

The Impact of Airborne Doppler Aerosol Wind (DAWN) Lidar Wind Profiles on Numerical Simulations of Tropical Convective Systems during the NASA Convective Processes Experiment (CPEX)

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ABSTRACT

High-spatiotemporal-resolution airborne Doppler Aerosol Wind (DAWN) lidar profiles over the Caribbean Sea and Gulf of Mexico region were collected during the NASA Convective Processes Experiment (CPEX) field campaign from 27 May to 24 June 2017. This study examines the impact of assimilating these wind profiles on the numerical simulation of moist convective systems using an Advanced Research version of the Weather Research and Forecasting (WRF) Model (WRF-ARW). A mesoscale convective system and a tropical storm (Cindy) that occurred on 16 June 2017 in a strong shear environment and on 21 June 2017 in a weak shear environment, respectively, are selected as case studies. The DAWN wind profiles are assimilated with the NCEP Gridpoint Statistical Interpolation analysis system using a three-dimensional variational (3DVar) and a hybrid three-dimensional ensemble-variational (3DEnVar) data assimilation systems to provide the initial conditions for a short-range forecast. Results show that the assimilation of DAWN wind profiles has significant positive impacts on convective simulations with the two assimilation approaches. The assimilation of DAWN wind profiles creates notable adjustments in the analysis of the divergence field for WRF simulations with a good agreement of wind forecasts with radiosonde observations. The quantitative precipitation forecasting is also improved. In general, the 3DEnVar data assimilation method is deemed more promising for DAWN data assimilation. There are cases with Tropical Storm Cindy in which DAWN data have slight to neutral impact on rainfall forecasts with 3DVAR, implying complicated interactions between errors of retrieved wind data and background error covariance in the lower and upper troposphere.

1. Introduction

Moist convective systems are important atmospheric processes that determine the vertical turbulent transport of water vapor and heat, regulating the vertical thermodynamic structure of the atmosphere and large-scale circulation. They are also a critical source of upper-level clouds and intense rainfall events in the tropics and midlatitudes. In general, the upscale growth or organization of convective cells at the mesoscale results in mesoscale convective systems (MCSs), whose life cycle is longer than that of any individual convective element. Long-lived MCSs can be

responsible for flash floods and severe weather and thus have a negative societal impact. It has been recognized that MCSs contribute to a large proportion of warm-season rainfall and exhibit strong spatial variability of stratiform rain amount across both the tropics and midlatitudes (e.g., as reviewed by Houze 2004). However, numerical prediction and simulation of convective clouds and precipitation remain a great challenge (e.g., Arakawa 2004; Dirmeyer et al. 2012; Jayakumar et al. 2017). Some studies focusing on high-resolution simulations show less improvement in the structure of convection (e.g., Zhang et al. 2006; Rajendran et al. 2008) due to the limited capability of numerical models to represent moist physical processes, both in model physics and initial conditions (Bryan and Morrison 2012; Potvin et al. 2017; de Rooy et al. 2013).

To better understand and predict MCSs, many studies have been conducted on convective initiation, evolution,

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and associated cloud and precipitation processes (Zipser et al. 2006; Rasmussen and Houze 2016). Specifically, over the United States, most studies on MCSs emphasize the U.S. Great Plains because of the notable severe storms that occur over that region; examples include the well-known field programs of International H₂O Project (IHOP_2002; Weckwerth et al. 2004) and the recent Plains Elevated Convection at Night (PECAN) project (Geerts et al. 2017). However, the Gulf of Mexico, which also has very active MCSs and has a significant influence on severe weather systems over the U.S. coastal region, has not yet been well studied due to a lack of observations, although the region has occasionally been sampled during the hurricane season.

To understand convective storm initiation, evolution, and dissipation over the Gulf of Mexico, the NASA Convective Processes Experiment (CPEX) aircraft field campaign took place in the North Atlantic–Gulf of Mexico–Caribbean oceanic region during the early summer of 2017. During the field campaign, NASA's DC-8 aircraft logged 100 h of flight time and was equipped with multiple instruments capable of taking measurements that were expected to help scientists improve their understanding of convective processes, including radars, dropsondes, and the Doppler Aerosol Wind (DAWN) lidar. In general, wind lidars extract information from the Doppler frequency shift in backscattered signals from aerosols or molecules. Previous studies have indicated that the high temporal and spatial resolution of Doppler wind lidar data provides useful datasets. For instance, during the THORPEX Pacific Asian Regional Campaign (TPARC) field experiments, numerical results with the assimilation of airborne wind lidar profiles showed positive impacts on both the track and intensity of Typhoon Nuri (Pu et al. 2010). During the IHOP_2002 field campaign, the assimilation of Goddard Lidar Observatory for Winds (GLOW) wind profiles suggested a significant influence on numerical simulations of convective initiation and evolution (Zhang and Pu 2011).

Similar to other Doppler lidar instruments, the DAWN system derives information from the motion of aerosol and cloud particles. It was first aboard the NASA aircraft during the Genesis and Rapid Intensification Processes (GRIP) experiment (Braun et al. 2013). Specifically, DAWN can retrieve winds through an airborne wind profiling algorithm at altitudes with a high signal-to-noise ratio (SNR) (Beyon et al. 2013). During CPEX, DAWN provided effective three-dimensional wind data in the oceanic region to support the quantitative evaluation and numerical model simulation of convective systems. The dataset also offers a unique opportunity for evaluating the effectiveness of observing systems (wind lidar) for enhancing the prediction skill of tropical convection over

the ocean in the North Atlantic–Gulf of Mexico–Caribbean region. Therefore, the goal of this paper is to examine the impact of the high-temporal-resolution wind data from DAWN on short-range numerical simulations of tropical convective systems. Specifically, we choose two convective cases occurring during CPEX over the Gulf of Mexico and the Caribbean Sea to evaluate the analysis and forecast impact of DAWN wind profiles. In addition, different assimilation methods are used and compared to assimilate the wind profiles.

The paper is organized as follows. In section 2, the DAWN wind profiles and two convective cases are briefly described. The numerical model, data assimilation (DA) system, and numerical experiments are introduced in section 3. The DA results and sensitivity experiments are presented in section 4. The influence of errors in DAWN wind profiles is discussed in section 5. Concluding remarks are made in the final section.

2. Overview of DAWN data and convective cases

a. DAWN system and wind profile observations

The DAWN system is a pulsed, 2-micron, coherent-detection system, developed at the NASA Langley Research Center (Kavaya et al. 2011). Kavaya et al. (2014) describe all the components of this system, including the advanced laser energy, optimized telescoped filed, and other lidar sensitivity improvements that allow improved performance over a range of almost 10 km. This compact airborne instrument integrated into DC-8 flights is shown in Fig. 1a. Its nominal scan pattern uses a 30° off nadir elevation angle oriented in five azimuth angles, which are -45° , -22.5° , 0° , 22.5° , and 45° relative to the forward direction of the fuselage. Three azimuth directions are necessary for horizontal wind derivation, and more azimuth angles help improve wind measurement accuracy (Kavaya et al. 2011). This laser system receives the backscattered portion of its transmitted laser pulse at a 10-Hz rate from aerosols and cloud particles that move with the wind. Then, line-of-sight winds can be determined by the sign and magnitude of frequency shift. When this operation is repeated in five different scanner azimuth angles, horizontal wind vector may be calculated with a set of Doppler shift equations. Vertical wind velocity is not computed in this baseline dataset currently. Due to contamination of flight motion, all DAWN data during turns with banks greater than 1.5° or climb/descents greater than 7 ms^{-1} have been rejected. The reasonable baseline quality is the goodness of fit (GoF) for the vector products derived from a best-fit solver. The detailed retrieval algorithm can be found (Emmitt and Greco 2019).

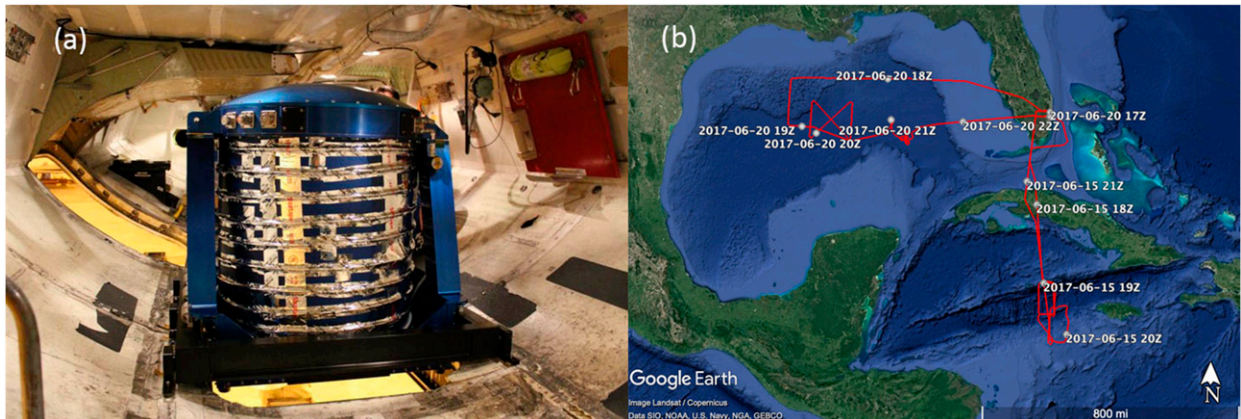


FIG. 1. (a) DAWN lidar optics container (<https://cpex.jpl.nasa.gov>) and (b) snapshot of flight tracks of CPEX campaign on 15 and 20 Jun 2017 (the background image is copyright 2019 by Google Earth).

The CPEX mission from May to June 2017 is the second science campaign of the DAWN lidar instrument for research applications after NASA's GRIP field program. Almost 100 h of flight time provide more than 5000 DAWN wind profiles from flight level down to the ground in cloud-free areas or near scattered convective regions. Figure 1b is a snapshot of the flight tracks on 15 and 20 June 2017, launched from Florida and then observed wind velocity profiles in the Caribbean Sea and Gulf of Mexico, respectively. These correspond to the period of organized convection formation and the development of Tropical Storm Cindy. The following subsection will provide a detailed description of these two convective processes.

b. Case overview

Tropical wave motion is very active during the CPEX field experiment. Typically, strong organized precipitation in the Caribbean and Gulf of Mexico occurs as a tropical wave moves through these areas. During the day on 16 June 2017, the tropical waves move slowly northwest, the classical inverted-V-shaped cloud bands over the central Caribbean Sea are well developed, and new cloud clusters over the southeastern Caribbean Sea and along the east coast of Central America continue to develop (Fig. 2a). Because of strong wind shear, nine hours later (Fig. 2b) they aggregate to form a mesoscale convective system, as indicated by the broad, thick, and cold area of clouds. During the day on 20 June 2017, a closed circulation associated with tropical waves over the central Gulf of Mexico further develops and moves northwest in a weak wind shear environment and then forms a tropical storm (Cindy) over the western Gulf of Mexico. As shown in Figs. 2c and 2d during the next day, the storm nears the coast of Texas, with cloud bands on the northeast side

over Louisiana and offshore. In this study, the MCS over the Caribbean Sea is designated as case 1, and Tropical Storm Cindy is case 2.

