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An application of the LTP_DSEF model to heavy precipitation forecasts of landfalling tropical cyclones over China in 2018

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Abstract Recently, a track-similarity-based Dynamical-Statistical Ensemble Forecast (LTP_DSEF) model has been developed in an attempt to predict heavy rainfall from Landfalling Tropical cyclones (LTCs). In this study, the LTP_DSEF model is applied to predicting heavy precipitation associated with 10 LTCs occurring over China in 2018. The best forecast scheme of the model with optimized parameters is obtained after testing 3452 different schemes for the 10 LTCs. Then, its performance is compared to that of three operational dynamical models. Results show that the LTP_DSEF model has advantages over the three dynamical models in predicting heavy precipitation accumulated after landfall, especially for rainfall amounts greater than 250 mm. The model also provides superior or slightly inferior heavy rainfall forecast performance for individual LTCs compared to the three dynamical models. In particular, the LTP_DSEF model can predict heavy rainfall with valuable threat scores associated with certain LTCs, which is not possible with the three dynamical models. Moreover, the model can reasonably capture the distribution of heavier accumulated rainfall, albeit with widespread coverage compared to observations. The preliminary results suggest that the LTP_DSEF model can provide useful forecast guidance for heavy accumulated rainfall of LTCs despite its limited variables included in the model.

Keywords Landfalling tropical cyclones, Heavy precipitation forecasts, LTP_DSEF model

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1. Introduction

A tropical cyclone (TC) is a rapidly rotating convective storm that develops over vast tropical oceans, and is one of the most dangerous natural hazards to human society and the environment. It devastates coastal regions, and causes floods and inland erosion through its strong winds, storm surges, and particularly heavy rainfall after landfall (Jiang and Zipser, 2010; Chen and Xu, 2017). Therefore, it is extremely important to improve our ability to forecast heavy precipitation of landfalling tropical cyclones (LTCs) with high priority.

Three approaches have been used for LTC precipitation forecasts: numerical weather prediction (NWP) by dynamical models, statistical models, and a combination of dynamical and statistical models (i.e., the dynamical-statistical method) (Ren and Xiang, 2017). For the first approach, some studies have focused on data assimilation to improve the

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quality of initial fields (Xiao et al., 2007; Zhao et al., 2012; Zhang and Pu, 2014) while others invoke improving parameterization schemes for physical processes (Tuleya et al., 2016) or exploring effective ensemble methods (Zhang et al., 2010; Hsiao et al., 2013; Hong et al., 2015). Since precipitation is an end product involving complicated multiscale interactions from larger-scale flows to cumulus convection, and cloud microphysical processes (Zhang et al., 1994; Liu et al., 1997), current dynamical models do not include the associated physical processes at all scales (Gao et al., 2013). In addition, owing to the complicated convective structures in TCs, limited model resolution, and lacking observations over vast oceans, dynamical models have limited capability to predict LTC precipitation and it is challenging to make breakthroughs in its forecasting skills (Tuleya et al., 2007; Marchok et al., 2007; Wang et al., 2012). In contrast, in some statistical models, integration, extrapolation, principal component analysis (Wei, 2012), and stepwise regression (Huang et al., 2018) are used to provide quantitative precipitation forecasts for LTCs (Li et al., 2015). However, this approach lacks physical basis and nonlinearity in dynamics; therefore, it does not consistently perform well in LTC precipitation forecasts despite the use of a large amount of historical data.

Because of the above-mentioned strengths and weaknesses associated with the statistical and dynamical approaches, a combination of the two (i.e., the dynamical-statistical approach) has been adopted to predict LTC rainfall. Koo (1958) suggested that NWP may be treated as a problem of "initial-value" and "evolution" so that the historical data can be introduced to improve weather forecasts. Chou (1974, 1986) further indicated that the dynamical-statistical approach represents an important advancement in weather prediction technology, whose essence is to reduce the prediction error in numerical models by introducing historical observations. This approach has proven to be a promising research area because it has a sound physical basis and utilizes a huge amount of historical data.

There have been three schools of the dynamical-statistical model development for TC rainfall forecasts (Ren and Xiang, 2017). The first school makes TC rainfall forecasts from the perspective of a climate mean by combining TC track forecasts from dynamical models and historical rainfall observations (Marks et al., 2002; Lee et al., 2006; Lonfat et al., 2007). The second school predicts TC rainfall by adopting TC track forecasts and the rainfall integration from initial rainfall rates (Kidder et al., 2005; Liu, 2009; Ebert et al., 2011). The third group forecasts TC rainfall by constructing a dynamical-statistical scheme that consists of various internal TC variables and its environmental fields (Li and Zhao, 2009; Zhong et al., 2009).

The steady improvement in TC track forecasts has been the most successful achievement in operational NWP models over the past 30 years (Rappaport et al., 2009; Langmack et al., 2012; Cangialosi and Franklin, 2015; Peng et al., 2017). Considering the close relationship between TC tracks and rainfall, improvements to dynamical-statistical models for predicting TC rainfall would depend on the effectiveness of combining TC track forecasts with massive historical observations. Although TC track forecasts have been adopted in some dynamical-statistical models, little work has been conducted to seek similarities to historical TCs from the perspective of their track characteristics (Ren and Xiang, 2017).

