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Simulation of forest fire spread based on artificial intelligence

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ABSTRACT

This article aims to provide a more practical forest fire spread model for predicting and managing forest fires in Heilongjiang Province, China. Heilongjiang is dominated by spatially heterogeneous combustible forests with undulating terrain and steep slopes. In this article, an artificial neural network framework is used to generate an accurate flame propagation map. Considering inherent fire propagation uncertainties, a fire propagation model containing multidimensional physical and environmental variables is established. Based on fire propagation predictions, the physical fire propagation method is also effectively understood. Additionally, the artificial neural network model can analyse spatial time series patterns and is not a traditional fire spread model. Moreover, this study established a forest fire spread prediction model combining Heilongjiang's cellular automata and Wang Zhengfei's model for comparison with the artificial neural network model. After repeated training and testing, the forest fire prediction results based on the artificial neural network, were found to have average accuracy, sensitivity, and F-measure values of 85.02%, 95.26%, and 89.85%, respectively. The proposed model is suitable for prediction of fire spread beyond large forest fires (more than 1 ha and less than 100 ha of affected forest). Therefore, the model facilitates a better understanding of fire cover propagation behaviours and quickly generates fire peak profiles. The proposed model can enable forest managers and firefighting agencies to plan better firefighting operations and improved firefighting strategy effectiveness.

1. Introduction

Forests are the largest terrestrial ecosystem in the world and are an important part of the global ecosystem. They play a very effective role in maintaining soil and water conditions and regulating the climate (Wu et al., 2021). Forest fires are a key factor in breaking the ecological balance of forests (Sileshi and Mafongoya, 2006; Johnstone et al., 2016; Molina et al., 2019); these severe natural disasters cause serious economic damage and property losses every year. According to statistics, an average of 200,000 forest fires occur every year around the world (Yunmao et al., 2009). The area burned by forest fires each year accounts for more than 1% of the world's total forest area. More than 10,000 forest fires occur in China every year, and the annual burned area accounts for more than 5% of China's total forest area (Zhong et al., 2003). The northeast forest region is the largest forest region in China. In accordance with the continuous development of forestry in Heilongjiang, the province issued relevant forest fire prevention policies in 2018 (Hu et al., 2018).

Due to these forest fire protection policies, the forest ecosystems in Heilongjiang are protected from disturbances by forest fires. Predicting the occurrence and spread of forest fires quickly and accurately is the most important step in fire protection plans and in reducing forest fire hazards (Chowdhury and Hassan, 2015). To achieve this goal, scientists have conducted extensive research in recent decades. Studies have shown that the spread of forest fires is determined not only by static factors such as topography and vegetation types but is also a dynamically driven process influenced by factors such as climatic factors and the surface water content. Greenhouse gas emissions lead to constant changes in the climate. This will lead to higher temperatures, longer dry periods and lower humidity. These factors will directly lead to an increase in the frequency of forest fires and an increase in the area and intensity of forest fires (Tian and Liu, 2011; Fahad et al., 2021b; Fahad et al., 2021c; Fahad et al., 2021d; Fahad et al., 2021a). Therefore, the spread of forest fires is mainly related to four types of factors, namely climatic factors, Terrain factors, Combustible factor variables, and Land cover type variables (Guo et al., 2017).

Changes in climate factors are closely related to the moisture contents of wildfire combustibles (Ganteaume et al., 2013; Seager et al.,

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2015; Zhou and Vacik, 2017). Moreover, the flames stretch and bend to the unfired area due to the size of the wind, thus directly shortening the distance between the new flame and fuel (Sun et al., 2013). Winds blowing in the fire spread direction directly increase the real-time rate of spread (ROS) (Chen et al., 2012; Boer et al., 2017; Hu et al., 2017;). The slope also has a significant impact on the ROS of the line of fire (Eugenio et al., 2016; Mota et al., 2019). Moreover, the temperature drops by 0.5 °Celsius for every 100-m increase in elevation (Dong and Huang, 2015; Najafabadi et al., 2015). The water content of the surface would increases with increasing elevation (Abdollahi et al., 2019). Studies have also shown that the soil and vegetation on southern slopes are drier than those on slopes facing other directions (Fidanova and Marinov, 2016). For land cover type variables, studies have shown that the surfaces of anthropogenic structures create isolated regions in forest areas that can prevent fires from spreading (Nunes et al., 2005; Pereira et al., 2014; Elia et al., 2020). The nature of forest combustibles depends on the type of vegetation that constitutes the forest, and the vegetation type directly affects the nature and quantity of combustibles in the forest (Clarke et al., 2014). Previous studies have also shown that the surface moisture content directly affects the humidity of combustibles, thereby affecting the spread rates of forest fires (Slijepcevic et al., 2018).

In forest fire spread prediction work published in recent years, fire protection and forest management methods have mainly been guided by fire mathematical models (Simpson et al., 2016; Rim et al., 2018). The field of wildfire behaviour research mainly involves the use of the ROS of fires, the fire intensity and the flame length (Ji-li et al., 2012; Brun et al., 2014; Rim et al., 2018). Existing fire spread models can be mainly divided into three categories. The first type of fire spread prediction model is a physical model (Yassemi et al., 2008), in which the physical model is based on the law of conservation of energy. After a forest fire spread model was first created by W.R. Fons in 1946 (Byram and Fons, 1952), other models have been derived, such as the American Firetec and Wfds models (Barovik and Taranchuk, 2010; Hoffman et al., 2016), the Greek AIOLOS-F model (Linn and Cunningham, 2005), and the French model FIRESTAR model as well as and other physical models (Morvan and Larini, 2001). However, physical models require many parameters and have complicated model structures. Due to the destructive nature of forests, collecting real-time ignition data from forest fires is impractical. Studies have shown that less than 5% of forest fire spread can be accurately predicted by physical models. Similarly, there is currently no mature model that can be applied to a real large-scale fire field. The prediction results obtained with existing models are similar only to observation results obtained in local experiments or wind tunnel test rooms (Cruz and Alexander, 2013).

The second type of fire spread model includes empirical models. Empirical forest fire spread models are mainly used to determine the temporal and spatial distributions of historical forest fire data and to analyse these data in combination with meteorological factor information. These models do not include any physical mechanism influencing the spread of forest fires and instead only statistical model forest fire behaviour. For example, the most widely used empirical forest fire spread models are the Australian forest fire and grassland fire spread models called the McArthur model (Tang et al., 2002; Sullivan, 2009) and the Canadian fire risk rating system called the Canadian Forest Fire Danger Rating System (CFFDRS) (Wang et al., 2017). The calculations involved in empirical models are simple and easy to implement, but these methods require long-term actual measurement data. The use of empirical models for predicting forest fire spread is subject to the measurement accuracy of the utilized images, so the practicability of these model is poor (Rothermel, 1994).

The third model type includes semiempirical forest fire spread models (Perry, 1998). These models are derived on the basis of physical models and empirical models. Among them, the Rothermel model proposed by Richard C. Rothermel in 1972 through a combination of field burning experiments and indoor experiments with the law of conservation of energy is the most widely used model in the United States (Rothermel, 1994). However, the model has 11 input parameters, the combustible input parameters must be obtained experimentally, and nested relationships exist among the parameters. The model thus must be run under some simplification requirements, such as a continuous combustion bed, uniform combustibles, and no slope and wind images. Therefore, the Rothermel model is difficult to use in practical applications (Andrews et al., 2013). To date, fire spread simulation and prediction research has mostly involved the use of computer-simulated empirical models or empirical models to guide actual forest-firefighting work.

