An Initialization Scheme for Weak Tropical Cyclones in the South China Sea

Jihang LI, Qilin WAN*, Daosheng XU, Yanyan HUANG, and Xubin ZHANG

Guangzhou Institute of Tropical and Marine Meteorology, China Meteorological Administration, Guangzhou 510640

(Received April 20, 2020; in final form November 5, 2020)

ABSTRACT

Variations in the initial structure of tropical cyclones (TCs) inevitably affect prediction results; however, the bogus model cannot accurately describe the structure of a weak tropical cyclone with increased initial field resolution. This study aims to construct a model to improve the prediction of weak TC in southern China. Based on the ECMWF 0.1° analysis data, several vortices were filtered out from tropical depressions and tropical storms in 2018 and 2019 to represent a weak TC reservoir in the South China Sea. For different simulation objects, filtered vortices were combined with the TC environmental field to form ensemble members. The observed TC information was assimilated for simulating TCs Bebinca, Mun, and Ewiniar to verify the feasibility of the proposed model, based on the Global/Regional Assimilation and Prediction Enhanced System (GRAPES) 9-km model developed by the Guangzhou Institute of Tropical and Marine Meteorology. The results show that the initialization scheme of the weak tropical cyclone model improved the intensity prediction of the TC by 26.81% (Bebinca), 18.65% (Mun), and 47.00% (Ewiniar), compared with the control experiment. Because typhoon intensity forecasting has not notably improved for many years, this scheme has certain scientific and operational significance.

Key words: tropical cyclones (TCs), intensity forecast, initialization scheme for weak TC

Citation: Li, J. H., Q. L. Wan, D. S. Xu, et al., 2021: An initialization scheme for weak tropical cyclones in the South China Sea. J. Meteor. Res., 35(2), 358–370, doi: 10.1007/s13351-021-0069-3.

1. Introduction

Approximately 80 tropical cyclones (TCs) occur annually in oceans worldwide; the Northwest Pacific has the highest storm frequency, containing one-third of all TCs (Jin et al., 2018). The 18,800-km coastline of China is vulnerable to the approximately seven TCs that make landfall each year.

TCs in southern China develop from tropical depressions generated in the South China Sea or the Pacific Ocean. According to data obtained over the past 30 years, approximately three TCs hit the South China Sea annually; most occurred near the Xisha and Zhongsha Islands between 10° and 20°N, and 112° and 120°E, respectively. The prevailing TC season, from July to October, accounts for 79% of annual TCs, mostly north of 15°N. TCs are most prevalent in September (23% of the annual total) and are absent from December to April. The TCs that occasionally occur south of 15°N are different from most TCs occurring in August throughout the Northwest Pacific and indicate a lower occurrence of storms in September.

A TC in the South China Sea has a small range, with a mean radius of approximately 200 km, lower vertical height, weak intensity (maximum surface wind speeds range from 17.2 to 32.6 m s⁻¹ with gusts over 32.7 m s⁻¹), irregular shape, variable direction, unpredictable landing site, and landfall that often occurs less than two days or even half a day after formation. This is meteorologically called an “abnormal TC” and has a long-term ocean presence near the South China Sea Islands. TCs originate near the islands, which are also affected by TCs approaching from the ocean to the east of the Philippines. The islands in the South China Sea are, therefore, the most vulnerable areas in China.

In the South China Sea, 70% and 30% of the TCs that
hit the islands are passing and native TCs, respectively. Strong TCs destroy trees and building and scour, and subsequently deform sandbanks and islands. In 1941, a strong TC struck Taiping Island, causing immense waves and destroying houses. In 1970, the 13th TC hit the Xisha Islands with a wind force greater than 12 and duration of more than 40 h. Many trees and branches fell on the islands, the sandbank of Yongxing Island was partially eroded by wind and waves, and the island area was reduced in size. On the northeast and southeast banks of Chenhang Island, large pieces of coral debris with widths of 10–30 m and heights of 3–5 m were accumulated by wind and waves, thereby increasing the area of the island. TCs also affect sea navigation; therefore, accurately predicting TCs in the South China Sea will significantly reduce human casualties and reduce national economic property loss.

