

Article

Spatiotemporal Characteristics, Causes, and Prediction of Wildfires in North China: A Study Using Satellite, Reanalysis, and Climate Model Datasets

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Abstract: Understanding the characteristics of wildfires in North China is critical for advancing regional fire danger prediction and management strategies. This study employed satellite-based burned area products of the Global Fire Emissions Database (GFED) and reanalysis of climate datasets to investigate the spatiotemporal characteristics of wildfires, as well as their relationships with fire danger indices and climatic drivers. The results revealed distinct seasonal variability, with the maximum burned area extent and intensity occurring during the March–April period. Notably, the fine fuel moisture code (FFMC) demonstrated a stronger correlation with burned areas compared to other fire danger or climate indices, both in temporal series and spatial patterns. Further analysis through the self-organizing map (SOM) clustering of FFMC composites then revealed six distinct modes, with the SOM1 mode closely matching the spatial distribution of burned areas in North China. A trend analysis indicated a $7.75\% \text{ } 10\text{a}^{-1}$ ($p < 0.05$) increase in SOM1 occurrence frequency, associated with persistent high-pressure systems that suppress convective activity through (1) inhibited meridional water vapor transport and (2) reduced cloud condensation nuclei formation. These synoptic conditions created favorable conditions for the occurrence of wildfires. Finally, we developed a prediction model for burned areas, leveraging the strong correlation between the FFMC and burned areas. Both the SSP245 and SSP585 scenarios suggest an accelerated, increasing trend of burned areas in the future. These findings emphasize the importance of understanding the spatiotemporal characteristics and underlying causes of wildfires, providing critical insights for developing adaptive wildfire management frameworks in North China.

Keywords: North China; burned area; SOM modes; fine fuel moisture code; atmospheric circulation



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1. Introduction

Wildfires are one of the Earth's most important natural driving forces as they destroy surface vegetation, release CO₂, and alter the carbon–water cycle [1]. Over the last 20 years, economic losses amounting to hundreds of billions have occurred due to wildfires, resulting in a deforestation area of $10.33 \times 10^9 \text{ hm}^2$ globally [2]. Although lightning and other natural causes have played important roles in wildfires for millions of years, wildfires caused by climate change have become more frequent in recent decades in many

regions worldwide [3–6]. The characteristics and contributions of wildfires have, therefore, garnered global research attention.

The anthropogenic factors driving prolonged temperatures and droughts, which facilitate the accumulation of dry fuels and the spread of wildfires, have been systematically investigated using Earth system models [5]. For instance, rising temperatures and reduced precipitation have heightened the probability of extreme climatic events in the western United States over the past four decades, contributing to the unprecedented severity and extent of recent wildfires [7–9]. Similarly, anthropogenic climate change has been shown to have increased the likelihood of the 2019–2020 Australian wildfires by 30%, leading to the destruction of thousands of homes [10]. A total of 1.3×10^5 forest wildfires have occurred in China over the past 20 years, covering an area of 3.86 million km² [2]. China contributes roughly 6% of the global total number of wildfires annually, highlighting the country's susceptibility to wildfire occurrence [11]. Since 1960, the incidence of wildfires has risen in the northeast and south China, while it has declined in the southwestern region [12,13]. Within the context of climate change, wildfire danger is expected to dramatically increase in both North China and Southwest China [14,15]. In February 2024, prolonged drought conditions in southwestern China led to 221 instances of mountain fires, with fires persisting for several days. These fires severely affected local communities and livelihoods, resulting in two fatalities, as reported by the Ministry of Emergency Management [16]. In March 2020, numerous forest fires in North China, such as those in Yanqing District in Beijing and Jinzhong City, caused significant damage to forests, severely disrupting the ecological environment and exacerbating the levels of air pollution [17]. Furthermore, some findings indicated that under high-emission scenarios, the burned area extent was projected to increase significantly with the increasing frequency of droughts and lightning-induced fires [18,19]. Additionally, future wildfire events are expected to elevate PM_{2.5} concentrations, leading to mortality rates that are substantially higher under high-emission scenarios compared to those under low-emission scenarios [20,21]. These findings highlight that the increasing frequency of extreme weather/climate events, driven by climate change, plays a significant role in influencing both the frequency and intensity of wildfires in the future.

North China is one of the major political and economic centers in China and even the world [22,23]. On the one hand, the region is bordered by the vegetation cover mountain areas in the west and north, respectively, while on the other hand, a higher risk of extremely high temperatures and severe drought under global warming has arisen in recent decades in North China [24,25]. The interaction between extreme weather/climate events and the availability of fuel may therefore contribute to an increased frequency of wildfires in North China. In addition, the fire weather danger model is derived using the time-lagged equilibrium moisture content theory [26,27], which has been applied in wildfire warning systems across various regions, including North China. It has also been utilized in studies examining the effects of climate change on wildfire danger [28–30]. The fire danger indices of the fire weather danger model were therefore used to research the impact of climate change on wildfires in North China.

The application of neural networks, such as self-organizing maps (SOM) and convolutional neural networks, have significantly broadened the technological scope of recent wildfire research. For instances, Rodrigues et al. (2019) [31] and Trouet et al. (2006) [32] demonstrated this capability through the SOM-based clustering of synoptic-scale circulation patterns—the former identifying fire-prone weather regimes in Mediterranean Spain, and the latter characterizing coastal wildfire drivers along the North American Pacific Northwest—and their findings provided new insights for fire risk prediction. A hybrid framework integrating random forest with physical models enhanced the regional fire risk assessment precision by integrating climate teleconnections, topographic factors, and

vegetation type, which addressed interpretability challenges [33,34]. Convolutional neural networks have demonstrated accuracy levels exceeding 90% in automated burned area mapping through the extraction of multi-spectral features from Sentinel-2 imagery [35,36]. Meanwhile, long short-term memory networks enhance fire spread prediction by effectively modeling the temporal dynamics of fuel [37]. These studies have innovatively advanced the understanding of fire–climate interactions, as well as burned area identification. However, there remains a lack of research attention on and understanding of the characteristics and causes of wildfires in North China based on neural network methods.

This study aimed to explore the spatiotemporal characteristics, causes, and prediction of wildfires in North China. We addressed the following questions: (1) What are the spatiotemporal characteristics of the wildfires in North China? (2) What are the spatial classifications of wildfires and dominant influencing factors? (3) What are the temporal variations in wildfires in the different shared socioeconomic pathway (SSP) scenarios? The remainder of this manuscript is structured as follows: Section 2 outlines the materials and methods, Section 3 presents the results, Section 4 provides the discussion, and Section 5 concludes the study.

2. Materials and Methods

2.1. Study Area

North China is geographically defined by the Taihang Mountains to the west, the Yanshan Mountains to the north, the Shandong Hills to the southeast, and the North China Plain in the central and southern regions, spanning longitudes 110° – 121° E and latitudes 34° – 47° N (Figure 1). The region's northern and western high-altitude areas are primarily covered by forests and grasslands, while the southern part is dominated by expansive croplands. Urbanization is concentrated in and around major cities. The region is characterized by a warm, temperate continental monsoon climate featuring cold, dry winters and hot, rainy summers. This climate pattern is primarily governed by the East Asian monsoon system [38,39].

