Remote Sensing of Environment 114 (2010) 1494–1503

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Modeling fire severity in black spruce stands in the Alaskan boreal forest using spectral and non-spectral geospatial data

K. Barrett [a,*], E.S. Kasischke [b], A.D. McGuire [c], M.R. Turetsky [d], E.S. Kane [e]

[a] USGS Alaska Geographic Science Office, 4230 University Drive, Anchorage, AK, United States
[b] Department of Geography, University of Maryland, College Park, MD, United States
[c] USGS, Alaska Cooperative Fish and Wildlife Research Unit, 214 Irving I Building, University of Alaska, Fairbanks, AK, United States
[d] Department of Integrative Biology, University of Guelph, Guelph, ON, Canada
[e] Michigan Technological University, School of Forest Resources and Environmental Science,1400 Townsend, Houghton, MI, United States

ARTICLE INFO

Article history:
Received 17 September 2009
Received in revised form 3 February 2010
Accepted 6 February 2010

Keywords:
Boreal forest
Fire severity
Alaska
Regression tree
Boosting

ABSTRACT

Biomass burning in the Alaskan interior is already a major disturbance and source of carbon emissions, and is likely to increase in response to the warming and drying predicted for the future climate. In addition to quantifying changes to the spatial and temporal patterns of burned areas, observing variations in severity is the key to studying the impact of changes to the fire regime on carbon cycling, energy budgets, and post-fire succession. Remote sensing indices of fire severity have not consistently been well-correlated with *in situ* observations of important severity characteristics in Alaskan black spruce stands, including depth of burning of the surface organic layer. The incorporation of ancillary data such as *in situ* observations and GIS layers with spectral data from Landsat TM/ETM+ greatly improved efforts to map the reduction of the organic layer in burned black spruce stands. Using a regression tree approach, the R^2 of the organic layer depth reduction models was 0.60 and 0.55 ($p<0.01$) for relative and absolute depth reduction, respectively. All of the independent variables used by the regression tree to estimate burn depth can be obtained independently of field observations. Implementation of a gradient boosting algorithm improved the R^2 to 0.80 and 0.79 ($p<0.01$) for absolute and relative organic layer depth reduction, respectively. Independent variables used in the regression tree model of burn depth included topographic position, remote sensing indices related to soil and vegetation characteristics, timing of the fire event, and meteorological data. Post-fire organic layer depth characteristics are determined for a large (>200,000 ha) fire to identify areas that are potentially vulnerable to a shift in post-fire succession. This application showed that 12% of this fire event experienced fire severe enough to support a change in post-fire succession. We conclude that non-parametric models and ancillary data are useful in the modeling of the surface organic layer fire depth. Because quantitative differences in post-fire surface characteristics do not directly influence spectral properties, these modeling techniques provide better information than the use of remote sensing data alone.

Published by Elsevier Inc.

1. Introduction

Disturbance of natural ecosystems, particularly forest environments, is critical to understanding carbon cycling and other important ecosystem processes on a regional to global scale (Chapin et al., 2006; Kurz et al., 2007; Running, 2008). Biomass burning is one of the primary vehicles of land cover change in the sub-arctic boreal forest, with the frequency of large fire years more than doubling over the past half century across the North American boreal forest (Kasischke & Turetsky, 2006) in response to overall warming (Gillett et al., 2004), as well as seasonal variations in temperature and precipitation that are driven by teleconnections with longer-term variations in ocean circulation (Skinner et al., 1999, 2006; Duffy et al., 2005).

The objective of this study is to determine the depth of burn for five large fires that occurred during the 2004, the largest fire year on record for interior Alaska. Variations in depth of burning of deep organic soils common to boreal forests can precipitate changes in post-fire succession (Johnstone & Kasischke, 2005; Johnstone & Chapin, 2006; Johnstone et al., 2009), and affect energy budgets (Chambers & Chapin, 2003; Randerson et al., 2006), net ecosystem carbon balance (Kasischke et al., 1995; Harden et al., 1997; Balshi et al., 2007), permafrost dynamics and hydrology (Zhuang et al., 2002; O'Donnell et al., 2009; Yi et al., 2009), and other ecosystem services, particularly subsistence resources used by Native Peoples in interior Alaska (Rupp et al., 2006; Natcher et al., 2007; Chapin et al., 2008; Nelson et al., 2008).

Fire severity is defined as the immediate post-fire environment, which interacts with site-specific conditions to determine burn severity over a longer time period (Lentile et al., 2006). The severity

* Corresponding author.
E-mail address: kbarrett@usgs.gov (K. Barrett).

0034-4257/$ – see front matter. Published by Elsevier Inc.
doi:10.1016/j.rse.2010.02.001

characteristic of interest, burn depth, is the most important effect on ecosystem functioning in the Alaskan boreal forest. The reduction of the surface organic layer impacts soil characteristics as well as post-fire regeneration, and is the primary focus of this analysis. This study is unique in that it combines spectral and ancillary geospatial data to analyze fire severity in the Alaskan boreal forest, although such a combination of data types has proven fruitful in other contexts (Rogan & Miller, 2006).

1.1. Background

Black spruce (*Picea mariana* (Mill.)) stands, the dominant species in majority of forested land cover of the Alaskan interior, are typically characterized by poor to moderate drainage and cool soil temperatures, which inhibits decomposition of organic matter. Deep soil organic layers are covered by a surface organic layer that insulates the ground from warmer summer temperatures when the surface is dry. In spring and winter, when the organic layer is wet or frozen, the thermal conductance is higher and the soil underneath is cooler (Burn & Smith, 1988); therefore the active layer under a deep organic layer is generally thinner than in areas with a thinner organic layer or exposed mineral soil (Kane et al., 2007). The organic material in these soils and surface materials is highly vulnerable to burning, particularly during more severe fires that consume more of the surface organic layer (Kasischke et al., 2000; Kasischke & Johnstone, 2005; Amiro et al., 2009). Black spruce trees are able to tolerate cool, moist soils and therefore dominate in flat areas and toe slopes north-facing back slopes. The soil organic layer in low productivity black spruce stands tends to be deeper than in other upland ecosystems because cool, moist soil conditions inhibit decomposition rates and provide resistance to deep-burning fires. Black spruce cones are semi-serotinous, but the trees are vulnerable to fire-induced mortality due to the thin bark.

In burned black spruce stands experiencing low to moderate levels of combustion of the surface organic layers, post-fire succession is likely to follow a self-replacement trajectory (Viereck, 1983; Johnstone & Kasischke, 2005; Johnstone & Chapin, 2006). In high-severity fires that consume most or all of the soil organic layer, there is an increased likelihood of a post-fire successional shift toward deciduous dominance (Johnstone & Kasischke, 2005; Johnstone & Chapin, 2006; Johnstone et al., 2009). Fire frequency and possibly severity have increased in interior Alaska in recent decades, which, if sustained, could shift the species composition of the region to a novel ecosystem: a mix of black spruce and aspen or birch. The region has not been dominated by such a mixture of coniferous and deciduous species since the early Holocene (~10,000 years BP) (Lynch et al., 2002, 2006; Lloyd et al., 2006).

A shift to increased deciduousness in Alaskan boreal forests can result from two types of modifications of the fire regime — decreased fire return interval and increased severity. Both modifications are likely in the context of predictions of a warmer and drier climate for the Arctic and sub-Arctic (Stocks et al., 1998; ACIA, 2004; Flannigan et al., 2005; Rupp et al., 2007). First, fire years with high annual area burned become more common in the Alaskan Interior, and the fire return interval for a given stand becomes shorter. The decrease in fire return interval in turn reduces the amount of seedling recruitment from black spruce because the slow-growing trees do not reach sexual maturity before the next fire (Johnstone & Kasischke, 2005; Johnstone & Chapin, 2006). Second, more severe fires that consume the soil organic layer favor recruitment and establishment of deciduous seedlings, which thrive on the exposed mineral soils and inhibit the growth of coniferous species (Johnstone & Kasischke, 2005).

The deciduous or mixed deciduous–conifer ecosystem that could result from these changes in fire regime characteristics is likely to alter ecosystem functions such as albedo and carbon cycling and may contribute to feedbacks among vegetation, climate, and fire. Establishment of deciduous species such as trembling aspen (*Populus tremuloides*) and paper birch (*Betula papyrifera*) in areas previously dominated by black spruce is likely to increase surface reflectance and to inhibit the establishment of black spruce seedlings (Johnstone & Chapin, 2006). While the deciduous species may have higher biomass and therefore store more carbon, increased heterotrophic respiration in drier and warmer soils may offset these gains. The net effect of post-fire radiative forcing and carbon emissions has been estimated to be a cooling effect (Randerson et al., 2006), although variations in severity exert considerable influence over these dynamics.