Current weak TC prediction in the South China Sea is inadequate, and weak TC structure does not adapt to the ideal bogus model (Huang et al., 2018; Li et al., 2018a). This study proposes an initialization scheme of a weak TC model to improve prediction. Existing 0.1° analysis data from the ECMWF were used to collect 30 tropical depressions and tropical storms in the South China Sea in 2018 and 2019. After filtering out the corresponding time-series vortices in the ECMWF analysis data, a weak TC reservoir in the South China Sea was formed. Thirty filtered vortices were combined with the filtered environmental field of the simulated object to form 30 TC ensemble samples. This method is called the weak TC model initialization scheme. To verify the feasibility of this scheme, three TCs (Bebinca, Mun, and Ewiniar) were simulated based on the Global/Regional Assimilation and Prediction Enhanced System (GRAPES) model and ensemble Kalman filter (EnKF). The simulation results of the control experiment and the bogus model (Yuan et al., 2011; Huang et al., 2016; Huang and Zheng, 2020), developed by the Guangzhou Institute of Tropical and Marine Meteorology, were compared to test the simulation effect of the weak TC model on the track and intensity of the three weak TCs.

2. Weak TC model initialization scheme

2.1 Vortex filtering

Weak TCs include tropical depressions, tropical storms, and severe tropical storms, with maximum surface wind speeds ranging from 10.8 to 32.6 m s⁻¹. The maximum observed wind speed of Bebinca and Mun at the beginning of the simulation (15 m s⁻¹) corresponds to a tropical depression, and the maximum observed surface wind speed of Ewiniar at the beginning of the simulation (18 m s⁻¹) falls into the tropical storm category. The TC reservoir in this research consequently comprises tropical depressions and tropical storms; therefore, TCs with maximum surface wind speeds ranging from 10.8 to 24.4 m s⁻¹ were collected.

The ECMWF analysis data utilized by the Guangzhou Institute of Tropical and Marine Meteorology of the China Meteorological Administration were upgraded to 1131 × 681 (increased to 0.1°) and ranged from 12°S to 56°N and 58° to 171°E beginning at 0000 UTC 25 January 2018. Data (0000 and 1200 UTC) were obtained daily. To facilitate the data format, 30 TCs in the South China Sea were collected with a maximum observed surface wind speed range of 10.8–24.4 m s⁻¹ from 25 January 2018 to 31 December 2019. At each time, the ECMWF 0.1° analysis field was used, the area within 400 km of the TC center was filtered out and saved as a vortex field, and the 30 time points corresponded to 30 vortex fields. For identification, the 30 vortex fields were named V₁, V₂, V₃, ..., V₃₀, and constituted the weak TC reservoir.

The vortex filtration scheme by Kurihara et al. (1995) is introduced below.

First, the disturbance field is separated by horizontal filtering from the ECMWF analysis field; then, the vortex circulation is separated by cylindrical filtering from the disturbance field. A three-point smoothing scheme is adopted for horizontal filtering, and the smoothing coefficient is as follows:

\[
\eta = \frac{1}{2} \left( 1 - \cos \frac{2\pi}{m} \right)^{-1},
\]

where \( m = 2, 3, 4, 5, 6, 7, 8, 9, 10 \); 11 continuous filtering times are created by latitude and longitude to obtain the disturbance field \( h_D \). The column filter is used to separate the vortex circulation \( h_V(r, \theta) \):

\[
h_V(r, \theta) = [1 - E(r)] [h_D(r, \theta) - \bar{h}_D(r_0)],
\]

where \( \bar{h}_D(r_0) \) is the average angle of \( h_D \) at the wind radius \( r_0 \). \( E(r) \) is the cylindrical filter function:

\[
E(r) = \frac{\exp \left( -(r - r_0)^2 / l^2 \right) - \exp \left( -r_0^2 / l^2 \right)}{1 - \exp \left( -r_0^2 / l^2 \right)},
\]

where \( r \) is the radius from the center of the vortex, and \( l \) is the parameter controlling the shape, \( l = r_0/5 \).

