

Article

Wind Speed Prediction Based on AM-BiLSTM Improved by PSO-VMD for Forest Fire Spread

Haining Zhu [†], Shuwen Liu [†], Huimin Jia, Sanping Li, Liangkuan Zhu ^{*} and Xingdong Li ^{*†} 

College of Mechanical and Electrical Engineering, Northeast Forestry University, Harbin 150040, China; 2023111785@nefu.edu.cn (H.Z.); liusw@nefu.edu.cn (S.L.)

^{*} Correspondence: zhulk@nefu.edu.cn (L.Z.); lixd@nefu.edu.cn (X.L.)

[†] These authors contributed equally to this work.

Abstract

This study focuses on enhancing wind speed prediction for wildfire spread simulation by proposing an integrated forecasting approach. The original wind speed series is first processed via variational mode decomposition (VMD), with its parameters $[K, \alpha]$ optimized via particle swarm optimization (PSO). Every intrinsic mode function (IMF) resulting from this decomposition is predicted using a bidirectional long short-term memory model incorporating an attention mechanism (AM-BiLSTM), and the final wind series is reconstructed from these predictions. Model training and validation were conducted using data from controlled burning experiments in the Mao'er Mountain area of Heilongjiang Province, China. Predictive performance is evaluated through multiple statistical metrics, error distribution analysis, and Taylor diagrams. To assess practical utility, the predicted wind field is further applied in FARSITE to drive wildfire spread simulations. Results demonstrate that the PSO-VMD-AM-BiLSTM model provides reliable wind forecasts and contributes to improved fire spread prediction accuracy, indicating its potential for decision support in wildfire management. To achieve accurate forest fire spread prediction, we construct the MCNN model, which is based on early perception of understory wind fields using predicted wind speed data and adopts a multi-branch convolutional neural network architecture to extract fire spread features. FARSITE is employed to simulate forest fire spread in the Mao'er Mountain region, generating a dataset for model training and testing. After 50 training epochs, the loss value of the MCNN model converges, achieving optimal prediction performance when the combustion threshold is set to 0.7. Compared to models such as CNN, DCIGN, and DNN, MCNN shows improvements in evaluation metrics including precision, recall, Sørensen coefficient, and Kappa coefficient. To validate the model's predictive performance in real fire scenarios, four field ignition experiments were conducted at the Liutiao Village test site: homogeneous fuel combustion, long fire line combustion, alternating fuel combustion, and multiple ignition source merging combustion. Comprehensive evaluation across the four experiments indicates that the model achieves precision, recall, Sørensen coefficient, and Kappa coefficient values of 0.940, 0.965, 0.953, and 0.940, respectively, with stable prediction errors below 6%. These results represent improvements over the comparative models DCIGN and DNN. The proposed MCNN model can adapt to forest fire spread prediction under different scenarios, offering a novel approach for accurate forest fire prediction and prevention.



Academic Editor: Xiaolei Zhang

Received: 8 December 2025

Revised: 15 January 2026

Accepted: 31 January 2026

Published: 2 March 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article

distributed under the terms and

conditions of the [Creative Commons](#)

[Attribution \(CC BY\)](#) license.

Keywords: wind speed prediction; hybrid architecture; BiLSTM; forest fire

1. Introduction

Forest fires are among the most destructive natural disasters in forest ecosystems, causing severe damage to vegetation structure, ecological functions, and environmental sustainability [1,2]. Fire behavior is governed by complex interactions among fuel characteristics, terrain, and meteorological conditions, among which wind plays a dominant role [3,4]. In recent decades, rising global temperatures and increasingly frequent and prolonged droughts have significantly intensified wildfire occurrence and severity worldwide, resulting in extensive forest loss, greenhouse gas emissions, and ecosystem degradation [5,6]. Beyond direct impacts on vegetation, wildfires also affect water resources, air quality, and wildlife habitats [7,8]. Consequently, rapid and accurate prediction of wildfire spread is critical for effective firefighting decision-making and risk mitigation [9].

Wildfire spread modeling generally includes physical, empirical, and data-driven approaches [10,11]. Physical models, such as FIRESTAR, FIRETEC, and Phoenix, simulate fire propagation based on combustion physics and fluid dynamics [12–14]. Empirical models, such as the Rothermel model from the United States and the McArthur model from Australia, derive statistical relationships between fire behavior and key influencing factors using experimental and observational data [15,16]. With the rapid development of machine learning, data-driven models have also been increasingly applied to wildfire prediction. For example, deep convolutional and recurrent neural networks have demonstrated strong capabilities in modeling the spatiotemporal evolution of wildfire fronts [17,18]. However, many existing models rely heavily on real-time wind observations, which are often unavailable or unreliable in complex wildfire environments [19].

Wind serves as a key driver in the propagation of wildfires, directly determining the rate, direction, and spatial extent of fire propagation [20,21]. To address wind uncertainty, coupled fire–atmosphere models have been developed, enabling dynamic interactions between combustion processes and atmospheric flow fields. Representative coupled systems include ForeFire–MesoNH, WRF–SFIRE, and DEVS–FIRE–ARPS. Previous studies have demonstrated that such coupled models can capture important fire–atmosphere feedback mechanisms and improve prediction accuracy [22–26]. Despite their effectiveness, these approaches require parallel computation of atmospheric and wildfire spread processes, leading to high computational costs and limited applicability for real-time operational use. Therefore, efficient and accurate wind speed prediction methods with low computational overhead are essential for practical wildfire spread forecasting.

Wind speed prediction remains challenging due to its strong nonlinearity, randomness, and sensitivity to atmospheric pressure and temperature variations. Existing wind speed prediction methods can be broadly categorized into physical, statistical, and hybrid models [27]. Physics-based models depend on detailed meteorological and geographical descriptions and typically rely on numerical weather prediction data updated at coarse temporal resolutions [28], limiting their applicability in regions with limited observations or complex terrain. In contrast, statistical and data-driven methods, such as time series analysis, machine learning, and neural networks, offer greater flexibility and predictive capability [29–32]. Although many of these methods were originally developed for wind power forecasting, their ability to model nonstationary and highly volatile wind speed sequences demonstrates strong transferability to wildfire-related applications, where similar issues arise [33].

Recent studies have shown that hybrid approaches combining signal decomposition techniques and deep learning architectures can effectively improve wind speed prediction performance. For instance, Lin et al. integrated variational mode decomposition with attention-based LSTM networks for wind–fire coupling scenarios [33]. Li et al. proposed a wind speed prediction model combining particle swarm optimization, bidirectional LSTM, and variational mode decomposition, demonstrating robustness under extreme weather conditions [34]. Wumaier et al. developed an ultra-short-term wind speed prediction framework based on successive VMD and optimized LSTM networks [35]. These studies highlight a growing trend toward decomposition-assisted deep learning models for wind speed forecasting. However, existing approaches often suffer from high computational complexity or potential future information leakage, limiting their suitability for real-time wildfire applications [35,36].

These studies highlight the growing trend of combining decomposition algorithms with deep learning techniques in wind velocity forecasting, demonstrating the stability and practical effectiveness of such hybrid approaches. Based on the current research status, the innovative aspects and primary contributions of this paper are summarized as follows:

1. A hybrid wind speed prediction model is developed for complex forest fire scenarios, integrating variational mode decomposition (VMD) with long short-term memory-based architectures to capture the non-linear and highly fluctuating characteristics of wind.
2. A particle swarm optimization-based strategy is employed to adaptively determine VMD parameters, thereby enhancing the decomposition precision of wind speed time series for the prediction model.
3. Bi-directional LSTM and attention mechanisms are incorporated to effectively model temporal dependencies and highlight critical patterns in wind speed sequences.
4. Predicted wind speed sequences are integrated into forest fire spread modeling to demonstrate the practical utility of accurate wind prediction in guiding fire propagation forecasts.
5. Extensive evaluation shows that the proposed hybrid model outperforms existing physical, statistical, and machine learning methods, demonstrating its robustness and applicability in real-world scenarios.
6. The model's generalization is validated through four field burning experiments in Liutiao Village, covering uniform fuel combustion, long fire line combustion, alternating fuel combustion, and multi-source merging combustion, demonstrating its applicability across diverse fire scenarios, fuel types, and regions.

The rest of the paper is structured as follows. Section 2 describes the data sources and methods used in the article. Section 2.1 describes the data sources used to generate the datasets in this work. Section 2.2 describes the hybrid neural network architecture proposed in this article, including the PSO-VMD and the AM-BiLSTM. Section 2.3 presents the approach for forest fire spread prediction based on forecasted wind speed sequences. Section 2.4 describes the metrics used to measure model performance. Section 3 reports the model results, highlights its performance advantages compared with existing approaches, and demonstrates the importance of wind speed prediction for forest fire propagation. Section 4 discusses the results. Section 5 summarizes the findings of the research and outlines future work.

In the FARSITE simulation setup for the Mao'er Mountain region, we adopted a spatial resolution of $10\text{ m} \times 10\text{ m}$ to capture fine-scale fire dynamics. The fuel models were based on standard Rothermel fuel types (e.g., grass and shrub models adjusted for understory vegetation in Northeast China). Topography data was derived from a digital elevation model (DEM) with elevation variations up to 200 m, incorporating slope and aspect effects. Ignition conditions simulated a point-source fire start at coordinates (45.5° N , 127.5° E), with initial fire perimeter set to 50 m radius under dry weather scenarios. This configuration was used to generate a dataset of 500 simulated fire spread images for training and testing the model.

2. Materials and Methods

2.1. Data Source

The Mao'er Mountain region is located in Harbin City, Heilongjiang Province, at 45° N and 126° E . According to the Koppen and Geiger climate classification system, the area is a Dwb climate (humid continental) [36]. The winters are long and cold and the summers are rainy. Throughout the winter, snow accumulates on the ground, acting as a thermal barrier for the soil and restricting moisture infiltration into deeper layers. This results in dry and highly combustible surface conditions, which significantly elevate the risk of wildfire occurrence as temperatures rise in the spring and summer [37]. Therefore, the area was selected for the study to obtain data. We conducted burning experiments at Mao'er Mountain during March 2023 and collected data on wind speed, terrain, and combustibles to build the dataset used for training and testing in this paper. The exact location of the Mao'er Mountain region is shown in Figure 1a, and a schematic illustration of the data collection process is shown in Figure 1b. Wind speed and wind direction measurements were obtained using on-site anemometers, while local topography and combustible characteristics were acquired using UAVs equipped with radar cameras and other instruments. The final dataset consists of 2000 wind speed and direction records, with a time resolution of 60 s.



