Front. Earth Sci. 2019, 13(4): 733–743
https://doi.org/10.1007/s11707-019-0794-4

RESEARCH ARTICLE

Ensemble data assimilation and prediction of typhoon and associated hazards using TEDAPS: evaluation for 2015–2018 seasons

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Abstract The initial condition accuracy is a major concern for tropical cyclone (TC) numerical forecast. The ensemble-based data assimilation techniques have shown great promise to initialize TC forecast. In addition to initial condition uncertainty, representing model errors (e.g. physics deficiencies) is another important issue in an ensemble forecasting system. To improve TC prediction from both deterministic and probabilistic standpoints, a Typhoon Ensemble Data Assimilation and Prediction System (TEDAPS) using an ensemble-based data assimilation scheme and a multi-physics approach based on Weather Research and Forecasting (WRF) model, has been developed in Shanghai Typhoon Institute and running real-time since 2015. Performance of TEDAPS in the prediction of track, intensity and associated disaster has been evaluated for the Western North Pacific TCs in the years of 2015–2018, and compared against the NCEP GEFS.

TEDAPS produces markedly better intensity forecast by effectively reducing the weak biases and therefore the degree of underdispersion compared to GEFS. The errors of TEDAPS track forecasts are comparative with (slightly worse than) those of GEFS at longer (shorter) forecast leads. TEDAPS ensemble-mean exhibits advantage over deterministic forecast in track forecasts at long lead times, whereas this superiority is limited to typhoon or weaker TCs in intensity forecasts due to systematical underestimation. Four case-studies for three landfalling cyclones and one recurving cyclone demonstrate the capacities of TEDAPS in predicting some challenging TCs, as well as in capturing the forecast uncertainty and the potential threat from TC-associated hazards.

Received March 31, 2019; accepted September 20, 2019

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Keywords ensemble data assimilation, ensemble forecasting, tropical cyclones

1 Introduction

Tropical Cyclones (TCs) can cause a tremendous disaster through extreme rainfall, severe floods, and damaging winds. Track is the most key factor for determining TC disasters as it is related to landfall. Although there has been a steady decrease in track forecast error, large uncertainties still exist in the operational forecasts mainly caused by TC sharp recurvatures (Peng et al., 2015), let alone the less skill in intensity, structure and rainfall prediction. Numerical prediction of TCs continues to be a challenging and hot topic.

Recently, ensemble Kalman filter (EnKF) and EnKF-Variational hybrid techniques have gained considerable attention for TC initialization (Zhang et al., 2009; Torn 2010; Wang, 2011; Yang et al., 2012). These ensemble-based data assimilation (EDA) techniques are potentially able to recognize the existence of TC vortex, adjust its position and amplitude, better describe the asymmetric structure of TC and maintain the dynamic and thermodynamic balance in the initial field due to the involved flow-dependent ensemble background error covariance (Cavallo et al., 2013; Li et al., 2015). In TCs application, the way that EDA assimilated observations influence their surrounding area is a function of the cyclone flow pattern which provides especially attractive benefits for vortex initialization. EDA has shown great promise in improving TC track and intensity forecast (e.g. Hamill et al., 2011; Aberson et al., 2015) as well as associated hazard forecast, such as precipitation and wind (Zhang and Weng, 2015).

Since the model forecast will never be "perfect," ensemble forecasting continues to be essential to operational early warning. It shifts away from deterministic forecast toward the uncertainty and probability of the alerts which are useful for communities and governments in determining disaster actions (Nakamura et al., 2015). The EDA method has the inherent facility to initialize an ensemble forecasting and to produce probabilistic forecasts by using its analyzed ensemble members.

Aiming at improving TC numerical forecast and providing associated disaster information through advanced data assimilation and ensemble forecasting, Shanghai Typhoon Institute (STI) has developed a Typhoon Ensemble Data Assimilation and Prediction System (TEDAPS), put it into real-time run since 2015. This article evaluates its performance in the 2015–2018 Western North Pacific TC seasons.

The rest of the manuscript is organized as follows. Section 2 provides a description of TEDAPS system and involved strategies. The performance of TEDAPS relative to GEFS on track and intensity is presented in Section 3. Results of wind and rainfall forecasts for two TC cases are described. Section 5 provides conclusions and discussion.

2 The real-time TEDAPS

2.1 Data assimilation

TEDAPS includes a data assimilation system based on the Grid-point Statistical Interpolation (GSI) system and a three-dimensional ensemble-variational (3DEnsVar) hybrid assimilation scheme. The hybrid system combines ensemble background error covariance (BEC) with static BEC by modifying the cost function and extending the control variable. For mathematical details of GSI-based hybrid, readers are referred to Wang (2010) and Luo et al. (2013). In its real-time application, TEDAPS uses 20 ensemble members plus one unperturbed control member (control or deterministic forecast, hereafter). The initial background fields and lateral boundary conditions (LBCs) for the control are taken from the NCEP Global Forecast System (GFS) $0.5^\circ \times 0.5^\circ$ products and pre-processed into the Advanced Research core of the Weather Research and Forecasting (ARW-WRF) model. The background ensemble perturbations are obtained by subtracting each ensemble member of the NCEP Global Ensemble Forecast System (GEFS) $1.0^\circ \times 1.0^\circ$ products from their mean and then interpolated to TEDAPS 27 km domain. The control background and the 20 ensemble members are inputted into the 3DEnsVar hybrid assimilation system. More details of this system are summarized in Li et al. (2015, cold-start approach therein) where the system has been successfully applied to a real typhoon case and obtained promising results.

Observations assimilated include rawinsondes, stations, ships, buoys, aircraft, real-time estimates of TC position and minimum seal level pressure (TCVitals), and microwave satellite radiance (AMSU). The full ensemble BEC approach is used in 3DEnsVar, i.e. zero weight to static BEC and 100% weight to ensemble BEC.

2.2 WRF ensemble forecasting

TEDAPS issues 72 h forecasts twice daily at 0000 and 1200 UTC. Each TC case includes 20 ensemble forecasts plus one control forecast. After data assimilation, the 21 ensemble members are updated and then advanced 72 h using ARW-WRF with horizontal grid spacing of 27-km and 36 vertical levels. The version of WRF used in 2015–2017 was 3.3 and updated to 3.9.1 in 2018. For the control forecast, the following physics are applied: Rapid Radiative Transfer Model (RRTM) longwave radiation, the Dudhia shortwave radiation, Thompson microphysics, Kain-Fritsch cumulus convection with trigger, Yonsei University (YSU) planetary boundary layer, Unified Noah land-surface physics, and Monin-Obukhov surface-layer physics. For the 20 ensemble forecasts, the combination of multiple physical schemes is listed in Table 1, other non-listed physics are the same with the control forecast. Our choices of parameterizations are somewhat arbitrary, aiming to provide additional ensemble diversity to partially account for model errors. Thus, the uncertainties in the initial conditions (ICs) and model physics are both considered in TEDAPS.

