ABSTRACT

Title of Document:	EVALUATING THE POTENTIAL OF THE NORMALIZED BURN RATIO AND OTHER SPECTRAL INDICES FOR ASSESSMENT OF FIRE SEVERITY IN ALASKAN BLACK SPRUCE FORESTS.
	Elizabeth E. Hoy, Master of Arts 2007
Directed By:	Dr. Eric S. Kasischke, Department of Geography

This thesis presents an assessment of the potential of the differenced Normalized Burn Ratio (dNBR) and other spectral indices for mapping fire severity in Alaskan black. Using simple linear regression, the dNBR derived from Landsat TM and ETM+ data was correlated with ground measures of fire severity including the Composite Burn Index (CBI), depth of the organic soil remaining after the fire, reduction in the depth of the organic layer, and Canopy Fire Severity Index; these being measures of fire severity used to assess the ecological effects of fire. Regression analyses yielded weak correlations: the highest R^2 for a comparison between the dNBR and CBI was 0.52, $p<0.0001$. However, the mid-infrared ratio showed higher potential than other spectral indices in many comparisons. Overall, these results indicate 1) validation of the dNBR is needed and 2) burn severity mapping schemes which are more comprehensive than the dNBR should be developed.

EVALUATING THE POTENTIAL OF THE NORMALIZED BURN RATIO AND OTHER SPECTRAL INDICES FOR ASSESSMENT OF FIRE SEVERITY IN ALASKAN BLACK SPRUCE FORESTS.

By

Elizabeth E. Hoy.

Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Master of Arts
2007

Advisory Committee:
Professor Eric S. Kasischke, Chair
Professor Samuel N. Goward
Dr. Simon Trigg

Dedication

The LORD is exalted over all the nations, his glory above the heavens.

Psalm 113:4

For God, who said, “Let light shine out of darkness,” made his light shine in our hearts to give us the light of the knowledge of the glory of God in the face of Christ.

2 Corinthians 4:6

I dedicate this work first to the Lord and second to my husband, my family and my friends who have seen me through this feat.

Acknowledgements

The research presented in this thesis was supported by NASA through Grant NNG04GD25G and the Bonanza Creek Long-Term Ecological Research program (USFS grant number PNW01-JV11261952-231 and NSF grant number DEB-0080609). I thank Eric Kasischke, Merritt Turetsky, Evan Kane, Evan Ellicott, Nancy French, Gordon Shetler, Luz Silverio, and Sam Upton for assisting in the collection of field data. I would also like to thank my advisor Eric Kasischke for guiding me through the completion of this project.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Black spruce *(Picea mariana)* forests are an important component of the boreal ecosystems of Alaska and Canada, representing some fifty percent of the forest cover in the region (Kasischke and Johnstone, 2005). In Alaska alone, these forests cover 26 x 10^6 ha and contain deep surface organic layers that store a substantial fraction of the terrestrial carbon present in this boreal region.

Interior Alaska is the region which contains its boreal forest and experiences summer fires due to high temperatures and low precipitation (Kasischke et al., 2002; Sorbel and Allen, 2005). Forest fires in the summer of 2004 burned over 2.7 x 10^6 ha of land, much due to natural causes (Sorbel and Allen, 2005). Documenting these fires and accurately recording burned area and fire severity can be difficult due to their large areas and remote locations. However, advances have been made in using satellite remote sensing data to monitor the fire regime. Monitoring active fires and post-fire effects, such as burned area or perimeter mapping and methods used to assess surface changes have allowed researchers to better understand the fire regime and assess changes to this regime (Lentile et al., 2006).

Motivating this study is the need to quantify fire severity, the direct effects of the combustion process, in terms of the levels of surface fuel consumption, i.e., the burning of dead organic matter lying on top of mineral soil (Harden et al., 2000; Jain 2004; Kasischke et al., 2005). Studies show that black spruce forests make up > 70% of the area burned in Alaska and > 50% of burned area across Canada (Amiro et al., 2001). Quantifying carbon emissions for this region can be important considering the large amount of carbon which can be emitted due to fire. The deep surface organic layers found in black spruce forests can release from 10, and up to 100, t ha^{-1} of carbon. Variations in depth of burning represent a major source of uncertainty in estimating emissions from boreal fires (French et al., 2004; Kasischke et al., 2005). This study assesses multiple methods to determine the fire severity of the surface fuel consumption through comparison spectral indices derived from Landsat TM and ETM+ satellite data and ground measurements of fire severity.

Numerous spectral indices have been derived from satellite remote sensing data to quantify and spatially map burn severity, the environmental characteristics following the fire, across the landscape (Jain 2004). While some research has been carried out to correlate spectral indices with ground measurements to determine the potential of the spectral index to accurately quantify burn severity on the landscape, there is still a need for further study. The approach used operationally by the fire management community in the in the United States is to empirically determine the relationship between the differenced or delta Normalized Burn Ration (dNBR) with a specific set of field measures of burn severity, known as the Composite Burn Index (CBI) using regression analysis (Key and Benson,2006). The relationship between the dNBR and CBI is then extrapolated throughout the entire burned area. However, what has yet to be demonstrated is: a) whether the dNBR is correlated to CBI over a single forest cover type and b) whether the dNBR or other spectral indices are correlated to other measures specifically designed to assess specific characteristics of fire severity.

This research tests the sensitivity of different spectral indices to different metrics of fire severity. The objectives of the study are to 1) evaluate the potential of the dNBR and CBI approach for mapping fire severity, 2) evaluate the potential of dNBR for mapping other measures of fire severity, and 3) analyze the potential of different spectral indices designed to quantify forest change for assessing fire severity. I present an assessment of thirteen single-date and fourteen two-date remotely sensed indices designed for mapping land surface characteristics, and potentially fire severity. This study was carried out by correlating the indices to surface measures of fire severity, including the CBI and other fire severity measures that can be used to estimate fuel consumption during fires including the consumption of the forest canopy, consumption of the soil organic layer, and the depth of remaining soil organic layer.

Chapter 2: Background

2.1 Fire in the Boreal Forest

On a global scale, the boreal region contains the world's second largest store of soil organic carbon (30%), while it consists of only 17% of the Earth's land surface (Kane et al., 2005; Kasischke 2000). The boreal forest region of Alaska consists of six main tree species: two coniferous species – black spruce (*Picea marianna*) and white spruce (*Picea glauca*), as well as three deciduous species – trembling aspen (*Populus tremuloides*), balsam poplar (*Populus balsamifera*), paper birch (*Betula neoalaskana*) and one deciduous coniferous species – larch (*Larix laricina*) (Borgeau-Chavez et al., 2000; Kasischke et al., 2000). These tree species occur either in pure or mixed forest stands, all of which are at risk from fire. However, black spruce forests represent > 70% of the forested areas that burn in Alaska (Kasischke et al., 2005). Black spruce forests are at an especially high risk of burning due to the vegetation structure of the individual trees – they retain dead lower branches and during periods of low precipitation, the needles of this species are highly flammable. Also, ericaceous vegetation found in the understory of these forests contains a high content of volatile organic oils which increases flammability. All these components result in a highly flammable fuel matrix that supports the rapid spread of surface and crown fires during dry conditions (Johnson 1992).

Fire is a natural occurrence in Alaskan forests and has serious consequences at local, regional, and global scales. The release of carbon into the atmosphere following a fire can affect global climate, however the local ecosystems and the regional environment can be altered in other ways as well. For example erosion and mudslides can occur, potentially altering conditions for those living downstream of the burned area (Sorbel and Allen, 2005). Also, it has been proposed that fire may permanently change the ecosystem by altering the succession of species post-fire (Johnston and Kasischke, 2005). For example, what may have been a black spruce stand capable of storing vast quantities of carbon may grow back as a deciduous stand capable of storing less (Kasischke 2000). Understanding this ecosystem and its fire dynamics is becoming increasingly important as land managers use information regarding the severity of a fire to make policy decisions for the surrounding area (Epting et al., 2005; Sorbel and Allen, 2005).

However, there is an overall lack of the detailed spatial information needed to reduce uncertainty in carbon consumption estimates due to wildfire (French et al., 2004). An important process in the carbon cycle is the emission of carbon from the burning of the organic soil layer (SOL). Deep burns in this SOL, which can occur due to drier climactic conditions in this region, can lead to increases in carbon emissions. Conditions such as this are projected by various general circulation models that changes in the climate of the boreal region due to global warming could result in a longer fire season and an increased probability that severe fire weather will occur (Stocks and Kasischke, 2000; Flannigan et al., 2005; Chapin et al., 2006). Over the last 30 years, it has been shown that annual surface temperatures in the Alaskan boreal and arctic regions, the Canadian boreal region, and in North America overall have increased by five degrees Celsius, although it is not yet clear that this temperature increase is responsible for changes in fire weather in Alaska (Chapin et al., 2006).

Many terms have been used over time to describe the effects and impacts of fire, fire severity and burn severity (Figure 1). Generally, fire severity can be defined as the direct effect of the combustion process with respect to vegetation mortality, biomass consumption, the heating and physical transformation of soils, and the production of smoke (Jain 2004). Burn severity can be defined as how the environment and ecosystems respond to the impacts of fire, such as changes in the erosion of soils into streams, the release seedlings from serotinous cones by coniferous trees, and the changes to nutrient cycles (DeBano et al., 1998; Bourgeau-Chavez et al., 2000), and the establishment of new plant species following the fire (Jain 2004). Thus burn severity can actually be thought of as a function of fire severity. It is for this reason that understanding fire severity is of such importance – without an understanding of the direct effects of the combustion process, it will be difficult to accurately assess post-fire responses of the environment.

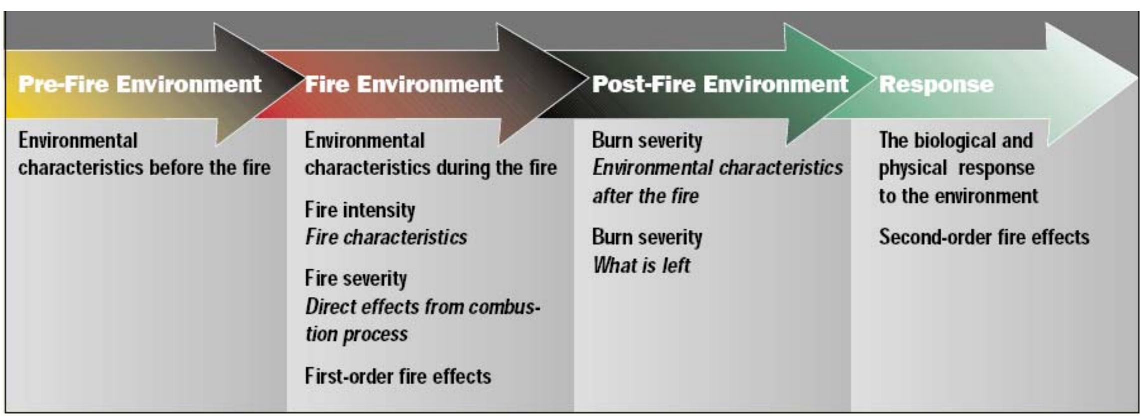

Figure 1: The fire disturbance continuum. Fire severity is seen as a first-order fire effect, while burn-severity is a factor of the post-fire environment (Jain 2004).

Black spruce forests experience three types of fire – ground, surface, and crown fires – and each can lead to different changes in the ecosystem. A ground fire can result in the exposure of mineral soil and immediate erosion, while in a crown fire it may take more time for the effects of burning (such as the death of the tree and the drop of needles to the ground) to become evident on the landscape (Jain 2004). Ground measurements of these three types of fire were analyzed in this study to capture the full range of variability in this system. To be consistent with the Key and Benson (2006) approach (described in the Landscape Assessment documentation produced by the FIREMON program), data to calculate the CBI measurement were collected. However, while the CBI is intended to provide an assessment of fire and burn severity, it may not accurately assess fire severity in areas with deep organic soils, such as those in the Alaskan black spruce forests (Kasischke et al., in review). Other ground measures considered to be of interest in this study included changes to the surface organic layer and canopy. Fire severity can play an important role in the post-fire environment (Figure 2). Severe ground fire severity can lead to consumption of the soil organic layer, as in the extreme fire severity site (Figure 2c), and the downing of trees within the stand. In low and moderate fire severity sites, varying degrees of surface and/or canopy fuels may remain (Figure 2a and 2b). This type of response can have implications for the spectral signature of the site (discussed in further detail in section 2.2). Also, as the spectral signature has been found to vary based on vegetation cover types and stand density, this was of particular interest in the study.

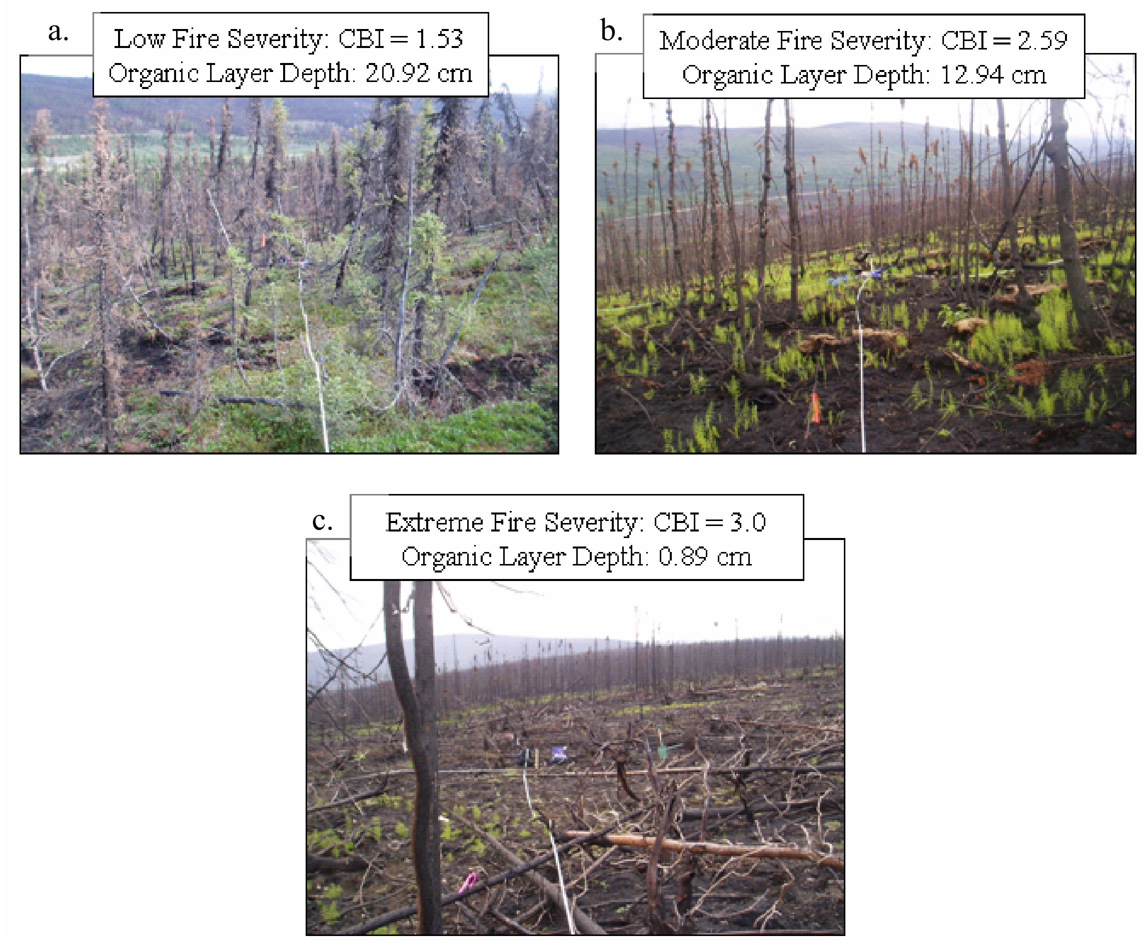

Figure 2: Variability within black spruce forests. All three of the above images are from the Boundary fire sites analyzed in this study, although each has varying degrees of fire severity including low (a), moderate (b), and extreme (c). ***Photographs courtesy of E.Kasischke.***

2.2 Satellite Assessment of Fire Severity

The large size of individual fires and their remote locations can lead to difficulties in quantifying the fuel consumption and carbon storage. Satellite data have provided a much needed source of information to monitor the boreal region, and the availability of moderate- and coarse-resolution satellite data has greatly increased the ability to understand fire regimes in this ecosystem (Sukhinin et al., 2004; Lentile et al., 2006). The quantification of burned areas and burn severity is important globally to better assess impacts of biomass burning on the carbon cycle. The application of satellite data to mapping burned areas and fire severity has increased in recent years. Many burned area and fire severity mapping methods have been developed including band ratios, indices and linear transforms to both map burned area and assess and quantify f severity (Lentile et al., 2006).

