Numerical Simulation of Rapid Weakening of Hurricane Joaquin with Assimilation of High-Definition Sounding System Dropsondes during the Tropical Cyclone Intensity Experiment: Comparison of Three- and Four-Dimensional Ensemble-Variational Data Assimilation

SHIXUAN ZHANG^a AND ZHAOXIA PU

Department of Atmospheric Sciences, University of Utah, Salt Lake City, Utah

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ABSTRACT

Observations from High-Definition Sounding System (HDSS) dropsondes, collected for Hurricane Joaquin during the Office of Naval Research Tropical Cyclone Intensity (TCI) field experiment in 2015, are assimilated into the NCEP Hurricane Weather Research and Forecasting (HWRF) Model. The Gridpoint Statistical Interpolation (GSI)-based hybrid three-dimensional and four-dimensional ensemble-variational (3DEnVar and 4DEnVar) data assimilation configurations are compared. The assimilation of HDSS dropsonde observations can help HWRF initialization by generating consistent analysis between wind and pressure fields and can also compensate for the initial maximum surface wind errors in the absence of initial vortex intensity correction. Compared with GSI-3DEnVar, the assimilation of HDSS dropsonde observations using GSI-4DEnVar generates a more realistic initial vortex intensity and reproduces the rapid weakening (RW) of Hurricane Joaquin, suggesting that the assimilation of high-resolution inner-core observations (e.g., HDSS dropsonde data) based on an advanced data assimilation method (e.g., 4DEnVar) can potentially outperform the vortex initialization scheme currently used in HWRF. Additionally, the assimilation of HDSS dropsonde observations can improve the simulation of vortex structure changes and the accuracy of the vertical motion within the TC inner-core region, which is essential to the successful simulation of the RW of Hurricane Joaquin with HWRF. Additional experiments with GSI-4DEnVar in different configurations also indicate that the performance of GSI-4DEnVar can be further improved with a high-resolution background error covariance and a denser observational bin.

1. Introduction

Understanding and predicting changes in tropical cyclone (TC) intensity are challenging problems (e.g., Zhang et al. 2011; Gall et al. 2013). Specifically, studies have indicated that we have a very limited ability to produce realistic initial vortex structures and to predict intensity changes due to the lack of high-resolution TC inner-core observations (e.g., DeMaria et al. 2005; Elsberry et al. 2007; Pu et al. 2009; Zhang et al. 2011; Pu et al. 2016).

^a Denotes content that is immediately available upon publication as open access.

^a Current affiliation: Pacific Northwest National Laboratory, Richland, Washington.

Corresponding author: Dr. Zhaoxia Pu, Zhaoxia.Pu@utah.edu

To understand changes in TC intensity and structure, and also to improve our ability to forecast TC intensity, recently, major field campaigns, including the National Oceanic and Atmospheric Administration (NOAA) Hurricane Research Division (HRD) Intensity Forecast Experiments (IFEX; Rogers et al. 2006, 2013), the National Aeronautics and Space Administration (NASA) Genesis and Rapid Intensification Processes (GRIP) field program (Braun et al. 2013), and the National Science Foundation (NSF) Pre-Depression Investigation of Cloud-systems in the Tropics (PREDICT; Montgomery et al. 2012), have been conducted to obtain observations within various environments during the TC life cycle. These data have proven to be useful for understanding TC intensity changes. For instance, observational studies and model-observation comparisons based on these field campaigns (e.g., Black et al. 2002; Rogers et al. 2003; Houze et al. 2006; Jaimes et al. 2015) further proved the importance of vertical wind

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shear and sea surface temperature to the tropical cyclone evolution (e.g., [Riehl and Shafer 1944](#); [Palmén 1948](#)). Other studies based on these field campaigns have also found that low-level to midlevel dry air (e.g., [Dunion and Velden 2004](#)) and TC internal structure evolution (e.g., [Pu et al. 2009](#); [Chen et al. 2011](#); [Chen and Zhang 2013](#); [Li et al. 2014](#)) are essential to the variations in a TC's intensity during its lifetime.

However, limited improvements in the forecasts of TC intensity change can be achieved by target dropsonde observations from field campaigns (e.g., [Torn and Hakim 2009](#); [Aberson 2010](#); [Torn 2014](#)), although many studies have shown that the assimilation of these additional observations can reduce the average track errors by 10%–30% ([Pu et al. 2008](#); [Aberson 2010](#); [Chou et al. 2011](#); [Wu et al. 2012](#)). Despite the performance of dropsonde data assimilation (DA), the DA method, and the density of other available observations (e.g., [Torn and Hakim 2009](#); [Weissmann et al. 2011](#)), the instrumentation technology limitation in existing dropsonde systems leaves the upper-tropospheric TC outflow layers largely unsampled (e.g., [Doyle et al. 2017](#)). Recent research (e.g., [Komaromi and Doyle 2017](#)) based on observations from the Hurricane and Severe Storm Sentinel (HS3) field campaign ([Braun et al. 2016](#)) suggests that TC outflow can directly cause changes in TC secondary circulation, which is critical to variations in TC intensity.

New capabilities and technology have been developed for dropsonde observation systems to compensate for the sampling issue in the upper troposphere. For instance, the Office of Naval Research (ONR), together with the Naval Research Laboratory, industry, and universities, executed the Tropical Cyclone Intensity (TCI) field program ([Doyle et al. 2017](#)), an observing field program over the eastern Pacific, Gulf of Mexico, and Atlantic Ocean. During TCI, the High-Definition Sounding System (HDSS) and expendable digital dropsonde (XDD) technology (e.g., [Black et al. 2017](#)) allowed for unprecedented high-fidelity observations of the outflow layer and inner-core structure of three prominent TCs (e.g., [Doyle et al. 2017](#)). Fortunately, during the TCI field campaign, the rapid weakening (RW) phase of Hurricane Joaquin (2015) over the Atlantic Ocean was well sampled. Specifically, high-resolution pressure, relative humidity, air temperature, horizontal wind speed, and wind direction observations within the hurricane inner-core region were collected from the High-Definition Sounding System (HDSS) dropsondes based on NASA's WB-57 aircraft. With these observations, TCI offered an unprecedented opportunity to examine the influence of improved model initialization in the upper troposphere, which is difficult to obtain from existing dropsonde

observations, such as those from IFEX, GRIP, and PREDIC, for TC analysis and simulation. The questions that arise here are: 1) Can such improvements in model initialization from TCI HDSS dropsondes indeed enhance the simulation of TC intensity changes? 2) In what way can the potential benefit from these observations be maximized in the model initialization?

