A Case Study on the Impact of Ensemble Data Assimilation with GNSS-Zenith Total Delay and Radar Data on Heavy Rainfall Prediction

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ABSTRACT

The performance of a numerical weather prediction model using convective-scale ensemble data assimilation with ground-based global navigation satellite systems-zenith total delay (ZTD) and radar data is investigated on a heavy rainfall event that occurred in Taiwan on 10 June 2012. The assimilation of ZTD and/or radar data is performed using the framework of the WRF local ensemble transform Kalman filter with a model grid spacing of 2 km. Assimilating radar data is beneficial for predicting the rainfall intensity of this local event but produces overprediction in southern Taiwan and underprediction in central Taiwan during the first 3 h. Both errors are largely overcome by assimilating ZTD data to improve mesoconvective-scale moisture analyses. Consequently, assimilating both the ZTD and radar data show advantages in terms of the location and intensity of the heavy rainfall. Sensitivity experiments involving this event indicate that the impact of ZTD data is improved by using a broader horizontal localization scale than the convective scale used for radar data assimilation. This optimization is necessary in order to consider more fully the network density of the ZTD observations and the horizontal scale of the moisture transport by the southwesterly flow in this case.

1. Introduction

Mesoscale convective systems or strong convective systems that are either embedded in mei-yu fronts or that develop in the prefrontal areas can bring heavy rainfall and severe disasters such as mudflows or flooding

to Taiwan, endangering lives and the economy. The intensity and location of heavy precipitation can be modified by complex terrain, such as the Central Mountain Range in Taiwan. A data assimilation system coupled with a high-resolution dynamic model and a spatially dense, temporally frequent observation network is important for improving heavy rainfall prediction (Miyoshi et al. 2016).

Efforts to improve precipitation monitoring and nowcasting in Taiwan include a radar observation network covering Taiwan and the establishment of the Weather

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Research and Forecasting (WRF) local ensemble transform Kalman filter (WRF-LETKF) radar data assimilation system (Tsai et al. 2014). This data assimilation system has provided positive impacts for heavy rainfall predictions associated with typhoons (Tsai et al. 2016) and mei-yu-related events (Shao 2015; Cheng 2017; Cheng et al. 2018). These studies show that the assimilation of radar radial velocity improves the dynamic conditions, such as the convergence field, while the assimilation of radar reflectivity improves the precipitating process, including rainfall intensity variation and model spinup. Earlier studies have derived similar conclusions on radar data assimilation (Xiao and Sun 2007; Sun and Wang 2013). However, the performance of radar data assimilation can be limited if there are initial dynamical/thermodynamical errors in the environment or model errors associated with the microphysics process. Cheng (2017) showed that enhancing the large-scale moisture transport into the convective area in the model state leads to a great improvement of the efficiency of radar data assimilation and rainfall prediction. Combining with the impact from radar data, previous studies have demonstrated that assimilating observations associated with the ambient preconvective and near-convection environments brings benefit in convective-scale precipitation prediction (Kawabata et al. 2007; Pan et al. 2018).

The accuracy of the moisture field is important from convective to synoptic scales because it can affect precipitation occurrence, coverage and intensity. However, the number of humidity observations is relatively lower than that of wind or temperature observations. Among the observing systems that provide moisture information, such as satellites and radiosondes, global navigation satellite systems (GNSS) are becoming important for providing reliable moisture information (Bengtsson et al. 2003; Ma et al. 2011; Yang et al. 2014). GNSS-based observations take advantage of the fact that the radio rays emitted by GNSS satellites are bent when passing through the atmosphere, causing signaling delays as the rays are received. The degree of bending depends on the change in the density of the atmosphere, which is primarily related to the temperature and humidity conditions. One great advantage of GNSS observations is that radio rays are little affected by clouds and thus can therefore depict the temperature and moisture information in all weather conditions. Studies with assimilation of spaceborne GNSS radio occultation (RO) data demonstrate positive impacts on both global weather prediction (Anlauf et al. 2011; Healy 2008). The impact of GNSS RO on precipitation prediction with regional models is also identified in previous studies (Huang et al. 2005; Liu et al. 2012; Yang et al. 2014;

Huang et al. 2016). However, the RO observational density is not sufficient for adequate convective-scale data assimilation.

Ground-based GNSS receiver also measures the delay in the path in the receipt of a signal from a GNSS satellite (Bevis et al. 1992). This delay is expressed as the excess pathlength along the zenith direction and referred to as zenith total delay (ZTD). In many countries, the ZTD observation network has been established with a high spatial and temporal resolution. The ZTD can be considered to comprise two components: the zenith hydrostatic delay (ZHD) and zenith wet delay (ZWD). The former is the delay due to hydrostatic pressure, while the latter is the delay due to the amount of water vapor along the ray path. The hydrostatic component remains stable over time without the rapid change of pressure, such as during the passage of a low pressure cyclone. In contrast, the wet component is small but highly variable in time and space due to the moist conditions in the atmosphere. Although the ZWD contributes only less than 10% of the total delay, this component is an important indication of the variations in atmospheric water vapor. Based on ZTD, the total precipitable water (TPW), information directly related to the moisture, can be retrieved (Yeh et al. 2016). Many studies have shown that the assimilation of ground-based GNSS data, such as ZTD or TPW, at a horizontal model grid resolution on the order of 10 km has potential for assisting general data assimilation and prediction accuracy, particularly for humidity and rainfall forecasting (De Pondeca and Zou 2001; Vedel and Huang 2004; Yan et al. 2009; Bennitt and Jupp 2012; Shoji et al. 2011; Lindskog et al. 2017).

Cucurull et al. (2004) noted that assimilating ZTD has more benefits than assimilating TPW since deriving TPW requires surface pressure information, which may not be measured at all GNSS ground stations. Directly assimilating ZTD rather than TPW may be more desirable since deriving TPW from ZTD also requires the model information. Seko et al. (2004) points out that the moisture impact from the ZTD data is more prominent when other rapid meteorological data, such as radar data or wind profilers, are also assimilated. This is confirmed in a recent study. Mahfouf et al. (2015), with a quasi-operational data assimilation system, showed that ZTD data can systematically improve humidity in short-range forecasts compared with other informative water vapor observation systems, despite the relatively small fraction of the ZTD data in all assimilated observations. Since the ZTD data are available at a high temporal frequency, these data have an important role to fill in the observation gaps between radiosondes and satellite measurements, providing valuable rapid moisture

information for very short-term forecasts with rapid update analysis cycles (de Haan 2013) and quantitative precipitation estimation (Bauer et al. 2015). However, studies with assimilation of the ground-based GNSS observations in a convective-scale ensemble-analysis framework are few and mainly are done with the TPW data (Seko et al. 2011; Oigawa et al. 2018). Also, there are limited literature discussing impact of assimilating ground-based GNSS observation on prefrontal heavy-rainfall events occurring over complex terrain.