1.2. Spectral and ancillary geospatial data

Studies of severity characteristics such as burn depth typically use *in situ* observations, which are limited in spatial extent because of the need for site accessibility. Plot-based samples, even those located across a range of burn conditions, cannot fully account for all of the variability in burn conditions within a large (>10 km^2) burn perimeter (Turner et al., 2003; Greene et al., 2004). Extrapolation of plot-based observations of severity to an entire burn or an even broader extent is difficult without information regarding the spatial heterogeneity of conditions at these scales (Turner et al., 1999; Turner, 2005) both pre-fire (such as species composition, topography, and other factors that influence severity) and post-fire (such as spectral indicators of severity from remote sensing).

A variety of approaches have been evaluated for using remote sensing data to assess fire/burn severity (for a review, see French et al., 2008). Fire severity mapping is typically conducted using a combination of information from the visible, near-infrared, and mid-infrared portions of the EM spectrum (e.g., Lopez-Garcia & Caselles, 1991; Key & Benson, 1999; Miller & Thode, 2007). These are the bands most sensitive to variations in soil color (visible and mid-infrared), soil composition (mid-infrared), and moisture and chlorophyll (near-infrared), which are significantly affected by fire severity. The spectral signature of severity immediately following a fire is composed of the reflectance properties of soil, char, ash, moisture and living and dead vegetation (Rogan & Franklin, 2001). If the entire surface organic layer is consumed during the fire, the subsequently exposed mineral soils will have a much higher reflectance value across the spectrum compared to organic soils. Additionally, mineral soils, with a higher bulk density than organic soils hold more moisture than mineral soils, and are likely to exhibit a spectral signature more attenuated by water absorption bands. Across a burned area char or ash may dominate in the immediate post-fire environment, depending on combustion completeness (Smith & Hudak, 2005). White ash, indicative of complete combustion (Stronach & McNaughton, 1989; Robinson, 1991; Landmann, 2003), causes high spectral reflectance (Smith & Hudak, 2005; Smith et al., 2005) in contrast with char, which increases absorption across the spectrum (Smith et al., 2005).

For this reason, recent studies have focused on using moderate- to coarse-grain remotely sensed data for mapping fire severity in the Alaskan interior (e.g., Epting et al., 2005; Duffy et al., 2007; Allen & Sorbel, 2008; Hoy et al., 2008; Murphy et al., 2008). The broad spatial extent sampled by these medium-to-coarse-grain sensors (from Landsat scenes of about 30,000 km^2 to MODIS scenes of about 6,000,000 km^2) can cover a range of ecological conditions where burns occur, and analysis of their spectral data has the potential to produce indices of fire severity (Key & Benson, 2006; Lentile et al., 2006).

Recently, the focus of remote sensing research on fire severity has sought to correlate measures of site-level fire severity characteristics (such as the Composite Burn Index, or CBI) with remotely sensed spectral indices of severity (such as the Normalized Burn Ratio [NBR] family) to produce regional estimates of severity characteristics (e.g., Epting et al., 2005; Miller & Thode, 2007; Allen & Sorbel, 2008; Murphy et al., 2008) Other attempts to correlate remotely sensed and field-based observations of severity have not demonstrated that fire severity characteristics such as burn depth can be reliably derived from remote sensing based indices alone (Hoy et al., 2008; Verbyla & Lord, 2008). Overall, the relationship between ground-based and remote sensing based indices is inconsistent in black spruce forests (Hoy et al., 2008).

2. Methods

In this analysis, information derived from remote sensing data (spectral indices of severity as well as other relevant information regarding fire regime characteristics such as seasonal timing of burning) and ancillary data (e.g., meteorological data and topography) are combined in a regression tree model to estimate depth of burn. A gradient boosting algorithm, which uses regression trees as the base learner, was applied to the data to improve accuracy. The data used to develop the depth of burn algorithm were from a number of 2004 Alaskan fire events. These algorithms were then applied to a single fire event to produce a map of severity.

2.1. Study area

The sites used to develop a model of depth of burning were located within fire events that occurred during 2004 in the boreal region of interior Alaska. The 88 sites were located within 5 fire events: Bolgen Creek, Boundary, Dall City, Porcupine, and Tors (Fig. 1). These fire events and sites are described in detail in Kasischke et al. (2008). Mean annual temperature in this region ranges between −5 and −7 °C (Beget et al., 2006), with a high degree of seasonal variation. Precipitation ranges between 215 and 300 mm (Beget et al., 2006), with about two-thirds occurring as snowfall. The average elevation in the region where our observations were taken is 168 m, though there is significant topographic relief (standard deviation = 127 m, minimum = 20 m, maximum = 1280 m). The majority (>99%) of the burning in this region occurs at elevations <900 m, which reflects limits of fuel availability above treeline (Kasischke et al., 2002).

Mature black spruce stands account for 35% of the vegetation cover and 70% of the mature forests in interior Alaska. Low-growing branches are common to this species, and act as a fire ladder to promote crown burning. In this region fire cycles range from <120 to 240 years (Kasischke et al., 2002). Based on data from Kasischke et al. (2008), the average stand age in mature stands (a surrogate for time since fire in black spruce stands) is about 112 years.

There is much variability in area burned from year to year, with large fire years (>5000 km^2) occurring in Alaska about once every five years over the last fifty years (Kasischke & Turetsky, 2006). In 2004 approximately 27,000 km^2 burned in the state, compared with 2400 km^2 in 2003. Average annual area burned in Alaska has nearly doubled over the past 25 years (1984–2008) compared to the previous 25 year period (1959–1983), from 2430 km^2 to 4730 km^2.

The Boundary Fire in Eastern Alaska burned almost 218,000 ha over five weeks between mid-June and the beginning of August, 2004. The burned area was the largest of any single fire in 2004, which was the largest fire year on record for interior Alaska. Drought conditions and elevated wind speeds helped the fire to spread quickly across the landscape until management efforts aided by precipitation events extinguished it.

2.2. Data

The dependent variables as well as some of the independent variables used in our modeling activities were based on field observations collected in sites located in five fire events that occurred in 2004. These sites were selected to represent a range in fire severity, from light to severe (relative organic layer depth reduction mean = 0.60, minimum = 0.156, maximum = 0.997). The sites were sampled for various factors related to site and stand characteristics and fire severity. Details of the sampling procedures used to collect these data can be found in Kasischke et al. (2008).

Site characteristics used as dependent variables included measurements of pre-burn depth of the surface organic layer and depths of the organic layers after the fire. Some burn depth data were derived from direct measurements of pre- and post-fire organic layer depth (those collected by the USFS), while most of the observations utilized the height of the adventitious roots above mineral soil to estimate pre-fire organic layer depth (Kasischke & Johnstone, 2005; Kasischke et al., 2008).

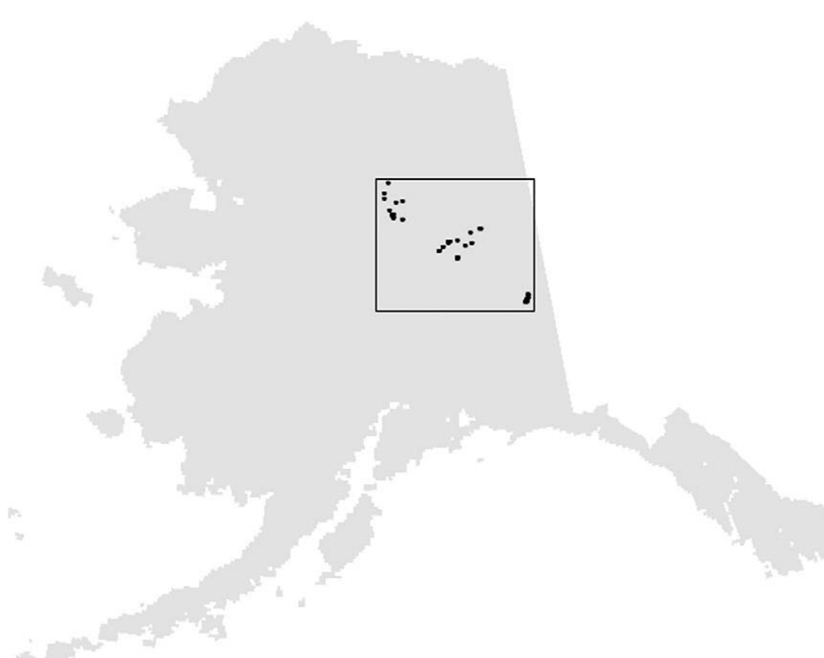

Fig. 1. Study area of the Alaskan interior, points mark the locations of burn depth observations.

