Cloud-to-ground lightning and near-surface fire weather control wildfire occurrence in Arctic tundra

Jiaying He[1,2], Tatiana V. Loboda[2], Dong Chen[2], and Nancy H. F. French[3]

[1]Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies,Tsinghua University, Beijing 100084, China.
[2]Department of Geographical Sciences, University of Maryland, College Park, MD 20742, US.

[3]Michigan Technological Research Institute, Michigan Technological University, Ann Arbor, MI 48105, US.

Corresponding author: Jiaying He (hejiaying0608@gmail.com)

Key Points:

- Cloud-to-ground lightning probability is the key driver of fire occurrence in Arctic tundra.
- Warmer and drier near-surface fire weather conditions also support tundra burnings.
- Empirical-dynamic framework combining WRF and statistical learning methods shows strong capability for modeling of tundra fire occurrence.

Abstract

Wildfire is common across the pan-Arctic tundra. Tundra fires exert significant impacts on terrestrial carbon balance and ecosystem functioning. Interactions between fire and climate change can enhance their impacts on the Arctic. However, the driving mechanisms of tundra fire occurrences remain poorly understood. This study focuses on identifying key environmental factors controlling fire occurrence in Arctic tundra of Alaska. Our random forest models, considering ignition source, fuel, fire weather, and topography, have shown a strong predictive capability with an overall accuracy above 91%. We found cloud-to-ground (CG) lightning probability by far the dominant driver controlling tundra fire occurrence. Warmer and drier near-surface weather was required to support burning, while fuel composition and topography have modest impacts on fire occurrence. Our results highlight the critical role of CG lightning in driving tundra fires and that incorporating lightning modeling is essential for fire monitoring, forecasting, and management in the Arctic.

Plain Language Summary

Wildfire is a dominant disturbance agent that drives ecosystem change, climate forcing, and carbon cycle in Arctic tundra. Tundra fires can exert a considerable influence on the local ecosystem functioning and contribute to climate change. However, the drivers and mechanisms of tundra fires are still poorly understood. Research on modeling contemporary fire occurrence in the tundra is also lacking. Here we examined the key environmental factors that drive tundra fire occurrence with numeric weather prediction and statistical models. We found that tundra fire occurrence is primarily controlled by cloud-to-ground lightning. Warmer and drier fire weather conditions also support burnings in the tundra. We recommend the integration of lightning modeling with numeric weather prediction model for fire monitoring and forecasting in the data-scarce regions like the Arctic.

1 Introduction

Wildfire plays an essential role in altering ecosystem functioning, driving land cover change, and affecting carbon balance in boreal forest and tundra ecosystems (Bret-Harte et al., 2013; Mack et al., 2011; Randerson et al., 2006; Rocha and Shaver, 2011; van Wees et al., 2021; Wang et al., 2021). Though typically less severe than the boreal forest fires, tundra fires are widespread across the pan-Arctic region. Particularly, Alaskan tundra burns more than any other tundra region across the globe, according to satellite-based observations (He et al., 2019; Loboda et al., 2017). In recent years, several large fire seasons have occurred in Alaskan tundra, including the 2010 fire season in the Noatak River Valley, the 2015 fire season in Southwest Alaska, and the now infamous extreme 2007 Anaktuvuk River fire on the North Slope.

Tundra fires can lead to shrub expansion, alter organic soil properties and affect the surface energy budget in the local ecosystems (Bret-Harte et al., 2013; Frost et al., 2020; He et al., 2021; Rocha and Shaver, 2011). They also have the potential to release the ancient carbon stored in the frozen organic soil and cause widespread permafrost degradation and thermokarst development (Jones et al., 2015; Mack et al., 2011). Moreover, habitat suitability and forage availability for numerous wildlife species, e.g. caribou, are threatened by such fires, affecting the living resources of local human societies (Gustine et al., 2014; Joly et al., 2012). Under the rapid climate warming in the Arctic, the tundra could become more vulnerable to burnings due to the increased danger of lightning activity and extreme fire weather (French et al., 2015; McCarty et al., 2021; Young et al., 2017), which will threaten permafrost carbon and result in substantial feedbacks into regional to global climate systems, and circumpolar indigenous and nonnative communitites (Bogdanova et al., 2021; Chen et al., 2021; Forbes, 2013; Hu et al., 2015). However, tundra fires attract less scientific attention compared to fires in other ecosystems. Current research primarily focuses on evaluating post-fire impacts with comparatively little attention to understanding driving mechanisms and modeling tundra fire occurrence.