The ground-based ZTD observation network has been established in Taiwan, and the data can be processed at near-real time (Yeh et al. 2016). With the advantages of inexpensive instrumentation and easy installation over Taiwan, one of the goals in the local operational forecast center has been to assimilate these ZTD data and understand how they improve very short-term predictions (Tsai and Hong 2012). In particular, the ZTD data in Taiwan are expected to capture the meso-alpha-scale moisture interacting with topography, such as the moisture transport during the mei-yu season. In this study, we investigate the impact of the ZTD data on the performance of an ensemble-based radar data assimilation system coupled with the WRF model with a focus on heavy rainfall prediction in Taiwan. The convective-scale ensemble-based data assimilation system has the advantage of using the flow-dependent background error covariance, which is crucial for performing data assimilation over complex terrain of Taiwan. This system also has the benefit for convective-scale ensemble prediction that provides the probability quantitative precipitation forecast. Nevertheless, we should note that an advantage of the flow-dependent background error covariance for convective scales is the difficulty of defining a well-balanced static background error covariance for convective scales (Duda et al. 2019). In comparison, the variational analysis framework requires the adjoint of the observation operator and model and it is not trivial to consider the convective-scale analysis corrections over complex terrain (Tai et al. 2017).

In particular, we examine whether and how the ZTD data could improve the performance of convective-scale assimilation based on radar data and the synergy between two types of rapidly updated information systems. The impacts are assessed based on a case study of the heavy-rainfall event on 10 June 2012 with a high-resolution (2 km) ensemble data assimilation and prediction framework. This event occurred during a prefrontal episode involving a strong interaction of the convective system and with the local topography. The use of a high-resolution model allows a better representation of the topography that is needed for evaluating

the model pressure at the GNSS sites (De Pondeca and Zou 2001).

This paper is organized as follows. Section 2 provides a general review of the heavy rainfall event on 10 June 2012. Section 3 introduces the observation data and operators used in the convective-scale data assimilation. Section 4 introduces the data assimilation system and experimental setup. Sections 5 and 6 present the results of the analyses, forecasts, and the results of the sensitivity experiments, respectively. The sensitivity experiments are designed to justify the impact of the ZTD data. Finally, a summary and conclusions are given in section 7.

2. The heavy rainfall event of 10 June 2012

During the period from 10 to 12 June 2012, abnormally heavy rainfall persisted in Taiwan. The heavy rainfall on late 10 to early 11 June was related to abnormally high water vapor present from low to midlevels, low-level moisture convergence and topographic lifting, while the rainfall on 11–12 June was more directly related to the movement of the mei-yu front and its interactions with the local low-level jet (Chen and Li 1995; Chen et al. 2007; Chen et al. 2018). This study aims to examine the impact of assimilation of ZTD and radar data on predicting the torrential precipitation event from 1200 UTC (2000 LST) 10 June to 1200 UTC (2000 LST) 11 June 2012 (Chu 2013; Chen et al. 2018). Here, we briefly discuss the synoptic conditions that generated this torrential precipitation event.

Starting at 0000 UTC (0800 LST) 10 June 2012, a high-level trough north of Taiwan began to deepen and move eastward. A low pressure system at a low level over the South China region was associated with this trough. This low pressure system moved southeastward and developed into a stationary front system on 11 June, hovering around Taiwan. The synoptic-scale pattern generated a large area of low-level convergence extending from the South China Sea to Taiwan, high-level divergence in the same area, and an associated ascending zone in the prefrontal area. Meanwhile, a low-level southwesterly flow prevailed in the prefrontal area on 10 June, bringing abundant moisture with a TPW maximum over Taiwan (Fig. 1). Heavy rain developed over the mountainous area in central and southern Taiwan from the afternoon of 10 June to late evening. This rainfall was fed by the prevailing moist unstable flow impinging on steep terrain from the southwest. Later, the deep and strong convection organized over South China moved eastward with the surface low-level low pressure system and resulted in extreme precipitation in Taiwan on 11–12 June. As shown in Fig. 2, strong

FIG. 1. Total precipitable water (kg m^{-2} , color shading), moisture flux ($\text{kg kg}^{-1} \times \text{m s}^{-1}$, arrows), and water vapor convergence ($2 \times 10^{-7} \text{ kg kg}^{-1} \times \text{s}^{-1}$, contour) from the ECMWF analysis at 0600 UTC 10 Jun 2012.

reflectivity with a value larger than 40 dBZ appeared offshore of southwestern Taiwan and the mountainous area during the assimilation period of 0600 UTC (1400 LST) to 1200 UTC (2000 LST) 10 June. After 1200 UTC (2000 LST) 10 June, strong reflectivity occurred mainly in the mountainous area. Consequently, three maxima in the accumulated rainfall were observed in the mountainous area in Nantao, Kaoshiung, and Pingtung counties (Fig. 3). In particular, the last maximum had an amplitude of 678 mm in Kaoshiung county on 11 June, reaching the criterion of extremely torrential rain (>500 mm in 24 h) in the Taiwan area. From this point forward, these areas with heavy rainfall are referred to as areas N, K, and P, respectively.

3. Observations and operators

a. Zenith total delay

The primary source of data for this study is the network of continuously operating global positioning system (cGPS) stations installed and operated by the Central Weather Bureau (CWB) to monitor deformation of the island for earthquake hazard applications. Figure 4a shows the 66 GNSS ground stations in Taiwan used in this study. The observation density is approximately 15 km between stations, except over the higher mountains. This network comprises Trimble 5700 receivers equipped with TRM41249.00 antennas. Among these ground stations, 30 stations also measure meteorological variables, including temperature, surface

pressure and relative humidity. An estimate of the ZTD, which is the slant delay mapped to the zenith, is determined for each GNSS receiver. Currently, the ZTD data from the 66 stations on the island of Taiwan are routinely derived at the CWB using Bernese V5.0 (GNSS) software, which was developed by the University of Bern in Switzerland (Dach et al. 2007). In the data processing procedure, the individual ZTD for each GNSS station is obtained by using the double-difference strategy to minimize the systematic errors. The analysis uses final satellite orbits provided by the International GNSS Service (IGS) to eliminate satellite and receiver clock errors. From this network, ZTD is computed at 30-min intervals along with horizontal gradient parameters associated with the thickness of Earth's atmosphere (Yeh et al. 2016). The observation error for data assimilation is 10 mm (Tsai and Hong 2012; Eresmaa and Järvinen 2005).

Figure 5 shows an example of variations in the ZTD data that are sensitive to changes in the atmospheric conditions on 10 June. Figure 5a shows the time series of ZTD (solid line) and ZWD (dashed) from the station located at 24.715°N , 120.95°E (S1 in Fig. 4a). ZWD is estimated as the difference between the observed ZTD and model ZHD, which takes the information of the surface pressure measurement at the same location. This figure shows that the variations in ZTD are mostly dominated by ZWD, denoting the variations in the moisture field. This characteristic reveals the utility of ZTD data in providing auxiliary humidity information. In addition, Fig. 5b shows the ZTD deviations averaged from four stations in northwestern Taiwan framed by the box shown in Fig. 4a. The values deviate from the mean diurnal ZTD variations averaged from the total 66 stations in Taiwan from 0000 UTC (0800 LST) 10 June to 0000 UTC (0800 LST) 11 June. The ZTD deviations generally show an increasing trend, corresponding to the moisture transport by the southwest-westerly flow from 10 to 11 June and associated with the movement of the front system.

b. ZTD data operator

The ZTD observation operator simulates the ground-based ZTD value given a model vertical profile at the observation location. As the first step, the model state is interpolated into a vertical profile of temperature and humidity at a given ground-based GNSS site. Information on the modeled surface pressure and surface altitude at this location is also required. The operator implemented in the WRF-LETKF system follows Vedel and Huang (2004). The ZTD is estimated based on two components, the ZHD and ZWD ($\text{ZTD} = \text{ZHD} + \text{ZWD}$). The estimation of ZHD is based on Saastamoinen (1972),

FIG. 2. Composite radar reflectivity (dBZ) from 0600 to 2100 UTC 10 Jun 2012.

which has a very high accuracy compared to more elaborate methods (Vedel et al. 2001). The ZWD is related to the vertical integration of water vapor. Further corrections are required to consider the difference between the model surface height and the altitude of the station. If the altitude of the site is higher than the model terrain, the correction removes the extra ZTD estimation by considering the vertical integration of the refractivity from the model terrain to this site altitude, and vice versa.

