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Temperature-based fire frequency analysis using machine learning: A case of Changsha, China

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ABSTRACT

Previous studies mainly focused on the influences of climate change on wildfires. However, other types of fires are also weather-related (especially temperature-related). The present study is aimed to analyze the influences of climate warming on fire risk. By data joining and processing, a dataset was born which includes 20,622 fire incidents and the related weather data from 2011 to 2017 in Changsha, China. Predictive models of fire frequency were established based on different regression methods of machine learning (random forest, support vector machine and polynomial). Among them, random forest regression models had the best fitting performance, and were selected to predict the fire frequency under climate warming scenarios. Under the current warming rate in Changsha, the annual fire frequency in 2067 (50 years after 2017) will increase by 0.69% to 0.89%. By rebuilding predictive models for other cities based on the proposed methods in this study, the influences of climate warming on their fire frequencies can also be analyzed.

1. Introduction

Fires affect the safety and sustainability of cities and societies (Bowman et al., 2009; Mhawej et al., 2017; McNamee et al., 2019; Liu et al., 2020). The seasonal variation characteristics of fire occurrence have been shown in previous studies (Li et al., 2014; Wang et al., 2015). According to reports from the Fire Department of China, a total of 346,701 fires occurred in 2015, of which 41,577 occurred in cold February, compared with only 21,070 in cool September (Fire Department of Ministry of Public Security, 2017). In China, it seems that fires can occur more easily in cold seasons (especially in January and February) (Li et al., 2014; Liu et al., 2019a). Therefore, it is necessary to deeply analyze how temperature affects the fire frequency. Global warming is definitely occurring, which also has a significant impact on China (Shi et al., 2018; Zhang and Ma, 2019; Kay, 2020). Therefore, it is necessary to study how fire frequency will change in the background of global warming.

In previous studies, many efforts focused on the relationship between fire occurrence and weather conditions (especially temperature), and most of them were related to wildfires. In Great Britain, fires about electric and space heating increased in severe cold weather (Chandler, 1982). According to the monthly fire data from 1997 to 2006 in Beijing, the relationship between urban fires and meteorological factors such as rainfall, temperature, relative humidity, and wind speed was studied (Huang and Liu, 2008). The massive electricity consumption during winter led to the increase of fire occurrences in Lærdalsøyri, Norway (Log, 2016). That extreme hot weather could increase fire occurrences in SE France (Fox et al., 2018). Study on the fire risk increase caused by climate change is

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becoming more and more popular. As the climate changes, the frequency of extreme hot weather and extreme cold weather may increase, which will lead to an increase in the number of fires (Goodess, 2013). Through investigating the changes in fire weather from 1959 to 2015, ongoing climate changes led to an increase of fire weather danger in the French Alps (Dupire et al., 2017). Garbolino et al. (2016) thought forest fire risk would increase within 2100 in Corsica because of climate change. Global warming reduces air humidity, which makes California more prone to forest fires. In essence, global warming led to the big wildfires in Australia (Yu et al., 2020). Under warming of 2.0 °C, the fire danger of summer is estimated to triple in France (Fargeon et al., 2020). However, to the best of our knowledge, few studies have focused on the relationship between non-wildfire fire risk and temperature. Moreover, few studies have analyzed the impact of global warming on other types of fire (e.g. structural fire and vehicle fire).

Machine learning has been widely used for classification, regression, and clustering in various fields, such as predictive analysis, computer vision, and risk analysis (Madaio et al., 2016; Liu et al., 2019a; D'Amico et al., 2019; Li and Zhao, 2020). Common machine learning algorithms include generalized linear models, support vector machines (SVM), random forests, neural network, etc. (Raschka and Mirjalili, 2017). Moreover, different machine learning algorithms have been applied in studies on the influence of weather factors on fire occurrence. Maxent (a statistical software embedded with machine learning algorithm) was used to analyze the influence of climate on structure loss under fire in California (Syphard et al., 2019). Random forest was used for predicting fire severity based on weather, topography and fuel conditions in southwestern Oregon, and it was found the main predictor was weather (Zald and Dunn, 2018). SVM algorithm was used to predict the area with high forest fire risk based on different weather conditions (relative humidity, temperature, precipitation, etc.) (Rajagopal et al., 2018). In addition, random forest and SVM were applied to develop a forest fire susceptibility map for Dayu, which is a county in China (Hong et al., 2018). Therefore, the relationship between temperature and fire frequency can be analyzed based on machine learning methods. However, non-wildfire fire frequency was rarely analyzed and predicted based on machine learning methods (Liu et al., 2019a).

This present study is aimed to propose methods for analyzing the influences of global warming on fire frequency (except wildfires). We gathered a dataset including 20,622 fires during 2011–2017 from the fire department of Changsha City. Then, temperature-based predictive models were built based on different machine learning regression methods (polynomial regression, random forest regression, and SVM regression) in Python. Based on the predictive models with better performance, the influences of climate warming on fire frequency were analyzed.

2. Data processing and data mining

2.1. Study area

Changsha City is the economic, cultural, and political center of Hunan Province in South China, and it has an area of 11,816 km^2 and consists of nine districts (or counties) including Yuelu, Wangcheng, Changsha County and Tianxin, etc, as shown in Fig. 1. The central urban area of Changsha City mainly includes five districts: Yuelu, Kaifu, Furong, Yuhua, and Tianxin. In addition, Changsha has a subtropical monsoon climate, which is hot in summer and cold in winter. In 2017, the annual average temperature of Changsha was 18.4 °C, the extreme maximum temperature was 39.9 °C, the extreme minimum temperature was −2.4 °C, the rainfall was 1,632.5 mm, and the total sunshine hours were 1,494.5 h (Changsha Bureau of Statistics, 2019). Its total resident was 7.92 million, and its urban resident population was 6.14 million in 2017. The gross domestic product of Changsha reached about 1.05 trillion yuan in 2017.

The weather dataset was built based on historical meteorological data including wind force, precipitation, daily maximum temperature, daily minimum temperature, and other weather features of 2,557 days from 2011 to 2017.

