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Static and dynamic controls on fire activity at moderate spatial and temporal scales in the Alaskan boreal forest

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Abstract. Wildfire, a dominant disturbance in boreal forests, is highly variable in occurrence and behavior at multiple spatiotemporal scales. New data sets provide more detailed spatial and temporal observations of active fires and the post-burn environment in Alaska. In this study, we employ some of these new data to analyze variations in fire activity by developing three explanatory models to examine the occurrence of (1) seasonal periods of elevated fire activity using the number of MODIS active fire detections data set (MCD14DL) within an 11-day moving window, (2) unburned patches within a burned area using the Monitoring Trends in Burn Severity fire severity product, and (3) short-to-moderate interval (<60 yr) fires using areas of burned area overlap in the Alaska Large Fire Database. Explanatory variables for these three models included dynamic variables that can change over the course of the fire season, such as weather and burn date, as well as static variables that remain constant over a fire season, such as topography, drainage, vegetation cover, and fire history. We found that seasonal periods of high fire activity are associated with both seasonal timing and aggregated weather conditions, as well as the landscape composition of areas that are burning. Important static inputs to the model of seasonal fire activity indicate that when fire weather conditions are suitable, areas that typically resist fire (e.g., deciduous stands) may become more vulnerable to burning and therefore less effective as fire breaks. The occurrence of short-to-moderate interval fires appears to be primarily driven by weather conditions, as these were the only relevant explanatory variables in the model. The unique importance of weather in explaining short-to-moderate interval fires implies that fire return intervals (FRIs) will be sensitive to projected climate changes in the region. Unburned patches occur most often in younger stands, which may be related to a greater deciduous fraction of vegetation as well as lower fuel loads compared with mature stands. The fraction of unburned patches may therefore increase in response to decreasing FRIs and increased deciduousness in the region, or these may decrease if fire weather conditions become more severe.

Key words: Alaska; boreal; remote sensing; scale; wildfire.

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Introduction

The boreal forest ecosystem is largely shaped by fire activity that is highly variable at multiple spatiotemporal scales. It is important to study the factors that control the spatial and temporal distribution of fire in order to understand the consequences for combustion emissions and post-fire

Table 1. Boreal fire regime characteristics and measurement approaches.

Fire regime characteristics	What is measured	Measurement approaches	Examples
Annual area burned	How much area is burned on an annual basis, for a specific region	Large fire databases, fire statistics, satellite imagery	Duffy et al. (2005), Balshi et al. (2007), Martell and Sun (2008), Parisien et al. (2011*a*)
Long-term fire frequency	How often fires occur in a specific region or site	Paleo data, dendroecological data	MacDonald et al. (1991), Carcaillet et al. (2001), Heyerdahl et al. (2001), Lynch et al. (2003, 2004), Lloyd et al. (2006), Higuera et al. (2009)
Fire return intervals	Susceptibility of the landscape to repeat burning	Large fire databases, satellite imagery, dendroecological data	Romme and Despain (1989), Larsen (1997), Bergeron (2000), Bergeron et al. (2004), Cyr et al. (2007)
Fire seasonality	The seasonal patterns of fire activity	Fire reports, satellite imagery	Abatzoglou and Kolden (2011), Barrett and Kasischke (2013)
Fire occurrence	Where fire occurs on the landscape (i.e., fire suitability or risk)	Large fire databases, satellite imagery	Drever et al. (2008), Parisien and Moritz (2009), Parisien et al. (2011*b*)
Fire size	How large are fires in a specific region	Large fire databases, satellite imagery	Beverly and Martell (2005), Hély et al. (2010)
Unburned patches within burn perimeters	Size and/or area of unburned patch within a burn perimeter	Satellite imagery	Kasischke and Hoy (2012), Kolden et al. (2012), Hoy (2014)
Ignitions	The potential for boreal fires to start	Ground-based lightning strike observation networks, distance to roads or towns	Nash and Johnson (1996), DeWilde and Chapin (2006), Krawchuk et al. (2006), Peterson et al. (2010)
Fire behavior	Rate of spread, head fire intensity, front length, smoldering vs. flaming combustion	Modeled behavior, direct observation, active fire detections from satellite imagery	Bessie and Johnson (1995), Hély et al. (2001), Ryan (2002)
Fire severity	Consumption of surface organic layers, above-ground live vegetation, percentage mortality, crown fire severity	Satellite imagery and ancillary geospatial data, ground-based observation	Arseneault (2001), Boby et al. (2010), Barrett et al. (2011), Turetsky et al. (2011)
Fire intensity	The amount of energy released by active fires	Direct observation, satellite data	Wooster and Zhang (2004), Ichoku et al. (2008), Kaiser et al. (2012), Barrett and Kasischke (2013)

ecosystem recovery, as well as impacts on ecosystem services and on society. Boreal fire regime characteristics have been studied using a variety of approaches to measuring fires and post-fire environments (Table 1). Such research in the Alaskan boreal forest has highlighted the role of vegetation type and the amount of fuels available for combustion, climate/weather conditions, and topography/drainage characteristics that promote or retard the progress of burning across the landscape (Abatzoglou and Kolden 2011, Kasischke and Hoy 2012). Quantifying the relative importance of these factors is critical to improving our understanding of how climate change influences fire regimes both directly through changing temperature and precipitation regimes and indirectly through vegetation and soil changes and permafrost degradation. The debate regarding fuels vs. climate/weather can be expanded to explore the role of temporal and spatial scale of factors that influence fire behavior and burn patterns.

There are two categories of explanatory variables that control the amount and distribution of fire across the landscape: (1) dynamic factors related to weather and soil moisture conditions (which vary over the course of the fire season and in turn control fuel moisture and fire behavior) and (2) static factors such as site drainage, vegetation composition, and topography. The dynamic and static variables that affect the occurrence of wildfire have received considerable research attention (Harden et al. 2001, Duffy et al. 2007, Krawchuk et al. 2009). Weather conditions at the time of the fire are an important set of variables that regulate fuel conditions and the initiation and spread of fires, whereas the vegetation composition, site drainage conditions, and topographic position constitute the context in which the disturbance occurs (O'Neill 1986, Turner et al. 2001, Barrett et al. 2011). The importance of various explanatory variables of fire risk and burned area has not been consistent across scales (Parisien et al. 2011*a*), although the primary drivers have been found to be a mix of dynamic and static inputs (Parisien and Moritz 2009). Some studies suggest that at longer temporal scales available from the paleo data record, climate is the driving factor in boreal fire disturbance (Carcaillet et al. 2001), while others have found vegetation type to be more important (Lloyd et al. 2006, Higuera et al. 2009). At finer temporal scales (e.g., interannual variability), the amount of fuel available for combustion may limit fire activity until late-successional stands dominate, at which point weather conditions and fire suppression become important (Romme and Despain 1989). The relative importance of drivers may also be ecosystem dependent (Parisien and Moritz 2009, Krawchuk and Moritz 2011).

While many landscape parameters controlling fire activity are likely to be affected by projected climate change, the state of the Alaskan boreal forest over the next 50–100 yr will be largely determined by either the immediate climate response of dynamic drivers or a lagged response of some static controls (Genet et al. 2013). This study addresses dynamic and static conditions associated with seasonal fire activity, as well as the presence of unburned patches within a burn perimeter and areas of short-to-moderate fire interval.

Seasonal periods of high fire activity are important because much of boreal biomass burning occurs during such sporadic periods of high fire activity, when fires are likely to be more severe (Barrett and Kasischke 2013). It is important to understand when these periods occur to improve our ability to model wildfire activity levels at a seasonal scale. The conditions under which elevated periods of seasonal fire activity occur are important because of the potential relationship to depth of burn, particularly if more burning occurs when fires tend to be more severe (Turetsky et al. 2011).

Unburned areas within a burn perimeter can influence post-fire regeneration by preserving live vegetation (Madoui et al. 2010) and seed stocks (Greene and Johnson 1999), and are an important consideration when estimating emissions from wildfire and carbon uptake during regrowth. In Alaskan boreal fires, unburned areas typically account for 20% of the area within a burn perimeter (Kasischke and Hoy 2012). Unburned patches at a landscape scale form part of the mosaic of stand-age conditions and vegetation type that can promote or restrict the spread of fire. The elucidation of which factors lead to these patches will improve simulations of fire and vegetation dynamics. Areas that consistently resist fire will likely hinder fire progression, but if unburned patches are more strongly related to dynamic drivers such as weather, their occurrence may not affect future fires, or even promote them due to the buildup of fuels.