3. Numerical model simulation design

a. Numerical model and assimilation system configuration

An Advanced Research version of the Weather Research and Forecasting (WRF) Model (WRF-ARW), version 3.9.1, is used for convective process simulations. The model is based on compressible nonhydrostatic equations and is capable of supporting multiple scales of meteorological applications ranging from tens of meters to thousands of kilometers (Skamarock et al. 2008). The model physical options used in this study include the WRF single-moment 6-class microphysics scheme (WSM6) with ice, snow, and graupel processes (Hong and Lim 2006); the new Tiedtke cumulus scheme with convective available potential energy closure (Zhang et al. 2011) and other well-tested physics schemes [more details can be seen on "tropical" physics suites in WRF 3.9.1 updates online (<http://www2.mmm.ucar.edu/wrf/users/>)], such as the new version of the Rapid Radiative Transfer Model for GCMs (RRTMG) for longwave and short-wave radiation (Iacono et al. 2008); the revised MM5 surface layer scheme (Jiménez et al. 2012); the Noah land surface model (Chen and Dudhia 2001); and the Yonsei University (YSU) planetary boundary layer scheme (Hong et al. 2006). The cumulus parameterization is turned off in the innermost domain.

A four-level nested domain is used in these two case studies. The model horizontal spacing in both the zonal and meridional directions is 27, 9, 3, and 1 km from outer to inner domains. Figure 3 shows the model domain

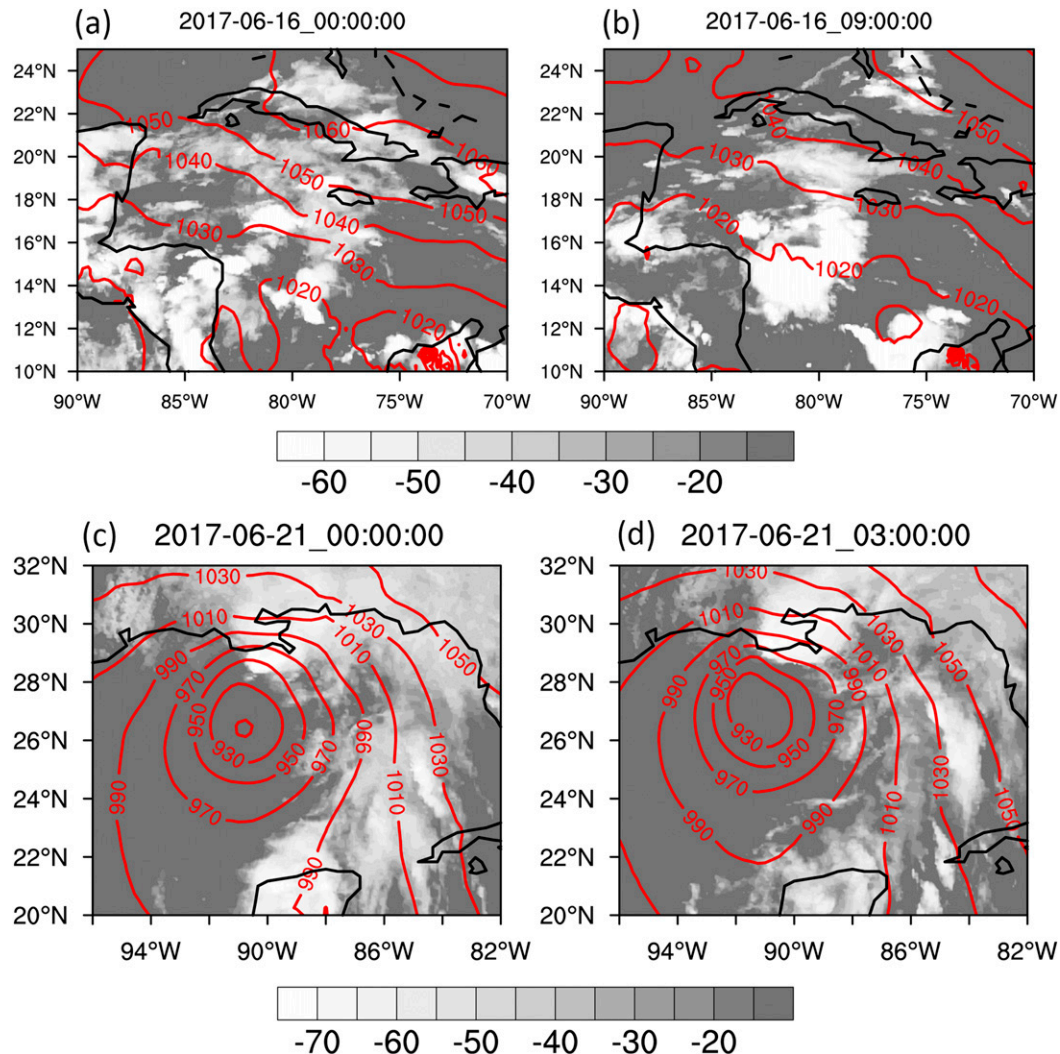


FIG. 2. Satellite infrared radiation brightness temperature (colored shading; °C) from ISCCP B1 Gridded Satellite (GridSat-B1) observations and geopotential height (red lines; m) at 900 hPa from the ERA5 reanalysis dataset for (a),(b) case 1 and (c),(d) case 2.

configuration with satellite IR brightness shaded for case 1 and case 2 in all experiments. The locations of DAWN lidar wind profile observations in the two cases are also marked during 15 and 20 June 2017, respectively. Specifically, for case 1, the sizes of the model grids are 163×147 , 196×196 , 367×295 , and 661×442 in order from the outermost to innermost domains. The intermediate two-level nested domains cover most of the DAWN data collection area, and the innermost domain corresponds to the main area where the meso-scale convective system occurs over the Caribbean Sea. For case 2, the sizes of the model grids are 150×150 , 322×271 , 700×595 , and 1201×985 in order from the outermost to innermost domain. As with case 1, the two intermediate domains are centered on the central Gulf

of Mexico and contain the location of all DAWN data samples. The innermost domain is the main area for our analysis and model validation results. The model vertical structure in these two cases comprises 30 and 42 eta levels, respectively, both with the model top set at 50 hPa. The final analysis products of the National Centers for Environmental Prediction (NCEP)'s Global Data Assimilation System (GDAS) at $0.25^\circ \times 0.25^\circ$ horizontal resolution are used in this study to derive the initial and boundary conditions for WRF simulations.

The NCEP Gridpoint Statistical Interpolation analysis system (GSI) is a state-of-the-art DA system. The GSI can be applied in a three-dimensional variational data assimilation (3DVar) technique, as well as in a 3D ensemble-variational (3DENVar) hybrid system.

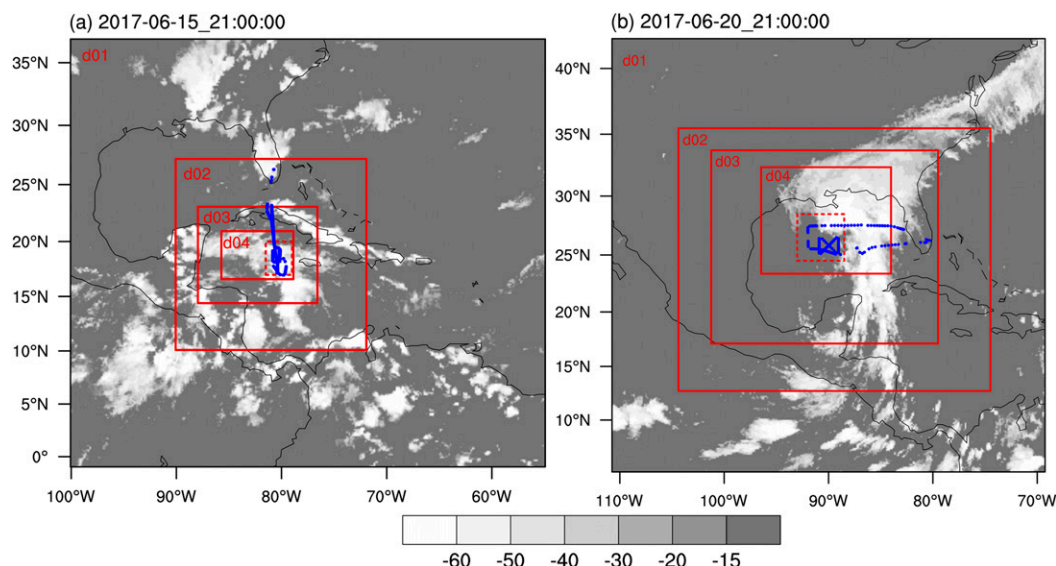


FIG. 3. Simulation domain configuration for (a) case 1 and (b) case 2 with brightness temperature distribution from GridSat-B1 observations (colored shading; $^{\circ}\text{C}$) valid at 2100 UTC 15 and 2100 UTC 20 Jun 2017, respectively. The locations of DAWN wind profiles used in assimilation are marked by blue dots. The area shown by the dashed lines indicates the region used for some of the following analysis verification.

Both systems have been implemented operationally for both global and regional applications (Wu et al. 2002; Wang et al. 2013; Kleist and Ide 2015; Tong et al. 2018). The background error covariance in GSI-3DVar is the static background error covariance generated by the National Meteorological Center method. GSI-3DEnVar incorporates ensemble covariance in the variational framework, and a detailed mathematical derivation and description can be found in Wang et al. (2013). The flow-dependent ensemble background error component is directly calculated from external ensemble forecasts instead of with the ensemble Kalman filter (EnKF) technique.

b. Experiment design

This study focuses on evaluating the data impact of DAWN profiles from the CPEX field campaign on convection simulation and analyzing possible mechanisms (i.e., improved divergence profiles) associated with the improvement of precipitation simulation through assimilation of dynamic variables. The performance of the WRF Model accompanied by assimilation of DAWN wind profiles is evaluated based on three assimilation experiments (Table 1) for the two cases described above. The control experiment (CTL) assimilates conventional data retrieved from NCEP Automated Data Processing (ADP) global upper air and surface weather observations with the GSI-3DEnVar method. This ADP dataset includes wind reports from the Global Telecommunications System (GTS), profiler

and U.S. radar-derived winds, and SSM/I oceanic winds and satellite wind data from the National Environmental Satellite, Data, and Information Service (NESDIS), but no satellite radiances. These data are available in 6-h time windows centered at each synoptic time. The other two assimilation experiments, 3DVAR and HYBRID, assimilate both NCEP ADP observations with same assimilation configuration as in experiment CTL, along with DAWN wind profiles using the GSI-3DVar and GSI-3DEnVar methods, respectively. Therefore, as shown in Table 2, for case 1, the WRF Model is initialized at 1200 UTC 15 June 2017 and spins up until 1800 UTC 15 June 2017 to provide background for DA in all experiments. In CTL, the ADP data are assimilated during two 6-h DA cycles at 1800 UTC 15 and 0000 UTC 16 June 2017, and then 12-h forecasts are conducted up to 1200 UTC 16 June 2017. In the 3DVAR and HYBRID experiments, the configuration for ADP data is the same as in CTL. The DAWN data are added with hourly DA cycles from 1800 to 2200 UTC

TABLE 1. The list of assimilation experiments for two cases.

