

Article

Spatiotemporal Dynamics of Forest Fire Risk in Southeastern China Under Climate Change: Hydrothermal Drivers and Future Projections

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Abstract

Forest fire regimes are undergoing systematic reorganization under climate change, particularly in monsoon–human coupled ecosystems such as Southeastern China, where risk dynamics remain poorly quantified. This study proposes a meteorology-driven machine learning model designed to assess long-term forest fire risk. Using kernel density estimation and standard deviational ellipse analysis, we assessed the spatiotemporal patterns of fire risk during the observational period and their future shifts across the SSP1-2.6 and SSP5-8.5 scenarios. The results indicate a significant overall decline in fire frequency from 2008 to 2024 (−467.3 fires/year, representing an annual average reduction of 10.8%, $p < 0.001$), which is attributed primarily to enhanced regional fire prevention and control measures, yet with a notable reversal after 2016 in Guangdong and Fujian. Fires are highly seasonal, with 74% occurring in the dry season (December–March). The meteorologically driven random forest model exhibited excellent performance ($R^2 = 0.889$), validating meteorological conditions as key drivers of regional fire dynamics. It is projected that intensified warming (+5.5 °C under SSP5-8.5) and increased precipitation variability (+23%) are likely to drive pronounced northward and inland migration in high-risk zones. Our projections indicate that by the end of the century, high-risk area coverage could expand to 19.2%, with a shift from diffuse to clustered patterns, particularly in Jiangsu and Zhejiang. These findings underscore the critical role of hydrothermal reconfiguration in reshaping fire risk geography and highlight the need for dynamic, region-specific fire management strategies in response to compound climate risks.

Keywords: forest fire risk; climate change scenarios; random forest; spatiotemporal migration; hydrothermal drivers; standard deviational ellipse; Southeastern China



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1. Introduction

In recent years, anthropogenic climate change has been increasing the frequency of extreme forest fires globally [1]. As one of the most intense ecological disturbances, wildfires are reshaping the terrestrial carbon cycle [2], biodiversity [3], and human security landscapes [4], posing major challenges to the stability of ecosystems and the safety of human life and property. Thus, wildfires have attracted extensive attention from academics and the public. Empirical studies of regional wildfire frequency [5] and global-scale

analyses of fire risk trends [6] have revealed that warmer temperatures significantly increase the risk of extreme fires by altering drought conditions and fuel moisture [7]. Southeastern China represents a quintessential coupled monsoon–human system featuring globally significant population density, economic activity, and complex forest–agriculture mosaics within its latitudinal band [8]. Consequently, its fire risk profile is undergoing profound reconfiguration under the combined pressures of global warming and intensified human activities. However, research and management focused on forest fires in China has focused predominantly on high-incidence regions in Northeast China and Southwest China [9]. Yet recent studies suggest that Southeastern China is experiencing an increasing trend in fire weather conditions and ignition probabilities under climate scenarios [10], indicating that the perceived “low” risk may be misleading. This perception masks and ignores the potential amplification effects of climate change on hydrothermal conditions, vegetation flammability, and spatial and temporal risk migration. Therefore, investigating the dynamic patterns of forest fire risk in this region under climate change holds significant academic and practical importance.

Wildfire occurrence is driven by a combination of factors, including fire weather conditions, fuel availability and characteristics, and the presence of ignition sources [11–14]. In addition, climate change-driven declines in fuel moisture and human-induced land use/cover changes have led to increasing frequencies and intensities of wildfires globally [15,16]. Therefore, understanding and predicting future wildfire risk patterns, especially under changing climatic conditions, is critical for minimizing potential fire risk. Although wildfire risk attribution and prediction are active fields in global change research, systematic fire risk studies focusing on the unique geographical context of Southeastern China remain notably lacking. The internationally established Canadian fire weather index (FWI) effectively captures meteorological influences on fire risk [17] and performs well in northeastern and southwestern China [18,19]. However, it has limited applicability in Southeastern China [20]. The FWI system was originally developed and calibrated for boreal forests (e.g., Jack Pine and Lodge Pole Pine) in Canada [21,22], which differ substantially from the subtropical monsoon climate and evergreen broadleaved forests of Southeastern China. These differences in climate and fuel types can lead to misestimation of fuel moisture dynamics and fire potential in the region [23]. On the other hand, several studies in China have examined nationwide trends in fire frequency and burned area [24,25], and the spatial migration of high-risk areas and their driving mechanisms in Southeastern China have not been sufficiently explored. In particular, no clear conclusions have been drawn on key issues, such as how nonlinear changes in hydrothermal conditions reshape the spatial and temporal patterns of fire risk under climate change scenarios and the potential impacts of monsoon fluctuations on the dry season fire risk period. These gaps in research make it difficult to formulate regional fire prevention and control strategies without precise scientific support and to cope with extreme fire threats that may intensify in the future.

This study employs a “data–model–scenario” framework, integrating multisource satellite, meteorological, and climate projection data with machine learning and spatial analysis to systematically address three key research questions: (1) What are the spatiotemporal distribution characteristics of forest fires in Southeastern China? (2) How are hydrothermal conditions projected to evolve under climate change? (3) What are the future migration trends of high-risk areas?” These findings advance our understanding of the dynamics of forest fires and hydrothermal conditions in Southeastern China and provide a scientific foundation for developing differentiated forest fire prevention and control strategies.

2. Materials and Methods

2.1. Study Area

This study focuses on Southeastern China (Figure 1), which encompasses South Central China (primarily Henan, Hubei, Hunan, Guangxi, Guangdong, Hainan Provinces) and East China (primarily Shandong, Jiangsu, Anhui, Zhejiang, Jiangxi, Fujian Provinces). Data were unavailable for Shanghai, Hong Kong, Macau, and Taiwan. This region lies within a typical tropical and subtropical monsoon climate zone, with average annual temperatures ranging from 16.3 to 25.7 °C and abundant but unevenly distributed annual precipitation. The topography of the area is dominated by low hills, and the typical vegetation is subtropical evergreen broad-leaved forest and mixed coniferous and broad-leaved forest. Moreover, as one of the most densely populated, economically active, and highly urbanized areas in China, human activities are highly intertwined with natural ecosystems, and significant monsoon climate fluctuations are superimposed, which makes the area a typical environmental carrier for nurturing and increasing the risk of forest fires against the background of climate change.

