

Article

Spring Dust Intensity Monitoring at Hourly Intervals Using Himawari-8 Satellite Images and Artificial Intelligence Method

Jiafu Zhao ^{1,2}, Pengfei Chen ^{1,3,*}  and Xiaolong Sun ⁴
¹ State Key Laboratory of Resources and Environment Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; zhaojiafu23@mailsucas.ac.cn

² University of Chinese Academy of Sciences, Beijing 100049, China

³ National Earth System Science Data Center, National Science and Technology Infrastructure of China, Beijing 100101, China

⁴ Inner Mongolia Eco- and Agro-Meteorological Center, Hohhot 010051, China; sxldreamcast@163.com

* Correspondence: pengfeichen@igsnr.ac.cn; Tel.: +86-10-64889895

Highlights

What are the main findings?

- Time-series data can be used to monitor dust intensity with high accuracy.
- Combining CNN and BiLSTM can achieve high accuracy for dust intensity monitoring.

What is the implication of the main findings?

- Progressive dust temporal (PDT) features proposed based on time-series data are important variables for dust intensity prediction.
- The PCBNNet model proposed in this study by combining CNN and BiLSTM using PDT features has the best performance for dust intensity prediction among all tested models.

Abstract

To achieve accurate monitoring of dust intensity, this study developed a coupled model based on a convolutional neural network (CNN) and a bidirectional long short-term memory network (Bi-LSTM) to monitor dust intensity in a 24 h dynamic pattern. During this process, progressive dust temporal (PDT) features reflecting the temporal dynamics of dust events, including clear-sky state values, adjacent observation state values, and current observation state values for spectral indices and brightness temperatures, were first designed. Then, a PCBNNet model combining CNN and Bi-LSTM was established and compared with PCLNet (CNN and LSTM), random forest (RF), and support vector machine (SVM) using only single-time observations, as well as PDT-RF and PDT-SVM, which used PDT features as inputs. Finally, a dust intensity product was generated by the optimal model, and its relationship with PM₁₀ concentrations at air quality stations was examined. Furthermore, a dust storm event in April 2021 was analyzed to evaluate the ability of the products to capture event dynamics. The results indicate that PCBNNet achieved the highest accuracy among all models on the validation dataset. Predicted dust intensity levels were well correlated with PM₁₀ concentrations, and the monitoring product effectively tracked the spatiotemporal evolution of dust event.

Keywords: dust intensity; CNN; Bi-LSTM; Himawari-8; 24-h continuous monitoring



Academic Editor: Dimitris Kaskaoutis

Received: 17 August 2025

Revised: 29 September 2025

Accepted: 9 October 2025

Published: 11 October 2025

Citation: Zhao, J.; Chen, P.; Sun, X. Spring Dust Intensity Monitoring at Hourly Intervals Using Himawari-8 Satellite Images and Artificial Intelligence Method. *Remote Sens.* **2025**, *17*, 3407. <https://doi.org/10.3390/rs17203407>

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1. Introduction

Dust weather is a common natural disaster that has negative effects on human health, ecosystems, and socioeconomic activities, such as increasing the incidence of respiratory and cardiovascular diseases [1], increasing soil erosion [2], and disrupting transportation and other activities [3,4]. In accordance with the national standards of China, dust weather can be classified into five intensity levels, namely, floating dust, blowing sand, dust storms, strong dust storms, and extremely strong dust storms, on the basis of near-surface wind speed and visibility [5]. Dust of different intensity levels has differing degrees of harm to human society. It is highly important to monitor the intensity and dynamics of dust weather in a timely manner to adopt locally adapted strategies for realizing precise dust prevention.

Owing to the highly uncertain and complex spatiotemporal distribution of dust in the atmosphere, traditional ground-based observation methods often have difficulty in meeting the requirements of large-scale, real-time monitoring [6]. Remote sensing technology enables the continuous monitoring of the formation, propagation, and dissipation processes of dust events on a large scale [7–9]. Therefore, remote sensing technology offers irreplaceable advantages in the field of dust weather monitoring. Satellite platforms for dust monitoring can be classified into two categories: polar-orbiting satellites and geostationary satellites. Polar-orbiting satellites, such as Terra, Aqua, Suomi NPP, and FY-3D, operate in orbits passing over the Earth's poles, enabling coverage of most global regions and providing imagery with relatively high spatial resolution. However, these methods have the disadvantage of low temporal resolution, making them less suitable than other methods for the dynamic monitoring of dust events [10]. In contrast, geostationary satellites, such as the GOES series satellites, Meteosat series satellites, Himawari-8, and FY-4A, enable continuous monitoring of a fixed region, providing advantages such as the real-time dynamic monitoring of dust events [11,12]. Considering the Himawari-8 satellite provides data over East Asia and the Western Pacific at 10 min intervals, and has higher spatial resolution and more bands than other satellites covering the same area [13], it offers valuable information for characterizing the formation, propagation, and dissipation of dust storms. Therefore, it represents an important data source for developing dust monitoring technologies.

Existing remote sensing-based dust storm monitoring methods can be classified into two main types: spectral index-based methods and machine learning-based methods. Spectral index-based methods combine multiband information from the visible, near-infrared, and thermal infrared bands to determine the unique characteristics of dust and use this information to identify dust storms. For example, the brightness temperature difference (BTD) index was designed on the basis that dust particles have different emissivity in different infrared bands, resulting in a brightness temperature difference, which can be used to identify dust [14]. Because dust is characterized by high reflectance in the near-infrared band and low reflectance in the blue band, the normalized difference dust index (NDDI) indicates sensitivity to dust signals on the basis of the difference between normalized reflectance levels [15]. The thermal infrared integrated dust index (TIIDI) is an integrated index for dust detection that is based on the differences in brightness temperature across multiple MODIS thermal infrared bands, including 3.7 μm , 8.6 μm , 11 μm , and 12 μm . It can effectively distinguish dust from clouds and surface features [16]. Overall, the spectral index-based method has the advantages of simplicity and computational efficiency. However, this approach relies on spectral information from a limited number of bands, making it unable to capture complex nonlinear relationships between image signals and dust, and it has limited adaptability to different environmental backgrounds and is easily influenced by external factors, such as surface type [10]. Machine learning methods use information from all bands of imagery to form an input set, rely on complex network architectures to autonomously learn dust characteristics by a large training dataset, and

then achieve dust prediction on the basis of a trained model. Support vector machines (SVMs), random forests (RFs), and convolutional neural networks (CNNs) are commonly used methods. On the basis of MODIS satellite images, Shi et al. [17] developed a dust storm monitoring model using an SVM model and detected dust storms in areas of the Arabian Desert, Gobi Desert, and Taklamakan Desert. Similarly, based on MODIS satellite data, Souri and Vajedian [18] constructed a dust monitoring model based on the RF algorithm, which outperformed spectral index-based methods for dust storm monitoring in the Middle East region. Furthermore, based on FY-4A images, Jiang et al. [19] developed a dust monitoring model using a CNN and successfully detected dust storms in the Tarim Basin. The machine learning method can capture the complex nonlinear relationships between image signals and dust, thereby enhancing the accuracy and robustness of dust monitoring. However, most existing machine learning-based studies have focused on analyses of single-time imagery for dust storm detection, neglecting the utilization of time series imagery. In fact, the spectral characteristics of the atmosphere undergo a series of dynamic changes before the arrival of dust storms, and these temporal changes are crucial for improving dust identification accuracy. At present, few studies on dust monitoring based on time series imagery via machine learning methods exist. Only Zhen et al. [20] combined a CNN and a long short-term memory (LSTM) model to construct a dust identification model for identifying dust and non-dust areas in the Taklamakan Desert region in southern Xinjiang, China, on the basis of FY-4A satellite data. Nevertheless, when processing time series information, the CNN-LSTM model can capture information only in a forward direction, limiting its ability to extract complex time series features. The bidirectional long short-term memory (Bi-LSTM) network is an improvement in the LSTM. It processes time series data in both forward and backward directions [21]. By addressing information in both directions, a Bi-LSTM model can capture valuable contextual information from time series data [22]. Dust events exhibit distinct temporal evolution patterns. The changes in spectral information inherent in images before and after a dust event provide an important basis for event identification. Although coupling CNN and Bi-LSTM models has great potential for application in dust monitoring, it has rarely been explored to date. Additionally, simply distinguishing dust from non-dust is insufficient to support precise dust prevention, and information about dust intensity needs to be obtained. Therefore, it is important to conduct research to monitor dust intensity by combining CNN and Bi-LSTM models on the basis of time series imagery.

