Identifying Woodland Wildfires By applying a Method Combining Cell-Based Models and Machine Learning

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ABSTRACT

As an important natural hazard, forest fires ruin enormous tracts of forest every year, putting ecosystems, people, and property at risk. For optimal firefighting and risk mitigation, timely and precise fire spread prediction is essential. The two components of the Forest Fire Spread Habit Prediction (FFSBP) system—the Forest Fire Spread Process Prediction (FFSPP) model and the Forest Fire Spread Results Prediction (FFSRP) system—are shown in this paper. To predict the direction and rate of fire spread, the FFSPP model blends the Wang Zhengfei model with Cellular Automata. To anticipate the extent of the burned area, the FFSRP model use collective machine learning techniques. Verification of the "3.29 Forest Fire" instance in China and data from Portugal's Montesinho National Forest Park show better accuracy Validation with data from Portugal's Montesinho National Forest Park and the "3.29 Forest Fire" instance in China reveals more precise results over current models, notably for small to medium fires. It is plenty of potential to better forest fire management procedures with the provided norm.

Keywords: wildfire management, cellular automata, machine learning, fire spread simulation, forest fire prediction, including

I. INTRODUCTION

yearly, forest fires destroy millions of hectares globally, causing one of the most fatal natural disasters. They endanger infrastructure and people in along with severely impacting the ecosystem. Making accurate choices during wildfire events needs a knack to accurately forecast fire conduct, including its spread direction, pace, and total burned area. Modern prediction techniques vary in their accuracy and practical applicability due to the often rely on a lot of past data or rely on distinct factors. It suggests an extensive strategy that combines modern machine learning methods with Cellular Automata (CA) to address these issues. With the use of short-term data inputs, the model seeks to forecast both the dynamic process of fire spread and its final result in terms of burned area. By the aid of short-term data inputs, the model aims to foresee both the dynamic process of fire spread and the ultimate impact in terms of burned area. It improves accuracy in forecasting and offers helpful details for assessing risks and resource allocation in firefighting.

II. LITERATURE REVIEW

"Simulation Forest Fire Occurrence with Artificial Neural Networks in China," published J. Wu and M. Li, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, no. 9, pp. 8432-4043, in September 2021. Forest fires have devastating consequences on both the environment and human life. For forest fires to be reduced, knowing their occurrence is essential. The prediction of forest fires in China over longer time scales is currently the subject of fewer studies. This is because forest fires become hard to predict. The risk of forest fires is influenced by an array of factors. It is unclear from traditional assessments how each factor directly contributes to the occurrence of forest fires.[1]

"Geographically Weighted Logistic Regression for Human-Induced Forest Fire Prediction in Northern China," by Y. Guo, H. Zhang, and X. Chen, IEEE Access, vol. 9, pp. 122433–122446, 2021.A geographically weighted logistic regression (GWLR) model is presented in this piece to project the occurrence of blazes in forests fuelled by men in Northern China. Using historical fire data and environmental and human activity measures, the GWLR procedure was compared to global logistic models that took physical heterogeneity into account. According to the results, GWLR performs noticeably better to classical logistic regression models in terms of overall accuracy in forecasting, model fit, and decreased spatial autocorrelation of residuals. It emerged that key drivers varied internationally, including vegetation, terrain, weather, and distance from infrastructure. These regional changes are successfully captured by GWLR, yielding better and spatially confusing fire risk models.[2]

"Meteorological Influences on Wildfire Occurrence and Spread: A Data-Driven Approach," in H. Preisler and A. Westerling, Vol. 58, No. 4, pp. 2881–2891, IEEE Transactions on Geoscience and Remote Sensing, April of 2020. a data-driven model nr applied to historical fire and weather records, this study examines the effects of meteorological variables in wildfire ignition and spread. A variety of important meteorological variables on the occurrence and course of arson are evaluated, including temperature, relative humidity, wind speed, and drought indices. To investigate how these factors determine fire probability and spread patterns in multiple places and seasons, the authors use statistical and machine learning models.

Strong associations between antecedent drought (which are referred as the Palmer Drought Severity Index), high temperatures, low humidity, and an increase in the number and magnitude of flames are among the striking findings. The study additionally explores how combinations of these weather variables account for temporal and local variations in wildfire crisis. Findings imply that forecasting and management approaches for burns can be optimised by integrating those factors into models for forecasting.[3]

IEEE Access, vol. 10, pp. 108332–108344, "Integrating MODIS Data with Machine Learning for Forest Fire Risk Assessment in China," L. Xu and T. Zhao This study assesses the threat of brush fires across China employing machine learning methods, such as Support Vector Machine (SVM) and Random Forest (RF), with MODIS remote-sensing data (active fire hotspots, vegetation indices, and land cover). Anthropogenic, biophysical, climatic, and land use variables were all used in a prediction models. The RF model outperformed SVM (~89%) with an accuracy of over 94%. The models gave maps of national susceptibility, showing about 20% of China to be at very high risk, and they showed a rising trend in the rate of forest fires, especially since 2015.[4]

