On the Improvement of the DSAEF_LTP Model to Heavy Precipitation Simulation of Landfalling Tropical Cyclones over China in 2018

CHEN Yu-xu (陈毓旭) 1,2, JIA Li (贾 莉) 1, JIA Zuo (贾 作) 1, DING Chen-chen (丁晨晨) 1, REN Fu-min (任福民) 1, LI Guo-ping (李国平) 1

1. College of Atmospheric Sciences, Chengdu University of Information Technology, Chengdu 610225 China; 2. State Key Laboratory of Severe Weather, Chinese Academy of Meteorological Sciences, Beijing 100081 China

Abstract: In this study, the Dynamical-Statistical-Analog Ensemble Forecast model (DSAEF_LTP model) for landfalling tropical cyclone (LTC) precipitation was employed to simulate the precipitation of 10 LTCs that occurred over China in 2018. With similarity region scheme (SRS) parameter values added and TC intensity introduced to the generalized initial value (GIV), four groups of precipitation simulation experiments were designed to verify the forecasting ability of the improved model for more TC samples. Results show that the simulation ability of the DSAEF_LTP model can be optimized regardless of whether adding SRS values only, or introducing TC intensity into GIV, while the experiment with both the two improvements shows a more prominent advantage in simulating the heavier precipitation of LTCs. Compared with four NWP models (i.e., ECMWF, GFS, GRAPES and SMS-WARMS), the overall forecasting performance of the DSAEF_LTP model achieves a better result in simulating precipitation at the thresholds over 250 mm and performs slightly better than NWP models at the thresholds over 100 mm.

Key words: landfalling tropical cyclone; heavy precipitation; simulation; the DSAEF_LTP model; similarity region scheme

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1 INTRODUCTION

Worldwide, China is one of the countries most seriously affected by tropical cyclones (TCs), and, in particular, regularly experiences a relatively high frequency of landfalling TCs (LTCs) (Li et al. [1]; Chen and Meng [2]). As the major manifestation of typhoon disasters, typhoon rainstorms tend to be concentrated in the period around landfall (Cheng et al. [3]), which often poses a serious threat to people’s lives and property in the coastal cities of China (Wang and Ying [4]; Huo et al. [5]; Jiang and Zipser [6]).

Currently, the capability of numerical weather prediction (NWP) models to provide accurate quantitative rainfall forecasts is still quite limited (Mohanty et al. [7]; Zhong et al. [8]; Zhang et al. [9]). Related studies have focused on improving the prediction accuracy of LTC-related precipitation, a major part of which is promoting the present prediction level in NWP models. There are two approaches generally applied to achieve this goal: (1) improving the NWP model, which is the most common method (Bauer [10]; and (2) making use of a dynamical-statistical method, which is perhaps the more efficient way to solve the problem. For the second approach, there are presently three schools of thought with respect to dynamical-statistical model development for TC rainfall forecasts (Ren and Xiang [11]), where different statistical parameters have been applied. The first makes TC precipitation predictions from the perspective of the climate mean by combining TC track forecasts from dynamical models with historical rainfall observations (Marks et al. [12]; Lee et al. [13]; Lonfat et al. [14]). The second predicts TC precipitation by applying TC track forecasts and the rainfall integrated from initial rainfall rates (Kidder et al. [15]; Liu [16]; Ebert et al. [17]). And the third makes TC precipitation predictions by constructing a dynamical-statistical scheme that consists of various internal TC variables and their environmental fields (Zhong et al. [18]; Li and Zhao [19]).

To further improve the dynamical-statistical method in predicting TC rainfall, Ren et al. [20] developed an objective TC track similarity area index (TSAI) to screen similar historical TCs for precipitation forecasting. Subsequently, Ren et al. [21] proposed the Dynamical-Statistical-Analog Ensemble Forecast Model for Landfalling Tropical Cyclone Precipitation (DSAEF_LTP). In this model, the precipitation forecast of the target TC is obtained by assembling the observed precipitation of similar historical TCs, which are selected by identifying GIV (generalized initial value).
analogs. In the primary stage, there were only two similarity variables (i.e., TC track and landfall season) in the GIV.

Recently, further research has been conducted on developing the DSAEF_LTP model. Ding et al.\cite{26} introduced TC intensity into the GIV and applied the improved DSAEF_LTP model in forecasting the accumulated precipitation for 21 target TCs in South China. Meanwhile, new ‘similarity region scheme’ (SRS) (Jia et al.\cite{16}) were added to the precipitation prediction experiment associated with super typhoon Lekima (2019) and results showed that the simulation capability of the model could be optimized by improving the parameterization scheme. Considering that the SRS improvement was only applied in individual typhoon sample, experiments with more TC samples need to be conducted to further verify the adaptability of model improvements, which is the main purpose of this study.

In this study, 10 TCs that made landfall in China in 2018 are selected as samples for precipitation simulation experiments. Section 2 introduces the data and methods used in this study. Section 3 describes the experiment design. Section 4 presents the results of the simulation experiments. The summary and discussion are provided in Section 5.

