fire

Communication

Driving Factors and Future Trends of Wildfires in Alberta, Canada

Maowei Bai [1], Qichao Yao [1], Zhou Wang [1,*], Di Wang [1], Hao Zhang [2], Keyan Fang [3] and Futao Guo [4]

1 Wildfire Research Center, National Institute of Natural Hazards, Beijing 100085, China; maoweibai@ninhm.ac.cn (M.B.); qichaoyao@ninhm.ac.cn (Q.Y.); wangdi@ninhm.ac.cn (D.W.)
2 College of Forestry, Northeast Forestry University, Harbin 150040, China; azhanghao@nefu.edu.cn
3 Key Laboratory of Humid Subtropical Eco-Geographical Process, College of Geographical Sciences, Fujian Normal University, Fuzhou 350007, China; kfang@fjnu.edu.cn
4 College of Forestry, Fujian Agriculture and Forestry University, Fuzhou 350002, China; guofutao@126.com
* Correspondence: wangzhou@ninhm.ac.cn

Abstract: Departures from historical wildfire regimes due to climate change have significant implications for the structure and composition of forests, as well as for fire management and operations in the Alberta region of Canada. This study analyzed the relationship between climate and wildfire and used a random forest algorithm to predict future wildfire frequencies in Alberta, Canada. Key factors driving wildfires were identified as vapor pressure deficit (VPD), sea surface temperature (SST), maximum temperature (Tmax), and the self-calibrated Palmer drought severity index (scPDSI). Projections indicate an increase in wildfire frequencies from 918 per year during 1970–1999 to 1151 per year during 2040–2069 under a moderate greenhouse gas (GHG) emission scenario (RCP 4.5) and to 1258 per year under a high GHG emission scenario (RCP 8.5). By 2070–2099, wildfire frequencies are projected to increase to 1199 per year under RCP 4.5 and to 1555 per year under RCP 8.5. The peak number of wildfires is expected to shift from May to July. These findings suggest that projected GHG emissions will substantially increase wildfire danger in Alberta by 2099, posing increasing challenges for fire suppression efforts.

Keywords: climate change; wildfire; random forest; VPD; RCP

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1. Introduction

Boreal forests account for approximately 30% of the world's forest area [1]. Boreal forests play an important role in global forest ecosystems due to their ecosystem functions and carbon sequestration capacity [2,3]. Anthropogenic climate warming is rapidly changing boreal forest environments [4] and complicating forest disturbance mechanisms such as wildfires in boreal forest-covered areas [5].

Previous studies have shown that higher temperatures [6], drought [7], and vapor pressure deficits [8] can lead to an increase in the number of wildfires, an earlier wildfire season, and increased wildfire risk and severity. Increased wildfire activity has been documented in a variety of forest ecosystems, including the United States [9,10], Canada [11], and Russia [12].

Previous studies have also shown that machine learning (such as models based on deep learning [13], deep neural networks [14], graph neural networks [15], multi-layer neural networks [16], etc.) has a higher predictive ability for wildfires than fire hazard weather indices. For example, Spyros K. et al. used deep learning to predict the risk of wildfires in fire-prone areas of the Eastern Mediterranean the next day, and the results showed that this method paved the way for more robust, accurate, and reliable data-driven predictions of wildfires [13].

Since the 1970s, increasingly severe fire weather has led to an increasing area burned by wildfires in western Canada [17,18]. Due to extreme weather and limited firefighting resources, western Canada is facing significant issues from spring wildfires [19]. For example, extensive wildfires broke out in the spring in 2011 (Alberta), 2014 (Northwest Territories), 2015 (Alberta and Saskatchewan), 2016 (Alberta), 2017 and 2018 (British Columbia), 2019 (Alberta), and 2023 (Alberta).

In Alberta, nearly all structural losses are associated with spring wildfires [20]. Therefore, the ongoing and expected changes in wildfire disturbance regimes have attracted widespread attention. This study used a random forest algorithm to analyze the key climate factors that affect wildfire occurrence in Alberta, as well as the intra-annual and inter-annual changes in Alberta wildfires under the background of future climate change.

