EnKF Assimilation of Satellite–retrieved Cloud Water Path to Improve Tropical Cyclone Rainfall Forecast

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Abstract: Tropical cyclone (TC) rainfall forecast has remained a challenge. To create initial conditions with high quality for simulation, the present study implemented a data assimilation scheme based on the EnKF method to ingest the satellite-retrieved cloud water path (Cw) and tested it in WRF. The scheme uses the vertical integration of forecasted cloud water content to transform control variables to the observation space, and creates the correlations between Cw and control variables in the flow-dependent background error covariance based on all the ensemble members, so that the observed cloud information can affect the background temperature and humidity. For two typhoons in 2018 (Yagi and Rumbia), assimilating Cw significantly increases the simulated rainfalls and TC intensities. In terms of the average equitable threat score of daily moderate to heavy rainfall (5–120 mm), the improvements are over 130%, and the dry biases are cut by about 30%. Such improvements are traced down to the fact that Cw assimilation increases the moisture content, especially that further away from the TC center, which provides more precipitable water for the rainfall, strengthens the TC and broadens the TC size via latent heat release and internal wind field adjustment.

Key words: tropical cyclone; data assimilation; EnKF; cloud water path.

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1 INTRODUCTION

Tropical cyclone (TC) - induced inland rainfall often causes serious casualties and property losses (Ding [1]; Chen and Xu [2]). Although the forecast of the track and intensity of TCs has been improved significantly, forecast of TC related precipitation has remained a challenge (Houze et al. [3]; Gao et al. [4]; Huang et al. [5]). TC associated inner core rainfall is sensitive to its fine structure, including the location and shape of the eyewall and spiral rainbands, while outer region rainfall is influenced by its interaction with the ambient background circulation and synoptic systems (Chen et al. [6]). Capturing these factors is still challenging for numerical models.

One way to improve TC rainfall forecast is to prepare a high-quality initial condition by introducing observations into the model via data assimilation methods (e.g., Zhu et al. [7]; Yue et al. [8]; Bao et al. [9]). With the ability to observe radial wind velocity within a semi-sphere, shore-based Doppler radars can provide much information about the 3-D wind structure of landing TC. Many studies tried to assimilate Doppler radar data to improve TC rainfall forecast. Tsai et al. [10] assimilated Doppler radar data in the quantitative precipitation nowcasting of Typhoon Morakot (2009), improving the short-time rainfall intensity and distribution. For the same TC, Bao et al. [9] improved the rainfall forecast with both initial wind and humidity structures modified by radar data assimilation, and Yue et al. [8] indicated that the performance of radar assimilation is sensitive to the number of radars and assimilation timing. Wang et al. [11] applied a technology named the TC circulation Tracking Radar Echo by Correlation (T-TREC; Wang et al. [12]) to retrieve a 3-D wind field from radar reflectivity and introduced it in the forecast of Typhoon Jangmi (2008), and the improvements in TC intensity, track, structure and precipitation indicate an advantage of T-TREC-retrieved wind over radial wind. Zhu et al. [7] analyzed the impact of radar data on the predictability of Typhoon Vicente (2012), finding that the assimilation can improve the depiction of TC inner-core structure, which in turn improves the forecast of heavy rainfall inland. In these studies, improvement of rainfall forecast mainly resulted from the modification of wind structure, and few works focused on the moisture fields critical to TC rainfall.

Environmental humidity field significantly impacts TC rainfall. In general, evaporation of cloud and rain weakens the TC and related precipitation (Zhu...
and Zhang [13]; Lin et al. [14]), but evaporation cooling acts quite differently in different regions and stages of the TC (Wang [15]; Li et al. [16, 17]; Sawada and Iwasaki [18, 19]). Moreover, the radiative effects of cloud are not negligible. The strong radiative cooling of clear sky at nighttime drives a thermal circulation between the cloud system and the environment, which enhances convective activity and increases the rate of cyclogenesis (Nicholls [20]). The cloud-radiative forcing enhances convective activity in the TC outer core, leading to a wider eye, a broader tangential wind field, and a stronger secondary circulation (Bu et al. [21]). The radiative effects of water clouds decrease rainfall, which is opposite for ice clouds (Xu et al. [22]). Given the important role of vapor and cloud in the development of TC, a successful rainfall forecast demands a high quality of the initial condition in terms of humidity distribution in the atmosphere. 

Although the radar reflectivity is related to the hydrometeor mixing ratios, it is not easy to improve the structure of vapor and cloud in the initial condition by assimilating radar reflectivity. The complex microphysical relationship between reflectivity and the particles of water/ice brings great uncertainty into the assimilation system (e.g., Dowell et al. [23]). Moreover, the radar data do not have the coverage over ocean far from the coast. Satellite-retrieved data does not have such deficiencies. Meanwhile, the algorithms to retrieve cloud water path (denoted by $C_w$) from satellite-borne microwave radiometers have been developed for many years and are quite reliable. A 20-year global dataset of $C_w$ retrieved from different satellites has been created (Wentz and Schabel [24]; Greenwald et al. [25]), which might be a good addition to the radar data. Since $C_w$ has a simple relationship with model variables, it can affect the model initial condition a lot. Thus, this paper designed a method to assimilate satellite-retrieved $C_w$, with ensemble Kalman filter (EnKF; Evensen [26]), and explored its impact on the forecast of TC-induced rainfall. The remainder of this paper is organized as follows. Section 2 describes the algorithm to assimilate the $C_w$. Section 3 gives the details of the data to be used, the TC events, and the numerical experimental design. Section 4 shows the evaluation of each experiment. Section 5 discusses the impact of assimilated $C_w$ on the forecast, and a summary is given in Section 6.

2 DATA ASSIMILATION SCHEME

2.1 EnKF

With development of supercomputing technology, ensemble-based assimilation methods have been widely used because they dynamically estimate the background error covariance (BEC) so that the observed information spreads more reasonably (e.g., Weng et al. [27]; Dong and Xue [28]; Gao et al. [29]). Based on ensemble forecast, the EnKF method uses the spread of ensemble members to dynamically estimate the BEC. The model state is updated by

$$x^i = x^i + K[y - H(x^i)]$$

where $x^i$, $x^i$, and $y$ are the model-forecasted updated analysis, background and observation, respectively. $H$ is an observation operator matrix which transforms the background variables to observation space. $K$ is the Kalman gain matrix calculated by

$$K = P^bH^T(R + HP^bH^T)^{-1}$$

where $P^b$ and $R$ are the BEC matrix and observation error, respectively. To reduce the computational cost, instead of generating an extremely large matrix $P^b$, the assimilation system directly estimates $P^bH^T$ and $HP^bH^T$ based on ensemble members:

$$P^bH^T = \frac{1}{m-1}\sum_{i=1}^{m}(x^i - \bar{x})(H(x^i) - \bar{H}(\bar{x}))^T$$

and

$$HP^bH^T = \frac{1}{m-1}\sum_{i=1}^{m}[H(x^i) - \bar{H}(\bar{x})][H(x^i) - \bar{H}(\bar{x})]^T$$

where $m$ is the ensemble size, $\bar{x}$ is the background ensemble mean, and $x^i$ is the $i$-th ensemble member. $x^i$ can be divided into $\bar{x}$ and a perturbation $x^i = \bar{x} + x^i$. Thus, Eq. (1) is also divided into 2 parts. The updating algorithms for the ensemble mean and perturbations are respectively

$$\bar{x} = \bar{x} + K[y - H(\bar{x})]$$

and

$$x^i = x^i - \alpha K H(x^i)$$

where $\alpha = [1 + \sqrt{R/\bar{H}(\bar{x})}]^{-1}$ is a coefficient to eliminate the systematic underestimation of analysis error without perturbed observations (Whitaker and Hamill [30]).

