https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

A deep learning method for convective weather forecasting : CNN-BiLSTM-AM (version 1.0)

Jianbin Zhang[1,3], Zhiqiu Gao[1,2], Yubin Li[1], Yuncong Jiang[1]

[1] School of Atmospheric Physics, Nanjing University of Information Science & Technology, Nanjing, 210044, China

[2] State Key Laboratory of Planetary boundary layer Physics and Atmospheric chemistry, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing,100081,China

[3] College of Artificial Intelligence, Henan University, Kaifeng, 475000, China

Correspondence to: Dr. Zhiqiu Gao (zgao@nuist.edu.cn) and Dr. Yubin Li (liyubin@nuist.edu.cn)

Abstract. This work developed a CNN-BiLSTM-AM model for convective weather forecasting using deep learning algorithms based on reanalysis and forecast data from the NCEP GFS, the performance of the model was evaluated. The results show that: (1) Compared to traditional machine learning algorithms, the CNN-BiLSTM-AM model has the ability to automatically learn deeper nonlinear features of convective weather. As a result, it exhibits higher forecasting accuracy on the convective weather dataset. Furthermore, as the forecast lead time increases, the information value provided by this model also changes. (2) In comparison to subjective forecasts by forecasters, the objective forecasting approach of the CNN-BiLSTM-AM model demonstrates advantages in metrics such as Probability of Detection (POD), False Alarm Rate (FAR), Threat Score (TS), and Missing Alarm Rate (MAR). Specifically, the average TS score for heavy precipitation reaches 0.336, which is a 33.2% improvement compared to the forecaster's score of 0.252. Moreover, due to the CNN-BiLSTM-AM model's ability to automatically extract classification features based on a large sample dataset and consider a comprehensive range of convective parameters, it effectively reduces the FAR. (3) The interpretability study of the machine learning-based convective weather mechanism reveals that the importance ranking of convective weather forecasting factors arranged by machine learning methods largely aligns with the subjective understanding of forecasters. For example, the total precipitable water (PWAT) is identified as a critical factor for short-term heavy precipitation forecasting, regional factors have significant impacts on convective weather, and vertical motion at 300 hPa provides dynamic lifting conditions for convection. This objective analysis of factor ranking not only further confirms the effectiveness of machine learning in automatically extracting convective weather features but also validates the rationality of the sample set construction. Overall, the use of the CNN-BiLSTM-AM model in convective weather forecasting

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

demonstrates superior performance compared to traditional machine learning algorithms and subjective forecasting methods.

1 Introduction

The forecasting of severe convective weather primarily focuses on violent weather phenomena that occur on small spatial and temporal scales, including hail, thunderstorms, strong winds, short-duration heavy rainfall, tornadoes, and other hazardous and dangerous weather conditions. Due to the regional intensity and rapid development characteristics of severe convective weather, forecasting is extremely challenging (Han et al., 2009; Zheng et al., 2015). Such weather often has a high intensity that can potentially cause severe casualties and property losses (Wang et al., 2007). For instance, the "Eastern Star" ship sinking incident in 2015 (Zheng et al., 2016a), the EF4 level tornado event in Funing, Jiangsu in 2016 (Zheng et al., 2016b), and the massive "720" rainstorm event in Zhengzhou, Henan in 2021 (Gao et al, 2022). In monitoring and predicting severe convective weather, traditional methods that solely rely on statistical results or forecaster experience exhibit significant limitations. Firstly, the occurrence condition and threshold characteristics of severe convective weather will undoubtedly vary among regions with different seasons, terrains, and climatic backgrounds. This diversity makes it challenging to use a unified set of physical quantity thresholds to predict categories of severe convective weather in various areas. Secondly, the volume of data needed to be processed during weather forecasting is considerable, and the features and threshold ranges of physical quantities extracted by forecasters through statistics or subjective judgement may not fully capture beneficial information or subtle changes in the data, especially those at smaller scales. Additionally, due to the complex variations of severe convective weather, if forecasters lack comprehensive and profound understanding of the rules governing the development of severe convection, they are unable to completely grasp the useful features during the development process of such weather. Even though some objective forecasting algorithms exist based on physical principles and statistical properties of relevant physical quantities, thoroughly extracting these features remains challenging. Moreover, when extracting features of physical quantities, forecasters' abilities are constrained by their experiential knowledge and understanding.

The brisk advancement of artificial intelligence in recent years has spurred changes across numerous domains. Notably, AI algorithms underpinned by deep learning and machine learning have achieved

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

substantial progress and found effective applications across diverse sectors. The integration of these algorithms with meteorological big data often forms an efficacious toolset for severe convective weather forecasting (McGovern et al., 2017; Reichstein et al., 2019). Li et al. (2018) successfully employed the random forest algorithm to categorize potential severe convective weather phenomena. Based on this, they developed forecasting models for short-duration intensive rainfall, thunderstorms, hail, and severe convection. The training of these models involved leveraging convective indices and physical quantities possessing explicit physical meanings. Furthermore, they integrated real-time forecast field data from NCEP's Global Forecast System (GFS) into their predictions. The forecast outcomes of 85 severe convective occurrences indicated a total misjudgment rate of 21.9% with zero omissions, thereby confirming the model's extensive suitability for severe convective weather predictions. Herman et al. (2018) employed NOAA's global ensemble forecast system data to construct a machine learning model by using the random forest algorithm. This model encapsulates not only numerical forecasting elements like convective indices, temperature, pressure, humidity, and wind field but also includes numerous background forecasting components such as the maximum, minimum, median, longitude, and latitude values of 1-year and 10-year average recurrence intervals (ARIs). This model has proven successful in predicting extreme precipitation events 2-3 days ahead. Using the Bayesian approach, Liu et al. (2019) conducted correlation analysis for thermal and dynamic factors within high-frequency lightning storm cloud processes. Their findings underscored convective potential energy, convective inhibitory energy, and low-level wind shear as the most influential forecasting factors – providing crucial insights for high-frequency lightning storm cloud predictions. In contrast to traditional machine learning algorithms (e.g., shallow neural networks, random forest), deep learning is capable of modeling intricate nonlinear systems and offering superior levels of abstraction. Importantly, deep learning can express broad function sets unattainable by shallow networks more flexibly and succinctly. It demonstrates substantial superiority over traditional methodologies across various fields, including speech processing and image recognition (Krizhevsky et al., 2012; Lecun et al., 1995; Szegedy et al., 2013). Deep learning has also found initial applications in short-term meteorological forecasting. For example, Lin et al. (2019) built a Convolutional Long Short-Term Memory (ConvLSTM) model based on the Weather Research and Forecasting (WRF) model and lightning data to extract spatiotemporal characteristics for future 12-hour lightning predictions. Similarly, Gope (2016) constructed a rainstorm prediction model using deep neural

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

networks (specifically, stacked autoencoders) based on historical climatic data, capable of forecasting intense rainfall scenarios in regions like Mumbai and Kolkata, India, 6 to 48 hours in advance.

With the continuous improvement of small and medium-scale observation networks, the gradual enrichment of observational methods, and the rapid growth of observational data, exploring the occurrence and development mechanisms in each severe convective weather process, identifying characteristic parameters and threshold ranges of various types of severe convective weather from a large amount of numerical model data, and comprehensively considering the geographical and climatic environment of each region have become key factors for effective forecasting of severe convective weather. Deep learning algorithms can automatically extract important features from big data, deeply extract effective information, and comprehensively consider geographical and climatic differences across regions, which will significantly optimize the results of severe convective weather forecasting. The latest Pangu-Weather model is capable of predicting meteorological elements, including temperature, wind speed, and pressure, with high accuracy and fast prediction speed (Bi et al., 2023). Based on the reanalysis and forecast data from NCEP GFS global numerical model, our research uses deep learning algorithms to establish a severe convective weather forecasting model and objective forecasting method that can provide real-time objective forecast products nationwide.

2 Data and methods

2.1 NCEP FNL analysis data

The training and testing data in this study were obtained from the NCEP GFS 0.25°×0.25°FNL (final) analysis data for the period of 2015-2020. The NCEP FNL analysis data provides global analysis fields four times daily (02:00, 08:00, 14:00, and 20:00). The selection of forecast factors includes not only basic meteorological elements such as temperature, geopotential height, humidity, and wind field, but also commonly used physical quantities reflecting conditions related to water vapor, dynamics, and energy, such as precipitable water (PWAT), Convective inhibition (CIN), and K-index (Tian et al., 2015). Additionally, in order to consider geographical variations in convective activity, features such as elevation, longitude, and latitude are included, resulting in a total of 144 features (see Table 1) to be analyzed.