The R-localization method (Hunt et al. 2007), in which the observation errors increase as the distance between the observation and analysis grids increases, is used in the LETKF assimilation to suppress the detrimental impact from sampling error due to the use of a limited ensemble size. The R localization has a

similar concept of background error covariance localization. The observation error is still assumed uncorrelated. In this study, the height of the observation is defined at the height of the GNSS station, even though the observation is actually a vertically integrated effect. This assumption is reasonable since the presence of moisture is usually greatest near the surface. The vertical localization for the ZTD data is described by a Gaussian function with 3 km as the standard deviation (localization scale).

Using the flow-dependent background error covariance in the ensemble Kalman filter (EnKF) allows the moisture corrections to be sensitive to the characteristics of the background moisture and the landcover types. Figure 6 shows examples of assimilating a single ZTD

FIG. 3. 12-h rainfall accumulation (mm) from 1200 UTC 10 Jun to 0000 UTC 11 Jun 2012.

data at 23.021°N , 120.348°E in southwestern Taiwan and 24.272°N , 120.692°E in central Taiwan at 0600 UTC (1400 LST) 10 June. These two locations were chosen for this study because they have characteristically distinct vertical moisture gradients in the background mean state. The former is located in the area with developing clouds amid a deep layer of moisture with minimal vertical gradient. The latter is located in a cloud-free area and has a very shallow and moist layer near the surface. At this time, the heavy precipitation has initialized in southwestern Taiwan and mountainous areas, while there is very little precipitation over the coastal area over northern Taiwan. With assimilation of the ZTD data, both locations exhibit strong analysis correction in the vertical up to 5 km (Figs. 6e,f). At 23.021°N , 120.348°E , a large analysis correction appears at 2 km (near 750 hPa). Horizontally, the moisture correction is also derived offshore of the southwestern coast near the surface (Fig. 6a). The moisture correction becomes more locally oriented along the coastline at higher levels (Fig. 6c), indicating that the moist air can be lifted by topography and increase the moisture aloft, a benefit from using a flow-dependent background error covariance. At 24.272°N , 120.692°E there is a

FIG. 4. (a) Observation locations of ZTD stations. S1, S2, and S3 are the selected stations used for Figs. 5 and 6. The locations are categorized by the altitude (m) of the station. (b) Superobservations of radar data at 1200 UTC (2000 LST) 10 Jun 2012.

strong negative moisture correction below elevation of 1 km and a strong positive moisture correction between 1 and 4 km elevation (Fig. 6f). Such a correction can adjust the shallow moisture layer near the surface and enhance moisture in the midlevel. This result may reflect a condition of enhanced vertical mixing, as the land surface has been heated up at this time (14 LST).

FIG. 5. Time series of (a) ZTD and ZWD from the station located at 24.715°N, 120.95°E on 10 Jun and (b) mean ZTD perturbations averaged from four stations over northwestern Taiwan on the same date. The perturbations are deviations from the mean diurnal cycle.

In addition, there is generally positive moisture correction in the offshore region, indicating a potential to enhance simulated moisture transport. In a brief summary, assimilating the ZTD data can have a large impact on depicting the moisture field at low to midlevels, which can benefit precipitation forecasts.

c. Radar data

In this study, we assimilate the radial velocity (V_r) and reflectivity (Z_h) data from four S-band radars at Wufenshen (RCWF), Hualien (RCHL), Chigu (RCCG), and Kenting (RCKT) in Taiwan (Fig. 7). The horizontal scanning range at the lowest elevation is 230 km for V_r and 460 km for Z_h , and there are a total of 9 scanning elevations. The radar data have been processed with different quality control steps to take into account nonmeteorological echoes, such as ground/sea clutter, beam blocking and attenuation (Chang et al. 2009; Zhang et al. 2011). The original resolution of the radar data is 250 m horizontally every 7.5 min. We adopt the superobbing strategy (Lindskog et al. 2004) to thin the data and avoid spatial correlations between observations. For each radar, fan-shaped areas are defined

with 2 km and 2° intervals in the radial and azimuthal directions, respectively. The center of each fan-shaped area is the location of a superobservation, and the value is obtained by summing the radar data within this area with a distance-based Gaussian weighting factor. The superobservations are processed to be available every hour using the radar data spanning within ± 30 min. The observation errors are 3 ms^{-1} for V_r and 5 dBZ for Z_h (Tsai et al. 2014).

Figure 4b shows an example of superobservations of radar Z_h at 1200 UTC (2000 LST) 10 June. Data are available in the scanning range of all four radars, especially south and east of Taiwan during the assimilation period and in the mountainous area. Although the radar superobservations at this time cover little convection offshore of southwestern Taiwan, observations are available in this region for antecedent times (Figs. 2a,b).

There are also some limitations when applying radar data in convective-scale data assimilation. For example, there is a data-void region related to the nonprecipitating but moist conditions located in the plains of central to northwestern Taiwan. These moist conditions allow for the convective storms to be regenerated in Nantou County after 1800 UTC (0200 LST) (Fig. 2e). Additionally, radar signals can be blocked or reflected by topography, which can negatively affect data quality and impact the accuracy of radar data assimilation over mountainous areas. Underrepresented moisture fields that result in the model state can lead to inaccuracies in predicted precipitation in the radar data-void or mountainous areas.

d. Radar observation operators

The LETKF radar data assimilation system has been established for the purpose of very short-term rainfall prediction in Taiwan (Tsai et al. 2014; Tsai et al. 2016). This system has the advantage of using a flow-dependent background error covariance over the complex terrain. In addition, the analysis ensemble can be used for convective-scale ensemble prediction, providing products such as probability quantitative precipitation forecasts. The observation operators convert the model state to radar radial velocity and reflectivity. The radial velocity is then calculated following Sun and Crook (1997). The operator of the reflectivity in this study is in accordance with the Goddard cumulus ensemble (GCE) microphysics scheme (Tao et al. 2003), in which rainwater, snow and graupel are the hydrometeor species observable by radar. In contrast to Tsai et al. (2014), which considered only the reflectivity factor from rainwater, the current operator incorporating the contributions of snow and graupel is feasible to assimilate the reflectivity

FIG. 6. Analysis increments of water vapor mixing ratio (g kg^{-1}) at 0600 UTC (1400 LST) 10 Jun at (a) 950 hPa, (c) 750 hPa, and (e) on an east–west vertical cross section from assimilating one ZTD datum at 23.021°N , 120.348°E (S2 in Fig. 4a). (b), (d), (f) As in (a), (c), (e), but the assimilation is performed with the ZTD datum at 24.272°N , 120.692°E (S3 in Fig. 4a).

data above the melting layer (Gao and Stensrud 2012). This system has been evaluated for rainfall prediction associated with typhoons and mei-yu cases and has demonstrated significant improvement in nowcasting (Tsai et al. 2016).