2. Materials and Methods

2.1. Study Area

The province of Alberta is located between 49°–60° N and 110°–120° W, cut off in the southwest by the Canadian Rockies (Figure 1). The province has a total land area of approximately 661,000 km^2, with landscapes ranging from farmland in the south to foothills, grasslands, and boreal forests in the north. Alberta has a semiarid continental climate, with mean annual precipitation ranging from less than 350 mm in the southeast to more than 500 mm in the northwest [21]. Winters are cold, with temperatures typically ranging from −25.1 °C to −9.6 °C. Summers are warm, with temperatures ranging from 8.7 °C to 18.5 °C. Mean annual temperatures range from 3.6 °C to 4.4 °C [22]. The majority of conifer species in the study area are Picea abies (black spruce), Picea Picea (white spruce), Pinus pine (jack pine), and Larix laricina (eastern larch). Most broadleaved tree species include Populus tomentosa (Quake Populus), Populus euphratica (Basmatiaceae Populus), and Betula alba (Betula platyphylla) [23].

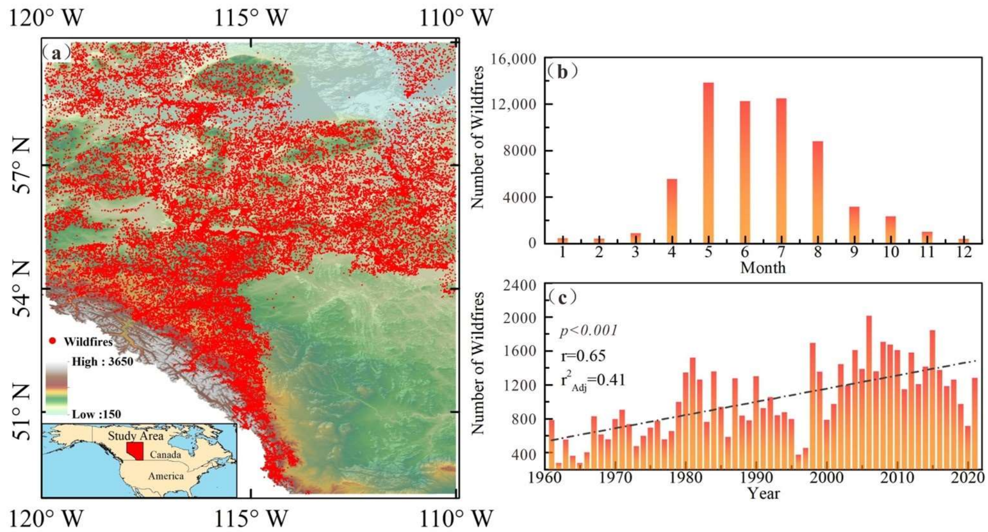

Figure 1. Spatial and temporal distribution characteristics of wildfires in the Alberta region, Canada. (**a**) spatial distribution of wildfires; (**b**) monthly distribution of wildfire numbers from 1961 to 2021; (**c**) time series of annual wildfire numbers from 1961 to 2021.

2.2. Datasets

The Alberta Forest Service initiated the modern era of wildfire recordkeeping in 1931, the first complete fire season under provincial jurisdiction. Starting in 1961, reports were entered and stored on a mainframe. Historical wildfire data for Alberta from 1961 to 2021 are available from the Alberta Open Government Program (https://open.alberta.ca/opendata (accessed on 10 May 2023)). These wildfire datasets include information on the cause, size, location (latitude and longitude, legal land description, and forest area), time and duration, weather conditions, staffing, physical resources used to fight the fire, and area burned. This is a very complete fire history dataset from which we used fire occurrence. The UK Commodity Research Institute observational climate dataset for the period 1901–2022, this dataset offers long-term historical climate data, which we used to examine climate trends over the century and correlate these with changes in wildfire patterns. Temperature (Temp), minimum temperature (Tmin), maximum temperature (Tmax), diurnal temperature range (DTR), precipitation (Prec), cloud cover (CC), self-calibrating Palmer Drought Severity Index (scPDSI), Arctic Oscillation (AO), Atlantic Multidecadal Oscillation (AMO), and sea surface temperature (SST) are from this dataset. The ERA5 reanalysis climate dataset covering January 1950 to the present, provided by the ECMWF, includes relative humidity (RH), U-wind (U), V-wind (V), and wind speed (WS) reanalysis data. Its high spatial and temporal resolution makes it particularly useful for detailed climate condition analysis at the times and locations of recorded wildfires. And CMIP5 datasets for historical and future periods (1861–2100) have been downloaded from the following websites: https://climexp.knmi.nl/ (accessed on 14 August 2023) and https://rda.ucar.edu/ (accessed on 14 August 2023). These datasets include climate indices and model outputs that help in understanding broader climatic influences and potential future scenarios of climate change.