Regional Investigation of Forest Fire Triggers Using Remote Sensing and Socioeconomic Data, an IEEE Transaction on Intelligent Transportation Systems, vol. 23, no. 5, pp. 4471–4480, May 2022, J. Ma, R. Chen, and Q. Liu.This study uses economic indicators like population density and road proximity along with satellite-derived variables like vegetation health, land cover, and terrain to study the roots of regional forest fires in China. The authors assess geographic differences in driver value and pinpoint key factors influencing fire activity using statistical models and machine learning. Our results provide regional risk maps to help custom fire prevention by showing key connections between vegetation conditions, fire incidence, and human presence.[5]

Z. Li, S. Wang, and Y. Yang, "Quantitative Effects of Climate and Topography on Forest Fire Severity," IEEE JSTARS, vol. 13, pp. 2990–2998, Jul. 2020.This study quantifies how climatic variables (temperature, humidity) and terrain features (elevation, slope) influence forest fire severity in China. Using geospatial modeling and remote-sensing-derived fire severity metrics, the authors apply regression and machine learning techniques to determine variable contributions. Significant associations were found: higher temperatures, lower humidity, and steep slopes correlated strongly with increased fire severity. The findings support more precise fire risk modeling and adaptive management approaches.[6]

"Simulation of Forest Fire Spread Using Cellular Automat with Percolation-Based Rules," IEEE Access, vol. 8, pp. 150400–150412, 2020, by R. Aleixo, T. Silva,andM.Fernandes.
A cell automata (CA) model for predicting the spread of forest fires is given in this work. The model takes seriously regional variability of weather, topography, and fuel loads by including percolation theory. Accurate replica of spread dynamics under various conditions is proven by testing of simulation results against observed fire patterns The method was shown to be effective in predicting how forest fires could move over different climates.[7]

H. Rui, "Large-Scale Forest Fire Spread Modeling Using Geographic Cellular Automata," IEEE Trans. on Computational Social Systems, vol. 6, no. 4, pp. 798–808, Aug. 2019.This study introduces a geographic cellular automata model to simulate large-scale forest fire spread. The model integrates spatial data like elevation and vegetation, and uses dynamic weather inputs to govern spread probabilities.

Evaluations across extensive landscapes show that the model captures both ignition and propagation phases Sregional fire risk assessment and planning.[8]

S. Mahdizadeh and N. Navid, "Wildfire Spread Simulation Using Enhanced Cellular Automata with Spatio-Temporal Factors," IEEE Trans. on Systems, Man, and Cybernetics: Systems, vol. 52, no. 2, pp. 981–991, Feb. 2022.This paper proposes an enhanced cellular automaton model for wildfire spread simulation, enriched with spatio-temporal influences like daily wind patterns, fuel moisture changes, and human interventions. The model outperforms traditional CA in replicating fire front propagation, especially under dynamic environmental conditions. Validation using historical wildfire events indicates improved realism and predictive accuracy.[9] Q. Xu and J. Zhang, "Hybrid LSSVM and Cellular Automata Model for Wildfire Spread Prediction Considering Wind Effects," IEEE Access, vol. 8, pp. 219738–219747, 2020.

This study presents a hybrid model combining Least Squares Support Vector Machine (LSSVM) with cellular automata (CA) to predict wildfire spread, explicitly incorporating wind effects. The LSSVM estimates local spread probabilities based on environmental variables, while the CA propagates these probabilities over the landscape. Tested on real wildfire cases, the model shows higher accuracy than traditional methods, particularly under varied wind conditions.epidemiological rules, or hybridizing CA with machine learning (e.g., LSTM, SVM) have improved simulation fidelity. However, many existing approaches either neglect critical factors or rely heavily on long-term historical datasets, limiting their adaptability to rapidly changing fire conditions. This research aims to address these gaps by integrating multiple firedriving factors with short-term data in a hybrid CA and machine learning framework.[10]

III. EXISTING SYSTEM

Prior studies have explored various factors influencing forest fires, including human activity, meteorological conditions, topography, and vegetation. Models such as artificial neural networks, logistic regression, and geographically weighted regression have been employed to predict fire occurrence probability and patterns. Cellular Automata-based models simulate fire spread by considering spatial and temporal driving factors like wind, vegetation density, and elevation. Several hybrid methods combine CA with machine learning algorithms such as Long ShortTerm Memory (LSTM) networks or Support Vector Machines (SVM) to enhance prediction accuracy. However, these models often suffer from limitations such as insufficient integration of multiple critical fire-driving factors or reliance on extensive historical data, which reduces their effectiveness in real-time or shortterm predictions.