Expt	Observation assimilated and configuration
CTL	Convective data on domains 2 and 3 with the GSI-3DEnVar method
3DVAR	Add DAWN wind profile with the GSI-3DVar method
HYBRID	Add DAWN wind profile with the GSI-3DEnVar method

TABLE 2. List of DAWN DA configurations for case 1 and case 2.

Case	DAWN data available time period (June 2017)	DA and forecast (FCST) period (June 2017)
Case 1	1813 UTC–2158 UTC 15	DA: 1800 UTC 15–0000 UTC 16 FCST: 0000–1200 UTC 16
Case 2	1758 UTC–2329 UTC 20	DA: 1800 UTC 20–0000 UTC 21 FCST: 0000–1200 UTC 21

15 June 2017, recognizing the high temporal resolution of DAWN wind profiles and early test results that indicated the hourly cycles outperform 6-hourly cycles for DAWN DA. As with case 1, this suite of assimilation experiments is also performed for case 2. Specifically, the WRF Model is initialized at 1200 UTC 20 June 2017 and allowed to spin up to 1800 UTC 20 June 2017. Six-hourly cycled DA with ADP data is conducted from 1800 UTC 20 to 0000 UTC 21 June 2017, and then followed by 12-h forecasts. In 3DVAR and HYBRID, the DAWN data are added with hourly DA and the forecast cycle is from 1800 to 2300 UTC 20 June 2017. DA in all experiments for case 1 and case 2 is performed on domains 2 and 3, and domain 4 starts the simulation from the initial forecast time in case 1 and case 2, namely, at 0000 UTC 16 and 0000 UTC 21 June 2017, respectively.

In this study, the self-consistent WRF ensemble covariance (e.g., Pu et al. 2016) is derived from downscaling outputs of 21 WRF ensemble members initialized by the members of the NCEP Global Ensemble Forecast System (GEFS). The downscaling ensemble forecasts are then used to generate this flow-dependent background error covariance. The background error covariance and horizontal localization scales in GSI-3DVar are treated differently in case 1 and case 2 for assimilation of DAWN data. In the case 1 analysis, the covariance is a combination of 50% static and 50% ensemble covariance, realizing the sampling issue of a small ensemble size. The weighting of ensemble covariance increases to 80% for case 2, considering that the correlation structure of the storm scale cannot be effectively represented in static covariance. This change also allows more information in representing the inhomogeneous features of tropical storm vortices in the hybrid method due to the flow-dependent feature of ensemble forecasts. The horizontal localization scale used for assimilation in case 1 and case 2 is 1000 and 100 km, respectively. The vertical localization scale and half-time window for both cases is three grid levels and 2 h, respectively.

In addition, the quality of the DAWN baseline products is represented by the goodness of fit from a best-fit solver (Emmitt and Greco 2019). Most errors are less than 1 m s^{-1} (the minimum value of the wind error in the current GSI version); thus, the observation

error is uniformly set to 1 m s^{-1} . Data thinning is also performed on the horizontal thinning grid size of 9 km, the same as the horizontal grid spacing of WRF domain 2 in both cases.

4. Impacts of DAWN data assimilation

a. Wind fields

Figure 4 shows the times series of DAWN wind profiles used in both the GSI-3DVAR and GSI-3DVar DA analyses. The vertical wind profiles are available from the near surface up to 200 hPa. The high density of DAWN data is concentrated below 850 hPa and above 500 hPa, and the data in the middle level are sparse because of the scattered clouds or thin clouds contamination, especially in case 2 (as shown by Fig. 4b). At the same time, these profiles also reveal the different

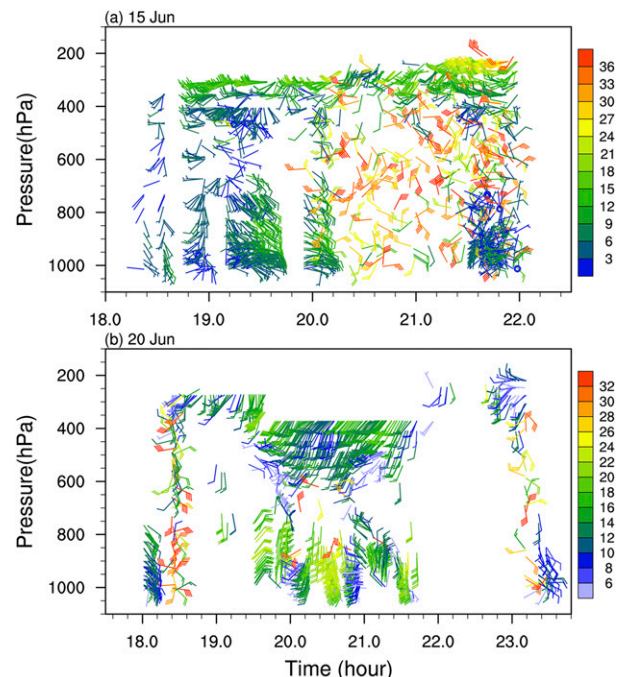


FIG. 4. Panorama display (time–pressure level) of DAWN-retrieved wind bars along the flight track for (a) 15 Jun and (b) 20 Jun 2017, with colored marks showing the magnitude of wind speed (m s^{-1}).

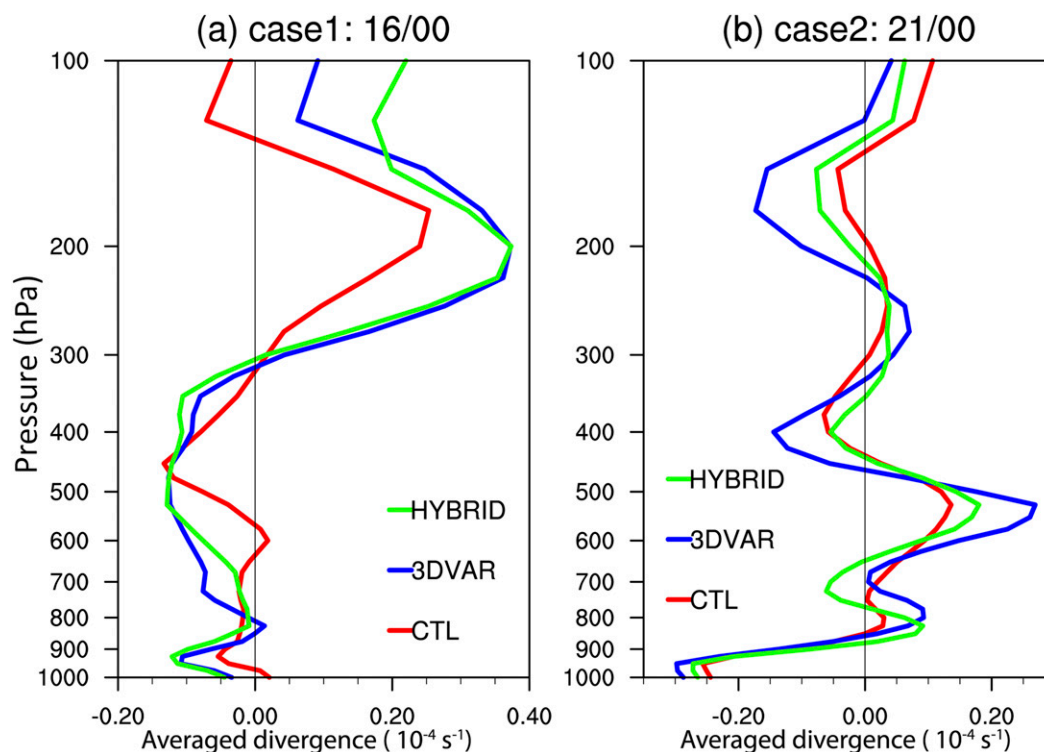


FIG. 5. Spatial averaging divergence profiles in (a) case 1 and (b) case 2 at their initial forecast time (case 1: 0000 UTC 16 Jun 2017; case 2: 0000 UTC 21 Jun 2017). The areas used for spatial averaging in the two cases are denoted by the red dashed square in Fig. 3. The horizontal axis indicates the magnitude of divergence (10^{-4} s^{-1}), and the solid black line represents the isoline of zero divergence in the vertical direction for reference.

characteristics of the circulation before the occurrence of the two convective cases. Specifically, in the initiation phase of the mesoscale convective system (case 1), an easterly prevails in the lower level and a westerly dominates the upper level. There is a strong wind direction shear. However, in the formation of the tropical storm (case 2), zonal wind and vertical wind shear are weak and the whole layer of the atmosphere shows a clear southerly component, which provides a favorable environment for intensification of the tropical storm.

To illustrate the impact of assimilating DAWN wind profiles on the wind field, Fig. 5 shows the averaged divergence profile over the data-rich coverage region, indicated by the dashed box in Fig. 3 at 0000 UTC 16 and 0000 UTC 21 June 2017, which corresponds to the last DA cycle for case 1 and case 2, respectively. Obvious adjustments of the convergence field in all vertical levels in both 3DVAR and HYBRID compared to CTL are evident. The detailed impacts from the two cases have different behaviors. Specifically, assimilation of DAWN wind profiles in case 1 increases the low-level convergence (below 900 hPa) and the upper-level divergence (100–300 hPa). The convergent

layer in the middle level (300–800 hPa) tends to extend both downward and upward, but 3DVAR shows a slight downward shift and weak divergence between 800 and 900 hPa. These changes in the divergence profile suggest an enhanced convergence layer from the surface to 300 hPa and a divergence layer above, which provides a favorable environment for the generation of the large-scale precipitation cloud system. For case 2, assimilation of DAWN data causes a significant increase in the convergence field near the ocean surface (below 900 hPa) and upper troposphere (100–250 hPa). In addition, the divergence layer centered around 250 hPa tends to move downward slightly. The main adjustment difference shows that 3DVAR exhibits a larger amplitude. However, the changes in the alternating convergent–divergent flow in the middle and lower troposphere indicate strong disagreement in 3DVAR and HYBRID, which may result from DAWN data sparseness in the middle level and differences in background error spread. According to the best-track data (from National Hurricane Center), at this time, the vortex center is inside this area, suggesting that the internal vortex has stronger inflow and compensated outflow. The overall impacts of DAWN