Techniques to remotely measure fire severity using satellite data contain various levels of complexity, but all attempt to analyze changes in the surface characteristics of the environment. Fire-induced changes to the ecosystem detectable using satellite imagery include changes within the vegetation and soil structure, as well as changes to the moisture content of the vegetation and soil (Cocke et al., 2005; Miller and Thode, 2007). Fire can lead to various levels of char, white ash, bare mineral soil, and changes from healthy green vegetation to brown vegetation. Soil composition and structure can be altered through deposits of white ash and could be important in analyzing the spectral response of burned areas, but the relatively small size of these deposits could mean that they are difficult to recognize with medium resolution satellite imagery (Smith et al., 2005). Fire can also down trees as it often consumes the organic soil and root layer of the trees, thus the tree falls due to a lack of support. This affects the spectral response through changing the degree of shadowing and the composition of surface reflections from the ground (Key and Benson, 2006).

Burnt areas can also exhibit changes in hydrological patterns from the pre-fire environment. Evapotranspiration can decrease due to the death of vegetation, and runoff can increase in areas of steeper slopes due to reduction in the presence of litter and duff (Miyanishi 2001). Finally, increased hydrophobicity of some soils can occur following fire due to changes in soil chemistry. As a result of these changes in hydrology, soil moisture conditions can vary in the extreme compared to the pre-fire site conditions, which can have impacts on the spectral signature of the site (Doerr et al., 2006).

Of particular interest in mapping burned areas and fire severity have been the regions from the red (0.63 to 0.69 μm) through the short wave infrared (SWIR: 2.08 – 2.35 μm) portions of the EM spectrum (Table 1). Traditionally, this range has yielded the highest degree of sensitivity to changes in vegetation structure and moisture levels, both of which are correlated to the impacts of fire (van Wangtendonk et al., 2004; Miller and Thode, 2007). These changes are due in part to the tendencies of the healthy green vegetation to generally have low reflectance in the red (0.63 to 0.69 μm) and SWIR (2.08 – 2.35 μm) wavelengths and high reflectance in the NIR wavelengths (0.76 – 0.90 μm in TM and 0.78 – 0.90 μm in the ETM+ sensor's respectively).

Following fire, it has been found that the spectral response of the sites in the NIR wavelength reflectance decreases in direct relation to the fire intensity (Jakubauska et al., 1990). Reflectance in this region generally decreases following fire due to damage to, and possible removal of, the leaf tissue. In contrast, reflectance in the SWIR (Landsat

TM Band 7) section of the spectrum generally increases due to decreasing moisture levels at the site and a difference in forest shadows (Epting et al., 2005; Key and Benson, 2006). For this reason, assessments of these two bands were included in the study. Extreme fire severity (Figure 2c) could potentially be causing changes in forest shadows as the loss of the organic soil layer can lead to downed trees and changes in the spectral signatures of the forested areas.

Graphs of the spectral reflectance of the two fire events studied in this project and measured using TM wavelength regions (Figure 3) show the different spectral signatures between the pre- and post-fire environment of forested areas. It can be seen that for both Landsat TM and ETM+ Band 4 and Band 7, large shifts in the pre-burn and post-burn spectral response patterns are evident (Table 1). While the wavelengths region characterized by Band 4 (the NIR Landsat Band) typically decrease following fire in forested areas, wavelengths in the region characterized by Band 7 typically increases following fire in these same environments (Table 1 and Figure 3) (Key and Benson, 2006). Landsat Band 5 (1.55 - 1.75 µm) can be affected by soil moisture levels as it too is a short wave infrared Band. Two indices using Band 5 and one other infrared wavelength band are included in the study (TM 4/5 ratio and TM 7/5 ratio). Band 1 (0.45 - 0.52 µm) and Band 2 (TM: 0.52 - 0.60 µm. ETM+: 0.53 - 0.61 µm) are not included in this study as traditionally only slight changes in these spectral wavelengths have been observed from the pre-fire to post-fire environment (Figure 3) (Miller and Thode, 2007). Also, Band 6 (10.4 - 12.5 µm), due to its lower spatial resolution, is not analyzed in this study, although others have found measures of this band to be responsive to changes due to fire in forested environments (Epting et al., 2005; Holden et al., 2005).

Spectral Component	Affected By	Impact on Reflectance
NIR 0.76 – 0.90 µm (TM Band 4)	Leaf tissue damage and removal, crown shadowing	Post-fire decrease
SWIR 1.55 – 1.75 µm (TM Band 5)	crown shadowing, soil moisture levels	Post-fire decrease*
SWIR 2.08 – 2.35 µm (TM Band 7)	Crown shadowing, soil moisture levels	Post-fire increase
NIR minus SWIR	Normalizes for brightness, removes within scene topographic effects, removes between scene solar illumination effects	Differences due to fire isolated.

Table 1: Impacts on reflectance due to fire or other types of forest disturbance. *: The impact of fire on Band 5 has been much less in magnitude than that of the other infrared Landsat bands, however, a small decrease in reflectance has been observed.

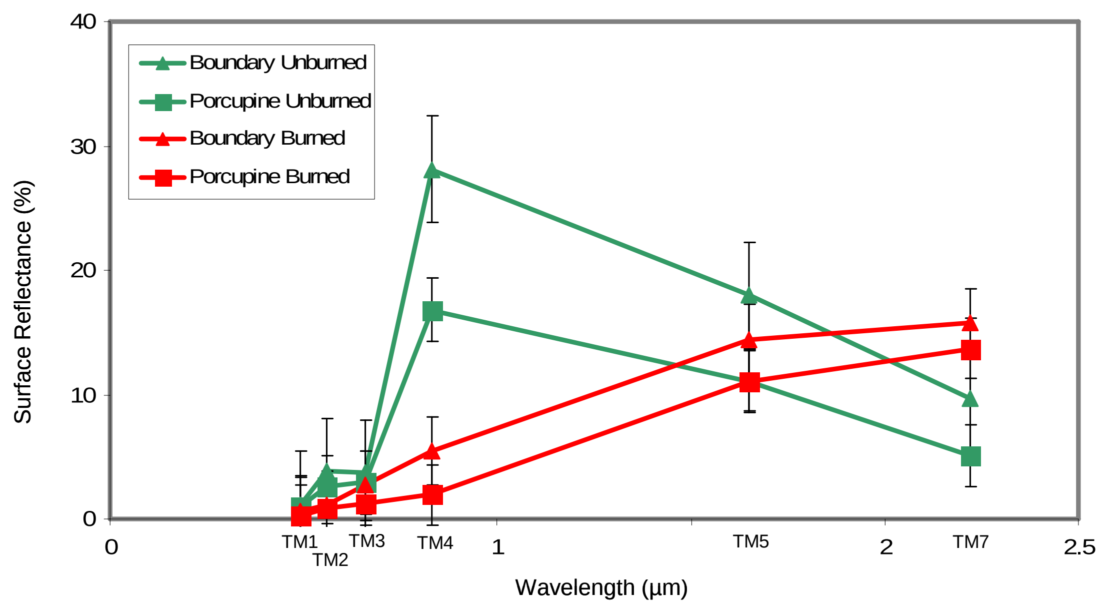

Figure 3: Variations in pre-fire and post-fire spectral signatures. The average surface reflectance at each band of the Landsat TM/ETM+ data is shown, along with the associated standard error. The post-fire effects in the NIR (Band 4) and SWIR (Band 7) are visible in measurements from both the Boundary and Porcupine fires.

The advantage in using the near-infrared wavelength band of Landsat TM and ETM+ data (0.76 – 0.90 μm, TM Band 4) and the short wave infrared Landsat band (2.08 – 2.35 μm, TM Band 7) in mapping fire severity is due to the opposite nature of their changes in magnitude in the post-fire environment (Table 1, Figure 3). Some have found that the NIR wavelengths are more strongly correlated with fire severity than the shortwave-IR regions of the spectrum (DeSantis and Chuvieco, 2007). The red region of the EM spectrum (0.63 to 0.69 μm) can also be used to map fire severity; although, issues of atmospheric contamination due to dust and smoke can add error and noise to the analysis, thus limiting their potential to map fire severity immediately post-fire (Cocke et al., 2005). However, the prevalence of red bands on most satellite systems has lead to the continued use and analysis of this wavelength region, with some successful results, when used in combination with NIR and SWIR bands in mapping burned severity (Chuvieco et al., 2002).

However, it should be noted also that multiple remote sensing platforms and data analysis techniques have been used to assess fire severity and post-fire changes to the environment. van Wagtendonk et al., (2004) presented reflectance spectra using airborne hyperspectral data, while Smith et al. (2005) and DeSantis and Chuvieco (2007) presented reflectances derived using theoretical values and simulated data. Trigg and Flasse (2001) used a handheld radiometer to collect data for analysis.

2.2.1 Spectral Indices

Spectral indices offer many advantages in mapping fire severity based on the opposite changes in post-fire spectral responses of the NIR and SWIR portions of the spectrum. As the pre-fire to post-fire changes in reflectance can be large in magnitude and in opposite direction in the NIR (TM4) and SWIR (TM7) regions of the spectrum, many indices use these wavelength regions to isolate the changes to the landscape due to fire (Table 1, Figure 3). These indices can be relatively quick and simple to implement as, in some cases, minimal processing is required to compute the index, leading to increased usability and quicker production of results for decision makers in a time of crisis. For example, in the United States, burned area maps are created immediately post-fire to aid in remediation projects (Bobbe et al., 2002). However, indices relying on only two bands of data can also provide selective information when mapping fire severity– only variation in specific regions of the EM spectrum is used, while variations in other portions of the EM spectrum may be missed.

Some spectral indices have a normalized form, which has the advantage of accounting for some of the variations in brightness levels within a scene of data and within the two bands composing the index. Normalization can also account for some of the noise not related to the burned area signal of interest on the earth's surface, such as that due to topographic influences, although it would not fully eliminate this noise (Colby 1991; Key and Benson, 2006).

Many of the indices used to map wildland fire were originally developed for mapping other land disturbances. However, the differences in the NIR and SWIR regions of the spectrum have been especially important in mapping fire severity related to vegetation structure and soil moisture has led to the development of some indices unique to fire monitoring (Trigg and Flasse, 2001; Key and Benson, 2006).

When using Landsat TM and ETM+ imagery, spectral indices include simple ratios such as Band 7 divided by Band 5, 7 divided by 4, and Band 4 divided by Band 5.

Jakubauska et al. (1990) used the 7/5 ratio to analyze fire severity data to successfully detected differences in the intensity of the fire. Other band combinations make use of the differences between the NIR and SWIR sections of the spectrum.

One index that has been widely applied to land cover change due to the sensitivity it has shown to changes in vegetation is the normalized difference vegetation index (NDVI). Changes in spectral reflectances between the pre- and post-disturbance environment can occur due to high levels of green vegetation in undisturbed areas to decreased levels of live vegetation in disturbed areas. This index has been applied specifically to mapping fire severity (Garcia-Haro 2001; Chuvieco et al., 2002; Isaev et al., 2002; Diaz-Delgado et al., 2003). However, since this index uses the red a portion of the spectrum, contamination from smoke can be a problem. As the NDVI has been used in past studies and has been found to correlate with fire severity characteristics, it was included in this study.

When spectral indices for mapping vegetation were first introduced, extraneous factors that had an undesired influence on index values were not always considered; however over time, researchers began to include such factors in their studies (Verstraete et al., 1996). For example, some found that the NDVI can be affected by soil brightness, and attempts have been made to minimize this influence (Huete 1988; Qi et al., 1994). Huete (1988) experimented with adjusting vegetation indices for differences in light and dark colored soil substrates using the Soil Adjusted Vegetation Index (SAVI). When performing optimally, this index was designed to have different soil substrates provide the same index value; optimality is achieved through the application of a constant to the red-NIR index in use. This adjustment was designed for use in the red-NIR spectral space and for use to distinguish vegetation differences and reduce soil noise in the case of cotton and range grass. While this can be advantageous for some applications, it may provide mixed results in the boreal region where differences in the surface organic layer are of interest. Also, it has been found that the use of the SAVI can decrease the magnitude of the vegetation response, requiring one to use caution when interpreting results (Qi et al., 1994).

The Modified Soil Adjusted Vegetation Index (MSAVI) was derived from the SAVI to better account for variations in soil structure and moisture as captured in the red-NIR spectral space recorded by the sensor (Qi et al., 1994). While the SAVI required knowledge of the vegetation cover type and amount to produce a correction, the MSAVI self-adjusts to reach an optimal performance of the index which would includes a large dynamic range for the vegetation response and a small amount of noise due to soil types (Qi et al., 1994). As with the SAVI though, this index was developed using cotton fields as study sites and aircraft data, not satellite data. Qi et al. (1994) suggest that this approach be extended to satellite imagery and its performance assessed based on additional factors such as sensor viewing angles, atmospheric conditions and solar illumination conditions.

2.2.2 The Normalized Burn Index

One index that is receiving great interest in the fire science and fire monitoring community is the Normalized Burn Ratio (NBR). This spectral index is now used operationally by inter-agency Burned Area Emergency Response Teams (BAER) throughout the United States to both map burned areas and assess the burn severity of these areas (Bobbe et al., 2002). The goal of BAER teams is to quickly provide burned area and severity maps to local land managers following a fire such that decisions can be made regarding remediation and rehabilitation needs.

While BAER provides maps as soon as possible following a fire, there is a new program in the United States designed to look at the long-term fire regimes across the country. This program, the Monitoring Trends in Burn Severity mapping project (MTBS), overseen by the Wildland Fire Leadership Council, an inter-governmental group charged with management of the National Fire Plan and Federal Wildland Fire Management Policies, is also relying on the dNBR approach to provide 30 m resolution burn severity maps from Landsat imagery from 1984 to the present for various regions of the United States (Monitoring Trends in Burn Severity, 2006).