Figure 1. The image of study area. (a) Location of Mao'er Mountain region. (b) Data acquisition.

The predicted wind speed and direction fields from the PSO-VMD-AM-BiLSTM model were integrated into FARSITE at a temporal resolution of 1 min intervals, using bilinear interpolation to ensure smooth transitions across the simulation grid. Wind fields were assumed spatially uniform across the 1 km $\times$ 1 km simulation area for simplicity, though future extensions could incorporate spatially varying winds based on multi-station data from the IoT system.

2.2. Methods

2.2.1. Variational Mode Decomposition (VMD)

Variational mode decomposition (VMD) is adopted in this study for its superior ability to decompose non-stationary and nonlinear time series, such as wind speed data in forest fire environments. Unlike empirical mode decomposition (EMD), which often suffers from mode mixing, VMD employs a variational optimization framework to adaptively extract intrinsic mode functions (IMFs) with reduced noise and better feature separation. This makes VMD particularly effective for handling the high volatility of understory winds influenced by terrain, vegetation, and fire-induced convection, thereby improving the input quality for subsequent AM-BiLSTM prediction and enhancing overall forecast accuracy in wildfire spread simulations. Wind speed data is a highly complex and strongly nonlinear time series. It is often decomposed into multiple scales of different frequencies to mitigate its non-stationarity for analysis and processing.

Variational mode decomposition (VMD), proposed by Konstantin Dragomiretskiy in 2014, is an adaptive and fully non-recursive method for modal variation and signal processing [38]. It overcomes the endpoint effect and mode mixing issues of empirical mode decomposition (EMD) and has a stronger mathematical foundation. VMD effectively reduces the nonstationarity of time series with high complexity and nonlinearity, providing decomposed sub-series that exhibit relative stability at different frequency scales. The core idea is to construct and solve a variational problem as shown in the following Equation (1).

$$\min_{\{v_k\}, \{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\delta(t) + \frac{j}{\pi t} \right] * v_k(t) e^{-j\omega_k t} \right\|_2^2 \right\} \quad \text{s.t.} \quad \sum_k u_k = f \quad (1)$$

where v_k and ω_k are the set of all modes and their center frequencies, respectively. $\delta(t)$ is an impulse function, κ is modal component number and f is the original signal. Then, the augmented Lagrangian is introduced to render the problem unconstrained as follows:

$$\begin{aligned} L(\{v_k\}, \{\omega_k\}, \lambda) = & \alpha \sum_k \left\| \partial_k \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} - f(t) \right\|_2^2 \\ & - \sum_k \|u_k(t)\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \end{aligned} \quad (2)$$

where α is a quadratic penalty term and λ is Lagrangian multipliers.

The computation flow of VMD is illustrated on the left-hand side of Figure 2. Firstly, the value of K is set, and the parameters are initialized. The $\hat{v}_k$ and ω_k are updated according to the equations, and whether the desired number of decompositions is achieved is checked. If the desired number of decompositions is not reached, $\hat{\lambda}$ is iterated using the equation in Figure 2, and then whether the convergence condition is met is checked. If the convergence condition is satisfied, the decomposition results are obtained, otherwise the iteration continues.

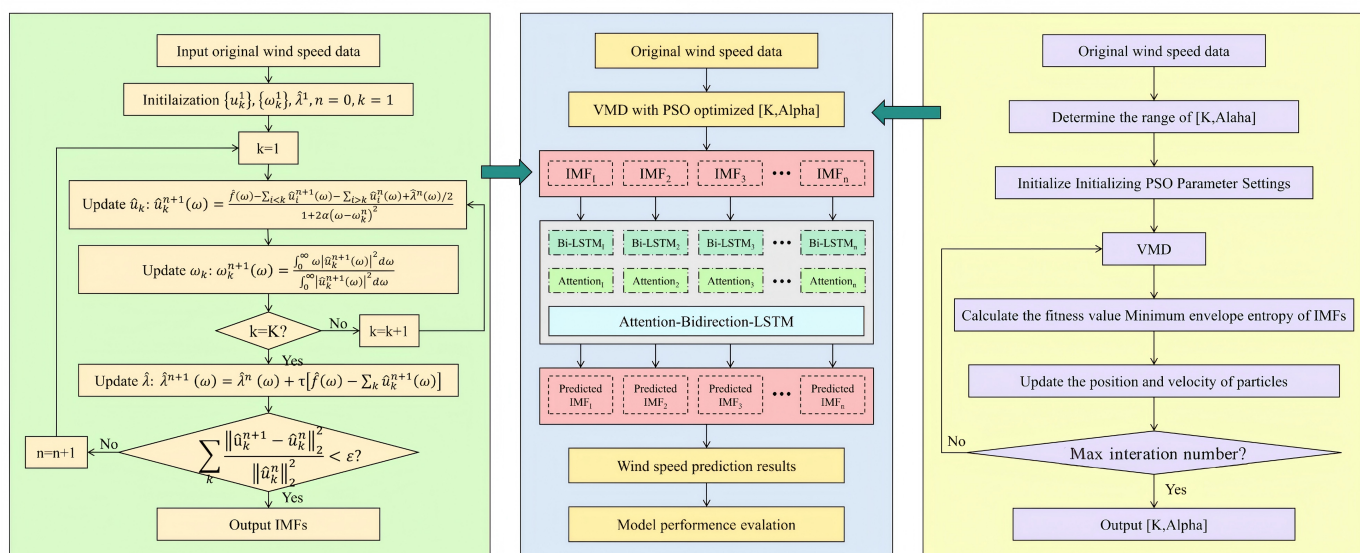


Figure 2. Structure of the PSO-VMD-AM-BiLSTM model.

The number of decomposition modes K and the penalty factor α significantly affect the performance of the VMD. K controls the completeness of the decomposed signal. A too small value of K may result in an incomplete decomposition of the signal. However, an excessively high value of K can cause over-decomposition, introducing noise or unnecessary details. α controls the smoothness of the decomposition modes. The selection of an appropriate alpha value depends on the desired trade-off between capturing global trends and preserving local details in the signal. Therefore, determining a suitable $[K, \alpha]$ parameter set is crucial when applying VMD to decompose wind speed sequences [39], and the adoption of the PSO algorithm is proposed to solve this problem.

2.2.2. Particle Swarm Optimization (PSO)

The particle swarm optimization (PSO) algorithm is a population-oriented optimization method motivated by collective behaviors observed in bird flocks. It employs a group of interacting particles that progressively explore the parameter space to identify an optimal solution. Each particle corresponds to a candidate solution and updates its position by considering both its historically best position (pbest) and the global best position achieved by the entire swarm (gbest) [40], as illustrated in Equation (3).

$$v_{id}(t+1) = \lambda v_{id}(t) + k_1 r_1 (pbest(t) - x_{id}(t)) + k_2 r_2 (gbest(t) - x_{id}(t)) \quad (3)$$

where d denotes the dimensionality of the particle, λ represents the inertia coefficient, κ_1 and κ_2 denote the acceleration (learning) coefficients, r_1 and r_2 are stochastically generated values, and α denotes the constraint parameter. The particle position update rule is given in Equation (4).

$$x_{id}(t+1) = x_{id}(t) + \alpha v_{id}(t) \quad (4)$$

The selection of an appropriate fitness function is crucial in VMD-PSO to capture the characteristics of wind speed signals effectively, improve the accuracy of capturing fundamental frequency components, and enhance the reconstruction of the original signal. Enveloping entropy, which reflects the sparsity characteristics of the signal, is chosen as the fitness function [41]. Its value is inversely correlated with the periodicity of the signal, meaning that a stronger periodicity leads to a smaller enveloping entropy value. This is particularly suitable for wind speed signals in forest fire scenarios, as these signals exhibit high nonstationarity and volatility due to terrain, vegetation, and fire-induced convection;

envelope entropy helps optimize VMD parameters by promoting decompositions that separate periodic components from noise, thereby improving the stability and predictability of the intrinsic mode functions (IMFs) for subsequent AM-BiLSTM modeling. The formula for enveloping entropy is as follows:

$$E_p = - \sum_{i=1}^n p_i \log_2 p_i \quad (5)$$

$$p_i = \frac{a(i)}{\sum_{i=1}^n a(i)} \quad (6)$$

$$a(i) = \sqrt{[u(i)]^2 + [H[u(i)]]^2} \quad (7)$$

where E_p is the enveloping entropy, p_i is the sequence of probability distributions of $a(i)$, and $a(i)$ is the envelope obtained through Hilbert demodulation of $H[u(i)]$. Here, $u(i)$ refers to the intrinsic mode functions (IMFs) derived from the VMD decomposition in Section 2.2.1. The process of selecting $[K, \alpha]$ of VMD using the PSO is shown on the right side of Figure 2.