The fire incident dataset includes all kinds of fires (except wildfires) that occurred in Changsha City from 2011 to 2017. The fire

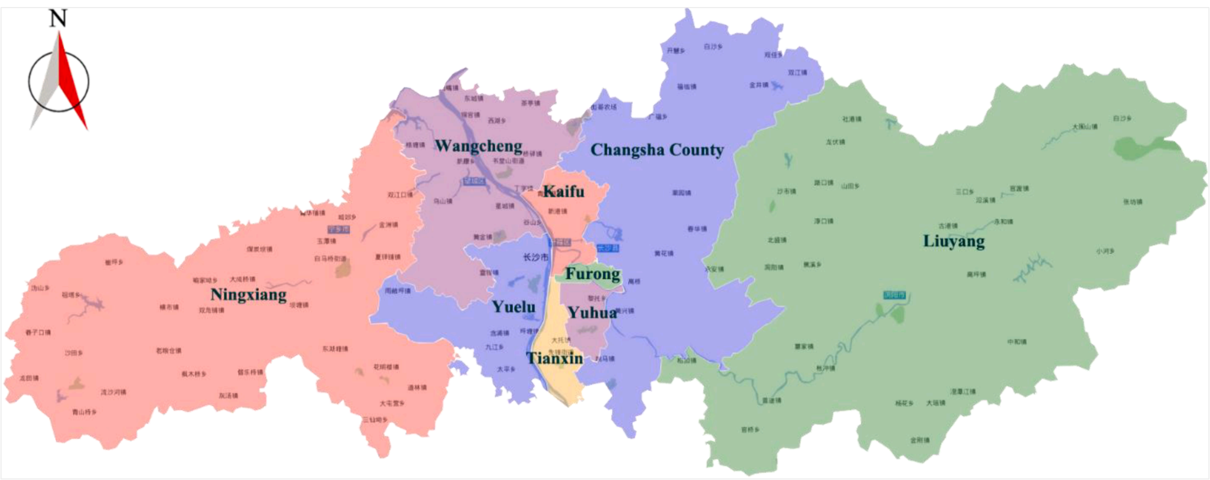

Fig. 1. Administrative division map of Changsha City.

incident dataset contains the information of the time, location, fire cause, civilian deaths, civilian injuries, property loss of 20,622 fires. With the transformed sigmoid risk model based on the heat map method (a kernel density clustering algorithm), fire incidents were visualized (see Fig. 2) (Liu et al., 2019b). It can be seen from Fig. 1 and Fig. 2 that the high-density fire risks are mainly distributed in the central urban area, and the medium-density and low-density fire risks are mainly distributed around the urban area. In addition, due to the lack of wildfire data, there is almost no fire risk distribution in mountainous areas.

2.2. Data joining and processing

Both the fire incident dataset and the weather dataset were based on time series, and a new dataset was born by integrating fire incidents and weather datasets based on date as shown in Fig. 3. The new joined dataset contains every day's fire frequency (F), the daily minimum temperature (T_{min}), and the daily maximum temperature (T_{max}). F had a maximum value of 86 and a minimum value of 0 from 2011-01-01 to 2017-12-31 (see Table 1). T_{min} had a minimum value of -5 °C, but the maximum value of T_{max} was 40 °C.

The sum number of days (D_{sum}) from 2011-01-01 to 2017-12-31 at different temperatures were calculated by mining the new joined dataset. Similarly, the sum of fire frequency (F_{sum}) at different temperatures of T_{max} and T_{min} were obtained. The mean of daily fire frequency (F_{mean}) equals F_{sum} divided D_{sum} (see Eq. (1)).

$$F_{mean} = F_{sum}/D_{sum} \tag{1}$$

2.3. Data mining and feature selection

The number of fires, average T_{max} (AT_{max}) and average T_{min} (AT_{min}) in different months were obtained based on data mining (see Table 2). January had the largest number of fires, with the lowest AT_{max} as shown in Table 2. July was the hottest month, with 2,046 fires accounting for 9.92% of the total, which owns the second largest number of fires. However, May had moderate temperatures accompanying the least number of fires. The number of fires in winter (including December, January, and February) was the largest, with 6,544, accounting for 31.73%. The number of fires in summer (including June, July, and August) was the second largest, with 5,415, accounting for 26.26%. It can be inferred that fires are more likely to occur in cold and hot seasons, and temperature can affect fire frequency.

In addition, the fire statistics of different fire causes were shown in Table 3. The number of electrical fires was the largest, with 9,860, accounting for 47.81%. Certainly, the leading cause of fires was about electric. Careless use was the second leading cause of fires, and there were 3,873 unclassified fires. As the main and leading cause, it seemed that electrical fires are closely related to the occurrence of fire. In winter, more electricity is consumed for heating, drying, boiling and so on. In rural areas, firewood, charcoal, and coal are also used for heating. If they are used carelessly, fires can be led easily. In summer, a lot of electricity is consumed for cooling, ventilation and so on. Moreover, electrical equipment is more prone to aging or damage at high temperatures. But at other comfortable temperatures, the high-power electrical equipment (electric water heater, air conditioner, electric heater, and electric fan) would be rarely used. In this study, daily fire frequency and daily temperatures (T_{max} and T_{min}) were selected as the principal components in this study.

For pre-analysis, T_{max} and T_{min} were divided into seven ranges, respectively. F_{sum}, D_{sum} and F_{mean} were calculated and obtained based on different T_{max} and T_{min} ranges (see Table 4 and Table 5). Whether based on T_{max} or T_{min}, the values of F_{mean} were maximum in the lowest temperature range. The minimum value of F_{mean} was distributed in 20 °C < T_{min}, T_{max} ≤ 25 °C rather than the highest temperature. It indicated that there is a nonlinear relationship between F_{mean} and daily temperatures (T_{max} and T_{min}).

