

Wildfire Spread Risk Challenge

Subjects: Meteorology & Atmospheric Sciences

Contributor: Jingjing Sun, Wenwen Qi, Yuandong Huang, Chong Xu, Wentao Yang

Wildfires are sudden and destructive natural hazards that pose significant challenges in response and relief efforts. Wildfires occur annually across the globe, influenced by factors such as climate, combustible materials, and ignition sources. In recent years, researchers have shown increasing interest in studying wildfires, resulting in a large number of related studies. These studies cover a variety of topics including wildfire forecasting and forecasting, spatial and temporal pattern analysis, ecological impact assessment, simulation of wildfire behavior, identification of contributing factors, development of risk assessment models, management techniques for combustible materials, firefighting decision-making techniques, and fire protection. burning method. Understanding the factors that influence wildfire spread behavior, employing modeling methods, and conducting risk assessments are critical for effective wildfire prevention, mitigation, and emergency response.

Keywords: wildfire spread ; driving factors ; simulation ; risk assessment ; wildfire

1. Introduction

Wildfire is a common natural disaster, characterized by the uncontrolled spread and propagation of fire. These wildfires exhibit suddenness, high uncertainty, and significant hazards, resulting in the severe loss of forest resources and damage to natural ecosystems ^[1]. Notably, in 2020, Australia witnessed the largest recorded forest fire in history, lasting several months and scorching approximately 11.46 million hectares of forest, causing irreparable ecological damage ^{[2][3]}. Similarly, in 2019, Muli County, Liangshan Prefecture, Sichuan Province, experienced a forest fire that rapidly spread due to sudden changes in wind direction and intensity, resulting in the tragic loss of 31 lives ^[4]. In another incident in 2020, a forest fire occurred at the junction of Jingjiu Township and Anha Town, Pijia Mountain Ridge, Xichang City, Liangshan Prefecture. During the rescue operation, 19 people lost their lives as the fire engulfed an area of 3047.78 hectares ^[5]. These frequent forest fire incidents not only cause substantial economic losses and ecological damage, but also result in severe human casualties. Analysis reveals that the fundamental reason behind these incidents is a lack of an understanding of forest fire spread behavior, leading to inadequate predictions of spread speed, intensity, and extent. Consequently, this has hindered the collection, feedback, and simulation of wildfire spread behavior information, allowing the fires to reach uncontrollable states. Therefore, it is crucial to comprehensively understand the various aspects of wildfire spread behavior, conduct in-depth research on the propagation process, collect and simulate fire behavior information, and assess the impact of environmental factors on fire spread behavior.

2. Wildfire Spread Behavior and Risk Assessment System

From **Figure 1**, it can be observed that the overall keywords related to forest fires/wildfires (referred to as “wildfires” collectively) are divided into four clusters. “Wildfires” are the most central and core term, located in the center of the network graph. In the red cluster on the left side, “severity”, “vegetation”, “fire regime”, and “diversity” are some of the typical keywords. In the literature, this cluster mainly represents research in the field of regional ecology, such as studies related to vegetation after wildfires ^{[6][7]}. In the yellow cluster below, “soil”, “rainfall”, “erosion”, and “organic-matter” are some representative keywords. The research direction of this cluster primarily focuses on the chemical changes in the environment (especially soil) after wildfires ^{[8][9][10]}. It also includes some concurrent disasters, such as rainfall and debris flows ^{[11][12]}. The blue cluster on the right side of the map includes representative keywords such as “impact”, “emission”, “smoke”, and “air pollution.” The research related to these keywords is mostly focused on the atmospheric environment field, such as studies on gas emissions and air pollution caused by fires ^{[13][14][15][16]}.