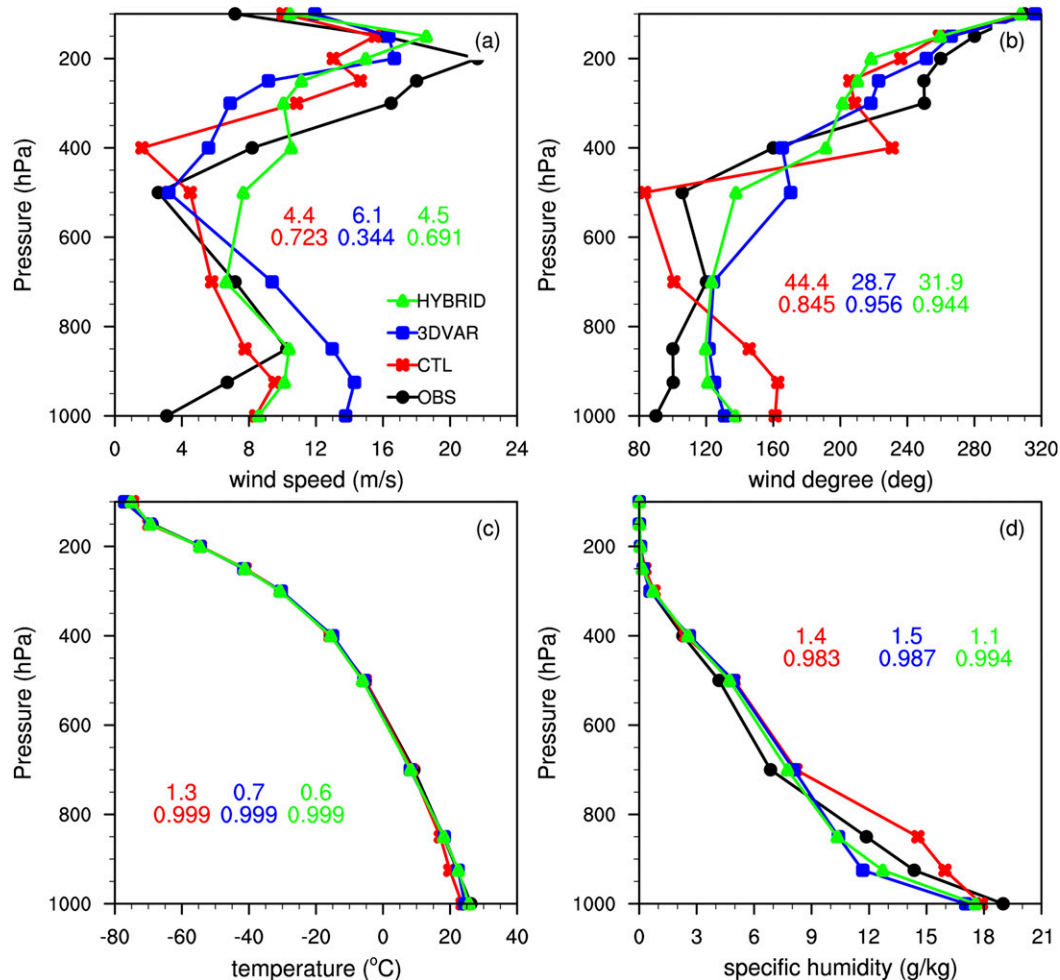


FIG. 6. Comparison of vertical profiles of (a) wind speed, (b) wind direction, (c) temperature, and (d) specific humidity at a station (19.3°N, 81.37°W) from radiosonde observations (black line), CTL (blue line), 3DVAR (red line), and HYBRID (green line) for case 1 at 1200 UTC 16 Jun 2017. The colored number in the first row of each panel denotes the root-mean-square error for the experiments corresponding to the line colors. Similarly, the colored number in the second row indicates the correlation coefficient with observations.

DA imply a stronger interaction between the vortex and its environment field during tropical storm genesis.

b. Comparison with radiosonde observations

In the forecast period, there is no dropsonde or DAWN wind profile for model validation. Convective sounding data from the ADP dataset available in the innermost model domain are employed for comparison. To verify whether the meteorological fields in the numerical simulations are realistic, Figs. 6 and 7 show the vertical distribution of wind speed, wind direction, temperature, and specific humidity in both observations and 12-h forecasts for case 1 and case 2, respectively. The corresponding root-mean-square error (RMSE) and correlation coefficients are also calculated. In simulations of case 1, although the wind speed does not show slight

degradation (e.g., RMSE increases and correlation coefficients decrease in two assimilation experiments), the wind direction in the experiment with the assimilation of DAWN profiles matches observations better than that in CTL, especially in the low-level troposphere. Its vertical variability is closer to observation in assimilation experiments (i.e., higher correlation coefficients). The negative bias of temperature and the positive bias of specific humidity in CTL at the lower level are also reduced when DAWN data are assimilated, suggesting better representation of wind shear and low-level thermodynamic characteristics in both 3DVAR and HYBRID. As for the simulations in case 2 (Fig. 7), assimilation of DAWN wind still suggests some benefits (e.g., lower RMSE and higher correlation coefficients) to the vertical change of wind speed

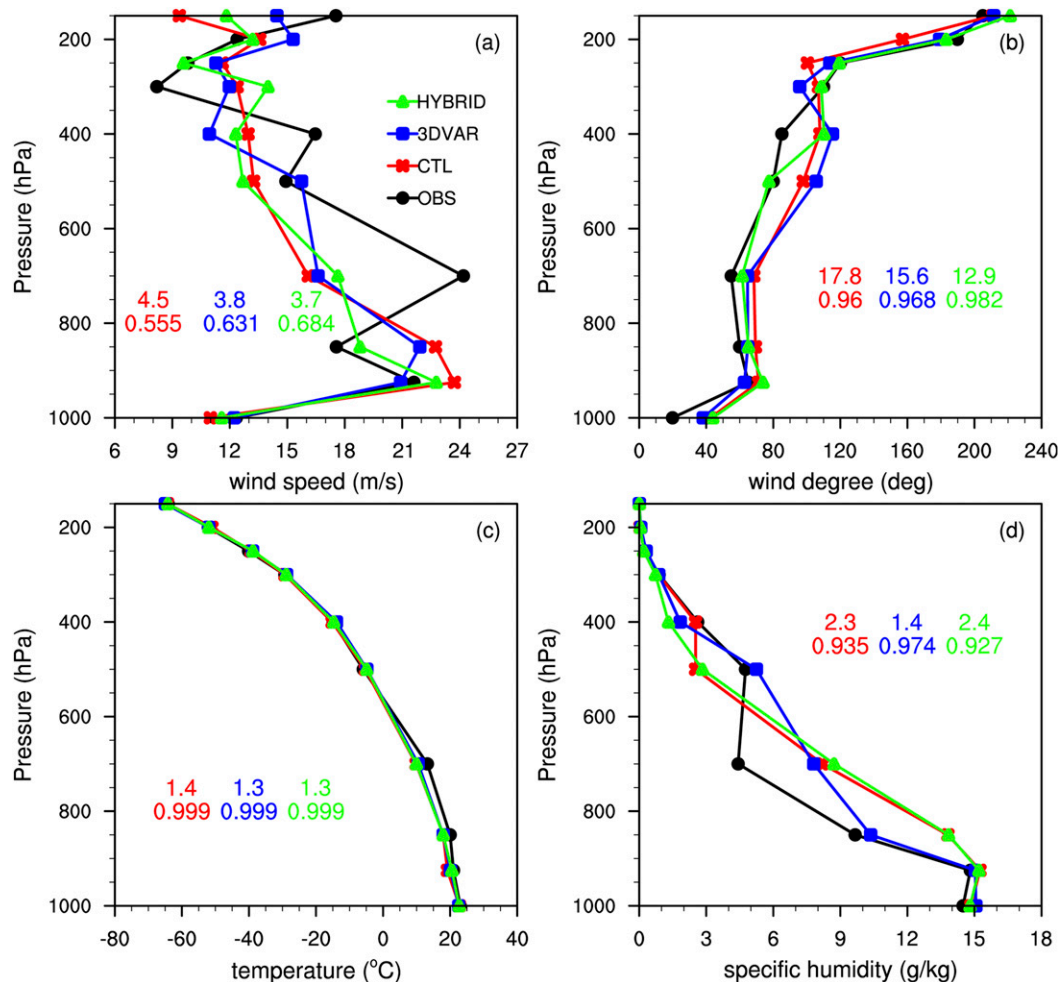


FIG. 7. As in Fig. 6, but for the station (30.13°N, longitude: 93.22°W) and for case 2 at 1200 UTC 21 Jun 2017.

and direction, although some mixed impacts (e.g., larger biases on some vertical layers in the assimilation experiments) are seen at this forecast time. In addition, the assimilation experiments also give small temperature and humidity bias in the middle and lower troposphere.

c. Precipitation

An important aspect of convective systems is their precipitation forecast. In the description and simulation of case 1, we see that the precipitation area is near the Caribbean Sea. Because of the operational difficulty of implementing rain gauges over the ocean, satellite-based precipitation analysis is used for precipitation validation. Specifically, the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA), which has been applied for the NASA Global Precipitation Measurement (GPM) mission, provides a fine-scale rainfall dataset for many hydrological applications

(Huffman et al. 2007). Figure 8 shows the 3-hourly rainfall rate from TMPA (e.g., TRMM) and all experimental forecasts valid at 0600 UTC 16 June 2017. It is clear that the precipitation location is better predicted in HYBRID than in CTL. Recently, the transition from TMPA to the Integrated Multisatellite Retrievals for GPM (IMERG) extended the sensor package to support much finer resolution than that in TRMM. For case 1, the comparison of the precipitation forecast with IMERG still exhibits similar results (figure not shown).

For case 2, the precipitation occurs mainly on the northeast side of the tropical storm, where it is close to the coast of the contiguous United States and some offshore areas. Satellite-based rainfall shows large uncertainties over land compared to over ocean (e.g., Rauniyar et al. 2017). In this study, the Climatology-Calibrated Precipitation Analysis (CCPA) product keeps the spatiotemporal patterns of the NCEP stage

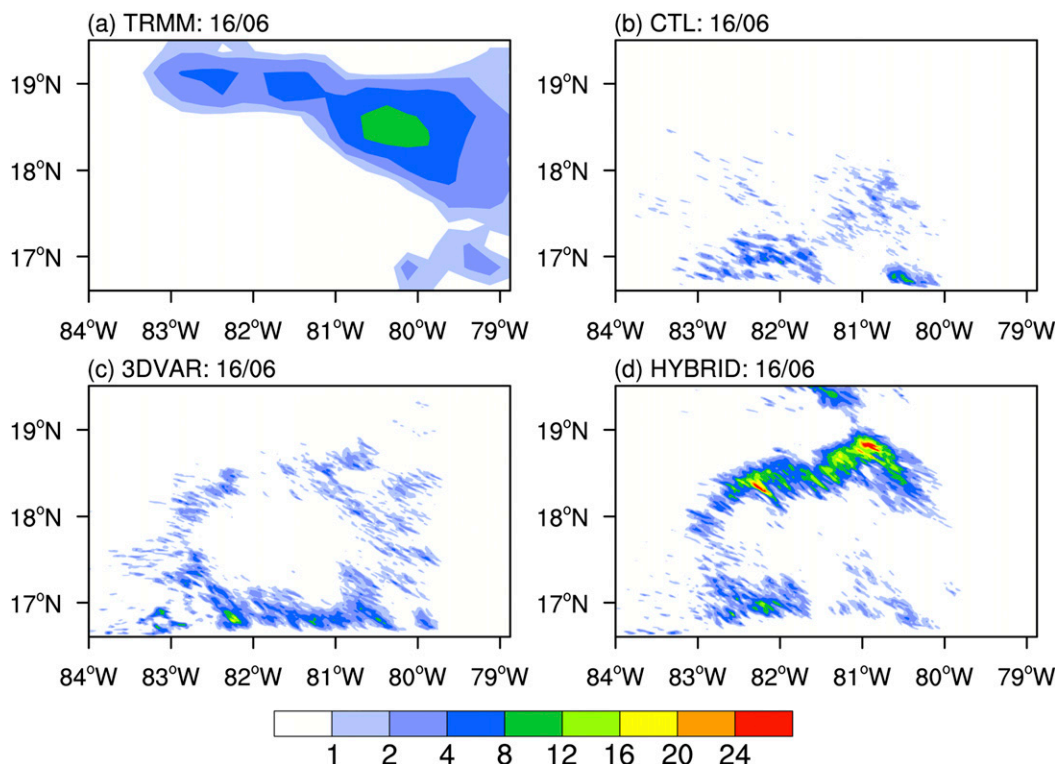


FIG. 8. Three-hourly rainfall rate (mm h^{-1}) for case 1 centered at 0600 UTC 16 Jun 2017: (a) TRMM, (b) CTL, (c) 3DVAR, and (d) HYBRID.