By exploring the answers to these questions, this study evaluates the potential impact of assimilating these new, innovative HDSS dropsonde observations from the TCI field campaign on improving the numerical simulations of TC intensity changes with a research version of the NCEP Hurricane Weather Research and Forecasting (HWRF) Model. Specifically, the HDSS dropsonde observations are assimilated into the HWRF Model ([Tallapragada et al. 2015](#)) during the intensity change phases of Hurricane Joaquin (2015). Various DA and numerical simulation experiments with both ensemble–three-dimensional variational and ensemble–four-dimensional variational hybrid DA methods based on the Gridpoint Statistical Interpolation (GSI) system are performed and compared. The paper proceeds as follows. An overview of study cases and the dropsonde observations during TCI is introduced in [section 2](#), while [section 3](#) provides a brief description of HWRF and its DA system. The results from a set of numerical experiments for Hurricane Joaquin during its rapid weakening (RW) phase are provided in [section 4](#). Additional experiments and DA configurations are discussed in [section 5](#). [Section 6](#) presents a summary of the conclusions and a discussion.

2. HWRF Model, vortex initialization, and DA methods

a. HWRF Model

The HWRF Model, version 3.7a (HWRF V3.7a; [Gopalakrishnan et al. 2011](#); [Tallapragada et al. 2015](#)), was the newest version available for the research community when this study was conducted. The model configuration was functionally comparable to the 2015 operational HWRF. The dynamical core employed in HWRF V3.7a is the same as that in NCEP's WRF Nonhydrostatic Mesoscale Model (NMM; [Janjić et al. 2010](#)). It adopts a two-way interactive, movable, triply nested grid procedure with three nested domains, d01, d02, and d03, with domain sizes of about 9000 km × 9000 km, 1300 km × 1200 km, and 800 km × 700 km, and grid resolutions of 18, 6, and 2 km, respectively (see [Fig. 1](#)). In addition, the atmospheric component of the NMM core in HWRF V3.7a is formulated with 61 vertical levels and a model top at 2 hPa. A suite of

FIG. 1. HWRf Model forecast domains are denoted as d01, d02 (blue dashed line area), and d03 (black solid line area). HWRf data assimilation domains are indicated by ghost d02 (black shaded area) and ghost d03 (pink shaded area between solid and dashed lines). Sea level pressure (shaded contours; hPa) from the forecast field and the storm center from NHC best track (black hurricane symbol) at 1800 UTC 3 Oct 2015 for Hurricane Joaquin are also indicated.

advanced physical parameterizations developed for tropical cyclone applications (Bao et al. 2012), including the Ferrier–Aligo microphysical parameterization, the Noah Land Surface Model, the Geophysical Fluid Dynamics Laboratory (GFDL) surface-layer parameterization, the modified GFDL shortwave and longwave radiation scheme, the Global Forecast System (GFS) planetary boundary layer (PBL) scheme, and the GFS simplified Arakawa–Schubert (SAS) cumulus scheme on the outermost two domains, are also employed in HWRf V3.7a (detailed information about these schemes can be found in Tallapragada et al. 2015).

b. GSI-based DA systems

A GSI-based ensemble–three-dimensional variational hybrid (GSI-3DEnVar, see also Tallapragada et al. 2015) DA system is used to incorporate the observations and improve HWRf initial conditions. In this system, the analysis increment is achieved by minimizing a cost function:

$$J(\mathbf{x}'_f, \boldsymbol{\alpha}) = \beta_f \frac{1}{2} (\mathbf{x}'_f)^T (\mathbf{B}_f)^{-1} (\mathbf{x}'_f) + \beta_e \frac{1}{2} (\boldsymbol{\alpha})^T (\mathbf{L})^{-1} (\boldsymbol{\alpha}) + \frac{1}{2} (\mathbf{y}' - \mathbf{H}\mathbf{x}')^T \mathbf{R}^{-1} (\mathbf{y}' - \mathbf{H}\mathbf{x}'), \quad (1)$$

where the first two terms on the right-hand side are the background terms associated with the static background error covariance $\mathbf{B}_f$ and the flow-dependent error covariance, respectively. The third term is the observational term, which is the same as in a traditional three-dimensional variational DA (3DVar) system except that $\mathbf{x}'$ is the total analysis increment, which is the sum of the increment connected with the static background error covariance $\mathbf{x}'_f$ and the increment associated with the ensemble covariance. The terms β_e and β_f are two weighting factors that define the weights assigned to the ensemble background error covariance and the static background error covariance. To achieve a hybrid DA, the two weighting factors β_f and β_e satisfy $\beta_f^{-1} + \beta_e^{-1} = 1$. The system sets β_f^{-1} and β_e^{-1} equal to 0.2 and 0.8, respectively, giving more weight is given to the ensemble background term. Detailed information regarding this hybrid algorithm can be seen in Wang (2010).

More recently, the GSI-3DEnVar system has been extended to include four-dimensional (4D) ensemble perturbations (e.g., GSI-4DEnVar). Following Kleist and Ide (2015), the analysis increment in GSI hybrid 4DEnVar is obtained by minimizing a cost function:

$$J(\mathbf{x}'_f, \boldsymbol{\alpha}) = \beta_f \frac{1}{2} (\mathbf{x}'_f)^T (\mathbf{B}_f)^{-1} (\mathbf{x}'_f) + \beta_e \frac{1}{2} (\boldsymbol{\alpha})^T (\mathbf{L})^{-1} (\boldsymbol{\alpha}) + \frac{1}{2} \sum_{k=1}^K (\mathbf{y}'_k - \mathbf{H}\mathbf{x}'_k)^T \mathbf{R}^{-1} (\mathbf{y}'_k - \mathbf{H}\mathbf{x}'_k), \quad (2)$$

where the third term is extended to use the asynchronous observations up to K time levels compared with Eq. (1), and the other terms are the same as those in Eq. (1). In the GSI hybrid 4DEnVar, the tangential linear model and adjoint model in the traditional 4DVar are avoided by using the model forecast and preconditioned ensemble perturbations in each observational bin. Detailed explanations of the GSI hybrid 4DEnVar algorithm can be found in Wang and Lei (2014) and Kleist and Ide (2015). The GSI-4DEnVar system has been applied in the NCEP operational GFS system since 2015, but this scheme has not been implemented into HWRf V3.7a before and during this study, requiring revisions to the GSI hybrid system in order to incorporate GSI-4DEnVar into HWRf V3.7a.

c. Vortex initialization

The HWRf system includes a vortex initialization (VI) process before DA in order to create a better background field for the DA system (e.g., Tallapragada et al. 2015). Previous studies (e.g., Pu et al. 2016; Lu et al. 2017; Zhang et al. 2018) have demonstrated that VI before DA in HWRf can be a factor in causing degraded data impacts in some cases. To account for this

factor in the HDSS dropsonde DA, *two revised VI processes* are used for HWRF initialization in this study.