Recently, Ren et al. (2018) developed an objective TC track similarity area index (TSAI) to objectively calculate the degree of similarity for two TCs, whereby a track-similarity-based Dynamical-Statistical Ensemble Forecast model for LTCs precipitation (LTP_DSEF) is established. Together with Ding et al. (2019), they applied the LTP_DSEF model to rainfall forecast tests of 21 LTCs over South China from 2012 to 2016. Preliminary results demonstrate that the LTP_DSEF model is superior to three current widely used operational global NWP models, i.e., the European Centre for Medium-Range Weather Forecasts (ECMWF) model, the Global Forecast System (GFS) of the National Centers for Environmental Prediction, and the global spectral model (T639) of the China Meteorological Administration (CMA)/National Meteorological Center. The model proved especially effective in predicting heavy rainfall accumulations.

To increase the credibility of the LTP_DSEF model and further improve its forecast performance, more studies need to be conducted to evaluate its rainfall forecast skills for more recent LTCs. For this purpose, the "busy" TC season of 2018 is selected in this study. During this season, a total of 10 TCs made landfall over China, a number that exceeds the climatological annual mean of 7–8 TCs. In particular, the associated heavy rainfall amounts with large coverage from the southern to northeastern coastal regions of China provide a great challenge to test the performance of LTC rainfall forecasts by the LTP_DSEF model. The LTC rainfall forecast performance is further evaluated by comparing predictions from the LTP_DSEF model with those from three current operational global models, i.e., ECMWF, GFS, and the Global and Regional Assimilation and Prediction System (GRAPES).

The next section describes the data used in this study and the main componen*ts* of the LTP_DSEF model. Section 3 illustrates the test designs by describing the basic variables included in the LTP_DSEF model, and procedures on how to obtain optimized values for various parameters and to achieve the best scheme for predicting heavy rainfall associated with the 10 LTCs. Section 4 provides the LTC rainfall forecast results with the best scheme and compares them with results from the three operational models. A summary and concluding remarks are given in the final section.

2. Data and methodology

Table 1 lists the identifications, names, and peak rainfall amounts of the 10 LTCs selected for the forecast tests. Their tracks, from both the best tracks and operational NWP model-forecast tracks, are obtained from the CMA/National Information Meteorological Center. The historical best tracks at 6-h intervals during 1960–2017, which are to be used to identify analogue tracks, are obtained from the CMA/Shanghai Typhoon Institute.

Historical observed precipitation data during 1960–2018 are archived at 24-h intervals starting at 12:00 UTC each day by the CMA/National Meteorological Information Center, which include 2026 rain gauge stations over most of China, i.e., with 2003 over mainland China and 23 over Taiwan Island (the latter are unavailable in 2018, so only the former are used for the study period). To verify the LTC rainfall forecasts for the 2018 TC season produced by the LTP_DSEF model, the corresponding rainfall forecast data are obtained from the ECMWF model, the GFS model by the US/National Weather Service, and the GRAPES model run by CMA, with horizontal resolutions of 0.1°×0.1°.

To produce LTC rainfall forecasts, the LTP_DSEF model includes the following four steps: (1) obtain the forecast track of the target TC; (2) identify its track similarity to historical TC tracks; (3) determine the similarities between other variables influencing LTC precipitation and those of historical TCs; and (4) make an ensemble prediction of LTC rainfall. Among these steps, TSAI is used to identify the extent of similarity between any two TCs, and the Objective Synoptic Analysis Technique (OSAT, Ren et al., 2001, 2007) is adopted to identify the historical LTC precipitation objectively in step (4). More detailed forecast procedures for testing the 10 LTCs are described in the next section.

Table 1 List of 10 TCs that made landfall over China in 2018 including their identification (ID) numbers, names, and single-station-observed maximum total rainfall

ID No.	Name	Maximum total rainfall (mm)
1804	EWINIAR	441.4
1808	MARIA	184.5
1809	SON-TINH	119.9
1810	AMPIL	263.8
1812	JONGDARI	182.7
1814	YAGI	267
1816	BEBINCA	618.9
1818	RUMBIA	424.1
1822	MANGKHUT	403.7
1823	BARIJAT	116.4

3. Forecast procedures and test design

In this study, the LTP_DSEF model consists of seven characteristic parameters. Table 2 provides the values and physical significances of these parameters as well as their optimized values for the best scheme. Because each parameter has several different values, numerous combinations are possible; each combination is called a forecast scheme. The purpose of the rainfall forecast tests is to identify the optimized parameter values that produce the best scheme for predicting heavy rainfall from the 10 LTCs with minimum forecast errors. The procedures to determine the optimized vales of the parameters are described as follows.

