced strong correlations. Of the bi-temporal spectral indices, dKTG, RdNBR, and RdSAVI produced the highest individual correlations, while dNBR, RdSAVI, RdNBR, and RdNDWI produced the highest median correlations (Figure 6). For the single-date, post-fire spectral metrics, indices that represented greenness levels or high reflectance in the NIR (Band 4 of Landsat), had the strongest correlations to CBI metrics (Figure 7), including KTG, EVI, SAVI, and B4.

3.2 Assessment of downscaled MODIS data

Landsat-derived indices produced higher overall correlations to CBI when compared with downsampled, MODIS-derived spectral indices, for both the single-date indices and the bitemporal indices ($R^2 = 0.86$ for the June 2008 KTG index, the LL dKTG index, and the LM dKTG index). The paired t-test indicated that correlations between the 22 CBI metrics and the LL indices were significantly stronger than those between CBI
metrics and LM and MM indices ($p < 0.0001$), while there was no significant difference between the LM and MM correlations to CBI metrics. The difference in $R^2$ values between the bi-temporal sensor combinations and the individual spectral indices further illustrate the most consistent spectral indices across the different image sources (Table 4). For example, while Landsat-derived (LL and LM) dKTG produced the strongest correlations to CBI ($R^2 = 0.86$) (Figure 6), the MM-derived dKTG correlation to CBI ($R^2 = 0.59$) is considerably weaker. In the sensor combination correlations (Table 4), LL-dKTG and LM-dKTG are perfectly correlated ($R^2 = 1.00$) but the MM-dKTG is only weakly correlated to LL and LM-dKTG (Table 4). The reason for this difference between the Landsat-derived KTG and MODIS-derived KTG is evident in a visual inspection of the downsampled July 2007 MODIS data, where a barely visible atmospheric haze is detectable in the blue band (but not evident in the original 500 m MODIS data), and negatively impacts the ability of MM-dKTG to delineate burn severity. In contrast, the coefficients of determination between CBI and RdNBR are strong between all three pairs ($R^2 = 0.84, 0.84,$ and $0.78$ for LL, LM, and MM, respectively), a relationship that is echoed in the comparisons of sensor combinations (Table 4), suggesting that RdNBR is more consistently measured across the spectrum of imagery because it is not affected by the haze in the July 2007 MODIS data.

Finally, the unburned areas around the fire in the MM and LM data have a significantly lower mean dNBR value than in the LL data ($p < 0.0001$). This indicates a significantly greater difference in the vegetation phenology between the pre- and post-fire image acquisition dates for the LL dates (July 2001 and June 2008) than for the MM or LM dates.
4. Discussion

Spectral indices tested here, and particularly the NBR suite of indices, adequately reflect tundra vegetation consumed by the Anaktuvuk River Fire, but not soil organic material consumed. This is consistent with previous findings that dNBR captures above-ground biomass consumption in other ecotypes (Miller et al., 2009). The weak correlations between estimated pre-fire conditions and spectral indices may be indicative of the difficulty in estimating pre-fire vegetation cover and soil depth on a fire where few unburned islands exist within the perimeter, and no pre-fire observations are available. Additionally, the sub-surface organic horizon was a significant component of the total organic biomass in the pre-fire scene, but could not be detected by a change in spectral reflectance in the one-year post-fire scene model, consistent with findings in the Alaskan boreal forest (Murphy et al.; 2008; Kasischke et al., 2008).

There are several noteworthy outcomes from the correlations of ground observations to spectral indices. First, the indices that respond to the percent of healthy green vegetation in a scene as a group performed well, with some of the highest correlations to both individual CBI metrics and to the summary CBI values. A notable exception to this generally strong performance is the NDVI suite of indices (NDVI, dNDVI, and RdNDVI), with all three indices demonstrating weak, and non-significant correlations to the CBI metrics. This is in contrast to other studies that have found NDVI values to be strongly correlated to CBI, albeit in ecotypes outside of Alaska (Thode, 2005;
Miller and Thode, 2007). NDVI has not previously been assessed for correlation to CBI metrics in tundra.

Second, the results agree with previous efforts to link field-based CBI and spectral indices in Alaska that have found no significant difference between a bi-temporal and single-date approach to mapping burn severity in interior spruce forests (Epting et al., 2005; Hudak et al., 2005; Hoy et al., 2008). The single-date approach (e.g., NBR) has merit given the difficulties encountered in obtaining cloud-free Landsat imagery at near-peak phenology in Alaska; it was more strongly correlated to immediate post-fire soil conditions in two previous studies (Epting et al., 2005; Hudak et al., 2007) and it removes the potential for geometric registration errors between images to be confused with actual fire-related change. However, it is worth examining why the bi-temporal approach is still recommended (Key and Benson, 2006), particularly in Alaska. Since the single-date approach measures post-fire condition, it is an absolute measure of burn severity when it is strongly correlated to ground metrics such as CBI. The bi-temporal approach, however, is a measure of the magnitude of change from a fire that takes into account pre-fire conditions, meaning that fires mapped across time from different images can be compared more equally. The bi-temporal approach is useful for eliminating invariant features of the landscape (such as the thermokarst lakes dotting the Alaskan tundra) and critical for differentiating phenological change from actual burn severity. For example, the dNBR values characterizing the unburned areas (where the expected dNBR value is 0) in the LL image had an average value of 400, a significant difference in NBR values associated with the advance in phenology between June 14 (the post-fire image acquisition date) and July
35

14 (the pre-fire date). The average dNBR of unburned areas for the MM differenced image (July 3, 2007 – July 4, 2008) was only 200, demonstrating the utility of having near-repeat date imagery.

Finally, the dNBR correlation with CBI ($R^2=0.85$) complements previous work in Alaskan tundra that found strong correlations ($R^2=0.77$ to $R^2=0.78$) between dNBR and CBI on three predominantly low-severity fires in the Bering tundra of western Alaska (Allen and Sorbel, 2008). CBI values occur along a scale of zero to three, and most of the Anaktuvuk River Fire burned at higher severity (all associated burned area CBI values exceeded 1.5) (Figure 8). In Allen and Sorbel’s (2008) assessment of tundra severity, the majority of their CBI points had a value below 1.5. The authors specifically noted that their high CBI-dNBR correlations might have resulted from their three tundra fires burning primarily at low severity, and that higher severity fires might yield a lower correlation to dNBR. However, when Allen and Sorbel’s (2008) CBI data are combined with the CBI plots from this study to represent the entire spectrum of tundra burn severity from low to high (n = 112), the combined CBI values are significantly correlated to dNBR ($R^2 = 0.69$, p < 0.0001) (Figure 9). The strength of this correlation between CBI and dNBR across two distinct tundra regions is further evidence of the utility of dNBR for mapping burn severity on Alaskan tundra sites.

5. Conclusions

The Anaktuvuk River Fire was a record fire that burned primarily at high severity (Figure 9) in contrast with previous tundra fires in Alaska, provoking speculation on the
potential impacts of climate change on high latitude fire regimes. The Anaktuvuk River Fire also drew much attention from researchers addressing issues of increased potential for carbon contributions from wildfires, impacts on the Central Arctic caribou herd and other wildlife, and impacts on the gas and oil extraction industry. Given the need to address these issues in light of projections that include further warming in the region, it is critical to explore methods for measuring and monitoring wildfire characteristics in this region, and to focus on developing methods that are accurate, efficient, and accessible to fire managers.

The results of this study indicate that several Landsat metrics easily produced by federal fire managers familiar with Geographic Information Systems are highly correlated to ground measurements of CBI. Bi-temporal spectral indices, including dKTG, RdNBR, and RdSAVI, produced the highest correlations with CBI metrics, and the Percent of Foliage Altered ground measurement was the most highly correlated with the indices. Included in the highly correlated indices are both the dNBR and the RdNBR, which are being produced by the MTBS project for every new large fire in the U.S. (<400ha), and are available to the public through a web download interface. Downsampling of MODIS data shows promise for mapping wildfire burn severity in lieu of Landsat data, with some spectral indices produced from both Landsat and MODIS-derived images highly correlated across sensors (e.g., RdNBR), while other indices (i.e., dKTG) showed significant differences between the two approaches. Overall, this study indicates that existing methods can be applied to accurately characterize and wildfire impacts from two different remotely
sensed data platforms in tundra ecotypes. This fills a critical monitoring need in the rapidly changing Arctic.

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Table 1. Indicators of burn severity measured on CBI plots.

<table>
<thead>
<tr>
<th>Pre-fire Conditions</th>
<th>Variable ID</th>
</tr>
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<tbody>
<tr>
<td>% Litter Cover</td>
<td>P1</td>
</tr>
<tr>
<td>% Duff Cover</td>
<td>P2</td>
</tr>
<tr>
<td>% Soil/Rock Cover</td>
<td>P3</td>
</tr>
<tr>
<td>% Tussock Cover</td>
<td>P4</td>
</tr>
<tr>
<td>Litter Depth (in)</td>
<td>P5</td>
</tr>
<tr>
<td>Duff Depth</td>
<td>P6</td>
</tr>
<tr>
<td>Fuel Bed Depth</td>
<td>P7</td>
</tr>
<tr>
<td>% Herbacious/Graminoid Cover</td>
<td>P8</td>
</tr>
<tr>
<td>% Moss/Lichen Cover</td>
<td>P9</td>
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<tr>
<td>% Shrubs (&lt;1m) Cover</td>
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<tr>
<td>Duff Char</td>
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<tr>
<td>Woody fuel/Tussock Basal Area Consumed</td>
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<td>Exposed Mineral Soil</td>
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<td>Moss/ Lichens</td>
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<tr>
<td>%Foliage Altered</td>
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<td>Frequency/ %Living Herbacious, Shrubs, Forbs</td>
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<th><strong>Total Plot Metrics</strong></th>
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<td>Substrate</td>
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<tr>
<td>Surface</td>
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<tr>
<td>CBI</td>
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<td>Percent of 30m radius burned</td>
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Table 2. Image dates and pairings created to test the utility of downsampled MODIS data modeled from the STARFM algorithm (Gao et al. 2006).