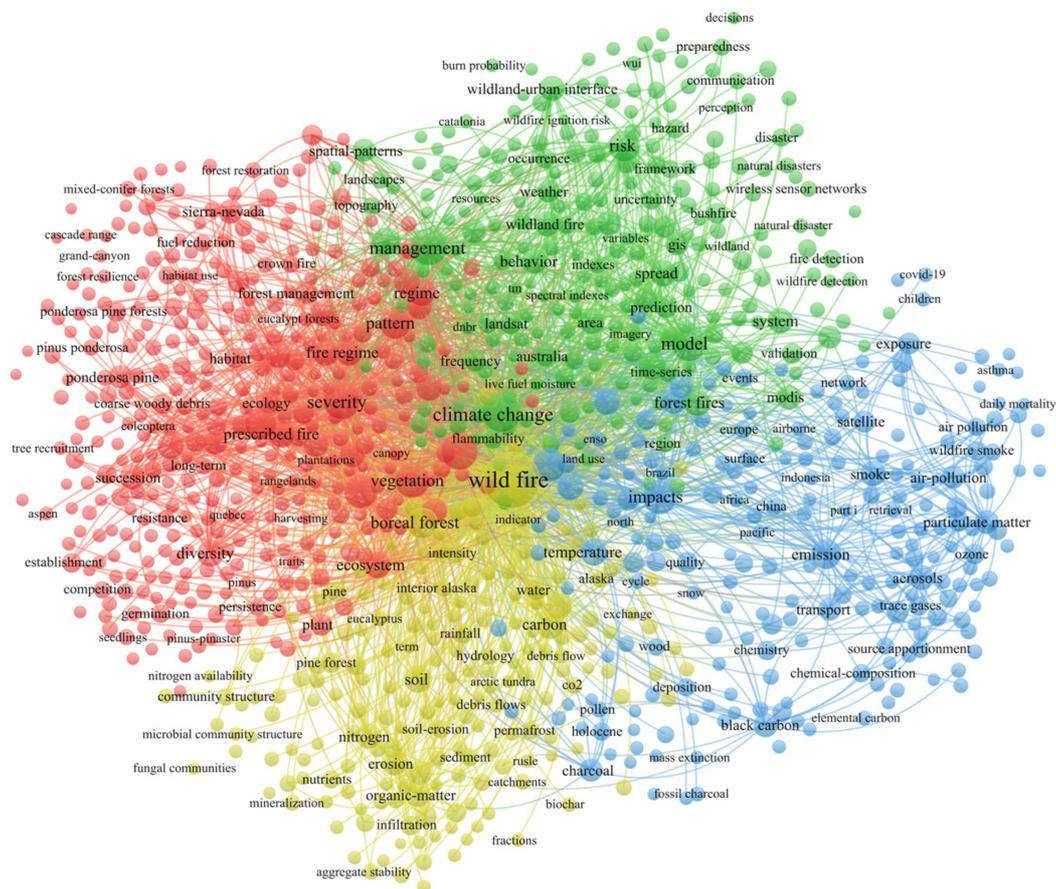


Figure 1. The co-occurrence graph of keywords.

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The green cluster in the upper-right part of the map includes representative keywords such as “spread”, “risk”, “model”, “behavior”, “climate change”, and “prediction.” The research content associated with these keywords focuses on the study of wildfire spread behavior and risk assessment [21][22][23]. Based on the above content, it is sufficient to demonstrate that the research on wildfire spread behavior and risk assessment is closely related and constitutes important aspects of wildfire research.

Wildfire spread is a highly complex combustion process that occurs as a result of multiple factors acting together [24]. Although wildfires exhibit certain patterns, they also display nonlinear and complex characteristics [25]. The driving factors of wildfire spread are generally classified into four categories: meteorological, fuel, topographical, and human factors. These factors collectively influence the behavior of wildfire spread [26].

2.1. Meteorological Factors

In recent years, many forest ecosystems have undergone changes due to the influence of global climate warming [27]. As a result, the occurrence of wildfires has been influenced, with climate change contributing to an increase in both the frequency and intensity of wildfires [28]. Among the meteorological factors, wind speed and wind direction play crucial roles in influencing the spread of wildfires. Wind speed significantly affects the duration of a fire, influencing its spread rate and coverage. Under the combined influence of wind speed and wind direction, the efficiency of heat transfer and the real-time rate of fire spread are directly impacted [29]. Wind accelerates the spread of wildfires through several pathways: (1) Wind can accelerate the drying of fuel, providing sufficient oxygen and dry fuel within the burning area, which serves as the medium for the occurrence of wildfires and accelerates their spread. (2) Unburned fuel within the forest can be ignited

more rapidly under the influence of wind, leading to an accelerated spread of wildfires to surrounding areas. Due to its carrying capacity, wind can transport embers generated during the forest burning process to other unburned areas, resulting in new ignition points at the periphery of the fire, this phenomenon is known as spotting. Spotting makes it easier for the wildfire to rapidly expand its range of spread [30][47]. (3) Altering the spatial distribution pattern of fuel can greatly affect the rate of wildfire spread. For example, increasing fuel density or changing the orientation of flammable materials can have a significant impact on the spread rate of wildfires [31].