The forecast track of the target TC is first obtained from the operational TC forecast data according to the initial time (*P*1), i.e., the time when the LTC precipitation falls on land, which can include rainfall from spiral rainbands. Then, this forecast track is put together with its observed track prior to the initial time. At this step, the TSAI of the target TC track is calculated point by point with the tracks of all historical TCs in the given similarity region (*P*2), which is determined by the landfalling location of the target TC or needs of any forecast. For a given similarity region, a smaller TSAI indicates a greater similarity of the two TC tracks, as determined by the three parameters of TSAI, i.e., *P*2, *P*3, and *P*4. All historical TCs are ranked in order of their TSAI values from small to large, and then the seasonal similarity (*P*5) is adopted to screen out historical TCs with large differences in landfall time from the target TC. As a final step, the predicted precipitation for the target TC is obtained by assembling the observed rainfall associated with the remaining n top-ranked historical TCs (*P*6) with one kind of ensemble forecast scheme (*P*7). Since the threat score [*TS*=hits/(hit+false alarms+misses)) is a common verification metric for operational rainfall forecasts, it is employed to measure the performance of a forecast scheme or dynamical model in predicting TC rainfall with a focus on accumulated LTC rainfall categories of ≥250 mm and ≥100 mm, respectively.

As shown in Table 2, all possible combinations of the seven parameters give a total of 54000 forecast schemes for each TC. However, some TCs cannot be fully valued on certain parameters, such as the initial time (*P*1) or the similarity region (*P*2); therefore, the number of common schemes suitable for all 10 TCs should be equal to or less than 54000. For this reason, common schemes are identified in advance to address a scenario where no result from a forecast scheme is obtained for a TC. Clearly, the best forecast scheme should be found from the common schemes, i.e., whichever has the largest value of $TS_{250}+TS_{100}$, where TS_{250} and TS_{100} represent the average threat scores for predicting accumulated rainfall of ≥250 mm and ≥100 mm, respectively, associated with all 10 LTCs.

Table 2 Parameters included in the LTP_DSEF model and their optimized values for the best scheme among the heavy rainfall ensemble forecast tests

Parameters (1–7)	Tested values	Optimized values
Initial time (*P*1)	The time when the LTC precipitation falls on land. 1–2 for 00 UTC or 12 UTC	*P*1=2
Similarity region (*P*2)	A parameter of TSAI defined as a rectangle with the diagonal points A and B. A is the TC locations at 0, 12, 24, 36, or 48 h prior to the initial time, and B is 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). 1–15	*P*2=2 (0 h before the initial time and 12h before the maximum lead time)
Threshold of the segmentation ratio of a latitude extreme point (*P*3)	A TSAI parameter: 1–3 for 0.1, 0.2, and 0.3, respectively	*P*3=3
The overlapping percentage threshold of two TC tracks (*P*4)	A TSAI parameter: 1–6 for 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9, respectively	*P*4=1
Seasonal similarity (*P*5)	1–5 for the whole year, May to Nov, July to Sept, the same landfall month as the target TC, and within 15 days of the target TC landfall time, respectively	*P*5=2
Number (N) of TCs with the top N closest track similarity (*P*6)	1–10 for 1, 2, …, and 10, respectively	*P*6=10
Ensemble forecast scheme (*P*7)	1–2 for a mean and a maximum, respectively	*P*7=2
Total number of schemes	2×15×3×6×5×10×2=54000	

4. Results

To better understand the results, it is necessary to describe some basic characteristics of the 10 LTCs used in the present study. As listed in Table 1, all 10 TCs had single-station accumulated maximum rainfall of ≥100 mm, but only six of them produced ≥250 mm, i.e., TC1804, TC1810, TC1814, TC1816, TC1818, TC1822 (each TC is represented herein by its identification (ID) number, e.g., TC1804 indicates the 4th TC occurring in 2018). In addition, Figure 1 indicates the following three geographical characteristics of the 10 LTCs: their landfalls occurred over either South China or East China; LTCs over East China moved northward after landfall; and none made landfall over Taiwan Island or across Taiwan Strait. Thus, the 10 LTCs are sorted into two groups: LTCs occurring over South China (STC), including TC1804, TC1809, TC1816, TC1822, and TC1823; and LTCs moving northward after landfall over East China (NTC), including TC1808, TC1810, TC1812, TC1814, and TC1818.

Given these described LTC characteristics, it was only possible to test 3452 common schemes for the 10 LTCs. Figure 2 shows scatter plots of the threat scores (i.e., TS_{100}-TS_{250}) associated with all 10 LTCs from the 3452 forecast schemes for the LTP_DSEF model. Based on the procedures described in Section 3, the best scheme is determined with TS_{250}=0.042 and TS_{100}=0.1513, as indicated by a red dot in Figure 2 with their optimized parameter values given in Table 2. In the best scheme, the initial time (*P*1) is at 12 UTC of the day when LTC precipitation was first recorded by any continental rain gauge station; the similarity region (*P*2) is a rectangle with the diagonal of the TC location at 0 h and 12 h prior to the initial and maximum lead times, respectively; the seasonal similarity (*P*5) spans the months of May to November; the number of TCs with the top (10) closest track similarities (*P*6) is 10; the ensemble prediction scheme (*P*7) is the maximum total rainfall; and the other two parameters (*P*3 and *P*4) for TSAI are 0.3 and 0.4, respectively.

