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Spatio-temporal Analysis of Fire Risk in Beijing

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Abstract: *Forest fire safety is extremely important to forest safety. Forest is not only the place with the richest forest resources, but also the place with the most abundant species. Once a forest fires, the damage caused is immeasurable, especially in near the edge of the city. But at the same time, the traditional manual field survey method is time-consuming and labor-intensive, and also carries great uncertainty. This study is based on the representative months of 2019 in Beijing, comprehensively integrated NDVI index, meteorological factors, terrain factors and other comprehensive indicators, using reasonable mathematical models, using ArcGIS, SPSS and other statistical analysis software to explore the fire risk in Beijing The temporal and spatial distribution of the index.*

Keywords: *Forest Fire, Risk Index, Impact Factor, Model.*

1. Introduction.

Due to the global climate change, human urbanization expansion, industrialization and many other factors, the number and frequency of forest fires in various places have increased year by year [1]. Therefore, risk assessment of fires around the world has become an urgent matter. Forest fires not only destroy the living environment of forest animals and reduce forest biodiversity, but also bring greater economic losses to forestry [2]. Through scientific assessment of the economic losses of forest fires, it is helpful to strengthen economic and technical measures, effectively control forest fires, and minimize the occurrence of forest fires and the huge losses that may be caused. At the same time, according to the wildfire triangle model, in addition to meteorological factors, the occurrence of wildfires is also closely related to ground combustible information and terrain elements [3].

As we all know, Beijing, as the country’s economic, cultural and political center, naturally plays a unique role in the development of the country’s modernization. Therefore, it is imperative to analyze various potential factors to analyze the fire situation in Beijing. Forest fires in its surrounding suburbs the risk prevention and control of Beijing is the top priority. In the winter and spring in Beijing, the temperature changes greatly, the climate is relatively dry, and there will be windy weather, and the precipitation is small but the evaporation is the highest period of the year. It is very easy to cause fire under the severe weather conditions [4].

2. Data and Methods

2.1. Overview of the Study Area

Beijing, the capital of the People's Republic of China, is the political and cultural center of the country, a world-famous ancient capital and a modern international city. Beijing is located at 39 degrees 56 minutes north latitude and 116 degrees 20 minutes east longitude. It is located in the northern part of the North China Plain, adjoining Tianjin to the east, and neighboring Hebei Province. The terrain is high in the northwest and low in the southeast. The west, north and northeast are surrounded by mountains on three sides, and the southeast is a plain sloping gently towards the Bohai Sea. The climate of Beijing belongs to the semi-humid and semi-arid monsoon climate in the warm temperate zone as shown in the figure 1.

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Figure 1: Beijing, China, research area.

2.2. Data Source and Processing

2.2.1. Meteorological Data

ERA-Interim is the latest global atmospheric reanalysis product released by the European Centre for Medium-Range Weather Forecasts (ECMWF) [5]. This product has been released since January 1989 and has released data in near real-time over time. The ERA-Interim data is an improvement of the ERA-40 data, and has a significant improvement in data quality. Its data format is mainly raster, and the spatial resolution can reach up to 0.125 ° [6]. The land surface parameters are released every few hours These parameters include the air temperature at 2 meters on the ground, the dew point temperature at 2 meters on the ground, the wind speed in the longitude (U) and latitude (V) directions at 10 meters on the ground, accumulated rainfall, and other meteorological data.

2.2.2. Terrain Data

A global elevation model jointly developed by the United States Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA)-2010 global multi-resolution terrain elevation data[7,8] Use ArcGIS software to obtain slope and aspect information through elevation.

2.2.3. Vegetation Data

Download Landsat images through the geospatial data cloud, and calculate through NDVI = (NIR-R)/ (NIR+R)

Where NIR: reflectivity value in the near-infrared band R: reflectivity value in the red band. Negative values indicate that the ground is covered with clouds, water, snow, etc., which is highly reflective to visible light. 0 means rock or bare soil, etc., and NIR and R are approximately equal. A positive value indicates that there is vegetation coverage, and it increases as the coverage increases [9].