The Inner Mongolia Autonomous Region is located in the northern part of China and is a typical arid and semiarid region in China. This region features a complex geographical environment encompassing vast grasslands, deserts, and gobi areas and is classified as a climate-sensitive zone with a relatively fragile ecosystem [23]. With global warming and the intensification of human activities, the environment of Inner Mongolia is facing severe challenges. The frequent occurrence of dust storms has had significant negative impacts on the ecosystem and socioeconomic development of the region [24]. Therefore, effective monitoring of dust and the provision of early warnings to mitigate their negative impacts are urgently needed. In this study, a dust intensity monitoring model based on Himawari geostationary meteorological satellite imagery and time series deep learning methods is developed. Specifically, the objectives of this study are (1) to design a time-series dust intensity identification feature and to propose a dust intensity monitoring model that couples the CNN and Bi-LSTM methods on the basis of these features, and (2) to compare the proposed model with existing methods to provide a reference for users in selecting the optimal approach.

2. Materials and Methods

2.1. Study Area

The Inner Mongolia Autonomous Region ($37^{\circ}24'N$ – $53^{\circ}23'N$, $97^{\circ}12'E$ – $126^{\circ}04'E$) is located in northern China. The region has an elongated shape, with a north–south extent exceeding 2400 km and a total area of 1.183 million square kilometers (Figure 1). The topography of the region generally slopes from the high western areas to the lower eastern areas. The eastern part is characterized predominantly by grasslands and river valleys, whereas the western part is characterized by plateaus and mountainous terrain [25]. Desert, sandy, and semidesert areas are concentrated in the central and western regions, including the Kubuqi Desert, Tengger Desert, Alxa Desert, and Ulan Buh Desert.

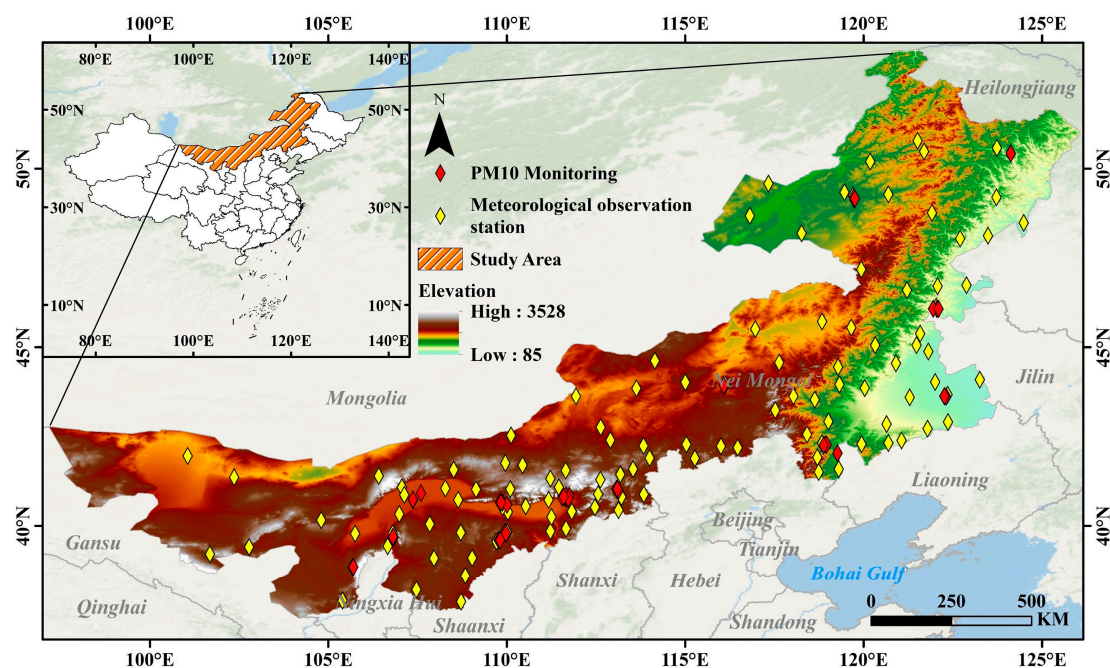


Figure 1. Study area and locations of observation stations.

The Inner Mongolia Autonomous Region is an important dust source and transportation pathway for dust storms in northern and eastern China. The climate of the region is arid and characterized by low precipitation and strong winds. Grasslands and shrubs are the predominant vegetation types in the region [26]. In the western desert and sandy regions, the loose soil structure is highly susceptible to wind erosion [27]. Dust weather in the region usually occurs in spring. Under the influence of strong winds, dust particles are easily dispersed, leading to the formation of dust storms that extend to central and southern China, significantly affecting the regional ecological environment [28].

2.2. Data Collection

2.2.1. Advanced Himawari Imager (AHI) Data

Himawari-8 (H8) and Himawari-9 (H9) are new-generation geostationary meteorological satellites deployed by the Japan Meteorological Agency. H8 officially began operational service in 2015, whereas H9 was launched in 2022 and took over as the primary operational satellite in 2023. The two satellites have highly consistent observation capabilities and are both equipped with the Advanced Himawari Imager (AHI), ensuring the temporal continuity and long-term stability of remote sensing data. The AHI can provide high-quality multispectral imagery every 10 min. It has an observation range from $60^{\circ}S$ to $60^{\circ}N$ and $80^{\circ}E$ to $160^{\circ}W$, covering East Asia and the western Pacific. The imagery spans 16 bands,

covering wavelengths from 0.4 to 14 μm . Thus, imagery from the AHI provides distinct advantages for monitoring and tracking dust events [29].

Because the objective of this study was to monitor dust intensity continually for 24 h (including both daytime and nighttime), only the thermal infrared bands were used to construct the dust intensity monitoring model, as shown in Table 1. AHI Level-1B data products were collected for all hourly time points during the spring seasons (March–May) from 2019 to 2023 in the Inner Mongolia Autonomous Region. The spatial resolution of this product is 2 km. In addition, the cloud masking algorithm proposed by Yamamoto et al. [30] was employed to remove cloud-contaminated pixels under various observational conditions, including daytime, nighttime, and twilight. It should be noted that in order to realize the real-time monitoring of the dust intensity, unlike Yamamoto et al. [30], the data of the previous 15 days of the observation time were used to synthesize the cloud-free image in this study instead of using the data of all the days of the month in which the observation time was observed. In addition, to improve the accuracy of cloud removal and prevent dust pixels from being mistakenly identified and excluded as clouds, the dust index proposed by Hansell et al. [31] was further incorporated to assist in distinguishing between clouds and dust.

Table 1. The AHI bands used in this study.

Band Number	Central Wavelength (μm)	Spectral Range (μm)
7	3.9	3.74–3.96
8	6.2	6.06–6.43
9	6.9	6.89–7.01
10	7.3	7.26–7.43
11	8.6	8.44–8.76
12	9.6	9.54–9.72
13	10.4	10.3–10.6
14	11.2	11.1–11.3
15	12.4	12.2–12.5
16	13.3	13.2–13.4

2.2.2. Station Observation Data

Visibility data and wind speed data from 119 meteorological observation stations and PM_{10} concentration data from 39 air pollution monitoring stations across the Inner Mongolia Autonomous Region were collected for the spring seasons (March–May) from 2019 to 2023. The locations of these stations are shown in Figure 1. The visibility data and wind speed data were provided by the Inner Mongolia Ecological and Agricultural Meteorological Center, with a temporal resolution of 1 h. As stated previously, dust is classified into different intensity levels on the basis of visibility and wind speed data in China. Therefore, visibility and wind speed data were used to calculate the dust intensity in this study. PM_{10} data were obtained from the China National Environmental Monitoring Centre (<http://www.cnemc.cn> accessed on 11 March 2025), and the data quality was controlled according to the Ambient Air Quality Standard (GB3095-2012) [32]. The temporal resolution of the PM_{10} data was also 1 h.

2.3. Data Analysis Methods

2.3.1. Dust Spectral Indices

Spectral indices were derived from specific band reflectance, with bands selected on the basis of physical principles. This approach helps reduce the impact of environmental background noise and improves sensitivity to the target parameters. In accordance with previous studies and considering the characteristics of AHI imagery, several spectral indices

with the potential to estimate dust storm intensity were selected. They were used as inputs to the machine learning model along with the brightness temperature from each band. The selected dust spectral indices included three typical brightness temperature difference (BTD) indices, the three-band volcanic ash product (TVAP), the thermal infrared dust index (BADI), and the thermal infrared composite dust index (TIIDI). The formulas for each index are shown in Table 2.

Table 2. Dust spectral indices used in this study.