Table 1. The selection of parameters

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions
Open Access
EGU

	parameters	level/(hPa)
Multi-level physical quantities	T（Temperature）、TD（Dew point）	1000、925、850、700、500、300、200
	H（Potential height）	
	Wind_Speed、Wind_Drection、W（P-coordinate system vertical velocity）	
	Rh（Relative humidity）、TDD（Temperature dew point difference）、Q（Specific humidity）、VAPFLUXDIV（Water vapor flux divergence）	
	PV（Potential vorticity）、TMPADV（Temperature advection）、SITASE（Pseudo-equivalent potential temperature）、DIV（divergence）、VOR（vorticity）、VORADV（vorticity advection）	
Commonly used strong convective physical quantities	BCAPE（Bulk Convective Available Potential Energy）、BLI（Bulk Lifted Index）、CIN（Convective inhibition）、DCAPE（Downdraft Convective Available Potential Energy）、K（K-index）、LI（Lifted Index）、Z0（Altitude of the 0 °temperature layer）、Z20（Altitude of the -20 °temperature layer）、PWAT（Precipitable water）、SHIP（Large hail index）（Allen et al，2015）、SHR1（0-1km wind shear）、SHR3（0-3km wind shear）、SHR6（0-6km wind shear）、SI（Sha index）、TOAT（Total Index）	
Other quantities	ELEVATION、LON（Longitude）、LAT（Latitude）	

2.2 Severe convective weather data

In this study, the convective data used were sourced from observational data collected by Chinese surface meteorological stations and archived by the National Meteorological Information Center. The National Meteorological Information Center performs quality checks and error data corrections on timed observations and daily extreme value data for 19 major elements, including temperature, pressure, precipitation, humidity, and sunshine duration, from over 2400 ground stations nationwide. This process

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

addresses systematic issues that may arise during the digitization process, such as data omissions or duplication. The data undergoes three levels of quality control review at the station, provincial, and national levels within the routine operations of the meteorological data departments.

2.3 Selection of experimental area

The Henan region is not only one of China's important agricultural production areas but also a zone where modern cities and rural areas coexist with complex terrain due to extensive industrial development. Furthermore, being located in the mid-latitudes, Henan frequently experiences cold air invasions, while warm and humid air masses can also reach the region during the summer, often leading to intense rainfall events resulting from the convergence of warm and cold air masses. Additionally, numerous signs indicate that China's climate is entering a transitional period, potentially leading to a shift from low rainfall in summer to higher rainfall in northern regions. Therefore, selecting the Henan region (as illustrated in Figure 1) as the study area for this research is highly appropriate. Undoubtedly, it will lay the foundation for future improvements in severe weather warnings and disaster prevention and mitigation capabilities in the region, reflecting a forward-looking study with a strategic perspective.

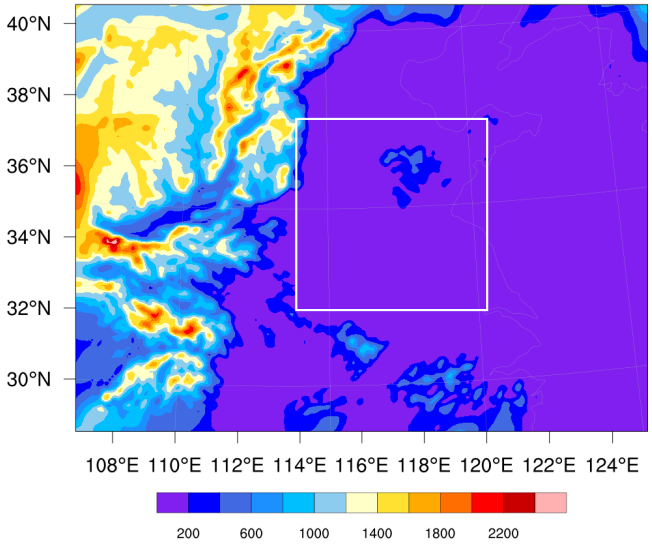


Figure 1: The selected area of experiment (The white rectangle denotes the selected area: Henan, 31°-37° N，110°-117° E); Distribution of topography (shaded; unit: m)

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions
Open Access
EGU

3 Deep learning model

3.1 Deep learning model structure

To forecast severe convective weather more accurately, this study develops a CNN-BiLSTM-AM-based model for convective prediction. The model consists of Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and Attention Mechanism (AM). The CNN extracts features from the input inventory data, while the BiLSTM effectively captures the interdependencies in the temporal sequence data. The AM is a mechanism that improves results by capturing the impact of past feature states on heavy rainfall. The model primarily comprises the CNN, BiLSTM, and AM layers, including an input layer, CNN layer (with one-dimensional convolutional and pooling layers), BiLSTM layer (with forward and backward LSTM layers), AM layer, and output layer (see Figure 2 for details)(Lu et al，2021). During weather forecasting, we analyze historical meteorological images and numerical products to draw conclusions. To summarize this process briefly, we first analyze meteorological images or various forecast products to generate situational forecasts. Then, combining the situational forecasts with local real-time meteorological data, we obtain element forecasts. If we simplify these two steps further, the first step involves extracting features from meteorological images or forecast products (i.e., situational forecasting), and the second step involves fitting the extracted features with local historical meteorological information to obtain the required forecast values (i.e., element forecasting). In the CNN-BiLSTM-AM model, these two steps are transformed accordingly: using the CNN for data feature extraction and subsequently applying the BiLSTM and AM to match historical meteorological information in order to derive the element values. Prior to inputting the data into the CNN-BiLSTM-AM model, we normalize the data and convert it into matrix form. Once these settings are completed, the model can be trained.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions
Open Access
EGU

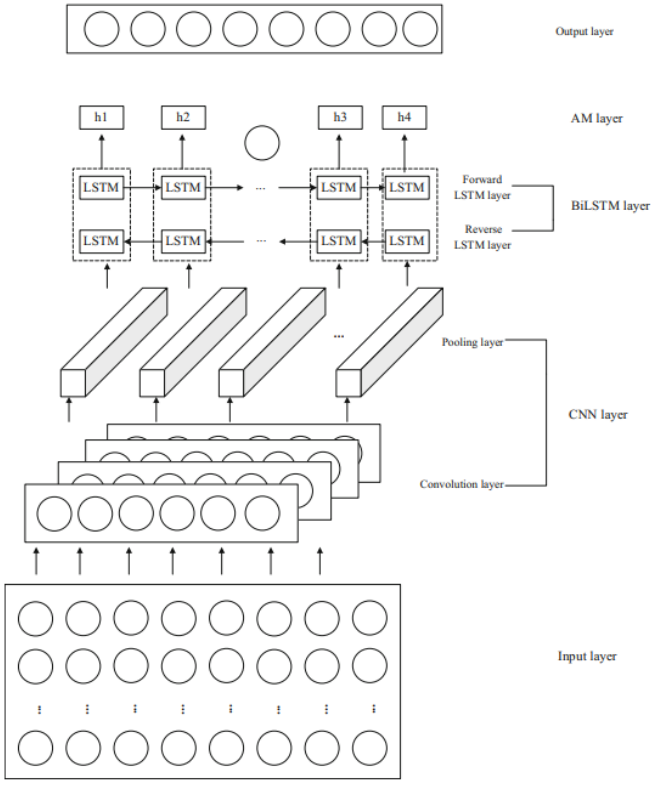


Figure 2: CNN-BiLSTM-AM model structure diagram

The training process of CNN-BiLSTM-AM is illustrated in Figure 3, with the main steps outlined as follows:

1）Input Data: Provide the necessary data for training CNN-BiLSTM-AM.

2）Input Data Normalization: To enhance model training performance, the input data is standardized due to its significant variations. The normalization formula is expressed as Equation (1):

$$y_i = \frac{x_i - \bar{x}}{s} \tag{1.1}$$

Among them, y_i is the standardized value, x_i is the input data, $\bar{x}$ is the average value of the input data, and s is the standard deviation of the input data.

3）Network Initialization: Initialize the weights and biases of each layer in CNN-BiLSTM-AM.

4）CNN Layer Computation: Pass the input data sequentially through the convolutional and pooling layers within the CNN layer to extract features and obtain output values.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

5）BiLSTM Layer Computation: Use the hidden layer of the BiLSTM layer to compute the output data from the CNN layer and obtain output values.

6）AM Layer Computation: Compute the output data from the BiLSTM layer using the AM layer and obtain output values.

7）Output Layer Computation: Calculate the output value of the model by computing the output value of the AM layer.

8）Error Calculation: Compare the computed output value from the output layer with the true value of the data set and calculate the corresponding error.

9）Check if the termination conditions for the training process are met: Successful termination conditions include completing a predetermined number of cycles, reaching a weight below a certain threshold, or achieving a prediction error rate below a specific threshold. If any of these conditions are met, the training is completed; otherwise, the training continues.

10）Error Backpropagation: Propagate the calculated error in the opposite direction, updating the weights and biases of each layer, and then return to step 4 to continue the training.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

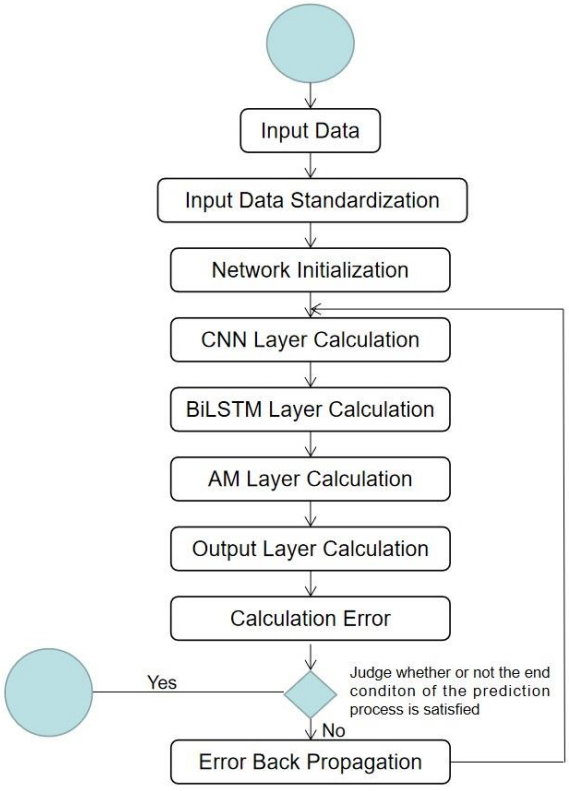


Figure 3: Flow chart of CNN-BiLSTM-AM training process

The prediction process of CNN-BiLSTM-AM is illustrated in Figure 4 and consists of the following main steps:

1) Input Data: Provide the input data required for prediction.