2.2. Combustible Factors

Fuel is the material basis for the occurrence and combustion of wildfires [32]. Macroscopically, fuels can be classified into live fuels and dead fuels based on their vitality [33]. Here, live fuels refer to vegetation. As of September 2022, according to the resource inventory data released by the National Forestry and Grassland Administration, China's forest coverage rate has reached 24.02%, with a forest area of 331 million hectares. China's grassland area is 392.8 million hectares, accounting for 40.90% of the total land area. Due to variations in geographical locations, vegetation exhibits variations in coverage, area, density, structure, and chemical composition. Consequently, different vegetation types have varying ignition points and burning rates to some extent [34][35]. Research has shown that the occurrence of wildfires follows certain patterns, adhering to typical time patterns determined by environmental conditions and vegetation phenology cycles. The time span can vary from one day to one year [36]. Dead fuel primarily refers to litter or dead vegetation material [37]. Surface litter, with its low density, is the most effective fuel during wildfire combustion. Its impact on fire occurrence is primarily due to the larger gaps between materials, which provide ample oxygen storage as a crucial combustion medium.

2.3. Topography Factors

Basic topographic factors that affect wildfire spread include elevation, slope, and aspect. All three factors are considered static variables [38]. The impact of topography on wildfire spread rate can be observed in the following aspects: (1) Elevation is an important factor influencing wildfire spread. Different ecological conditions exist at different elevations. Higher elevations are associated with lower temperatures, lower humidity, higher relative humidity, and higher plant moisture content, which reduces the likelihood of ignition. In contrast, lower elevations have lower plant moisture content and are more susceptible to burning [39][40]. (2) The impact of slope on wildfires is manifested in its effect on the moisture content of combustible materials. Different slopes have varying durations of rainfall retention, which in turn affects the moisture content of combustible materials. Steeper slopes allow less time for rainfall to stay on the slope, resulting in a quicker drying of combustible materials under the combined influence of temperature and wind after rainfall. This increases the likelihood of fire occurrence. On the other hand, gentle slopes retain a higher percentage of rainfall, which increases the moisture content in combustible materials and reduces the probability and potential for wildfires. Additionally, changes in slope alter the spatial relationship between the burning surface of the wildfire and unburned combustible materials, thereby influencing the spread rate of the wildfire. Generally, uphill and steep slopes exhibit faster spread rates, while downhill and gentle slopes exhibit slower spread rates, although the impact is relatively weaker [41][42]. (3) The impact of aspect on the spread rate of wildfires refers to the influence of solar exposure. Sun-facing slopes (southern or western aspects in the Northern Hemisphere) receive stronger solar radiation, resulting in lower humidity and relatively dry microclimatic conditions.

2.4. Human Factors

The majority of wildfires currently occurring are caused by human factors [43]. Human factors have both positive and negative impacts on wildfires. On one hand, population density directly influences the occurrence of wildfires. Human activities frequently occur in wildland areas, increasing the likelihood of intentional or accidental ignition sources and, consequently, elevating the risk of wildfire spread. High population density in wildland areas increases the likelihood of such ignition sources [44]. According to data from the National Bureau of Statistics of China, there was a decrease in the number of wildfires from 8859 in 2009 to 2034 in 2016. One of the reasons for this decline is the implementation of the "Forest Fire Prevention Regulations" in 2009, which essentially prohibited outdoor fires [45].

3. Wildfire Spread Behavior Simulation Application

3.1. Simulation Application Based on Huygens' Principle

Huygens' principle [46] on the process of wildfire spread is illustrated in **Figure 2**. Wildfire spread behavior is a complex process involving the interaction of multiple factors. Around the fire scene, each control point is considered as an independent ignition point influenced by external factors such as wind direction, wind speed, and terrain. These factors

affect the rate and direction of fire propagation, thereby determining the spread boundary of the fire scene. Typically, the spread boundary of a fire scene presents an elliptical shape, forming an elliptical fire perimeter.