2.3. Methods

In this study, Temp, Tmin, Tmax, DTR, Prec, CC, scPDSI [24], VPD, RH, U, V, WS, AO, AMO, and SST [25] were used as predictors to estimate the number of wildfires occurring.

VPD is an important fire-related meteorological quantity [8]. It combines temperature and water vapor content information. Following the equations used by Murray [26], we first calculated the saturation vapor pressures (SVP, Pa) using the temperature (Temp, °C) and relative humidity (RH, %):

$$\text{SVP} = 610.78 \times \exp(\text{Temp}/(\text{Temp} + 237.3) \times 17.2694) \tag{1}$$

Then, VPD (Pa) is calculated as follows:

$$\text{VPD} = (1 - \text{RH}/100) \times \text{SVP} \tag{2}$$

We used a random forest model to rank the relative importance of wildfire drivers in Alberta, which mainly include Temp, Tmin, Tmax, DTR, Prec, CC, scPDSI, VPD, RH, U, V, WS, AO, AMO, and SST [27]. To reduce overfitting, we employed five-fold cross-validation during the training of the random forest model. In each run of the five-fold cross-validation, we selected data from three consecutive years between 1961 and 2021 as out-of-bag samples. This approach helped reveal the true performance of the model in predicting wildfires. To validate our model, we compared its predictions with actual historical wildfire data from the Alberta Open Government Program dataset covering the period from 1961 to 2021. We used the F1 Score, precision, recall, and accuracy metrics to assess the accuracy and reliability of the model. We further used accumulated local effects (ALE) maps to examine detailed relationships between wildfires and key drivers. We then analyzed the intra-annual and inter-annual variability of wildfires in Alberta under moderate and high greenhouse gas emissions scenarios (RCP 4.5 and RCP 8.5). The analysis was performed in the R environment using the randomForest package and the rfPermute package [28–31].

3. Results

3.1. Drivers of Wildfires

Of all climate factors, 80% of the data are used to train the model, 10% of the data are used to test the model, and 10% of the data are used to validate the model. The random forest model performed well in simulating the number of wildfires, with an overall accuracy of 68% based on cross-validation of the observed data. The F1 score (0.90), accuracy (0.97), recall rate (0.84), and accuracy (0.83) metrics demonstrate the accuracy and reliability of the model. Variable importance analysis showed that the top four predictors of wildfire occurrence were VPD, SST, Tmax, and scPDSI (Figure 2). VPD was the most important variable driving these predictions, consistent with previous research [8].

