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ORIGINAL PAPER

Prediction of forest fire occurrence in China under climate change scenarios

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Abstract Climate change has an impact on forest fire patterns. In the context of global warming, it is important to study the possible effects of climate change on forest fires, carbon emission reductions, carbon sink effects, forest fire management, and sustainable development of forest ecosystems. This study is based on MODIS active fire data from 2001–2020 and the influence of climate, topography, vegetation, and social factors were integrated. Temperature and precipitation information from different scenarios of the BCC-CSM2-MR climate model were used as future climate data. Under climate change scenarios of a sustainable low development path and a high conventional development path, the extreme gradient boosting model predicted the spatial distribution of forest fire occurrence in China in the 2030s (2021–2040), 2050s (2041–2060), 2070s (2061–2080), and 2090s (2081–2100). Probability maps were generated and tested using ROC curves. The results show that: (1) the area under the ROC curve of training data (70%) and validation data (30%) were 0.8465 and 0.8171, respectively, indicating that the model can reasonably predict the occurrence of forest fire in the study area; (2) temperature, elevation, and precipitation were strongly correlated with fire occurrence, while land type, slope, distance from settlements and roads, and slope direction were less strongly correlated; and, (3) based on future climate change scenarios, the probability of forest fire occurrence will tend to shift from the south to the center of the country. Compared with the current climate (2001–2020), the occurrence of forest fires in 2021–2040, 2041–2060, 2061–2080, and 2081–2100 will increase significantly in Henan Province (Luoyang, Nanyang, Sanmenxia), Shaanxi Province (Shangluo, Ankang), Sichuan Province (Mianyang, Guangyuan, Ganzi), Tibet Autonomous Region (Shannan, Linzhi, Changdu), Liaoning Province (Liaoyang, Fushun, Dandong).

Keywords Climate change · Scenarios · XGBoost model · Forest fires · China

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Introduction

Natural and human activities influence climate change; global atmospheric CO_2 concentrations have been increasing at an accelerated rate, and average global surface temperatures by 1.1 (0.9–1.2) ℃ over the period 2011–2020 compared to 1850–1900 (Liu and Li 2019),Climate warming has become a serious global problem in the 21st century, with the most obvious warming trend in the northern hemisphere in the middle and high latitudes (Lucht et al. 2002). China is a sensitive area for global climate change, and average land warming is faster than the global average (Liu et al. 2004). Forests have a considerable impact on terrestrial ecosystems, and are important in carbon sequestration and oxygen release, landscaping, and global warming mitigation (Baskent and Keles 2009; Qiu et al. 2020). However, forest fires are one of the most destructive events to forest ecosystems, one of the major sources of greenhouse gas emissions (Naderpour et al. 2019) and negatively affect erosion rates and surface water runoff (Wittenberg et al. 2014; Kastridis et al. 2022).

In China, wildfires occur frequently, destroying forest resources while also reducing their function as carbon sinks and their sustainability (Adams and Shen 2015).

Climate is an important factor on forest fire occurrence, and a warming climate will increase their frequency and intensity (Clark 1988; Neary et al. 1999). At different spatial units, climate warming changes the distribution, composition, and productivity of forests (Johnstone et al. 2010; Margiorou et al. 2022).

Future climate warming may to outpace human activities and will play a greater role in fire activities (Zhang et al. 2016). Studies show that warming has increased the growing period in China, especially on the Qinghai-Tibet Plateau and in the northern regions (Zhao and Shu 2007). Warmer and drier climates will enhance the effects of fires and increase forest loss (Liu et al. 2010). Temperature and precipitation are key factors in fire activity (Ma et al. 2020). Weather affects the fire triangle, i.e., oxygen, heat, and fuel. The rise of temperatures, accelerated wind speeds, increased forest combustion activities and increased forest productivity due to climate warming will have a significant impact on the occurrence of forest fires (DeLucia et al. 1999; Hu et al. 2012; Yue et al. 2020). Warming also leads to an increase in the frequency and intensity of extreme weather events, causing massive vegetation damage and mortality and providing an accumulation of combustible material for forest fires. Global warming also increases the frequency of lightning and wildfires (Price and Rind 1994).

China's surface temperature will continue to rise in this century, with more warming in the north than in the south, and more in winter and spring than in summer and autumn (Zhao and Shu 2007). As the global climate continues to warm, predicting the occurrence of forest fires under future climates is of practical significance for the formulation of prevention and management measures (Sun et al. 2014). At present, research on climate change impacts on forest fires in China is mainly carried out at regional scales (Wu 2020), and most are "climate/meteorology-forest fire" correlations (Li et al. 2000, 2011). There is an absence of research on climate change-driven future forest fire simulations on a national scale. Therefore, this research will: (1) establish the relationship between forest fire occurrence and climate, vegetation, topography and social-humanities based on the eXtreme Gradient Boosting (XGBoost) model; (2) study the response to forest fires under the background of climate change; and, (3) simulate the occurrence of forest fires in China under different future climate scenarios.