Previous studies have shown that forest fire spread modelling and prediction methods are highly nonlinear, and it is impossible to use a fixed expression to reflect the spread of fires (Jimenez et al., 2008; San José et al., 2014; Cruz and Alexander, 2017). In addition, there are many uncertainties in the forest fire spread process, so it is very difficult to use a linear regression model to predict forest fire spread (Guo et al., 2017).

Currently, artificial neural networks (ANNs) have been successfully used to predict physical problems (Ding et al., 2013). ANNs can predict new inputs through knowledge collected by self-learning methods. Moreover, by relying on electronic computers in combination with the concept of finite elements or limited volumes, through numerical calculations and image display methods, research on forest fires has become increasingly popular. There are two types of fire computer simulation technologies. The first involves grid-based models, and the other involves vector-based models. Some researchers have used machine learning methods to create different weather and fire forecast models (Safi and Bouroumi, 2013; Castelli et al., 2015; Cao et al., 2017). McCormick proposed a method for predicting the final burning area of a forest fire, but the model predicts only the final burning area and does not consider the dynamic relationship of the fire peak under temporal changes (McCormick, 2001; McCormick, 2002). Some researchers also use back-propagation (BP) neural network training to obtain real-time spread rate (ROSs) of fires and use the narrow-band level set method to predict fire peaks (Zhai et al., 2020). However, no available ANN model can consider forest fuel, weather, terrain, and land cover type factors to estimate the time-resolved spatial evolution of wildland fire peaks.

Based on the above considerations, the main purpose of this research is to develop a wildfire spread model based on an ANN to: (1) analyse the main factors influencing forest fire spread in Heilongjiang Province; (2) create an ANN model to predict forest fire peaks in Heilongjiang Province; (3) create a Wang Zhengfei-CA model that is suitable for Heilongjiang Province and evaluate the performance of these two models to obtain a relatively reliable forest fire spread prediction model in Heilongjiang Province; and (4) optimize the fire control configuration through the use of a forest fire spread model with an improved accuracy, thus promoting forest management.

2. Materials and methods

2.1. Study area

This study selected Heilongjiang Province as the research area, shown in Fig. 1. The research area covers the region from 121°11′ E in the west to 135°05′ E in the east and from 43°26′ N in the south to 53°33′ N in the north. The study area accounts for approximately 58% of the total provincial area; the plateau area is between 200 and 350 m above sea level, accounting for approximately 14% of the total area of the province; the elevation of the plain region is between 50 m and 200 m above sea level and covers approximately 28% of the province's total area. The Heilongjiang forestland region was selected for this research. Heilongjiang Province has a forest area of 8.46 million hectares. The forest area accounts for 22% of the province's land area and 11.7% of the country's forest area. Vegetation is unevenly distributed in this region, and the terrain is undulating. The climate of the Heilongjiang forest area is extreme and the study area is located in the cold temperate

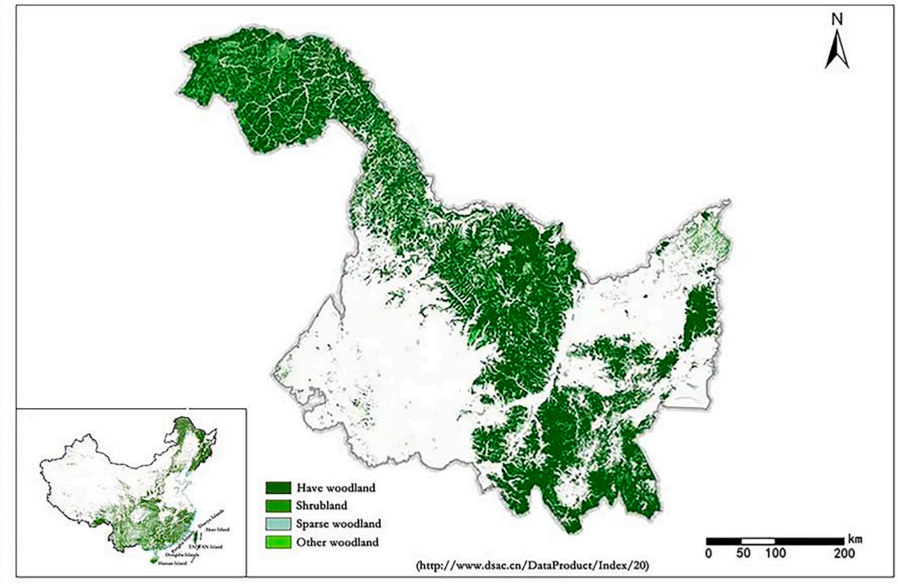

Fig. 1. The Heilongjiang forest area selected as the study area and the spatial distribution map of forestland resources.

climate zone to the temperate continental monsoon climate zone. Compared to other forest areas, substantial temperature changes occur among the four seasons in the Heilongjiang forest area.

The Heilongjiang forest area also has a great annual temperature difference. According to statistics published by the China Meteorological Administration, the historical extreme minimum temperature in the study region is −52.3 °C, and the extreme maximum temperature in summer reaches 41.6 °C. The frost-free period lasts approximately 130 days. The precipitation in the Heilongjiang forest area increases from west to east. The western plain area receives only 400–450 mm annual precipitation, the eastern mountain front land receives approximately 500 mm, and the eastern mountain area receives 500–600 mm. The mountainous region receives more precipitation than the plain region, and the windward slope receives more precipitation than the leeward slope. Therefore, the precipitation distribution is extremely uneven. The forest area also has typical rugged terrain with steep slopes and deep trenches. In addition, there are many anthropogenic surface structures in the Heilongjiang forest area, such as buildings, roads, railways, and water wells. The Heilongjiang forest area is a main component of the terrestrial natural ecosystem in Northeast Asia, and its ecological status is very important. The Heilongjiang forest area is the key target of forest fire prevention and control measures in China. Therefore, it is necessary to formulate effective forest fire management policies to reduce the harm caused by forest fires to the ecosystem and the environment and to reduce the adverse effects caused by fires to the economy and local populations.

As shown in Fig. 2, large forest fires (fires for which the affected forest area is more than 1 ha and less than 100 ha), major forest fires (for which the affected forest area is more than 100 ha and less than 1000 ha), and particularly severe forest fires (for which the area of affected forest is more than 1000 ha) that occurred in Heilongjiang from 2002 to 2020. More large forest fires occurred than major and particularly major forest fires. Compared with the Changbai Mountains and the Daxing'an Mountains, the Xiaoxing'an Mountains have the largest number of historical forest fires.

The selected study area is summarized as follows.

(1) The topography of the selected study area is complex. The area comprises high mountains, moderate mountains and hills, as well as vast high plains and floodplains. The vegetation in the forest area is unevenly distributed and covered by artificial buildings.

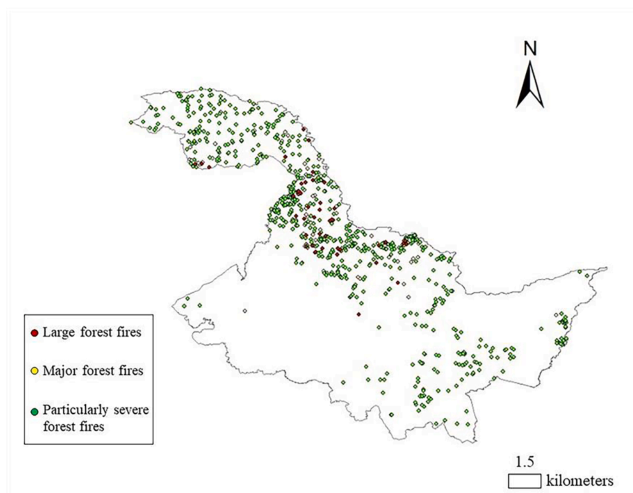

Fig. 2. Locations of historical forest fires in the Heilongjiang forest area.

