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Research Progress on the Disaster Causing Mechanism of Forest Fires due to the Coupling of Multiple Factors

Kaixun Dong[a], Zhongliang Gao[b, *], Lianli Fu[c], Guohui Chen[d], Xiaojie Ma[e], Na Li[f], Wenquan Chen[g], Xiaohui Pu[h], Ming Zhou[k]

School of Civil Engineering, Southwest Forestry University, 650224, Kunming, China

[a]2561024838@qq.com, [b]winalite@swfu.edu.cn, [c]2765874572@qq.com, [d]2353708942@qq.com, [e]2814117929@qq.com, [f]3450482867@qq.com, [g]3387679390@qq.com, [h]1279918531@qq.com, [k]3143714363@qq.com

* Corresponding author

Abstract: As a global high-frequency natural disaster, the occurrence and spread of forest fires are the results of the complex coupling of multiple elements such as meteorological conditions, vegetation characteristics, topography and geomorphology, human activities, and the distribution of fire sources. With the increasing intensification of global climate change and the strengthening of human activity interference, the frequency and combustion intensity of forest fires have significantly increased. An in-depth exploration of the disaster causing mechanism of the coupling of multiple factors has become the core scientific proposition for solving the difficult problem of fire prevention and control. In recent years, under the dual influence of climate change and human interference, the frequency and intensity of forest fires have increased significantly, and the disaster causing mechanism of the coupling of multiple factors has become a key issue in fire prevention and control. This paper systematically reviews the research progress on the disaster causing mechanism of the coupling of multiple factors in forest fires, with a focus on discussing the dynamic interaction between multiple factors and the coupling-induced disasters, reflecting the profound impact of this interaction on the occurrence and development of fires. At the same time, it analyzes the influence mechanism of topographic factors (slope, aspect, altitude, etc.) on fire behavior and elaborates the propagation characteristics of fires under different topographic conditions. In addition, it studies the indirect driving role of human activities (land use, fire source management, etc.) in the occurrence of fires and clarifies the important contribution of human activities to fire risks. It also summarizes the application of multi-source data fusion and model simulation in fire risk prediction and evaluates the advantages of these technologies in improving prediction accuracy. Finally, it is pointed out that in the future, it is necessary to strengthen the coupling analysis of multiple scales and multiple processes and develop high-precision dynamic early warning technologies to achieve precise prevention and control of forest fires and provide stronger theoretical support for ecological protection.

Keywords: Forest Fire; Coupling of Multiple Factors; Disaster Causing Mechanism; Risk Assessment; Current Situation.

1. Introduction

Forest fires are one of the major natural disasters faced by humanity. Compared with urban fires, forest fires occur in open forest areas. It is not easy to detect them in the initial stage of ignition. Under the relatively continuous state of combustibles, large-scale fires are likely to form. Moreover, forest fires mostly occur in mountainous areas, and the firefighting work is greatly affected by the terrain and wind direction, making it more difficult [1]. The factors affecting the occurrence of forest fires mainly include meteorological factors, topographic factors, vegetation factors, and human factors, etc. Among them, meteorological factors mainly include temperature, humidity, precipitation, wind direction, wind speed, etc.; topographic factors include longitude, latitude, altitude, slope, aspect, etc.; vegetation factors are mainly divided into two categories: vegetation type and vegetation coverage, and human factors are GDP, residential areas, roads, population density, etc. China is a region with frequent forest fires. From 1950 to 2010 (including Hong Kong, Macau, and Taiwan), there were an average of 12,683 forest fires per year, with an average burned area of 674,800 hectares. The annual loss is about 20 billion yuan, and the number of deaths exceeds 300 people [2]. Scientifically and reasonably evaluating the disaster risk of forest fires and minimizing the losses caused by forest fires have great practical significance both theoretically and realistically [3].