First, similar to the operational HWRF procedure, initialization is achieved by combining VI with the DA system; here we refer to this process as “OPR_VI_DA.” The VI scheme (Liu et al. 2006) performs relocation, resizing, and intensity correction using the NHC tropical cyclone vital statistics (TCVitals) database to correct the storm position and intensity approach to the real-time estimation (see details in Tallapragada et al. 2015). After VI, observations are assimilated by the DA system to further improve the initial conditions for the HWRF forecast.

The second initialization is also similar to the operational HWRF, but only vortex relocation is turned on; here we refer to this process as “OPR_RL_DA.” The vortex from the previous cycle’s HWRF 6-h forecast is relocated to the position from the real-time estimation, and observations are then assimilated by the DA system to further improve the initial conditions for the HWRF forecast.

In addition, in the operational HWRF configuration, a “blending” scheme is activated after the VI and DA processes. This scheme blends the vortex from the VI process with the vortex after DA and use the blended vortex in the final analysis for the HWRF forecast. The effect of this scheme will eliminate the DA increments within 150 km of the center below 400 hPa. However, the blending scheme is *turned off* in OPR_RL_DA in this study.

In both OPR_VI_DA and OPR_RL_DA, the DA is performed in two larger domains that are extended from the forecast domains d02 and d03. As shown in Fig. 1, these two domains are referred to as ghost d02 (about 3000 km $\times$ 3000 km) and ghost d03 (about 1200 km $\times$ 1200 km) and are used to incorporate more data into the hurricane and its nearby environment. The initial conditions for the HWRF forecasts are produced by interpolating the analysis of ghost d02 (ghost d03) back to d02 (d03). Also, the data assimilation of ghost d02 utilizes all satellite and conventional data (the list of data types can be found at http://www.emc.ncep.noaa.gov/mmb/data_processing/prepbuftr.doc/table_18.htm and http://www.emc.ncep.noaa.gov/mmb/data_processing/prepbuftr.doc/table_2.htm), while the data assimilation of ghost d03 utilizes conventional data only.

3. Experiment design

A set of experiments includes running a cycling GSI-based DA system coupled with HWRF V3.7a with different VI and DA configurations, assimilating data with and without HDSS dropsonde observations. The cases are chosen based on two criteria: 1) the system experiences an intensity change, and 2) the HDSS dropsonde

observations are collected before the intensity changes during the TCI field campaign. Considering the limited observational time window of the TCI field campaign for an individual hurricane, a 24-h DA period with five consecutive 6-h cycles of DA is used for each HWRF simulation. To eliminate the impacts of model spinup on the DA results, a regular HWRF analysis and DA cycle, initialized by the HWRF initialization package using the GFS forecasts (NOAA/NCEP 2015), is performed for 24 h, and a 6-h forecast is then made to produce a first-guess field for the first cycle of GSI-based DA experiments. Six different sets of HWRF analyses are produced, which differ by the VI and DA configurations and the set of observations that are assimilated. The first experiment, VI-3D-CTRL, uses GSI-3DEnVar with OPR_VI_DA (with VI) and assimilates all observations as mentioned in section 2, except HDSS dropsondes from the TCI field campaign. In contrast, the second experiment, VI-3D-TCI, uses OPR_VI_DA and assimilates all observations, including HDSS dropsondes deployed within ± 3 h of the analysis time. RL-3D-CTRL and RL-3D-TCI are the same as VI-3D-CTRL and VI-3D-TCI, respectively, except that OPR_RL_DA instead of OPR_VI_DA is used for VI before DA. Finally, RL-4D-CTRL and RL-4D-TCI are the same as RL-3D-CTRL and RL-3D-TCI, respectively, except that GSI-4DEnVar is replaced by GSI-4DEnVar in the DA system. The observational bin for GSI-4DEnVar is 3 h, which means each analysis cycle (6 h) is divided into three observational bins (e.g., -3 , 0 , $+3$ h). The 3-h bin is used here in order to perform parallel comparisons with the second set of experiments to indicate the sensitivity of HDSS dropsonde DA to different choices of DA method. This setup ensures that the only difference between these two sets of experiments is the DA method. Detailed experimental configurations are listed in Table 1.

Note that the boundary conditions for these simulations are provided by GFS forecasts, and the flow-dependent background error covariance is generated from the NCEP operational GFS 80-member ensemble forecast at a resolution of T574 (~ 23 km; Tallapragada et al. 2015). The experiments in Table 1 are used to gain insight into (i) the impacts of high-resolution HDSS dropsonde observations on HWRF analyses and forecasts/simulations of the RW of Hurricane Joaquin; and (ii) the sensitivity of the HDSS dropsonde data impact to DA configurations.

4. Rapid weakening of Hurricane Joaquin (2015)

Hurricane Joaquin (2015) was selected as a study case because TCI field observations were obtained during its

TABLE 1. List of data assimilation experiments. Data assimilation in HWRF is performed on ghost d02 and ghost d03. Satellite observations (obs.) are assimilated in ghost d02 only.

Exp.	Initialization	DA scheme	DA data	Experiment description
VI-3D-CTRL	VI	Hybrid 3D-EnVar	Conventional data, satellite obs.	The control experiment, which corresponds the current operational HWRF practice of VI, and DA with GSI-3D-EnVar to assimilate the conventional and satellite data; no TCI dropsonde is included in DA
VI-3D-TCI	VI	Hybrid 3D-EnVar	Conventional data, satellite obs., HDSS dropsondes	TCI HDSS dropsonde DA experiment, which corresponds to a possible extension of the current operational practice to assimilate both HDSS dropsonde observations in the TC core and large-scale TC environment
RL-3D-CTRL	Relocation	Hybrid 3D-EnVar	Conventional data, satellite obs.	The sensitivity experiment, which is similar to VI-3D-CTRL but turns off the TC intensity correction in VI; this experiment is conducted to evaluate the impact of VI on current HWRF operational practice
RL-3D-TCI	Relocation	Hybrid 3D-EnVar	Conventional data, satellite obs., HDSS dropsondes	The sensitivity experiment, which is similar RL-3D-CTRL, but assimilates the TCI HDSS dropsonde observation; this experiment is conducted to evaluate the impact of VI on TCI HDSS dropsonde DA
RL-4D-CTRL	Relocation	Hybrid 4D-EnVar	Conventional data, satellite obs.	The sensitivity experiment, which is similar to RL-3D-CTRL, but uses GSI-4D-EnVar instead of GSI-3D-EnVar for DA; this experiment is conducted to evaluate the impact of different DA methods on current HWRF operational practice
RL-4D-TCI	Relocation	Hybrid 4D-EnVar	Conventional data, satellite obs., HDSS dropsondes	The sensitivity experiment, which is similar to RL-4D-CTRL, but assimilates the TCI HDSS dropsonde observation; this experiment is conducted to evaluate the impact of different DA methods on TCI HDSS dropsonde DA
RL-4D-RES-TCI	Relocation	Hybrid 4D-EnVar	Conventional data, satellite obs., HDSS dropsondes	The sensitivity experiment, which is similar to RL-4D-TCI, but uses a high-resolution background error covariance and a denser observational bin for GSI-4D-EnVar; this experiment is conducted to evaluate the impact of different DA configurations in GSI-4D-EnVar on TCI HDSS dropsonde DA

approach toward the East Coast of the United States, while the hurricane experienced a reintensification followed by RW, making it a good case to investigate the impact of DA on numerical simulations of TC intensity changes. A detailed description of Hurricane Joaquin is provided in [Berg \(2016\)](#). In this study, the period from 1800 UTC 2 October to 1800 UTC 6 October 2015 is selected to perform the DA and HWRF simulations

because of the availability of TCI HDSS dropsonde observations (see [Table 1](#) for details). The HWRF forecasts are made for the RW period from 1800 UTC 3 October to 0000 UTC 5 October 2015 in order to investigate the forecasting impacts of TCI HDSS dropsonde data on the hurricane intensity changes.