(2) According to statistics, in the past few decades, the forest areas of Heilongjiang Province have experienced many different degrees of meteorological abnormalities, including abnormally high temperatures and dry weather conditions.

Combining the characteristics of the Heilongjiang forest area, multidimensional environmental conditions are introduced and fire spread behaviours under physical conditions into the ANN model to try to establish a multidimensional data-driven forest fire spread prediction model.

2.2. Data collection

2.2.1. Response variables

To study the technology for predicting forest fire spread in Heilongjiang Province, the study area was divided into multiple grids of 500×500 m to explore the spread of forest fires in historical fire sites in Heilongjiang. Historical forest fire disturbance data of Heilongjiang were collected from the Heilongjiang Forestry Bureau from 2002 to 2020. The data include the specific forest fire occurrence time, extinguishing time, geographic location information, fire cause, and fire area. Through these forest fire disturbance data, the corresponding moderate-resolution imaging spectroradiometer (MODIS) images were downloaded, and specific fire information was collected, such as the forest fire spreading process, burned area, and burning process (Zhang and Jing, 2004; Chand et al., 2007).

The four Earth observation data types from the MODIS series satellite products based on historical fire records are MOD09GA, MYD09GA, MOD02HKM and MYD02HKM (Xiao-cheng and Xiao-qin, 2011; Yun, 2011; Roy and Kumar, 2017). The satellite products contain four scenes per day, and the resolution of the downloaded products is 500×500 m.

Although the system by which fires spread is complex, the global fire spread behaviour as was regarded a collection of simple unit behaviours. To achieve the above goals, this study formulated the following rules for inputting the fire data into the ANN model.

(1) Record a forest fire occurring in a grid as “1″.
(2) Record that no forest fire occurs in a grid as “0″.

The normalized burn index (NBR) and difference-normalized burn index (dNBR) considering multitime phase differences were used to extract the line of fire and the state of each fire (Veraverbeke et al., 2011). The NBR is used to identify the burned area (Equation (1)). The theoretical value of the NBR index ranges from 1 to −1, and the index is negatively correlated with the forest fire intensity. On this basis, the difference-normalized burn index (dNBR) threshold method is used to detect the fire state (Equation (2)). The dNBR values range from 2 to −2. To facilitate the subsequent analysis and processing steps, 1000 was used as the multiplication factor for conversion to integers in the dNBR calculation. The dNBR calculation method developed by Mazuelas in past research was used to estimate the threshold range of the fire state (Mazuelas Benito and Fernández Torralbo, 2012) (Table 1).

$$NBR = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}} \tag{1}$$

$$dNBR = NBR_{pre-fire} - NBR_{post-fire} \tag{2}$$

In the formula, $NBR_{pre\text{-}fire}$ is the NBR value of the image before the fire and $NBR_{post\text{-}fire}$ is the NBR value of the image after the fire.

For explanatory variables, due to the compatibility of the cell space with geographic information system (GIS) raster data, the explanatory variables of each cell were mapped to the cell. This study collected climate variables, terrain variables, combustible factor variables, and land cover type variables for modelling (Table 2). Therefore, each cell was assigned its own set of attributes, including land cover type, temperature, and humidity information. This kind of frame structure can improve the fire simulation ability and facilitate greater understanding.

2.2.2. Choice of explanatory variables

Regarding climatic factors, the hourly relative humidity, temperature, precipitation, wind speed, and wind direction data corresponding to the collected forest fire history data in the study area were used as explanatory variables and input into the model for training. Changes in climatic factors are closely related to the moisture content of wildfire combustibles. The moisture content is one of the main factors affecting forest burning. The higher the moisture content is, the less combustible the combustibles in the forest are and the stronger the fire resistance is.

Table 1
Threshold ranges of forest fire status.

Severity level	1000* dNBR ranges
Unburned	less than299
Low	300–499
Moderate	500–799
High	greater than800

Table 2
Variables needed to build the model.

Variable type	Variable name	Source	Code
Climatic factors	Relative humidity per hour	China Meteorological Data Network data.cma.cn/	Humidity
	Hourly temperature		Temperature
	Precipitation per hour		Precipitation
	Wind speed per hour		Wind speed
	Hourly wind direction		Wind direction
Topographic variables	Slope Aspect Elevation	Geospatial Data Cloud www.gscloud.cn/	
Combustible factor variables	Vegetation cover type	Institute of Botany, Chinese Academy of Sciences www.ibcas.ac.cn/	Vegetation
	Surface water content		TVDI
Land cover type variables	Roads Railways Settlements Lakes Ditches Wells	National Catalogue Service for Geographic Information www.webmap.cn/	Lrdl Lrrl redl Hyda hydl hydp

Terrain factors also heavily influence forest fire spread and spatial patterns (Zhao et al., 2010; Jones et al., 2015). This study collected three terrain factor variables to construct and train the ANN: the slope, aspect, and elevation. As shown in Fig. 3, especially when a forest fire moves downwind, the ROS of the uphill terrain increases significantly while the radiation heat transfer of the downhill-terrain fire decreases significantly. The slope definition is expressed mathematically as follows (Eq. (3)).

$$slope\beta = \frac{\Delta h}{\Delta s} \tag{3}$$

The term ΔS denotes the length of the horizontal distance, while Δh is the length of the vertical distance. According to the formula above, it finds that the slope definition is equivalent to terrain with a larger slope and that forest fires spread faster on upslopes and smaller slopes.

As the altitude increases, the temperature gradually decreases. At the same time, the change of slope will also lead to the change of soil moisture content. In particular, the Heilongjiang forest area is

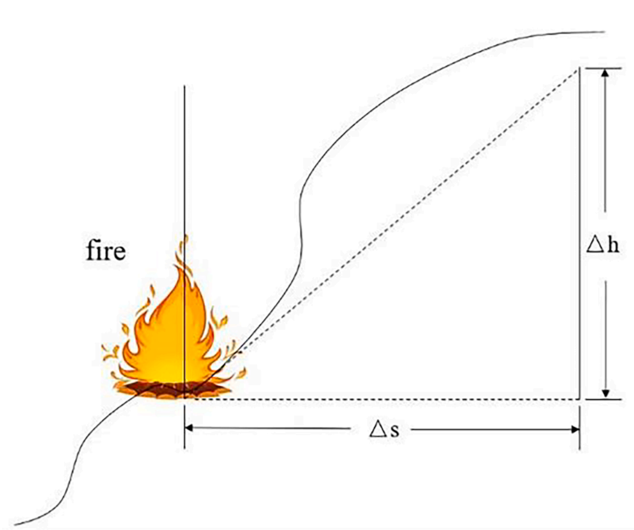

Fig. 3. Schematic diagram of the spread of forest fires at certain slopes.

dominated by mountainous areas, including special landforms such as cliffs, faults, and fold mountains. The influence of these terrain types on the spread of forest fires should thus be prominent in this region.