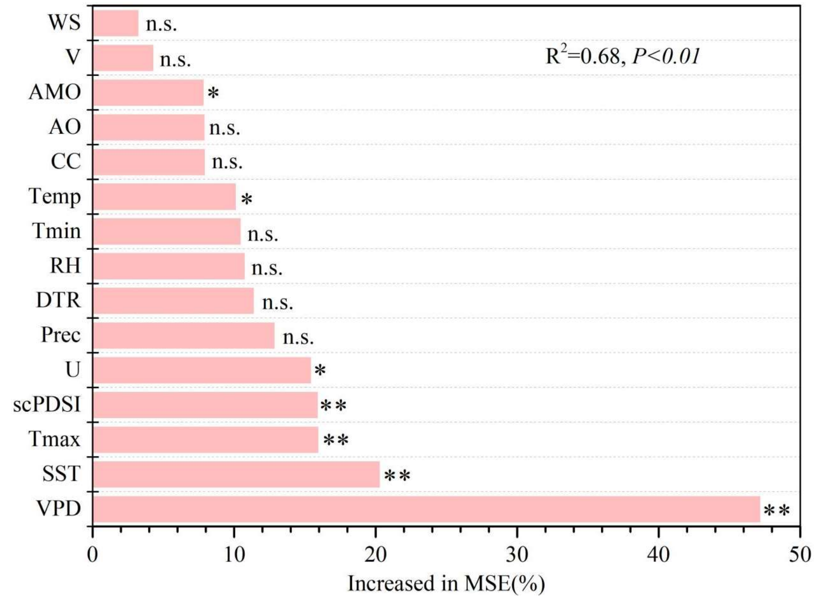

Figure 2. Main predictors of wildfires in the Alberta region, Canada. The figure shows the random forest mean predictor importance (the percentage of increase in the mean variance error (MSE)) of meteorological variables on wildfires. The cross-validated R^2 and significance of random forest models are shown. Significance levels: ** $p < 0.01$; * $p < 0.05$; n.s., non-significant ($p > 0.05$).

The ALE graph shows that VPD and SST have an approximately linear growth relationship with the number of wildfires, while PDSI has an inverse linear relationship. However, Tmax has an exponential growth relationship with the number of wildfires (Figure 3).

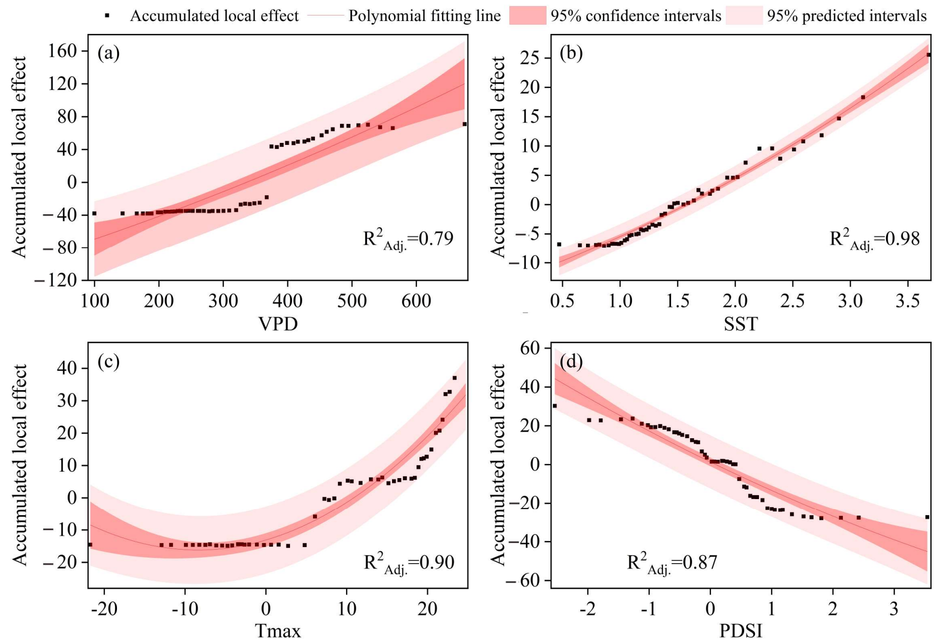

Figure 3. Sensitivity of wildfire occurrences to meteorological variables. Accumulated local effect (ALE) plots show the relationship between wildfire risk and the top four key drivers. The x-axes represent the independent covariates, and the y-axes represent the size of the mean effect each covariate has on wildfire occurrences. Variables are ranked in order of their relative importance in random forest models from high to low (**a**–**d**).