2 DATA AND METHODS

2.1 Data

Historical observed daily precipitation data at 24-h intervals, starting at 12:00 UTC each day over the period 1960–2018, were obtained from the China Meteorological Administration (CMA). The data include 2027 rain gauge stations over most of China, with 2006 over the Chinese mainland and 21 over Taiwan Island, whose distribution is displayed in Fig. 1.

![Figure 1. Distribution of 2027 rain gauge stations in China.](Image)

Historical data (track, time and wind) at 6-h intervals for TCs were obtained from the best-track dataset of the CMA’s TC database (http://tddata.typhoon.org.cn/zjilijili_zlhq.html) covering the period 1960–2018 (Ying et al.\cite{23}). These data were used to identify the analog tracks.

The predicted information (track, time and wind) of the target TCs was obtained from real-time operational forecasting data issued by the CMA’s National Meteorological Center (NMC).

In order to evaluate the performance of the DSAEF_LTP model, the gridded precipitation forecast data of NWP models are interpolated to station for the purpose of comparison with the simulation from DSAEF LTP. The gridded precipitation forecast data of four NWP models used in this paper were obtained from (1) the European Centre for Medium-Range Weather Forecasts (ECMWF), (2) the Global Forecast System (GFS) of the US National Centers for Environmental Prediction, (3) the Global / Regional Assimilation and Prediction Enhanced System (GRAPES) (http://www.cma.gov.cn/en2014/research/features/201409/t20140918_261659.html) of the CMA, and (4) the Shanghai Meteorological Service WRF ADAS Real-Time Modeling System (SMS-WARMS) (Wang et al.\cite{22}). The corresponding rainfall forecast data of these models were obtained with horizontal resolutions of 0.1°×0.1°.

2.2 Brief overview of the 10 LTCs in 2018

The identifications (IDs), names, maximum total rainfall amounts, station name that maximum rainfall occurs and numbers of stations with accumulated precipitation exceeding 250 mm and 100 mm associated with the 10 LTCs selected for the precipitation simulation experiments are listed in Table 1. All these 10 LTCs produced more than 100 mm of single-station accumulated maximum precipitation, and eight of them produced over 250 mm—namely, TC1804, TC1808, TC1809, TC1814, TC1816, TC1818, TC1822, and TC1823 (each TC is represented by its ID number, e.g., TC1804 indicates the 4th TC that occurred in 2018). Fig. 2 demonstrates the best observed tracks and ID numbers of the 10 LTCs, the landfalls of which occurred intensively over either South China or East China and none of them over Taiwan Island or across the Taiwan Strait. Therefore, the 10 LTCs could be roughly sorted into two types: LTCs that occurred over South China (STCs), including TC1804, TC1809, TC1816, TC1822, and TC1823; and LTCs that moved northward or inland after landfall over East China (NTCs), including TC1808, TC1810, TC1812, TC1814, and TC1818.

2.3 Methods

2.3.1 OBJECTIVE SYNOPTIC ANALYSIS TECHNIQUE

The Objective Synoptic Analysis Technique (OSAT) (Ren et al.\cite{16-17}; Wang et al.\cite{22}) is used for partitioning TC precipitation in order to identify the precipitation associated with TCs over China.

2.3.2 OBJECTIVE TC TRACK SIMILARITY AREA INDEX

The objective TC track similarity area index (TSAI) represents an area of the enclosed scope surrounded by two TC tracks and two line segments connecting the initiating and ending points of the two tracks. The smaller the area value, the higher the similarity of the two TC tracks, where a value of 0 indicates that the two
The third step was to identify analogs between target TC and construct the generalized initial value (GIV); which is an important parameter for TSAI. In addition, similarity grades of TC intensity are applied to evaluate the performance of the prediction of precipitation. The TS, calculated with the formula TS = hits / (hits + misses + false alarms) and ranging from 0 to 1, demonstrates the fraction of correctly predicted forecast events. The Bias, calculated with the formula Bias = (hits + false alarms) / (hits + misses), is used to evaluate whether the forecast model has a tendency to underforecast (Bias < 1) or overforecast (Bias > 1) events.

In addition, the precipitation thresholds in excess of 100 mm and 250 mm are frequently used to measure the prediction effect in operational rainfall forecasts. In view of the superiority of the DSAEF_LTP model in forecasting extreme rainfall events, TS100 (Bias100) and TS250 (Bias250), which are the TS (Bias) at two thresholds over 100 mm and 250 mm, were chosen to be applied in this study. TS\textsubscript{sum} = TS250 + TS100 and Bias\textsubscript{sum} = ± (|Bias100 - 1| + |Bias250 - 1|), whose symbol depends on whether (Bias100 + Bias250 - 2) is positive or negative. The best forecast scheme of each experiment should have the largest value of TS\textsubscript{sum}, and a smaller absolute value of Bias\textsubscript{sum} also indicates a better forecast performance.