Fire occurrence results from a combination of ignition and propagation. Cloud-to-ground (CG) lightning and, to a lesser extent, human activity (due to minimal human presence) are the primary ignition sources in tundra ecosystems. Three types of forces generally control fire propagation: fuel, weather, and topography, as summarized by the “Fire Environment Triangle” (Pyne et al., 1996). Fuel type, representing properties of the fuel itself, and fuel moisture state, related to vegetation moisture content, are critically important factors controlling fire-environment interactions by affecting fuel flammability and fire characteristics. Topography also influences fire propagation directly by altering wind patterns or upslope preheating, and indirectly by controlling fuel moisture state through exposure to sunlight and moisture pooling. Finally, fire weather is frequently the dominant contributor to wildfire occurrence across different temporal scales through impacts on fuel moisture state and ignition source. Various fire danger rating systems, that implicitly or explicitly bundle weather impacts on fuel moisture, have been developed to capture the broader impact of weather on expected fire growth and quantify the potential fire risk. Specifically, the National Fire Danger Rating System (NFDRS) implemented in the US and the Canadian Forest Fire Weather Index System (CFFWIS) are the best known and most broadly used in the high northern latitudes (HNL).

Previous studies in the HNL have not reached a consensus regarding the relative impacts of various environmental factors on wildfire occurrence. The majority of the existing studies focused on the boreal forests when examining the environmental drivers of wildfire behaviors. Liu et al. (2012) found out that lightning-ignited fires were controlled by fuel moisture and vegetation type in the boreal forests of Northeast China. While studies in North America emphasized the impacts of atmospheric stability, count of lightning strikes, and dry weather on boreal forest fires (Peterson et al., 2010). Veraverbeke et al. (2017) suggested that lightning activity explained the burned area trends in the boreal forests of North America during recent large fire years. Though lightning characteristics like polarity and peak current were found significant in modeling fire occurrences (Müller and Vacik, 2017; Vecín-Arias et al., 2016), they did not function as major contributors in other studies (Adámek et al., 2018; Pineda et al., 2014).

Nevertheless, these findings in the boreal forests are not readily transferrable to the treeless tundra, as the land-atmosphere interactions differ substantially between the two ecosystems (Chambers et al., 2005; Dissing and Verbyla, 2003; Jiang et al., 2015; Van Heerwaarden and Teuling, 2014). Previous studies have modeled historical or future tundra fire regimes with ecosystem or statistical models (Higuera et al., 2011; Joly et al., 2012; Sae-Lim et al., 2019; Young et al., 2017). Specifically, Young et al. (2017) modeled future fire occurrence probability in Alaska accounting for climate and landscape features. Masrur et al. (2018) found that warm and dry conditions affect the spatiotemporal patterns across the circumpolar Arctic tundra. Yet, efforts on examining the driving mechanisms and contemporary modeling of fire occurrence have been lacking in the tundra ecosystems in existing research. Critical factors such as lightning, were not considered in these studies.

This study investigates the key environmental factors controlling fire occurrences in Arctic tundra via contemporary modeling during 2001 – 2019. We defined the wildfire occurrence as the start of an individual fire event detected by satellite sensors. We developed an empirical-dynamical framework to predict the fire occurrence probability by combining numerical weather prediction (NWP) and machine learning models. We considered factors that control wildfire behaviors, including fuel, fire weather, topography, and ignition source.

2 Materials and Methods

2.1 Data and variable preparation

2.1.1 Wildfire occurrence detection in Alaskan tundra

We defined the extent of Arctic tundra in Alaska with the commonly used Circumpolar Arctic Vegetation Map (Walker et al., 2009). MODIS Thermal Anomalies/Fire locations product (MCD14ML; Giglio et al., 2003) was chosen to determine the locations and dates of fire occurrences. We first identified individual fire events with MCD14ML data based on its consistent information of active fire points. We designed a spatiotemporal clustering method designed based on the Density-Based Spatial Clustering of Applications with Noise (DBSCAN; Ester et al., 1996) algorithm (Text S1; Figure S1). The maximum distance between two neighboring fire points in a cluster was set to 2.5 km (Loboda and Csiszar, 2007). Since fire events that occurred during different time periods could be grouped into the same cluster, we further separated points of different fire events in a spatial cluster with a temporal gap of 4 days, as suggested by Loboda and Csiszar (2007). The locations and dates of the active fire points with the earliest acquisition time were then extracted to represent the tundra fire occurrences.

2.1.2 CG lightning and fire weather simulation with WRF

CG lightning strikes and fire weather conditions are important factors affecting fire behaviors and are highly dynamic across space and time. Due to the lack of weather stations and very coarse resolution of climatology data in the remote tundra region, we adopted the Weather Research and Forecast (WRF) model as a downscaling tool to simulate CG lightning probability and near-surface weather conditions at 5km resolution. We used the National Centers for Environmental Prediction Final Operational Global Analysis data (NCEP FNL; National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce, 2000) at 1-degree resolution and 6-hour interval for model initialization. We ran two-way nested simulation for Alaska following the parameterization settings from He and Loboda (2020).