Site characteristics that were used as independent variables included topographic position, slope, aspect, percent of the surface covered by charred organic soil, average basal diameter of the canopy trees (live and dead), number of live/dead trees standing, and the composite burn indices (CBI), including total CBI and CBI for individual layers (e.g., canopy CBI, understory CBI, and substrate CBI). Unlike the other independent variables used in the model, none of these *in situ* observations are available at a regional level, a requirement for expanding the predictive model beyond the burned areas sampled in the field.

Other independent variables were derived from analysis of remotely sensed data, weather records, and topographic data. We obtained Landsat TM/ETM+ spectral imagery and NBR-family severity metrics from the Monitoring Trends in Burn Severity (Eidenshink et al., 2007) website (see http://mtbs.gov/methods.html for information on pre-processing and specific information on index calculation). The imagery used in the analysis is listed in Table 1. All images were Level 1 terrain-corrected and georeferenced Landsat (L1T) TM/ETM+ data. Clouds in imagery were masked from the analysis, and ETM+ images obtained with SLC-off were masked for missing data.

In addition to using the spectral reflectances from Landsat TM/ETM+ Bands 4, 5, and 7, a number of different spectral indices were included in the analysis (Table 2). Post-fire reflectance in the near-infrared and mid-infrared portions of the electromagnetic spectrum is related to changes in vegetation cover and exposed soil. Ratios created using bands in the near and mid IR that have proven useful in minimizing illumination effects (Ekstrand, 1996). The Normalized Burn Ratio (Key & Benson, 1999), and the normalized differenced vegetation index (Tucker 1979) can be used to distinguish variations in fire severity in some ecosystems (Díaz-Delgado et al., 2003; Epting et al., 2005). Modifications of these ratios include comparison of pre- and post-burn indices, such as the post-fire change in NBR (dNBR) and a relativized form of dNBR (RdNBR) (Miller & Thode, 2007). Finally, the brightness, greenness, and wetness output from the Kauth–Thomas transformation (Kauth & Thomas, 1976) were included to analyze variations in surface reflectance related to soil exposure, vegetation cover, and moisture content, respectively.

Additional data layers derived from remotely sensed data included burned area and proportion of unburned “islands” within the fire perimeter (through analysis of Landsat TM/ETM+ imagery) and burn date (from MODIS active fire detection). Pre-fire land cover was determined from *in situ* observations of the species of standing dead trees to ensure that the land cover type evaluated was black spruce.

All of the meteorological data used as independent variables in the analysis came from Remote Automated Weather Stations operated by cooperative effort between the U.S. Bureau of Land Management, the State of Alaska, the U.S. Fish and Wildlife Service, the National Park Service, and the U.S. Forest Service. There are 142 such stations in Alaska, 46 of which are in the study region. Fire weather indices were created by averaging the conditions for polygons measuring 1° latitude by 5° longitude. The 1° by 5° sampling unit was used to insure that a sufficient number of weather stations (between 3 and 6) determined the weather characteristics of each burned area polygon.

Table 1
Remote sensing imagery used in the analysis.

Path/row	Sensor	Image date	Fire name	AFS number
68/14	ETM+	16-Aug-05	Wolf Creek	158
69/14	ETM+	22-Jul-05	Boundary	193
71/14	TM	26-Jun-05	Fort Hamlin Hills	241
66/15	ETM+	31-Aug-04	Taylor Complex	293
68/14	ETM+	16-Aug-05	Central Complex	372
71/13	ETM+	20-Jul-05	Dall City	384
68/15	TM	21-Jun-05	n/a	477
71/13	ETM+	20-Jul-05	Hodzana River	583

Table 2
Independent variables based on spectral reflectance.

	Description	Wavelenth (μm) or formula
B7/B5	Ratio of band 7 to band 5	B7/B5
NBR	Normalized Burn Ratio	B4 − B7/B4 + B7
dNBR	Differenced Normalized Burn Ratio	Pre-fire NBR − post-fire NBR
RdNBR	Relative differenced Normalized Burn Ratio	dNBR/SQRT(pre-fire NBR)
NDVI	Normalized difference vegetation index	B4 − B3/B4 + B3
TC1	Tasseled cap brightness	(B1*0.3561) + (B2*0.3972) + (B3*0.3904) + (B4*0.6966) + (B5*0.2286) + (B7*0.1596)
TC2	Tasseled cap greenness	(B1*0.3344) + (B2* − 0.3544) + (B3* − 0.4556) + (B4*0.6966) + (B5* − 0.0242) + (B7* − 0.2630)
TC3	Tasseled cap wetness	(B1*0.2626) + (B2*0.2141) + (B3*0.0926) + (B4*0.0656) + (B5* − 0.7629) + (B7* − 0.5388)

The Fire Weather Index System (FWIS) is part of the Canadian Forest Fire Danger Rating System (CFFDRS) created by the Canadian Forest Service (Stocks et al., 1998). The purpose of the CFFDRS is to provide fire managers with a set of simple indices that can be used to estimate the probability of fire ignition and spread based on current and seasonal weather patterns. These indices are generated using commonly-collected meteorological measurements such as air temperature, wind speed, precipitation, and relative humidity. The indices represent fuel moisture conditions (fine fuel moisture code, duff moisture code, and drought code), and potential fire behavior (initial spread index, buildup index and fire weather index) (Van Wagner, 1987). The fire weather indices used in this study were calculated by the Alaska Fire Service (AFS) from 2004 weather data obtained from the Remote Automated Weather Stations located within the region of our field observations. Finally, topographic information was derived from a digital elevation model from the US Geological Survey with a spatial resolution of 60 m.

2.3. Analytical approaches

The goal of this study was to produce a model of organic layer depth reduction, either as absolute burn depth or a ratio of post-fire depth relative to pre-fire conditions. In this study we ran a regression tree analysis [using rpart in R (Therneau & Atkinson, 2010)] to produce estimates of relative and absolute burn depth as a function of topography. Finally, a gradient boosting approach [mboost in R (Hothorn & Bühlmann, 2007)] that uses regression trees as a base learner was employed to boost the accuracy of the burn depth estimates.

2.3.1. Regression trees

Regression tree algorithms are performed using observations of the dependent variable and corresponding independent variables provided by the user (Breiman et al., 1984). The regression tree algorithm iteratively splits the dataset into two groups based on every value given for every input variable, selecting the split that minimizes the user-specified loss function, such as squared error (Breiman et al., 1984; Franklin, 1998; Lawrence et al., 2004). Each bifurcation of the data is known as a node, and the terminal nodes contain the model output values.

The effectiveness of regression trees has been shown in the context of image classification (where they are referred to as classification trees given the categorical output) (Hansen et al., 2000; Rogan et al., 2002; Lawrence et al., 2004; Hansen et al., 2008) and to a lesser extent change detection (Rogan & Franklin, 2001; Rogan et al., 2003; Im & Jensen, 2005; Im et al., 2008; Liu et al., 2008). The continuous output from a regression tree model can be used to map non-discrete features such as fire severity.

There are many options for user input in creating regression trees, including the number of iterations to perform the binary recursive partitioning as well as the minimum number of observations to include in a terminal node. Post-processing of the regression tree can be performed by selecting nodes for removal, known as pruning.

Regression tree algorithms differ in terms of the rule used to create new nodes. Generally speaking, the split that minimizes the loss function (least squares) for both groups is chosen as a node. In this case, squared analysis of variance (ANOVA) was used to evaluate within group and between group variance (F-test) for each side of a split. The algorithm runs an ANOVA test on every possible split (all values of all independent variables) and chooses the split that maximizes the F-statistic (between group variance divided by within group variance). It is recognized that spatial autocorrelation in the response variables may violate the assumption that all observations are independent, which in turn impacts significance and may affect model performance. The response variables were tested for spatial autocorrelation using Moran's I. Autocorrelation was significant, though weak, for both relative (Moran's Index = 0.05, $p = 0.02$) and absolute depth reduction (Moran's Index = 0.22, $p = 0.0001$).

2.3.2. Ensemble techniques

Regression trees, while effective at incorporating disparate data types, non-normal distributions and non-linear relationships, do not allow for tree optimization, and accuracy may suffer in the presence of outliers and non-balanced datasets (Breiman, 1996; Lawrence et al., 2004) Ensemble techniques, also known as voting techniques, use the mean of multiple regression tree runs to increase accuracy and stabilize the algorithm so that variations in input data do not disproportionately influence the output (Freund & Schapire 1999; DeFries & Chan, 2000). While ensemble techniques generally perform better than regression trees, the algorithm used to predict a value is unique for each observation, therefore interpretation of the model is different from the single regression tree approach.