Table 1 Summary of physical schemes for TEDAPS ensemble forecasting

Ensemble members	Microphysics	Cumulus	Boundary layer	Surface-layer
1–6	Thompson	Kain-Fritsch	YSU	Monin-Obukhov
7–8	Thompson	Kain-Fritsch	MYJ	Monin-Obukhov (Janjic)
9–10	Thompson	Betts-Miller-Janjic	YSU	Monin-Obukhov
11–12	Thompson	Betts-Miller-Janjic	MYJ	Monin-Obukhov (Janjic)
13–14	WSM-6	Kain-Fritsch	YSU	Monin-Obukhov
15–16	WSM-6	Kain-Fritsch	MYJ	Monin-Obukhov (Janjic)
17–18	WSM-6	Betts-Miller-Janjic	YSU	Monin-Obukhov
19–20	WSM-6	Betts-Miller-Janjic	MYJ	Monin-Obukhov (Janjic)

2.3 Uncertainty products

Besides deterministic forecast products (not shown), TEDAPS produces various uncertainty and probability products for track, intensity, wind, and rainfall forecasts (Fig. 1). Hit probability is calculated as the ratio of counted ensemble number to the total ensemble number at each model grid point within a 400-km radius of cyclone position. The wind probability is defined as probability of 10-m wind speed at least 17.2, 24.5, or 32.7 m/s for every 12-h forecast time interval, while the cumulative wind probability represents the wind probability over the entire 72-h forecast period. Similarly, various precipitation probabilities of daily precipitation (0–24 h, 24–48 h, 48–72 h) and 0–72 h total precipitation are designed.

3 Performance of TEDAPS on track and intensity

3.1 General verification

The performance of TEDAPS on track and intensity forecast for 2015–2018 TC cases were verified and compared with NCEP GEFS at T574L64 (~34 km at equator) resolution in 2016–2018 and T254L42 (~70 km at equator) resolution in 2015. The cyclones track and intensity data of GEFS are available online through NCAR.

To ensure a fair or "homogeneous" comparison, the following criteria were applied: 1) the ensemble-mean was computed only if at least two-third of ensemble members predict 10-m maximum wind ($V_{\max}$ thereafter) exceeding 10.8m/s; 2) in comparison between two systems, both ensemble-mean forecasts must have been available; 3) the observed TC must have continued to be of at least tropical depression strength at the particular lead time being evaluated (Hamill et al., 2011). Total (869–710) homogeneous samples from 101 TCs were obtained for different lead times.

All forecast samples were evaluated against the post-processed best-track data estimated by CMA (Ying et al., 2014). Figure 2 shows the average absolute forecast errors verified against the best-track. Overall, The TEDAPS EM (ensemble-mean) track forecasts are slightly worse than those of GEFS EM over the first 60 h and seem to be comparable with GEFS at 66–72 h. Track forecasts in GEFS EM are more skillful than those in GEFS CNTL (control forecast) at all lead times, while TEDAPS EM outperforms its control at long leads. For the less improvement of ensemble-mean relative to its control in TEDAPS compared to that in GEFS, the reason is unclear but could be related to the different approaches used to represent model uncertainties in the two systems. TEDAPS uses multi-physics approach in which the choice of physics for the control forecast is "optimal" and there is no guarantee that the model ensemble perturbations among different physics are Gaussian distribution. In contrast, a stochastic total tendency perturbation, STTP, used in GEFS (Hou et al., 2008) should be more Gaussian. For intensity,

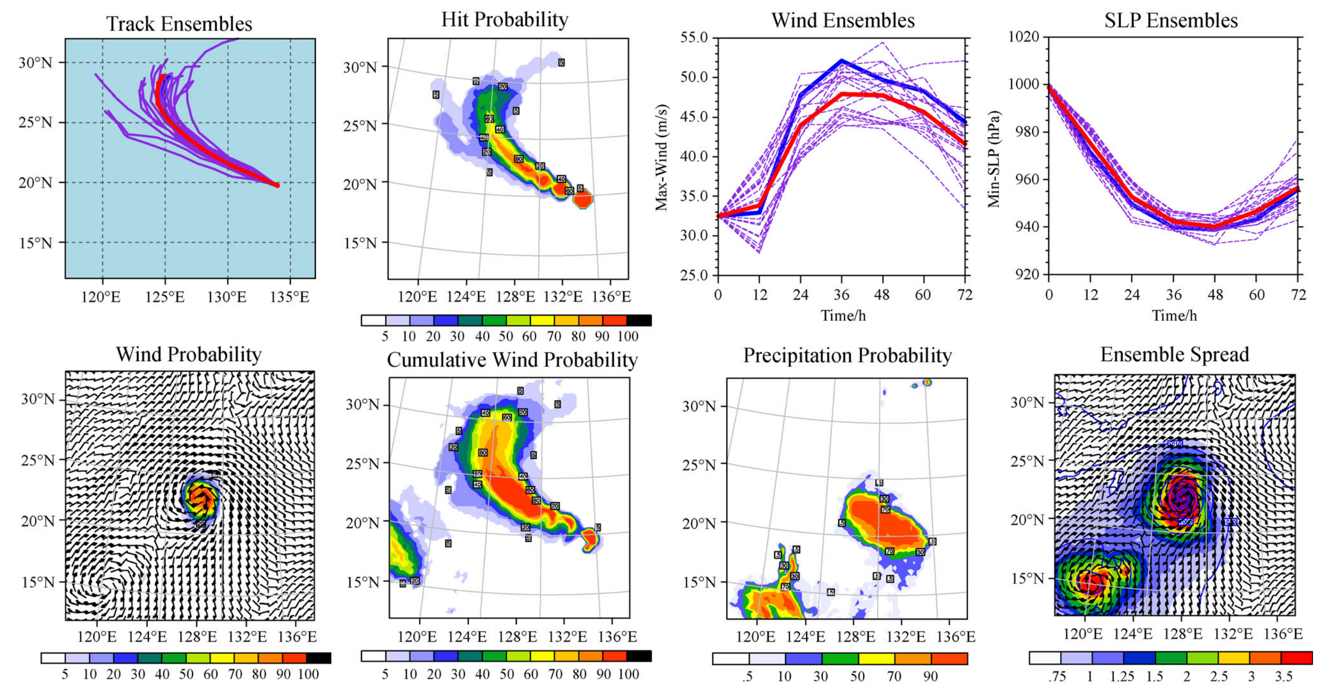

Fig. 1 Illustration of uncertainty products. Deterministic forecasts are denoted with blue, ensemble members with purple, ensemble-mean with red. Color-bars indicate values of probability (0–100%) in the plots of hit, wind and precipitation probabilities, and value of ensemble spread for a height or wind field at a specific vertical level (e.g. wind field at 850 hPa).