IV analysis (e.g., Nelson et al. 2016), with correction of the Climate Prediction Center (CPC) analysis (Hou et al. 2014) was employed for comparison. Figure 9 compares the 6-hourly accumulated precipitation from CCPA and case 2 numerical simulations. All experiments have predicted precipitation band along the coast, but the distribution of precipitation maxima has large differences. Specifically, CTL tends to overestimate the precipitation along the coastline of western Louisiana, while the experiments with DAWN DA produce a better spatial pattern of precipitation over the coastal region of eastern Louisiana, Mississippi, and western Florida.

To further examine the impact of assimilating DAWN wind profiles on the precipitation forecasts, the quantitative precipitation forecast (QPF) skill is evaluated for all numerical experiments in both cases. Threat scores (TS) are computed for six hours of accumulated precipitation in all three experiments. A higher TS represents a better precipitation forecast. Figure 10 presents the TS values for accumulated precipitation at different thresholds for both cases. The calculations performed over the region in case 1 and case 2 shown in Figs. 8 and 9, respectively. The observed precipitation products used for TS calculation are consistent with the above precipitation analysis. In general, the assimilation of DAWN

wind profiles has a positive impact on QPF skill, in both light and heavy rainfall. As indicated by the colored numbers, the average TS skill across almost all precipitation thresholds implies a better performance by HYBRID than by 3DVAR, especially in case 1, where HYBRID tends to produce high precipitation forecast skill at higher thresholds. In case 2, 3DVAR shows a slight negative impact at some thresholds compared with CTL, while HYBRID mitigates the negative impact. The differences between 3DVAR and HYBRID can be attributed to the limited representation of the static background error covariance matrix of error patterns in the numerical model when the tropical storm occurs.

d. Sensitivity of DA to horizontal and vertical localization scales

The localization scale used in the hybrid method avoids the impact of spurious error correlations estimated between two distant points by the ensemble covariances due to sampling issues. Spatial localization is applied both horizontally and vertically through a recursive filter transformation (Hayden and Purser 1995). Distances are measured in kilometers and grid units for horizontal and vertical localization scales, respectively. To investigate the sensitivity of DAWN DA to the

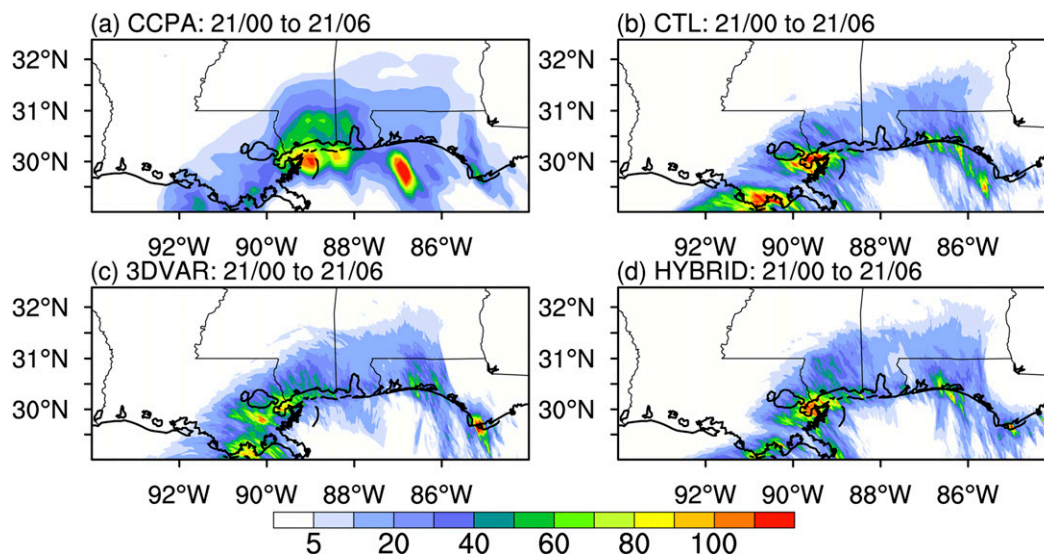


FIG. 9. Six-hourly accumulated precipitation (mm) from (a) CCPA, (b) CTL, (c) 3DVAR, and (d) HYBRID for case 2 valid at 1200 UTC 21 Jun 2017.

horizontal and vertical localization scales, a series of sensitivity experiments with alternative horizontal scales of 500 and 1500 km for case 1, and of 50 and 500 km for case 2, as well as experiments with a vertical scale of one and five grid units for both cases, are conducted. Figure 11 shows the detailed results of all these sensitivity experiments for divergence field differences (Figs. 11a,b) from the HYBRID experiments mentioned above in both cases and the precipitation forecast skill (Figs. 11c,d). Overall, the divergence field is more sensitive to vertical localization scale

than to the horizontal scale in case 1, while it is more sensitive to the horizontal scale in case 2. When increasing the vertical localization scale in case 1, the lower- to middle-level convergences decrease, with significant improvement in the precipitation forecasts. However, when the horizontal localization scale increases in case 2, the amplitude of the alternating convergent–divergent flow at the lower to middle level tends to strengthen, with reduction of the precipitation forecast skill at light to moderate rainfall amounts. The obvious differences between these two

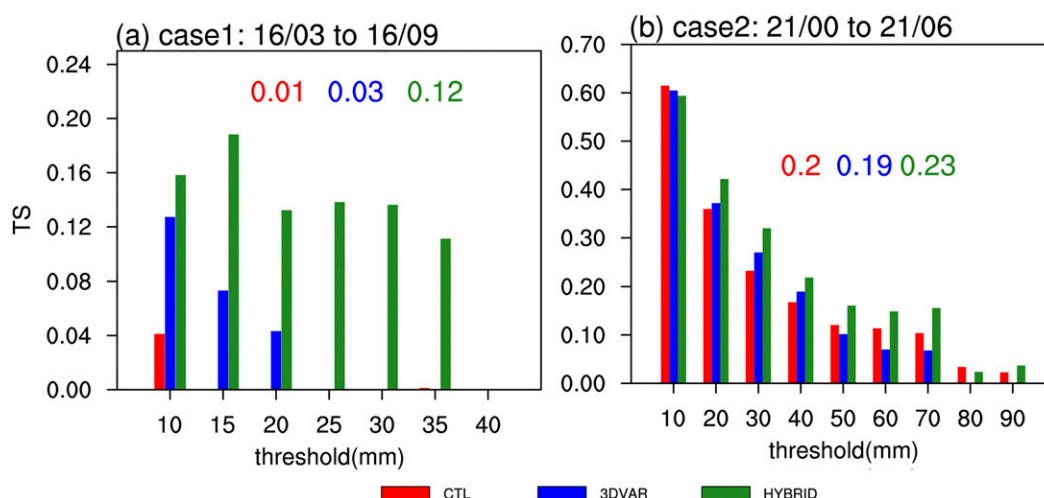


FIG. 10. Threat scores (TS) of the 6-h accumulated precipitation for (a) case 1 against TRMM precipitation analysis over the area covered by Fig. 8 and (b) case 2 against CCPA precipitation analysis over the region covered by Fig. 9, respectively. The x axis represents the precipitation threshold. The red, blue, and green stand for the CTL, 3DVAR, and HYBRID experiments, respectively, and the corresponding colored numbers denote the mean TS over all thresholds.