4. Assimilation system and experimental setup

a. WRF-LETKF assimilation system

The assimilation of the ZTD and radar data are conducted under a framework coupling the local ensemble

FIG. 7. The WRF Model domain used in this study with 10- and 2-km grid spacings for the outer and inner domains, respectively. The red triangles indicate the locations of the radar sites at Wufenshen (RCWF), Hualien (RCHL), Chigu (RCCG), and Kent-din (RCKT). The circles are the observation range of Z_h , which is about 230 km.

transform Kalman filter (Hunt et al. 2007) with the WRF Model (Skamarock and Klemp 2008). The WRF-LETKF system has two components, one of which assimilates conventional observations for the synoptic-to-mesoscale weather systems characterized by several hundreds of kilometers (Yang et al. 2014, 2017) and the other assimilates radar data for convective-scale weather systems characterized by a few tens of kilometers (Tsai et al. 2014). In both components, R-localization and multiplicative covariance inflation are used. ZTD data assimilation is a new component for convective-scale data assimilation, and the operator uses the package developed for assimilating GNSS-RO data (Yang et al. 2014), including calculating the geodetic height and refractivity index. In addition, in this study, when both the ZTD and radar data are assimilated, radar data assimilation is conducted sequentially after ZTD data assimilation. This strategy provides a more representative background moisture field for radar data assimilation. When using ensemble-based radar data assimilation, updating the moisture variable is relatively challenging due to the indirect relationship between water vapor and V_r/Z_h . It is more likely to be affected by the sampling errors (Houtekamer and Mitchell 1998). Therefore, we adopted the strategy to assimilate ZTD data to improve the moisture field and constrain the ensemble spread of the moisture field first. Another concern is that the ZTD data is assimilated with larger horizontal localization. Following the concept of successive correction method, the larger-scale corrections should be derived

first and then the smaller-scale corrections are used for fine tuning.

b. Experimental setup

In this study, we use the version of the CWB OP25 model based on WRFV3.3.1 with nested, two-way interacted model domains with horizontal grid spacings of 10 km for domain 1 and 2 km for domain 2 (Fig. 7). The horizontal dimensions are 300×300 and 420×420 for the outer and inner domains, respectively. There are 52 levels vertical levels between the surface and 10 hPa. All the experiments use the same model parameterization, including the Rapid Radiative Transfer Model (RRTM) longwave radiation scheme (Mlawer et al. 1997), the Dudhia (1989) short-wave radiation scheme, the Yonsei University (YSU) planetary boundary layer (PBL) scheme (Hong et al. 2006), the Grell–Devenyi ensemble cumulus scheme (Grell and Dévényi 2002), and the GCE microphysics scheme (Tao et al. 2003). No cumulus parameterization scheme was necessary for the inner domain due to its high spatial resolution being fine enough to resolve convection directly. The time step used for domain 1 is 90 s.

To initialize the high-resolution ensemble at 0600 UTC (1400 LST) 10 June, the National Centers for Environmental Prediction (NCEP) $1^\circ \times 1^\circ$ global final operational global analysis at 0000 UTC (0800 LST) 8 June 2012 is downscaled to the 10-km domain and perturbed by 40 sets of perturbations stochastically drawn according to the background error covariance default in the WRF three-dimensional variational data assimilation system. The WRF-LETKF assimilation is performed for the 10-km domain with a 6-h analysis interval from 0000 UTC (0800 LST) 8 June to 0000 UTC (0800 LST) 10 June with conventional meteorological observations. Starting at 0000 UTC 10 June, a 6-h ensemble forecast using the two-way nested domains is conducted to spin up the convective-scale structures in the ensemble perturbations. The convective-scale data assimilation with rapid update cycling is performed from 0600 UTC (1400 LST) to 1200 UTC (2000 LST) 10 June with a 1-h analysis interval. The two-day regional LETKF assimilation before the convective-scale assimilation helps establish the flow-dependent ensemble perturbations that correspond to the background dynamics, including the mei-yu front, moisture transport from the South China Sea and the thermodynamically unstable conditions for strong convection over the Taiwan area. Cold-starting the model with random, flow-independent perturbations leads to an unrealistic pattern of reflectivity, which is overly smoothed and widespread.

This step can affect the performance of assimilating reflectivity data.

Three experiments are conducted by assimilation of only radar data, only ZTD data or both, and these experiments are referred to as RDA, ZDA, and BOTH, respectively. Although the radar and ZTD data are assimilated at the same resolution (2 km), different horizontal localization scales are adopted. The horizontal localization scale is 4 km following Tsai et al. (2014) when assimilating radar data and 50 km for ZTD data. There are two reasons for such choices. First, we consider the observation density of these data. Second, considering the horizontal-scale characteristic of the moisture conditions (section 2), the moisture field is expected to have a broader extent than fields related to strong convection, such as rainwater or vertical velocity. Section 6 will include further discussion on the impact of using different choices of localization.

The 12-h deterministic and ensemble forecasts are initialized from the analysis of all the assimilation experiments mentioned above at different analysis times. The impact of ZTD or radar data assimilation is evaluated according to the performance of precipitation prediction. Although the 1–3 h forecast is mainly evaluated for very short-term precipitation prediction, evaluations targeted on 6- and 12-h rainfall accumulation are also major concerns in our operational center. This is because the heavy rainfall, such as the event in this study, can last for more than 6 h due to the abundant moisture transport and the topography lifting with time scales longer than convective time scale.

5. Results of analyses and forecasts

In this section, we discuss the general impact of assimilating radar, ZTD and both sets of data on the moisture and wind fields and how these data can affect the following heavy rainfall prediction.

a. Results of analyses

To evaluate the impact of assimilation, a control run, referred to as CTR, is prepared by the deterministic forecast initialized from the mean of the forecast ensemble at 0600 UTC (1400 LST) 10 June (i.e., the background mean at the first analysis time). Figures 8a and 8b show the TPW and wind at 925 hPa for CTR and RDA at 1200 UTC (2000 LST) 10 June, the end of the assimilation period. The CTR 6-h forecast and analyses of assimilation experiments are similar in terms of large-scale features. However, there are differences in smaller scales and they are related to the effects of data assimilation (ensemble update) and nonlinear dynamics (ensemble forecast). The differences over the Taiwan area

are mainly attributed to the assimilation of observations in Taiwan (Fig. 8c versus Fig. 8d). First, assimilating radar data has strong impacts on the wind and moisture fields. Compared to CTR, the RDA analysis exhibits a localized moisture tongue offshore of southwestern Taiwan, and a more westerly wind component offshore. Such moisture enhancement in RDA is not directly obtained from the assimilation of radar data at this analysis time, but from dynamic updating through successive forecast–analysis cycles.