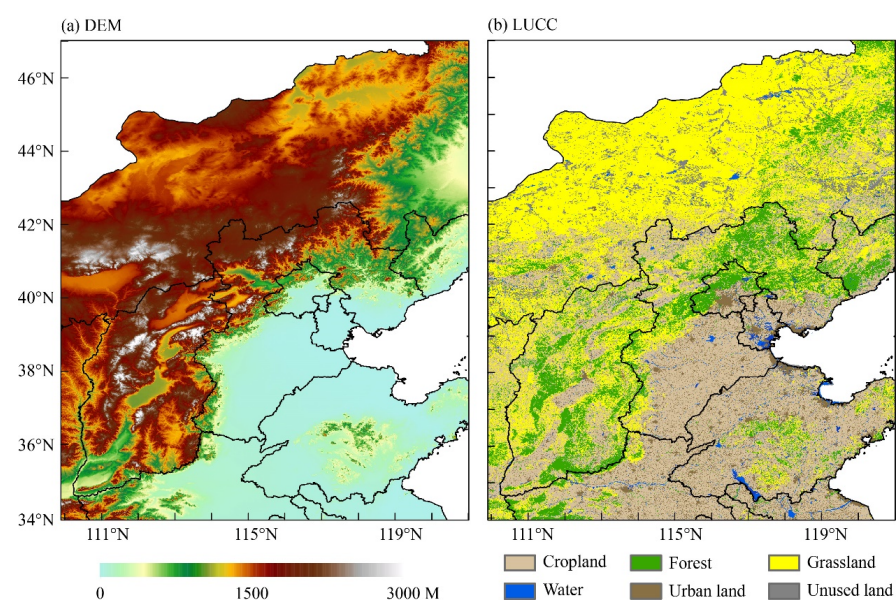


Figure 1. Terrain (a) and land use type in 2020 (b) in the North China (The black line denotes the provincial boundary).

2.2. Data

The datasets used include ERA5 from the European Centre for Medium-range Weather Forecasts (ECMWF), the Global Fire Emissions Database version 5 (GFED v5), a land use type dataset, a gridded population dataset, and simulation outputs from the Coupled Model Intercomparison Project Phase 6 (CMIP6).

ERA5 global reanalysis meteorological data originate from the fifth-generation ECMWF atmospheric reanalysis of the global climate and replace ERA-Interim data [40]. ERA5 offers much higher spatial ($0.25^\circ \times 0.25^\circ$) and temporal (hourly) resolutions and more pressure levels (a total of 137 levels) than earlier reanalysis products. Many studies have also shown that the use of ERA5 improves other surface weather reanalysis methods, such as wind [41] and precipitation [42]. We downloaded ERA5 hourly data from 1981 to 2020, such as the maximum surface air temperature (Tmax), relative humidity (RH), wind speed (WS), precipitation, multiple geopotential height (200 hPa and 500 hPa), and sea level pressure.

GFED v5 is a satellite-derived dataset of biomass burning emissions based on a top-down calculation methodology [43]. The GFED dataset provides $0.25^\circ \times 0.25^\circ$ -resolution biomass burning emissions from 2002 to 2022, including the burned area, $PM_{2.5}$ concentration, carbon mass, dry matter mass, and contribution of each burning type to the total emissions. GFED v5 performs notably better than its predecessors (i.e., GFED v3 and GFED v4) due to considering the contribution of small fires [44,45].

The DEM dataset is derived from the Shuttle Radar Topography Mission (SRTM) data collected by the United States Endeavour Space Shuttle. A land use type dataset for 2020 was extracted from the National Land Use Datasets of China involved in Resource and Environment Science and Data Center, Chinese Academy of Sciences (RESDC-CAS, <https://www.resdc.cn/>, accessed on 20 July 2024). The dataset is based on Landsat ETM/TM/OLI, ZY-3, HJ-1A, and other satellite images and relies on a unified standard artificial digital interpretation that comprises six classes (i.e., cropland, forest land, grassland, water, urban and rural construction land, and unused land). Importantly, the average classification accuracy of the dataset is more than 90% [46,47].

Jiang et al. (2022) [48] created a gridded population dataset, which has a temporal resolution of years, a spatial resolution of $0.5^\circ \times 0.5^\circ$, and a coverage span of 2010–2100. This dataset considered the impact of population policy changes on the demographic structure and economy and was relatively close to the national conditions of China, which has been widely used for population exposure assessment [49].

Daily simulation outputs (Tmax, RH, WS, precipitation) were derived from 16 Earth system models (Table 1) via the CMIP6. Three sets of experiments were collected, including historical simulations and simulations under the SSP245 and SSP585 scenarios. The historical simulations involved real-time, dynamic external forcings (e.g., greenhouse gasses and LUCC). SSP245 and SSP585 are future scenarios with different social development patterns and greenhouse gas emissions [50].

Table 1. Details of the 16 CMIP6 global climate models, including model names, countries, as well as atmospheric resolutions.

ID	Model Name	Institution and Country	Atmospheric Resolution (lon $\times$ lat: Number of Grids, L: Vertical Levels)
1	ACCESS-CM2 *	Commonwealth Scientific and Industrial Research Organization, Australian Research Council Centre of Excellence for Climate System Science, Australia	192 $\times$ 145, L85

Table 1. Cont.

ID	Model Name	Institution and Country	Atmospheric Resolution (lon × lat: Number of Grids, L: Vertical Levels)
2	ACCESS-ESM1-5 *	Commonwealth Scientific and Industrial Research Organization, Australia	192 × 145, L38
3	CanESM5 *	Canadian Centre for Climate Modelling and Analysis, Canada	128 × 64, L49
4	CMCC-ESM2 *	Euro-Mediterranean Centre for Climate Change Foundation, Italy	288 × 192, L30
5	EC-Earth3 *	EC-Earth Consortium, Europe	512 × 256, L91
6	FGOALS-g3 *	Chinese Academy of Sciences, China	180 × 80, L26
7	GFDL-CM4 *	National Oceanic and Atmospheric Administration, Geophysical FluidDynamics Laboratory, USA	288 × 180, L49
8	INM-CM4-8 *	Institute for Numerical Mathematics, Russia	180 × 120, L21
9	INM-CM5-0 *	Institute for Numerical Mathematics, Russia	180 × 120, L73
10	IPSL-CM6A-LR *	Institute Pierre Simon Laplace, France	144 × 143, L79
11	MIROC6 *	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan	256 × 128, L81
12	MIROC-ES2L *	National Institute for Environmental Studies, The University of Tokyo, Japan	128 × 64, L40
13	MPI-ESM1-2-HR *	Max Planck Institute for Meteorology, Germany	384 × 192, L95
14	MPI-ESM1-2-LR *	Max Planck Institute for Meteorology, Alfred Wegener Institute, Germany	192 × 96, L47
15	MRI-ESM2-0 *	Meteorological Research Institute, Japan	320 × 160, L80
16	NorESM2-LM *	NorESM Climate Modeling Consortium, Norway	144 × 96, L32

Note: * includes two SSP scenarios.

2.3. Methods

The workflow of this study is shown in Figure 2, including spatial pattern of monthly burned areas, spatial classification of fire danger index based on SOM, the impact of synoptic pattern on spatial classification of fire danger index, trend analysis of hazard PM_{2.5} and population exposure and burned areas prediction in different SSP scenarios. The detailed methodological content is as follows.