<table>
<thead>
<tr>
<th>Pre-fire Data</th>
<th>Pair ID</th>
<th>Post-fire Data</th>
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</thead>
<tbody>
<tr>
<td>Landsat ETM+</td>
<td>LL</td>
<td>Landsat TM</td>
</tr>
<tr>
<td>July 14, 2001</td>
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<td>June 14, 2008</td>
</tr>
<tr>
<td>Path/Row 74/11</td>
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</tr>
<tr>
<td>STARFM-MODIS</td>
<td>LM</td>
<td>Landsat TM</td>
</tr>
<tr>
<td>2007-161*</td>
<td></td>
<td>June 14, 2008</td>
</tr>
<tr>
<td>Tile h12v02</td>
<td></td>
<td>Path/Row 75/11</td>
</tr>
<tr>
<td>Downsampled using July 14, 2001 Landsat/MODIS</td>
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<td>MM</td>
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<td>Downsampled using July 14, 2001 Landsat/MODIS</td>
<td></td>
<td>Downsampled using June 14, 2008 Landsat/MODIS</td>
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* Julian day 161 = June 10; 185 = July 4
Table 3. Spectral indices assessed for correlation with burn severity metrics. Equations for each metrics utilizing Landsat TM/ETM+ bands are given, with units of measure given where data are not transformed by an equation.

<table>
<thead>
<tr>
<th>Single Date Spectral Indices</th>
<th>Metric ID</th>
<th>Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat Band 1 Reflectance</td>
<td>B1</td>
<td>Percent Reflectance</td>
</tr>
<tr>
<td>Landsat Band 2 Reflectance</td>
<td>B2</td>
<td>Percent Reflectance</td>
</tr>
<tr>
<td>Landsat Band 3 Reflectance</td>
<td>B3</td>
<td>Percent Reflectance</td>
</tr>
<tr>
<td>Landsat Band 4 Reflectance</td>
<td>B4</td>
<td>Percent Reflectance</td>
</tr>
<tr>
<td>Landsat Band 5 Reflectance</td>
<td>B5</td>
<td>Percent Reflectance</td>
</tr>
<tr>
<td>Landsat Band 7 Reflectance</td>
<td>B7</td>
<td>Percent Reflectance</td>
</tr>
<tr>
<td>Band 7/ Band 4 Ratio</td>
<td>7/4 Ratio</td>
<td>(B7) ÷ (B4)</td>
</tr>
<tr>
<td>Band 7/ Band 5 Ratio</td>
<td>7/5 Ratio</td>
<td>(B7) ÷ (B5)</td>
</tr>
<tr>
<td>Char fraction of SMA</td>
<td>CHAR</td>
<td>Fraction of pixel area</td>
</tr>
<tr>
<td>Green vegetation fraction of SMA</td>
<td>GV</td>
<td>Fraction of pixel area</td>
</tr>
<tr>
<td>Non-photosynthetic fraction of SMA</td>
<td>NPV</td>
<td>Fraction of pixel area</td>
</tr>
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<td>First principal component</td>
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<tr>
<td>Second principal component</td>
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<tr>
<td>Third principal component</td>
<td>PCA3</td>
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<td>KTB</td>
<td>TM coefficients from Mather (1989);</td>
</tr>
<tr>
<td>Kauth-Thomas Greenness Tranform</td>
<td>KTG</td>
<td>ETM+ coefficients from Huang et al. (2002)</td>
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<tr>
<td>Enhanced Vegetation Index</td>
<td>EVI</td>
<td>(B4 - B3) ÷ (L + B4 + C1B3 - C2B1)</td>
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<tr>
<td>Normalized Diff. Vegetation Index</td>
<td>NDVI</td>
<td>(B4 - B3) ÷ (B4 + B3)</td>
</tr>
<tr>
<td>Soil-Adjusted Vegetation Index</td>
<td>SAVI</td>
<td>(B4 - B3) ÷ (B4 + B3 + L)</td>
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<tr>
<td>Normalized Burn Ratio</td>
<td>NBR</td>
<td>(B4 - B7) ÷ (B4 + B7)</td>
</tr>
<tr>
<td>Normalized Diff. Water Index</td>
<td>NDWI</td>
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<tr>
<td>Change in 7/5 Ratio</td>
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</tr>
<tr>
<td>Change in CHAR fraction</td>
<td>dCHAR</td>
<td></td>
</tr>
<tr>
<td>Change in GV fraction</td>
<td>dGV</td>
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</tr>
<tr>
<td>Change in NPV fraction</td>
<td>dNPV</td>
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</tr>
<tr>
<td>Change in KTB</td>
<td>dKTB</td>
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</tr>
<tr>
<td>Change in KTG</td>
<td>dKTG</td>
<td>(Pre-Fire) - (Post-fire)</td>
</tr>
<tr>
<td>Change in KTW</td>
<td>dKTW</td>
<td></td>
</tr>
<tr>
<td>Change in EVI</td>
<td>dEVI</td>
<td></td>
</tr>
<tr>
<td>Change in NDVI</td>
<td>dNDVI</td>
<td></td>
</tr>
<tr>
<td>Change in SAVI</td>
<td>dSAVI</td>
<td></td>
</tr>
<tr>
<td>Change in NBR</td>
<td>dNBR</td>
<td></td>
</tr>
<tr>
<td>Change in NDWI</td>
<td>dNDWI</td>
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</tr>
<tr>
<td>Relative change in EVI</td>
<td>RdEVI</td>
<td>(Pre-fire) - (Post-fire)</td>
</tr>
<tr>
<td>Relative change in NDVI</td>
<td>RdNDVI</td>
<td>SQRT(ABS(Pre-fire*1000))</td>
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Table 4. Coefficients of determination ($R^2$) between CBI and the bi-temporal indices derived from the two original Landsat images (LL), a pre-fire MODIS image and a post-fire Landsat image (LM), and two MODIS images (MM). The most and least consistent bi-temporal indices that were also strongly correlated to CBI are highlighted, although it should be noted that the ‘MM’ combination included a MODIS scene with haze.
Figure 1. Location and dominant land cover (NLCD 2001) of the Anaktuvuk River and Kuparuk River wildfires of 2007.
Figure 2. Artic tundra burn severity scene model components for the fire include: (a) low severity plot with unburned inclusions, (b) moderate severity with elements of char and NPV, (c) high severity with example of oxidized soils, (d) unburned pre-fire, (e) post-fire but pre-green up, and (f) post green-up, with tussock regeneration. Photos courtesy of R. Jandt, Alaska Fire Service.
Figure 3. Boxplots of correlation coefficients ($R^2$) between the 108 total spectral indices and the 18 individual CBI measurements indicated in Table 1. Group “P” are pre-fire estimates of fuels, “SB” are post-fire substrate measurements, and “SF” are post-fire surface measurements. Boundaries represent interquartile range, notches represent confidence limits around median line, whiskers represent standard deviations, and red crosses represent statistical outliers.
Figure 4. Boxplots of correlation coefficients ($R^2$) between the 108 total spectral indices and the four summary measures of burn severity: Substrate (all soil and duff measurements), Surface (all litter and vegetation measurements), CBI (total burn severity for plot), and %Burned (the estimated percent of the area burned within a 30m radius of plot center). Boundaries represent interquartile range, notches represent confidence limits around median line, whiskers represent standard deviations, and red crosses represent statistical outliers.
Figure 5. Percent area burned metric plotted against an example index, the differenced Kauth-Thomas Green transform, shows the dichotomous nature of the former.
Figure 6. Boxplots of correlation coefficients ($R^2$) between the bitemporal spectral indices and the eight post-fire and four summary measures of burn severity. Boundaries represent interquartile range, notches represent confidence limits around median line, whiskers represent standard deviations, and red crosses represent statistical outliers.
Figure 7. Boxplots of correlation coefficients ($R^2$) between the single date spectral indices and the eight post-fire and four summary measures of burn severity. Boundaries represent interquartile range, notches represent confidence limits around median line, whiskers represent standard deviations, and red crosses represent statistical outliers.
Figure 8. Final dNBR map for the Anaktuvuk River Fire, with Kuparuk Fire (also burning in 2007) for comparison.

Figure 9. All CBI plots from Anaktuvuk River Fire (solid circles) and three fires from Allen and Sorbel (2008) (open squares) regressed to dNBR value for associated pixel, with regression line \( y = 0.0023x + 0.3144 \).
Chapter 2

Evidence for changing fire regimes associated with increasing temperature in
Alaskan interior boreal forest

Crystal A. Kolden

For submission to Geophysical Research Letters
Evidence for changing fire regimes associated with increasing temperature in Alaskan interior boreal forest

(1) Abstract

A record wildfire season in 2004 followed by large wildfire years in 2005 and 2009 in Alaska fueled speculation that observed increases in temperature have enabled an increase in the occurrence, extent, and severity of wildfires. While prior analyses have quantified fire occurrence and area burned in Alaska and their relationship to temperature, other components of fire regimes, such as fire severity, have not been comprehensively addressed for boreal forests. Here, three fundamental assumptions are tested: 1) wildfire severity is increasing; 2) larger wildfires burn more severely; and 3) more severe wildfires are enabled by anomalously warm temperatures. Wildfire severity data, derived from Landsat satellite imagery, for a random subset of large wildfires in the boreal Alaska interior shows that while wildfire size has increased over the 23 year (1985-2007) period, average severity has not significantly changed. Wildfire size is shown to have a negative relationship to wildfire severity, with a greater fraction of the wildfire burning at higher severity in smaller fires than larger fires. Likewise, mean summer temperature anomalies are shown to have a negative relationship with wildfire severity, with a greater fraction of the wildfire burning at higher severity in cooler summers than warmer summers. These findings challenge traditional assumptions about fire severity in the boreal forest and indicate that understanding fire impacts requires a more complex approach in boreal ecosystems.
1. Introduction

