Tropical Cyclone Forecast Using Multitask Deep Learning Framework

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***Abstract*—A tropical cyclone is a robust weather system that affects human daily life. Accurate and rapid tropical cyclone forecast can guide human disaster prevention and mitigation work against tropical cyclones. The mainstream tropical cyclone forecasting method is numerical forecasting, which requires abundant prior knowledge and luxurious calculation. Nowadays, machine learning methods have received increasing attention for they can overcome these disadvantages. However, existing machine learning methods usually ignored some potential factors due to they mainly concentrated on one aspect of the tropical cyclone forecast. This letter proposes a multitask machine learning framework to forecast tropical cyclone path and intensity, which possesses two modules: one is the prediction module, the other is the estimate module. We use an improved generative adversarial network as the prediction module to predict the tropical cyclone spatial data at a certain moment in the future. Then, we use two different deep neural networks as the estimation module to extract the position and intensity from the generated prediction data. The method we propose is a general and relatively accurate tropical cyclone forecast method. We reach a 24h path forecast error of 116km and a 24h intensity forecast error of 13.06kt.**

***Index Terms*—Tropical Cyclone Forecast, Generative Adversarial Network, Wasserstein Distance.**

I. INTRODUCTION

TROPICAL cyclones are cyclonic circulations that occur over the sea in tropical and subtropical regions. It is a complicated and severe weather system. The power release of a mature tropical cyclone can reach the level of one hundred terawatts, which will bring a series of meteorological disasters such as gale, storm surge, and heavy rain. Therefore, accurate and rapid forecasting of tropical cyclone indicators can help guide human disaster prevention and mitigation work against tropical cyclones. It also has important implications in the scientific use of tropical cyclones. Among all the indicators, position and intensity are the most crucial indicators.

The forecast of tropical cyclone path movement is usually based on a general and accurate understanding of tropical cyclone motion. This law is affected by many complex factors, such as large-scale weather patterns, sea level, and atmospheric temperature, land topographic characteristics, the structure and intensity of tropical cyclones, so it is very difficult to accurately describe it with existing models [1]. Furthermore, forecasting the intensity of tropical cyclones is more difficult than forecasting the path. Researchers believe that this is because the physical process that causes the intensity changement of tropical cyclones is so complicated that we process little knowledge of it [2]. These two factors affect each other during tropical cyclone development, so it's challenging but significant work to combine these two tasks together.

In this letter, we proposed a framework that can give a quick and reliable forecast of tropical cyclone path and intensity based on the infrared image. The framework has a prediction module to predict the future spatial data of tropical cyclones and an estimation module to determine the value of the indicator from the predicted result. We set a retrospective CycleGAN [3] using Wasserstein loss [4] in the prediction module. Then in the estimation module, we build a new model called TIENet to predict the intensity and use TCLNet to predict position. Our work achieves an average 6-hour path forecast error of 61km and an average 24-hour path forecast error of 116km, while our 6-hour intensity error and 24-hour intensity forecast error respectively reach 14.20kt and 13.06kt. These results are produced with the last 24 hours data within less than 10 seconds. In addition, the path forecast error is 10% better than Rüttgers' work [5], which has the best precision in existing models. It is also a flexible framework. On one hand, the input can be not only the infrared images but also satellite images, meteorological reanalysis data. On the other hand, the output can be diverse with different tropical cyclone data analyse models. The overview of the forecast framework is shown in Fig 1. Briefly, our work has several distinct contributions as follows:

- First, the framework consisting of three networks provides a one-step solution which can forecast the path and intensity of tropical cyclones at the same time.
- Second, we combine retrospective CycleGAN [3] with Wasserstein loss [4], which strengthens the adversariness between the generator and discriminator. This helps obtain high-similar results to the ground truth. This new network can also be used in the area of predicting video frames.
- Third, the TIENet can be a new tool for tropical cyclone image interpretation.

II. RELATED WORK

We survey the development of neural network methods used in the tropical cyclone forecast and generative adversarial networks. Here are some details.