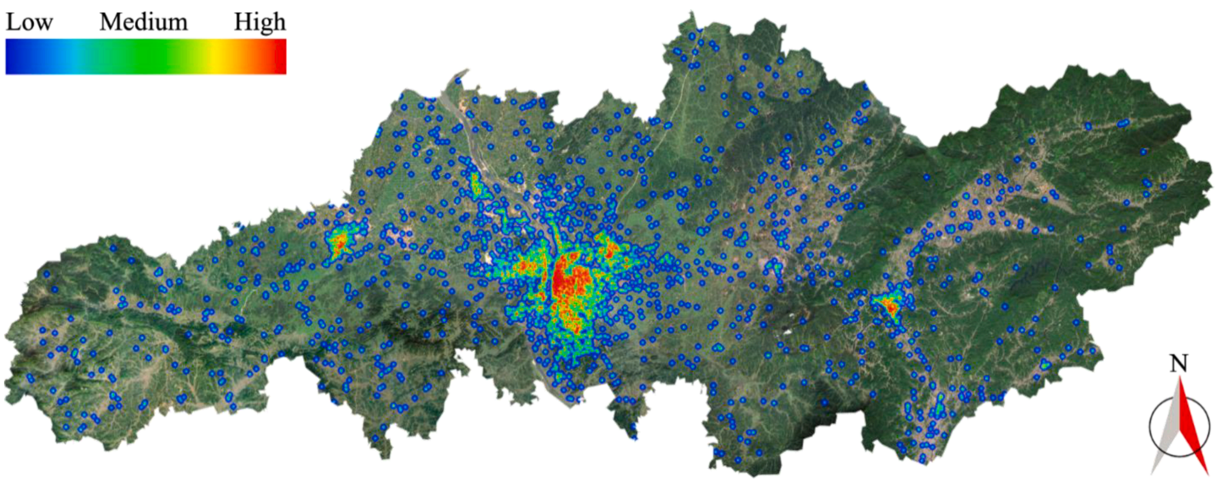

Fig. 2. Heat map visualization of fire incidents.

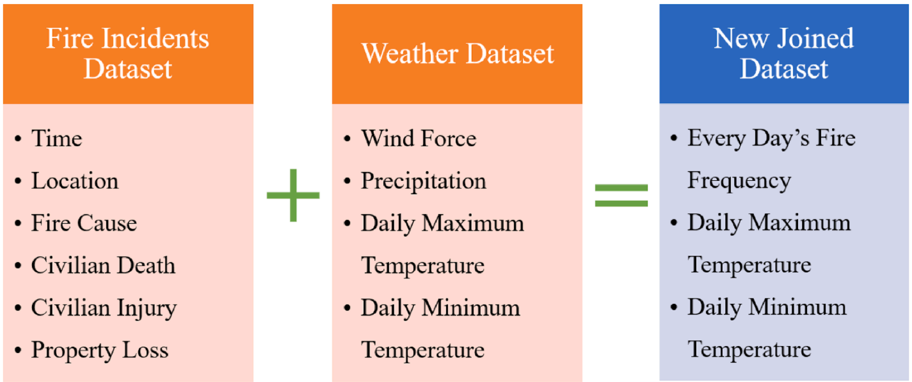

Fig. 3. Data joining based on date.

Table 1
Data characteristics of new joined dataset.

	Date Range	F	T_{max}	T_{min}
Maximum Value	2017–12-31	86	40 °C	31 °C
Minimum Value	2011–01-01	0	0 °C	−5 °C

Table 2
Number of fires, AT_{max} and AT_{min} in different months.

Month	Number of Fires	Ratio (%)	AT_{max}	AT_{min}
January	2,786	13.51%	11.21 °C	4.31 °C
February	1,943	9.42%	11.34 °C	4.87 °C
March	1,574	7.63%	17.07 °C	9.87 °C
April	1,333	6.46%	22.93 °C	15.25 °C
May	1,299	6.30%	27.17 °C	19.70 °C
June	1,491	7.23%	31.03 °C	24.37 °C
July	2,046	9.92%	34.70 °C	27.47 °C
August	1,878	9.11%	33.90 °C	26.72 °C
September	1,479	7.17%	29.04 °C	21.74 °C
October	1,631	7.91%	24.98 °C	16.53 °C
November	1,347	6.53%	16.56 °C	10.39 °C
December	1,815	8.80%	11.32 °C	4.06 °C

Table 3
Number of fires with different fire causes.

Fire Cause	Number of Fires	Ratio (%)
Electric	9,860	47.81%
Careless Use	4,210	20.42%
Cigarette	1,365	6.62%
Self-ignition	600	2.91%
Machinery	550	2.67%
Intentional	137	0.66%
Thunder	27	0.13%
Unclassified	3,873	18.78%

3. Model selection and evaluation

3.1. Model selection

The regression models of machine learning can be divided into linear regression and nonlinear regression models (Friedman et al., 2010). In general, linear regression models include ridge regression, selection operator (Lasso) regression, least absolute shrinkage, ordinary least squares, etc. As for nonlinear models, polynomial regression, random forest, SVM, neural network and so on can fit well. Because of the nonlinear relationship between F_{mean} and daily temperatures (T_{max} and T_{min}), random forest, SVM and polynomial

Table 4
F_{sum}, D_{sum} and F_{mean} in different T_{max} ranges.

T_{max} Range (°C)	F_{sum}	D_{sum}	F_{mean}
≤5	1,023	94	10.88
(5, 10]	2,349	285	8.24
(10, 15]	3,031	359	8.44
(15, 20]	2,874	352	8.16
(20, 25]	2,526	389	6.49
(25, 30]	3,657	511	7.16
> 30	5,162	567	9.10

Table 5
F_{sum}, D_{sum} and F_{mean} in different T_{min} ranges.

T_{min} Range (°C)	F_{sum}	D_{sum}	F_{mean}
≤0	983	79	12.44
(0, 5]	3,584	388	9.24
(5, 10]	3,288	390	8.43
(10, 15]	2,784	388	7.18
(15, 20]	3,050	448	6.81
(20, 25]	3,442	507	6.79
>25	3,491	357	9.78

regression were selected as the regression models.