Materials and methods

General description of the study area

China has diverse forest ecosystems, complex topography, and high terrain in the west and low in the east. In comparison with other countries, the total forest resources is small and *per capita* possession low (Shao et al. 2022a). In this study, China has been divided into the following eight eco-geographical zones according to climate types (Fig. 1) (Shaohong et al. 2010):

Active fire data and other data

Moderate resolution imaging spectroradiometer (MODIS) active fire data have the advantage of wide spatial and temporal coverage and can be shared freely worldwide. It is an effective data program for characterizing large-scale fire conditions (Hantson et al. 2013). In this study, MODIS data are obtained from NASA (Davies et al. 2009). The dataset contains information on the date of occurrence, latitude, and longitude, and confidence level with 1000 m resolution. Fire active points with a confidence level greater than 80% were selected. The Digital Elevation Model data population and Gross Domestic Product came from the Resources and Environment Data Center of CAS (Liu et al. 2005; Xu 2017). The datasets for roads and residential areas were downloaded from the National Geographic Information Resource Catalog System (Jiang 1999). Based on the DEM data, slope and aspect were extracted using ArcGIS 10.4 software. For vegetation data: the Chinese vegetation cover map was used (Ran et al. 2012), with a spatial resolution of 1 km and 17 classification systems. This dataset maintains the overall accuracy of China's forest land cover and increases the attribute information with the fusion of multi-source information and land cover data (Ran et al. 2012). The object of

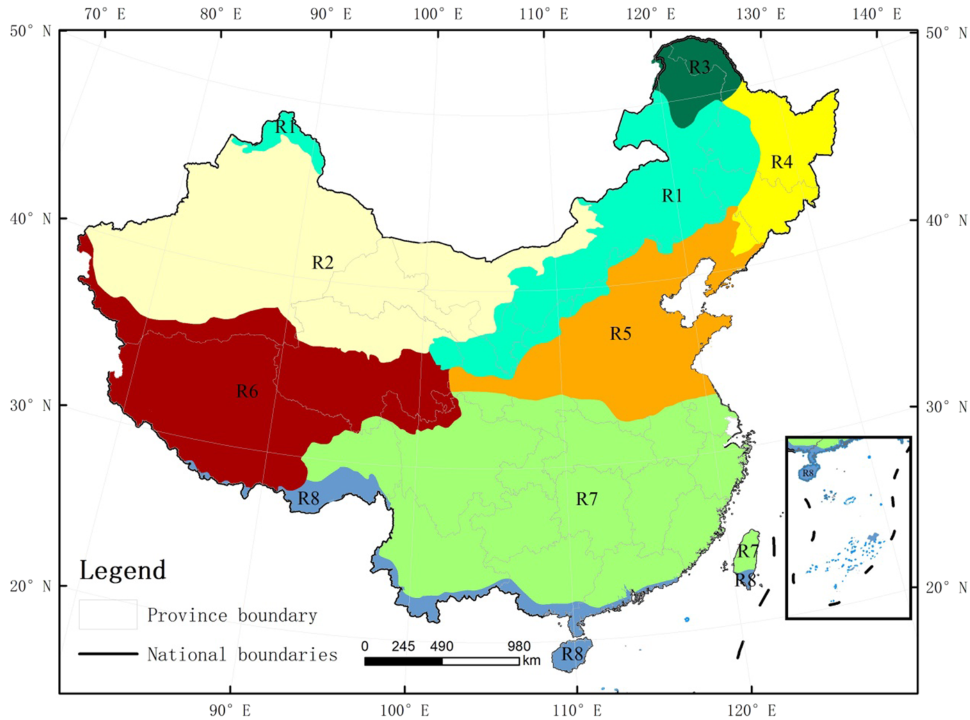

Fig. 1 Geographic zones of China (R1: Temperate grasslands;R2: Temperate deserts; R3: Cold-temperate coniferous forest; R4: Temperate coniferous and deciduous broad-leaved mixed forests; R5: Warm temperate deciduous broad-leaved forest regions; R6: Alpine vegetation zone of the Qinghai—Tibet Plateau; R7: Subtropical evergreen broad-leaved forest; R8: Tropical monsoon rain forest)

this study is to forest active fire ignitions. Six forest types were studied: evergreen coniferous, evergreen broadleaf, deciduous coniferous, deciduous broadleaf, mixed species, and shrub forest. A large sample of 255,697 fire points and an equal number of non-fire points were used to construct the sample set, distributed in a 7:3 ratio for training and validating the model (Shao et al. 2022b). Temperature data were obtained from He et al. (2021), and a new high-resolution, monthly gridded temperature dataset with a 1-km resolution was obtained by the Gaussian process regression (GPR) method based on weather station data divided into monthly mean, maximum, and minimum temperatures. Precipitation data were obtained from Qu et al. (2020), consisting of a monthly precipitation interpolation dataset calculated using the climate data spatial interpolation software Anusplin with a spatial resolution of 1 km from more than 2400 meteorological stations.

Data for different carbon emission scenarios were obtained from the World Climate website (Eyring et al. 2016; Hurtt et al. 2020).

The correlation coefficients of simulated and observed temperatures and precipitation from 1850 to 2005 by the BCC-CSM2-MR model were 0.86 and 0.73, respectively, which have good simulation ability (Xin et al. 2019).

The BCC-CSM2-MR climate model with a resolution of 2.5 min was selected. The SSP126 (sustainable low development pathway) and SSP585 (high conventional development pathway) for different scenarios were used to simulate future forest fires in the periods 2021–2040, 2041–2060, 2061–2080, and 2081–2100. The data were re-sampled at a spatial resolution of 1 km for different future climate scenarios and the raster data extracted based on the Chinese vector boundary map.