Considering the computing complexity of WRF, we sampled years with different fire season severities between 2001 and 2019 and ran WRF simulations for all the detected fire events from these years for further modeling efforts. We adopted the empirical-dynamical modeling framework developed by He and Loboda (2020) to model the probability of CG lightning strikes using WRF simulated variables and random forest (RF) algorithm. CG lightning probability was then used as input data for representing ignition sources of wildfires. To describe fire weather conditions that affect burnings in the tundra, we extracted near-surface weather conditions, including air temperature, relative humidity (RH), wind speed, and 24-hr precipitation. We then calculated the Canadian Forest Fire Weather Index System (CFFWIS; Van Wagner, 1987) using WRF-simulated variables. The CFFWIS tracks the moisture content of distinct fuel layers with three fuel moisture codes – Fine Fuel Moisture Code (FFMC), Drought

Moisture Code (DMC), and Drought Code (DC). The three fire behavior indices – Initial Spread Index (ISI), Buildup Index (BUI), and Fire Weather Index (FWI) – provide numeric ratings of the fire spread process. Though not explicitly designed for the tundra, this system is suitable for describing fire weather conditions and quantifying fire danger in the ecosystems of the HNL (French et al., 2015; Mölders, 2010).

2.1.3 Fuel and topographic properties

We used the fractional cover maps of major fuel components across Alaskan tundra (He et al., 2019) to represent fuel type distribution. Here we considered three fuel components, namely woody, herbaceous and nonvascular fuels. Four vegetation indices that are directly related to leaf water content were adopted as estimates of fuel moisture state for large-scale monitoring (Yebra et al., 2008), including two Normalized Difference Infrared Indices using MODIS bands 6 and 7 ($NDII_6$ and $NDII_7$; Hardisky et al., 1983), Normalized Difference Water Index (NDWI; Gao, 1996), and Global Vegetation Moisture Index (GVMI; Ceccato et al., 2002). We computed these indices using the MODIS 8-day surface reflectance data (MOD09A1; Vermote et al., 2015) for our study area (Table S1). The 5m Digital Elevation Model (DEM) data developed with airborne Interferometric Synthetic Aperture Radar (IfSAR) data for Alaska was then used to extract topographical features, including elevation, slope, aspect, and roughness.

2.2 Tundra fire occurrence modeling

Five groups of influencing factors were used as independent variables for modeling tundra fire occurrence: fuel type, fuel moisture state, fire weather, topography, and ignition source (Figure S2). Fire weather, ignition source (CG lightning probability), and fuel moisture state are weather-related conditions and can change rapidly on a daily basis throughout a short period. Although vegetation shifts and fuel type transitions can occur from years to decades under disturbances or climatic variability and change, the vegetation compositions and fuel type distributions are relatively stable without substantial seasonal or diurnal changes.

To fully understand how these dynamic weather-related variables affect the probability of tundra fire occurrence, we developed two types of models, referred to as “Current-day model” and “Previous-day model”. Here we categorized the ignition source, fire weather and fuel moisture state as “dynamic” variables considering their temporal variabilities during fire seasons. While topographic properties and fuel type distributions were considered as “static” variables. The two types of models selected the dynamic variables on different dates as independent variables. The “Current-day model” adopts the dynamic variables simulated on the exact dates of fire occurrence, while the “Previous-day model” uses those extracted from the dates before the detected fire occurrence. Fire occurrence points detected in Section 2.1.1 were used to represent the presence of “Fire” events. We randomly sampled points across the tundra regions on the same fire ignition dates to represent “No Fire” events.

Empirical models were then developed with both the RF classification and logistic regression algorithms to identify the key factors driving tundra fire occurrence and quantify their impacts. Although RF algorithms can provide relative rankings of variable importance in predicting the dependent variable, they are limited in showing the quantitative relationships between each independent variable and fire occurrence probability. We therefore developed logistic regression models as well, to quantify the impacts of environmental factors. Before modeling, we tested the correlations of variables among the five groups of environmental factors using Pearson's r correlation and removed the highly correlated ones. For both RF classification and logistic regression models, 70% of the records were randomly selected for model training, and the rest 30% were reserved for validation. Welch's t-test was also conducted to assess the differences of environmental factors between "Fire" and "No fire" events across the study area.

3 Results

3.1 Wildfire occurrences in Arctic tundra of Alaska

Individual fire events were first identified using the MCD14ML data between 2001 and 2019 (Figure 1). The occurrences of wildfire events vary across space in Arctic tundra of Alaska. The majority of the fires occurred in Southwest Alaska (~39.62%), followed by the North Slope (~36.92%) and the Seward Peninsula (~23.46%). A slightly increasing trend of tundra fire occurrences was found during the study period (Figure 1 b). Temporal variability also exists regarding fire season severity, as indicated by the number of annual fire events. During 2001 and 2019, thirteen years have relatively low fire events (< 20 fires per year), and four years have a moderate fire season with 20 ~ 30 fire events per year. An exceptionally severe fire season was detected in 2015, with 49 fire events in total. To cover a variety of fire season severities, we sampled five seasons (2002, 2006, 2008, 2013, 2017) with light severity, two years with moderate severity (2007, 2010), and the year of 2015 as severe with very high fire activity for model development (Table S2).