To see how well the best scheme of the LTP_DSEF model predicts the LTC maximum rainfall amounts, Figure 3 compares its two threat scores (i.e., TS_{250}=0.042 and TS_{100}=0.1513) associated with the 10 LTCs to those produced by the three dynamical models described in Section 1. The TS_{250} and TS_{100} values obtained for ECMWF, GFS, and GRAPES are 0.01146, 0.0375, and 0.00789; and 0.12971, 0.17216, and 0.11465, respectively. Evidently, TS_{250} from the LTP_DSEF model ranks the first (0.042), slightly above the second (0.0375), and significantly above the third (0.01146) and the fourth (0.00789); while TS_{100} from the LTP_DSEF model ranks second (0.1513), which is inferior to GFS (0.17216), but better than the third (0.12971) and fourth (0.11465).

Figure 4 compares the threat scores associated with individual LTCs from the best scheme of the LTP_DSEF model to those from the three dynamical models, together with their single-station accumulated maximum total rainfall. Of significance is that *TS* values for all forecast models tend to be higher for LTCs with larger single-station observed maximum total rainfall, excluding the TS_{100} associated with TC1822, indicating likely their better performance in predicting the intensities of stronger TCs. Figure 4a shows only six LTCs with a single-station observed maximum total rainfall of ≥250 mm because the other four LTCs produced maximum rainfall amounts < 250 mm. In predicting the ≥250 mm rainfall, none of the forecast models gives a larger than null *TS* for NTC1810 and NTC1814, which have single-station accumulated maximum

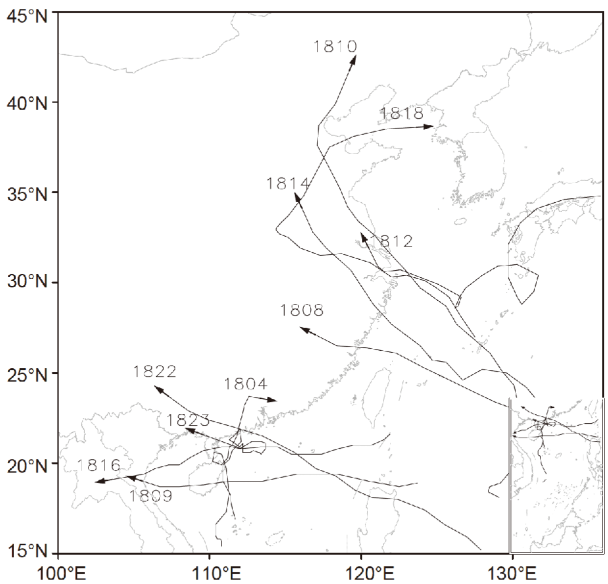

Figure 1 The best tracks of the 10 LTCs, as indicated by their identification numbers (see Table 1), occurring in 2018 over the eastern portion of China.

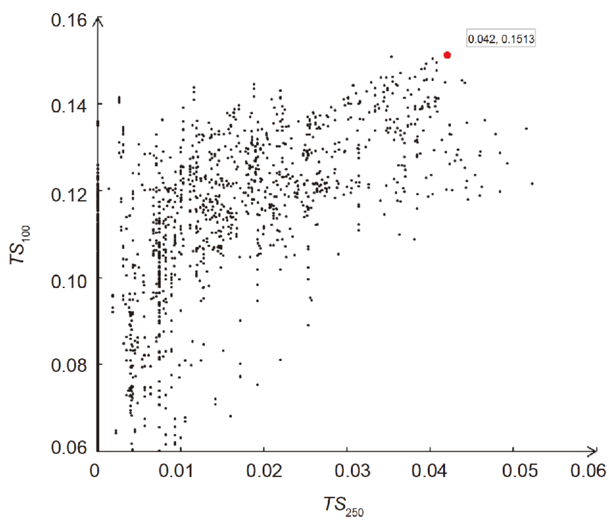

Figure 2 Scatter plots of the threat scores (TS_{100}-TS_{250}) from the 3452 forecast schemes for the LTP_DSEF model. TS_{250} and TS_{100} represent the average threat scores for predicting accumulated rainfall of ≥250 mm and ≥100 mm, respectively, associated with the 10 LTCs that occurred over China in 2018. The red dot indicates the best forecast scheme with the highest values of TS_{250}+TS_{100}.

rainfall amounts slightly in excess of 250 mm. This could be attributed to the fact that it is challenging for a forecast model to capture more localized heavy rainfall regions with amounts slightly above the high rainfall threshold. Nevertheless, for the remaining LTCs, LTP_DSEF has greater than null *TS*s, providing the best estimates for STC1804, NTC1818 and STC1822, and the second-best estimates for STC1816, whereas the three dynamical models have greater than null *TS*s only for two LTCs (i.e., STC1804 and STC1816). Moreover, only LTP_DSEF produces greater