Technical workflow

The technical flow chart of this study is shown in Fig. 2. (1) The spatial distribution of forest fire occurrence in China under current climate conditions was analyzed and forecast based on MODIS fire product data from 2001–2020, combined with meteorological, vegetation, topographic, and human activity data; (2) the XGB model was used to identify the influence of these factors on forest fire occurrence and to establish the relationship amongst each factor; (3) the extreme gradient boosting model was used to identify the influence of factors on forest fire occurrence, establish the relationship between each factor and the occurrence of forest fires, construct a forest fire prediction model, and evaluate the accuracy of model prediction using Recall, F1, and AUC evaluation indexes; and (4) based on the BCC-CSM2-MR climate model, greenhouse gas emission scenarios SSP126 and SSP585 were selected to build models to predict and map the risk of forest fires over the periods previously described under future climate change scenarios.

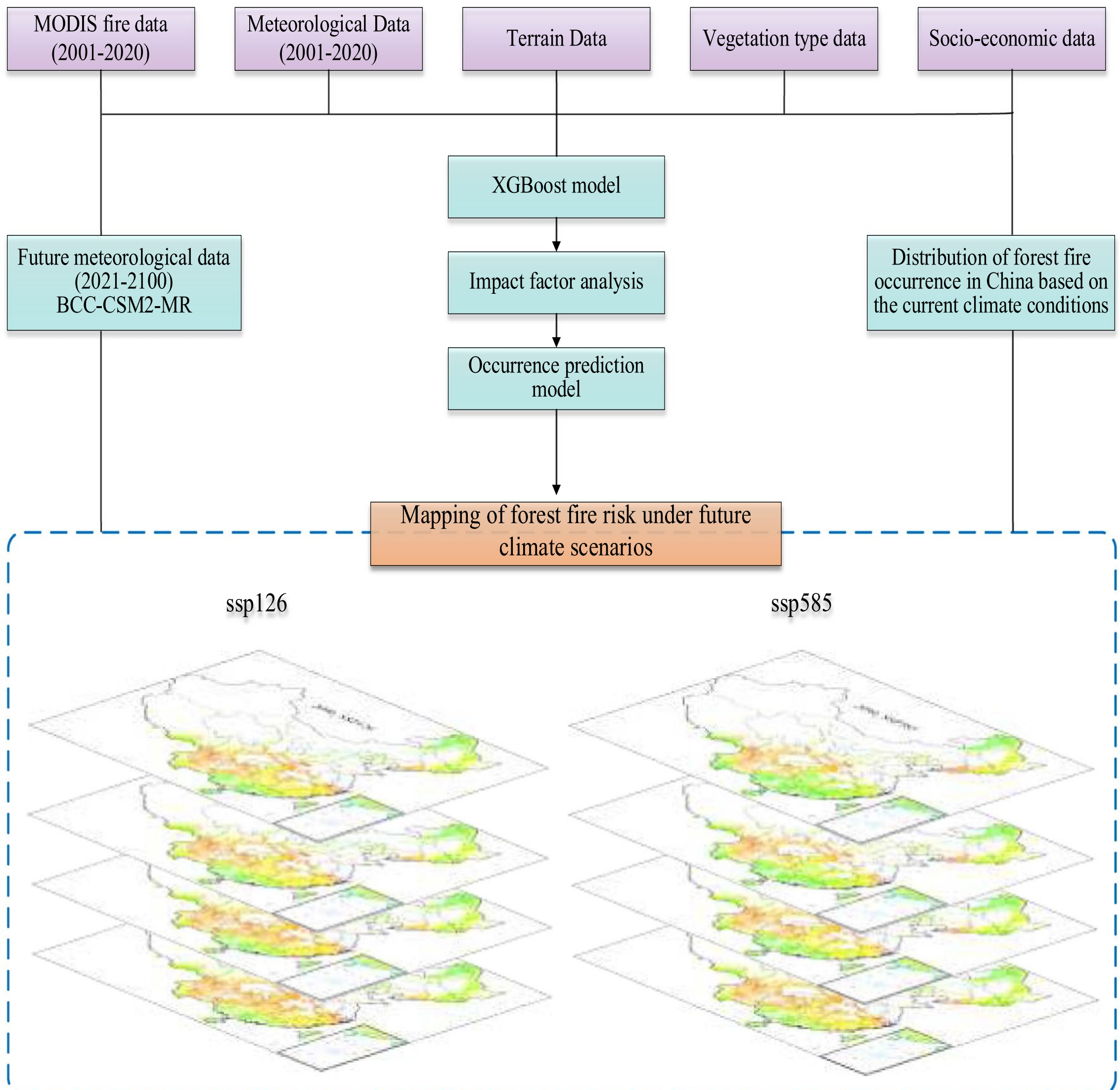

Fig. 2 Technology workflow in this study

XGBoost (extreme gradient boosting)

The XGBoost model (Fig. 3) uses the classification and regression tree (CART) as the base classifier decision tree. A gradient boosting method (weak learners to strong learners) was used for additive training to combine multiple individual classifiers into an integrated classifier to improve accuracy and speed (Chen and Guestrin 2016). Feature splitting was performed by continuously adding decision trees to the model, and the residuals of previous predictions were fitted with the new functions formed by the added trees. The results of all tree predictions were summed as the final prediction (Chen and Guestrin 2016). The algorithm has the advantages of being efficient and flexible, of automatic multi-threaded parallel computation, effective control of overfitting, and independent of the quality of training data (Chen et al. 2020).