Two common ensemble techniques are known as bagging and boosting. Bagging involves creating many regression trees by varying slightly the observations used for each tree. A boosting operation utilizes the decision tree as a base learner. After each iteration, the model output is compared with the training data and miscalculations are assigned a greater weight so that, in the next iteration, the algorithm pays greater attention to those cases that are more difficult to predict. The boosting algorithm learns to predict the dependent variable based on multiple attempts to correctly classify training data. When a maximum number of boosting operations have been performed the algorithm chooses the mean of the output from every tree created as the final output value. In this case, 50 iterations were used in both models, a number that reflects the point at which training error (evaluated by comparing output with observations not included in model construction, or out-of-bag observations) is effectively minimized.

2.4. A case study: the 2004 Boundary Fire

To calculate the average depth of the organic layer before the fire, we subtracted the depth reduction from the decision tree model from pre-fire organic layer depth. We used field-based observations of pre-fire organic layer depth that were collected across all topographic positions where black spruce forests are located. Observations ($n = 29$) were taken from Harden et al., 2004, 2006; Kane et al., 2005, 2007; Kasischke & Johnstone, 2005; Kasischke et al., 2008; Shetler et al., 2008 and are summarized in Turetsky et al. (in review). Using these data, mean organic layer depth was calculated for three backslope categories: (i) north, (ii) east and west, and (iii) south-facing slopes; and two flat or toe slope categories: (i) upland and (ii) lowland. These mean values were used along with the area of each topographic position in the Boundary Fire.

Pre-fire organic layer depth was used in conjunction with the depth reduction models (described in Section 3.3) to estimate the organic layer depths remaining following fire activity in the area of the Boundary Fire. Post-fire organic layer depth was used to determine which areas are vulnerable to a shift in post-fire species dominance. We evaluated only those areas classified as conifer prior to the burn (about 60% of the burned area according to the National Land Cover Database), which we assumed were all black spruce.

The regression tree approach, which produces decision rules to estimate organic layer depth reduction, lends itself to producing maps of the output variable quite easily. The absolute and relative depth reduction models were used in combination with an estimate of pre-fire organic layer depth to identify areas with <3 cm of surface organic layer after the fire, the critical post-fire organic layer depth in terms of shifting post-fire succession (Johnstone & Kasischke, 2005; Johnstone & Chapin, 2006).

3. Results

3.1. Regression tree analysis

Regression tree analysis using relative organic layer depth reduction as the dependent had an overall goodness of fit of $R^2 = 0.60$. The first split used topographic position to bifurcate the data (Fig. 2). Flat lowland areas, typically cool with highly fire-resistant sphagnum hummocks, had the shallowest relative depth reduction (0.322). The next split divided the observations into south, east, and west facing slopes (average reduction = 0.74) versus north, northeast, northwest, southeast and southwest facing slopes (average reduction = 0.55). Additional splits incorporated information from remote sensing indices (ratio of TM bands 7/5) and air temperature.

The regression tree analysis using absolute depth reduction as the dependent variable had an overall goodness of fit of $R^2 = 0.55$ (Fig. 3). This regression tree incorporated similar factors of topographic information and remotely sensed indices, and additionally incorporated burn date and two of the fire weather indices. The first split occurred at slopes greater than 11.5%, which burned the deepest (19.79 cm). Drought code, which generally increased toward the end of the burn season reflecting increased drying of ground-layer fuels, was chosen for the second split. High DC (above 532) tended to burn deeply. The next split incorporated the post-fire normalized differenced vegetation index, associated with deciduous vegetation in severely burned areas. Additional splits included the shallowest burns occurring in lowland flat areas, a later burn date, and the initial spread index of the fire.

3.2. Gradient boosting

A gradient boosting algorithm was applied to the dataset, using the regression tree as the base learner. Similar to the regression trees, overall goodness of fit between the relative and absolute depth

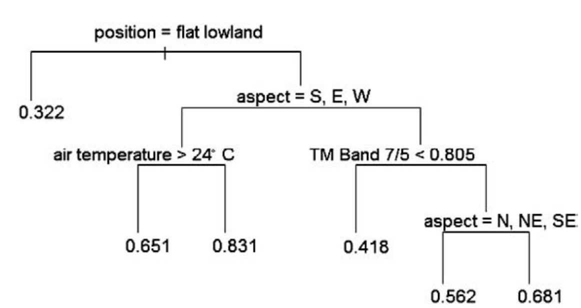

Fig. 2. Decision tree model for relative organic layer depth reduction.

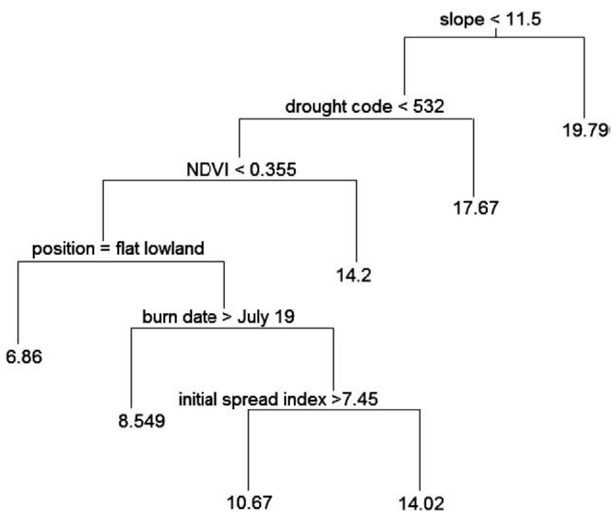

Fig. 3. Decision tree model for absolute organic layer depth reduction.

reduction models was similar (0.80 and 0.79 for absolute and relative depth reduction, respectively), although the distribution of the modeled values is somewhat different, reflecting the distribution of the dependent variables (Figs. 4 and 5).

The predicted values in the relative burn depth model appear to be more regularly distributed around the regression line. In the output from the absolute depth reduction model there are no predicted values between 18 and 20 cm, reflecting the lack of observed burn depth values between 20 and 24 cm. The relative depth reduction shows no such gap. There is one extreme outlier in the absolute depth reduction model, where the model predicted a burn depth of 11 cm and the observed value was nearly twice that amount. Without the outlier the regression equation changes only slightly (slope = 1.16 versus 1.15, intercept = 2.33 versus 2.02, $R^2 = 0.84$ versus 0.80). The confusion may have resulted from the fact that, although the area was on a south-facing slope, it burned relatively early in the season (June 24), while the drought code was relatively low (226.4, which is in the first quartile of values for the variable). The slope for this observation (7%) was also below the threshold chosen for the deepest-burning fires (11.5%). There were no obvious outliers in the relative depth reduction model. The model residuals are normally distributed and appear random.

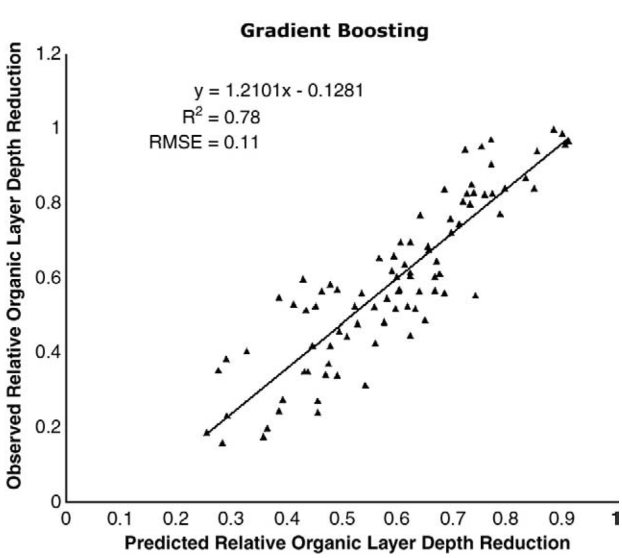

Fig. 4. Model fit using the gradient boosting technique, relative organic layer depth reduction as dependent variable.

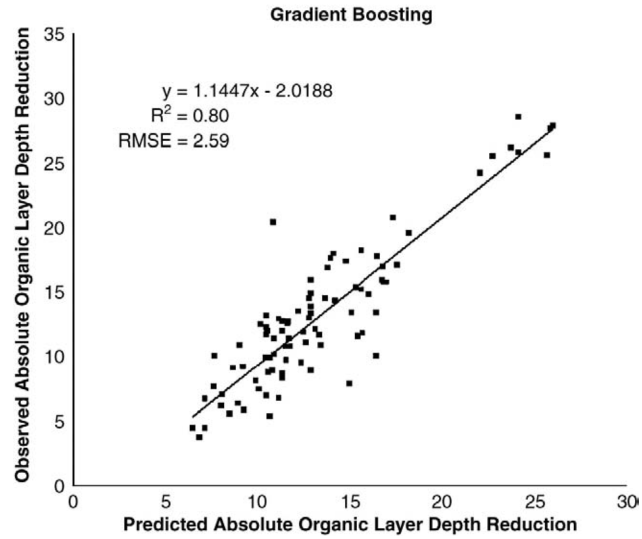

Fig. 5. Model fit using the gradient boosting technique, absolute organic layer depth reduction as dependent variable.