2.3. Research Methods

2.3.1. Basic Principles of the Model

This article intends to use the Logistic regression model to calculate the Wildfire Risk Index (Wildfire Risk Index, WRI). The wildfire risk index is a quantitative representation of the degree of wildfire risk. The value varies between 0 and 1. The larger the value, the higher the wildfire risk. . The purpose of adopting the wildfire risk index is to replace the traditional wildfire risk assessment classification rules, such as low-risk, medium-risk, and high-risk, which are very vague assessment descriptions, by quantifying the degree of wildfire risk.

Logistic Regression Model is essentially a two-category model. The result is a decimal that fluctuates between 0 and 1, which represents the probability of the occurrence of a target event. This model is often used for data mining, economic prediction, and disease. Diagnosis and other fields. In recent years, many forest fire researchers have applied this model to wildfire risk assessment, proving the effectiveness of the model in wildfire risk assessment [10]. This paper will be based on wildfire inducing factors and use the model to calculate the wildfire risk index to characterize the degree of wildfire risk. The calculation formula is as follows:

$$Pz=\frac{1}{1+e^{-z}} \tag{1}$$

Where Pz represents the degree of wildfire risk, that is, the WRI value, and z is a multivariate linear equation system, which can be expressed as:

$$Z=\beta0+\beta1x1+\beta2x2\ldots\beta nxn \tag{2}$$

Where β0 is the constant in the model, which represents the intercept; n is the number of independent variables, where it represents the number of wild-inducing factors; Xi represents the type of wildfire-inducing factors; βi (i=l, 2...n) represents the The variable parameter corresponding to Xi.

2.3.2. Model Construction

2.3.2.1. Discrete Factor Processing

The logistic regression model cannot effectively identify discrete factors and continuous factors, so discrete factors cannot be directly brought into the model, and dummy variables or dummy factors need to be set [11]. The slope and precipitation in this book belong to the category of discrete factors.

The aspect data is transformed from the Elevation data in ArcGIS software. The value is 0-360°, indicating the angle with the true north direction. However, the value of the aspect data is not the meaning of the value itself, but indicates the azimuth. For example, in the azimuth representation, 0° and 360°. All indicate the true north direction. If the aspect is brought into the model for calculation as a continuous factor, it will result in different results for 0° and 360° that also indicate the north direction. Therefore, the aspect data should be converted into discrete factors and added to the model as virtual factors. First, the aspect data should be discretized according to the orientation represented by the aspect data, as shown in Figure 2. This paper divides the slope direction into 8 directions, centered on the 8 directions of north, northeast, east, southeast, south, southwest, west and northwest, and then moves to the left and right by 22.5°. For example, the north is declared with code 0, the range of the indicated aspect is the union of 337.5-360° and 0-22.5°; the northeast is declared with the code 1, the range of the indicated aspect is 22.5-67.5°, other aspect codes The meaning is similar here. In addition, there are some pixels in the study area that are horizontal, that is, there is no aspect, but the number of such pixels is small, so they are classified as north and still declared with the 0 code.

Whether Rain data itself is already a binary factor, code 0 means that there is no rain on the day, and code 1 means that there is rain on the day. The virtual factor is represented by 0 or 1. The number of virtual factors needs to follow certain principles:

When the regression model has an intercept term or a constant term, and a certain factor has n genera types, only (n-1) dummy factors need to be introduced into the model. That is, Aspect data will be added in the form of 7 virtual factors in the model, and Whether Rain will be added in the form of 1 virtual factor. As shown in the table (1), it shows the form of Aspect and Whether Rain transformed into virtual factors in the model. For Aspect data, northbound 0 is coded as (1 0 0 0 0 0 0 0), northeast 1 is coded as (0 1 0 0 0 0 0), and east 2 is coded as (0 0 1 0 0 0 0), the coding in other directions is similar, and there is 1 in the coding. But the code of northwest direction 7 is an exception, its code is (0 0 0 0 0 0 0). When calculating in the model, the dummy variables in the northwest direction do not participate in the calculation, that is, the aspect data represented by the 8 dummy factors only have 7 dummy factors in the model. In the same way, the encoding method of While Rain is the same. The data of While Rain represented by two virtual factors has only one virtual factor involved in the calculation in the model.