Short-to-moderate interval burns occur before a stand has reached reproductive maturity since the time of the last fire (Johnstone 2006). These typically occur as areas of overlap among burns and, similar to unburned areas, represent patches within a burned area of stand-age discontinuity. We used the overlap of fire polygons in the Alaska Large Fire Database (ALFD; Kasischke et al. 2002) to identify short-to-moderate interval fires (<60 yr since last fire). Such areas may be discontinuous with respect to vegetation type as early- to mid-successional stages are frequently deciduous dominated or codominant. Short interval fires in the boreal forest substantially reduce the amount of carbon stored in surface organic material (Brown and Johnstone 2011, Hoy 2014) and can result in post-fire shifts in vegetation type (Johnstone and Chapin 2006), reduced stocking density (Johnstone 2006), and even recruitment failure (Brown and Johnstone 2012).

The objective of this study was to determine the drivers of sub-annual and within-burn-perimeter disturbances to improve the ability to model interactions between climate and fire regime characteristics. In addition to the contribution of dynamic and static explanatory variables, we studied qualitative differences in large vs. small fire years and the effects of fire-promoting vs. fire-hindering variables. We expected that periods of elevated seasonal fire activity and short-to-moderate interval fires would occur in conditions "optimized" to burning (e.g., high temperature, low precipitation, coniferous vegetation, well-drained conditions), and unburned patches would occur in areas less vulnerable to fire (e.g., deciduous vegetation, poorly drained conditions).

Materials and Methods

Study area

The extent of the study area is the boreal forest within interior Alaska, defined by Nowacki et al. (2003), a total of about 500,000 km^2. The borders of this region generally follow the July 13°C isotherm, closely associated with the boreal biome (Larsen 1980). The Alaskan boreal forest is characterized by high-intensity crown fires with fire return intervals (FRIs) of about 160 yr, although these are decreasing due to increased fire activity over the past two decades (Kasischke et al. 2010). The Alaskan Interior is dominated by black spruce stands with an understorey of feather moss or Sphagnum, and underlain by patches of permafrost in flat, lowland areas (Van Cleve et al. 1983). Summers are typically short, soils are cool and moist, and decomposition rates are therefore low, leading to an accumulation of surface organic material that composes most of the fuel consumed during combustion (Kasischke and Hoy 2012). There is substantial variability in the amount of area burned each year in the boreal forest, and more frequent large fire years (defined as years during which greater than 1% of the area burns) have occurred the past decade than any preceding decade in the fire data record, beginning in 1950. Variability in weather conditions preceding and during a fire has been found to influence fire size and likelihood of fire spread (Abatzoglou and Kolden 2011, Podur and Wotton 2011).

Explanatory variables

Explanatory variables for all three models were related to fire seasonality, weather, vegetation type, topography, drainage, and previous fire history where available (Table 2). Day of burn is related to the thawing ground ice, which creates wet conditions earlier in the season and much drier conditions by the end of the summer when the aquatard has been removed. The depth of thaw can also limit how much of the surface organic material is available for combustion.

Intra-seasonal fire characteristics were computed using the date of burn, derived from a map of active fire detections, similar to the methods used by Billmire et al. (2014). Weather conditions preceding the burn were estimated from an inverse distance-weighted interpolated surface from the three closest weather stations. The temperature and relative humidity values were adjusted based on the adiabatic lapse rate, which was calculated daily based on all weather stations in the data set, a more robust estimate than implementing a constant rate (e.g., 10°C/km; Thornton et al. 1997). The weather data (temperature, relative humidity, wind speed, and precipitation) were used to calculate fire weather indices following the Canadian Forest Fire Danger Rating System methodology (Amiro et al. 2005) for each point. The weather and fire weather index data were calculated for the day of the burn and aggregated to (mean or cumulative) values 10 d prior and 30 d prior to the burn to account for lagged effects such as drying from persistently high wind speeds.

The vegetation at the time of the burn was derived from the 2001 National Land Cover Database (Homer et al. 2004) map. This represents that state of pre-burn vegetation relative to the study period. Topographic characteristics including slope, aspect, and water flow accumulation were derived from the National Elevation Dataset (Gesch et al. 2002). Water flow accumulation has been used to assess the degree of water flow across regions of differing elevations (Kasischke and Hoy 2012). Using the topographic and hydrologic data set, a drainage categorization was produced that included four categories: flat (<2° slope) with water flow accumulation, flat regions without water flow accumulation, sloped regions (≥2° slope) with water flow accumulation, and sloped regions without water flow accumulation. These categories capture the range of possible landscape positions within a site, from poorly drained stands with the potential for permafrost development (flat areas with water flow) to well-drained upland areas that would have little pooling water for permafrost development. Using these four categories, we were able to assess the influence of topography and hydrology on the fire patterns within a burned area.

Table 2. Explanatory variables used by the temporal model and two spatial models of wildfire disturbance.

Explanatory Variable	SA	SMI	UNB
Active fire characteristics (MODIS active fire detections)			
Julian date	XX	X	X
Fire Weather Indices (remote automated weather stations)			
Air temperature (day of burn, 10-day and 30-day mean)	XX	XX 30-day	XX 30-day
Relative humidity (day of burn, 10-day and 30-day mean)	XX	XX 30-day	XX 30-day
Precipitation (day of burn, 10-day and 30-day cumulative)	XX	XX 30-day	XX 30-day
Wind speed (day of burn, 10-day and 30-day mean)	XX	XX 30-day	XX 30-day
Fine fuel moisture code	XX	X	X
Duff moisture code	XX	X	X
Drought code	XX	X	X
Initial Spread Index	XX	X	X
Build Up Index	XX	X	X
Fire Weather Index	XX	X	X
Daily severity rating	XX	X	X
Topography (National Elevation Dataset)			
Slope	X	X	X
Fraction of north-facing slopes	X	X	X
Fraction of south-facing slopes	X	X	X
Fraction of east- or west-facing slopes	X	X	X
Fraction of flat lowland areas	X	X	X
Fraction of flat upland areas	X	X	X
Drainage			
Fraction of well drained	XX	X	X
Fraction of moderately drained	XX	X	X
Fraction of poorly drained	XX	X	X
Fuel Type (National Land Cover Database)			
Vegetation type		X	XX
Fraction of deciduous stands	X		
Fraction of conifer stands	X		
Fraction of mixed stands	X		
Fraction of Shrub Vegetation	X		
Stand characteristics (Alaska Large Fire Database)			
Stand age			XX
The number of previous burns			X

Notes: SA, seasonal activity; SMI, short-to-moderate interval; UNB, unburned patches. Some explanatory variables were removed from the final, parsimonious model to improve model performance. Those variables that were retained are indicated by (XX), followed by the aggregation level for weather data. Variables that were omitted from the parsimonious model are indicated by (X).

Previous fire history information, such as the number of previous burns, was obtained from the ALFD. Information regarding stand age and the number of previous burns was available only for areas that burned at least once after 1950 and before 2010. Stand age was calculated as the number of years since the last recorded fire.

Creation of random forest models

In this analysis, explanatory models of seasonal fire activity, short-to-moderate interval fires, and unburned patches were constructed using a random forest algorithm with both dynamic and static inputs (Table 2). Classification and regression trees (CARTs) are a powerful technique that can incorporate a broad range of data types without the assumptions that constrain traditional regression analysis (Breiman et al. 1984, Breiman 1994), such as normally distributed inputs or linear relationships between explanatory and response variables. An individual decision or regression tree can be useful in determining how inputs affect the dependent variable, but individual trees are not particularly robust. Random forests produce a more consistent characterization of the relationship between inputs and the dependent variable by creating hundreds of CARTs (Breiman 2001, Liaw and

Wiener 2002, Cutler et al. 2007) and determining the final output based on the "votes" cast by each model iteration.

Each independent tree in a random forest is created using a subset of all the observations with replacement to equal the number of observations in the whole data set. This form of bootstrap aggregation (bagging) is different from boosting in that there is no information from previous trees to help train the algorithm, which can lead to model overfitting (Diniz-Filho et al. 2008). Further randomization is introduced because the number of explanatory variables is also limited in each iteration to a subset of all available inputs, with the same number of inputs for every tree. The number of explanatory variables in each classification tree balances the tendency of too many inputs to increase the correlation between trees and too few inputs to reduce tree strength, both of which increase model errors. The relationship between explanatory and response variables in CART is univariate, so interactions between inputs are not explored in this analysis.