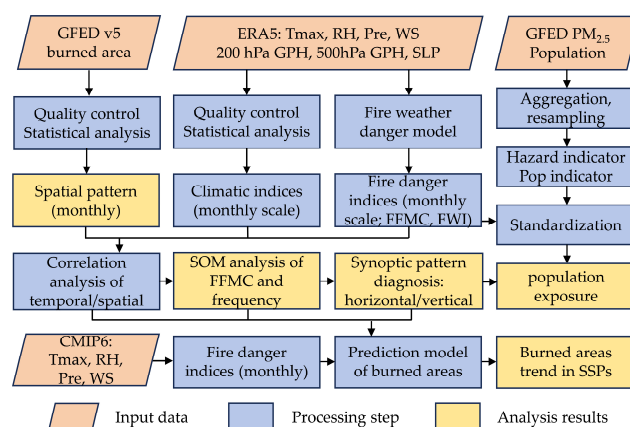


Figure 2. The workflow of this study. Tmax: maximum surface air temperature; RH: relative humidity; WS: wind speed; Pre: precipitation; GPH: geopotential height; SLP: sea level pressure.

2.3.1. Fire Weather Danger Model

The fire weather danger model is founded on the time-lag equilibrium moisture content theory, which establishes a direct relationship between meteorological variables and fuel moisture content. Generally, climate indices are regarded as indicators of whether meteorological conditions are conducive to wildfire occurrence. Notably, the fire weather danger indices exhibit strong positive correlations with the burned area across most of the global burnable land mass [51].

A total of six indices comprises the fire weather danger model: initial spread index (ISI), duff moisture code (DMC), drought code (DC), fine fuel moisture code (FFMC), build-up index (BUI), and fire weather index (FWI). These fire weather danger model components can be calculated based on daily meteorological records of Tmax, RH, WS, and precipitation. The FWI directly combines the BUI (indicating the available fuel index calculated by Tmax, RH, and precipitation) and the ISI (indicating the wildfire spread rate index calculated by WS) [26,52].

However, the fire weather danger model was originally designed for Canada. Certain parameters do not apply globally. For instance, the FFMC is a numerical index that quantifies the moisture content of litter and other cured fine fuels, serving as an indicator of their susceptibility to ignition and combustibility. The parameters (i.e., the effective day length factor, Le) of the FFMC in the initial fire weather danger model are constant, depending on the latitude of Canada. It is unreasonable to apply the initial parameter Le in North China. Some researchers have found that the applicability and accuracy of the fire weather danger model varied significantly across different latitudes, particularly in northern mid-high-latitude regions [53]. It is, therefore, necessary to perform targeted adjustments to the model parameter Le to ensure its accuracy and reliability in applications [54]. Considering that Le is affected by the latitude, we revised the Le value in each month based on the latitude in each grid cell.

$$Le = 12 + \left(2 \times \arcsin \left(\tan(\theta) \times \tan \left(23.45 \times \sin \left(2\pi \times \frac{284 + n}{N} \right) \right) \right) \right) / 15^\circ \quad (1)$$

where θ is the latitude of the grid cell. N is 365/366 for a common/leap year, and n is the number of days, i.e., 1, 2, ..., 365/366 (common/leap year).

To avoid systematic biases in individual climate models, multi-model ensemble means (MMEs) were derived by averaging the fire danger index values across 16 climate models.

2.3.2. Self-Organizing Map Analysis

A Self-organizing map (SOM) is a neural network-based clustering technique that has recently gained traction in earth sciences for characterizing the continuum of spatial patterns within datasets [55,56]. A SOM analysis of wildfire patterns is akin to a traditional principal component analysis, where the nodes of the SOM correspond to the dominant modes of the underlying wildfire field. In practice, this feature increases the likelihood that the SOM corresponds to physically plausible patterns [57]. First, we performed a standardization process on the fire danger indices for the North China region, conducted on a grid-by-grid basis. We then used an $m \times n$ (where $m/n = 2, \dots, 6$) grid topology and the weight vectors were initialized through PCA orthogonalization. The weight vectors of the neighboring nodes were adjusted by modifying the neighborhood function, bringing them closer to the input samples. The training process was completed through multiple iterations, with the neighborhood range and learning rate gradually decreasing until the network converged. The training parameters were set as follows: an initial learning rate of 0.5 (exponentially decaying to 0.01), a neighborhood radius decreasing from 3 to 1 (Gaussian decay), and 1000 training cycles. Finally, through a synthetic analysis, it was found that the

2×3 network topology yielded the best results for the fire danger indices classification in North China. The SOM algorithm generated spatial patterns that optimized their similarity to the underlying wildfire fields, assigning each daily wildfire field to the pattern that most closely matched it. The application of neural networks, such as self-organizing maps (SOMs), has significantly broadened the technological scope of recent wildfire research. For instance, Rodrigues et al. (2019) [31] and Trouet et al. (2006) [32] demonstrated this capability through SOM-based clustering of synoptic-scale circulation patterns—the former identifying fire-prone weather regimes in Mediterranean Spain, and the latter characterizing coastal wildfire drivers along the North American Pacific Northwest—and their findings provide new insights for fire risk prediction.

2.3.3. Population Exposure

Exposure is defined as the number of individuals exposed to air pollution, such as $PM_{2.5}$. It is calculated for each grid cell by multiplying the $PM_{2.5}$ concentration by the estimated number of people exposed to $PM_{2.5}$. The population exposure is derived using the following equation:

$$E_i = PM_{2.5_i} \times Pop_i \quad (2)$$

$$X = (x - x_{min}) / (x_{max} - x_{min}) \quad (3)$$

where i represents the year, E denotes population exposure, and Pop refers to the number of people. To account for the differing units of the $PM_{2.5}$ and population datasets, both are normalized to ensure a reasonable estimation of population exposure. The normalization method is defined in Equation (3), where X represents the number of people and the $PM_{2.5}$ concentration, respectively. This method has been widely studied in terms of wildfire smoke pollution and its impact on population exposure. For example, reliable associations have been established between wildfire smoke exposure and the risk of cardiovascular diseases [58], as well as mortality rates in aging populations [59].

2.3.4. Prediction Model of Future Burned Areas

A linear regression model is developed to predict the burned areas in North China, using the March–April FFMC. The model is expressed by the following equation:

$$\text{Predicted BA} = a_1 \times \text{FFMC} + a_0 \quad (4)$$

where a_0 and a_1 denote the coefficients determined through the variable regression procedure for BA, and FFMC is the important predictor variable used in the model.

The prediction model employs the “leave-one-out” cross-validation approach [60]. Leave-one-out cross-validation is an unbiased cross-validation estimation method used to evaluate the generalization performance of statistical models. The core idea is as follows: at each iteration, one sample is withheld from the dataset to serve as the test set, while the remaining samples are used as the training set. This process is repeated until each sample has been used as the test set once. The model performance is then evaluated according to the mean error of all the test results. Its primary advantage lies in its ability to validate statistical models constructed from small sample datasets. By maximizing the utilization of limited data, it circumvents the potential information loss associated with random partitioning of training and test sets. In detail, to predict the burned area in 2020, the regression coefficients are calculated using data from all years except 2020 (i.e., 2002–2019). The model is then fitted with the data from 2002 to 2019, and the burned area for 2020 is predicted. This process is repeated for each year, yielding predicted burned values for the period 2002–2020. The coefficients a_0 and a_1 , determined through the multivariable regression procedure, vary annually. The use of “leave-one-out” cross-validation enhances

the reliability of the predictions and effectively demonstrates the operational capability of the model in forecasting BA in North China.