Abbreviation	Full Name	Formula	Designer(s)
BTD _{11–12}	Brightness temperature difference between 11.2 µm and 12.4 µm	$BTD_{11-12} = BT_{11.2} - BT_{12.4}$	[33]
BTD _{3–11}	Brightness temperature difference between 3.9 µm and 11.2 µm	$BTD_{3-11} = BT_{3.9} - BT_{11.2}$	[14]
BTD _{8–11}	Brightness temperature difference between 8.6 µm and 11.2 µm	$BTD_{8-11} = BT_{8.6} - BT_{11.2}$	[34]
TVAP	Three-band volcanic ash product	$TVAP = 60 + 10(BT_{12.4} - BT_{11.2}) + 3(BT_{3.9} - BT_{11.2})$	[35]
BADI	Brightness temperature adjusted difference index	$BADI = \frac{2}{\pi} \times \arctan\left(\frac{BDI}{BDI_{0.95}}\right)$ $BDI = (BT_{3.9} - BT_{12.4})^2 \times (BT_{11.2} - BT_{12.4})$ $TIIDI = (BT_{12.4} - BT_{11.2}) \times \exp\left(\frac{BT_{8.6} - BT_{11.2}}{a}\right)$ $\times (BT_{3.9} - BT_{11.2})$	[15]
TIIDI	Thermal infrared integrated dust index	$a = \begin{cases} 5, & \text{if } BT_{8.6} - BT_{11.2} > 0 \\ 10, & \text{otherwise} \end{cases}$	[36]

2.3.2. Construction of Progressive Dust Temporal (PDT) Features

Considering the progression of dust generation and transport processes, a series of temporal features, hereafter referred to as progressive dust temporal (PDT) features, were derived from spectral indices and multiband brightness temperature information to characterize the dynamic evolution of dust events in this study.

In this process, the designed temporal features included clear-sky state values, adjacent observation state values, and current observation state values for spectral indices and brightness temperatures. Among them, clear-sky state values refer to the spectral index values and brightness temperature values calculated from clear-sky imagery composited from the previous 7 days of satellite images prior to the observation time. Data composition can provide stable baseline information for the status of a spatial unit without dust, mitigating observational errors or cloud interference present in single-time imagery. The 7-day composite was chosen because dust storms typically do not persist beyond 7 days. For image composition, the 11.2 µm band (channel 14) is used to select the image corresponding to the maximum brightness temperature during the 7-day period as a reference, on the basis of the finding that lower brightness temperatures in this band are associated with stronger dust intensity [37]. The adjacent observation state values were calculated using a weighted composite method to better reflect the temporal characteristics of dust events during their developmental stages, mitigating observational errors or cloud effects compared to single-time images. Specifically, spectral indices and brightness temperatures were first calculated from images within the 30 h preceding the observation time, forming a time series. Then, exponential weighted averaging was applied using Formulas (1) and (2) to obtain the final state values for each pixel. The 30 h time window was selected on the basis of the study by Yao et al. [38] on typical dust storm evolution processes in the Alxa

region, which is a representative area for the study area. To ensure the integrity of the time series data, missing values were interpolated before the composite calculation. In this process, the interpolation method was dynamically selected on the basis of the number of valid observations. If there were two or more valid observations in a sequence, piecewise cubic Hermite interpolating polynomial (PCHIP) interpolation was applied. This method performs well in preserving the shape and trend of the data and effectively suppresses the overshoot artifacts commonly associated with traditional spline interpolation [39]. Notably, when only two valid points were available, linear interpolation was applied. If there was only one valid observation, the nearest neighbor method was used. If the entire sequence was missing, no interpolation was performed, and the missing state was retained. Notably, in all the samples used in this study, the number of valid points within the 30 h sequence was never fewer than three, so all the interpolation operations met the conditions for PCHIP. The current observation state values correspond to the spectral index values and brightness temperature values calculated directly from the image at the observation time. These PDT features serve as the basis for subsequent model development (Section 2.3.3).

$$X(x, y) = \sum_{i=1}^n w_i \cdot I_i(x, y) \quad (1)$$

where $X(x, y)$ represents the final spectral index value or brightness temperature value at pixel (x, y) in the composited image; $I_i(x, y)$ denotes the spectral index or brightness temperature value at pixel (x, y) from the image at the i -th hour; and w_i is the weight assigned to the image at the i -th hour.

$$w_i = \frac{e^{\lambda \cdot i}}{\sum_{j=1}^n e^{\lambda \cdot j}} \quad (2)$$

where w_i represents the weight of the i -th hour and λ is a constant that controls the rate of weight increase, which is set to 0.5 in this study; n denotes the total number of hours used for compositing, and in this study, n was set to 30, with the number of hours numbered from the 30th hour to the 1st hour prior to the observation time ranging from 1 to 30.

2.3.3. New Proposed Model and Other Models Used for Comparison in This Study

To effectively leverage the PDT features for dust intensity monitoring, a deep learning model was constructed by combining a one-dimensional convolutional neural network (1D-CNN) and a bidirectional long short-term memory (BiLSTM) network, hereafter referred to as PCBNNet. Considering the station observations are at point-scale, the 1D-CNN was adopted as a front-end feature extractor to process spectral indices and brightness temperature feature sequences at each time step, corresponding to the monitored data from ground. By leveraging local receptive fields and weight sharing, the 1D-CNN can efficiently capture local variation patterns within one-dimensional feature vectors [40–42]. In the model structure, the three input vectors at different time points, X_{t-2} , X_{t-1} , and X_t , which represent the clear-sky state values, adjacent observation state values, and current observation state values of the spectral indices and brightness temperatures, were first processed using the 1D-CNN method individually. The 1D-CNN method contains multiple 1D-convolutional layers, normalization, and pooling operations to generate a feature vector for each time, denoted as F_{t-2} , F_{t-1} , and F_t (Figure 2a). Then, F_{t-2} , F_{t-1} , and F_t were used as inputs to the BiLSTM network to estimate the dust intensity level. Based on this structure, it ensures that a 1D-CNN method can extract comprehensive features from different parameters while preventing the mixing of features from different time steps before they enter into the BiLSTM. Then, the BiLSTM was used to extract the feature from time series

and connected the features to the dust intensity. The BiLSTM hidden layer consisted of two subnetworks responsible for extracting information from the forward and backward flows.

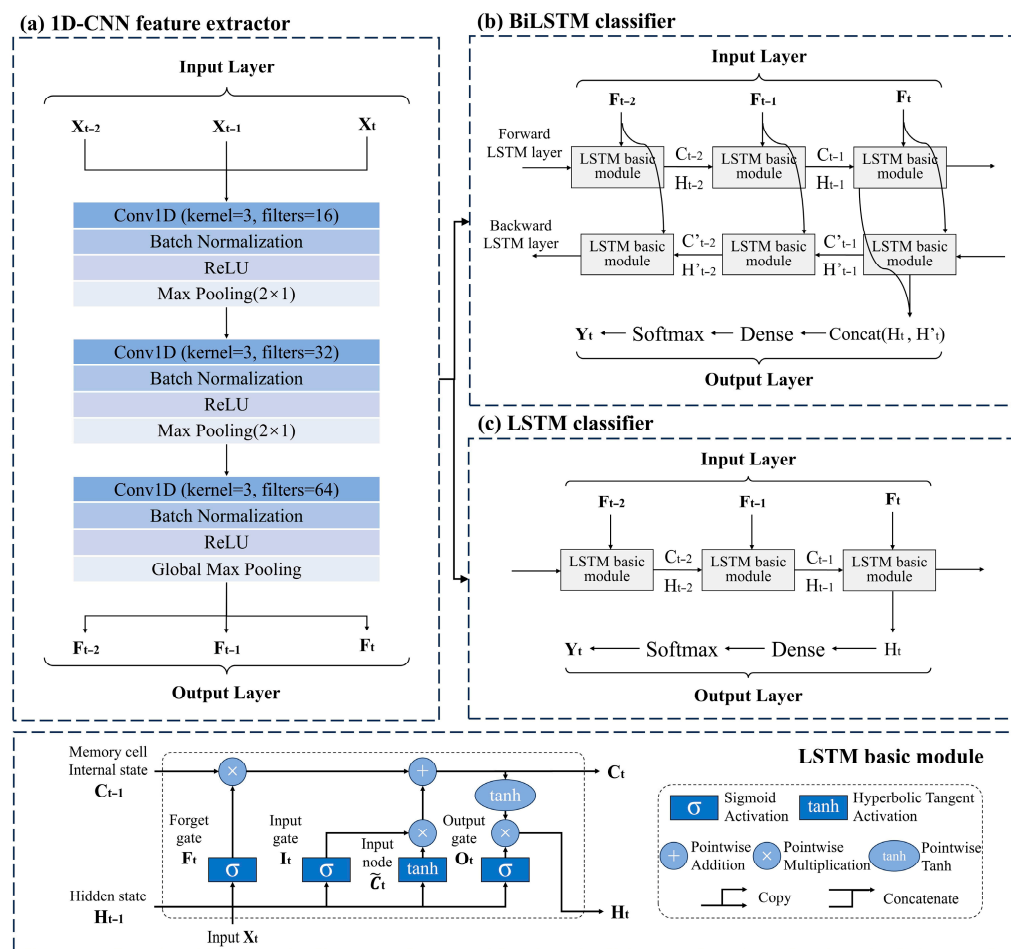


Figure 2. Structures of the progressive dust temporal CNN-BiLSTM network (PCBNet) and progressive dust temporal CNN-LSTM network (PCLNet) used in this study.