3.2. Intra-Annual Changes of the Future Wildfires

During the period 1961–2021, the number of wildfires in Alberta peaked in May and reached an annual minimum in winter (December to February). Simulation results show that under the RCP4.5 and RCP8.5 scenarios, the number of wildfires in Alberta in May in the mid- and late-21st century is not significantly different from historical periods, while the number of wildfires in July–September will increase significantly. In addition, under the RCP4.5 and RCP8.5 scenarios, the number of wildfires in Alberta will peak in July in the mid- and late-21st century, respectively. Moreover, the number of wildfires in the summer is expected to increase by 93% by the late-21st century under RCP 8.5 (Figure 4). As shown in Figure 5, under the RCP4.5 and RCP8.5 scenarios, VPD, SST, Tmax, and PDSI in Alberta, Canada, change significantly in the mid- and late-21st century compared with the historical period, especially from July to September (Figure 5). Specifically, the Vapor Pressure Deficit (VPD) and the Palmer Drought Severity Index (PDSI) show more pronounced changes during the summer months. High VPD, indicative of drier air, and lower PDSI, signaling drought conditions, both contribute to increased wildfire risk during this period. These conditions facilitate the drying of vegetation, making it more flammable and susceptible to ignition. Conversely, the maximum temperature (Tmax) exhibits a notable increase during the winter months. However, there is also a discernible rising trend in summer Tmax values. This rise in temperatures can exacerbate the drying conditions, further enhancing the likelihood of wildfires. Sea Surface Temperature (SST) changes are more pronounced during the winter. While SST primarily influences climatic patterns over broader timescales and regions, its impact on regional climate systems can alter precipitation patterns and temperatures, indirectly affecting wildfire conditions. The interplay of these factors is critical in shaping the seasonal and annual patterns of wildfire occurrences. During summer, the combination of high VPD, low PDSI, and elevated Tmax creates optimal conditions for wildfires. In winter, while the direct influence of Tmax and SST on wildfires is less pronounced, their role in shaping broader climatic patterns cannot be overlooked.

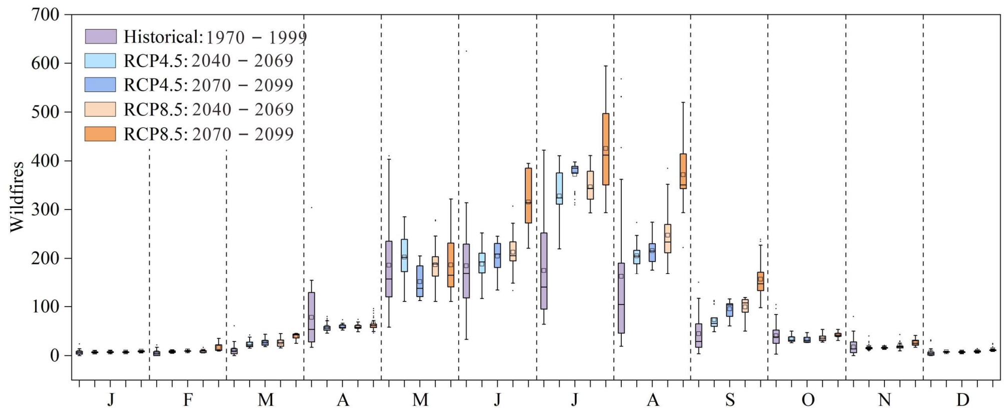

Figure 4. Seasonal variations in the earth system model (ESM) ensemble mean number of wildfires. Monthly wildfire numbers for the end of the 20th century (1970–1999) and the middle (2040–2069) and end (2070–2099) of the 21st century in the Alberta area are shown. Wildfire number simulations for the moderate (RCP4.5) and high (RCP8.5) emission climate change scenarios are compared here. Meaning of boxplot elements: central line: median, box limits: upper and lower quartiles, upper whisker: min (max (x), Q3 + 1.5 × IQR), lower whisker: max (min (x), Q1 − 1.5 × IQR), black dots: outliers.