3. Results

3.1. Spatiotemporal Characteristics of the Burned Area Fraction in North China

North China has experienced significant climate variability and extreme climate events (e.g., heatwaves and droughts) against the background of global warming. Considering that winter wheat and summer corn straw materials in North China would be burned, these may affect the identification of natural fire spots from satellite remote sensing. We, therefore, focused only on the satellite-derived GFED products in forests and grasslands. Figure 3 illustrates the spatial patterns of the monthly average burned area fraction in North China over the period from 2002 to 2020. The white areas indicate that non-forest or grassland; the gray areas indicate that the burned area fraction is zero in forest and grassland. The spatial patterns of the burned areas varied in different months for North China, but these could be roughly categorized into four types: The first type is burned forest and grassland concentrated in Shanxi Province, western and northern Hebei, western and northern Beijing, western Liaoning, and the eastern and southwestern parts of central Inner Mongolia. This spatial type is observed in March and April, representing 51.94% and 59.78%, respectively, of grids with burned areas from the total number of forest and grassland grids. The second type refers to burning concentrated in the eastern and southern Shanxi Province, the western and northeastern Hebei Province, the northern Beijing, and the eastern of central Inner Mongolia. These similar spatial patterns were observed in May, August, September, and October, with 41.40%, 30.97%, 34.41%, and 42.04% of burned areas, respectively. The third spatial type is mainly concentrated in Shanxi Province, western and northeastern Hebei, and so on, with the spatial patterns of burned areas being similar in February, June, July, and November, with 34.73%, 31.51%, 29.57%, and 36.24%, respectively. The fourth spatial type of burned area was observed in January and December, which had similar spatial patterns and the smallest values of burned areas in all months, with 21.08% and 16.34%, respectively. Overall, the burned areas are mainly in western Shanxi and Hebei, with no burning in the remaining regions.

The abovementioned findings suggest that the extent and intensity of the burned area are maximized during March–April based on the satellite-based GFED burned area products, and we, thus, define March–April as the high wildfire season in North China. Meanwhile, we will focus primarily on the relationship between variations in burned areas and climate change during the months of March and April.

Figure 4 shows the March–April standardized temporal series of the different indices and their varying spatial distributions of trends. We found that the trend in the burned area from 2002 to 2020 was dominated by an increasing trend of 1.18×10^{-1} . The two fire danger indices (FFMC and FWI) have likewise been dominated by increasing trends over the past 20 years. In detail, the correlation coefficient (r) between the FFMC and burned area was 0.55, which was statistically significant at the 95% confidence level. Although the r value between FWI and the burned area was 0.31, it failed the 90% significance test, suggesting that the fine fuel moisture was more closely related to the burned area of forest and grassland in North China. We also analyzed the trend changes in the two climate indices (temperature and precipitation) and found that the temperature was dominated by an increasing trend, but the precipitation was dominated by a decreasing trend. The r value between the temperature and burned area was 0.16, which did not pass the 95% significance test, but the r value between the precipitation and burned area was -0.49 and passed the 95% significance test. This suggests that the decrease in precipitation may be contributing to the increase in the burned area extent in North China. Meanwhile, we also

verified the correlation between the fine fuel moisture index and precipitation and found a high negative correlation ($p < 0.01$), thus suggesting that a decrease in spring precipitation within the past 20 years may have led to a decrease in moisture, which in turn induced wildfires and an increasing trend in burned area.

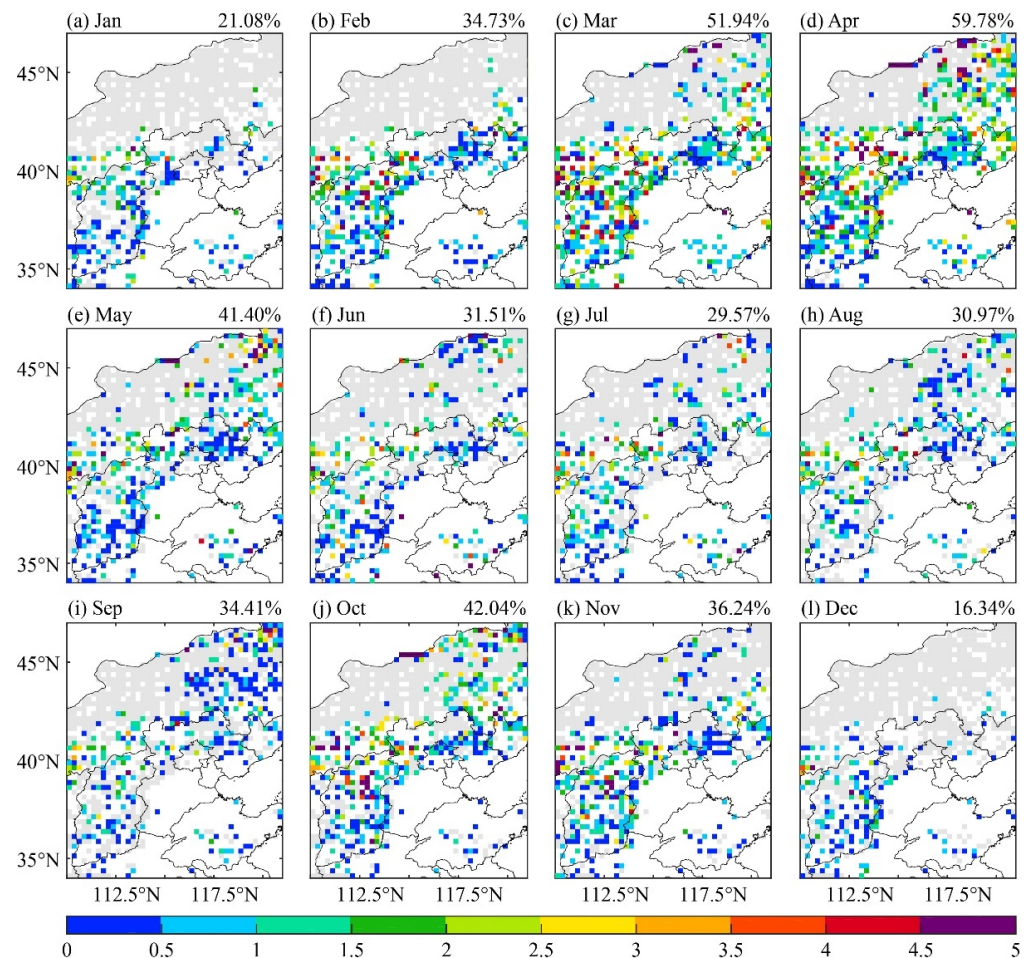


Figure 3. Spatial patterns of the monthly average burned area fraction in North China during 2002–2020 (units: %; the value in the upper right corner indicates the percentage of grid numbers with burned area fraction greater than 0 of the total grid numbers of forest and grassland).

In addition to temporal series trend analyses of multiple indices, we also analyzed the spatial characteristics of trends in fire danger indices and climate indices. We found that the trend changes in the FWI and FFMCI from 1991 to 2020 were predominantly increasing in most regions, with maximum values of 0.64 and 0.74, respectively. However, the increasing trend in the FFMCI was more extensive in the northeastern part of North China than the change in FWI. The percentages of grid numbers with trend more than zeros of the total grid numbers were 76.91% and 85.45% in the FWI and FFMCI, respectively. The temperature trend changes were dominated by an increase over most of the region, but only about 70% of the total region was greater than zero. The trend change in precipitation from 1991 to 2020 was dominated by a decrease in most areas, and the maximum value of the decreasing trend was -0.77 , respectively. The percentage of grid numbers with a trend of less than zero was 76.08%.