2) Data Standardization: Normalize the input data.

3) Prediction: Feed the standardized data into the trained CNN-BiLSTM-AM model and obtain the corresponding output values.

4) Data Standardization Recovery: The output values obtained from CNN-BiLSTM-AM are in standardized form. To restore them to their original values, apply Equation (2) to convert the standardized values back.

$$x_i = y_i * s + \bar{x} \tag{1.2}$$

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Among them, x_i represents the recovered value of the standardized value, y_i represents the output value of CNN-BiLSTM-AM, s represents the standard deviation of the input data, and $\bar{x}$ represents the mean value of the input data.

5) Output Results: Present the recovered results after restoration as the completion of the prediction process.

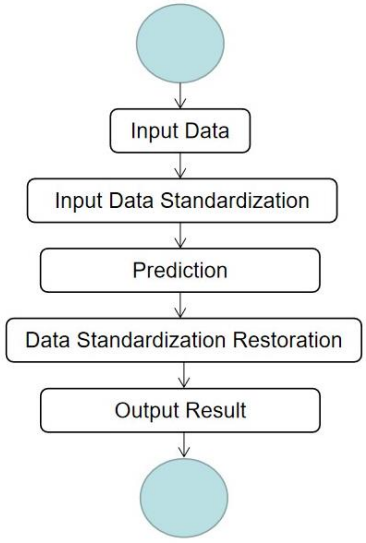


Figure 4: Flow chart of CNN-BiLSTM-AM prediction process

3.2 Construction of training and testing datasets

The prediction of severe convective weather can be viewed as a binary classification problem, distinguishing between its occurrence (labeled as 1) and non-occurrence (labeled as 0). Consequently, we can utilize actual severe weather data to calibrate the numerical analysis field, thus constructing training and testing sample datasets. Since NCEP FNL provides both analyzed and forecasted grid-based fields while the observed data is in scattered form, the observed data needs to be gridded. If a related weather event occurs within a grid radius of R, it is considered that the event occurs at that grid point (labeled as 1); otherwise, it is considered that the event does not occur at that grid point (labeled as 0). Considering that convective weather is typically associated with mesoscale weather systems, we conducted experiments and determined to use R=20km. Setting R too small may result in missing severe convective events, whereas setting it too large may lead to false alarms.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

The occurrence probability of severe convective weather is relatively low, resulting in a significant class imbalance where positive samples (i.e., samples with severe convective events) are much fewer than negative samples (i.e., samples without severe convective events). This presents a typical issue of imbalanced data (Krawczyk et al., 2016). To address this, we employed the oversampling technique (Buda et al., 2017) by randomly duplicating positive samples to achieve a balanced distribution between positive and negative samples. With this approach, we constructed the training and testing datasets using real-time data from January to December between 2015 and 2020, as well as NCEP FNL data. The testing dataset consisted of one randomly selected day from each month during the aforementioned period, totaling 72 days, while the training dataset comprised the remaining samples. During the training process, we utilized the ADAM optimizer (Kingma and Ba, 2014) with a learning rate set at 10^{-4}, and default values were used for other settings (Perol et al., 2017). The CNN-BiLSTM-AM model was trained for 30 epochs with a batch size of 64. Through training and parameter tuning, we obtained the optimal prediction model. This model can incorporate NCEP FNL data and transform features into a four-dimensional array of M×28×32×1 (M represents the number of samples), enabling predictions for severe convective weather.

4 Results

4.1 Evaluation methods

Commonly used verification measures for evaluating forecast results include the Probability of Detection (POD), the Threat Score (TS), the Equitable Threat Score (ETS), the Bias (BIAS), the False Alarm Ratio (FAR), and the Missed Alarm Ratio (MAR). These measures are defined as follows:

$$\mathrm{POD} = \frac{h}{h+m} \tag{1.3}$$

$$\mathrm{TS} = \frac{h}{h+m+f} \tag{1.4}$$

$$\mathrm{ETS} = \frac{h-h_{random}}{h+f+m+-h_{random}}, h_{random} = (h+f)*(h+m)/(h+m+f+c) \tag{1.5}$$

$$\mathrm{BIAS} = \frac{h+f}{h+m} \tag{1.6}$$

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

$$FAR = \frac{f}{h + f} \tag{1.7}$$

$$MAR = \frac{m}{h + m} \tag{1.8}$$

Among them, h represents the number of occurrences when both the forecast and observed events appear, m represents the number of occurrences when the observed event appears but the forecast does not, f represents the number of occurrences when the forecast event appears but the observed event does not, and c represents the number of occurrences when neither the forecast nor the observed event appears.

4.2 Evaluation of different models

To investigate the differences between the CNN-BiLSTM-AM model and traditional machine learning algorithms, this study compared their forecasting performance on convective weather test dataset from 2015 to 2017. Figure 5 presents a comparative analysis of predicted and observed precipitation between the observations and various models. The figure suggested that the SVM and KNN methods resulted in subpar precipitation prediction, as evidenced by their relatively high RMSE values of 2.42mm and 2.79mm respectively. Compared to the WRF model, these figures represent reductions of 22.68% and 10.86%. Additionally, the correlation coefficients between the predicted and actual precipitation were low due to more dispersed distributions. On the contrary, RF and GBDT methods demonstrated superior performance in precipitation prediction. They achieved smaller RMSE values between the predicted and actual rainfall, reaching 1.62mm and 1.89mm respectively, representing reductions of 48.24% and 39.62% when compared with the WRF model. These methods also exhibited stronger correlations, indicated by higher correlation coefficients, suggesting concentrated distributions of predicted rainfall and actual precipitation errors. However, despite the promising results obtained by RF and GBDT methods, the CNN-BiLSTM-AM model proposed in this study outperformed them. The distribution of the predicted and actual precipitation using the CNN-BiLSTM-AM method was notably more concentrated, leading to the smallest overall error. Specifically, the RMSE value for the CNN-BiLSTM-AM model was merely 1.22mm, marking reductions of 61.02%, 49.59%, 56.27%, 35.45%, and 24.9% in comparison to WRF, SVM, KNN, GBDT, and RF models respectively. Furthermore, it reached an impressive correlation coefficient of approximately 99% between the predicted precipitation and the actual data. Based on this evidence, it is clear that the CNN-BiLSTM-AM model substantially surpasses traditional machine-

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions
Open Access
EGU

learning algorithms such as SVM, KNN, GBDT, and RF in the context of precipitation prediction.