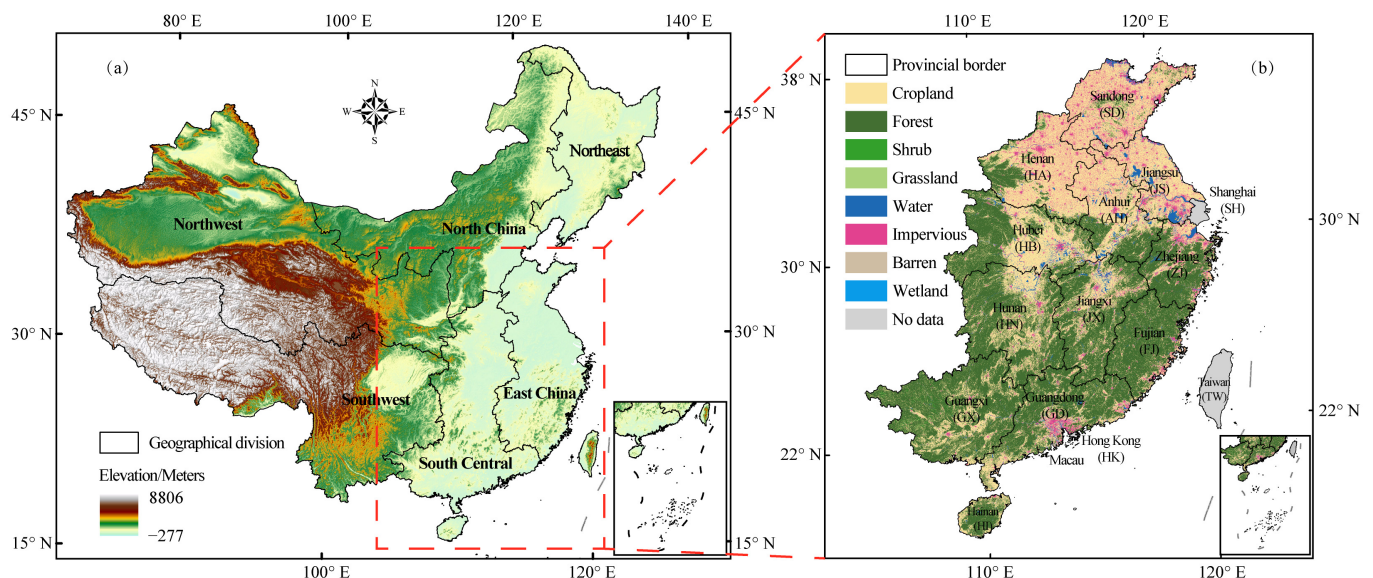


Figure 1. (a) Geographic location of the study area in China. (b) Land use and land cover classification map of the study region. The abbreviations for all Chinese provinces mentioned in this study are defined in this map.

2.2. Data Source

The satellite monitoring data of forest fires (2008–2024) were obtained from the National Forest and Grassland Fire Prevention and Suppression Information Sharing Platform (<https://slcygxpt.slcyfh.mem.gov.cn/> (accessed on 11 June 2025)). Satellite fire detection information includes the date and time of fire occurrence, longitude and latitude, number of pixels, continuity, land type, and feedback information. These data represent ground-verified fire monitoring records, and their reliability has been established in previous studies [8,24].

Meteorological data (mean temperature, relative humidity, mean wind speed, and precipitation) for constructing the fire prediction model were sourced from national ground observation stations (<http://data.cma.cn/> (accessed on 11 June 2025)). Only stations with $\leq 5\%$ missing data were selected for any variable during the study period. The selected stations were subjected to outlier detection and missing value imputation. In this study, a bilinear interpolation algorithm [26] was used to uniformly resample the predictor variables to a 1 km resolution to ensure spatial and temporal consistency.

This study assesses the impact of climate change on future forest fire potential in Southeastern China via CMIP6 climate model data (<https://esgf-node.ipsl.upmc.fr/search/cmip6-ipsi> (accessed on 15 June 2024)). We employ two contrasting shared socioeconomic pathway (SSP) scenarios that exhibit the greatest divergence: the sustainable development pathway SSP1-2.6, characterized by declining CO₂ emissions beginning in approximately 2020 and achieving net-zero emissions by 2100, and the fossil-fueled development pathway SSP5-8.5, which represents continued high greenhouse gas emissions throughout the 21st century and closely aligns with current trajectories [27]. The historical period 1985–2014 serves as the baseline. Projected changes are evaluated for the mid-21st century (2021–2050) and the end-21st century (2071–2100). To increase reliability and mitigate the parametric and structural uncertainties inherent in individual models [28], a multi-model ensemble mean (MME) approach is applied [25]. The ensemble incorporates four models—CanESM5, CMCC-CM2-SR5, EC-Earth3, and EC-Earth3-Veg-LR—selected on the basis of their established performance over China, as reported in prior validation studies [29,30].

2.3. Risk Assessment

Considering the spatiotemporal unpredictability and stochastic distribution of fire occurrence [31,32] and building upon the fire risk concept of [33], we define forest fire risk as the probability weight of fire occurrence for a given grid cell under specific driving factor combinations. This probability weight was quantified via kernel density estimation (KDE) to represent the risk index [34,35]. It is defined as:

$$\lambda_b(s) = \frac{1}{c_b(s)} \sum_{i=1}^n k_{ib}(s - s_i)$$

where $s_i, \dots, s_n$ represent the locations of n observed fire events (or attribute points); $\lambda_b(s)$ represents the estimated spatial density (fire risk index) at location s ; k_{ib} represents the kernel function value; and c_b represents the edge correction factor at s .

To ensure spatial consistency, a regular grid ($0.1^\circ \times 0.1^\circ$ resolution; 8372 cells) was overlaid on the study area, and all variables were resampled or aggregated to this grid. We implemented a random forest (RF) regression model to predict forest fire probability on the basis of meteorological drivers. By constructing a multitude of decision trees and outputting their mean prediction, the model robustly captures complex, nonlinear predictor-response relationships. Its inherent use of bagging and feature randomness provides strong protection against overfitting. We partitioned the data into a 70% training set and a 30% testing set, and conducted hyperparameter optimization via Bayesian search with fivefold cross-validation. Model performance was evaluated using four metrics: (1) the coefficient of determination (R^2), which measures the proportion of variance explained; (2) the mean absolute error (MAE), which indicates overall prediction accuracy; (3) the root mean square error (RMSE), which reflects the magnitude of the prediction error; and (4) the concordance correlation coefficient (CCC), which reflects the agreement between the predicted and observed values [36–38]. We conducted all the statistical analyses via R software version 4.2.2. The computational environment was consistently maintained throughout this study.