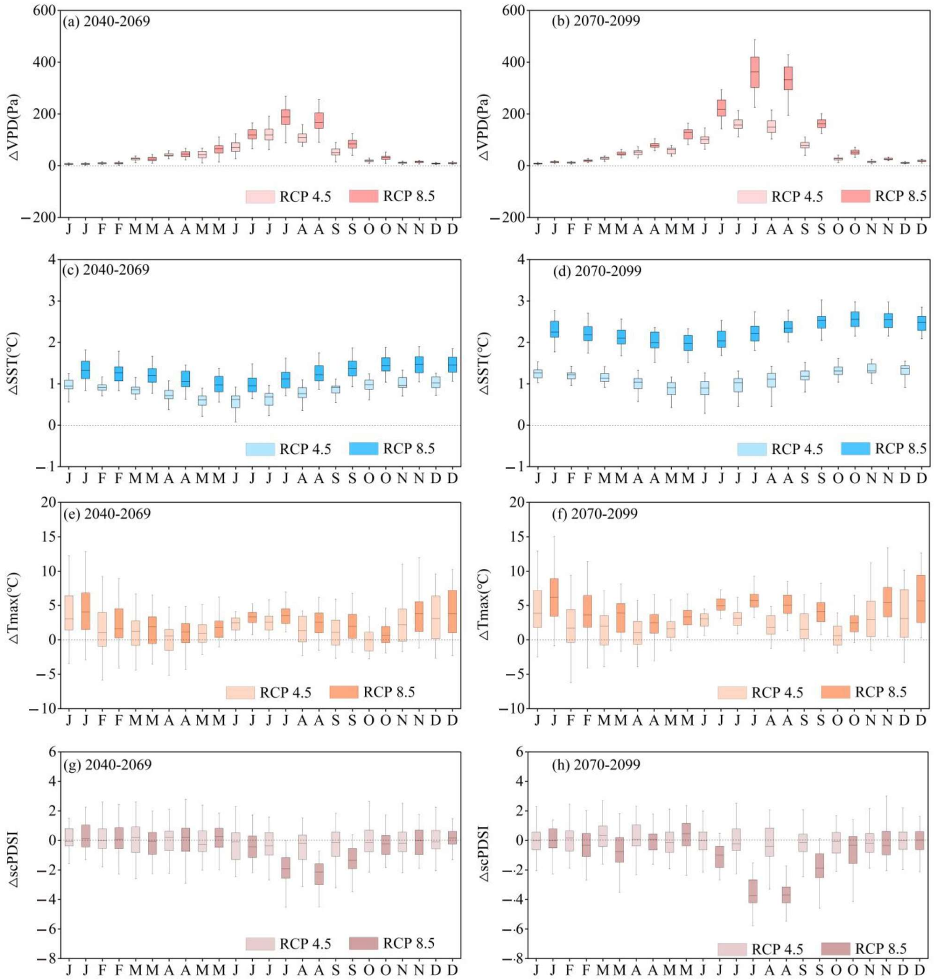

Figure 5. Earth system model (ESM) ensemble-mean changes in simulated VPD (**a**,**b**), SST (**c**,**d**), Tmax (**e**,**f**), and scPDSI (**g**,**h**) by the middle (**a**,**c**,**e**,**g**, 2040–2069) and end (**b**,**d**,**f**,**h**, 2070–2099) of the 21st century compared with the historical period (1970–1999) for the RCP4.5 and RCP8.5 scenarios. Meaning of boxplot elements: central line: median, box limits: upper and lower quartiles, upper whisker: min (max (x), Q3 + 1.5 × IQR), lower whisker: max (min (x), Q1 − 1.5 × IQR), black dots: outliers.

3.3. Changes of the Future Wildfires

The simulation results show that the number of wildfires in Alberta will continue to increase in the mid- and late-21st century under the RCP 4.5 and RCP 8.5 scenarios. By the mid-21st century (2040–2069), the average annual number of wildfires in Alberta will increase from 918 in the historical period (recorded in 1970–1999) to about 1151 under the RCP 4.5 scenario, and the average annual number of wildfires will increase to 1258 under the RCP 8.5 scenario. By the end of the 21st century (2070–2099), the average annual number of wildfires in Alberta will increase from 918 in the historical period (recorded in 1970–1999) to about 1199 under the RCP 4.5 scenario, and the average annual number of wildfires will increase to 1555 under the RCP 8.5 scenario (Figure 6). Based on CMIP5 data, we calculated the historical and future inter-annual changes of VPD, SST, Tmax, and scPDSI. The results show that under the RCP4.5 and RCP8.5 scenarios, Alberta will experience varying degrees of warming and drying in the mid- and late-21st century compared to historical periods (Figure 7).