Boreal forests and peatlands across the high latitudes contain an estimated third of global terrestrial carbon stocks [Kasischke et al., 1995], however, evidence indicates that high latitude regions are experiencing accelerated rates of change in response to global temperature gains [Hinzman et al., 2005]. Wildfire is the primary ecological disturbance in the interior boreal forest of Alaska [Chapin et al., 2006], and a critical, but poorly understood contributor to calculations of global greenhouse gas emissions [Levine and French et al., 2004; Turquety et al., 2007]. A record fire year in 2004 in Alaska coincided with the warmest June temperatures in the Fairbanks climate record [Shulski et al., 2005], leading to speculation that wildfires in Alaska, like other regions of the US [Holden et al., 2007; Miller et al., 2008], are increasing in frequency, severity, and extent in response to increasing temperatures (Figure 1a) [Kasischke and Turetsky, 2006]. While previous work has provided quantitative evidence for increasing frequency and area burned in North American boreal forests [Kasischke et al., 2002; Kasischke and Turetsky, 2006], changes in fire severity have not yet been addressed in the region. Quantifying trends and drivers of fire severity (also known as burn severity) is critical to predicting fire impacts on land cover change in the boreal forest [Kasischke and Stocks, 2000; Keeley, 2009]. Burn severity is also of interest to fire management agencies, as more severe wildfires pose greater risks to human infrastructure, have greater negative impacts on ecosystem services, and are more difficult and costly to manage.
Burn severity has been defined using a variety of approaches and ecological metrics, most recently as the rate of consumption of both above and below-ground organic matter by a wildfire [Keeley, 2009]. In this study, the differenced Normalized Burn Ratio (dNBR), a metric based on the difference from pre-fire to post-fire conditions as observed in Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper-plus (ETM+), is utilized as a proxy for surface fire severity and impacts. Previous efforts have proven inconclusive as to the ability of dNBR and NBR to adequately represent wildfire consumption of deep organic soil horizons in Alaska boreal forests [French et al., 2008; Kasischke et al., 2008, Murphy et al., 2008], but numerous studies in Alaska and elsewhere have found dNBR to be an accurate and consistent representation of overall fire impacts, particularly on above-ground vegetation [Epting et al., 2005; Zhu et al., 2006; Holden et al., 2007; Miller et al.; 2008]. Due to its consistency across ecotypes and over time it is used by the U.S. Geological Survey as the primary metric of severity for the Monitoring Trends in Burn Severity program [Eidenshink et al., 2007]. Given the conflicting use of the term ‘burn severity’ in Alaska and elsewhere [French et al., 2008; Keeley, 2009], ‘burn severity’ is here used to mean the heterogeneous fire impacts as measured by the magnitude of change between the pre-fire and one-year post-fire surface averaged across a 30 m space, as observed by Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper-plus (ETM+), and transformed by the dNBR.

Burn severity data are used to identify heterogeneous wildfire impacts within a burned area perimeter, and to relate the ecological impact of a wildfire’s variable intensity to the landscape [Key and Benson, 2006; Lentile et al., 2006]. Monitoring burn severity
over multiple decades informs habitat and succession models and disaggregates the relative importance of climate and topographic influences on fire intensity. For example, in-season precipitation variability controls fire severity in southwestern US pine forests [Holden et al., 2007], while increasing temperature and precipitation over the last quarter-century has produced an increase in high severity fire in California mixed conifer forest [Miller et al., 2008]. Based on these results, a preliminary assessment of a positive relationship between fire size and severity in Alaska [Duffy et al., 2007], and findings of increasing frequency and extent of large fires concurrent to warming trends and longer fire seasons in Alaska [Kasischke and Turetsky, 2006], a positive relationship between fire severity, fire size, and anomalously warm and dry conditions is assumed in Alaskan boreal forests.

Here, we present an analysis of fire severity over 23 years (1985-2007) for the boreal forests of interior Alaska using a subset of 100 randomly sampled large wildfires. This collection of burn severity data allows for the examination of three fundamental assumptions that have been made about wildfire severity in Alaska: (i) burn severity is increasing, (ii) larger wildfires burn more severely, and (iii) anomalously warm and drier fire season conditions promote higher severity wildfires.

2. Methods

A 100-fire subsample representative of both the 23-year period and the range of fire sizes was randomly selected from the Alaska Large Fire Database (available from the Alaska Fire Service) within the Alaskan interior boreal forest, as defined by the Yukon River Basin boundaries and the Bailey Ecotypes (n = 677 potential samples). All years
from 1985 through 2007 were represented except 1989, when there were very few wildfires in Alaska (and none was randomly selected). For each fire, Landsat TM/ETM+ imagery was selected and processed according to best practices outlined in Key [2006] and following the methodology from the MTBS project [Key and Benson, 2005] to produce a dNBR database of 30 m burn severity.

Climate variables were derived from Parameter-elevation Regressions on Independent Slopes Model (PRISM) monthly climatology data [Daly et al, 1994] and gridded monthly precipitation and temperature data from Arctic RIMS (Rapid Integrated Monitoring System, http://rims.unh.edu/data/data.cgi). The PRISM data incorporate fine-scale geographic controls on precipitation and temperature to provide high resolution (2 km) maps of static climatological normals (1961-1990) across the study area. To account for interannual variability as well as the inherent time bias between the period of calculated normals in PRISM and that of the observed fire record (1985-2007), temperature and precipitation anomalies from the Arctic RIMS data (native resolution 25 km) were regridded to 2-km resolution and superposed on the PRISM dataset. Monthly climate data (temperature and precipitation, raw values and anomalies) were extracted and aggregated within the perimeter of each of the 100 fires mapped to produce a single set of climate variable values for each fire.

Fire variables were extracted from the ALFD (i.e., year burned, area burned, ‘out’ date) or calculated from the dNBR database (i.e., average severity and percent Low, Moderate and High Severity). Previous studies have ultimately used either arbitrary thresholds [i.e., Collins et al., 2007] or Composite Burn Index ground data plots [i.e.,
Miller et al., 2008] to delineate an arbitrary number of burn severity classes. Since ground data are not available for historic years, a novel alternative statistical method to delineate severity classes was applied by using the aggregated distribution of dNBR for all pixels in the subset of 100 fires. The dNBR exhibited a predominantly normal distribution once the unburned pixels within the perimeter of each fire were removed, accomplished by excluding pixels within \( \frac{1}{2} \) sigma of a dNBR of zero for each fire. All fires were then compiled and thresholds between severity classes delineated as statistical percentiles of the entire dataset (deemed representative of the historical range of wildfire severity), using quartiles as threshold points. Pixels with a dNBR value less than the 25\(^{th}\) percentile value (dNBR < 327) were classified as Low Severity, pixels between the 25\(^{th}\) and 75\(^{th}\) percentile (327 \( \leq \) dNBR < 728) were classified as Moderate Severity, and pixels valued above the 75\(^{th}\) percentile (728 \( \leq \) dNBR), High Severity. In addition to the classification, the average dNBR value across each wildfire was calculated.

To determine if fire severity has increased over the study period, linear trends were assessed for the percent of the annual area burned in each of the severity classes, and for the average severity of each fire. Statistical significance of linear trends is determined by the 95% confidence level using the method of Santer (2000) that accounts for temporal autocorrelation in time series. To assess the relationship between severity and climate conditions, monthly climate variables for each fire beginning January the year prior to the fire year (18 to 20 months prior to fire start date) were correlated to the severity variables (i.e., percent Low, Moderate, and High Severity; average dNBR) of the fire.
While mean dNBR across the burned area of a fire provides a single metric of burn severity, an examination of the dNBR distribution for an individual fire provides far more relevant information regarding fire heterogeneity which is critical in assessing fire impacts. Since wildfire impacts tend to occur along a continuous gradient, often without distinguishable ecological or spectral breakpoints between severity classes, it was also desirable to maintain the continuous dNBR structure (ranging from 0 to 2000) in comparing fires over time and other variables (i.e., size, temperature, precipitation, and date of final extinguishment). To achieve this, a series of comparative tests were conducted by examining differences in dNBR between two groups of wildfires (variable(s) in parentheses): earlier versus later fires (by year), larger vs smaller fires (by area burned), early versus late fire extinction dates (by date of extinguishment), warmer versus cooler conditions (by JJA temperature anomaly and climatology), and wetter versus drier conditions (by June and August precipitation anomaly).

It was also desirable to conduct a more robust comparison analysis by avoiding the arbitrary selection of thresholds in order to divide the mapped fires for hypotheses testing (e.g., by arbitrarily setting the “cutoff” for Earlier Fires as the year 1997, or large versus small fires by the median fire size). Bootstrapping was applied by sub selecting groups of 80 fires from the 100 fire database. The bootstrapping method is used as a means to better quantify the uncertainty of the sample distributions and to reduce the impact of outliers in testing the hypotheses. A total of 1,000 sample populations of 80 fires were ranked, the top 25 and bottom 25 percent (20 fires each) of the sample population were assigned to the appropriate group (e.g. the top 25 percent were assigned to the “larger fires” group, the
bottom 25 percent were assigned to the “smaller fires” group), and both a mean dNBR
distribution and a 95% confidence interval were calculated from the 1000 sample
populations in each group. The exception to this was for the “Earlier vs Later” comparison
of the year the fire burned, where the 80-fire ranked subsample was split into two halves
for each of the samples since the fires are not evenly distributed over the temporal period.
To examine the continuous dNBR field for each fire, pixels are binned by dNBR every 20
units, and then normalized by the number of pixels burned by the fire. The group dNBR
distributions were assessed both as total area burned and normalized to percent of area
burned, with the latter group presented here to amplify the significant differences between
groups.