- Lack of exploration into advanced sampling techniques to improve model robustness and accuracy.

- Limited adoption of modern machine learning trends such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) for better prediction performance.
- Insufficient integration of comprehensive fire-driving factors into existing CA-based models.
- Dependence on long-term historical data, which may not reflect real-time fire behavior changes.

IV. PROPOSED SYSTEM

This work introduces the Forest Fire Spread Behavior Prediction (FFSBP) model, designed to predict both the fire spread dynamics and the final burned area. The model includes two core components: the Forest Fire Spread Process Prediction (FFSPP) and the Forest Fire Spread Results Prediction (FFSRP). The FFSPP model integrates the Wang Zhengfei model with

Cellular Automata to forecast the fire's direction and speed accurately. Concurrently, the FFSRP model employs ensemble learning algorithms to predict the total burned area based on input features. Validation of the FFSPP model was conducted using the "3.29" forest fire incident in Anning, China, while the FFSRP model was tested with wildfire data from Montesinho National Forest Park, Portugal. The results demonstrate enhanced accuracy and practical applicability across varying fire sizes.

METHODOLOGY

Cellular automata model simpulates the spatial and temporal spread of the forest fire.Predicting the burned area provides crucial data for resource planning and overall fire management. Additionally, the model's straightforward computational process and adaptability to diverse datasets facilitate its deployment and optimization in different geographical contexts.

System Architecture

Fig1. System Architecture

V. MODULE DESCRIPTION

1. **Module Name:** Data Collection **Purpose:** Gather wildfire-related data from historical records and real-time sensors. **Functionality:** Collect meteorological, topographical, vegetation, and fire event data for model input.
2. **Module Name:** Data Preprocessing **Purpose:** Clean and prepare raw data for analysis.

Functionality: Handle missing values, normalize features, and perform feature selection relevant to fire spread.

3. **Module Name:** Fire Spread Process Prediction (FFSPP)

Purpose: Predict direction and speed of fire spread.

Functionality: Utilize Cellular Automata integrated with the Wang Zhengfei model to simulate fire dynamics in discrete time and space.

4. **Module Name:** Burned Area Prediction (FFSRP)

Purpose: Forecast total burned area after fire event.

Functionality: Apply ensemble machine learning techniques (e.g., Random Forest, Gradient Boosting) using features from fire spread simulation and environmental data.

5. **Module Name:** Model Validation **Purpose:** Evaluate the prediction accuracy of the developed models. **Functionality:** Compare predicted results against actual wildfire case data from China and Portugal to compute error metrics.

6. **Module Name:** Visualization and Reporting **Purpose:** Provide visual outputs for predicted fire spread and burned areas.
Functionality: Generate maps and graphs to assist decision-makers and firefighters.

VI. RESULT

The proposed Forest Fire Spread Behavior Prediction (FFSBP) model exhibited strong predictive capabilities when evaluated using real-world wildfire data. Specifically, during the simulation of the "3.29" forest fire incident in Anning, China, the Forest Fire Spread Process Prediction (FFSPP) component estimated a burned area of approximately 286.81 hectares, with a relative error of 28.94%. This level of accuracy surpasses that of widely used fire behavior models such as Farsite and Prometheus. Furthermore, the Forest Fire Spread Results Prediction (FFSRP) component demonstrated high reliability in estimating burned areas for small to medium-scale fires, validating its effectiveness across varied fire scenarios. Overall, the model delivered improved accuracy in both the fire spread simulation and damage prediction tasks.

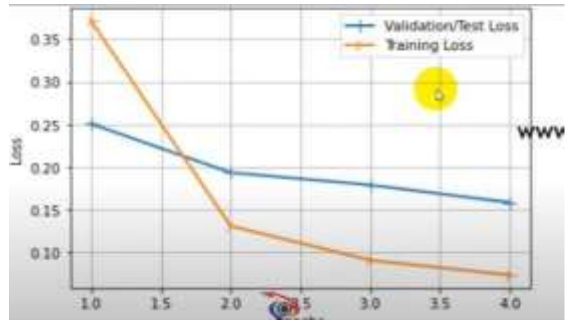

Fig2. Result Graph

VII. CONCLUSION

This research presents the FFSBP model as a comprehensive and efficient solution for predicting wildfire dynamics and impact. By integrating Cellular Automata with machine learning techniques, the model successfully forecasts both the spatial spread and the overall affected area of forest fires. Its adaptable framework allows for application across different datasets and environmental conditions. The results affirm the model's potential in supporting strategic firefighting decisions and resource planning. Future enhancements may involve the incorporation of real-time environmental sensor data and the exploration of advanced deep learning models to further refine predictive accuracy and real-time responsiveness.the speed and reliability of damage evaluations.

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