There are many anthropogenic structures in the study area, including roads, houses, and railways; these structures also directly affect the fire spread pattern (Dash et al., 2016). Fig. 4 shows the impact of anthropogenic obstacles on the spread of forest fires; fires cannot continue to spread through these structures, thus forming an isolation belt to hinder the spread of fires. The spatial distributions of different land cover types have different effects on the fire spread behaviour. Therefore, it collected information on existing roads, railways, settlements, lakes, ditches, and wells in each grid for this research.

Forest fires spread due to the chemical reactions associated with forest combustibles and oxidation combined with heat transfer and mass transfer flow (Xiaorui et al., 2004; Guo et al., 2017). The basis by which forest fires spread is the burning of combustibles. Different types of combustibles have different combustion properties. And the surface moisture content will directly affect the humidity of combustibles. Under high humidity conditions, the surface moisture contents hinder the fire spread rate and even prevent fire spread. Therefore, for combustible variables, it collected information on the surface water content and vegetation type for the model construction and research performed herein.

2.3. Model selection and construction

2.3.1. Variable screening

The Boruta feature-screening method was used to sort and filter the fifteen extracted variables. The Boruta algorithm is currently a very popular feature-selection method; it is a wrapper based on the random forest classification algorithm (Jayasinghe et al., 2021). The Boruta feature-selection method was implemented using the “boruta_py” extension package in the “sklearn” package in Python (Kursa and Rudnicki, 2010). The purpose of this step was to delete unimportant related variables to improve the prediction accuracy of the model and thus more effectively predict the spread of forest fires in the study area. The principle of this method involves selecting a variable set that is related to the dependent variable by reducing the average precision value to understand the factors influencing the dependent variable more

Place A: Artificial surface structure

Place B: Ditch

Place C: Road

Fig. 4. Schematic diagram of the spread of forest fires at certain slope conditions.

comprehensively; the original real features were shuffled to construct shadow features, the real features and shadow features were stitched to form a feature matrix for training, and finally, the feature importance scores of the shadow features were applied as the reference basis. This study selected the set of features that were truly related to the dependent variables derived from the real features. The core of this method is based on two ideas: shadow features and binomial distributions. The final set of variables is divided into two types: confirmed and rejected variables. To screen and sort the feature variables using the Boruta algorithm, the dataset was divided into two subsets: one subset comprised 70% of the total data and was used for model training, and the other subset included 30% of the data and was used for data verification and testing.

Boruta’s method can be summarized as follows (Ismail and Mutanga, 2016; Jayasinghe et al., 2021).

(1) For each variable R in the data, randomly shuffle the feature order to obtain the shadow feature matrix S. After stitching to the real features, a new matrix N = [R,S] is obtained.
(2) Use the new feature matrix (N) to train the model using the random forest algorithm and obtain the importance of the real features and shadow features.
(3) First, obtain the maximum value (S_max) contained in the feature matrix. If the importance of the true feature matrix (R) is greater than S_max, a hit is recorded.
(4) Use the cumulative hits derived in step (3) to list the importance of the machine features and sort them.
(5) Delete the less important features and repeat steps (1)-(4) until all the features are marked.

The final set of variables is divided into two types: confirmed and rejected variables.

K-nearest neighbors (KNN) classification algorithm was used to sort and filter the 16 different variables. The implementation principle of the KNN method involves referring to the previous sample and the known sample and calculating the distance between the unknown sample and the known sample. In this method, the K known samples that are closest to the unknown sample are selected, and according to the majority-vote rule, if the unknown sample and the K nearest samples have more categories, they are classified into one category. The KNN algorithm uses the Mahalanobis distance shown in the following formula to discriminate and calculate the importance of variables:

$$D_M(x,y) = \sqrt{(x-y)^T \sum^{-1}(x-y)} \tag{4}$$

where Σ is a covariance matrix of multidimensional random variables.

2.3.2. Construction of the forest fire spread model

2.3.2.1. Building the ANN model. When constructing an ANN, data preprocessing is extremely important. Data preprocessing for ANN construction refers to the processing of a large amount, incomprehensible and non-uniform data before the model can be constructed in order to standardize the data format and eliminate abnormal values to facilitate computer operations. Therefore, it carried out outlier removal, normalization and data segmentation steps on the original data. This normalized the raw data used to train the ANN to unify the data to values between 0 and 1 and to divide the data into two subsets. One subset occupied 70% of the data and was used to train the ANN. The other subset comprised 30% of the data and was used for model verification to obtain the model training accuracy. To prevent a weak model generalization ability due to overfitting, it randomly selected a number of nonfire grids (0) that matched the number of forest fire grids (1) and assigned the same numbers of grids with the attribute “0″ and the attribute ”1″ to construct the model.

Since the forest fire line can only be extracted in historical burned areas, a method is required to predict the line of fire in unburned areas. The spread of forest fires is a highly nonlinear process, so it is difficult to predict the spread of forest fires using linear expressions. An ANN is a nonlinear, adaptive information-integrated processing system that is interconnected by a large number of processing units. ANNs simulate and abstract human brain neurons from the perspective of information processing, build models, and compose different network structures according to different connection methods. An ANN is a kind of computing model that is composed of a large number of combined and connected neuron structures. Each neuron represents a specific output function that is also called an activation function. Each connection between two neurons has a different signal weight determined through the connection. The artificial neurons that compose an ANN exist in two different states, activation or inhibition, showing a nonlinear relationship. Moreover, ANNs have self-adaptive and self-learning capabilities.

The double-hidden-layer ANN structure shown in Fig. 5 was used to predict forest fires in Heilongjiang Province. In the ANN model constructed herein, the input parameters were represented by the vector g = [g (1), g (2)…, g (N)] and included the 16 variables listed in Table 2. For the hidden layer in the middle with the "tanh" hyperbolic tangent activation function. The tanh function has a mean value of 0 and is conducive to improving the model training efficiency. In the output layer, the "sigmoid" function is used. The sigmoid function is very clear for prediction methods, with values very close to 0 or 1, and the gradient is smooth, thus avoiding the appearance of jumps in the output values.

After creating a data-driven forest fire spread model based on an ANN, this study used a 3×3 median filter to reduce the noise. The median filter is very commonly used in ANNs and is very useful for removing speckle noise and salt-and-pepper noise. Since the values predicted by the ANN range from 0 to 1, it is necessary to identify a fire probability threshold to determine whether each grid is a fire pixel. The range of this threshold is 0.01 to 0.99. This threshold was fixed and was used to process the subsequent forest fire prediction model.

2.3.2.2. Model construction combining Wang Zhengfei's model and CA. This paper considers Wang Zhengfei's model (Sun et al., 2013), and also develops a method based on a combination of CA and Wang Zhengfei's model to predict the spread of forest fires in Heilongjiang. The aim was to compare the accuracy of these two models and obtain a reliable model for future applications. Considering the forest vegetation characteristics and complex terrain structure in the Heilongjiang forest area in China, Wang Zhengfei's model was used to combine with CA. Wang Zhengfei's model resulted from hundreds of forest fire ignition experiments conducted by Wang Zhengfei's team in Heilongjiang Province and the southwestern region of China. As it is a semiempirical model, most of the input parameters can be easily obtained through statistical analyses (Zhang et al., 2010). In contrast, the popular Rothermel model requires the collection of the dead fuel percentage, moisture content of the extinct material, silica content and other parameters (Rothermel, 1972; Berjak and Hearne, 2002). Most of these parameters are difficult to collect in real fire scenes.