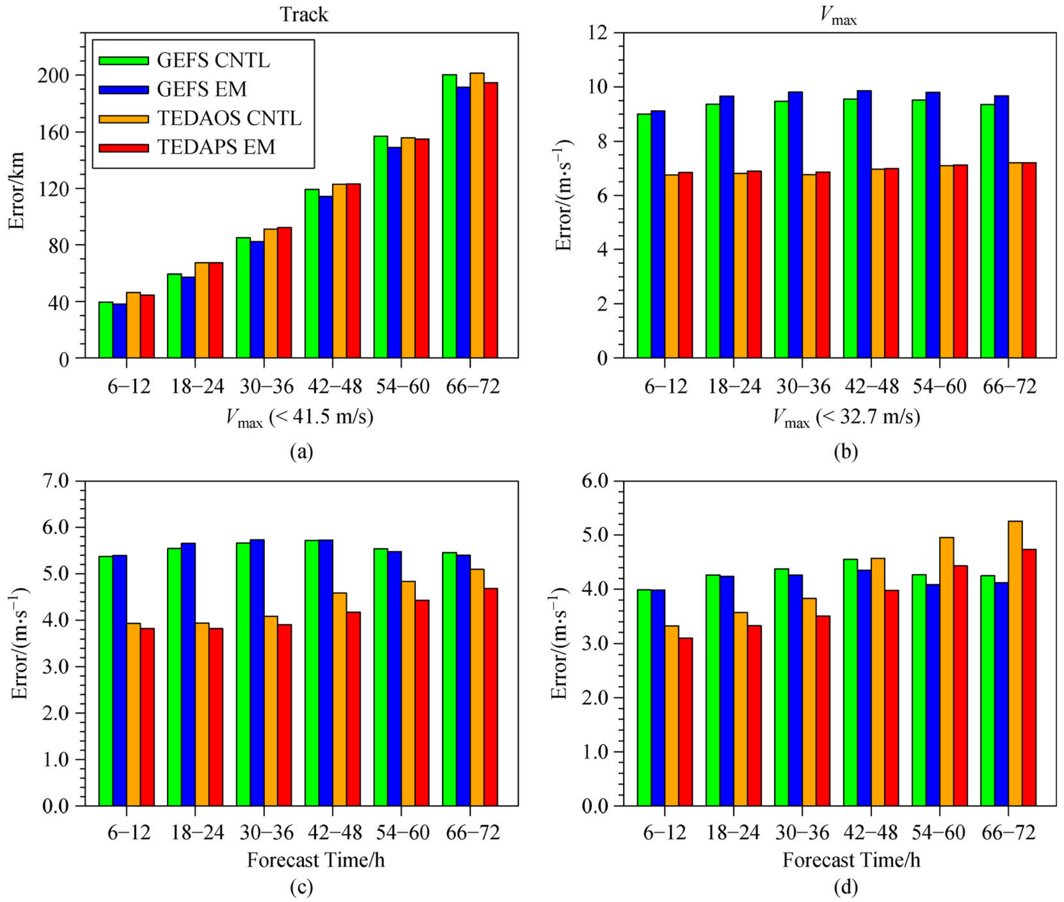

Fig. 2 Homogeneous comparison of average absolute errors of track (a) and V_{max} (b) as a function of forecast lead times for GEFS control forecast (green), GEFS ensemble mean (blue), TEDAPS control forecast (orange) and TEDAPS ensemble mean (red). For further comparisons, errors of V_{max} less than 41.5 m/s (c) or 32.7 m/s (d) are given.

TEDAPS dramatically outerperforms GEFS with much smaller V_{max} errors at all forecast lead times. We notice that unlike track forecast, the ensemble mean of intensity is slightly worse than the control forecast in both TEDAPS and GEFS. To understand this contradictory, the intensity forecasts were re-assessed for observed V_{max} less than 41.5 m/s (by excluding sever-typhoon and super-typhoon cases) and less than 32.7 m/s (by excluding typhoon, sever-typhoon and super-typhoon cases) (Figs. 2(c) and 2(d)) since large intensity errors in both TEDAPS EM and GEFS EM are dominated by large weak biases (Fig. 3) due to their insufficient resolutions. By excluding sever- and super-typhoon cases (< 41.5 m/s), the intensity errors of ensemble mean of TEDAPS are evidently lower than those in the control, while comparable errors are found between GEFS EM and its control. Considering more serious biases in GEFS EM (Fig. 3), we further excluded all typhoon and stronger cases (< 32.7 m/s). It is seen that ensemble-mean outperforms its control forecast in both two systems especially during longer lead times, while this improvement is more pronounced in TEDAPS than in GEFS. It is interesting to see better performance of GEFS at 54–72 h in this weak TCs scenario.

The absolute ensemble spreads of both TEDAPS and GEFS were calculated according to Hamill et al. (2011) and averaged over cases (Fig. 3). TEDAPS shows similar track spread with GEFS, both are somewhat underdispersed relative to their mean errors. Although the intensity spreads are similar in two systems, GEFS exhibits evidently larger underdispersions due to larger mean errors than TEDAPS. Both systems systematically underestimate TC intensity, while more serious weak biases are found in GEFS, corresponding to its larger mean errors.

3.2 Examination of specific cases

The previous section presents the statistics of verification. Here, we consider several significant storms: three landfalling TCs causing tremendous disasters in mainland China (1713 Hato; 1810 Ampil; 1814 Yagi), and one super-typhoon (1718 Talim) which was officially predicted to have potentially huge threat to China but actually did not affect.

Figures 4(a) and 4(c) shows the track and intensity forecasts for sever Typhoon Hato. Both TEDAPS and GEFS successfully predicted Hato's landfall location,