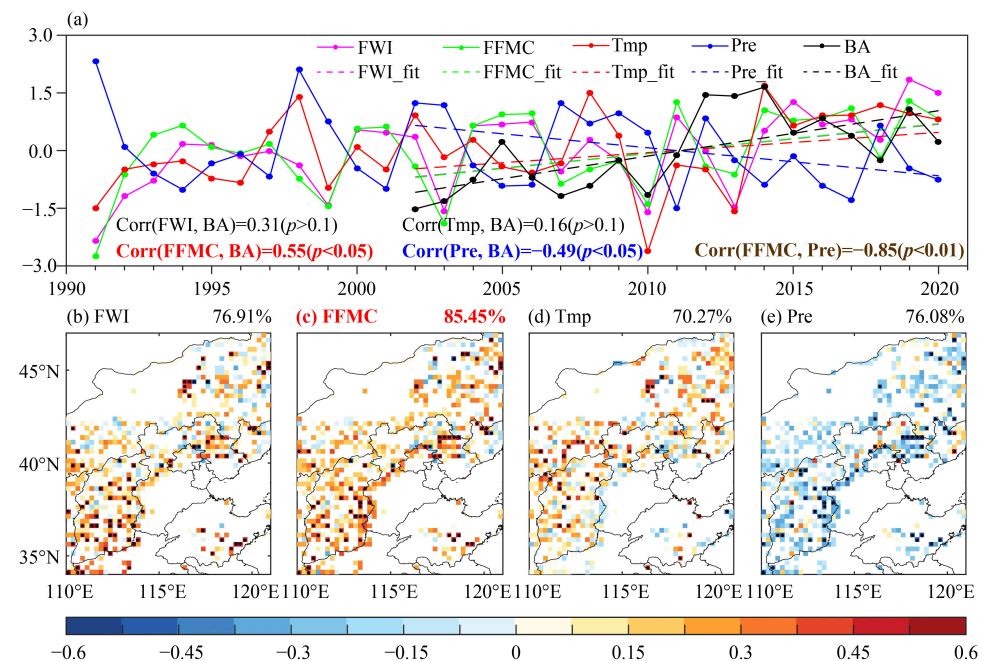


Figure 4. March–April standardized temporal series of fire danger indices (i.e., FWI and FFMFC), climate indices (i.e., temperature and precipitation), and burned areas in North China (a); the values in the bottom indicate the correlation coefficient between fire danger/climate indices and burned areas), and spatial distribution of FWI trend (b), FFMFC trend (c), temperature trend (d), and precipitation trend (e) during 1991–2020 (the black dots indicate statistically significant anomalies at the 5% level; the value in the upper right corner indicates the percentage of grid numbers with trend more/less than zeros of the total grid numbers of forest and grassland).

The abovementioned results indicate a stronger relationship between the FFMFC and burned areas, both in terms of temporal trends and spatial patterns. Several studies have explored the impact of fuel moisture on wildfires across diverse regions, such as forests and grasslands. For instance, Huang et al. (2021) [61] demonstrated that in northeastern China, lower fuel moisture during dry seasons significantly increases both the fire intensity and burned area. Luo et al. (2019) [62] found that dry fuel conditions under specific weather patterns substantially enhance the fire spread and burned area in southern China. Overall, these studies underlined the importance of fuel moisture as a key determinant of wildfires. We, therefore, decided to investigate which spatial pattern of the FFMFC contributes to burned areas by analyzing the spatial clustering variation in the daily FFMFC.

3.2. SOM Analysis of the FFMFC Composites

To determine the dominant spatial patterns of wildfires, we performed a SOM analysis of the FFMFC composites field in North China. Figure 5 shows six spatial SOM types of FFMFC composites in North China and temporal variations in frequencies of corresponding modes. The first SOM pattern was that the FFMFC was high throughout North China, ranging from 75.46 to 92.64, with an average of 86.18. This spatial pattern had the highest percentage of all spatial patterns, up to 44.32%. The annual frequency showed a significant ($p < 0.05$) increase from 1991 to 2020, with trends up to $7.75\% \text{ } 10\text{a}^{-1}$. The second SOM pattern was “a higher FFMFC in the southwest and slightly lower FFMFC in the northeast of North China”. This SOM mode appeared in 15.52% of all modes and ranked third. The annual frequency of this SOM pattern was low in the remaining years, with an average of only 14.19%, except for the year 2013, with a high frequency of up to 54.10%. Its annual frequency had shown a slight decreasing trend over the past 30 years, with a trend of $-0.33\% \text{ } 10\text{a}^{-1}$. The third spatial pattern was “high in the southwest and low in the

northeast” of North China, in which the western part of Shanxi Province was the center for the high FFMC value, which reached 80, and the northern part of Beijing and the northern part of Hebei Province were the centers for the low FFMC value. The frequency of this spatial pattern among all patterns was relatively low at only 5.79%. The annual frequency trend showed a slight downward trend of only $-0.74\% 10a^{-1}$. The fourth spatial pattern was “slightly lower in the southwest and higher in the northeast”, in that in which the FFMC in Shanxi Province was relatively low, and the rest of the region was consistently high. This SOM mode has the opposite spatial pattern to the SOM2 mode and had the second highest frequency of all spatial types at 20.27%. The annual frequency of this mode had shown a slightly decreasing trend over the last 30 years, with a trend of $-3.67\% 10a^{-1}$. The fifth spatial pattern was “low in the southwest and high in the northeast”, and the frequency of this spatial pattern accounts for only 8.74% of the total patterns. Over the past 30 years, the annual frequency of this pattern had a slightly decreasing trend of only $-1.82\% 10a^{-1}$. The sixth spatial type was the overall consistently low FFMC, which had the lowest frequency, accounting for only 5.36%. Its annual frequency was slightly decreasing with a trend of $-1.14\% 10a^{-1}$.