Random forest algorithm is a machine learning ensemble method based on randomized decision trees (Breiman, 2001). When employing regression with decision trees, the mean squared error (*MSE*) is used as regression criteria instead of maximum information gain as Eq. (2). In Eq. (2), N_t represents the number of training samples in node *t*, D_t represents a subset of training samples of node *t*, $y^{(i)}$ represents the true target value, and $\widehat{y}_t$ represents the predicted target value. Bootstrap sampling method and majority voting system are applied to random forest models. Therefore, the predicted value accuracy is mainly determined by the number of decision trees in the forest. In this study, the number of decision trees was 30.

$$I(t) = MSE(t) = \frac{1}{N}\sum_{i\in D_t}\left(y^{(i)} - \widehat{y}_t\right)^2 \tag{2}$$

Hyper-planes are constructed by SVM in a high dimensional space, which can be used for regression, classification, and other tasks (Burges, 1998). SVM maps low-dimensional space to high-dimensional space through kernel function, which includes linear, polynomial, sigmoid and radial basis function (RBF). Among them, RBF kernel can be expressed as Eq. (3), and was used for support vector machine models in this study.

$$k\left(x^{(i)}, x^{(j)}\right) = exp\left(-\frac{\|x^{(i)} - x^{(j)}\|^2}{2\sigma^2}\right) \tag{3}$$

Polynomial regression can be thought of as extending linear models with basic functions. The formula of multiple linear regression is expressed as Eq. (4). By modeling *Y* as the *n*th degree polynomial and assuming $x_i^1 = x_1, x_i^2 = x_2, x_i^3 = x_3 \ldots, x_i^p = x_p$, the polynomial regression model is yield as Eq. (5) (Coelho and Neto, 2017). If the value of *n* is too large, it may result in overfitting; if it is too small, it may result in underfitting. The degree of the polynomial features was 4 in polynomial models in this study.

$$Y = b_0 + b_1x_1 + b_2x_2 + \cdots\ldots + b_px_p + \varepsilon, \varepsilon \sim N\left(0, \sigma^2\right) \tag{4}$$

$$Y_i = b_0x_i^0 + b_1x_i^1 + b_2x_i^2 + \cdots\ldots + b_px_i^p + \varepsilon\ (i = 1, 2, \ldots n), \varepsilon \sim N\left(0, \sigma^2\right) \tag{5}$$

The scikit-learn package integrates many algorithms related to data preprocessing, regression, classification, model selection and dimensionality reduction, and it is a Python module of machine learning and data mining (Pedregosa et al., 2011). By employing the scikit-learn package, the daily minimum temperature and the daily maximum temperature were selected as independent variables to establish regression models (polynomial, random forest, SVM). Different modules in scikit-learn were used for different regression models, 'RandomForestRegressor' module for random forest, 'SVR' module for SVM, and 'PolynomialFeatures' and 'LinearRegression' modules for polynomial.

3.2. Model performance evaluation

The better predictive models should be selected by evaluating the performances of different models. The sum of squared errors can be expressed as *SSE*. *MSE* is the average of *SSE*, and is always used as the main index for evaluating regression and fitting performance. The value of *MSE* can be calculated as Eq. (6). In Eq. (6), y_i represents the vector of observed values of the variable being predicted, and

$\hat{y}_t$ represents the vector of n predictions generated from a sample of n data points on all variables. The smaller the MSE, the better the fitting performance.

$$MSE = \frac{1}{n}SSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

The correlation coefficient (R^2) is a standardized version of MSE. The fitting performance can be evaluated with R^2 more efficiently. In other words, R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variable(s). In essence, R^2 can also be calculated with SSE and the sum of squares of total residuals (SST) (see Eq. (7)). If the value of MSE is 0, the value of R^2 will be 1. The closer R^2 is to 1, the more accurate the model is.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \mu_y\right)^2} = 1 - \frac{SSE}{SST} \tag{7}$$

In this study, R^2 and MSE were used as the principal factors to evaluate each model's fitting performance. In scikit-learn, R^2 can be calculated with "r2_score" module, and MSE can be calculated with "r2_score" module.

4. Results and discussion

4.1. Regression visualization

With the 2D plotting Python library-matplotlib, regression results based on polynomial, random forest, and SVM were visualized (see Figs. 4–6) (Nelli, 2018). All regression curves are U-shaped. All regression models can fit well based on either T_{max} or T_{min}. But, more of the original points deviate from the SVM regression curve, indicating that the predicting performance of SVM regression model was not as well as the other two.

As can be seen from Figs. 4–6, the temperature has a significant effect on the fire frequency. The lowest values of F_{mean} are distributed in 20 °C < T_{min}, T_{max} ≤ 25 °C. The influence of temperature on fire frequency depends on many factors.

Previous studies have also shown that electricity consumption increases with temperature decreasing in cold weather with temperatures below 7 °C, while that increases with temperature increasing in hot weather with temperatures above 25 °C (Li et al., 2019). The number of electrical fires was the largest in Changsha City. When in 20 °C < T_{min}, T_{max} ≤ 25 °C, high-power electrical equipment (electric water heater, air conditioner, electric heater, and electric fan) was used less frequently. Therefore, it could be inferred that temperature mainly affects electricity consumption and then fire occurrence. In addition, a more energy-efficient heating and cooling policy should be developed to reduce the electrical fire frequency. The influence of temperature on fire frequency may decrease with the renewal of high-power electrical equipment and wires in the future. However, with the improvement of people's living standards, the per capita power consumption will increase, which will increase the influence of temperature on fire frequency.

In cold weather, some residents in rural areas use firewood, charcoal, and coal for heating, and it will lead fires with careless use. In recent years, China has formulated very strict environmental protection policies, and the use of coal and charcoal in rural areas is becoming less and less. This may reduce the number of fires caused by careless use in winter.

In China, the number of electric bicycles exceeds 250 million and is increasing year by year (Fire and Rescue Department of Ministry of Emergency Management, 2020). There are also a large number of electric bicycles in Changsha. In hot weather, the phenomenon of battery thermal runaway is more likely to occur, causing fires to occur more easily when electric bicycles are being charged (Ying et al., 2017; Mao et al., 2020). The probability of vehicle fire in hot weather is also much higher than that in cold weather