3 EXPERIMENT DESIGN

3.1 Introduction of TC intensity

In this study, TC intensity—a significant variable related to TC precipitation—is introduced into the GIV. Its introduction can be summarized by the following two steps: (1) determination of the category of TC intensity to compare the similarity of TC intensity; (2) division of similarity grades of TC intensity.

| TC Number | Name      | Maximum total rainfall (mm) | Name of Station which observed the maximum total rainfall | Numbers of stations with accumulated precipitation exceeding 250 mm and 100 mm |
|-----------|-----------|-----------------------------|----------------------------------------------------------|--------------------------------------------------|
| 1804      | EWINIAR   | 469.5                       | Zhengshan in Guangdong                                    | 39 and 141                                      |
| 1808      | MARIA     | 306.7                       | Bamboo Lake in Taiwan                                     | 1 and 16                                        |
| 1809      | SON-TINH  | 424.5                       | Wanning of Hainan                                         | 10 and 25                                       |
| 1810      | AMPIL     | 224.8                       | Baodi in Tianjin                                          | 0 and 53                                        |
| 1812      | JONGDARI  | 182.7                       | Jiaxing in Zhejiang                                       | 0 and 10                                        |
| 1814      | YAGI      | 295.7                       | Suizhong of Liaoning                                      | 2 and 69                                        |
| 1816      | BEBINCA   | 631.6                       | Lin’gao in Hainan                                         | 23 and 82                                       |
| 1818      | RUMBIA    | 301.9                       | Lingbi in Anhui                                           | 30 and 203                                      |
| 1822      | MANGKHUT  | 393.1                       | Yangjiang in Guangdong                                    | 4 and 51                                        |
| 1823      | BARIJAT   | 610.5                       | Bamboo Lake in Taiwan                                     | 4 and 12                                        |

Figure 2. Best tracks of the 10 LTCs, as indicated by their ID numbers, that occurred in 2018 over China.
Thereinto, wind speed (the 2-min average maximum wind speed at 10 m height near the center of the tropical cyclone) is used to represent the intensity of tropical cyclone. And there are four categories of TC intensity determined (i.e., the maximum intensity on the first day that TC produces rain over land and so on) and five levels used to divide the differences in intensity between the target tropical cyclone and the historical tropical cyclone. More details such as the principle of defining the grades could be found in Ding et al. [4].

3.2 Improvement of SRS

SRS is a rectangle with the diagonal points A and B, which is used for calculating the TSAI. A is the TC locations at 0, 12, 24, 36 or 48 hours prior to the initial time, and B is the TC locations at 0, 12 or 24 hours prior to the maximum lead time (i.e., at which the predicted TC track ends), and totally, there are 15 experimented values for SRS according to the combination of A and B.

Recently, Jia et al. [6] added five SRS values to the primary model, which were applied in this paper. Given the maximum diameter of TCs, which is approximately 2000 km, a square with a side length of 2000 km is considered as the maximum similarity region. The schematic diagram in Fig. 3 shows ABCD; the first kind of parameter value of the original similarity region; and A1B1C1D1, a square with a side length of 2000 km, is the 16th scheme of the similarity region. In order to construct a similar medium-sized region, the midpoint of B and B1 is taken as B2 and the midpoint of D and D1 is taken as D2 which makes A2B2C2D2 the 17th scheme. The 18th to 20th approaches are made by shifting A1B1C1D1 (the 16th scheme) to the right by the distance of D1D2, down by the distance of B1B2, and to the right by the distance of D1D2 along with down by the distance of B1B2 (i.e., A3B3C3D3, A4B4C4D4 and A5B5C5D5 correspond to 18th to 20th schemes).

3.3 Four simulation experiments

![Figure 3. Schematic diagram of newly added similarity regions. C represents the TC locations at the initial time; A represents the TC locations at the maximum lead time (i.e., the time at which the predicted TC track ends); ABCD is the first kind of parameter value of the primary similarity region (i.e., the black rectangle). Colored rectangles denote the newly added similarity regions: A1B1C1D1 is a square with a side length of 2000 km; B2 is the midpoint of band B1; D2 is the midpoint of D and D1. A2B2C2D2 is a medium-sized rectangle; shifting A1B1C1D1 to the right by the distance of D1D2, down by the distance of B1B2, and to the right by the distance of D1D2 and down by the distance of B1B2, produces A3B3C3D3, A4B4C4D4 and A5B5C5D5, respectively.](image)

The DSAEF_LTP model contains eight characteristic parameters, whose physical significance and values are shown in Table 2. While each parameter determines the value, the combination of the values of each parameter is referred to as a forecast scheme, which can provide a precipitation forecast result. Therefore, the forecast scheme owing the maximum TS_max in each experiment would be regarded as the best scheme of that experiment. What’s more, usually, the values of parameters of best scheme from different experiment are not the same. In this study, four simulation experiments were performed to explore promotion of the capacity of the DSAEF_LTP model in forecasting TC precipitation. In experiment 1, GIV only includes two factors—TC track and landfall season as in Jia et al. [7]. In experiment 2 and 3, intensity similarity and five additional SRS values were considered, respectively, on the basis of experiment 1. In experiment 4, all the parameters in
Table 2 were applied, including the track, seasonal similarity, intensity similarity and five additional SRS values.