3. Results

No significant trends were observed over the 23-year period for either the
percentage of the area burned per severity class or the total area burned per severity class
(Figure 1b). Years with fewer ha burned exhibited a greater percentage of High severity
fire, including fires burned during the early part of the study period (e.g., 1986). This is
particularly evident when normalizing by area and assessing the percentage of area burned
in each severity class. Years of higher or lower proportions of severity were widely
dispersed across the study period, with years of predominantly Low severity occurring in
1987, 1997, and 2006, and years of predominantly High Severity occurring in 1985, 1986,
1998, 1999, and 2003. The average severity (i.e., mean dNBR value) of mapped fires
decreased slightly (significant at \( p < 0.1 \)) over the 23-year period (Figure 2a).
Differences between earlier versus more recent fires are far more apparent in the sample distribution dNBR normalized by area burned (Figure 2b). More recent fires are skewed toward lower severities, whereas a significantly larger percentage of the fire burned at higher severity for earlier fires. Between larger and smaller fires, a significantly larger percentage of the area burned during large fires occurred over lower dNBR values, while the dNBR distribution of smaller fires was skewed toward higher severity (Figure 2c).

Antecedent temperature and precipitation were not good predictors of mean dNBR, but in-season conditions (i.e. JJA temperature, June precipitation, and August precipitation) and climatology (i.e. JJA temperature normals) demonstrated significant predictive power that was further explored through comparing dNBR distributions. Fires that burned during significantly positive (warmer) JJA temperature anomalies exhibited a significantly larger fraction of the area burned at lower severity, and a significantly lower fraction of area burned at higher severity when compared to fires that burned during cooler temperature anomalies (Figure 3a). By contrast, fires that occurred in areas that are climatologically warmer burned more severely than those burning in climatologically cooler locations (Figure 3b).

Timing of in-season precipitation produced significant differences in burn severity distributions. While there was no significant difference in fire severity distributions associated with June conditions (i.e., June precipitation anomaly) (Figure 3c), fires burned significantly more severely during years marked by an anomalously wet August compared to years with an anomalously dry August (Figure 3d). The area burned by the group of
fires occurring during these wetter August anomalies was three to five times greater than the area burned during negative (drier) August precipitation anomalies (Figure 3e), indicating that the lack of precipitation during anomalously dry periods enabled the larger fires, these fires burned primarily at lower severity. Additionally, fires that were called ‘out’ earlier in the season burned at a significantly higher severity than fires that were extinguished later in the year (Figure 3f).

4. Discussion and Conclusions

Our results do not support prior hypotheses and assumptions regarding increasing wildfire severity associated with either warming trends or wildfire size for interior Alaska. There is no significant evidence that burn severity increased over the 23-year study period, with the assessment of average dNBR values indicating a slight negative trend over the period (Figure 2a). None of the three classes (i.e., low, moderate, or high severity) showed any significant trends over the 23-year period (Figure 1b). Furthermore, through analyzing the continuous distribution of dNBR, fires burning in more recent years were significantly less severe than fires that burned in earlier years (Figure 2b).

Smaller fires burned significantly more severely than larger fires, challenging the second assumption of a positive relationship between fire size and severity. This was true across the entire 23-year period when assessing both average dNBR per fire (Figure 2a) and maintaining the dNBR distribution (Figure 2c). This is in direct contrast to the positive relationship between fire size and severity found by Duffy et al. [2007]. However, Duffy et al. [2007] utilized a small, non-random sample set (n = 24), and only the post-fire
Normalized Burn Ratio [NBR], which cannot be normalized so as to be comparable across years, fails to address the change between pre- and post-fire conditions, and often mistakes non-vegetated, high reflectance features (e.g., water, ice, and soil) for wildfire-related change [Key, 2006].

Fires burning during relatively cool boreal summers burned significantly more severely than fires burning during relatively warmer summers, but fires burning in climatologically “warmer” locations burned more severely than those burning in “cooler” locations. The precipitation associations further illuminate the conditions under which these less severe, larger fires burned. While June precipitation was not significant, August precipitation dictated whether or not fires were extinguished earlier or later in the season. Fires burning during summers with an anomalously wet August were called “out” earlier and had a distribution skewed toward higher dNBR values. Fires burning during summers with an anomalously dry August were called “out” much later in the season and were skewed towards a significantly lower dNBR distribution. When the total area burned, stratified by August precipitation, is also examined (Figure 3e), it is evident that fires that burned later in the season during drier Augusts were significantly larger, but less severe fires than those that burned more severely and earlier in the season.

The results can be summarized to highlight two primary types of fires in Alaska. First, smaller fires burn during both cooler and warmer years, but burn predominantly at higher severity on climatologically warmer sites. These fires also tend to be extinguished earlier in the fire season, inhibiting their ability to increase in size. Second, larger fires burn primarily during anomalously warm JJA seasons with lower than normal August
precipitation (resulting in an extended fire season), but will burn on climatologically cooler sites and burn predominantly at lower severity. In the Alaskan interior, the primary wet season extends from August to November [Shulski et al., 2005], and these results suggest that a delayed onset of the wet season may be a primary driver of large fire years.

Results also suggest a potential link between climatologically cooler sites dominated by vegetation that only becomes flammable during anomalously warm and dry years, but burns at lower severity due to higher fuel moisture levels. An examination of the record 2004 and 2005 wildfires further illustrates additional questions raised by this hypothesis. Fires burning in 2004, the warmest JJA on record, occurred throughout interior Alaska, but many of the large fires burned across stands of deciduous forest and shrubland (dominated by Salix, Betula, and Populus spp.). These deciduous patches historically have been utilized as natural fire breaks due to the high moisture levels found in the live fuels and lack of soil carbon to carry the fire, but during 2004 were apparently dry enough to burn. Because they are fairly wet sites, however, many of the sites experienced substantial vegetative regrowth by the time of the one year post-fire image acquisition, resulting in a classification of predominantly Low Severity.

Wildfires in Alaska, contrary to previous assessments and assumptions [i.e., Kasischke et al., 2002; Duffy et al., 2007], are not increasing in severity in association with warming trends in the region, nor do larger fires burn more severely than smaller fires. These results do not address the mechanisms that control fire impacts on the landscape, and they do not reflect the level of carbon consumption by wildfires as a measure of severity, since dNBR is not significantly correlated to depth of organic soil horizon
consumption (Kasischke et al., 2008). To better understand changing wildfire regimes in Alaska, a closer examination is needed of burn severity definitions and the mechanisms drive fire severity patterns across large areas, not just isolated fires. Previous burn severity assessments (e.g., Epting et al., 2005; Duffy et al., 2007) in Alaska have addressed wildfire regime characteristics through only a few fires that were not a randomly selected subsample of the larger ALFD. By assessing the historic spatiotemporal range of wildfires in this study, new patterns were found that were not initially consistent with previous assumptions about wildfire trends in Alaska, but instead pointed to the more complex nature of changing wildfire regimes, and helped to identify the mechanisms by which ecotypes that previously were considered “non-burnable” are able to burn during anomalously warm and dry years. This type of ecological delineation is critical for increasing the accuracy of land-cover change models in projecting the impacts of climate change on ecological systems at scales relevant to land management. It is also critical for fire and land management and conservation agencies tasked with developing adaptive management practices for a changing environment.

References


Figure 1. (a) Annual area burned by year for all large (>400ha) fires within the study region (bar), superimposed by average JJA maximum temperature (line) over interior Alaska from 1985 to 2007. (b) Area burned (ha) in the 100 fire representative sample for each severity class by year, delineated low (green), moderate (yellow), and high (red) severity along the left y-axis. Total area burned (black dashed line) on the right y-axis for comparison of time series. No fires (in the random sample) occurred in 1989.
Figure 2. (a) Mean dNBR for each fire (red circles) grouped by year, with fire size indicated by size of graduated circle, average dNBR for all burned area in each year (black dashed line), and trend in dNBR over the 23-year period (solid black line). No fires (in either sample or original data) occurred in 1989 (gray column). (b) Percent of area burned (ha) per dNBR bin (bins of 20), earlier years (red, solid line) vs later years (black, dashed line). The bold lines show the distribution taken from the 100 fire sample, while the envelopes show the 95% confidence interval for the sub-sample distribution as obtained from bootstrap resampling. (c) Percent of area burned per dNBR bin (bins of 20), large fires (black, dashed line) vs small fires (green, solid line), envelopes as defined in (b).
Figure 3. The percent of area burned across the range of dNBR (bin size 20) as a comparison between (a) cooler (blue dashed line) vs. warmer (solid red line) JJA temperature anomaly for year of fire; (b) cooler (blue dashed line) vs. warmer (red solid line) JJA temperature climatology; (c) wetter (blue dashed line) vs. drier (red solid line) June precipitation anomaly for year of fire; (d) wetter (blue dashed line) vs. drier (red solid line) August precipitation anomaly; (e) the number of ha burned between wetter (blue dashed line) and drier (red solid line) August precipitation anomaly for year of fire, and (f) earlier (green solid line) vs. later (black dashed line) “out” date.
Chapter 3

Climate and Vegetation Influences on Fire Impacts in Alaskan Boreal Forest:
Implications for Carbon and Fire Management

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Climate and Vegetation Influences on Fire Impacts in Alaskan Boreal Forest: Implications for Carbon and Fire Management

Abstract

Boreal forest fires contribute a substantial component of terrestrial carbon emissions, particularly during years of widespread wildfires. Most regional and global carbon emission models utilize the area burned by fires as an input, and assume that wildfire impacts and the resulting tons of carbon emitted are spatiotemporally homogeneous, and burn primarily spruce forests with deep duff soil layers. Previous work in interior Alaska showed regional-scale fire impacts to be heterogeneous, with smaller fires burning during cooler, wetter years and having significantly higher fire impacts as characterized by the differenced Normalized Burn Ratio (dNBR). Observations of climate, vegetation type, area burned and fire impacts for large fires (2002-2009) across the Alaskan boreal landscape were examined to test previously held assumptions of carbon emission modeling. Results indicate that while Coniferous vegetation, particularly spruce forests and spruce bogs, comprised the majority of the area burned in all years, Shrubs comprised a substantial proportion (up to 35%) of the area burned during warmer years. Interannual climate variability significantly influenced both the proportion of vegetation classes burned and the dNBR distribution across years and vegetation classes. Results indicate that fire impacts are sensitive to both the vegetation consumed and climatic conditions, and suggest that these components are needed to effectively model carbon emissions. It also shows that regional area burned is an inadequate input metric to increasingly refined carbon emissions
models, and may produce significant errors in the estimation of carbon emissions if it continues to be used.