In addition to PCBNet, three comparative models were implemented to evaluate performance: random forest (RF), support vector machine (SVM), and a 1D-CNN-LSTM hybrid network. RF and SVM have been widely used in dust event monitoring tasks [43]. Moreover, Zhen et al. [20] coupled convolutional neural networks (CNNs) with long short-term memory (LSTM) networks for dust classification. However, in their design, the CNN extracted features from spectral vectors across all time steps simultaneously before passing them to the LSTM. This approach may mix temporal information, thereby weakening the ability of the LSTM to extract sequential dependencies. To address this issue, we adopted a strategy consistent with PCBNet, where 1D-CNNs were applied separately to spectral vectors at each time step to produce features (F_{t-2} , F_{t-1} , and F_t), which were subsequently fed into the LSTM. The network structure for this 1D-CNN-LSTM-based dust intensity monitoring model, hereafter named the progressive dust temporal CNN-LSTM network (PCLNet), is illustrated by combining Figure 2a,c. For the PCBNet and PCLNet models, the training objective was defined using the sparse categorical cross-entropy loss function, which is widely used in multi-class classification tasks, optimized with the Adam optimizer.

2.3.4. Comparison Experiment

To comprehensively evaluate the performance of the proposed model, a comparison experiment was designed in this study. The overall technical workflow is illustrated in Figure 3, including data preparation, model training, and validation.

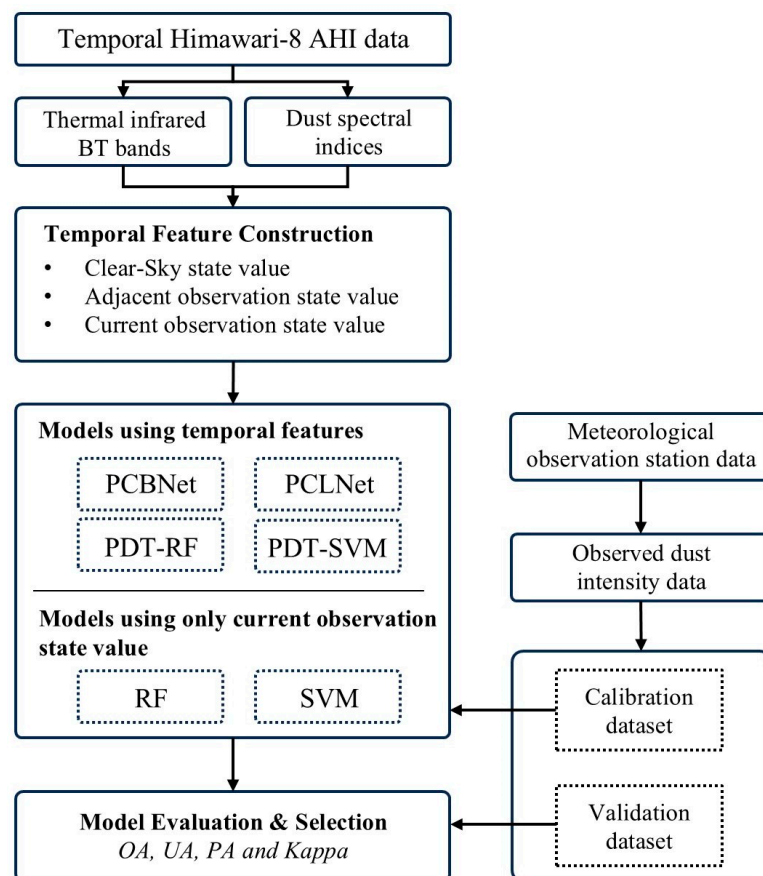


Figure 3. Flow chart for comparing different methods for dust intensity monitoring. PCBNet: progressive dust temporal CNN-BiLSTM network; PCLNet: progressive dust temporal CNN-LSTM network; PDT-RF: progressive dust temporal features + random forest; PDT-SVM: progressive dust temporal features + support vector machine; RF: random forest; SVM: support vector machine.

For data preparation, as dust storms are low-probability events, to ensure sample balance and improve the dust monitoring performance of each model, this study constructed training and validation datasets using only dust intensity data from meteorological stations on days when dust storms occurred, along with the corresponding image data required by each model. Notably, the occurrence of dust events on a given day does not imply that all stations recorded dust; rather, dust events were observed only in certain areas within the study region. Therefore, the dataset includes both records with detected dust and those without dust at the station level. According to the Chinese national standard GB/T 20480-2017 [5] for sand and dust weather classification, dust intensity can be categorized into five levels on the basis of visibility and wind speed data: extremely severe sandstorm (ESSS): visibility < 50 m; severe sandstorm (SSS): $50 \text{ m} \leq \text{visibility} < 500 \text{ m}$; sandstorm (SS): $500 \text{ m} \leq \text{visibility} < 1000 \text{ m}$; blowing sand (BS): $1000 \text{ m} \leq \text{visibility} < 10,000 \text{ m}$; floating dust (FD): $1000 \text{ m} \leq \text{visibility} < 10,000 \text{ m}$, with a wind speed $\leq 5.4 \text{ m/s}$ ($\leq$ level 3); and dust free (DF): visibility $\geq 10,000 \text{ m}$. As the main difference in dust intensity with FD level and BS level is the wind speed, which cannot be reflected in imagery, FD and BS are considered the same category in this study. In addition, dust intensity with ESSS seldom occurs in the research area. From 2019 to 2023, only 13 samples can be obtained from monitoring data.

Thus, ESSS and SSS were also treated as the same category in this study. Dates of the monitoring data from the meteorological observation station used in this study and the number of samples corresponding to different levels of dust storm intensity are shown in Table 3. For model development, dust events from 2021 to 2023 were used as training samples, while those from 2019 to 2020 were reserved for validation. To address the imbalance in the number of samples across different dust intensity levels and to improve the generalization of the models, Gaussian white noise with intensities of 0.1, 0.2, 0.3, and 0.4 was separately added to the samples for data augmentation. After augmentation, 1000 samples were randomly selected from each category to construct the final training dataset.

Table 3. Dates on which the monitoring data were obtained at the meteorological observation stations selected in this study and the number of samples corresponding to different dust intensity levels.

Sandstorm Events	ESSS/SSS *	SS *	FD/BS *	DF *	Sandstorm Events	ESSS/SSS *	SS *	FD/BS *	DF *
17 April 2019	0	0	197	671	6 May 2021	1	23	588	308
11 May 2019	10	30	93	369	3 March 2022	2	5	579	933
15 May 2019	2	38	477	1029	13 March 2022	7	20	416	454
11 May 2020	1	8	207	305	20 April 2022	2	29	271	433
15 May 2020	0	0	167	431	9 March 2023	8	20	343	1042
14 March 2021	69	48	318	274	10 March 2023	3	13	432	398
15 March 2021	29	72	403	627	14 March 2023	0	0	177	546
16 March 2021	0	9	509	477	20 March 2023	11	7	529	817
17 March 2021	2	6	187	233	21 March 2023	67	129	934	308
18 March 2021	9	16	289	261	22 March 2023	0	7	603	515
19 March 2021	3	1	287	354	9 April 2023	1	7	749	672
27 March 2021	41	165	840	765	10 April 2023	14	40	998	388
14 April 2021	7	14	194	906	11 April 2023	0	1	572	908
15 April 2021	4	14	532	430	13 April 2023	1	14	208	340
26 April 2021	0	7	425	622	19 May 2023	1	42	605	486
5 May 2021	2	5	268	429					

* ESSS/SSS refers to extremely severe sandstorm/severe sandstorm, SS refers to sandstorm, FD/BS refers to floating dust/blowing sand, and DF refers to dust-free conditions.