The quick and simple nature of spectral indices and the advantage of a normalized index have helped the NBR gain support in mapping burn severity. NBR is defined as (Eq. 1):

$$[(NIR - SWIR)/(NIR + SWIR)]*1000 \qquad \textit{Eq. 1}$$

In the above equation, the NIR (Landsat TM or ETM+ Band 4: 0.76 – 0.90 μm) and SWIR (Landsat TM or ETM+ Band 7:2.08 – 2.35 μm) spectral reflectance can be shown as either top of atmosphere or surface reflectance, as long as there is consistency throughout the study (Key and Benson, 2006). This formula is similar to the Normalized Difference Vegetation Index (NDVI) but differs in that Band 7, not Band 3, is used to generate the index. The (NIR – SWIR) difference found in Eq. 1 is used to normalize images for overall brightness within and between bands through partially aiding in the removal of within-scene topographic effects and between-scene solar illumination effects, thus ideally isolating reflectance differences due to fire (Table 1) (Key and Benson, 2006).

Additionally, greater accuracy in the NBR has been found through multi-temporal analysis (Key and Benson, 2006). To calculate a differenced or delta Normalized Burn Ratio (dNBR), values for the NBR are calculated for both pre-fire and post-fire Landsat scenes:

$$\mathrm{dNBR} = NBR_{pre\text{-}fire} - NBR_{post\text{-}fire} \qquad \text{Eq. 2}$$

A new index, a relative version of the dNBR (RdNBR) has recently been developed by Miller and Thode (2007). This formulation for this approach is:

$$RdNBR = \left(NBR_{pre-fire} - NBR_{post-fire}\right) / \sqrt{\left|NBR_{pre-fire}/1000\right|} \qquad \text{Eq. 3}$$

The RdNBR has been found to allow for better comparisons across spatial and temporal scales than that of the dNBR alone (Miller and Thode, 2007). Also, this index has been shown to provide higher accuracy for high severity fires in heterogeneously burned landscapes. The square root normalization is performed to account for a non-linear relationship CBI and dNBR, which has been seen to exist in higher fire severity sites (van Wagtendonk et al., 2004; Miller and Thode, 2007). Miller and Thode (2007) have found this normalization technique to provide a sufficient first-order correction to establish a linear relationship with the CBI and dNBR. While developed in the Sierra Nevada mountain range in California, it merits further examination in other ecosystems; thus I have included it in this study to compare it with other satellite measures of fire severity.

2.2.3 Linear Transformations

While the study of burned areas using spectral indices can be quick and simple in many cases, linear transforms can offer additional information when applied to surface characterizations and change detection analysis. Linear transformations, such as principal components analysis (PCA) and the tasseled cap (TC) transformation can be advantageous in mapping burned areas because, unlike spectral indices, they use information from a wider variety of spectral wavelengths, and are not limited to one or two bands. While PCA is able to detect within scene variations, in order to apply this technique to burned areas a significant portion of a scene must contain the burned area as PCA can be biased based on the majority type of pixels in a scene, either unburned or burned (Garcia-Haro et al., 2001; Patterson and Yool, 1998). Because of this, Garcia-Haro et al. (2001) found PCA to be too dependant on scene effects to accurately quantify burned areas and instead found a bi-temporal NDVI approach to perform more effectively.

The tasseled cap (TC) transformation is similar to principal components analysis as data is transformed from its original axes into other axes. Originally developed to analyze changes in agricultural fields within the growing season using Landsat MSS data (Kauth and Thomas, 1976), it has been modified over the years for Landsat TM and Landsat ETM+ reflectance factor data (Crist and Cicone, 1984; Crist 1985; Crist and Cicerone, 1986). Others have used these techniques in forest change detection studies over the years (Collins and Woodcock, 1996; Potere et al., 2004; Healey et al., 2005; Jin and Sader, 2005). Also, numerous studies have used the tasseled cap to assess scene characteristics. For example, Cohen and Spies (1992) used the tasseled cap to estimate structural attributes of forested stands, and later used this transform for estimating tree canopy characteristics (Cohen et al., 2005). The tasseled cap is included in this study as it has been found to account for shadowing within the scenes and has been shown to have axes which remain constant from one scene to the next, a distinct advantage over principal components analysis in using this transformation to map burn severity over multiple scenes of data and multiple dates (Crist and Cicone, 1984). In addition, the tasseled cap does have some sensitivity to changes in soil, but this is still an area which requires further research.

In the case of the tasseled cap transformation and Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data, six bands of data (the thermal IR band is not used) are transformed into three major components: brightness, greenness and wetness. It has been shown that these three components can explain over 97 percent of the variation within a scene of data (Huang et al., 2002). The multi-temporal approach of the tasseled cap transformation, known as the Kauth Thomas transformation, was originally developed to detect forest canopy changes due to insect damage and drought, but its scope of use has been expanding (Rogan et al., 2002). The TC transformation has previously yielded higher potential to accurately map burnt areas and fire severity than the PCA (Patterson and Yool, 1998). In a comparison study of PCA and the TC, Patterson and Yool (1998) found that the TC transformation lead to classification accuracies 17% higher than those of the PCA. This difference was attributed to variations in the first three components of the TC: brightness, greenness and wetness components; they found these components to be related to fire severity. The changes in the spectral reflectance was determined to be due to the fire disturbance and not simply noise, however the components on the ground which lead to this conclusion were not isolated in the study. Additionally, Epting et al. (2005) included both the TC and PCA in their analysis of boreal forests, although both yielded mixed results, although low R^2 values were found.

2.2.4 Review of NBR verses CBI Studies

Since its inception in 1991 by Lopez-Garcia and Caselles (1991), many studies have focused on the validation of the NBR method to assess fire severity. Validation studies using the CBI have been performed in the western United States (van Wagtendonk et al., 2004; Cocke et al., 2005). Other studies have focused on validating the NBR in other ecosystems, such as African savanna ecosystems (Smith et al, 2005; Roy et al., 2006). Still others have focused on analyzing the NBR in the northern boreal regions (Sorbel and Allen, 2005; Epting et al., 2005; Roy et al., 2006).

It has been hypothesized that the dNBR is directly correlated with changes to surface characteristics occurring on the ground at the site of the burn (Key and Benson 2006). To characterize the appropriate relationship between the dNBR and actual burn severity, considered by Key and Benson (2006) to be the ecological impact of fire and the post-fire response, in-situ observation are used. The ground measurement used with the dNBR approach, the Composite Burn Index (CBI), was developed, originally for the coniferous forests of the western United States (Key and Benson 2006). The information contained on the CBI form is intended to provide a quick and simple, yet detailed look at the characteristics related to the burn severity of a site following fire. This ground measure is determined through a visual examination of the study site. Following site selection, the vertical structure of the ground and vegetation are observed and partitioned into five strata: (a) substrate; (b) herbs and low shrubs, and trees; (c) tall shrubs and small trees ; (d) intermediate trees ; and (e) tall trees. Damage to each of the five vertical levels of the site is then recorded on a scale of 0 to 3, with 3 being the highest fire severity. This ground fire/burn severity measure can then be compared with the dNBR to properly calibrate classes of fire/burn severity when creating classification maps of a burnt area (Key and Benson, 2006).

The use of the NBR has been driven partially due to its use operationally in the United States, although few validation attempts have been made to assess the optimality of the index (Roy et al., 2006). Studies have been done to assess if there is any affect from the nearness to roads on burn severity (McHugh and Finney, 2003). Others have used the dNBR to create maps of species habitats disrupted by fire (Kotliar et al., 2003). Others have studied the dNBR approach to determine if incorporate the thermal infrared wavelengths would lead to higher accuracy in mapping fire severity (Holden et al., 2004; Epting et al., 2005). Holden et al. (2004) found that the successful use of such spectral methods can vary based on such biotic factors as the vegetation type, fire severity, vegetation mortality and vegetation recovery, while imagery acquisition can also play a factor in the effectiveness of the approach. More recently, a governmental report was recently released detailing the successes and potential areas of improvement for the CBI and dNBR approach (Zhu et al., 2006).

Smith et al. (2005) used the dNBR approach to examine fire severity in African savannahs. While not in the same ecosystem as the focus of this study, Smith et al. (2005) compared the dNBR approach ground measures of biomass combusted and nitrogen volatilized at their study sites. The study presented in this thesis also incorporates additional ground measures (aside from CBI) related to losses to the soil organic layer. Smith et al. (2005) found dNBR to be relatively poorly, although significantly, correlated with both biomass consumed and nitrogen volatilized in the environment ($R^2 = 0.39$, n = 40, $p < 0.001$ and $R^2 = 0.23$, n = 39, $p < 0.005$, respectively).

In the boreal region, comparisons between the dNBR and CBI values using linear regression models performed by Sorbel and Allen (2005) resulted in R^2 values of between 0.46 and 0.84 for different burned areas. The closed and open needleleaf forest sites studied by Epting et al. (2005) yielded R^2 values of 0.14 and 0.28 respectively; although comparisons across all burned forested types yielded R^2 values between 0.37 and 0.67. Epting et al. (2005) found the dNBR to rank in the top three correlations for only three of the four study sites as compared with other satellite measures of fire severity (Epting et al. 2005). The differences found within these studies lead to the need for further analysis of the dNBR and other potential methods to analyze fire severity in boreal regions.

Chapter 3: Approach

This study was performed using satellite observations and field data from black spruce sites within two separate fire events that burned during the summer of 2004 in the Alaskan boreal forest. The sites were sampled during the summers of 2005 and 2006. Data collected at each site included observations required to estimate the CBI, the depths of the remaining organic layer (consisting of litter, lichen, mosses, char and fibric, mesic and humic soil), measurements of the depth of the topmost adventitious root above mineral soil, and a visual estimate of the canopy fire severity. Fire severity characteristics derived from the field observations were then correlated with spectral indices derived from Landsat TM and ETM+ data.

Both a single-date and two-date approach was used to better assess the potential of the spectral indices. In the single-date analysis, a single post-fire image of the fire event was examined and analyzed; while in the two-date analysis, both pre-fire and post-fire images were analyzed. In the two-date approach, the post-fire index result was subtracted from the pre-fire index. Such a procedure is performed to minimize differences between images due to factors other than disturbance (Key and Benson, 2006). In this thesis, satellite and field data from two fires were considered: the Boundary (n = 28 sites) and the Porcupine (n = 29 sites) (Figure 4).

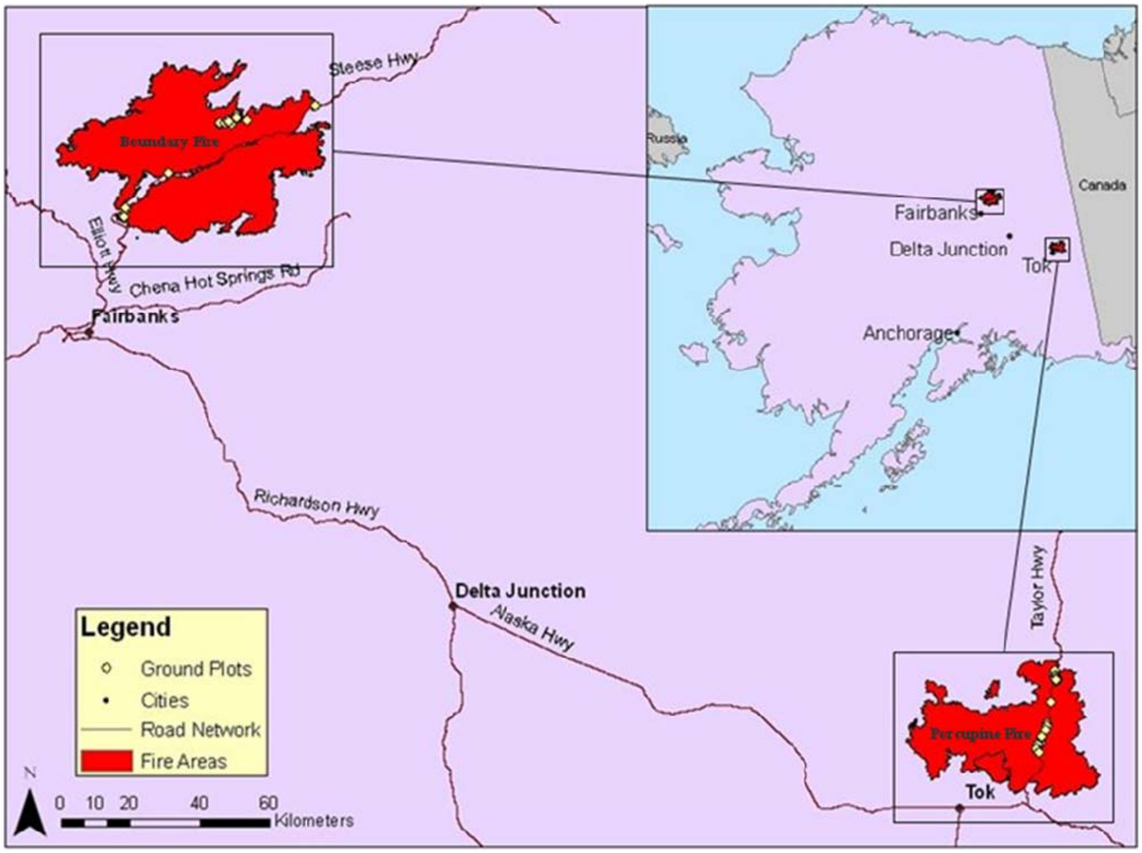

Figure 4: A subset of the fires studied in the summer of 2004. This study focuses on two fires: the Boundary fire and the Porcupine fire. Twenty-eight field sites in the Boundary fire and twenty-nine sites in the Porcupine fire are analyzed in this study.

3.1 Satellite Image Processing

Landsat 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper Plus data were used in this study (Table 2). These data were initially processed for the inter-agency Burned Area Emergency Response Team (BAER) for the Alaska region to Level 1 Terrain (L1T), meaning that the data had previously been radiometrically (to top of atmosphere reflectance values), geometrically, and precision corrected (Key and Benson, 2006; Landsat 7 Science Data Users Handbook, 2007). Band 6, the thermal band, was not used in this analysis as it was not a part of the product provided by the BAER team and as it lacks the level of spatial resolution provided in the other bands; as such, no indices based on thermal IR emittance were used in this study.

While the orthorectification process includes a correction for local topographic relief, it does not account for variable illumination angles and sun-sensor geometry differences due to slope angles and orientations (Colby 1991). An additional step, a topographic normalization procedure, would be necessary to further calibrate the imagery for this affect. However, on examination of the images, it was determined that no further georegistration procedures were possible that would improve the geometric correction of the images. This determination was made through comparisons of the images with a highly accurate road dataset produced by the Alaska Highway Service which showed the images to be well registered. The area of Alaska included in this study, at approximately 63 degrees north latitude, was not included in the recent Shuttle Radar Topography Mission which mapped terrain across much of the United States at 30 meter resolution. Such a detailed level of digital elevation models (DEMs) could have potentially reduced uncertainties in the orthorectification process by limiting errors due to local incidence angles; however they are currently unavailable in this region.

Fire Event (date burned)	Pre-Fire			Post-Fire		
	Image Date	*Path/Row*	*Sensor*	*Image Date*	*Path Row*	*Sensor*
Boundary (late June 2004)	07/18/2003	68/14	TM	08/04/2004	69/14	ETM+
Porcupine (late June – early July 2004)	09/10/2001	64/16	ETM+	09/08/2004	66/15	TM

Table 2: Landsat image acquisition dates and sensor information for two fires that occurred in the summer of 2004 in interior Alaska.