Key words: carbon, wildfire, Alaska, boreal forest, dNBR, climate

1. Introduction

Wildfire activity is widely forecast to increase across the boreal ecosystems in response to climate change (Flannigan et al. 2005; Higuera et al. 2008; Balshi et al. 2009a; Flannigan et al. 2009). This projected increase in wildfire extent, frequency, and intensity has numerous undesirable impacts at local to global scales, including the potential for positive feedbacks through increased carbon emissions (EPA 2007, Flannigan et al. 2009). Boreal forests store an estimated one-third of global terrestrial carbon stocks (Apps et al., 1993; Kasischke et al., 1995; Kasischke, 2000); primarily as undecomposed organic material in the surface soil horizon of late succession forests and bogs (Kasischke et al. 1995). Carbon in boreal forests is released by direct wildfire consumption and in subsequent post-fire years due to increased soil respiration rates (Kasischke et al. 1995, Richter et al. 2000). Potential implications of changing wildfire activity in boreal regions include increased levels of carbon consumption associated with greater area burned, longer periods of amplified respiration following wildfires, and the potential for alternative fire regimes and succession processes to reduce carbon storage capacity (Kasischke and Stocks 2000; Balshi et al. 2009b). To-date, carbon research in boreal ecosystems has focused almost entirely on estimation of emissions for past years (Amiro et al. 2001; Kasischke et
al. 2003; Soja et al. 2004; Turquety et al. 2007). Recent efforts, however, have focused on future emissions, producing estimates that boreal wildfires will emit 2.5-4.4 times more carbon by the end of the 21st century (Balshi et al. 2009b) based on changing climate conditions and a 50 percent increase in area burned from the 20th century (Balshi et al. 2009a).

Carbon emissions estimates to-date have utilized area burned as the metric of fire activity [e.g. MOPITT (Turquety et al. 2007)]. This approach fails to account for the heterogeneity of biomass consumed (i.e., vegetation type and fuel volume), fire intensity, and post-fire effects (e.g., rates of vegetation regeneration and soil respiration) within the fire perimeter (but see Kasischke et al. 2005), all of which contribute significantly to annual emissions from wildfires. To maximize accuracy in projections of future carbon emissions, process-based models need to account for both the spatial and the temporal variability of wildfire impacts across a landscape (i.e., the range and distribution of fire frequency and severity in different vegetation types across years and decades) (Mihalek et al. 2001; French et al. 2004, Balshi et al. 2009b). The range and distribution of fire metrics such as ignition frequency, fire return interval (years between successive fires at a location), burn severity distribution (percent of mixed versus stand-replacing fire), average area burned, and spatial pattern (continuity of burn impacts) comprise the fire regime for an ecotype; much of this information is currently lacking in boreal ecotypes. This knowledge gap concerning boreal fire regimes exists in part due to the inaccessibility of boreal regions (French et al. 2008). Since most boreal wildfires are stand-replacing, the
boreal fire knowledge gap also stems from a lack of the high-quality proxy data available in ecotypes where fire scars are preserved in tree rings.

Existing knowledge of boreal fire regimes in Alaska comes primarily from a few active data collection sites (e.g., Bonanza Creek Long-Term Ecological Research site), and from remotely sensed data (Chapin et al. 2006). Spruce (Picea spp.) is the dominant Alaskan ecotype consumed by wildfire, as late-succession spruce stands [both black (P. mariana) and white spruce (P. glauca)] harbor the greatest volume of soil carbon, have the greatest fuel loadings, and have historically been the most flammable (Chapin et al. 2006; Kasishke and Chapin 2008). Post-fire succession initially includes herbaceous grasses and shrub recruitment, then increased shrub cover leading to deciduous and spruce forest, ranging from white spruce (P. glauca) dominance on the warmer, well-drained sites to black spruce (P. mariana) dominance on the cooler, poorly-drained sites. Spruce bogs (dwarf spruce trees and peat bogs) lay atop poorly-drained sites underlain by permafrost (Kasishke et al. 2000; Kasischke and Chapin 2008).

Fire regimes in Alaska are primarily stand-replacing, with the degree of burn severity often characterized by the depth of soil carbon consumption (Kasischke et al. 1995). Burn severity varies significantly across the burned area, with consumption of the stored carbon on high severity sites an average of 3.8 times greater than on low severity sites (Michalek et al. 2000). Historically, larger fires have burned later in the season during years of above-average summer temperatures and a prolonged summer drought that carries into August (Kasishke et al. 2002; Kasischke and Turetsky 2006). Fire return intervals in the Alaskan boreal forest have been estimated at 97-540 years based on stand ages and
paleorecords (Kasischke et al. 2002; Higuera et al. 2009), but there is little high resolution proxy data (i.e., dendrochronologies) to further refine these estimates.

Previous work described an increase in fire frequency and mean area burned for North American boreal wildfire regimes over the past half-century, and speculated that fire severity has also increased (Kasischke and Turetsky 2006). To-date, however, only limited efforts have been made to characterize Alaska fire regimes by the composition and variability of land cover burning, the frequency of fires burning in earlier stages of succession (e.g., during the shrub stage), or the interannual variability of burn severity, particularly at a regional scale (but see Kasischke et al. 2002; Duffy et al. 2007). Kolden (Paper 2 of this dissertation) found a decreasing trend in Alaskan burn severity (as represented by the differenced Normalized Burn Ratio [dNBR]) from 1985 to 2007, with larger fires burning less severely than smaller fires, despite burning under hotter, drier conditions. These results are in contrast to studies from the contiguous US (CONUS) that found trends of increasing burn severity and larger fires under hotter, drier conditions (Miller et al. 2008).

One key component missing from previous studies of Alaskan wildfire regimes is vegetation stratification at high resolution. The Alaskan interior boreal forest has historically been generalized as a single ecozone/fire regime in wildfire characterization studies (Kasischke and Turetsky 2006), and it was not possible to stratify high-resolution ecological studies by vegetation type in Alaska until the 2006 completion of the high-resolution (30 m) National Land Cover Database (NLCD). Previous work has assumed that spruce forest is both the dominant ecotype and the primary vegetation burned by wildfires
across the interior due to its flammability (Chapin et al. 2006), but there has been no regional, high-resolution assessment of the interannual variability in vegetation types burned. Similarly, there has been no prior assessment of the interannual variability of burn severity within vegetation types. Stratifying Alaskan area burned and dNBR trends by vegetation type may provide insight to the results found by Kolden (Paper 2 of this dissertation). It will also provide considerable information for carbon emission modeling, which currently derives emissions by assuming consumption occurs homogeneously in climax stage succession (i.e., spruce forest with rich soil carbon). This assumption of homogeneity potentially produces considerable over-estimation of carbon released by boreal wildfires, as significantly more tons of carbon is consumed per ha of spruce forest and bog than ha of shrubs or grasslands.

To increase the accuracy of carbon emissions models and add to the limited knowledge of Alaskan boreal forest fire regimes, the primary goal of this study was to explore regional interannual variability of fire characteristics (i.e., area burned and impacts [dNBR]) across different vegetation types in the Alaskan boreal forest. Specifically, the objectives were to assess: 1) whether certain ecotypes burn preferentially in the Alaskan interior (e.g. spruce forest); 2) whether the proportion of vegetation and area burned vary in response to climatic conditions and; 3) if fire impacts (as represented by dNBR) are significantly different across years and across vegetation types. While Kolden (Paper 2 of this dissertation) uses dNBR to represent burn severity, Kasischke et al. (2008) argue that burn severity in the boreal forest is defined as the depth of organic soil consumption during the wildfire, and they argue that dNBR does not represent this specific metric accurately
(French et al. 2008, Murphy et al. 2008, Hoy et al. 2008). Other work has found dNBR to be representative of cumulative fire impacts in boreal forests (as measured by the Composite Burn Index) (Epting et al. 2005, Allen and Sorbel 2008, Hall et al. 2008), thus, I here use the term fire impacts to represent the cumulative effects of consumption and one year post-fire regeneration on a site as represented by dNBR.

2. Methods

Previous studies addressing wildfire regimes stratified vegetation type from one of two sources: historic landcover maps that were created prior to any recorded fire disturbance (Holden et al. 2007, Miller et al., 2008), or recent land cover maps that assume a consistent vegetation type over time despite any disturbance (e.g., the LANDFIRE Potential Natural Vegetation map). In Alaska, however, wildfires are primarily stand-replacing and multiple decades often pass before a spruce forest regenerates (Kasishke and Chapin 2008). Thus, a fire “footprint” of early-succession vegetation from fires occurring after 1980 is evident on the NLCD, and renders it useless for multidecadal fire assessments that pre-date the acquisition of Landsat imagery used in its creation (2001). Alternatively, this study utilizes two types of fire data (fire perimeters and dNBR) spanning the period 2002-2009, NLCD, and a suite of climate and weather variables produced from a derived dataset to assess fire and vegetation relationships through a multifaceted approach.

Data
Wildfire perimeters for 2002 to 2009 were obtained from the Alaska Large Fire Database (ALFD) (BLM 2009), and include 282 large (>1,000 ha), boreal summer (May – August) fires greater than 400 ha that fall within the Boreal forest Bailey ecoregion (Bailey 1992) of the Yukon River Basin (Figure 1). Fire impact data included a 30 m dNBR atlas for a subset of 30 randomly selected large wildfires occurring between 2002 and 2007 (Kolden, Paper 2 of this dissertation). The dNBR atlas was produced from Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper-plus (ETM+) imagery following methods from Key and Benson (2005) (Kolden, Paper 2 of this dissertation).