For model comparison, six models were compared in this study. They included the PCBNNet, PCLNet, RF, and SVM models using the time series features developed in this study as inputs (referred to as PDT-RF and PDT-SVM, respectively) and the RF and SVM models using only the spectral indices and brightness temperatures at the observation time as inputs. Based on the calibration dataset, hyperparameters of all models were optimized through grid search combined with 10-fold cross-validation. For PCBNNet and PCLNet, the key hyperparameters included the number of hidden nodes, batch size, number of training epochs, learning rate, and optimizer. For PDT-RF and RF, the hyperparameters included the number of trees, maximum depth, and maximum number of features for splitting. For PDT-SVM and SVM, the hyperparameters included the kernel function, regularization parameter (C), and epsilon-insensitive loss. The detailed hyperparameter settings are provided in Table 4. For model validation, they were evaluated using the independent validation dataset. Confusion matrices were constructed, and four accuracy metrics were calculated: overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and the Kappa coefficient. Their calculations are shown in Formulas (3)–(6). These indices enabled a comprehensive comparison of the predictive accuracy and reliability of different models.

$$PA_i = \frac{n_{ii}}{\sum_j n_{ij}} \times 100\% \quad (3)$$

$$UA_i = \frac{n_{ii}}{\sum_j n_{ji}} \times 100\% \quad (4)$$

$$OA = \frac{\sum_i n_{ii}}{N} \times 100\% \quad (5)$$

$$Kappa = \frac{N \sum_i n_{ii} - \sum_i (\sum_j n_{ij})(\sum_j n_{ji})}{N^2 - \sum_i (\sum_j n_{ij})(\sum_j n_{ji})} \quad (6)$$

where n_{ii} is the number of correctly classified samples in class i , $\sum_j n_{ij}$ and $\sum_j n_{ji}$ are the row and column sums of the confusion matrix for class i , and N is the total number of samples.

Table 4. Hyperparameter settings for different models.

Model	Hyperparameter Settings
PCLNet; PCBNNet	Number of nodes: 64, 128, 256, 512; Batch size: 16, 32, 64, 128, 256; Number of epochs: 50, 100, 150, 200; Learning rate: 0.1, 0.01, 0.001; Optimizer: Adam.
PDT-RF; RF	Number of estimators: 10, 100, 500, 1000; Max depth: 10, 50, 100; Max features: 0.5, 'log2', 'sqrt'.
PDT-SVM; SVM	Kernel: 'linear', 'poly', 'rbf', 'sigmoid'; C: 0.001, 0.01, 0.1, 1.0, 10, 20; Epsilon: 0.001, 0.01, 0.1, 1.0, 10, 20.

2.3.5. Dust Intensity Monitoring Datasets Based on the Optimal Method and Their Validation

Aerosol optical depth (AOD) measurements and the Ångström index from AERONET sites are widely utilized in accuracy assessments of dust detection algorithms [44]. However, only one AERONET site in the study area provides valid observation data, limiting the applicability of this validation method in the region. In contrast, PM₁₀ concentrations are highly sensitive to large near-surface particles, especially dust particles, and can reflect variations in dust intensity [26,45]. Therefore, PM₁₀ concentration data were used to validate the dust intensity classification datasets generated by the optimal dust monitoring model [46,47]. During this process, the dust intensity levels at each station were extracted from the above datasets, and then the PM₁₀ concentration data were classified into different groups according to dust intensity levels. Analysis of variance (ANOVA) was performed on these groups to determine whether the PM₁₀ concentrations in the different groups significantly differed ($p < 0.05$). In addition, correlation analysis was also carried out between PM₁₀ concentration and predicted dust intensity levels. Furthermore, to assess the potential of the proposed method for the dynamic monitoring of dust storm processes, a typical severe dust storm event from 14 April to 15 April 2021 was used as an example to demonstrate the ability of satellite-derived dust level data to capture the spatial evolution of dust events. During this process, the predicted dust intensity and observed dust intensity at meteorological observation stations were compared and a confusion matrix was made. In addition, the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model was used to track the trajectories of the dust storm. The obtained trajectories were compared with the monitored dynamics of the dust storm in this study.

3. Results and Analysis

3.1. Comparison of the Performance of Different Dust Intensity Monitoring Models

The optimal hyperparameter settings determined by cross-validation are shown in Table 5. All models were evaluated using the independent validation dataset and the results are illustrated in Table 6. In addition, the confusion matrixes for each model are shown in Appendix A.

Table 5. Optimal hyperparameter settings of different models.

Model	Hyperparameter Settings
PCBNet	Nodes = 128; Batch size = 16; Epochs = 100; LR = 0.001; Optimizer = Adam
PCLNet	Nodes = 128; Batch size = 32; Epochs = 150; LR = 0.001; Optimizer = Adam
PDT-RF	Estimators = 1000; Max depth = 50; Max features = log2
PDT-SVM	Kernel = rbf; C = 1.0; Epsilon = 0.1
RF	Estimators = 500; Max depth = 50; Max features = sqrt
SVM	Kernel = rbf; C = 10; Epsilon = 0.01

Table 6. Performance of different models for dust intensity estimation using data from an independent validation dataset.

	ESSS/SSS (%)		SS (%)		FD/BS (%)		DF (%)		OA (%)	Kappa
	PA	UA	PA	UA	PA	UA	PA	UA		
PCBNet	85.00	76.12	86.78	82.85	87.95	86.82	91.35	99.30	88.50	0.8368
PCLNet	98.33	74.68	74.92	85.99	86.32	80.79	94.23	94.84	86.14	0.8039
PDT-RF	88.33	85.48	74.58	83.97	85.67	78.04	94.87	94.57	85.42	0.7925
PDT-SVM	75.00	84.91	75.93	83.27	87.95	80.60	95.19	93.69	85.83	0.7976
RF	66.67	59.70	68.47	83.47	85.34	74.43	93.59	93.29	81.72	0.7402
SVM	66.67	70.18	62.71	82.96	87.62	71.73	93.27	91.22	80.60	0.7231

Considering the prediction accuracy of different dust intensities, it seems all models can predict dust intensity at the DF level well, with UA and PA values all above 90%. For dust intensity at FD/BS levels, the PCBNet model obtained the highest and most balanced PA and UA with values both higher than 85%. The PCLNet model and PDT-SVM model were followed. PDT-RF, RF, and SVM achieved the worst results, with the PA and UA values very unbalanced. For dust intensity at SS levels, the PCBNet model also achieved the highest and most balanced PA and UA with values both higher than 82%. The performances of the other models were not good, with very unbalanced PA and UA values, especially the RF model and SVM model. For dust intensity at ESSS/SSS levels, the PDT-RF model obtained the highest and most balanced PA and UA with values both higher than 85%. The PCBNet model was followed with slightly lower but very balanced PA and UA values. The performances of the other model were not good, with very unbalanced PA and UA values.

For the overall performance, among all the models, the PCBNet model achieved the best results, with an OA value of 88.50% and a Kappa coefficient value of 0.8368. This was followed by the performance of the PCLNet model, with an OA value of 86.14% and a Kappa coefficient value of 0.8039. The traditional machine learning models performed worst. For traditional machine learning models, the PDT-RF model achieved an OA value of 85.42% and a kappa value of 0.7925, which performed better than the RF model with an OA value of 81.72% and a kappa value of 0.7402. The PDT-SVM model achieved an OA value of 85.83% and a kappa value of 0.7976, which performed better than the SVM model with an OA value of 80.60% and a kappa value of 0.7231. This means the models that used

time series information as input performed better than the corresponding models that did not use time series information.

3.2. Validation of the Produced Dust Intensity Products Using the PM₁₀ Dataset

Using the PCBNNet model, an hourly dust intensity monitoring product was produced for the spring season (March–May) from 2019 to 2023. To validate the accuracy of the product, PM₁₀ concentration data from air quality monitoring stations were first grouped based on the predicted dust intensity levels at each site and time (DF, FD/BS, SS, and ESSS/ESSS) [48]. ANOVA was then used to assess whether significant differences existed among the PM₁₀ levels of the different groups. The results are shown in Figure 4. The average PM₁₀ concentrations increased with increasing dust intensity, with mean values of 165.11 µg/m³, 401.41 µg/m³, 1873.91 µg/m³, and 5086.61 µg/m³ for DF, FD/BS, SS, and ESSS/ESSS, respectively. ANOVA indicated that the differences among the different groups were statistically significant ($p < 0.05$). Furthermore, Tukey's HSD post hoc tests revealed that all pairwise groups were significantly different (Figure 4a). In addition, a regression analysis between PM₁₀ concentration and dust intensity level was performed with dust intensity levels of DF, FD/BS, SS, and ESSS/ESSS set to 1, 2, 3, and 4. It yielded an R^2 value of 0.6856, indicating a strong positive relationship. These results demonstrate that the dust intensity products generated by the proposed model are highly consistent with observed PM₁₀ concentrations at the monitoring stations.