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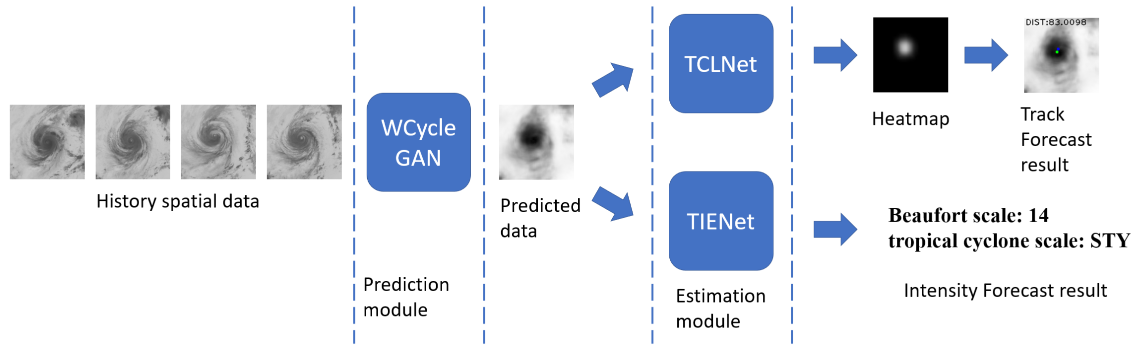

Fig. 1. An overview of the forecast framework. WCycleGAN generates the predicted data from historical data, next TCLNet and TIENet extract the position and intensity information from it. The green point shows the forecast location, besides the blue point shows the ground truth location.

The research of neural network methods used in the tropical cyclone forecast started at the end of the last century. Until the 2010s, MLP and BP network were the mainstream neural network methods for forecasting the intensity and path of tropical cyclones [6] [7]. Since the mid-2010s, due to the development of deep learning, more new methods have been introduced into the forecast of tropical cyclones. Recurrent neural network(RNN) is a class of neural networks that exhibit temporal dynamic behavior, Moradi Kordmahalleh et al. [8] and Alemany et al. [9] used this method to forecast the path of tropical cyclones in 2016 and 2019, while Pan et al. [10] used this method to forecast the intensity of tropical cyclones in 2019. Rüttgers et al. [5] introduced GAN into the tropical cyclone path forecast field in 2018. The LSTM network also plays an important role in tropical cyclone forecast, Kim et al. [11] used convLSTM to forecast the tropical cyclone path. Meanwhile, Chen et al. [12] combined LSTM with CNN to forecast the intensity. These methods mainly concentrated on one aspect of the tropical cyclone forecast, so they were inclined to use specialized data. Furthermore, they ignored some potential factors due to this operation. Meanwhile, it means we have to call several different models to obtain our expected results.

Since the generative adversarial network was proposed in 2014, it has become a research hotspot these years. Researchers have made a lot of effort to improve its performance. On one hand, researchers changed the network's structure, for example, DCGAN [13], LAPGAN [14], and CycleGAN [15], to help the network fit more tasks. On the other hand, researchers adjusted the loss function of the network, for example, LSGAN [16] and WGAN [4], to help strengthen the adversariness between generator and discriminator, which can lead into a higher-quality result. These high-performance models are of great help to meteorological research. Among all these works, the CycleGAN is widely applied in computer vision as a result of its ability to build connections among unpaired pictures, while others mainly handle paired data. However, Zhu et al. used the LSGAN's loss function; hence, it may be difficult to get a perfect result in some situations.

III. METHODOLOGY

This method can be regarded as a simple application of the framework that we proposed. We only use two networks to accomplish the path and intensity forecast although this framework can complete more tasks. In this section, we will talk about the details of the three networks in the two modules that compose our framework.

A. Prediction module

This module consists of one network which we call WCycleGAN. The network is inspired by Kwon et al. [3] in predicting future frames. We use the same retrospective method as they did, and we adopt their network architecture and change the input and output layers to adapt the grayscale image. This GAN has two discriminators, one is the frame discriminator likes others own, the other one is the sequence discriminator that we use to enhance the relationship between the inputs and outputs. We improved the loss function with the idea of Wasserstein distance [17], for the original discriminator loss so rapidly converges to zero that it can't provide instructions for the generator. We apply Wasserstein distance by using gradient penalty [4]. It successfully solves this problem and provides a better result. We also believe the Wasserstein loss can help find out the connection between long interval sequence data such as the image of tropical cyclones. The generator loss can be formulated as follows:

$$L_G = L_{image} + \lambda_1 L_{LoG} + \lambda_2 L_{Gadv}^{frame} + \lambda_3 L_{Gadv}^{seq} \tag{1}$$

where λ_1, λ_2, λ_3 are parameters. We call the first two items in the formula as reconstruction losses and the last two adversarial losses. The reconstruction losses can be formulated as follows:

$$L_{image} = \frac{1}{6} \sum_{(p,q)\in S_{m,n}^{pair}} l_1(p,q) \tag{2}$$

$$L_{LoG} = \frac{1}{6} \sum_{(p,q)\in S_{m,n}^{pair}} l_1(LoG(p), LoG(q)) \tag{3}$$

where

$$S_{m,n}^{pair} = \left\{ \begin{matrix} (x_m, x'_m), (x_m, x''_m), (x'_m, x''_m), \\ (x_{n+1}, x'_{n+1}), (x_{n+1}, x''_{n+1}), (x'_{n+1} x''_{n+1}) \end{matrix} \right\} \tag{4}$$

where x_m is the first picture in a sample, x_{n+1} is the last picture in a sample, x' and x'' respectively represent the two generated results in a loop. The adversarial losses can be formulated as follows:

$$L_{Gadv}^{frame} = \frac{1}{4} \sum_{\widetilde{x} \in P_{m,n}} E\left[D_{frame}\left(\widetilde{x}\right)\right] \tag{5}$$

$$L_{Gadv}^{seq} = \frac{1}{4} \sum_{\widetilde{X} \in M_{m,n}} E\left[D_{seq}\left(\widetilde{X}\right)\right] \tag{6}$$

where

$$P_{m,n} = \left\{x_m^{'}, x_m^{''}, x_{n+1}^{'}, x_{n+1}^{''}\right\} \tag{7}$$

$$M_{m,n} = \left\{ \begin{matrix} \left(x_m, \cdots, x_{n+1}^{'}\right), \left(x_m, \cdots, x_{n+1}^{''}\right), \\ \left(x_m^{'}, \cdots, x_{n+1}\right), \left(x_m^{'}, \cdots, x_{n+1}\right) \end{matrix} \right\} \tag{8}$$

Here are two kinds of discriminator losses, one is the frame loss, the other one is the sequence loss. The frame discriminator loss can be formulated as follows:

$$L_D^{frame} = \frac{1}{4} \left(\begin{matrix} \sum\limits_{\widetilde{x} \in P_{m,n}, x \in Q_{m,n}} \left(-E\left[D_{frame}(x)\right] + E\left[D_{frame}\left(\widetilde{x}\right)\right]\right) \\ -\lambda_4 \mathbb{E}\left[\left(\|\nabla_{\widetilde{x} \in P_{m,n}} D_{frame}\left(\widetilde{x}\right)\|_2 - 1\right)^2\right] \end{matrix} \right) \tag{9}$$

where $P_{m,n}$ is same with $P_{m,n}$ in L_{Gadv}^{frame}, λ_4 is a parameter, $Q_{m,n} = \{x_m, x_{n+1}\}$, $\mathbb{E}\left[\left(\|\nabla_{\widetilde{x} \in P_{m,n}} D_{frame}\left(\widetilde{x}\right)\|_2 - 1\right)^2\right]$ is the gradient penalty, which is used to ensure the Lipschitz continuity. The sequence discriminator loss can be formulated as follows:

$$L_D^{seq} = \frac{1}{4} \left(\begin{matrix} \sum\limits_{\widetilde{x} \in M_{m,n}, x \in N_{m,n}} \left(-E\left[D_{seq}(x)\right] + E\left[D_{seq}\left(\widetilde{x}\right)\right]\right) \\ -\lambda_5 \mathbb{E}\left[\left(\|\nabla_{\widetilde{x} \in P_{m,n}} D_{seq}\left(\widetilde{x}\right)\|_2 - 1\right)^2\right] \end{matrix} \right) \tag{10}$$

where $M_{m,n}$ is same with $M_{m,n}$ in L_{Gadv}^{seq}, λ_5 is a parameter, $N_{m,n} = (x_m, \cdots, x_{n+1})$, $\mathbb{E}\left[\left(\|\nabla_{\widetilde{x} \in P_{m,n}} D_{seq}\left(\widetilde{x}\right)\|_2 - 1\right)^2\right]$ is also the gradient penalty.