After obtaining the vortex disturbance circulation, the large-scale environmental field \( h_E \) is obtained:

\[
h_E = h - h_V,
\]

where \( h \) is the initial model prediction (ECMWF analysis)
According to the above method, the vortex and environmental field of the weak TC case (sample 31) must be separated to be simulated in the same way. For convenience, the filtered vortex field of the 31st sample (V_{31}) is not used. The corresponding environmental field (E_{31}) is applied in the next combination step.

Table 1 shows the specific information of the 30 weak TC samples collected in this study. For example, 2019070112 represents 1200 UTC 1 July 2019.

Figures 1 and 2 show the geopotential height field and temperature field distributions of the 30 filtered vortices at 500 hPa, respectively, demonstrating highly significant differences among the samples. The centers of the vortices for the height and temperature fields are significantly negative and positive, respectively.

Figure 3 shows the 10-m wind field distribution of the filtered vortices. The different shapes and lack of obvious symmetry of the 30 vortices reflect the structural characteristics of weak TCs (Li et al., 2018a).

2.2 Vortex and environmental field synthesis

After the filtering scheme successfully separated the vortex and the environmental field, the 30 vortices (V_1, V_2, V_3, ..., V_{30}) and the environmental field (E_{31}) of the simulated TC were synthesized to obtain 30 ensemble samples.

The following is a clarification of the sample synthesis principle: the variable \( A \) (including temperature, height, \( u \) wind speed, \( v \) wind speed, or specific humidity) can be divided into \( \bar{A} \) and \( A' \), where \( \bar{A} \) and \( A' \) are the average and disturbing components of \( A \), respectively.

\[
A = \bar{A} + A'.
\]

For the synthesized sample, \( \bar{A} \) corresponds to the variables in the filtered environmental field (E_{31}) of the 31st sample, and \( A' \) corresponds to one of the 30 samples (V_1 or V_2 or V_{30}).

According to the steps outlined above, all 30 samples (M_1, M_2, M_3, ..., M_{30}) were synthesized.

2.3 Tropical region assimilation model for the South China Sea (TRAMS) and EnKF assimilation

The TRAMS is an operational forecasting system developed based on the GRAPES regional model to provide TC numerical prediction products in the South China Sea for coastal southern China. The latitude range of the model is 0.8°–50.57°N and the longitude range is 81.6°–160.89°E, which covers the Northwest Pacific and the South China Sea regions. Currently, the horizontal

| Number | Time      | TC (numbering) | Minimum sea level pressure (hPa) | Maximum surface wind speed (m s\(^{-1}\)) |
|--------|-----------|----------------|----------------------------------|------------------------------------------|
| 1      | 2019070112| Mun (1904)     | 995                              | 15                                       |
| 2      | 2019070200| Mun (1904)     | 995                              | 15                                       |
| 3      | 2019070212| Mun (1904)     | 995                              | 15                                       |
| 4      | 2019073012| Wipha (1907)   | 996                              | 15                                       |
| 5      | 2019082800| Podul (1912)   | 998                              | 18                                       |
| 6      | 2018123112| Pabuk (1901)   | 1004                             | 13                                       |
| 7      | 2018071700| Son-Tinh (1809)| 995                             | 18                                       |
| 8      | 2018071712| Son-Tinh (1809)| 992                             | 20                                       |
| 9      | 2019083112| Kajiki (1914)  | 1002                             | 15                                       |
| 10     | 2018111700| Toraji (1827)  | 1006                             | 14                                       |
| 11     | 2018061412| Gaemi (1806)   | 994                              | 15                                       |
| 12     | 2018061500| Gaemi (1806)   | 994                              | 15                                       |
| 13     | 2018061512| Gaemi (1806)   | 994                              | 15                                       |
| 14     | 2018061600| Gaemi (1806)   | 992                              | 18                                       |
| 15     | 2019090100| Kajiki (1914)  | 1002                             | 15                                       |
| 16     | 2018080712| Yagi (1814)    | 1000                             | 15                                       |
| 17     | 2018080800| Yagi (1814)    | 1000                             | 15                                       |
| 18     | 2018080812| Yagi (1814)    | 998                              | 18                                       |
| 19     | 2018080900| Yagi (1814)    | 998                              | 18                                       |
| 20     | 2018080900| Bebinca (1816)| 998                              | 14                                       |
| 21     | 2019090112| Kajiki (1914)  | 1002                             | 15                                       |
| 22     | 2019090200| Kajiki (1914)  | 998                              | 15                                       |
| 23     | 2019090212| Kajiki (1914)  | 995                              | 15                                       |
| 24     | 2019102900| Matmo (1922)   | 1003                             | 15                                       |
| 25     | 2019102912| Matmo (1922)   | 1003                             | 15                                       |
| 26     | 2019122200| Phanfone (1929)| 998                             | 18                                       |
| 27     | 2018062812| Prapiroon (1807)| 1004                           | 15                                       |
| 28     | 2018062900| Prapiroon (1807)| 998                            | 18                                       |
| 29     | 2018062912| Prapiroon (1807)| 995                            | 20                                       |
| 30     | 2019110412| Nakri (1924)   | 1002                             | 15                                       |
resolution of the TRAMS model is 9 km, the vertical direction adopts 65 levels of terrain following coordinates, and the top height of the model layer is 31 km. Physical process schemes include the Weather Research and Forecasting (WRF) model single-moment 6-class microphysics scheme (WSM6) microphysical process, simplified Arakawa–Schubert (SAS) convection parameterization, medium-range forecast model (MRF) boundary layer parameterization, five-layer slab soil model (SLAB) land surface process, and Rapid Radiative Transfer Model for global climate models (RRTMG) long and short wave radiation scheme. In this model, the initial boundary conditions for generating analytical and prediction fields were created by using the ECMWF 0.1° analysis data.

