Understanding the Influence of Assimilating Satellite-Derived Observations on Mesoscale Analyses and Forecasts of Tropical Cyclone Track and Structure

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UNIVERSITY OF MIAMI

UNDERSTANDING THE INFLUENCE OF ASSIMILATING SATELLITE-DERIVED OBSERVATIONS ON MESOSCALE ANALYSES AND FORECASTS OF TROPICAL CYCLONE TRACK AND STRUCTURE

By

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UNDERSTANDING THE INFLUENCE OF ASSIMILATING SATELLITE-DERIVED OBSERVATIONS ON MESOSCALE ANALYSES AND FORECASTS OF TROPICAL CYCLONE TRACK AND STRUCTURE

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This dissertation research explores the influence of assimilating satellite-derived observations on mesoscale numerical analyses and forecasts of tropical cyclones (TC). The ultimate goal is to provide more accurate mesoscale analyses of TC and its surrounding environment for superior TC track and intensity forecasts. High spatial and temporal resolution satellite-derived observations are prepared for two TC cases, Typhoon Sinlaku and Hurricane Ike (both 2008). The Advanced Research version of the Weather and Research Forecasting Model (ARW-WRF) is employed and data is assimilated using the Ensemble Adjustment Kalman Filter (EAKF) implemented in the Data Assimilation Research Testbed.

In the first part of this research, the influence of assimilating enhanced atmospheric motion vectors (AMVs) derived from geostationary satellites is examined by comparing three parallel WRF/EnKF experiments. The control experiment assimilates the same AMV dataset assimilated in NCEP operational analysis along with conventional observations from radiosondes, aircraft, and advisory TC position data. During Sinlaku and Ike, the Cooperative Institute for Meteorological Satellite Studies (CIMSS) generates hourly AMVs along with Rapid-Scan (RS) AMVs when the satellite RS mode is
activated. With an order of magnitude more AMV data assimilated, the assimilation of hourly CIMSS AMV dataset exhibit superior initial TC position, intensity and structure estimates to the control analyses and the subsequent short-range forecasts. When RS AMVs are processed and assimilated, the addition of RS AMVs offers additional modification to the TC and its environment and leads to Sinlaku’s recurvature toward Japan, albeit prematurely. The results demonstrate the promise of assimilating enhanced AMV data into regional TC models.

The second part of this research continues the work in the first part and further explores the influence of assimilating enhanced AMV datasets by conducting parallel data-denial WRF/EnKF experiments that assimilate AMVs subsetted horizontally by their distances to the TC center (interior and exterior) and vertically by their assigned heights (upper, middle, and lower layers). For both Sinlaku and Ike, it is found: 1) interior AMVs are important for accurate TC intensity, 2) excluding upper-layer AMVs generally results in larger track errors and ensemble spread, 3) exclusion of interior AMVs has the largest impact on the forecast of TC size than exclusively removing AMVs in particular tropospheric layers, 4) the largest ensemble spreads are found in track, intensity, and size forecasts when interior and upper-layer AMVs are not included, 5) withholding the middle-layer AMVs can improve the track forecasts. Findings from this study could influence future scenarios that involve the targeted acquisition and assimilation of high-density AMV observations in TC events.

The last part of the research focuses on the assimilation of hyperspectral temperature and moisture soundings and microwave based vertically-integrated total precipitable water (TPW) products derived from polar-orbiting satellites. A comparison is made
between the assimilation of soundings retrieved from the combined use of Advanced Microwave Scanning Radiometer and Atmospheric Infrared Sounder (AMSU-AIRS) and sounding products provided by CIMSS (CIMSS-AIRS). AMSU-AIRS soundings provide broad spatial coverage albeit coarse resolution, whilst CIMSS-AIRS is geared towards mesoscale applications and thus provide higher spatial resolution but restricted coverage due to the use of radiance in clear sky. The assimilation of bias-corrected CIMSS-AIRS soundings provides slightly more accurate TC structure than the control case. The assimilation of AMSU-AIRS improves the track forecasts but produces weaker and smaller storm. Preliminary results of assimilating TPW product derived from the Advanced Microwave Scanning Radiometer-EOS indicate improved TC structure over the control case. However, the short-range forecasts exhibit the largest TC track errors.

In all, this study demonstrates the influence of assimilating high-resolution satellite data on mesoscale analyses and forecasts of TC track and structure. The results suggest the inclusion and assimilation of observations with high temporal resolution, broad spatial coverage, and greater proximity to TCs does indeed improve TC track and structure forecasts. Such findings are beneficial for future decisions on data collecting and retrievals that are essential for TC forecasts.
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Chapter 1

Introduction

1.1 Satellite Data Applied to Tropical Cyclones

Improving forecasts of tropical cyclone track and intensity remains a challenge in numerical weather prediction (NWP) (Gall et al., 2013). This is largely due to the initial condition errors which are associated with TC structure and the surrounding environment (Torn and Hakim, 2009). Such errors often arise from the inability to accurately map the three-dimensional atmosphere and the underlying upper ocean due to the paucity of in-situ observations over the oceans being assimilated into present operational models. Since a TC spends most of its lifetime over the ocean, initial conditions are crucially dependent on the accurate assimilation of data from geostationary and polar-orbiting satellites. The recent progress in satellite instruments and advancement in data assimilation and numerical modeling of TCs have led to significant improvement in the understanding of TC structure and environmental interactions. Nevertheless, the accurate forecast of TCs, especially the intensity change, remains a challenging problem in NWP. More effort is needed to advance data assimilation with satellite observations in improving TC forecasting.
For more than three decades, the infrared imagery based Dvorak technique has served to provide TC intensity estimation in many operational weather centers worldwide where aircraft reconnaissance flights are not routinely deployed (Velden et al., 2006). The original algorithm relates the cloud signatures and brightness temperature values to TC intensity (Dvorak, 1984), and was later updated to Objective Dvorak Technique (ODT) and Advanced Objective Dvorak Technique (AODT) to automate the TC parameter selections by Olander and Velden (2007). Additional information provided by microwave sensors is often used to help improve the estimate of storm center position and intensity as complementary and/or independent estimations from the Dvorak Technique (Velden et al., 2006). This includes unique information such as convective organization, secondary eyewall formation, and replacement cycles that are more effectively detected in microwave imagery and are also critical to intensity change forecast (Wimmers and Velden, 2007). In addition to estimating TC intensity, satellite observations also help provide information on the environmental flow and atmospheric condition that are critical to TC movement and development (e.g., Soden et al., 2001; Dunion and Velden, 2004). Using the satellite-derived wind vector data, TC track forecasts have improved through a more accurate representation of the environmental steering flow (Langland et al., 2009; Berger et al., 2011).

Satellite observations from geostationary and polar-orbiting platforms, and as well as global positioning satellite (GPS) systems together provide the major observation sources (including in-situ and remote-sensing observations) assimilated in current operational NWP centers (e.g., McNally et al., 2014).

Geostationary satellites are the primary tools for providing hemispheric views at low to mid-latitudes with high temporal resolution. They are very suitable for monitoring severe weather events such as TC. However, geostationary sensors are restricted to visible (VIS) and infrared (IR) sounders with relatively low spatial resolution due
to their high orbital distance above the Earth (≈ 36,000 km above equator). The important information about TC internal structure is often hidden in VIS and IR imagery with the presence of clouds as well.

Unlike geostationary satellites, polar-orbiting satellites aim to provide superior spatial resolution measurements over a small field (along nadir or near-nadir paths) from a variety of onboard sensors (active and passive) at all latitudes from lower-orbital distance (≈ 800 km above the Earth). For example, NASA’s Earth Observing System (EOS) *Aqua* satellite has six different earth-observing instruments on board including AMSR-E\(^1\), MODIS\(^2\), AMSU-A\(^3\), AIRS\(^4\), HSB\(^5\), and CERES\(^6\). The lower orbital distance allows it to carry instruments with high spatial resolution including microwave sensors and hyperspectral infrared sounders (Hou et al., 2013; Chahine et al., 2006). However, the average revisit time of 12 hours for the same location leads to gaps in coverage and under-sampling of rapid TC evolution. Remedies such as carrying the same sensors/instruments on multiple polar-orbiting platforms (e.g., AMSU) can increase the frequency of similar measurements at the same locations, but not from the same satellite.

The GPS satellite network provides similar information over broader horizontal scales, but with very fine vertical resolution. The radio occultation (RO) technique, which obtains atmospheric soundings by making use of radio signals transmitted by GPS satellites (Kursinski et al., 1997), has become a powerful approach for providing global atmospheric monitoring with high precision, accuracy, and vertical resolution in all weather over both land and ocean (Kuo et al., 2004). Because of its insensitivity of the weather, the RO observations provide information of tropospheric moisture and

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\(^1\)the Advanced Microwave Scanning Radiometer-EOS  
\(^2\)the MODerate-resolution Imaging Spectroradiometer  
\(^3\)the Advanced Microwave Sounding Unit-Aqua  
\(^4\)the Atmospheric Infrared Sounder  
\(^5\)the Humidity Sounder for Brazil  
\(^6\)the Cloud’s and the Earth’s Radiant Energy System
temperature structure with high resolution (as small as a few hundred meters) over the tropics without being affected by clouds and precipitations (Biondi et al., 2011), which are crucial for TC genesis, intensity and track forecasts (Liu et al., 2012).

