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A New Technique for Landfalling Tropical Cyclone Quantitative Precipitation Forecast (QPF)

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Introduction

The progress of numerical weather prediction (NWP) over the past three decades in tropical cyclone (TC) forecasting research and operation has been concentrated on accurate TC track prediction. Compared with TC track forecast, TC precipitation forecast received limited attentions during the past thirty years (Tuleya et al., 2007 and Lonfat et al., 2007).

The LTP_DSEF Model

In this study, for quantitative TC precipitation forecast, a new technique, named as "track-similarity-based Landfalling Tropical cyclone Precipitation Dynamical -Statistical Ensemble Forecast (LTP_DSEF) model", has preliminarily been developed. The flow chart of the LTP_DSEF model (Figure 1) includes five steps ---- 1) To predict TC track, which means directly adopting the NWP TC track prediction, 2) Identification of track-similarity TCs, 3) Identification of other characteristics -similarity TCs, 4) Ensemble forecast of TC precipitation and 5) Selection of the best forecast scheme.

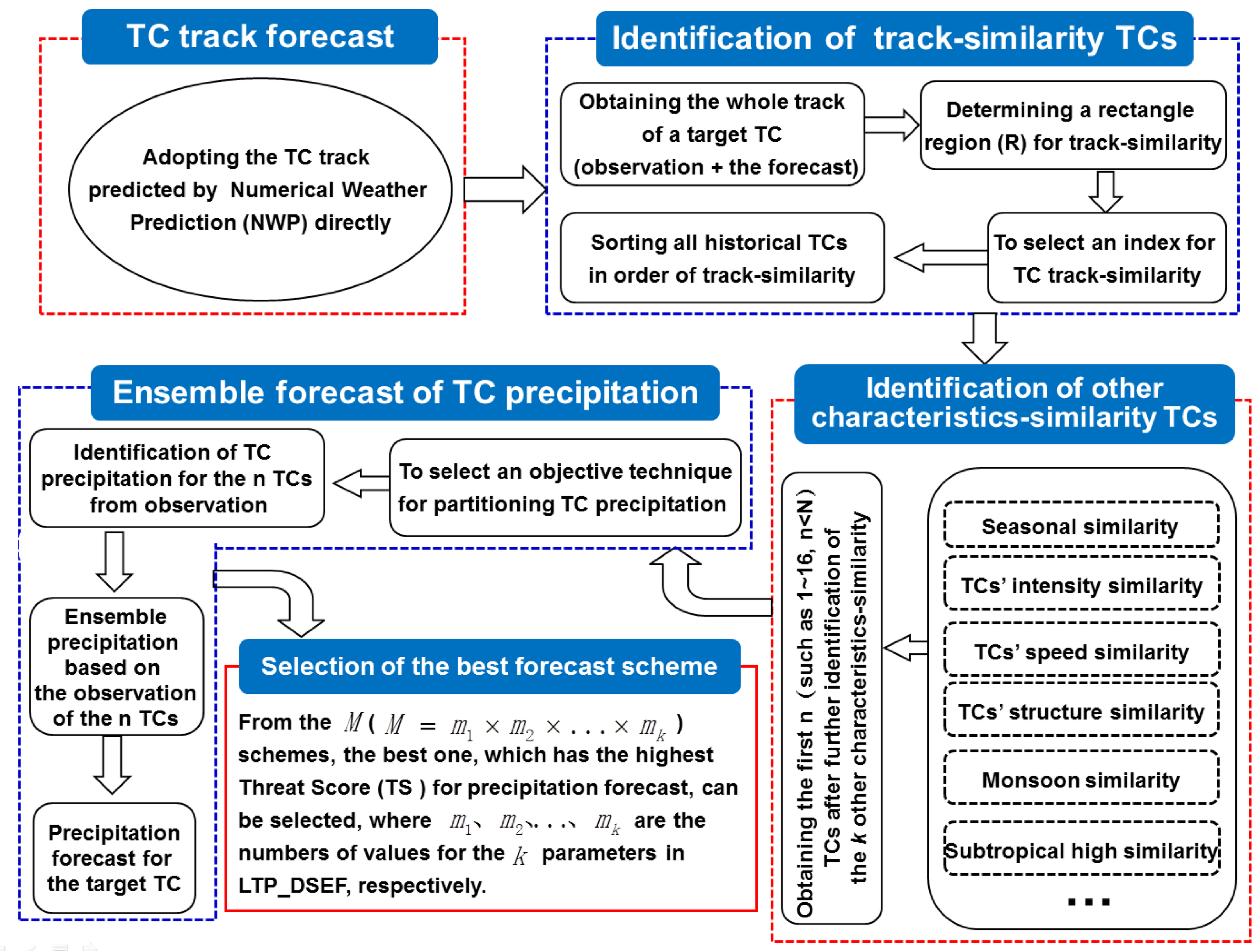

Figure 1. The flow chart of the LTP_DSEF model

There are two key techniques in the LTP_DSEF model. One is the tropical cyclone (TC) Track Similarity Area Index (TSAI) (Ren et al., 2018) for identifying TC track similarity, which is the area of the enclosed scope surrounded by two TC tracks (or track segments within a designated similarity region) and the two line segments, which connect the first two and the last two points (Figure 2). The other is the Objective Synoptic Analysis Technique (OSAT) (Ren et al., 2001 and 2007) for partitioning TC precipitation, which uses the distance from TC center and the closeness and continuity between neighboring raining stations to trace TC-influenced rain belts that may extend from 500 km to 1100 km away from a TC center.