At 1000 UTC (1800 LST), RDA has large corrections offshore of southwestern Taiwan in the lower atmosphere for fields of water vapor and rainwater mixing ratio (Figs. 9a,d); however, the signs of these corrections are opposite, showing an increase in rainwater but a reduction in water vapor (the black box in Fig. 9). These corrections are derived based on the flow-dependent error correlation estimated by the ensemble and reflect the physical relationship of water vapor being consumed to produce more rain in this area. Nevertheless, there is southerly wind correction in the same area of moisture reduction and northwesterly wind correction over southwestern Taiwan. The wind correction provides a condition of moisture convergence at the coast and offshore of the southwestern Taiwan (contour in Fig. 9b). Despite the moisture reduction at this analysis time, the moisture over southwestern Taiwan expands southwestward and is enhanced after one hour of model integration with the moisture transport from the west and converged at the coast (contour in Fig. 9c). The pattern of local moisture tongue over southwestern Taiwan persists till 1200 UTC (2000 LST) (Fig. 8b). Therefore, the moisture transport and convergence (dynamical update during the forecast step) overcomes the data assimilation effect (observation update during the analysis step) and enhances the moisture in this area. In comparison, the rainwater over southern Taiwan is increased at both the analysis and forecast steps (Figs. 9d,f). The rainwater correction is strong and abundant during the assimilation period since there is wide range of strong convection developing southwest of Taiwan (Figs. 2a,b). As will be discussed later, this can lead to large precipitation amount over southern Taiwan.

Compared with RDA, assimilating ZTD data produces higher TPW from offshore to the coastal area of northwestern Taiwan and offshore of southeastern Taiwan but lower TPW offshore of southwestern Taiwan (Fig. 8e). A large difference seen to be the east of Taiwan is linked to the discrepancy in the amount of data between RDA and ZDA. When both radar and ZTD data are assimilated, the TPW is generally higher than that in RDA from offshore to coastal areas of

FIG. 8. TPW (kg m^{-2}) and wind (m s^{-1}) at 925 hPa from the (a) CTR and (b) RDA analyses at 1200 UTC (2000 LST) 10 Jun. The TPW differences between (c) RDA and CTR, (d) ZDA and CTR, (e) ZDA and RDA, and (f) BOTH and RDA analyses.

FIG. 9. (a) The RDA analysis increment of water vapor mixing ratio (g kg^{-1}) at 875 hPa at 1000 UTC (1800 LST), (b) analysis mean of water vapor mixing ratio (g kg^{-1}) at 1000 UTC (1800 LST), and (c) background mean of water vapor mixing ratio (g kg^{-1}) at 1100 UTC (1900 LST). (d)–(f) As in (a)–(c), but for the rainwater mixing ratio. The vectors in (a), (d) are the analysis increment of the wind at 950 hPa at 1000 UTC (1800 LST) and vectors in (b), (c) are the wind at 875 hPa. The analysis increment is defined as the difference between the ensemble mean analysis and ensemble mean background. The contour in (b) is the moisture flux convergence of $1.5 \times 10^{-3} \text{ g kg}^{-1} \text{ s}^{-1}$. Contours in (c) are the moisture increase between the ensemble mean analysis at 1000 UTC and ensemble mean forecast at 1100 UTC with values of 0.5, 1.5, and 2 g kg^{-1} .

Taiwan but is particularly lower in the southwestern interior of Taiwan (Fig. 8f). The differences in TPW between ZDA and BOTH show that the ZTD data can be complementary to the radar data. This is further illustrated by comparing the analysis increment from RDA and BOTH. At 1200 UTC (2000 LST), there is limited radar data available over northwestern Taiwan due to nonprecipitating conditions (Fig. 4b) and thus the amount of analysis corrections on the moisture and wind fields will also be limited in BOTH and RDA analyses (Figs. 10b,c). The ZTD data in this area provide significant moisture and southwesterly wind corrections in the BOTH analyses (Fig. 10a). In particular, wind corrections with ZTD data exhibit convergence in the area with positive moisture increments in the coastal area, resulting that the area of moisture

convergence in BOTH over northwestern Taiwan is broader than that from RDA. In comparison, assimilating ZTD data reduces the moisture at the coast of southwestern Taiwan and enhances the onshore flow (Fig. 10a). The analysis increment from assimilating the radar data is rather limited since the radar data at the coast and offshore of southwest Taiwan at this time is less than those at previous cycles (black box in Fig. 2b versus Fig. 2c), even though the wind correction is still strong at the coast. With the impact from ZTD data assimilation, the conditions for deep convection is modified. We note that the analysis correction in BOTH from assimilating the radar data has smaller amplitude but its pattern is similar to that from RDA. This suggests that the benefit of radar data is not overwhelmed by assimilating the ZTD data. The ZTD

FIG. 10. Analysis increment of TPW (g kg^{-1}) and wind (m s^{-1}) at 1200 UTC 10 Jun. (a) From assimilating ZTD data in BOTH and (b),(c) from assimilating radar data in BOTH and RDA, respectively. The dashed contours denote the terrain height at 1 and 2 km.

data provide a robust moisture correction since these data are directly related to the moisture field (section 3b) and the data are available regularly at the GNSS stations. The dynamical relationship between moisture and wind allows the ZTD data to provide strong wind corrections as well. Since the moisture information is not required in the radar operator, the moisture correction mainly relies on the ensemble-based background error covariance between moisture and simulated radar observations and is limited in the nonprecipitating area.

b. Deterministic forecast evaluation

In terms of the performance of the short-term precipitation prediction, the differences among experiments are most evident during the first 6-h forecast. Figure 10 shows the rainfall accumulation from the first to the 12th forecast hours accumulated from 1200 UTC (2000 LST) 10 June to 0000 UTC (0800 LST) 11 June. Three areas (N, K, and P) experienced heavy precipitation during that period, characterized by different temporal rainfall variations, with area N reaching the strongest intensity (15.5 mm h^{-1}) during the first three hours. The rainfall in area K exhibits a stronger intensity 5 h later.

As shown in Fig. 11, the CTR prediction captured the general rainfall pattern, but the amounts of precipitation and locations of the heavy rainfall are misrepresented and underestimated during the first 6-h forecast, especially in Pingtung County (southern Taiwan). Additionally, the heavy rain northwest of Taiwan suggests that the rainband over the Taiwan Strait moves too fast

toward Taiwan (Fig. 11q versus the black box in Fig. 2f). The CTR rainfall prediction is slightly better than that directly initialized from the NCEP global FNL analysis at 1200 UTC (2000 LST) 10 June, especially during the first 3 h (figure not shown). This also indicates that the synoptic-to-mesoscale conditions can determine the general pattern of the rainfall associated with the mei-yu front system. However, features leading to strong convections in the mountainous areas cannot be well represented in the downscaled analysis which may require additional spinup time.