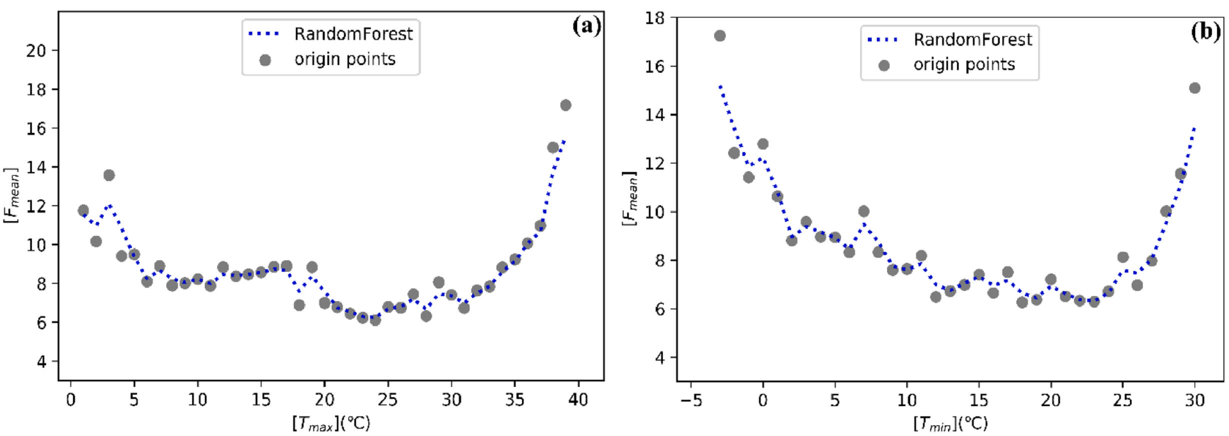

Fig. 4. Random forest regressions for (a) T_{max} and (b) T_{min}.

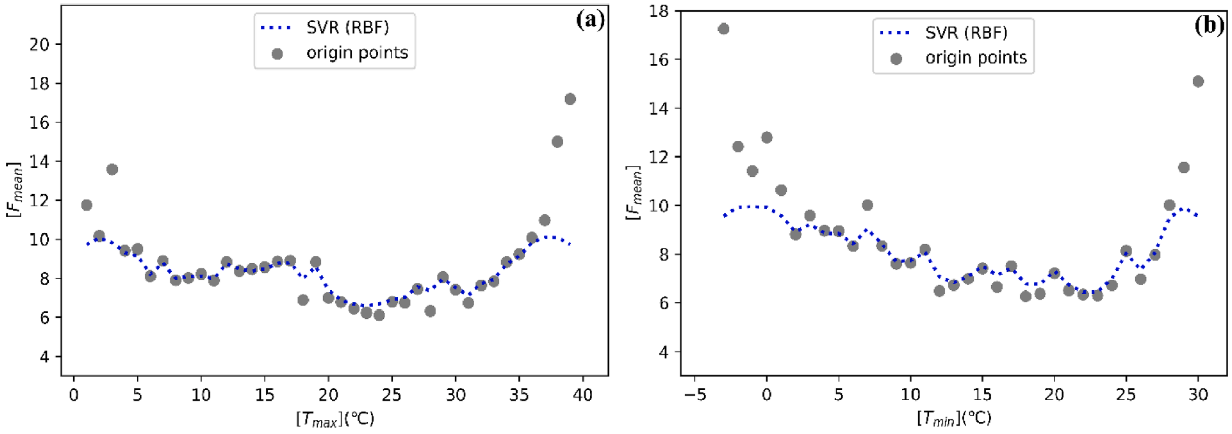

Fig. 5. SVM regressions for (a) T_{max} and (b) T_{min}.

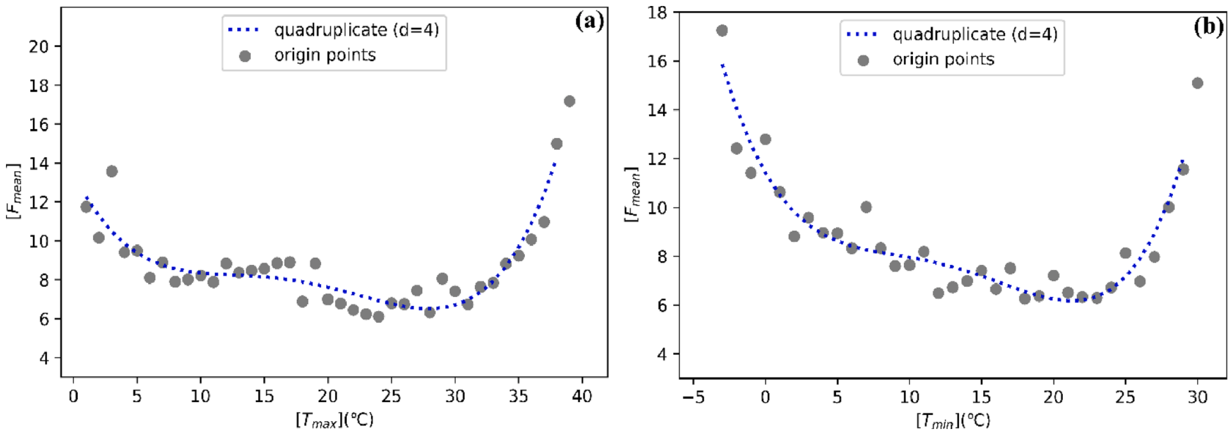

Fig. 6. Polynomial regressions for (a) T_{max} and (b) T_{min}.

(Zhang et al., 2019). With the increase of the number of vehicles (including electric vehicles) and electric bicycles, this may further increase the fire frequency in summer.

In summary, there are many factors and mechanisms that determine the influence of temperature on fire frequency. It is very important to find more influencing factors and mechanisms with more detailed data in further research.

4.2. Model performance

MSE and R^2 of different regression models were calculated as shown in Table 6. Random forest regression models show the best fitting performance, polynomial regression models come second, and SVM regression models have the worst fitting performance. Both random forest and polynomial regression models based on T_{min} had better performance than those based on T_{max}. However, SVM regression models based on T_{min} had the worse fitting performance than these based on T_{max}. The close correlation between temperature and fire occurrence was demonstrated in these models (especially in random forest and polynomial models).

Polynomial regression models based on T_{max} and T_{min} can be formulated as Eqs. (8) and (9), respectively. With these formulas, predictive models can be well understood by firefighters and decisionmakers. The predictive models of Eqs. (8) and (9) were established based on fire data and meteorological data of Changsha City from 2011 to 2017. Therefore, they can only be applied in Changsha City. But similar predictive models can be established for other cities based on the methods of this study.

$$F_{mean} = 13.4821 - 1.3336T_{max} + 0.1272T_{max}^2 - 0.0053T_{max}^3 + 0.0001T_{max}^4 \tag{8}$$

$$F_{mean} = 11.4132 - 1.0305T_{min} + 0.1270T_{min}^2 - 0.0073T_{min}^3 + 0.0001T_{min}^4 \tag{9}$$

However, random forest regression models have the best performance. Therefore, we selected random forest regression models to predict fire frequency in Changsha under global warming scenarios.