The formula is as follows Xu et al. (2021):

$$\hat{y}_i = \sum_{k=1}^{K} f_k\left(x_i\right), \quad f_k \in F, \tag{1}$$

where $\hat{y}_i$ denotes the predicted value of the model, K the number of decision trees, x_i is the i-th sample, f_k the k-th submodel, and F represents the set of all decision trees. The optimization rule of the decision tree is to optimize the trees

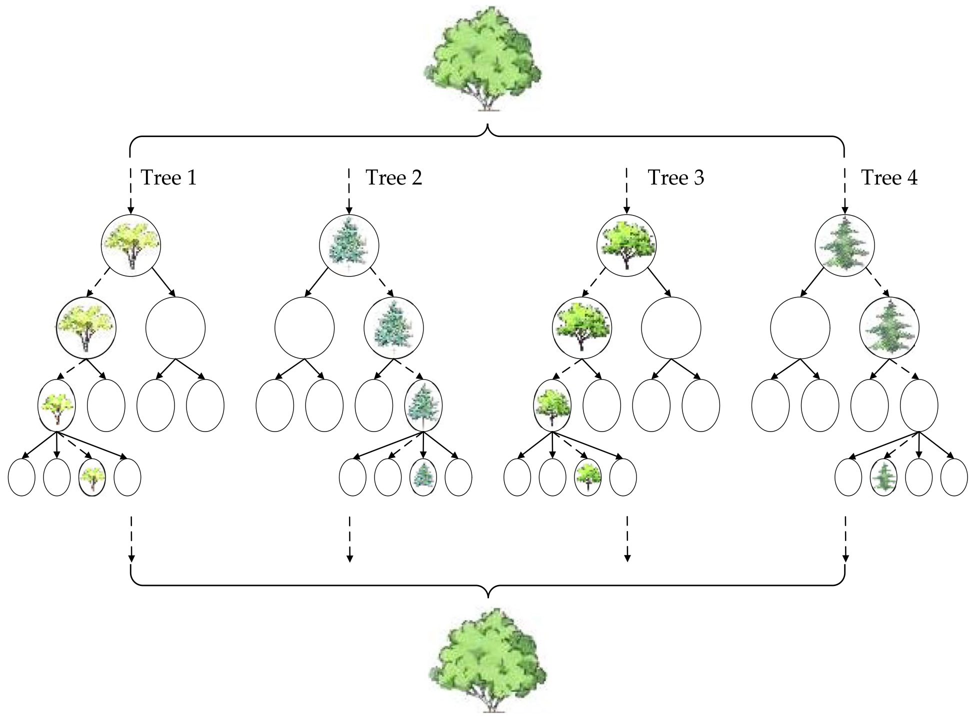

Fig. 3 Schematic diagram of XGBoost model

sequentially starting from the 1st tree and ending with the K -th tree (Xu et al. 2021).

The XGBoost model is a loss function to measure the training error and a regularization term to control the complexity, respectively, as follows (Wang et al. 2020):

$$L(\phi)^t = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_k), \tag{2}$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel \omega \parallel^2 \tag{3}$$

where $L(\varphi)^t$ represents the objective function of the t-th iteration; $\hat{y}_i^{(t-1)}$ the previous $t-1$ iteration value; Ω is a regular term; $\Omega(f_k)$ represents the complexity of the k-th tree to control the complexity of the model from preventing overfitting; γ and λ represent the regular term coefficient to prevent the decision tree from being too complex; γ is used to control the number of leaf nodes; λ ensures that the fraction of leaf nodes is not too large; T represents the number of leaf nodes of the model.

The XGBoost classifier was used and the learning rate set to 0.1 and number of trees to 1000 for iterative training. Recall, F1, and AUC were used to verify the accuracy of the model (Shao et al. 2022a).

Recall refers to the proportion of the number of correct information bars extracted to the number of information bars in the sample, and the formula (Syafrullah and Salim 2011):

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

The F1 value is used to evaluate the classification model with the formula (Shaojun et al. 2012):

$$\text{F1} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{5}$$

TP indicates that the sample is correctly predicted as positive, FN falsely predicts positive sample as negative, and FP falsely predicts negative sample as positive.

The calculation of AUC (area under the ROC curve value) considers the classification ability of the classifier for both positive and negative cases, and can be used as an average indicator of the category imbalance distribution; the larger the AUC is above 0.5, the higher the correct classification rate (Jin and Ling 2005).