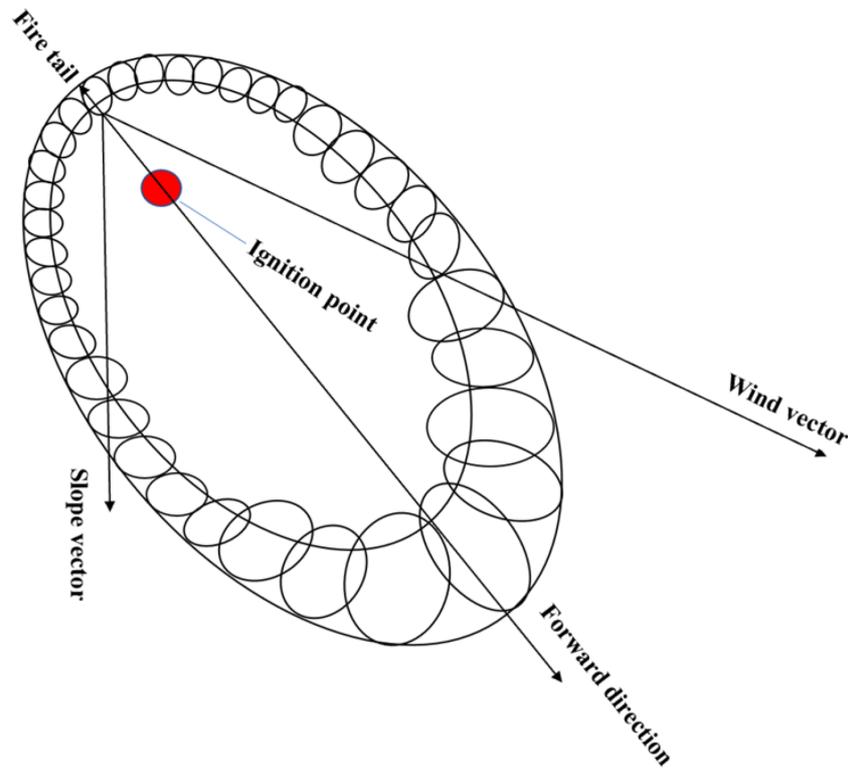


Figure 2. Huygens' principle.

3.1.1. Prometheus

Prometheus was developed in 1999 as a deterministic wildfire growth simulation application. This application integrates the science of wildfires, computer technology, and mathematics. Based on daily meteorological data, it employs computer simulation to model the behavior of wildfire spread. The development of this software is built upon the foundation of the Canadian Wildland Fire Growth System (FBP) ^[47], which is a simulation software developed based on a typical empirical modeling approach. Prometheus's spatial input data includes slope, aspect, fuel type, weather conditions, etc. Based on the Huygens principle, it uses the Richards wave propagation model to treat the fire perimeter as a collection of independent elliptical fires ^[48].

3.1.2. FARSITE

The FARSITE application was developed at the Missoula Fire Sciences Laboratory of the United States Forest Service (US-FS). It is a two-dimensional vector simulation system that integrates thermal physics, combustion science, and experimental theory ^[49]. FARSITE can simulate the spread of various types of fires, such as surface fires, crown fires, and spotting fires, under different environmental conditions. The simulation results closely resemble the actual fire behavior in the field, making it widely used worldwide ^[50]. FARSITE requires support from GIS (Geographic Information System) and RS (Remote Sensing) for spatial input data. The basic data needed for wildfire spread simulation using FARSITE includes landscape element data, weather data, wind field data, and fuel moisture data. Numerous studies have been conducted both domestically and internationally using FARSITE for wildfire spread research.

3.1.3. FlamMap

FlamMap is a landscape-level application simulation program that integrates fire behavior modeling, fuel management, and map visualization. It is capable of simulating potential fire behavior characteristics, such as spread rate, flame length, and fire intensity. Additionally, it can simulate fire growth and spread, as well as conditional burning probability, under constant environmental conditions such as weather and fuel moisture. FlamMap combines various aspects of fire analysis, allowing for a comprehensive assessment and prediction of fire behavior in a given landscape ^[51]. Burning probabilities and fire sizes in FlamMap are calculated using the Minimum Travel Time fire growth algorithm (MTT), which was developed by Finney ^[52] and has been widely used in spatial fire behavior modeling studies worldwide ^{[53][54]}.