Satellites also carry active sensors that send out signals to illuminate the object and measure the return signal. With higher energy equipped with active sensors, they usually provide data with higher spatial resolution. For example, scatterometers estimate wind speed and direction by using the attenuated return energy due to the roughness of ocean surface (e.g., Yueh et al., 2003). The wind retrievals are used at operational forecast centers to estimate TC location, intensity and wind radii (Brennan et al., 2009). It has been shown to help refine 34-kt wind radii (Chou et al., 2010) that are critical for timing and placement of coastal watches and warnings. Finer-resolution retrievals are also available for improving hurricane eye determination (Halterman and Long, 2006). In addition to ocean surface wind fields, microwave radar instruments onboard satellites also provide altimeter data to estimate heat content of the upper ocean, which provide fuel for intensification of TC (Katasaros et al., 2002). Precipitation radar (e.g. TRMM's PR; Simpson et al. 1988) designed to provide vertical structure information of TC is used to understand the cloud and precipitation structure and latent heat distribution in TCs (Hence and Houze, 2012).

Equipped with multiple channels, advanced satellite sounders provide measurements that are no longer confined to 2-D or near the ocean surface, and are capable of resolving vertical states of atmospheric condition with accuracies approaching those of conventional radiosondes. One example is the hyperspectral infrared spectrometer known as the AIRS (Chahine et al. 2006) from which temperature and moisture profiles are retrieved under clear to partly cloudy conditions (Susskind et al., 2003). Unlike regular sounders on geostationary platforms, hyperspectral infrared sounders take measurements over thousands of infrared channels and therefore largely reduce
the uncertainty in vertical profiles of retrieved quantities (Jones and Stensrud, 2012). However, the low temporal refresh rate of the polar-orbiting platforms largely restricts the continuous monitoring of the retrieved vertical profile in the vicinity of TCs. To observe the state and evolution of rapid-evolving systems such as TC at high vertical resolution, a hyperspectral sounder in geostationary platforms is needed (Wang et al., 2007). Although it is not ready yet in the next generation Geostationary Operational Environmental Satellite R series (GOES-R; Goodman et al. 2012), both China and Europe have planned to launch geostationary hyperspectral sounders in the next decade.

Finally, unlike conventional observations, satellite sensors do not directly measure atmospheric variables such as temperature, wind, precipitation, etc. Satellite sensors, including both active and passive, measure the radiation emitted and/or transmitted by the atmosphere that reaches the top of the atmosphere at various spectral channels in the quantity of radiance or brightness temperature. Radiances are sensitive to earth surface characteristics and atmospheric variables such as temperature, humidity, clouds, and precipitation within broad layers of the atmosphere. These quantities are then retrieved through the use of radiative transfer equations. Due to the uncertainties and additional observational errors introduced by the various retrieval algorithms for different satellite platforms, the direct assimilation of radiances has been encouraged in operational NWP models (Derber and Wu, 1998). In order to do so, the radiative transfer model (RTM) should be included in the observation operator ($H$, which interpolates or maps the model variables to observed quantities) to compute radiances from forecast model variables at every observation point.
1.2 Assimilation of Satellite Data in Numerical Models of Tropical Cyclones

TC track forecasts have improved over the past few decades with the advanced data assimilation and in-situ and remote-sensing observing techniques incorporated into operational NWP models (Rogers et al., 2006; Goerss, 2009). TC intensity change has had only modest improvement in forecast accuracy since 1990 (Rappaport et al., 2009). In contrast, TC intensity forecasting is a much more complicated problem since the intensity change is primarily governed by convective-scale and mesoscale dynamics and thermodynamics, which the global model, data assimilation system, and current observations are unable and inadequate to resolve. In order to improve the representation of the processes that govern TC intensity change, there is a need to provide a more accurate initial condition of TC structure and the surrounding environment for mesoscale models by appropriately assimilating available observations.

As NWP systems have recently improved dramatically in regards to model grid resolution and convective physics (e.g. the Hurricane Weather Research and Forecast System model, HWRF; Tallapragada et al. 2013), much attention has turned to using state-of-the-art mesoscale models and data assimilation schemes directed towards TC forecasting. With satellite observations being the majority of data ingested into NWP models, there is a huge demand for mesoscale configurations on higher (temporal and spatial) resolution satellite observations (Goodman et al., 2012). Operational NWP centers generally use satellite observations thinned to a spatial resolution on the order of ~ 100 km with large uncertainty in the vertical distribution of derived atmospheric quantities (Goldberg et al., 2003) and update cycles in 3- to 6- hourly intervals (Berger et al., 2011). However, with the increasing quantity, variety, and resolution of new satellite data, the present operational use of satellite data is less...
applicable for mesoscale approaches. It is necessary to seek optimal methods to exploit the use of these multiple and integrated satellite datasets in mesoscale data assimilation and forecasting. Such methods include more frequent updates with the use of higher density and temporal resolution observation datasets and the choice of superobbing and error assignments of these observations that better suit the TC scales being analyzed (Bedka et al., 2009). Advanced satellite retrieval algorithms along with data assimilation techniques are required to adequately assimilate rain and cloud contaminated satellite observations near the inner-core TC and surrounding environments into mesoscale numerical models (Zupanski et al., 2011). Shorter lead-time forecasts and faster update cycles also require extensive computing resources. Furthermore, a better understanding of the physics of TC evolution and accurate representation of initial structure of the vortex with contemporary NWP models is required to lessen the inconsistency between model states and observations in rapidly changing weather events for efficient data assimilation.

The field of data assimilation specific to TCs has evolved rapidly in recent years. In particular, the Ensemble Kalman Filter (EnKF; Evensen 2003) has become widely used in the research community, due in part to the practicality of its application and the physical realism of the flow-dependent error covariance structure, especially suitable for the highly (multi)variate TC environment (Liu et al., 2012). The EnKF method combines short-term ensemble forecasts from numerical models with observations through a Kalman Filter analysis update with statistics drawn from the ensemble. It has been demonstrated to effectively provide a realistic initial representation of the TC structure and environment, and therefore an improved forecast through the assimilation of a variety of data including airborne Doppler radar, surface best track data, GPS radio occultation refractivity (e.g. Chen and Snyder, 2007; Torn and Hakim, 2009; Wu et al., 2010; Zhang et al., 2011; Aksoy et al., 2013; Jung et al.,
In order to offer more robust statistics, Torn (2010) employed a mesoscale EnKF in the Weather Research and Forecasting (WRF) model framework for a sample of ten Atlantic Basin TCs and concluded that the EnKF-initialized WRF forecasts possessed lower errors in track and TC wind radii than corresponding WRF forecasts initialized from the NCEP Global Forecast System (GFS) and Geophysical Fluid Dynamics Laboratory (GFDL) analyses. The EnKF has already become a viable alternative among operational centers, since it has been shown to be comparable to the current operationally favored 4D-Var in most circumstances (Lorenc, 2003). Nevertheless, assimilation of satellite data into mesoscale models of TCs is relatively limited in comparison to those studies that assimilate in-situ observations from reconnaissance flights and other conventional data. Recent Observing System Experiments (OSEs) have shown that assimilating high-density AMV data into mesoscale models yield improvements and insights into TC track and intensity forecasts (e.g., Pu et al., 2008; Kieu et al., 2012), although more TC cases and studies with more satellite data are necessary.

Geostationary satellite observations may naturally benefit the TC data assimilation with their high refresh rate. For example, during Typhoon Sinlaku in 2008, MTSAT-1 scanned images every 30 minutes, and GOES-East scanned images every 15 minutes during Hurricane Ike in 2008. High temporal and spatial resolution atmospheric motion vectors (AMV) were then postprocessed and prepared at hourly intervals by the Cooperative Institute for Meteorological Satellite Studies (CIMSS) using routinely available multispectral image triplets. In order to exploit the use of the hourly CIMSS AMV dataset and its impact on the analysis and forecast of TC, Chapter 3 of this dissertation reports on a detailed investigation by comparing two assimilation experiments, one that utilizes the hourly CIMSS AMV dataset and an-
other that uses the conventional 6-hourly AMV dataset assimilated at NCEP. More frequent AMV data can also be retrieved if the scanning interval is reduced by activating satellite ‘Rapid-Scan’ imaging mode (Langland et al., 2009). On the other hand, with weak spectral resolution, geostationary satellite observations are limited by their low vertical resolution and unable to efficiently represent convective scale structures that are crucial in TC genesis and intensity change.