2.4. Statistical Analysis

To characterize the evolution of high forest fire risk zones, fire risk was classified on the basis of multiples of the standard deviation from the mean risk value [39,40]. The classification threshold (α) is calculated as:

$$\alpha = \frac{x_i - \bar{x}}{\delta}$$

where x_i is the risk value at location i , $\bar{x}$ is the mean value, and δ is the standard deviation of the risk values. The risk levels were assigned as follows: high risk ($\alpha > 1$), moderate risk ($0 < \alpha \leq 1$), low risk ($-1 < \alpha \leq 0$), and no risk ($\alpha \leq -1$).

Additionally, the standard deviational ellipse (SDE) method was employed to characterize the directional trends and spatial evolution of high-risk forest fire zones [41]. SDE quantifies the central tendency, dispersion (major and minor axes), and orientation of spatial distributions. The centroid coordinates are calculated as:

$$\bar{X} = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}, \bar{Y} = \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i}$$

where i is the grid cell, n is the total number of grid cells; w_i is the weight of the i th grid cell, which represents different levels of forest fire risk values; $\bar{X}$ and $\bar{Y}$ are the coordinates of the center of gravity of the standard deviation ellipse.

3. Results

3.1. Characteristics of Forest Fires

Forest fire frequency across Southeastern China exhibited a highly significant declining trend ($p < 0.001$) from 2008 to 2024, decreasing at an average rate of 467.3 fires/year (an annual reduction of 10.8%) (Figure 2a). In terms of temporal distribution, the high incidence of fires in Southeastern China was mainly concentrated from 2008 to 2014 (>6500 fires per year) and then decreased significantly to 1574 in 2024. Regional analysis revealed South Central China as the primary fire occurrence area (Figure 2b), accounting for 63.2% (40,250 fires) of the regional total. Guangdong (13,170 fires), Guangxi (13,654 fires), and Hunan (9896 fires) were the fire hotspot provinces within this subregion. Fires in South Central China also declined significantly ($p < 0.001$) at a faster rate (−309.5 fires/year, annual reduction of 11.7%) than those in East China (−157.9 fires/year, annual reduction of 9.6%). This trend was further differentiated at the provincial scale: the core provinces in South Central China, such as Guangdong (−128.7 fires/a) and Hunan (−95.1 fires/a), presented the most significant decreases ($p < 0.001$).

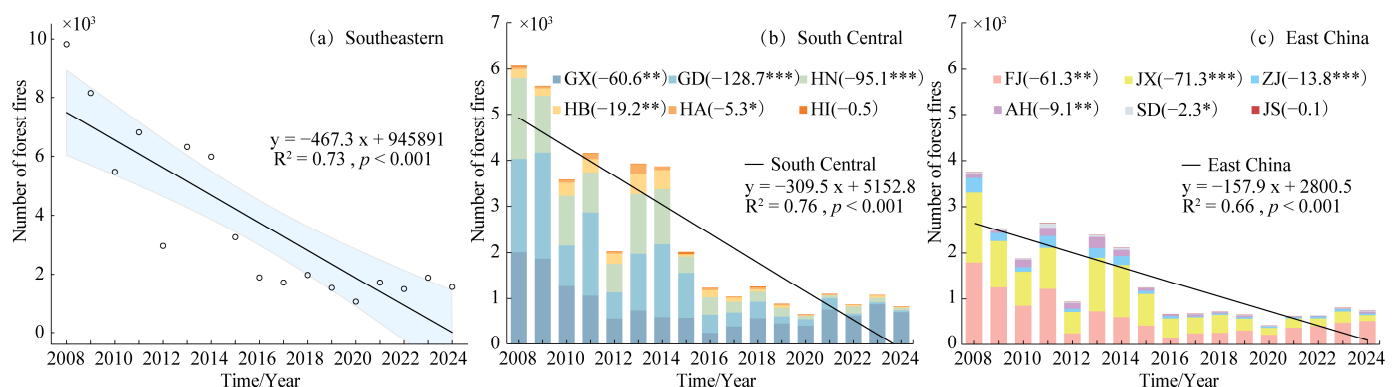


Figure 2. Characteristics of the annual distribution of forest fires in Southeastern China. (a) Total number of fires across the entire Southeastern China. (b) Annual number of fires for South Central China subregion and its constituent provinces. (c) Annual number of fires for East China subregion and its constituent provinces. The numbers in parentheses denote the rate of linear change (fires/year) for the corresponding region or province. Asterisks indicate the statistical significance of the trend: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Within East China, fires were predominantly concentrated in Fujian (9997 fires) and Jiangxi (9993 fires) Provinces (Figure 2c), contributing 85.2% of the subregional total. In contrast, Shandong and Jiangsu recorded fewer than 500 fires each. The significant down-

ward trend in East China ($p < 0.001$) was driven primarily by Jiangxi (-71.3 fires/year, $p < 0.001$) and Fujian (-61.3 fires/year, $p < 0.001$). Notably, however, Guangdong and Fujian—the provinces with the highest fire frequencies in South Central China and East China, respectively—both showed significant declines from 2008 to 2016 ($p < 0.01$), followed by significant increases from 2016 onward ($p < 0.01$). Consequently, their combined contribution to the total number of fires in Southeastern China rose from 31.9% (2008–2016) to 52.8% (2016–2024). This countertrend increase in key provinces warrants attention despite the overall regional decline.

Forest fires in Southeastern China exhibited a pronounced unimodal seasonal distribution concentrated in the dry season (Figure 3), closely aligning with the monsoon-driven precipitation pattern. December to March accounted for 74.0% of the annual fires (47,171 fires), peaking sharply in January (12,053 fires). Fire occurrence was significantly suppressed during the rainy season (May–September) by abundant precipitation. Particularly low activity was observed from June to August, with a monthly average of only 172 fires ($<1.4\%$ of the January peak). Provincial-level seasonal patterns in both South Central and East China mirrored this regional unimodal distribution, which is characterized by high fires in the winter-spring dry season and low forest fires in the summer rainy season.