Results

Factor importance and model validation

The learning rate of the XGBoost classifier was set to 0.1, and trained for 1000 iterations. The AUC of the training data (70%) and validation data (30%) were 0.8465 and 0.8171,

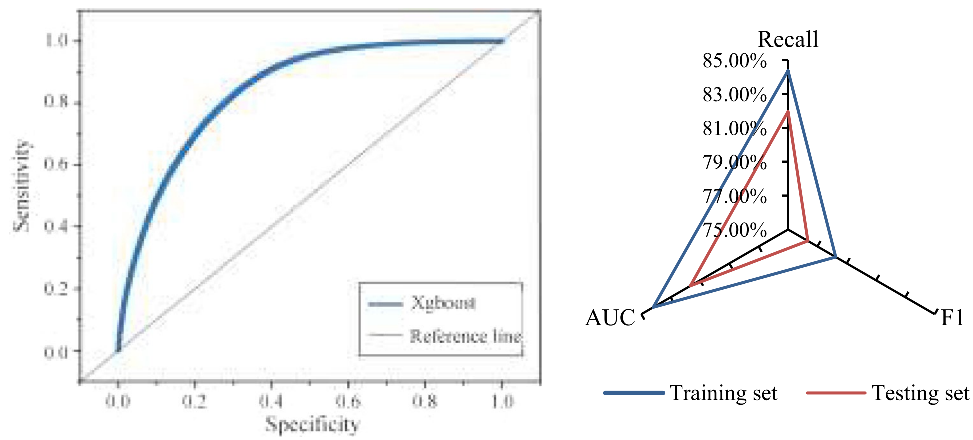

Fig. 4 Comparison of the precision levels of the XGBoost model (Recall is the proportion of the number of correct information bars, F1 value is used to evaluate the classification model, AUC is an average indicator of the category imbalance distribution)

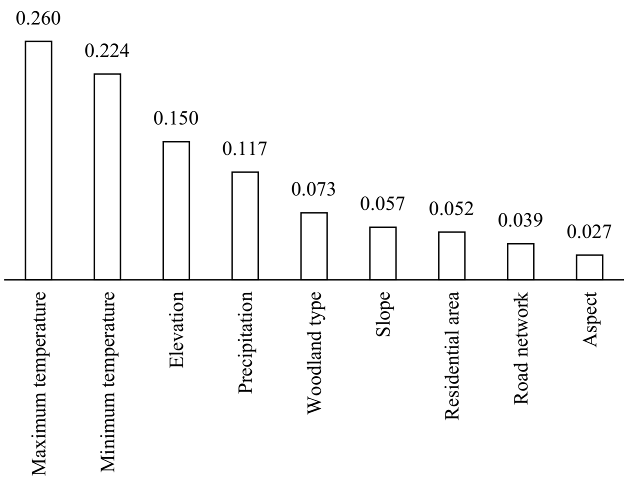

Fig. 5 Influences of factors on forest fire occurrence probability

respectively (Fig. 4). In addition, the F1 and Recall of the training data were 78.2 and 84.2%, respectively, and the F1 and Recall of the validation data were 76.4 and 81.6%.

The largest contributor to the occurrence of forest fires was maximum temperature (26.0%), while the remaining contributing factors were minimum temperatures (22.4%), elevation (15.0%), precipitation (11.7%), forest type (7.3%), slope (5.7%), distance from settlements (5.2%), and distance from roads (3.9%) (Fig. 5).

Distribution of forest fire occurrence based on current climate conditions

As shown in Fig. 6, the red areas have high fire risk probability, i.e., very fire-prone sites. Both past fire sites and predictions under the current climate show obvious spatial distribution and clustering characteristics, mainly in the southwest and southeast and parts of the northeast. The main areas are: (1) southwest: mainly in the southern part of Sichuan Province (e.g., Panzhihua City and parts of Liangshan Yi Autonomous Prefecture), Yunnan Province (e.g., Xishuangbanna and Pu'er City), with high mountains and dense mixed coniferous and broad forests, dry and windy winters and springs, and occasionally extremely dry weather;

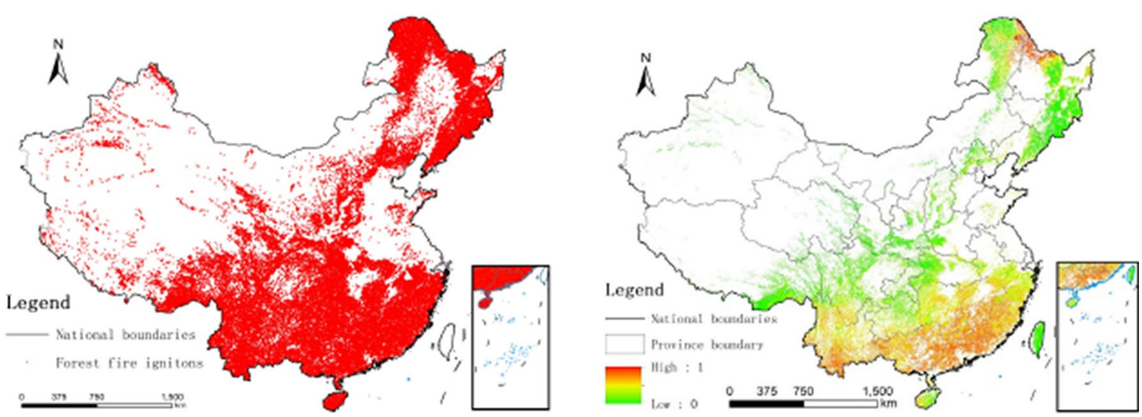

Fig. 6 Active fires observed by MODIS (2001–2020); mapping of forest fire risk using the XGB model based on current climate