Table 2. Parameters of the DSAEF_LTP model.

| Parameter | Description | Experimeted Values |
|-----------|-------------|---------------------|
| P1 Initial time | Complete track of the target TC, consisting of the observed track before the initial time and the forecast track after the initial time. | 1: 12 UTC on Day 1 | 2: 00 UTC on Day 1 |
| | | 3: 12 UTC on Day 2 | 4: 00 UTC on Day 2 |
| | | 5: 12 UTC on Day 3 | 6: 00 UTC on Day 3 |
| (Day 2: the day of TC precipitation occurring on land; Day 1: the day before Day 2; Day 3: the day after Day 2) |
| P2 Similarity region | A designated region within which the TSAI is calculated. It is a rectangle with the diagonal points A and B. A represents the TC locations at 0, 12, 24, 36 or 48 h prior to the initial time, and B the TC locations at 0, 12 or 24 h prior to the maximum lead time (i.e., at which time the predicted TC track ends). | |
| P3 Threshold of the segmentation ratio of a latitudinal extreme point |A parameter of TSAI that represents the bending degree of TC tracks. | 1: 0.1 |
| | 2: 0.2 |
| | 3: 0.3 |
| P4 Overlapping percentage threshold of two TC tracks | A parameter of TSAI that represents the degree of longitudinal or latitudinal overlap of TC tracks. | 1: 0.4 |
| | 2: 0.5 |
| | 3: 0.6 |
| | 4: 0.4 |
| | 5: 0.5 |
| | 6: 0.6 |
| P5 Seasonal similarity | Parameter indicating the TC landfall time. | 1: Whole year |
| | 2: May-Nov |
| | 3: Jul-Sept |
| | 4: Same landfall month as the target TC |
| | 5: Within 15 days of the target TC landfall time |
| P6 Intensity similarity | Parameter indicating the differences between the TC intensity of the target TC and historical TCs. There are four categories of TC intensity that can be chosen. The similarity of TC intensity is divided into five levels. | Four categories: |
| | 1: Average intensity on the first rainy day |
| | 2: Maximum intensity on the first rainy day |
| | 3: Average intensity on all rainy days |
| | 4: Maximum intensity on all rainy days |
| | 5: All grades |
| | 2: Target TC intensity is the same grade or above the historical TCs |
| | 3: Same grade or below |
| | 4: Only the same grade |
| | 5: Same grade or one grade difference |
| P7 Number (N) of analog TCs screened for the ensemble forecast | N historical TCs with the first N most similar GIVs to that of the target TC. | 1-10 for 1, 2... and 10, respectively |
| P8 Ensemble forecast scheme | Ensemble forecast method | 1: Mean |
| | 2: Maximum |

4 RESULTS

4.1 Comparison of results from the four experiments

The parameter values of the best scheme from each experiment are listed in Table 3. The optimal scheme of each experiment was determined by the maximum of TS\textsubscript{sum}. It should be noted that some TCs could not be fully valued on all the parameters of the DSAEF_LTP model, such as the initial time or the limits of similarity region; therefore, the number of common schemes suitable for all 10 TCs should be equal to or less than the number under ideal conditions, whose value is equal to the product of all the parameters. Actually, there are only 1,125,473 schemes, 25,587,438 schemes, 1,473,051 schemes and 33,071,606 schemes available for experiment 1, experiment 2, experiment 3
and experiment 4, respectively. Scatterplots of the TSs (i.e., TS100 vs TS250) associated with all 10 LTCs from the four experiments are displayed in Figs. 4a to 4d, respectively, where each scatter point represents a common scheme and the red dot stands for the best scheme of a single simulation experiment.

Table 3. Optimized values for the best scheme among the heavy rainfall ensemble simulation experiments.

| Parameters (P1–8)                          | Experiment 1 | Experiment 2 | Experiment 3 | Experiment 4 |
|-------------------------------------------|--------------|--------------|--------------|--------------|
| Initial time (P1)                         | 1            | 2            | 1            | 1            |
| Similarity region (P2)                    | 14           | 20           | 14           | 20           |
| Threshold of the segmentation ratio of a latitudinal extreme point (P3) | 1            | 2            | 1            | 1            |
| Overlapping percentage threshold of two TC tracks (P4) | 5            | 3            | 5            | 6            |
| Seasonal similarity (P5)                  | 3            | 3            | 3            | 3            |
| Intensity similarity (P6)                 | 3/5          | 2/5          |              |              |
| Number of analog TCs screened for the ensemble forecast (P7) | 3            | 5            | 3            | 3            |
| Ensemble forecast scheme (P8)             | 1            | 2            | 1            | 2            |
| Available number of schemes               | 162000       | 216000       | 3240000      | 4320000      |