B. Estimation module

This module consists of two networks, one is the TIENet, the other is the TCLNet. We propose a novel network termed as TIENet to determine the intensity, whose output is a predicted Beaufort scale when input is the predicted image out from the WCycleGAN. Unlike other methods predicting the specific wind speed of the tropical cyclone, this trick can reduce the calculation amount while evaluating the effect well. We stress the importance of the detailed structure of tropical cyclones, so we choose 5 convolutional layers with convolution kernels doubling and a stride of 1. This network has far fewer parameters than the ResNet50 but provides similar performance. We choose the cross-entropy among the predicted Beaufort scales and the real intensity labels as its loss function. The structure of TIENet is illustrated in Fig 2.

The TCLNet comes from Tan C.'s work [18] Its output is a heatmap when input is the predicted image out from the WCycleGAN. It uses an improved MSE loss to describe the difference between the generated heatmap and the real heatmap and is trained to narrow this difference. The coordinate which has the highest pixel value of the generated heatmap represents the location of the tropical cyclone center.

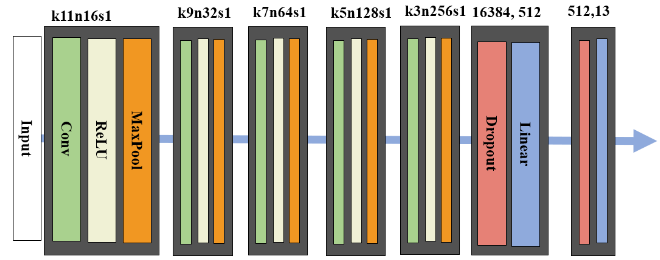

Fig. 2. The structure of TIENet. It has 5 convolution layers and 2 liner layers.

IV. EXPERIMENTS AND RESULT

A. Datasets

1) Tropical cyclone infrared time series dataset: This dataset comes from the infrared window channel in the US grid satellite dataset (GridSat) [19]. We intercept a tropical cyclone at a certain time t according to BST dataset [20] with a resolution of 256 x 256 pixels (20 latitudes multiply 20 longitudes) and 6h, whose center is ensured to locate in the center of the picture. Afterward, keep the position of this window in the GridSat global image unchanged, and intercept the images at time $t-24$, $t-18$, $t-12$, $t-6$, t, $t+6$, $t+12$, $t+18$, $t+24$ under this window in turn. All these images compose a sequence consisting of 9 pictures, and one example is shown in Fig 3. Next, we extract 5 continuous images from each tropical cyclone sequence as training samples, and each sequence provides 5 training samples.

2) Estimation dataset: This dataset uses the results obtained by the WCycleGAN as the input image. The 6h prediction results are the direct outputs of the network while the 24h prediction results are the 4-step outputs. We get the coordinate(u,v) of the tropical cyclone center in the image according to the BST dataset, and the intensity label comes from the maximum wind speed near the tropical cyclone center extracted from the BST dataset, which is divided into 13 categories according to Beaufort scale, corresponding to 7-17+ levels. The heatmap can be produced as the formula:

$$H(x,y) = \exp\left(\frac{(x-u)^2 + (y-v)^2}{-2\sigma^2}\right) \tag{11}$$

where $H(x,y)$ means the pixel value at (x,y) in the heatmap, σ is a parameter, which takes 15 here. An example of a set of images in location and intensity determination dataset is shown in Fig 4.

B. Training Details

To train our networks, we use 4,930 training samples from 986 tropical cyclone sequences. In WCycleGAN, we set $\lambda_1 = 0.005$, $\lambda_2 = \lambda_3 = 0.003$, $\lambda_4 = \lambda_5 = 10$ according to Kwon et al.'s work [3] and Gulrajani et al.'s work [4]. We use adam optimizers [21] with $\beta_1 = 0.5, \beta_2 = 0.999$ and the learning rate is set as follows: for WCycleGAN, first, we use the learning rate of 0.0001 to train for 20 epochs, then reduce it to 0.00005 for 30 epochs, finally to 0.00001 for 40 epochs; for TCLNet, after 4 epochs of training with a learning rate of 0.001, it is reduced to 0.00005 for 1 epoch; for TIENet, we train 10

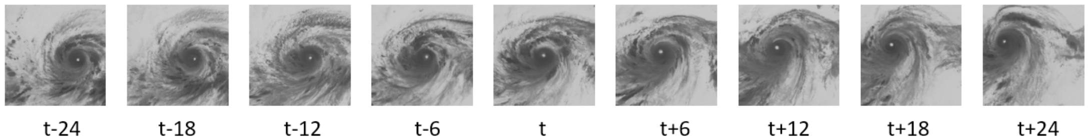

Fig. 3. An example of the sequence in the tropical cyclone infrared time series dataset.