The sampling error due to a limited ensemble size is inevitable. As a result, the ensemble spread decreases while the assimilation and forecast system is running, which can significantly underestimate the background error, weakening the influence of observation. This paper applied a multiplicative covariance inflation proposed by Whitaker and Hamill [31] to inflate the posterior ensemble spread:

$$(\beta \sigma^2 - \sigma^2 + 1)x^i \rightarrow x^i$$

where $\sigma^2$ and $\sigma^2$ are the prior and posterior ensemble standard deviations, $\beta$ is the inflation parameter to control the degree of inflation, and $\rightarrow$ denotes replacement. $\beta = 0$ means the spread is not inflated, while $\beta = 1$ makes the posterior spread the same as the prior one. Another consequence of sampling error is the unrealistic distant correlation in the BEC, which generates a false increment far away from the observation. Thus, ensemble inflation and localization
are necessary for EnKF (Houtekamer and Zhang [32]). This paper applied the localization method proposed by Gaspari and Cohn [33] to limit the scope of observation innovation. A smooth correlation function $\rho$ is inserted into the Kalman gain matrix $K$ in Eq. (2):

$$
\gamma = \begin{cases}
1 - \frac{5}{3} \left( \frac{z}{L} \right)^2 + \frac{5}{8} \left( \frac{z}{L} \right)^3 + \frac{1}{2} \left( \frac{z}{L} \right)^4 - \frac{1}{4} \left( \frac{z}{L} \right)^5, & 0 \leq z \leq L \\
-\frac{2}{3} \left( \frac{z}{L} \right)^3 + 4 - 5\left( \frac{z}{L} \right)^2 + \frac{5}{3} \left( \frac{z}{L} \right)^4 + \frac{5}{8} \left( \frac{z}{L} \right)^5 - \frac{1}{2} \left( \frac{z}{L} \right)^4 + \frac{1}{12} \left( \frac{z}{L} \right)^5, & L < z \leq 2L
\end{cases}
$$

where $L$ is the localization scale. Vertical localization is done with the same method except the horizontal distance $z$ is replaced by logarithm of quotient of pressures for model grid and observation: $\ln(p/p_o)$. $L$ is apparently different for horizontal and vertical localization scale.

2.2 Assimilation of the $C_z$

Since $C_z$ is not a model variable, the priority to ingest it within the updating process is to generate the correlation between it and the model-forecasted background, which is straightforward, since $C_z$ can be diagnosed using model variables:

$$
C_z = \frac{1}{\rho_s} \int_0^{z_o} \rho q dz
$$

where $z_o$ is the height of top model layer, $\rho_s$ is the density of liquid water, $q$ is the cloud water mixing ratio, and $\rho$ is the air density, which can be diagnosed by air pressure $p$, air temperature $T$ and vapor mixing ratio $q$:

$$
\rho = \frac{p}{RT (1 + 0.6089q)}
$$

where $R$ is the gas constant for dry air. If the control variables for EnKF include $T$, $q$, and geopotential $H$, then the background can be denoted by

$$
x^b = \begin{bmatrix} T \\ H^b \\ q^b \\ q_o^b \end{bmatrix}
$$

regardless of spatial heterogeneity. Since $x^b$ contains adequate information to diagnose $C_z$, Eq. (10-11) act as the transform matrix $H$ which uses $x^b$ to diagnose the model forecasted $C_z$ at the observation point. Hereafter, the forecasted and observed cloud water paths are denoted by $C_z^f$ and $C_z^o$.

The EnKF scheme sequentially assimilates each observation datum, using the analysis updated by a datum as the background to assimilate the next one. For a single $C_z^o$, the estimation of BEC (i.e., Eq. (3-4)) can be specified by

$$
P^o H^T = \frac{1}{m-1} \sum z \left( x^f - x^o \right) (C_z^{o_m} - C_z^o)
$$

$$
H P^o H^T = \frac{1}{m-1} \sum (C_z^{o_m} - C_z^o)^2
$$

where $C_z^o$ and $C_z^{o_m}$ are the forecasted cloud water paths for the ensemble mean and the $i$-th member. Both $P^o H^T$ and $H P^o H^T$ contain the ensemble spread for $C_z^o$, while $P^o H^T$ also contains the correlation between $C_z^o$ and control variables of the background. This correlation reflects the impacts of synoptic-scale forcing and structure of temperature and humidity on the water cloud.

To assimilate the $C_z$, the model forecasted cloud water path $C_z^f$ is diagnosed by Eq. (10-11), followed by the BEC being generated by Eq. (13-14) and the Kalman gain matrix being generated by Eq. (8) with localization, then the ensemble mean and members are updated by Eq. (5-6) and covariance inflation is done by Eq. (7). Note that winds are not state variables in the $C_z$ assimilation (Eq. (12)), since cloud and wind field are not directly related. However, the state variables for assimilating other observations include $U$ and $V$.

3 NUMERICAL EXPERIMENTS

3.1 TC events

2 typhoons landing in East China with northwestern tracks, Typhoon Yagi (2018) and Typhoon Rumiba (2018), were investigated. Synoptic backgrounds and intensities for the 2 TCs were similar. Yagi made landfall on the coast of Zhejiang Province with a maximum surface wind (MSW) of 25 m s$^{-1}$ and a minimum sea level pressure (MSLP) of 985 hPa at 15:35 UTC 12 Aug. The landfall site is to the southwest of the subtropical high (Fig. 1a), making Yagi move towards the northwest. Rumiba makes landfall in Shanghai with an MSW of 25 m s$^{-1}$ and an MSLP of 982 hPa at 20:05 UTC 16 Aug. It is moved westward by the steering easterly south of the subtropical high (Fig. 1c).

The summer monsoon brought abundant vapor for both TCs, which led to heavy inland rainfall over Eastern China and affected several densely populated cities. With similar intensities, the 2 TCs caused quite different rainfall amounts, indicating a big difference between their thermal structures. Caused by Yagi, the maximum daily rainfall (from 12 UTC 12 Aug to 12 UTC 13 Aug) recorded by automatic weather stations (AWS) is 159.1 mm, while Rumiba induced a
maximum daily rainfall of 355.9 mm from 12 UTC 16 Aug to 12 UTC 17 Aug. Maxima existed near TC tracks and close to the coastline (Figs. 1b, d).