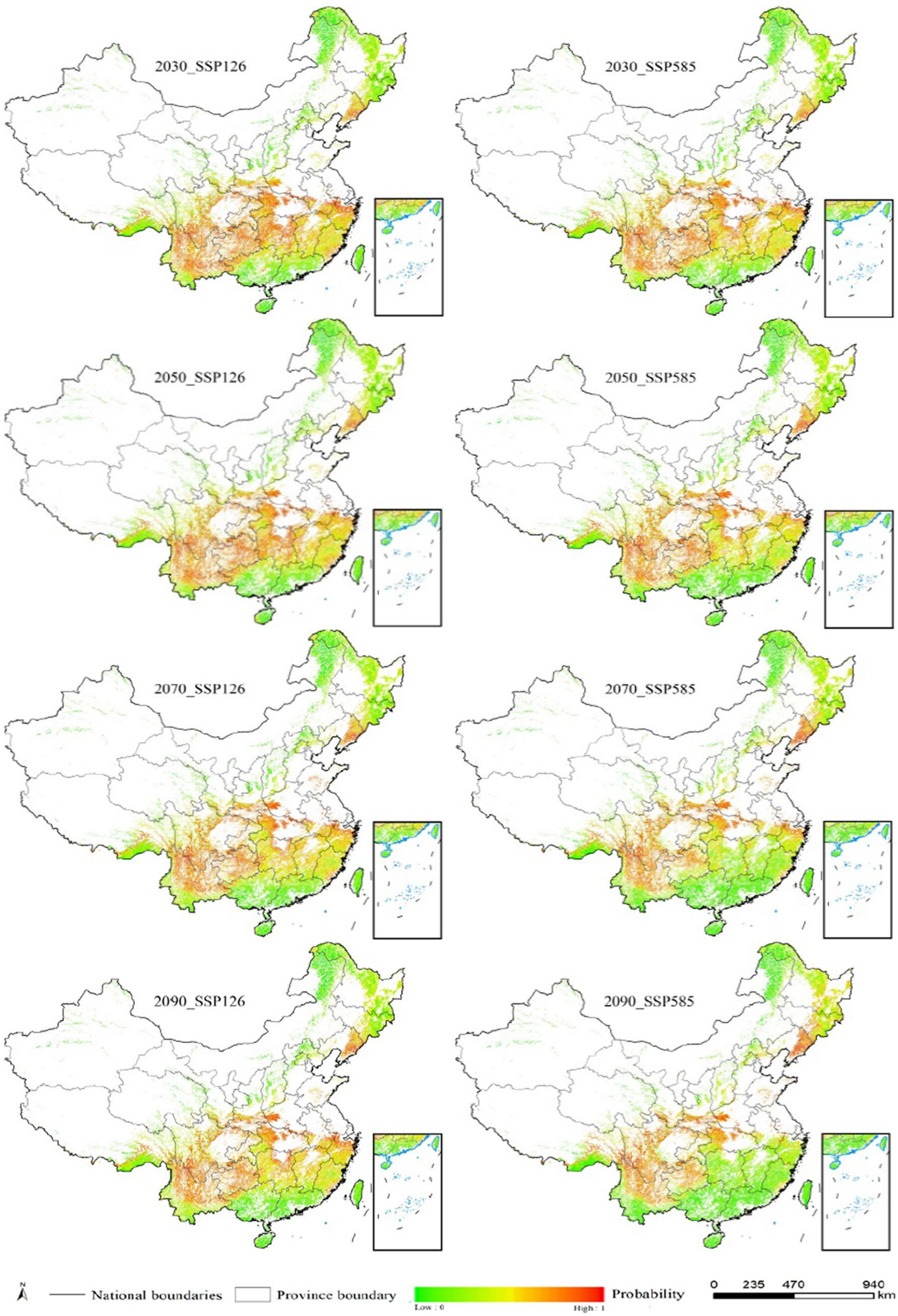

Fig. 7 Prediction of forest fire occurrence in China under the BCC-CSM2-MR scenarios from 2030 to 2090