Hyperspectral spectrometers onboard polar-orbiting satellites are one of the advanced sensors that aim to address this issue, for example the AIRS instrument on board the NASA’s Aqua satellite. Many studies have found positive impact of assimilating these profiles into mesoscale models on TC track and intensity forecasts (Li and Liu, 2009; Liu and Li, 2010; Pu and Zhang, 2010). The assimilation of AIRS data in the study by Wu et al. (2006) also confirmed that the Saharan Air Layer (SAL) is able to suppress Atlantic TC activity by modifying the vertical shear and moisture so as to further stabilize the low-level environment as suggested by Dunion and Velden (2004). However, bias is also a known problem in these profiles, and Pu and Zhang (2010) has shown that it is possible for bias correction of these assimilated profiles to further reduce forecast errors.

In addition, microwave instruments on board polar-orbiting satellites provide broad coverage of the moisture distribution of TC more efficiently than IR and VIS sounders. Among its many important products, the vertically integrated total precipitable water (TPW) depicts the moisture present at all levels, especially at low-levels where most of the water vapor is concentrated. A previous study by Liu et al. (2011) found that the assimilation of MODIS IR TPW resulted in moisture increment and enhanced convective clouds that modulated vertical wind shear. The forecasts that utilized MODIS IR TPW exhibited more accurate track and intensity than the forecasts that utilized MODIS near-IR TPW and AIRS/AMSU TPW (a combination of
AIRS IR and AMSU microwave product), respectively. However, investigations on assimilating microwave-only TPW, for example, AMSR-E TPW are important for TC forecasting but have had only limited studies.

There has been much concern about whether the direct assimilation of radiance is more effective than the assimilation of retrievals based on an equivalent comparison (Joiner and Dee, 2000). The direct assimilation of radiance significantly increases the data volume and the need for additional calls to the RTM, and the assimilation of cloud and precipitation-affected satellite radiances is rather challenging and also an active area of research (Vukicevic et al., 2006). Many discussions regarding whether assimilating satellite retrievals or radiance in NWP systems have arisen due to the advance in RTM and data assimilation technique (Migliorini, 2012). However, the most current satellite data application assimilates retrievals and/or radiances under clear-sky conditions. The work associated with cloudy radiance and precipitation assimilation is challenging and resource-intensive because work toward more accurately representing clouds and precipitation processes in current RTM is under development. On the other hand, the use of retrieval products, which are more resource-friendly and physically-intuitive, has been preferred in TC data assimilation mostly because of its availability. Understanding the assimilation of these satellite retrievals (satellite-derived observations) still remains an active research topic since satellite data have been advanced and updated rapidly.

This research focuses on the use of satellite-derived observations in TC data assimilation to understand and further exploit their uses in current NWP systems. These satellite-derived observations include enhanced geostationary AMV observations, high-resolution hyperspectral atmospheric soundings, and microwave TPW data from polar-orbiting satellites. The ultimate goal is to provide more accurate mesoscale analyses for TC forecasts.
With this, several assimilation experiments are utilized to examine the following scientific questions:

- How are the model states modified when each satellite-derived dataset is assimilated?

- Have the short-range ensemble forecasts improved with improved analyses through assimilating satellite-derived observations?

- If the answer is yes, how long do the forecasts retain the influence of assimilated data, in terms of track, intensity, and storm size forecasts?

- Given that polar-orbiting satellite observations are less frequent and more sparse in the vicinity of the TCs in comparison to geostationary satellite observations, what is their value in mesoscale TC data assimilation?

Hypotheses:

1. With broad spatial coverage and good quality, the enhanced AMVs provide better representations of the upper-level wind structure and the environmental steering flows. The assimilation of the enhanced AMVs should lead to more accurate analyses and further improve track and intensity forecasts.

2. Temperature and moisture soundings with high vertical resolution and microwave TPW data in the vicinity of TC are critical for representing the environment, in particular when it is favorable for TC development. The assimilation of these data should improve the forecast of TC intensity change, especially during rapid intensification.

3. Given that dynamic datasets such as the enhanced AMVs has higher spatial and temporal availability than thermodynamic datasets, it is anticipated that
the assimilation of dynamic satellite-derived data will dominate the impacts of the analyses and forecasts on the TC structure and environment.

This dissertation is organized as follows. First, the TC case overview, satellite-derived observations and the mesoscale data assimilation system utilized in this research along with the experimental design are summarized in Chapter 2. The influence of assimilating the enhanced geostationary satellite AMVs on Typhoon Sinlaku (2008) is addressed in Chapter 3. Chapter 4 further examines the relative influence of spatial and vertical subsets of AMVs through conducting parallel data-denial experiments for both Typhoon Sinlaku and Hurricane Ike (2008) in two different TC basins; In Chapter 5, attention is shifted to temperature and moisture observations from polar-orbiting satellite and the influence of their assimilations on the analyses and forecasts for both TC cases. Implications of this research and a discussion of future directions are provided in Chapter 6.
Chapter 2

Cases, Data and Methodology

2.1 Case Overview

Two TCs, Typhoon Sinlaku (2008) and Hurricane Ike (2008) are selected for this study. Both of them had a significant societal impact and high sensitivity in their operational forecasts prior to their landfall.

Figure 2.1: (a) Satellite IR image on 10 September and (b) VIS image on 11 September show strong Typhoon Sinlaku as it approaches Taiwan. (c) Radar image on 13 September shows a clear eye of Typhoon Sinlaku on its way to landfall over northern Taiwan.
2.1.1 Typhoon Sinlaku (2008)

As reported in Leroux et al. (2013) and many other studies, the evolution of Sinlaku was complicated. After its formation east of the Philippines on 0000 UTC 8 September 2008, the storm was upgraded to Tropical Storm Sinlaku by the Japan Meteorological Agency (JMA) at 1800 UTC on the same day. Sinlaku then underwent rapid intensification, reaching Typhoon status at 1200 UTC on 9 September, and intensifying further to 937 hPa by 1800 UTC 10 September with two concentric eyewalls (Fig. 2.1a-b). After this period, the inner eyewall dissipated, and the minimum sea level pressure did not fall back below 950 hPa over the subsequent two days. During the period between its formation and landfall in Taiwan on 13 September (Fig. 2.1c), the motion of Sinlaku was slow and meandering, with high uncertainty in its track forecasts (Yamaguchi and Majumdar, 2010). After landfall and subsequent recurvature on 15 September, Sinlaku decayed to Tropical Storm status. As it traveled northeastward towards Japan, Sinlaku then re-intensified into a typhoon on 18 September (Fig. 2.2).

![Figure 2.2: Typhoon Sinlaku (2008) track and central pressure (mb) from JMA best track dataset.](image)

In order to examine questions on TC predictability and data assimilation, the Office of Naval Research (ONR) Tropical Cyclone Structure 08 (TCS-08) / THORPEX
Pacific Asian Regional Campaign (T-PARC) field experiment was conducted in the western North Pacific basin in 2008. The most intensively observed TC during the field campaign was Typhoon Sinlaku. Many papers have been published on Sinlaku, describing the evolution of its structure (Wu et al., 2012; Huang et al., 2012), sensitivity of the track forecast to the environmental flow (Komaromi et al., 2011; Majumdar et al., 2011a; Yamaguchi and Majumdar, 2010) and the impact of assimilating data from dropwindsondes and in-situ observations (Harnisch and Weissmann, 2010; Kim et al., 2010; Kunii et al., 2012). In this research, attention is focused on improving the analysis and forecast of Sinlaku’s track, structure and intensity during the period of rapid intensification, prior to its landfall in Taiwan.

2.1.2 Hurricane Ike (2008)

Figure 2.3: Montage of Hurricane Ike (2008) from GOES-12 IR imagery shows its evolution from genesis to final landfall at southern Texas, US.
Following its formation early on 1 September 2008, the tropical depression strengthened into Tropical Storm Ike later that day, west of the Cape Verde Islands. As it moved west-northwestward under the influence of a strong Atlantic subtropical ridge to its north, Ike intensified steadily over the next two days followed by rapid intensification to a Category 4 hurricane by 0600 UTC 4 September. Over the following two days, Ike began to weaken due to the influence of northeasterly shear, and it turned further west as the mid-level subtropical ridge built further. Ike then turned unexpectedly towards the west-southwest around 0000 UTC 6 September, at which time the shear also relaxed. After returning to Category 4 intensity by 1800 UTC 6 September, Ike made two landfalls over Cuba, first on 8 September as a Category 4 hurricane and then on 9 September as a Category 1 hurricane before entering the Gulf of Mexico (Fig. 2.3).

Ike’s intensity continued to fluctuate as it entered the Gulf of Mexico on 10 September with an expanded wind field. Its track forecast was a particular challenge in the several days leading up to its eventual landfall in Galveston, Texas on 13 September. Several studies have been published on Ike, including the sensitivity of the track forecast to the environmental flow (Brennan and Majumdar, 2011; Komaromi et al., 2011), and the influence of assimilating data from airborne Doppler radar and coastal radar (Zhao and Xue, 2009; Zhang et al., 2011). Our study considers the period from 3-10 September, including the U.S. landfall forecasts.