The images were then examined for evidence of atmospheric contamination. At the time of data acquisition (late summer of 2004), some fires were still burning in the areas being imaged and smoke and other atmospheric contamination was a concern. While the pre-fire images occurred on clear days, post-fire images free of smoke and cloud cover were not always available. The visible bands (red, green and blue) were analyzed to determine if atmospheric contamination was present. The visible portions of the spectrum are highly sensitive to heavy smoke and thick atmospheric conditions, making them ideal to determine the presence of contamination. As variable smoke in an image cannot be effectively corrected for, sites affected by smoke or thick atmospheric conditions in the two post-fire images were not used in the study. Fortunately, no sites in the Boundary fire region were affected by smoke, although in the Porcupine fire six plots were removed from the analysis due to atmospheric contamination. One Boundary fire site did have to be removed from the analysis due to issues with the scan line corrector being off in the Landsat 7 ETM+ post-fire image used.

A dark object subtraction procedure was performed to normalize the image pairs (e.g., pre- and post-fire) for possible atmospheric effects. In this processing step, I found three low-reflectance water bodies (large glacial lakes), visible in both the pre-fire and post-fire images. I then extracted the values from the lakes for each Landsat band used in this study (1-5 and 7), and then averaged each band's dark object values. These values were assumed to represent atmospheric scattering and were subtracted from the respective channels to normalize each image (Chavez 1989).

A further consideration when analyzing the imagery was the choice of images to use based on the acquisition dates of the imagery (Table 2). When performing bi-temporal analysis, it is best to use images only one or two years apart collected on an anniversary date (Key and Benson, 2006). For example, the imagery for the Porcupine fire is ideal from the standpoint of anniversary dates as the images are only two days apart from one another in the growing season (Table 2), although there are three years between the images, which could introduces errors in the analysis due to disturbance other than that caused by fire. When choosing imagery for the Boundary fire, I attempted to use pre-fire and post-fire imagery from the same period of the growing season; however the best available match was two weeks apart due to the cloud cover and smoke in Alaska during the late summer months. In these cases, the best available imagery was used (Table 2). Also, since I was interested in analyzing the immediate impacts of fire rather than an ecosystem's response to fire, I focused this analysis on Landsat imagery collected the same year as the fire.

Using the processed data, spectral indices were calculated (Table 3). To estimate average reflectance in each band, bilinear resampling techniques (as suggested by Key and Benson (2006) to determine cell values based on a weighted distance of the four nearest input pixels) were used to extract the spectral values for each site. In this study, the SAVI was implemented in accordance with the approach specified by Huete (1988) (Table 3). A value of 0.5 is used for the constant L as it is this value which is recommended for intermediate vegetation amounts and it is also believed to offer advantages across a large range of vegetation conditions (Huete 1988; Epting et al., 2005). In this study, the $MSAVI_2$ is used as described in Qi et al. (1994) and used by Epting et al. (2005) (Table 3).

The first of the linear transformed analyzed in this study, the tasseled cap (TC) transformation, was performed using the coefficients provided in Crist (1985) for Landsat TM reflectance factor data. While the pre- and post-fire image comparisons used data from both TM and ETM+ data, this difference is not expected to cause error in the results as the wavelength bands for each sensors are similar (Huang et al., 2002). The second transform, the principal components analysis (PCA) was performed using the function provided in the ENVI imaging software package. A covariance matrix was created and band loadings are provided (Table 4). Patterson and Yool (1998) have found TC1 and PCA1 to be related (brightness), as well as TC2 and PCA2 (greenness). However, Patterson and Yool (1998) also found that TC3 and PCA3, generally wetness components, were not strongly correlated. This discrepancy was believed to be in part to the tendency of the PCA to be highly impacted by the dominant pixel values in the scene, in this case, unburned pixels (Patterson and Yool, 1998). The TC1 component, brightness, was not included in the study as it was not believed that it would show potential throughout the entire range of fire severity conditions present at a site. Future work should include this measure to gain a better understanding of high severity fires in which losses to the soil organic layer occur. In these situations, it may be possible for brightness values to increase as mineral soil is exposed.

Spectral Index	Method of Calculation
NBR	$[(NIR - SWIR)/(NIR + SWIR)]*1000$
dNBR	$NBR_{\text{pre-fire}} - NBR_{\text{post-fire}}$
RdNBR	$(NBR_{pre-fire} - NBR_{post-fire})/\sqrt{\lvert NBR_{pre-fire}/1000 \rvert}$
Band4	*NIR* (0.76 – 0.90 µm)
Band5	*SWIR* (1.55 – 1.75 µm)
Band7	*SWIR* (2.08 – 2.35 µm)
Ratio7/5	*SWIR/SWIR*
Ratio7/4	*SWIR/NIR*
Ratio4/5	*NIR/SWIR*
NDVI	$(NIR\text{-}R)/(NIR+R)$
SAVI	$(NIR\text{-}R/NIR+R+L)*(1+L)$, $L=0.5$
$MSAVI_2$	$0.5[(2*NIR+1)-\sqrt{2(NIR+1)^2-8*(NIR-R)}]$
TC2	Linear transformation contrasting TM 3 and TM 4
TC3	Linear transformation contrasting TM 1,2,3,4,5 and 7
PCA1	Linear transform based on correlation matrix of original Landsat bands 1,2,3,4,5 and 7
PCA2	
PCA3	

Table 3: Summary of spectral bands and indices analyzed in study.

Fire Event	Image Path/Row		Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Boundary	Pre-fire 68/14	TM1	0.0405	0.1078	0.1100	0.7725	0.5385	0.2965
		TM2	-0.1397	-0.1448	-0.2371	0.6095	-0.4878	-0.5422
		TM3	-0.4518	-0.5312	-0.6057	-0.1000	0.3596	0.0871
		TM4	-0.0776	0.0355	0.2718	-0.1363	0.5603	-0.7657
		TM5	-0.8494	0.0980	0.4737	0.0163	-0.1545	0.1428
		TM7	0.2174	-0.8212	0.5163	0.0547	-0.0702	0.0621
	Post-fire 69/14	TM1	0.0721	0.1307	0.1351	0.7528	0.5587	0.2838
		TM2	-0.2779	-0.2645	-0.3607	0.5717	-0.3063	-0.5496
		TM3	-0.4839	-0.4894	-0.4425	-0.2266	0.4428	0.2883
		TM4	-0.0044	0.1210	0.1341	-0.2298	0.6196	-0.7284
		TM5	0.6540	0.1311	-0.7354	-0.0341	0.1138	-0.0100
		TM7	0.5056	-0.8010	0.3114	0.0322	0.0340	-0.0600
Porcupine	Pre-fire 64/16	TM1	0.4384	0.4653	0.4928	0.5614	0.1559	0.0948
		TM2	0.3344	0.2545	0.2202	-0.4140	-0.6982	-0.3407
		TM3	0.2227	0.1281	0.2490	-0.6929	0.4134	0.4701
		TM4	-0.7354	0.1017	0.5905	0.0004	-0.2334	0.2137
		TM5	0.0486	0.2491	-0.4256	0.1321	-0.4541	0.7286
		TM7	0.3212	-0.7937	0.3418	0.1261	-0.2382	0.2783
	Post-fire 66/15	TM1	0.1187	0.1731	0.2219	0.6124	0.6361	0.3566
		TM2	0.3929	0.3977	0.3841	0.3954	-0.4701	-0.4032
		TM3	0.4069	0.3473	0.3717	-0.6128	0.0401	0.4455
		TM4	0.0939	-0.0383	0.2303	-0.2946	0.5923	-0.7065
		TM5	0.5998	0.2069	-0.7584	0.0096	0.1289	-0.0747
		TM7	-0.5453	0.8044	-0.1921	-0.0792	0.0733	-0.0842

Table 4: Principal components analysis loadings for each image used in the study.

3.2 Field Methodology

The aim was to estimate CBI and other field measurements of fire severity. Initial reconnaissance of potential study sites was carried out in early June of 2005. During this reconnaissance, a number of burned black spruce forest sites within the Boundary and Porcupine burns were identified that contained a suitably large tract of forest that was homogeneous in terms of tree diameter, density and fire severity. From these candidate sites, a sub-set was selected for sampling; this subset was chosen to cover the range of topographic positions and fire severities that existed within perimeters of the fires that could be observed from the road network.

Detailed site data was collected throughout the summer months of 2005 and in June of 2006. The center of each site was marked using a handheld GPS unit. At this time, the general site conditions (such as the slope, aspect and elevation of the site) were noted and four surface photographs of the site were collected. Next, a 20 by 20 meter site was laid out for the collection of observation required to estimate the CBI, in accordance with the design of Key and Benson (2002). Additionally, a set of sample transects were laid out for collection of the fire severity measures. Data to estimate fire severity were then collected, as described in the following sections.

3.2.1 The Composite Burn Index

Data to calculate the CBI were collected from observations made within a 20x20 m site located within a relatively homogenous measure of fire severity using a standard data sheet developed by Key and Benson (2003, 2004). The data required to fill in the CBI form were obtained by visually examining 5 strata: (a) substrate; (b) herbs and low shrubs, and trees (> 1 m); (c) tall shrubs and small trees (1-2 m); (d) intermediate trees (2 to 8 m); and (e) tall trees (> 8 m) and rating damage on a scale of 0 to 3 for a number of characteristics within each strata, with 3 being the highest fire severity. There are three scores calculated for the CBI: the overall or average CBI (here referred to as Overall CBI), the Understory CBI [an average of components (a) through (c)] and the Overstory CBI [an average of components (d) and (e)]. For this study, data to estimate the CBI were primarily collected during the summer of 2005, the year following the fire, with data from one additional site collected in early June 2006.

For assessing fire severity in Alaska, the CBI form was modified based on discussions between representatives of the research and fire management communities (see Kasischke et al., in review) to account for the presence of grass tussocks and for the shorter shrub and tree heights that are found in Alaska. For example, the “big trees” category was very rarely rated as Alaskan Black Spruce trees do not reach the height requirement for this category (> 8m). Even with the modifications to the CBI form for the Alaskan boreal forest ecosystem, the measures for the ground strata may still not fully capture the variability of this system (Kasischke et al., in review).

3.2.2 Crown and Ground Layer Fire Severity

The sampling for the ground and crown layer fire severity measurements was initiated by establishing a 40 meter long baseline oriented in a random direction through the center of each site. Three 30 meter long sample transects were then established that bisected the baseline at right angles: one at the site center, and one on each side of the center located at a random distance between 5 and 20 m along the baseline. Every overstory tree greater than one meter in height within ±1 meter of each transect was sampled by noting the level of consumption of foliage and branches based on a scale of 0 to 6 (see Table 5). Every five meters along each sample transect, a core of the remaining surface organic layer was extracted and the depths of the different layers (char, moss, lichen and fibric, mesic and humic soil) measured to within 0.5 cm. An organic layer core was also extracted and measured every 10 m along the baseline. Every five meters along the sample transects, the distance of the topmost adventitious root above mineral soil was measured on the nearest canopy tree above two meters in height. This distance was used to estimate the pre-fire depth of the surface organic layer following Kasischke et al. (in review).

From the surface organic layer measures, fire severity measures were calculated including: (a) the average depth of the remaining surface organic layer; and (b) the absolute depth reduction in the surface organic layer and (c) the relative reduction in depth of the surface organic layer. The depth of organic soil remaining was measured based on the distance from the top of the organic soil layer remaining to the top of the A horizon. This measure was considered to relate to fire severity as the more severely an area burned, the less soil organic layer one would expect to remain on the site. The absolute depth reduction is a measure of the difference between the pre-fire depth of the surface organic layer and the post-fire surface organic layer. When combined with the pre-fire organic layer depth, this measure can be used to estimate fuel consumption and carbon emissions. Finally, the relative depth reduction is a measure of the percentage of the depth burned during the fire compared to the pre-fire soil organic layer.

Level	Criteria
0	No tree mortality
1	Tree deceased, no branches/foliage consumption
2	Needles and some small branches consumed
3	Some secondary branches remain
4	No secondary branches, >30% of primary branches remain
5	Less than 30% primary branches remain
6	No primary branches remaining, pole charring occurred

Table 5: Criteria of the Canopy Fire Severity index. This is an arbitrarily defined measure of fire severity which analyzes the degree of scorching occurring only within the dominant tree species of the site, thus it is only a measure of the severity of crown fires. The criteria, developed for this study, are based predominantly upon the percentages of branches consumed by fire and the survivorship or mortality of individual overstory trees.

3.3 Analyses

In this study, the satellite measures of fire severity (independent variables) were analyzed and correlated using the ground measures (dependant variables) described above. Simple linear regression analysis using the least-squares approach was utilized to correlate the spectral indices and ground variables for both a single-date post-fire image approach and the two-date pre- and post-fire image approach. Presented in this paper are adjusted R^2 values and their level of statistical significance (p). This methodology was chosen to be consistent with prior comparisons of the dNBR and CBI approach (Key and Benson, 2006; Epting et al., 2005). Also, this study followed the same general approach as Epting et al. (2005), with additional (to CBI) ground measures used to determine the correlation of various spectral indices not only with the CBI, but to other measures of fire severity. Finally, additional spectral indices were incorporated into this study, all three principle components were analyzed [not only PCA2 and PCA3 as in Epting et al. (2005)] and the RdNBR was also incorporated (Patterson and Yool, 1998; Miller and Thode, 2007).

Chapter 4: Results

The potential of the different satellite indices is discussed below in relation to the various ground measures gathered at each site. First, the traditional approach using the dNBR and CBI is considered; then, the alternate spectral indices are considered and compared with the various ground assessments of fire severity.

4.1 CBI Comparisons

4.1.1 Single-date Comparisons (Table 6)

The single-date comparisons between the different spectral indices and the three components of the CBI analyzed generally produced weak correlations (Table 6; Figure 5). The R^2 values for the Boundary fire and Porcupine fire show considerable variation when using the single-date approach. Linear regression showed moderate to low R^2 values between the single-date post-fire NBR the Overall CBI and for data from the Boundary (adj. $R^2 = 0.59$, $p \leq 0.0001$) and the Porcupine fires (adj. $R^2 = 0.30$, $p = 0.0062$) (Figure 5). Generally, the post-fire single-date spectral indices showed higher sensitivity when compared with the Overall CBI measure than when with the Understory or Overstory components of the CBI (Table 6). The index that showed the most sensitivity to the Overall CBI was not the post-fire NBR, but the TM 7/5 ratio (Boundary: adj. $R^2 = 0.66$, $p < 0.0001$; Porcupine: adj. $R^2 = 0.42$, $p = 0.0008$). The TM 7/5 ratio also showed higher potential than the NBR when compared with the Understory CBI component (Boundary: adj. $R^2 = 0.61$, $p \leq 0.0001$; Porcupine: adj. $R^2 = 0.40$, $p = 0.001$) (Figure 5).

The linear transforms also did not show sensitivity to the CBI ground measures analyzed in this study. The wetness component of the tasseled cap (TC3) showed no significant ($p \leq 0.05$) relationship to any of the CBI components in either of the two fires studied (Table 6). However, in the Porcupine fire only, PCA2 (Overall CBI: adj. R^2 = 0.18, $p = 0.0305$; Understory CBI: adj. R^2 = 0.15, $p = 0.0466$; Overstory CBI: adj. R^2 = 0.17, $p = 0.0368$) and PCA3 (Overall CBI: adj. R^2 = 0.29, $p = 0.0071$; Understory CBI: adj. R^2 = 0.25, $p = 0.0133$; Overstory CBI: adj. R^2 = 0.26, $p = 0.0111$) did show some significant correlations with the three measures of CBI studied, although these correlations were very low (Table 6). PCA1 was correlated significantly ($p \leq 0.05$) with ground measures of fire severity only in the case of the Boundary fire, again showing the variability between the two fire sites.