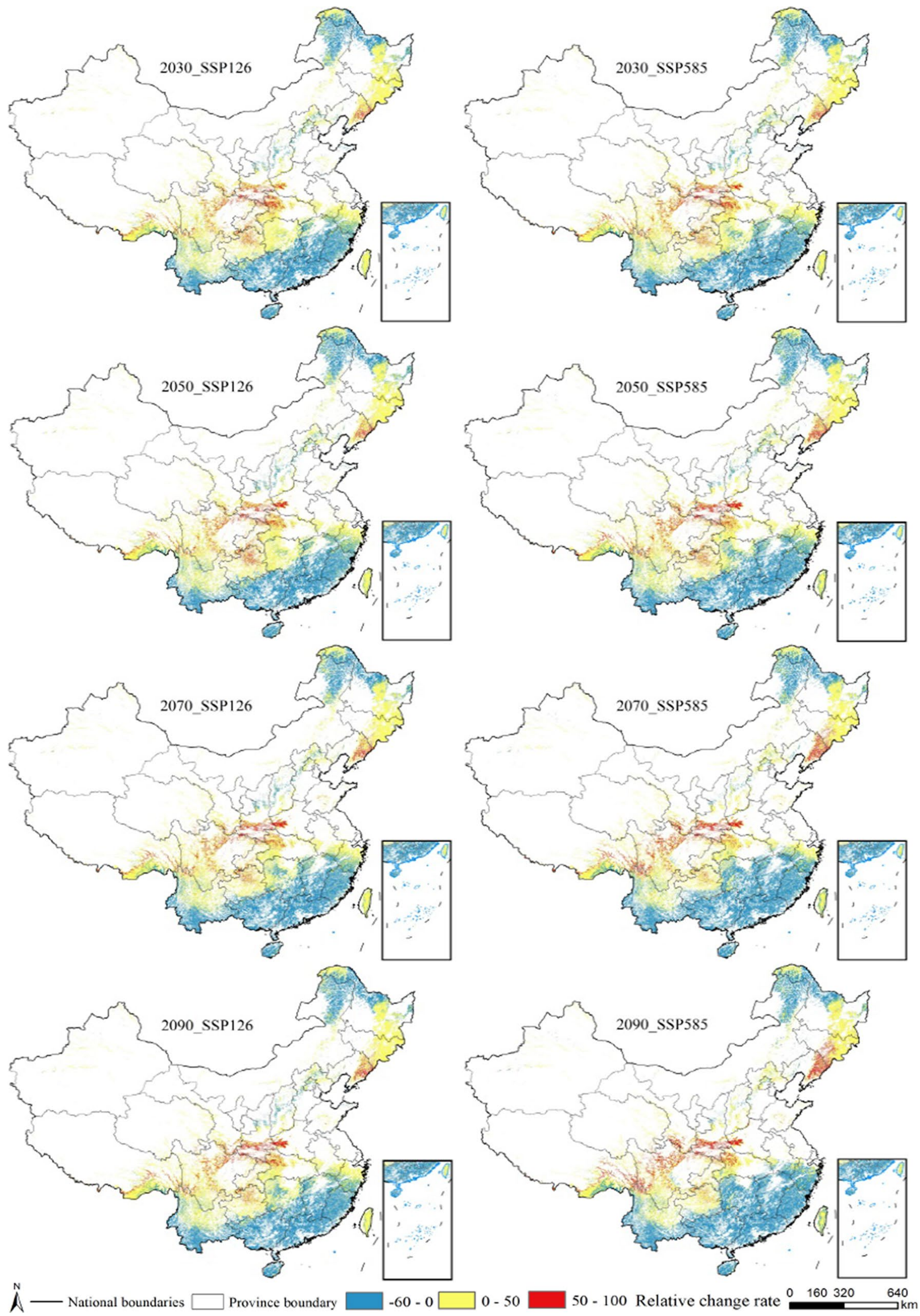

Fig. 8 Relative changes in forest fire occurrence between current and future climate scenarios for the BCC-CSM2-MR

(2) south: Guangdong Province (e.g., Huizhou and Heyuan areas), Guangxi Province (e.g., Wuzhou, Hezhou, Yulin), Fujian Province (parts of Nanping City), with rich forest resources, considerable intermingling of forests and agricultural land, frequent human activities, and difficulties in fire management; and, (3) Heihe City and parts of Daxinganling in the northeast, with dense distribution of forest resources, relatively flat terrain, and occasional thunderstorms (Gao 2015). The driving factors in the various regions are different and reflect terrain conditions, climate, social economies and other factors (Shao et al. 2022a).

China's forest fire projections under future climate change

Figures 7 and 8 show that the spatial distribution of forest fires under a future climate scenario is significantly larger than the current climate. Higher probability areas are mainly concentrated in: (1) southwest China: Guizhou Province (Guiyang, Tongren, Zunyi), Sichuan Province (Liangshanyi Autonomous Prefecture, Bazhong, Ya'an), Chongqing, and Tibet Autonomous Region (Shannan, Linzhi, and Chamdo); (2) central China: most of Hunan Province (Changde, Yiyang, Hengyang), Hubei Province (Shiyan, Yichang, Jingmen), Henan Province (Nanyang City, Luoyang City, Xinyang City); (3) east China: Anhui Province (Xuancheng City, Liuan City), Jiangxi Province (Fuzhou, Ganzhou), Zhejiang Province (Ningbo, Shaoxing, Hangzhou); (4) Northeast China: Liaoning Province (Liaoyang, Fushun, Dandong), Tonghua City, Jilin Province. (5): Fuzhou City, Fujian Province; (6) northwest Region: Shaanxi Province (Shangluo, Ankang City). The probability of forest fire occurrence in 2090 is slightly higher than in 2030 where the risk in some areas of Fujian Province is weaker under the SS585 scenario. As shown in Fig. 8, the relative change of SS126 and SS585 scenarios increased considerably, mainly in Henan Province (Luoyang city, Nanyang City, Sanmenxia City), Shaanxi Province (Shangluo City, Ankang City), Sichuan Province (Mianyang City, Guangyuan City, Ganzi City), Tibet Autonomous Region (Shannan City, Nyingchi City, Qamdo City), and Liaoning Province (Liaoyang City, Fushun City and Dandong City). With future climate changes, the occurrence of forest fires in China may expand from the southwest and southeast to central and eastern China. Increasing temperatures lengthen the growing season and increase the accumulation of combustible materials. With global warming, the number of days of high temperatures and drought conditions increase, precipitation and humidity decrease, wind speeds increase, and the fire danger period is extended. Rising temperatures increase atmospheric evaporation, thereby enhancing drought conditions and raising the risk of wildfires, especially in forested areas where combustible materials are abundant. Forest fire occurrence frequencies and rate of combustion, as affected by climate change, tend to move from the south to the center of the country (Wu et al. 2020). The northeastern region also extends to the south. Dryness of combustible materials in the north due to relatively low rainfall and the increase in temperatures leads to enhanced evapotranspiration, furthering exacerbating the water deficit (Liu et al. 2012). Therefore, the increasing forest fires in the north. Global warming affects the spatial distribution and combustion characteristics of fire sources which increases the probability of forest fires (Wang et al. 2007).