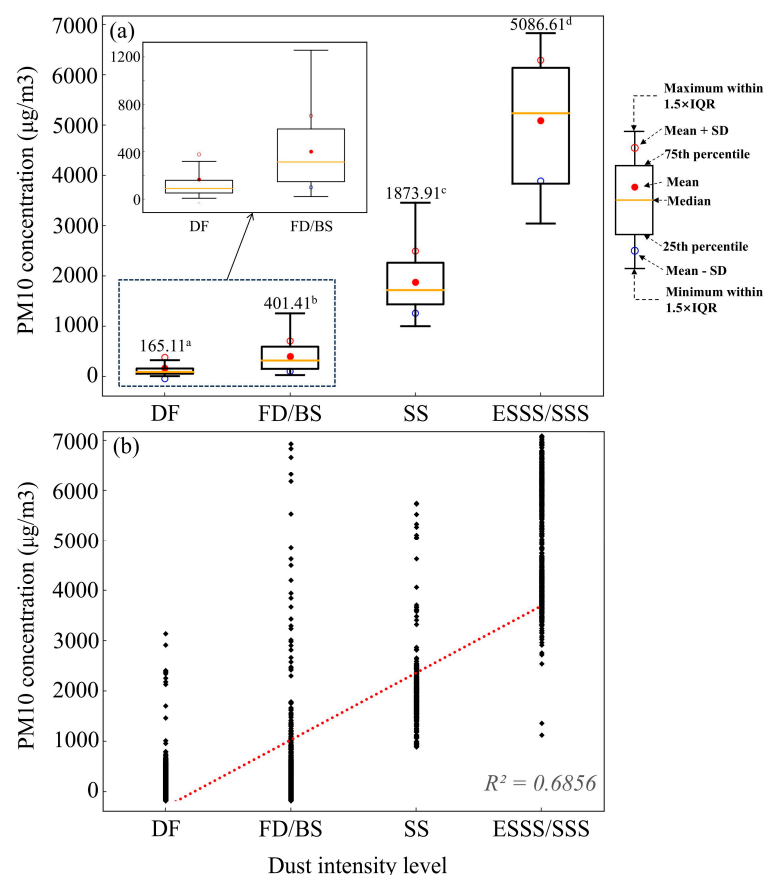


Figure 4. (a) PM₁₀ concentrations at monitoring stations grouped according to the corresponding dust intensities predicted by the proposed model. The numbers represent the mean values, and those followed by different letters are significantly different between treatments according to Tukey's HSD test ($p < 0.05$); (b) the relationship between dust intensity levels and PM₁₀ concentrations with dust intensity levels of DF, FD/BS, SS and ESSS/ESSS set to 1, 2, 3, and 4.

3.3. Case Study Analysis

From 14 to 15 April 2021, northern China experienced a large-scale dust storm event characterized by high intensity, long duration, and rapid expansion. This event stands out as one of the most typical and representative severe dust storms in recent years. To qualitatively evaluate the capability of the dust intensity classification product developed in this study to characterize the evolution of such events, we examined its performance using hourly data as shown in Figure 5. Between 08:00 and 13:00 UTC on 14 April, dust was first detected in the western part of Alxa League (AL), with intensities mainly at the FD/BS level. Localized SS were observed, but the overall affected area remained limited. From 14:00 to 20:00 UTC, the dust-affected region expanded significantly eastward, accompanied by a marked increase in intensity. Dust gradually spread from AL to Bayannur City (BC), Baotou City (BTC), Xilingol League (XL), Ordos City (OC), Hohhot City (HC), and Ulanqab (UC), with intensities rising from FD/BS to SS, and in some areas reaching ESSS/SSS. From 21:00 UTC on 14 April to 03:00 UTC on 15 April, the event reached its peak phase. The spatial extent of the dust storm continued to expand and move eastward. Large areas of SS-level storms were concentrated in BC, BTC, and UC, while some regions—such as western XL and southern OC—experienced ESSS/SSS levels, marking the most intense stage of the event. Between 04:00 and 08:00 UTC on 15 April, the intensity of the dust storm declined. During this stage, the ESSS/SSS zones nearly dissipated, and the dominant dust levels shifted to SS and FD/BS. The affected region included portions of HC, UC, and OC. From 09:00 UTC onward on 15 April, the dust intensity gradually decreased. SS-level zones significantly shrank and were largely replaced by FD/BS levels. By 13:00 UTC, the dust storm had weakened considerably, with only small areas of residual dust (FD/BS) observed in HC, OC, BTC, and UC. To verify whether the above monitoring results are accurate, the comparison between observed and predicted dust intensity levels at each observation station and time is shown as a confusion matrix in the bottom-right of Figure 5. The confusion matrix indicates strong agreement: the per-class producer's accuracy (PA) for DF, FD/BS, SS, and ESSS/SSS is 96%, 82%, 96%, and 100%, respectively; the corresponding user's accuracy (UA) is 94%, 91%, 81%, and 80%. The overall accuracy (OA) is 93%. In addition, two locations were randomly selected in the general direction where the dust cloud last dissipated, and the HYSPLIT model was used to monitor the backward propagation paths of the dust storm at three different heights (500 m, 1000 m, and 1500 m). The simulation results are shown in Figure 6. The trajectories indicate that the sandstorm moved from northwest to southeast, which is consistent with the results presented in Figure 5. Overall, the dust intensity product generated using the method proposed in this study effectively captured the complete evolution of this dust event—from its initial development and intensification to its peak and eventual dissipation—demonstrating strong potential for practical applications in dust monitoring and early warning.

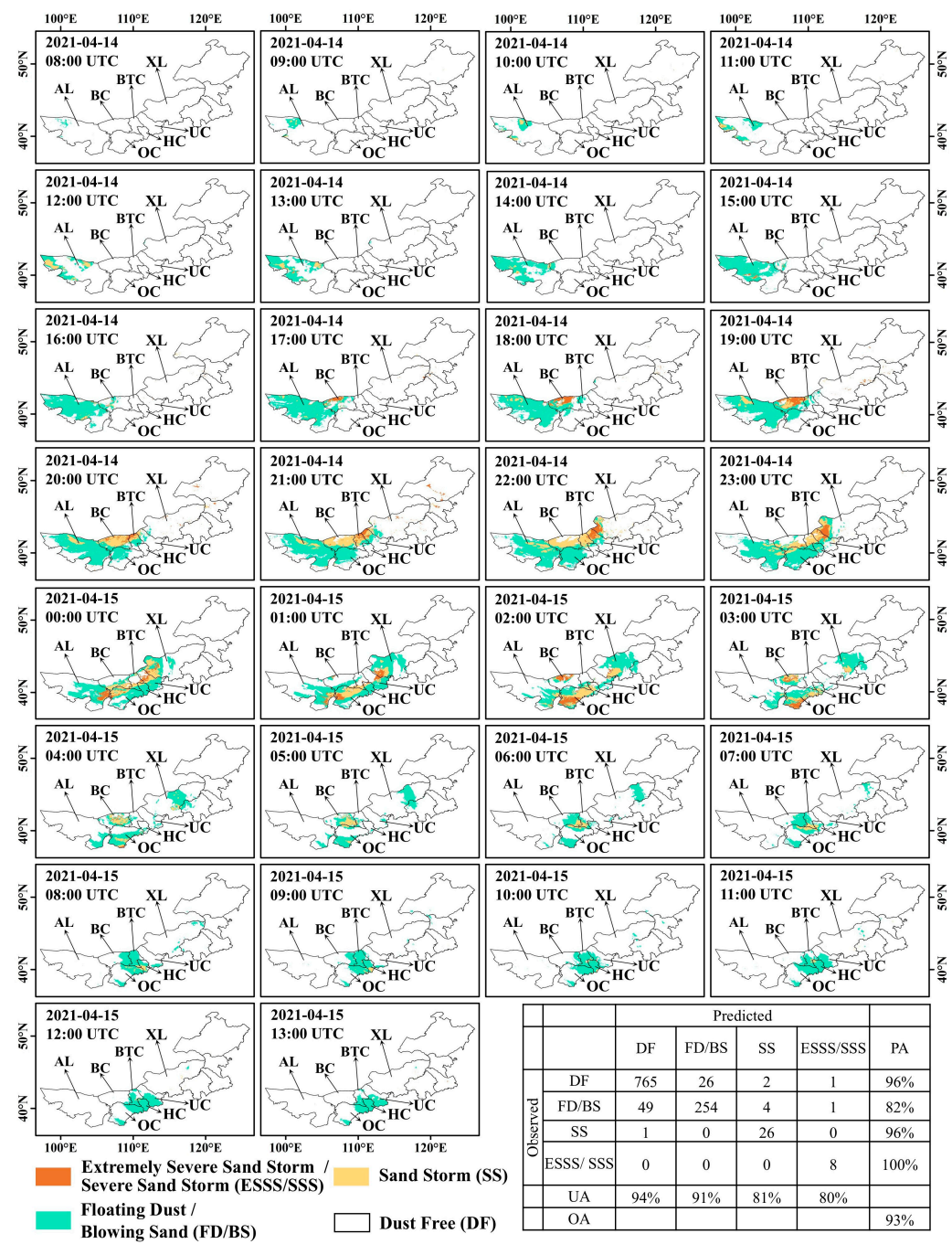


Figure 5. Spatiotemporal evolution of a special dust event tracked by the dust intensity product produced in this study. Abbreviations denote key cities in Inner Mongolia, China: AL—Alxa League; BC—Bayannur city; BTC—Baotou city; XL—Xilingol League; OC—Ordos city; HC—Hohhot city; and UC—Ulanqab city. The confusion matrix in the bottom-right corner shows the comparison between the observed and predicted dust intensity at each observation station and time during the dust storm event.