EnKF has been widely used in previous studies owing to its better availability and effectiveness at various weather scales (Zhang et al., 2004; Meng and Zhang, 2008a, b; Zhu et al., 2016; Li et al., 2018b, c). The WRF-based EnKF system was first developed for regional-scale data assimilation by Meng and Zhang (2008a, b). The control variables are stream function, velocity potential, and unbalanced pressure. The perturbed variables include horizontal wind components \( (u, v) \), potential temperature, and mixing ratio for water vapor (QVAPOR); standard deviations are 2 m s\(^{-1}\) for wind, 1 K for temperature, and 0.5 g kg\(^{-1}\) for mixing ratio (Meng and Zhang, 2008a, b). Similar perturbations have been used to represent the boundary condition uncertainties of the ensemble. The covariance relaxation method proposed by Zhang et al. (2004) was used to inflate the background error covariance with a relaxation coefficient of 0.8. According to Zhu et al. (2016), the prognostic variables of perturbation potential temperature \( (\bar{T}) \), vertical velocity \( (\bar{W}) \), horizontal wind components \( (\bar{U} \text{ and } \bar{V}) \), QVAPOR, cloud water (QCLD), rainwater (QRAIN), perturbation geopotential (PH), perturbation dry air mass in the column (MU), surface pressure (PSFC), and perturbation pressure \( (\bar{P}) \) were updated. The horizontal length of the covariance localization was set to 30 km, whereas the vertical length of the covariance localization was set to
six layers. In the following experiments, the observed track and intensity of the TCs were assimilated.

3. Result analysis of individual experiments

This section reviews the TC observations. The first simulation was of the 16th TC Bebinca, in 2018. Bebinca had a complex track, long life history, multiple landings, and heavy rainfall. The storm made landfall in Hainan, moved northeast, made landfall in Yangjiang, moved southwest, turned southeast, and moved slowly to the west of Guangdong Province, with more than two offshore gyrations. Bebinca lasted for more than eight days from 0000 UTC 9 August 2018, far longer than any other TC in South China Sea.

The second simulation conducted in this study was of the fourth TC Mun, in 2019. Mun made landfall in the coastal area of Hele Town, Wanning City, Hainan Province at 1645 UTC 2 July. Maximum surface wind speed and minimum sea level pressure at landfall were 18 m s\(^{-1}\) and 992 hPa, respectively. Mun moved from the vicinity of Sigeng Town, Dongfang City towards the Beibu Gulf, approached the northern coast of Vietnam, and made landfall again in the coastal area of Taiping Province in Vietnam at 2245 UTC 3 July. Maximum surface wind speed and minimum sea level pressure at landfall remained at 18 m s\(^{-1}\) and 992 hPa, respectively.