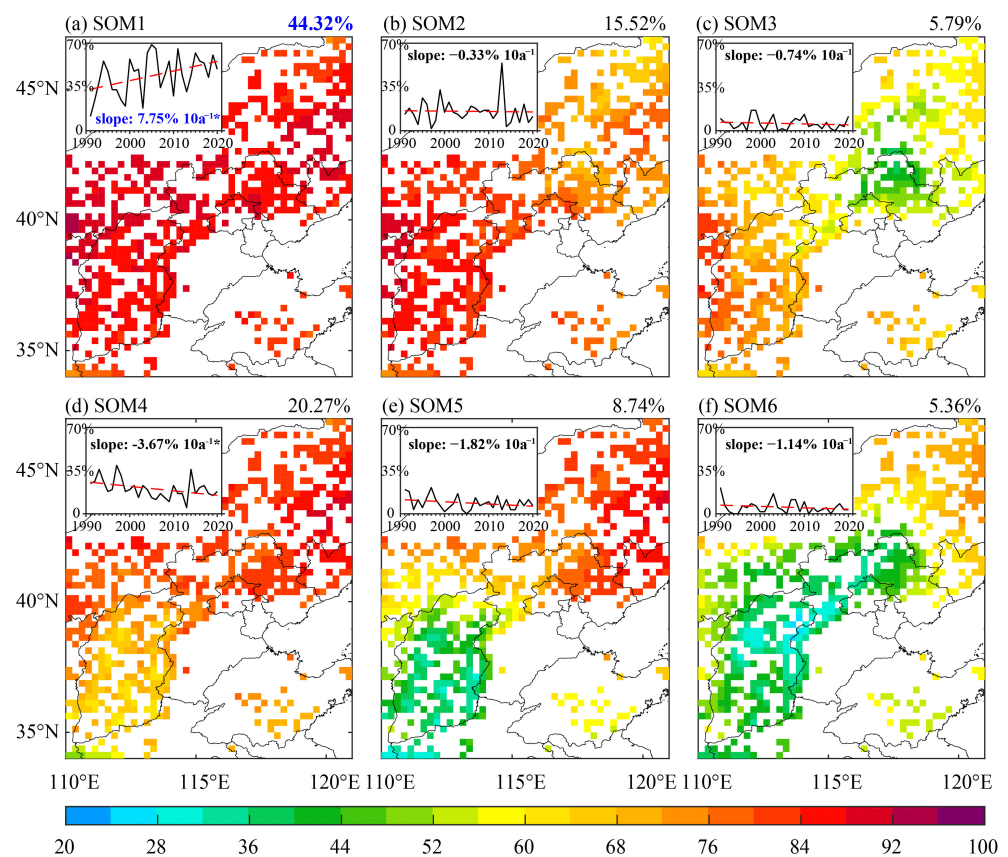


Figure 5. Six spatial modes of FFMC values composites analysis derived from SOM in North China from 1991 to 2020 and temporal variations in the frequency of SOM modes (the upper right corner values indicate the percentage of occurrence of corresponding pattern; slope represents the frequency variability per 10 years; * indicates statistically significant anomalies at the 5% level).

The abovementioned findings revealed that the spatial pattern frequency of the SOM1 mode was relatively high, and the annual frequency showed an increasing trend. These are consistent with the characteristic of the burned area in North China strengthening year by year and confirming the high correlation ($r = 0.55$; $p < 0.05$) between the fuel moisture content and the burned area.

3.3. Atmospheric Circulation

The weather type that drives wildfires cannot be attributed solely to one atmospheric circulation field because the factors that cause these events are complex and influenced by the matching of several weather types. To investigate the relationship between atmospheric circulation and the FFMC-derived SOM mode, we examined the anomalies in the geopotential height at 200 and 500 hPa, wind at 850 hPa, sea level pressure, and latitudinal–vertical structure of omega anomalies under the SOM1 mode with a high FFMC throughout North China (Figure 6). Through multiple atmospheric circulation elements, we determined the possible causes of wildfire occurrence.

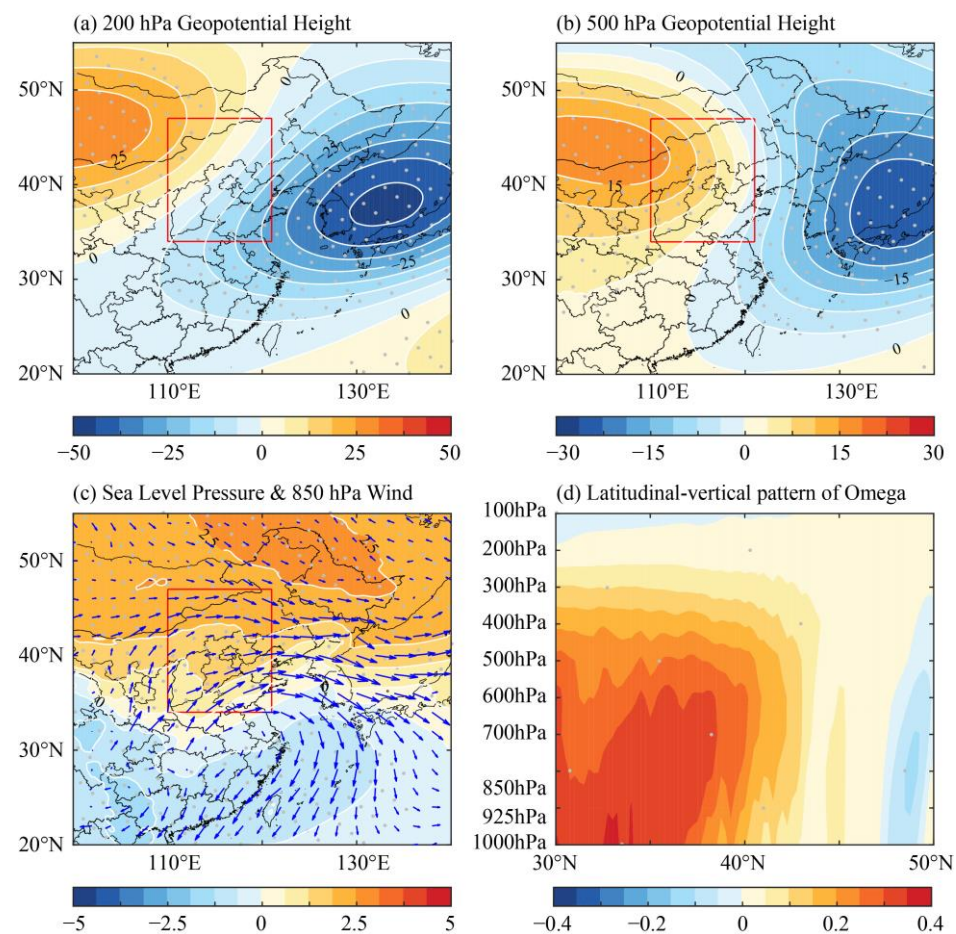


Figure 6. Spatial pattern of the geopotential height anomalies composites in SOM1 mode at pressure levels of 200 hPa ((a); units: Pa; the gray dots denote significance at a confidence level of 0.05), 500 hPa ((b); units: Pa), and sea level pressure anomalies composites and wind anomalies composites at pressure levels of 850 hPa ((c), units: Pa), and latitudinal–vertical of omega anomalies composites of 110°E–121°E (d); sigma less than 0 denotes upward and sigma more than 0 denotes downward).

Both the geopotential height anomalies at pressure levels of 200 hPa and 500 hPa revealed a high-pressure system over the Mongolian Plateau and a low-pressure system over the Sea of Japan. From the perspective of 200 hPa, the high-pressure system was located on the western side of the Mongolian Plateau. The forest and grassland regions in northern and western North China were predominantly influenced by high-pressure systems, whereas southeastern North China was primarily governed by low-pressure systems. From the perspective of 500 hPa, the high-pressure system moved eastward, with high-value centers located in southern Mongolia and central Inner Mongolia, while North China lay under the control of strong high pressure. Looking at the middle to upper

troposphere, there was likely to be a baroclinic system over North China, with high pressure becoming more pronounced at lower levels, and as a result, North China was likely to be characterized by drought. Meanwhile, the northern part of the continent was characterized by high-pressure systems, while the southern part of the continent and the ocean were characterized by low pressure. Among them, North China was under the control of the sea-level high-pressure system and bordered the sea-level low-pressure system, which may have led to the air pressure gradient force from land to ocean in North China. Combined with the 850hPa wind anomalies, it could be found that the northern and western parts of North China showed westerlies, and as the westerlies from land brought a lack of water vapor conditions, it would be unfavorable to the occurrence of precipitation in North China. In addition, we also analyzed the latitudinal–vertical of omega anomaly composites of 110°E–121°E. We found that in the central to southern part of North China from the upper troposphere at 200 hPa to the ground, there was a significant downward movement of air, and the closer to the ground, the more obvious the downward movement. Meanwhile, the movement of the northern part of North China was weaker than that in the central to southern part of North China.