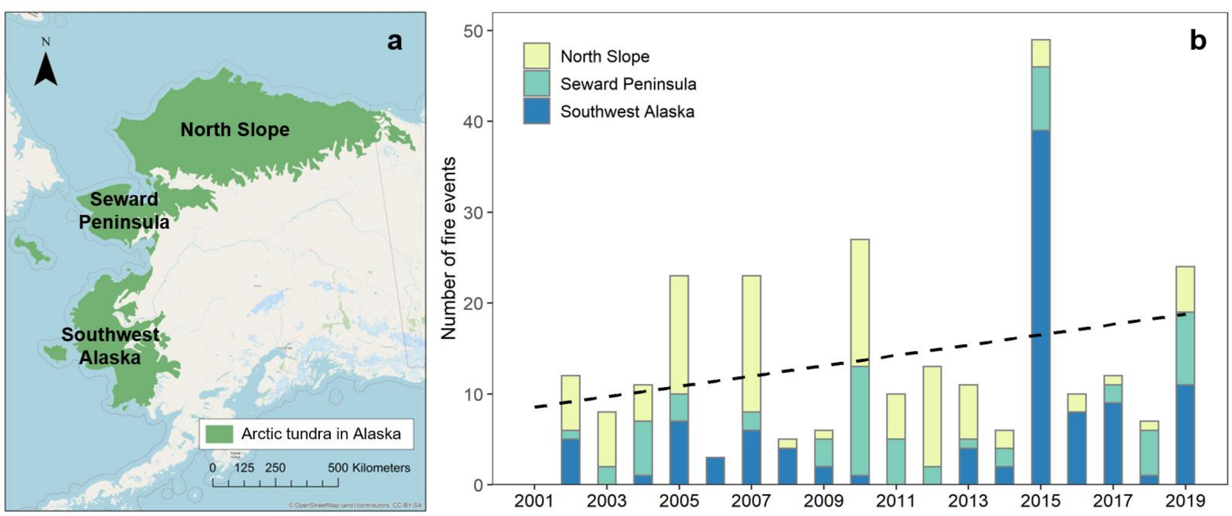

Figure 1. (a) Arctic tundra region in Alaska as defined by CAVM. (b) Number of fire events detected with MCD14ML data from 2001 to 2019.

3.2 Empirical modeling performances

Three groups of independent variables show very strong correlations, including the vegetation indices representing fuel moisture state, the CFFWIS components representing fire weather conditions, and the topographic features, with Pearson's *r* above 0.8 (Figure S3). Since all vegetation indices were highly correlated with Pearson's *r* above 0.95, we only adopted $NDII_6$ to estimate fuel moisture state for further modeling efforts. Strong correlations were also found between the fire behavior indices (ISI and BUI) and fuel moisture codes (FFMC and DMC) of the CFFWIS. Since we did not focus on fire propagation, we only selected the three fuel moisture codes to represent fire weather conditions. Although the near-surface weather variables show moderate correlations with the CFFWIS components, they were included to account for meteorological conditions irrespective of fuels. Additionally, slope and roughness were removed for modeling due to their strong correlations with elevation.

Both the “Current-day model” and “Previous-day model” developed with the RF classification algorithm have shown a strong capability in predicting the fire occurrence probability in the tundra. The overall out-of-bag (OOB) error rate of the “Current-day model” is 6.03%, with the overall accuracy reaching 93.97% (Table S3). The “Previous-day model” shows slightly lower modeling performance, with an overall OOB error rate of 8.75% and an accuracy of 91.25%. Validation performed against the reserved dataset shows that both models can reflect (with the “Current-day model”) and forecast (with the “Previous-day model”) fire occurrence probability, as indicated by the Receiver Operating Characteristic (ROC) curves (Figure S4). The Area Under the Curve (AUC) values reached 0.97 and 0.96 for the “Current-day model” and the “Previous-day model”, respectively.

3.3 Environmental factors driving tundra fire occurrence

CG lightning probability was identified as the most important variable in both the “Current-day model” and “Previous-day model” for predicting tundra fire occurrence, with Mean Decrease in Accuracy (MDA) of 50.06% and 34.58%, respectively (Figure 2 a-b). A significant positive relationship was confirmed between CG lightning and fire occurrence via logistic regression models ($p < 0.001$; Table 1), suggesting that regions with larger lightning probability are likely to experience higher fire risks. On fire-occurrence days, the lightning probability of the “Fire” events were higher than 0.50 on average across the tundra region and reached over 0.62 in the North Slope and Southwest Alaska (Figure 2 c). In contrast, the lightning probability was below 0.15 on average when no fire occurred. Similarly, on the previous days of fire occurrence, though lower than that on fire-occurrence days, the lighting probability of the “Fire” events, was significantly higher (~0.48) than that of the “No fire” events (< 0.12) on average (Figure 2 d).