Previous efforts relating fire regime characteristics to vegetation in Alaska (i.e., Kasischke et al., 2002; Duffy et al., 2007) used coarse-resolution, unvalidated land cover data (Bailey 1992, Fleming 1992). Finer-scale land cover data were desired for this analysis to match the resolution of Landsat (30 m) and capture localized topographic variability of the landscape. The National Land Cover Database (NLCD) is the first high-resolution (30 m) vegetation map covering the entire Alaskan interior, and was classified from 1998-2001 Landsat TM/ETM+ images, with an overall accuracy of 76 percent (Selkowitz 2009). Consistent with NLCD efforts in CONUS, the Alaska NLCD represents 19 vegetation classes. For this study, non-vegetated classes and classes with too few pixels burned (less than one percent) to be significant were removed from the analysis. The remaining six NLCD classes were cross-walked to the dominant Alaska vegetation classes described by Viereck et al. (1992) in order to identify key species of the class (D. Selkowitz, personal communication).
Class 41 (Deciduous) includes the broadleaf species that characterize the middle succession stages of boreal forest, including aspen (*Populus tremuloides*), balsam poplar (*P. balsamifera*), willow (*Salix* spp.), and birch (*Betula* spp.). Class 42 (Evergreen) is dominated in the interior region by open and closed-canopy spruce, with no distinction between black spruce (*P. mariana*) and white spruce (*P. glauca*). Class 43 (Mixed) is a heterogeneous mix of deciduous and spruce. Classes 51 (Dwarf Scrub) and 52 (Scrub/Shrub) are comprised of shrub versions of the deciduous trees (e.g., *Populus* spp., *Betula* spp.), willow (*Salix* spp.) and shrubs (*Vaccinium* spp.). Class 90 (Wooded wetlands) represents the black spruce bogs and peatlands that occur atop poorly-drained sites, where a shallow active permafrost layer can only support less than 25 percent canopy cover of dwarf trees and sphagnum mosses abound.

The percent of area burned in each NLCD class was calculated for each fire, and then aggregated and stratified by year and by NLCD class. To determine whether certain ecotypes burn preferentially in interior Alaska, the percentage of the study area covered by each NLCD class was also calculated. We compared percent of area for each ecotype burned annually against the percent of that ecotype on the landscape using the assumption that more ‘flammable’ ecotypes burn at a higher rate than the percentage of the total landscape comprised of that ecotype (e.g., there will be a higher percent of spruce area burned than spruce forest in the interior). For the 30 fires in the burn severity atlas (Kolden, Paper 2 of this dissertation), the NLCD class and the dNBR value were extracted.

Previous research addressing climate-wildfire connections in Alaska has utilized monthly and seasonal temperature and precipitation data derived from Alaskan weather
stations (Duffy et al. 2005), which are limited and inconsistent. For this study, climate variables were derived from a dataset (Abatzoglou 2009) that incorporates climatological normals from 2-km PRISM (Parameter-elevation Regressions on Independent Slopes Model; Daly et al. 1994), gridded monthly precipitation and temperature data from 25-km Arctic RIMS (Rapid Integrated Monitoring System, http://rims.unh.edu/data/data.cgi), and sub-daily temperature, precipitation and relative humidity data from 32-km NARR (North American Regional Reanalysis, http://dss.ucar.edu/pub/narr). Daily and monthly temperature and precipitation data (raw values and anomalies) were extracted and aggregated within the perimeter of each of the 282 fires to produce a single set of eleven climate variables for each fire. These included four seasonal (June-August, JJA) climatology anomalies, four burning period climatology anomalies defined by fire ignition and conclusion dates, and three burning period descriptors that describe the seasonality and length of the fire. Monthly and seasonal climate data have typically been assessed for relationships to fire activity (e.g., Duffy et al. 2005), but Abatzoglou (2009) found that meteorology at sub-monthly time scales occurring after fire ignition to be key predictors of fire activity, making the need to assess climate anomalies for a specific burning period relevant.

For this study, the ‘Start Date’ for each fire was defined as the Julian date of fire ignition, as recorded in the ALFD. A ‘Fire Length’ for each fire was calculated as the number of days from the Start Date to the date when the Alaska Fire Service recorded the fire as contained, or “out”. In practice, out dates often occur weeks after fire growth has ceased, so a ‘Dry Spell’ period was also calculated for each fire. The ‘Dry Spell’ was
defined as the number of days between the ‘Start Date’ and the first subsequent date from
the meteorological data that fit the Alaska Fire Service definition of a “fire-ending event”
defined by recording at least 12.5 mm of precipitation over a 5-day period that includes at
least a 25-hour duration of precipitation and an average relative humidity (RH) over the 5-
day period of at least 50% (AFS 2008).

To derive anomalies, climatologies were first calculated for temperature,
precipitation, RH, and the Duff Moisture Code (DMC) averaged over June, July, and
August (JJA) from 1979-2008. The DMC is a component of the Canadian Forest Fire
Danger Rating System that incorporates several variables into a long-term indicator of the
capacity for the organic soil horizon to burn (Stocks et al. 1989), and is commonly used in
Alaska as a proxy for fire potential. Seasonal anomalies (denoted as Temp JJA, Prec JJA,
RH JJA, and DMC JJA) were calculated as the seasonal departure from 1979-2008
normals, while burning period anomalies were calculated as the departure for the ‘Dry
Spell’ period when the fire is assumed to be most actively burning (denoted as Temp Fire,
Prec Fire, RH Fire, DMC Fire).

**Analysis**

Three basic analyses were undertaken. First, the annual percentage of area burned
attributed to each NLCD class was compared to the baseline percentage of each class
found in the study area to determine if vegetation classes are comparatively more or less
‘flammable’; that is, if they burn preferentially in significantly higher or lower proportions
than they occur across the study area. The null hypothesis was that the proportion of
vegetation classes in burned areas is similar to the proportion of vegetation classes across the Alaskan interior as a whole.

Second, climate influences on the amount and proportion of the six different vegetation types burned were assessed. An exploratory analysis between climate variables and both the proportion of and total area burned was conducted using a Monte Carlo resampling method. For each of 10,000 iterations, 200 of the 282 fires from 2002-2009 were randomly sampled, ranked by their associated climate variable value, and the top and bottom 20 percent of the sample were placed into a new ‘Higher’ and ‘Lower’ dataset, respectively (e.g., Higher JJA Temp, Lower JJA Temp). Although only comprising an eight year period, the spatiotemporal variability in meteorological conditions across the study period are significant, allowing one to examine, for example, whether a given vegetation class (e.g., Shrub) burns preferentially during wet or dry conditions. The null hypothesis was that there was no significant difference ($p < 0.05$, assessed using resampling confidence intervals) between the ‘Higher’ and ‘Lower’ datasets for each variable.

Third, the relationship between the vegetation composition and dNBR (as a proxy for burn severity) was assessed to test the null hypotheses 1) that different vegetation types do not burn at significantly different severity distributions; and 2) that individual vegetation types do not burn at significantly different severity distributions across years. To test these hypotheses, dNBR and NLCD values were extracted from 30 randomly sampled fires that burned between 2002 and 2007. Pixels were stratified first by vegetation class and then by year, and binned by their dNBR value (bin size of 40). For each dNBR bin, the mean area burned (hectares) and percent of area burned values were calculated, and a histogram
created for the comparison of interest: all NLCD classes (no stratification by year), each NLCD class individually (stratified by year), and each year individually (stratified by NLCD class). The 95 percent confidence interval bounds were calculated to test for significant difference between curves at the $p < 0.05$ level.

3. Results

Conifers (NLCD Class 42) comprised the greatest portion of the area burned in all years (Figure 2). This is not unexpected as the distribution of Conifer on the landscape is also larger than any other class; however every year, the percentage of Conifer burned area exceeded the occurrence of the Conifer area on the landscape, making Conifers the most flammable class over the study period. In contrast, the proportion of Deciduous area burned was less than the occurrence of Deciduous across the study area for all years making Decidious the least flammable class. For the other four classes, the occurrence of the NLCD class across the landscape was within the range of the proportion of area burned across the study period. A time series of the proportion of each NLCD class burning each year from 2002 to 2009 shows strong interannual variability (Figure 3). While Conifer dominates the burned vegetation each year, there is an inverse relationship between the percent of area burned in the Shrub and Bog classes. Shrubs, although not typically considered a highly flammable ecotype in interior Alaska (due to their high live fuel moisture and lack of soil duff), account for over 30 percent of the burned area in 2002, 2005, and 2007.
The proportion of the fire burning each vegetation class was significantly impacted by climate and timing (Table 1). For the Conifer class, both a significantly greater percent of area burned per fire (Figure 4a) and a significantly greater total area burned (Figure 4b) for fires that burned during higher JJA temperatures and DMC values, as well as during fires having a longer Fire Length. For the Shrub class, a significantly greater percent of the area burned per fire (Figure 4c) and significantly greater area burned (Figure 4d) associated with lower precipitation, higher temperature, and lower RH during the fire period. No single climate variable was significant across all six vegetation classes, although Fire Length was a predictor of significantly higher area burned for all six classes.

Assessment of dNBR stratified by vegetation class revealed that the dNBR distributions of the Deciduous and Mixed classes were not significantly different, suggesting they should be merged into a single class for the fire impacts assessment. This is not surprising since the Mixed class is a combination of Deciduous and Conifer. The dNBR distribution curves for the resulting five primary vegetation groups (Deciduous/Mixed, Conifer, Shrub, Herbaceous, and Bog) indicate that when all burned area is aggregated by vegetation types, the different NLCD classes produce significantly different dNBR severity curves (Figure 5). All five of the vegetation types display a bimodal dNBR curve, particularly when the data are normalized by area burned (Figure 5a). This is significantly different that the normal dNBR curve produced by Kolden (Paper 2 of this dissertation) for the 1985-2007 study period.