Each model in the analysis was simplified by removing inputs that did not improve explanatory power. If no variables of a given type (e.g., Julian date, fire weather, topography, drainage) were among the 10 most important variables, we attempted to run the model without any variables of the given type, and maintained the exclusion if model explanatory power was not reduced. The removal of extraneous variables often improved model performance, and minimizing the number of required inputs is helpful to those models of the interactions between vegetation and fire that become more computationally expensive as the number of explanatory variables increases.

The spatial models were based on a 1-km sampling grid, and 100 grid locations were randomly chosen in both unburned and burned areas (unburned patches [UNB] model), or short-to-moderate interval (SMI) and longer-interval fires (SMI model). In cases where there were fewer than 100 potential sample locations, all of the samples were maintained. This sampling method produced sample sizes that were independent of fire size, judged by the correlation between the number of samples per fire and the size of the burn ($r = 0.09$ and $r = 0.04$ for the UNB and SMI models, respectively). There were 137 burn perimeters and 41,942 points sampled in the UNB model, and there were 176 burn perimeters and 52,571 points used in the SMI model.

Seasonal activity model.—For the seasonal activity (SA) model, MODIS active fire detections (MCD14DL; Justice et al. 2002, Giglio et al. 2003) served as the sampling locations for input data sets. Detections from both Aqua and Terra satellites were used in the analysis, although the Aqua data record does not begin until mid-2002. The lack of Aqua detections for part of the first year of the analysis does not bias the analysis because we do not study the temporal trends in the number of detections.

Active fire detections were restricted to the period from May through September, and filtered to remove observations with low confidence (i.e., observations with confidence <30; see Giglio et al. 2003 for information regarding the calculation of detection confidence). A total of 585 d and 135,454 fire detections were included in the analysis. The response variable used in the analysis was the total count of active fire detections that occurred within an 11-day (date ± 5 d) moving window. We integrated over the 11-day period based on the observation that periods of elevated fire activity in the region tend to last for several days (Fig. 1). Omissions in the active fire detection database due to low fire intensity, persistent cloud cover, or thick smoke may lead to individual overpasses appearing to lack fire activity, so integration over a longer period results in a more stable characterization of intraseasonal fire activity.

SMI model.—The response variable in the SMI model is binary, and the model predicts whether or not holdout sample locations are in short-to-moderate interval burns. Areas of SMI were identified from overlapping polygons in the ALFD (Kasischke et al. 2002). Polygons of burned area between 2002 through 2010 were compared with previous burned area polygons as far back as 1950. The total area that burned in SMI fires between 2002 and 2010 was 18,236 km^2, or 24% of the total area burned in the region over the same period.

UNB model.—Similar to the SMI model, the response variable in the UNB model is binary, and the model predicts whether holdout samples are unburned patches. The UNB model was created using data from the MTBS project (Eidenshink et al. 2007). The qualitative maps

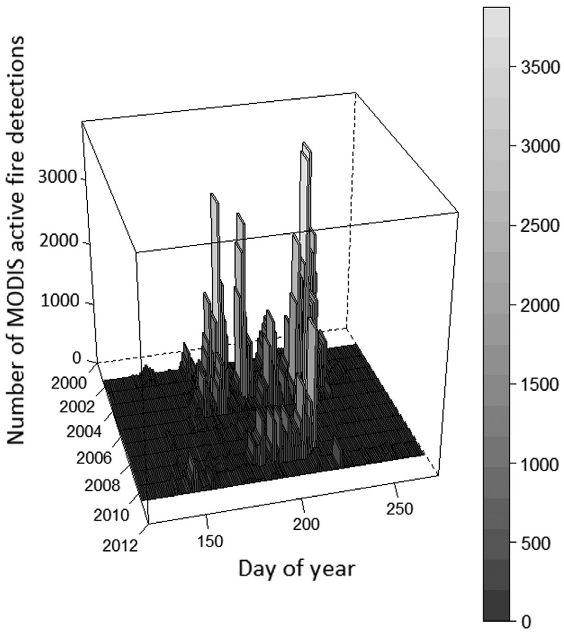

Fig. 1. MODIS active fire detections (MJJAS) from 2002 to 2010.

of burn severity from MTBS were used to differentiate between burned and unburned areas within burn perimeters from the period between 2002 and 2010, with a minimum patch size of 1 km^2. As in the model of SMI, the area of unburned patches was smaller than the area that burned, accounting for 18% of the burned area during the study period.

Explanatory model assessment

The classification tree model out of bag (OOB) error rate was used to assess overall model performance for the binary SMI and UNB models. The OOB error is calculated by comparing the model created in each iteration with the observations left out of the model (Breiman 2001). The number of times that the model misclassified an observation divided by the total number of iterations is the class OOB error, and these values are averaged to give the OOB error for the whole model. The continuous SA model was evaluated using the percentage of variance explained by the model, also calculated using the OOB error rate (Liaw and Wiener 2002). The importance of explanatory variables for all models was determined using the decrease in accuracy that occurs when an input is omitted from the analysis. The relationship with the response variable was assessed through the partial dependence on explanatory variables. Plots of partial dependence explain the effect of the explanatory variable (x-axis) on the model output (y-axis) when all other inputs are held constant. Initially, each model included every explanatory variable. Models were subsequently simplified to improve model performance by removing variables that increased model error, and to reduce the number of required inputs for a predictive model.

Results

We found that a mix of static and dynamic explanatory variables were generally important across the models, which are described below in greater detail. The full spatial models (SMI and UNB) were more similar to each other than the temporal model (SA), in that weather played a dominant role in SMI and UNB, whereas SA depended on a broader range of inputs.

Fifty percentage of the MODIS active fire detections in the Alaskan boreal forest occur during just 36 d of burning between 2002 and 2010, or 0.03% of the study period (May–September only; Fig. 1). The SA model explained 80.44% of the variability in 11-day active fire counts. The SMI model had an error rate of 11.63%, and the full UNB model had an error rate of 38.29%. More parsimonious models of SMI and UNB were created using only the most important classes of inputs to the full model, provided that there was no reduction in model accuracy (Table 2). Furthermore, parsimonious models were run separately with fire weather indices, daily weather, 10-day weather, and 30-day weather variables, to test the effect of different types of aggregation and both performed best with 30-day information. The model of UNB was also run just on those areas that burned multiple times since the start of the data record to assess the role of stand age and fire history on unburned patches. Errors of omission and commission were fairly evenly divided (commission error = 0.07, 0.42, omission error = 0.12, 0.29 for the parsimonious models of SMI and UNB, respectively). We mapped errors based on the predicted output for parsimonious models of UNB and SMI, neither of which exhibited a clear spatial pattern (Fig. 2).

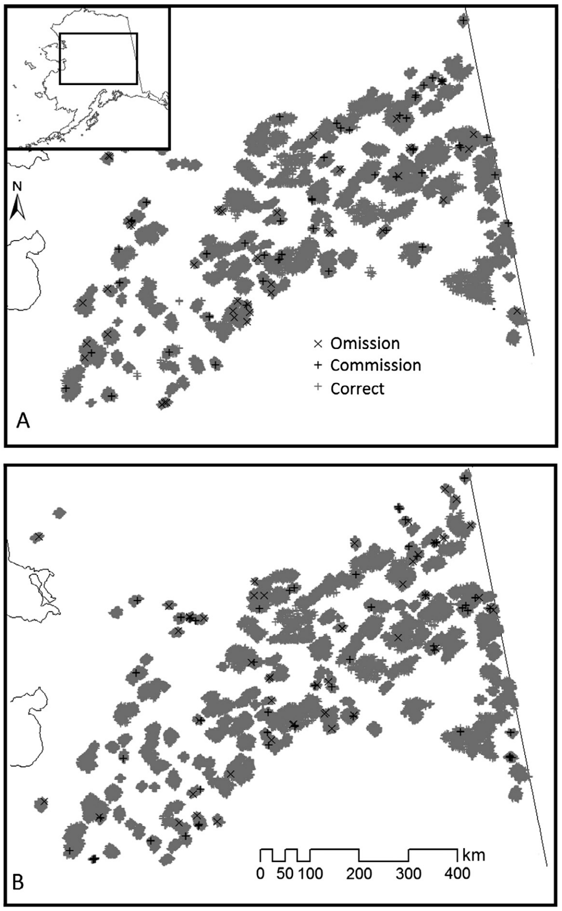

Fig. 2. (A) Spatial pattern of errors in the full model of (A) short-to-moderate interval fires (SMI) and (B) unburned enclosures (UNB).