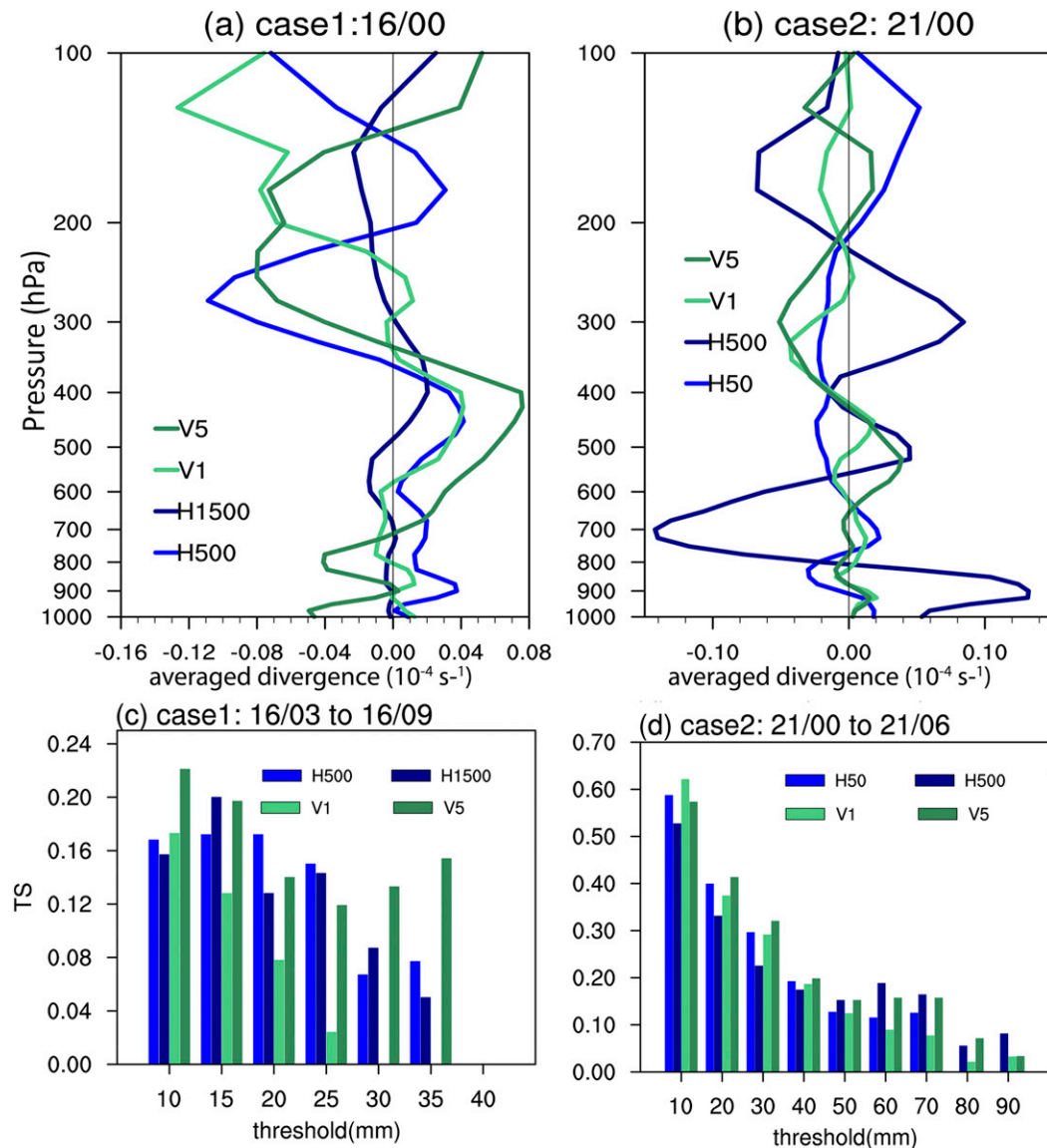


FIG. 11. Vertical profiles of (a),(b) averaged divergence deviation from the HYBRID experiment with the horizontal localization scale of 1000 km and vertical localization scale of three grid units, and (c),(d) the TS of 6-h accumulated precipitation in sensitivity experiments with a different localization scale. In the (left) case-1 configuration, H500 and H1500 denote the sensitivity experiments with the same vertical localization of three grid units but different horizontal localization scales of 500 and 1500 km, respectively; V1 and V5 represent the sensitivity experiments with the same horizontal localization of 1000 km but different vertical scales of one and five grid units, respectively. Similarly, in (right) case 2, H50 and H500 correspond to the horizontal scale of 50 and 500 km with the same vertical scale of three grid units, while V1 and V5 correspond to the vertical scale of one and five grid units with the same horizontal scale of 100 km.

cases indicate the strong flow-dependent influences of DA in terms of data impacts.

5. Influence of uncertainties in DAWN wind data

Although the above results show that DAWN data have an overall positive impact on both convective cases,

neutral and slightly negative data impacts are also noticed in case 2 simulation for some threshold of QPF. To better understand the impact of the DAWN data, we further examine the possible influence of uncertainties in retrieved wind on DA results. According to the assimilation framework proposed in GSI-3DVAR and the subsequent GSI-3DEnVar system (Wang et al. 2013; Wu et al. 2002),

Profile @182649Z (lat:27.29N, lon: 83.17W)

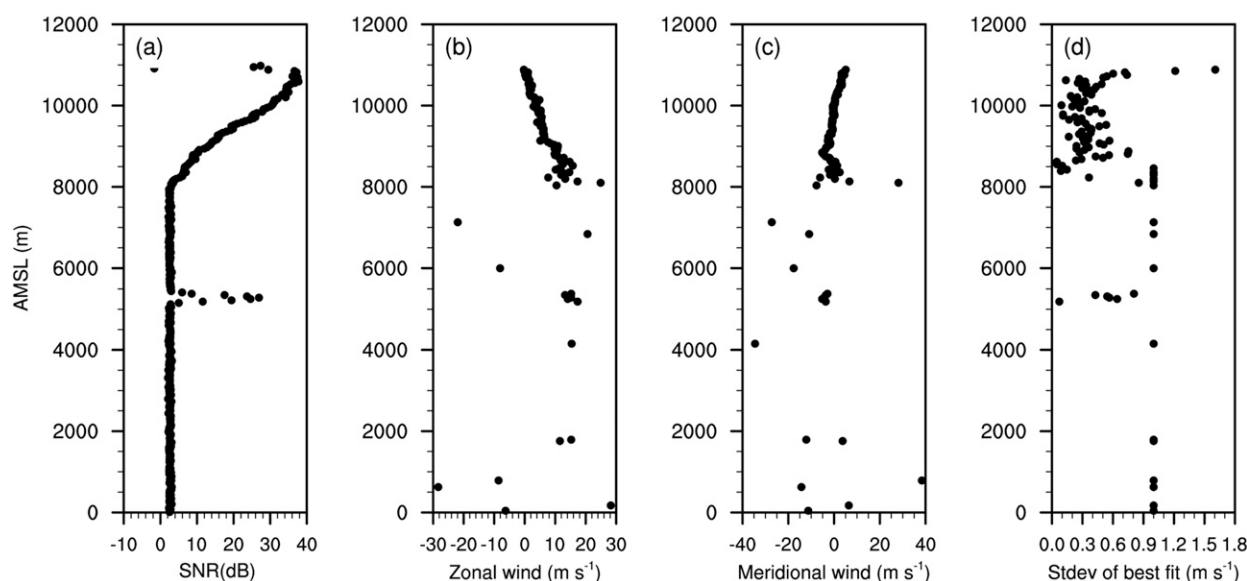


FIG. 12. DAWN vertical profile of (a) SNR, (b) zonal wind, (c) meridional wind, and (d) standard deviation from best fit at each altitude above mean sea level (label AMSL) at 1826 UTC 20 Jun 2017.

the optimal behavior of the assimilation depends mainly on the estimation of background error statistics and observation error statistics for the wind profiles. For background error covariance, the intrinsic defects of the time-independent characteristic of the static component have been discussed in a wide range of variational assimilation systems (e.g., Lorenc 2003). Therefore, here we emphasize the characteristics of the ensemble background error covariance. Meanwhile, we further examine the observational error statistics.

There are some uncertainties in the DAWN wind retrieval algorithm. Figure 12 shows an example of DAWN SNR and wind profile data. In the middle and lower troposphere, SNR is much closer to zero, and the derived zonal and meridional wind exhibit large spread between adjacent vertical levels. This condition implies that the retrieved profile tends to be noisy when the signal is weak, but the corresponding wind speed error from a best-fit solver (Fig. 12d) at these levels is almost constant and limited to 1 m s^{-1} , which almost certainly not fully explain the high-noise characteristics of the DAWN profile. This situation of error vertical distribution would lead to the assimilation system being less capable of filtering out the observation noise and effectively utilizing useful information. In this case, the error specification ($-\text{SNR}$ and GoF) of these datasets needs to be employed to avoid degrading the analysis.

Meanwhile, as in Wang et al. (2008) and Whitaker et al. (2008), two quantities, the innovation variance (i.e., the expectation value of squared observation

innovation) minus the observation variance and ensemble variances, are examined to characterize the performance of the ensemble spread in the hybrid DA method. If these two quantities are similar, which primarily reflects the “ideal” of ensemble spread representation for all assimilation system errors. Figure 13 shows the square root of ensemble spread versus square root of the observation innovation variances minus the observation error variance averaged for each pressure level. The average is computed over the observation locations within the layer that is 50 hPa above and below that level. The number of observations in each pressure level varies with the assimilation cycle time due to the DAWN data available. Over both assimilation domains (domains 2 and 3), the overall ensemble spread of meridional winds (Figs. 13b,d) matches the overall first-guess error, which shows perfect in-phase variation in the vertical direction. The ensemble is underdispersive in the lower and upper troposphere and somewhat overdispersive in between. For zonal winds (Figs. 13a,c), the ensemble spread tends to be underdispersive in the whole vertical layer. This means that the hybrid analysis will weigh the first guess field too much in the lower and upper troposphere. The DAWN data in these levels cannot be effectively used in the hybrid method, and this corresponds to the areas where DAWN data are dense.

This deficiency can be further demonstrated by the statistical residual of observation minus background (OMB) and observation minus analysis (OMA). The distributions

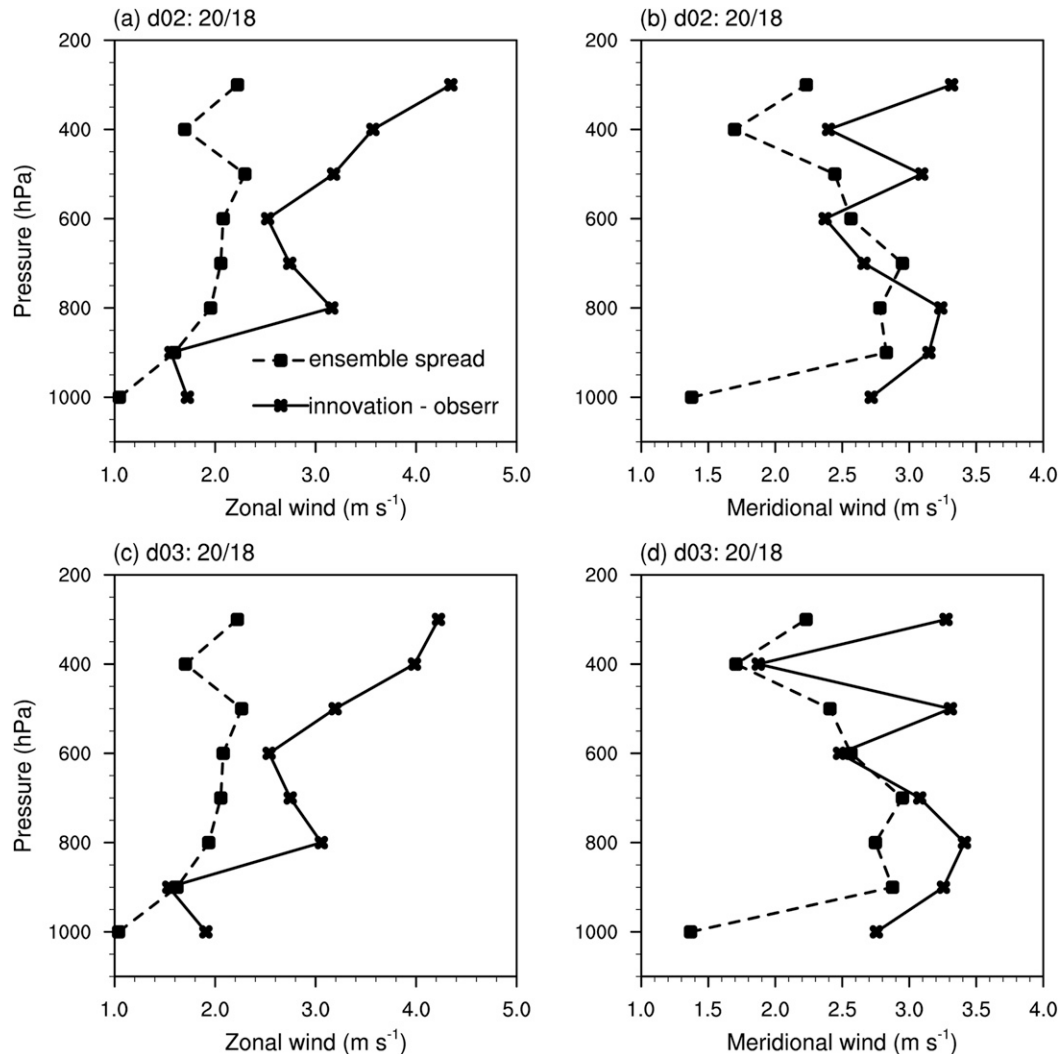


FIG. 13. Vertical profiles of the ensemble spread (dashed line) and square root of innovation variance minus observation error variance (solid line) for (a),(c), zonal and (b),(d) meridional wind over (top) domain 2 and (bottom) domain 3 in case 2 at 1800 UTC 20 Jun 2017.