The three most widely burned vegetation groups (Conifer, Shrub, and Bog) all exhibit significantly different dNBR curves when stratified by year. First, dNBR for each
type varies significantly across the 2002-2007 study period (Figure 6). For example, Conifer dNBR values (Figure 6a) were left-skewed in 2003, right-skewed in 2006, bimodal in 2005, and more normally distributed in 2002, 2004 and 2007. When the three classes are compared to each other but stratified by year (Figure 7), significant differences between the dNBR curves of the individual vegetation classes are noted for all years. For example, curves for 2004 and 2006 were right-skewed towards lower dNBR (i.e. lower fire impacts) for all three vegetation classes, whereas dNBR values for fires in 2005 exhibited bimodality for Conifer and Bog classes and a left-skewed distribution for Shrubs. The 2003, 2006 and 2007 curves show the greatest overlap in dNBR distribution between the three types; a function of greater uncertainty about the distribution during the years when the lowest number of pixels burned. This is supported by examining the dNBR curves not normalized by area, which show that in some years nearly all of the pixels burned were Conifer, but in years where substantial area burned was Shrubs, there are significant differences in the dNBR curves between the two types (Figure 8). For example, Shrubs, which comprised 35 percent of the area burned during 2005, exhibited a left-skewed dNBR curve (i.e. higher fire impacts), whereas the dNBR curve for the Conifer class exhibited bimodality that was weighted more heavily to lower dNBR values.

4. Discussion

The results indicate that fire impacts and vegetation burning in the Alaskan boreal forest are significantly different from year to year, in part, as a product of climate conditions. The overall distribution of vegetation burned supports the considerable body of
research that describes Coniferous species, such as black and white spruce and spruce bogs, as the primary fire carriers in interior Alaska. However, the interannual distribution of vegetation burned (Figure 2) also points out the occurrence of years when a substantial proportion of the vegetation burned is shrub and dwarf scrub. Very little research has been conducted on fire in shrub ecotypes in Alaska, and the bulk of the literature available indicates that fire does not burn in the shrub successional stage (reviewed in Chapin et al. 2006), in part because there is substantially less fuel available compared to late-succession spruce forests and bogs, when fire can carry in the trees or in the thick duff and moss layers. This result shows that there is considerable interannual variability in the composition of vegetation burned, and while Conifer is the most flammable ecotype, Shrubs and other classes are also considerably more flammable than normal during some years due to climatic influences.

While the study only covers eight years, the significant relationships between climatic anomalies and the vegetation burned indicate that interannual climate variability dictates what fuel and vegetation types are available to burn. While it is not surprising that more area is burned for all vegetation types during a longer fire as compared to a shorter one, the contrasts between meteorological conditions conducive to fire in some vegetation types but not others may provide insight into how climate controls fire regimes in Alaska. For example, a Bog burned preferentially when RH was higher and conditions were cooler and wetter during the fire period, but Shrubs burned preferentially when RH was lower and conditions were warmer and drier during the fire period. When this observation is taken in context with the total area burned across the study years, it indicates that while a
substantial extent of area burned every year is Conifer and Bog vegetation, anomalously warm and dry conditions are conducive to increased fire consumption of Shrubs, potentially associated with increased drought stress on live fuels and the lower RH dropping fuel moistures below the moisture of extinction threshold. These same warm and dry conditions are also conducive to fires burning a greater extent of Deciduous forest.

These distinctions may be indicative of two distinct fire regimes in the Alaskan interior: one marked by a longer fire return interval that allows for succession all the way to spruce forest, and a second one marked by a shorter fire return interval that culminates in fire consuming shrubs and deciduous stands during anomalously warm events. A considerably longer record is needed to further explore this hypothesis, but it has considerable implications for carbon emissions models, as shrub-dominated sites store significantly less carbon than spruce-dominated sites. Any kind of shift in the area burned under the two different fire regimes due to climate change would also have significant implications for fire suppression efforts. For example, realized projections of warmer JJA conditions may induce increased burning of Deciduous forest and Shrubs, which fire management has historically used as natural, high fuel moisture fire breaks for fire suppression.

The significantly different distributions of dNBR across the NLCD classes indicate that fire has variable interannual impacts on different vegetation types. One characterization of a fire regime is to describe the normal range of variability of fire impacts on the landscape. The normal range of dNBR variability of a representative random sample of interior Alaska large fires over a 23-year period was a unimodal curve with a peak at dNBR = 400
and a slight right skew (Kolden, Paper 2 of this dissertation). From the period 2002-2007, the distribution of dNBR for all vegetation types was bi-modal, with Conifer and Shrub pixels producing generally higher dNBR values than the 23-year normal distribution, and Deciduous/Mixed, Herbaceous, and Bog pixels producing lower dNBR. This bi-modality is also a characteristic of fire regimes in Alaska that deviates from previous assumptions. It has been standard practice in burn severity assessments to classify dNBR into a minimum of three classes of severity (Low, Moderate, and High) (Key and Besnon 2005; Zhu et al. 2006; Eidenshink et al. 2007). However, a predominantly bi-modal dNBR distribution indicates that fire impacts are falling primarily into just two classes: Low and High. This was noted previous in a case study in Alaska by Michalek et al. (2000) but has not yet been addressed at a regional level.

Since the dNBR is a proxy for fire impacts one-year post-fire, it includes any regeneration that has occurred in the interim between the fire event and the post-fire imagery acquisition date (Key 2006). From dNBR alone, therefore, the impact of the fire intensity on vegetation is difficult to distinguish from the influence of interannual climatic variability on potential regeneration, particularly since climate data are a much coarser spatial scale than dNBR data. However, if climate had no influence on fire impacts, we would expect no significant differences between the dNBR curves for a single vegetation type from year to year. Likewise, if climate was the primary driver of fire impacts, we would expect no significant differences between the dNBR curves of the different vegetation types. Instead, the three most widely-burned vegetation types (Conifer, Shrub, and Bog) produce significantly different dNBR distributions in most years (Figure 7), and
all exhibit significant interannual variability in their dNBR distribution curves (Figure 6), including right-skew years of predominantly lower dNBR values (e.g., 2006 for all three types), left-skew years of predominantly higher dNBR (e.g., 2003 for Conifer), bi-modal, and normally distributed years (e.g., 2007 for all three types). These distributions (Figure 7) indicate that in some years (e.g., 2007) where dNBR curves overlap, climate drivers control fire impacts, while the vegetation burning is the predominant control of fire impacts in other years (e.g., 2005), where significantly different curves represent each vegetation type.

Results of this study confirm that there is significant interannual and spatial variability in both what is burning and the severity and impacts of the fire and therefore significant variability in carbon emissions. Assumptions of homogeneous vegetation burning and fire impacts in modeling carbon emissions may therefore produce a worst-case emissions scenario that has implications for developing carbon emissions policies. These results also suggest that considerable research on fire in boreal shrubs is needed, as anecdotal evidence tends to classify shrub and deciduous forest as non-flammable successional stages often utilized by managers as natural fire breaks (R. Jandt, personal communication, October 2008). Warmer and drier conditions result in lower live fuel moistures and make deciduous vegetation more available to burn; if the projected warming trend in Alaska induces increased burning of early-successional stages, this could potentially reduce the total area of late-succession spruce forest, where the greatest carbon storage occurs.

5. Conclusion
Carbon emissions models assume homogeneous fire impacts in boreal forests, based on nearly a half-century of research on fire in Alaska boreal forest that has identified the primary fire regime as black spruce forest (*P. mariana*) burning infrequently (i.e., 100+ years) at stand-replacing, high severity. These results build on previous work to suggest that there is significant interannual variability in the composition of vegetation burning, and significant spatiotemporal variability in fire impacts. Heterogeneity of fire impacts is determined both by vegetation type burned and by climatic conditions, although it is difficult to disaggregate the influence of each component at the landscape scale utilizing dNBR as a proxy for fire impacts both because dNBR utilizes one year post-fire information and because there is no high-resolution vegetation classification for Alaska prior to 2001. This complexity challenges the assumptions of carbon emissions models by indicating that there may be multiple fire regimes in interior Alaska emitting considerably different quantities of carbon than has been previously estimated. It also indicates that model assumptions of homogeneity may lead to significantly over- or underestimated carbon emissions from boreal wildfires in the emerging field of carbon emissions forecasting for the next century. More importantly, the results indicate that considerably more research is needed to provide more accurate description and quantification of wildfire regimes in boreal regions, particularly given the observed changes in climate and projected warming for the region.

6. References

Abatzoglou, J.T. 2009. Climate change impacts on burn severity in Alaska, Part I:


Table 1. Relationships between vegetation burned and climate variables, where a greater percent of the area burned or the total area burned for each pre-fire vegetation type is associated with either lower (L) or higher (H) values (for Dry Spell and Fire Length, lower values are shorter periods; for Start Date, a lower value is an earlier-starting fire). Significant relationships at the 95% confidence interval are in bold, shaded boxes.