[Figure 2](#) illustrates the distribution of HDSS dropsonde observations and conventional observations from

FIG. 2. Horizontal distribution of observations from other instruments (red triangles) and TCI dropsonde data (blue dots) assimilated by GSI for hurricane Joaquin at (a) 1800 UTC 2 Oct 2015 and (b) 1800 UTC 3 Oct 2015; and the vertical distribution of observations from other instruments (red triangles) and TCI dropsonde data (large orange dots for u, v wind; small blue dots for temperature and humidity) assimilated by GSI for Hurricane Joaquin at (c) 1800 UTC 2 Oct 2015 and (d) 1800 UTC 3 Oct 2015. The black symbol in (a) and (b) indicates the storm center at the current time, and the x axis in (c) and (d) represents the distance to the storm center.

other instruments assimilated by GSI at 1800 UTC 2 and 1800 UTC 3 October 2015. There are about 66 total profile observations within a 6-h window around 1800 UTC each day, including relative humidity, temperature, and wind speed and direction. These dropsonde observations have been quality controlled via a combined “subjective-objective” procedure utilizing the Atmospheric Sounding Processing Environment (ASPEN) software (Bell et al. 2016). As shown in Fig. 2, the HDSS dropsonde observations provide substantive compensation for the lack of observations in the hurricane inner-core region (Figs. 2a,b), especially in the middle and upper troposphere (Figs. 2c,d). In addition, the HDSS dropsonde temperature and humidity observations can extend from 1000 to 200 hPa (orange dots), while the wind observations can further

extend to 90 hPa (magenta dots). The total number of dynamical and thermal observations from HDSS dropsondes assimilated by the HWRF DA system is nearly even in the mid- (400–700 hPa) and upper troposphere (above 400 hPa), while there are about two times more observations within the lower troposphere (below 700 hPa) than in the other layers (Figs. 2c,d). However, more wind observations are assimilated by the HWRF DA system in the upper troposphere (above 400 hPa) relative to the temperature and humidity data (see the numbers at the top of Figs. 2c,d).

a. RMS error reduction in HWRF analyses and forecasts

To examine the impacts of HDSS dropsonde observations on HWRF analyses and forecasts in various DA

FIG. 3. (a)–(c) RMS errors between the analysis field [i.e., temperature (K), specific humidity (g kg^{-1}), and wind speed (m s^{-1})] and the HDSS dropsonde data at 1800 UTC 3 Oct 2015, and (d)–(f) RMS errors between the 24-h forecast field and the HDSS dropsonde data at 1800 UTC 4 Oct 2015. Dashed lines are for the control experiments and solid lines are for the DA experiments with HDSS dropsonde data. Blue lines indicate the experiments with VI (VI-3D-CTRL and VI-3D-TCI), red lines indicate the experiments without VI (RL-3D-CTRL and RL-3D-TCI), and black lines represent the assimilations with GSI-4DEnVar (RL-4D-CTRL and RL-4D-TCI).

configurations, Fig. 3 illustrates the root-mean-square (RMS) errors of the analysis fit to the HDSS dropsonde observations at 1800 UTC 3 October 2015 and the forecast fit to the HDSS dropsonde observations at 1800 UTC 4 October 2015. Overall, the assimilation of HDSS dropsondes improves the RMS errors of the forecast and analysis fit to the HDSS dropsonde observations in most cases. In addition, the improvements in the wind field (Figs. 4c,f) are more sensitive to the VI configuration and DA method than those in the temperature (Fig. 4a,d) and humidity (Figs. 4b,e) fields. Specifically, VI-3D-CTRL and VI-3D-TCI reveal much larger RMS errors than the other simulations, especially in the lower and midtroposphere (below 400 hPa), and the assimilation of HDSS dropsondes only slightly reduces the RMS in VI-3D-TCI. This is possibly due to the intensity correction and blending scheme used in these two simulations. As indicated in section 2 and in Tallapragada et al. (2015), the intensity correction uses the estimated surface maximum wind speed and empirical balance relationship to correct the 3D vortex structure, which

can produce an unrealistic vortex structure, and thus the large RMS error between the analysis fields and HDSS dropsonde observations. Moreover, the blending scheme used in VI-3D-CTRL and VI-3D-TCI will exclude the analysis increments from DA in the lower- to midtropospheric TC inner-core region. As a result, the data impact from HDSS dropsonde observations is partially omitted in VI-3D-TCI, leading to the small RMS error reduction in the analysis and forecast field with the assimilation of HDSS dropsonde observations. Nevertheless, VI-3D-TCI leads to significant RMS error reduction in the upper troposphere where the blending scheme does not take effect, suggesting that the HWRF analysis is still improved with the assimilation of upper-tropospheric HDSS dropsonde observations. Furthermore, there are no substantive differences observed between the solid red (RL-3D-TCI) and solid black (RL-4D-TCI) lines in Figs. 3a–c regarding the RMS errors of the forecast and analysis fit to the dropsonde data, suggesting that GSI-3DEnVar and GSI-4DEnVar produce undistinguishable analyses at 1800 UTC

FIG. 4. Forecast tracks for Hurricane Joaquin from 1800 UTC 3 Oct to 1800 UTC 6 Oct 2015 from (a) VI-3D-CTRL and VI-3D-TCI; (b) RL-3D-CTRL and RL-3D-TCI; and (c) RL-4D-CTRL and RL-4D-TCI. The forecast tracks are compared with the observed track in 6-h intervals. The forecast track from operational HWRf (HWRf-OPR) is also plotted as a reference (green lines; data available online at http://www.emc.ncep.noaa.gov/gc_wmb/vxt/HWRf/tcall.php?selectYear=2015&selectBasin=North+Atlantic&selectStorm=JOAQUIN11L). The numbers in the parentheses of each legend represent the average track errors over the whole 72-h HWRf simulation. All forecasts discussed in this study are from d03 (3-km horizontal resolution).