The formula of Wang Zhengfei's model is as follows:

$$R = R_0 K_S K_W K_\varnothing \tag{5}$$

$$K_W = e^{0.1783V} \tag{6}$$

$$K_\varnothing = e^{3.533(tan\varnothing)\cdot 1.2} \tag{7}$$

where R is the fire spread speed, in units of m/min; R0 is the initial spread speed when there is no wind, in units of m/min; Kϕ is the terrain slope correction coefficient; Kw is the wind speed correction factor; ϕ is the terrain slope; and Ks is a correction coefficient used to characterize the flammability of combustibles and the combustion configuration (physical characteristics). Ks varies both temporally and spatially.

The spread of forest fires can be viewed as a collection of simple behaviours in individual cells. Each cell has its own set of discrete states at different times (Sirakoulis et al., 2005). According to the different behavioural patterns and transfer rules identified in each cell, the forest fire spread process can be determined. In Fig. 6, an example of a simulated forest fire is shown. In the example, there are X cells on the horizontal axis and Y cells on the vertical axis, for a total of X*Y cells., and each cell corresponds to different environmental conditions and attributes, including different wind direction, wind speed, and terrain conditions. Thus, a multidimensional CA model is constructed.

To ensure that simple interactions occur among the CA cells, it set the cells to four different states: the "cannot burn state (-1)", "unburned state (0)", "burned state (1)" and "burned state (2)".

It drew up a rule in which the cell element (i, j) spreads at time t, as shown in Fig. 7. The rule is explained as follows.

(1) If the state of cell (i, j) at time t is "-1″, the state of "t + 1″ at the next time is still "-1″. This means that the cell contains roads, water bodies, etc.

(2) If the state of cell (i, j) at time t is "1″, the state of "t + 1″ is "2″. This means that the cell is burning at the current moment and has been burned at the next moment.

(3) If the state of cell (i, j) at the current time (t) is 2, the state at the

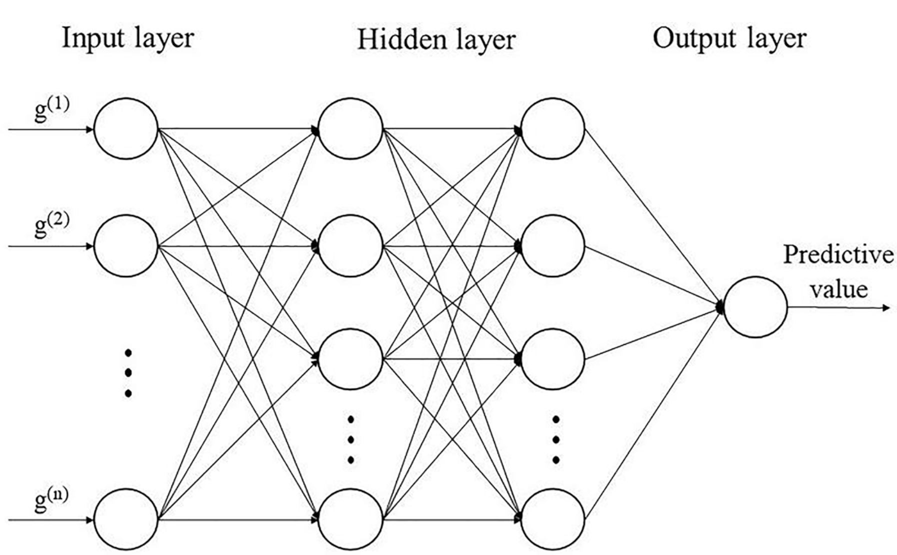

Fig. 5. Schematic diagram of the constructed multilayer ANN.

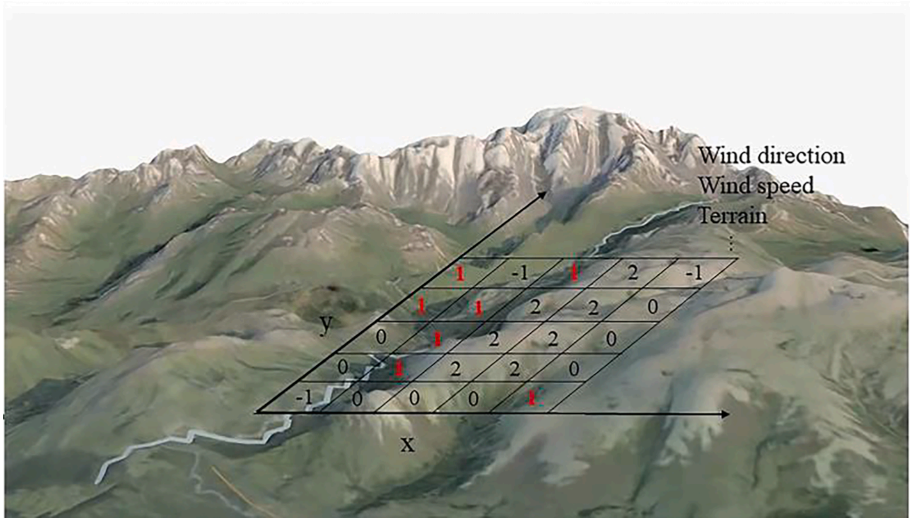

Fig. 6. CA data space derived based on GIS data.

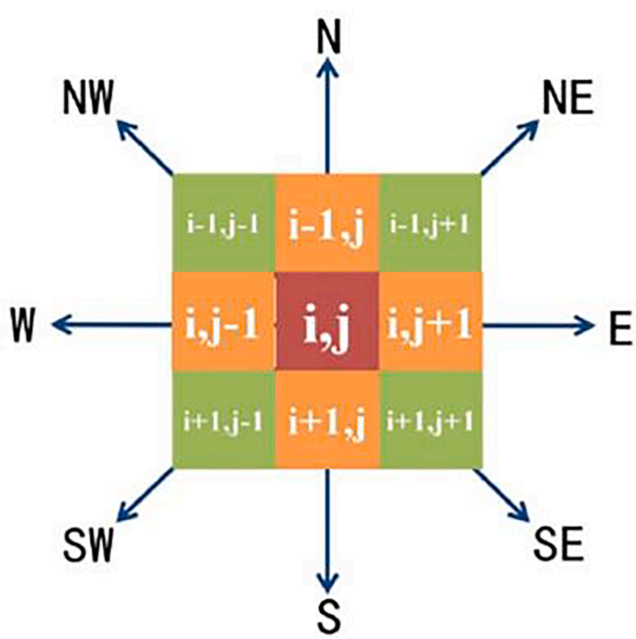

Fig. 7. CA spreading rule.

next time is also 2. This means that the cells that have been burnt no longer absorb energy to burn.

(4) If the state of cell (i,j,t) = 1, the cell state (i ± 1,j ± 1,t + 1) corresponds to the probability of burning p. This means that cell (i, j) is already in a burning state, and the energy will propagate to neighbouring cells at the next moment. This propagation process is controlled by the probability P.

2.4. Performance metrics

Researchers have also proposed several performance indicators to analyse the spread of wildfires (Hodges and Lattimer, 2019). These indicators usually analyse the area value characterized by the predicted line of fire intersecting with the real line of forest fire. Performance indicators such as accuracy and sensitivity are often used in image prediction and classification processing to describe the over- or under-prediction of a model. For each evaluation index, the value range is 0–1, and the larger the value is, the better the model performance is.