Spectral Index	Overall CBI	CBI Understory	CBI Overstory	Canopy Fire Severity Index	Depth Remaining	Absolute Depth Reduced	Relative Depth Reduced
Boundary							
NBR	**0.59^{A}**	**0.55^{A}**	**0.42^{A}**	**0.53^{A}**	0.37^{B}	0.08	0.00
Band4	0.39^{B}	0.37^{B}	0.24^{C}	0.38^{B}	0.29^{B}	0.09	0.00
Band5	0.11	0.10	0.04	0.10	0.16^{C}	0.07	0.12^{C}
Band7	0.06	0.04	0.08	0.02	0.00	0.00	0.00
Ratio7/5	**0.66^{A}**	**0.61^{A}**	**0.49^{A}**	**0.52^{A}**	**0.51^{A}**	0.12^{C}	0.22^{C}
Ratio7/4	**0.49^{A}**	**0.47^{A}**	0.31^{C}	**0.43^{A}**	0.31^{C}	0.12^{C}	0.30^{C}
Ratio4/5	**0.50^{A}**	**0.48^{A}**	0.32^{B}	**0.47^{A}**	0.26^{C}	0.06	0.24^{C}
NDVI	**0.53^{A}**	**0.52^{A}**	0.29^{C}	0.37^{B}	0.36^{B}	0.10	0.11^{C}
SAVI	**0.53^{A}**	**0.53^{A}**	0.30^{B}	0.38^{B}	0.36^{B}	0.10	0.23^{C}
MSAVI	**0.54^{A}**	0.53^{A}	0.29^{C}	0.38^{B}	0.36^{B}	0.11^{C}	0.16^{C}
TC2	**0.54^{A}**	**0.52^{A}**	0.34^{B}	**0.49^{A}**	0.40^{B}	0.10	0.23^{C}
TC3	0.00	0.00	0.00	0.00	0.00	0.00	0.21^{C}
PCA1	0.14^{C}	0.14^{C}	0.06	0.14^{C}	0.16^{C}	0.06	0.22^{C}
PCA2	0.17^{C}	0.14^{C}	0.14^{C}	0.11^{C}	0.04	0.00	0.00
PCA3	0.00	0.00	0.04	0.00	0.00	0.00	0.18^{C}
Porcupine							
NBR	0.30^{C}	0.25^{C}	0.28^{C}	**0.83^{A}**	0.28^{C}	0.00	0.21^{C}
Band4	0.27^{C}	0.21^{C}	0.28^{C}	**0.56^{A}**	0.14^{C}	0.00	0.10
Band5	0.00	0.00	0.00	0.07	0.02	0.00	0.01
Band7	0.22^{C}	0.20^{C}	0.18^{C}	**0.59^{A}**	0.33^{C}	0.00	0.25^{C}
Ratio7/5	0.42^{B}	0.40^{C}	0.24^{C}	**0.55^{A}**	0.33^{B}	0.00	0.24^{C}
Ratio7/4	0.23^{C}	0.23^{C}	0.09	0.40^{C}	0.24^{C}	0.00	0.17^{C}
Ratio4/5	0.20^{C}	0.16^{C}	0.21^{C}	0.81^{A}	0.26^{C}	0.00	0.20^{C}
NDVI	0.14	0.11	0.14	0.44^{B}	0.24^{C}	0.00	0.15^{C}
SAVI	0.15^{C}	0.12	0.15^{C}	0.46^{B}	0.24^{C}	0.00	0.15^{C}
MSAVI	0.15^{C}	0.13	0.13	0.37^{C}	0.22^{C}	0.00	0.14^{C}
TC2	0.33^{C}	0.27^{C}	0.35^{C}	**0.82^{A}**	0.31^{C}	0.00	0.23^{C}
TC3	0.11	0.09	0.10	0.46^{B}	0.23^{C}	0.00	0.18^{C}
PCA1	0.00	0.00	0.00	0.06	0.03	0.00	0.02
PCA2	0.18^{C}	0.15^{C}	0.17^{C}	**0.62^{A}**	0.28^{C}	0.00	0.21^{C}
PCA3	0.29^{C}	0.25^{C}	0.26^{C}	**0.73^{A}**	0.38^{B}	0.00	0.29^{C}

Table 6: Post-fire single-date adjusted r-squared values for correlations in the two study fires. The following f significance values are shown: A= ≤0.0001 (in bold), B=≤0.001, and C=≤0.05. For the boundary fire, n=28. Samples sites varied slightly across ground measures in the Porcupine Fire: CBI and Canopy Fire Severity values are n=21 and depth values are n=27.

Spectral Index	Overall CBI	CBI Understory	CBI Overstory	Canopy Fire Severity Index	Depth Remaining	Absolute Depth Reduced	Relative Depth Reduced
Boundary							
dNBR	**0.52^{A}**	**0.48^{A}**	0.37^{B}	**0.48^{A}**	**0.46^{A}**	0.13^{C}	0.29^{C}
RdNBR	**0.58^{A}**	**0.54^{A}**	**0.43^{A}**	**0.53^{A}**	0.37^{B}	0.08	0.21^{C}
Band4	0.01	0.00	0.05	0.00	0.26^{C}	0.00	0.10
Band5	0.00	0.00	0.00	0.00	0.15^{C}	0.00	0.04
Band7	0.26^{C}	0.24^{C}	0.21^{C}	0.26^{C}	0.12^{C}	0.01	0.05
Ratio7/5	**0.55^{A}**	**0.51^{A}**	**0.42^{A}**	**0.43^{A}**	**0.58^{A}**	0.13^{C}	0.35^{B}
Ratio7/4	**0.49^{A}**	**0.47^{A}**	0.30^{C}	**0.43^{A}**	0.32^{B}	0.12^{C}	0.23^{B}
Ratio4/5	0.00	0.00	0.00	0.00	0.02	0.00	0.00
NDVI	**0.45^{A}**	**0.43^{A}**	0.29^{C}	0.36^{B}	**0.42^{A}**	0.10	0.25^{C}
SAVI	**0.46^{A}**	**0.44^{A}**	0.29^{C}	0.36^{B}	**0.43^{A}**	0.10	0.25^{C}
MSAVI	**0.51^{A}**	**0.49^{A}**	0.30^{C}	0.38^{B}	0.40^{B}	0.11^{C}	0.26^{C}
TC2	0.02	0.00	0.06	0.00	0.29^{C}	0.00	0.11^{C}
TC3	0.11^{C}	0.11^{C}	0.06	0.16^{C}	0.00	0.00	0.00
PCA1	0.00	0.00	0.00	0.00	0.19^{C}	0.00	0.06
PCA2	0.18^{C}	0.16^{C}	0.17^{C}	0.15^{C}	0.29^{C}	0.04	0.14^{C}
PCA3	0.11^{C}	0.09	0.10	0.11^{C}	0.00	0.00	0.00
Porcupine							
dNBR	0.34^{C}	0.29^{C}	0.31^{C}	**0.82^{A}**	0.29^{c}	0.00	0.21^{c}
RdNBR	0.30^{C}	0.25^{C}	0.28^{C}	**0.80^{A}**	0.26^{C}	0.00	0.20^{C}
Band4	0.18^{C}	0.19^{C}	0.06	**0.64^{A}**	0.20^{C}	0.00	0.12^{C}
Band5	0.00	0.00	0.00	0.00	0.05	0.29^{C}	0.09
Band7	0.29^{C}	0.23^{C}	0.28^{C}	**0.57^{A}**	0.35^{B}	0.00	0.27^{C}
NDVI	0.15^{C}	0.12	0.16^{C}	0.42^{B}	0.22^{C}	0.00	0.14^{C}
SAVI	0.16^{C}	0.12	0.17^{C}	0.44^{B}	0.22^{C}	0.00	0.14^{C}
MSAVI	0.16^{C}	0.13	0.14	0.36^{B}	0.21^{C}	0.00	0.13^{C}
Ratio7/5	0.45^{B}	0.41^{B}	0.31^{C}	**0.61^{A}**	0.29^{C}	0.00	0.19^{C}
Ratio7/4	0.23^{C}	0.23^{C}	0.09	0.41^{C}	0.25^{C}	0.00	0.17^{C}
Ratio4/5	0.00	0.00	0.02	0.00	0.00	0.00	0.00
TC2	0.20^{C}	0.19^{C}	0.12	**0.67^{A}**	0.22^{C}	0.00	0.14^{C}
TC3	0.19^{C}	0.15^{C}	0.17^{C}	0.41^{C}	0.36^{B}	0.05	0.32^{C}
PCA1	0.00	0.01	0.00	0.04	0.00	0.10	0.00
PCA2	0.10	0.05	0.18^{C}	0.06	0.21^{C}	0.20^{C}	0.22^{C}
PCA3	0.29^{C}	0.26^{C}	0.21^{C}	**0.65^{A}**	0.39^{B}	0.00	0.31^{C}

Table 7: Two-date image adjusted r-squared values for correlations in the two study fires. The following p significance values are shown: A= ≤0.0001 (in bold), B=≤0.001, and C=≤0.05. For the boundary fire, n=28. Samples sites varied slightly across ground measures in the Porcupine Fire: CBI and Canopy Fire Severity values are n=21 and depth values are n=27.

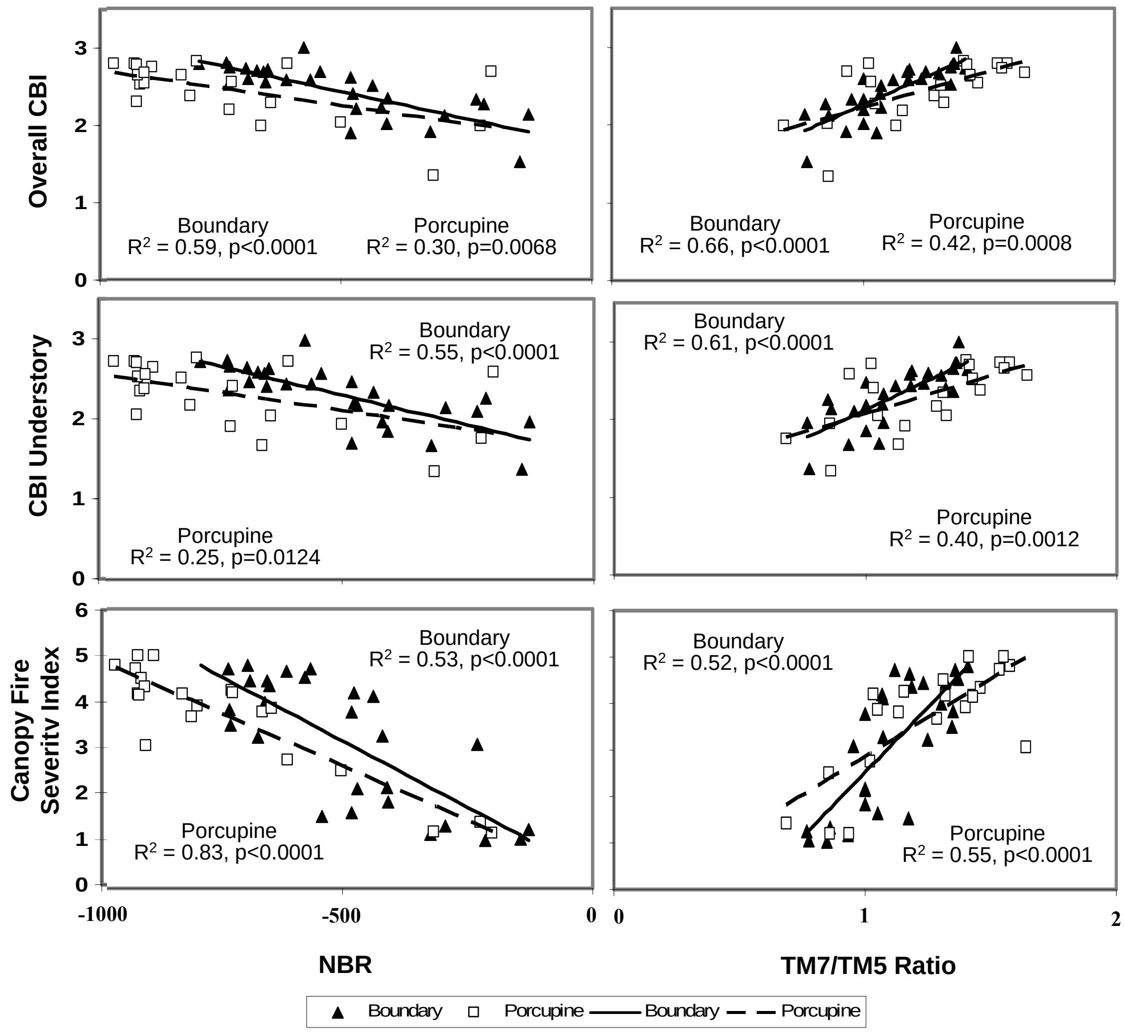

Figure 5: Single-date comparison of two spectral indices which showed higher potential than others overall, graphed with three different ground measures analyzed. Presented are adjusted R^2 values and p values for both the Boundary and Porcupine fires.

4.1.2 Two-date Comparisons (Table 7)

The two-date approach did improve correlations between certain spectral indices and the CBI components as compared with the single-date approach, but not in all cases (Table 7; Figure 6). In the Boundary fire, the linear correlation between the dNBR and the Overall CBI actually yielded an R^2 value slightly lower than that for the single-date NBR comparison (adj. $R^2 = 0.52$, $p < 0.0001$), although the two-date approach improved the R^2 value for the same comparison in the Porcupine fire (adj. $R^2 = 0.34$, $p < 0.0001$) (Table 7, Figure 6). This again shows variability between the two fire events. Generally, the spectral indices showed higher correlations for data from the Boundary fire as compared to the Porcupine fire for all three measures of CBI (e.g., Overall, Understory, and Overstory).

Also, the spectral indices showed higher potential when assessed against the Overall CBI than when using the either the Understory or Overstory CBI components separately or the alternative indices. The dNBR and Overall CBI comparison resulted in higher R^2 values than the RdNBR in the Porcupine fire, although this was not the case for the Boundary fire (Table 7, Figure 6). As with the single-date analysis, the TM 7/5 Ratio, when regressed against the Overall CBI, yielded a higher R^2 value in both fires as compared to the other spectral indices (Table 7, Figure 6).