2.2.3. Bidirectional Long Short-Term Memory (BiLSTM)

LSTM is a specialized type of recurrent neural network (RNN) that alleviates the gradient vanishing problem while retaining temporal dependencies in time series data [42]. Figure 3a illustrates the architecture of LSTM, which consists of three main components, input gate, output gate, and forget gate, denoted as i_t , o_t , and f_t , respectively. The computational process of LSTM can be described as follows:

$$i_t = \sigma(W_i[h_{t-1}; x_t] + b_i) \quad (8)$$

$$o_t = \sigma(W_o[h_{t-1}; x_t] + b_o) \quad (9)$$

$$f_t = \sigma(W_f[h_{t-1}; x_t] + b_f) \quad (10)$$

$$c_t = c_{t-1} * f_t + \tilde{c}_t * i_t \quad (11)$$

$$\tilde{c}_t = (W_c[h_{t-1}; x_t] + b_c) \quad (12)$$

$$h_t = \tanh(c_t) * o_t \quad (13)$$

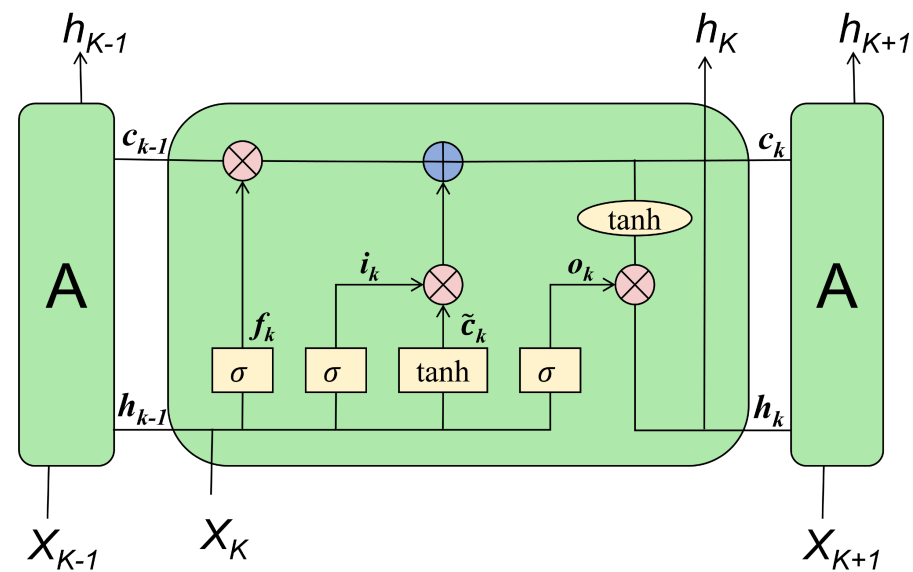
where h_t is the hidden layer state, W_i , W_o , W_f and W_c are the weight matrices, b_i , b_o , b_f and b_c are offset vectors, and σ and $\tanh$ are sigmoid and hyperbolic tangent functions, respectively. In order to capture both past and future context information, a variant of LSTM called BiLSTM is employed for wind speed prediction [43]. By performing forward and backward computations, the BiLSTM network obtains a more comprehensive context representation. The structure of BiLSTM is illustrated in Figure 3b. The following equations describe the computation method:

$$\vec{h}_t = \text{LSTM}(h_{t-1}; In_t) \quad (14)$$

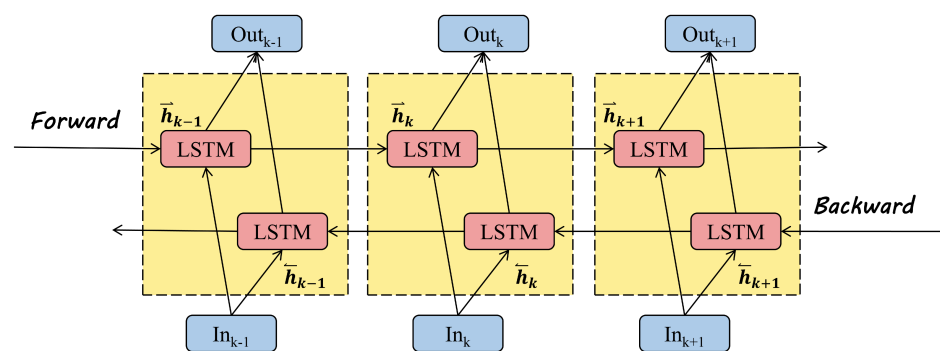
$$\overleftarrow{h}_t = \text{LSTM}(h_{t+1}; In_t) \quad (15)$$

$$h_t = W^f \vec{h}_t + W^b \overleftarrow{h}_t + b \quad (16)$$

where $\vec{h}$ and $\overleftarrow{h}$ are forward and backward hidden states, respectively. LSTM is the application of Equations (8)–(13), where W^f and W^b are the forward and backward LSTM weights, and b is the offset vector.



(a)



(b)

Figure 3. The structure of LSTM and BiLSTM. (a) LSTM. (b) BiLSTM.

2.2.4. Attention Mechanism (AM)

Attention mechanism (AM) is a cognitive-inspired mechanism that simulates human attention [44]. It assigns different weights to input elements according to their relevance, allowing the model to emphasize more important features while reducing the influence of less important ones. This weighting is based on the similarity between a query vector and each input element (key), so features that are more relevant to the query contribute more to the output. The attention weights are calculated as follows:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^T \exp(e_i)} \quad (17)$$

$$e_t = \tanh(Wh_t + b) \quad (18)$$

2.2.5. The Proposed Model

In order to better predict the wind speed sequence, we propose a wind speed prediction model based on a hybrid structure of PSO-VMD and AM-BiLSTM, i.e., the PSO-VMD-AM-BiLSTM model. The specific structure is shown in Figure 2. The running process of the model is as follows.

- Step 1: Collect the original wind speed sequence and input it into the model.
- Step 2: PSO is used to select the optimal VMD parameters $[K, \alpha]$. A particle swarm size of 10 and 100 iterations are chosen based on preliminary experiments to balance computational cost and convergence. The fitness function is the minimum envelope entropy of the decomposed sequence, ensuring effective parameter selection for VMD.
- Step 3: The original wind speed sequence is decomposed of VMD to obtain K mutually independent subsequences IMF_1 to IMF_K , and the oscillation frequency increases gradually with K .
- Step 4: The IMFs are divided into training and testing sets according to 7:3, and the predicted $IMF'_1(t)$ to $IMF'_K(t)$ are generated by AM-BiLSTM neural network.
- Step 5: Reconstruct the predicted $IMF'_i(t)$ to generate wind speed prediction results as follows:

$$x'(t) = \sum_{i=1}^K IMF'_i(t) \quad (19)$$

where $x'(t)$ is the reconstructed sequence of predicted wind speeds at time step t , and $IMF'_i(t)$ is the predicted result for the i -th IMF at time step t .

No additional post-processing steps (such as smoothing, normalization, or error correction) are applied during the reconstruction, as the VMD decomposition ensures that the sum of the IMFs theoretically reconstructs the original signal with negligible error, and the AM-BiLSTM predictions preserve this property.

- Step 6: Evaluate the performance of the model.

2.3. Fire Spread Prediction

The fire area simulator, FARSITE, is a widely used fire behavior modeling system that was developed to simulate the spread and behavior of wildland fires [45]. It is designed to assist fire managers and researchers in understanding and predicting fire behavior under a range of environmental conditions. The FARSITE model operates on a gridded landscape, in which each cell corresponds to a specific spatial area [46]. It incorporates factors such as topography, fuel characteristics, and weather conditions to reproduce fire growth and behavior. The output of FARSITE includes maps and graphical representations of fire behavior parameters such as flame length, rate of spread, and fire perimeter.

In order to verify the level of influence of wind speed prediction on fire spread prediction, five fires were simulated using FARSITE (version 4.6) on an area of Mao'er Mountain, in which the predicted sequence was used as an input condition for fire spread prediction. The input parameters required for FARSITE launch and their ranges are shown in Table 1. The location of the experimental area and its topographical maps are shown in Figure 4, which has a size of 480 * 480 and each pixel represents a surface area of 30 square meters.

Table 1. The input parameters required for the FARSITE simulation and their ranges.

Parameter Type	Parameter	Unit	Min	Max
Terrain	Elevation	Meters	261	767
	Slope	Degrees	0	60
	Aspect	Degrees	0	359
Fuel	Fuel Model	Class	1	204
	Canopy	Percent	0	95
	Stand Height	Meters	0	50
Climate	Wind Speed	Mph	0	5
	Wind Direction	Degrees	0	359

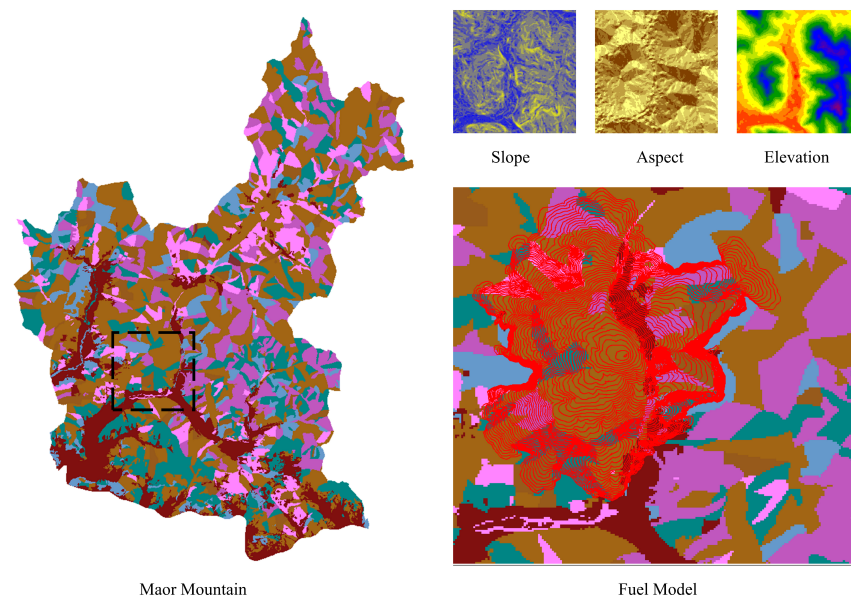


Figure 4. Schematic of FARSITE parameters for Mao'er Mountain. **(Left)** The entire Mao'er Mountain area, with colors representing elevation (green: low, brown: high). The experimental area is circled in black dashed lines. **(Right top)** Elevation, slope, and aspect maps of the experimental area; color gradients indicate increasing values from low (blue/light) to high (red/dark). **(Right bottom)** FARSITE fire simulation with fuel models, where different colors represent different fuel types (e.g., grass, shrub), the black solid line indicates the fire perimeter at a given time step, and the red area represents the burned region.