Table 6
MSE and R^2 of different regression models.

Regression Models	*MSE*	R^2
Random forest (T_{max})	0.29	0.95
Random forest (T_{min})	0.31	0.95
SVM (T_{max})	2.62	0.51
SVM (T_{min})	3.32	0.50
Polynomial (T_{max})	0.71	0.87
Polynomial (T_{min})	0.61	0.91

4.3. Predictive analysis under climate warming scenarios

According to the Paris Agreement, the global warming after industrialization should be less than 2.5 °C, and strive to keep within 1.5 °C (Gao, 2016). The latest research of the Intergovernmental Panel on Climate Change shows that global warming should be controlled within 1.5 °C to avoid the serious impact of climate change (Allen et al., 2018). Global warming has also had a significant impact on China. In the past 60 years, the long-term trend of daily average temperature in China has been rising uniformly, especially in winter and spring in the northern region (Qi et al., 2019). Due to the lack of meteorological data of Changsha before industrialization, the annual fire frequencies under warming of 1.5 °C and 2.0 °C cannot be analyzed in this study. In the past 50 years, the daily average temperature of Changsha has also risen, and T_{max} and T_{min} have different rising rates in different seasons (Luo and Yu, 2017). The rising rates of T_{max} in spring, summer, autumn, and winter are 0.37 °C·10a^{-1}, 0.01 °C·10a^{-1}, 0.22 °C·10a^{-1}, and 0.31℃·10a^{-1}, respectively. The rising rates of T_{min} are 0.31 °C·10a^{-1}, 0.15 °C·10a^{-1}, 0.22 °C·10a^{-1}, and 0.31 °C·10a^{-1}, respectively (Luo and Yu, 2017).

Random forest regression models were established based on the fire incidents from 2011 to 2017. Based on Table 2, AT_{max} and AT_{min} in different months of 2067 (50 years later) can be estimated (see Table 7 and Table 8). Using random forest regression models, F_{mean} in different months of 2067 can be predicted as shown in Table 7 and Table 8. F_{sum} in different months can be calculated by multiplying F_{mean} by days of the corresponding month. According to the current warming rate in Changsha, the annual fire frequency in 2067 will be 0.69% to 0.89% higher than that in 2011–2017.

Overall, global warming will lead to an increased probability of fires in Changsha. In addition, due to urbanization, the population and the number of buildings in Changsha are increasing, which may further increase fire frequency. If the fire prevention technology is improved, and people's awareness of fire prevention is also raised, it will help to reduce the impact of warming on fire frequency. In China and the world, there are many cities like Changsha. Therefore, global warming may pose severe challenges to future fire safety.

5. Conclusions

In this study, methods based on data mining and machine learning were used to analyze the influence of global warming on fire frequency (except wildfires). The fire incident dataset which includes 20,622 fires (with 0 wildfire) and the weather dataset in Changsha were gathered as case studies. A new dataset was born by joining the fire incident dataset and the weather dataset based on time series. Through data mining of the new dataset, the characteristics of temperature and fire frequency in different months were obtained. The results show that the number of fires in winter was the most, followed by that in summer.

Different machine learning regression methods (random forest regression, SVM regression, and polynomial regression) were selected to establish fire frequency predictive models based on T_{max} and T_{min}. Among them, random forest regression models had the best fitting performance, and were selected to predict the fire frequency under climate warming scenarios. Under the current warming rate in Changsha, the annual fire frequency in 2067 (50 years after 2017) will increase by 0.69% to 0.89%.

Table 7
Predictions of F_{mean}. and F_{sum} based on AT_{max}.

Month	2011–2017			2067		
	AT_{max}	F_{mean}	F_{sum}	AT_{max}	F_{mean}	F_{sum}
January	11.21 °C	8.10	251.05	11.96 °C	8.46	262.16
February	11.34 °C	8.10	226.76	12.09 °C	8.55	239.28
March	17.07 °C	8.48	262.86	18.92 °C	8.38	259.77
April	22.93 °C	6.30	188.96	24.78 °C	6.70	200.91
May	27.17 °C	7.12	220.70	29.02 °C	7.58	235.11
June	31.03 °C	7.09	212.57	31.08 °C	7.09	212.57
July	34.70 °C	9.13	283.14	34.75 °C	9.13	283.14
August	33.90 °C	8.61	266.93	33.95 °C	8.61	266.93
September	29.04 °C	7.58	227.52	30.14 °C	7.28	218.35
October	24.98 °C	6.70	207.60	26.08 °C	6.89	213.66
November	16.56 °C	8.68	260.27	17.66 °C	7.61	228.19
December	11.32 °C	8.10	251.05	12.07 °C	8.55	264.91
Sum			2,859.42			2,884.98

Table 8
Predictions of F_{mean}.and F_{sum} based on AT_{min}.

Month	2011–2017			2067		
	AT_{min}	F_{mean}	F_{sum}	AT_{min}	F_{mean}	F_{sum}
January	4.31 °C	9.02	279.57	5.86 °C	8.45	262.05
February	4.87 °C	8.93	249.98	6.42 °C	8.53	238.83
March	9.87 °C	7.61	235.91	11.42 °C	7.74	239.85
April	15.25 °C	7.28	218.45	16.80 °C	7.16	214.86
May	19.70 °C	6.94	215.09	21.25 °C	6.48	200.91
June	24.37 °C	6.90	207.07	25.12 °C	7.79	233.85
July	27.47 °C	8.35	258.81	28.22 °C	10.26	317.91
August	26.72 °C	8.04	249.39	27.47 °C	8.35	258.81
September	21.74 °C	6.37	191.08	22.84 °C	6.31	189.28
October	16.53 °C	7.16	222.02	17.63 °C	6.65	206.02
November	10.39 °C	7.67	230.07	11.49 °C	7.74	232.11
December	4.06 °C	9.02	279.57	5.61 °C	8.45	262.05
Sum			2,837.02			2,856.53

In general, warming will increase the fire probability in Changsha. By improving fire prevention technology and raising people's awareness of fire safety, the adverse effects of warming may be reduced. The influences of climate warming on the fire frequencies of other cities can also be analyzed by rebuilding predictive models based on the proposed methods in this study.