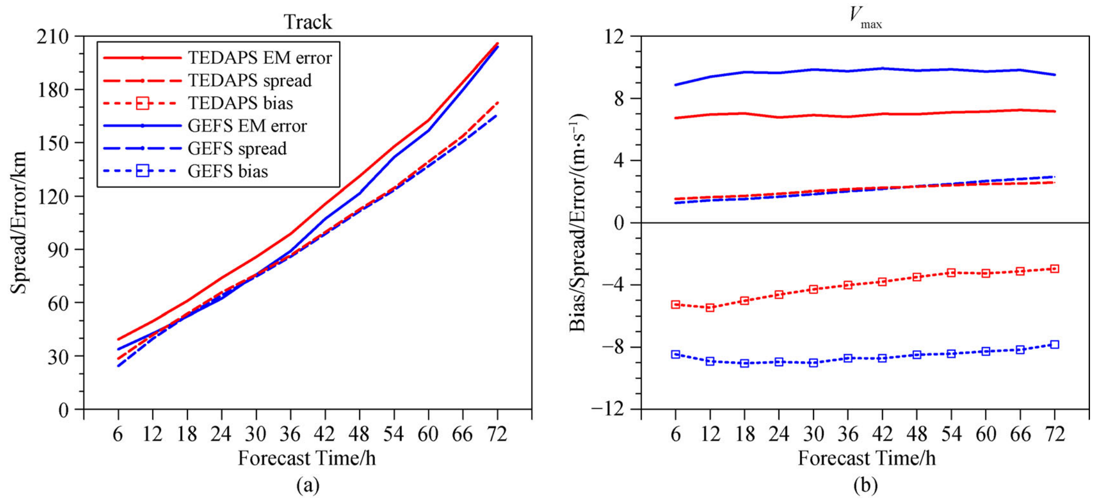

Fig. 3 Ensemble spread (dashed) and absolute errors (solid) of ensemble mean in TEDAPS (red lines) and GEFS (blue lines) for track (a) and V_{max} (b) as a function of forecast lead times. Dotted lines with squared marks correspond to the biases for V_{max}.

better than the CMA official subject forecasts (denoted as CMA OFCL). The most notable feature of Hato is its rapid-intensification (RI) before landfall. TEDAPS exhibited the most accurate forecast for both intensification rate and peak intensity. In contrast, GEFS and CMA OFCL failed to capture this RI event. For Super-Typhoon Talim (Figs. 4(b) and 4(d)), the biggest challenge is in track forecast. The CMA official and GEFS forecasts had a large westward bias, keeping the predicted cyclone landfall in China. Ensembles of TEDAPS perfectly captured the north-eastward offshore recurvature though the tracks were somewhat fast. Besides, TEDAPS was able to predict a wind speed exceeding 50 m/s though the peak occurred earlier than the best-track. The predicted cyclones in GEFS were too weak once again. For Ampil (Figs. 5(a) and 5(c)), GEFS showed the most accuracy in track forecast whereas TEDAPS had westward bias. TEDAPS and GEFS well predicted the weakening process after landfall, not as rapid as OFCL, leading to a longer lifetime and longer inland path than those of OFCL, and prolonged heavy rainfall (seen in Section 4). For Yagi (Figs. 5(b) and 5(d)), both TEDAPS and GEFS had large northward biases and ensembles of TEDAPS failed to capture its landfall possibility of the observed track, while OFCL forecast was reasonable though northward bias also existed. Future work will aim at better understanding the performance of TEDAPS in the four cases.

Now we turn our attention to the uncertainties in TEDAPS. Overall, the ensemble forecasts covered well the observed track, and reasonably simulate the observed intensity. Among the four cases, the largest track (intensity) spread was found in forecasts of Talim (Hato). For Talim, the ensembles could cover the possibilities in predicting a recurving path. The markedly large spread well reflected the great uncertainties. As well, the track spread grew rapidly around the turning point, indicting the capability of predicting forecast uncertainty. For Hato, large spread was found in intensity rather than in track. The intensity spread increased during the RI period and reached a maximum at the time of peak intensity, suggesting the low predictability of RI, and confirming once again the ability of TEDAPS for capturing forecast uncertainty. In addition, it is worth noting that even for the "failed case" Yagi, the large track spread was consistent with the corresponding large mean track error despite the serious northward bias.

4 Forecasts associated with TC hazards

Although focusing on track and intensity forecasts, TEDAPS provides products for TC hazard forecasts including heavy rainfall and damaging winds. In this section, the performance of TEDAPS will be further studied with emphasis on hazard forecasts by examining two landfalling TCs (Hato and Ampil), both of which intruded into inland with a long-lived path and caused severe disaster over vast areas. The general statistics on rainfall and wind is beyond the scope of this paper.

TEDAPS produces deterministic forecasts of daily accumulated precipitation. Those rainfall forecasts for Hato and Ampil was verified against the CMA multi-sensor rainfall estimates (Shen et al., 2014) which are analyzed real-time with resolution of 0.05° based on ground rain-gauge, radar and satellite observations by CMPAS (CMA Multi-source merged Precipitation Analysis System). Since this "observed" rainfall over ocean are estimated solely from satellite which greatly underestimates precipitation especially for heavy rainfall (Yu et al., 2009), the academic researches usually do not compare model produced rainfalls with the satellite estimates over ocean. Thus, our verification here goes to the comparison over land only, though the plots include rainfall over ocean (Fig. 6). For Hato, TEDAPS predicted reasonably for both