3.2. Cellular Automata-Based Simulation Modeling

Cellular Automaton (CA) is a dynamic system that can simulate spatial and temporal characteristics. In the process of fire spread, fuel and terrain conditions are assumed to be uniform within each cell, and fire propagates on a grid-based on each cell. CA is a grid-based dynamic model that follows certain causal relationships [55]. CA is easily integrated with digital data from Geographic Information Systems (GIS) or other sources to generate applications for specific environments. Table 2 provides specific information on applications based on the CA framework. Sullivan and Knight et al. [56] developed a hybrid two-dimensional meta-automata model system with convective-wind interactions, which spread application is based on a meta-automata spread approach and a semi-physical model of thermal convection to simulate wildfire spread boundaries during wildfire occurrence. The application used in Mutthulakshmi's study [57] was based on the CA framework, which was improved and optimized to simulate wildfire spread, analyzing the factors that influence fire spread and determining which factors play a key role in the spread of wildfires Rui [58] constructed an improved model system that couples a meta-cellular automaton with an existing wildfire model. The system considered the effect of time step on simulation accuracy to provide optimal time step values with high temporal and spatial consistency. Xu [59] proposed a new fire spread modeling approach, LSSVM-CA, which combines the least squares support vector machine (LSSVM) with a three-dimensional wildfire CA framework and considers the effect of adjacent winds on fire spread patterns for analysis. To summarize the cases, the combination of wildfire spread visualization and the application system developed by meta-automata has become a popular and viable choice in simulating wildfire spread behavior.

4. Wildfire behavior risk assessment

4.1. Overview of Wildfire Risk Assessment

The wildfire risk assessment method based on wildfire prediction has high accuracy and is greatly affected by weather forecast factors. They are suitable for medium size ranges. On the other hand, the method of establishing a risk index for wildfire risk assessment takes into account a variety of factors and is more suitable for macro-level applications. Methods based on information diffusion theory are more suitable for analyzing small samples due to their inherent characteristics. In recent years, with the rapid development of scientific and technological capabilities, comprehensive wildfire risk assessment using "3S" technology and wildfire risk assessment based on deep learning have been widely used. However, they require strict data accuracy. The accuracy of wildfire risk assessment method and wildfire spread behavior simulation based on wildfire behavior influencing factors is high.

4.2. Wildfire Risk Assessment Based on Wildfire Spread Behavior

4.2.1. Wildfire Risk Assessment Based on Influencing Factors

From the preceding discussion it is evident that wildfire risk assessments are designed to take into account various factors including weather, topography, fuel and human factors. Predicting and assessing the main drivers of wildfire spread provides a scientific basis for dynamic fire management and prevention. An in-depth study of fire drivers provides insight into the potential paths, speed and intensity of fire spread. This awareness enables resource allocation, firefighting strategies, early warning systems, and emergency evacuation measures to minimize potential hazards to individuals, property, and the environment, and to protect the ecological environment and human safety.

4.2.2. Behavior-Based Simulation for Wildfire Risk Assessment

Wildfire risk assessment based on historical fire ignition data combined with fire spread influencing factors or fire spread models is a highly accurate and precise method. By simulating wildfire spread behavior, it is possible to predict the speed, direction, and extent of fire propagation, thus quantitatively assessing the level of wildfire risk. Carmel et al. [60] created a distribution map of wildfires in Mount Carmel, Israel, covering 20 years of historical fire data. They generated Monte Carlo simulations for fire spread based on these data and used FARSITE software (FlamMap includes FARSITE, currently does not support separate download) to simulate fire spread for 500 fire points. This approach provided a long-term strategic plan for fire prevention activities in the area.

References

1. Arif, M.; Alghamdi, K.; Sahel, S.; Alosaimi, S.; Alsahaft, M.; Alharthi, M.; Arif, M. Role of machine learning algorithms in forest fire management: A literature review. *J. Rob. Autom.* 2021, 5, 212–226.
2. Boer, M.M.; Resco de Dios, V.; Bradstock, R.A. Unprecedented burn area of Australian mega forest fires. *Nat. Clim. Chang.* 2020, 10, 171–172.