	Southeastern	GD	GX	HN	HB	HA	HI	South Central	FJ	JX	ZJ	AH	SD	JS	East China
Jan.	12,053	2961	1815	1759	465	102	9	7111	2322	2100	278	216	20	6	4942
Feb.	11,743	2433	2299	1913	501	135	12	7293	1660	2264	333	168	23	2	4450
Mar.	12,820	2449	2107	2221	778	321	49	7925	1750	2219	490	303	130	3	4895
Apr.	5130	1027	1472	549	289	126	64	3527	605	565	195	108	127	3	1603
May	1608	376	627	67	24	12	8	1114	248	144	57	25	15	5	494
Jun.	402	118	134	11	5	6	2	276	34	8	10	10	57	7	126
Jul.	302	100	99	24	6	0	4	233	43	16	6	4	0	0	69
Aug.	438	82	93	123	25	0	2	325	28	59	22	4	0	0	113
Sept.	806	77	272	158	17	1	0	525	88	148	22	22	1	0	281
Oct.	3029	657	846	518	70	19	1	2111	344	409	73	78	13	1	918
Nov.	4818	839	1517	764	69	26	0	3215	819	585	56	122	19	2	1603
Dec.	10,555	2051	2373	1789	312	69	1	6595	2056	1476	174	225	24	5	3960

Figure 3. Monthly distribution of forest fires in Southeastern China. The histogram shows the total number of fires recorded monthly across all regions and their respective provinces throughout the entire study period (2008–2024).

3.2. Evaluation of Machine Learning Methods

The meteorologically driven forest fire prediction model for Southeastern China demonstrated excellent performance. The model was evaluated using fivefold cross-validation, with consistent assessment metrics across folds (Table 1). The overall means were RMSE = 0.0564, MAE = 0.0316, $R^2 = 0.885$, and CCC = 0.936. The low RMSE and MAE values (<0.06 and <0.032 , respectively) indicate minimal prediction bias and high overall model accuracy. Concurrently high R^2 and CCC values (both >0.885) suggest the model’s strong explanatory power for fire variability and high agreement between the predictions and observations. The narrow ranges of R^2 (0.878–0.889) and CCC (0.932–0.938) across folds further support robust performance and generalizability. Figure 4a shows a scatter plot of the predicted versus observed fire risk values, illustrating a strong agreement between the two. The residuals were normally distributed with a mean approaching zero (Figure 4b), further indicating model reliability. These results collectively demonstrate the model’s suitability for assessing future forest fire potential in Southeastern China and highlight the key role of meteorological conditions in driving regional forest fire dynamics.

Table 1. Performance metrics of the random forest model across the five folds of cross-validation. (RMSE: root mean square error; MAE: mean absolute error; R^2 : coefficient of determination; CCC: concordance correlation coefficient).

Model	RMSE	MAE	R^2	CCC
Fold1	0.0556	0.0310	0.885	0.936
Fold2	0.0557	0.0314	0.889	0.937
Fold3	0.0577	0.0323	0.878	0.932
Fold4	0.0553	0.0312	0.887	0.938
Fold5	0.0577	0.0322	0.886	0.935
Mean	0.0564	0.0316	0.885	0.936

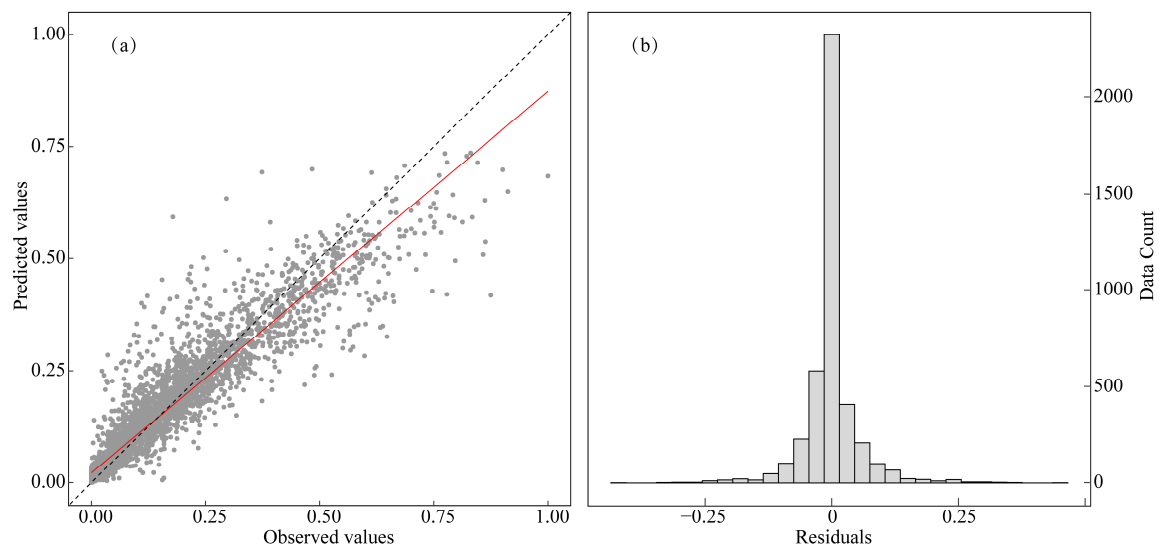


Figure 4. (a) Agreement between the observed and predicted values. (b) Distribution of residuals to assess the normality of prediction errors.

3.3. Changes in Hydrothermal Conditions

Figure 5 presents the projected spatiotemporal changes in hydrothermal conditions for Southeastern China under various climate change scenarios. To minimize the influence of data fluctuations, we calculated 18-month moving averages and standard deviations for each meteorological factor. Given the pronounced seasonality inherent in meteorological data, the 18-month moving average effectively dampens seasonal fluctuations, facilitating clearer identification of long-term trends and enhancing the stability of statistical analyses.

The historical baseline (1985–2014) mean temperature was 18.4 °C, exhibiting a significant upward trend ($p < 0.05$) attributable to global warming. According to our projections, temperatures are expected to increase highly significantly ($p < 0.001$) by the end-21st century (2071–2100) under both scenarios. Under SSP1-2.6, the mean temperature reaches 19.9 °C, whereas SSP5-8.5 leads to a more substantial increase to 23.9 °C, representing a warming of 5.5 °C. Warming was more pronounced in inland areas and at higher latitudes. Future precipitation across Southeastern China is also projected to show a highly significant increasing trend ($p < 0.001$), increasing from the historical baseline of 120.6 mm to 150.1 mm (SSP1-2.6) and 152.5 mm (SSP5-8.5). The difference in the increase in precipitation among the scenarios was relatively minor. Spatially, increases were significantly greater in coastal areas (e.g., Shandong and Fujian) than in inland areas. Temporally, the standard deviation of future precipitation is projected to increase by 23%, indicating amplified fluctuations between the wet and dry seasons.