Figure 4. Scatterplots of the TSs (TS100 vs TS250) from 129,564 forecast schemes in Experiment 1 (Fig. 4a); 2,407,380 forecast schemes in Experiment 2 (Fig. 4b); 2,407,380 forecast schemes in Experiment 3 (Fig. 4c); 2,407,380 forecast schemes in Experiment 2 (Fig. 4d). TS250 and TS100 represent the TSs for predicting accumulated rainfall amounts in excess of 250 mm and 100 mm, respectively, associated with 10 LTCs. The red dot indicates the best forecast schemes with the highest values of TS_{sum} (TS_{sum} = TS250 + TS100).
In order to gain a more intuitive understanding of the forecasting performance, Fig. 5 presents a histogram of the TS (containing TS$_{sum}$, TS100 and TS250) for the optimal schemes of the four experiments associated with the 10 LTCs. As mentioned above, the best scheme was determined by the maximum TS$_{sum}$ for each experiment. It can be seen from Fig. 5 that the TS$_{sum}$ is 0.1933 in Experiment 1 (which is the same result as examined in Jia et al. [7]), 0.3481 in Experiment 2, 0.3333 in Experiment 3, and 0.3927 in Experiment 4. To corroborate whether or not the forecasting performance of the DSAEF_LTP model with intensity similarity introduced was promoted, we can compare between Experiments 1 and 3 and Experiments 2 and 4. The TS, not only at thresholds above 250 mm but also in evaluating the overall precipitation simulation performance of all 10 LTCs, is increased to some extent, which indicates amelioration of the performance of the best scheme in the DSAEF_LTP model along with the introduction of TC intensity. While attention is only paid to the effect of precipitation simulation following the improvement of similarity regions, it is evident that overall simulation performance and the capability of simulating heavy rainfall centers are likewise promoted by comparing the TS$_{sum}$ and TS250 from Experiments 1 and 2 and Experiments 3 and 4, respectively. As a whole, in comparison to the simulation of precipitation exceeding 100 mm, the simulating performance of the overall precipitation region and heavy rainfall center is certainly improved after the introduction of intensity similarity and an increase in the similarity region, which proves that the model performance can be promoted in line with the introduction of new variables that influence TC precipitation and parameter optimization.

Judging from the simulation performance of these four experiments, Experiment 4 showed excellent performance, which was mainly reflected in the top ranking of its TSs while simulating accumulated precipitation exceeding the thresholds of 250 mm and 100 mm for the 10 LTCs. Therefore, the precipitation simulation conducted by the best scheme of experiment 4—the experiment that involved the introduction of intensity similarity and an increase in the similarity region—was used for comparative analysis of the DSAEF_LTP model with the four operational dynamical models.

4.2 Comparison of the simulation results of the DSAEF_LTP model with four operational dynamical models

To evaluate the simulation effect of the best scheme of the DSAEF_LTP model in real prediction scenarios, Fig. 6 compares its three TSs (i.e., TS$_{sum}$=0.3927, TS250 = 0.1865, TS100 = 0.2062) associated with the 10 LTCs to those produced by the four dynamical models mentioned above. As shown in Fig. 6, the TS$_{sum}$, TS250 and TS100 values obtained from ECMWF, GFS, GRAPES and SMS-WARMS are 0.1821, 0.2315, 0.1311 and 0.2012; 0.0095, 0.0375, 0.0110 and 0.0052; and 0.1726, 0.1940, 0.1201 and 0.1960, respectively. It can be clearly seen that the TS250 produced by the DSAEF_LTP model ranks first (0.1865), which significantly exceeds the equivalent values from the four dynamical models (0.0095, 0.0375, 0.0110 and 0.0052); while the TS100 produced by the DSAEF_LTP model is slightly superior to SMS-WARMS, GFS and ECMWF, but far better than that of GRAPES. Generally, the overall simulation performance of the DSAEF_LTP model at the two thresholds (i.e. TS$_{sum}$) is likewise superior to those of the four dynamical models, which is mainly manifested by the simulation strengths of DSAEF_LTP along with the increase in TC precipitation intensity.
No. 3 CHEN Yu-xu (陈禹旭), JIA Li (贾莉), et al. 239

Figure 6. The TSs (TSsum, TS250 and TS100) from the best scheme of the DSAEF_LTP model compared with those from the four dynamical models (i.e., ECMWF, GFS, GRAPES and SMS-WARMS) associated with the 10 LTCs that occurred over China in 2018.