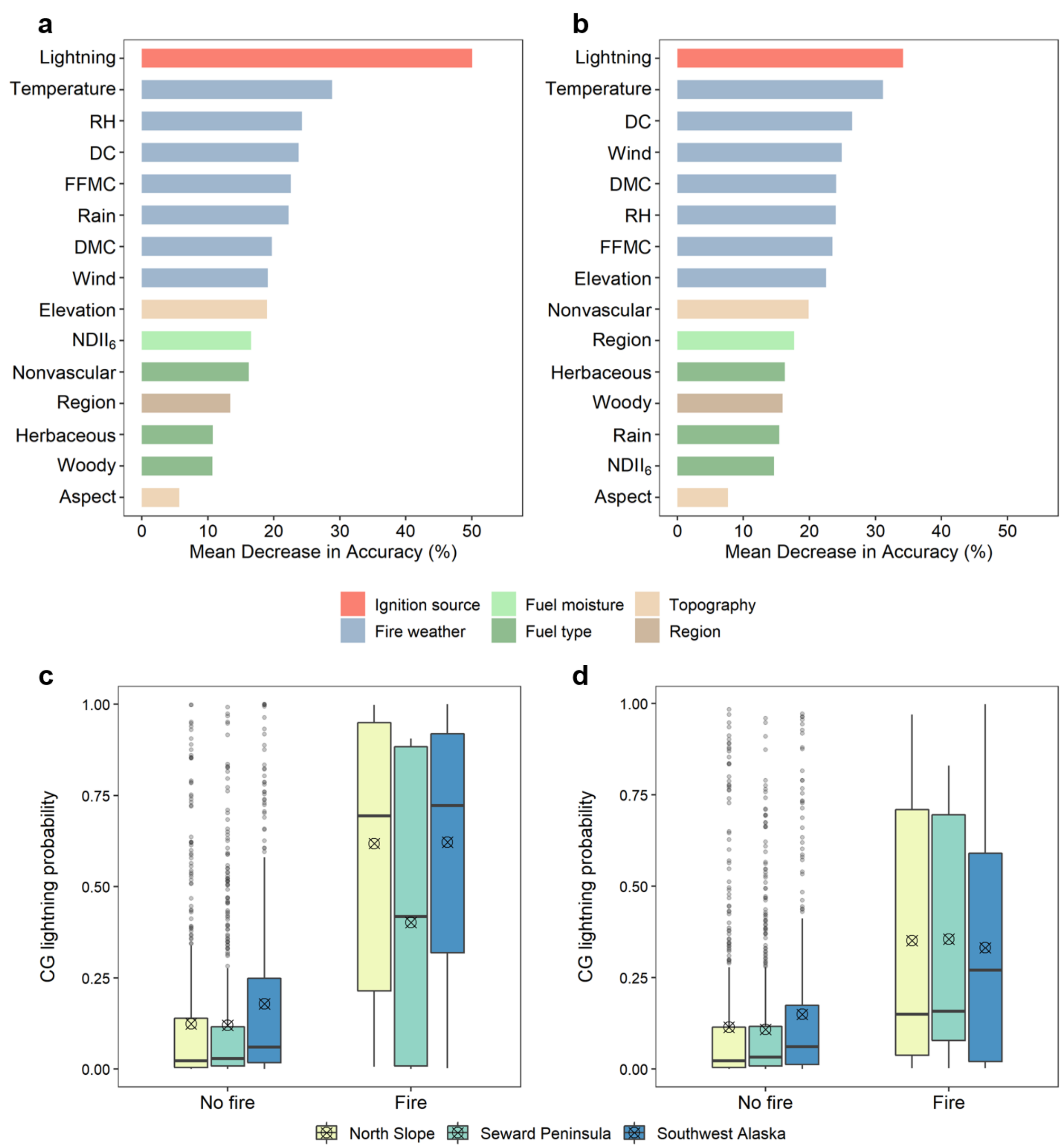

Figure 2. Variable importance rankings of (a) the “Current-day model” and (b) the “Previous-day model”. Boxplots of CG lightning probability for the “Fire” and “No fire” events in the three tundra regions on (c) fire-occurrence days and (b) the previous days before occurrence.