Seasonal activity

The most important inputs to the SA model (Figs. 3, 4) were total precipitation 10 d prior to the burn (dynamic), the fraction of burning that occurred in areas of moderate drainage (static), the mean day of year (dynamic), and the fraction of burning in deciduous stands (static). Given the mix of input type (i.e., weather, drainage, seasonality, and vegetation type) among the most important explanatory variables, we did not attempt to reduce the number of model inputs for a parsimonious version of the SA model. The most important explanatory variables to SA were a mix of spatial and temporal factors for large fire years, but primarily weather-related factors in small fire years (Fig. 5). Interestingly, the seasonal pattern of active fire detections increased toward the end of the fire season in large fire years, whereas they decreased over the season during small fire years (Fig. 5).

Short-to-moderate interval fires

Land cover (static) was highly important to the SMI model (Fig. 6), more so than any other explanatory variable. The partial dependence plot for vegetation type (static; Fig. 7) showed that re-burns were most likely to occur in shrub and scrub vegetation. This is likely due primarily to the fact that shrubs represent younger, regenerating stands. For this reason, we excluded land cover type from the parsimonious SMI model, as its contribution was likely not due to its effect on re-burning, but the way that the class is defined (i.e., young stands are those that have burned most recently). The parsimonious SMI model (Fig. 8) had a lower error rate than that of the full model (11.30% vs. 11.63%). The most important inputs to SMI were then related to weather and the fire weather indices (dynamic).

In contrast to the SA model, SMI areas responded to weather conditions (dynamic) to the exclusion of other inputs. The SMI model was not strongly affected by information about large vs. small fire years, drainage, or topography (static) characteristics. Ultimately, the exact effect of weather conditions on short-to-moderate interval fires was unclear, as the partial dependence plots (Fig. 8) exhibit erratic relationships between weather conditions and SMI.

Unburned patches

Similar to the SMI model, land cover (static) was the most important model input to UNB (Fig. 9) followed by weather and fire indices (dynamic). Unburned patches were least likely to occur in coniferous forests; therefore, land cover (static) was maintained in the parsimonious model (Fig. 10). Stand age (static) was the most important explanatory variable in the model of areas with fire history information, followed by cumulative 30-day precipitation (dynamic), land cover (static), mean 30-day temperature, wind speed, and relative humidity (dynamic; Figs. 10, 11). The parsimonious model with information on fire history (static) had an error rate of 34.26%, an improvement on the full model, with an error rate of 38.29%.

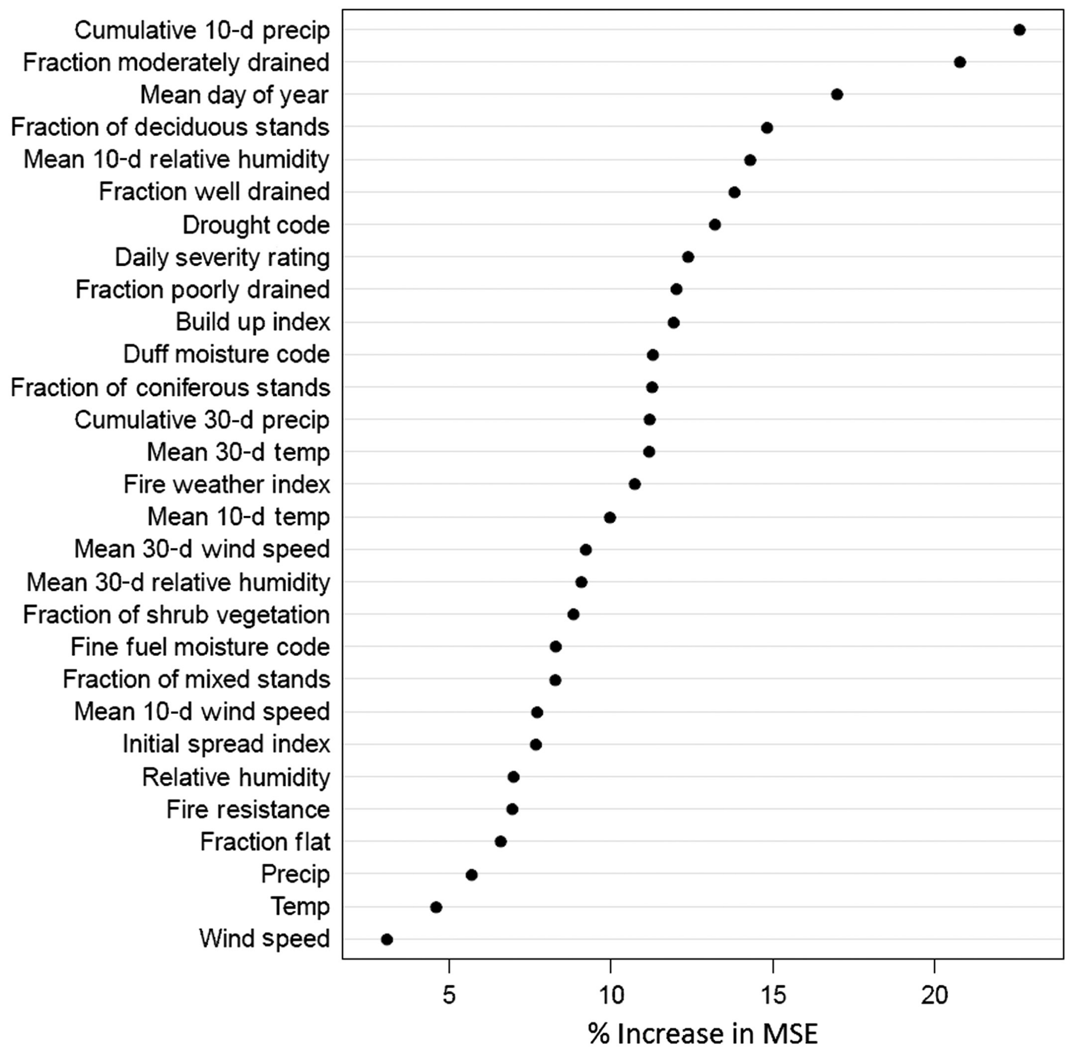

Fig. 3. Full model of seasonal fire activity (SA) variables listed in order of importance (greatest to least).

Discussion

The results of the analysis indicate that the contribution of static and dynamic inputs varies by model. Conditions that promote or hinder fire spread were not consistently associated with seasonal fire activity, short-to-moderate interval fires, or unburned patches. There is a qualitative difference between large and small fire years in terms of the seasonal pattern of fire activity. The findings for each explanatory model are discussed in detail below. The data and methods used in this analysis allow us to study more fine-grained variability in fire activity and burn patterns than have previously been studied in the Alaskan boreal forest (Table 1).

Static vs. dynamic explanatory variables

Our finding that a mix of static and dynamic inputs are important across the models of fire activity and spatial pattern is consistent with other studies that have studied the drivers of fire occurrence and annual area burned (Parisien and Moritz 2009, Parisien et al. 2011*a*). Static conditions related to drainage and land cover were highly important to the SA model (Fig. 3), consistent with other studies that have demonstrated the importance of weather in driving wildfire ignitions and occurrence