The third simulation was of the fourth TC Ewiniar, in 2018. Ewiniar made first landfall in Xinliao Town, Xuwen County, Zhanjiang City in Guangdong Province at 2225 UTC 5 June 2018 and made a second landfall on the coast of Haikou City at 0650 UTC 6 June. Maximum surface wind speed and minimum sea level pressure at first landfall were 18 m s\(^{-1}\) and 995 hPa, respectively. The storm made a third landfall in the coastal area of Yangjiang in Guangdong Province, at approximately 1230 UTC 7 July. Maximum surface wind speed and minimum sea level pressure were 20 m s\(^{-1}\) and 995 hPa, respectively.

The simulation period of the three TCs was 48 h (from 0000 UTC 10 to 0000 UTC 12 August 2018 for Bebinca, from 1200 UTC 1 to 1200 UTC 3 July 2019 for Mun,

![Fig. 2. As in Fig. 1, but for temperature field distribution (°C).](image-url)
The E31 environmental field was obtained after the separation of the vortex and environmental field of the 31st sample (Fig. 4; see Section 2.1).

In accordance with the method described in Section 2.2, the vortex was combined with the environmental field. Take Bebinca for example, Fig. 5 shows the 10-m wind field of the 30 samples combined with 30 vortices (V1, V2, ..., V30) and the new environmental field (E31). The combinations differ markedly but are all in the weak TC category.

The bogus model experiment was conducted to compare the effect of the initialization scheme of the weak TC model. For convenience, the control experiment, bogus model experiment, model initialization scheme, and observation are denoted as C, B, M, and O, respectively.

For TC Bebinca, the central boundary of the TC constructed by the bogus model was clear, and the area of maximum surface wind speed was east of the center (Fig. 6a). Compared with the initial ECMWF field (Fig. 4a), the TC circulation in the analysis field was clearly enhanced, and the maximum surface wind area was transferred from south side of the circulation center to the east side. The intensity of the analysis field obtained by the weak TC model was weaker than that of the initial ECMWF field (Fig. 6b).

For Mun, the TC constructed by the bogus model was quite symmetrical with a well-defined center and regular circulation (Fig. 6c). This was stronger than that of the initial field of ECMWF analysis data (Fig. 4d). The circulation pattern obtained by M (Fig. 6d) was relatively similar to that of the initial ECMWF field, and the scope of the TC center narrowed.

TC Ewiniar constructed by B was quite symmetrical, with a well-defined eye area (Fig. 6e); the circulation intensity was obviously stronger than that of the analysis field in Fig. 4g. The circulation pattern of M was similar to that of the initial ECMWF field, but the intensity of the wind field in southeast of the center was slightly en-
Fig. 4. The 10-m wind (m s$^{-1}$) fields. The first column represents the wind field before filtering (the initial ECMWF field); the second column represents the environmental wind field after filtering; and the third column vortex represents the wind field after filtering. The times represented by the three columns from left to right are 0000 UTC 10 August 2018, 1200 UTC 1 July 2019, and 0000 UTC 5 June 2018.

For Bebinca (Fig. 7a), the analysis increase of the bogus model was evident compared with that of the control experiment for the wind and height fields. The height field decreased significantly, whereas the northerly wind in the wind field increased significantly. Figure 7b indicates that the decrease in the height field of the weak TC model (compared with that of the control experiment) helped enhance vortex strength. The counterclockwise circulation of the wind field increase also affected vortex
For Mun, the analysis increase of B in Fig. 7c was significant; the height field decreased considerably, whereas the wind field strongly converged and diverged on the west and east sides of the TC center, respectively. Compared with C, the height field of M (Fig. 7d) decreased, thereby enhancing vortex intensity. Simultaneously, the wind field weakly converged and diverged to the west.

Fig. 5. The 10-m wind (m s$^{-1}$) fields after combining the 30 vortices and the environmental field at 0000 UTC 10 August 2018.
Fig. 6. The 10-m wind ($\text{m s}^{-1}$) fields at (a, b) 0000 UTC 10 August 2018, (c, d) 1200 UTC 1 July 2019, and (e, f) 0000 UTC 5 June 2018. The first column represents the bogus model wind field; the second column represents the wind field after EnKF.
and east of the TC center, respectively.