Fig. 4. An example of a set of images in location and intensity determination dataset.

epochs with a learning rate of 0.1, then reduce it to 0.01 for 20 epochs, finally to 0.001 for 30 epochs.

C. Metrics

We use PSNR, SSIM, and MSE (we multiplied the original MSE by a factor of 100 to show the difference) to measure the quality of the result of WCycleGAN. We use path forecast error(L_D) to measure the quality of the result of TLCNet. Here is its calculating formula:

$$L_D = P_D \div 256 \times 20 \times 1.852 \times 60 \times 0.866 \tag{12}$$

the P_D in L_D is the pixel distance between the ground truth and predicted position. We calculate 0.866 based on there are 0.866 nautical miles for each change in latitude and longitude in the mid-latitude area. We use intensity forecast error(S_E) of intensity forecast to measure the quality of the result of TIENet. Here is its calculating formula:

$$S_E = \frac{1}{N} \times |WS^p - WS^{gt}| \tag{13}$$

the WS here means wind speed. We use the middle wind speed of each Beaufort scale as the predicted wind speed.

D. Results

1) Overall result: We test our method on 10 tropical cyclones in the western Pacific. Our forecast method has an average path forecast error of 116km and an intensity forecast error of 13.06kt under the forecast time limit of 24 hours. In terms of path prediction, we set expected errors of 60km and 110km for 6h and 24h path forecast. Accordingly, the eligibility rates are 60% and 40%, which need to be further improved. As to intensity prediction, we consider the predicted tropical cyclones scale matching the ground-truth as a successful forecast. Based on this, the accuracy rates of 6h and 24h intensity forecasts are 36% and 40%. The intensity forecast results ignore the changes during a short time interval. This may be solved by using a more efficient intensity estimate model. More details are shown in Table I.

TABLE I

Overall result. 50 6h-test samples. 10 24h-test samples. PSNR, SSIM are the larger the better, while MSE, L_D and S_E are the smaller the better.

Metrics	6h	24h
Average PSNR	22.46	19.77
Average SSIM	0.65	0.64
Average MSE	5.89	11.10
Average L_D	61 km	116 km
Max L_D	122 km	192 km
Average S_E	14.20 kt	13.06 kt
Max S_E	38.49 kt	38.49 kt

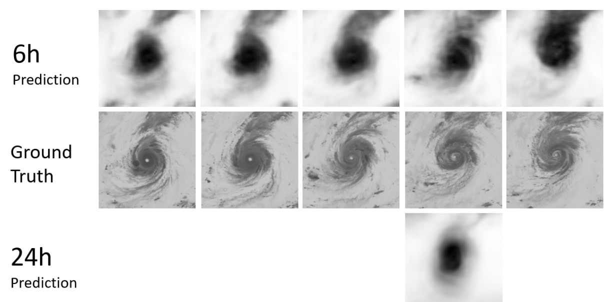

Fig. 5. The output of WCycleGAN of Typhoon Trami.

2) Sample result: Here are the forecast results of Typhoon Trami, the No. 24 in 2018. The output of WCycleGAN is shown in Fig 5, the result of TCLNet is shown in Fig 6, the 6h forecast result of the TIENet is shown in Table II and the 24h forecast result of the TIENet only exists at 2018.09.26 00:00, when Beaufort scale is 14 and tropical cyclone scale is STY. It can be seen from the above chart that concerning path forecasting, whether it is a 6h forecast or a 24h forecast, it can have a good forecast effect; concerning intensity forecast, the accuracy rate needs to be further improved, but for tropical cyclone level judgment is basically accurate.