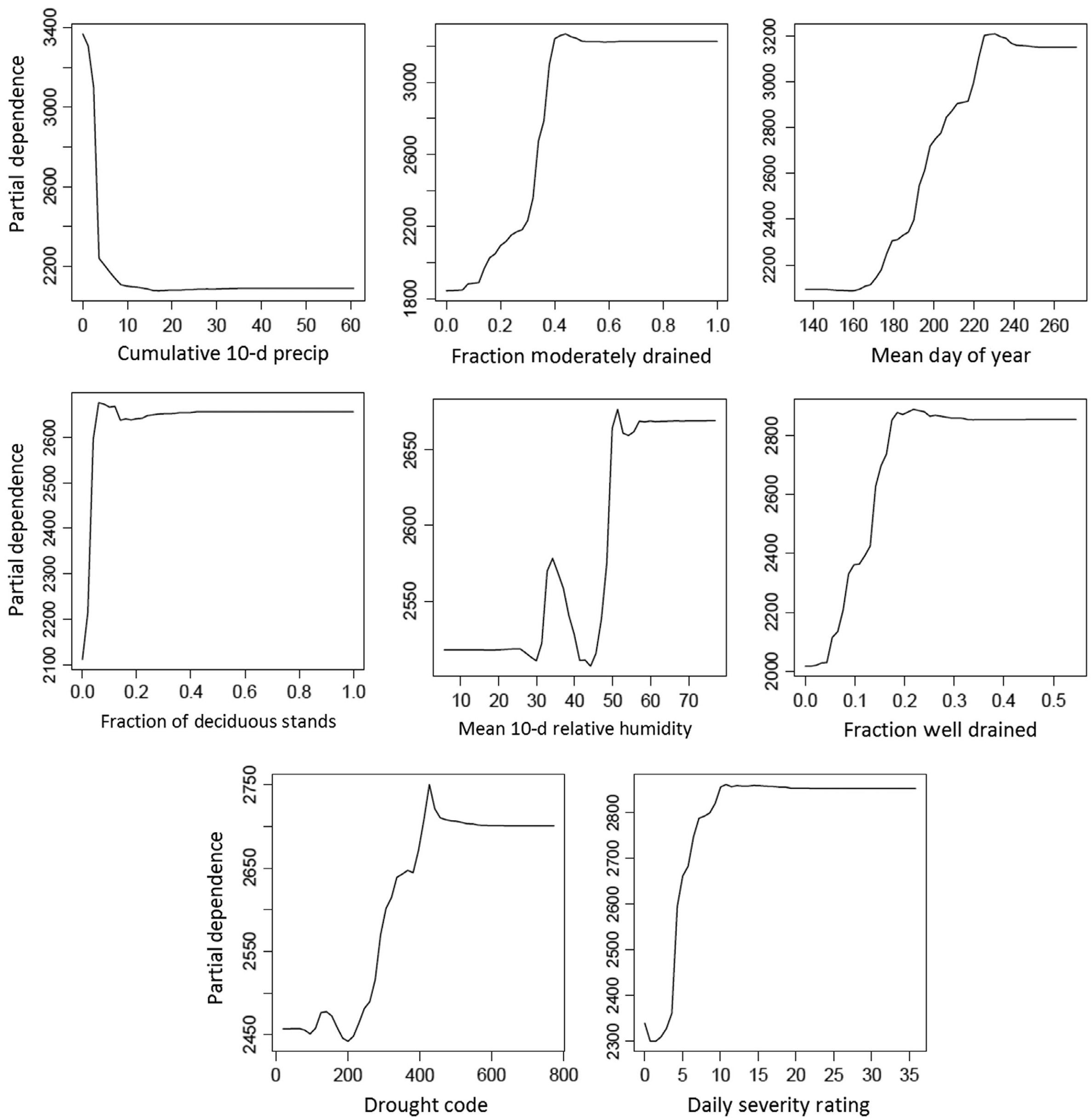

Fig. 4. Partial dependence plots of the most important inputs to full model of seasonal fire activity (SA). Plots of partial dependence explain the effect of the explanatory variable (x-axis) on the model output (y-axis) when all other inputs are held constant.

(Krawchuk et al. 2006, Abatzoglou and Kolden 2011, Krawchuk and Moritz 2011) and fire size (Beverly and Martell 2005, Abatzoglou and Kolden 2011).

The importance of vegetation type to the SA model suggests potential feedbacks to the climate–fire–vegetation system when changes in vegetation communities occur post-fire. Such feedbacks have been observed in maintaining vegetation shifts in the boreal forest (Johnstone et al. 2010) and elsewhere (Mayer and Khalyani 2011). The contribution of static variables such as drainage type to the SA model also suggests that fire activity is at least partly path dependent. Our results are consistent with previous observations that the pattern of land cover and connectivity is

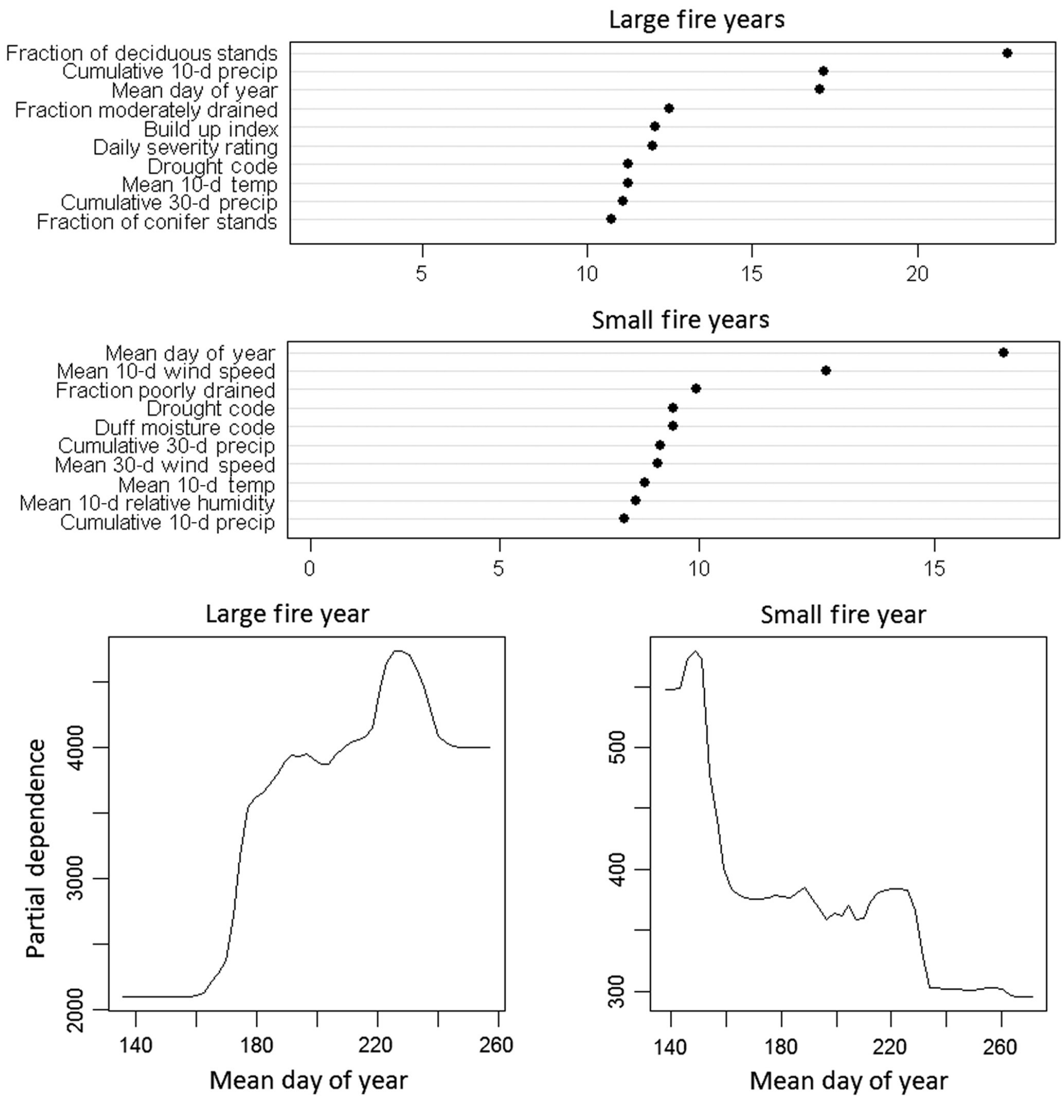

Fig. 5. Full model of seasonal fire activity (SA) variables listed in order of importance (greatest to least) for large fire years (2002, 2004, 2005, 2009) and small fire years (2003, 2006, 2007, 2008, 2010). Partial dependence plots for the day of year in large and small fire years shown at bottom.

related to fire spread (Turner 1989, Green 1994, Miller and Urban 2000).

Seasonal timing of a fire (the day of year) strongly affected the number of active fire detections within an 11-day window, with observations more likely to occur toward the end of the season (Fig. 4). This is likely due to the progressive thawing and drying out of duff layers that comprise most of the fuel consumed in boreal forest fires over the course of the fire season (Johnson 1996, Miyanishi and Johnson 2002). The effect of seasonality in large fire years is consistent with results from a previous study that found that low fire activity often dominates during the fire season with periods of high fire activity occurring sporadically in large fire years (Barrett and Kasischke 2013).