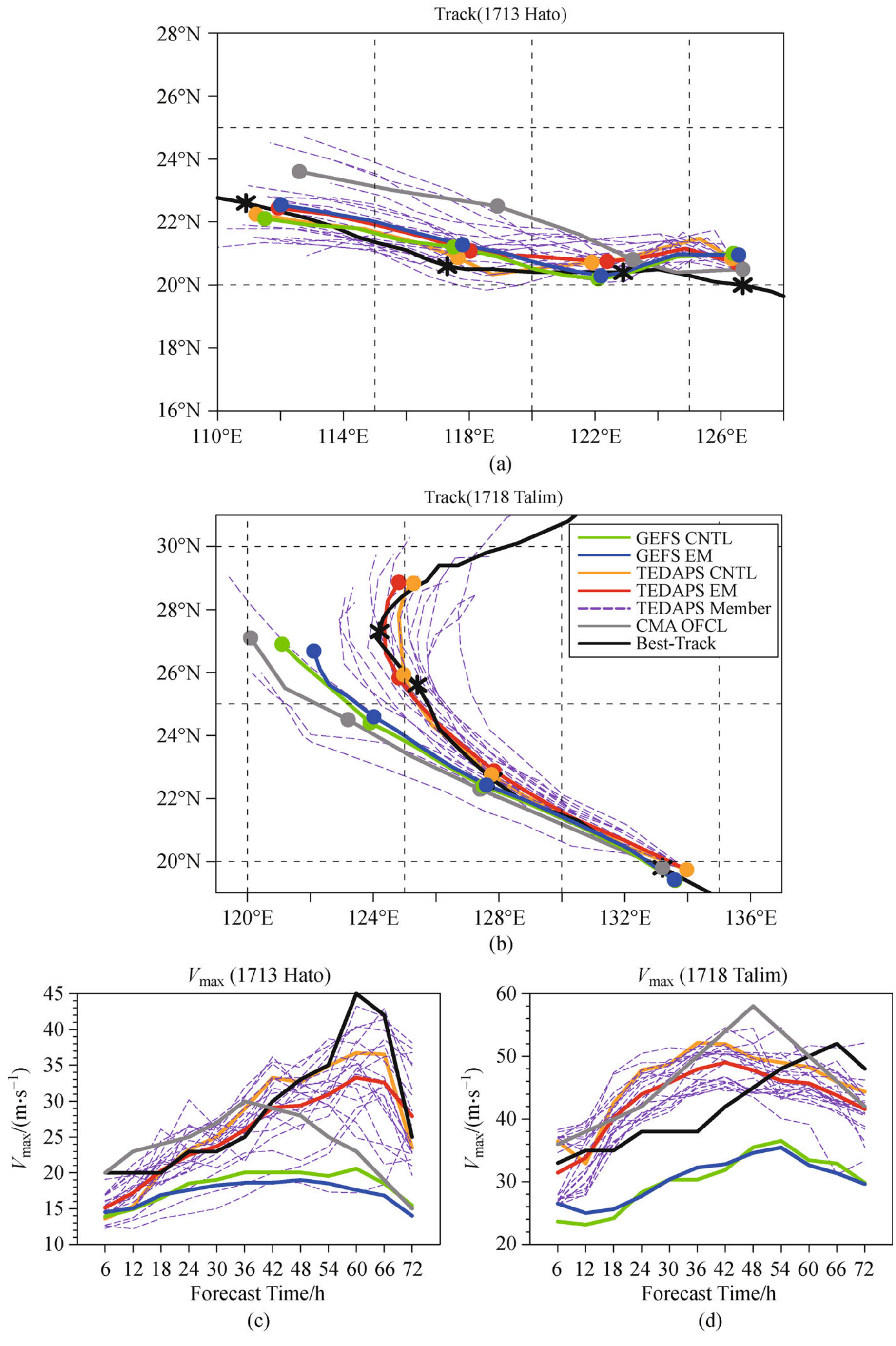

Fig. 4 Track and Intensity forecasts of 1713 Hato (initialized at 1200 UTC 20 August 2017) and 1718 Talim (initialized at 1200 UTC 11 September 2017) for TEDAPS (control in orange, mean in red, members in purple), GEFS (control in green, mean in blue) and CMA official forecasts (OFCL in gray). The best-track is in black with black '*' symbol indicating observed positions at 0-h, 24-h, 48-h, 72-h respectively. Colored dots denote the corresponding positions for each predicted track.

pattern and rainfall strength over land despite coarser structure (due to coarse model resolution) relative to that of observations of 0.05° resolution. For Ampil, TEDAPS successfully predicted the severe inland flooding along its intruding path with three major rainfall centers, one around the landfalling location, one in southern Shandong Province, one in Hebei Province centered at capital Beijing and stretching further to the north-eastern China.

In addition to deterministic prediction, several probabilistic products were derived for rainfall and wind forecasts, which could have greater value for making decisions than the output from a deterministic prediction. Taking Ampil as an example, Fig. 7 depicts the probabilities of daily precipitation (0–24 h, 24–48 h, 48–72 h) and three days'

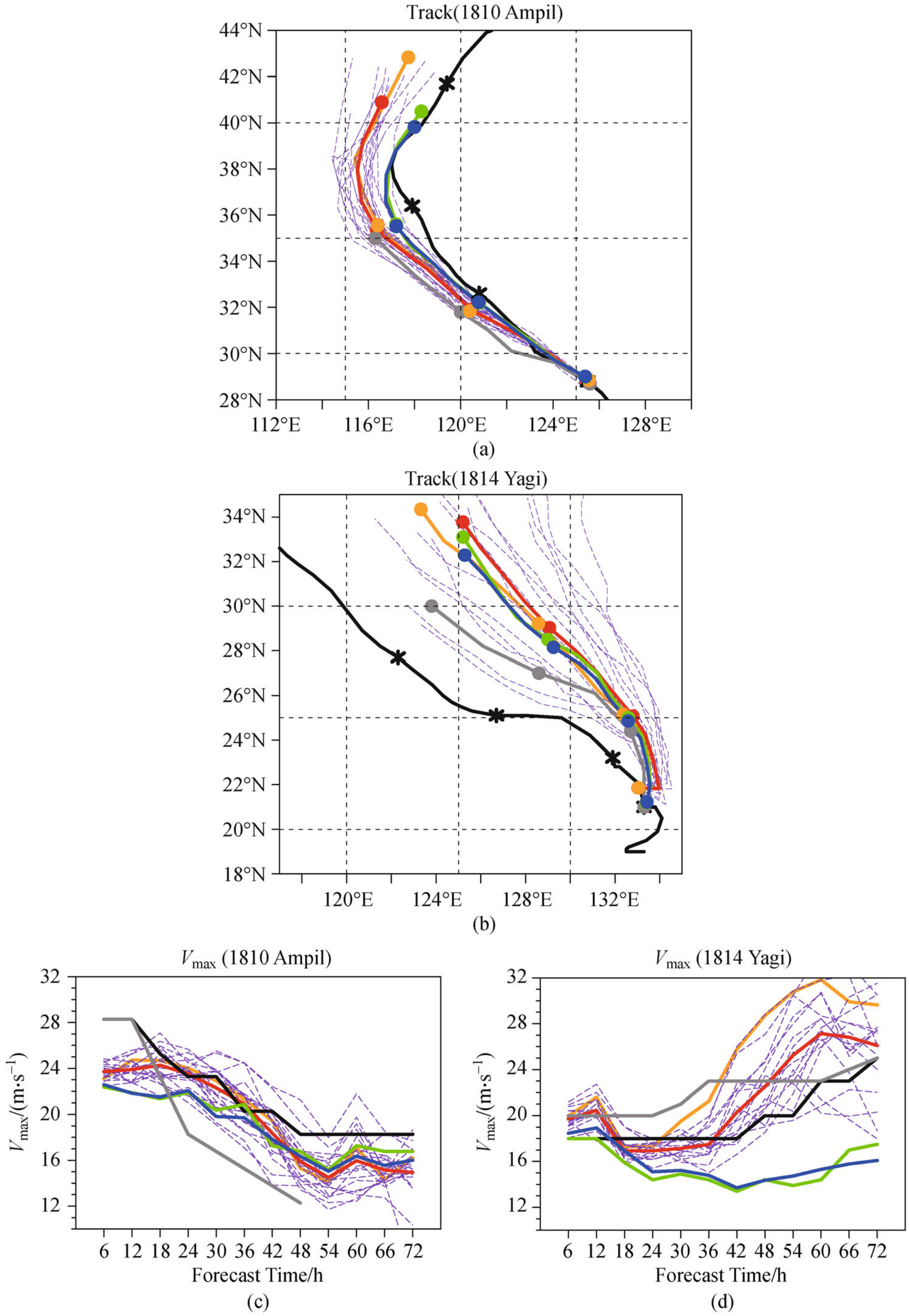

Fig. 5 As in Fig. 4, but for forecasts of 1810 Ampil (initialized at 1200 UTC 21 July 2018) and 1814 Yagi (initialized at 1200 UTC 9 August 2018).

total precipitation exceeding various thresholds (25-mm, 50-mm and 100-mm). It is clearly indicated that 50mm rainfall impacts were over very large areas starting from the landfalling city Shanghai through the north-eastern China (Fig. 7(b)), with day- 1's impact in northern Shanghai and southern Jiangsu Province (Fig. 7(k)), day-2's impact in Jiangsu and Shandong Provinces (Fig. 7(h)), and day-3's impact in Hebei and Liaoning Provinces (Fig. 7(e)). In contrast, 100-mm rainfall impacts were confined in three smaller areas (Figs. 7(l), 7(i), 7(f) or Fig. 7(c)), fairly consistent with the three rainfall centers described by the deterministic forecasts (Fig. 6(d)).