Research on forest fires has found that the occurrence of forest fires has temporal and spatial regularities, and its spatio-temporal distribution pattern is affected by factors such as terrain, climate, vegetation type, and human activities [4]. Scholars at home and abroad have launched a series of studies on the disaster-causing mechanism of the coupling of multiple factors in forest fires. Fasullo [5] et al. judged the impact of different climate environments and human factors on forest fires through simulation. The simulation results show that human factors can affect meteorological factors, resulting in an increase in the frequency and risk of fires. Robinne [6] et al. explored the impact of human activities on the risk of forest fires, introduced factors such as the distance from roads and the density of the energy network, compared and analyzed areas with frequent human activities and areas with few human traces, and established a model. Prapas [7] et al. used daily meteorological data such as temperature, humidity, and wind, and satellite data such as the Normalized Difference Vegetation Index (NDVI) to calculate the daily fire risk, and the simulation effect was good. Izet [8] et al. used common factors such as meteorological factors and topographic factors to establish two models for the probability of forest fire occurrence and the fire spread speed respectively, and used the natural clustering method to analyze the two models and calculate the fire risk index. Pablo [9] et al. established Logistic models and neural network models respectively for

9 driving factors such as population density. After evaluation by the ROC curve and verification using the actual burned area, the results show that the neural network model has better performance, and the main driving factors of the burned area are altitude and NDVI value. Gonzalo [10] considered driving factors such as vegetation characteristics, climate, and terrain, and established binary Logistic regression models in pure forests and mixed forests respectively. The results show that the probability of forest fire spread increases with the increase of the understory shrub load and decreases with the increase of tree size. Cancela [11] et al. divided the known driving factors into 4 categories: terrain, vegetation, and human factors, and explored the interaction between these factors. It was concluded that in secondary forests and plantation forests, the lower the altitude, the higher the fire risk, but primary forests are obviously an exception; the structure of primary forests is similar to that of plantation forests, but the causes of ignition are closer to agricultural land; the closer the shrub forest is to the pasture, the higher the fire risk. Kaiwei [12] et al. established a model through the combustible moisture content and burned area extracted by MODIS, and obtained the combustible moisture content threshold for the occurrence of forest fires in the southwestern region. Vollmar [13] et al. established a model according to driving factors such as altitude and land use type. The results show that evergreen forests and shrub forests have the highest fire risk, and meteorological factors play a decisive role in the occurrence of fires.

In China, the research on forest fire factors is relatively rich, and a large number of factors are used to establish models. Zhao Pengwu [14] et al. used 6 driving factors such as population density and road network density, and used the clustering analysis method to evaluate the forest fire risk of 21 forest areas in the Daxing'anling region. The results show that the area with the first-level fire risk in this region exceeds 96% of the total area. Wu Mingshan [15] et al. evaluated the forest fire risk value within the small forest compartment and found that resin tapping can change the fire risk value, but generally speaking, the fire risk of forest stands is at a relatively high level. Wang Jin [16] proposed a forest fire prediction model based on buffer resampling, selected 15 driving factors such as temperature and wind speed for multicollinearity testing, used the factors that passed the test to build a model, and used the ROC curve for testing. The results show that the result of the LSTM algorithm is better than those of the random forest and support vector machine algorithms. Zhu Xin [17] et al. selected three algorithms, namely the neural network, support vector machine, and random forest algorithms, to build models using driving factors such as combustible characteristics and meteorological factors, and compared and analyzed the three models using the ROC curve and AUC value. It was concluded that the neural network model needs to be improved and optimized before use, and the support vector machine is not suitable for linear or massive data; the random forest algorithm has relatively high stability and accuracy. Ruan Jiangtao et al. [18] studied the fire spread process, believing that the two-way coupling model of fire-wind can improve the simulation accuracy of the fire spread process, and discussed its future development trend. Hui Shan et al. [19] proposed a forest fire spread simulation method coupling cellular automata for the problems existing in the forest fire spread process. Yin Changming et al. [20] established a remote sensing inversion algorithm for forest fire combustion intensity based on multi-mode coupling. At present, the research on forest fires and their influencing factors at home and abroad mainly focuses on their driving factors, and there is a lack of research on the coupling mechanism between forest fires and factors.