![Model domains and AWS locations for Typhoon Yagi (a-b) and Rumiba (c-d). Blue contours show the 500 hPa geopotential height (m) at the initial time (12 UTC 12 Aug for Yagi and 12 UTC 16 Aug for Rumiba). Thick lines show observed and forecasted TC tracks during forecast time. Yellow dots locate the maximum daily rainfall.](image)

**Figure 1.** Model domains and AWS locations for Typhoon Yagi (a-b) and Rumiba (c-d). Blue contours show the 500 hPa geopotential height (m) at the initial time (12 UTC 12 Aug for Yagi and 12 UTC 16 Aug for Rumiba). Thick lines show observed and forecasted TC tracks during forecast time. Yellow dots locate the maximum daily rainfall.

### 3.2 Data

The initial and lateral boundary conditions for the simulation were derived from the ERA5 reanalysis, which has a horizontal resolution of 0.25° and 37 pressure levels. The gridded observed $C_n$ data are retrieved from the satellite-borne Special Sensor Microwave Imagers (SSMI) and Special Sensor Microwave Imagers Sounders (SSMIS) and have a resolution of 0.25°. They are produced by Remote Sensing Systems. Other assimilated observations include routine radiosonde and surface measurements, and brightness temperatures from satellite-borne Advanced Microwave Sounding Unit B (AMSU-B), High Resolution Infrared Radiation Sounder 4 (HIRS-4) and Microwave Humidity Sounder (MHS). Observed rainfalls at dense AWSs for the evaluation (Figs. 1b, d) over the Eastern China are provided by China Meteorological Administration (CMA). All observation data have gone through quality control (QC) before published by the institutions, and each datum has a QC flag as basis for sifting. “Bad” data are abandoned by assimilation system.

### 3.3 Experimental design

The Weather Research and Forecasting (WRF) model Version 3.8.1 was used for simulation. Fig. 1 shows the two-way nesting model domain used. The horizontal resolutions for D1 and D2 are 15 km and 3 km respectively. For each TC event, D1 has $141 \times 101$ grid points, while D2 has $401 \times 301$, and both domains have 51 vertical levels. Following Yun et al. [3], this paper used Morrison 2-moment scheme (Morrison et al. [13]) for microphysics and MYJ boundary layer scheme (Janjic [30]). Note that cumulus parameterization was turned off for domain 2 since its resolution is higher than 5 km, so that the convection can be explicitly solved by model. Other details of WRF configuration are listed in Table 1.

The Grid-point Statistical Interpolation (GSI)/EnKF system Version 3.5 (Shao et al. [17]) was used for data assimilation. Assimilation was implemented only in the outer domain, while forecast results come from the inner domain. The forecast started when the TC moved close to the land (Figs. 1a, c). 3 numerical experiments were conducted for each TC event (Table 2). The first one (denoted by Exp-YO/RO), acting as control experiment, assimilated routine radiosonde and surface observations and satellite-retrieved brightness temperatures (denoted by OBS). The second one (denoted by Exp-YC/RC) assimilated both OBS and SSMI/SSMIS-retrieved $C_n$. The third one (denoted by Exp-YCnO / RcnO) assimilated $C_n$ only. The Community Radiative Transfer Model (CRTM)
Table 1. WRF configuration.

| Model option                        | Specification                  |
|-------------------------------------|--------------------------------|
| Time step                           | 60 s for D1, 12 s for D2       |
| PBL scheme                          | MYJ (Janjic [35])              |
| Cumulus parameterization            | Kain-Fritsch (Kain and Fritsch [36]) for D1, none for D2 |
| Microphysics                        | Morrison (Morrison et al. [37]) |
| Long-shortwave radiation            | RRTMG scheme (Iacono et al. [38]) |
| Land surface model                  | Noah (Chen and Dudhia [39])    |

Table 2. Experimental configuration.

| Experiment | TC event   | Assimilation window | Duration of model forecast | Assimilated observation |
|------------|------------|---------------------|----------------------------|-------------------------|
| Exp-YO     | Typhoon Yagi | 06−12 UTC 12 Aug    | 12 UTC 12 Aug to 12 UTC 13 Aug | OBS                     |
| Exp-YC     | Typhoon Yagi | 06−12 UTC 12 Aug    | 12 UTC 12 Aug to 12 UTC 13 Aug | OBS and $C_w$            |
| Exp-YCrnO  | Typhoon Yagi | 06−12 UTC 12 Aug    | 12 UTC 12 Aug to 12 UTC 13 Aug | $C_w$                   |
| Exp-RO     | Typhoon Yagi | 06−12 UTC 12 Aug    | 12 UTC 12 Aug to 12 UTC 13 Aug | OBS                     |
| Exp-Rc     | Typhoon Yagi | 06−12 UTC 12 Aug    | 12 UTC 12 Aug to 12 UTC 13 Aug | OBS and $C_w$            |
| Exp-RcnO   | Typhoon Yagi | 06−12 UTC 12 Aug    | 12 UTC 12 Aug to 12 UTC 13 Aug | $C_w$                   |

Developed by the Joint Center for Satellite Data Assimilation (JCSDA) is employed by the GSI system to transform control variables into simulated brightness temperatures. The biases in satellite brightness temperatures are concerned as they might significantly contaminate the assimilation. The GSI system uses a linear regression to determine the satellite biases with state-dependent predictors, and the estimation of regression coefficients is obtained by minimizing the distance of observed and revised simulated brightness temperatures (Auligne et al. [38]). For each TC event, a 6 h-cycled assimilation ran in Aug 2018 with only satellite brightness temperatures to generate the updated coefficients which were then used by each experiment. $C_w$ is a 2-D observed variable. Its vertical location might significantly affect the assimilation, since the vertical localization will limit the analysis increment within a certain range of height. It is not desirable if any model level was immune to the observation. Thus, the observed $C_w$ was set to mid-troposphere with pressure of 500 hPa, and its vertical localization was shut down, so that low-level temperature and humidity can be modified completely based on the correlation regardless of vertical distance. Note that a small spread of $q$ at some level makes assimilating $C_w$ hardly affect $q$ here, but if spread of $q$ is large and highly correlated to $C_w$, assimilation can still significantly change the humidity structure. Shutting down vertical localization is very important for the improvement of low-level temperature and humidity since the relationship between TC clouds and low-level vapor transport is nonnegligible. The horizontal localization scale ($L$ in Eq. (9)) is 200 km for OBS (default and recommended in GSI system) and 50 km for $C_w$. The resolution of observed $C_w$ is $\sim 25$ km, and a choice of 50 km localization scale makes the covariances between a model grid point and 4−5 nearest observations cut to over 50%, according to Eq. (7). These 4−5 nearest observations significantly affect the grid point, while further observations have a minor superimposition impact. In fact, one-moment $C_w$ updating tests show that 30−70 km localization scales give similar analysis increments. Other details for the assimilation are listed in Table 3.