Figure 7 presents the TSs (TSsum, TS250 and TS100) associated with individual LTCs from the best scheme of the DSAEF_LTP model compared with those from the four dynamical models, together with their single-station accumulated maximum total rainfall. Fig. 7a shows the TSs at above the thresholds of 250 mm of only eight LTCs with the single-station accumulated maximum precipitation over 250 mm. It can be seen from Fig. 7a that none of the forecast models is able to give a better than null TS for NTC1814 and NTC 1818–two LTCs that produced single-station accumulated precipitation slightly beyond 250 mm—which suggests that forecast models are still faced with a challenge when predicting a more accurate precipitation distribution for accumulated rainfall slightly beyond the high rainfall threshold. Meanwhile, when simulating precipitation over 250 mm, only the DSAEF_LTP model produces a higher than null TS for NTC1808, STC1809, STC1822 and STC1823, giving the best assessment for STC1804 and the second best assessment for STC1816; whereas, ECMWF and GRAPES are capable of forecasting the process of precipitation for only two LTCs (i.e., STC1804 and STC1816). Equally, SMS-WARMS compares inadequately to the DSAEF_LTP model in predicting accumulated rainfall exceeding 250 mm. As far as TC track types are concerned, the DSAEF_LTP model shows clear superiority in simulating precipitation distribution in excess of 250 mm for TCs that made landfall over South China, but performs comparatively poorly in simulating the heavy rainfall distribution of TCs that move northward after landfall over East China.

Figure 7b compares the TS at above the thresholds of 100 mm from the best scheme of the DSAEF_LTP model with those from the four dynamical models. As depicted in Fig. 7b, none of forecast models except SMS-WARMS yields a higher than null TS for accumulated rainfall over 100 mm for STC1812—the TC with the least amount of single-station accumulated maximum rainfall among the 10 LTCs. From the perspective of forecasting ability, only the DSAEF_LTP, GFS and ECMWF models are able to produce a greater than null TS100 value for the remaining LTCs. In addition, it can be seen from Fig. 7b that the TS100 value given by DSAEF_LTP for five STCs is commonly higher than that for five LTCs, which is based on the fact that even the maximum TS100 value of the LTCs (i.e., 0.2105 from NTC1808) is smaller than the minimum of the STCs (i.e., 0.2353 from STC1823).

Table 4 and Table 5 list the Bias scores of forecasting precipitation at the thresholds over 250 mm and 100 mm (i.e., BS250 and BS100) from the best scheme of the DSAEF_LTP model with those from the four dynamical models, which intuitively display the forecast deviation of each model to a certain precipitation threshold. When the value of Bias score is above 20.0 (below ~20.0), it is recorded as 999 (~999). As depicted in Table 4, the values of BS250 produced by DSAEF_LTP rank first, meaning the simulating performance by DSAEF_LTP is more consistent with the observation, for all the TCs except for STC1816. Moreover, according to the maximum total rainfall amounts and numbers of stations with accumulated precipitation exceeding 250 mm of the 10 LTCs shown in Table 1, DSAEF_LTP model inclines to oversimulate for the TCs with heavier and more widely distributed rainfall and undersimulate for the TCs opposite to those mentioned before. According to Table 5, the DSAEF_LTP model overforecasts and underforecasts half of the 10 LTCs, respectively, while simulates rainfall distribution exceeding 100 mm. Relatively, the four dynamical models especially ECMWF and GRAPES tend to underforecast the precipitation at thresholds over 100 mm of the 10 LTCs. When all the forecasting models oversimulate or undersimulate the precipitation distribution over 100 mm likewise for a single TC, the TC precipitation simulated by DSAEF_LTP is often more identical with the
Table 4. The Bias scores at the thresholds over 250 mm from the best scheme of the DSAEF_LTP model compared with those from the four dynamical models (i.e., ECMWF, GFS, GRAPES and SMS-WARMS) associated with the 10 LTCs that occurred over China in 2018.

| TC    | DSAEF_LTP | ECMWF | GFS  | GRAPES | SMS-WARMS |
|-------|-----------|-------|------|--------|-----------|
| TC1804| 0.69      | 0.69  | -999 | -999   | 0.08      |
| TC1808| 3.00      | -999  | -999 | -999   | -999      |
| TC1809| 0.50      | -999  | -999 | -999   | -999      |
| TC1810| 999       | -999  | -999 | -999   | -999      |
| TC1812| -999      | -999  | -999 | -999   | -999      |
| TC1814| 16.50     | -999  | -999 | -999   | -999      |
| TC1816| 0.87      | 0.74  | 1.04 | 0.09   | 0.087     |
| TC1818| 0.13      | -999  | -999 | -999   | -999      |
| TC1822| 2.00      | -999  | -999 | -999   | -999      |
| TC1823| 1.25      | -999  | -999 | -999   | -999      |

Figure 7. Individual TSs (vertical colored bars) for simulating the accumulated rainfall using the DSAEF_LTP model compared with those predicted by the four dynamical models (ECMWF, GFS, GRAPES and SMS-WARMS). Dashed lines represent the single-station observed maximum total rainfall (mm) associated with each TC. (a) Accumulated rainfall of ≥ 250 mm associated with eight LTCs (TC1804, TC1808, TC1809, TC1814, TC1816, TC1818, TC1822 and TC1823; the other two LTCs are not shown because their single-station accumulated maximum rainfall was less than 250 mm). (b) Accumulated rainfall of ≥ 100 mm associated with all 10 LTCs.
Table 5. The Bias scores at the thresholds over 100 mm from the best scheme of the DSAEF_LTP model compared with those from the four dynamical models (i.e., ECMWF, GFS, GRAPES and SMS-WARMS) associated with the 10 LTCs that occurred over China in 2018.