2.2 High Resolution Satellite-Derived Observations

2.2.1 Atmospheric Motion Vectors

Atmospheric motion vectors (AMV) are routinely produced by operational satellite data centers in 3- to 6-hour intervals (Fig. 2.4). Although the algorithm for deriving
AMVs in each operational satellite data center differs in some extent (Genkova et al., 2008), the general concept of the derivation of AMVs is by tracking targets such as cirrus cloud edges, gradients in water vapor and small cumulus clouds, etc from sequential satellite images in channels including IR, VIS, and water-vapor (WV) (Velden et al., 1997) as illustrated in Fig. 2.4. A final height is assigned to each AMV according to the radiative properties of the tracked targets and point-to-point comparison between AMV and collocated radiosonde and local 3-D wind model analyses. AMVs derived from IR channels typically capture flow features in both the upper and lower troposphere, whereas AMVs derived from VIS channels generally track cumuliform cloud motions in the lower troposphere. Mid- to upper-tropospheric water vapor features are tracked in cloud-free scenes using imagery derived from WV-sensitive spectral bands that are present on most of the current operational environmental satellites (Holmlund, 1993).

![Schematic diagram that shows the AMV tracking algorithm.](image)

**Figure 2.4:** *Schematic diagram that shows the AMV tracking algorithm.*

Operational AMVs are routinely verified against collocated rawinsondes (Bedka et al., 2009). The ever-increasing horizontal and vertical resolution of numerical weather prediction models puts a greater demand on satellite-derived wind products to monitor flow accurately at smaller scales and higher temporal resolution. Bedka et al. (2009) compared AMVs with collocated rawinsondes and concluded that the
vector height assignment is the dominant factor in AMVs uncertainty, contributing up to 70% of the error. Sears and Velden (2012) verified AMVs with collocated dropsondes employed during Pre-Depression Investigation of Cloud-Systems in the Tropics (PREDICT) 2010 for tropical disturbance cases and found that analysis initialized with the inclusion of GOES-11 AMV is better than the global analysis from GFS.

AMVs are the only data types that provide good coverage of middle to upper tropospheric wind data at higher latitudes over the ocean. The assimilation of AMVs has been shown to produce significant positive impacts on the accuracies of global model initial conditions (Le Marshall et al., 2008; Goerss, 2009). AMV datasets are assimilated into relatively coarse-resolution global numerical models about 2-4 times a day. However, the assimilation strategy does not exploit the advantage of frequent observations made by geostationary satellite remote sensing. By increasing the frequency of data sampling, more frequent sequential images and therefore a higher volume of AMVs are available for continuous data assimilation systems. If the numerical forecast model and data assimilation system can be improved to better extract and carry the information of AMVs, the increased detail captured in the cloud structure evolution by AMVs can, in principle, have positive contributions to the prediction of TC intensity. Most relevant AMVs studies have indicated that AMVs can improve the track forecast by more accurately capturing the steering flow of TC (Berger et al., 2011; Soden et al., 2001). However, relatively few diagnostic studies have looked at the impacts of AMVs on TC structure and its evolution (Pu et al., 2008).

During our study period in 2008, AMVs derived from the geostationary satellite MTSAT-1R were produced operationally by JMA every 6 hours over East Asia and the western North Pacific ocean. These datasets were accessible to NCEP for real-time assimilation into the Global Forecast System (GFS) model. However, only a fraction
of the available JMA AMVs that pass through the NCEP thinning and quality control processes are accepted and included in the operational assimilation. These AMV datasets constitute what is assimilated in our study control runs, since our assimilation experiments employ the operational NCEP GFS as background fields. Additionally, during the TCS-08/T-PARC field campaign in 2008, high-resolution (space and time) AMV datasets were postprocessed and prepared at hourly intervals by CIMSS for each TC case using routinely available multispectral image triplets (Berger et al., 2011). For the Sinlaku case in 2008, MTSAT-1 scanned images every 30 minutes; for Ike in 2008, GOES-East scanned images every 15 minutes. These AMV datasets (derived from IR, VIS and WV imagery) are denoted as ‘H’ for hourly in this study. The CIMSS AMV automated derivation algorithm is similar to what is employed operationally at NOAA National Environmental Satellite, Data, and Information Service (NESDIS) for GOES AMV dataset production. Although operational AMV processing centers and CIMSS generally derive a similar volume of AMVs from common geostationary satellite imagery (IR, VIS and WV) over the same region, the CIMSS processing method provides more detailed coverage of AMVs over tropical cyclones when they are present (Velden et al., 1998; Sears and Velden, 2012).

AMVs can be further enhanced in both quantity and quality if the time separation between images is reduced, which allows more coherent tracking of clouds (Velden et al., 2005). When a satellite Rapid-Scan (RS) mode is activated, the more frequent sequential images yield a higher volume of AMVs than the hourly AMVs. The RS mode of the geostationary satellite MTSAT-2, which was operated experimentally by JMA in 2008, was activated shortly after 1200 UTC 10 September 2008. By this time, Sinlaku had already reached Category 2 intensity, and was two days away from its landfall in northern Taiwan. During this period, RS AMV datasets (from IR and VIS only) were derived by CIMSS at hourly intervals using successive 15-min image
Figure 2.5: Examples of superobed AMVs spatial distribution from (a) the same dataset assimilated in NCEP operational analysis, (b) CIMSS hourly dataset and (c) CIMSS hourly and Rapid-Scan dataset. The AMVs are grouped into four layers (100-250 mb, 251-400mb, 401-700mb and > 700mb) by their assigned heights and are shown by the corresponding colors with numbers indicating the total amount of AMVs in each grouped layer. The concentric contour is centered at the JMA best track location of Sinlaku at 0000 UTC 11 September 2008, and the interval is 200 km.
triplets. In the North Atlantic region, RS from the GOES geostationary satellites is routinely used for operational tasking. In 2008, GOES-12 had an activated RS mode throughout the lifetime of Ike. The GOES RS allows 7.5 minute image scanning, and these were employed by CIMSS to produce RS AMV datasets at hourly intervals during Ike.

An example of the horizontal and vertical distribution of AMVs in TC Sinlaku and its vicinity on 0000 UTC 11 September 2008 is illustrated in Fig. 2.5. Fig. 2.5a shows the spatial distribution of the AMVs from the NCEP dataset. Fig. 2.5b shows the CIMSS hourly dataset. As previously indicated, the volume of AMVs in Fig. 2.5a is greatly reduced due to the strict quality control employed by the NCEP system. In contrast, the AMV coverage from the CIMSS hourly dataset is much broader and the number of AMV is almost 10 times that present in the NCEP dataset. Although the majority of the CIMSS hourly AMVs are located above 400 hPa, about 20% are located below 700 hPa. Fig. 2.5c shows the spatial distribution of AMVs from the combined CIMSS hourly and Rapid-Scan datasets. The activation of the Rapid-Scan mode yields many more vectors below 400 hPa. This dataset feature is attributable to the enhanced tracking ability of low-level cumuliform type cloud tracers, mainly from the visible channel, when higher frequency imagery is available.

The CIMSS AMV data records come with two appended parameters that estimate each vector’s quality: a Quality Indicator (QI) and an Expected Error (EE). The QI consists of vector coherency and consistency checks (Holmlund, 1998), with normalized values ranging from 0 to 1. The EE is a modified QI that converts to the more physically intuitive units of m s\(^{-1}\), and also includes consideration of the vector speed, the environmental wind shear and temperature, and the assigned vector pressure level (Le Marshall et al., 2004). In this study, the hourly CIMSS AMVs are assimilated only if the QI is equal to or larger than an empirically-determined 0.5, and for the
RS AMVs of slightly higher quality the QI threshold is \( \geq 0.6 \). In addition, AMVs meeting these QI thresholds but with EE values \( \geq 4.5 \text{ m s}^{-1} \) are filtered out unless the AMV is \( > 25 \text{ m s}^{-1} \) and with an attending QI \( \geq 0.7 \). This latter constraint is invoked since the EE is sensitive to higher wind speeds. This is most evident in Fig. 2.6, which shows the distribution of the two CIMSS AMV datasets as a function of QI and EE. The RS VIS AMVs are more prevalent near the storm center where higher wind speeds exist, leading to higher EE values. No AMVs are derived from the water-vapor channel (WV) in RS mode since WV AMVs do not benefit from the more frequent imaging (Velden et al., 2005).