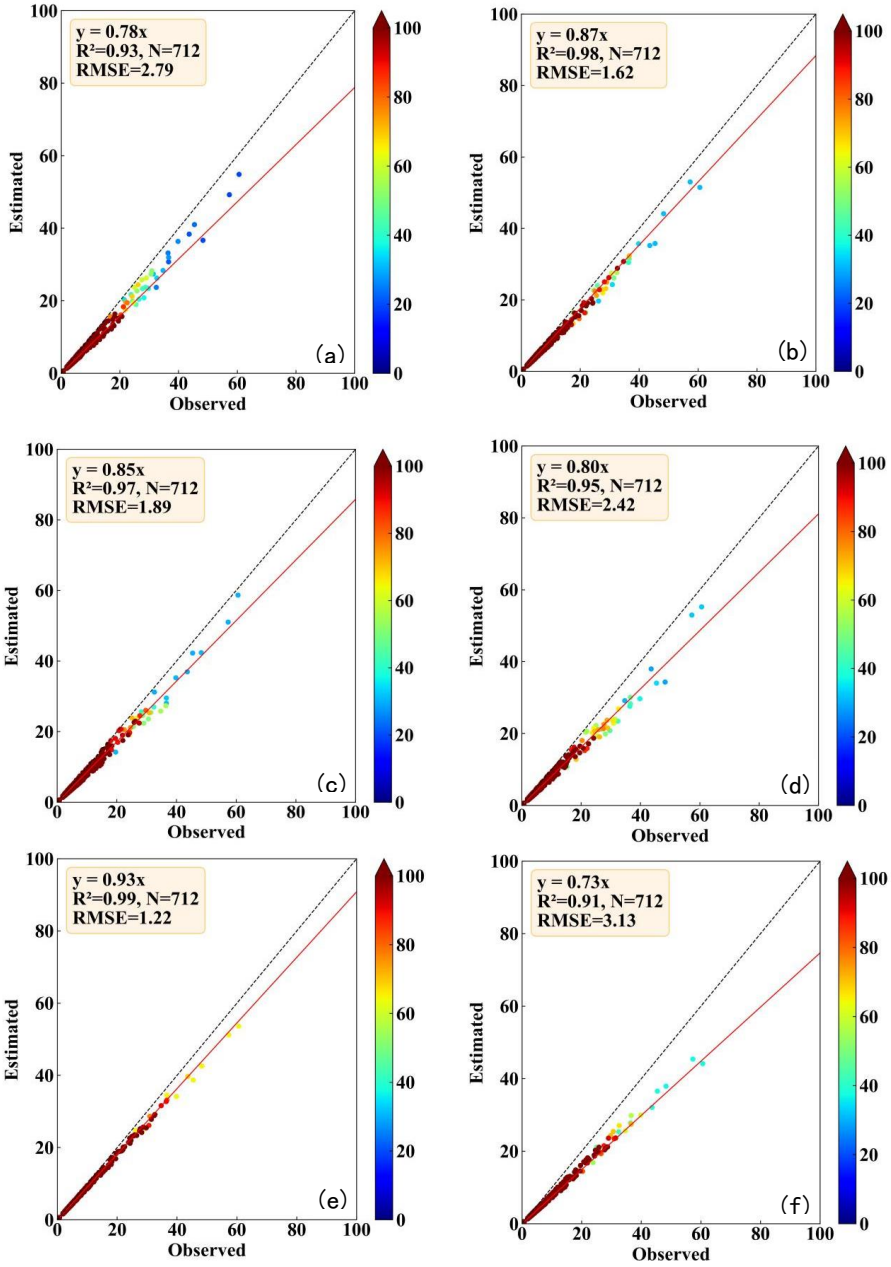


Figure 5: Scattered density plots of the observed and machine-learning corrected precipitation (a: 10-fold cross-validation training dataset of KNN model, b: 10-fold cross-validation training dataset of RF model, c: 10-fold cross-validation training dataset of GBDT model, d: 10-fold cross-validation training dataset of SVM model, e: CNN-BiLSTM-AM model forecasts, and f: WRF forecasts)

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions
Open Access
EGU

To further investigate the reliability of the CNN-BiLSTM-AM model, we compared it with the other five models using the cumulative distribution probability scatter plots and Taylor plots, and the results were shown in Figure 6. From the data provided in the figure, it was evident that the CNN-BiLSTM-AM model outperforms the other models significantly. It exhibited a standard deviation of 1.02 and a correlation coefficient of 0.99. Following closely behind as the second most accurate model is the RF model, boasting a standard deviation of 1.12 and a correlation coefficient of 0.97. The KNN model demonstrated the weakest performance, with a standard deviation and correlation coefficient of 1.26 and 0.90 respectively. The accuracy metrics of the SVM, and GBDT models fell between those of the superior (CNN-BiLSTM-AM and RF) and inferior (KNN) models. Specifically, their standard deviations and correlation coefficients were recorded as follows: SVM - 1.24 and 0.91; GBDT - 1.20 and 0.94. In conclusion, the CNN-BiLSTM-AM model held a distinct advantage in its ability to effectively extract the development characteristics of convective weather, thereby achieving superior precipitation prediction.

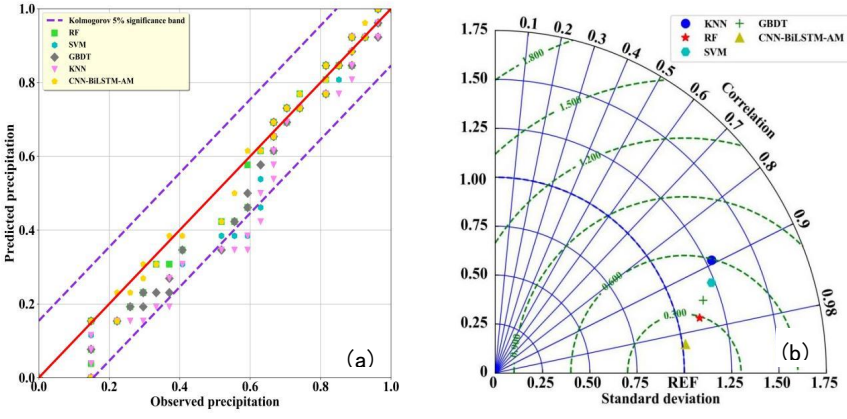


Figure 6: The cumulative distribution probability scatter plots of the observed precipitation and the predicted precipitation of 6 models(a) ; Taylor distribution plot of different model performance(b)

4.3 Individual Case Forecast Evaluation

On July 22, 2022, widespread thunderstorms and short-term heavy precipitation occurred in Henan and central Inner Mongolia, China. The forecast performance of this weather process is illustrated in Table 2 and Figure 7. From the comparison of various prediction methods in the table, we can conclude that: Regardless of whether it was the CNN-BiLSTM-AM model or other algorithms such as Gradient

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

Boosting Decision Trees (GBDT), Random Forests (RF), Support Vector Machines (SVM), or K-Nearest Neighbors (KNN), the forecast performance for convective weather showed a decreasing trend with increasing forecast duration. Additionally, the Probability of Detection (POD) and Threat Score (TS) significantly decreased, while the False Alarm Ratio (FAR) significantly increased. This can be attributed to the nonlinear and complex nature of convective system development, which leads to diminishing predictability with longer forecast durations. Among the five learning models tested, the CNN-BiLSTM-AM model demonstrated the best predictive performance in the 2-6 hour forecast duration. For example, within the 2-6 hour time range, the POD, Equitable Threat Score (ETS), and TS values for the CNN-BiLSTM-AM model were 0.550, 0.524, 0.484, 0.470, 0.463, 0.495, 0.453, 0.384, 0.310, 0.245, and 0.440, 0.375, 0.338, 0.306, 0.226, respectively. Compared to the second-ranked RF model, they improved by 15.30%, 23.88%, 17.48%, 16.34%, 19.64%, 21.32%, 26.89%, 21.52%, 14.81%, 20.69%, and 17.33%, 23.76%, 25.19%, 60.21%, 88.33%. Overall, the CNN-BiLSTM-AM model showed a significant improvement in forecast performance compared to other machine learning algorithms. As the forecast duration increased, the CNN-BiLSTM-AM model outperformed other machine learning models in terms of forecast results. For example, at the 3rd hour, the difference in TS values between the CNN-BiLSTM-AM model and GBDT, RF, SVM, KNN models were 0.129, 0.072, 0.152, 0.163, representing improvements of 52.44%, 23.76%, 68.16%, 76.89%. At the 6th hour, the corresponding TS differences were 0.110, 0.106, 0.111, 0.112, showing improvements of 94.83%, 88.33%, 96.52%, 98.25%. Therefore, it can be observed that beyond the 2-hour forecast stage, the CNN-BiLSTM-AM model performs more prominently in convective weather forecasting. The figure 6 clearly illustrates the variations in forecast performance across different models. In the 1-hour forecast duration, both deep learning and machine learning algorithms did not exhibit significant changes in forecast performance. This can be attributed to the fact that within the 0-1 hour time range, convective system morphology undergoes minimal changes, and the NCEP fnl analysis data contains sufficient information about the initial stage of convection, allowing effective prediction relying solely on analysis data. However, within the 2-6 hour forecast duration, the CNN-BiLSTM-AM model consistently outperformed the machine learning methods, particularly as the lead time extended. The performance gap between the CNN-BiLSTM-AM model and other machine learning models gradually widened. This indicates that the CNN-BiLSTM-AM model possesses nonlinear evolution recognition and prediction capabilities, with its provided information

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

becoming more valuable as the forecast duration increases. These findings further confirm the advantages of deep learning methods in severe convection forecasting.

Table 2. Comparison of various models on convective weather case on July 22, 2022

Models	Forecast duration	POD	FAR	ETS	TS
CNN-BiLSTM-AM	1h	0.618	0.389	0.501	0.484
	2h	0.550	0.430	0.495	0.440
	3h	0.524	0.454	0.453	0.375
	4h	0.484	0.482	0.384	0.338
	5h	0.470	0.538	0.310	0.306
	6h	0.463	0.646	0.245	0.226
GBDT	1h	0.633	0.386	0.486	0.473
	2h	0.433	0.558	0.277	0.319
	3h	0.427	0.652	0.200	0.246
	4h	0.409	0.733	0.145	0.197
	5h	0.402	0.783	0.111	0.164
	6h	0.372	0.824	0.083	0.116
RF	1h	0.651	0.412	0.477	0.481
	2h	0.477	0.525	0.408	0.375
	3h	0.423	0.632	0.357	0.303
	4h	0.412	0.721	0.316	0.270
	5h	0.404	0.790	0.270	0.191
	6h	0.387	0.803	0.203	0.120
SVM	1h	0.413	0.405	0.459	0.451
	2h	0.249	0.545	0.138	0.271
	3h	0.186	0.636	0.088	0.223
	4h	0.126	0.710	0.047	0.182
	5h	0.094	0.790	0.025	0.170
	6h	0.076	0.854	0.013	0.115
KNN	1h	0.391	0.400	0.328	0.253