3.3. Boundary Fire case study

According to the map of absolute organic layer depth reduction, about 12% of the burned area in the Boundary Fire had organic layer depth shallower than 3 cm after the burn. While the model using relative depth reduction showed general agreement with the spatial pattern of post-fire organic layer depths, no areas were estimated to have <3 cm depth after the fire. Overall the absolute organic layer depth reduction model estimated shallower post-fire organic layers than the relative reduction model (absolute reduction mean post-fire depth = 7.7 cm, relative reduction mean post-fire depth = 10.8 cm, SD = 3.8 and 4.7, respectively).

4. Discussion

4.1. Dependent variable selection

The use of absolute versus relative organic layer depth reduction as a measure of fire severity determines what questions one can address, where the dependent variable can be selected to represent the time frame of interest. Absolute depth reduction gives us information about what was removed from the soil during the fire event, and represents the logical severity measure if one is interested in estimating carbon loss or emissions. In contrast, relative depth reduction is more relevant for questions regarding the ecosystem response to the fire.

Absolute depth reduction is useful to studies of mass and energy exchanges from fire, combustion rates, and other factors related to the fire event itself. The impact of the fire on ecosystem functioning may utilize information on absolute burn depth to determine the amount of carbon released to the atmosphere, as the carbon content of soils varies with depth. With respect to post-fire characteristics, deeper burning fires are more likely to smolder (Gleixner et al., 2001) and to create less labile black carbon in the process. A higher proportion of black carbon in the soil means less carbon will be available for post-fire decomposition.

Relative depth reduction is more important to studies of ecosystem functioning than the direct effects of fire on mass and energy exchanges, and the relevance of relative depth reduction is likely to persist for many years post-fire. The greater the proportion of material that is combusted, the less there is to maintain post-fire ecosystem structure and function. The combustion of plant propagules important to post-fire recruitment such as seeds and vegetative material from surface organic layers directly affects post-fire succession. In black spruce sites with low severity (i.e., deep residual organic layers), post-fire shrub recruitment occurs as a result of vegetative reproduction (Zasada et al., 1983). In deep-burning fires, the sources (roots, stems) for vegetative reproduction are eliminated, therefore changing community compositions to species recruited from seeding from outside the stand (Johnstone & Kasischke, 2005). Fire also affects soil bulk density by removing low-density surface organic layers and leaving inorganic material such as loess that accumulated in the combusted material prior to the burn. The bulk density of the top most organic layer remaining after the fire controls water availability for seed germination and growth. Thus, the low bulk densities of organic layers in shallow fires tend to be too dry to support germination and growth of tree species with small seeds (e.g., aspen and birch), whereas species with larger seeds (black spruce) have a higher rate of survival and recruitment (Johnstone et al., 2009). Finally, deep organic layers in black spruce forest insulate the ground layer, and thus facilitate the formation of permafrost (Yoshikawa et al., 2002). As a result, the soil temperature and moisture in both unburned (Kane et al., 2007) and burned (Kasischke & Johnstone, 2005) black spruce stands are proportional to the depth of the organic layer, and deeper burning, more severe fires, result in warmer and drier sites post-fire.

4.2. Regression tree architecture

Whether relative or absolute post-fire organic layer depth reduction was employed as the dependent variable, the regression tree outputs were similar in the types of variables included. The exact same variables were not included in both models because regression trees are not particularly robust and a difference at the root (or primary node) will generally produce a very different tree. While the tree architectures were different, both included topographic indicators close to the root, highlighting their importance. The model of absolute depth reduction employed slope in the first node, with the areas greater than 11.5% having an average burn depth of 19.79 cm and 11.79 cm in all other areas. The first node of the relative depth reduction model was based on topographic position, with flat lowland areas losing 0.33 of the surface organic layer and all other areas losing an average of 0.64. Post-fire spectral characteristics, particularly band ratios (NDVI in the case of absolute depth reduction, TM band 7/TM band 5 for relative depth reduction) were chosen in the third level split for both nodes. Fire weather indices (initial spread index in the case of absolute depth reduction, air temperature in the case of relative reduction) were used toward the terminal nodes, aiding in the finer-level separations. In addition to selecting similar input variables, the regression trees appeared to perform with roughly the same level of accuracy ($R^2 = 0.55$ and 0.60).

Interestingly, the position of different types of independent variable in the tree is generally indicative of the scale at which ecological processes related to fire operate. Landscape related variables such as topography, are located near the root of both trees, and operate at broad spatial scales. The steeper slopes (chosen as the first split in the absolute depth reduction model) are better drained and therefore less fire-resistant. The flat, lowland areas (chosen by the relative depth reduction model) are more likely to be inundated, and may be shadowed in regions of high topographic relief. At the next level, the spectral characteristics that are related to post-fire succession become important. The soil and vegetation characteristics that attenuate the spectral signature are related to regional to local scale variations. Finally, the last data partitioning uses short-term variations in fire weather-related variables (initial spread index in the case of absolute depth reduction, air temperature in the case of relative depth reduction).

Differences between the regression trees to determine relative or absolute burn depth may be related to differences in the contribution of landscape related variables versus instantaneous fire conditions. While the first split for both trees is based on topography, in the case of absolute depth reduction, the next node splits the data based on the drought code (areas that burned on a day with a drought code >532 lost an average of 18 cm, when drought code was <532 11 cm of organic layer was lost). Relative depth reduction is split first based on upland versus lowland areas and then aspect with south, east and west facing slopes having an average depth reduction of 0.74, all other areas lost 0.57. The fact that landscape factors are more prevalent in the first branches of the relative depth reduction tree may mirror the fact that this variable is linked more closely with landscape characteristics than absolute depth reduction, which incorporates more data splits based on fire weather and seasonality of the burn.

Interestingly, in the model of absolute depth reduction, areas that burned later than July 19 had a shallower burn depth than those that burned prior to that date. While fire severity is less dependent on seasonality during large fire years, it seemed strange that severity would decrease as warmer conditions continued through the fire season. Upon inspection of the weather indices, it appears that the decreased burn depth may have been caused by increased precipitation that mitigated fire severity. The precipitation from June 1 to July 20 (40 mm) is 67% of the amount that fell in the following 50 day period (July 20 to September 6, 60 mm) (Fig. 6).

4.3. Boundary Fire case study

The maps of absolute and relative depth reduction reflect the importance of the input variables included in each tree and the proportion of the landscape covered by the output fire severity values (Fig. 7). In the case of absolute depth reduction, the majority (64%) of the Boundary Fire burn was dominated by the first split in the tree, with a slope greater than 11.5%. In areas with less extreme topography it is likely that more of the nodes would be apparent in the model of depth reduction. In terms of relative depth reduction, the areas with the shallowest burn depth (the first node) are those in flat lowland areas. In the Boundary Fire, very little of the area burned is characterized as flat lowland, and therefore the area with a burn depth of 0.32 is small. Instead, aspect (the second node) is a dominant factor in determining relative depth reduction, given the dramatic relief of the burned area.

The post-fire organic layer depth results from the interaction of the disturbance event (the mechanisms by which organic layer depth reduction occurs) with the context of the disturbance (the constraints on organic layer depth reduction). For this reason, deeper organic layers in flat lowland areas and non-south-facing slopes are less vulnerable to severe depletion and the subsequent post-fire successional shifts. Within the Boundary Fire perimeter, the areas most vulnerable to reduction were south-facing backslopes which are typically well-drained and fuels may become very dry due to greater

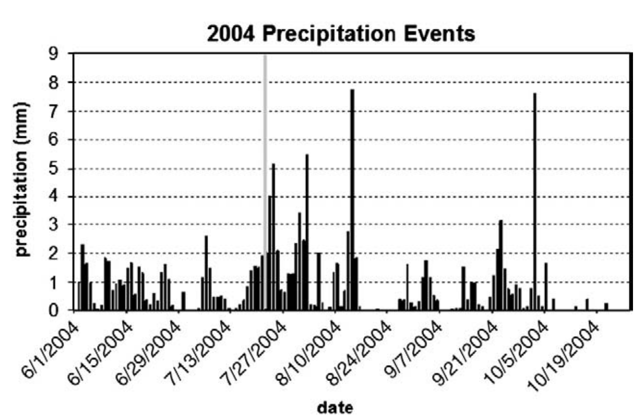

Fig. 6. Mean precipitation across all weather stations in the study area for 2004. Precipitation from 1 June to 20 July, identified as the grey bar, 40 mm compared with 60 mm in the following 50 day period.