Discussion and conclusions

This study predicts the spatial distribution of forest fire occurrences in China from 2030–2100 based on MODIS fire point data, historical meteorological, topographical, vegetation, and social data, combined with temperature and precipitation data from future scenario data. The results show that temperature, elevation, and precipitation are strongly correlated with the occurrence of forest fires. As temperature increases, it affects relative humidity within a forest, accelerating the evaporation of water from combustible materials. An increase in temperature will also increase the probability of high winds, increasing the probability of forest fires and expanding fire spread (Sun et al. 2014). Precipitation directly affects the water content of combustible materials, and an increase in plant water content reduces the possibility of forest fires (Zhang et al. 2000). Under historical climate conditions, it is predicted that the occurrence of forest fires in China will be concentrated in the southwestern and southeastern parts and the northeastern parts, which is consistent with the results of the study using deep learning and multi-source data prediction (Shao et al. 2022b). In the future BCC-CSM2-MR climate model, the frequency and intensity of extreme precipitation are gradually enhanced in the higher carbon emission scenario SSP585 compared with the lower emission scenario SSP126, mainly in eastern China (Kong and Sun 2021; Liu et al. 2021). Summer precipitation also tends to increase in most areas of the southwest (Yang et al. 2021). In the BCC-CSM2-MR climate model, our prediction results of fire occurrence based on the XGBoost model showed fire occurrence probability moving from the south to the central part of the country, which is consistent with the prediction results of Wu et al. (2020) based on the GFDL-CM3 model enhanced regression tree. Similar fire point data, (Gu et al. 2020) gave the predicted AUC value of 0.73 for forest fires under climate change in Jiangxi Province, and in the whole of China, AUC can reach 0.84. However, due to the complex non-linear interactions between weather, vegetation and people (Hu et al. 2021), it is difficult to determine the severity and intensity of fires under future climate change, one of the shortcomings of this study.

Future studies will be carried out on the effects of large-scale climate fluctuations on the occurrence of forest fires and carbon emissions (Hu et al. 2021). In addition, studies on the environmental, ecological and evolutionary effects of forest fires will be carried out (Yue et al. 2020).

This study considers the changes in forest fire occurrence in China caused by[different climate scenarios,] and that changes in forest age and structure will occur in the next 100 years (Qiu et al. 2020). In particular, forest resources in China are affected by the government management policy intervention. Therefore, the results of the forest fire risk assessment in China from 2021 to 2100 only reflect the possible fire risk changes caused by future climate change. Forest fire data over a long time series and large scales are important for predicting the effects of forest fires to climate change. However, spatially and temporally explicit historical forest fire data are often difficult to obtain. Forest fire and climate data and topographic factors over 20 years from 2001–2020 were used to predict future forest fire occurrence, but short-term climate data may not capture the long-term variability in fire-climate relationships (Hawbaker et al. 2013). This could affect the comparability of fires in the current (2001–2020) and future climates (2030–2090). Climate conditions before fire occurrence can be assessed in the future. In the context of global warming, the growing season is extended, increasing the frequency of forest fires (Wotton et al. 2010). Because specific forest fire occurrence models may not be widely applicable, when developing such models using publicly available data, the versatility of model development methods can be enhanced and applied elsewhere (Szpakowski and Jensen 2019).

Under future climate change scenarios, forest fire risk in China shows an increasing trend, with more areas under the high-risk zone. Our study may be considered as a study of the long-term probability estimates of fire occurrence in China. However, the anthropogenic impact of changing land use patterns may influence our results when we strengthen the study of the impact of multi-factor simulations and future extreme climate events on the spatial and temporal dynamics of forest fire occurrence. Based on active fire data, multiple factors were combined to identify China's forest fire occurrences under future climate change scenarios, which can provide effective reference and data support for China's prediction of future forest fire occurrence, prevention and mitigation, and the development of sustainable forest management.

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Author contributions Conceptualization, GF, ZF and YS; data curation, YS and GF; formal analysis, YS and GF; funding acquisition, GF and ZF; investigation, YS and GF; methodology, ZF, YS and GF; project administration, GF, ZF and YS; resources, GF, ZF and YS; supervision, YS, GF and ZF; validation, GF, ZF, YS, LS, XY, TM, HF, and AW; visualization, YS and GF; writing—original draft, Y.S. and G.F.; writing—review and editing, YS, GF, ZF, LS, XY, TM, HF, and AW All authors have read and agreed to the published version of the manuscript.

Data availability The MODIS active fire data came from NASA's FIRMS (https://earthdata.nasa.gov); the DEM, POP, GDP data came from the Resources and Environment Data Center of CAS (https://www.resdc.cn). The datasets for roads and residential areas were downloaded from the National Geographic Information Resource Catalog System (https://www.webmap.cn). The Chinese vegetation cover map came from Big Earth Data for Three Poles (http://poles.tpdc.ac.cn/zh-hans/). The carbon emission scenarios were obtained from the World Climate website (http://worldclim.org/); We acknowledge the World Climate Research Program.

Conflicts of Interest The authors declare no conflict of interest.

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