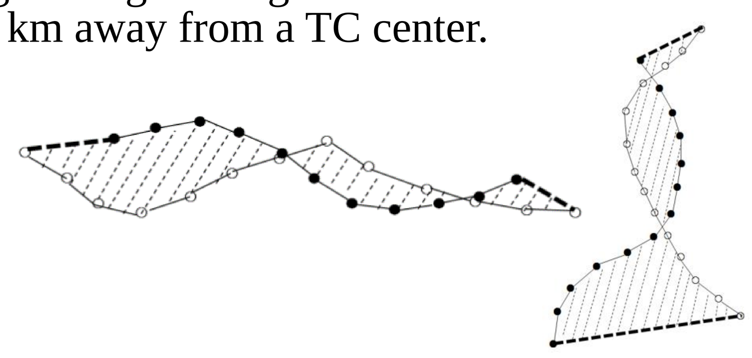

Figure 2. Schematic diagram of the enclosed scope (shaded area) surrounded by two TC tracks (dotted line) and the two line segments (thick broken line) connecting the first two points and the last two points of the two TC tracks (left) zonal and (right) meridional patterns.

Preliminary application in LTC precipitation forecasting (1)

In the test, the LTP_DSEF model was applied for the forecasting of accumulated precipitation associated with Landfalling Tropical Cyclones (LTCs) in South China (Figure 3) and only the TCs that produced more than 100 mm of daily precipitation to at least one station in the region were selected. To carry out verification of the precipitation forecast for the LTP_DSEF model with NWP models, the period 2012–2016 (during which data are available for the three dynamical models – ECMWF, GFS and T639/China) is selected as the analysis period, with 2012–2014 for the training sample and 2015–2016 for the independent sample. There are a total of 21 TCs (Figure 4), with 15 for 2012–2014 and 6 for 2015–2016, while the TC dataset, which is for identifying analogue TCs, is the best track data from the CMA Tropical Cyclone Database (http://tcdata.typhoon.org.cn/en/zjljsjj_sm.html) during 1958~2016. The training sample differs from the independent sample in that a TC of the former can have an analogue TC that occurs after it while a TC of the latter can't. To do verification, the precipitation forecasts by the three NWP models are interpolated with inverse distance weighted interpolation algorithm onto the 191 stations over South China (Figure 3).