Table 3. Specifications of assimilation for different observations.

| Observations                                      | Channels of satellite brightness | Observation errors | Localization scale ($L$) | Available time | Inflation parameter ($\beta$) |
|---------------------------------------------------|----------------------------------|---------------------|--------------------------|----------------|-----------------------------|
| Routine radiosonde and surface observations       |                                  |                     | Static, provided by GSI/EnKF system | 200 km for horizontal localization, 0.4 for vertical localization | 06−12 UTC, 0.9 |
| AMSU-B/HIRS-4/MHS radiance                        | Channel 1-5 for AMSU-B, Channel 1-19 for HIRS-4, Channel 1-5 for MHS |                     |                          |                |                             |
| SSMI/SSMIS radiance                               |                                  |                     |                          |                |                             |
| SSMI / SSMIS-retrieved $C_w$                      |                                  | 0.2 mm              |                          | 50 km for horizontal localization |                |

Table 4. Specifications of assimilation for different observations.
This paper used the WRF data assimilation system (Barker et al. [39]) to generate 30 ensemble members for each experiment. The system applies the Random Control Variables (RandomCV) method to create random perturbations with mean values of 0 and standard deviations from the NCEP BEC for each variable. The random perturbations are superimposed on the background to generate the ensemble members. Fig. 2 shows the processes for Exp-YC and Exp-RC, while other experiments were conducted in the same way except for the absence of some observation. Ensemble members were generated 12 h before forecast, and the first 6-h is spin-up time for WRF, which is a frequently used configuration for TC forecast (e.g., Dong and Xue [28]; Wang et al. [11]; Yue et al. [8]). WRF ran with the members hourly updated by observation using EnKF for the next 6 h. The analysis ensemble mean at 12 UTC was used as the forecast initial condition.

A reasonable EnKF assimilation is achieved when the background has equilibrated to the model climate. Fig. 3 shows the variation of forecasted $C_w$ for Typhoon Rumiba (mean value of $31 \times 31$ grids around TC center). The forecasted $C_w$ decreases sharply from 0.9 mm to 0.5 mm before 05 UTC, while $C_w$ ensemble spread decreases from 0.35 mm to 0.05 mm. Without the impact of observed $C_w$ (Exp-RO), the forecasted $C_w$ and its spread barely change within the next 7 h. The $C_w$ jumping for Exp-RC corresponds to available observation over TC at 06, 08 and 10 UTC. The spread jumps to a lower value but gradually increases back, which proves an appropriate ensemble inflation. Likewise, without assimilation, the spreads of other control variables all asymptote to steady values before 06 UTC, indicating that the background is sufficiently spun-up.

4 EVALUATION

4.1 TC track and intensity

For each experiment, the forecasts reasonably capture the moving direction and speed of the TC (Figs. 1a, c). As shown in Table 4, the track errors, defined as the standard deviations of forecasted TC center coordinates, are less than 100 km. Track error for Exp-YC/YCnO is 0.94/3.79 km larger than Exp-YO, while that for Exp-RC/RCnO is 16.96/9.49 km larger than Exp-RO. The forecasted TC tracks are quite similar, indicating that the observation hardly affects movement of TC. This is straightforward since
the movement of TC mainly depends on steering flow related to the synoptic-scale circulation, which can be well captured by model.

Forecasted TC intensity is weaker than observation. The observed MSLP of Typhoon Yagi is 980~985 hPa before landfall (at 15:35 UTC), and gradually rises to 995 hPa since then (Fig. 4a). Correspondingly, the observed MSW decreases from 25 m s\(^{-1}\) to 18 m s\(^{-1}\). The forecasted MSLP is 990~995 hPa and varies slightly over time, while the forecasted MSW decreases from ~20 m s\(^{-1}\) to ~15 m s\(^{-1}\). For Typhoon Rumiba, both the observed and forecasted MSLPs vary little, and both the observed and forecasted MSWs decrease over time (Fig. 4b). For each experiment, the forecasted MSLP/MSW is higher/weaker than the observed most of the time, and experiments with assimilated \(C_e\) (i.e., Exp-YC and Exp-RC) forecasts a lower/stronger MSLP/MSW than those without (i.e., Exp-YO and Exp-RO), making their biases and RMSEs smaller (Table 4), indicating an improvement in forecasted TC intensity. For example, the bias of MSW for Exp-RC is ~2 m s\(^{-1}\) smaller than Exp-RO. Errors for Exp-YcnO/RcnO that assimilated only \(C_e\) lie between Exp-YO/RO and Exp-YC/RC.

![Figure 4](image_url) Observed and forecasted intensities of Typhoon Yagi (a) and Typhoon Rumiba (b). Solid lines denote the minimum sea level pressure (MSLP), while dash lines denote the maximum surface wind.

Table 4. Average forecasted errors for TC track and intensity.

|         | Track error (km) | Minimum sea level pressure (hPa) | Maximum surface wind (m s\(^{-1}\)) |
|---------|-----------------|----------------------------------|-----------------------------------|
|         | RMSE            | Bias                             | RMSE                              | Bias                             |
| Exp-YO  | 91.93           | 5.64                             | 4.91                              | ~4.16                            |
| Exp-YC  | 92.87           | 4.24                             | 4.27                              | ~3.66                            |
| Exp-YCnO | 95.72           | 4.74                             | 4.17                              | ~3.25                            |
| Exp-RO  | 56.27           | 9.56                             | 5.48                              | ~5.11                            |
| Exp-RC  | 73.23           | 7.24                             | 3.57                              | ~2.83                            |
| Exp-YcnO | 65.76           | 7.82                             | 4.16                              | ~3.40                            |
| Exp-RCnO | 62.98           | 10.40                            | 6.01                              | ~5.66                            |

Suppose the relationships among model variables are correct, true information about clouds can force temperature and humidity structure to match the true atmosphere. The forecasted TC intensity deficits weaken synoptic convergence, probably leading to a weaker vapor transport and less clouds. If Assimilation of \(C_e\) can fix the problem and provide abundant vapor, it can significantly improve the rainfall forecast. In other words, forecasted TC intensity errors give a good chance to check the performance of \(C_e\) assimilation.