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

	2h	0.332	0.512	0.165	0.443
	3h	0.281	0.616	0.143	0.212
	4h	0.245	0.709	0.098	0.180
	5h	0.170	0.801	0.062	0.142
	6h	0.101	0.868	0.038	0.114

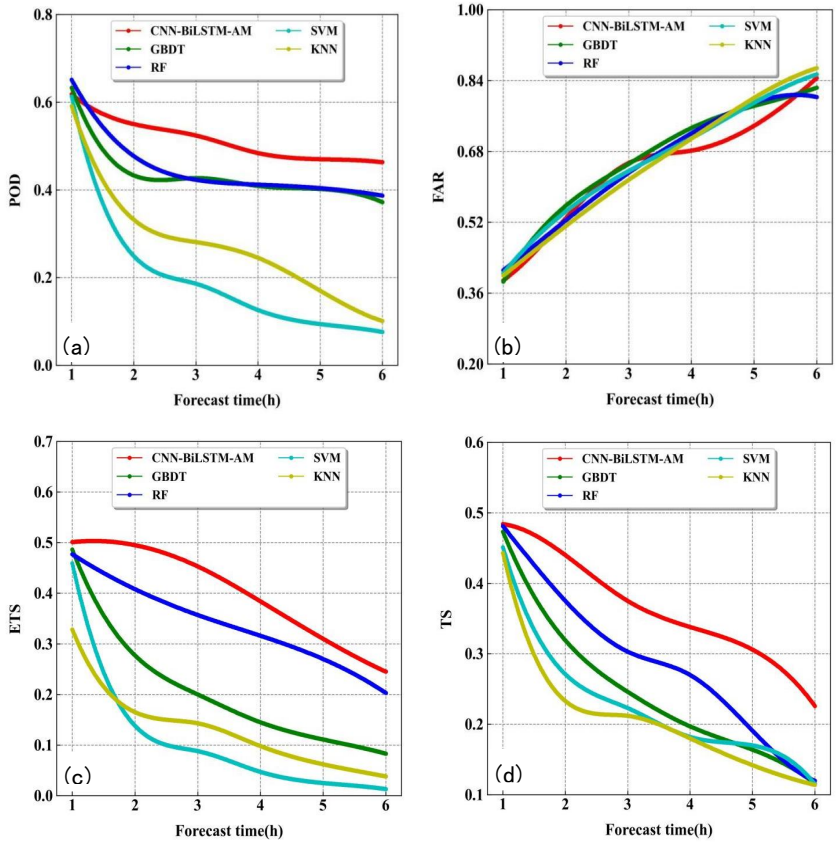


Figure 7: Comparison of forecast performance of different models

To assess how errors vary in different models, we selected Zhengzhou in Henan as specific region for evaluation and analysis. The boxplots of the predicted precipitation and the actual precipitation of 6 models at 12 stations in Zhengzhou show that(see Figure 8), the CNN-BiLSTM-AM gave more accurate results than the other models, its difference between the observed precipitation and the predicted precipitation was very small, which is significantly superior to those of the other models; For the RF and GBDT models, the difference between the observed precipitation and the predicted precipitation was not

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

significant and both showed better performance than KNN and SVM models. Overall, the CNN-BiLSTM-AM model showed the best performance with higher accuracy for all stations, and the KNN and SVM model illustrated the lowest performance among other models and approaches.

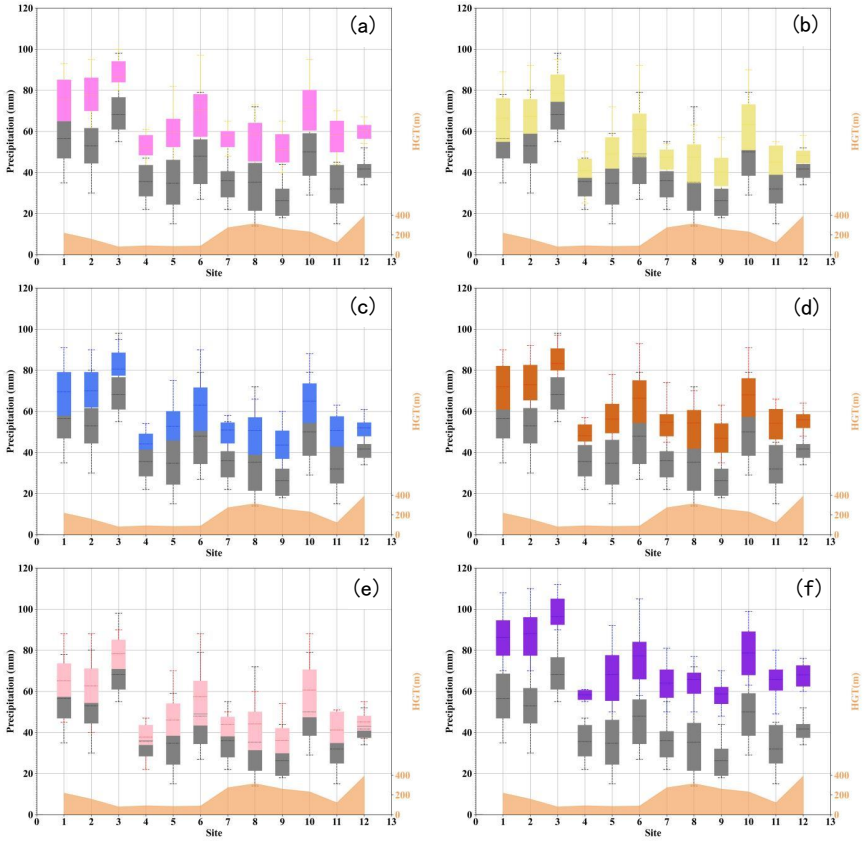


Figure 8: The boxplots of the predicted precipitation of the KNN(a), RF(b), GBDT(c), SVM(d), CNN-BiLSTM-AM(e), and WRF(f) models at 12stations and the boxplots of the actual precipitation (gray).

4.4 Spatial–temporal variations in the best model

Figure 9 depicts the diurnal variations offered by diverse models in July 2022, and also shows the diurnal fluctuation in precipitation in the initial WRF forecast. The precipitation forecast by the original WRF weather prediction model exhibits noticeable inaccuracies. As can be seen from the figure, WRF's precipitation forecast displays a distinct diurnal variation trait, characterized by substantial discrepancies between early morning and afternoon hours, namely between 9:00 am and 13:00 pm (Figure 9f). This

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

indicates that WRF's precipitation forecast tends to be inaccurate and displays significant errors in diurnal variation.

Compared to the precipitation forecast results of different ML models, the diurnal variation error was considerably lessened (Figure 9a, b, c, d, and e). Initially, the mean precipitation forecast by the CNN-BiLSTM-AM model aligns well with the actual average precipitation trajectory, with minimal error and devoid of diurnal variation (Figure 9e). This suggests that the predicted and actual distributions of precipitation are in agreement. However, the results performed between 9:00 am and 13:00 pm during January 2021 were not very satisfactory. This could be attributed to the inadequate generalization abilities of the training model and the excessive volatility of actual precipitation at these specific times. Based on the above comparative analysis, it can be inferred that the CNN-BiLSTM-AM model outperforms other models.

In oreder to facilitate a more intuitive comparison, we visualized the distribution of forecast results for different models (see Figure 10). As can be seen from Figure 10, the RMSE (Figure 10a, b, c, d, and e) distribution of precipitation of 5 models show that the performance of the CNN-BiLSTM-AM model is better than the other machine learning models, RMSE value is mostly between 0.11mm and 3.87mm. The performances of the RF, SVM, GBDT, and KNN models are not as good as CNN-BiLSTM-AM, their RMSE were recorded as follows: RF: 0.10mm-4.25mm, SVM: 0.38mm-4.31mm; GBDT: 0.33mm-4.68mm, KNN: 0.56mm-4.82mm. From the 24-hour forecast scores (Fig.8f), the CNN-BiLSTM-AM model consistently outperformed the subjective predictions of the forecasters. This indicates that the CNN-BiLSTM-AM model, based on deep learning techniques, significantly improved the forecast accuracy for this severe convective weather event, providing forecasters with valuable guidance and reference.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