As with rainfall, wind probability could also be useful. Figure 8 shows the cumulative wind probability of 10-m maximum wind exceeding various threshold values during the entire 72-h forecast period. For Hato, the impact of

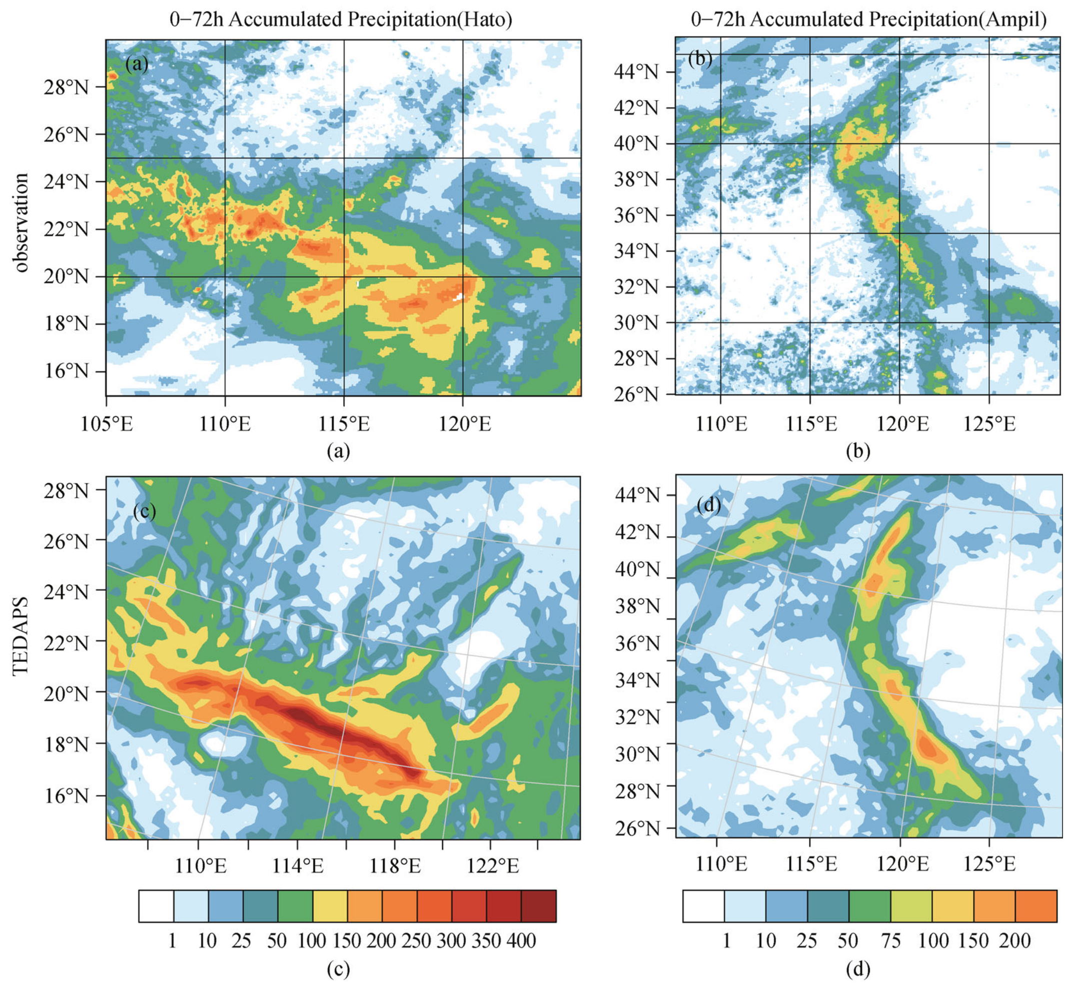

Fig. 6 0–72h accumulated precipitation (unit: mm) from CMA observational estimates (a and b) and TEDAPS control forecasts (c and d) for Hato initialized at 0000 UTC 22 August 2017 (a and c) and Ampil initialized at 1200 UTC 21 July 2018 (b and d).

typhoon-force wind (⩾32.7m/s) was mainly over ocean and on few offshore locations, while gale-force wind (⩾24.5m/s) impacted in slightly wider areas along the coastline and tropical storm-force wind (⩾17.2m/s) intruded into inland impacting over large areas. Thus, TEDAPS could capture the potential threat and be helpful for early warning in disaster prevention. For Ampil, the wind impact over land was relativity small and confined to a narrow area along the eastern coast, there was no possibility of gale-force wind (⩾24.5m/s) over land.

In summary, the probability information of rainfall and wind by TEDAPS provides not only the possibility of TC associated hazard at various degrees for public individuals at a specific location, but also the area and size of hazard for governmental emergency management office.

5 Conclusions and discussion

This manuscript investigates the performance of a real-time Typhoon Ensemble Data Assimilation and Prediction System (TEDAPS) during the 2015–2018 Western North Pacific TC seasons. TEDDAPS utilizes the advanced 3DEnVar data assimilation and multi-physics ensemble with 21 members to improve TCs forecast skill and meanwhile to provide various uncertainty and probability forecasts with respect to track and intensity as well as TC-associated hazard. Objective verification was carried out to evaluate the performance of TEDAPS and to compare with GEFS. Three landfalling TCs (1713 Hato; 1810 Ampil; 1814 Yagi) and one recurving TC (1718 Talim) are examined in more details.