Accuracy, P, is a measure of commission errors and refers to the fact that there is no fire in a given cell grid, but the model predicts that there is a fire; that is, this metric refers to the accuracy of the predicted fire grid. The formula is defined as follows:

$$P = \frac{t_p}{t_p + f_p} \tag{8}$$

Sensitivity, S, is the omission error, meaning that a forest fire exists in the analysed cell, but no fire is predicted; that is, this metric refers to the proportion of the number of grids that are correctly predicted in the real line of fire. The formula is defined as follows:

$$S = \frac{t_p}{t_p + f_n} \tag{9}$$

The F-measure, F, is defined as the harmonic mean of P and S and is the overall measure of model performance. The formula is defined as follows:

$$F = 2\bullet\frac{\mathrm{P}\bullet\mathrm{S}}{\mathrm{P}+\mathrm{S}^{\bullet}} \tag{10}$$

In formulas (8–9), t_p is the number of grids in which forest fires are correctly predicted, f_p is the number of grids in which predict fires are incorrectly prediction, and f_n is the number of grids that are predicted to be nonfire grids but actually contain fires.

3. Results

3.1. Variable screening results

By sorting and filtering the four types of variables using the Boruta algorithm, this study selected the set of features that were truly related to the dependent variables derived from the real features. As a result, it was found that compared with elevation, which was the most important variable, the variables indicating whether railways and residential areas were located in a given grid were of lower importance; thus, these two variables were judged as “rejected” by the Boruta algorithm (Fig. 8).

After sorting and filtering the 16 variables with the k-nearest (KNN) classification algorithm, the results are shown in Fig. 9. Elevation is the most important variable affecting the spread of forest fires in Heilongjiang. The two variables indicating the presence or absence of railways and residential areas have weaker contributions to predicting forest fire spread. These results are consistent with the Boruta algorithm “rejects”, thus confirming the reliability and repeatability of the results.

Due to the variable screening and sorting results, it eliminated the

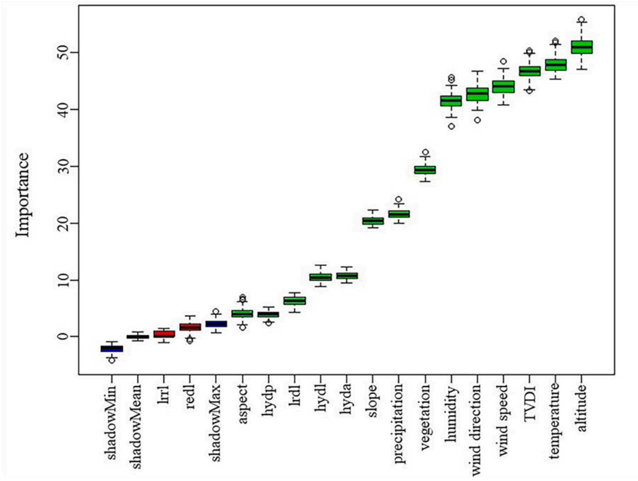

Fig. 8. Variable sorting results obtained with the Boruta algorithm.

two variables indicating whether there railways and residential areas were present in the grid. As a result, the accuracy of the Heilongjiang forest fire spread prediction model based on the ANN increased from 82.50% to 85.02%.

3.2. Performance and results of the built model

3.2.1. Postprocessing

Through 1000 iterations of a simulation training and registration correction on the 2414 combustion images, it was found that the range of the F-measure was mainly concentrated within the range 0.2–0.6 (Fig. 10). Through calculations, it was determined that the best threshold value for postprocessing is 0.47, and the F-measure is the largest for this value.

3.2.2. Prediction of forest fire spread in Heilongjiang based on the constructed ANN

The constructed model has the characteristics of high precision and high stability. The ANN model created herein and the Wang Zhengfei-CA model were used to map forest fire predictions in Heilongjiang. Taking a forest fire that occurred at Yinlonghe Forest Farm in Wudalianchi, Heihe City, on October 9, 2010, as an example, according to data from the Heilongjiang Forestry Bureau, the fire started at 11:50 and ended at 23:40. Fig. 11a and 11b show two raster data sets reflecting the real fire development. Fig. 11c and Fig. 11d show the fire line prediction results obtained with the ANN model in this study. Fig. 11e and 11f are diagrams of the prediction results obtained using the constructed Wang Zhengfei-CA model.

To analyse the performance of the constructed models, including the ANN model and the combination Wang Zhengfei-CA model, it extracted and compared three indicators: the average accuracy, sensitivity and F-measure. The results are shown in Table 3. The values of each indicator range from 0 to 1, and the closer the indicator value is to 1, the better the model performance is.

4. Discussion

4.1. Influence of climate variables and combustible variables on the spread of forest fires

Heilongjiang's hourly relative humidity, temperature, precipitation, wind speed and wind direction conditions were selected as five

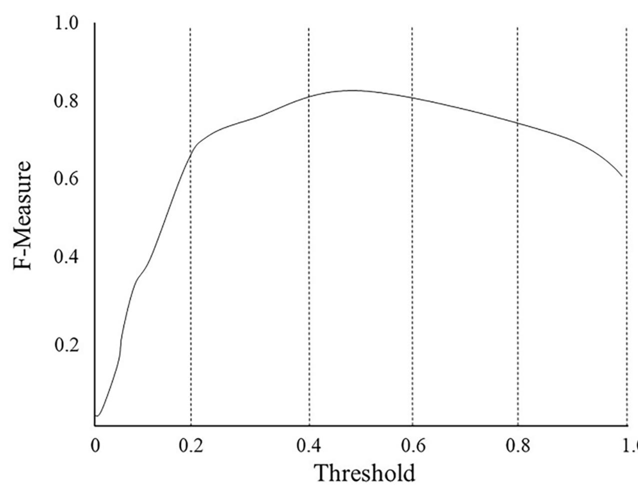

Fig. 10. The ANN predictions of the average F-measures under different thresholds for 2414 combustion maps.

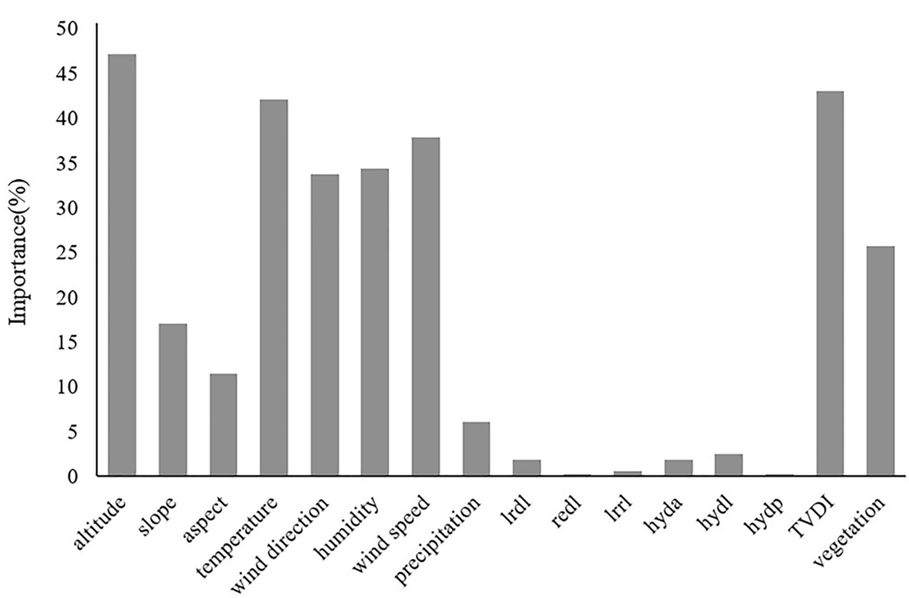

Fig. 9. The KNN classification algorithm ranking of the importance of the 16 analysed variables.