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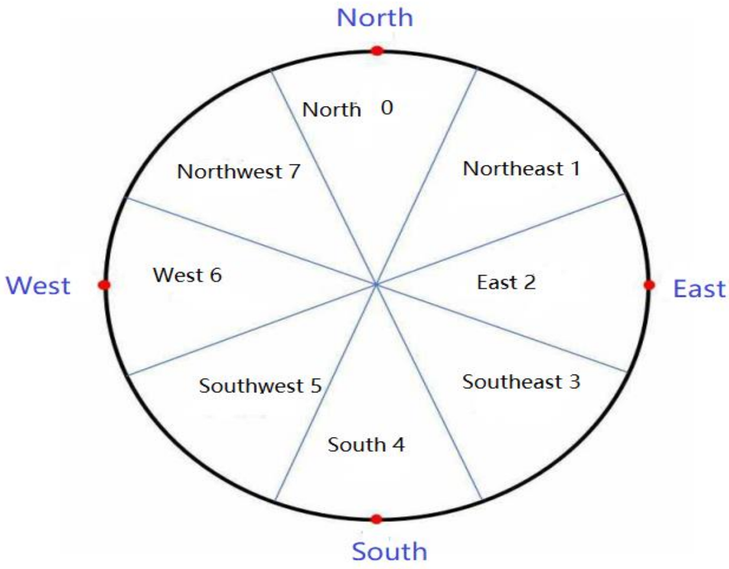

Figure 2: Schematic diagram of data discretization.

Table 1: Discrete factor is transformed into virtual factor comparison table

	Parameter code	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Aspect	0	1	0	0	0	0	0	0
	1	0	1	0	0	0	0	0
	2	0	0	1	0	0	0	0
	3	0	0	0	1	0	0	0
	4	0	0	0	0	1	0	0
	5	0	0	0	0	0	1	0
	6	0	0	0	0	0	0	1
	7	0	0	0	0	0	0	0
Whether Rain	0	0						
	1	1						

2.3.2.2. Model training

When the logistic regression model is trained, this paper uses a backward iterative algorithm to bring the factors into the model. The basic idea is: first, all factors are entered into the model for training, and then according to the value of each factor in the model The significant effect Sig value is eliminated, and the factor with the largest Sig value among the factors that do not meet the significance effect limit is eliminated each time; then the remaining factors are brought into the model for retraining, and the filter is performed again until the remaining factors in the model are Until all Sig values meet the significance condition (Sig<0.05), the whole process is called iterative training process.

3. Results

Through the above model, the collected various data are brought into the model to calculate the risk coefficient. Starting from November 2018, take a representative day every three months and use the above model to calculate, and then get The visualized risk coefficient is divided in detail, 90-100 is divided into one level, 80-90 is divided into one level, 60-80 is divided into one level, and the part below 60 is divided into first level . Get the result as shown in the figure 3:

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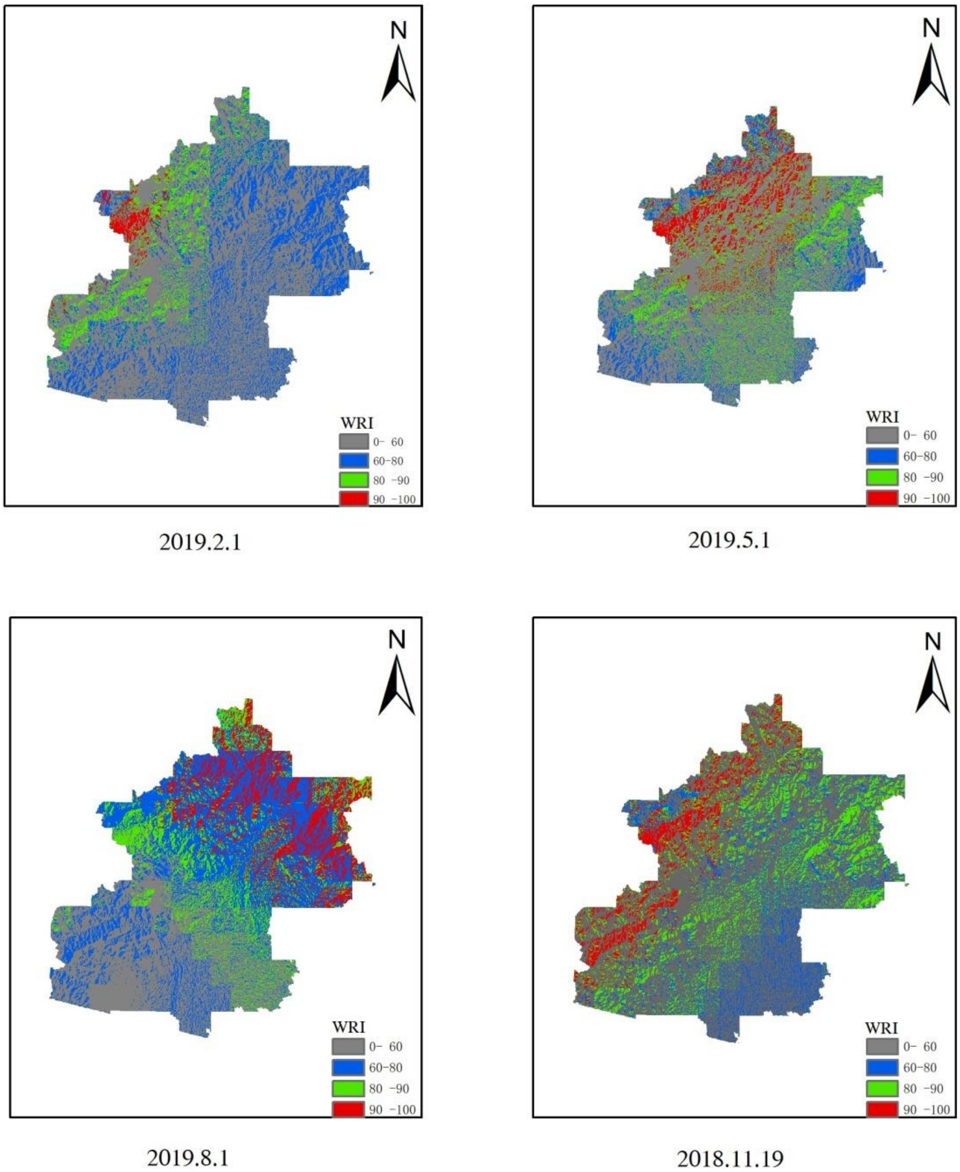

Figure 3: Calculation Results of Beijing Risk Coefficient, Risk ranges (WRI) represented by various colors

It can be seen from the figure that from the perspective of time, as the temperature gradually rises from May to August, the high-risk areas in Beijing gradually expand. From November to February of the following year, the areas with high risk indexes gradually decreased.

From the perspective of space, the fire risk index of most parts of northwest Beijing, a small part of southwest and northeast of Beijing in the same season is significantly higher than that of other regions.

4. Conclusion

This paper studies the wildfire risk assessment method and its application in Beijing's forest fire assessment, taking into account the vegetation, terrain, weather and other factors commonly used in the fire triangle model, and using the model to comprehensively evaluate the fire risk situation in Beijing. The purpose of collecting relevant satellite remote sensing data is to realize fire risk assessment without using on-site measurement methods. Therefore, using remote sensing technology, without on-site surveys, we finally obtained the calculation results of the forest fire risk coefficient in Beijing, and analyzed it from the time and space dimensions.

It provides strong decision-making support for the forest fire prevention work of the Beijing Fire Bureau. The next task is how to plan the best rescue path in the high-risk area where the fire occurs.

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