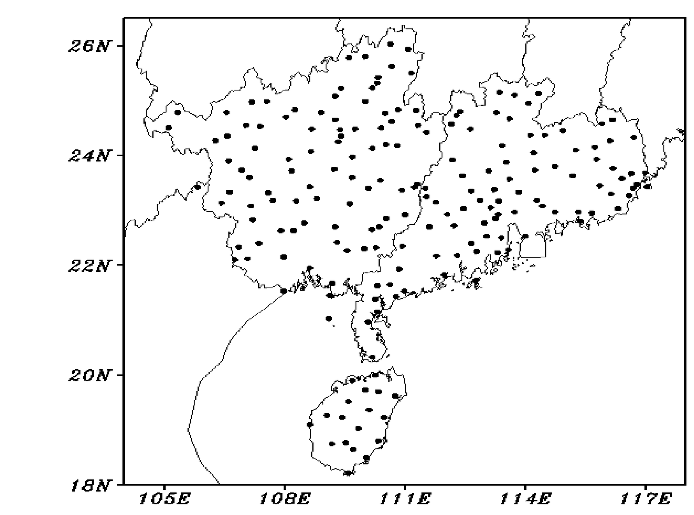

Figure 3. Distribution of the 191 stations over South China

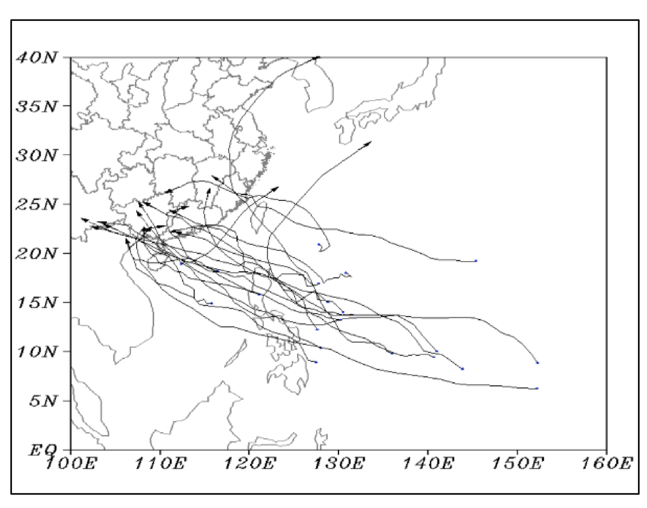

Figure 4. The 21 TCs which has been selected in this test

There are seven parameters, which are initial time (P_1), Similarity region (P_2), threshold of the segmentation rate of a latitudinal extreme point (P_3), threshold of the overlap rate of the two TC tracks (P_4), seasonal similarity (P_5), number of the most similar TCs (P_6) and ensemble scheme (P_7), in the LTP_DSEF model (Table 1). Considering these numerous parameters with different values or settings which are listed in Table 1, ideally there are a total of 103680 (= $4\times15\times3\times6\times3\times16\times2$) different schemes. However, because some of the 21 TCs produce rainfall soon after genesis and those TCs can influence the number of values for parameters P_1 and P_2, this will result in a decrease in the total number of schemes for the test. Therefore, the final total number of schemes is 15,552.

Preliminary application in LTC precipitation forecasting (2)

Table 1 Parameters and the total number of schemes of the LTP_DSEF model

Parameter	The way for getting value	Number of values
Initial time	12:00UTC and 0:00 UTC within two days before the first day with TC precipitation appearing on land	2×2=4
Similarity region	A parameter of TSAI: TC locations at the initial time (point A) and the maximum lead time (point B) are the first diagonal points; and point A can be the TC locations at 12 h or 24 h before the initial time, while point B can be the TC locations at 12 h, 24h, 36 h or 48 h before the maximum lead time	3×5 = 15
Threshold (r_0) of segmentation rate of a latitude extreme point	A parameter of TSAI and its value can be 0.1, 0.2 or 0.3	3
Threshold (c_0) of overlap rate of two TC tracks	A parameter of TSAI and its value can be 0.9, 0.8, 0.7, 0.6, 0.5 or 0.4	6
Seasonal similarity	Its value can be the whole year, May ~Nov. and Jul. ~ Sep.	3
Number of the most similarity TCs	Its value can be 1~16	16
Ensemble prediction scheme	Its value can be "mean" or "the maximum"	2
Total number of schemes	4×15×3×6×3×16×2	103,680