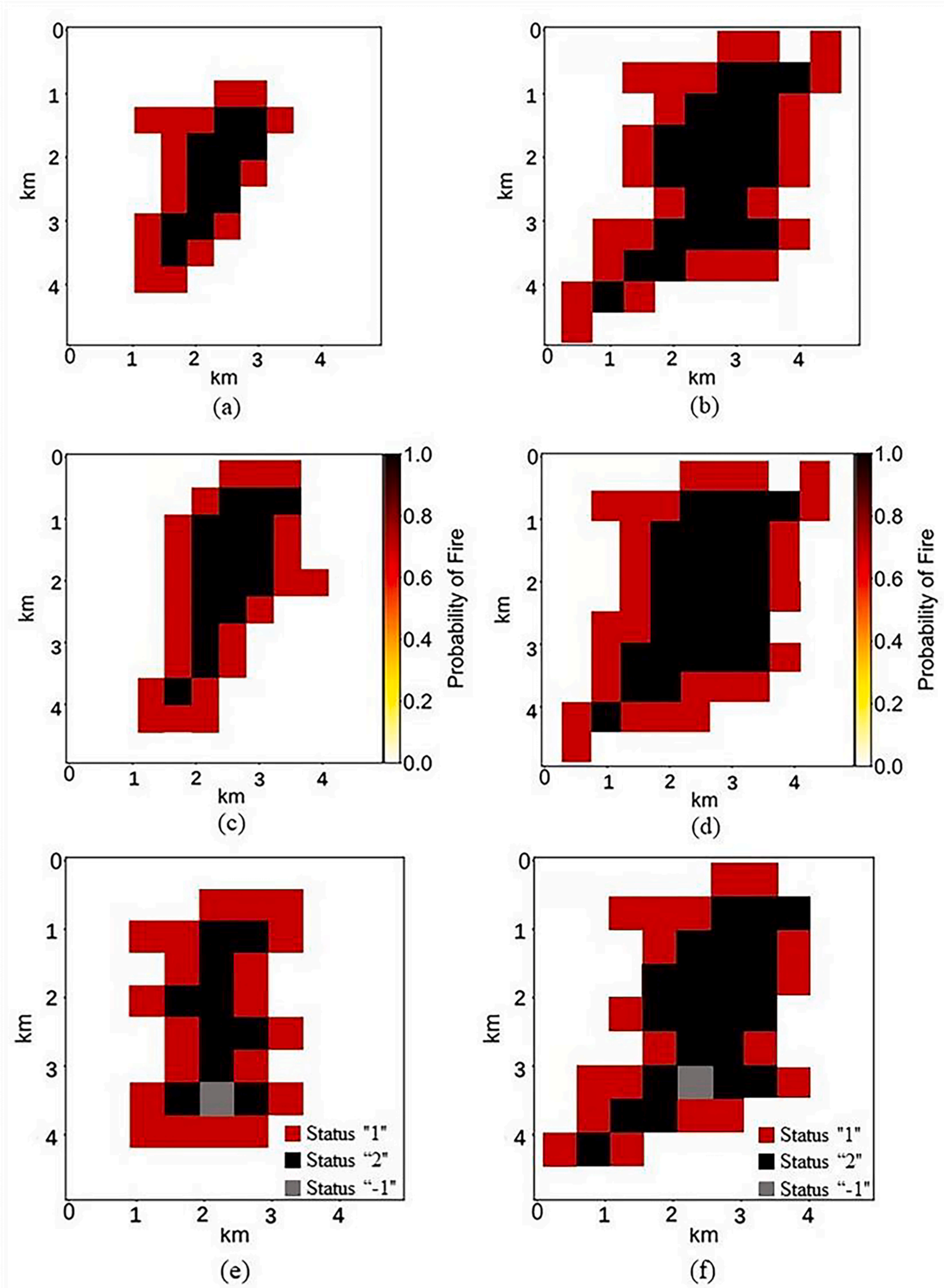

Fig. 11. Comparison of real fire lines and ANN-predicted fire.

Table 3
Performance comparison between the ANN and Wang Zhengfei-CA models.

Model	P	S	F-measure
ANN	0.85	0.95	0.90
CA	0.78	0.83	0.80

important climatic factors affecting the prediction of forest fire spread in Heilongjiang. Compared with other factors, climate factors contribute more to the spread of fire. The average temperature is the most important variable among climatic factors, and the wind speed and direction are more important than precipitation. These results were also consistent with the findings of previous studies (Wotton et al., 2003; Maingi and Henry, 2007). The magnitude and direction of the wind directly affect the rate and direction of forest fire spread, and high precipitation and relative humidity help increase the moisture content of combustibles, thus reducing or even preventing the spread of forest fires. Temperature directly affects the evaporation of plants and reduces the moisture content of fire combustibles, thereby affecting the spread of forest fires (Chuvieco et al., 2004). It is worth noting that although the average temperature is the most important variable among the climatic factors, previous studies have also shown that high temperatures seemed to inhibit the occurrence and spread of fires in Fujian (Guo et al., 2017). According to previous studies, there may be a threshold relating temperature and forest fires (Wu et al., 2015). It is also possible that during high-temperature periods, forest managers' awareness of fire prevention is increased, thus substantially improving the spread of fire. This concept has also been supported by other researchers (Zhang et al., 2014).

Moreover, with the increase in human activities and the continuous emission of greenhouse gases, the impact of climate change on climate zones and precipitation is very complex. Studies have shown a very strong link between climate change and fire behaviour, and that climate change can alter fire behaviour through its effects on forest cover and the type and load of combustibles (Sung et al., 2010; Canadell et al., 2021). The vegetation cover type and soil moisture index are also important in affecting the spread of forest fires; previous studies have shown that the vegetation cover type is an important indicator affecting the spread of forest fires (Chuvieco et al., 2004).

4.2. Influence of terrain variables on fire spread predictions

According to our variable screening results, elevation is the most important factor affecting the spread of forest fires in Heilongjiang. In previous studies, many researchers have confirmed the results of this study and determined that elevation is among the most important drivers of forest fire spread (Miranda et al., 2011; Pereira et al., 2015; Guo et al., 2016). Compared to elevation, the importance of aspect is lower. This may be because solar radiation has little difference among aspects in relatively flat terrain, causing fires to spread. The impact of aspect is thus very small.

4.3. Influence of human factors on the spread of forest fires

According to previous studies, the spread of forest fires is related to human activities and surface buildings (Syphard et al., 2007; Pereira et al., 2011). Therefore, it collected data on whether railways, roads, houses, lakes, ditches and wells were present in the analysed grid. However, the results showed that the importance of these land cover type variables was relatively low compared to other variables, similar to the results of previous studies (Garcia et al., 1995; Miranda et al., 2011; Guo et al., 2016). This may have been due to the low population density in the Heilongjiang forest area. With the continuous development of Heilongjiang's industry and the urbanization process in recent years, most of the population has become concentrated in places with developed industries and low forest coverage.

4.4. Prediction of the spread of forest fires

The data-driven forest fire spread model constructed in this study based on an ANN has a good predictive ability and a high stability. The actual results are basically consistent with the predicted results. Regarding the spatial heterogeneity of the Heilongjiang forest area, the proposed model has a high operability and accuracy and can be used to obtain meaningful predictions. The artificial neural network model structure can evolve continuously, optimizing the model based on the processing of changing data. This also shows the advantages of artificial neural networks being non-limiting and non-long-term qualitative.