3 October 2015. However, as will be discussed in the following sections, the experiments with GSI-4DEnVar lead to better track and intensity forecasts than those with GSI-3DEnVar.

b. Forecast impact from HDSS dropsondes

1) STORM TRACK

Figure 4 illustrates the track forecasts from different experiments between 1800 UTC 3 October and 1800 UTC 6 October 2015. The operational HWRf forecast (HWRf-OPR) for Hurricane Joaquin (green lines) during the same period is also overlaid in each panel in order to provide a more realistic assessment for the simulations in this study. Except for the model spinup time and ocean coupling, VI-3D-CTRL uses the same configuration as HWRf-OPR. The results from VI-3D-CTRL versus HWRf-OPR show a slight difference in the track forecast, implying that VI-3D-CTRL is very similar to the HWRf-OPR forecast. Thus, we focus mainly on the intercomparisons of the simulations in this study. Note that the initial vortex position in all experiments is nearly the same because the relocation scheme is used in all experiments, as indicated in section 4. The average track errors over the 72-h forecasts (the great-circle difference between the TC's forecast center position and the best track position at every 6 h is calculated first, then average all of the great-circle differences within a 72-h forecast window) are also calculated and shown (numbers in the end of each legend) in order to quantitatively

demonstrate the sensitivity of the storm track forecasts to the DA configuration and the HDSS dropsonde assimilation. With VI (Fig. 4a), the storm tracks from the NHC best track data are well captured by VI-3D-CTRL and VI-3D-TCI, with average track errors of 57 and 50 km, respectively, over the 72-h forecasts. The average track errors in VI-3D-CTRL and VI-3D-TCI are not significantly different in context of a t test, implying that the impact of HDSS dropsonde data assimilation on the track forecast in VI-3D-TCI is nearly neutral. Without VI (Fig. 4b), the storm tracks are degraded in both RL-3D-CTRL and RL-3D-TCI due to an increase in cross-track errors. The average track error over the 72-h forecasts in RL-3D-TCI with the assimilation of HDSS dropsonde data is 108 km, which is larger than that in RL-3D-CTRL (88 km). However, the difference between RL-3D-CTRL and RL-3D-TCI are not significant in the context of a t test. The experiment using GSI-4DEnVar (Fig. 4c) produces better storm tracks than the experiments using GSI-3DEnVar without (Fig. 4b) VI. The average track error over the 72-h forecast in RL-4D-CTRL (42 km, Fig. 4c) is reduced and by 52%, compared with that in RL-3D-CTRL (88 km, Fig. 4b). The difference between RL-4D-CTRL and RL-3D-CTRL is significant at a confidence level of 99% based on the t test. Overall, the impact of the HDSS dropsonde data on the track forecast is not very significant, which is expected due to the relocation scheme and the DA configurations in the current HWRf system. The relocation scheme substantially removes the initial

FIG. 5. Forecasts (at 6-h intervals) of (a)–(c) MSLP (hPa) and (d)–(f) MSW (m s^{-1}) for Hurricane Joaquin from 1800 UTC 3 Oct to 1800 UTC 6 Oct. The forecast MSLP and MSW from operational HWRf (HWRf-OPR) are also plotted as a reference (green lines; data available online at http://www.emc.ncep.noaa.gov/gc_wmb/vxt/HWRf/tcall.php?selectYear=2015&selectBasin=North+Atlantic&selectStorm=JOAQUIN11L). The numbers in the parentheses of each legend represent the average MSLP or MSW errors over the RW of Hurricane Joaquin from 1800 UTC 3 Oct to 0600 UTC 5 Oct 2015.

position error, while DA in the current HWRf cannot contribute to the large-scale environment that controls TC motion because DA is performed only in the TC inner-core region and its nearby environment.

2) INTENSITY

Figure 5 shows the forecasts of minimum sea level pressure (MSLP) and maximum surface wind speed (MSW) from different experiments. In contrast to the track forecast, the intensity forecast in VI-3D-CTRL seems to be different from HWRf-OPR. This can be attributed to the different configurations (e.g., ocean coupling in HWRf-OPR) in these two simulations. However, VI-3D-CTRL and HWRf-OPR show the same problems associated with the intensity forecast in operational HWRf. As shown in Fig. 5, the MSLP in HWRf-OPR is largely underestimated compared to best track data, while the MSW is well reproduced and close to the best track data. In fact, the average forecast error of MSLP over the 72-h period in HWRf-OPR reaches 20.3 hPa, which implies that the “good” MSW forecast is untrustworthy because the inconsistency between MSLP and MSW implies an unrealistic wind–pressure relationship in this forecast, and thus a false mechanism for the RW of Hurricane Joaquin. The inconsistent variations of MSLP and MSW during the first 12-h forecast are also shown in VI-3D-CTRL. Meanwhile, the variation of MSLP in

VI-3D-CTRL is very similar to that in HWRf-OPR during the 72-h forecast (Fig. 5a). The average MSLP errors over the 72-h forecast in VI-3D-CTRL are not significantly different to those in HWRf-OPR in the context of a Student’s t test. Thus, the analyses of VI-3D-CTRL and other simulations in our study can still help us understand the problems associated with the operational HWRf Model.

The underestimation of MSLP in VI-3D-CTRL can be relieved by the assimilation of HDSS dropsonde observations. As shown in Fig. 6a, VI-3D-TCI with the assimilation of HDSS dropsonde data eliminates the unrealistic wind–pressure relationship in the first 12-h forecasts, although the underestimation of MSLP shows up again after the 12-h forecasts. As a result, VI-3D-TCI significantly reduces the MSLP error by 40% (at 99% confidence level) over the first 48-h forecast compared with that in VI-3D-CTRL (Fig. 6a). The average MSW forecasts errors over the first 48-h forecast in VI-3D-TCI (5.8 m s^{-1}) are very similar to those in VI-3D-CTRL (6.0 m s^{-1}) as the difference between the two simulations is not statistically significant. Overall, the improvements in VI-3D-TCI are mainly concentrated in the MSLP forecast. These improvements suggest that the upper-tropospheric HDSS dropsonde observations play an important role in the intensity forecast of Hurricane Joaquin during its RW phase, as the RMS error reduction in

FIG. 6. ETS for the accumulated 30-h precipitation (from 1800 UTC 3 Oct to 0000 UTC 5 Oct 2015) for (a) VI-3D-CTRL and VI-3D-TCI, (b) RL-3D-CTRL and RL-3D-TCI, and (c) RL-4D-CTRL and RL-4D-TCI against TRMM 3B42 precipitation products with thresholds of 80, 90, 100, 110, 120, 130, 140, and 150 mm.

the VI-3D-TCI analysis is concentrated mainly in the upper troposphere, as shown in Fig. 3.