2.4. Performance Metrics

Appropriate evaluation indicators play an important role in evaluating the performance of the model [31]. MAE, CC, RMSE, R^2 , MAPE, SSE, TIC, PBIAS, Recall and F1 scores were selected as the evaluation indexes of this paper. Among them, Recall and F1 score are used to evaluate two-dimensional datasets. The specific explanation of the evaluation index can be expressed as follows:

- (1) Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - y'_i| \quad (20)$$

- (2) Correlation Coefficient (CC):

$$\text{CC} = \frac{\sum_{i=1}^n (y_i - \bar{y})(y'_i - \bar{y}')}{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2} \sqrt{\frac{1}{n} \sum_{i=1}^n (y'_i - \bar{y}')^2}} \quad (21)$$

- (3) Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y'_i)^2} \quad (22)$$

- (4) Coefficient of Determination R^2 :

$$R^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{\frac{1}{n} \sum_{i=1}^n (y'_i - \bar{y}')^2} \quad (23)$$

- (5) Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - y'_i}{y_i} \right| \times 100\% \quad (24)$$

- (6) Sum of Squared Errors (SSE):

$$\text{SSE} = \sum_{i=1}^n (y_i - y'_i)^2 \quad (25)$$

- (7) Theil Inequality Coefficient (TIC):

$$\text{TIC} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y'_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2} + \sqrt{\frac{1}{n} \sum_{i=1}^n (y'_i)^2}} \quad (26)$$

- (8) Percent Bias (PBIAS):

$$\text{PBIAS} = \sum_{i=1}^n \left| \frac{y_i - y'_i}{y_i} \right| \times 100\% \quad (27)$$

- (9) Recall:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (28)$$

- (10) F1-Score:

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (29)$$

where y_i represents the observational data of the i th sample, y'_i the predicted data of the i th sample, $\bar{y}$ the mean of the observational data for all samples, and $\bar{y}'$ the mean of the predicted data for all samples. $\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$. TP, FP, and FN are calculated by a confusion matrix [47], as shown in Table 2.

Table 2. Confusion matrix that counts true samples and predictions.

Reference \ Prediction	Positive	Negative
Positive	TP	FN
Negative	FP	TN

3. Results

3.1. Autocorrelation Analysis

Autocorrelation function (ACF) is a statistical tool that helps to provide insight into the relationship between past observations and current observations in time series data [48]. ACF analysis was performed on the original wind speed series to determine if auto correlation exists. The ACF test yielded a test statistic of -3.99 with a p -value of less than 0.05 , indicating strong evidence to reject the null hypothesis. Furthermore, comparing the ACF test statistic of -3.99 with the critical value at the 1% significance level (-3.43), we found that the ACE test statistic was lower than the critical value. Hence, the null hypothesis of the presence of a unit root is decisively rejected. Consequently, it can be concluded that the data is stationary, and time series forecasting can be conducted. These results provide robust support for the assertion that the dataset exhibits a stationary pattern, which is a crucial prerequisite for reliable time series forecasting. It is reasonable to assert that the dataset is suitable for time series analysis and forecasting.

3.2. VMD and IMF Prediction

To enhance the accuracy of the VMD, the PSO algorithm was employed to select the optimal $[K, \alpha]$ parameters. The parameter ranges were set as follows: K values ranged from 2 to 12, and α values ranged from 100 to 4000. After 100 iterations of the PSO, the best parameter set $[6, 604.75]$ was obtained, resulting in a minimum envelope entropy of 1.181. Using these optimized parameters, the original wind speed sequence was decomposed using the VMD, and the resulting intrinsic mode functions (IMFs) are shown in Figure 5. The frequency of each IMF increases with an increase in K , which suggests a finer resolution in representing the oscillatory components. The low-frequency components exhibit less pronounced periodicity, while as the oscillation frequency increases, the periodicity becomes more evident, accompanied by a decrease in amplitude. The AM-BiLSTM was utilized to forecast the IMFs, and the results are depicted in Figure 6, with a bar chart illustrating four performance metrics provided on the right side. Subsequently, the predicted results were reconstructed to obtain the final wind speed predictions. It is evident that the two curves align remarkably well. The close agreement between the reconstructed wind speed predictions and the true values highlights the effectiveness of the proposed model in capturing the underlying patterns and dynamics of the IMFs. The visual comparison lends support to the model's ability to generate accurate and reliable predictions.

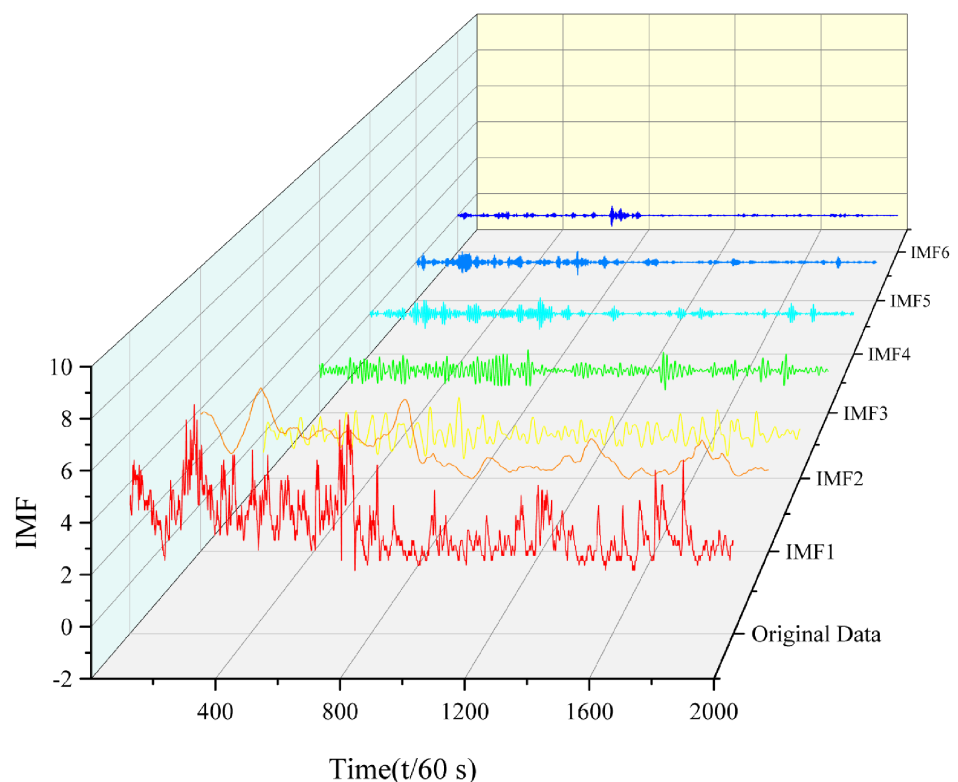


Figure 5. Visualization of the original wind sequence and IMFs. The decomposition effectively separates the wind speed series into multi-scale components, with higher K IMFs showing increased frequency and reduced amplitude.

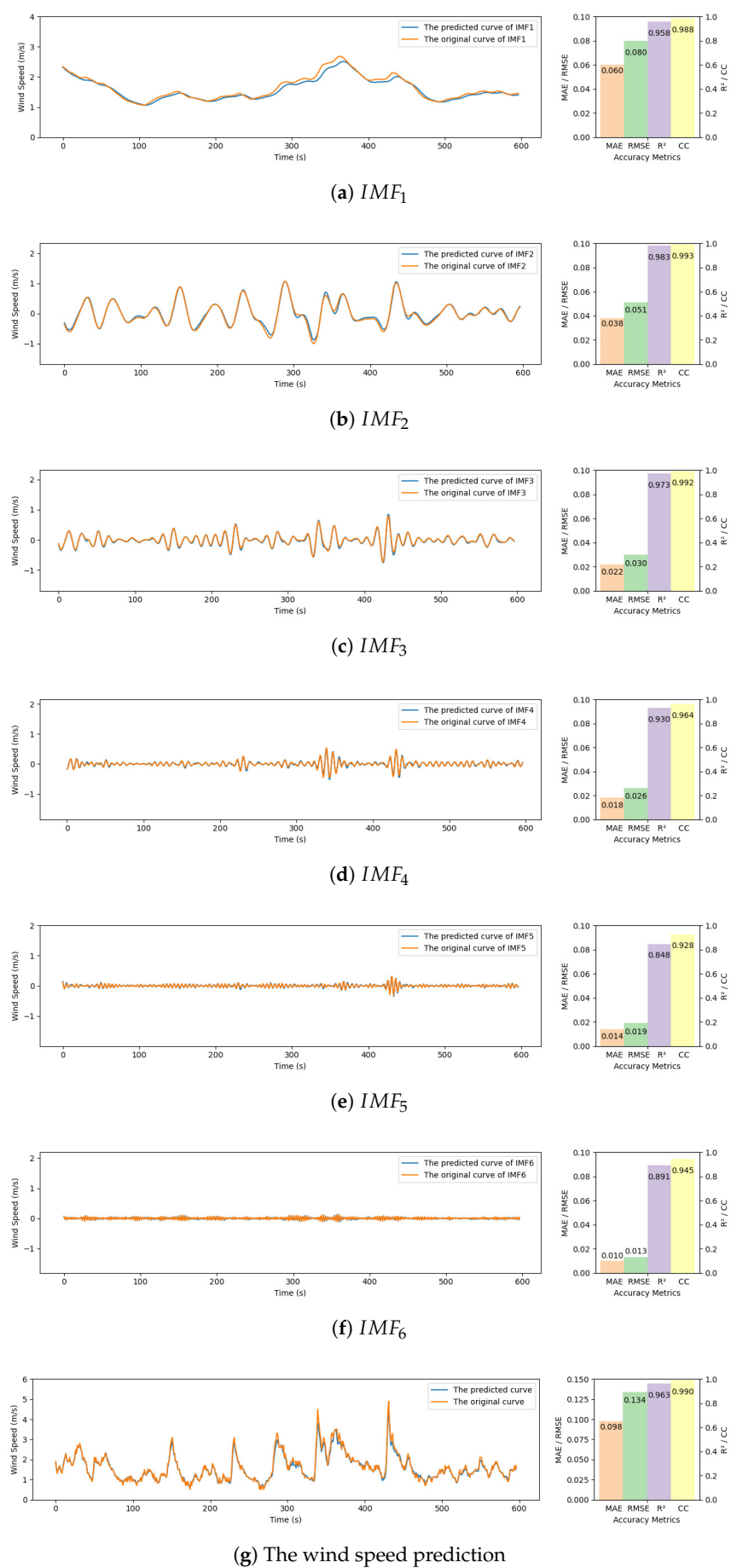


Figure 6. Prediction results of each IMF and reconstructed wind speed prediction.

3.3. Comparison Models

To validate the effectiveness of each component of the proposed model, various benchmark models including LSTM, BiLSTM, AM-BiLSTM, and VMD-AM-BiLSTM were employed for a performance comparison in terms of wind speed prediction. The predicted wind speed sequences of each model are illustrated in Figure 7, with a magnified view provided on the right side, where the x -axis represents the time step and the y -axis represents the wind speed. The blue line represents the true wind speed values, and the orange line represents the predictions generated by the proposed model in this study, while the other four lines of different colors correspond to the four benchmark models with distinct configurations.