In this regard, based on the comprehensive consideration of multiple disaster-causing factors of forest fires, this paper constructs a multi-factor N-K coupling measurement model and modifies the model using the entropy weight method to find the combination of disaster-causing factors for the frequent occurrence of forest fires. This project is based on the research on the disaster-causing mechanism of multi-field coupling of forest fires and the theory of forest fire causes. Using the decoupling principle, it conducts research on forest fire prevention and mitigation.

2. Disaster-causing Factors of Forest Fires

2.1. Disaster-generating Environment

The occurrence of forest fires requires a specific environment, namely the disaster-generating environment. There is an interaction between the disaster-generating environment and the disaster-causing factors. The disaster-generating environment determines the effectiveness of the disaster-causing factors, mainly influencing them through meteorological conditions and topographic conditions. In turn, the disaster-causing factors exert their effects through the disaster-generating environment. That is to say, the same fire source behaves differently under different combustion environments. Therefore, the disaster-generating factors for forest fire risk are the environmental factors within the disaster-generating environment that trigger forest fires [21]. The disaster-generating environment is mainly affected by meteorological factors and topographic factors.

2.1.1. Meteorological Factors

Climate change directly affects the occurrence, spread, and periodic fluctuations of forest fires through changes in meteorological factors [22]. Different meteorological factors have varying degrees of influence on forest fires, and the combined effect of these factors affects the occurrence and development of forest fires. Tian Yongli et al. [23] utilized the meteorological and fire data of the California region from 2009 to 2018 and employed a comprehensive analysis method of anomalies and circulation. They found that the forest fires in California were caused by extreme weather. There is a significant relationship between the atmospheric temperature and the occurrence of forest fires. The occurrence of forest fires is closely related to temperature. As the air temperature rises and the humidity decreases, the moisture in the combustibles is evaporated and dried out, and the temperature of the combustibles themselves also increases[24]. This greatly reduces the amount of heat required to reach the ignition point. The rise in air temperature can indirectly affect the characteristics of combustibles by changing the environmental conditions, such as reducing the moisture content and increasing the dryness, thus significantly increasing the fire risk level. This mechanism is an important driving factor for the continuous increase in the forest fire risk level in the Kunming area in recent years. The lower the relative humidity, the drier the air, and the higher the forest fire risk level. Low humidity directly reduces the moisture content of combustibles, enhances their flammability, affects the combustion conditions, and further indirectly changes the behavior characteristics of forest fires, such as the spread speed and intensity. Zhang Luxuan et al. [25] based on the daily meteorological data from 2010 to 2017 and the forest fire data of Zhejiang Province, concluded that the occurrence of forest fires is negatively correlated with daily precipitation and relative humidity, and positively correlated with the daily maximum temperature, wind speed, and the number of consecutive precipitation-free days under light drought or no drought conditions. The occurrence of forest fires is closely related to long-term drought weather. Drought dries out deep and heavy combustibles, causes vegetation to mature prematurely (withering at the top), lowers the water level of rivers, removes the natural firebreaks, and exposes organic matter, greatly increasing the amount of effective combustibles. It reduces the water content of decayed combustibles to the lowest level and increases the probability of flying fire ignition [26]. In China, the drought is most severe from January to March, and about two-thirds of the land is affected by drought on average every year [27], which is also the season with the most forest fires. Pausas et al. [28] studied the relationship between forest fires and temperature and precipitation in the eastern part of the Iberian Peninsula through regression tests and F-tests, and concluded that warm and dry summers will lead to an increase in the frequency of forest fires.