Fig. 11 shows that the ANN can accurately predict the development of forest fires in Heilongjiang. Fig. 12 shows that the pixels predicted by the ANN model that do not match the real fire pixels. The black pixels show the prediction errors (there is no fire in the real pixel, but the predicted results indicate the presence of fire), while the orange pixels represent the omission errors of the prediction results (the real line of fire indicates that there is a fire in the pixel, but the predicted pixel contains no fire). Through analysis, the ANN model constructed herein was found to make false reports due to the presence of noncombustible surfaces (roads, rivers, etc.). However, in the examined fire, noncombustible surfaces covered only a few pixels. Due to this small number of pixels, these pixels were often deleted during the downsampling process. Pixel-level continuous combustible load data were also lacking in this study. This may also directly lead to decreased in the prediction accuracy of the ANN model.

However, the ANN model constructed herein underwent fixed training to predict the spreading mode of each fire configuration. Therefore, overprediction may occur in the later stages of forest fire development because the network overcorrects the initial value under the predicted expansion rate. It input constant weather conditions similar to wind speed in the created ANN model. However, studies have shown that during a forest fire, the changes that occur in the woodland microclimate have a certain correlation with the spread of the fire (Just et al., 2016; Ruthrof et al., 2016). The temporal and spatial laws of forest fire changes vary with changes in forest microclimates, and different tree types and topography affect the wind speed in woodlands. Therefore, it is very important to be able to capture nonuniform climatic factors.

Currently, CA have become popular methods for simulating fire behaviours (Berjak and Hearne, 2002; Collin et al., 2011). A model was created combining Wang Zhengfei's physical speed model and CA based on the Heilongjiang forest area. The analysis found that the accuracy of this combined model was worse than that of the constructed ANN model. This was because Moore's neighbour rule was more strictly defined in the CA model (Karafyllidis, 2004; Zaitsev, 2017). In CA, the radius r is usually used to define neighbours; that is, all cells surrounding a given cell are considered its neighbours, directly causing the transformation rules of CA to not be applied to further units (Zhang et al., 2006). However, in real fires, the irregularities, feedback and other complex features presented by geographic and environmental systems directly lead to a decrease in the accuracy of the CA.

Because MODIS satellites can scan the same location at least 4 times a day. The satellite can monitor forest fires in time, and can accurately locate and dynamically track fires. In this study, the normalized combustion index (NBR) and differential normalized combustion index (dNBR) of multiple phase differences were used to extract the fire line and forest fire status. The NBR index represents an improvement upon the normalized difference vegetation index (NDVI) (Abd-El Monsef and Smith, 2017). The reflectivity of fire areas in MODIS images in the near-infrared (NIR) and mid-infrared (SWIR) bands undergo great changes before and after the occurrence of a fire; the NIR band reflectivity is reduced, and the SWIR reflectivity is increased. dNBR uses multi-temporal technology, combined with the NBR index, to more accurately extract the fire line and define the fire state. This is in line with previous research. (Mazuelas Benito and Fernández Torralbo, 2012).

Many studies use MODIS for forest fire spread observation and prediction (Zhang and Jing, 2004; Roy and Kumar, 2017). The principle of forest fire monitoring and prediction using MODIS is to judge the fire point based on the fact that the fire point is higher than the ambient temperature. The basis of its judgment is the relationship between thermal radiation intensity and wavelength. This method has the advantages of wide range and high accuracy. However, the resolution of 500 × 500 m is not sufficient for continuous monitoring of the development and spread of small forest fires. The spatial resolution of MODIS is also relatively low, so there will be a problem of mixed pixels. Some studies have also shown that when using remote sensing images to count the number of fires in a large-scale range, a single fire scene may be represented by multiple fire point data on the remote sensing image. How to use remote sensing to accurately count the number of fires in different areas is still an urgent problem to be solved (Roy and Kumar, 2017). This situation may also directly lead to delays and errors in the judgement of forest fire and management personnel on forest fires.

5. Conclusions

In this article, this study compared the importance of climatic factors, terrain factors, combustible factors, and land cover types as drivers to predict forest fire spread in Heilongjiang. An ANN method was proposed to predict the temporally resolved spatial evolution of forest fires.

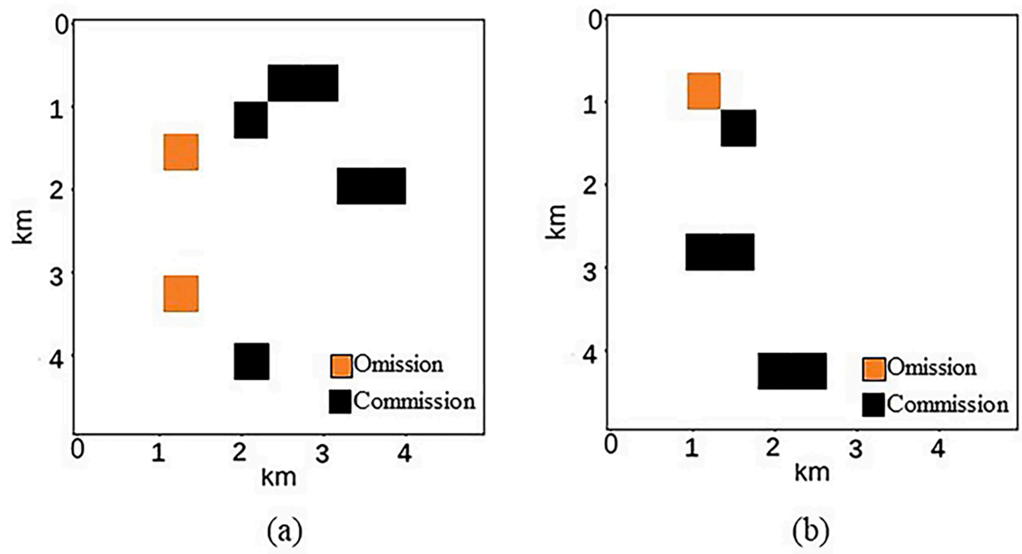

Fig. 12. Comparison of real fire lines and ANN-predicted fire lines.

After analysis, it found that the ANN-based method could predict the spread of forest fires in Heilongjiang. Based on the work conducted herein, a method based on the combination of Wang Zhengfei's model and CA was also proposed. The constructed ANN model had a higher prediction accuracy than this combined model because the ANN model was related to the multidimensional combustion performance and various environmental factors, thus improving the simulation of steady-state fire conditions and the prediction accuracy of the entire model. The study found that elevation is the most important factor influencing the spread of forest fires in Heilongjiang. In addition, climate factors are more important overall than other factors. Such research results can also be applied to supplement the rescue work performed by forest firefighters. Certain specific structural characteristics of the forest understory cause small-scale climate conditions near the ground level and in the upper soil layer. These forest microclimates are closely related to forest fire development. As a scalable model, in the future, it is vital to study the temporal and spatial distributions of forest microclimate-related factors in-depth, analyse the law of coordinated changes and combine microclimate factors in the model simulation and training processes. Additionally, accurate fuel models can be integrated to verify the model calibration process in further research.

CRediT authorship contribution statement

Zechuan Wu: Software, Writing – original draft. **Bin Wang:** Conceptualization, Methodology, Investigation, Data curation, Writing – review & editing, Project administration. **Mingze Li:** Conceptualization, Resources, Data curation, Funding acquisition. **Yuping Tian:** Validation, Investigation. **Ying Quan:** Visualization, Supervision. **Jianyang Liu:** Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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