In order to further validate the predictive performance, four commonly used models, namely ARIMA, SVM, CNN, and RNN, were selected for comparison with the proposed model. The comparison of the predicted curves generated by these five models with the original wind speed curve is shown in Figure 8. The figure allows a direct comparison of the performance among the different models, highlighting any differences in their predictive capabilities. The blue line represents the true wind speed values, while the orange line represents the predicted values generated by the proposed model in this study. The remaining four lines, each in a distinct color, correspond to the benchmark models used for comparison. By examining the overlapping of the lines, it becomes possible to assess the accuracy and effectiveness of the models in capturing the wind speed patterns.

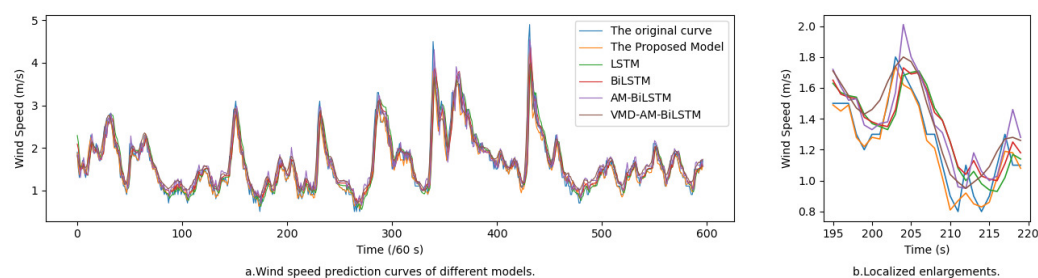


Figure 7. Comparison of the prediction effect of different components.

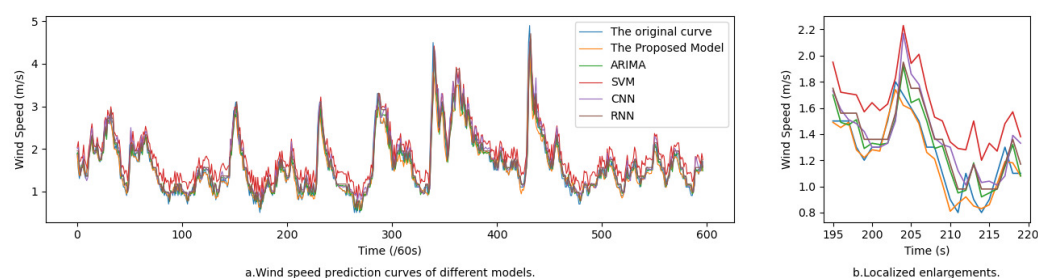


Figure 8. Comparison of wind speed prediction performance between the proposed model and other commonly used models (ARIMA, SVM, CNN, and RNN).

3.4. Quantitative Evaluation of Fire Spread Simulations

To quantitatively assess the impact of the predicted wind speed on forest fire spread, FARSITE simulations were conducted under three scenarios: (1) no wind (wind speed = 0 m/s), (2) measured (observed) wind speed, and (3) predicted wind speed from the PSO-VMD-AM-BiLSTM model. Simulations were run for 120 min, matching the duration of controlled burning experiments in the Mao'er Mountain region and Liutiao Village.

Key quantitative fire spread metrics were extracted, including final burned area (ha), maximum fire perimeter (m), and average rate of area growth (ha/min). The results are summarized in Table 3.

Table 3. Quantitative comparison of fire spread metrics in FARSITE simulations under different wind scenarios (averaged across four field experiments).

Scenario	Final Burned Area (ha)	Maximum Perimeter (m)	Avg. Area Growth Rate (ha/min)
No Wind	2.50 (error > 10%)	800	0.021
Measured Wind	8.00	2000	0.067
Predicted Wind	7.52 (error < 6%)	1920	0.063

Compared to the no-wind scenario, the predicted wind scenario reduces the burned area error (relative to measured wind) from over 10% to below 6%, as indicated in the field experiments. This demonstrates that the proposed wind forecasting model significantly improves the accuracy of fire spread simulation, with metrics closely matching measured data. These quantitative results confirm the practical value of accurate wind forecasts in wildfire management and decision support.

4. Discussion

4.1. The Proposed Model Prediction Analysis

To visualize the prediction results for each IMF sequence more directly, bar charts of MAE, RMSE, CC, and R^2 for each sequence were plotted. As shown in Figure 6, with an increase in oscillation frequency, the amplitude gradually decreases, and the MAE and RMSE decrease, indicating an improvement in prediction accuracy. The CC and R^2 initially increase and then decrease. This could be due to the fact that the range of values for IMF₁ is much larger than that of IMF₆, as CC represents the linear relationship and R^2 represents the goodness of fit.

This suggests that accurate prediction of high-frequency components is more challenging than that of low-frequency components. To quantitatively express the prediction errors for each IMF, an error box plot was constructed, as shown in Figure 9a. In the plot, the middle line of the left half-box represents the median error, the rectangle represents the values between the first quartile (Q1) and the third quartile (Q3). The right side shows error scatter points, and the gray dashed line represents the fitted normal distribution curve. The error box plot allows a direct assessment of the error distribution. From IMF₁ to IMF₆, the median errors are −0.04, 0.01, −0.01, 0, and 0, and the error distribution is concentrated around 0.2 to −0.3. IMF₁ exhibits the most distributed and the widest range of errors, while IMF₆ shows the most concentrated distribution, confirming the changes in the evaluation metrics for IMF_s. After reconstructing the overall predicted sequence, a comparison was made with the original sequence revealing a good fitting effect, as shown in Figure 6f. However, there is some underestimation at sudden wind speed increases, which is consistent with the underestimation observed in IMF₁.

The four evaluation metrics are 0.098, 0.134, 0.963, and 0.990 for MAE, RMSE, CC, and R^2 , respectively, indicating good performance. MAE and RMSE are close to 0, while CC and R^2 are close to 1. In summary, AM-BiLSTM achieves accurate predictions for each IMF_s, and the reconstructed wind speed sequence closely matches the original data, demonstrating that the proposed model satisfies the requirements for precise wind speed forecasting.

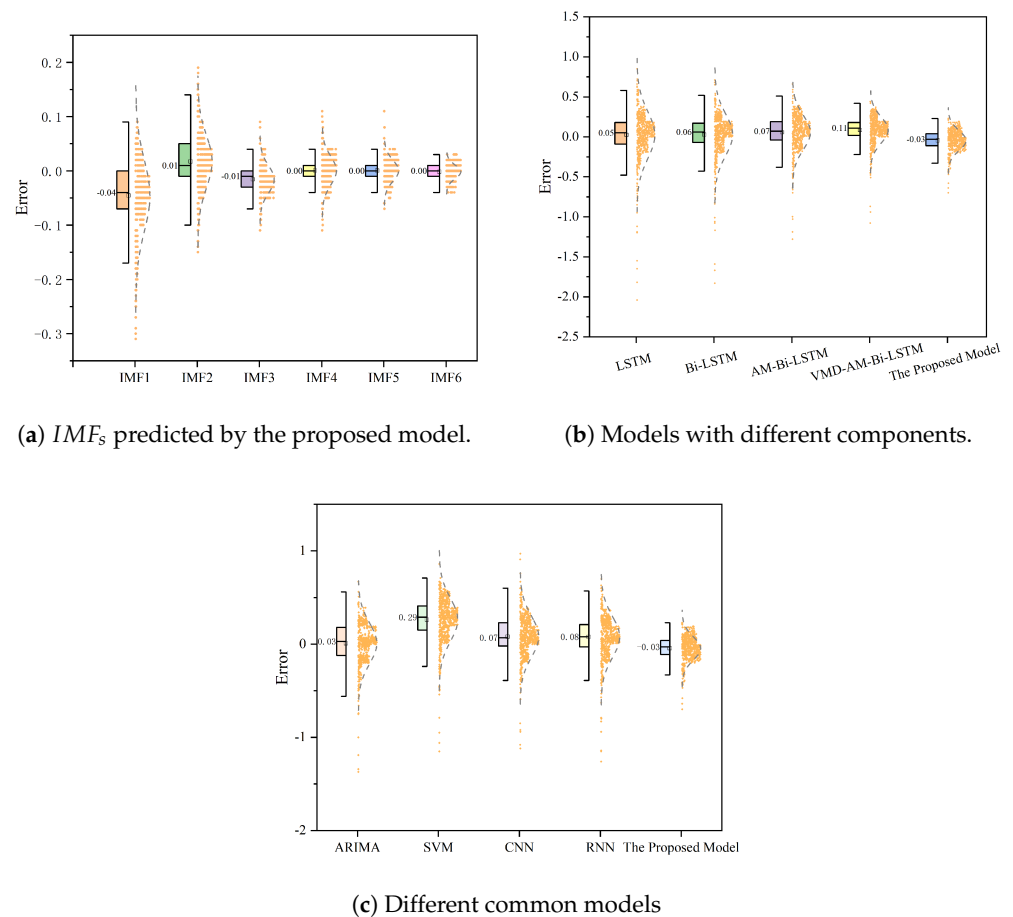


Figure 9. Prediction error box plots.

4.2. Model Component Analysis

Wind speed curves of the proposed model and five models with different components is shown in Figure 6. It is evident that the proposed model closely align with the true wind speed curve, indicating superior predictive performance. The degree of discretization of LSTM and BiLSTM exhibits a resemblance to the true curve; however, they suffer from a temporal lag, leading to suboptimal performance. Additionally, three evaluation methods, namely the performance evaluation table, error boxplot, and Taylor diagram, are adopted to quantify the predictive performance of the models.

The evaluation metrics for each prediction model are computed using Equations (20)–(27), and the results are presented in Table 3. As components increase, the overall performance gradually improves. The model with VMD exhibits better performance than the model without, indicating that VMD is beneficial for wind speed prediction. The overall performance of the proposed model surpasses that of VMD-AM-Bi-LSTM, demonstrating that it is crucial to optimize the $[K, \alpha]$ of the VMD using PSO. It is worth noting that the PBIAS of LSTM and BiLSTM is relatively low, which may be due to the “time lag prediction” phenomenon mentioned earlier. Furthermore, the PBIAS of the proposed model is negative, which is evident from the overall lower predicted values, especially when there is a sudden increase in wind. However, considering the comprehensive analysis, the proposed model exhibits the best performance.