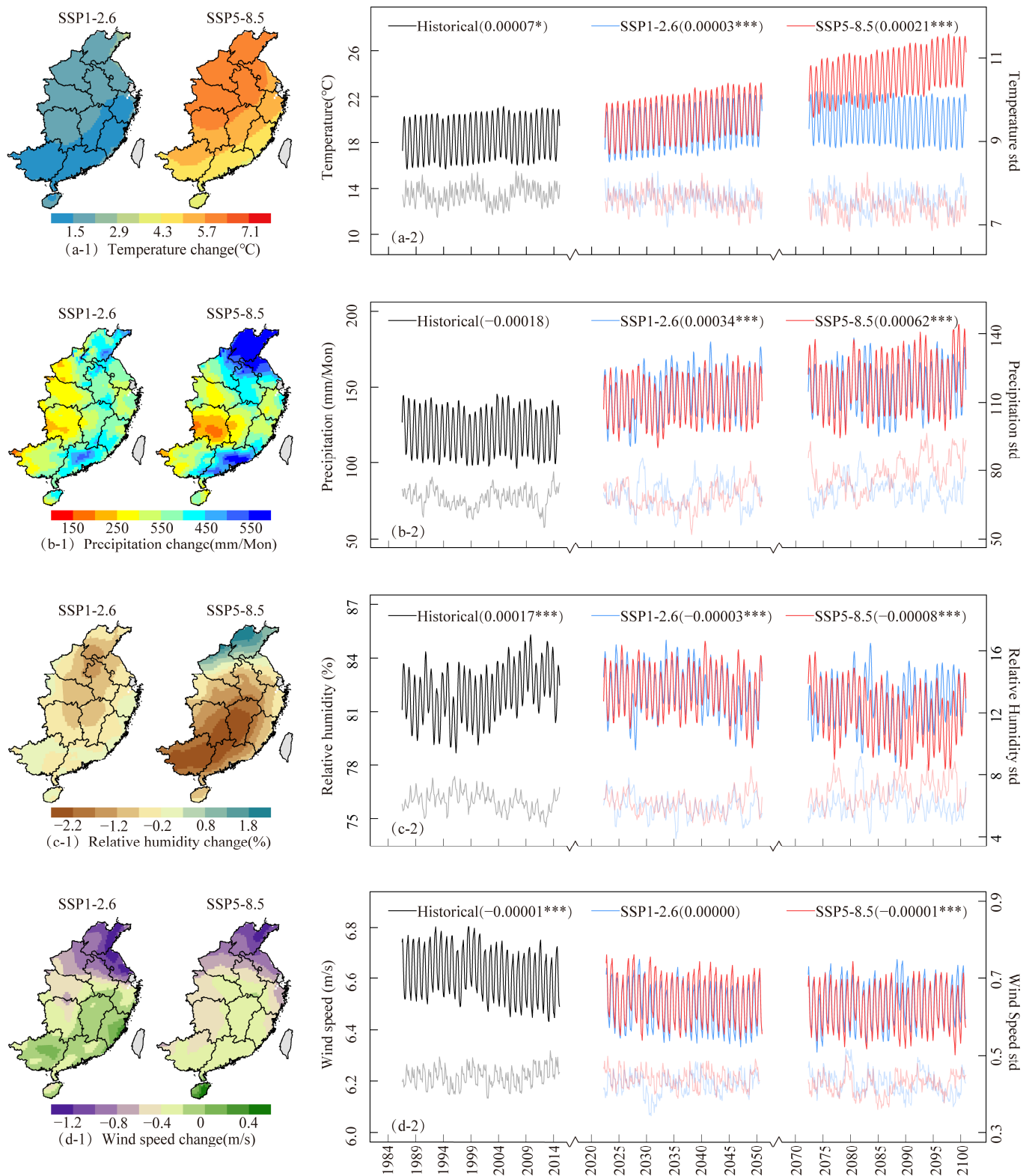


Figure 5. Projected changes in hydrothermal conditions (temperature, precipitation, relative humidity, and wind speed) for Southeastern China under different scenarios. The left column (a-1–d-1) shows the spatial pattern of the differences in the 30-year averages between the historical baseline (1985–2014) and the end-21st century (2071–2100) at a spatial resolution of 0.1° . The right column (a-2–d-2) presents the corresponding 18-month moving average time series for each variable, with the linear trend slope and its significance indicated in the legends (* $p < 0.05$, *** $p < 0.001$).

The future relative humidity exhibited a significant decreasing trend ($p < 0.001$), although the magnitude of decrease was small (0.5–1.1%). The historical baseline mean was 82.1%, which decreased to 81.6% (SSP1-2.6) and 81.0% (SSP5-8.5). Spatially, the pattern of humidity decreases differed between the scenarios: SSP1-2.6 presented greater declines primarily in the north, whereas SSP5-8.5 presented stronger decreases concentrated in the south. The drivers of this spatial variability require further investigation. The changes in the wind speed were less pronounced than those in the other factors. The historical baseline mean was 6.62 m/s, decreasing slightly to 6.50 m/s (SSP1-2.6) and 6.49 m/s (SSP5-8.5). However, the spatial pattern of this reduction varied considerably, with the largest decreases (>1.28 m/s across scenarios) concentrated in northern Southeastern China by the end-21st century.

3.4. Projection of Forest Fire Potential

Multiple-scenario climate model projections (SSP1-2.6, SSP5-8.5) revealed significant spatiotemporal differences in forest fire risk across Southeastern China in response to climate change (Figure 6).