The abovementioned findings suggested that from the horizontal circulation perspective, North China was predominantly influenced by a high-pressure system and prevailing westerlies, resulting in a lack of water vapor conditions, which left the area prone to drought. From the vertical circulation perspective, North China was characterized by downward movement from the upper to the lower troposphere. This would be unfavorable to the water vapor lift condensation process and, likewise, was not conducive to precipitation. This was consistent with the above findings of a significant positive correlation between burned areas and fuel moisture.

3.4. Trend of Pollution Concentration and Population Exposure

Figure 7 shows the spatial pattern of the trend of PM_{2.5} concentration and population exposure trend in North China based on the GFED v5 dataset. We found that the trends of PM_{2.5} concentration produced by forest and grassland burning were lower in local areas than those in surrounding areas based on the satellite-based GFED v5. The March–April PM_{2.5} concentrations in most areas of forests and grasslands in North China showed a non-significant increasing trend or even a decreasing trend in some areas, such as Shanxi and western Hebei. The PM_{2.5} concentration in the forest and grassland areas of Inner Mongolia, such as the areas bordering Liaoning in the east and Shanxi in the west, showed a significant increasing trend, up to a maximum of about $12.5 \text{ } 10\text{a}^{-1}$. However, the PM_{2.5} concentration showed a significant increasing trend in most North China Plain. Compared with the trends of PM_{2.5} concentration under different land use types, we found that forest and grassland had the smallest increase of nearly $1 \text{ } 10\text{a}^{-1}$, but urban area and cropland in North China had the most pronounced increase of about $3.5 \text{ } 10\text{a}^{-1}$, which was about 2.5 times larger than the increase in forest and grassland. Combined with the 850 hPa wind anomalies, it was found that the westerlies located in southern North China were the strongest, suggesting that this may have been influenced by the wind, which resulted in PM_{2.5} produced by burned forests or grasslands in the west being transported to the North China Plain. In addition, through an analysis of population exposure to PM_{2.5}, we observed an overall increase in exposure across most regions of North China, with the most notable rises occurring in areas directly impacted by higher PM_{2.5} concentrations. This suggests that the increase in population exposure was not only due to the increase in population but also to the increase in PM_{2.5} concentrations.

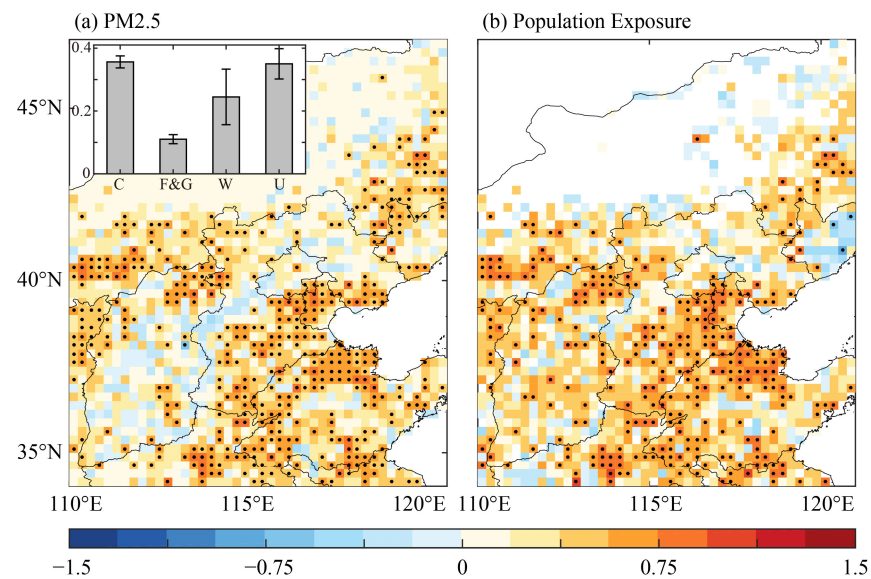


Figure 7. Spatial pattern of March–April standardized PM_{2.5} concentration trend (a) and normalized population exposure trend (b) in North China during 2002–2020 in the context of high fire danger season (bars represent trends in PM_{2.5} concentration under different land use types, which C is cropland, F&G are forest and grassland, W is water and U is urban land; the black dots indicate statistically significant anomalies at the 5% level; the white areas indicate non-population).

The abovementioned findings suggested that during the high fire danger season, PM_{2.5} produced by forests or grasslands burning in March–April was transported to the North Plains downstream of them by wind anomalies, which also led to increased population exposure.

3.5. Predicted Burned Areas Under the Different SSP Scenarios

As not all global system models provide burned area datasets under future SSP scenarios, these are insufficient to support research on future burned areas in North China. We, therefore, constructed a prediction model of FFMC-based burned areas based on the high correlation between the FFMC and burned areas via the above analysis. Figure 8 shows the temporal series of the burned area fraction in North China from 1991 to 2100. We found that both the FFMC prediction-based and satellite observation-based burned areas during 2002–2020 had a significant increasing trend, with trends of $13.19\% \text{ } 10\text{a}^{-1}$ and $9.87\% \text{ } 10\text{a}^{-1}$, respectively. The r value between the prediction and observation was 0.45, which was statistically significant at the 95% confidence level. We, therefore, indicated that the FFMC prediction-based burned areas could be shown to be credible in terms of trend and variability characteristics. We found that the burned areas in North China under the SSP245 scenario increased slowly. Compared with the base period (1991–2020), the extent of the burned areas increased 1.32 times by the end of the century. The SSP585 scenario showed a rapid increase in the burned area extent in North China and an increase of 2.93 times at the end of the century compared to the baseline period. The rate of increase in the SSP585 scenario was 2.72 times higher than that in the SSP245 scenario. Meanwhile, the extent of the burned areas under the SSP585 scenario was significantly higher than that of SSP245 after the 2070s, but the differences between them were not significant before then.

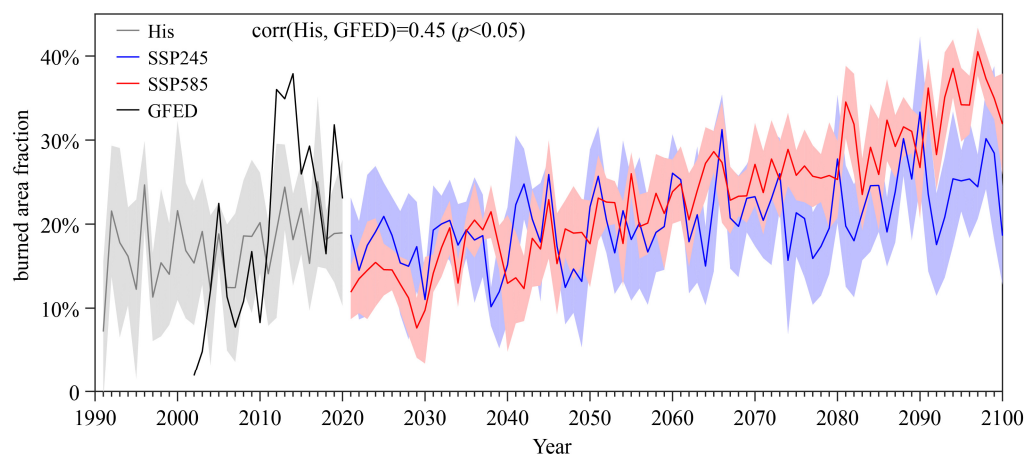


Figure 8. March–April temporal series of burned area fraction in North China from 1991 to 2100 based on multi-model ensemble (the shaded areas represent the 95% confidence intervals; the values in the top indicate the correlation coefficient between FFMFC prediction-based burned areas and satellite observation-based burned areas).