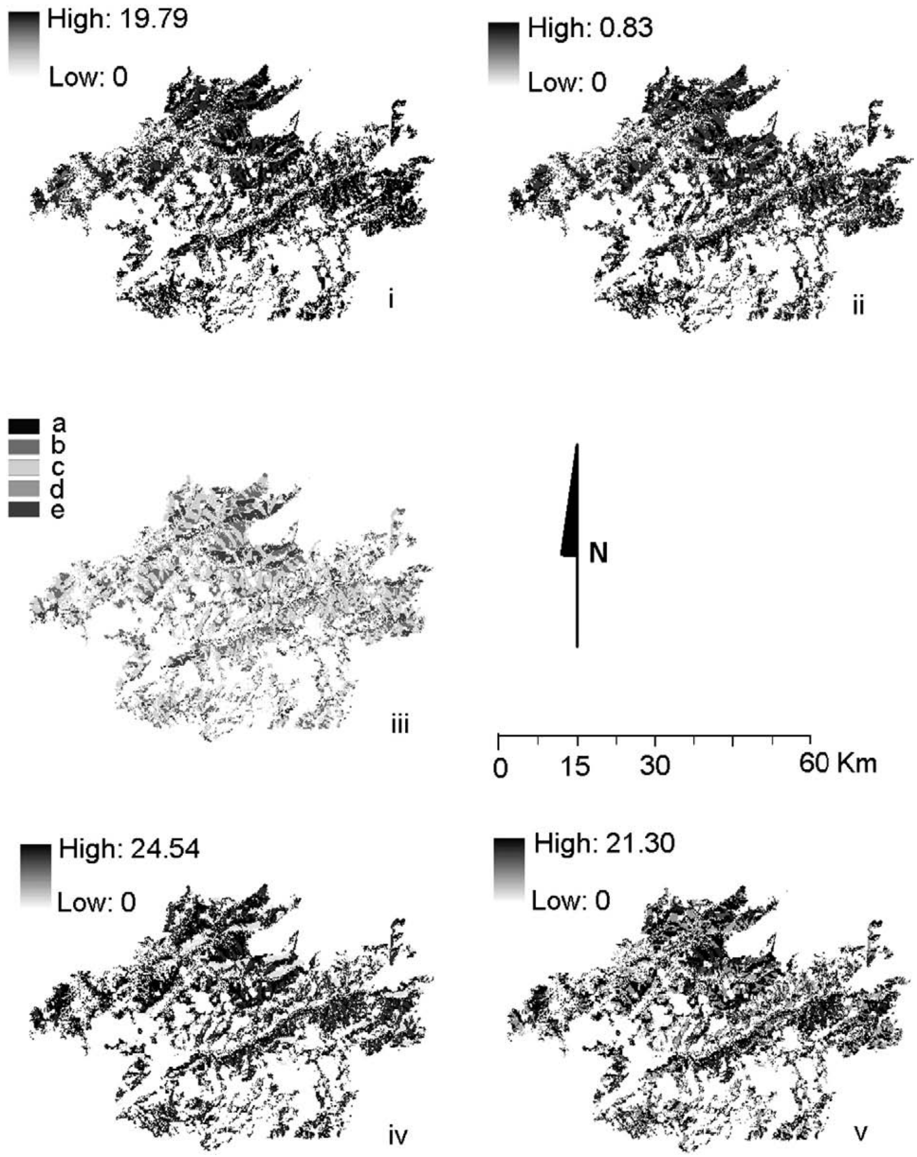

Fig. 7. Maps of the Boundary Fire: (i) modeled absolute depth reduction; (ii) relative depth reduction; (iii) topographic positions: (a) flat lowland, (b) north-facing slope, (c) east and west facing slope, (d) flat upland, (e) south-facing slope; (iv) modeled post-fire organic layer depth based on absolute reduction model; and (v) modeled post-fire organic layer depth based on relative reduction model.

insolation than other topographic positions, as well as the fact that these sites typically have deeper active layers than other topographic positions (Kane et al., 2007). In burned areas with significant topographic variability, particularly those areas with a large area of south-facing slopes, the post-fire organic layer depth reduction could significantly alter successional patterns if predicted climate changes lead to an increase in fire severity and shorter fire return interval.

5. Conclusions

Previous studies estimating fire severity using satellite spectral indices alone produced inconsistent results for the Alaskan boreal forest region. The results from our study show that the potential for using satellite remote sensing data for mapping fire severity is greatly improved when other geospatial data are used as well.

The regression tree model output was useful in determining which independent variables were most important in determining burn depth, but had lower predictive ability than the gradient boosting method. An unanticipated feature of the regression tree output was that the splitting process reflected the spatial scale at which the independent variables operate. Topography, the broadest impact was selected close to the root of the regression tree, factors related to soil and post-fire succession were selected in the intermediate stages, and local fire-related weather indices appear close to the terminal nodes.

While gradient boosting appears to be an effective method at predicting burn depth, there are a few caveats. The factors that influence burn depth in a large fire year versus a small fire year may be very different, and the application of the model derived from this data are assumed to be applicable in 2004 only. This is reflected in the fact that later burning fires in the region did not burn as deeply because of mid-season precipitation. Because this is not typical of burn season weather conditions, the regression tree model may prove insufficient to characterize burn depth even for other large fire years.

Future plans for work include applying the same techniques to small fire years to compare the differences with 2004. Extending the analysis using the same techniques to look at burn depth at a regional scale could yield further insights to the spatial pattern of fire regime characteristics in the region. In the absence of constraints on the number of observations for which remote sensing and *in situ* data are available, it would be interesting to divide the dataset into early season and late season fires to see if the independent variables chosen by the regression tree algorithm are similar.

The ability to model specific characteristics of fire severity, such as the reduction of the surface organic layer depth, is instrumental in predicting ecosystem responses to fire. It is important to be explicit about the severity characteristic of interest, as few general severity indices (such as the NBR family) included in the analysis correlate with more than one or two field observed variables. This study highlights the importance of incorporating data from remote sensing and *in situ* observations, as well as exploring the application of non-parametric techniques including machine learning algorithms.

Acknowledgements

The research presented in this manuscript was supported by the U.S. Geological Survey by a Mendenhall Fellowship to K.B. Support was provided to E.K. through grants from the National Aeronautics and Space Administration (Grant numbers NNG04GD25G and NNX06AF85G) and the Bonanza Creek Long-Term Ecological Research program (USFS grant number PNW01-JV11261952-231 and NSF grant number DEB-0080609).

References

ACIA. (2004). *Impacts of a warming Arctic.* Cambridge: Cambridge University Press.

Allen, J., & Sorbel, B. (2008). Assessing the differenced Normalized Burn Ratio's ability to map burn severity in the boreal forest and tundra ecosystems of Alaska's national parks. *International Journal of Wildland Fire*, *17*, 463−475.

Amiro, B. D., Cantin, A., Flannigan, M. D., & de Groot, W. J. (2009). Future emissions from Canadian boreal forest fires. *Canadian Journal of Forest Research*, *39*, 383−395.

Balshi, M. S., McGuire, A. D., Zhuang, Q., Melillo, J., Kicklighter, D., Kasischke, E., et al. (2007). The role of historical fire disturbance in the carbon dynamics of the pan-boreal region: A process-based analysis. *Journal of Geophysical Research, Biogeosciences*, *112*, G02029. doi:10.1029/2006JG000380.

Beget, J. E., Stone, D., & Verbyla, D. L. (2006). *Regional overview of interior Alaska.* Alaska's changing boreal forest. New York: Oxford University Press.

Breiman, L. (1996). Bagging procedures. *Machine Learning*, *24*, 123−140.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees.* Belmont, CA: Wadsworth International Group.

Burn, C. R., & Smith, C. A. S. (1988). Observations of the "thermal offset" in near-surface mean annual ground temper-atures at several sites near Mayo, Yukon Territory, Canada. *Arctic*, *41*, 99−104.

Chambers, S. D., & Chapin, F. S., III (2003). Fire effects on surface-atmosphere energy exchange in Alaskan black spruce ecosystems: Implications for feedbacks to regional climate. *Journal of Geophysical Research*, *108*, 8145.

Chapin, F. S., III, Hollingsworth, T. N., Murray, D. F., Viereck, L. A., & Walker, M. D. (2006). Floristic diversity and vegetation distribution in the Alaskan boreal forest. In F. S. ChapinIII, M. W. Oswood, K. Van Cleve, L. A. Viereck, & D. L. Verbyla (Eds.), *Alaska's changing boreal forest*. New York: Oxford University Press.

Chapin, F. S., III, Randerson, J. T., McGuire, A. D., Foley, J. A., & Field, C. B. (2008). Changing feedbacks in the climate–biosphere system. *Frontiers in Ecology and the Environment*, *6*, 313−320.

DeFries, R. S., & Chan, J. C. W. (2000). Multiple criteria for evaluating machine learning algorithms for land cover classification from satellite data. *Remote Sensing of Environment*, *37*, 35−46.