Further comparisons between Fig. 5a (Fig. 5d) and Fig. 5b (Fig. 5e) suggest that the above problem seems to be related to the VI scheme, as the underestimation of MSLP is significantly mitigated by RL-3D-CTRL without VI. Correspondingly, the average MSLP forecast errors over the first 48-h period in RL-3D-CTRL are reduced to 5.7 hPa, which is much smaller than 24.7 hPa in VI-3D-CTRL. These error reductions are statistically significant at a 99% confidence level from the Student's t test. However, RL-3D-CTRL produces a large initial MSW error and an overall underestimation of MSW over the 72-h forecast period, especially during the RW of Hurricane Joaquin. As shown in Fig. 5e, the initial MSW error in RL-3D-CTRL is about 10 ms^{-1} , and the average MSW error over the first 48-h forecast is $\sim 10.7 \text{ ms}^{-1}$, both of which are larger than in VI-3D-CTRL (Fig. 5d). The problem in RL-3D-CTRL, especially the initial MSW error, will not be improved to a great extent only by updating the DA method. As shown in Figs. 5e,f, the initial MSW error in RL-4D-CTRL is still comparable with that in RL-3D-CTRL. Also, the differences of average MSW errors over the first 48-h forecast among VI-3D-CTRL (6.0 ms^{-1}), RL-3D-CTRL (10.7), and RL-4D-CTRL are not statistically significant from the Student's t test.

The assimilation of the HDSS dropsonde observations can significantly mitigate the initial MSW errors and improve the intensity forecast compared against the control experiments in this study, especially during the RW of Hurricane Joaquin. The initial MSW error can be reduced by 50% in RL-3D-TCI (Fig. 5e) and by 90% in RL-4D-TCI (Fig. 5f) compared with those in the control experiments without the assimilation of HDSS dropsonde observations (RL-3D-CTRL, RL-4D-CTRL). Consistently, the MSLP (MSW) error over the first 48-h forecast can be reduced by 39% (36%) in RL-3D-TCI (Figs. 5b,e), and by 41% (45%) in RL-4D-TCI (Figs. 5c,f)

compared with those in the control experiments (RL-3D-CTRL, RL-4D-CTRL). The Student's t test also suggests that the reduction of MSLP error in RL-3D-TCI and RL-4D-TCI is statistically significant at 95% confidence level, and the reduction of MSW error in RL-4D-TCI is statistically significant at 90% confidence level. Thus, the assimilation of HDSS dropsonde data using GSI-4DEnVar without VI leads to overall the best improvements in intensity forecasts. In particular, RL-4D-TCI well reproduces the RW of Hurricane Joaquin with consistent variations between MSLP and MSW (Figs. 5b,c,e,f). The best performance of intensity forecasts in RL-4D-TCI with HDSS dropsonde data assimilation suggests that DA with high-resolution inner-core observations (e.g., HDSS dropsonde data) based on an advanced DA method (e.g., 4DEnVar) can potentially outperform the VI scheme used in the current operational HWRF by mitigating the negative effects of this scheme on the HWRF intensity forecast.

3) PRECIPITATION

To objectively understand various data and forecast impacts, quantitative precipitation is further assessed. Figure 6 shows the equitable threat scores (ETSS) (Wilks 1995) of heavy rainfall for the accumulated precipitation (values of more than 80 mm are only compared in this study) from 1800 UTC 3 October to 0000 UTC 5 October 2015 in different DA experiments compared with satellite-merged precipitation from version 7 of TRMM 3B42 products (Huffman et al. 2007; Huffman and Bolvin 2013). The impacts of HDSS dropsonde observations on quantitative precipitation forecasts depend on the initialization and DA configurations. Specifically, VI seems to omit the positive impacts of HDSS dropsonde observations on quantitative precipitation forecasts, as VI-3D-TCI leads to lower ETS scores than does VI-3D-CTRL (Fig. 6a), while the assimilation of HDSS dropsonde observations without VI but using GSI-3DEnVar (RL-3D-TCI) improves the

FIG. 7. Radius–height cross section of azimuthal mean temperature anomaly (colored contours; $^{\circ}\text{C}$) and azimuthal mean tangential wind (black contours; m s^{-1}) from (a),(d) HDSS dropsonde, (b),(e) RL-4D-CTRL, and (c),(f) RL-4D-TCI at (top) 1800 UTC 3 Oct 2015 and (bottom) 1800 UTC 4 Oct 2015. The blue lines indicate the radius of maximum wind speed at pressure levels from 1000 to 600 hPa.

prediction of heavy rainfall only within a range of 80–110 mm relative to the control experiment (RL-3D-CTRL) (Fig. 6b). However, the assimilation of HDSS dropsonde observations without VI but using GSI-4D-EnVar (RL-4D-TCI) improves the prediction of heavy rainfall within the whole range of 80–150 mm relative to the control experiment (RL-3D-CTRL) (Fig. 6c). Although the analysis here is narrow, as only 30 h of accumulated precipitation from the DA cycle of 1800 UTC 3 October 2015 is selected, the intercomparisons between the control experiments and those with HDSS dropsonde data assimilation suggest that the assimilation of HDSS dropsonde data can potentially improve the precipitation forecast in HWRF.

4) VORTEX STRUCTURE CHANGES

The results so far confirm that the assimilation of HDSS dropsonde data can, in some cases/configurations, result in

improved track, intensity, and precipitation forecasts. In particular, the RW of Hurricane Joaquin is well captured by the simulations with the assimilation of HDSS dropsonde data. In this section, RL-4D-CTRL and RL-4D-TCI are selected for further study the role of the HDSS dropsonde observations in capturing the vortex structure and its changes during the intensity changes of Hurricane Joaquin.

Figure 7 shows the azimuthally averaged temperature anomaly (shading) and wind speed (contours) from two selected simulations at 1800 UTC 3 October and 1800 UTC 4 October 2015, compared against the synthetic analysis from the HDSS dropsonde observations. Compared with the observations from HDSS dropsonde (Figs. 7a,d), HWRF forecasts produce a stronger vortex and warmer inner core (Figs. 7b,c,e,f). Meanwhile, RL-4D-CTRL and RL-4D-TCI versus the observations suggests that the assimilation of the HDSS dropsonde

FIG. 8. Time–height cross section of averaged quantities within a $3^{\circ} \times 3^{\circ}$ box centered on the storm center from 1800 UTC 3 Oct to 1800 UTC 6 Oct 2015 for (left) RL-4D-CTRL and (right) RL-4D-TCI. (a),(d) RH (%), (b),(e) RV ($\times 10^{-4} \text{ s}^{-1}$) overlaid with RH isolines of 40%, 50%, 60%, and 70%, and (c),(f) vertical mass flux overlaid with RH isolines of 40%, 50%, 60%, and 70%. The dashed lines indicate the end of RW for Hurricane Joaquin.

observations can well reproduce the vortex structure changes during the RW of Hurricane Joaquin. As shown in the observations and RL-4D-TCI, the strong upper-level warm core (above 300 hPa) and tangential wind structure at 1800 UTC 3 October (Figs. 7a,c) are significantly weakened at 1800 UTC 4 October (Figs. 7d,f). Accordingly, a looser tangential wind structure and the tilt of RMW with height at 1800 UTC 4 October are also clearly observed in the observations (Figs. 7a,d) and RL-4D-TCI (Figs. 7c,f). However, the change of tangential wind structure is relatively weak in RL-4D-CTRL (Figs. 7b,e), and the tilt of RMW with height in Fig. 7f is not shown in Fig. 7e.