2.1.2. Topographic Factors

The occurrence, development, and spread of forest fires are closely related to topographic factors. Topographic features such as altitude, slope, and aspect can affect local climatic conditions and the distribution of combustibles, thereby influencing the behavior of fires. In high-latitude areas, the temperature is generally relatively low, and the humidity in the air is relatively high, so the possibility of a fire occurring is relatively small. In contrast, in low-latitude areas, the situation is just the opposite. In areas with lower terrain, the temperature is high, there is a large amount of vegetation, and it is dry, making forest fires more likely to occur[29]. Moreover, in low-latitude regions, there is more human activity, increasing the possibility of human-introduced fires. The slope has a particularly significant impact on the spread speed of a fire. The steeper the slope, the faster the fire spreads upward, because the thermal radiation and convection of the flames are more likely to propagate upward on a sloped terrain [30]. In addition, in steep-slope areas, it is difficult to extinguish forest fires, as firefighters and equipment are not easily accessible, increasing the difficulty of fire suppression. The aspect affects the degree of vegetation drought by influencing the absorption of solar radiation. The sunny slope (southern slope) is characterized by strong sunlight, high temperature, large evaporation, less plant moisture, and a higher likelihood of spontaneous combustion, and the fire spreads rapidly after ignition. On the shady slope (northern slope), due to the high moisture content of the vegetation, the likelihood of a fire is relatively small, and the fire spreads at a relatively slow rate. In addition, the aspect can also affect the wind direction, which in turn affects the spread direction of the fire. For example, when the south wind is blowing, a fire on the sunny slope is more likely to spread to the shady slope. Holden et al. [31] concluded that due to receiving more solar radiation, the vegetation on the sunny slope is usually drier, and the fire risk is higher. Fang et al. [32] took the forests in the Daxing'anling region as an example and used an improved regression tree model to analyze the occurrence of forest fires. The results showed that factors such as forest vegetation and terrain have a significant impact on the intensity of forest fires. Jia Xu et al. [33] used MODIS remote sensing data to study the spatial distribution of fires in Inner Mongolia and found that the spatial distribution of fires is affected by topographic factors and exhibits an obvious topographic gradient. As the altitude increases, the number of fire spots gradually increases and then gradually decreases, while as the terrain elevation increases, the number of fire spots shows a gradually decreasing trend.

2.2. Disaster-bearing Body

For a long time, the research on predicting the risk level of forest fires has mainly focused on the analysis of meteorological factors, including key indicators such as temperature, relative humidity, precipitation, and wind speed. Some scholars have further proposed incorporating the phenomenon of terrestrial gas emissions (such as soil gas release) as supplementary evaluation parameters into the fire risk assessment system. However, the existing methods generally have the following limitations: (1) The linear analysis framework is dominated by single causal factors; (2) There is insufficient quantification of the nonlinear coupling effects among factors in the comprehensive evaluation of multiple factors; (3) There is a lack of consideration for spatiotemporal heterogeneity in the dynamic evolution of the disaster-prone environment during the incubation period. This paper conducts an analysis from another perspective, that is, from the aspect of combustibles of the disaster-bearing body. It approaches the issue from two aspects, namely forest stand factors and human factors, to evaluate the forest fire risk in China. Thus, it summarizes the current situation of the disaster-bearing bodies of forest fires in China, providing a reference for forest fire risk early warning and management.

2.2.1. Forest Stand Factors

The influence of forest stand factors on forest fires is manifested in many aspects. Below, the analysis will focus on vegetation characteristics. Pausas et al. [34] compared the combustion characteristics of coniferous forests and broad-leaved forests and found that litter is prone to accumulate in coniferous forests, and the needles are rich in oil, making coniferous forests more flammable than broad-leaved forests. Forest combustibles are a key factor triggering forest fires. Burton [35] et al. analyzed the land cover types after forest fires in the boreal ecological region of Alaska, Canada, and clarified the vegetation characteristics of forest fires. Qin Naihua et al. [36] analyzed the combustibility of surface combustibles in different forest stands in Shandong Province and concluded that the combustibility of Chinese pine forests is the strongest, while that of poplar forests is the weakest. In the same type of forest stand, the ignition point of litter is lower than that of humus. The introduction of the Normalized Difference Vegetation Index (NDVI) has alleviated the complex work of field sampling and calculation required for determining the forest combustible load. Zhou Yufei et al. [37] analyzed and concluded that there is a linear correlation between NDVI and the forest surface combustible load, and NDVI can indirectly represent the forest surface combustible load. Currently, NDVI has been proposed multiple times in the research on influencing factors of forest fires [38-40].