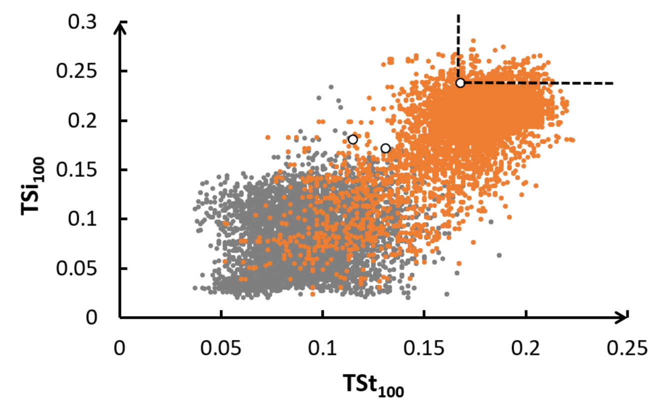

Figure 5. Training sample-independent sample threat score (represented by TSt_{100} and TSi_{100}, respectively, where "m", "i", and "100" mean the training sample, independent sample, and accumulated precipitation ≥ 100 mm, respectively) cross-section distribution for the 15,552 schemes in the TC precipitation prediction of the LTP_DSEF model. Grey and yellow points indicate the ensemble scheme "mean" and "the maximum", respectively. The three "∘" symbols represent the three dynamical models (ECMWF, GFS, and T639), and the two dotted lines represent the highest values of TSt_{100} (0.168) and TSi_{100} (0.238) for the three dynamical models (both are from GFS).

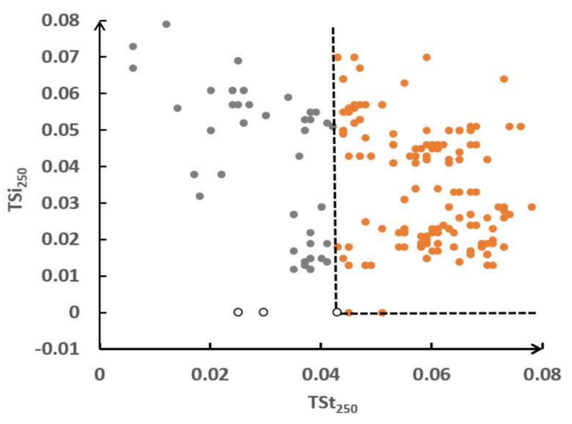

Figure 6. Training sample-independent sample threat score (represented by TSt_{250} and TSi_{250}, respectively, where "250" means accumulated precipitation ≥250 mm) cross-section distribution for the 259 schemes that have better-than-NWP-model performance in the accumulated precipitation ≥100 mm in the TC precipitation prediction of the LTP_DSEF model. The three "∘" symbols represent the three dynamical models (ECMWF, GFS, and T639), and the two dotted lines indicate the highest values of TSt_{250} (0.043) and TSi_{250} (0.0) for the three dynamical models (both are from GFS).

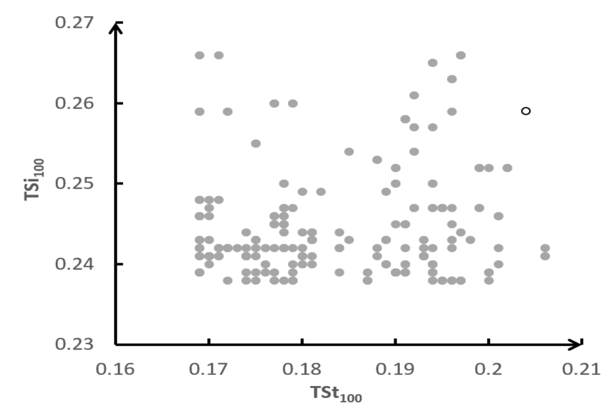

Figure 7. Training sample-independent sample threat score (represented by TSt_{100} and TSi_{100}, respectively) cross-section distribution for the 202 schemes that have better-than-NWP-model performance in the accumulated precipitation of ≥100 mm and ≥250 mm in the TC precipitation prediction of the LTP_DSEF model. The scheme marked with the "∘" symbol, which has the highest value of TSt_{100} + TSi_{100}, is selected as the best one.

To obtain suitable schemes for both the training and the independent samples, the skill measure used is the threat score (TS: $TS = \frac{hits}{hits + misses + false\ alarms}$) for the precipitation above the different thresholds (r ≥ R_0, where R_0 has six values of 0.1 mm, 10 mm, 25 mm, 50 mm, 100 mm, and 250 mm).