During the historical baseline, the risk pattern was predominantly low-to-moderate (Figure 6a), with high-risk areas accounting for only 12.9% of the total area. These factors were primarily concentrated in the southern coastal provinces of Guangxi (high-risk proportion: 43.0%, risk index: 0.60) and Fujian (35.0%, risk index: 0.61). In contrast, high-risk areas were scarce ($<1\%$) in northern provinces such as Shandong, Henan, Hubei, and Jiangsu. Under SSP1-2.6 (Figure 6b), the median regional risk index increased to 0.53, accompanied by notable reorganization: high-risk area coverage is projected to rise to 18.3%, shifting inland to central provinces such as Hubei (risk index: 0.60) and Hunan (0.62), whereas it significantly decreases in Guangxi (0.49) and Fujian (0.55). The high-emission SSP5-8.5 scenario (Figure 6c) intensified this migration trend, with high-risk area coverage potentially increasing to 19.2%. Dramatic shifts occurred in specific provinces: Zhejiang's low-risk area share plummeted from 45.2% (historical) to 3.4%, whereas its high-risk share surged to 59.6%. Similarly, Jiangsu's high-risk proportion jumped from 0.8% to 79.5%, reaching a median maximum risk index of 0.83. Conversely, the share of the total study area's low-risk zones located in Guangdong, Guangxi, and Jiangxi increased to 95.7%, 82.7%, and 76.6%, respectively.

Using the SDE method, we quantified the spatial dynamics of high-risk forest fire areas (Figure 7, Table 2), revealing their migration patterns under climate change. During the historical baseline (1985–2014), the centroid of high-risk areas was located near the Guangdong–Hunan border ($X = 817.71$ km, $Y = 2704.25$ km). By the mid-21st century (2021–2050), under both the SSP1-2.6 and SSP5-8.5 scenarios, the centroid is projected to migrate northward near the Jiangxi–Hubei border. The northward shift (ΔY) was substantial (435.51 km for SSP1-2.6, 473.24 km for SSP5-8.5), whereas the eastward shift (ΔX) was minimal (<93 km). This northward migration intensified by the end of the 21st century (2071–2100), particularly under SSP5-8.5. Here, the centroid shifted sharply further north and east ($X = 1052.02$ km, $Y = 3268.47$ km) near the Hubei–Anhui border, representing a net shift of 564.22 km north and 234 km east relative to the historical baseline. This trajectory indicates the expansion of high-risk areas into densely populated inland regions of East China, such as Jiangsu and Hubei. The centroid migration path of the SDE closely aligns with the spatial evolution of fire risk depicted in Figure 6, revealing a pronounced northward shift that accelerates under high emissions (SSP5-8.5). Furthermore, compared with those in the mid-21st century, reductions in the SDE area, major axis, and minor axis by the end-21st century indicate a transition from diffuse areas to more spatially aggregated high-risk areas. This aggregation effect was amplified under the high-emission scenario.

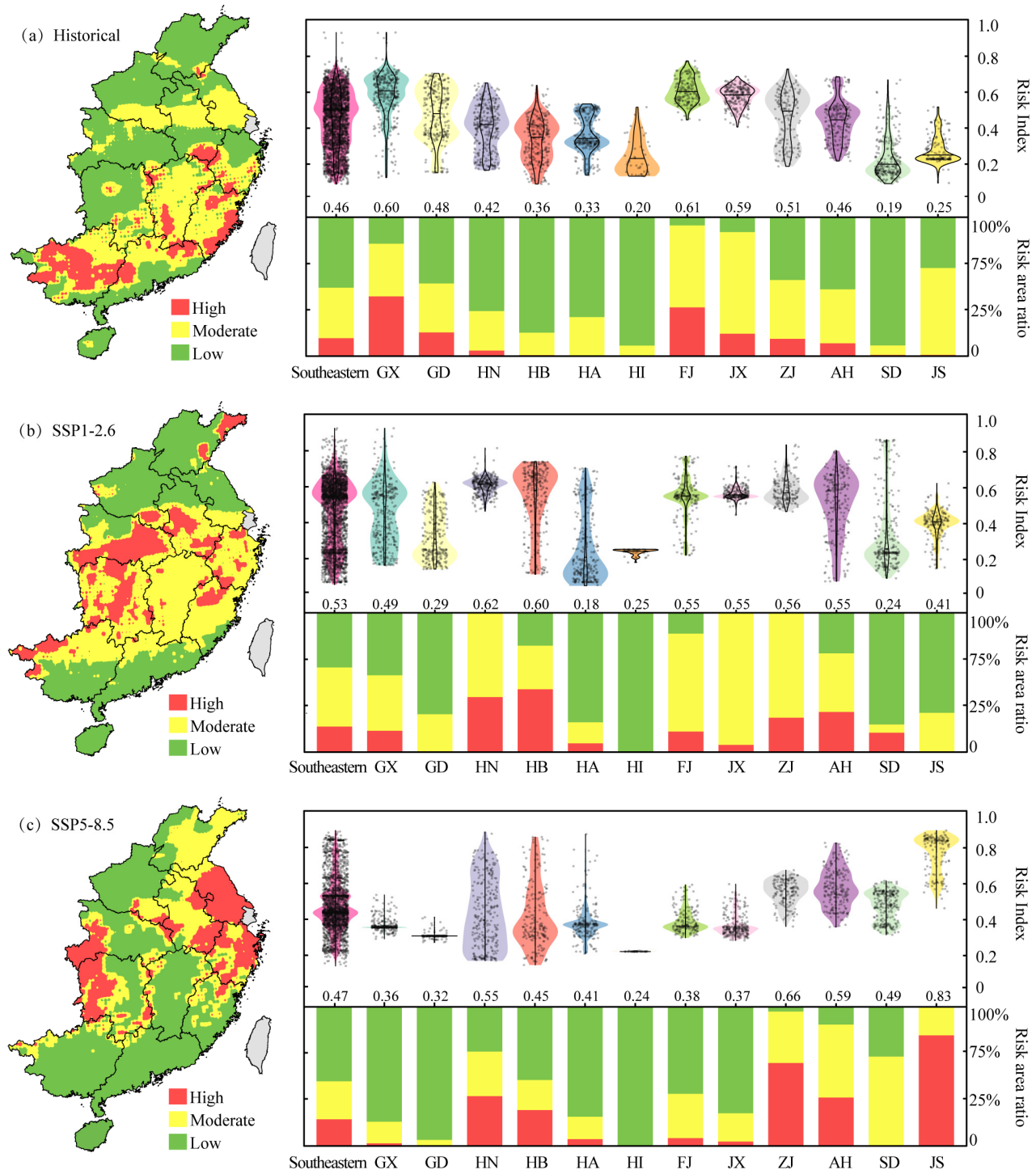


Figure 6. Spatiotemporal evolution of forest fire risk under climate change scenarios. Spatial distribution of the forest fire risk index during (a) the historical baseline period (1985–2014), (b) the end-21st century under SSP1-2.6, and (c) the end-21st century under SSP5-8.5. For each period, the bar charts quantify the proportional area coverage of different risk levels (low, moderate, high) for the entire study region and key provinces, whereas the violin plots depict the corresponding probability density distribution and median value of the risk index.