2.2.2. Human Factors Human factors

are one of the factors contributing to the occurrence of forest fires. Among them, human-induced fires are the direct cause of forest fires. Additionally, activities such as deforestation for farming, the cultivation of economic forests, and tourism development also indirectly affect forest fires. With population growth and economic development, human utilization of and interference with forest resources have been continuously increasing, leading to a significant rise in fire risks [41]. Zhang Yuhong [42] classified forest fires into three types according to the causes of occurrence: human-induced fires, lightning-induced fires, and fires of unknown origin. Through a long-term sequential analysis with a statistical unit of three years, it was found that from 1971 to 2000, human-induced fires and fires of unknown origin occurred frequently in densely populated areas in Heilongjiang Province, reflecting the close relationship between the occurrence of forest fires and human activities. Activities such as agricultural reclamation, forestry logging, and infrastructure construction can change the structure and composition of forests, increase the accumulation of combustibles, and may also introduce fire sources. Balch et al. [43] studied forest fire data from 2002 to 2012 and found that agricultural burning and outdoor fires were the main causes of forest fires in the United States. In addition, changes in land use during the urbanization process can also affect the occurrence and spread of fires. The "forest-urban interface" at the junction between cities and forests has particularly prominent fire risks due to frequent human activities [44]. Therefore, strengthening the management and regulation of human activities and improving public awareness of fire prevention can reduce the occurrence of forest fires [45].

2.3. Disaster-causing Factors

The occurrence of forest fires is the result of the combined action of multiple disaster-causing factors. Due to the unique geographical environment and climatic characteristics, the fire risks in different local areas exhibit significant spatio-temporal heterogeneity. This paper systematically analyzes the main disaster-causing factors of forest fires from two dimensions: fire sources and fire frequencies, aiming to provide a theoretical basis for regional fire risk early warning and prevention and control. Disaster-causing factors interact with fire sources and fire frequencies. An in-depth analysis of the relationship among them is helpful for optimizing fire source control strategies and reducing fire risks. The occurrence frequency of forest fires in various regions is highly correlated with human-induced fire sources, especially those related to agricultural and forestry production and daily life. Through the classified control of fire sources and precise spatio-temporal intervention, the fire risk can be effectively reduced. In the future, it is necessary to combine remote sensing and big data technologies to construct a dynamic fire source monitoring network, achieving an intelligent upgrade of fire prevention and control.

2.3.1. Fire Sources

Forest underground fires mostly occur in situations of long-term drought or no rainfall, with long sunshine hours, large evaporation, high temperature, and low humidity. According to the existing data, regardless of whether it is a coniferous forest, a broad-leaved forest, or a mixed coniferous and broad-leaved forest, wherever there are surface fires, there is a possibility of underground fires occurring[46]. In addition, in areas with thunderstorms, when trees are ignited by lightning, the flames will spread to the roots of the trees, which is a surface fire. In an environment with arid climate and a rising fire risk level, once a wild fire source appears, it will first ignite the flammable substances on the ground surface. When the wind speed is weak, the surface fire burns in a relatively stable state. However, once it encounters extremely flammable objects such as dry tussock grass mounds and exposed tree roots, the fire will break through the constraints of the ground surface and invade into the coarse humus layer. With the continuous roasting of high temperature, the flames penetrate into the ground continuously as if they have vitality. Eventually, forest underground fires are generated and continue to spread, posing a more hidden and lasting threat to the forest ecosystem. When the underground fire spreads to areas with a thinner humus layer or surface cracks, it may break out of the ground again and transform into a surface fire. If the fire spreads to a multi-layered uneven-aged forest, it may further develop into a crown fire. The large-scale carbon emissions caused by underground fires can transform the burned area from a "carbon sink" into a "carbon source", releasing a large amount of organic carbon and smoke. This not only impoverishes the soil but also causes regional smog phenomena, damaging the ecological environment [47]. Due to the incomplete combustion characteristics of smoldering, underground fires will produce more incomplete oxidation products and harmful macromolecules such as PM2.5, carbon monoxide, and polycyclic aromatic hydrocarbons [48]. The essence of underground fires is the combustion of organic matter in the soil. Continuous and slowly spreading underground fires will kill plant roots and seeds, causing a large area of forest trees to die and weakening the secondary succession ability of forest land after a fire [49].