Assimilation of radar data (the third column in Fig. 11) significantly improves the amounts and locations of the precipitation, such as alleviating the overprediction in Nantou county and increasing the rainfall in Pingtung county (Fig. 11m versus Fig. 11l). However, the heavy precipitation in the RDA forecast begins too early and is too strong in southern Taiwan (Figs. 11c,h). It is also less optimal in terms of the location of the heavy rainfall. At 6-h, the RDA forecast shows too much heavy rain over Chiayi and southern Kaohsiung while at the same time underestimating the heavy rainfall in the northern Kaohsiung county (Fig. 11m), where the maximum rainfall is observed (Fig. 11k). Although the precipitation amount in area N is less than observation during the early forecast hours, the rainfall is significantly overpredicted at 12 h (Fig. 11r) and the predicted rainfall maximum is displaced to the south of observation area N.

The 6-h accumulated rainfall in the ZDA forecast reaches an intensity comparable to the observations,

FIG. 11. Rainfall accumulation (mm) from (first column) observation and (second to fifth columns) CTR, RDA, ZDA, and BOTH forecasts initialized at 1200 UTC (2000 LST) 10 Jun. Rainfall is accumulated for 1, 3, 6, and 12 h.

and the locations of heavy rainfall are also well represented (Fig. 11n versus Fig. 11k) compared with those of the CTR forecast. It improves the rainfall location over southern Taiwan and alleviates the overprediction in Nantou. This result indicates that ZTD data assimilation alone is also very useful for improving short-term forecasts and that moisture adjustment can improve the location and intensity of heavy rainfall. However, without the direct information of hydrometeors, the simulated rainfall intensity is weaker than that from RDA.

In comparison, the rainfall prediction from BOTH shows a performance between the RDA and ZDA forecasts. For this case, assimilating the ZTD data in addition to the radar data is helpful for improving the overall rainfall amount in area N, and in one hour, the rainfall in Miaoli and Taichung counties has increased (Fig. 11e). Compared to the 6-h accumulated rainfall in area N in the RDA forecast, the maximum in BOTH is located in Taichung, closer to the observation. In addition, BOTH suppressed the overpredicted rainfall intensity in southern Kaohsiung county from the 6-h RDA forecast (Fig. 11m versus Fig. 11o), especially in area P. Such improvements are associated with the moisture corrections provided by the ZTD data (Fig. 10a). Furthermore, the difference at the initialization affects in the rainfall field within a very short time frame, indicating that rapid updating of the moisture field also plays an important role in very short-term rainfall prediction. The overprediction in area P in the RDA forecast suggests that the moisture reduction derived at the analysis time (Fig. 9a) is useful correction suppress the excessive moisture but not enough to reduce the excessive rainwater brought by forecast–analysis cycling. Assimilating the ZTD data additionally strengthens the moisture reduction and avoids the overprediction in southern Taiwan.

The results showing improvement can also be further supported by examining additional forecast verification metrics. Compared with rain gauge data, Fig. 12 shows the root-mean-square error (RMSE) of rainfall prediction accumulated from the first to 12th hours. The RMSE of the CTR rainfall forecast is largest during most of the forecast hours. Assimilations of radar, ZTD or both data successfully reduce the RMSE of the CTR rainfall forecast. The RDA forecast has a larger RMSE than those of the ZDA or BOTH forecasts during the first 6 h due to the overpredicted rainfall but then shows the best performance in terms of the accumulated rainfall amount during the 8–12-h forecast. The changes in RMSE of RDA forecast reflects the spinup issue. The BOTH rainfall forecast exhibits the smallest RMSE during the first 4-h forecast and its RMSE is

FIG. 12. RMSEs (mm) of the rainfall accumulation predictions from different experiments at different forecast hours.

largest during the 8–12-h forecast among three assimilation experiments. The changes in RMSEs of BOTH indicates that additional assimilation of ZTD data mitigates the spinup issue in RDA but some disadvantages inherited from both data makes the RMSE worse than either RDA or ZDA (e.g., the overprediction in the Nantou county related to the RDA and underprediction in Pingtung county related to the ZDA). The impact of ZTD data will be justified by other verification metric in the following.

A positive and similar impact from additionally assimilating the ZTD data is also found in the precipitation predictions initialized at 1000 UTC (1800 LST) and 1100 UTC (1900 LST). Especially, the overpredicted rainfall with RDA is improved (figure not shown). The overall performance of 6-h forecasts initialized at three analysis times is summarized by a score diagram (Fig. 13), including the probability of detection (abscissa), success ratio (ordinate), threat score (TS, green contours), and bias (dashed lines) for 6-h rainfall accumulation. As shown in Fig. 13, a good forecast skill is indicated at the diagonal, and perfect skill is denoted at the upper-right corner. Different colors indicate the forecast skills evaluated at different precipitation thresholds.

Results in Fig. 13 indicate that while the CTR forecasts have the lowest skill for all the thresholds, assimilation of either ZTD or radar data can improve the CTR forecast skill in terms of the four different forecast verification metrics. Generally, the ZTD data improves the success ratio while the radar data improves the

FIG. 13. Forecast skill diagram for 6-h rainfall accumulation predictions. The probability of detection, success ratio, threat score, and bias are indicated with the abscissa, ordinate, green contours, and brown dashed lines, respectively. Different colors indicate forecast skills evaluated at different precipitation thresholds.

probability of detection. This can be interpreted that assimilation of the ZTD improves the location of the heavy rainfall and thus reduces the false forecast while assimilation of radar data leads to stronger intensity and broader area of rainfall. Among all the experiments, the BOTH forecasts carry the advantage from using information from both datasets, and this advantage is more evident for thresholds of heavy rainfall. For example, at the threshold of 60 mm in 6 h, BOTH has a higher success ratio and TS, indicating a benefit from assimilating both data in predicting both the location and intensity of rainfall prediction. In terms of the rainfall amount, ZDA shows smaller biases compared to CTL and BOTH shows biases in between the performance of ZDA and RDA.

c. Ensemble forecast evaluation

In addition to deterministic forecasting, ensemble forecasting is also performed to validate the impact from assimilating the ZTD data for this case. Figure 14 shows the Brier scores of the probability quantitative precipitation forecast (PQPF) in the areas of central and southern Taiwan. The Brier score calculates the RMSE of the observation and prediction probabilities: the lower score the better the prediction. The advantage of the BOTH forecast over the RDA forecast appears when the precipitation thresholds are larger than 15 mm $(6\text{ h})^{-1}$ and persists for thresholds of heavy precipitation till 45 mm $(6\text{ h})^{-1}$. In southern Taiwan, the PQPF with ZDA shows the best forecast skill, while the PQPF with RDA has the poorest skill. The reason that the RDA ensemble forecast has the poorest skill is because some of

FIG. 14. The Brier scores of the 6 h, from 1200 UTC (2000 LST) to 1800 UTC (0200 LST) 10 Jun, probability quantitative precipitation forecast for (a) central Taiwan (23.75°–24.55°N, 120.6°–121.3°E) and (b) southern Taiwan (22.1°–23.6°N, 120.3°–121.1°E).

the members overestimate the rainfall over the hillside. Assimilating the ZTD data can reduce the moisture in that area in this case, and thus, the PQPF better corresponds to the observations. Consequently, Fig. 14 further supports the conclusion that ZTD data assimilation further improves the analysis compared to radar data assimilation.