Díaz-Delgado, R., Lloret, F., & Pons, X. (2003). Influence of fire severity on plant regeneration by means of remote sensing imagery. *International Journal of Remote Sensing*, *24*, 1751−1763.

Duffy, P. A., Epting, J., Graham, J. M., Rupp, T. S., & McGuire, A. D. (2007). Analysis of Alaskan burn severity patterns using remotely sensed data. *International Journal of Wildland Fire*, *16*, 277−284.

Duffy, P. A., Walsh, J. E., Graham, J. M., Mann, D. H., & Rupp, T. S. (2005). Impacts of large-scale atmospheric-ocean variability on Alaskan fire season. *Ecological Applications*, *15*, 1317−1330.

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z., Quayle, B., & Howard, S. (2007). A project for monitoring trends in burn severity. *Fire Ecology*, *3*, 3−21.

Ekstrand, S. (1996). Landsat TM-based forest damage assessment: Correction for topographic effects. *Photogrammetric Engineering and Remote Sensing*, *62*, 151−162.

Epting, J., Verbyla, D., & 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., & Stocks, B. J. (2005). Future area burned in Canada. *Climate Change*, *72*, 1−16.

Franklin, J. (1998). Predicting the distribution of shrub species in southern California from climate and terrain-derived variables. *Journal of Vegetation Science*, *9*, 733−748.

French, N. H. F., Kasischke, E. S., Hall, R. J., Murphy, K. A., Verbyla, D. L., Hoy, E. H., et al. (2008). Using Landsat data to assess fire and burn severity in the North American boreal forest region: An overview and summary of results. *International Journal of Wildland Fire*, *17*, 443−462.

Freund, Y., & Schapire, R. E. (1999). A short introduction to boosting. *Journal of Japanese Society for Artificial Intelligence*, *14*, 771−780.

Gillett, N. P., Weaver, A. J., Zwiers, F. W., & Flannigan, M. D. (2004). Detecting the effect of climate change on Canadian forest fires. *Geophysical Research Letters*, *31*, L18211. doi:10.1029/2004GL020876.

Gleixner, G., Czimczik, C., Kramer, C., Luhker, B. M., & Schmidt, M. W. I. (2001). Plant compounds and their turnover and stability as soil organic matter. In E. D. Schulze (Ed.), *Global biogeochemical cycles in the climate system* (pp. 201−213). London, UK: Academic.

Greene, D. F., Noël, J., Bergeron, Y., Rousseau, M., & Gauthier, S. (2004). Recruitment of *Picea mariana*, *Pinus banksiana*, and *Populus tremuloides* across a burn severity gradient following wildfire in the southern boreal forest of Quebec. *Canadian Journal of Forestry Research*, *34*, 1845−1857.

Hansen, M. C., DeFries, R. S., Townshend, J. R. G., & Sohlberg, R. (2000). Global land cover classification at 1 km resolution using a decision tree classifier. *International Journal of Remote Sensing*, *21*, 1331−1365.

Hansen, M. C., Roy, D. P., Lindquist, E., Adusei, B., Justice, C. O., & Altstatt, A. (2008). A method for integrating MODIS and Landsat data for systematic monitoring of forest cover and change in the Congo Basin. *Remote Sensing of Environment*, *112*, 2495−2513.

Harden, J. W., Manies, K. L., Neff, J. C., & Turetsky, M. R. (2006). Effects of wildfire and permafrost on soil organic matter and soil climate in interior Alaska. *Global Change Biology*, *12*, 2391−2403.

Harden, J. W., Neff, J. C., Sandberg, D. V., Turetsky, M. R., Ottmar, R., Gleixner, G., et al. (2004). Chemistry of burning the forest floor during the FROSTFIRE experimental burn, interior Alaska, 1999. *Global Biogeochemical Cycles*, *18*, GB3014. doi:10.1029/2003GB002194.

Harden, J. W., O'Neill, K. P., Trumbore, S. E., Veldhuis, H., & Stocks, B. J. (1997). Moss and soil contributions to the annual net carbon flux of a maturing boreal forest. *Journal of Geophysical Research*, *102*, 28,805−28,816.

Hothorn, T. and Bühlmann, P., 2007. Mboost: Model-based boosting. R package version 0.5-8. Available at http://CRAN.R-project.org/.

Hoy, E. E., French, N. H., Turetsky, M. R., Trigg, S. N., & Kasischke, E. S. (2008). Evaluating the potential of Landsat TM/ETM+imagery for assessing fire severity in Alaskan black spruce forests. *International Journal of Wildland Fire*, *17*, 500−514.

Im, J., & Jensen, J. R. (2005). A change detection model based on neighborhood correlation image analysis and decision tree classification. *Remote Sensing of Environment*, *99*, 326−340.

Im, J., Jensen, J. R., & Tullis, J. A. (2008). Object-based change detection using correlation image analysis and image segmentation. *International Journal of Remote Sensing*, *29*, 399−423.

Johnstone, J. F., & Chapin, F. S., III (2006). Effects of soil burn severity on post-fire tree recruitment in boreal forest. *Ecosystems*, *9*, 14−31.

Johnstone, J. F., & 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.

Johnstone, J. F., Hollingsworth, T. N., Chapin, F. S., III, & Mack, M. C. (2009). Changes in fire regime break the legacy lock on successional trajectories in Alaskan boreal forest. *Global Change Biology*. doi:10.1111/j.1365-2486.2009.02051.x.

Kane, E. S., Kasischke, E. S., Valentine, D. W., Turetsky, M. R., & McGuire, A. D. (2007). Topographic influences on wildfire consumption of soil organic carbon in black spruce forests of interior Alaska: Implications for black carbon accumulation. *Journal of Geophysical Research*, *112*, G03017. doi:10.1029/2007JG000458.

Kane, E. S., Valentine, D. W., Schuur, E. A. G., & 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., & Johnstone, J. F. (2005). Variation in post-fire organic layer thickness in a black spruce forest complex in interior Alaska and its effects on soil temperature and moisture. *Canadian Journal of Forestry Research*, *35*, 2164−2177.

Kasischke, E. S., & Turetsky, M. R. (2006). Recent changes in the fire regime across the North American borealregion — Spatial and temporal patterns of burning across Canada and Alaska. *Geophysical Research Letters*, *33*, L09703.

Kasischke, E. S., Christensen, N. L., Jr., & Stocks, B. J. (1995). Fire, global warming, and the carbon balance of boreal forests. *Ecological Applications*, *5*, 437−451.

Kasischke, E. S., O'Neill, K. P., French, N. H. F., & Bourgeau-Chavez, L. L. (2000). Controls on patterns of biomass burning in Alaskan boreal forests. In E. S. Kasischke, & B. J. Stocks (Eds.), *Fire, climate change, and carbon cycling in the North American boreal forest.* New York: Springer-Verlag.

Kasischke, E. S., Turetsky, M. R., Ottmar, R. D., French, N. H. F., Hoy, E. E., & Kane, E. S. (2008). Evaluation of the composite burn index for assessing fire severity in Alaskan black spruce forests. *International Journal of Wildland Fire*, *17*, 515−526.

Kasischke, E. S., Williams, D., & Barry, D. (2002). Analysis of the patterns of large fires in the boreal forest region of Alaska. *International Journal of Wildland Fire*, *11*, 131−144.

Kauth, R. J., & Thomas, G. S. (1976). The tasseled cap — A graphic description of the spectral temporal development of agricultural crops as seen by Landsat. *Proceedings of the symposium on machine processing of remotely sensed data, Purdue University, West Lafayette, Indiana*.

Key, C. H., & Benson, N. C. (1999). *The Normalized Burn Ratio, a Landsat TM radiometric index of burn severity incorporating multi-temporal differencing.* http://www.nrmsc.usgs.gov/research/ndbr.htm.

Key, C. H., & Benson, N. C. (2006). *Landscape analysis (LA) sampling and analysis methods.* U.S.D.A. Forest Service.

Kurz, W. A., Stinson, G., Rampley, G. J., Dymond, C. C., & Neilson, E. T. (2007). Risk of natural disturbances makes future contribution of Canada's forests to the global carbon cycle highly uncertain. *PNAS*, *105*, 1551−1555.