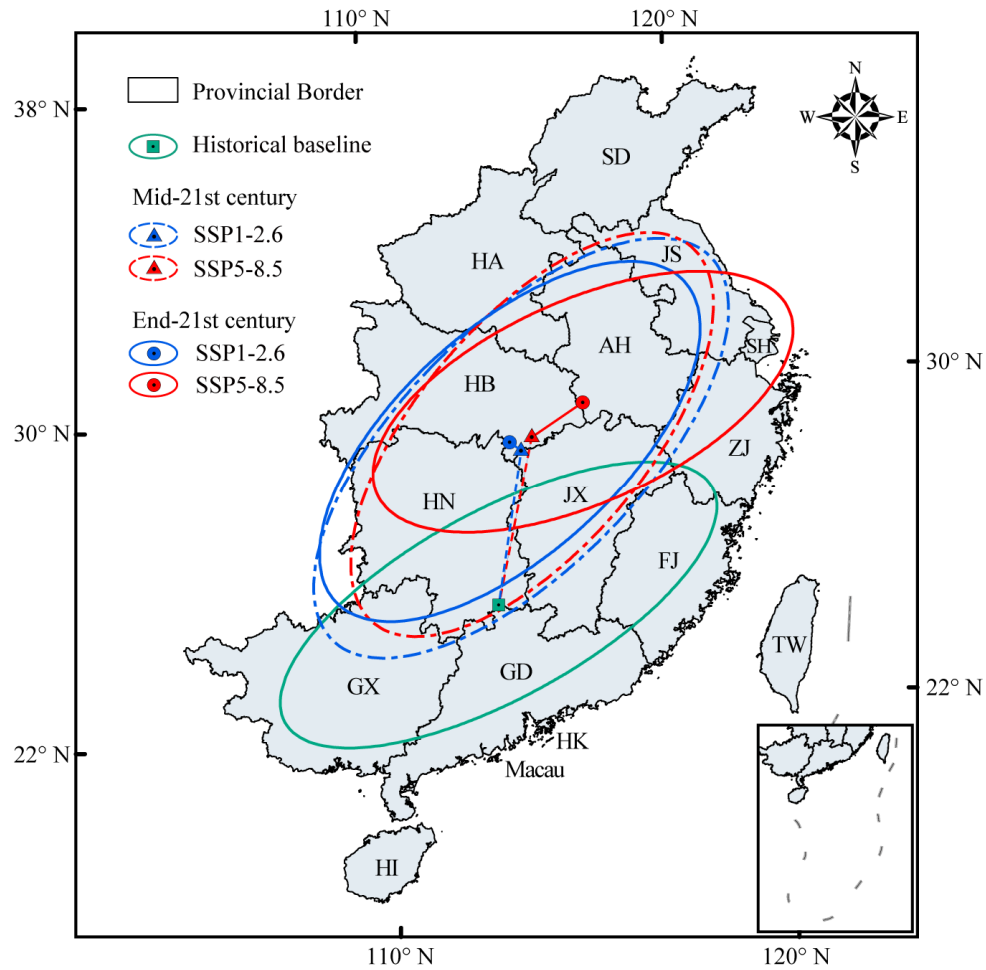


Figure 7. Northward migration and spatial aggregation of high-risk areas. The standard deviational ellipses depict the centroid shift and dispersion changes in high-risk zones from the historical baseline to the mid- and end-21st century under SSP1-2.6 and SSP5-8.5 scenarios.

Table 2. Standard deviation ellipse parameters for high-risk areas of forest fires in Southeastern China.

Period	Scenario	Ellipse Area (10 ⁴ km ²)	Centroid X (km)	Centroid Y (km)	Major Axis (km)	Minor Axis (km)
Historical (1985–2014)	Historical baseline	55.06	817.71	2704.25	677.09	258.90
Mid-21st century (2021–2050)	SSP1-2.6	79.02	880.26	3139.76	748.04	336.31
	SSP5-8.5	68.26	910.69	3177.49	684.42	317.48
End-21st century (2071–2100)	SSP1-2.6	64.47	848.97	3158.22	658.01	311.88
	SSP5-8.5	55.42	1052.02	3268.47	626.80	281.47

4. Discussion

Our analysis systematically elucidates the spatiotemporal differences in forest fire risk in Southeastern China under climate change, identifying significant northward and inland migration in future high-risk areas. This shift reflects complex interactions among climate, ecology, and societal factors. The pronounced regional decline in fire frequency from 2008–2024 can be attributed to China’s long-standing aggressive fire suppression policies. The enhanced forest fire prevention framework, particularly since the revision and strengthening of the Forest Fire Prevention Regulations in 2009, has played a critical role by reinforcing legal liabilities, increasing penalties, and advancing proactive measures in fire source control, public education, and professional firefighting capacity [42,43]. At the

same time, large-scale ecological initiatives—such as the Three-North Shelterbelt Forest Program [44], the Natural Forest Protection Project [45], and the comprehensive ban on commercial logging in natural forests rolled out since 2015—have also contributed to short-term fire control [46], while simultaneously altering forest structure and fuel loads [47]. However, the countertrend increase observed since 2016 in the core fire provinces of Guangdong and Fujian—whose combined share rose by 20.9%—suggests that localized climatic and human pressures may be beginning to overcome even these intensified suppression efforts. This aligns with the well-documented “fire paradox,” where highly effective short-term suppression can lead to long-term risk accumulation by allowing for continuous fuel buildup [48], a phenomenon strongly evidenced in western U.S. forests [49].

More critically, our projections under the high-emission SSP5-8.5 scenario suggest a dramatic northward shift in the high-risk centroid by 564.22 km from the historical location near the Guangdong–Hunan border to the Hubei–Anhui border. Concurrently, high-risk area coverage increased in densely populated provinces such as Jiangsu (from <1% to 79.5%) and Zhejiang (from <1% to 59.6%) relative to the historical baseline (Figure 6). This spatial reorganization was directly linked to projected drastic changes in hydrothermal conditions. To investigate this linkage and predict future fire risk, we developed a high-performing meteorologically driven prediction model via the random forest algorithm ($R^2 = 0.889$). This model validates the key regulatory role of meteorological conditions in regional fire dynamics. While the widely used fire weather index (FWI) effectively captures meteorological influences on fire risk globally [17] and performs well in Northeast and Southwest China [18,19], its applicability in Southeastern China is limited because of its distinct local vegetation and climatic characteristics [20]. By capturing region-specific meteorological interactions, our model provides a more reliable alternative for the long-term prediction of forest fire risk in Southeastern China.