4.2 Rainfall

To objectively compare the experiments, the forecasted hourly rainfall at each AWS used the nearest grid value, and the bias and RMSE were calculated from the forecasted and observed rainfalls. The heavy rain area is the most important information for disaster prevention and control. Thus, the equitable threat score (ETS) and the bias score (BS) were used to judge the forecasted accumulated rainfall:

\[
ETS = (N_{hit} - P) / (N_{hit} + N_{miss} - P) \quad (15)
\]

\[
P = N_{hit} \times (N_{hit} + N_{miss}) / N_{total} \quad (16)
\]

\[
BS = N_{hit} / (N_{hit} + N_{miss}) \quad (17)
\]

where \(N_{hit}\) is the number of stations where both observed and forecasted rainfalls are beyond a given threshold, \(N_{hit}\) is the number of stations with forecasted rainfall above the threshold, \(N_{miss}\) is the number of stations where observed/forecasted rainfall is below the threshold, and \(N_{total}\) is the number of all verification stations. Moreover, the “vague” scores were also calculated to include more grid points in forecasted rainfall through a neighborhood-based method following Clark et al. [40]. In this method, forecasted rainfall within a radius of influence (RI) are taken into account. If the rainfall is observed at a station, it is a
hit if any grid point within RI meets forecasted rainfall. If the rainfall is not observed, it is a false only if all the grid points within RI meet forecasted rainfalls.

The model reasonably forecasts the rain area but underestimates the rainfall without assimilated Cw. As shown in Figs. 5a–d, the rain area for Typhoon Yagi extends from southeast to northwest. The coastal area encounters the heaviest rain, and most daily rainfall records above 50 mm are located east of 119°E. The patterns of forecasted rain areas for 3 experiments are similar with observation, and Exp-YC forecasts much heavier rainfall. The forecasted 60+ mm rain area for Exp-YO is small and located mistakenly, with only 11 stations hit, while that for Exp-YC/YCnO is larger and hits 86/26 stations. ETSs for lighter rain are similar between the 2 experiments, while ETS for heavy rain is much higher for Exp-YC (Fig. 5e). The mean ETS of 5–120 mm rainfall for Exp-YC/YCnO improves 135%/46% over Exp-YO. This improvement can be attributed to the enhancement of heavy rain area. As shown in Fig. 5g, Exp-YO has a BS lower than 0.2 for heavy rainfall, while that for Exp-YC is over 0.4. The improvement of BS for Exp-YC/YCnO is 46%/4%. ETSs/BSs become higher/lower with RI=5 km (Figs. 5f, h), but the advantage of assimilating Cw remains significant.

![Figure 5](image-url)

**Figure 5.** Observed and forecasted daily rainfalls for Typhoon Yagi from 12 UTC 12 Aug to 12 UTC 13 Aug (a–d). ETS and BS for different daily rainfall thresholds with RI=0 (e, g) and RI=5 km (f, h). Percentages in parentheses denote the improvements of other experiments over Exp-YO.

Because the movement of simulated TC lagged behind observed TC by ~6 h. The bias of hourly rainfall is less than −0.5 mm within 12–18 UTC and increases within 18–00 UTC (Fig. 6). The average bias for Exp-YO/YC/YCnO is −0.42/−0.28/−0.38 mm, while the average RMSE for Exp-YO/YC/YCnO is 3.25/3.40/3.23 mm. As shown in Fig. 7, the rain area moves inland following TC while shrinking rapidly, and the heavy rain mainly occurs within the first 12 h. Exp-YC overwhelms Exp-YO in that it forecasted a stronger coastal rainfall within 12–18 UTC and a southeast-northwest rain area within 18–00 UTC.

Typhoon Rumiba brings much stronger and more widespread rainfall than Yagi, and the underestimation by model is also serious. Almost all the land area north of 29°N is affected by the TC-induced rainfall (Fig. 8a). 2355 out of 8847 stations record daily rainfall >60 mm, and Exp-RO/RC/RCnO misses 96%/86%/92% stations. Exp-RC/RCnO produces a larger rain area for both light and heavy rainfall, so that its
average ETS increases by 132%/80% over Exp-RO, and its BS increases 18%/10% (Figs. 8e, g). Again, the inclusion of RI does not change the advantage of Exp-RC (Figs. 8f, h). The average hourly rainfall bias for Exp-RO/RC/RcnO is −1.05/−0.75/−0.87 mm, while the average RMSE is 4.12/4.23/4.19 mm (Fig. 9). Unlike Yagi, the dry biases for Rumiba grow larger during forecast, resulting from more serious underestimation of inland rainfall. As shown in Fig. 10, both the observation and forecast show the typical features of TC spiral rain band. Exp-RC forecasts a stronger coastal rainfall within 12−18 UTC, and the southwest rainfall is stronger than Exp-RO throughout time, which are closer to observations, indicating that assimilating $C_w$ might bring more precipitable water or generate stronger convections inland. Comparison between Fig. 5 and Fig. 8 shows a difference between improvements by assimilating $C_w$ for the 2 TCs. The most significant improvement is for heavy rainfall for Typhoon Yagi and moderate rainfall for Typhoon Rumiba (Figs. 5e, 8e). It comes from different forecast errors. For Exp-YO, light rainfall is well predicted (ETS is over 0.3), while heavy rainfall meets a serious underestimation. Figs. 5a, b show that rainfall is very
Figure 8. Same as Fig. 5 except for Typhoon Rumiba and the daily rainfalls are accumulated from 12 UTC 16 Aug to 12 UTC 17 Aug. Percentages in parentheses denote the improvements of other experiments over Exp-RO.

Figure 9. Same as Fig. 6 except for Typhoon Rumiba. Percentages in parentheses denote the improvements of other experiments over Exp-RO in bias/RMSE.
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heavy near the coast, which is not predicted by model. Assimilating $C_v$ well fixes this problem and gives a better simulation of heavy rainfall, so that ETS of heavy rainfall is improved a lot by Exp-YC. On the other hand, forecast error for Typhoon Rumiba is larger. Its rain area is much larger and Exp-RO misses moderate rainfall a lot, mostly around $30^\circ$N (Fig. 8a). Assimilating $C_v$ fixes this problem, but still underestimates heavy rainfall.

Overall, assimilating $C_v$ improves the forecast by enhancing the intensities of TCs and increases the TC-induced rainfalls. The ETS of daily rainfall improves by over 130% times for Typhoon Yagi/Rumiba (shown by comparison between Exp-YC/RC and Exp-YO/RO), indicating a significant contribution of assimilation to TC rainfall forecast. Other observations also have positive impact on rainfall forecast, since Exp-YC/RC overwhelms Exp-YCnO/RCnO.

5 IMPACT OF ASSIMILATED $C_v$

TC rainfall is influenced by synoptic lifting, convection and water vapor transport, all of which are connected to the cloud structure. According to the choice of control variables (Eq. (12)), the BEC contains a correlation between water cloud and atmospheric temperature and humidity. The introduction of $C_v$ can lead to the variations of other variables. Thus, the improvement of forecasted rainfall results from a complex interaction chain.

This section discusses the mechanism of assimilated $C_v$ affecting the forecasted rainfall. The analysis increments (i.e., $x' - x$) and their effects on the initial condition are shown. The moisture is eliminated from control variables for a sensitivity experiment to discuss its importance in improving the forecast. The assimilated $C_v$ plays similar roles for both TC events, and Typhoon Rumiba is discussed since the analysis increments for Exp-RC are much more significant.