Both of the spatial models relied primarily on information about dynamic weather conditions, one of them (SMI) exclusively so. Static conditions were generally not strongly important to the SMI and UNB models, so these patterns

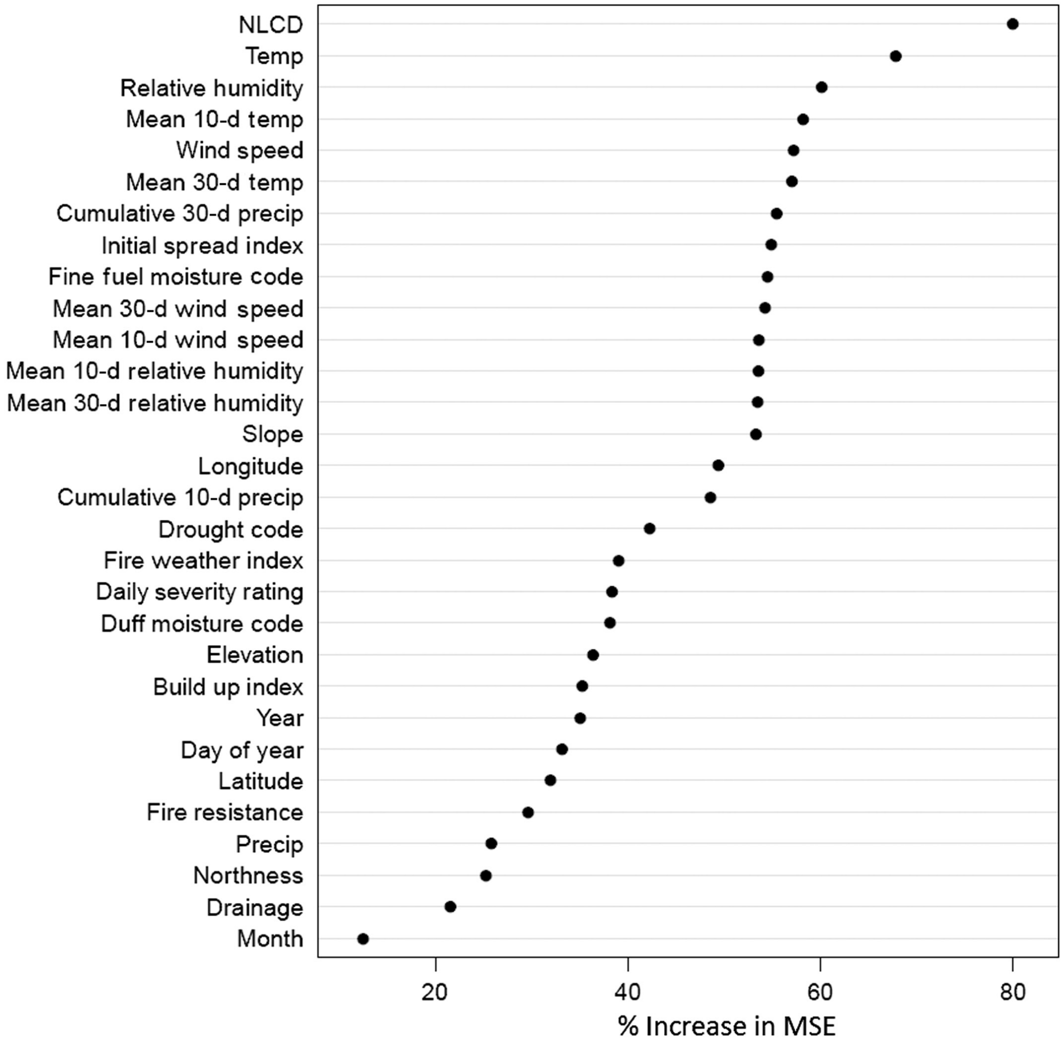

Fig. 6. Full model of short-to-moderate interval fires (SMI) variables listed in order of importance (greatest to least).

may be largely a function of climate/weather. The relationships between weather variables and unburned patches or short-to-moderate interval fires are not clear from the partial dependence plots for these models (Figs. 8, 11), so the impact of a changing climate on these patterns is not likely to be straightforward.

Fire-facilitating vs. fire-hindering explanatory variables

We did not find, as we expected, that seasonal periods of high fire activity and re-burns are necessarily more likely when burn conditions were "optimized," that is, late in the season, during periods of warm temperatures and low precipitation, in well-drained sites and conifer-dominated stands. Nor were conditions less conducive to fire associated with unburned patches.

In some cases, there was a clear causal relationship between explanatory and response variables, such as unburned patches being more likely in younger, more deciduous stands, and greater seasonal fire activity likely when 10-day cumulative precipitation is low (Fig. 11). Unburned patches were least likely to occur in coniferous forests, probably due to a higher flammability and greater available fuel

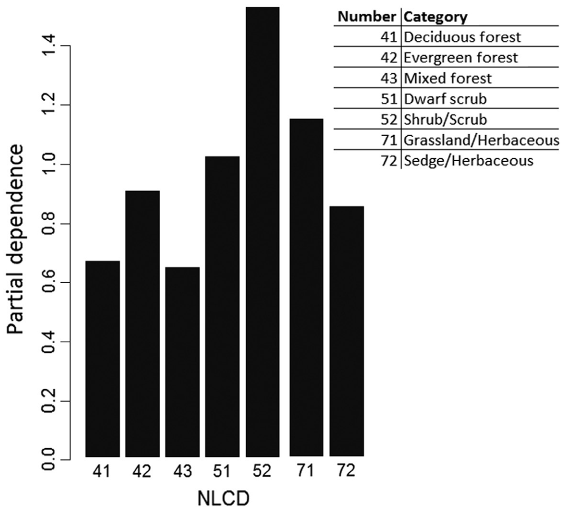

Fig. 7. Partial dependence plot for vegetation type for the model of short-to-moderate interval fires (SMI). Plots of partial dependence explain the effect of the explanatory variable (x-axis) on the model output (y-axis) when all other inputs are held constant.

load (particularly sphagnum) than deciduous vegetation (Johnson 1996, Hély et al. 2000). However, no model was consistently characterized by "fire-promoting" or "fire-hindering" variables.

Counter to our expectation, elevated 11-day active fire counts were observed not only when precipitation was low, and the proportion of moderately drained areas was higher, but also when fires occurred more in areas dominated by deciduous vegetation (Fig. 4). While low precipitation and moderate drainage might be expected to increase seasonal fire activity, deciduous-dominated stands are generally more resistant to fire than coniferous forests (Pu et al. 2007, Kasischke and Hoy 2012). Based on these results, an apparent threshold where fires in deciduous stands compose more than 10% of active fire detections (Fig. 4) may be an indication that the effectiveness of deciduous stands as a fire break decreases under more extreme fire weather conditions. Land cover could therefore serve as a deterrent to fire spread up to a certain point or threshold of fire activity (Johnson 1996, Hély et al. 2000), as exhibited by the strong thresholding effect in the partial dependence plots.

Similarly, fire conditions associated with unburned patches are generally fire hindering, but not exclusively so (Figs. 9, 10). Interestingly, unburned patches tend to happen in younger, more deciduous stands (consistent with results from Cumming 2001, Kasischke and Hoy 2012) and when 30-day precipitation levels are higher, but also when wind speed and temperatures are high. It is possible that under more severe fire weather, unburned patches occur because areas that are normally resistant to burning are subject to conditions that promote combustion. Such complexity in the case of the UNB model could have affected the model performance, although random forests are supposed to be particularly well suited to nonlinear relationships between explanatory and response variables.

The importance of weather conditions that both promote fire (high wind speed and temperature) and hinder it (high 30-day cumulative precipitation) may reflect the tendency for unburned patches to occur (1) when fire weather conditions are poor or (2) when warmer temperatures and higher wind speeds promote fire spread into areas that are more resistant to burning (e.g., due to fuel limitations or high canopy moisture). The first scenario leaves unburned patches due to the dynamic variable inputs, whereas the second is a function of the static inputs. This result is consistent with the finding that fire-resistant areas (i.e., those areas that become unburned patches under "normal" fire conditions) may become more vulnerable to fire under extreme conditions.