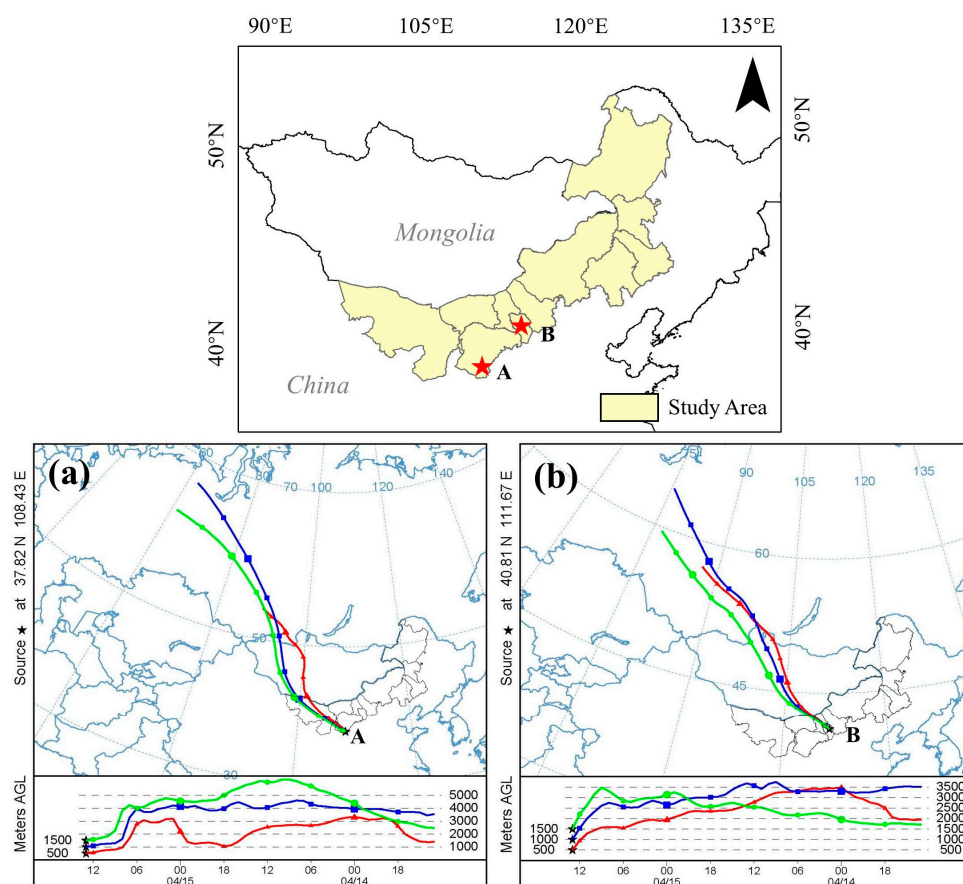


Figure 6. HYSPLIT back trajectories for location A (a) and B (b) during dust event in April 2021. The star indicates the trajectory starting point.

4. Discussion

4.1. Importance of the Proposed Time Series Features for Dust Intensity Monitoring

Most traditional dust monitoring models only use current observation data. Considering that dust events exhibit distinct temporal evolution patterns, a series of temporal features were designed from spectral indices and multiband brightness temperature information, including clear-sky state values, adjacent observation state values, and current observation state values. The SHapley Additive exPlanations (SHAP) framework is widely used in model interpretability analysis. It calculates the contribution of each input variable to the model prediction results, providing a unified and additive framework for feature importance evaluation [49]. To verify the role of these features in dust intensity monitoring, the SHAP method was used to analyze the importance of the input variables in the models that used time series features. The PCNet, PCLNet, PDT-RF, and PDT-SVM models were analyzed using appropriate SHAP explainers according to model type. Specifically, DeepExplainer was used for deep learning models (PCLNet and PCNet), TreeExplainer was used for the tree-based model (PDT-RF), and KernelExplainer was used for the kernel-based model (PDT-SVM). In this process, 400 samples were randomly selected from the dataset to construct the SHAP explainer, ensuring stable and representative estimation of feature contributions. The higher the SHAP value, the greater the contribution of that feature to the model's prediction. The top 10 variables ranked by mean absolute SHAP values are presented in Figure 7, highlighting the dominant spectral and temporal parameters in dust intensity prediction.

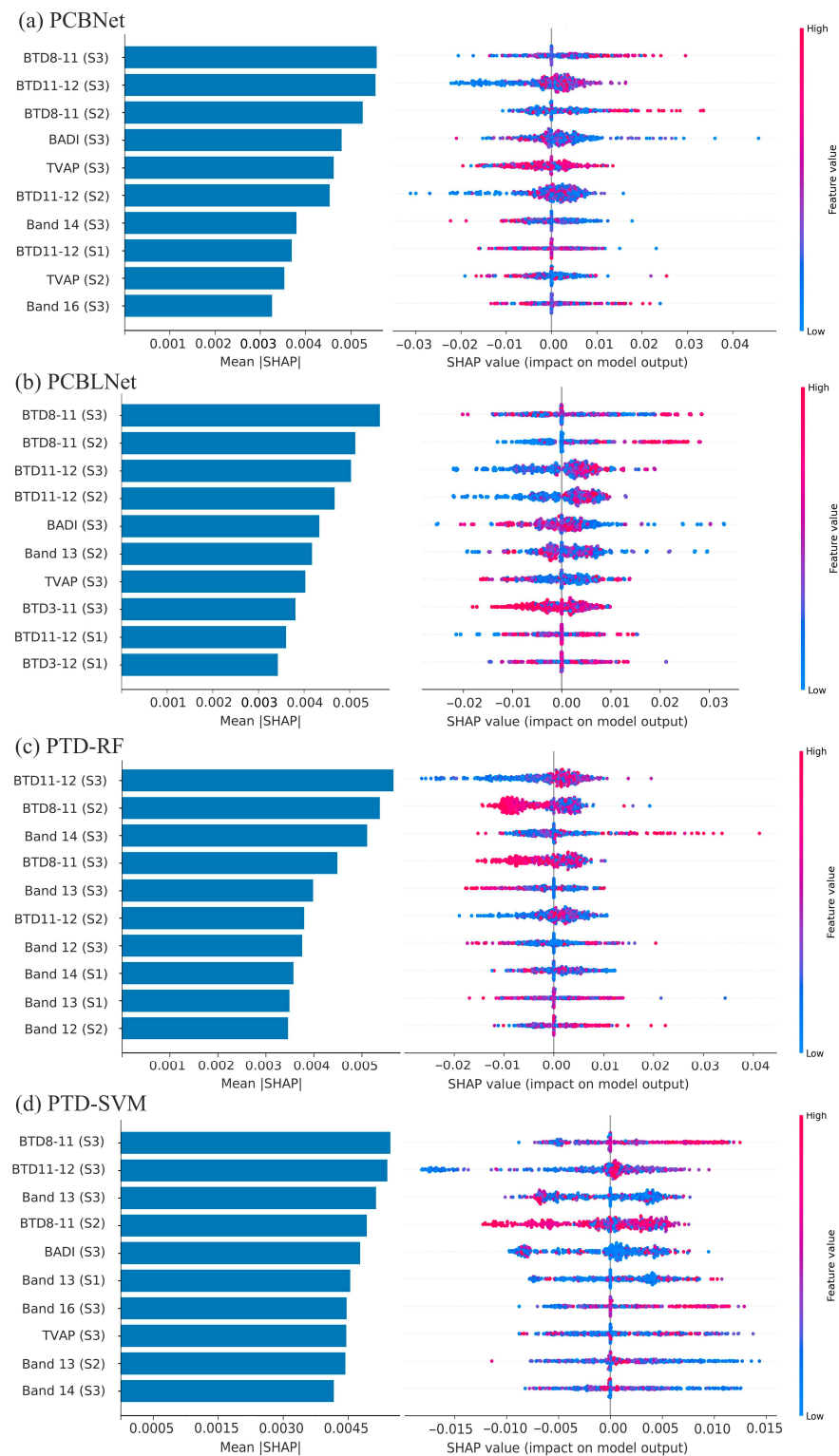


Figure 7. Variables in the top 10 SHAP values for different models. S1, S2, and S3 denote the clear-sky state value, adjacent observation state value, and current observation state value, respectively.