3. Finney, M.A. The challenge of quantitative risk analysis for wildland fire. *For. Ecol. Manag.* 2005, 211, 97–108.
4. Du, J.; Wang, K.; Cui, B. Attribution of the extreme drought-related risk of wildfires in spring 2019 over southwest China. *Bull. Am. Meteorol. Soc.* 2021, 102, S83–S90.
5. Feng, H. Exploration and thinking on related mechanisms of forest fire prevention. In *Proceedings of the 2021 International Conference on Social Science: Public Administration, Law and International Relations (SSPALIR 2021)*, Moscow, Russia, 16–17 June 2021; pp. 13–18.
6. Tian, X.; Dai, X.; Wang, M.; Zhao, F.; Shu, L. Forest fire risk assessment for China under different climate scenarios. *Chin. J. Appl. Ecol.* 2016, 27, 769–776.
7. Halofsky, J.E.; Peterson, D.L.; Harvey, B.J. Changing wildfire, changing forests: The effects of climate change on fire regimes and vegetation in the Pacific northwest, USA. *Fire Ecol.* 2020, 16, 4.
8. De la Rosa, J.M.; Faria, S.R.; Varela, M.E.; Knicker, H.; González-Vila, F.J.; González-Pérez, J.A.; Keizer, J. Characterization of wildfire effects on soil organic matter using analytical pyrolysis. *Geoderma* 2012, 191, 24–30.
9. Moody, J.A.; Martin, D.A.; Cannon, S.H. Post-wildfire erosion response in two geologic terrains in the western USA. *Geomorphology* 2008, 95, 103–118.
10. Shakesby, R. Post-wildfire soil erosion in the Mediterranean: Review and future research directions. *Earth-Sci. Rev.* 2011, 105, 71–100.
11. Hoch, O.J.; McGuire, L.A.; Youberg, A.M.; Rengers, F.K. Hydrogeomorphic recovery and temporal changes in rainfall thresholds for debris flows following wildfire. *J. Geophys. Res. Earth Surf.* 2021, 126, e2021JF006374.
12. Touma, D.; Stevenson, S.; Swain, D.L.; Singh, D.; Kalashnikov, D.A.; Huang, X. Climate change increases risk of extreme rainfall following wildfire in the western United States. *Sci. Adv.* 2022, 8, eabm0320.
13. Hu, Y.; Zhan, J.; Zhou, G.; Chen, A.; Cai, W.; Guo, K.; Hu, Y.; Li, L. Fast forest fire smoke detection using MVMNet. *Knowl.-Based Syst.* 2022, 241, 108219.
14. Knorr, W.; Dentener, F.; Lamarque, J.-F.; Jiang, L.; Arnoeth, A. Wildfire air pollution hazard during the 21st century. *Atmos. Chem. Phys.* 2017, 17, 9223–9236.
15. Urbanski, S. Wildland fire emissions, carbon, and climate: Emission factors. *For. Ecol. Manag.* 2014, 317, 51–60.
16. Zhan, J.; Hu, Y.; Zhou, G.; Wang, Y.; Cai, W.; Li, L. A high-precision forest fire smoke detection approach based on ARGNet. *Comput. Electron. Agric.* 2022, 196, 106874.
17. Van Leeuwen, W.J.; Casady, G.M.; Neary, D.G.; Bautista, S.; Alloza, J.A.; Carmel, Y.; Wittenberg, L.; Malkinson, D.; Orr, B.J. Monitoring post-wildfire vegetation response with remotely sensed time-series data in Spain, USA and Israel. *Int. J. Wildland Fire* 2010, 19, 75–93.
18. Moody, J.A.; Martin, D.A.; Cannon, S.H. Post-wildfire erosion response in two geologic terrains in the western USA. *Geomorphology* 2008, 95, 103–118.
19. Knorr, W.; Dentener, F.; Lamarque, J.-F.; Jiang, L.; Arnoeth, A. Wildfire air pollution hazard during the 21st century. *Atmos. Chem. Phys.* 2017, 17, 9223–9236.
20. Zhan, J.; Hu, Y.; Zhou, G.; Wang, Y.; Cai, W.; Li, L. A high-precision forest fire smoke detection approach based on ARGNet. *Comput. Electron. Agric.* 2022, 196, 106874.
21. Banerjee, T.; Heilman, W.; Goodrick, S.; Hiers, J.K.; Linn, R. Effects of canopy midstory management and fuel moisture on wildfire behavior. *Sci. Rep.* 2020, 10, 17312.
22. Radeloff, V.C.; Helmers, D.P.; Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Bar-Massada, A.; Butsic, V.; Hawbaker, T.J.; Martinuzzi, S.; Syphard, A.D. Rapid growth of the US wildland-urban interface raises wildfire risk. *Proc. Natl. Acad. Sci. USA* 2018, 115, 3314–3319.
23. Radke, D.; Hessler, A.; Ellsworth, D. FireCast: Leveraging deep learning to predict wildfire spread. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, Macao, China, 10–16 August 2019; pp. 4575–4581.
24. Pausas, J.G.; Keeley, J.E. Wildfires and global change. *Front. Ecol. Environ.* 2021, 19, 387–395.
25. Zhang, G.; Wang, M.; Liu, K. Forest fire susceptibility modeling using a convolutional neural network for Yunnan province of China. *Int. J. Disaster Risk Sci.* 2019, 10, 386–403.
26. Guo, F.; Wang, G.; Su, Z.; Liang, H.; Wang, W.; Lin, F.; Liu, A. What drives forest fire in Fujian, China? Evidence from logistic regression and Random Forests. *Int. J. Wildland Fire* 2016, 25, 505–519.
27. Hurteau, M.D.; Bradford, J.B.; Fulé, P.Z.; Taylor, A.H.; Martin, K.L. Climate change, fire management, and ecological services in the southwestern US. *For. Ecol. Manag.* 2014, 327, 280–289.