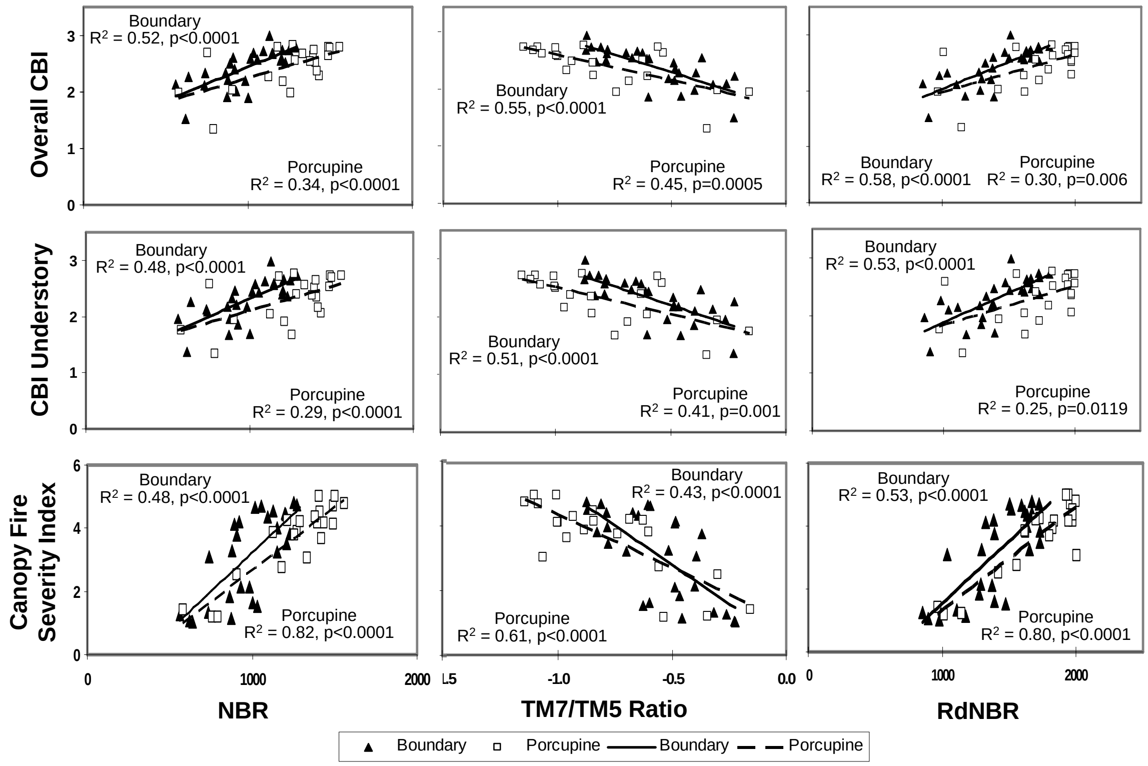

Figure 6: Two-date comparison of three spectral indices which showed higher potential than others overall and three different ground measures analyzed. Presented are adjusted R^2 values and p values for both the Boundary and Porcupine fires

4.2 Canopy Fire Severity Index Comparisons

Significant correlations between the spectral indices and the Canopy Fire Severity Index (a ground measure quantifying the effect of fire on the canopy only) were, in many cases, similar to the results of the Overall CBI correlations. Also, R^2 values were generally higher when the spectral indices were compared with the CFSI than with the Overstory CBI, especially in the spectral indices analyzed for the Porcupine fire single-date and two-date analyses (Tables 6 and 7, Figures 5, 6 and 9).

In the single-date analysis, correlations of the Canopy Fire Severity Index and the NBR yielded the highest R^2 value found in the study (adj. $R^2 = 0.83$, $p < 0.0001$) (Table 6, Figure 5). Results for the same correlation from the Boundary fire (adj. $R^2 = 0.59$, $p < 0.0001$) showed lower correlations than those found in the Porcupine fire. As with the CBI comparisons, correlations between the single-date TM 7/5 ratio and the Canopy Fire Severity Index were moderate (Boundary: adj. $R^2 = 0.52$, $p < 0.0001$; Porcupine: adj. $R^2 = 0.55$, $p < 0.0001$). Also, the single-date TM 4/5 ratio yielded high correlations when compared with the Canopy Fire Severity Index in the Porcupine fire, but not in the Boundary fire (Boundary: adj. $R^2 = 0.47$, $p = 0.0001$; Porcupine: adj. $R^2 = 0.81$, $p < 0.0001$).

The two-date analysis using the Canopy Fire Severity Index also showed some of the higher correlations of the study (Table 7, Figure 6). The dNBR and RdNBR showed similar sensitivities to the ground measures in both fire events, although in the Boundary fire the RdNBR yielded higher R^2 values than in the Porcupine fire (dNBR: adj. $R^2 = 0.48$, $p < 0.0001$; RdNBR: adj. $R^2 = 0.53$, $p < 0.0001$); the reverse was true for the Porcupine fire (dNBR: adj. $R^2 = 0.82$, $p < 0.0001$; RdNBR: adj. $R^2 = 0.80$, $p < 0.0001$). And finally, while the single-date TM 4/5 ratio showed higher correlations with the

Canopy Fire Severity Index in the Porcupine fire only, no significant correlations in the two-date comparison for either of the two fires occurred when using this spectral index (Table 7).

4.3 Soil Organic Layer Comparisons

4.3.1 Soil Organic Layer Depth Remaining

No spectral index which was tested was found to have a high potential for determining the soil organic layer (SOL) depth remaining on site following a fire. The spectral indices did not predict the depth of the organic layer or the reduction in the organic layer (absolute or relative), as is seen by the low R^2 values and non significant results for many of the single-date and two-date correlations between the spectral indices and SOL ground measures (Table 6). In some cases, correlations between the variations in the depth of the remaining SOL and the NBR/dNBR were similar. In many instances, in both the single-date and two-date comparisons using the Porcupine fire, the SOL depth remaining correlation was higher than any of the three CBI components (Tables 6 and 7). In only one instance though was the SOL depth remaining the ground measure most strongly correlated with a spectral index (Boundary single-date PCA1: adj. $R^2 = 0.16$, $p = 0.0215$) (Table 6). In only a few correlations were results highly significant ($p < 0.0001$), and in these cases other ground measures showed higher correlations with the various spectral indices than the SOL depth remaining. The highest correlations using the SOL depth remaining measure occurred when this measure was compared to the two-date TM 7/5 ratio for the Boundary fire (Boundary: adj. $R^2 = 0.58$, $p < 0.0001$). However the correlation between the two-date TM7/5 ratio and SOL depth remaining was not the highest correlation for the Porcupine fire (adj. $R^2 = 0.29$, $p < 0.0022$). For the Porcupine fire, the two-date correlations with Band 7 (adj. $R^2 = 0.35$, $p < 0.0007$) and TC3 (adj. $R^2 = 0.36$, $p < 0.0006$) were the strongest in this category, although these results are low compared to that which would be needed to accurately map fire severity with confidence.

4.3.2 Depth reduction

No spectral index was sensitive to the reduction in the depth of the SOL (neither absolute nor relative depth reduction). Neither the absolute nor the relative depth reduction measures correlated highly with the spectral measures of fire severity using either the single-date or two-date analyses (Tables 6 and 7). In fact, the absolute depth reduction measurement showed no correlations with any indices in the single-date analysis of the Porcupine fire. The two-date correlation analysis, again as applied to the Porcupine fire, produced somewhat significant ($p < 0.05$) results when compared with the PCA2 (adj. $R^2 = 0.20$, $p < 0.0122$). Correlations using data from the Boundary fire resulted in higher significance levels than those found in the Porcupine fire, although the R^2 values in all correlations were low. The highest single date R^2 values between the various spectral indices and the depth reduction measures occurred when using the TM 7/5 ratio and the TM 7/4 ratio, while the highest two-date R^2 values occurred were the dNBR and the TM 7/5 ratio.

The relative depth reduction also did not relate well to the spectral indices used, although they were more highly correlated to the spectral indices than the absolute depth reduction measures (Tables 6 and 7). The single-date comparisons between the relative depth reduction and spectral indices resulted in correlations of only adj. $R^2 = 0.30$ ($p = 0.0014$) for the TM 7/4 ratio (Boundary fire) and adj. $R^2 = 0.29$ ($p < 0.0023$) for PCA3 (Porcupine fire). Using the two-date techniques did not improve correlations across the different spectral indices. The highest correlations for the comparison between spectral indices and the relative depth burned was adj. $R^2 = 0.35$ ($p < 0.0005$) for the correlation with the TM 7/5 ratio (Boundary) and adj. $R^2 = 0.31$ ($p < 0.0016$) again with the PCA3 spectral index (Porcupine). Also, it should be noted that the highest correlation between the PCA2 two-date spectral index for the Porcupine occurred when correlated with the relative depth reduction ground measure (adj. $R^2 = 0.22$, $p = 0.0085$).

Chapter 5: Discussion and Conclusions

5.1 The dNBR vs. CBI approach

Overall, the traditional approach using the NBR, dNBR and CBI was highly variable across the two fire events used for this study. Comparisons which showed modest correlations in the Boundary fire showed low correlation in the Porcupine fire. The non-transferability of this traditional approach to assess fire or burn severity across multiple fire events in a region of similar ground conditions casts doubt on the use of dNBR as a portable measure of fire severity. An approach which yields such variable results across study sites can lead to difficulties for operational remote sensing of fire severity. While the dNBR was designed to be completed quickly for operational use, this approach could lead to inaccurate fire severity maps being distributed to local personnel.

Proponents of the CBI and dNBR method have considered the versatility of the CBI to be an important feature of that ground measure, as it incorporates five vertical levels of the environmental site of interest to capture the variability of the site and relate to the NBR, and more importantly the dNBR. Unfortunately, the dNBR approach does not appear sensitive enough to capture variations in fire severity in the Alaskan boreal region, even with the modifications to the CBI form for this area. Traditionally, high and consistent correlations have been used as indicators between the dNBR and CBI have indicated that the dNBR can be used to reliably map fire/burn severity. Although, in this study, the rather tepid performance of the CBI and dNBR approach calls to question this assumption, and the reliability of the approach in the Alaskan black spruce forests.

One factor which may be influencing the results of the dNBR analysis is the small amount of variation in the Overall CBI scores recorded. Many of the black spruce stands analyzed in this study have high fire severity CBI values (Figures 7 and 8). An analysis of the CBI values for the sites used in this study, graphed per each of the two fire areas, shows that many of the sites are from an Overall CBI value of 2.4 and above (Figure 7 and Table 8). Most importantly, the range in CBI values compared to other studies is extremely small and distribution of the Overall CBI scores from the sites studied appears to be skewed towards higher Overall CBI values, thus again indicating higher Overall CBI scores (Figure 8) (Epting et al., 2005; van Wagtendonk et al., 2005; Sorbel and Allen, 2005; Miller and Thode, 2007).

van Wagtendonk et al. (2004) found that the correlation of the dNBR and CBI (Overall) is non-linear in higher burn or fire severity sites (Figure 8), although a linear correlation was found for lower severity fires. Interestingly, CBI values peaked at a dNBR of about 750 and then, as the dNBR values continued to rise, the CBI values actually started to decline. While van Wagtendonk et al.'s (2004) results could indicate that the current CBI protocol may not provide a good means for estimating fire severity (Kasischke et al., in review), the study also did not did not characterize the surface materials responsible for the changes in the dNBR. A better characterization of these surface materials is needed to better understand the sensitivity of the dNBR and CBI when higher severity fires are occurring. Overall, the spectral indices used in this thesis were not sensitive to the SOL measurements – the depth remaining and depth reduced (both absolute and relative). A further investigation might include an assessment of the absolute rise in red reflectance proportional to the depth of the SOL lost due to burning. While the spectral indices studied in this thesis were not shown to be sensitive to the changes in the SOL, a better understanding of the red reflectance of a site may shed insight into overall fire severity. Additions of char to the site following fire and the exposure of mineral soil in high severity fires could lead to increases in red reflectance as the mineral soil is exposed on a site.

Such a conclusion supports the need for further research in developing and evaluating alternate approaches for measuring fire severity, particularly in evaluating depth of burning in Alaska's boreal region (Kasischke et al., in review). Roy et al. (2006) have suggested that the dNBR is not an optimal method to measure fire severity as this index was designed to determine burned areas and not to determine the severity of the fire, thus it has not been tested for relevant theory of spectral index design. They have advocated for a more comprehensive method to measure fire severity which would include the pre-fire to post-fire displacement of vegetation samples in multi-spectral space. Lentile et al. (2006) have also recommended further refining the satellite mapping of fire/burn severity approach to link fire processes with remotely sensed imagery. As evident from this study, further refinement of methods to assess changes occurring to the soil organic layer, are needed – if even possible at all– as they are not currently well understood using a spectral index approach. As the consumption of the soil organic layer during fire plays an important role in the carbon storage capacity of this ecosystem, a better understanding of how to analyze this variable remotely is still needed.

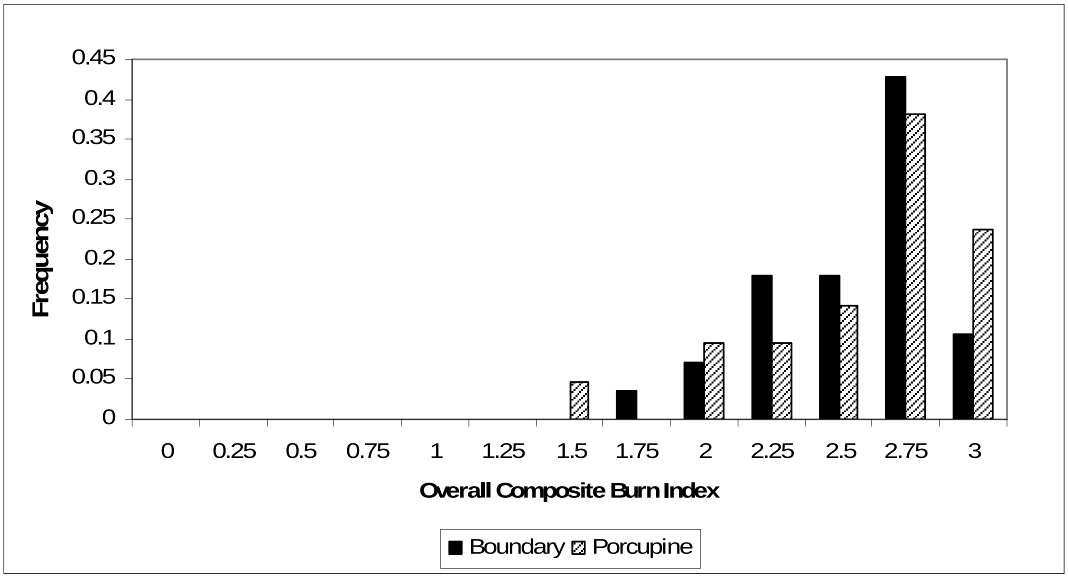

Figure 7: Variability of CBI within the study. Many of the CBI sites gathered were in the moderate to severity range of Overall CBI, which could influence the results.

Fire Area	Overall CBI		Understory CBI		Overstory CBI	
	Average	SD	Average	SD	Average	SD
Boundary	2.43	0.34	2.31	0.37	2.81	0.32
Porcupine	2.45	0.38	2.31	0.41	2.86	0.39

Table 8: Average CBI scores for each fire and associated standard deviations (SD).

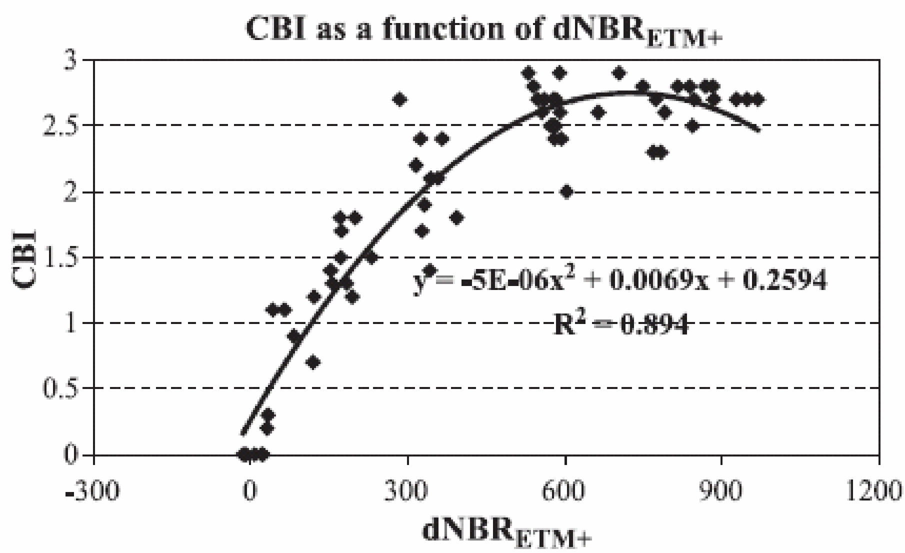

Figure 8: The non-linear relationship between dNBR and CBI (van Wagtendonk et al., 2004).