**Figure 2.6:** Scatterplot of Expected Error (EE) of raw (before superob) CIMSS AMVs from hourly dataset in (a) IR channel, (b) VIS channel and (c) WV channel as function of Quality Index (QI; y-axis) and wind speed (m s\(^{-1}\); x-axis) after blocking out the VIS AMVs above 600 hPa. (d)-(f), similar to (a)-(c), but for raw CIMSS AMVs from 15-min Rapid-Scan dataset with numbers on top of each subfigure indicating the total amount of AMVs in the specific channel.
At this point, the superobbing is performed on those AMVs that pass the above QC tests. The horizontal dimension of the prism within which the AMVs are averaged is chosen to be 90 x 90 km, reflecting 2-3 times the model grid size which is empirically used (Ryan Torn, personal communication). The vertical dimension of the prism is 25 hPa. We did different tests on the sensitivity of the horizontal dimension of the superob prism and found that the size of 90 km provided the most accurate analyses of initial track and intensity of Sinlaku. AMVs within this 90 km x 90 km x 25 hPa prism are averaged with uniform weight (i.e. arithmetic mean). The final preprocessing step is the assignment of observation errors for the superobbed AMVs. The NCEP and CIMSS hourly AMV datasets follow the operational NCEP observation error statistics for AMV as shown in Table 2.2. The assigned errors are a function of AMV height. Due to the greater ambiguity in the broad height assignment of WV AMVs, the observation errors are relatively higher than those AMVs that are derived from infrared or visible channels which mainly reflect more discrete cloud tops. For the Rapid-Scan AMVs, there is a greater chance of high EE values (Fig. 2.6), and therefore the observation errors in Table 2.2⁸ are multiplied by 1.5 when the respective EE exceeds 3.0. With these varying characteristics of AMVs, a more appropriate strategy might be a flow-dependent error assignment scheme (a subject for future investigation).

2.2.2 Hyperspectral Atmospheric Soundings

In addition to temperature profiles, the precise and continuous water vapor vertical structure is an extremely important variable for severe weather forecasting, due to its strong relation to the formation of clouds and precipitation (Kuo and Guo, 1993). Various satellite instruments are capable of detecting the presence of water vapor

⁸The error statistics of AMVs at NCEP can also be found at http://research.metoffice.gov.uk/research/interproj/nwpsaf/satwind,eport/amvusage/ncepmodel.html
Table 2.1: NCEP global model assigned observation errors (m s$^{-1}$) for satellite derived AMV observations from JMA. AMVs derived from visible (VIS) channel, infra-red (IR) channel and water vapor (WV) channel have observation errors as functions of height.

<table>
<thead>
<tr>
<th>Heights</th>
<th>VIS and IR channels</th>
<th>WV channel</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-250 hPa</td>
<td>5.0</td>
<td>7.0</td>
</tr>
<tr>
<td>300 hPa</td>
<td>4.6</td>
<td>6.6</td>
</tr>
<tr>
<td>350 hPa</td>
<td>4.3</td>
<td>6.3</td>
</tr>
<tr>
<td>400 hPa</td>
<td>4.0</td>
<td>6.0</td>
</tr>
<tr>
<td>450 hPa</td>
<td>3.0</td>
<td>5.0</td>
</tr>
<tr>
<td>500 hPa</td>
<td>2.1</td>
<td>4.1</td>
</tr>
<tr>
<td>550-600 hPa</td>
<td>2.0</td>
<td>4.0</td>
</tr>
<tr>
<td>650-700 hPa</td>
<td>1.9</td>
<td>3.9</td>
</tr>
<tr>
<td>750-1100 hPa</td>
<td>1.8</td>
<td>3.8</td>
</tr>
</tbody>
</table>

and therefore providing atmospheric moisture information. Instruments that detect IR frequencies (near-IR is included; e.g., MODIS) measure moisture over land and ocean in clear sky condition. On the other hand, instruments that use microwave frequencies (e.g., Special Sensor Microwave Imager; SSM/I) measure moisture under both clear and cloudy conditions but the measurements are limited to ocean only and can be contaminated by precipitation.

Satellite-based advanced IR sounding measurements are primary sources of temperature and water vapor profiles over the tropical ocean where conventional observations are relatively sparse (Li and Liu, 2009). As part of NASA’s EOS mission, AIRS and its two companions, AMSU and HSB, consist of the integrated atmospheric sounding system including VIS, IR, and microwave sensors on board the Aqua satellite since 2002. Being the first of the new generation of meteorological advanced sounders for operational and research use (e.g., The NOAA Cross-track Infrared Sounder, CrIS, and the Infrared Atmospheric Sounding Interferometer, IASI, on the operational European METOP polar-orbiting platform), the primary goal of AIRS is to achieve near-radiosonde-quality retrievals of atmospheric temperature and moisture profiles.
with high spectral resolution (2378 channels, see Table 2.2) and spatial resolution of 13.5 km at and near nadir and 45 km at the limb (Chahine et al., 2006). The current AIRS standard retrieval products are known as the level 2 (L2), Version 6 (Olsen et al., 2013). The L2 temperature and moisture profile products are retrieved from the combined AIRS IR and AMSU microwave channels with a cloud-clearing technique (Susskind et al., 2003). The spatial resolution of L2 temperature and moisture profiles is reduced to \( \sim 45 \) km due to the lower resolution of the AMSU microwave instrument, i.e., the AIRX2RET dataset. This L2 AIRX2RET dataset provides temperature retrievals in 28 pressure levels and moisture retrievals (including water vapor mixing ratio and relative humidity) in 15 pressure levels (or 14 pressure layers). From here and for future reference, “AMSU-AIRS sounding” is used instead of “the AIRS standard L2 AIRX2RET sounding” for simplicity and avoidance of further confusion with the research AIRS product developed by the CIMSS group which will be introduced later.

\textbf{Table 2.2: The characteristics of the AIRS sounding instrument.}

<table>
<thead>
<tr>
<th>Instrument</th>
<th>AIRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral range</td>
<td>3.7-15 ( \mu )m</td>
</tr>
<tr>
<td>Spatial resolution</td>
<td>13.5 km (at nadir)</td>
</tr>
<tr>
<td>Number of channels</td>
<td>2378</td>
</tr>
<tr>
<td>( \Delta \lambda/\lambda )</td>
<td>( \sim 1/1200 )</td>
</tr>
<tr>
<td>Vertical resolution</td>
<td>( \sim 1 ) km</td>
</tr>
<tr>
<td>Temperature accuracy</td>
<td>1 K accuracy in 1 km layers</td>
</tr>
<tr>
<td>Moisture accuracy</td>
<td>15 % accuracy in 2 km layers</td>
</tr>
</tbody>
</table>

Le Marshall et al. (2006) first assimilated full spatial resolution radiances, available in real time from AIRS, into the NCEP GFS. The positive impact in forecast skill over both the Northern and Southern Hemisphere for January 2004 suggests that a considerable opportunity to improve operational analyses and forecast with
hyperspectral dataset. The tremendously large volume of full AIRS radiance data product is still a learning process for data assimilation centers. So far, only less than 1% of the AIRS spectra provided by NOAA-NESDIS are selected to be used for data assimilation (Chahine et al., 2006). European Centre for Medium-Range Weather Forecasts (ECMWF), NCEP and UK Met Office have been assimilating AIRS data operationally in their forecast models and have reported encouraging results due the inclusion of AIRS radiances. In the meantime, the assimilation of relatively smaller volume of retrieved parameters including temperature and water vapor profiles from AIRS is being studied (Atlas, 2005; Gao et al., 2007; Liu and Li, 2010).

However, the full spatial resolution (or single field-of-view, SFOV) and high spectral resolution IR soundings are needed for mesoscale applications, especially for storm genesis where measurements of the atmospheric instability is critical (Li et al., 2012). In addition to the AIRS standard L2 products, Li and Huang (1999) and the CIMSS science team has developed an algorithm called CIMSS hyperspectral IR Sounder Retrieval (CHISR) to derive temperature and moisture profiles from advanced IR radiance measurements alone in clear skies and some cloudy sky conditions on a SFOV basis (Li and Huang, 1999; Zhou et al., 2007; Weisz et al., 2007). This algorithm has three steps: 1) IR sounder sub-pixel cloud detection using a high spatial resolution imager cloud mask product (for AIRS, the cloud mask from MODIS, which is also onboard NASA’s EOS Aqua satellite, is used. See Li et al. 2004); 2) perform an eigenvector regression on the hyperspectral IR radiance measurements for a first guess of temperature and moisture profile; 3) update the first guess by performing a one-dimensional variational retrieval algorithm with a Quasi-Newton iteration technique. Radiance measurements from all IR channels are used in this sounding retrieval process. In this CIMSS AIRS sounding product, radiance measurements from all 2378 IR channels are used in the retrieval process. The CHISR algorithm provides
AIRS soundings with more vertical layers (101 pressure layers from approximately 0.05 hPa to 1100 hPa) and accuracy with good horizontal spatial resolution (13.5 km) in the vicinity of TCs, whereas the AMSU-AIRS sounding products have spatial resolution of 45 km at nadir.