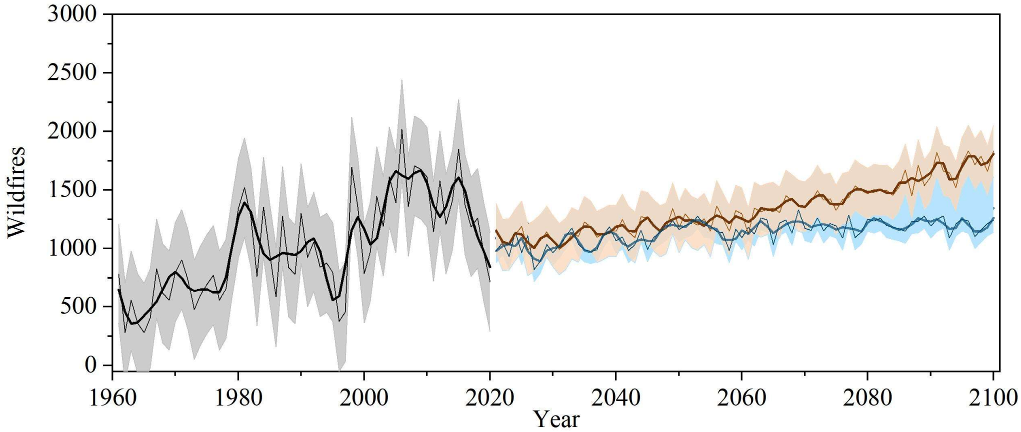

Figure 6. Earth system model (ESM) ensemble means the simulated annual number of wildfires. Both the historical (grey, 1961–2020) and future (blue/tan, 2021–2099, blue: moderate emission scenario, RCP4.5, tan: high emission scenario, RCP8.5) variations of these variables are shown. Shaded areas represent ±1 standard deviation. A low-pass filter was applied to remove the highest 20% frequencies to reduce noise in the time series.

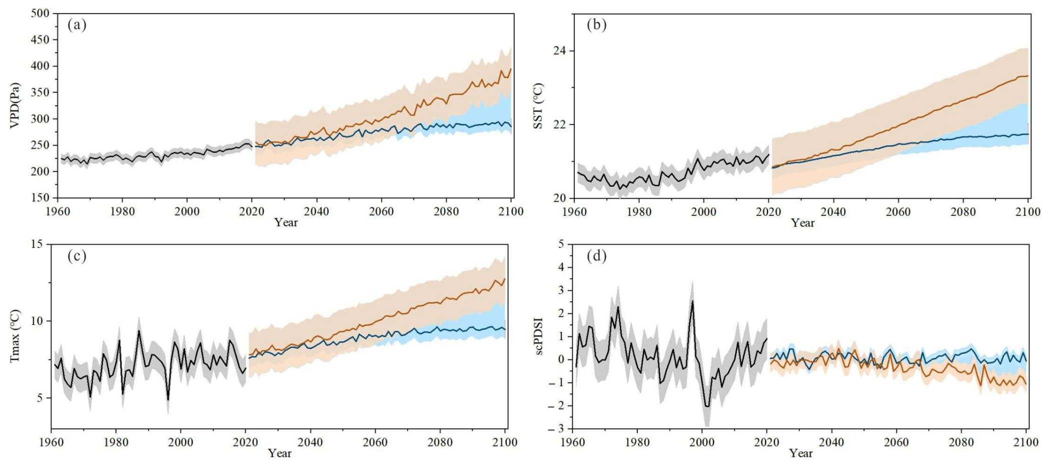

Figure 7. Earth system model (ESM) ensemble mean changes in simulated VPD (**a**), SST (**b**), Tmax (**c**), and scPDSI (**d**). Both the historical (grey, 1961–2020) and future (blue/tan, 2021–2099, blue: moderate emission scenario, RCP4.5, tan: high emission scenario, RCP8.5) variations of these variables are shown. Shaded areas represent ±1 standard deviation.

4. Discussion

The random forest model has robustness when dealing with large datasets with complex nonlinear relationships between variables. Random forests effectively capture complex, nonlinear interactions between variables, which is crucial in accurately modeling wildfire occurrences that depend on a myriad of interlinked factors. Unlike some other algorithms, random forests require minimal data preprocessing and are less sensitive to outliers, making them ideal for ecological data that often contain anomalies. While the random forest model is generally robust, random forests can still overfit if not properly tuned, especially when dealing with very noisy data. And the model can be computationally demanding, which might limit its applicability in real-time prediction scenarios.