5.2 Canopy Fire Severity Index

Many of the spectral indices showed high sensitivity to the Canopy Fire Severity Index, especially in the single- and two-date comparisons of the Porcupine fire. Interestingly, when comparing the CFSI and the Overstory component of the CBI – both of which are solely measuring the Overstory canopy of a site – the CFSI lead to much higher R^2 values, especially when compared with the dNBR values (Figure 9). It can be seen that the CFSI provides a greater range in values than the Overstory CBI measure, which in turn, has lead to higher correlations (Figures 5, 6, and 9). The Overstory CBI measure appears to saturate at its highest value (3), while the CFSI, with a range from 0-6, allows for development of a better linear relationship with the spectral indices. Such an index may provide useful in further understanding the fire severity of black spruce forests when analyzing satellite imagery. While the canopy component does not directly relate to the degree of SOL consumption during the fire, high CFSI values could indicate increased levels of SOL consumption. A high CFSI value could also lead to the shadowing at a site to change, and it could be this factor that is influencing the results of the spectral indices as determined for a site.

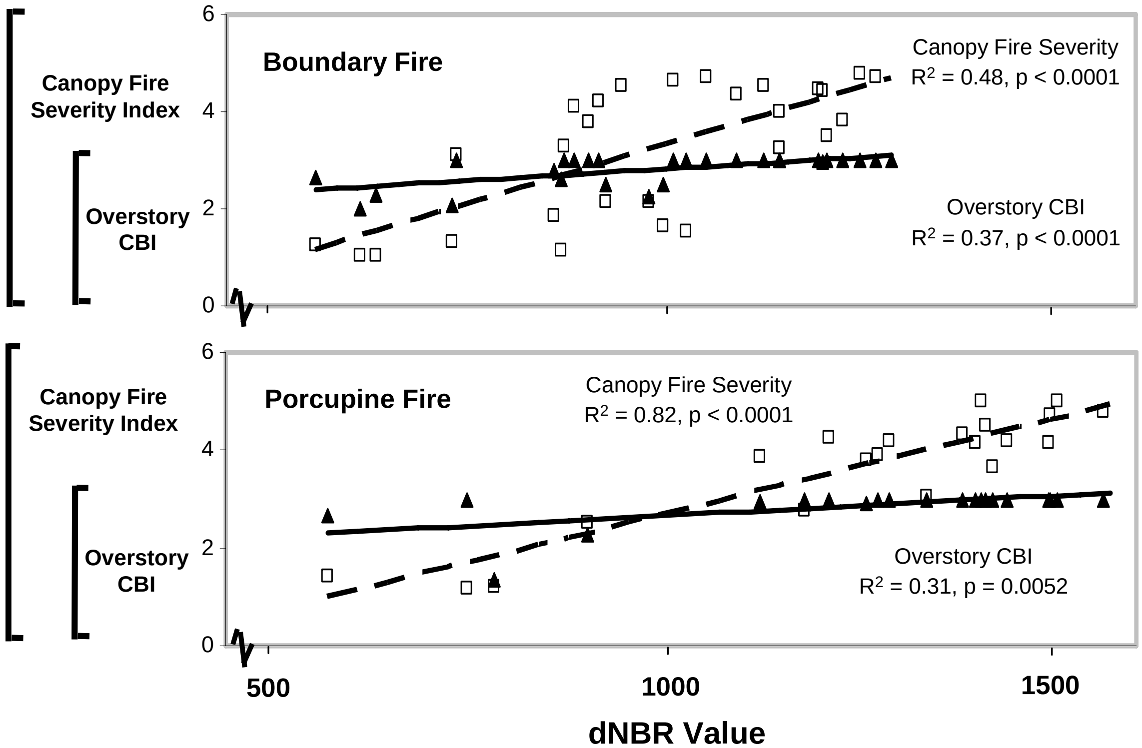

Figure 9: Comparisons between the Canopy Fire Severity Index and the Overstory CBI measure for both fires. The Overstory CBI appears saturated at the high end of its range (3) when compared with the canopy severity scale (range of 0-6).

5.3 Alternative Spectral Indices vs. Ground Measures

The ratio of Landsat Band 7 divided by Landsat Band 5 (the SWIR/NIR) was the index most sensitive to variation in the ground based measures. It was this index which co-varied most strongly with the various ground measures explored in this study – for both the single-date and two-date comparisons across both fire events. The high correlation of the TM 7/5 ratio and the various ground measures observed for both fires and both the single-date and bi-temporal analysis show that this index should be further investigated in comparison with fire severity environmental effects. These high correlation results may be due to the generally high severity fires (high Overall CBIs as reported in Table 8 and Figure 7) sampled in this study. This would be consistent with result found by Jakubauska et al. (1990) when it was found that the intensity of the fire has a direct relation with the infrared wavelengths. Thus, higher intensity fires – in terms of both ground and crown fire effects – would be more prone to respond to the TM 7/5 ratio than low severity fires. Also, it may be that the TM 7/5 ratio is able to remove non-fire severity related factors causing the non-linearity exhibited in van Wagtendonk et al.'s (2004) study – such as crown shadowing.

The tasseled cap transformation, which has traditionally worked well for previous studies of forest disturbance, did not show high correlation with any of the fire severity measures (Patterson and Yool, 1998). Differences between burned and non-burned areas are very clear when using this transformation, thus it is possible to map burned areas, although not to estimate fire severity. I had expected areas affected by fire to contain lower greenness and wetness than surrounding areas in component two (greenness) due to the loss of reflective needles (especially in the near-infrared band). In component three (wetness), which is affected by the soil moisture, I had expected to also see a decrease in the spectral signatures as more soil would be exposed. The low responsiveness of the tasseled cap transformations to the ground measures may have occurred as more mineral soil is exposed in the more extensively burned sites thus the wetness component may actually increase in value for more severely burned ground fires.

5.4 Variations in Spectral Indices

It is hypothesized that some of the variability in R^2 values between the Boundary fire and the Porcupine fire could be due to the differences in the acquisition dates of the imagery of the imagery as well as the local angle of incidence. While the one year and three year differences between the pre- and post-fire images of the fire events studied are not believed to have played a role in the low R^2 values (as spectral indices in both the single-date and two-date approach resulted in low R^2 values), perhaps the differences between comparisons of September dates in the Porcupine fire and comparisons of July and August dates in the Boundary fire are impacting the differences observed between the fire events (i.e. – two-date dNBR comparisons with the CFSI in the Porcupine fire lead to an adj. $R^2 = 0.82$ and $p < 0.0001$, while in the Boundary fire this correlation resulted in an R^2 value of only 0.53, $p < 0.0001$). The low solar angles in this region of high latitude throughout the year could cause differences in imaging dates of only a few weeks to be leading to extreme changes in the spectral response of a site. Also, the stands studied in this thesis predominantly burned in late June (Boundary and Porcupine fires) and early July (Porcupine fire only) of 2004, thus the time since the fire and before the acquisition of the post-fire image would be slightly different between the two fire events (although this difference is considered to be minimal.

Aside from the differences in the acquisition dates, the use of single-date and bi-temporal approaches could also be contributing to the variability of the results. In some instances, two-date analysis lead to improvements in the correlation analysis (Canopy Fire Severity Index and some soil organic layer measurements), however this was not always the case (some CBI correlations). These bi-temporal approaches can introduce additional errors such as those associated with sun-sensor geometry, calibration and preprocessing, atmospheric conditions, and vegetation phenology due to the different acquisition dates (Key and Benson, 2002; Chuvieco et al., 2002).

Additionally, a source of variability in this study could be due to the rugged topography of this region. Many of the study sites used were on north or south facing slopes, which can greatly affect both the true fire severity of a site, but also the level of shadowing present at a site (Kane et al., 2006). In Figure 10, differences between pre-fire and post-fire spectral signatures based on aspect can be seen. Also, while post-fire imagery was used from late summer 2004, immediately following the burn, ground severity measurements were collected in the summer of 2005 and June 2006, thus potentially impacting the correlation of the ground and satellite variables.

Topographic issues such as those due to sites on both north and south facing slopes can further exacerbate the situation (Figures 10 – 12). For example, when performing terrain corrections, reflectance values from north and south facing slopes should be normalized, however they cannot be completely accounted for. For this study, sites were located in different topographic positions (e.g., flat regions, toe slopes and backslopes,) as well as in different aspects (e.g., north and south-facing slopes). Higher sloped positions could lead to changes in the reflectance due to bi-directional effects. Figure 10 shows averages of two types of sites (North- and South-facing sites) from each of the fires studied (Boundary and Porcupine). While each pair of sites had similar pre-fire stand density values and post-fire fire/burn severity values, there are differences in reflectance between the pairs of sites (Figure 11). In both the Boundary and Porcupine fires, south slope sites have higher reflectances in both unburned and burned stands (Figure 12). Also, the Boundary images, taken earlier in the growing season, have overall higher reflectances than the Porcupine sites (Figure 11). This indicates that variations in local angle of incidences result in variations in reflectance. In turn, these variations can lead to changes in the NBR and dNBR that are not related to variations in fire severity (Figure 12).

Fire Area	Slope Position	Overall CBI	Basal Diameter (cm)	Stems/ha	dNBR
Boundary	North Facing	2.50	5.54	4731	1084
	South Facing	2.40	6.69	3793	988
Porcupine	North Facing	2.06	5.35	8422	1178
	South Facing	2.58	6.36	5863	1392

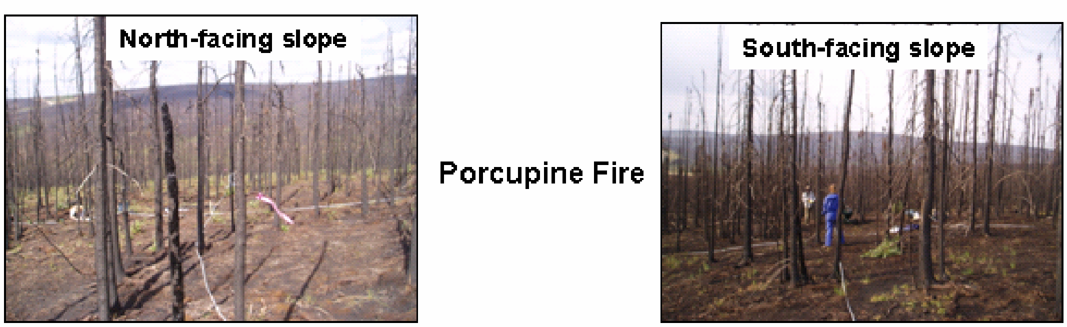

Figure 10: Variability of sites based on slope position for the Porcupine and Boundary Fires. ***Photographs courtesy of E.Kasischke.***

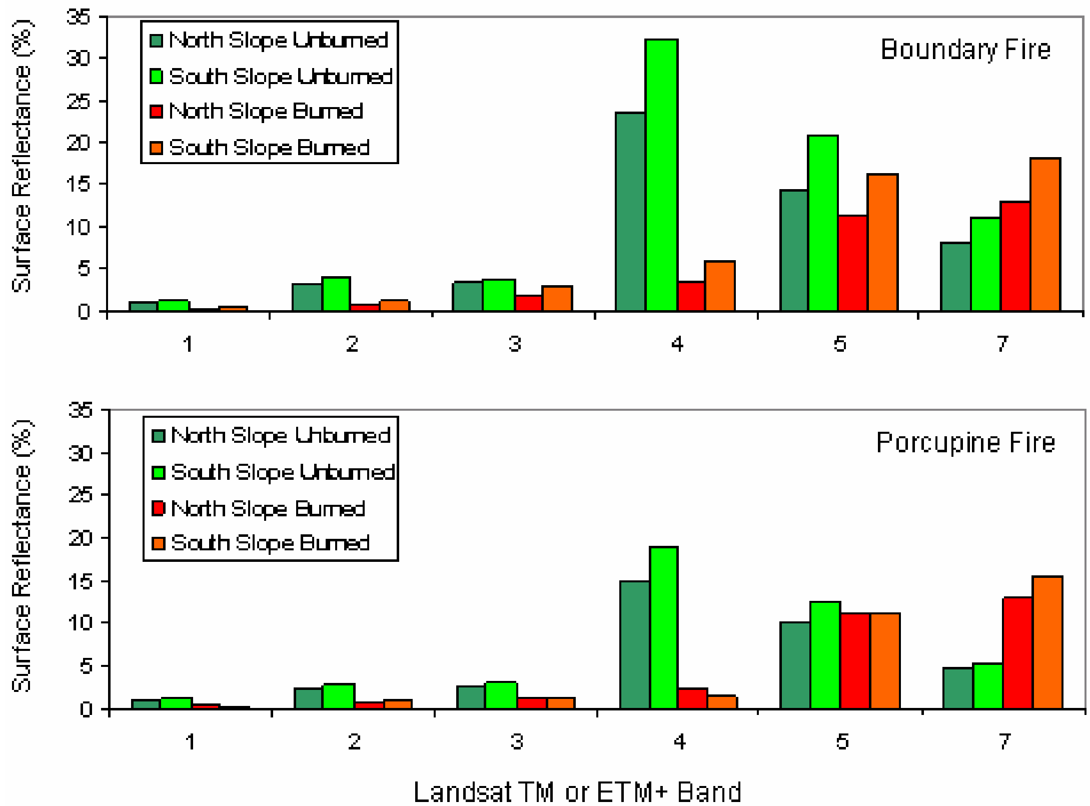

Figure 11: Variation in reflectance values of the Boundary and Porcupine fires based on slope position and pre- and post-fire differences. Averages for each slope position are shown (for Boundary – North Slope n = 6, South Slope n= 11; for Porcupine – North Slope n = 7, South Slope n = 10).

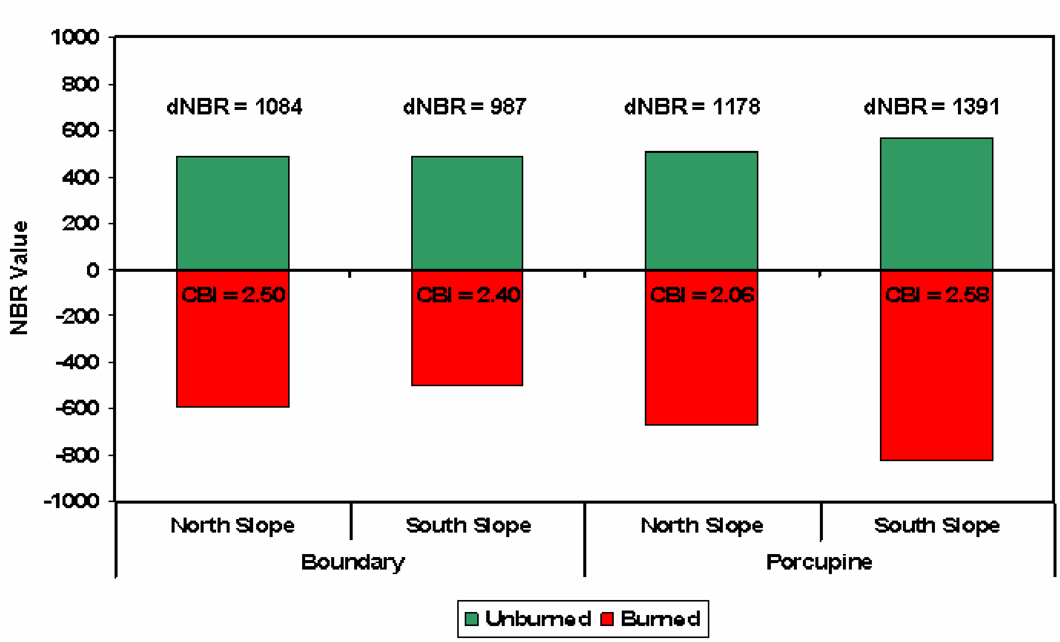

Figure 12: Comparisons between average pre-fire and post-fire NBR values for each fire based on slope position (for NBR values: Boundary – North Slope n = 6, South Slope n= 11; Porcupine – North Slope n = 7, South Slope n = 10). Also shown are associated Overall CBI and dNBR values for each slope position.