Figure 2.7: (a) Side view of an AIRS swath shows the vertical resolution of the AMSU-AIRS sounding products. (b) 1-day spatial coverage of the AMSU-AIRS sounding products. AIRS soundings are grouped 3-hourly and color-coded by the swath times. (c)-(d), similar to (a)-(b), but for CIMSS AIRS sounding products.
An example of the spatial distribution of these two sounding datasets is illustrated in Fig. 2.7. The AMSU-AIRS dataset has broader horizontal coverage over north Western Pacific and South East Asia continent due to the additional information from AMSU, but its vertical coverage is limited to the 28 pressure levels (Fig. 2.7a-b). In order to remain the higher spatial resolution, CIMSS AIRS use the IR channel only algorithm that only allows retrievals from SFOV clear skies and some cloudy sky condition. Thus, more vertical pressure levels are available (Fig. 2.7c). On the other hand, limited spatial coverage is largely offset by better vertical and spatial resolution (Fig. 2.7d). Li and Liu (2009) and Liu and Li (2010) performed WRF/EnKF assimilation experiments with the CIMSS IARS sounding products on two TC cases and demonstrated the potential application of these high spatial and vertical resolution soundings retrieved from advanced IR sounder radiance measurements in improving hurricane track and intensity forecasts.

2.2.3 Microwave Total Precipitable Water

Microwave radiation penetrates the atmosphere and clouds more effectively than visible and infrared radiation, therefore providing crucial information of the hydrological cycles over the globe. The most important microwave products for atmospheric science are total precipitable water, cloud liquid water, and rain rate. The total precipitable water (TPW) is a measure of atmospheric moisture which describes the the amount of water that can be obtained from the surface to the top of the troposphere if all of the water and water vapor were condensed to a liquid phase. Unlike traditional infrared water vapor imagery (6.7 µm) which mainly detects mid- and high-level moisture, microwave TPW imagery depicts the moisture present at all levels, especially at low-levels where most of the water vapor is concentrated. TPW, represented as depth of liquid water ranges from near zero at the poles to near 80 mm in the deep
tropics, is accurately measured by the microwave imager/sounder on various satellite platforms.

Kuo and Guo (1993) used the Newtonian nudging technique to assimilate precipitable water in addition to surface humidity, temperature and wind data. It was found that the assimilation of precipitable water was effective in recovering the vertical structure of water vapor than from statistical retrieval based on climatology. Similar to their work, Kuo and Guo (1996) assimilated precipitable water measurements from 3-h soundings collected during the Severe Environmental Storms and Mesoscale Experiment (SESAME) into a mesoscale model with its 4DVar data assimilation system. The improved analysis due to assimilation leads to improved short-range precipitation forecasts. Dunion and Velden (2004) have shown that total precipitable water analysis from microwave imagery has the potential to provide a better method for identifying the Saharan Air Layer (SAL) than current global model analyses. Hence, the better representation of dry air intrusion or moisture capacity from TPW products will benefit the TC track and intensity forecasts especially in its developing and decaying stages.

In addition to Special Sensor Microwave/Imager (SSMI) and TRMM Microwave Imager (TMI), AMSR-E aboard NASAs *Aqua* spacecraft was launched on May 4, 2002 and was expected to provide broader coverage of global data with its wider swath of 1445 km and almost no gap between successive orbits, especially at low-latitudes. AMSR-E is a passive microwave radiometer that measures the dual polarization in six microwave bands between 6.925 GHz and 89 GHz and is modified for *Aqua* from the design of AMSR aboard Japanese Advanced Earth Observing Satellite-2 (ADEOS-2) (Shibata et al., 2003). With higher spatial resolution and additional channels, the retrieved products from AMSR-E should be more accurate.
The AMSR-E Level 2 standard products are provided with a quarter degree and include eight geophysical parameters. While total precipitable water (integrated water vapor), integrated cloud liquid water, sea surface wind speed, sea surface temperature, and sea ice concentration are provided over the global ocean, snow water equivalent (or depth) and soil moisture content are provided over land. Precipitation, including surface rain rate and accumulated rain, are available over both water and land (Kawanishi et al., 2003). In comparison to TPW products retrieved from microwave soundings, the CIMSS sounding team developed a TPW algorithm for MODIS onboard both Aqua and Terra satellites with much higher spatial resolution (5 km from IR and 1 km from near IR). Although the spatial resolution of the standard AMSR-E L2 TPW is coarser and available only over the ocean, the spatial coverage is much better than the MODIS TPW because microwave is able to see through clouds more effectively (Fig. 2.8). AMSR-E TPW has been operationally assimilated in JMA Mesoscale Model with their 4DVar system, and has also been considered to be operationally assimilated into the JMA Local Forecast Model in 2012 in order to obtain near real time moisture information over the ocean (Kazumori et al., 2012).

Figure 2.8: 1-day spatial coverage of (a) Terra MODIS, (b) Aqua MODIS, and (c) AMSR-E TPW (cm) over oceans on 10 September 2008. (Courtesy of Jun Li, CIMSS University of Wisconsin-Madison)
2.3 Forecast Model and Data Assimilation System

2.3.1 Forecast Model

This study employs the regional Weather Research and Forecasting model with its Advanced Research core (WRF-ARW). WRF is a mesoscale model that is designed to be used in a broad range of applications across scales, including hurricane research. Davis et al. (2008) ran real-time prediction of Atlantic and eastern North Pacific TCs with WRF-ARW during 2004-2007 and found the performance being generally competitive, and occasionally superior to, other operational forecasts for TC positions and intensity. The WRF code has been maintained and supported by the Mesoscale and Microscale Meteorology (MMM) Division of NCAR, and the currently most updated version 3.6 was released in April, 2014. The WRF-ARW version 3.1.1 (Skamarock et al., 2008) is employed in this study since it was first released at the beginning of this work in July 2009.

![WRF domains for (left) Sinlaku and (right) Ike (both in 2008).](image)

In order to account for interactions between the TC and the remote environment, an outer fixed domain with 27-km resolution grid covering the western North Pacific
(5805 x 5535 km$^2$) for Typhoon Sinlaku (2008) case, and the same 27-km resolution grid covering the north Atlantic and continental U.S. (8100 x 5805 km$^2$) for Hurricane Ike (2008) case (see Fig. 2.9) are used. There are 36 vertical levels from the surface to the model top, 50 hPa. The same movable nest of 9-km grid spacing with the size of 1791 x 1791 km$^2$ are implemented for both TC cases. This is a compromise of the operational HWRF (domain 1/2/3: 27km/9km/3km) domain design due to computational limitations. Note that in order to include all relevant atmospheric features throughout Ike’s life cycle, the size of the 27-km domain of Ike case is selected to be larger ($\sim 1.3$ times) than that of Sinlaku case due to its long and steady westward track.

To help resolve the thunderstorms and their associated updrafts and downdrafts, the Kain-Fritsch convective scheme (Kain and Fritsch, 1990) is activated in the 27-km domain for both TC cases. Following the work from Davis et al. (2008) and Nolan et al. (2009), the Yonsei University (YSU) scheme, a first-order closure scheme with an explicit treatment of entrainment process to avoid excessive vertical mixing during strong wind events, is selected to use for planetary boundary layer parameterization (Noh et al., 2003). The WRF single-moment 6-class (WSM6) scheme is an extension of the single-moment 5-class scheme (WSM5) with inclusion of graupel as another predictive variable (Hong and Lim, 2006). The WSM6 is activated for microphysics parameterization instead of WSM5 in this study. For radiation parameterizations, Rapid Radiative Transfer Model (RRTM) longwave radiation (Mlawer et al., 1997) and the Dudhia shortwave scheme (Dudhia, 1989) are selected as they were used in Torn (2010) under a similar WRF-ARW EnKF framework for 10 TCs cases. Note that the 9-km moving domains have no parameterizations.
2.3.2 Data Assimilation Scheme

Data assimilation seek to provide estimates of the state of the system by combining the model of the dynamics of a system and observations of the system, given their error statistics. Ensemble-based data assimilation techniques, which utilize an ensemble of parallel data assimilation and forecast cycles, provide alternatives to current operational 3D or 4D variational data assimilation techniques. Ensemble forecasts are used to estimate the flow-dependent uncertainty of the forecast. In data assimilation techniques, accurate estimates of forecast uncertainty are required to optimally blend the forecasts and observations to provide updated analysis.