The mix of fire-promoting and fire-hindering conditions in these models suggests that the relationship between response and explanatory variables was not consistently one of cause and resulting effect. For example, vegetation type had to be removed from the model of short-to-moderate interval fires because the contribution was likely not due to its effect on re-burning, but the way that the vegetation classes are defined. Perhaps similarly, the fraction of fire detections in deciduous stands were higher during periods of greater fire activity, likely because deciduous stands are more susceptible to fire when there is more fire activity overall (Johnson 1996, Hély et al. 2000). Ideally, it would be more useful to have annual data sets of vegetation type for temporal analyses, to accurately represent the pre-fire vegetation for each year. Careful inspection

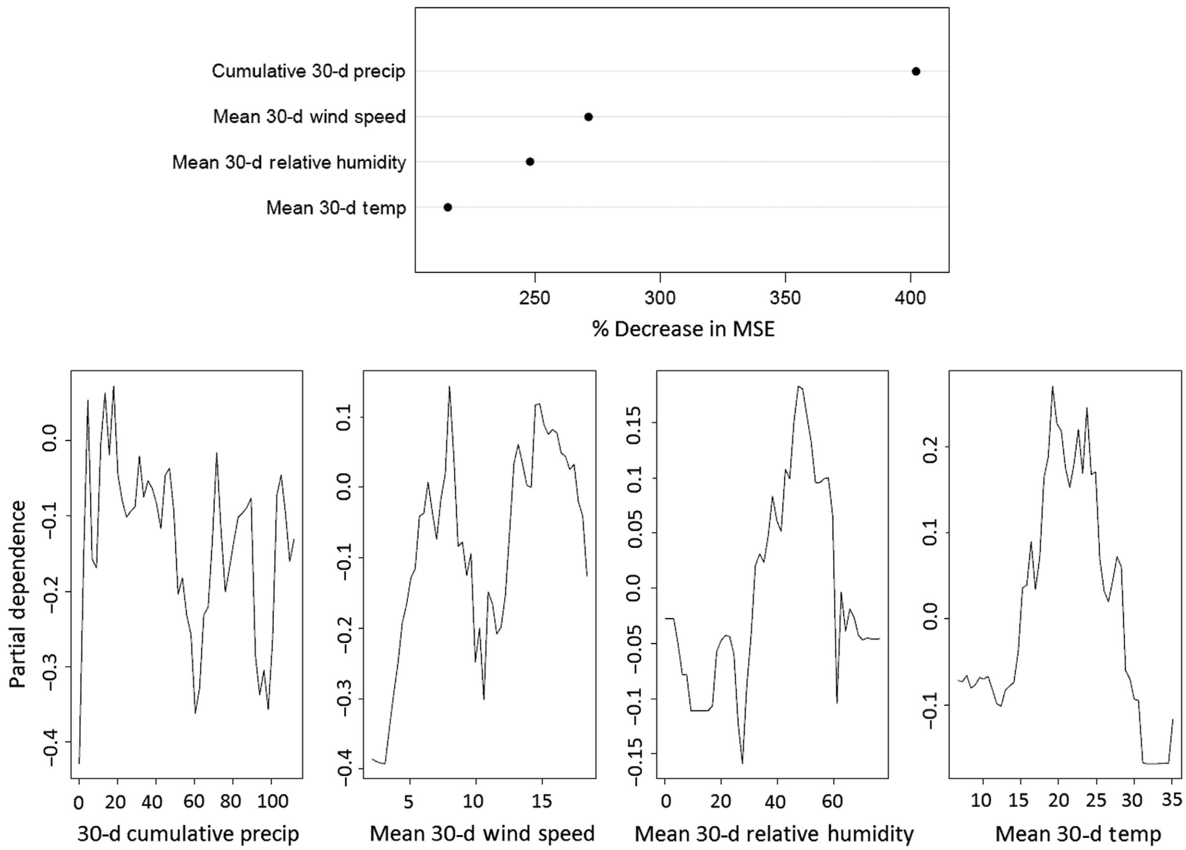

Fig. 8. Parsimonious model of short-to-moderate interval fires (SMI) variables listed in order of importance (greatest to least) and partial dependence plots.

of results is therefore advised to avoid circular logic and to determine which explanatory variables should be maintained and how the relationship with the response variable should be interpreted.

Qualitative differences in annual area burned and individual fire size

Fire size was of minor importance to the UNB model, and not at all in the SMI model. Annual area burned (i.e., large vs. small fire years) was not an important variable to either spatial model (and was excluded from the SA model due to conflation with the response variable). Therefore, any qualitative differences in area burned are not driving differences in unburned patches or short-to-moderate interval fires. However, there are differences between large and small fire years related to the trajectory of active fire detections over the course of the fire season. With respect to seasonal fire activity, there are large increases around Julian days 170 and 220 (29 June and 8 August, respectively) during large fire years. Similar thresholds occur during small fire years, albeit in the opposite direction, as the number of detections decreases over the course of the season (Fig. 5). Critical times in the early and late fire season may therefore be opportunities to become a large or small fire year. Certainly, the general trajectory of a growing number vs. a reduction in active fire detections suggests that there are qualitative differences between the progression of fire in large and small fire years. Interestingly, the most important explanatory variables to SA were a mix of spatial and temporal factors for large fire years, but primarily weather-related factors in small fire years (Fig. 5).

Several studies have highlighted the difference between large and small fire years

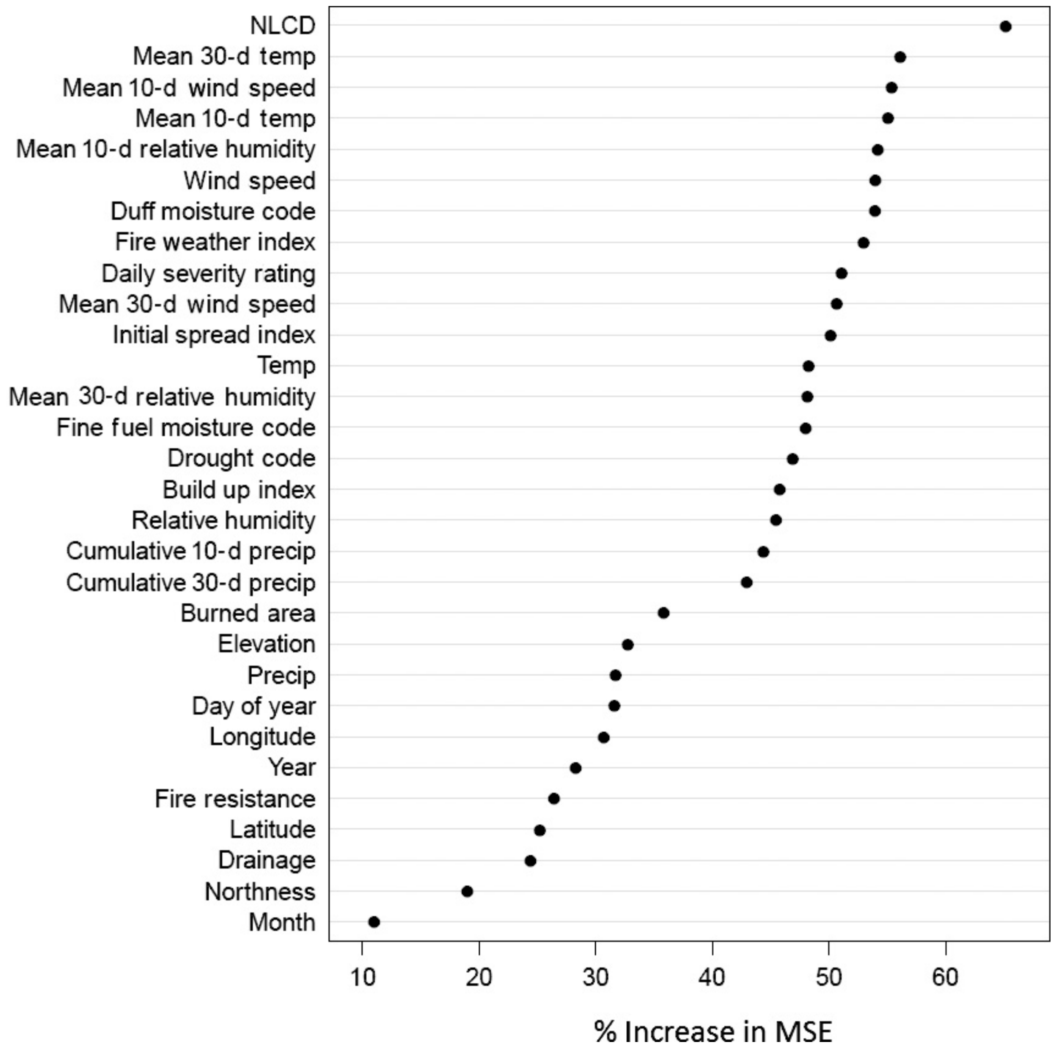

Fig. 9. Full model of unburned patches (UNB) variables listed in order of importance (greatest to least).

in terms of fire severity (Turetsky et al. 2011), intensity (Barrett and Kasischke 2013), and emissions (French et al. 2011), although no significant difference was found in the fraction of unburned patches (Kasischke and Hoy 2012). While other studies have examined various drivers of individual fire size, particularly for large fires (Beverly and Martell 2005, Hély et al. 2010, Abatzoglou and Kolden 2011), there has been less research regarding the characteristics of fires based on size. Our results suggest that there are important differences in the seasonal fire activity of large fire years vs. small fire years, but the effects of individual fire size were not pronounced.