Chapter 6: Future Perspectives

It is important to continue to explore satellite-based measures of fire severity as a means for large scale mapping of fire severity in boreal forests. Throughout this study, it was shown that there are numerous problems with measuring the ground carbon in the boreal region. Noise in the spectral response of a site due to shadowing from terrain and the forest canopy, as well as a potential inability to use current spectral indices to map changes in the SOL affect the accuracy of carbon emission estimates which can be derived from satellite data. The infrared Landsat bands (4, 5, and 7) do show some potential to mapping fire severity in the boreal region. If true assessments of fire severity are to be made in this region using satellite data, the spectral reflectance of these bands must be better understood. As spectral indices using only one or two bands did not show high potential for mapping fire severity, perhaps a combination of all three infrared Landsat bands would be possible. Such a combination could potentially lead to the cancellation of shadowing effects on the spectral reflectance. Also, such an index may better measure the combination of factors causing high fire severity on a site (including the surface reflectance due to differing ground cover, soil moisture and the loss of vegetation).

The dNBR and the CBI were developed in ecosystems far different from those found in the boreal region, and due to the importance of the boreal region to carbon storage, more must be known about the particular functioning of this ecosystem. While the CBI was modified for the Alaskan ecosystem, the dNBR approach did not account for variations in surface reflectance due to variations in local topography and temporal variations in solar illumination. Remote sensing of fire severity may require the use of more wavelengths and individual bands in the construction of an index, or alternate mapping method, as well as incorporation of more detailed information regarding changes in vegetation and other surface characteristics due to fire (Roy et al., 2006).

The fire science community must go beyond testing the potential of different spectral indices and move to the development of fire severity models which can be validated with additional site data. It is recommended that the test sites be expanded to include more than the 53 ground truthing sites used in this study and that validation of the equations developed in this experiment be performed to make the analysis more statistically robust and to truly test the performance of the dNBR. This could be done through integrating data collected by other researchers during 2004 and other years in Alaska. Additionally, data from fires occurring in other years could be examined. Programs such as the North American Carbon Program and the Joint Fire Science Research Program aid in bringing researchers together for this type of interdisciplinary research, which can significantly aid the science community.

Also, improvements at the preprocessing stage could decrease the overall error rate of the study and potentially improve the significance of the results. It is recommended that higher resolution DEMs for this area be developed and incorporated into the preprocessing. SAR data, taken near Alaskan cities, has already been incorporated into some higher resolution DEMs used to increase the accuracy of the terrain correction process; however there is still a need for this detailed level of mapping in much of Alaska's boreal regions.

Additionally, micro-site differences could affect both the spectral reflectance of the sites, as well as any statistical analysis of the area. For these reasons, analyzing the spectral signature in relation to such site conditions as slope, aspect, drainage at the site, stand age and even the amount of shadowing at the site (due to the position of the trees following the fire) can be important when analyzing fire severity (Epting et al., 2005; Kane et al., 2006). In conclusion, this analysis showed differences between burned and unburned areas well, but further analysis needs to be performed to determine the most appropriate method to map fire severity and the losses to the organic soil layer due to the severity of the fire.

Bibliography

Bobbe, T., Finco, M.V., Quayle, B. and Lannom, K., 2002. Field measurements for the training and validation of burn severity maps for spaceborne, remotely sensed imagery, Joint Fire Science Program.

Bourgeau-Chavez, L.L., E., A.M., Stocks, B.J. and Kasischke, E.S., 2000. Distribution of Forest Ecosystems and the Role of Fire in the North American Boreal Forest. In: E.S. Kasischke and B.J. Stocks (Editors), Fire, Climate Change, and Carbon Cycling in the Boreal Forest. Springer, New York, pp. 111-131.

Chapin, F.S., III et al., 2005. Role of land-surface changes in Arctic summer warming. Science, 310: 657-660.

Chavez, P.S., Jr., 1989. Radiometric Calibration of Landsat Thematic Mapper Multispectral Images. Photogrammetric Engineering and Remote Sensing, 55(9): 1285-1294.

Chuvieco, E., Martin, M.P. and Palacios, A., 2002. Assessment of different spectral indices in the red-near-infrared spectral domain for burned land discrimination. International Journal Remote Sensing, 23(23): 5103-5110.

Cocke, A.E., Fule, P.Z. and Crouse, J.E., 2005. Comparison of burn severity assesments using Differenced Normalized Burn Ratio and ground data. International Journal of Wildland Fire, 14: 189-198.

Cohen, W.B. and Spies, T.A., 1992. Estimating structural attributes of Douglas-Fir / Western Hemlock forest stands from Landsat and SPOT imagery. Remote Sensing of Environment, 41: 1-17.

Cohen, W.B., Spies, T.A. and Fiorella, M., 1995. Estimating the age and structure of forests in a multi-ownership landscape of western Oregon. International Journal of Remote Sensing, 16(4): 721-746.

Colby, J.D., 1991. Topographic normalization in rugged terrain. Photogrammetric Engineering and Remote Sensing, 57(5): 531-537.

Collins, J.B. and Woodcick, C.E., 1996. An assessment of several linear change detection techniques for mapping forest mortality using multitemporal Landsat TM data. Remote Sensing of Environment, 56: 66-77.

Crist, E.P., 1985. A TM tasseled cap equivalent transformation for reflectance factor data. Remote Sensing of Environment, 17(3): 301-306.

Crist, E.P. and Cicone, R.C., 1984. A physically based transformation on thematic mapper data - tasseled cap. IEEE Transactions on Geoscience and Remote Sensing, GE-22(3): 256-263.

Crist, E.P. and Cicone, R.C., 1984. Application of the Tasseled Cap concept to simulated Thematic Mapper data. Photogrammetric Engineering and Remote Sensing, 50(3): 343-352.

Crist, E.P., Laurin, R. and Cicone, R.C., 1986. Vegetation and soils information contained in transformed Thematic Mapper data. International Geoscience and Remote Sensing Symposium, 3: 1465-1470.

De Santis, A. and Chuvieco, E., 2007. Burn severity estimation from remotely sensed data : Performance of simulation versus empirical models. Remote Sensing of Environment.

DeBano, L.F., Neary, D.G. and Ffolliott, P.F., 1998. Fire's Effects on Ecosystems. John Wiley & Sons, New York.

Diaz-Delgado, R., Lloret, F. and Pons, X., 2003. Influence of fire severity on plant regeneration by means of remote sensing imagery. International Journal of Remote Sensing, 24(8): 1751-1763.

Doerr, S.H. et al., 2006. Effects of differeing wildfire severities on soil wettability and implications for hydrological response. Journal of Hydrology, 319: 295-311.

Epting, J., Verbyla, D. and Sorbel, B., 2005. Evaluation of remotely sensed indices for assessing burn severity in interior Alaska using Landsat TM and ETM+. Remote Sensing of Environment, 96: 328-339.

Flannigan, M.D., Logan, K.A., Amiro, B.D., Skinner, W.R. and Stocks, B.J., 2005. Future area burned in Canada. Climactic Change, 72: 1-16.

French, N.H.F., Goovaerts, P. and Kasischke, E.S., 2004. Uncertianty in estimating carbon emissions from boreal forest fires. Journal of Geophysical Research, 109: 1-12.

Garcia-Haro, F.J., Gilabert, M.A. and Melia, J., 2001. Monitoring fire-affected areas using Thematic Mapper data. International Journal of Remote Sensing, 22(4): 533-549.

Graham, R.T., 2003. Hayman Fire Case Study. RMRS-GTR-114, Rocky Mountain Research Station.

Harden, J.W. et al., 2000. The role of fire in the boreal carbon budget. Global Change Biology, 6(1): 174-184.

Healey, S.P., Cohen, W.B., Zhiqiang, Y. and Krankina, O.N., 2005. Comparison of tasseled cap-based Landsat data structures for use in forest disturbance detection. Remote Sensing of Environment, 97: 301-310.

Holden, Z.A., Smith, A.M.S., Morgan, P., Rollins, M.G. and Gessler, P.E., 2005. Evaluation of novel thermally enhanced spectral indices for mapping fire perimeters and comparisons with fire atlas data. International Journal of Remote Sensing, 26(21): 4801-4808.

Huang, C., Wylie, B., Yang, L., Homer, C. and Zylstra, G., 2002. Derivation of a tasselled cap transformation based on Landsat 7 at-satellite reflectance. International Journal of Remote Sensing, 23(8): 1741-1748.

Huete, A.R., 1988. A Soil-Adjusted Vegetation Index (SAVI). Remote Sensing of Environment, 25: 295-309.

Isaev, A.S. et al., 2002. Using remote sensing for assessment of forest wildfire carbon emissions. Climactic Change, 55: 231-255.

Jain, T.B., 2004. Tounge - tied: Confused meanings for common fire terminology can lead to fuels mismanagement, Wildfire, pp. 22-26.

Jakubauskas, M.E. and Lulla, K.P., 1990. Assessment of vegetation change in a fire altered forest landscape. Photogrammetric Engineering and Remote Sensing, 56(3): 371-377.

Jin, S. and Sader, S.A., 2005. Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances. Remote Sensing of Environment, 94: 364-372.

Johnson, E.A., 1992. Fire and Vegetation Dynamics: Studies from the North American Boreal Forest. University Press, Cambridge, England.

Johnstone, J.F. and Kasischke, E.S., 2005. Stand-level effects of soil burn severity on postfire regeneration in a recently burned black spruce forest. Canadian Journal of Forest Research, 35: 2151-2163.

Kane, E.S., Valentine, D.W., Schuur, E.A.G. and Dutta, K., 2005. Soil carbon stabilization along climate and stand productivity gradients in black spruce forests of interior Alaska. Canadian Journal of Forest Research, 35: 2118-2129.

Kasischke, E.S. et al., 2005. Influences of boreal fire emissions on Northern Hemisphere atmospheric carbon and carbon monoxide. Global Biogeochemical Cycles, 19: GB1012.

Kasischke, E.S. and Johnstone, J.F., 2005. Variation in postfire organic layer thickness in a black spruce forest complex in interior Alaska and its effects on soil temperature and moisture. Canadian Journal of Forest Research, 35: 2164-2177.

Kasischke, E.S., Turetsky, M.R., Ottmar, R., French, N.H.F., Hoy, E., Kane, E.S. and G. Sheffler, Evaluation of the composite burn index for assessing fire severity in Alaskan black spruce forests, Int. J. Wildland Fire, in review.

Kauth, R.J. and Thomas, G.S., 1976. The tasseled cap - a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. Proceedings - Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafaye(29 June - 1 July 1976): 4b41 - 4b51.

Key, C.H. and Benson, N.C., 2006. FIREMON Landscape Assessment. RMRS-GTR-164-CD, United States Department of Agriculture Forest Service.

Kotliar, N.B., Simonson, S., Chong, G. and Theobald, D., 2003. Effects on Species of Concern. In: R.T. Graham (Editor), Hayman Fire Case Study. Rocky Mountain Research Station, pp. 127-130.

Landsat 7 Science Data User's Handbook. NASA Space Flight Center. Greenbelt, Maryland: Landsat Project Science Office. http://landsathandbook.gsfc.nasa.gov/handbook/handbook_toc.html.

Lentile, L.B. et al., 2006. Remote sensing techniques to assess active fire characteristics and post-fire effects. International Journal of Wildland Fire, 15: 319-345.

López, M.J. and Caselles, V., 1991. Mapping Burns and Natural Reforestation Using Thematic Mapper Data. Geocarto International, 6(1): 31-37.

Miller, J.D. and Thode, A.E., 2007. Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). Remote Sensing of Environment.

Monitoring Trends in Burn Severity, 2006. United States Forest Service. 5 Apr. 2007 http://svinetfc4.fs.fed.us/mtbs/.

Miyanishi, K., 2001. Duff Consumption. In: E.A. Johnson and K. Miyanishi (Editors), Forest Fires: Behavior and Ecological Effects. Academic Press, San Diego:437-476.

Patterson, M.W. and Yool, S.R., 1998. Mapping fire-induced vegetation mortality using Landsat Thematic Mapper data: A comparison of linear transform techniques. Remote Sensing of Environment, 65: 132-142.

Pereira, J.M., 1999. A comparative evaluation of NOAA/AVHRR vegetation indexes for burned surface detection and mapping. IEEE Transactions on Geoscience and Remote Sensing, 37(1): 217-226.

Potere, D.T., Van Dellen, C. and Pollack, C., 2004. Multitemporal Kauth-Thomas change detection of the Appalachain Trail corridor in 17 New England counties. IEEE: 3402-3404.

Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H. and Sorooshian, S., 1994. A Modified Soil Adjusted Vegetation Index. Remote Sensing of Environment, 48: 119-126.

Rogan, J., Franklin, J. and Roberts, D.A., 2002. A comparison of methods for monitoring multi-temporal vegetation change using Thematic Mapper imagery. Remote Sensing of Environment, 80: 143-156.

Roy, D.P., Boschetti, L. and Trigg, S.N., 2006. Remote sensing of fire severity: Assesing the performance of the normalized burn ratio. IEEE Geoscience and Remote Sensing Letters, 3(1): 112-116.

Smith, A.M.S. et al., 2005. Testing the potential of multi-spectral remote sensing for retrospectively estimating fire severity in African Savannahs. Remote Sensing of Environment, 97: 92-115.

Sorbel, B. and Allen, J., 2005. Space-based burn severity mapping in Alaska's national parks, Alaska Park Science, pp. 4-11.

Stocks, B.J. and Kasischke, E.S., 2000. Information requirements and fire management and policy issues. In: E.S. Kasischke and B.J. Stocks (Editors), Fire, Climate Change, and Carbon Cycling in the Boreal Forest. Springer, New York, pp. 7-17.

Sukhinin, A.I. et al., 2004. AVHRR-based Mapping of Fires in Eastern Russia: New Products for Fire Management and Carbon Cycle Studies. Remote Sensing of Environment, 93: 546-564.

Trigg, S. and Flasse, S., 2001. An evaluation of different bi-spectral spaces for discriminating burned shrub-savannah. International Journal of Remote Sensing, 22(13): 2641-2647.

van Wagtendonk, J.W., Root, R. and Key, C.H., 2004. Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. Remote Sensing of Environment, 92: 397-408.

White, J.D., Fayan, K.C., Key, C.H. and Running, S.W., 1996. Remote sensing of forest fire severity and vegetation recovery. International Journal of Wildland Fire, 6: 125-136.

Zhu, Z., Key, C.H., Ohlen, D. and Benson, N.C., 2006. Evaluating sensitivities of burn-severity mapping algorithms for different ecosystems and fire histories in the United States. JFSP 01-1-4-12, Joint Fire Science Program.