of zonal wind and meridional wind observations by the residuals of OMB and OMA in both 3DVAR and HYBRID over all assimilation cycles are presented in Fig. 14. The corresponding bias μ and standard deviation σ of the frequency distribution are also appended in Fig. 14. Results show that zonal wind and meridional wind in the background with large innovations (e.g., exceeding 4 m s^{-1}) account for a large proportion of all DAWN observations, and meridional wind exhibits a larger bias and standard deviation than zonal wind. These two wind component analyses tend to be close to observations with both the variational and hybrid methods, which denotes that the minimization process of the cost function converges well for the two wind components. These two assimilation

methods are effective in significantly reducing the mean departures of the wind analysis wind, but their performance is different due to the introduction of ensemble covariance in the hybrid method. Specifically, over both assimilation domains for zonal wind, the bias and standard deviation of OMB in the hybrid method show a slightly smaller magnitude than in the variational method. Meanwhile, a Gaussian-like pattern of OMA with a smaller standard deviation in the hybrid method is observed. However, it is worth noting that for the bias of OMA, the hybrid method exhibits even larger bias than the variational method, reflecting the issues of ensemble spread discussed earlier. In addition, for meridional winds over the two domains, although the hybrid suggests smaller

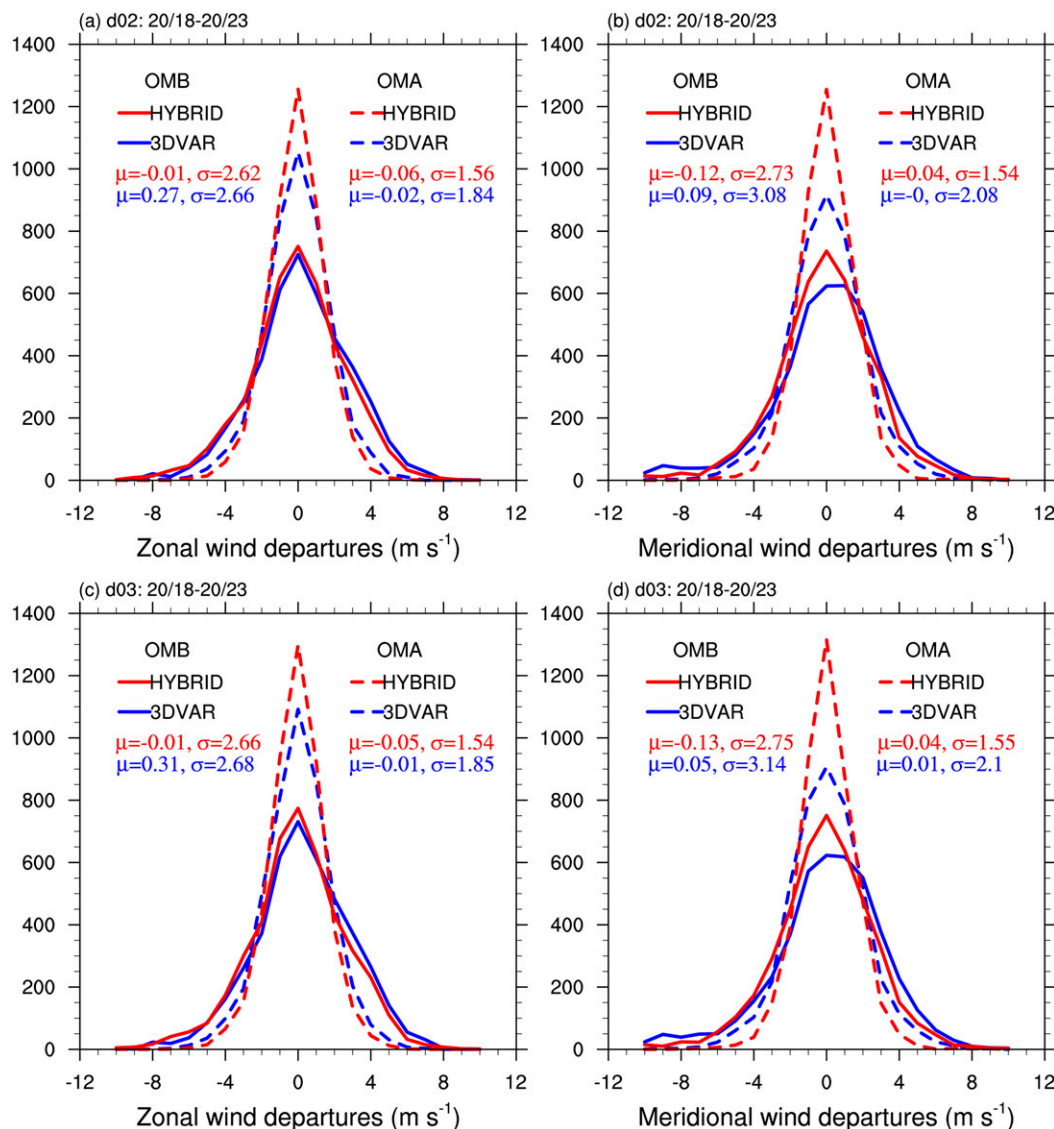


FIG. 14. Histogram of (a),(c) zonal wind and (b),(d) meridional wind departure from DAWN wind profiles for the first guess (solid line; OMB) and GSI-analysis (dashed line; OMA) across all assimilation cycles from 1800 to 2300 UTC 20 Jun 2017 for calculated statistics over (top) domain 2 and (bottom) domain 3. The μ and σ in the panels denote the bias and standard deviation of OMB and OMA, respectively. The vertical axis represents the number of observations.

standard deviations and a large number of wind analyses close to observations, this method states a slightly larger bias in both OMB and OMA than the variational method.

6. Concluding remarks and discussion

During the NASA CPEX field campaign, DAWN measurements provide a broad area of high-temporal-and-vertical-resolution wind data sources for both observational divergence field characteristic analysis and data impact studies on numerical simulation and

prediction in the convective system research domain. This paper initially quantifies the impact of DAWN high-density wind profiles on the short-range prediction of moist convective systems through GSI-based 3DVar and hybrid 3DVar approaches based on case study. A convection system that occurred over the central Caribbean Sea on 16 June 2017 is studied along with Tropical Storm Cindy, which developed during 21 June 2017. Simulation results indicate that assimilation of DAWN wind profiles has a significant influence on the area-averaged divergence profile of

initial convective system for WRF Model simulations, which implies that this detailed wind information results in the redistribution of the wind field in both the horizontal and vertical directions. Relative to the radiosonde observations, more benefits for the wind fields in the 12-h forecast are produced in both the 3DVAR and HYBRID experiments than in the CTL simulation. Moreover, the precipitation comparison also suggests better precipitation location and rainfall estimation in 3DVAR and HYBRID, as quantitatively represented by the enhanced QPF skill in the two cases. Therefore, two-cases simulation implies that the assimilation of DAWN wind profiles produces relatively realistic simulations of convective system initiation and evolution. More detailed convective processes, including dynamic and thermodynamic perspectives, can be further understood and verified based on these simulation results in future work.

Overall, the hybrid assimilation performs better than the variational assimilation, especially in the case 1 simulation. However, in case 2, both assimilation methods slightly degrade the performance of the precipitation simulation relative to CTL at the light rainfall threshold, and 3DEnVar underperforms 3DVar at this threshold qualification. To understand these discrepancies, the system error was investigated. Two main concepts need to be considered. First, the DAWN wind profiles in the middle and lower troposphere are usually noisy because of a low SNR value, and their related wind uncertainty is not sensitive (e.g., keeps constant) to wind variations in the vertical direction. Second, the spread of the ensemble in this study is underdispersive in the lower and upper troposphere. Both of these factors can lead to the limited efficiency of DAWN data usage. In addition, the OMB and OMA statistics provide some explanation of the different performance of the hybrid and variational methods, which shows that OMA exhibits smaller standard deviations but larger bias in the HYBRID experiments than in 3DVAR for both zonal and meridional wind.

Note that the ensemble spread is always smaller than the background forecast error near the surface, which agrees well with the description in Wang et al. (2008). The main reasons for these results may arise from the less accurate error representation of the ensemble forecasts with a single suite of physics parameterizations. It is expected that the hybrid approach would give more encouraging results if the ensemble member size were improved and if multiple parameterizations were used to alleviate the sampling issue of ensemble forecast statistics. Moreover, in this pilot study, we employed the same time assimilation window but two sets of hybrid localization scale configurations in the two cases. The optimal values obtained through sensitivity

experiments to these assimilation parameters could be case dependent, which means they depend heavily on the typical spatial scale and time variability of convective systems, as well as interactions with the large-scale environment and land surface conditions. Moreover, traditional data thinning with large distance will result in a larger number of observations being discarded. To better use of high-frequency DAWN winds, the diagnostics of observation error correlation for DAWN wind is required, and other decorrelation methods (e.g., Bauer et al. 2011; Waller et al. 2016) and superobbing approaches may also need to be tested. With only two cases, the results provided in this study represent a preliminary evaluation of the impact of DAWN wind profiles on convective system simulations. More work to filter DAWN data using SNR and GoF parameters is needed to explore the greatest potential of DAWN data to enhance simulations and prediction of convective cases in future work. More comprehensive evaluation and verification are also necessary with the operational prediction model and data assimilation systems, pending on the continuous availability of DAWN measurements.

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REFERENCES

- Arakawa, A., 2004: The cumulus parameterization problem: Past, present, and future. *J. Climate*, **17**, 2493–2525, [https://doi.org/10.1175/1520-0442\(2004\)017<2493:RATCPP>2.0.CO;2](https://doi.org/10.1175/1520-0442(2004)017<2493:RATCPP>2.0.CO;2).
- Bauer, P., R. Buizza, C. Cardinali, and J. Noël Thépaut, 2011: Impact of singular-vector-based satellite data thinning on NWP. *Quart. J. Roy. Meteor. Soc.*, **137**, 286–302, <https://doi.org/10.1002/qj.733>.
- Beyon, J. Y., G. J. Koch, M. J. Kavaya, and T. J. Ray, 2013: Airborne wind profiling algorithms for the pulsed 2-micron coherent Doppler lidar at NASA Langley Research Center. *Proc. SPIE*, **8731**, 87310K, <https://doi.org/10.1117/12.2015952>.
- Braun, S. A., and Coauthors, 2013: NASA's Genesis and Rapid Intensification Processes (GRIP) field experiment. *Bull. Amer. Meteor. Soc.*, **94**, 345–363, <https://doi.org/10.1175/BAMS-D-11-00232.1>.