2.3.2. Fire Frequency

The presence of natural disaster-causing factors and human-induced disaster-causing factors has contributed to the occurrence of fire frequency. Among them, natural disaster-causing factors are mainly classified into climatic factors, vegetation characteristics, and topographic factors. However, human-induced disaster-causing factors manifest in multiple aspects. The continuous increase in population density and frequent human economic activities have led to an increase in fire frequency. Coupled with management factors such as fire prevention policies, it has ultimately resulted in the occurrence of fires.

3. Coupling Methods for Forest Fires

3.1. Research Methods

3.1.1. N-K Coupling Model

The N-K model includes two parameters: N represents the number of factors that make up the system. If there are N factors in the system and each factor has n components, then there are n^N possible combinations [50]. K represents the number of interrelated relationships in the network. The maximum value of K is N - 1, and the minimum value is 0. If there are N risk factors in the system and each factor has n different states, then there are n^N possible combination methods for risk coupling. In forest fire prevention, the risk factors mainly include meteorological factors, vegetation factors, topographic factors, and human factors. The N-K coupling model is mainly used for risk assessment, early warning prediction, and prevention and control optimization, with an emphasis on the interaction between human activities and natural factors and the non-linear coupling relationship of multiple factors.

3.1.2. Entropy Weight Method

The entropy weight method objectively determines the weight of each evaluation index according to the information provided by these indexes. As the entropy weight used as the weight coefficient, by processing the data of each year with the entropy weight method, it can not only objectively reflect the importance of a certain index in the index system during decision-making, but also reflect the change situation of the index weight over time [51]. There are many indexes for forest fire risk assessment. In order to overcome the differences in the attributes and dimensions of each index, before weighting, the original data is first normalized by the range method. The entropy weight method is an objective evaluation method based on data weighting, which can determine the objective weight according to the magnitude of the variability of the indexes and depends on the samples [52-53]. The formulas are as follows:

For positive indexes:

$$\acute{X}_{ij} = \left[X_{ij} - \min\left(X_{ij}\right)\right] / \left\lfloor \max\left(X_{ij}\right) - \min\left(X_{ij}\right) \right\rfloor$$

For negative indexes:

$$\acute{X}_{ij} = \left\lfloor \max\left(X_{ij}\right) - X_{ij} \right\rfloor / \left\lfloor \max\left(X_{ij}\right) - \min\left(X_{ij}\right) \right\rfloor$$

Where: X ij is the normalised value of the ith project index on the jth unit index; X ij is the ith index (i=1, 2, n; j=1, 2, n; j=1, 2, n); where max (Xij) is the maximum value of the ith index; min (Xij) is the minimum value of the ith index. The entropy weighting method is an objective weighting method, and its basic idea is that the greater the change in the value of an index, the lower its information entropy, and the corresponding power is proportional to the amount of information the index can provide. On this basis, an entropy-weight-based forest fire risk assessment indicator system is proposed. Its calculation method [54] is as follows:

$$P_{ij} = \acute{X}_{ij} / \sum_{i=1}^{m} \acute{X}_{ij}$$

$$gi = 1 - \left[-k \sum_{i=1}^{m} p_{ij} \ln p_{ij}\right]$$

$$\omega_i = \frac{g_i}{\sum_{j=1}^{m} g_i}$$

where: P ij is the weight of index i on index i; g i is the coefficient of variation of index i; ω i is the weight of index i; and m is the number of areas to be assessed.

3.1.3. Forest Cellular Automata

Cellular automata are essentially dynamic systems that evolve in discrete time and spatial dimensions, where discrete units with finite states follow specific rules. In mathematical terms, it is determined by five elements: grid space, state variables, neighborhood type, state transition function, and initial state function. There are three classic types of neighborhoods in cellular automata: the Von Neumann neighborhood, the Moore neighborhood, and the extended Moore neighborhood. This model utilizes the Moore neighborhood, taking into account the eight cells surrounding the central cell. In this representation, the highlighted cell indicates the cell that is currently burning. The simulation area is discretized into a grid space, and the size of each cell is 30 m × 30 m.