The error boxplot for each model is depicted in Figure 7b. The central errors of the models are gradually approaching zero, with values of 0.05, 0.06, 0.07, 0.11, and -0.03 , respectively. The size of the boxplot decreases, indicating reduced error fluctuations with model improvements. The scatterplot on the right shows that as the algorithm is

enhanced, the outliers gradually decrease and the errors better follow a normal distribution. The Taylor diagram, proposed by J.R. Taylor in 2001, is a commonly used graphical tool for comparing the similarity and differences between model predictions and observed data [49]. It is widely applied in fields such as meteorology, oceanography, and climatology. The Taylor diagram presents the correlation coefficient, centered root-mean-square error, and standard deviation between different model predictions or simulations and observed data in polar coordinates. Each point in the diagram represents a prediction model or simulation result. By comparing the positions of different models on the Taylor diagram, the differences between them and the observed data can be visually evaluated. It is apparent from Figure 10a that the proposed model exhibits the closest proximity to the observed values, indicating the best predictive performance. The evaluation metrics, error boxplots, and the Taylor diagram provide comprehensive assessments of the models' performance, highlighting the superiority of the proposed model.

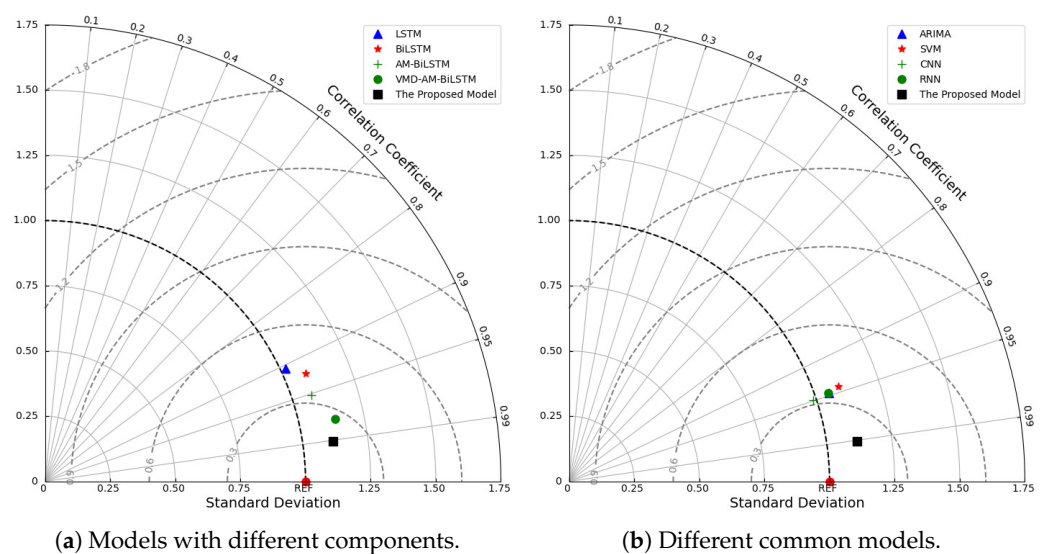


Figure 10. Taylor diagrams.

4.3. Different Model Predictions Analysis

The wind speed curves of each model are shown in Figure 10. The calculation of correlation evaluation metrics for each prediction model is presented in Table 4. It can be observed that the proposed model has the best predictive performance, followed by ARIMA, CNN, RNN, and SVM. The MAPE value of the proposed model is 6.119, which is lower than ARIMA, SVM, CNN, and RNN by 4.192, 17.136, 5.945, and 6.769, respectively, indicating the best fit between predictions and the true values. The correlation coefficient is 0.99, which is higher than ARIMA, SVM, CNN, and RNN by 0.042, 0.056, 0.042, and 0.043, respectively, demonstrating the strongest correlation. Regardless of the evaluation criteria used, the proposed model has the smallest evaluation error and the highest evaluation coefficient.

Table 4. Comparison of prediction errors of the proposed model with different component models.

Model	MAE	RMSE	R ²	MAPE (%)	PBIAS	SSE	TIC	CC
LSTM	0.199	0.295	0.820	12.345	1.403	51.965	0.158	0.907
Bi-LSTM	0.180	0.263	0.857	11.801	1.610	41.393	0.158	0.927
AM-Bi-LSTM	0.166	0.221	0.899	11.767	3.363	29.080	0.159	0.953
VMD-AM-Bi-LSTM	0.148	0.185	0.929	11.118	5.249	20.399	0.149	0.980
The Proposed Model	0.098	0.143	0.963	6.119	−2.835	10.748	0.077	0.990

The error boxplots for each model are depicted in Figure 9c. From the left boxplot, the central errors for ARIMA, SVM, CNN, RNN, and the proposed model are 0.03, 0.29, 0.07, 0.08, and -0.03 , respectively. Both ARIMA and the proposed model have an absolute error of 0.03, but the rectangular box of the proposed model is the smallest, indicating a narrower range of error fluctuations. The scatterplot on the right-hand side shows that the errors of the proposed model are the most concentrated, with the fewest outliers. Furthermore, the performance comparison of the models, as illustrated by the Taylor diagram in Figure 10b, demonstrates that the proposed model achieves the highest predictive accuracy.

In conclusion, the ensemble model proposed in this paper demonstrates more reliable handling of time series data compared to other commonly used model architectures.

4.4. Fire Spread Prediction Analysis

Accurate prediction of wind speed in wildfire scenarios is crucial for forecasting fire behavior and effectively managing firefighting resources, thereby ensuring firefighter safety. The interaction between wind and fire plays a significant role in fire spread dynamics [50]. As the wind blows, the flames are influenced by its size and direction, causing them to stretch and bend towards unburned areas [51]. This phenomenon leads to a shorter distance between the advancing flame front and available fuel, resulting in more rapid fire spread [52,53]. Therefore, it is essential to forecast wind speed in fire-prone areas and incorporate this information as an input for wildfire spread prediction models to better anticipate the direction and intensity of fire spread.

In order to validate the effectiveness of the proposed wind speed prediction model for wildfire spread forecasting, the predicted wind speeds were used as FARSITE inputs for wildfire spread prediction. The real wildfires were simulated using true wind speeds and directions, while the control experiments were conducted without wind inputs. Five wildfire simulations were performed, and metrics such as MAE, RMSE, R^2 , RECALL, and FI-score were calculated to evaluate the performance of the wind prediction in wildfire spread. The results were compared with the no-wind scenario to assess the impact of wind prediction. The evaluation results are presented in Table 5.

Table 5. Comparison of prediction errors between the proposed model and other commonly used models (ARIMA, SVM, CNN, RNN).

Model	MAE	RMSE	R^2	MAPE (%)	SSE	TIC	CC
AROMA	0.155	0.221	0.899	10.331	29.243	0.140	0.948
SVM	0.305	0.350	0.747	23.255	73.125	0.295	0.944
CNN	0.176	0.236	0.884	12.064	33.372	0.166	0.948
RNN	0.177	0.237	0.884	12.888	33.506	0.191	0.947
The Proposed Model	0.098	0.134	0.963	6.119	10.748	0.077	0.990

The wind prediction model exhibited superior performance compared to the no wind scenario. The predicted wind condition consistently yielded lower MAE and RMSE values and higher R^2 , recall, and F1-score values compared to no wind condition. Considering the five wildfire scenarios collectively, the predicted wind condition achieved an R^2 of 0.914, while the no wind condition had an R^2 of 0.777, resulting in an improvement of 0.137. Furthermore, the predicted wind condition exhibited an RMSE of 29.563, whereas the no-wind condition had an RMSE of 46.475, indicating a decrease of 16.912. The overall analysis demonstrates that the proposed model improves the accuracy, reliability, and comprehensiveness of wildfire spread prediction. These findings emphasize the importance of incorporating wind prediction into wildfire spread models. The insights gained from this study thus add value to the field of wildfire management by endorsing the application of

wind prediction models to better allocate firefighting resources and enhance operational safety during wildfire events.

To comprehensively evaluate the model's predictive performance in the homogeneous fuel combustion experiment, the mean values of Precision, Recall, the Sørensen coefficient, and the Kappa coefficient were calculated for the model predictions, with the results presented in Tables 6 and 7.

The MCNN model demonstrated superior predictive performance across all evaluated metrics. Specifically, it achieved a precision of 0.952, representing an improvement of 0.044 (4.84%) and 0.051 (5.66%) over the DCIGN (0.908) and DNN (0.901) models, respectively. In terms of recall, MCNN attained a value of 0.973, which was 0.046 (4.96%) and 0.045 (4.85%) higher than those of DCIGN (0.927) and DNN (0.928). The Sørensen coefficient for MCNN was 0.962, outperforming DCIGN (0.917) and DNN (0.914) by 0.045 (4.91%) and 0.048 (5.25%), respectively. As a composite metric balancing precision and recall, the Sørensen coefficient reflects the more balanced and accurate predictive capability of the MCNN model. Furthermore, the Kappa coefficient of MCNN reached 0.951, exceeding the values of DCIGN (0.899) and DNN (0.896) by 0.052 (5.78%) and 0.055 (6.13%), respectively. The Kappa coefficient, which assesses the agreement between model predictions and observed data beyond chance, provides additional evidence for the reliability of the MCNN model.

Table 6. Comparison of prediction errors of the proposed model with different models.

Fire Num	Wind Condition	MAE	MAPE RMSE	R ²	Recall	F1-Score
1	Predicted wind	5.158	45.513	0.832	0.889	0.925
	No wind	5.777	47.452	0.814	0.859	0.914
2	Predicted wind	3.190	40.498	0.863	0.929	0.950
	No wind	3.175	50.968	0.763	0.917	0.950
3	Predicted wind No wind	1.839	41.148	0.813	0.926	0.955
	No wind	2.315	49.721	0.703	0.894	0.942
4	Predicted wind No wind	1.931	30.501	0.929	0.970	0.969
	No wind	3.401	49.184	0.799	0.891	0.938
5	Predicted wind No wind	1.453	35.703	0.897	0.970	0.973
	No wind	3.231	51.471	0.775	0.936	0.940
6	Predicted wind No wind	2.533	29.563	0.914	0.936	0.954
	No wind	3.366	46.475	0.777	0.900	0.937

Table 7. Evaluation Metrics for Experiment.