<table>
<thead>
<tr>
<th></th>
<th>Deciduous</th>
<th>Conifer</th>
<th>Mixed</th>
<th>Shrub</th>
<th>Herb</th>
<th>Bog</th>
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<tr>
<td><strong>Percent Area Burned</strong></td>
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<td>PPT Fire</td>
<td>H</td>
<td>H</td>
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<td>L</td>
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<td>PPT JJA</td>
<td>L</td>
<td>L</td>
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<td>Temp Fire</td>
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<td>H</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>H</td>
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<td>Temp JJA</td>
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<td>H</td>
<td>H</td>
<td>L</td>
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<td>DMC Fire</td>
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<td>H</td>
<td>L</td>
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<tr>
<td>Dry Spell</td>
<td>H</td>
<td>H</td>
<td>H</td>
<td>L</td>
<td>H</td>
<td>H</td>
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<td>Start Date</td>
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<td>H</td>
<td>H</td>
<td>H</td>
<td>L</td>
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</tbody>
</table>

|                |           |         |       |       |      |     |
| **Area Burned** |           |         |       |       |      |     |
| PPT Fire       | L         | L       | L     | L     | L    | L   |
| PPT JJA        | L         | L       | L     | L     | L    | H   |
| Temp Fire      | H         | H       | H     | L     | L    | H   |
| Temp JJA       | H         | H       | H     | L     | L    | H   |
| DMC Fire       | H         | H       | H     | H     | L    | H   |
| DMC JJA        | H         | H       | H     | H     | L    | H   |
| Dry Spell      | H         | H       | H     | H     | L    | H   |
| Fire Length    | H         | H       | H     | H     | L    | H   |
| Start Date     | L         | L       | L     | H     | H    | L   |
Figure 1. The boreal forest ecoregion of the Alaskan interior, the Yukon River Basin, showing the 282 fires from 2002-2009 that were stratified by proportion of vegetation burned (light grey), and the 30 fires for which dNBR was produced (black).
Figure 2. Percent of area burned in each NLCD vegetation class for the years 2002-2009 (large, open gray circles), with the mean percent of area burned over that period (small, closed gray circles), and the percent of the study area covered by the NLCD class as of 2001 (black triangles).
Figure 3. Time series of proportion of area burned each year attributed to each NLCD class for Deciduous (black dashed line with solid circle), Conifer (red solid line with open square), Mixed (brown solid line with open circle), Shrub (dark green dashed line with solid square), Herbaceous (light green dashed line with solid triangle), and Wooded Wetlands/Spruce Bog (blue solid line with open triangle).
Figure 4. Climate variables that have a significant influence on the percent of area burned (left) and the total area burned (right) for Conifer (top) and Shrub (bottom) vegetation. White columns indicate higher values (e.g., higher temperature or longer fire length), while gray columns indicate lower values. Error bars indicate the 95% confidence interval.
Figure 5. The dNBR distribution (binned by 40) of all pixels burned from 2002 to 2007 for 30 fires in each of the five primary vegetation classes: deciduous/mixed forest (teal solid line), conifer forest (red dashed line), shrub/scrub (green solid line), herbaceous (black solid line), and spruce bogs (blue dashed line). Left graphic portrays percent of area burned per bin, right graphic portrays total area burned (ha). For each class, the shaded area represents the 95% CI.
Figure 6. Distribution of dNBR (binned by 40) by percent of area burned for the three vegetation types with the greatest area burned [conifer (top), shrub (middle), spruce bog (bottom)] by year for 2002 (red solid line), 2003 (green dashed line), 2004 (blue solid line), 2005 (black dashed line), 2006 (teal solid line), 2007 (pink dashed line). Shaded envelope represents the 95% CI.
Figure 7. Distribution of dNBR (binned by 40) by percent of area burned for the three vegetation types with the greatest area burned [conifer (red solid line), shrub (green dashed line), spruce bog (blue solid line)] by year for (a) 2002, (b) 2003, (c) 2004, (d) 2005, (e) 2006, (f) 2007. Shaded envelope represents the 95% CI.
Figure 8. Distribution of dNBR (binned by 40) by area burned for the three vegetation types with the greatest area burned [conifer (red solid line), shrub (green dashed line), spruce bog (blue solid line)] by year for (a) 2002, (b) 2003, (c) 2004, (d) 2005, (e) 2006, (f) 2007. Shaded envelope represents the 95% CI.
CONCLUSION

Over the past half-century, wildfire regimes have been characterized largely at predominantly local spatial scales and constructed from proxy data such as tree-ring dendrochronologies, charcoal-laden sediment cores, hand-drawn fire maps, and thousands of ground observation plots. In localities where these types of data are sparse or difficult to collect, there are considerable knowledge gaps of fire regime characteristics. A prime example is the circumpolar boreal forest, where wildfire is the primary agent of widespread ecological disturbance but fire regimes are poorly understood, particularly at regional and continental spatial scales. It is at these spatial scales, however, that boreal fire regimes must be characterized in order to most accurately inform process-based models that include wildfire inputs, such as global climate models and greenhouse gas emissions scenarios.

This dissertation utilizes novel approaches to examine temporal trends and spatial patterns of wildfires in Alaskan tundra and boreal forest. Paper 1 assessed novel methods for mapping and monitoring wildfire burn severity on Arctic tundra, an ecotype that has had few historical fires, but where fire activity is expected to increase as a consequence of climate change. The results indicate that several remotely sensed indices accurately capture the consumption of above-ground organic biomass, including the differenced Normalized Burn Ratio (dNBR), which is widely utilized by fire managers to map wildfire burn severity in CONUS, but has not been fully tested for accuracy in Alaskan ecotypes. The results also indicate that data from the Moderate-resolution Imaging Spectroradiometer (MODIS) can be downscaled to provide a fine-resolution alternative to Landsat data, which have experienced numerous problems over the last several years, and are
increasingly less reliable for burn severity mapping. These methods were applied to the Anaktuvuk River Fire of 2007 to show that it burned at predominantly high severity.

Paper 2 tested three basic hypotheses about wildfire trends in Alaskan boreal forests: that larger fires burn more severely, that fires have burned more severely in recent years, and that fires burn more severely under warmer and drier conditions. A new method of burn severity classification was introduced that utilized statistical designation of thresholds based on a historic range of variability, and a novel comparison method that preserves the continuous nature of dNBR as a burn severity proxy was introduced to test the hypotheses. Results disproved all three hypotheses. Larger fires burned more total area, and thus more area at higher severity, but burned significantly less severely on average. Fires that burned less recently in the 1985-2007 study period burned significantly more severely than fires burning more recently in the period. Fires burning under warmer and drier conditions burned significantly less severely than those burning under cooler, wetter conditions. The results suggest that wildfire regimes in boreal forests are more complex than was assumed (Kasischke and Turetsky 2006), and will likely require considerably more research to fully characterize fire impacts across the highly diverse Alaskan interior. More importantly, the contrast between the two evident regimes (warm, dry, less severe large fires versus cool, wet, more severe small fires) suggests that variability in vegetation flammability is likely a key factor in fire characteristics in boreal forests, and that spruce ecotypes are likely not the only ecotype burning in Alaska. These hypotheses were further explored in paper 3. .
Paper 3 examines the spatiotemporal variability of Alaskan wildfire patterns through the lens of vegetation and climate. The results of this paper indicate that the spatiotemporal variability of wildfire patterns is a product of both the vegetation burning and climatic conditions. Most of the area burned from 2002-2009 was spruce forest and bog, a result that agrees with previous research (cite). However, the high percentage of shrubs burning in warm years (over one-third of area burned in 2005) is not in agreement with previous assessments of fire in the Alaskan interior. The results also indicated that different vegetation classes were differentially influenced by climatic conditions, and that wildfire impacts were highly variable from year-to-year and across vegetation types. As a whole, these results suggest that there are multiple wildfire regimes in the Alaskan interior associated with different ecotypes, and that treating the boreal forest interior as a single, high intensity, stand-replacing fire regime focused in spruce forests is not an accurate representation of complex fire ecology of the region. The results also suggest that carbon models assuming one, spatiotemporally homogenous fire regime are likely overestimating wildfire emissions given that late-succession spruce forests with deep, organic soils hold considerably more carbon stocks than early-succession shrublands and grasslands.

There has been considerable debate over the ability to assess fire regime characteristics and wildfire impacts from remotely sensed imagery in Alaska, primarily from studies finding that dNBR does not represent organic soil consumption depth or volume. This dissertation, however, suggests that dNBR is representative of organic biomass consumption in Alaska, and that spatiotemporal patterns of dNBR at the regional scale can inform a basic knowledge of fire regimes, and produce questions to be answered
through ground data acquisition or further exploration. An example of this features the
counterintuitive negative trends in burn severity found in paper 2. Considering the scene
model, lower dNBR values (i.e., low burn severity) can be either representative of lower
consumption during the wildfire, or of rapid vegetation regeneration prior to the
acquisition of the post-fire image. Spruce forests and bog have generally been observed to
burn at higher severity, and do not usually regenerate rapidly. Shrublands, however, can
regenerate rapidly, although anecdotal evidence from Alaska fire managers has indicated
that shrubland rarely burns. Paper 3 explored this issue further by stratifying area burned
and dNBR across vegetation types, and found that shrubs comprised nearly one-third of the
area burned during recent years.

Key contributions of this dissertation to fire science are summarized as follows:

1) Remotely sensed indices (e.g., dNBR and similar bi-temporal indices) can be used
effectively to map and monitor fire effects in Arctic tundra;

2) MODIS data can be downsampled to supplement sparse Landsat data for accurately
monitoring fire activity in Alaska;

3) Burn severity in Alaskan boreal forests appears to be lower for larger fires burning
more recently under warmer, drier climatic conditions;

4) Trends in burn severity may be indicative a mix of significantly different fire
regimes, and not necessarily reduced fire intensity and consumption;

5) Since 2002, the proportion of shrublands and grasslands burning significantly
increased during years when conditions are warmer and drier;
6) Different vegetation types burn at temporally differential severity depending on climatic conditions;

7) Multiple fire regimes likely intermix in the Alaskan boreal interior, not the single fire regime that is commonly assumed; and

8) The presence of multiple or changing fire regimes implications for fire managers, carbon modelers, and fire researchers who have to-date overlooked both the spatiotemporal variability of wildfire regimes in Alaska, particularly shrub fire regime characteristics.

This dissertation contributes considerably to the emerging use of remotely sensed data to characterize fire regimes. It also challenges critical assumptions about boreal forest fire regimes at a time when researchers strive for increased accuracy in the regional carbon emissions models using these assumptions. It provides novel methods for characterizing fire impacts, and shows the influence of both vegetation and climate on fire activity in Alaska. More importantly, it has provided numerous directions for future research. First, trends in burn severity likely have implications for changing landscape fragmentation and wildlife habitat. Second, shrub and grassland fires in the Alaskan interior have been almost entirely ignored by fire researchers since it was assumed they did not burn. Finally, the increased flammability of shrubs and grasslands during warmer and drier years has the potential to allow type-conversion of spruce forests into permanent shrublands and grasslands, if wildfires become more frequent and occur before a site succeeds to spruce forest. Recent observations of rapid climate change in Alaska have led to numerous hypotheses that wildfire activity will increase. This work suggests that increased fire
activity will likely have highly variable effects on the ecology of the Alaskan interior, and that more quantitatively precise and comprehensive studies will be required to accurately predict those effects.