5.1 Analysis increment

Within assimilation window of Exp-RC, the largest amount of $C_v$ around the TC center was found at 10 UTC 16 Aug. As shown in Fig. 11, the model underestimates the thickness and extent of TC-induced cloud for Exp-RC. According to the satellite observation, almost the whole sea area within $26-34^\circ$N is covered by the TC-induced clouds with total water content $>0.6$ mm. The forecasted cloud is distributed mainly in the southeast of the TC center, and its water content is much lower. Although the observed cloud information might contain errors, it can effectively reduce the underestimation by model. Driven by the positive observation innovation (i.e., $C_v' - C_v$), the updated analysis $C_v$ increases around the TC center.
The BEC gives a positive correlation between cloud water and moisture, so that the precipitable water content increases (Fig. 11d). The moisture increment is over 10 times of cloud water increment, which is consistent with the comparison of magnitudes of background $q_v$ and $q_c$. As shown in Fig. 12, the updated moisture / temperature increases / decreases in most areas at all the pressure levels. $C_w$ is a 2D observed variable, and the increments varies by height according to the covariances between forecasted $C_w$ and control variables at different levels. Temperature and humidity are the most related to $C_w$ around 850 hPa, and assimilating $C_w$ generates the largest increments at this level. At other updating times, the observation innovations and analysis increments are similar but much smaller than 10 UTC.

**Figure 11.** Satellite-retrieved $C_w$ (a), model forecasted $C_w$ (b), analysis increments of $C_w$ (c) and precipitable water content (d) at 10 UTC 16 Aug for Exp-RC. White area in (a) is covered by missing value. Purple dots locate the TC centers.

**Figure 12.** Analysis increments of temperature (colors) and vapor mixing ratio (contours, units: g kg$^{-1}$) at 500 (a), 700 (b), 850 (c) and 925 hPa (d) at 10 UTC 16 Aug for Exp-RC. Interval for contours is 0.4 g kg$^{-1}$ and dash lines indicate negative values. Black dots locate the TC centers.
5.2 Improvement of the initial condition

Within assimilation window, the analysis fields for Exp-RC and Exp-RO differs more over time, resulted from assimilated \( C_w \) and model dynamic /thermodynamic adjustments. As shown in Fig. 13, the initial condition for Exp-RC is wetter than Exp-RO. Due to the negative correlation between temperature and \( C_w \), the 850 hPa temperature significantly decreases (Fig. 13c). However, its difference between Exp-RC and Exp-RO is not so apparent at the initial time (Fig. 13a), since the release of condensation latent heat of increased vapor during lifting offsets the cooling. Both the moisture and cloud increase around the inner core (Fig. 13c). The increased vapor favors more condensation and strengthening the ascending motion and the convergence (Fig. 13d), so that the rising flow meets the largest increase where the cloud is thicker. The stronger ascending motion in turn deepens the TC (Fig. 13b). While the temperature above the height of 1.8 km increases, the low-level temperature slightly decreases (Fig. 13d). This results from the evaporation of heavier rainfall (Fig. 13e). The lower temperature does not force a divergent wind difference, indicating that the condensation of increased vapor is dominant in changing the wind. The rainfall and surface wind speed within 100–300 km meet significant increases for Exp-RC, indicating a larger TC size.

5.3 Effects of moisture increment

The positive moisture increment not only provides more precipitable water for rainfall, but also intensifies the TC with more condensation latent heat. But it is still not clear to what extent the moisture increment affects the forecasted rainfall. To answer this question, this paper made a sensitivity experiment which had the same configuration as Exp-RC but eliminated \( q \) from control variables. The background can be denoted by

\[
x^b = \begin{pmatrix} T^b \\ H^b \\ q^c \end{pmatrix}
\]  \( (13) \)

This experiment is denoted by Exp-RC2.

Fig. 14 shows the difference of initial conditions for Exp-RC2 and Exp-RO. Exp-RC2 does not change the initial moisture, cloud and temperature as much as Exp-RC, so that the wind is similar. For Exp-RC2, the 850 hPa temperature is 0.2–0.5°C lower than Exp-RO, and the vapor mixing ratio is 0.4–0.8 g kg\(^{-1}\) less north of TC center. Pressure and wind field differs slightly except for a slight increase of wind divergence. The low-level temperature for Exp-RC2 is lower than Exp-RO with evaporation of a slightly heavier rainfall (Figs. 14d, e). According to Table 4, its forecasted TC track and intensity change little. The RMSE/bias of MSLP increases by 0.84/0.86 hPa, and the RMSE/bias of MSW increases by 0.53/0.55 m s\(^{-1}\) in respect to Exp-RO.

As shown in Fig. 15, the forecasted rainfall for Exp-RC2 deteriorates. Compared with Exp-RO, the south part of forecasted rain area (where observed rainfall is beyond 60 mm) around 31°N is smaller, and a heavier rain falls around 34° N (Figs. 8b, 15a), making the error larger. Although the BSs for Exp-RO and Exp-RC2 are similar (Fig. 15d), the ETS falls more sharply with increasing rainfall threshold for Exp-RC2, and its average ETS is 33% lower than Exp-RO (Fig. 15c). The wet bias increases (Fig. 15b), indicating a lighter average rainfall. Although the increase of cloud water leads to a heavier rain over sea, the wetting effect cannot maintain since the magnitude of increased water content is small. On the other hand, the microphysics effect of cloud over the TC center is an important mechanism to increase the rainfall (Ren and Cui [43]), while the radiation effect of cloud decreases the rainfall (Lou and Li [42]; Xu et al. [23]). The interaction between these processes can hardly be well simulated, since the model parameterization brings a large uncertainty. Thus, the cloud increment for Exp-RC2 does not improve the forecasted rainfall.

Overall, the improvements of forecasted TC intensity and rainfall disappear without \( q \), and \( C_w \) in BEC is the dominant factor for the improvements.

6 SUMMARY

TC rainfall forecast has remained a great challenge. In order to create a model initial condition with high quality, previous research focused on improving the structure of TC wind field by assimilating radar data. Being aware of the significant impact of variations of cloud and vapor on TC-induced rainfall, this study designed an EnKF data assimilation scheme to ingest the satellite-retrieved cloud water path (\( C_w \)). In this scheme, the vertical integration of forecasted cloud water content acts as the observation operator matrix to transform control variables to the observation space, and the BEC contains the correlation between \( C_w \) and control variables. The scheme was used in forecasting rainfall induced by Typhoon Yagi (2018) and Typhoon Rumiba (2018). The evaluation by dense AWS observations shows that assimilating \( C_w \) decreases the dry bias of forecasted rainfall, and increases the average ETS of 5–120 mm/ day rainfall by over 130% for both TC events. The simulated TC intensity is also closer to the observation with the assimilation of \( C_w \).

For the EnKF method, the BEC is dynamically generated from ensemble members so that the variable correlations are related to the weather process. Since more vapor usually leads to a thicker cloud around the TC center, the BEC gives a positive correlation between vapor mixing ratio and \( C_w \). The positive observation innovation of \( C_w \) increases moisture at
and variables in $e^{-}$. (a) are azimuthal mean around the TC center.