Previous research has established that Vapor Pressure Deficit (VPD) and maximum temperature (Tmax) are critical drivers of wildfires [8,32]. Increases in both VPD and Tmax have been shown to significantly affect vegetation growth [33,34] and increase forest mortality [35]. Furthermore, these increases can limit transpiration across various biomes by altering the behavior of plant stomata [36], thereby drying out fuels and making them more flammable and likely to ignite. Drought conditions, often exacerbated by atmospheric ridges and blocking, reduce the moisture content in fuels, subsequently increasing wildfire activity [37]. Moreover, both average and extreme temperature rises contribute to the dryness of fuels, leading to more frequent and severe wildfires [9,38]. In Alberta, warmer and drier conditions are shifting the wildfire regime towards more frequent, severe, and widespread fires [23,39]. This trend is consistent with findings from other boreal forest regions in western Canada [17] and across North America [40]. However, it is important to note that the increased frequency of wildfires in Alberta is not confined to boreal forests but affects various ecosystems, including grassland areas. Studies documenting rising trends in fire activity across boreal biomes [41,42] further support this broader pattern. The significant relationship between climate change and increased wildfire activity in Alberta underscores the need to consider the impacts of VPD and Tmax across all ecological zones within the region. This comprehensive approach will provide a more accurate understanding of the dynamics at play and enhance the effectiveness of wildfire management strategies.

Under the RCP 4.5 and RCP 8.5 scenarios, the peak wildfire period in Alberta during the mid- to late-21st century shifts from May to July. This shift is likely due to wildfires reducing the viability of conifer seeds [43,44] and altering the soil substrate required for tree regeneration [45]. Over time, conifer regeneration densities decrease after wildfire [46] and shift toward less flammable, dominant broadleaf species [47]. Wildfires in areas covered by non-flammable, predominantly broadleaf forests require higher VPD, Tmax, and more severe drought conditions. Under the high GHG emission scenario (RCP 8.5), the VPD, Tmax, and drought severity in July of the mid-20th century were much greater than those in May (Figure 5). The same pattern was observed under the moderate greenhouse gas emissions scenario (RCP 4.5). By the end of the 21st century, the differences in these parameters between July and May became even more significant under the RCP 4.5 and RCP 8.5 scenarios, respectively (Figure 5). Although the observed shift in peak fire activity to July might initially suggest a response to changes in vegetation types and densities, it is important to clarify that such vegetative dynamics are not explicitly modeled in the current framework. Instead, the shift is more likely attributable to changes in climatic variables such as Vapor Pressure Deficit (VPD) and Palmer Drought Severity Index (PDSI), which are projected to peak during this month. Therefore, any inference regarding vegetation change affecting fire regimes should be approached with caution, as the model primarily reflects climatic influences rather than direct biological responses of vegetation to changing climate or fire recovery processes.

5. Conclusions

In the past 60 years, the climate in western Canada has become noticeably warmer and drier, which has directly affected the frequency of local wildfires. We have observed a significant increase in the number of wildfires during this period. Looking ahead, we also predict that the peak period for wildfires will shift from May to July. These changes in wildfire characteristics correspond to climate change. Our significant correlation analysis indicates that climate change will continue to alter wildfire characteristics in the boreal forests of western Canada. As climate change continues, we can expect these changes in wildfire characteristics to persist and possibly accelerate, posing even greater challenges for wildfire and forest management.

Author Contributions: Conceptualization, M.B.; methodology, M.B.; software, M.B.; validation, M.B.; formal analysis, M.B.; investigation, D.W. and H.Z.; resources, Q.Y. and Z.W.; data curation, M.B.; writing—original draft preparation, M.B.; writing—review and editing, Q.Y., Z.W., K.F. and F.G.; visualization, M.B.; supervision, D.W. and H.Z.; project administration, M.B.; funding acquisition, Q.Y. and Z.W. All authors have read and agreed to the published version of the manuscript.

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