|       | DSAEF_LTP | ECMWF | GFS | GRAPES | SMS-WARMS |
|-------|-----------|-------|-----|--------|-----------|
| TC1804 | 1.30      | 0.70  | 0.60| 1.34   | -999      |
| TC1808 | 1.13      | 1.50  | 1.25| 0.31   | 2.06      |
| TC1809 | 0.51      | 0.53  | 0.64| 0.07   | 0.02      |
| TC1810 | 0.96      | 0.72  | 1.74| -999   | 0.36      |
| TC1812 | 0.10      | -999 | -999| -999   | 2.00      |
| TC1814 | 2.77      | 0.43  | 0.68| 0.06   | 1.04      |
| TC1816 | 1.21      | 1.43  | 1.49| 0.48   | 0.67      |
| TC1818 | 0.55      | 0.86  | 0.67| 0.32   | 0.79      |
| TC1822 | 0.94      | 1.57  | 1.31| 0.39   | 1.24      |
| TC1823 | 2.64      | 0.25  | 0.67| -999   | 0.09      |

observation. It could be seen from the fact that the values of BS100 for STC1804, NTC1808, NTC1810, STC1816 and STC1822 produced by DSAEF_LTP are relatively closer to 1, while compared with those from the four dynamical models. Generally speaking, the simulation errors of precipitation at the thresholds over 250 mm simulated by DSAEF_LTP tend to be fewer than those by the four dynamical models, and be comparable to those from four dynamical models at the thresholds over 100 mm.

Combining the TSs conducted by the DSAEF_LTP model with the single-station accumulated maximum rainfall of each LTC, it is noticeable that the forecasting capability of the DSAEF_LTP model in simulating rainfall distribution at the thresholds exceeding 250 mm is significantly better than that of the four dynamical models, but its advantage is still not sharply overbearing in precipitation over 100 mm when compared with the SMS-WARMS model. According to station numbers with accumulated precipitation exceeding 250 mm and 100 mm listed in Table and judging from the performance of each forecasting models on TCs with different precipitation ranges, the DSAEF_LTP model unsatisfactorily simulates the rainfall distribution over 100 mm for those TCs with significantly wild precipitation ranges (i.e., STC1804, STC1816 and NTC1818), whereas dynamic models get better results. Nevertheless, DSAEF_LTP model appears to be efficient at simulating the TC precipitation with a relatively concentrated precipitation range instead. In short, compared with the four dynamical models, the main superiority of the DSAEF_LTP model is in its simulation of TC precipitation with heavy rainfall intensity and with a relatively concentrated precipitation range, as well as TCs that made landfall in South China.

4.3 Comparison of TC cases

To provide a clearer picture of the simulation performance using the best scheme of the DSAEF_LTP model, the accumulated maximum rainfall distribution produced by the best scheme from DSAEF_LTP and the four dynamical models, along with its observations, for three selected TCs (i.e., TC1809 of superior performance; TC1810 and TC1812 of inferior performance), are respectively displayed in Figs. 8 to 10, together with their observed tracks (red lines) and forecasted tracks (blue lines) produced by the DSAEF_LTP model. According to Fig. 7b, none of the forecast models, except for SMS-WARMS, has the ability to produce a higher than null TC for TC1812. As plotted in Fig. 8, the moving track of TC1812 is not a common and typical TC track, and there are few TCs with similar tracks in the past. Thus, only one of the three analog TCs, the 10th TC in 1998, screened by DSAEF_LTP for the ensemble forecast, landed in China to create rainfall that was lower than 100 mm. As a result, the precipitation distribution simulated by DSAEF_LTP is completely identical to that of the 10th TC in 1998. This largely proves that the amount of historical TCs plays a non-negligible role in yielding a more accurate result. With an increase in the number of historical TCs, which can provide a more abundant sample base for the model, the forecasting capability could be promoted accordingly.

As shown in Fig. 7, using the best scheme from the DSAEF_LTP model to simulate the precipitation of TC1809, the $T_{sum}$ and $Bias_{sum}$ are 0.4368 and 1.0111, respectively. In contrast, the $T_{sum}$ for the four dynamical models (i.e., ECMWF, GFS, GRAPES, and SMS-WARMS) are 0.2464, 0.1375, 0.0476 and 0.0222, respectively, while their $Bias_{sum}$ values are all values of minus infinity, which stands for insufficient prediction. Fig. 9 shows the observed precipitation of TC1809 together with the simulated rainfall distribution by the DSAEF_LTP model and the predicted precipitation by the four dynamical models. For rainfall exceeding 250 mm, the DSAEF_LTP model performs the best among all the forecast models, focusing on the capability of simulating the heavy rainfall centers in...
Figure 8. Accumulated precipitation distribution (mm) for TC1812 from (a) observation and (b) DSAEF_LTP model. Panels (c) to (e) are the accumulated precipitation distribution (mm) of three ensemble members (i.e., TC199810, TC199017 and TC201118) chosen from the best scheme of TC1822. The observed track and predicted track by DSAEF_LTP of these TCs are plotted with red line and blue line, respectively.