Figure 8 illustrates a time–height Hovmöller diagram of relative humidity (RH), relative vorticity (RV), and vertical mass flux (Mflux) at each model level from averages taken over a $3^{\circ} \times 3^{\circ}$ box. The vertical mass flux is calculated by $\rho w = -\omega/g$, where ρ is density, w is vertical velocity in height coordinates, ω is the model velocity in pressure coordinates, and g is the acceleration due to gravity. As can be observed in both RL-4D-CTRL

(Fig. 8a) and RL-4D-TCI (Fig. 8d), a layer of dry air in the upper troposphere appears to penetrate the storm inner-core region after the 6-h forecast at 0000 UTC 4 October 2015, although the center of this dry layer in RL-4D-CTRL (Fig. 8a) is weaker than that in RL-4D-TCI (Fig. 8d). The dry layer persists throughout the whole RW period and the subsequent weakening of hurricane Joaquin (Fig. 8a, d). Coincident with the intrusion of the dry air are the decreases in relative vorticity and vertical mass flux in RL-4D-TCI at 0000 UTC 4 October 2015 (Figs. 8e,f). However, these corresponding changes are not seen in RL-4D-CTRL without the assimilation of HDSS dropsonde observations (Figs. 8b,c), indicating the assimilation of HDSS dropsonde observation seems to improve the accuracy of the vertical motion in the inner core of Hurricane Joaquin.

The similar figures are also checked for RL-3D-CTRL and RL-3D-TCI. As shown in Fig. 9, the assimilation of TCI dropsonde observations with GSI-3DVar (Figs. 9b,d) can also lead to a better capture of vortex

FIG. 9. Radius–height cross section of azimuthal mean temperature anomaly (colored contours; $^{\circ}\text{C}$) and azimuthal mean tangential wind (black contours; m s^{-1}) from (left) RL-3D-CTRL and (right) RL-3D-TCI at (a),(b) 1800 UTC 3 Oct 2015 and (c),(d) 1800 UTC 4 Oct 2015. The blue lines indicate the radius of maximum wind speed at pressure levels from 1000 to 600 hPa.

structure changes from 1800 UTC 3 October to 1800 UTC 4 October 2015 compared to the control experiment that does not assimilate the TCI dropsonde observations (Figs. 9a,c). However, the storm structure in Fig. 9d is looser than those in Fig. 7d and Fig. 7f, as the radius of maximum wind in Fig. 9b is extended to ~ 100 km, while the radius of maximum wind in Fig. 7f (Fig. 7d) is extended to only ~ 70 km. This is consistent with the intensity forecasts in Fig. 5e and Fig. 5f in that RL-3D-TCI underestimates the MSW more than RL-4D-TCI does. The results here

suggest that the assimilation of TCI dropsonde observations with GSI-4DEnVar can produce better storm structure and thus better intensity forecasts than GSI-3DEnVar.

Overall, the analyses in this section indicate that the assimilation of the HDSS dropsonde observations can potentially improve the simulation of vortex structure changes and the accuracy of the vertical motion within the TC inner-core region, which could be essential to the successful forecast of the RW of Hurricane Joaquin in HWRF. In addition, GSI-4DEnVar is able

FIG. 10. (a) Forecast tracks, (b) MSLP, and (c) MSW for Hurricane Joaquin from 1800 UTC 3 Oct to 1800 UTC 6 Oct 2015 from RL-4D-TCI and RL-4DRES-TCI. The forecast tracks are compared with the observed track in 6-h intervals. The numbers in the parentheses of each legend in (a), (b), and (c) represent the average track errors over the whole 72-h HWRf simulation.

to produce better storm structure than GSI-3DEnVar, which partially explains why GSI-4DEnVar produces better intensity forecasts than GSI-3DEnVar.

5. Sensitivity of RL-4D-TCI to a different DA configuration

Despite the promising improvements in RL-4D-TCI for the forecast of Hurricane Joaquin during its RW phase, the question arises as to whether the performance of RL-4D-TCI can be further improved. In fact, GSI-4DEnVar used by RL-4D-TCI is configured with a 3-h observational bin and a flow-dependent error covariance provided by a coarser-resolution GFS ensemble forecast. These configurations are probably suboptimal for the GSI-4DEnVar system and the assimilation of HDSS dropsonde observations, as previous studies (e.g., Wang and Lei 2014; Pu et al. 2016) have demonstrated that the data impacts can be sensitive to these two important aspects of the EnVar system. Therefore, additional experiments are performed.

A set of experiments, RL-4DRES-TCI, is performed using GSI-4DEnVar configured with a high-resolution background error covariance and a denser observational bin. Specifically, a parallel run of the HWRf regional ensemble system (Zhang et al. 2014) initialized by the forecasts from the Global Ensemble

Forecast System (GEFS) is performed first to generate a 42-member self-consistent HWRf ensemble at 6-km resolution. The detailed treatments and parameters used for HWRf ensemble forecasts follow those in Zhang et al. (2014). These 42-member self-consistent HWRf ensembles (~6 km), instead of the 80-member GFS ensembles (~23 km), are used in the GSI-4DEnVar DA system for the operational HWRf initialization framework, in order to provide the flow-dependent background error covariances for the GSI-4DEnVar DA system in the revised initialization framework. The HWRf spinup process is the same as indicated in section 3. During the DA period from 1800 UTC 2 to 1800 UTC 3 October 2015, the DA window in each analysis cycle (6 h) is divided into 6 observational bins; the 3-, 4-, 5-, 6-, 7-, 8-, and 9-h self-consistent HWRf 42-member ensemble forecasts are employed to derive the flow-dependent background error covariance, realizing the time evolution of background error covariance. After the DA, a 72-h forecast for Hurricane Joaquin is made. All the other configurations in RL-4DRES-TCI are the same as those in RL-4D-TCI.