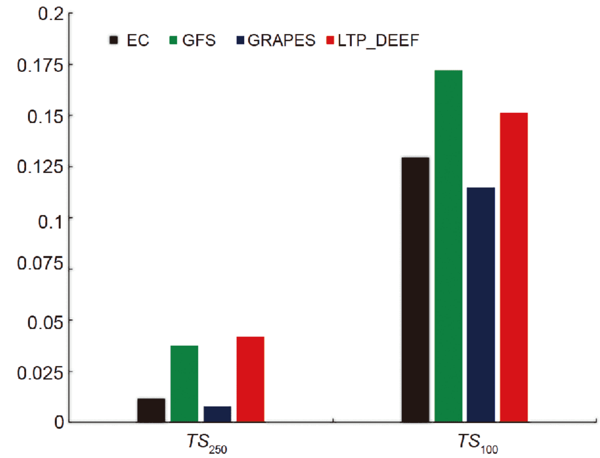

Figure 3 Threat scores (TS_{250} and TS_{100}) from the best scheme of the LTP_DSEF model compared with those from the three dynamical models (i.e., ECMWF, GFS and GRAPES) associated with the 10 LTCs that occurred over China in 2018.

than null *TS* values for NTC1818 and NTC1822. Figure 4 also shows that the GFS-produced TS_{250} values for all 10 LTCs are slightly lower than those produced from the LTP_DSEF (Figure 2) because the former model performs the best for STC1816 but only produces null *TS* values for all other LTCs. Similarly, both ECMWF and GRAPES compare poorly to LTP_DSEF in predicting accumulated rainfall ≥250 mm.

Figure 4b compares the threat scores for accumulated rainfall ≥100 mm (i.e., TS_{100}) associated with the 10 LTCs predicted by the best scheme of the LTP_DSEF model to those by the three dynamical models. For STC1823, none of the forecast models, including the best scheme, yields a greater than null TS_{100} value. LTP_DSEF has greater than null TS_{100} values for all remaining LTCs, and it is the only one that produces greater than null TS_{100} values for STC1809, NTC1812, and NTC1814. LTP_DSEF ranks the best for NTC1818, and second through fourth for STC1822, STC1804, and STC1816, respectively. The LTP_DSEF-produced TS_{100} values for the three LTCs over South China are slightly smaller than the highest TS_{100} values produced from the dynamical models. LTP_DSEF perform poorly only for NTC1808 and NTC1810; the poor performance for NTC1808 could be attributed to neglecting data from Taiwan Island in calculating *TS*s due to the lack of rain gauge station data in 2018. Nevertheless, the performance of LTP_DSEF for both STCs and NTCs is generally better than those of the dynamical models.

To gain better insight into the forecast performance using the best scheme of the LTP_DSEF model, horizontal distributions of the forecast total rainfall amounts of the 10 LTCs produced by all models are plotted and compared with observations. Data from three representative LTCs, i.e., STC1804, STC1816, and NTC1818, are shown in Figures 5–

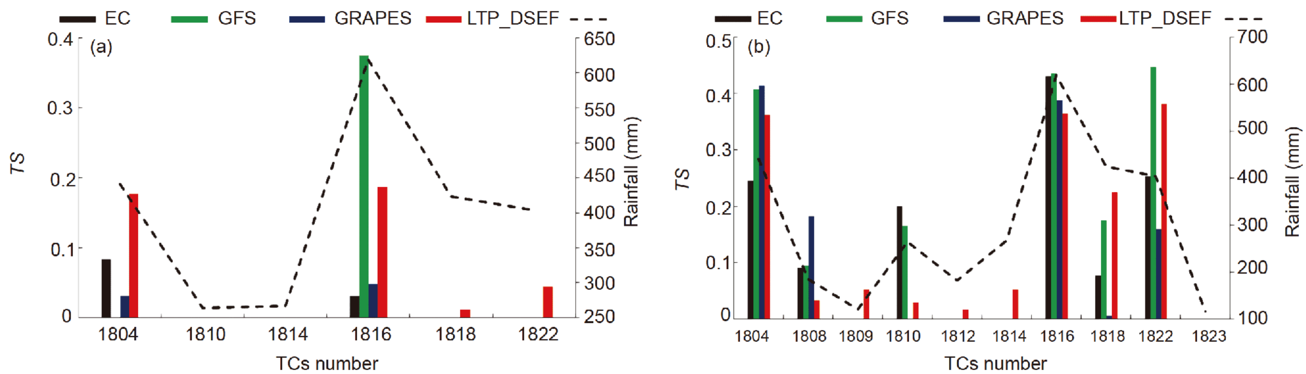

Figure 4 Individual threat scores (vertical color bars) for predicting the accumulated rainfall using the LTP_DSEF model compared with those predicted by the three dynamical models (ECMWF, GFS and GRAPES). Dashed lines denote the single-station observed maximum total rainfall (mm) associated with each TC. (a) Accumulated rainfall of ≥250 mm associated with six LTCs (STC1804, NTC1810, NTC1814, STC1816, NTC1818, and STC1822; the other four LTCs are not shown because their single-station accumulated maximum rainfall was <250 mm. (b) Accumulated rainfall of ≥100 mm associated with all 10 LTCs.