WRF-simulated near-surface meteorological variables and fuel moisture codes, particularly air temperature, RH, and DC, were also found important in modeling tundra fire occurrences, as indicated by MDA values from the RF models (Figure 2 a-b). Specifically, higher air temperature and drier fuels could contribute to increases in fire occurrence probability, according to the significantly positive relationships between temperature and DC with fire occurrence ($p < 0.05$; Table 1). The mean air temperature was significantly higher in most tundra regions when fires occurred, while RH was significantly lower (Table S4). On fire-occurrence days, the air temperature of the regions with fires can reach 24.8◦C and 23.5◦C in Southwest Alaska and the North Slope on average, respectively. In comparison, regions with no fires were much cooler, with 18.4◦C and 16.5◦C, respectively (Figure 3 a). As expected, drier conditions were also likely to support fire occurrence. The RH values of "Fire" events were about 9.6% lower than those of "No fire" events in these two tundra regions on average (Figure 3 b). In addition, all fire weather indices were significantly higher on fire days in North Slope and Southwest Alaska. Though Alaskan tundra is not a moisture-limited ecosystem, surface vegetation fuels can dry out rapidly to support burnings, with FFMC reaching above 80 across the tundra regions on the fire-occurrence days (Figure 3 c). Moreover, the significantly negative relationships between $NDII_6$ and fire occurrences in both logistic regression models indicated that drier fuels support burnings in the tundra ($p < 0.05$; Table 1). Mean values of the vegetation indices related to fuel moisture state were slightly but significantly lower for the "Fire" events (Figure S5; Table S4).

Table 1. Logistic regression results of the two models.

Variables	Current-day model			Previous-day model		
	Coefficient	Std. Error	P-value	Coefficient	Std. Error	P-value
Intercept	-4.550	2.607	0.08†	-2.003	2.367	0.796
Lightning	5.428	0.591	<0.001***	3.430	0.543	<0.001***
$NDII_6$	-12.69	2.028	<0.001***	-18.360	5.581	<0.001***
Rain	-0.136	0.064	0.033*	-0.043	0.037	0.208
Temperature	0.166	0.053	0.002**	0.098	0.042	0.021*
RH	0.005	0.019	0.791	-0.057	0.016	<0.001***
Wind speed	0.012	0.074	0.866	-0.225	0.076	0.003**
FFMC	-0.029	0.016	0.054†	-0.034	0.014	0.016*
DMC	0.008	0.031	0.781	0.0001	0.027	0.691
DC	0.006	0.002	<0.001***	0.005	0.002	0.003**
Region (Seward)	-1.220	0.520	0.019*	-1.176	0.432	0.005**
Region (SW)	-0.192	0.793	0.808	1.973	0.662	0.007**
Elevation	-0.002	0.001	0.008**	-0.001	0.001	0.069†
Aspect	-0.002	0.003	0.590	-0.0004	0.003	0.892
Woody cover	1.089	2.173	0.616	0.073	1.793	0.725
Herbaceous cover	3.625	1.953	0.064†	5.542	1.727	<0.001***
Nonvascular cover	-2.811	1.234	0.022*	-0.223	1.058	0.911

Notes: Significance levels of regression: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, and †$p < 0.1$.

Compared to ignition source and fire weather, fuel composition and topography did not strongly impact tundra fire occurrence (Figure 2 a-b). Logistic regressions suggested that fractional covers of woody and herbaceous components were positively related to the fire occurrences (Table 1). Fires in the North Slope and the Seward Peninsula tended to occur in regions with more woody fuels. In contrast, those in Southwest Alaska show the opposite (Figure S6). Significantly higher coverage of nonvascular fuels was found when fires occurred in Southwest Alaska, while an inverse relationship existed for fires in the North Slope (Table S4). The significantly negative relationship between elevation fire occurrence (Table 1) also suggests that tundra fires are more common in flat areas.