The primary driver of this northward high-risk area migration is spatiotemporal heterogeneity in future hydrothermal regimes. Our study indicates stronger future warming inland and at higher latitudes (Figure 5), which intensifies fire-conducive weather and consequently increases wildfire potential (Figure 6). This aligns with global trends [50,51] and further validates our model’s ability to predict high-risk area relocation. Moreover, precipitation increases exhibit coastal-high/inland-low asymmetry. This pattern, coupled with dramatic warming-induced increases in evapotranspiration demand [52], promotes aridification and warming trends in inland provinces. Droughts arising from this water–heat imbalance significantly reduce vegetation water use efficiency [53]. This process directly lowers the live fuel moisture content through reduced transpiration and increased tissue dehydration [54], thereby increasing vegetation flammability and regional fire risk. Seasonal-scale mechanisms also amplify risk. Although future mean precipitation increases, its variability intensifies (the standard deviation increases by 23%), indicating greater fluctuations between the wet and dry seasons. The historical concentration of 74% of fires in the dry season (December–March) may have intensified. This stems partly from a projected weakening of East Asian summer monsoon winds [55], which can shorten the rainy season, potentially leading to an earlier onset or prolongation of the dry season [56], thereby extending the fire risk period. The substantial surge in high-risk area coverage in Zhejiang (59.6%) likely reflects its position at the monsoon forefront, increasing sensitivity to precipitation fluctuations. Furthermore, human activities may exacerbate risks. Higher fire incidence occurs at wildland–urban interfaces than at natural forests [57]. In the highly urbanized Yangtze River Delta (e.g., Jiangsu, Zhejiang), high population density and expanding wildland–urban interfaces create dual vulnerability: abundant combustible material coupled with readily available ignition sources. Additionally, cultural fire practices, such as sacrificial burning during traditional festivals, may further contribute to ignition sources

in certain regions and seasons. This anthropogenic ignition potential, superimposed on climatic drying and warming, significantly elevates fire risk. However, while human activities significantly increase the probability of fire ignition [8,25], fire risk fundamentally represents the potential for fire occurrence within a disaster-prone environment. Therefore, when assessing fire potential, a distinction should be made between natural risk factors (objective) and human ignition behaviors (subjective), which are triggers for fire occurrence rather than the risk itself.

A primary limitation of this study is that our future projections of fire risk are based exclusively on climate drivers under SSP scenarios and do not explicitly model future changes in fire management policies or suppression efficacy. Our modeling approach was designed to isolate and quantify the climate-induced component of future fire risk, thereby answering the following question: “All else being equal, how will climate change alone alter the spatiotemporal patterns of fire risk?” This provides a crucial baseline understanding of the pure climate signal, against which the additional impacts of socioeconomic pathways and human interventions can be evaluated in future work. Notably, our risk assessment focused primarily on fire occurrence probability, as consistent, spatially explicit burned area data were unavailable for the study period; however, official reports indicate a concurrent declining trend in both fire frequency and total burned area in recent years. Another limitation is that the CMIP6 models do not fully incorporate warming effects on vegetation composition. Studies suggest that deciduous species gain a competitive edge under warmer, drought-prone conditions [58]. Succession from subtropical evergreen forests to deciduous forests could increase dry-season fuel loads. Neglecting such vegetation feedback may lead to the underestimation of long-term fire risk. Nevertheless, our core findings regarding the climate-driven spatiotemporal evolution of fire risk remain robust. This work projects that forest fire risk in Southeastern China is undergoing a historic transition, characterized by a spatial shift from coastal to inland areas and an evolution in spatial pattern from dispersed to aggregated. This transformation is fundamentally rooted in the disruptive reconfiguration of regional hydrothermal regimes caused by climate change. Furthermore, agricultural burning, a common practice in Southeastern China [59,60], typically occurs during spring and autumn [61]. We further speculate that a future monsoon recession prolonging the dry season could align the agricultural burning period with the climatic high-risk window. This potential overlap might create a dual-peak fire risk season in some provinces of Southeastern China.

5. Conclusions

Through multisource data fusion and machine learning modeling, this study reveals the meteorological factor-driven spatial reorganization of forest fire risk across Southeastern China. We observed a highly significant decreasing trend in fire numbers from 2008–2024. However, Guangdong and Fujian Provinces showed an upward trend after 2016 ($p < 0.01$), increasing their combined share by 20.9%, indicating a reconfiguration/shift in the spatial concentration of local risk patterns. Seasonally, fires were highly concentrated in the dry season (December–March, 74.0% of the total), which is consistent with the monsoon precipitation regime. Forest fire risk exhibited significant spatiotemporal variability and a clear response to climate change. During the historical baseline (1985–2014), high-risk areas covered 12.9%, were primarily concentrated in southern coastal provinces such as Guangxi and Fujian, and were scarce (<1%) in northern provinces. Multiple scenario simulations project a gradual inland and northward increase in forest fire risk by the end of the 21st century, a trend that is amplified under the high-emission SSP5-8.5 scenario. This axial migration northward (564 km) was nonuniform and accompanied by significant spatial aggregation. Climate change drove this aggregated northward migration of fire risk

into densely populated inland areas of Southeastern China through the reconfiguration of hydrothermal patterns.

Our findings demonstrate that climate change impacts forest fire risk not only by altering its magnitude but also by significantly reshaping its spatial distribution and driving the migration of high-risk areas. Therefore, future research should explore region-specific climate change impacts on fire risk, particularly responses under extreme climatic conditions. Additionally, sustained long-term climate observations and data accumulation are essential for enhancing the accuracy of future fire prediction models. The random forest model developed here effectively captures the nonlinear relationships between regional meteorological drivers and fire dynamics. This study overcomes the limitations of traditional fire risk indices and provides a scientific basis for developing tailored forest fire management and prevention strategies in Southeastern China. Given the increasing severity of climate change, future wildfire risk management must transition from static zoning to dynamic response systems. Emerging high-risk areas, notably the Yangtze River Delta and Mid-Yangtze River regions, require prioritized integration into key monitoring networks and differentiated prevention strategies to address the challenges of compound climate risks.

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