The underlying concepts of ensemble-based data assimilation are derived from a method known as the Kalman Filter (KF; Kalman and Bucy 1961). The KF is a well-established sequential data assimilation technique that approximates Bayesian state estimation under the assumptions of linear error growth and Gaussian error distributions. The KF and its variants can be broken into two components, an update step and a forecast step. In the analysis step, observations are assimilated with its weightings and an improved analysis state estimate and its error covariance are produced. The analysis state is then used as the initial condition for the following forecast step. In the forecast step, the system dynamical model is integrated forward to the time when the next observations become available. It is important that the forecast error covariance is also evolved in time in the forecast step. This feature is commonly referred to as flow dependence of the background errors. The KF equations are:

In the analysis step,

\[
x_t^a = x_t^b + K(y_t - H(x_t^b)) \tag{2.1}
\]

\[
K = P_t^{bH}H^T(HP_t^{bH}H^T + R)^{-1} \tag{2.2}
\]
where \( \mathbf{x} \) represents model state space variable such as temperature, pressure, wind, etc. The superscripts a and f denote analysis and forecast respectively. The subscript \( t \) and \( t+1 \) represent current and next times. \( y \) is observation and \( \mathbf{H} \) is linear the observation operator which maps the model state space estimates to observation space. \( \mathbf{R} \) is the observation error covariance pre-defined by observation instrument. \( \mathbf{R} \) is usually a simple diagonal matrix. \( \mathbf{P}^f \) and \( \mathbf{P}^a \) are the forecast error matrix and analysis error matrix respectively.

In the forecast step,

\[
\mathbf{x}^b_{t+1} = \mathbf{Mx}^a_t
\]

\[
\mathbf{P}^f_{t+1} = \mathbf{MP}^a_{t}\mathbf{M}^T + \mathbf{Q}
\]

The forecast state and forecast states and forecast error matrix, \( \mathbf{P}^f \), are updated through a linear dynamic model \( \mathbf{M} \) to time \( t+1 \). \( \mathbf{Q} \) represents model error covariance. In equation (2.1), the analysis state \( \mathbf{x}^a_t \) is estimated by correcting the forecast state \( \mathbf{x}^b_t \) toward the observation increment, \( y_t - \mathbf{H}(\mathbf{x}^b_t) \), with weighting from the Kalman gain \( \mathbf{K} \).

The KF is a useful data assimilation technique that guarantees unbiasedness state update, exact error covariance update, and optimal filter since the updated analysis equation (2.1) is equivalent to minimizing the cost function \( J \):

\[
J(x) = (\mathbf{x} - \mathbf{x}^f)^T(\mathbf{P}^f)^{-1}(\mathbf{x} - \mathbf{x}^f) + (y - \mathbf{Hx})^T\mathbf{R}^{-1}(y - \mathbf{Hx})
\]

The KF has never been used in operational NWP. One of the major drawbacks of KF is that it is only valid for linear system where NWP models are nonlinear dynamical models. The Extended Kalman Filter (EKF) was proposed to extend KF to nonlinear dynamical systems and nonlinear observations. The \( \mathbf{H} \) in equation
(2.1) and $M$ in equation (2.4) are replaced by their nonlinear variants, $H$ and $M$ respectively. The calculation of Kalman gain (equation 2.3) and error covariance update equations (2.2) and (2.5) remain the same, except that $H$ and $M$ now represent the tangent linear operators of $H$ and $M$ respectively.

However, the EKF relies on linear approximations to nonlinear operators and therefore is only valid for systems where nonlinearity is less pronounced. Also, many of the aforementioned good features of the KF are no longer preserved due to this approximation. The Ensemble Kalman Filter (EnKF) is an attempt to provide a better representation of nonlinearity by using Monte Carlo techniques. The details of the EnKF are addressed in the following section.

2.3.2.1 Ensemble Kalman Filter

The ensemble Kalman Filter was first introduced by Evensen (1994) and has been widely used in oceanic and atmospheric studies on data assimilation. Several advantages of EnKF include 1) the forecast (prior or background) error covariance is sampled by a group of ensemble members to estimate forecast error covariance and update ensemble analyses. The ensemble analyses can then be used to integrate forward in time to produce ensemble forecasts, while maintaining the property of “error of the day” or “flow-dependent”; 2) unlike KF or Extended KF, EnKF can use nonlinear dynamical models and requires no derivation of tangent linear model or its adjoint model to update forecast error covariance; 3) it is relatively easy to implement and the computational cost is affordable and comparable with other sophisticated data assimilation schemes. It is also well suited for parallel processing since each ensemble member is integrated independently.

The EnKF can be separated into two groups by how the analysis ensemble is generated. The first involves perturbing observations to include uncertainty due to
observation error and is conventionally called the stochastic method. Another group generates the analysis ensemble without perturbing observations, instead updates the forecast state into the analysis state via a matrix transformation. They are classified as deterministic method and Ensemble Adjustment Kalman Filter (EAKF), Ensemble Transfor Kalman Filter (ETKF), Local ETKF (LETKF), and Ensemble Square-Root Filter (EnSRF) belong to this category. For the following discussion, we will use \( i \) to denote each individual ensemble member and use \( N \) to denote the size of an ensemble. The ensemble of model states can be written as \( x_i \) \( (i = 1, 2, ..., N) \). The ensemble mean and the ensemble perturbation are defined as

\[
\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i; \quad x'_i = x_i - \bar{x}
\]  

(2.7)

For future convenience, we often use ensemble matrix

\[
X = \frac{1}{\sqrt{N-1}} \begin{pmatrix} x_1 & x_2 & \ldots & x_N \end{pmatrix}
\]

(2.8)

and the ensemble perturbation matrix

\[
X' = \frac{1}{\sqrt{N-1}} \begin{pmatrix} x_1 - \bar{x} & x_2 - \bar{x} & \ldots & x_N - \bar{x} \end{pmatrix}
\]

(2.9)

The ensemble covariance matrix can then be written by

\[
P = P_{ens} = X'X'^T
\]

(2.10)

From equation (2.2), the ensemble version of the Kalman gain can be expressed as

\[
K = K_{ens} = P_{ens}f^TH^T(HP_{ens}fH^T + R)^{-1} = P_fH^T(HP_fH^T + R)^{-1}
\]

(2.11)
The updated equation and covariance matrix for the EnKF are

\[ X^a = X^f + K(y - HX^f) \]  \hspace{1cm} (2.12)

and

\[ P^a = (I - KH)P^f \]  \hspace{1cm} (2.13)

where \( X^f \) and \( X^a \) are the forecast ensemble matrix and updated analysis ensemble matrix, respectively.

Equations (2.12) and (2.13) are the same as in KF except for the observation operator \( H \) in EnKF can be either linear or nonlinear, and the forecast error matrix \( P^f \) is represented by the ensemble that evolves through the full nonlinear dynamic model.

### 2.3.2.2 Deterministic Methods

The following discussion begins by defining \( Y \) and \( Y' \), the expected “observations” estimated by ensemble model states.

\[ Y = HX; \quad Y' = HX' \]  \hspace{1cm} (2.14)

We begin the derivation of deterministic EnKF by rewriting equation (2.11) in ensemble matrix form instead of ensemble covariance matrix form. One can save computation time and storage by not having to calculate the large covariance matrix. Here, Kalman gain is expressed as

\[ K = P^fH^T(HP^fH^T + R)^{-1} = X^f(YY^T)^{-1} \]  \hspace{1cm} (2.15)

Since \( (YY^T + R) \) is frequently used in the following discussion, we denote it as \( S \).
Then equation (2.13) becomes

\[
\mathbf{X}^a(\mathbf{X}^a)^T = \mathbf{P}^a = (\mathbf{I} - \mathbf{KH})\mathbf{P}^f
\]

\[
= [\mathbf{I} - \mathbf{X}^f(\mathbf{Y}^f)^T\mathbf{S}^{-1}\mathbf{H}]\mathbf{X}^f(\mathbf{X}^f)^T
\]

\[
= \mathbf{X}^f[\mathbf{I} - (\mathbf{Y}^f)^T\mathbf{S}^{-1}\mathbf{Y}^f](\mathbf{X}^f)^T
\]

Equation (2.16) can be rewritten as \( \mathbf{X}^a = \mathbf{X}^f\mathbf{T} \), where \( \mathbf{T} \) is a matrix square root of \([\mathbf{I} - (\mathbf{Y}^f)^T\mathbf{S}^{-1}\mathbf{Y}^f]\), such that

\[
\mathbf{T}\mathbf{T}^T = \mathbf{I} - (\mathbf{Y}^f)^T\mathbf{S}^{-1}\mathbf{Y}^f
\]

(2.17)

This is why it is called “square root filter (SRF)”. The forecast error covariance matrix is not explicitly calculated, in some cases such as ETKF (Bishop et al. 2001). However, there is no unique solution for matrix \( \mathbf{T} \) that satisfies equation (2.16) since \( \mathbf{T} \) can be replaced by \( \mathbf{T}\mathbf{U} \), where \( \mathbf{U} \) is an arbitrary \( N \times N \) orthonormal matrix (Tippett et al., 2003). There will clearly exist infinitively many ensembles with an error covariance equivalent to \( \mathbf{P}^f \) and \( \mathbf{P}^a \) that satisfy equation (2.16).