28. Westerling, A.L.; Hidalgo, H.G.; Cayan, D.R.; Swetnam, T.W. Warming and earlier spring increase western US forest wildfire activity. *Science* 2006, 313, 940–943.
29. Tariq, A.; Shu, H.; Siddiqui, S.; Mousa, B.; Munir, I.; Nasri, A.; Waqas, H.; Lu, L.; Baqa, M.F. Forest fire monitoring using spatial-statistical and Geo-spatial analysis of factors determining forest fire in Margalla Hills, Islamabad, Pakistan. *Geomat. Nat. Hazards Risk* 2021, 12, 1212–1233.
30. Ruan, J.; Li, J. Research progress on two-way fire-wind coupling simulation in forest fire spread. *Mod. C.* 2021, 37–42.
31. Keeley, J.E. Fire intensity, fire severity and burn severity: A brief review and suggested usage. *Int. J. Wildland Fire* 2009, 18, 116–126.
32. Chen, M.; Du, J.; Wang, W.; Yu, H.; Wang, B.; Gu, Z.; Liu, X. Characteristics and potential fire behavior of combustibles in the canopy of *Pinus tabuliformis* forest in Badaling Forest Farm of Beijing. *J. Beijing For. Univ.* 2022, 44, 55–64.
33. Deeming, J.E.; Brown, J.K. Fuel models in the national fire-danger rating system. *J. For.* 1975, 73, 347–350.
34. Hoffman, C.; Canfield, J.; Linn, R.; Mell, W.; Sieg, C.; Pimont, F.; Ziegler, J. Evaluating crown fire rate of spread predictions from physics-based models. *Fire Technol.* 2016, 52, 221–237.
35. Wu, Z.; Wang, B.; Li, M.; Tian, Y.; Quan, Y.; Liu, J. Simulation of forest fire spread based on artificial intelligence. *Ecol. Indic.* 2022, 136, 108653.
36. Ganteaume, A.; Camia, A.; Jappiot, M.; San-Miguel-Ayanz, J.; Long-Fournel, M.; Lampin, C. A review of the main driving factors of forest fire ignition over Europe. *Environ. Manag.* 2013, 51, 651–662.
37. Xu, W.; Wu, C.; Yang, L.; Xu, S.; Qing, M.; Wang, Q. Comparative study on surface litter load and fire intensity of *Pinus armandii* and *Pinus yunnanensis* in northeastern Yunnan Province. *J. Southwest For. Coll.* 2019, 39, 151–156.
38. Zhou, F.; Pan, H.; Gao, Z.; Huang, X.; Qian, G.; Zhu, Y.; Xiao, F. Fire prediction based on catboost algorithm. *Math. Probl. Eng.* 2021, 2021, 1929137. [Google Scholar] [CrossRef]
39. Kannan, M.; Saranathan, E.; Anbalagan, R. Comparative analysis in GIS-based landslide hazard zonation—A case study in Bodi-Bodimettu Ghat section, Theni District, Tamil Nadu, India. *Arab. J. Geosci.* 2015, 8, 691–699.
40. Li, W.; Xu, Q.; Yi, J.; Liu, J. Predictive model of spatial scale of forest fire driving factors: A case study of Yunnan Province, China. *Sci. Rep.* 2022, 12, 19029.
41. Dupuy, J.-L.; Maréchal, J.; Portier, D.; Valette, J.-C. The effects of slope and fuel bed width on laboratory fire behaviour. *Int. J. Wildland Fire* 2011, 20, 272–288.
42. Gralewicz, N.J.; Nelson, T.A.; Wulder, M.A. Factors influencing national scale wildfire susceptibility in Canada. *For. Ecol. Manag.* 2012, 265, 20–29.
43. Rodrigues, M.; Jiménez, A.; de la Riva, J. Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. *Nat. Hazards* 2016, 84, 2049–2070.
44. Pereira, M.; Malamud, B.; Trigo, R.; Alves, P. The history and characteristics of the 1980–2005 Portuguese rural fire database. *Nat. Hazards Earth Syst. Sci.* 2011, 11, 3343–3358.
45. Wang, M.; Xu, Y.; Zhao, M. Spatio-temporal distribution pattern and cause analysis of forest fires in my country in recent 10 years. *Bull. Agric. Sci. Technol.* 2021, 201–204.
46. Anderson, D.; Catchpole, E.; De Mestre, N.; Parkes, T. Modelling the spread of grass fires. *Anziam J.* 1982, 23, 451–466.
47. Lee, B.; Alexander, M.; Hawkes, B.; Lynham, T.; Stocks, B.; Englefield, P. Information systems in support of wildland fire management decision making in Canada. *Comput. Electron. Agric.* 2002, 37, 185–198.
48. Tymstra, C.; Bryce, R.; Wotton, B.; Taylor, S.; Armitage, O. Development and structure of Prometheus: The Canadian Wildland fire Growth Simulation Model. In *Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Information Report NOR-X-417*; Canadian Forest Service Publications: Edmonton, AB, Canada, 2010.
49. Finney, M.A. *FARSITE, Fire Area Simulator—Model Development and Evaluation*; US Department of Agriculture, Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 1998.
50. Finney, M.A.; Andrews, P.L. *FARSITE—A program for fire growth simulation*. *Fire Manage. Fire Manag. Notes* 1999, 59, 13–15.
51. Finney, M.A. An overview of FlamMap fire modeling capabilities. In *Fuels Management—How to Measure Success: Conference Proceedings*; USDA Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2006; p. 30.
52. Finney, M.A. Fire growth using minimum travel time methods. *Can. J. For. Res.* 2002, 32, 1420–1424.