The abovementioned findings suggested that the FFMFC-based burned area prediction model was credible. Both the SSP245 and the SSP585 scenarios showed a gradual increase in the burned area extent in North China. In the high-emission scenario (SSP585), both the rate and area of increase were significantly higher than in the medium-emission scenario (SSP245). We, therefore, need to further strengthen the implementation of emission reduction policies to slow down the increasing extent of burned areas.

4. Discussion

Many advancements have been achieved in understanding the bidirectional coupling mechanism between forest fire risk and the climate system. Climate change exerts a significant influence on fire danger through processes operating at multiple spatial and temporal scales. For instance, human-induced climate change increased the number of drying days for forest fuels in the western United States by 54% between 1984 and 2015, directly expanding the area of high-fire risk zones. Changes in precipitation patterns have, in turn, reshaped the spatiotemporal distribution of the fire season [7]. The Global Fire Weather Index system constructed by Jolly et al. (2015) [63] revealed that the fire season in Mediterranean climate regions has expanded by 23 days per decade in both the spring and autumn seasons. It is noteworthy that studies in Mediterranean climate regions have revealed a nonlinear threshold in fire–climate interactions, with fire risk sensitivity to precipitation anomalies increasing threefold [64]. Zhang et al. (2021) [65] demonstrated, through Earth system model simulations, that the 715 Tg CO₂ released from the 2019–2020 Australian wildfires led to a 40% increase in stratospheric aerosol concentrations in the Southern Hemisphere, triggering the regional redistribution of precipitation. Additionally, Lyons et al. (2008) [66] showed that the reduction in surface albedo following boreal forest fires can generate a radiative forcing, persistently affecting the regional energy balance. The suppressive effect of light-absorbing aerosols generated by Amazonian fires on cumulus cloud development has not yet been accurately decoupled from the cloud-promoting effects of biogenic VOC emissions [67]. These studies highlight the spatial heterogeneity of fire–atmosphere coupling mechanisms, emphasizing the importance of regional-scale climate change research. They also underscore the significance of the diagnostic analysis of wildfires in North China undertaken in this study.

The use of SOMs in recognizing fire weather patterns is advancing. Leveraging their abilities in terms of dimensionality reduction and clustering, SOMs have been used to

uncover the nonlinear coupling mechanisms between weather systems and wildfire events. For instance, Dong et al. (2021) [68] innovatively integrated a SOM with the Weather Research and Forecasting (WRF) model, targeting regions with complex terrain. They discovered that the foehn wind effect along the eastern foothills of the Rocky Mountains could increase local fire spread rates by 67% under specific configurations of the 850 hPa wind field. Some studies used SOM clustering to identify fire-prone weather patterns in Mediterranean Spain and wildfire drivers along the North American Pacific Northwest, respectively. Their work offers valuable insights for fire risk prediction [31,32]. A comparison of three weather pattern classification methods (composite analysis, EOF, and SOM) in identifying weather patterns associated with large wildfires in the Pacific Northwest of the United States revealed that the SOM method can capture more transitional patterns, which is significant for wildfire risk assessment [69]. Analyzing the SOM of fire danger indices and corresponding weather patterns in North China thus holds significant value for wildfire prediction.

Although this study provides a comprehensive analysis of wildfires in the North China region using multi-source data, some limitations still exist. Firstly, the spatial and temporal resolution of satellite data limits the ability to capture the details of wildfires. For example, satellite data may fail to accurately identify small-scale fires or early ignition points, thereby affecting the characterization of burned areas. Secondly, current reanalysis data may exhibit biases in characterizing local climate features in regions with complex terrain. This limitation could affect the accurate understanding of wildfire-driving factors. Moreover, climate models are typically based on parameterization schemes, which may introduce biases in the predicted probabilities of wildfire occurrence and burned areas. Going forward, we, therefore, hope to leverage the strengths of deep learning technologies in data information capture to optimize future research content.

5. Conclusions

We investigated the spatiotemporal characteristics, causes, and prediction of wildfires in North China based on multiple datasets (i.e., satellite, reanalysis, and climate model datasets). We found that the extent and intensity of burned areas were maximized during March–April based on the satellite-based GFED burned area products. We compared the temporal series and spatial pattern of fire danger indices (i.e., FWI and FFMCI), climate indices (i.e., temperature and precipitation), and burned areas in North China. The temporal series and spatial patterns of the FFMCI and burned areas were clearly more closely related. Through a SOM analysis of FFMCI composites, we identified six SOM mode patterns and explored the impact of weather patterns on the FFMCI. Among these, the SOM1 mode exhibited a relatively high frequency, with a significant increasing trend, which aligned with the observed strengthening of wildfire occurrences in North China. We found that high-pressure systems in the horizontal circulation, coupled with downward movements in the vertical circulation, inhibited water vapor transport and lifted condensation processes, reducing precipitation and increasing the FFMCI. These atmospheric conditions contributed to an environment conducive to the ignition and rapid spread of wildfires. Furthermore, we quantified the population exposure to air pollution, primarily PM_{2.5}, associated with wildfires. The PM_{2.5} generated by wildfires during March–April was transported to the North China Plain, where its concentration was exacerbated by westerly anomalies, thereby increasing the population's exposure to wildfire-related air pollution. We also predicted future burned areas under different SSP scenarios. Both the SSP245 and SSP585 scenarios suggested a gradual increase in burned areas in North China. Under SSP585, the rate and extent of the increase were significantly higher than under SSP245. These results underscore the importance of enhancing emission reduction policies to mitigate the escalating threat of

wildfires in the region. It is essential to improve the techniques of FWI system localization; furthermore, attribution analysis is important for future wildfire monitoring and, consequently, for obtaining a more comprehensive understanding of the wildfire responses to climate change. This study represents the first attempt to analyze the characteristics, causes, and prediction model of wildfires in North China using multi-source data and methods. Based on these results, it is possible to better assess the impacts of future climate change on wildfire activity in wildland–urban interface regions, which holds significant value for developing adaptive management strategies and addressing landscape conflicts.

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Data Availability Statement: All data used in this study are publicly available and can be downloaded from the corresponding websites. The GFED v5 used in this study can be archived at <https://www.globalfiredata.org/data.html?continueFlag=71a4366dbfa42f32ca48461ec1db7a1d>, accessed on 10 July 2024. The hourly ERA5 global reanalysis meteorological data were provided by the ECMWF (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels-monthly-means?tab=overview>, accessed on 20 July 2024). The global climate model data used in this study can be obtained from the CMIP6 archives at <https://esgf-node.llnl.gov/search/cmip6/>, accessed on 1 September 2024.

Conflicts of Interest: The authors declare no conflicts of interest.

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