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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References

Allen, M.R., Babiker, M., Chen, Y., Coninck, H. de, Connors, S., Diemen, R. van, Dube, O.P., Ebi, K.L., Engelbrecht, F., Ferrat, M., Ford, J., Forster, P., Fuss, S., Bolaños, T.G., Harold, J., Hoegh-Guldberg, O., Hourcade, J.-C., Huppmann, D., Jacob, D., Jiang, K., Johansen, T.G., Kainuma, M., Kleijne, K. de, Kriegler, E., Ley, D., Liverman, D., Mahowald, N., Masson-Delmotte, V., Matthews, J.B.R., Millar, R.J., Mintenbeck, K., Morelli, A., Moufouma-Okia, W., Mundaca, L., Nicolai, M., Okereke, C., Pathak, M., AntonyPayne, Pidcock, R., Pirani, A., Poloczanska, E., Pörtner, H.-O., Revi, A., Riahi, K., Roberts, D.C., Rogelj, J., Roy, J., Seneviratne, S. I., Shukla, P.R., Skea, J., Slade, R., Shindell, D., Singh, C., Solecki, W., Steg, L., Taylor, M., Tschakert, P., Waisman, H., Warren, R., Zhai, P., Zickfeld, K., 2018. Global Warming of 1.5°C. Inchon.

Bowman, D.M.J.S., Balch, J.K., Artaxo, P., Bond, W.J., Carlson, J.M., Cochrane, M.A., D'Antonio, C.M., DeFries, R.S., Doyle, J.C., Harrison, S.P., Johnston, F.H., Keeley, J.E., Krawchuk, M.A., Kull, C.A., Marston, J.B., Moritz, M.A., Prentice, I.C., Roos, C.I., Scott, A.C., Swetnam, T.W., van der Werf, G.R., Pyne, S.J., 2009. Fire in the earth system. Science (80-) 324 (5926), 481–484. https://doi.org/10.1126/science:1163886.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Burges, C.J.C., 1998. A tutorial on support vector machines for pattern recognition. Data Min. Knowl. Discov. 2, 121–167. https://doi.org/10.1023/A:1009715923555.

Chandler, S.E., 1982. The effects of severe weather conditions on the incidence of fires in dwellings. Fire Saf. J. 5 (1), 21–27. https://doi.org/10.1016/0379-7112(82)90004-2.

Changsha Bureau of Statistics, 2019. 2018 Changsha Statistical Yearbook [WWW Document]. China Stat. Press http://tjj.changsha.gov.cn/tjnj/2019/ (accessed 1.25.19).

Coelho, F., Neto, J.P., 2017. A method for regularization of evolutionary polynomial regression. Appl. Soft Comput. J. 59, 223–228. https://doi.org/10.1016/j.asoc.2017.05.047.

D'Amico, D.F., Quiring, S.M., Maderia, C.M., McRoberts, D.B., 2019. Improving the Hurricane Outage Prediction Model by including tree species. Clim. Risk Manag. 25, 100193. https://doi.org/10.1016/j.crm.2019.100193.

Dupire, S., Curt, T., Bigot, S., 2017. Spatio-temporal trends in fire weather in the French Alps. Sci. Total Environ. 595, 801–817. https://doi.org/10.1016/J.SCITOTENV.2017.04.027.

Fargeon, H., Pimont, F., Martin-StPaul, N., De Caceres, M., Ruffault, J., Barbero, R., Dupuy, J.-L., 2020. Projections of fire danger under climate change over France: where do the greatest uncertainties lie? Change Clim. https://doi.org/10.1007/s10584-019-02629-w.

Fire Department of Ministry of Public Security (FDMPS), 2017. National Fire Comprehensive Situation based on Month and Season in 2015 [WWW Document]. URL http://www.119.gov.cn/xiaofang/hztj/ 34154.htm (accessed 3.4.17).

Fire and Rescue Department of Ministry of Emergency Management, 2020. More than 233,000 fires reported in China in 2019 [WWW Document]. Fire and Rescue Department of Ministry of Emergency Management. URL https://www.119.gov.cn/article/3xBeEJjR54K (accessed 2.26.20).

Fox, D.M., Carrega, P., Ren, Y., Caillouet, P., Bouillon, C., Robert, S., 2018. How wildfire risk is related to urban planning and Fire Weather Index in SE France (1990–2013). Sci. Total Environ. 621, 120–129. https://doi.org/10.1016/j.scitotenv.2017.11.174.

Friedman, J., Hastie, T., Tibshirani, R., 2010. Regularization paths for generalized linear models via coordinate descent. J. Stat. Softw. 33, 1–22. https://doi.org/10.1016/j.jspi.2009.07.020.

Gao, Y., 2016. China's response to climate change issues after Paris Climate Change Conference. Adv. Clim. Chang. Res. 7 (4), 235–240. https://doi.org/10.1016/j.accre.2016.10.001.

Garbolino, E., Sanseverino-Godfrin, V., Hinojos-Mendoza, G., 2016. Describing and predicting of the vegetation development of Corsica due to expected climate change and its impact on forest fire risk evolution. Saf. Sci. 88, 180–186. https://doi.org/10.1016/j.ssci.2016.02.006.

Goodess, C.M., 2013. How is the frequency, location and severity of extreme events likely to change up to 2060? Environ. Sci. Policy 27, S4–S14. https://doi.org/10.1016/j.envsci.2012.04.001.

Hong, H., Tsangaratos, P., Ilia, I., Liu, J., Zhu, A.-X., Xu, C., 2018. Applying genetic algorithms to set the optimal combination of forest fire related variables and model forest fire susceptibility based on data mining models. The case of Dayu County. China. Sci. Total Environ. 630, 1044–1056. https://doi.org/10.1016/j.scitotenv.2018.02.278.

Huang, T., Liu, G.Z., 2008. Research on auto-regressive model of city fire and meteorological factors. J. Saf. Sci. Technol. 164–166.

Kay, J.E., 2020. Early climate models successfully predicted global warming. Nature 578 (7793), 45–46. https://doi.org/10.1038/d41586-020-00243-w.

Li, G., Lu, S., Mei, P., Zhang, H., Lo, S., 2014. Influences of time, location, and cause factors on the probability of fire loss in China: A correspondence analysis. Fire Technol. 50 (5), 1181–1200. https://doi.org/10.1007/s10694-014-0385-6.