	Precision	Recall	Sørensen Coefficient	Kappa Coefficient
MCNN	0.952	0.973	0.962	0.951
DCIGN	0.908	0.927	0.917	0.899
DNN	0.901	0.928	0.914	0.896

Comprehensive analysis indicates that the balanced performance of MCNN in both precision and recall underscores its effectiveness in mitigating both false positives and false negatives. These results suggest that the MCNN model is well-suited to the specific characteristics of homogeneous fuel combustion scenarios. Consequently, it holds significant potential for enhancing fire management strategies in environments characterized by homogeneous fuels, such as understory grassland fires.

The enhanced wind speed prediction accuracy of the PSO-VMD-AM-BiLSTM model (with MAE = 0.098, RMSE = 0.134, R² = 0.990, and prediction errors <6% across IMFs) substantially improves the practical utility of wildfire spread modeling in FARSITE. By supplying reliable forecasted wind fields that closely match observed data, the model reduces

uncertainties in fire perimeter dynamics, burned area estimation, and rate of spread. For example, as shown in Table 3 (or the wind condition comparisons), predicted wind inputs lead to significantly lower MAE/RMSE and higher R^2 /F1-score compared to the no-wind scenario, with overall R^2 improving from 0.777 to 0.914 and RMSE decreasing by approximately 17 units. This quantitative enhancement enables more precise anticipation of fire propagation direction and intensity under variable conditions, thereby supporting real-time firefighting decisions such as optimal resource deployment, safe evacuation planning, containment line establishment, and risk assessment for firefighter safety. Ultimately, integrating such accurate wind forecasts into operational wildfire management systems can reduce response delays, minimize unnecessary resource expenditure, and improve overall suppression effectiveness in complex forest environments.

Despite these promising results, the proposed approach has several limitations that should be explicitly acknowledged for future improvements:

- High computational demand: The PSO optimization of VMD parameters combined with AM-BiLSTM training is computationally intensive, limiting real-time deployment in resource-constrained field operations.
- Dependence on data quality and quantity: The model relies heavily on high-resolution IoT-collected wind data from specific sites (Mao'er Mountain and Liutiao Village); performance may degrade in regions with sparse observations, different fuel types, or extreme weather events.
- Assumptions in decomposition and simulation: VMD mode number (K) and penalty factor (α) are optimized but still require pre-tuning, potentially introducing subjectivity; FARSITE simulations assume spatially uniform wind fields, which may overlook fine-scale terrain-induced or fire-atmosphere feedback variations.
- Limited scope of validation: While validated across four diverse field experiments, the model has not been extensively tested in large-scale, multi-day wildfires, crown fires, or drastically different ecosystems (e.g., boreal or Mediterranean forests).
- Lack of uncertainty quantification: The current framework provides point predictions without confidence intervals or probabilistic outputs, which could better address the inherent stochasticity of wind in wildfire scenarios.

Future research could mitigate these limitations by exploring more efficient optimization algorithms (e.g., faster variants of PSO), incorporating adaptive decomposition techniques, expanding validation to diverse global fire regimes, integrating multi-source data for spatial heterogeneity, and developing probabilistic extensions to enhance robustness for operational wildfire forecasting.

4.5. Generalization and Limitations

The proposed approach demonstrates strong generalization potential, validated through four diverse field burning experiments in Liutiao Village, covering uniform fuel combustion (grass-dominated), long fire line (linear spread), alternating fuels (mixed shrub-grass), and multi-source merging (converging fires). Across these scenarios, the model maintained low prediction errors (<6%) and high metrics (Precision = 0.940, Recall = 0.965, Sørensen = 0.953, Kappa = 0.940), outperforming baselines like DCIGN and DNN. For broader applicability, the model's reliance on IoT-collected meteorological data allows adaptation to other regions (e.g., temperate vs. tropical forests) by retraining on local datasets. Fuel types can be adjusted via FARSITE's modular fuel models, and fire regimes (e.g., high-intensity crown fires) could be simulated with additional canopy wind data. Limitations include sensitivity to extreme weather; future work will test in varied ecosystems like Mediterranean or boreal forests.

5. Conclusions

In this article, a hybrid model based on PSO-VMD and AM-BiLSTM is proposed to address the wind speed prediction needs in wildfire scenarios. A field burning experiment was conducted in the Mao'er Mountain region of Heilongjiang Province to collect the necessary data. The original wind speed sequence was decomposed of VMD, where $[K, \alpha]$ of the VMD was optimally selected by PSO. The resulting IMF sequences were then fed into the AM-BiLSTM model for prediction, resulting in the reconstruction of the final predicted results. The role of each component in the model was analyzed and the model was compared with other commonly used models. Evaluation metrics, error boxplots and Taylor diagrams were used to quantify model performance. The results obtained were excellent with MAE, RMSE, R^2 , MAPE, SSE, TIC, CC of 0.098, 0.134, 0.963, 6.119, 10.748, 0.077, and 0.990, respectively. To demonstrate the effectiveness of the model in wildfire spread prediction, we used the predicted results as inputs for FARSITE. The model achieved an improvement of 0.137 in R^2 and a decrease of 16.9 in RMSE compared to the no-wind scenario. These findings highlight the significant contribution of the proposed model in enhancing wildfire prediction accuracy.

Based on the proposed model in this study, future work will focus on the following aspects:

1. Enhancing the performance of the model, particularly in predicting wind speeds during rapid increases in wind speed. This could involve refining the model architecture or incorporating additional techniques to capture sudden changes in wind conditions more accurately.
2. Considering more input variables and expanding the scope of predicted outcomes. For example, incorporating terrain and weather data as inputs to predict both wind speed and wind direction. Exploring the prediction of two-dimensional wind fields could also be considered.
3. Establishing a closer integration with wildfire spread models to develop a coupled wind–fire prediction model. This would involve linking the wind speed prediction model with wildfire spread models to improve the accuracy of wildfire spread prediction based on predicted wind conditions.

These future directions aim to enhance the overall performance and applicability of the proposed model. By improving the prediction accuracy, incorporating additional variables, and integrating with wildfire spread models, the proposed model can contribute to better wildfire management strategies and decision-making processes.

Author Contributions: Conceptualization, H.Z. and S.L. (Shuwen Liu); methodology, H.Z.; software, H.J.; validation, H.Z., S.L. (Sanping Li) and X.L.; formal analysis, H.J.; investigation, S.L. (Shuwen Liu); resources, L.Z.; data curation, H.Z.; writing—original draft preparation, H.Z.; writing—review and editing, S.L. (Sanping Li) and X.L.; visualization, H.J.; supervision, L.Z.; project administration, L.Z.; funding acquisition, L.Z. and X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Central Guidance for Local Science and Technology Development Special Project (Grant No. ZY24QY03), the National Natural Science Foundation of China (Grant No. 32471857), and the Central Finance Forestry Science and Technology Promotion Demonstration Project (Grant No. Hei[2024]TG11).

Data Availability Statement: All data and codes generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Acknowledgments: The authors would like to thank all the researchers and staff who participated in the field burning experiments in the Mao'er Mountain region and Liutiao Village for their valuable assistance and support.

Conflicts of Interest: The authors of this paper affirm that there are no financial or personal conflicts of interest that might be perceived as having biased the research presented herein.

References

1. Naderpour, M.; Rizeei, H.M.; Ramezani, F. Forest fire risk prediction: A spatial deep neural network-based framework. *Remote Sens.* **2021**, *13*, 2513. [\[CrossRef\]](#)
2. Molina, J.R.; Herrera, M.A.; Silva, F.R. Wildfire-induced reduction in the carbon storage of mediterranean ecosystems: An application to brush and forest fires impacts assessment. *Environ. Impact Assess. Rev.* **2019**, *76*, 88–97. [\[CrossRef\]](#)
3. Ghodrat, M.; Shakeriaski, F.; Fanaee, S.A.; Simeoni, A. Software-based simulations of wildfire spread and wind-fire interaction. *Fire* **2022**, *6*, 12. [\[CrossRef\]](#)
4. Guo, F.; Su, Z.; Wang, G.; Sun, L.; Tigabu, M.; Yang, X.; Hu, H.q. Understanding fire drivers and relative impacts in different chinese forest ecosystems. *Sci. Total Environ.* **2017**, *605–606*, 411–425. [\[CrossRef\]](#)
5. Jolly, W.M.; Cochrane, M.A.; Freeborn, P.H.; Holden, Z.A.; Brown, T.J.; Williamson, G.J.; Bowman, D.M.J.S. Climate-induced variations in global wildfire danger from 1979 to 2013. *Nat. Commun.* **2015**, *6*, 7537. [\[CrossRef\]](#)
6. Tyukavina, A.; Potapov, P.V.; Hansen, M.C.; Pickens, A.H.; Stehman, S.; Turubanova, S.; Parker, D.; Zalles, V.; Lima, A.; Kommareddy, I.; et al. Global trends of forest loss due to fire from 2001 to 2019. *Front. Remote Sens.* **2022**, *3*, 825190. [\[CrossRef\]](#)
7. Lyon, L.J.; Huff, M.H.; Hooper, R.G.; Telfer, E.S.; Schreiner, D.S.; Smith, J.K. *Wildland Fire in Ecosystems: Effects of Fire on Fauna*; USDA Forest Service, Rocky Mountain Research Station: Ogden, UT, USA, 2012. [\[CrossRef\]](#)
8. Neary, D.G.; Ryan, K.C.; DeBano, L.F. *Wildland Fire in Ecosystems: Effects of Fire on Soils and Water*; USDA Forest Service, Rocky Mountain Research Station: Ogden, UT, USA, 2005. [\[CrossRef\]](#)
9. Huot, F.; Hu, R.L.; Goyal, N.; Sankar, T.R.; Ihme, M.; Chen, Y.F. Next day wildfire spread: A machine learning dataset to predict wildfire spreading from remote-sensing data. *IEEE Trans. Geosci. Remote Sens.* **2021**, *60*, 4412513. [\[CrossRef\]](#)
10. Li, X.; Wang, X.; Sun, S.; Wang, Y.; Li, S.; Li, D. Predicting the wildland fire spread using a mixed-input crn model with both channel and spatial attention mechanisms. *Fire Technol.* **2023**, *59*, 2683–2717. [\[CrossRef\]](#)
11. Yin, K.; Shu, L.; Cheng, P.; Wang, M.; Huang, Y. DACSA: Deformable average channel and spatial attention model for wildfire prediction and drivers. *Stoch. Environ. Res. Risk Assess.* **2025**, *39*, 5647–5661. [\[CrossRef\]](#)
12. Finney, M. *Farsite: Fire Area Simulator: Model Development and Evaluation*; CreateSpace: North Charleston, SC, USA, 1998. [\[CrossRef\]](#)
13. Linn, R.R.; Harlow, F.H. *Firetec: A Transport Description of Wildfire Behavior*; Technical Report; Los Alamos National Laboratory: Los Alamos, NM, USA, 1997. [\[CrossRef\]](#)
14. Tolhurst, K.G.; Shields, B.; Chong, D.M. Phoenix: Development and application of a bushfire risk management tool. *Aust. J. Emerg. Manag.* **2008**, *23*, 47–54.
15. Rothermel, R.C. *A Mathematical Model for Predicting Fire Spread in Wildland Fuels*; Research Paper INT-115; USDA Forest Service, Intermountain Forest and Range Experiment Station: Ogden, UT, USA, 1972.
16. Shah, S.U.; Yebra, M.; Dijk, A.; Cary, G.J. Relating mcarthur fire danger indices to remote sensing derived burned area across australia. *Int. J. Wildland Fire* **2022**, *32*, 133–148. [\[CrossRef\]](#)
17. Hodges, J.L.; Lattimer, B.Y. Wildland fire spread modeling using convolutional neural networks. *Fire Technol.* **2019**, *55*, 2115–2142. [\[CrossRef\]](#)
18. Wang, X.; Wang, X.; Zhang, M.; Tang, C.; Li, X.; Sun, S.; Wang, Y.; Li, D.; Li, S. Predicting the continuous spatiotemporal state of ground fire based on the expended lstm model with self-attention mechanisms. *Fire* **2023**, *6*, 237. [\[CrossRef\]](#)
19. Zhu, J.; Liu, X.; Cheng, P.; Wang, M.; Huang, Y. Unveiling spatiotemporal patterns of wildfire risk: A transformer-based earth system analysis. *Clim. Dyn.* **2025**, *63*, 21. [\[CrossRef\]](#)
20. Albin, F.A. Response of free-burning fires to nonsteady wind. *Combust. Sci. Technol.* **1982**, *29*, 225–241. [\[CrossRef\]](#)
21. Abouali, A.; Viegas, D.X.; Raposo, J.R.N. Analysis of the wind flow and fire spread dynamics over a sloped-ridgeline hill. *Combust. Flame* **2021**, *234*, 111724. [\[CrossRef\]](#)
22. Peace, M.; Mattner, T.W.; Mills, G.; Kepert, J.D.; McCaw, L. Coupled fire-atmosphere simulations of the rocky river fire using wrf-sfire. *J. Appl. Meteorol. Climatol.* **2016**, *55*, 1151–1168. [\[CrossRef\]](#)
23. Dahl, N.; Xue, H.; Hu, X.; Xue, M. Coupled fire-atmosphere modeling of wildland fire spread using devs-fire and arps. *Nat. Hazards* **2015**, *77*, 1013–1035. [\[CrossRef\]](#)
24. Filippi, J.B.; Bosseur, F.; Balbi, J.H.; Veynante, D.; Lac, C.; Moigne, P.L.; Mari, C.; Strada, S.; Cuenot, B.; Cariolle, D. *A Coupled Atmosphere-Wildland Fire Meso-Scale Model*; Technical Report; Université de Corse/CNRS: Corte, France, 2009.