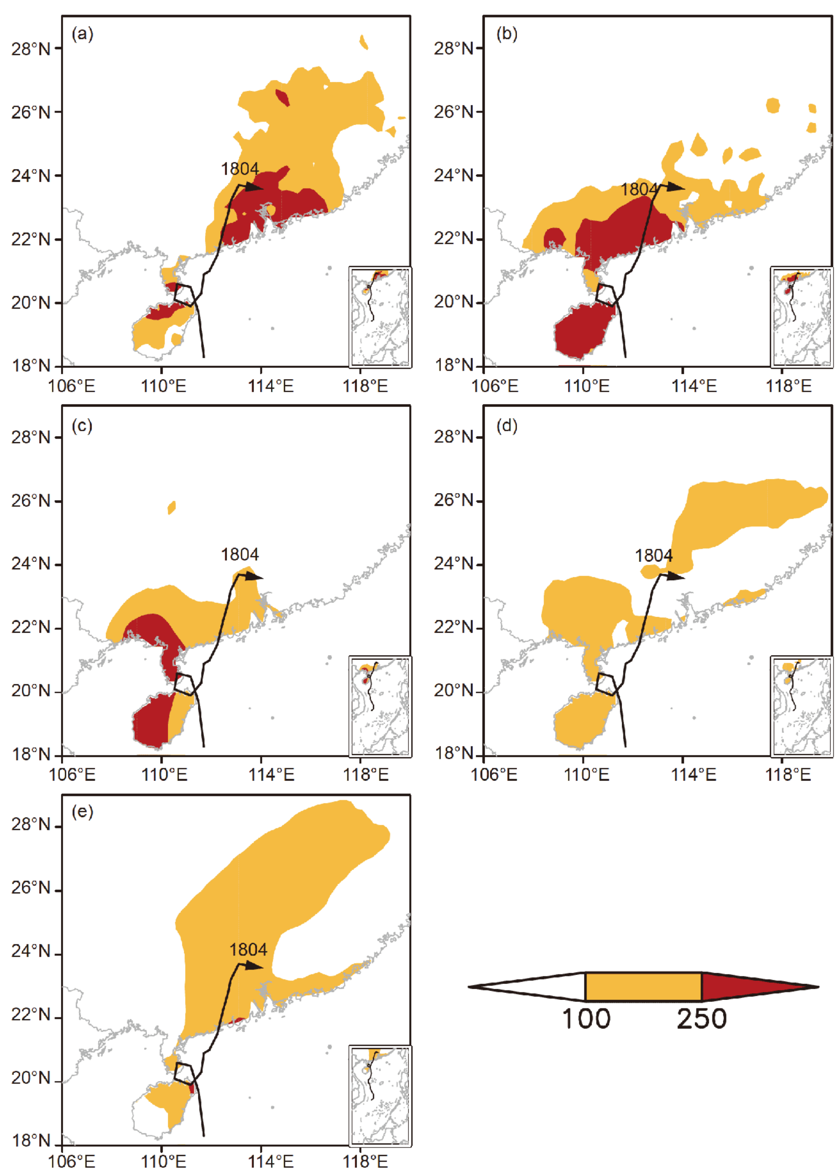

Figure 5 Horizontal distribution of the accumulated total rainfall amounts (mm) associated with TC1804 (EWINIAR) from rain gauge observations (a) and predictions from the LTP_DSEF (b), ECMWF (c), GFS (d), and GRAPES (e) models. The observed track is also plotted.

7, respectively, together with their observed tracks. LTP_DSEF predicts best the ≥250 mm rainfall distribution for STC1804, but performs slightly worse than GFS and GRAPES for the ≥100 mm rainfall patterns (cf. Figure 5b–5e), i.e., with underpredicted rainfall amounts in the north-eastern quadrant of the storm as compared with observations (Figure 5a). For STC1816, both the ≥100 mm and ≥250 mm rainfall patterns predicted using LTP_DSEF (Figure 6b) are quite reasonable among the forecast models, especially those along the southern coastal regions, except for the absence of a ≥250 mm rainfall center. By comparison, LTP_DSEF captures well the general distribution of ≥250 mm and ≥100 mm rainfall associated with NTC1818, except for producing too widespread heavy rainfall compared with observations (Figure 7a–7e). The predicted widespread rainfall pattern could be attributed to the inclusion of certain historical LTCs (i.e., herein *P*6=10) that might have different larger-scale conditions (e.g., vertical wind shear, static stability, moisture source) from those of the target LTC. These different conditions remain to be introduced as variables into the LTP_DSEF model (i.e., in Table 2). Nevertheless, these preliminary results indicate that while the LTP_DSEF model performs unsatisfactorily for some LTCs with high-threshold rainfall amounts, e.g., the ranked fourth for the ≥100 mm rainfall threshold of STC1816, its predicted heavy rainfall distribution still provides valuable information to local forecasters and hazard mitigation administrators.