3.2. Research Results and Prospects

3.2.1. Research Results

Forest fires are caused by the combined influence of multiple factors, mainly including topographic factors, climatic factors, and vegetation factors. The specific influences are as follows. High temperature, low humidity, and windy weather will significantly increase the probability of fire occurrence and the spreading speed. In high-altitude areas, the low temperature and low vegetation coverage result in a relatively low probability of fire occurrence. However, topographic conditions such as steep slopes and sunny slopes may accelerate the spread of the fire. Coniferous forests are more flammable than broad-leaved forests, and areas with high vegetation density and high combustible load have a higher fire risk. At the same time, the coupling relationship among multiple factors such as climate, terrain, and vegetation has the most significant comprehensive impact on the occurrence and development of forest fires. For example, under high-temperature and dry climatic conditions, coniferous forests on sunny slopes are more prone to fires, and due to the steep slopes, the fire spreads rapidly. Therefore, in response to this situation, a multi-factor coupling disaster-causing model should be established. Through means such as mathematical models or computer simulations, the interactions and synergistic effects among various factors should be quantitatively analyzed to improve the prediction accuracy of the probability of forest fire occurrence and the spreading trend.

3.2.2. Research Prospects

In the future, for forest fires in various regions, a dynamic coupling mechanism between climate change and fire risks should be established to improve accuracy and adaptability. More detailed meteorological, topographic, vegetation and other data from various regions should be collected, especially long-term and high-resolution data, in order to optimize model parameters and enhance the model's adaptability to the local complex geographical environment and climatic conditions, so as to more accurately simulate and predict the occurrence and development of forest fires. Factors that have not been fully considered before, such as soil moisture, the frequency of lightning activities, and the biodiversity of the forest ecosystem, should be incorporated into the model to more comprehensively reflect the disaster-causing mechanism of forest fires. In terms of technological applications, multi-source data should be integrated. By combining multi-source data such as satellite remote sensing, unmanned aerial vehicle monitoring, and ground sensor networks, more abundant and real-time information can be provided for the model, enabling all-round and dynamic monitoring and early warning of forest fires. Regarding fire prevention and suppression, precise prevention and control strategies should be formulated. Based on the research results of the model, precise forest fire prevention and suppression strategies should be developed for different regions and seasons in various areas, including the rational planning of firebreaks, the optimization of the deployment of firefighting forces, and the formulation of targeted fire source management measures. Risk assessment and zoning work should be carried out. Regular forest fire risk assessments should be conducted to divide high, medium, and low-risk areas, providing a scientific basis for land use planning, forest resource management, and residents' lives, and reducing the likelihood and severity of fire occurrences.

There are uncontrollable factors in forest fires in various regions, and the necessity of forest fire prevention should be emphasized. It is essential to vigorously promote the awareness of forest fire prevention and awaken people's understanding of the use of fire in forests and forest fire prevention. In terms of education, stronger collaboration with multiple disciplines should be carried out. In-depth cooperation should be conducted with disciplines such as meteorology, geography, ecology, and forestry to jointly study the complex mechanism of forest fires caused by the coupling of multiple factors, providing theoretical support and practical experience for model research from different perspectives. Under the firmly established concept that lucid waters and lush mountains are invaluable assets, forest fires can bring huge losses to society. In order to establish a relationship that can correctly handle the relationship between humans and nature, as well as development and security, and provide ecological security guarantees for the sustainable development of the economy and society and the construction of ecological civilization, the research results on the research progress of the mechanism of forest fires caused by the coupling of multiple factors can provide a theoretical basis for the prevention and suppression of local forest fires. This is conducive to the scientific and reasonable construction of a forest fire prevention and control system in the future, improving the management level of forest fires, and proposing major forest fire prevention and control measures.

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