25. Filippi, J.B.; Bosseur, F.; Mari, C.; Strada, S. Numerical experiments using mesonh/forefire coupled atmospheric-fire model. In Proceedings of the Eighth Symposium on Fire and Forest Meteorology, Kalispell, MT, USA, 13–15 October 2009; p. 9.
26. Filippi, J.B.; Pialat, X.; Clements, C.B. Assessment of forefire/meso-nh for wildland fire/atmosphere coupled simulation of the fireflux experiment. *Proc. Combust. Inst.* **2013**, *34*, 2633–2640. [\[CrossRef\]](#)
27. Sawant, M.M.; Patil, R.S.; Shikhare, T.; Nagle, S.; Chavan, S.; Negi, S.; Bokde, N.D. A selective review on recent advancements in long, short and ultra-short-term wind power prediction. *Energies* **2022**, *15*, 8107. [\[CrossRef\]](#)
28. Landberg, L. A mathematical look at a physical power prediction model. *Wind. Energy* **1998**, *1*, 23–28. [\[CrossRef\]](#)
29. Karakus, O.; Kuruoglu, E.E.; Altinkaya, M.A. One-day ahead wind speed/power prediction based on polynomial autoregressive model. *IET Renew. Power Gener.* **2017**, *11*, 1430–1439. [\[CrossRef\]](#)
30. Tian, Z.; Li, S.; Wang, Y.; Wang, X. Wind power prediction method based on hybrid kernel function support vector machine. *Wind Eng.* **2017**, *42*, 252–264. [\[CrossRef\]](#)
31. Wang, J.; Li, Z. Wind speed interval prediction based on multidimensional time series of convolutional neural networks. *Eng. Appl. Artif. Intell.* **2023**, *121*, 105987. [\[CrossRef\]](#)
32. Li, K.; Wang, Z.; Yan, B.; Yang, Q.; Zhou, X. A wind speed prediction methodology based on deep neural network without future information leakage. *SSRN Electron. J.* **2022**. [\[CrossRef\]](#)
33. Lin, C.F.; Li, X.; Shi, T.; Sheng, J.; Sun, S.; Wang, Y.; Li, D. Forecasting of wind speed under wind-fire coupling scenarios by combining hs-vmd and am-lstm. *Ecol. Inform.* **2023**, *77*, 102270. [\[CrossRef\]](#)
34. Li, J.; Song, Z.; Wang, X.; Wang, Y.; Jia, Y. A novel offshore wind farm typhoon wind speed prediction model based on pso-bi-lstm improved by vmd. *Energy* **2022**, *251*, 123848. [\[CrossRef\]](#)
35. Tuerxun, W.; Xu, C.; Guo, H.; Guo, L.; Zeng, N.; Cheng, Z. An ultra-short-term wind speed prediction model using lstm based on modified tuna swarm optimization and successive variational mode decomposition. *Energy Sci. Eng.* **2022**, *10*, 3001–3022. [\[CrossRef\]](#)
36. Masinda, M.M.; Li, F.; Liu, Q.; Sun, L.; Hu, T. Prediction model of moisture content of dead fine fuel in forest plantations on maoer mountain, northeast china. *J. For. Res.* **2021**, *32*, 2023–2035. [\[CrossRef\]](#)
37. 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. [\[CrossRef\]](#)
38. Dragomiretskiy, K.; Zosso, D. Variational mode decomposition. *IEEE Trans. Signal Process.* **2014**, *62*, 531–544. [\[CrossRef\]](#)
39. Wu, J.; Chen, X.; Zhu, M. A 1/f noise detection method for igbt devices based on pso-vmd. *Electronics* **2022**, *11*, 1722. [\[CrossRef\]](#)
40. Qi, P.; Chang, J.; Chen, X.; Wang, T.; Wu, M. Identification of rock properties of rock wall cut by roadheader based on pso-vmd-lssvm. *Front. Earth Sci.* **2022**, *10*, 884633. [\[CrossRef\]](#)
41. Peng, Z.; Bai, H.; Shiina, T.; Deng, J.; Liu, B.; Zhang, X. Led-lidar echo denoising based on adaptive pso-vmd. *Information* **2022**, *13*, 558. [\[CrossRef\]](#)
42. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. [\[CrossRef\]](#)
43. Bazi, R.; Benkedjouh, T.; Habbouche, H.; Rechak, S.; Zerhouni, N. A hybrid cnn-bilstm approach-based variational mode decomposition for tool wear monitoring. *Int. J. Adv. Manuf. Technol.* **2022**, *119*, 3803–3817. [\[CrossRef\]](#)
44. Yang, Y.; Zhang, Y. Multi-point wind power prediction in wind farms based on am-lstm. In *2021 IEEE Sustainable Power and Energy Conference (iSPEC)*; IEEE: Piscataway, NJ, USA, 2021; pp. 8–12. [\[CrossRef\]](#)
45. Phillips, R.J.; Waldrop, T.A.; Simon, D.M. Assessment of the farsite model for predicting fire behavior in the southern appalachian mountains. In *Proceedings of the 13th Biennial Southern Silvicultural Research Conference*; U.S. Department of Agriculture, Forest Service, Southern Research Station: Asheville, NC, USA, 2006; pp. 521–525.
46. Zigner, K.; Carvalho, L.M.V.; Peterson, S.H.; Fujioka, F.; Duine, G.; Jones, C.E.; Roberts, D.A.; Moritz, M.A. Evaluating the ability of farsite to simulate wildfires influenced by extreme, downslope winds in santa barbara, california. *Fire* **2020**, *3*, 29. [\[CrossRef\]](#)
47. Valero-Carreras, D.; Alcaraz, J.; Landete, M. Comparing two svm models through different metrics based on the confusion matrix. *Comput. Oper. Res.* **2022**, *152*, 106131. [\[CrossRef\]](#)
48. Tinungki, G.M. The analysis of partial autocorrelation function in predicting maximum wind speed. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *235*, 012097. [\[CrossRef\]](#)
49. Zhou, Q.; Chen, D.L.; Hu, Z.; Chen, X. Decompositions of taylor diagram and diso performance criteria. *Int. J. Climatol.* **2021**, *41*, 5726–5732. [\[CrossRef\]](#)
50. Filippi, J.B.; Bosseur, F.; Mari, C.; Lac, C. Simulation of a large wildfire in a coupled fire-atmosphere model. *Atmosphere* **2018**, *9*, 218. [\[CrossRef\]](#)
51. Sun, T.; Zhang, L.; Chen, W.; Tang, X.; Qin, Q. Mountains forest fire spread simulator based on geo-cellular automaton combined with wang zhengfei velocity model. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2013**, *6*, 1971–1987. [\[CrossRef\]](#)

52. Zhe, C. Forest fire spread fast model based on 3d cellular automaton in spatially heterogeneous area. *J. Beijing For. Univ.* **2012**, *34*, 86–91.
53. Boer, M.M.; Nolan, R.H.; Dios, V.R.; Clarke, H.; Price, O.F.; Bradstock, R.A. Changing weather extremes call for early warning of potential for catastrophic fire. *Earth's Future* **2017**, *5*, 1196–1202. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.