Li, P.u., Zhao, W., 2020. Image fire detection algorithms based on convolutional neural networks. Case Stud. Therm. Eng. 19, 100625. https://doi.org/10.1016/j.csite.2020.100625.

Li, Y., Pizer, W.A., Wu, L., 2019. Climate change and residential electricity consumption in the Yangtze River Delta. China. Proc. Natl. Acad. Sci. 116 (2), 472–477. https://doi.org/10.1073/pnas.1804667115.

Liu, D., Xu, Z., Fan, C., 2019a. Predictive analysis of fire frequency based on daily temperatures. Nat. Hazards 97 (3), 1175–1189. https://doi.org/10.1007/s11069-019-03694-1.

Liu, D., Xu, Z., Wang, Z., Zhou, Y., Fan, C., 2020. Estimation of effective coverage rate of fire station services based on real-time travel times. Fire Saf. J. 103021. https://doi.org/10.1016/j.firesaf.2020.103021.

Liu, D., Xu, Z., Zhou, Y., Fan, C., 2019b. Heat map visualisation of fire incidents based on transformed sigmoid risk model. Fire Saf. J. 109, 102863. https://doi.org/10.1016/j.firesaf.2019.102863.

Log, T., 2016. Cold climate fire risk; A case study of the Lærdalsøyri fire, January 2014. Fire Technol. 52, 1825–1843. https://doi.org/10.1007/s10694-015-0532-8.

Luo, Y., Yu, W., 2017. Climate change and mutation analysis of Changsha in recent 56 years. J. Anhui Agric. Univ. 44, 302–307. https://doi.org/10.13610/j.cnki.1672-352x.20170419.007.

Madaio, M., Chen, S.-T., Haimson, O.L., Zhang, W., Cheng, X., Hinds-Aldrich, M., Chau, D.H., Dilkina, B., 2016. Firebird: predicting fire risk and prioritizing fire inspections in Atlanta. In: Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16. ACM, New York, NY, USA, pp. 185–194. https://doi.org/10.1145/2939672.2939682.

Mao, B., Huang, P., Chen, H., Wang, Q., Sun, J., 2020. Self-heating reaction and thermal runaway criticality of the lithium ion battery. Int. J. Heat Mass Transf. 149, 119178. https://doi.org/10.1016/j.ijheatmasstransfer.2019.119178.

McNamee, M., Meacham, B., van Hees, P., Bisby, L., Chow, W.K., Coppalle, A., Dobashi, R., Dlugogorski, B., Fahy, R., Fleischmann, C., Floyd, J., Galea, E.R., Gollner, M., Hakkarainen, T., Hamins, A., Hu, L., Johnson, P., Karlsson, B., Merci, B., Ohmiya, Y., Rein, G., Trouvé, A., Wang, Y., Weckman, B., 2019. IAFSS agenda 2030 for a fire safe world. Fire Saf. J. 110, 102889 https://doi.org/10.1016/j.firesaf.2019.102889.

Mhawej, M., Faour, G., Adjizian-Gerard, J., 2017. A novel method to identify likely causes of wildfire. Clim. Risk Manag. 16, 120–132. https://doi.org/10.1016/j.crm.2017.01.004.

Nelli, F., 2018. Python Data Analytics: With Pandas, NumPy, and Matplotlib, 2nd ed. Apress, USA.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: machine learning in python. J. Mach. Learn. Res. 12, 2825–2830.

Qi, Q., Cai, R., Haixia, G., 2019. The climatic variations of temperature extremes in the eastern of China. Sci. Geogr. Sin. 39, 1340–1350. https://doi.org/10.13249/j.cnki.sgs.2019.08.016.

Rajagopal, A.S., Nishanth, M., Rajageethan, R., Rao, R., Ezhilarasie, R., 2018. Data mining approach to predict forest fire using fog computing. In: Proceedings of the 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 345 E 47TH ST, NEW YORK, NY 10017 USA, pp. 1582–1587.

Raschka, S., Mirjalili, V., 2017. Python Machine Learning - Second Edition. Packt Publishing.

Shi, Y., Zhang, D.-F., Xu, Y., Zhou, B.-T., 2018. Changes of heating and cooling degree days over China in response to global warming of 1.5 °C, 2 °C, 3 °C and 4 °C. Adv. Clim. Chang. Res. 9, 192–200. https://doi.org/10.1016/j.accre.2018.06.003.

Syphard, A.D., Rustigian-Romsos, H., Mann, M., Conlisk, E., Moritz, M.A., Ackerly, D., 2019. The relative influence of climate and housing development on current and projected future fire patterns and structure loss across three California landscapes. Glob. Environ. Chang. 56, 41–55. https://doi.org/10.1016/j.gloenvcha.2019.03.007.

Wang, Z., Zhang, X., Xu, B., 2015. Spatio-temporal features of China's urban fires: An investigation with reference to gross domestic product and humidity. Sustain. 7, 9734–9752. https://doi.org/10.3390/su7079734.

Ying, W., Yongping, Z., Fang, X., Jian, X., 2017. Analysis model for fire accidents of electric bicycles based on principal component analysis. In: 22017 IEEE International Conference on Computational Science and Engineering (CSE) and IEEE International Conference on Embedded and Ubiquitous Computing (EUC). IEEE, pp. 760–762 https://doi.org/10.1109/CSE-EUC.2017.149.

Yu, P., Xu, R., Abramson, M.J., Li, S., Guo, Y., 2020. Bushfires in Australia: a serious health emergency under climate change. Lancet Planet. Heal. 4, e7–e8. https://doi.org/10.1016/S2542-5196(19)30267-0.

Zald, H.S.J., Dunn, C.J., 2018. Severe fire weather and intensive forest management increase fire severity in a multi-ownership landscape. Ecol. Appl. 28, 1068–1080. https://doi.org/10.1002/eap.1710.

Zhang, W., Bai, C., Tian, M., Naren, T., 2019. Causes analysis and countermeasures of automobile fire. Fire Sci. Technol. 38, 730–734.

Zhang, X., Ma, X., 2019. Misplaced optimism in agricultural land usage driven by newly available climate resources: A case study of estimated and realized cropping intensity in northern and northeastern China. Clim. Risk Manag. 25, 100194 https://doi.org/10.1016/j.crm.2019.100194.