Landmann, T. (2003). Characterizing sub-pixel Landsat ETM+ fire severity on experimental fires in the Kruger National Park, South Africa. *South African Journal of Science*, *99*, 357−360.
Lawrence, R., Bunn, A., Powell, S., & Zambon, M. (2004). Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment*, *90*, 331−336.
Lentile, L. B., Holden, Z. A., Smith, A. M. S., Falkowski, M. J., Hudak, A. T., Morgan, P., et al. (2006). Remote sensing techniques to assess active fire characteristics and post-fire effects. *International Journal of Wildland Fire*, *15*, 319−345.
Liu, K., Li, X., Shi, X., & Wang, S. (2008). Object-based change detection using correlation image analysis and image segmentation. *Wetlands*, *28*, 336−346.
Lloyd, A. H., Edwards, M. E., Finney, B. P., Lynch, J. A., Barber, V., & Bigelow, N. H. (2006). Holocene development of the Alaskan boreal forest. In F. S. ChapinIII, M. W. Oswood, K. Van Cleve, L. A. Viereck, & D. L. Verbyla (Eds.), *Alaska's changing boreal forest*. New York: Oxford University Press.
Lopez-Garcia, M. J., & Caselles, V. (1991). Mapping burns and natural reforestation using Thematic Mapper data. *Geocarto International*, *6*, 31−37.
Lynch, J. A., Clark, J. S., Bigelow, N. H., Edwards, M. E., & Finney, B. P. (2002). Geographic and temporal variations in fire history in boreal ecosystems of Alaska. *Journal of Geophysical Research*, *108* Article no. 8152.
Lynch, H. J., Renkin, R. A., Crabtree, R. L., & Moorcroft, P. R. (2006). The influence of previous mountain pine beetle (*Dendroctonus ponderosae*) activity on the 1988 Yellowstone fires. *Ecosystems*, *9*, 1318−1327.
Miller, J. D., & 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*, *109*, 66−80.
Murphy, K. A., Reynolds, J. H., & Koltun, J. M. (2008). Evaluating the ability of the differenced Normalized Burn Ratio (dNBR) to predict ecologically significant burn severity in Alaskan boreal forests. *International Journal of Wildland Fire*, *17*, 490−499.
Natcher, D. C., Calef, M., Huntington, O., Trainor, S., Huntington, H. P., DeWilde, L., et al. (2007). Factors contributing to the cultural and spatial variability of landscape burning by native peoples of interior Alaska.*Ecology and Society*, *12* article no. 7.
Nelson, J. L., Zavaleta, E. S., & Chapin, F. S., III (2008). Boreal fire effects on subsistence resources in Alaska and adjacent Canada. *Ecosystems*, *11*, 156−171.
O'Donnell, J. A., Turetsky, M. R., Harden, J. W., Manies, K. L., Pruett, L. E., Shetler, G., et al. (2009). Interactive effects of fire, soil, climate, and moss on CO_2. *Ecosystems*. doi:10.1007/s10021-008-9206-4.
Randerson, J. T., Liu, H., Flanner, M. G., Chambers, S. D., Jin, Y., Hess, P. G., et al. (2006). The impact of boreal forest fire on climate warming. *Science*, *314*, 1030−1132.
Robinson, J. M. (1991). Fire from space: Global fire evaluation using infrared remote sensing. *International Journal of Remote Sensing*, *12*, 3−24.
Rogan, J., & Franklin, J. (2001). Mapping wildfire burn severity in southern California forests and shrublands using enhanced Thematic Mapper imagery. *Geocarto International*, *16*, 91−106.
Rogan, J., & Miller, J. (2006). Integrating GIS and remotely sensed data for mapping forest disturbance and change. In M. A. Wulder, & S. E. Franklin (Eds.), *Understanding forest disturbance and spatial pattern*. CRC Press.
Rogan, J., Franklin, J., & Roberts, D. A. (2002). A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. *Remote Sensing of Environment*, *80*, 143−156.
Rogan, J., Miller, J., Stow, D., Franklin, J., Levien, L., & Fisher, C. (2003). Land-cover change monitoring with classification trees using Landsat TM and ancillary data. *Photogrammetric Engineering & Remote Sensing*, *69*, 793−804.
Running, S. W. (2008). Ecosystem disturbance, carbon, and climate. *Science*, *321*, 652−653.
Rupp, T. S., Chen, X., & Olson, M. (2007). Sensitivity of simulated boreal fire dynamics to uncertainties in climate drivers. *Earth Interactions*, *11*, 1−21.
Rupp, T. S., Olson, M., Adams, L. G., Dale, B. W., Joly, K., Henkelman, J., et al. (2006). Simulating the influences of various fire regimes on caribou winter habitat. *Ecological Applications*, *16*, 1730−1743.
Shetler, G., Turetsky, M. R., Kane, E. S., & Kasischke, E. S. (2008). Sphagnum mossess control ground-layer fuel consumption during fire in Alaskan black spruce forests: Implications for long-term carbon storage. *Canadian Journal of Forestry Research*, *38*, 2328−2336.
Skinner, W. R., Stocks, B. J., Martell, D. L., Bonsal, B., & Shabbar, A. (1999). The association between circulation anomalies in the mid-troposphere and area burned by wildland fire in Canada. *Theoretical and Applied Climatology*, *63*, 89−105.
Skinner, W. R., Shabar, A., Flannigan, M. D., & Logan, K. (2006). Large forest fires in Canada and the relationship to global sea surface temperatures. *Journal of Geophysical Research*, *111*, D14106.
Smith, A. M. S., & Hudak, A. T. (2005). Estimating combustion of large downed woody debris from residual white ash. *International Journal of Wildland Fire*, *14*, 245−248.
Smith, A. M. S., Wooster, M. J., Drake, N. A., Dipotso, F. M., Falkowski, M. J., & Hudak, A. T. (2005). Testing the potential of multi-spectral remote sensing for retrospectively estimating fire severity in African Savannahs. *Remote Sensing of Environment*, *97*, 92−115.
Stocks, B. J., Fosberg, M. A., Lynham, T. J., Mearns, L., Wotton, B. M., Yang, Q., et al. (1998). Climate change and forest fire potential in Russian and Canadian boreal forests. *Climatic Change*, *38*, 1−13.
Stronach, N. R. H., & McNaughton, S. J. (1989). Grassland fire dynamics in the Serengeti ecosystem, and a potential method of retrospectively estimating fire energy. *Journal of Applied Ecology*, *26*, 1025−1033.
Therneau, T. M., & Atkinson, B. (2010). *The rpart package.* http://www.cran.r-project.org/doc/packages/rpart.pdf.
Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, *8*, 127−150.
Turetsky, M.R., Kane, E.S., Harden, J.W., Ottmar, R.D., Manies, K.L., & Kasischke, E.S. (in review). More severe burning and accelerated carbon losses due to a changing boreal fire regime, *Nature*.
Turner, M. G. (2005). Landscape ecology: What is the state of the science? *Annual Review of Ecology, Evolution and Systematics*, *36*, 319−344.
Turner, M. G., Romme, W. H., & Gardner, R. H. (1999). Prefire heterogeneity, fire severity, and early postfire plant reestablishment in subalpine forests of Yellowstone National Park, Wyoming. *International Journal of Wildland Fire*, *9*, 21−36.
Turner, M. G., Romme, W. H., & Tinker, D. B. (2003). Surprises and lessons from the 1988 Yellowstone fires. *Frontiers in Ecology and the Environment*, *1*, 351−358.
Van Wagner, C. E. (1987). *Development and structure of the Canadian forest fire weather index system* (pp. 37). Ottawa: Canadian Forest Service.
Verbyla, D., & Lord, R. (2008). Estimating post-fire organic soil depth in the Alaskan boreal forest using the Normalized Burn Ratio. *International Journal of Remote Sensing*, *29*, 3845−3853.
Viereck, L. A. (1983). The effects of fire in black spruce ecosystems of Alaska and northern Canada. In R. W. Wein, & D. A. MacLean (Eds.), *The role of fire in northern circumpolar ecosystems* (pp. 201−220). Chichester: John Wiley & Sons.
Yi, S., McGuire, A. D., Harden, J., Kasischke, E., Manies, K., Hinzman, L., et al. (2009). Interactions between soil, thermal and hydrological dynamics in the response of Alaska ecosystems to fire disturbance. *Journal of Geophysical Research*, *114*, G02015. doi:10.1029/2008JG000841.
Yoshikawa, K., Bolton, W. R., Romanovsky, V., Fukuda, M., & Hinzman, L. D. (2002). Impacts of wildfire on the permafrost in the boreal forests of interior Alaska. *Journal of Geophysical Research*, *107*(D1), 8148. doi:10.1029/2001JD000438.
Zasada, J. C., Norum, R. A., Van Veldhuizen, R. M., & Teutsch, C. E. (1983). Artificial regeneration of trees and shrubs in experimentally burned upland black spruce/feathermoss stands in Alaska. *Canadian Journal of Forest Research*, *13*, 903−913.
Zhuang, Q., McGuire, A. D., O'Neill, K. P., Harden, J. W., Romanovsky, V. E., & Yarie, J. (2002). Modeling soil thermal and carbon dynamics of a fire chronosequence in interior Alaska. *Journal of Geophysical Research*, *108*, 8147. doi:10.1029/2001JD001244.