3) Horizontal comparison: We also comprise our work with other methods, the result is shown in Table III. It can be seen that the path prediction results of this method have the

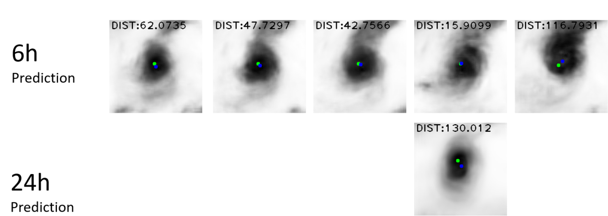

Fig. 6. The output of TCLNet of Typhoon Trami.

TABLE II
THE 6H FORECAST RESULTS FROM THE OUTPUT OF THE TIENET OF TYPHOON TRAMI IN 2018.

Time	6h forecast intensity	True forecast intensity
09.25 06:00	Beaufort scale: 14 Tropical cyclone scale: STY	Beaufort scale: 17 tropical cyclone scale: SuperTY
09.25 12:00	Beaufort scale: 14 Tropical cyclone scale: STY	Beaufort scale: 17 Tropical cyclone scale: SuperTY
09.25 18:00	Beaufort scale: 14 Tropical cyclone scale: STY	Beaufort scale: 16 Tropical cyclone scale: SuperTY
09.26 00:00	Beaufort scale: 14 Tropical cyclone scale: STY	Beaufort scale: 15 Tropical cyclone scale: STY
09.26 06:00	Beaufort scale: 14 Tropical cyclone scale: STY	Beaufort scale: 15 Tropical cyclone scale: STY

TABLE III
HORIZONTAL COMPARISON. THE LAST TWO METHODS ARE THE NUMERICAL MODELS, THE OTHERS ARE MACHINE LEARNING MODELS. THE L_D IS A PATH FORECAST INDEX, WHICH IS THE SMALLER THE BETTER. THE S_E IS AN INTENSITY FORECAST INDEX, WHICH IS THE LARGER THE BETTER.

Methods	6h Average L_D	24h Average L_D	6h Average S_E	24h Average S_E
OURS	**61 km**	116 km	14.20 kt	13.06 kt
RNN [8]	72 km	-	-	-
ConvLSTM [11]	141 km	-	-	-
CNN-LSTM [12]	-	-	-	**7.4 kt**
GAN [5]	67.2 km	-	-	-
ECMWF-IFS	-	**62 km**	-	14.3 kt
NCEP-GFS	-	-	-	12.9 kt

smallest average path forecast error among the neural network methods listed in the table, but it is near twice the error of the best numerical method. Besides, the intensity forecast level is close to the numerical method; the gap between CNN-LSTM and ours may lie in: we choose to give a range of the predicted wind speed while they give the specific numerical value.

E. Ablation study

We also study the impact of Wasserstein loss and LoG loss on the forecast, the results are shown in Table IV. It can be seen that Wasserstein loss and LoG loss significantly improve the quality of predicted spatial data, significantly reduce the error of the path forecast results, and remarkably improve the accuracy of the intensity forecast results.

TABLE IV
ABLATION STUDY. PSNR, SSIM ARE THE LARGER THE BETTER, WHILE MSE, L_D, S_E ARE THE SMALLER THE BETTER.

Metrics	OURS		Without Wasserstein loss		Without LoG loss		Without both	
	6h	24h	6h	24h	6h	24h	6h	24h
Average PSNR	**22.46**	**19.77**	22.39	18.99	22.41	18.53	22.20	17.95
Average SSIM	**0.65**	**0.64**	0.64	0.63	0.64	0.62	0.64	0.62
Average MSE	**5.89**	**11.10**	5.94	12.48	5.95	13.27	6.22	15.43
Average L_D	**61 km**	**116 km**	68 km	135 km	73 km	147 km	77 km	161 km
Average S_E	**14.20 kt**	**13.06 kt**	18.37 kt	18.96 kt	22.50 kt	23.71 kt	34.80 kt	38.22 kt

V. CONCLUSION

In this letter, we propose a flexible and reliable tropical cyclone forecasting framework, which can simultaneously forecast the path and intensity of tropical cyclones through a set of data. This method can handle multiple tasks at the same time with good scalability. Furthermore, the WCycleGAN is a more effective new model that handles unpaired images, and the TIENet is a specialized model for predicted tropical cyclone image interpretation. In the situation of lacking computing resources or professional meteorological knowledge, it is of great significance.

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