Figure 5 shows that, a total of 259 schemes are better than the dynamical models and are located in the first quadrant of the two dotted lines. Then, among the 259 schemes in Figure 6, there are a total of 202 schemes that are better than the dynamical models and are located in the first quadrant of the two dotted lines. This means that the 202 schemes show better-than-NWP-model performance in the accumulated precipitation of ≥100 mm and ≥250 mm in the TC precipitation prediction of the LTP_DSEF model.

To identify the best one among the 202 schemes, considering precipitation ≥100 mm already including that ≥250 mm, TSt_{100} and TSi_{100} are suitable for doing this. Figure 7 presents the training sample-independent sample TS (represented by TSt_{100} and TSi_{100}, respectively) cross-section distribution for the 202 schemes. The scheme marked with the "∘" symbol, which has the largest value of TSt_{100} + TSi_{100}, is selected as the best scheme. In this scheme, the seasonal similarity is the whole year, the number of the most similar TCs is nine, the ensemble prediction scheme is the maximum, the initial time is the latest one, and the other three parameters are those of TSAI (detailed information omitted).

Figure 8 presents a comparison of the training and independent sample TSs for precipitation above different thresholds for the best schemes of LTP_DSEF and the three dynamical models. Although the LTP_DSEF model does not show any advantages over the three dynamical models at small precipitation thresholds (0.1–25 mm), it shows much better prediction ability than the three dynamical models at large precipitation thresholds (100–250 mm) in the training and the independent samples. For example, for ≥100 mm precipitation, the TS values for the three dynamical models range between 0.115 and 0.168 (0.171 and 0.238) in the training (independent) sample, while that of the best scheme of the LTP_DSEF model is 0.198 (0.266).

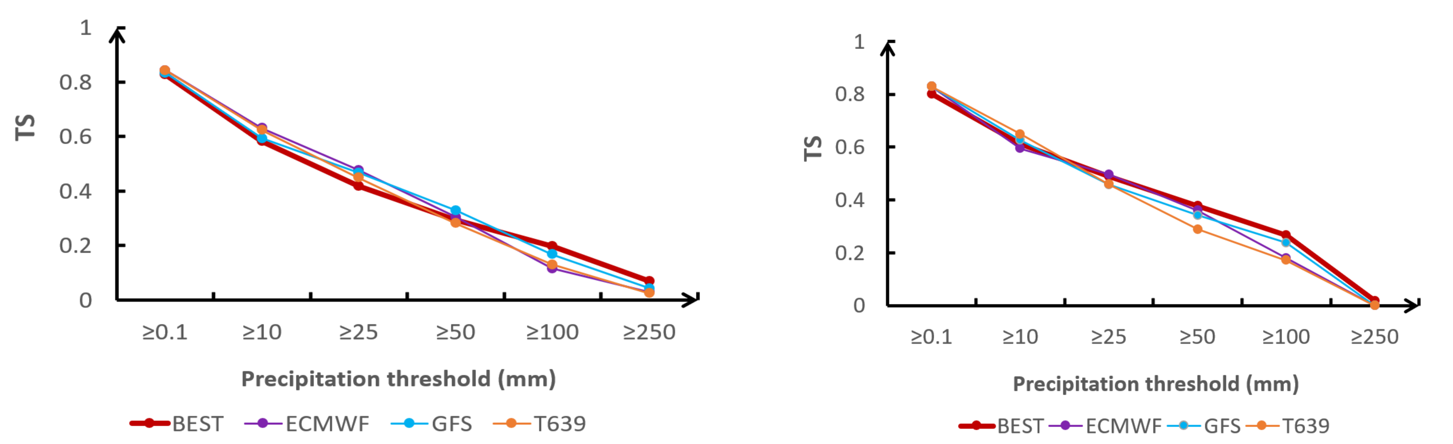

Figure 8. Comparison of the threat scores at different rainfall levels for the best scheme of the LTP_DSEF model (BEST) and the three dynamical models (ECMWF, GFS, and T639).
a) training sample; b) independent sample

Summary

(1) "Track-similarity-based Landfalling Tropical cyclone Precipitation Dynamical -Statistical Ensemble Forecast (LTP_DSEF) model" has been preliminarily developed.

(2) The application of the LTP_DSEF model shows that the performance of LTP_DSEF model is better than the three NWP global models.

(3) This is just a start, and it is believed that the LTP_DSEF model will have a bright future.

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