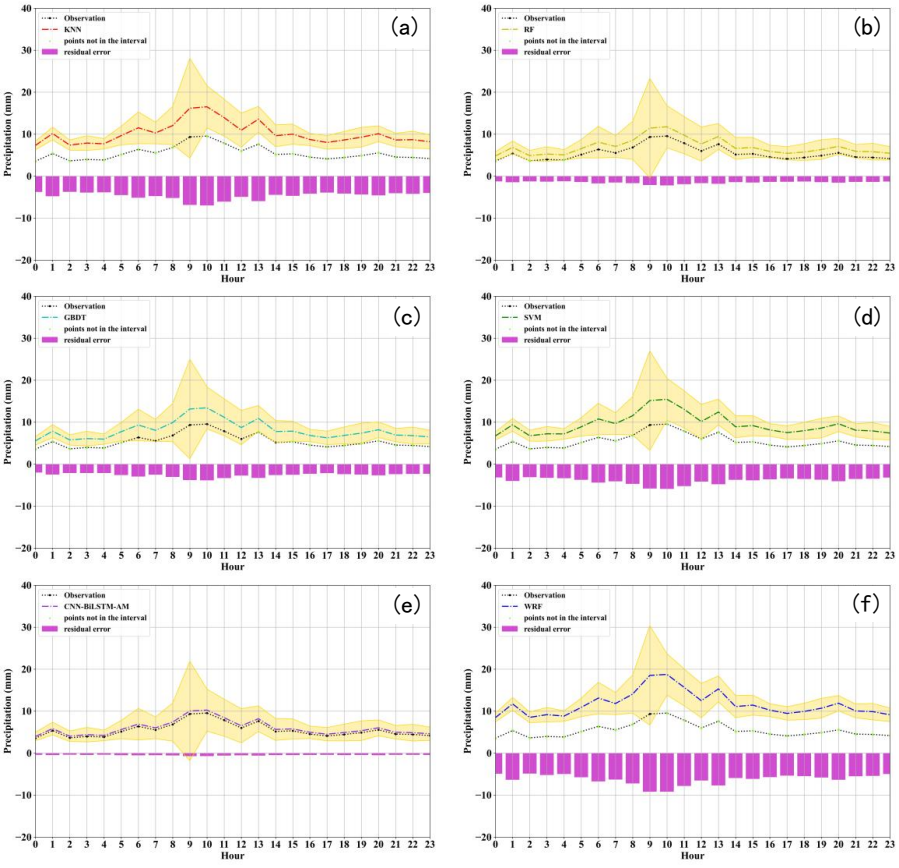


Figure 9: KNN(a), RF(b), GBDT(c), SVM(d), CNN-BiLSTM-AM(e), and WRF(f) daily variation of predicted and actual precipitation on July 2022.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

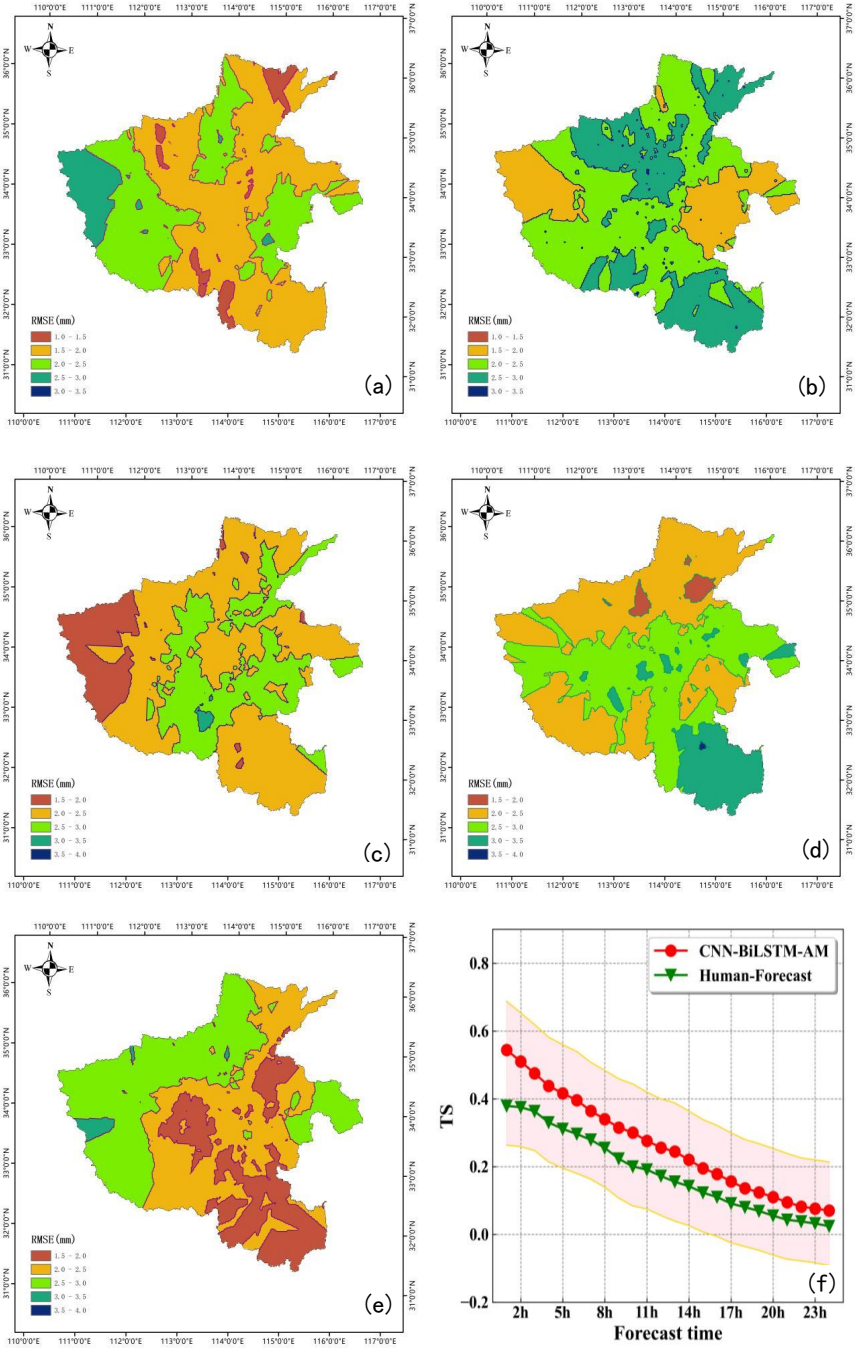


Figure 10: RMSE distribution of CNN-BiLSTM-AM(a), RF(b), SVM(c), KNN(d), GBDT(e) models in Henan; TS scores of strong convective weather on July 22, 2022 (f)

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

5 Discussion

5.1 Stability analysis of the proposed models

The preceding results presented the visualized outcomes of various correction methods, which may not fully prove the stability of different approaches. To further evaluate the stability of various machine-learning models, we compared their performance on strong convective weather forecasting during the flood season (April-September) from 2020 to 2022 by using six evaluation metrics: RMSE, FAR, MAR, POD, TS, and accuracy. The specific results are presented in Figure 11. This comprehensive analysis will provide a more accurate assessment of the stability of different models.

The RMSE values of the five machine-learning models were lower than that of the WRF model, with the CNN-BiLSTM-AM model having the smallest RMSE of 1.12mm. This represented a 63.04% reduction in RMSE compared to the output precipitation of the WRF model. From the perspective of solving regression problems, the model effectively corrected the deviation in precipitation predicted by the numerical forecast model. In comparison to other machine-learning algorithms, the accuracy of the CNN-BiLSTM-AM model showed a significant improvement, demonstrating the stability of deep-learning methods for nonlinear problems such as precipitation, often achieving superior application results.

FAR and MAR are two important indicators for evaluating precipitation forecasting accuracy, reflecting false and missing alarm rates, respectively. As shown in the figure, the FAR of the CNN-BiLSTM-AM model was higher than that of all the other corrected models, while its MAR was lower than that of all the other models. This situation might be due to the fact that while the CNN-BiLSTM-AM model effectively fits precipitation, it also has side effects, leading to precipitation forecasts in the absence of actual precipitation. The FAR and MAR values obtained by the other four machine-learning algorithms were lower than those of the WRF model, indicating that these machine-learning methods can reduce the false and missing rates of the WRF model precipitation forecasts to a certain extent.

Finally, the POD,TS and accuracy scores of the five machine-learning models were significantly higher than that of the WRF model, with the CNN-BiLSTM-AM model achieving the best performance among all models. These results indicate that the CNN-BiLSTM-AM model exhibits an ideal performance in correcting precipitation forecasts from the WRF model, outperforming other machine-learning methods in terms of precipitation correction.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

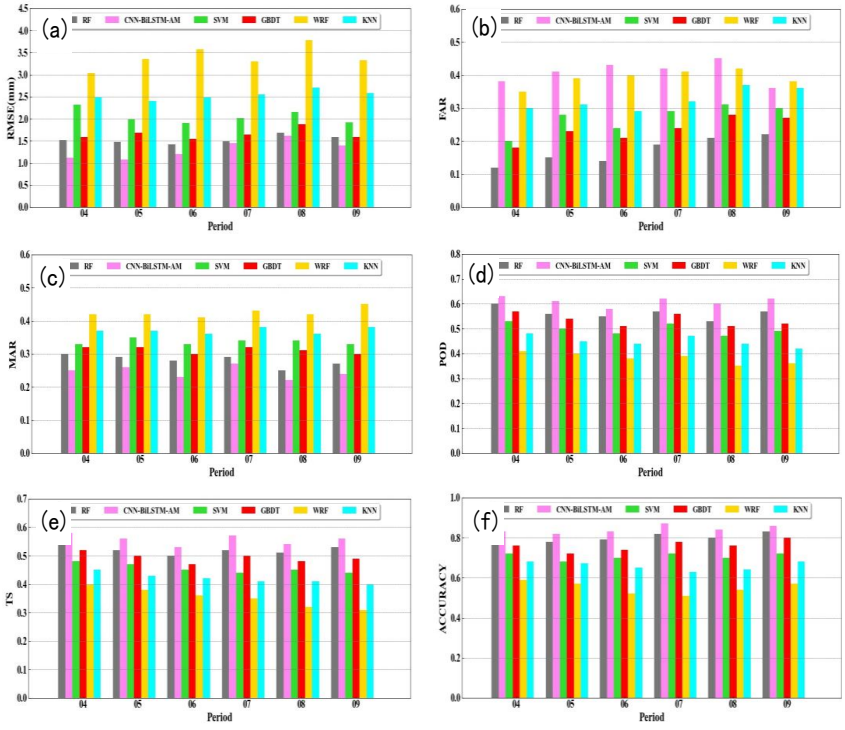


Figure 11: Evaluation histograms of precipitation predicted by 6 models and actual precipitation in different months ((a), (b), (c), (d), (e), and (f) represent RMSE(mm), FAR, MAR, POD, TS, and ACCURACY respectively).