Figure 10 presents the track and intensity regarding the MSLP and MSW produced by RL-4DRES-TCI and RL-4D-TCI from 1800 UTC 3 October to 1800 UTC 6 October 2015. RL-4DRES-TCI leads to overall better forecasts than RL-4D-TCI (Figs. 10a–c). Specifically, the

FIG. 11. Radius–height cross sections of the net radial force isopleths (per unit mass; $\text{m s}^{-1} \text{h}^{-1}$) in (a),(c) VI-4D-TCI, (b),(d) RL-4DRES-TCI for the (top) analysis at 1800 UTC 3 Oct 2015 and (bottom) 3-h forecast at 2100 UTC 3 Oct 2015. The contour interval is $20 \text{ m s}^{-1} \text{h}^{-1}$, and negative values are indicated by dashed lines. The zero contour is not plotted. The red lines indicate the radius of maximum wind.

average track error over the 72-h forecast is reduced by 31% in RL-4DRES-TCI compared with that in RL-4D-TCI at a confidence level of 95% from the t test (Fig. 10a), while the MSLP error over the first 48 h is also reduced by 34% in RL-4DRES-TCI compared with that in RL-4D-TCI at a confidence level of 90% (Fig. 10b). The average MSW error in RL-4DRES-TCI over the 48-h forecast is not significantly different from that in RL-4D-TCI in the context of a t test. However, RL-4DRES-TCI still produces a larger MSW error (5.7 m s^{-1}) than RL-4D-TCI (3.5 m s^{-1}) due to a faster weakening in RL-4DRES-TCI over the first 12-h forecast (Fig. 10c).

In addition, the adjustment of MSLP during the first 6-h forecast of RL-4D-TCI is not observed in RL-4DRES-TCI (Fig. 10b), implying that the high-resolution background error covariance and denser observational bin can possibly reduce the initial adjustment in HWRF after DA. Following Pu et al. (2016), the net radial force field F , which is defined as the difference between the sum of the Coriolis and centrifugal forces and the radial pressure gradient force, is calculated for RL-4D-TCI and RL-4DRES-TCI within the lower troposphere (1000–600 hPa). As shown in Fig. 11, RL-4D-TCI and RL-4DRES-TCI reveal similar subgradient wind imbalances ($F < 0$, dashed lines) in the boundary layers

(~ 850 hPa) in both analyses (Figs. 11a,b) and the 3-h forecast fields (Figs. 11c,d). These features are consistent with those in Pu et al. (2016). However, RL-4D-TCI (Fig. 11a) produces larger supergradient wind fields ($F > 0$, solid lines) within the inner-core region above the boundary layers (~ 850 hPa) during the analysis period at 1800 UTC 3 October 2015 than RL-4DRES-TCI does (Fig. 11a), while the supergradient winds become much weaker right after the 3-h forecast at 2100 UTC 3 October 2015 (Fig. 11c). In contrast, RL-4DRES-TCI produces much weaker supergradient wind fields above the boundary layers during the analysis period (Fig. 11b), and there is no significant adjustment of the supergradient wind field after the 3-h forecast (Fig. 11d). Despite the limitations of gradient wind imbalances as indicated in Pu et al. (2016), the results from Fig. 11 suggest that RL-4DRES-TCI tends to produce more balanced model initial conditions than RL-4D-TCI does, which can partially explain the reduction of the initial adjustment in RL-4DRES-TCI, as shown in Fig. 10b.

Overall, the performance of GSI-4DEnVar can be further enhanced with a denser observational bin, as the track and intensity forecast, as well as the balances in the initial conditions, can all be improved to some extent. This verifies that the performance of GSI-4DEnVar can be sensitive to the choice of observational bins and background error covariance. However, the higher computational cost of RL-4DRES-TCI is expected as the extra high-resolution HWRf ensemble forecast is required, which makes the improvements in RL-4DRES-TCI become less significant in contrast to RL-4D-TCI. Thus, GSI-4DEnVar with a large number of coarser-resolution global ensembles may be good enough for the operational use in considering of the computational efficiency.

6. Summary and discussion

The impacts of HDSS dropsonde data on HWRf forecasts of the RW of Hurricane Joaquin (2015) during ONR's TCI field campaign are assessed in this study. Results show that there are cases and configurations in which there is an advantage to assimilating the data from HDSS dropsondes, with improvements in intensity, track, and precipitation forecasts for Joaquin. A more precise capture of the RW in terms of the MSW of Hurricane Joaquin in HWRf forecasts is also observed. The HDSS dropsonde observations collected during the TCI field campaign are beneficial for studying the intensity changes of TCs, although the data impacts depend on the model configurations and DA schemes.

Specifically, VI in HWRf can produce inconsistent MSLP and MSW forecasts and weaken the data impact from HDSS dropsondes. The results from VI-3D-TCI suggest that VI can largely remove the data increments from the mid- and lower-tropospheric HDSS dropsonde observations. Thus, only upper-tropospheric HDSS dropsonde observations can play a role in the HWRf analysis. In contrast, the remove of VI can significantly mitigate the inconsistency between the MSLP and MSW forecasts. Additionally, the assimilation of HDSS dropsonde observations can significantly alleviate the initial MSW errors and further reduce the inconsistency between MSLP and MSW forecasts, which results in a substantive improvement in the intensity forecasts and better capture of the RW of Hurricane Joaquin in RL-3D-TCI.

Furthermore, compared with GSI-3DEnVar, GSI-4DEnVar with three observational bins shows additional improvements in the forecasts of the RW of Hurricane Joaquin. GSI-4DEnVar leads to smaller track and intensity forecast errors and produces a more realistic precipitation structure than GSI-3DEnVar. More importantly, the assimilation of the HDSS dropsonde observations with GSI-4D-EnVar can reproduce the RW of Hurricane Joaquin with good agreement of MSLP and MSW with the best track data. Further diagnoses indicate that the assimilation of the HDSS dropsonde observations can potentially improve the simulation of vortex structure changes and mitigate the inconsistency between the physical and dynamical processes within the TC inner-core region, which could be essential to the successful forecast of the RW of Hurricane Joaquin in HWRf. A test simulation for GSI-4DEnVar with a different configuration also indicates that the performance of GSI-4DEnVar with the TCI DA can be further improved with high-resolution background error covariance and a denser observational bin for GSI-4DEnVar.

Overall, the assimilation of HDSS dropsondes is essential to improving the forecast of the RW of Hurricane Joaquin in all of the different HWRf configurations and DA schemes. Since GSI-4DEnVar has been operational within the GFS system since 2015, there is a strong possibility that this method could be practical for operational HWRf. However, results in this paper are based solely on one case study due to limited observations available from an HDSS field experiment. A larger sample of hurricane cases will be necessary to evaluate the consistency of the impacts on the HWRf Model provided by HDSS dropsonde observations. For example, the HDSS dropsonde observations for Hurricanes Erika, Marty, and Patricia during different TC development periods

were also collected in TCI 2015 field experiments; future work of data assimilation experiments on these cases are necessary with the goal of providing guidance for operational centers to improve hurricane intensity forecasts, especially during changes in hurricane intensity.

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