6. Results of the sensitivity experiments

a. Impact of using different horizontal localization scales

In previous experiments, although assimilation of ZTD and radar data is performed at the same grid resolution

(2 km), the horizontal covariance localization for assimilating ZTD is larger than that of radar data. The choice is based on considerations of the observation density and the characteristics of moisture distribution (Fig. 1). To justify our choice, we conduct two additional experiments to assimilate both the ZTD and radar data using the same horizontal localization—one using 4 km and the other using 50 km—and these experiments are referred to as RD04 and RD50, respectively.

Changing the localization can modify the range of the observation impact on wind and moisture conditions near Taiwan. With its smaller localization scale, RD04 exhibits a TPW analysis similar to that of the RDA analysis, as indicated by similar difference patterns shown in Figs. 15b and 8f, and we lose the moisture increment offshore of northwestern Taiwan. By contrast, RD50 exhibits larger moisture and wind differences at a broader range, especially over the ocean east of Taiwan. Although we may be able to have the broader-range moisture correction from assimilation of ZTD in RD50, the moisture corrections are also strongly modified by assimilation of radar data with a larger localization scale. Figure 15c shows that, compared to BOTH, RD50 has more moisture in the area east of Taiwan and in the coastal area of central and southwestern Taiwan. Particularly near the coast of Kaohsiung, there is onshore wind near the coast. This feature is the result of expanding the impact of the radar data over the mountainous area outward. Nevertheless, RD50 also has a lower TPW, especially northwest, south and southeast of Taiwan. Such a result can be explained by two considerations. First, the wind difference between RD50 and BOTH shows a cyclonic circulation northeast of Taiwan, where the northward wind component enhances the moisture transport and the southward component reduces the moisture transport by southwesterly flow (Fig. 8b). This effect corresponds to the impact of assimilating the radar data over the Taiwan Strait and northeast of Taiwan (Figs. 2b,c) with a larger localization scale. As shown in Fig. 8c, the assimilation of radar data reduces the moisture in areas south and southeast of Taiwan compared to CTR. In RD50, such features expand outward. As discussed in Chung et al. (2013), the convective-scale background error correlation between the hydrometeor and wind or moisture is characterized by a short decorrelation scale. However, a finite ensemble size may not be able to describe such a correlation, and the moisture corrections by reflectivity data can be contaminated by sampling errors if a long localization scale is used.

As expected, the differences shown in Figs. 15b and 15c result in differences in the precipitation forecasts, as shown in Fig. 16. Large differences from BOTH are

mainly exhibited during the first 6 h. With a short localization scale, the benefit of the ZTD data shown in BOTH is reduced. The RD04 misrepresents the rainfall with a similar behavior as in the RDA forecast in areas K and P, but the intensity of 3-h rainfall there is weaker than that of RDA (Fig. 16e versus Fig. 11h). In area N, where ZTD data with a short localization are still beneficial in the radar data-void region, the rainfall intensity and location are similar to those shown in RDA with overprediction in Nantou county (Fig. 16i versus Fig. 10k). Compared to the 6-h rainfall in the RDA forecast, the intensity and location of the heavy rainfall in the RD04 forecast are closer to that in observations. This result again confirms that the moisture corrections in ZDA and BOTH are indeed useful for improving the precipitation prediction. However, when assimilating radar data using a long localization, the RD50 forecast has less rain, especially in area K, due to the reduction in the moisture field. Additionally, RD50 leads rapidly to an overly intense rainfall during the first 3-h forecast in areas N and P compared with BOTH (Fig. 16f versus Fig. 10j). This overestimation is related to enhancement of the moisture and convergence fields in the coastal areas in central and southern Taiwan, as discussed earlier. Also, the overpredicted rain over the coastal area of western Taiwan is most severe among all experiments and worsen with time (Fig. 16n). However, we should note that the large moisture reduction shown in Fig. 15c does not significantly reduce the precipitation amount in area P since that area is located in the downstream area of the prevailing southwesterly winds. Nevertheless, RD50 leads to the worst forecast skill of the set.

Tsai et al. (2014) proposed a mixed localization method that when assimilating radar data, the localization for updating the horizontal wind should be larger than that used for hydrometers. However, the precipitation prediction did not gain particular benefit from adopting such localization method in this case. Also, to show the benefit of assimilating the ZTD data, the horizontal localization for the ZTD data needs to be large enough to cover the offshore region; otherwise, the analysis corrections are dominated by the radar data. To summarize, when assimilating both the ZTD and radar data, it is preferred that ZTD data are assimilated with a larger horizontal localization scale to ensure proper moisture correction on rainfall intensity, while radar data are assimilated with a shorter localization to ensure precision in the location of strong convections.

b. Impact of using a different vertical localization scale

In the LETKF framework, covariance localization is performed with R-localization (Hunt et al. 2007;

FIG. 15. (a) TPW (kg m^{-2}) and wind (m s^{-1}) at 925 hPa from the BOTH analysis at 1200 UTC (2000 LST) 10 Jun and TPW differences between the BOTH and (b) RD04, (c) RD50, (d) VL, and (e) NoVL analyses.

FIG. 16. Rainfall accumulation (mm) from (a)–(d) RD04, (e)–(h) RD50, (i)–(l) VL, and (m)–(p) NoVL forecasts initialized at 1200 UTC (2000 LST) 10 Jun. Rainfall is accumulated for 1, 3, 6, and 12 h.

Greybush et al. 2011), in which the observation error increases with the distance between the observation location and analysis grid. The observation error is inflated according to a Gaussian-type function depending on this distance and thus the observation impact is damped if the observation is horizontally or vertically far from the analysis grid. The effect of the R localization is determined by the distance between the observation location and analysis grids. However, for observations with integrated properties in the vertical, such as the satellite data or the ZTD data used in this study, defining a specific vertical location for these observations is difficult. As a reasonable choice, the observation level for applying vertical localization for assimilating ZTD is defined at the altitude of the ZTD station and the decorrelation scale is 3 km (cutoff is 9 km). It is assumed that the ZTD data are strongly affected by surface moisture maxima. To justify our choice, we carry out another assimilation experiment following the same setup used in BOTH but redefining the observation level of ZTD at the mass center of the moist air column according to Eq. (1), where h^i and q_v^i are the altitude and water vapor mixing ratio at the i th model level and N is the total model level.

$$h_{\text{mc}} = \frac{\sum_{i=1}^{i=N} h^i q_v^i}{\sum_{i=1}^{i=N} q_v^i} \quad (1)$$

The newly defined observation level is always higher than the altitude of the ZTD station, and thus, the impact near the surface is slightly damped due to the application of vertical localization. The use of Eq. (1) is to consider the vertical variations of the moisture profile, instead of assigning the observation level to the station altitude. If the high moisture layer is shallow, h_{mc} is closer to the surface, and is always assigned at a height level higher than the surface if the high moisture layer is thick. With the background ensemble used for Fig. 6, Fig. 17 demonstrates the difference from the assimilation of one ZTD datum with vertical localization arranged at the surface or the mass center. Although the changes in moisture corrections are small, the new localization has less near-surface moisture correction (Fig. 17a) at where the correction in Fig. 6b is positive, and vice versa. But the sign of the correction difference at 750 hPa (Fig. 17b) is consistent with that shown in Fig. 6d, indicating that the moisture correction with the new localization is extended to the upper levels (Fig. 17c versus Fig. 6f).