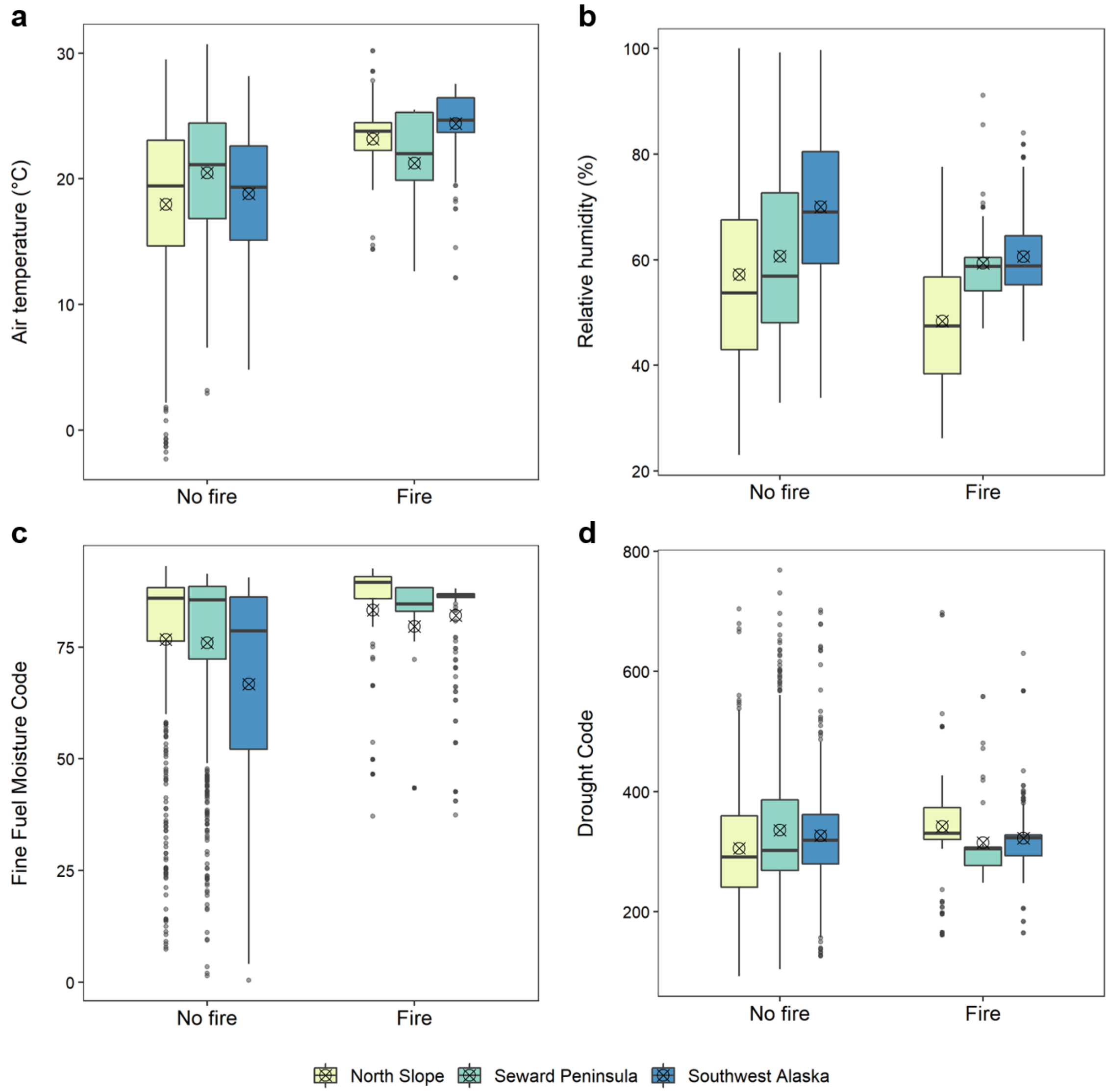

Figure 3. Boxplots of (a) air temperature, (b) RH, (c) FFMC, and (d) DC for the "Fire" and "No fire" events across the three tundra regions on fire-occurrence days.

4 Discussions

This study identifies the CG lightning probability as the key driver of tundra fire occurrence. Though lightning is normally assumed to be the primary ignition source in the tundra due to the remoteness of the region and the limited human activities, we provide the first quantitative piece of evidence that supports this assumption, as the results from all models in this study point to CG lightning probability as the most influential factor that predicts fire occurrence. This finding is consistent with previous research conducted in the boreal forests of North America (Veraverbeke et al., 2017). Yet, the role of lightning is not always emphasized in other ecosystems (Díaz-avalos et al., 2001; Liu et al., 2012; Vecín-Arias et al., 2016). Previous studies have also established relationships between fires and lightning characteristics observed from ground-based detection networks, such as the count, polarity, and peak current of lightning strikes (Peterson et al., 2010). This study, whereas, suggest that the probability of CG lightning modeled purely with atmospheric variables is a powerful indicator of tundra fire potential.

In addition to lightning, warmer and drier near-surface fire weather conditions support burnings in the tundra. With generally low temperatures and high water table, Arctic tundra is an unusual environment that is rarely moisture-limited and are not highly flammable, largely due to widespread underlying permafrost (Bliss et al., 1973; Wielgolaski and Goodall, 1997). Evidences from both modeling and statistical analyses in this study highlight the importance of warm and dry weather conditions in driving fire occurrence in Alaskan tundra, with near-surface air temperature and RH significantly related to fires. Higher temperature and lower moisture conditions have the potential to increase the flammability of the environment in general. In addition to the impacts of air temperature and RH on fuel flammability, they might also reflect the high likelihood of convective potential, which in turn leads to atmospheric instability and ultimately lightning occurrence. Moreover, despite the minimal elevation variations in the tundra, topographic features such as elevation could indirectly affect fire activity through their impacts on lightning potential, temperature and moisture availability (Dissing and Verbyla, 2003; Podur et al., 2003).