On average TEDAPS provides slightly worse (comparative) track forecasts to GEFS at shorter (longer) forecast times. Track forecasts in GEFS EM are more skillful relative to GEFS CNTL at all lead times, while TEDAPS EM shows advantage over its control at long leads. The different performances between GEFS and TEDAPS might be related to the different approaches used to represent model uncertainties in the two ensemble systems. In terms of intensity forecast, TEDAPS shows remarkable advantage over GEFS, with much smaller V_{max} errors over all

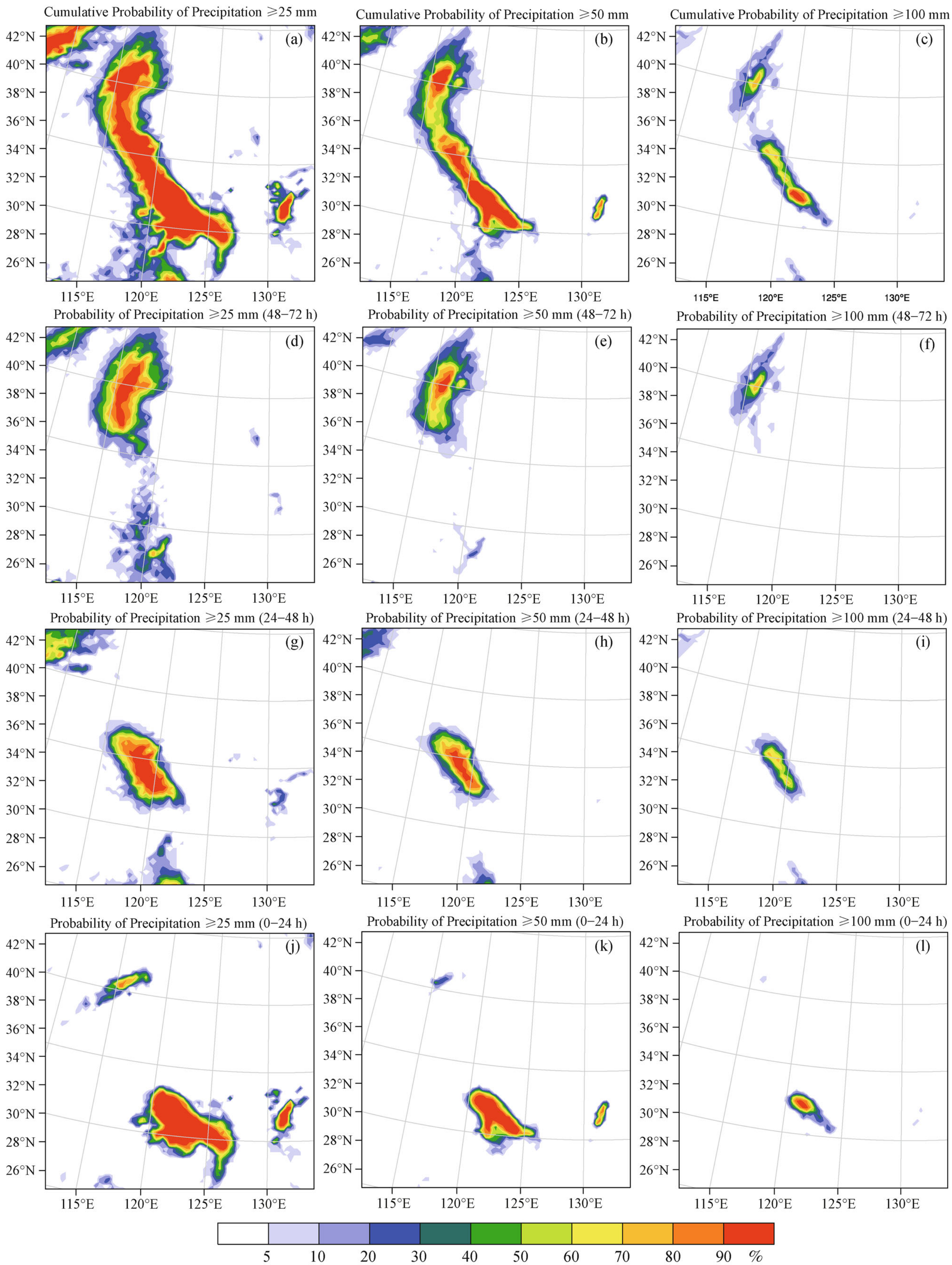

Fig. 7 Probability forecasts of accumulated precipitation exceeding 25-mm(left), 50-mm(middle) and 100-mm(right) over 0–24h (j,k,l), 24–48h (g,h,i), 48–72h (d,e,f) and the total 0–72h (a,b,c) predicted by TEDAPS for Ampil initialized at 1200 UTC 21 July 2018.