5. Summary and concluding remarks

In this study, the LTP_DSEF model consisting of TC track and landfall time with seven characteristic parameters is used to predict heavy precipitation with accumulated rainfall amounts of ≥250 mm and ≥100 mm associated with 10 LTCs that occurred in Southern and Eastern China during the year of 2018. The best scheme employed in the LTP_DSEF model is obtained after testing 3452 different forecast schemes for each LTC. Its performance is then compared to the predicted rainfall accumulations by three operational

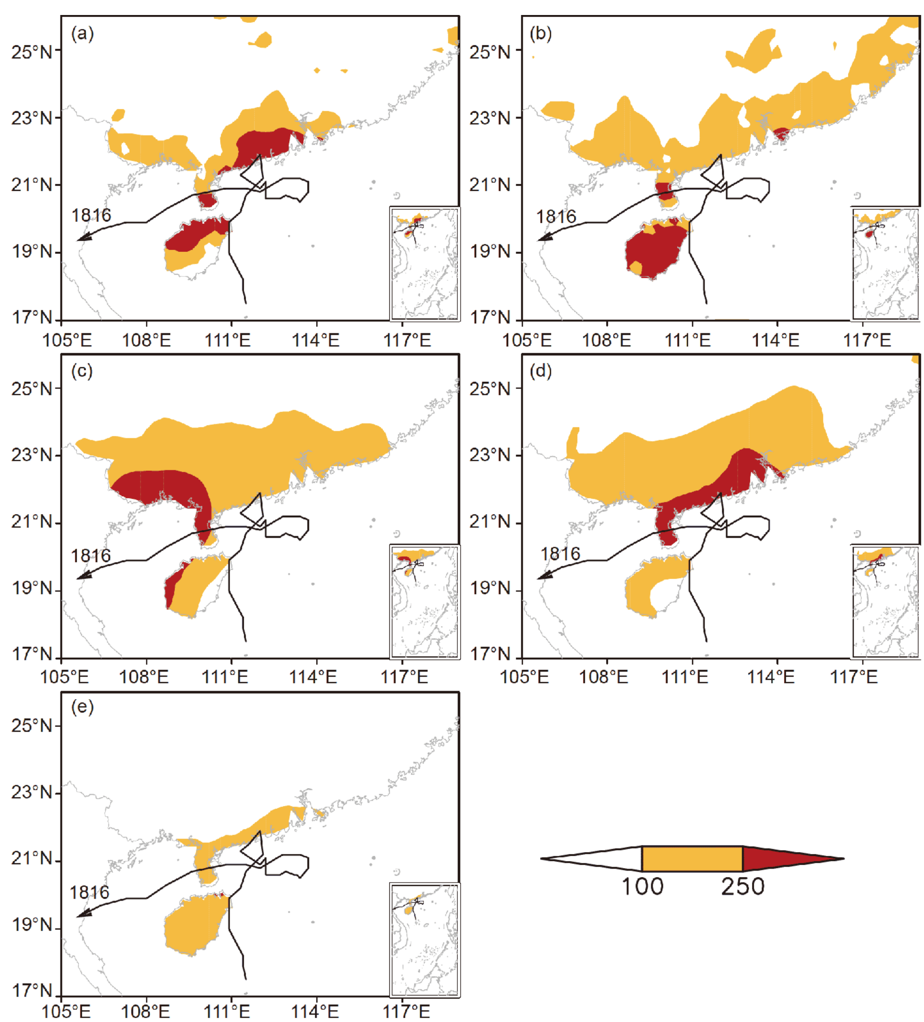

Figure 6 Horizontal distribution of the accumulated total rainfall amounts (mm) associated with TC1816 (BEBINCA) from rain gauge observations (a) and predictions from the LTP_DSEF (b), ECMWF (c), GFS (d), and GRAPES (e) models. The observed track is also plotted.