5.2 Explainability of the mechanism of severe convective weather based on machine learning

Although machine learning and deep learning methods have made significant breakthroughs in various fields, effectively predicting severe convective weather using these methods still remains a "black box" challenge (McGovern et al., 2019), with the specific details being difficult to ascertain. Currently, many researchers are attempting to uncover this "black box" and have developed several model interpretation and visualization (MIV) techniques. Through MIV, users of machine learning can gain a better understanding of the strengths, weaknesses, and optimal application scenarios of the models, thereby increasing trust in the models and enhancing their practicality. If the machine learning forecasts outperform human forecasters, MIV can also help improve subjective judgment and prediction results, as well as validate new scientific hypotheses and conjectures (McGovern et al., 2019). In this section, we apply a method of ranking the importance of forecast factors to analyze the forecasting process of the

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

deep learning model, aiming to unravel the mystery of the "black box" in deep learning for predicting severe convective weather.

5.2.1 Technical method

By employing the Random Forest (RF) algorithm, we can conduct an importance analysis of forecast factors to ascertain the significance of each predictor and establish a priority ranking. The fundamental principle involves measuring the contribution of each feature in every tree within the random forest, averaging these values, and then comparing the contributions among the features. Typically, we can utilize the Gini index or Out-of-Bag (OOB) error rate as evaluation metrics. In this study, we solely focus on the approach that employs the Gini index for assessment. Here, we denote Variable Importance Measures (VIM) as the score reflecting the importance of variables, GI represents the Gini index, $VIM_j^{(Gini)}$ denotes the Gini index score for the j-th feature (X_j). Assuming there are J features, X_1, X_2, X_3, ..., X_J, I decision trees, and C categories, the Gini index of node q in the i-th tree is calculated as follows:

$$GI_q^{(i)} = \sum_{c=1}^{|C|} \sum_{c' \neq c} P_{qc}^{(i)} P_{qc'}^{(i)} = 1 - \sum_{c=1}^{|C|} (P_{qc}^{(i)})^2 \quad (1.9)$$

Among them, C represents the categories, and P_{qc} denotes the proportion of category c at node q. The change in Gini index for a feature is given by:

$$VIM_j^{(Gini)(i)} = \sum_{q \in Q} VIM_{jq}^{(Gini)(i)} \quad (1.10)$$

Suppose there are I trees in the Random Forest (RF), then:

$$VIM_j^{(Gini)} = \sum_{i=1}^{I} VIM_j^{(Gini)(i)} \quad (1.11)$$

Finally, normalization is performed:

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

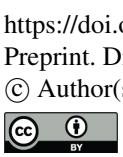
Geoscientific Model Development Discussions

$$VIM_j^{(Gini)} = \frac{VIM_j^{(Gini)}}{\sum_{j'=1}^{J} VIM_{j'}^{(Gini)}} \quad (1.12)$$

5.2.2 The interpretability of machine learning models

Using the RF algorithm, we conducted an importance analysis of forecast factors on the training and testing datasets of CNN-BiLSTM-AM model constructed by us, obtaining the relative rankings of each forecast factor's importance and their corresponding correlation coefficients (see Figures 12). From the figures, it is evident that moisture conditions are crucial for severe convective weather, with the most important feature being precipitable water (PWAT), which significantly outweighs the second-ranked feature. Geographic location also has a significant impact on severe convective weather, with longitude (LON) and latitude (LAT) ranking second and third among all indicators, respectively. As convective weather fundamentally arises from temperature variations, when the near-surface air absorbs sufficient heat and expands, its density decreases, leading to an unstable atmosphere that triggers convective weather. Therefore, the temperature (T) feature ranks fourth. Strong convection imposes certain requirements on atmospheric dynamic lifting conditions, with 300hPa vertical motion (W300) ranking fifth. Atmospheric energy conditions have some influence on severe convective weather but are not the most important factors, as Bulk Convective Available Potential Energy (BCAPE) and Lifted Index (LI) rank sixth and seventh, respectively. These features align closely with the importance distribution of physical quantities related to short-term severe convective weather obtained by Tian et al. (2015) through statistical analysis. Additionally, these features are consistent with the characteristics of various types of severe convective weather analyzed by forecasters in terms of moisture, energy, dynamics, and other conditions (Zeng & Yang, 2020; Zhang et al., 2020; Zhang et al., 2022).These results demonstrate the high effectiveness of machine learning in automatically extracting features and further confirm the rationality of constructing the sample dataset.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023



Geoscientific Model Development Discussions
Open Access
EGU

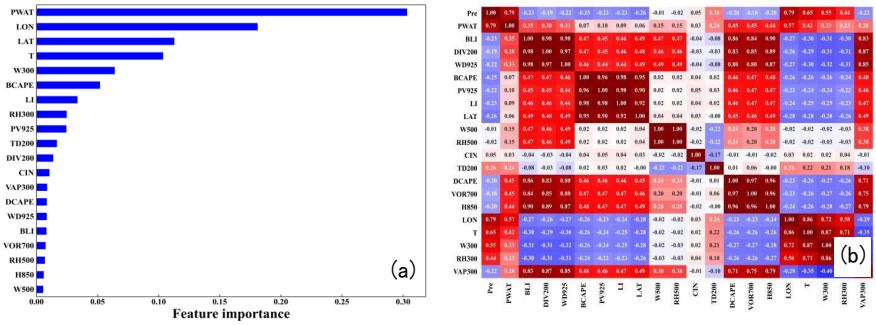


Figure 12: Relative importance of forecast factors (top 20 most important forecast factors); The correlation coefficient between each of the forecast factors

6 Summary

This study utilizes the NCEP Global Forecast System (GFS) reanalysis data and forecast data to construct a CNN-BiLSTM-AM model for predicting severe convective weather using deep learning techniques and comprehensively evaluate the performance of this model. Furthermore, to gain a better understanding of the "black box" principles of deep learning for severe convective weather prediction, we visualize the training process by ranking the importance of forecast factors. The main conclusions are as follows:

1）Compared to traditional machine learning algorithms such as Gradient Boosting Decision Trees (GBDT), Random Forest (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), the CNN-BiLSTM-AM model can automatically identify and learn deeper nonlinear features of severe convective weather. Consequently, it achieves higher prediction accuracy on the severe convective weather dataset. Moreover, as the lead time increases, all algorithms exhibit a decreasing trend in their forecasting performance.

2）In comparison to subjective forecasts made by meteorologists, the CNN-BiLSTM-AM model demonstrates good performance in forecasting severe convective weather, with improvements in scoring metrics such as Probability of Detection (POD), False Alarm Rate (FAR), Threat Score (TS), and Equitable Threat Score (ETS). Specifically, the average TS score of the CNN-BiLSTM-AM model for heavy precipitation reaches 0.336, representing a 33.2% improvement compared to the meteorologists' score of 0.252. Additionally, due to its training with a large-scale sample dataset, the model can automatically extract classification features and consider various parameters related to severe convective weather conditions. This enables it to assess the convective conditions at each grid point within the

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

forecast range, resulting in a lower miss rate than false alarm rate. This lower miss rate provides better guidance for meteorologists' forecasts.

3）Using the RF algorithm, we perform an importance analysis of forecast factors on the training and testing datasets of the CNN-BiLSTM-AM model, obtaining the relative rankings and correlation coefficients of each forecast factor. The analysis results reveal that for severe convective weather, precipitable water (PWAT) is the most critical moisture condition, with its importance significantly surpassing the second-ranked feature. Geographic location also has a significant impact, with longitude (LON) and latitude (LAT) ranking second and third among all factors, respectively. As convective weather fundamentally arises from temperature variations, temperature (T) ranks fourth. Strong convection imposes certain requirements on atmospheric dynamic lifting conditions, with 300hPa vertical motion (W300) ranking fifth. Atmospheric energy conditions have some influence on severe convective weather but are not the most important factors, as Bulk Convective Available Potential Energy (BCAPE) and Lifted Index (LI) rank sixth and seventh, respectively. Through this ranking analysis of forecast factors, we find that the order of importance determined by deep learning for severe convective weather prediction is roughly consistent with the subjective understanding of meteorologists. This further demonstrates the effectiveness of deep learning in automatically extracting features for severe convective weather and verifies the rationality of constructing the sample dataset.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

Code availability

The code and model are available at Zenodo via https://doi.org/ 10.5281/zenodo.8417134 (Zhang et al., 2023).

Data Availability

The data are available at Zenodo via https://doi.org/ 10.5281/zenodo.8417134 (Zhang et al., 2023).