- Bryan, G. H., and H. Morrison, 2012: Sensitivity of a simulated squall line to horizontal resolution and parameterization of microphysics. *Mon. Wea. Rev.*, **140**, 202–225, <https://doi.org/10.1175/MWR-D-11-00046.1>.
- Chen, F., and J. Dudhia, 2001: Coupling an advanced land surface–hydrology model with the Penn State–NCAR MM5 modeling system. Part II: Preliminary model validation. *Mon. Wea. Rev.*, **129**, 587–604, [https://doi.org/10.1175/1520-0493\(2001\)129<0587:CAALSH>2.0.CO;2](https://doi.org/10.1175/1520-0493(2001)129<0587:CAALSH>2.0.CO;2).
- de Rooy, W. C., and Coauthors, 2013: Entrainment and detrainment in cumulus convection: An overview. *Quart. J. Roy. Meteor. Soc.*, **139**, 1–19, <https://doi.org/10.1002/qj.1959>.
- Dirmeyer, P. A., and Coauthors, 2012: Simulating the diurnal cycle of rainfall in global climate models: Resolution versus parameterization. *Climate Dyn.*, **39**, 399–418, <https://doi.org/10.1007/s00382-011-1127-9>.
- Emmitt, G. D., and S. Greco, 2019: Readme file for CPEX DAWN data. NASA Langley Research Center Rep., 5 pp., https://eosweb.larc.nasa.gov/project/cpex/cpex_dawn_readme.pdf.
- Geerts, B., and Coauthors, 2017: The 2015 Plains Elevated Convection at Night field project. *Bull. Amer. Meteor. Soc.*, **98**, 767–786, <https://doi.org/10.1175/BAMS-D-15-00257.1>.
- Hayden, C. M., and R. J. Purser, 1995: Recursive filter objective analysis of meteorological fields: Applications to NESDIS operational processing. *J. Appl. Meteor.*, **34**, 3–15, <https://doi.org/10.1175/1520-0450-34.1.3>.
- Hong, S.-Y., and J.-O. J. Lim, 2006: The WRF single-moment 6-class microphysics scheme (WSM6). *J. Korean Meteor. Soc.*, **42**, 129–151.
- , Y. Hon, and J. Dudhia, 2006: A new vertical diffusion package with an explicit treatment of entrainment processes. *Mon. Wea. Rev.*, **134**, 2318–2341, <https://doi.org/10.1175/MWR3199.1>.
- Hou, D., and Coauthors, 2014: Climatology-calibrated precipitation analysis at fine scales: Statistical adjustment of stage IV toward CPC gauge-based analysis. *J. Hydrometeor.*, **15**, 2542–2557, <https://doi.org/10.1175/JHM-D-11-0140.1>.
- Houze, R. A., Jr., 2004: Mesoscale convective systems. *Rev. Geophys.*, **42**, RG4003, <https://doi.org/10.1029/2004RG000150>.
- Huffman, G. J., and Coauthors, 2007: The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *J. Hydrometeor.*, **8**, 38–55, <https://doi.org/10.1175/JHM560.1>.
- Iacono, M. J., J. S. Delamere, E. J. Mlawer, M. W. Shephard, S. A. Clough, and W. D. Collins, 2008: Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res.*, **113**, D13103, <https://doi.org/10.1029/2008JD009944>.
- Jayakumar, A., J. Sethunadh, R. Rakhi, T. Arulalan, S. Mohandas, G. R. Iyengar, and E. N. Rajagopal, 2017: Behavior of predicted convective clouds and precipitation in the high-resolution Unified Model over the Indian summer monsoon region. *Earth Space Sci.*, **4**, 303–313, <https://doi.org/10.1002/2016EA000242>.
- Jiménez, P. A., J. Dudhia, J. F. González-Rouco, J. Navarro, J. P. Montávez, and E. García-Bustamante, 2012: A revised scheme for the WRF surface layer formulation. *Mon. Wea. Rev.*, **140**, 898–918, <https://doi.org/10.1175/MWR-D-11-00056.1>.
- Kavaya, M. J., J. Y. Beyon, G. A. Creary, and G. J. Koch, 2011: DAWN coherent wind profiling lidar flights on NASA's DC-8 during GRIP. *16th Coherent Laser Radar Conf.*, Long Beach, CA, Universities Space Research Association, http://www.ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20110012978_2011013505.pdf.
- , —, G. J. Koch, M. Petros, P. J. Petzar, U. N. Singh, B. C. Trieu, and J. Yu, 2014: The Doppler Aerosol Wind (DAWN) airborne, wind-profiling coherent-detection lidar system: Overview and preliminary flight results. *J. Atmos. Oceanic Technol.*, **31**, 826–842, <https://doi.org/10.1175/JTECH-D-12-00274.1>.
- Kleist, D. T., and K. Ide, 2015: An OSSE-based evaluation of hybrid variational–ensemble data assimilation for the NCEP GFS. Part I: System description and 3D-hybrid results. *Mon. Wea. Rev.*, **143**, 433–451, <https://doi.org/10.1175/MWR-D-13-00351.1>.
- Lorenc, A. C., 2003: The potential of the ensemble Kalman filter for NWP—A comparison with 4D-Var. *Quart. J. Roy. Meteor. Soc.*, **129**, 3183–3203, <https://doi.org/10.1256/qj.02.132>.
- Nelson, B. R., O. P. Prat, D.-J. Seo, and E. Habib, 2016: Assessment and implications of NCEP stage IV quantitative precipitation estimates for product intercomparisons. *Wea. Forecasting*, **31**, 371–394, <https://doi.org/10.1175/WAF-D-14-00112.1>.
- Potvin, C. K., E. M. Murillo, M. L. Flora, and D. M. Wheatley, 2017: Sensitivity of supercell simulations to initial-condition resolution. *J. Atmos. Sci.*, **74**, 5–26, <https://doi.org/10.1175/JAS-D-16-0098.1>.
- Pu, Z., L. Zhang, and G. D. Emmitt, 2010: Impact of airborne Doppler wind lidar profiles on numerical simulations of a tropical cyclone. *Geophys. Res. Lett.*, **37**, L05801, <https://doi.org/10.1029/2009GL041765>.
- , S. Zhang, M. Tong, and V. Tallapragada, 2016: Influence of the self-consistent regional ensemble background error covariance on hurricane inner-core data assimilation with the GSI-based hybrid system for HWRF. *J. Atmos. Sci.*, **73**, 4911–4925, <https://doi.org/10.1175/JAS-D-16-0017.1>.
- Rajendran, K., A. Kitoh, R. Mizuta, S. Sajani, and T. Nakazawa, 2008: High-resolution simulation of mean convection and its intraseasonal variability over the tropics in the MRI/JMA 20-km mesh AGCM. *J. Climate*, **21**, 3722–3739, <https://doi.org/10.1175/2008JCLI1950.1>.
- Rasmussen, K. L., and R. A. Houze, 2016: Convective initiation near the Andes in subtropical South America. *Mon. Wea. Rev.*, **144**, 2351–2374, <https://doi.org/10.1175/MWR-D-15-0058.1>.
- Rauniyar, S. P., A. Protat, and H. Kanamori, 2017: Uncertainties in TRMM-era multisatellite-based tropical rainfall estimates over the Maritime Continent. *Earth Space Sci.*, **4**, 275–302, <https://doi.org/10.1002/2017EA000279>.
- Skamarock, W. C., and Coauthors, 2008: A description of the Advanced Research WRF version 3. NCAR Tech. Note NCAR/TN-475+STR, 113 pp., <http://doi.org/10.5065/D68S4MVH>.
- Tong, M., and Coauthors, 2018: Impact of assimilating aircraft reconnaissance observations on tropical cyclone initialization and prediction using operational HWRF and GSI ensemble–variational hybrid data assimilation. *Mon. Wea. Rev.*, **146**, 4155–4177, <https://doi.org/10.1175/MWR-D-17-0380.1>.
- Waller, J. A., D. Simonin, S. L. Dance, N. K. Nichols, and S. P. Ballard, 2016: Diagnosing observation error correlations for Doppler radar radial winds in the Met Office UKV model using observation-minus-background and observation-minus-analysis statistics. *Mon. Wea. Rev.*, **144**, 3533–3551, <https://doi.org/10.1175/MWR-D-15-0340.1>.
- Wang, X., D. M. Barker, C. Snyder, and T. M. Hamill, 2008: A hybrid ETKF–3DVAR data assimilation scheme for the WRF Model. Part II: Real observation experiments. *Mon. Wea. Rev.*, **136**, 5132–5147, <https://doi.org/10.1175/2008MWR2445.1>.
- , D. Parrish, D. Kleist, and J. Whitaker, 2013: GSI 3DVar-based ensemble–variational hybrid data assimilation for NCEP Global

- Forecast System: Single-resolution experiments. *Mon. Wea. Rev.*, **141**, 4098–4117, <https://doi.org/10.1175/MWR-D-12-00141.1>.
- Weckwerth, T. M., and Coauthors, 2004: An overview of the International H₂O Project (IHOP_2002) and some preliminary highlights. *Bull. Amer. Meteor. Soc.*, **85**, 253–278, <https://doi.org/10.1175/BAMS-85-2-253>.
- Whitaker, J. S., T. M. Hamill, X. Wei, Y. Song, and Z. Toth, 2008: Ensemble data assimilation with the NCEP Global Forecast System. *Mon. Wea. Rev.*, **136**, 463–482, <https://doi.org/10.1175/2007MWR2018.1>.
- Wu, W.-S., R. J. Purser, and D. F. Parrish, 2002: Three-dimensional variational analysis with spatially inhomogeneous covariances. *Mon. Wea. Rev.*, **130**, 2905–2916, [https://doi.org/10.1175/1520-0493\(2002\)130<2905:TDVAWS>2.0.CO;2](https://doi.org/10.1175/1520-0493(2002)130<2905:TDVAWS>2.0.CO;2).
- Zhang, C., Y. Wang, and K. Hamilton, 2011: Improved representation of boundary layer clouds over the Southeast Pacific in ARW-WRF using a modified Tiedtke cumulus parameterization scheme. *Mon. Wea. Rev.*, **139**, 3489–3513, <https://doi.org/10.1175/MWR-D-10-05091.1>.
- Zhang, F., A. M. Odins, and J. W. Nielsen-Gammon, 2006: Mesoscale predictability of an extreme warm-season precipitation event. *Wea. Forecasting*, **21**, 149–166, <https://doi.org/10.1175/WAF909.1>.
- Zhang, L., and Z. Pu, 2011: Four-dimensional assimilation of multitime wind profiles over a single station and numerical simulation of a mesoscale convective system observed during IHOP_2002. *Mon. Wea. Rev.*, **139**, 3369–3388, <https://doi.org/10.1175/2011MWR3569.1>.
- Zipser, E. J., D. J. Cecil, C. Liu, S. W. Nesbitt, and D. P. Yorty, 2006: Where are the most intense thunderstorms on Earth? *Bull. Amer. Meteor. Soc.*, **87**, 1057–1072, <https://doi.org/10.1175/BAMS-87-8-1057>.