Our results also demonstrate the suitability of fuel moisture codes from the CFFWIS for monitoring tundra fire potential. Primarily composed of herbaceous and dwarf shrub species, the dominant fuels in the tundra are considered fine surface fuels as defined in the CFFWIS (Innes, 2013). As the most influential indicator among all fire weather indices, DC is a slow-reacting code that tracks deeper drying of fuels that responds to changes in deep moisture levels in the tundra (Lawson and Armitage, 2008). Its significance in the logistic regression highlights that long-term dry conditions of tundra fuels that accumulate for days contribute more to burnings than the short-term changes. It is also worth mentioning that that FFMC is a highly predictive variable, since it is originally designed to describe the fine surface fuels in boreal forests (Lawson and Armitage, 2008). With larger FFMC indicating higher fuel flammability, FFMC of the "Fire" events can generally reach higher than 70 for the tundra, representing dry fuels for fire occurrence. Although the CFFWIS was originally developed for boreal forests and its ability to forecast tundra conditions was most generally assumed rather than tested, our study shows that both FFMC and DC provide a reasonable approximation of fuel moisture changes that can more readily support burning. Given the impacts of fire weather on fire potential, the future increase of FWI in the tundra (French et al., 2015) will absobutely contribute to higher fire risks in this region.

More importantly, our empirical-dynamic framework involving NWPs like WRF and statistical models has demonstrated its strong capability and effectiveness for contemporary fire modeling in data-scarce regions like the tundra. The modeling experiments with both the "Current-day model" and the "Previous-day model" further indicate that using data simulated from one day earlier can achieve reasonable accuracy in forecasting fire occurrence. The critical role of CG lightning probability also suggests that current fire management efforts are inadequate without incorporating CG lightning probability for fire danger monitoring and modeling in the tundra, where fires are primarily ignited by lightning. With the future increases of lightning in the HNL (Chen et al., 2021), Arctic tundra will experience higher fire occurrence in the future under the rapid climate warming. By monitoring lightning potential and fire weather, it is promising that fire occurrence can be predicted with high accuracy in remote regions at 5km resolution.

Though existing efforts have been made to incorporate lightning characteristics for fire modeling by matching lightning strikes detected by ground-based networks and fires (Peterson et al., 2010; Wotton and Martell, 2005), we recommend using simulated CG lightning probability for fire management efforts for several reasons. The ground-based lightning detection networks typically have a location accuracy of 1 ~ 5km and a detection efficiency of about 70% ~ 90% (Biagi et al., 2007; Dissing and Verbyla, 2003; Koshak et al., 2015; Nag et al., 2014). This suggests the potential missing of lightning strikes by the detection systems and the inaccuracy of the triangulated lightning locations. Therefore, the commonly used method of matching lightning and fire locations can largely miss the actual lightning strikes that ignite the fires, further introducing errors and uncertainties in the modeling and analysis efforts. The modeling results could be affected by the choices of matching methods as well (Moris et al., 2020). Finally, since no simulation of lightning characteristics has been developed based on existing NWPs so far, this limits the potential of integrating NWPs for fire ignition modeling and forecasting.

5 Conclusions

This study explores the key drivers of wildfire occurrences in Arctic tundra of Alaska by modeling the impacts of environmental factors on fire probability from 2001 to 2019. Among all factors, CG lightning probability is found to be the most important driver of tundra fire occurrences in Alaska, with a significant positive relationship between lightning and fire probabilities. Warmer and drier weather conditions also support burnings in the tundra. Air temperature, fuel moisture codes show significant positive relationships with fire occurrences, while RH is negatively related. Moreover, the empirical-dynamical modeling method in this study has demonstrated a strong capability in predicting fire occurrence probability, using the WRF-simulated fire weather variables on both fire ocurrence day and one day before. Our findings highlight the necessity of incorporating CG lightning modeling and the benefits of WRF simulation for wildfire monitoring efforts in data-scarce regions like tundra.

Availability Statement

- Data and software to support this manuscript are publicly and freely available online from their websites. CAVM was obtained from Alaska Geobotany Center, University of Alaska, Fairbanks (https://www.geobotany.uaf.edu/cavm/). MODIS fire product MCD14ML was obtained from NASA's Fire Information for Resource Management System (https://firms.modaps.eosdis.nasa.gov/). Fuel component maps were accessed from the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC; https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1761). MODIS surface reflectance data MOD09A1 was downloaded from NASA's Land Processes Distributed Active Archive Center (LP DAAC; https://e4ftl01.cr.usgs.gov/MOLT/MOD09A1.006/). IfSAR DEM product was downloaded from the Alaska Elevation Portal (https://elevation.alaska.gov) hosted by Alaska Division of Geological and Geophysical Surveys. NCEP FNL data were obtained from the Research Data Archive (https://rda.ucar.edu/datasets/ds083.2/) managemend by the National Center for Atmospheric Research (NCAR).
- The Advanced Research WRF Model Version 4.0 used for simulation lightning and near-surface weather is available via the Mesoscale and Microscale Meteorology Laboratory of NCAR (https://www2.mmm.ucar.edu/wrf/users/).

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