Figure 9. Accumulated precipitation distribution (mm) for TC1809 from (a) observation, (b) the DSAEF_LTP model, (c) ECMWF, (d) GFS, (e) GRAPES, and (f) SMS-WARMS. The observed track and predicted track by DSAEF_LTP of TC1809 are plotted with red line and blue line, respectively.
South China successfully, which the four dynamical models fail to accomplish. Moreover, although the precipitation region of over 100 mm produced by the DSAEF_LTP model is quite a bit smaller than the observed rainfall distribution, its performance in capturing the local rainfall region stands out relative to the dynamical models.

For TC1814, we compare the performance in predicting precipitation in excess of the 100 mm threshold among all the forecast models for the reason that none of them is able to produce a TS250 greater than null. The TS100 and Bias100 from the DSAEF_LTP model are 0.0078 and 2.77, while those of the four dynamical models (i.e., ECMWF, GFS, GRAPES and SMS-WARMS) are 0.0640, 0.0270, 0 and 0.0368, and 0.43, 0.68, 0.06 and 1.04, respectively. Combined with the predicted precipitation distribution along with the observed precipitation, which is plotted in Fig. 10, DSAEF_LTP produces an overly widespread heavy rainfall distribution compared with the observations. The rainfall region simulated by DSAEF LTP is mostly concentrated in Central China, East China, and part of South China, while the observed precipitation primarily spreads across East China and Northeast China. On the contrary, the dynamical models—especially ECMWF and SMS-WARMS—can satisfactorily predict the main range of precipitation exceeding 100 mm.

Figure 10. Accumulated precipitation distribution (mm) for TC1814 from (a) observation, (b) the DSAEF_LTP model, (c) ECMWF, (d) GFS, (e) GRAPES, and (f) SMS-WARMS. The observed track and predicted track by DSAEF_LTP of TC1814 are plotted with red line and blue line, respectively.

Despite the unsatisfactory simulation performance of the DSAEF_LTP model for some TCs slightly exceeding high-threshold rainfall amounts, including overpredicted precipitation, the heavy rainfall (>250 mm) distribution predicted by DSAEF_LTP still shows a significant and valuable reference for operational forecasting and hazard mitigation.

5 SUMMARY AND DISCUSSION

In this study, the DSAEF_LTP model was applied to carry out four experiments to simulate heavy precipitation with accumulated rainfall amounts over 250 mm and 100 mm associated with the 10 LTCs over China in 2018. The experiment with the addition of SRS
values and the introduction of TC intensity was selected for comparison with four dynamical models (i.e., EC, GRAPES, GFS and SMS-WARMS). The major results can be summarized as follows:

(1) After adding five SRS values along with introducing TC intensity into GIV, the TS250 and TS100 increased from 0.1346 and 0.1940 to 0.1865 and 0.2062, which shows a more prominent advantage in simulating the heavier precipitation of LTCs. Meanwhile, it was also proven that the simulation ability of the DSAEF_LTP model can be optimized regardless of whether adding SRS values only, or introducing TC intensity into GIV.

(2) Compared with four NWP models, the overall forecasting performance of the DSAEF_LTP model achieves a better result in simulating precipitation at the thresholds over 250 mm and performs slightly superior to NWP models at the thresholds over 100 mm.

(3) For individual TCs, the simulation performance of the DSAEF_LTP model improves with an increase in heavy accumulated precipitation and TC intensity. What's more, DSAEF_LTP performs better in simulating relatively concentrated TC precipitation. According to the simulation performance of the TC rainfall distribution for different track types, the DSAEF_LTP model shows significant simulation capability for TCs whose landing tracks pass through South China. This is also reflected in the accumulated precipitation exceeding 100 mm along the southern coastal area, as compared with the four dynamical models.

The simulation performance of the DSAEF_LTP model is certainly improved when TC intensity and the new SRS values are included, which has been proven in this paper through conducting simulation experiments covering relatively more LTC samples. Since the DSAEF_LTP model was proposed, related research has chiefly focused on improving its forecast capability by absorbing more variables that relate to TC characteristics into the GIV. Through testing with more TC samples in this study, it has been possible to further demonstrate that incorporating more effective parameter values into the model could also play a positive role in improving the model performance. Actually, there is still room for improvement for the DSAEF_LTP model in terms of its prediction performance and reduction of the false alarm ratio. In the future, further research associated with improving the DSAEF_LTP model will concentrate on introducing more new physical factors (e.g., TC speed, TC size, vertical wind shear, water vapor condition) and melliorating the existing parameterization schemes.

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