$3$, $b$ denote the temperature and wind $(u, w*10)$, while colors and vectors in (d) denote the temperature and wind. Line in (e) denotes the 3-h rainfall. Black dots in (a, b) locate the TC center, and variables in (c–e) are azimuthal mean around the TC center.

Figure 13. Difference of initial conditions for Exp-RC and Exp-RO (Exp-RC−Exp-RO). Colors and contours in (a) denote the temperature and vapor mixing ratio (units: g kg$^{-1}$) at 850 hPa, while vectors and contours in (b) denote the 10 m wind and sea level pressure (units: hPa). Colors and contours in (c) denote the mixing ratios of cloud water + ice and vapor (units: g kg$^{-1}$), while colors and vectors in (d) denote the temperature and wind. Line in (e) denotes the 3-h rainfall. Black dots in (a, b) locate the TC center, and variables in (c–e) are azimuthal mean around the TC center.

Figure 14. Same as Fig. 13 but for Exp-RC2–Exp-RO.

each level. The increased moisture provides more precipitable water for rainfall, enhancing the upward motion due to more condensation so that the TC is intensified and broadened. When the vapor mixing ratio is eliminated from the control variables, assimilating $C_v$ can increase neither rainfall nor intensity of the TC, indicating a dominant role the moisture increment plays in improving the forecast.

Despite of the encouraging results, further studies are still needed. SSMI / SSMIS-retrieved $C_v$ is
available only over the water. Observations involving cloud water over land should be introduced in further studies to cover the time after TC landfall.

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REFERENCES

1. DING Yi-hui. On the study of the unprecedented heavy rainfall in Henan Province during 4-8 August 1975: Review and assessment [J]. Acta Meteor Sin, 2015, 73(3): 411-424 (in Chinese), https://doi.org/10.11676/qxxb2015.067.

2. CHEN Lian-shou, XU Ying-long. Review of typhoon very heavy rainfall in China [J]. Meteor Env Sci, 2017, 40(1): 3-10 (in Chinese), https://doi.org/10.16765/j.cnki.1673-7148.2017.01.001.

3. HOUZE R A, CHEN S S, SMULL B F, et al. Hurricane intensity and eyewall replacement [J]. Science, 2007, 315 (5816): 1235-1239, https://doi.org/10.1126/science.1135650.

4. GAO S, MENG Z, ZHANG F, et al. Observational analysis of heavy rainfall mechanisms associated with severe tropical storm Bilis (2006) after its landfall [J]. Mon Wea Rev, 2009, 137(6): 1881-1897, https://doi.org/10.1175/2008mwr2669.1.

5. HUANG C Y, WONG C S, YEH T C. Extreme rainfall mechanisms exhibited by Typhoon Morakot (2009) [J]. Terrestrial, Atmospheric and Oceanic Sciences, 2011, 22(6): 613-632, https://doi.org/10.3319/TAO.2011.07.01.01(TM).

6. CHEN Lian-Shou, MENG Zhi-yong, CONG Chun-hua. An overview on the research of typhoon rainfall distribution [J]. J Marine Meteor, 2017, 37(4): 1-7 (in Chinese), https://doi.org/10.19513/j.cnki.issn2096-3599.2017.04.001.

7. ZHU L, WAN Q, SHEN X, et al. Prediction and predictability of high-impact western Pacific landfalling tropical cyclone Vicente (2012) through convection permitting ensemble assimilation of Doppler radar velocity [J]. Mon Wea Rev, 2016, 144(1): 21-43, https://doi.org/10.1175/MWR-D-14-00403.1.

8. YUE Jian, MENG Zhi-yong, YU Cheng-ku, et al. Impact of coastal radar observability on the forecast of the track and rainfall of Typhoon Morakot (2009) using WRF-based ensemble Kalman filter data assimilation [J]. Adv Atmos Sci, 2017, 34(1): 66-78, https://doi.org/10.1007/s00376-016-6028-8.

9. BAO X, WU D, LEI X, et al. Improving the extreme...
rainfall forecast of Typhoon Morakot (2009) by assimilating radar data from Taiwan Island and mainland China [J]. J Meteor Res, 2017, 31(4): 747-766, https://doi.org/10.1007/s13351-017-0607-8.

[10] TSAI C C, YANG S C, LIOU Y C. Improving quantitative precipitation nowcasting with a local ensemble transform Kalman filter radar data assimilation system: observing system simulation experiments [J]. Tellus A: Dyn Meteor Ocean, 2014, 66: 21804, https://doi.org/10.3402/tellusa.v66i04.21804.

[11] WANG M, XUE M, ZHAO K, et al. Assimilation of T-TREC-Retrieved winds from single-Doppler radar with an ensemble Kalman filter for the forecast of Typhoon Jangmi (2008) [J]. Mon Wea Rev, 2014, 142(5): 1892-1907, https://doi.org/10.1175/MWR-D-13-00387.1.

[12] WANG Ming-jun, ZHAO Kun, WU Dan. The T-TREC technique for retrieving the winds of landfalling typhoons in China [J]. Acta Meteor Sin, 2011, 25(1): 91-103, https://doi.org/10.1007/s13351-011-0007-x.

[13] ZHU T, ZHANG D. Numerical simulation of Hurricane Bonnie (1998), Part II: Sensitivity to varying cloud microphysical processes [J]. J Atmos Sci, 2006, 63(1): 109-126, https://doi.org/10.1175/JAS3599.1.

[14] LIN Wen-shi, WU Jian-bin, LI Jiang-nan, et al. A sensitivity simulation about cloud microphysical processes of Typhoon Chanchu [J]. J Trop Meteor, 2010, 16(4): 1066-8775, https://doi.org/10.3969/j.issn.1066-8775.2010.04.011.

[15] WANG Y. How do outer spiral rainbands affect tropical cyclone structure and intensity [J]. J Atmos Sci, 2009, 66 (5): 1250-1273, https://doi.org/10.1175/2008JAS2737.1.

[16] LI Q, WANG Y, DUAN Y. Effects of diabatic heating and cooling in the rapid filamentation zone on structure and intensity of a simulated tropical cyclone [J]. J Atmos Sci, 2014, 71(9): 3144-3163, https://doi.org/10.1175/JAS-D-13-0312.1.

[17] LI Q, WANG Y, DUAN Y. Impacts of evaporation of rainwater on tropical cyclone structure and intensity-A revisit [J]. J Atmos Sci, 2015, 72(4): 1323-1345, https://doi.org/10.1175/JAS-D-14-0224.1.

[18] SAWADA M, IWASAKI T. Impacts of evaporation from raindrops on tropical cyclones, Part I: Evolution and axisymmetric structure [J]. J Atmos Sci, 2010, 67(67): 71-83, https://doi.org/10.1175/2009JAS3040.1.