With the same setup used in BOTH, we conducted two sensitivity experiments: VL uses the new vertical

localization and NoVL does not use vertical localization when assimilating the ZTD data. Since the density of the atmosphere can vary in time and space, the defined observation level of ZTD will change adaptively in the VL experiment instead of a fixed station altitude used in BOTH. Compared to BOTH, there is a reduction in TPW over the plains of western Taiwan but enhancement from coast to mountainous areas in southern Taiwan (Fig. 15d). Compared to Fig. 8f, Fig. 15d suggests that the impact from the ZTD data is reduced. Without localization, the impact of ZTD data can extend upward. As shown in Fig. 15e, the TPW difference from BOTH is shown in Taiwan and east of Taiwan. This indicates that the modification in the upper levels propagates downstream with the prevailing wind.

Due to the slight moisture enhancement shown in Fig. 15d, the precipitation amounts in areas K and P in VL (Fig. 16k) increase compared with BOTH (Fig. 11o), but are still less compared to RDA (Fig. 11m). The rainfall in the mountainous area of Kaohsiung is now increased in VL and better corresponds to the observations. Generally, VL still preserves the advantage that assimilation of the ZTD data about the rainfall location, while alleviating somewhat the issue that the BOTH forecast underpredict the 6- and 12-h rainfall amount in areas K and P. Without localization, the benefit shown in the BOTH forecast from assimilating the ZTD data is suppressed in the NoVL forecast, in which the large rainfall (30 mm) in area N is overpredicted with an expansion southward and southwestward at 6- and 12-h (Figs. 16l,p). The heavy rainfall in southern Taiwan is more concentrated in south Kaohsiung County. From the one case, it may be difficult to conclude the impact of assigning the observation altitude for vertical localization given that the vertical distribution of moisture is dominated by the amount of moisture at lower levels, but the vertical localization is necessary to optimize the impact of ZTD data assimilation.

7. Summary and discussion

The performance of a convective-scale ensemble data assimilation with ground-based GNSS-ZTD and radar data is investigated based on a heavy rainfall event in Taiwan on 10 June 2012. This case was chosen because it contains the challenges of a large-mesoscale moist air mass interacting with topography to which the islandwise GNSS-ZTD data are well suited, and radar data alone are not enough to provide moisture corrections sufficient for improving rainfall location and intensity prediction. Assimilations of ZTD and radar data are performed using the WRF-LETKF framework with a model grid spacing of 2 km.

FIG. 17. Differences of the analysis increment of the water vapor mixing ratios (g kg^{-1}) between the mass center and the altitude of the GNSS-ZTD station used for vertical localization in ZTD data assimilation. The assimilation is done from assimilating one ZTD datum at 24.272°N , 120.692°E and the differences are taken at (a) 950 hPa, (b) 750 hPa, and (c) on the east–west vertical cross section.

Provided features at the synoptic scale are well described in the initial condition fields, assimilating radar data significantly improves predictions of the intensity and location of heavy precipitation. This improvement is attributed to local enhancements in moisture, rainwater and convergence fields. In particular, the moisture enhancement offshore of and at the coast of the southwestern Taiwan is because of the wind corrections that allow moisture convergence to take place during the following model integration. However, the analysis correction from RDA and its precipitation prediction are considered less optimized in two aspects compared to the rainfall observations. First, the precipitation

from central to northern Taiwan is underestimated during the early forecast (<3 h) but becomes over-predicted at 12 h. The location of the rainfall maximum is displaced to the south of the observed maximum. The slower precipitation spinup is related to limited correction for moisture convergence in the radar data-void region since the S-band radar data are only available after raindrops form. Second, in the areas where convective systems are strong and well established, especially the mountainous area in central to southern Taiwan during the early cycles of radar data assimilation, the amount of rainwater and low-level convergence is largely enhanced through assimilation

cycles, and heavy rainfall is overpredicted during the first 6-h forecast initialized at 1200 UTC 10 June.

ZTD data carry moisture information, and the moisture adjustment derived from assimilating the ZTD data can quickly alter the precipitation prediction and better represent the heavy rainfall location compared to assimilating the radar data only. But the rainfall amount in heavily precipitated areas is generally underestimated. When both data are assimilated, ZTD data increase the moisture in the radar data-void areas, further enhancing the moisture convergence over the slope and leading to improvements in precipitation prediction there. In southwestern Taiwan and the offshore region, assimilating the ZTD data reduces the amount of moisture. Consequently, the overprediction of rainfall in southern Taiwan from using just the radar data is alleviated. Therefore, the capability to correct the moisture field makes the ZTD data complementary to the radar data and assimilating both brings synergy to precipitation prediction. A basic difference between the ZTD and radar data is that the ZTD data can be available and regularly at the GNSS station while the distribution of radar data is inhomogeneous depending on the locations of the strong convection.

The skill of precipitation prediction initialized at different analysis times shows that BOTH gives the best performance in terms of success ratio and threat score as a benefit of improving the heavy rainfall location. The large skill differences among BOTH, RDA, and ZDA at high rainfall thresholds suggests that assimilating the ZTD data has a significant, beneficial impact on heavy rainfall prediction. The benefit of assimilating the ZTD data is also identified from the PQPF derived from ensemble prediction.

To justify the choice of localization applied to the ZTD data assimilation, different covariance localization scales are adopted for assimilating the ZTD and radar data. The assimilation of ZTD data requires a broader localization, with consideration of not only observation density but also the broader horizontal characteristic scale of moisture than those of the hydrometeors. With the same short localization used for the radar data, the impact of the ZTD data is limited. Similarly, the negative impact associated with sampling errors appears by using a long localization with radar data. In general, the experiment with a large localization scale for both data leads to the least reliable precipitation prediction and most different behavior among all the experiments using radar data with a shorter localization scale.

The ZTD data have a vertical integration property, which can lead to some ambiguity in defining the vertical localization used in the LETKF R localization.

An intuitive choice used in this study is to specify the “observation level” at the altitude of the ground-based ZTD station. A sensitivity experiment is conducted by setting the observation location at the mass center of water vapor mixing ratio to consider the vertical gradient of the moisture. After the moisture correction is extended upward, there is improvement in terms of precipitation prediction at later forecast hour. Since most moisture is concentrated in the lower atmosphere in the boundary layer, the impact of the ZTD data regarded near the surface or depending on the moisture vertical distribution should not give large difference. More cases should be carried out to systematically investigate the whether the vertical localization strategy depending on the vertical most gradient is sensitive to weather systems characterized by different moisture distribution.

Through control and sensitivity experiments, our approach has highlighted the robustness and effectiveness of the strategy to assimilate the ZTD data in rapid update cycles. However, very limited, but well-observed cases involving intense convective storms organized offshore and over Taiwan island were presented to more fully demonstrate the generality of our work. The 2012 case presented herein is one of the most important and most severe cases, which reflects our intent to illustrate the value of our work in an innovative sense. We anticipate that this innovative work elucidates way to showcase general impacts on prediction accuracy for more episodes in Taiwan and other places with similar scenarios.

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