For Ewiniar, the analysis increment of B in Fig. 7e was significant (compared with C) for the wind and height fields. The height field decreased significantly and
the northerly wind in the wind field increased significantly. The south side of the eye area experienced substantial divergence. The decreased height field (Fig. 7f) of the weak TC model (compared with that of the control experiment) enhanced vortex strength, and the increased wind field offset the counterclockwise circulation and affected vortex intensity.

Figures 8–9 and Tables 2–3 show the simulated results of the control experiment, the bogus experiment, and the weak TC model.

The observed track of Bebinca was complex, but the three experiments captured the recurving features (Fig. 8a). However, the details of the three simulated tracks differed significantly, and the TCs were tracked in the model at 850 hPa, according to the geopotential height.

Compared with that of B and M, the track error of C had the largest deviation from the observation (Table 2). The track of B was relatively simple. The track of M had the smallest deviation, with a shape more similar to that of the observation. B was closest to the observed track, and the track of Mun simulated by M did not improve (Fig. 8b; Table 2). For Ewiniar, the initial error of M was smaller than that of C and gradually increased; the deviation of B was more significant (Fig. 8c).

B had the largest intensity error compared with that of the observation, and the simulated intensity of Bebinca was significantly stronger (Fig. 9a). The observed and simulated intensities of M were similar to those of C, and both were stronger than those of the observation. The intensity error of M was smaller than that of B. Therefore, M improved the track and intensity simulation of TC Bebinca.

The initial error of M for the simulation of Mun was smaller then gradually larger than that of C (Fig. 9b). The intensity error curve trend of M was very similar to that of C, and both were weaker than the observed intensity of Mun. The intensity simulated by M was slightly stronger than that of C, and the error decreased. However, the intensity trend of B was markedly different from that of M and C. The simulated Mun of B was initially significantly stronger than that of the observation but closer to that of the observation when intensity weakened.

For Ewiniar, the intensity error of M was significantly lower than that of C and B (Fig. 9c; Table 3). The simulation intensity was significantly improved by M, especially in the first 24 h; thus, the simulated track did not
improve significantly, but the simulated intensity did significantly improve.

4. Conclusions

Initial storm structure and intensity are essential for TC prediction. This study proposes a feasible scheme to improve the initial structure of a weak TC. The corresponding vortices of tropical depressions and tropical storms in the South China Sea in 2018 and 2019 were filtered to form a weak TC reservoir based on existing ECMWF 0.1° analysis data. The 30 vortices were then combined with the environmental field filtered by the TC and simulated to form 30 ensemble members. Based on the TRAMS model, the samples were assimilated by EnKF to simulate three TCs (Bebinca, Mun, and Ewiniar). The initialization scheme of the weak TC model improved the intensity prediction of the three TCs compared to that of the control experiments and bogus model, possibly owing to the three-dimensional typhoon structure employed by this scheme. Furthermore, the initialization scheme of the weak TC model improved intensity prediction by 26.81% (Bebinca), 18.65% (Mun), and 47.00% (Ewiniar), compared with that of the control experiment; therefore, the scheme partially improved TC intensity. The typhoon intensity forecast has not significantly improved for many years; therefore, this scheme has scientific and operational significance.

The track simulation of Bebinca improved, but the track prediction effects of Mun and Ewiniar were poor. Therefore, improving intensity and track simulation is particularly important in future work. Because of the limited number of samples, the synthesized samples were fixed for the three simulation objects. The intensities of Bebinca, Mun, and Ewiniar were similar, but the initial structures were not. Until now, the ECMWF 0.1° analysis data were only available for 2018 and 2019, during which time the few weak TCs in the South China Sea often lacked data. Therefore, the number of samples was insufficient, but the situation will improve with time. The increased future occurrence of weak TCs in the South China Sea will increase the members of the weak TC reservoir. The samples and TCs should be adjusted as the TC reservoir expands. For example, according to minimum air pressure, maximum surface wind speed, or simulated object structure, 30 similar samples can be synthesized from the weak TC reservoir to significantly improve the simulation effect compared to that of the fixed weak TC reservoir.