Uncertainties

The nominal spatial resolution of the MODIS active fire detections data set is 1 km, although off-nadir pixels can be as large as 10 km. This can make fire location (and burn date, which was derived from the fire location product) somewhat uncertain (Justice et al. 2002, Giglio et al. 2003). Although the 11-day MODIS active fire detection counts were used to study periods of high fire activity, there was not sufficient information to study periods without fire activity, although any such period shorter than 11 d is captured in the aggregation. The purpose of this study was to investigate periods of high fire activity, to which the MODIS

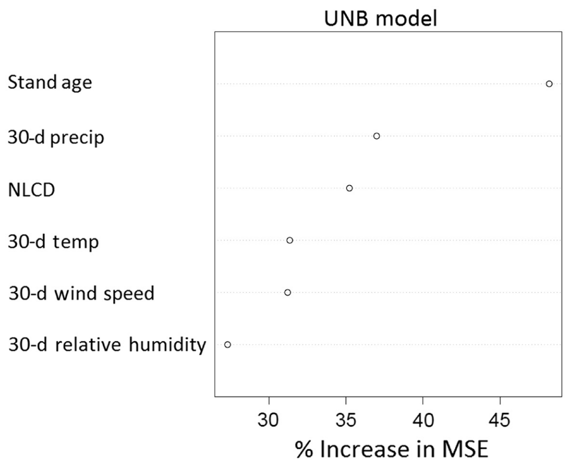

Fig. 10. Parsimonious model of unburned patches (UNB) variables listed in order of importance (greatest to least). If no variables of a given type (e.g., Julian date, fire weather, topography, drainage) were among the 10 most important variables, all variables of the type were excluded if the subsequent model explanatory power was not reduced.

active fire detection data are well suited. Characteristics of areas that burn during periods of high fire activity can be determined from an overlay of active fire detections and vegetation type, drainage conditions, and so on. Areas that did not burn cannot be similarly studied because it would require a summary of the entire landscape that did not burn, which would likely be quite heterogeneous. Some areas outside burn perimeters ostensibly do not burn because they resist fire, whereas others may have experienced different weather conditions, and still other areas might be able to burn, but have not experienced an ignition. It would be useful in future analyses, however, to study those periods without fire detections to see whether there are factors that reduce fire activity to zero.

The SMI model assumes that the entire area within a fire perimeter burned, and may therefore include areas that did not in fact burn. Due to this data limitation, stand age in the UNB model may also be overestimated, and the number of previous fires underestimated (Hoy 2014). There is also the potential for anthropogenic influences, such as fire suppression, to influence spatial and temporal patterns of burning. Fire suppression is limited in its application in Alaska due to the cost of managing large areas of uninhabited land. Within the management zones, the influence of suppression is complex and leads to an increase in the amount of burned area possibly due to greater fuel loads and dominance of more flammable late-successional black spruce stands (Calef et al. 2015).

Conclusions

We found that the information most important in explaining spatial and temporal patterns of burning is generally a mix of static and dynamic inputs. Landscape composition (and presumably, configuration), particularly conditions related to drainage, has a strong effect on fire activity during large fire years. Small-to-moderate interval fires are mostly a function of weather, as no context variables had a strong effect on the SMI model. The unique importance of weather to the model of SMI implies that FRI will be sensitive to projected climate changes in the region. Unburned patches occur more in younger stands, probably due to lower fuel loads and greater deciduousness and associated canopy moisture levels. The fraction of unburned patches may therefore increase in response to decreasing FRI and increased deciduousness in the region; however, additional findings from this research suggest that areas that normally resist fire may become less effective fire breaks under more extreme fire weather conditions. For example, seasonal fire activity is likely to be higher when more than 10% of the active fire detections occur in deciduous-dominated stands, likely due to the effect of greater fire activity on the vulnerability of deciduous stands to fire. Similarly, unburned patches are more likely when mean 30-day temperatures and wind speeds are higher, which may expose areas that normally resist burning to fire, but leaving some areas unburned. In the first instance, the explanatory variable (11-day active fire detection count) appears to be acting as a response to the nominal response variable, highlighting a challenge in interpreting the output of random forest models.

The information gained from this research can inform models of vegetation dynamics and carbon cycling (Rupp et al. 2007). Results of this analysis suggest that fire activity can be path

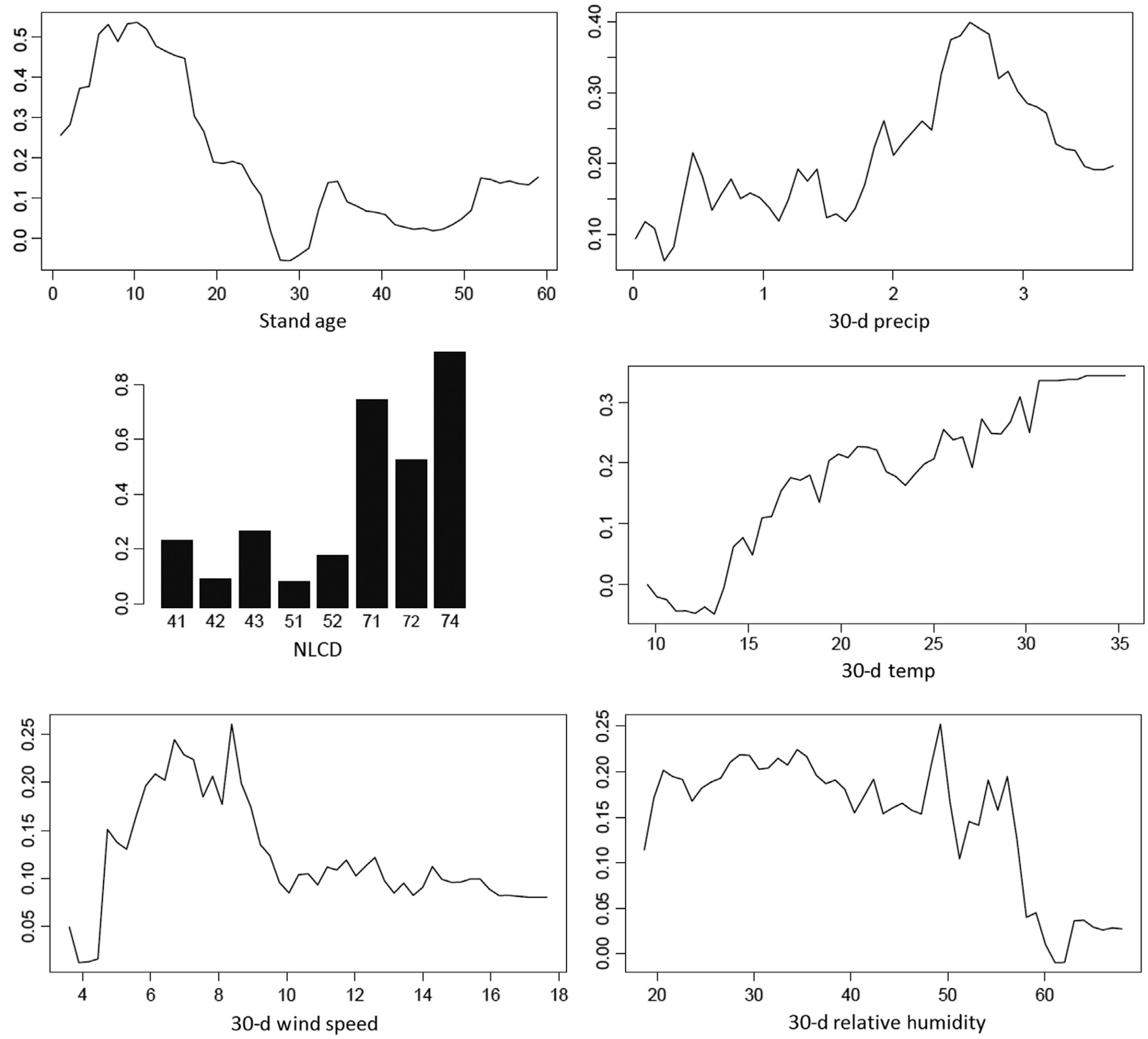

Fig. 11. Partial dependence plots of the most important inputs to parsimonious model of unburned patches (UNB). If no variables of a given type (e.g., Julian date, fire weather, topography, drainage) were among the 10 most important variables, all variables of the type were excluded if the subsequent model explanatory power was not reduced.

dependent and that incorporating landscape configuration and composition such as a contagion model is appropriate even at the sub-fire scale. Additionally, information about variability in cumulative weather conditions can improve models of fire spread, FRI, or seasonal fire activity.

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