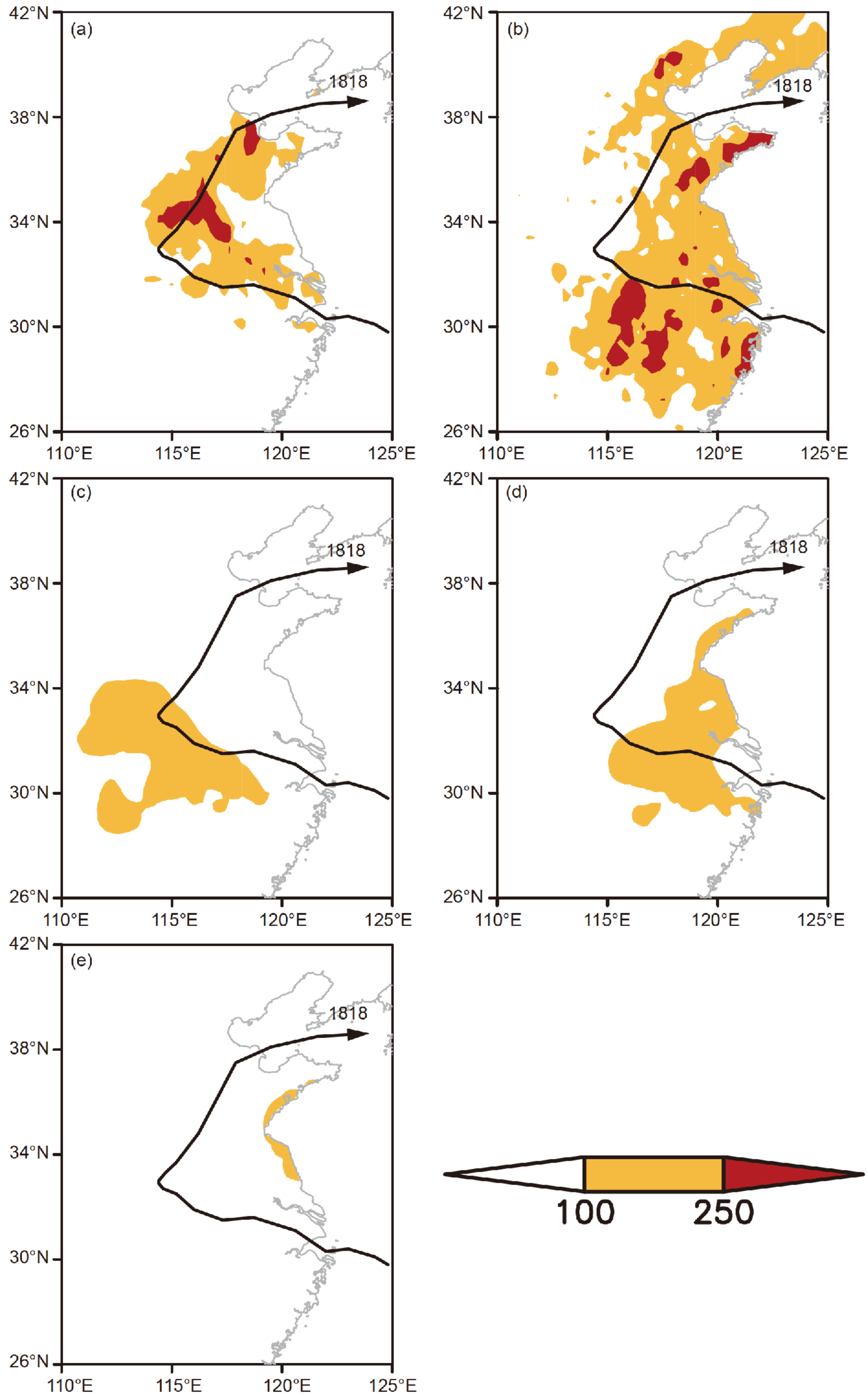

Figure 7 Horizontal distribution of the accumulated total rainfall amounts (mm) associated with TC1818 (RUMBIA) from rain gauge observations (a) and predictions from the LTP_DSEF (b), ECMWF (c), GFS (d), and GRAPES (e) models. The observed track is also plotted.

global NWP models (i.e., ECMWF, GFS and GRAPES). Major results are summarized as follows:

(1) Overall, the LTP_DSEF model has significant advantages over the three dynamical models in predicting LTC heavier rainfall, e.g., for the accumulated total rainfall of ≥250 mm for the 10 LTCs. The LTP_DSEF model produces TS_{250}=0.042 compared to TS_{250}=0.0079–0.0375 values produced by the three dynamical models. It ranks the second, with TS_{100}=0.1513, in predicting the accumulated total rainfall of ≥100 mm for the 10 LTCs. By comparison, the three dynamical models have TS_{100} values between 0.1147 and 0.1721.

(2) In general, the LTP_DSEF model is superior or slightly inferior to the three dynamical models in predicting accumulated total rainfall of ≥250 mm and ≥100 mm associated with individual LTCs. In particular, the model can predict heavy rainfall with valuable *TS*s associated with certain LTCs, for which the three dynamical models are unable to provide.

(3) The LTP_DSEF model better captures narrow or localized distribution of accumulated rainfall of ≥250 mm occurring in most LTCs and accumulated rainfall of ≥100 mm along the southern coastal region, as compared to the three dynamical models.

However, the LTP_DSEF model tends to predict too widespread heavy rainfall compared with observations, more significantly for certain LTCs moving along the east-coastal regions of China. In addition, the model is unable to predict correctly the quadrants in which heavy rainfall occurred in some LTCs. We attribute all these unsatisfactory aspects to the inclusion of certain historical LTCs with different environmental conditions from those associated with the target LTCs. Some shortcomings with the model forecast performance could also be attributed to the few deep-inland historical TCs that have occurred over northern China. Therefore, tracks of historical TCs should be lengthened from the location where they downgrade as tropical depressions in future work.

Based on the presented results, we may state that the LTP_DSEF model can perform better than much more comprehensive NWP models in predicting heavier accumulated rainfall (i.e., ≥250 mm) for most LTCs studied herein, despite the only use of TC track and landfall time as the two basic variables. For some LTCs, the LTP_DSEF model performs similarly or slightly less satisfactorily than the NWP models for accumulated rainfall of ≥100 mm. Clearly, there is considerable room for improving the model forecast performance, which can be achieved by incorporating more variables related to TC characteristics (e.g., intensity and size) and their environments (e.g., vertical wind shear, subtropical high, relative humidity, topography, and etc.), with extensive validation against historical LTCs. Our future research will focus on these improvements.

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