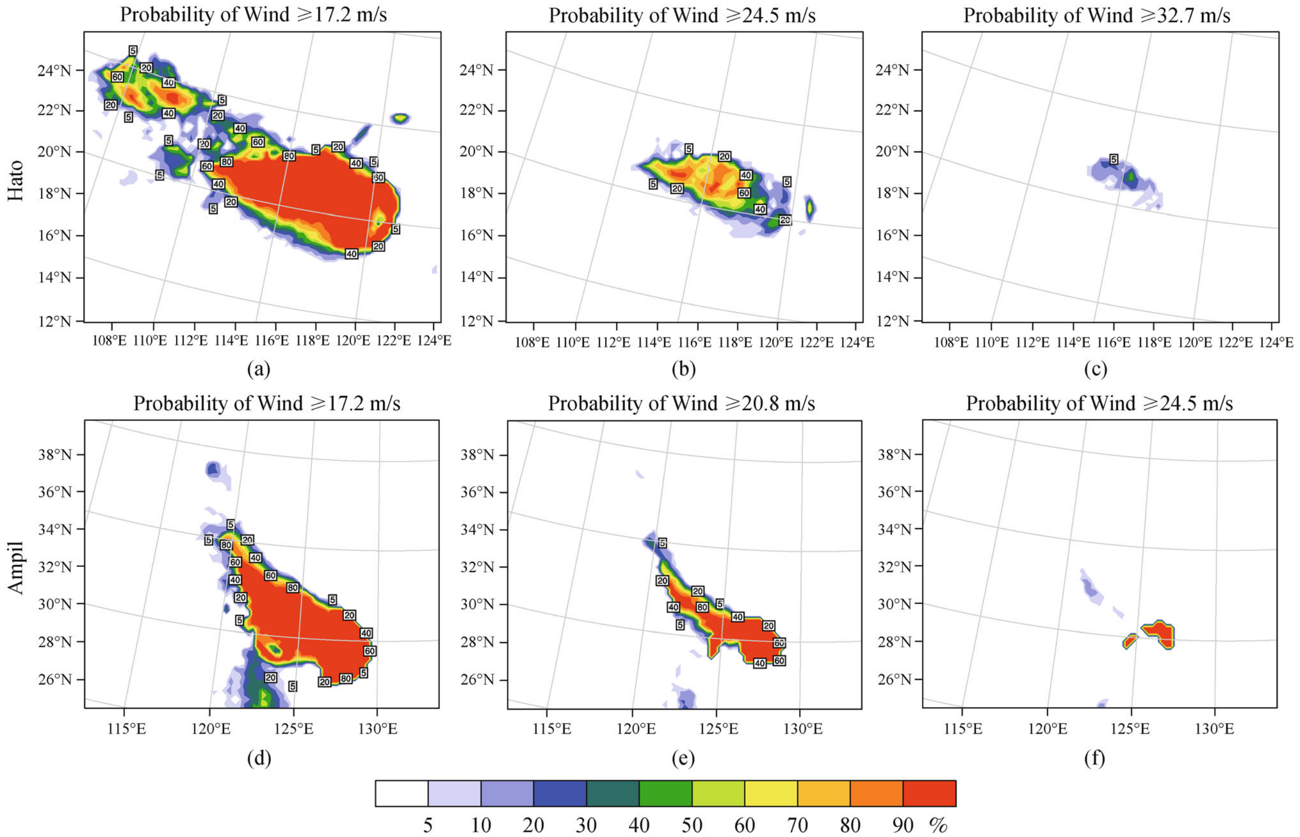

Fig. 8 Cumulative probability forecasts by TEDAPS of wind exceeding 17.2, 24.5 and 32.7m/s for Hato initialized at 0000 UTC 22 August 2017 (a, b and c), and of wind exceeding 17.2, 20.8 and 24.5m/s for Ampil (d, e and f) initialized at 1200 UTC 21 July 2018.

forecast lead times. The intensity error of ensemble mean is slightly (markedly) larger than that of the control in TEDAPS (GEFS) due to the fact that the weak biases in GEFS are more serious than those in TEDAPS. The ensemble spread in TEDAPS intensity forecasts is more consistent with the ensemble mean error than that in GEFS, though both of them are much underdispersive. It is inferred to increase model resolution (e.g. 3 km in Hurricane WRF, Zhang et al., 2011; 3 km in Zhang and Weng, 2015) for mitigating intensity bias and to enlarge ensemble spread by introducing more small-scale perturbations.

In the detailed examinations on four TC cases, TEDAPS presented better performance in track and especially in intensity compared to GEFS by well predicting Talim's recurvature and Hato's rapid intensification. Both systems failed in predicting Yagi's landfall. Furthermore, the ensemble spread in TEDAPS could properly capture forecast uncertainty and reflect forecast challenging. Moreover, the deterministic and probabilistic rainfall and wind predictions for two landfalling TCs were examined and showed benefit to TC-associated hazard pre-assessment and decision making.

Acknowledgements The authors would like to thank Dr. Lina Bai in STI for providing the best-track data. This research was primarily supported by National Key R&D Program of China (Grant No. 2018YFC1506404), the National Basic Research Program of China (Grant No. 2015CB452806), National Natural Science Foundation of China (Grant No. 41575107), and in part by Shanghai Sailing Program (Grant No. 19YF1458700), Scientific Research Program of Shanghai Science & Technology Commission (Grant No. 19dz1200101), National Programme on Global Change and Air-Sea Interaction (Grant No. GASI-IPOVAI-04), and Shanghai Typhoon Innovation Team grants to Shanghai Typhoon Institute.

References

Aberson S D, Aksoy A, Sellwood K J, Vukicevic T, Zhang X (2015). Assimilation of high-resolution tropical cyclone observations with an ensemble Kalman filter using NOAA/AOML/HRD's HEDAS: evaluation of the 2008–11 HWRF forecasts. Mon Weather Rev, 143(2): 511–523

Cavallo S M, Torn R D, Snyder C, Davis C, Wang W, Done J (2013). Evaluation of the advanced hurricane WRF data assimilation system for the 2009 Atlantic hurricane season. Mon Weather Rev, 141(2): 523–541

Hamill T M, Whitaker J S, Fiorino M, Benjamin S J (2011). Global ensemble predictions of 2009's tropical cyclones initialized with an ensemble Kalman filter. Mon Weather Rev, 139(2): 668–688

Hou D, Toth Z, Zhu Y, Yang W (2008). Impact of a stochastic perturbation scheme on global ensemble forecast. In: 19th AMS conference on probability and statistics, New Orleans, Louisiana

Li H, Luo J, Chen B (2015). Assimilation of real observational data with the GSI-based hybrid data assimilation system to improve typhoon forecast. J Trop Meteorol, 21(4): 400–407

Luo J, Chen B, Li H, Fan G Z, Wang X F (2013). Typhoon track forecast with a hybrid GSI-ETKF data assimilation system. Atmos Ocean Sci Lett, 6(3): 161–166

Nakamura J, Lall U, Kushnir Y, Rajagopalan B (2015). (2105). HITS: hurricane intensity and track simulator with North Atlantic Ocean applications for risk assessment. J Appl Meteorol Climatol, 54(7): 1620–1636

Peng S, Qian Y K, Lai Z, Hao S, Chen S, Xu H, Wang D, Xu X, Chan J C, Zhou H, Liu D (2015). On the mechanisms of the recurvature of Super Typhoon Megi. Sci Rep, 4(1): 4451

Shen Y, Zhao P, Pan Y, Yu J (2014). A high spatiotemporal gauge-satellite merged precipitation analysis over China. J Geophys Res D Atmospheres, 119(6): 3063–3075

Torn R D (2010). Performance of a mesoscale ensemble Kalman filter (EnKF) during the NOAA high-resolution hurricane test. Mon Weather Rev, 138(12): 4375–4392

Wang X (2010). Incorporating ensemble covariance in the Gridpoint Statistical Interpolation (GSI) variational minimization: a mathematical framework. Mon Weather Rev, 138(7): 2990–2995

Wang X (2011). Application of the WRF hybrid ETKF-3DVAR data assimilation system for hurricane track forecasts. Weather Forecast, 26(6): 868–884

Yang S C, Kalnay E, Miyoshi T (2012). Accelerating the EnKF Spinup for typhoon assimilation and prediction. Weather Forecast, 27(4): 878–897

Ying M, Zhang W, Yu H, Lu X, Feng J, Fan Y, Zhu Y, Chen D (2014). An overview of the China Meteorological Administration tropical cyclone database. J Atmos Ocean Technol, 31(2): 287–301

Yu Z, Yu H, Chen P, Qian C, Yue C (2009). Verification of tropical cyclone-related satellite precipitation estimates in Mainland China. J Appl Meteorol Climatol, 48(11): 2227–2241

Zhang F, Weng Y, Sippel J A, Meng Z, Bishop C H (2009). Cloud-resolving hurricane initialization and prediction through assimilation of Doppler radar observations with an ensemble Kalman filter: Humberto (2007). Mon Weather Rev, 137(7): 2105–2125

Zhang F, Weng Y (2015). Predicting hurricane intensity and associated hazards: a five-year real-time forecast experiment with assimilation of airborne doppler radar observations. Bull Am Meteorol Soc, 96(1): 25–33

Zhang X, Quirino T, Yeh K S, Gopalakrishnan S, Marks F, Goldenberg S, Aberson S (2011). HWRFx: improving hurricane forecasts with high-resolution modeling. Comput Sci Eng, 13(1): 13–21