Author contributions

YY and ZG were responsible for conceptualization, supervision and funding acquisition. SZ developed the software and prepared the original draft. SZ and YY developed the methodology and carried out formal analysis. XX and SZ validated data. ZG,YY, XX, ZD, and YL were reviewed and edited the text. SZ was responsible for visualization. All authors have read and agreed to the published version of the paper.

Competing interests

The authors declare that they have no conflict of interest.

Financial support

This research has been supported by the second batch of service public bidding projects for EHV transmission companies in 2022 (2022-FW-2-ZB) (grant no. CG0100022001526556).

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

Geoscientific Model Development Discussions

511 **References**

512 Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., and Tian, Q.: Accurate medium-range global weather
513 forecasting with 3D neural networks, Nature, https://doi.org/10.1038/s41586-023-06185-3, 2023.
514 Buda, M., Maki, A., and Mazurowski, M. A.: Systematic study of the class imbalance problem in
515 convolutional neural networks, arXiv preprint arXiv:1710.05381, 2017.
516 Zeng, Y. and Yang, L. M.: Analysis on Mesoscale Impact System and Atmospheric Vertical Structure
517 of Two Types of Heavy Rains in Urumqi. Plateau Meteorology，39, 774-787, https://doi.org/10. 7522/
518 j. issn.1000-0534.2019.00070，2020.
519 Gao, Z., Zhang, J.,Yu, M., Liu, Z., Yin, R., Zhou, S., Zong, L., Ning, G., Xu, X., Guo, Y., Wei H., and
520 Yang, Y.,: Role of water vapor modulation from multiple pathways in the occurrence of a record-
521 breaking heavy rainfall event in China in 2021, Earth and Space Science,9,e2022EA002357,
522 https://doi.org/10.1029/2022EA002357, 2022.
523 Gope, S., Sarkar, S., Mitra, P., and Ghosh, S.: Early Prediction of Extreme Rainfall Events: A Deep
524 Learning Approach[M]// Advances in Data Mining, Springer International Publishing, 2016.
525 Han, H., Lee, S., Im, J., Kim, M., Lee, M., Ahn, M., and Chung, S.: Detection of Convective Initiation
526 Using Meteorological Imager Onboard Communication, Ocean, and Meteorological Satellite Based on
527 Machine Learning Approaches, Remote Sens, 7(7):9184-9204, https://doi.org/10.3390/rs70709184,
528 2015.
529 Herman, G. R. and Schumacher, R. S.: Money Doesn't Grow on Trees, but Forecasts Do: Forecasting
530 Extreme Precipitation with Random Forests, Mon Wea Rev,146 (5):1571–1600,
531 https://doi.org/10.1175/MWR-D-17-0250.1, 2018.
532 Kingma, D. and Ba, J. A.: A Method for Stochastic Optimization, Int Conf Learn Represent,
533 https://doi.org/ 10.48550/arXiv.1412.6980, 2014.
534 Krawczyk, B.: Learning from imbalanced data: open challenges and future directions, Progr Artif Intell,
535 5(4):1-12, https://doi.org/10.1007/s13748-016-0094-0, 2016.
536 Krizhevsky, A., Sutskever, I., and Hinton, G. E.: Imagenet classification with deep convolutional neural
537 networks[C]// Proceedings of the 25th International Conference on neural information processing
538 systems, Red Hook, NY, United States: Curran Associates Inc: 1097-1105, 2012.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

539 LeCun, Y. and Bengio, Y.: Convolutional networks for images, speech, and time series[M] //Arbib M A.
540 The handbook of brain theory and neural networks, Cambridge: MIT Press: 255-258, 2019.
541 Lin, T. Y., Li, Q. Y., Geng, Y. A., and Jiang, L.: Attention-Based Dual-Source Spatiotemporal Neural
542 Network for Lightning Forecast, IEEE Access, (7): 158296-158307, https://doi.org/10.1109/ ACCESS.
543 2019. 2950328, 2019.
544 Liu, N. N., Liu, C. T., and Tissot, P. E.: A Bayesian-Like Approach to Describe the Regional Variation
545 of High - Flash Rate Thunderstorms From Thermodynamic and Kinematic Environment Variables,
546 Geophys Res: Atmos,124(23): 12507-12522, https://doi.org/10.1029/2019JD031254, 2019.
547 Li, W. J., Zhao, F., Li, M. J., Chen, L., and Peng, X.: Forecasting and Classification of Severe Convective
548 Weather Based on Numerical Forecast and Random Forest Algorithm, Meteor Mon, 44(12):49-58(in
549 Chinese), https://doi.org/10.7519/j.issn.1000 0526.2018.12.005, 2018.
550 Lu, W. J.， Li, J. Z.， Wang, J. Y., and Qin, L.: A CNN-BiLSTM-AM method for stock price predictiona,
551 Neural Computing and Applications,33:4741–4753, https://doi.org/10.1007/s00521-020-05532-z, 2021.
552 McGovern, A., Elmore, K. L., Gagne II, D. J., Haupt, S. E., Karstens, C. D., Lagerquist, R., Smith, T.,
553 and Williams, J. K.: Using artificial intelligence to improve real-time decision-making for high-impact
554 weather, Bul Amer Meteor Soc, 98(10): 2073-2090, https://doi.org/10.1175/BAMS-D-16-0123.1, 2017.
555 McGovern, A., Lagerquist, R., Gagne II, D. J., Jergensen, G. ,E., Elmore, K. L., Homeyer, C. R., and
556 Smith, T.: Making the black box more transparent: Understanding the physical implications of machine
557 learning, Bull Amer Meteor Soc,100(11): 2175-2199, https://doi.org/10.1175/BAMS-D-18-0195.1,
558 2019.
559 Perol, T., Gharbi, M. and Denolle, M.: Convolutional Neural Network for Earthquake Detection and
560 Location, Sci Adv, (4):2–10, https://doi.org/10.1126/sciadv.1700578, 2017.
561 Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., and Prabhat.: Deep
562 learning and process understanding for data-driven Earth system science, Nature, 566(7743): 195-204,
563 https://doi.org/10.1038/s41586-019-0912-1, 2019.
564 Szegedy, C. and Toshev, A., Erhan D.: Deep neural networks for object detection[C]// Proceedings of
565 the 26th International Conference on Neural Information Processing Systems, Red Hook, NY, United
566 States: Curran Associates Inc.2013: 2553-2561, 2013.

https://doi.org/10.5194/gmd-2023-187
Preprint. Discussion started: 25 October 2023

567 Tang, W., Zhou, Q., Liu, X., Zhu, W., Mao, X.: Analysis on Verification of National Severe Convective
568 Weather Categorical Forecasts, Meteor Mon, 43(1):67-76(in Chinese), https://doi.org/
569 10.7519/j.issn.1000-0526.2017.01.007, 2017.
570 Tian, F., Zheng, Y., Zhang, T., Zhang, X., Mao, D., Sun, J., and Zhao, S.: Statistical characteristics of
571 environmental parameters for warm season short-duration heavy rainfall over central and eastern China,
572 Meteor Res, (29): 370-384, https://doi.org/10.1007/s13351-014-4119-y, 2015.
573 Wang, X., Mao, W., Guo, J.: Statistics features of strong convection weather disaster in China in 2004
574 main flood period, J Nat Disasters, 16(1): 27-30(in Chinese), 2007.
575 Zhang, F.，Li, G.，Luo, X.: Some Influence Factors of a Sudden Rainstorm Event in Northeast Sichuan
576 Basin of China, Plateau Meteorology，39（2）：321-332, https://doi.org/10.7522/j.issn. 1000-
577 0534.2019. 00080，2020.
578 Zhang, J.，Gao, Z.，Yang, J.，Li, Y., and Jiang, Y.: Research and Numerical Simulation of Rainstorm
579 over Bosten Lake Area based on WRF Model, Plateau Meteorology，41（4）：887-895.
580 https://doi.org/10. 7522/j. issn. 1000-0534. 2021. 00029，2022.
581 Zheng, Y., Tian, F., Meng, Z., Xue, M., Yao, D., Bai, L., Zhou, X., Mao, X., and Wang M.: Survey and
582 Multi Scale Characteristics of Wind Damage Caused by Convective Storms in the Surrounding Area of
583 the Capsizing Accident of Cruise Ship “Dongfangzhixing”, Meteor Mon,42(1):1-13(in Chinese),
584 https://doi.org/10.7519/j.issn.1000-0526.2016.01.001, 2016.
585 Zheng, Y., Zhou, K., Sheng, J., Lin, Y., Tian, F., Tang, W., Lan Y., and Zhu, W.: Advances in Techniques
586 of Monitoring, Forecasting and Warning of Severe Convective Weather, J Appl Meteor Sci, 26(6): 641-
587 657(in Chinese), https://doi.org/10.11898/1001-7313.20150601, 2015.
588 Zheng, Y., Zhu, W., Yao, D., Meng, Z., Xue, M., Zhao, K., Wu, Z., Wang, X., Zheng, Y.: Wind Speed
589 Scales and Rating of the Intensity of the 23 June 2016 Tornado in Funing County, Jiangsu
590 Province[J].Meteor Mon,42(11):1289-1303(in Chinese), https://doi.org/10.7519/j.issn. 1000-0526.2016.
591 11.001, 2016.