[19] SAWADA M, IWASAKI T. Impacts of evaporation from rainbands on tropical cyclones, Part II: Features of rainbands and axisymmetric structure [J]. J Atmos Sci, 2010, 67(1): 84-96, https://doi.org/10.1175/2009JAS3195.1.

[20] NICHOLLS M E. An investigation of how radiation may cause accelerated rates of tropical cyclogenesis and diurnal cycles of convective activity [J]. Atmos Chem Phys, 2015, 15(5): 6125-6205, https://doi.org/10.5194/acp-15-6125-2015.

[21] BU Y P, FOVELL R G, CORBOSIERO K L. Influence of cloud-radiative forcing on tropical cyclone structure [J]. J Atmos Sci, 2014, 71(5): 1644-1662, https://doi.org/10.1175/JAS-D-13-0265.1.

[22] XU H, LIU R, ZHAI G, et al. Torrential rainfall responses of Typhoon Fitow (2013) to radiative processes: A three-dimensional WRF modeling study [J]. J Geophys Res, 2016, 121(23): 14127-14136, https://doi.org/10.1002/2016JD025479.

[23] DOWELL D C, WICKER L J, SNYDER C. Ensemble Kalman filter assimilation of radar observations of the 8 May 2003 Oklahoma City supercell: Influences of reflectivity observations on storm-scale analyses [J]. Mon Wea Rev, 2011, 139(1): 272-294, https://doi.org/10.1175/2010MWR3438.1.

[24] WENTZ F J, SCHABEL M. Precise climate monitoring using complementary satellite data sets [J]. Nature, 2000, 403(6768): 414-416, https://doi.org/10.1038/35000184.

[25] GREENWALD T J. A 2 year comparison of AMSR-E and MODIS cloud liquid water path observations [J]. Geophys Res Lett, 2009, 36(20): L20805, https://doi.org/10.1029/2009gl040394.

[26] EVENSEN G. Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics [J]. J Geophys Res, 1994, 99(C5): 10143-10162, https://doi.org/10.1029/94JC00572.

[27] WENG Y, MENG Z, ZHANG F. Advanced data assimilation for cloud-resolving hurricane initialization and prediction [J]. Computing in Science & Engineering, 2011, 13(1): 40-49, https://doi.org/10.1109/MCSE.2011.18.

[28] DONG J, XUE M. Assimilation of radial velocity and reflectivity data from coastal WSR-88D radars using an ensemble Kalman filter for the analysis and forecast of landfalling hurricane Ike (2008) [J]. Quart J Roy Meteor Soc, 2013, 139(671): 467-487, https://doi.org/10.1002/qj.1970.

[29] GAO X, GAO S, YANG Y. A comparison between 3DVAR and EnKF for data assimilation effects on the Yellow Sea fog forecast [J]. Atmos, 2018, 9(9): 346, https://doi.org/10.3390/atmos9090346.

[30] WHITAKER J S, HAMILL T M. Ensemble data assimilation without perturbed observations [J]. Mon Wea Rev, 2002, 130(7): 1913-1924, https://doi.org/10.1175/1520-0493(2002)130<1913:EDAWPO>2.0.CO;2.

[31] WHITAKER J S, HAMILL T M. Evaluating methods to account for system errors in ensemble data assimilation [J]. Mon Wea Rev, 2012, 140(9): 3078-3089, https://doi.org/10.1175/MWR-D-11-00276.1.

[32] HOUTEKAMER P L, ZHANG F. Review of the Ensemble Kalman Filter for atmospheric data assimilation [J]. Mon Wea Rev, 2016, 144(12): 4489-4532, https://doi.org/10.1175/MWR-D-15-0440.1.

[33] GASPARI G, COHN S E. Construction of correlation functions in two and three dimensions [J]. Quart J Roy Meteor Soc, 1999, 125(554): 723-757, https://doi.org/10.1002/qj.49712555417.

[34] YUN Y, LIU C, LUO Y, et al. Convection-permitting regional climate simulation of warm-season precipitation over Eastern China [J]. Clim Dynam, 2020, 54(3): 1469-1489, https://doi.org/10.1007/s00382-020-05172-y.

[35] MORRISON H, CURRY J A, KHVOROSTYANOV V I. A new double-moment microphysics parameterization for application in cloud and climate models, Part I: description [J]. J Atmos Sci, 2005, 62(6): 1665-1677, https://doi.org/10.1175/JAS3446.1.

[36] JANJIC Z I. The step-mountain eta coordinate model: Further developments of the convection, viscous sublayer, and turbulence closure schemes [J]. Mon Wea Rev, 1994,
37 SHAO H, DERBER J, HUANG X Y, et al. Bridging research to operations transitions: status and plans of community GSI [J]. Bull Amer Meteor Soc, 97: 1427-1440, https://doi.org/10.1175/BAMS-D-13-00245.1.

38 AULIGNE T, MCNALLY A P, DEE D P. Adaptive bias correction for satellite data in a numerical weather prediction system [J]. Quart J Roy Meteorol Soc, 2007, 133(624): 631-642, https://doi.org/10.1002/qj.56.

39 BARKER D, HUANG XY, LIU Z, et al. The Weather Research and Forecasting model’s community variational/ensemble data assimilation system: WRFDA [J]. Bull Amer Meteor Soc, 2012, 93(6): 831-843, https://doi.org/10.1175/BAMS-D-11-00167.1.

40 CLARK A J, GALLUS W A, WEISMAN M L. Neighborhood-based verification of precipitation forecasts from convection-allowing NCAR WRF model simulations and the operational NAM [J]. Wea Forecasting, 2010, 25(5): 1495-1509, https://doi.org/10.1175/2010WAF2222404.1.

41 REN Chen-ping, CUI Xiao-peng. The cloud-microphysical cause of torrential rainfall amplification associated with Bilis (0604) [J]. Sci China Earth Sci, 2014, 57(9): 2100-2111, https://doi.org/10.1007/s11430-014-4884-6.

42 LOU L, LI X. Radiative effects on torrential rainfall during the landfall of Typhoon Fitow (2013) [J]. Adv Atmos Sci, 2016, 33(1): 101-109, https://doi.org/10.1007/s00376-015-5139-y.

43 KAIN J S, FRITSCH J M. A one-dimensional entraining/detraining plume model and its application in convective parameterization [J]. J Atmos Sci, 1990, 47(23): 2784-2802, https://doi.org/10.1175/1520-0469(1990)0472.0.CO;2.

44 IACONO M J, DELAMERE J S, MLAWER R J, et al. Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models [J]. J Geophys Res, 2008, 113: D13103, https://doi.org/10.1029/2008JD009944.

45 CHEN F, DUDHIA J. Coupling an advanced land surface-hydrology model with the Penn State-NCAR MM5 modeling system, Part I: Model description and implementation [J]. Mon Wea Rev, 2001, 129(4): 569-585, https://doi.org/10.1175/1520-0493(2001)129<0569:CAALSH>2.0.CO;2.

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