53. Vilà-Villardell, L.; Keeton, W.S.; Thom, D.; Gyeltshen, C.; Tshering, K.; Gratzler, G. Climate change effects on wildfire hazards in the wildland-urban-interface–Blue pine forests of Bhutan. *For. Ecol. Manag.* 2020, 461, 117927.
54. Mitsopoulos, I.; Mallinis, G.; Zibtsev, S.; Yavuz, M.; Saglam, B.; Kucuk, O.; Bogomolov, V.; Borsuk, A.; Zaimis, G. An integrated approach for mapping fire suppression difficulty in three different ecosystems of eastern Europe. *J. Spat. Sci.* 2017, 62, 139–155.
55. Almeida, R.M.; Macau, E.E. Stochastic cellular automata model for wildland fire spread dynamics. In *Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2011; p. 012038.
56. Sullivan, A.; Knight, I. A hybrid cellular automata/semi-physical model of fire growth. In *Proceedings of the Engineering of Complex Computer Systems*, Florence, Italy, 14–16 April 2004; pp. 64–73.
57. Mutthulakshmi, K.; Wee, M.R.E.; Wong, Y.C.K.; Lai, J.W.; Koh, J.M.; Acharya, U.R.; Cheong, K.H. Simulating forest fire spread and fire-fighting using cellular automata. *Chin. J. Phys.* 2020, 65, 642–650.
58. Rui, X.; Hui, S.; Yu, X.; Zhang, G.; Wu, B. Forest fire spread simulation algorithm based on cellular automata. *Nat. Hazards* 2018, 91, 309–319.
59. Xu, Y.; Li, D.; Ma, H.; Lin, R.; Zhang, F. Modeling forest fire spread using machine learning-based cellular automata in a GIS environment. *Forest* 2022, 13, 1974.
60. Carmel, Y.; Paz, S.; Jahashan, F.; Shoshany, M. Assessing fire risk using Monte Carlo simulations of fire spread. *For. Ecol. Manag.* 2009, 257, 370–377.

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