REFERENCES

Huang, Y. Y., and B. Zheng, 2020: Tropical cyclone structure in the South China Sea based on high-resolution reanalysis data and comparison with that of ‘bogus’ vortices. Dyn. Atmos. Oceans, 89, 101128, doi: 10.1016/j.dynatmoce.2019.101128.

Huang, Y. Y., Z. T. Chen, G. F. Dai, et al., 2016: Investigation on effects of initial schemes for binary Typhoons Roke and Sonca in 2011. J. Trop. Meteor., 22, 1–14, doi: 10.16555/j.1006-8775.2016.S1.001.
Huang, Y. Y., J. S. Xue, Y. R. Feng, et al., 2018: An initialization scheme using forecast vortexes and its application in simulation of Typhoons Linfa and Chan-hom in 2015. *J. Trop. Meteor.*, 34, 598–609, doi: 10.16032/j.issn.1004-4965.2018.05.003. (in Chinese)

Jin, S. L., S. H. Wu, Z. Q. Liu, et al., 2018: Regional discrepancies of the impact of tropical Indian Ocean warming on northwest Pacific tropical cyclone frequency in the years of decaying El Niño. *J. Trop. Meteor.*, 24, 314–322, doi: 10.16555/j.1006-8775.2018.03.005.

Kurihara, Y., M. A. Bender, R. E. Tuleya, et al., 1995: Improvements in the GFDL hurricane prediction system. *Mon. Wea. Rev.*, 123, 2791–2801, doi: 10.1175/1520-0493(1995)123<2791:IITGHP>2.0.CO;2.

Li, J. H., Y. Y. Huang, and Q. L. Wan, 2018a: Comparative analysis of tropical cyclone’s structure between ECMWF high resolution reanalysis data and Bogus model in 2015. *J. Trop. Meteor.*, 34, 48–58, doi: 10.16032/j.issn.1004-4965.2018.01.005. (in Chinese)

Li, J. H., Y. D. Gao, and Q. L. Wan, 2018b: Sample optimization of ensemble forecast to simulate a tropical cyclone using the observed track. *Atmosphere-Ocean*, 56, 162–177, doi: 10.1080/07055900.2018.1500881.

Li, J. H., Q. L. Wan, Y. D. Gao, et al., 2018c: The effect of sample optimization on the ensemble Kalman filter in forecasting Typhoon Rammasun (2014). *J. Trop. Meteor.*, 24, 433–447, doi: 10.16555/j.1006-8775.2018.04.003.

Meng, Z. Y., and F. Q. Zhang, 2008a: Tests of an ensemble Kalman filter for mesoscale and regional-scale data assimilation. Part III: Comparison with 3DVAR in a real-data case study. *Mon. Wea. Rev.*, 136, 522–540, doi: 10.1175/2007MWR2106.1.

Meng, Z. Y., and F. Q. Zhang, 2008b: Tests of an ensemble Kalman filter for mesoscale and regional-scale data assimilation. Part IV: Comparison with 3DVAR in a month-long experiment. *Mon. Wea. Rev.*, 136, 3671–3682, doi: 10.1175/2008MWR2270.1.

Xu, D. S., B. L. Zhang, Q. C. Zeng, et al., 2019: A typhoon initialization scheme based on incremental analysis updates technology. *Acta Meteor. Sinica*, 77, 1053–1061, doi: 10.11676/qxxb2019.060. (in Chinese)

Yuan, J. N., L. L. Song, Y. Y. Huang, et al., 2011: A method of initial vortex relocation and numerical simulation experiments on tropical cyclone track. *J. Trop. Meteor.*, 17, 36–42.

Zhang, F., C. Snyder, and J. Z. Sun, 2004: Impacts of initial estimate and observation availability on convective-scale data assimilation with an ensemble Kalman filter. *Mon. Wea. Rev.*, 132, 1238–1253, doi: 10.1175/1520-0493(2004)132<1238:IOIEOA>2.0.CO;2.

Zhu, L., Q. L. Wan, X. Y. Shen, et al., 2016: Prediction and predictability of high-impact western Pacific landfalling Tropical Cyclone Vicente (2012) through convection-permitting ensemble assimilation of Doppler radar velocity. *Mon. Wea. Rev.*, 144, 21–43, doi: 10.1175/MWR-D-14-00403.1.