The results show that among all models, BTD8–11 and BTD11–12 in the current observation state, as well as BTD8–11 in the adjacent observation state, consistently have the highest SHAP values, indicating that these features are the most critical variables for dust intensity prediction. This can be explained by the radiative properties of thermal infrared bands. Under dust-free conditions, the 11 μm band exhibits higher radiance than the 12 μm band, while, under dust events, dust particles generate stronger radiative signals

at 12 μm than at 11 μm , resulting in a gradual reduction or negative values of BTD11–12. BTD11–12 has been widely used for dust identification [33,50]. In addition, since dust exhibits lower emissivity than the sandy surface at 11 μm while demonstrating higher emissivity at 8.6 μm , BTD8–11 can effectively distinguish dust in the atmosphere from sandy surfaces [34].

At the same time, BADI and TVAP in the current observation state also exhibit relatively high SHAP values in most models, including PCBNNet, PCLNet, and PDT-SVM. This further confirms the critical role of the adjacent observation state features in dust intensity prediction. Both BADI and TVAP are derived from BTD3–11 and BTD11–12, taking into account the further enhancement in the sensitivity of these split-window difference indices to dust [15,35]. Notably, some features from the clear-sky state (e.g., BTD8–11 and Band 13) also rank among the top ten SHAP values in at least two models. This indicates that the clear-sky state provides important reference baselines, which help the models more accurately separate dust signals from the sandy surface or other atmospheric processes.

In conclusion, the above results highlight that the time-series features made in this study are important for dust intensity prediction. The incorporation of this multi-temporal information enables the models to better characterize the temporal dynamics and spectral signatures associated with dust events.

4.2. Optimal Dust Intensity Monitoring Model

The differences in performance among the models in terms of predicting dust intensity levels mainly stem from their varying abilities to extract temporal features. Among them, PCBNNet and PCLNet achieved better performance overall across all the validation scenarios, as their temporal deep learning architectures effectively capture the dynamic evolution of dust storms from time series imagery and build robust nonlinear temporal dependency models. The main difference between PCBNNet and PCLNet lies in the structure of their classifiers. PCBNNet incorporates BiLSTM for modeling time series features, whereas PCLNet uses LSTM. BiLSTM is more effective in capturing both forward and backward temporal dependencies. As a result, PCBNNet performs better than PCLNet for sand intensity prediction. In contrast, although PDT-RF and PDT-SVM use the same temporal features as inputs, they are less capable of modeling interdependencies between different temporal information. Therefore, their performance in predicting dust intensity is lower than that of PCBNNet and PCLNet. Furthermore, the RF and SVM models, which rely exclusively on imagery data from the current observation time, yield lower accuracies than the corresponding PDT-RF and PDT-SVM models do. This is because they cannot utilize comparative information from images before and after a dust event.

4.3. Comparison with Existing Studies

Most existing research on dust monitoring has focused on binary classification tasks, with the aim of distinguishing dust and dust-free pixels via imagery at the current observation time [18,51]. Although Zhen et al. [20] analyzed time series imagery by combining CNN and LSTM models, the purpose of their research was still binary classification to identify dust and dust-free pixels. In practical applications, it is difficult to implement precision dust storm mitigation measures when information about dust storm intensity is not available. Considering existing studies on dust intensity monitoring, on the basis of AHI imagery, Jiang et al. [46] combined the BTD index and the multiband infrared dust index (MIDI) to identify dust pixels and then used the threshold of the infrared difference dust index (IDDI) to detect dust storm intensity. The results showed that the method is effective for identifying dust pixels in imagery and detecting dust intensity at the FD/BS level, whereas it cannot effectively detect dust intensity at the SS, SSS, and ESSS levels.

Compared with existing methods, the approach proposed in this study includes features that describe the dynamic changes in dust events to better capture the dust intensity information in time series images. On the basis of these features, the CNN and Bi-LSTM models were combined to realize 24 h monitoring of dust intensity with high accuracy. Using an independent dataset, the validation results revealed an OA value of 88.50% and Kappa value of 0.8368, demonstrating an improvement in both the accuracy and practicality of dust intensity monitoring compared with existing approaches.

4.4. Practical Implications and Limitations

To implement the dust intensity monitoring method proposed in this study, the following steps can be performed. First, the AHI imagery of the study area must be collected. Second, the time series features related to dust intensity monitoring proposed in this study should be calculated. Third, with these time series features as inputs, the PCBNNet model designed in this study is applied to produce a dust intensity map. Finally, on the basis of the dust intensity map, different dust disaster relief measures can be proposed for different dust intensity regions to achieve precision management.

Although this study achieves good results in dust intensity monitoring, limitations exist. First, the machine learning model is highly dependent on the training data, which inherently introduces regional and experiential biases. Although this study achieves promising results in dust intensity monitoring, the PCBNNet model was mainly trained on Inner Mongolia data and its applicability to other regions has not been validated. Changes in surface background and atmospheric conditions can affect the performance of the model. For future research, data from other regions can be collected and then transfer learning and domain adaptation methods can be used to make the model in this study so it can be used in other regions. Second, in this study, dust intensity was only monitored under cloud-free conditions. However, considering the frequent coexistence of clouds and dust, dust intensity needs to be monitored under cloudy weather conditions. For future research, the model proposed in this study can be combined with a physically based dust simulation model to carry out dust monitoring beneath clouds. Third, considering the Transformer-based model is a new state-of-the-art model and it has been demonstrated to have good performance in Earth surface parameter prediction, it will be used and compared with the model proposed in this study for dust intensity monitoring in future. Finally, samples of ESSS are rare and underrepresented in the dataset. This may be the reason the PCBNNet model performs slightly worse when predicting this level of dust. Considering this, physical constraints or meteorological data will be integrated with the model structure proposed in this study to further improve its prediction accuracy in future.

5. Conclusions

This study proposed a novel framework for dust intensity monitoring by constructing progressive dust temporal (PDT) features and developing a hybrid CNN–BiLSTM model. The PDT features effectively reflect the dynamic evolution of dust events, while the new proposed PCBNNet model in this study was demonstrated as the best dust intensity prediction model among all tested models. On this basis, an hourly dust intensity product was generated for 2019–2023 using the above proposed dust intensity monitoring framework. The product showed high consistency with independent PM₁₀ observation data, expressing high accuracy. In addition, taking a typical dust storm that occurred in April 2021 as an example, the product accurately captured the dynamic evolution of dust intensity, which verifies the usefulness of the model in continuously monitoring dust events in practice. It offered robust support for establishing precise dust storm disaster mitigation strategies.

Author Contributions: Conceptualization, P.C.; methodology, J.Z. and P.C.; data curation, J.Z.; writing—original draft preparation, J.Z.; writing—review and editing, P.C. and X.S.; supervision, P.C.; funding acquisition, P.C. and X.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Natural Science Foundation of Inner Mongolia Autonomous Region (2024ZD03), Innovation Project of LREIS (KPI009) and the National Research and Development Plan of China (2022YFB3903403, 2022YFB390340301).

Data Availability Statement: Datasets can be provided on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Confusion matrix of PCBNet model.

		Predicted			
		ESSS/SSS	SS	FD/BS	DF
Actual	ESSS/SSS	51	9	0	0
	SS	15	256	23	1
	FD/BS	1	35	270	1
	DF	0	9	18	285

Table A2. Confusion matrix of PCLNet model.

		Predicted			
		ESSS/SSS	SS	FD/BS	DF
Actual	ESSS/SSS	59	1	0	0
	SS	15	221	51	8
	FD/BS	3	31	265	8
	DF	2	4	12	294

Table A3. Confusion matrix of PDT-RF model.

		Predicted			
		ESSS/SSS	SS	FD/BS	DF
Actual	ESSS/SSS	53	4	3	0
	SS	7	220	57	11
	FD/BS	0	38	263	6
	DF	2	0	14	296

Table A4. Confusion matrix of PDT-SVM model.

		Predicted			
		ESSS/SSS	SS	FD/BS	DF
Actual	ESSS/SSS	45	13	2	0
	SS	7	224	49	15
	FD/BS	0	32	270	5
	DF	1	0	14	297

Table A5. Confusion matrix of RF model.

		Predicted			
		ESSS/SSS	SS	FD/BS	DF
Actual	ESSS/SSS	40	13	6	1
	SS	15	202	66	12
	FD/BS	10	27	262	8
	DF	2	0	18	292

Table A6. Confusion matrix of SVM model.

		Predicted			
		ESSS/SSS	SS	FD/BS	DF
Actual	ESSS/SSS	40	9	10	1
	SS	11	185	80	19
	FD/BS	1	29	269	8
	DF	5	0	16	291

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