2.3.2.3 Ensemble Adjustment Kalman Filter

Unlike the above-mentioned update that follows the form \( \mathbf{X}^a = \mathbf{X}^f\mathbf{T} \), the ensemble update in Ensemble Adjustment Kalman Filter (EAKF; Anderson 2001, Anderson 2003) follows the form \( \mathbf{X}^a = \mathbf{A}\mathbf{X}^f \). EAKF applies Bayesian estimation theory on a joint observation-state space with the assumption of Gaussianity in error statistics. The goal of the EAKF lies in the construction of an updated ensemble with a mean and variance that exactly satisfies

\[
\bar{\mathbf{z}}^a = \mathbf{P}^a[(\mathbf{P}^f)^{-1}\bar{\mathbf{z}}^f + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{y}]
\]

(2.18)
\[ P^a = [(P^f)^{-1} + H^T R^{-1} H]^{-1} \]  \hspace{1cm} (2.19)

where \( z \) is the join space state vector: \( z = [x, Hx] = [x, y] \), and \( P^f \) and \( P^a \) are the joint state forecast covariance and the updated analysis covariance.

It begins by rotating and scaling the joint space forecast error covariance, \( P^f \), and observation error covariance, \( H^T R^{-1} H \), in the square bracket of equation (2.19) to an identity matrix and a diagonal matrix.

First, the singular vector decomposition (SVD) is applied on \( P^f \) since it is symmetric

\[ P^f = FDF^T \quad \text{or} \quad D = F^T P^f F \]  \hspace{1cm} (2.20)

where \( F \) is a unitary matrix \( (FF^T = I, F^{-1} = F^T, (F^T)^{-1} = F) \) and \( D \) is a diagonal matrix. Applying \( F^T \) and \( F \) on \( P^f \) is equivalent to rotating \( P^f \) into a reference frame where it becomes diagonal. And then, a scaling is applied following the SVD to make it an identity matrix \( I \):

\[ (G^T)^{-1} F^T P^f F G^{-1} = I \]  \hspace{1cm} (2.21)

where \( G \) is a diagonal matrix.

At the same time, the observation error covariance, \( H^T R^{-1} H \), is multiplied by \( (G^T)^{-1} \), \( F^T \), \( F \), and \( G^{-1} \), but not necessarily make it an identity matrix:

\[ (G^T)^{-1} F^T H^T R^{-1} H F \quad \text{or} \quad F^T H^T R^{-1} H F G \]  \hspace{1cm} (2.22)

Similarly, another SVD is performed on equation (2.22) to ensure that it becomes a diagonal matrix with diagonal elements the singular value, \( \mu \):

\[ U^T G^T F^T H^T R^{-1} H F G U \]  \hspace{1cm} (2.23)
where $U$ is a unitary matrix ($U^{-1} = U^T; UU^T = I$). Equation (2.19) then becomes

$$
P^a = [(P_f)^{-1} + H^T R^{-1} H]^{-1}
= (F^T)^{-1} G^T (U^T)^{-1} \left\{ [U^T (G^T)^{-1} F^T P_f G^{-1} U + U^T G^T F^T H^T R^{-1} H F G U]^{-1} \right\} U^{-1} G F^{-1}
$$

(2.24)

so the term inside the curly brackets becomes $\text{diag}[1/(1+\mu_1), 1/(1+\mu_2), \ldots]$ and can be rewritten as $B^T (G^T)^{-1} F^T P_f G^{-1} F B$, where $B = \text{diag}[(1+\mu_1)^{-1/2}, (1+\mu_2)^{-1/2}, \ldots]$ since $(G^T)^{-1} F^T P_f G^{-1} F = I$ according to equation (2.21).

Then, equation (2.19) is now in the form $P^a = A P_f A^T$, where

$$
A = (F^T)^{-1} G^T (U^T)^{-1} B^T (G^T)^{-1} F^T
$$

(2.25)

After the ensemble update, the rotation and scaling can then be inverted to get the final updated ensemble. The mean of the updated ensemble is then calculated easily by equation (2.18). Following the form $P^a = A P_f A^T$, an update can be written as

$$
z^a = A^T (z^p - \bar{z}^p) + \bar{z}^u
$$

(2.26)

This update process can be viewed as making an “adjustment” to the forecast ensemble distribution by “shifting” the mean and “compacting” the variance to reach the updated (analysis) ensemble distribution.

2.3.2.4 Issues Related to Unrepresentative Ensemble

Evensen (2003) summarized a series of work based on EnKF in oceanographic problems and Hamill (2006) gave a similar summary for atmospheric data assimilation. Still, there are some disadvantages in which the EnKF only accounts for forecast error
due to uncertain initial conditions, neglecting forecast error due to model deficiencies (Tippett et al., 2003), and the need of prior quality control due to the assumption of a Gaussian distribution in the observation error. Furthermore, the error covariance is sample by a limited number of ensemble members that are supposed to statistically representative. If the ensemble is too small, the system is undersampled. Undersampling can further cause inbreeding, spurious correlations, and filter divergence that are commonly seen when using too small ensemble size.

Inbreeding is a situation where the analysis error covariances are systematically underestimated after each observation is assimilated, and can subsequently lead to spurious correlations and filter divergence. Spurious correlations are correlations in the forecast error covariance between state variables that are not physically related and are usually distant from each other. An example of spurious correlation is illustrated in Figs. 2.10a-b where the remote spurious correlations in 25-member ensemble are not seen when ensemble size is increased to 200. State variables may be incorrectly affected by an observation that is physically remote. Furthermore, the quality of analysis can be degraded (Hamill et al., 2001). Filter divergence is when the ensemble analyses are unable to be adjusted by assimilating observations in successive cycles to more accurately represent the true state. This is because less weighting is given to the observation when the forecast error covariance becomes overconfident.

Covariance localization and covariance inflation are proposed to negate these problems. In covariance localization, a Schur product, an element-by-element multiplication, of a correlation matrix with local support is applied to the forecast error covariance to cut off longer range correlations in the error covariance matrix at a specified distance (see Figs. 2.10c-d). The Schur product, written as $A \circ B$, where $A$ and $B$ have the same dimensions. The Gaspari-Cohn function is often used to specify the weighting as a function of distance. For EAKF and EnSRF, it is easy to apply covari-
Covariance inflation was first introduced by Anderson and Anderson (1999) to increase the forecast error covariance by inflating the deviation of the background error perturbation from the ensemble mean prior to the assimilation. The inflation factor, $r$, acts as

$$ r(X_i^f - \bar{X}^f) + X_i^f = \text{inflated } X_i^f $$

(2.27)

The inflation factor is usually specified to be slightly greater than 1.0. The choice of the magnitude of inflation factor depends on the size of the ensemble, the type of ensemble filter used, the forecast model implemented and many other factors. An adaptive covariance inflation algorithm based on a hierarchical Bayesian approach is proposed by Anderson (2007, 2009) and will be applied to the EAKF in this research.
All the above-mentioned different versions of deterministic EnKF share the same forecast step; they only differ from each other in the analysis step. As Tippett et al. (2003) pointed out, EnSRF, ETKF and EAKF can all be written in a square-root form by post-multiplying on the forecast error covariance to update analysis error covariance and assimilate observations serially. LETKF focuses on the localization and assimilates observation simultaneously in a local patch. However, as mentioned above, the square-root matrix is not unique, each method has its own advantage and it is not clear if there is a preferable choice among various implementations.

2.4 Overall Experimental Design

The type of EnKF data assimilation scheme used here is the EAKF. It has been implemented in the Data Assimilation Research Testbed (DART; Anderson et al. 2009). An 84-member ensemble is used in the cycling. Due to computational limitations, data assimilation is only performed on the 27-km domain and the 9-km domain is only activated in the forecast cycling when the tropical cyclone is present.

To initialize the WRF/EnKF assimilation cycles, ensemble mean initial and lateral boundary conditions are obtained from the 1°x 1° global analysis produced by NCEP. Random draws from a distribution of the forecast error covariance generated from the WRF 3-dimensional data assimilation system (Barker et al., 2004) are added to ensemble mean fields to generate 84 initial and lateral boundary ensemble perturbations (Torn et al., 2006).

A fixed horizontal and vertical localization (Gaspari and Cohn, 1999) is applied to all of the analysis increments from observations to reduce the impact of spurious covariance estimates. The half-width of the fixed horizontal localization is 650 km and the fixed vertical localization is 8 km. This means an observation will have no impact on the model state variables if it is located 1300 km beyond and 16 km above the model
grid of the state variables. In addition, a temporally- and spatially-varying adaptive inflation algorithm of Anderson (2007) is used to inflate the ensemble prior spread. To avoid potential over-inflation at the temporally-varying locations of observations (such as special dropwindsondes released near tropical cyclones), the inflation factor is reduced by 10% at each assimilation time. This is to ensure that the inflation factor will gradually return to 1 at these locations after the TC passed.

Several parallel WRF/EnKF cycles are initialized a week prior to the formation of both TCs: 0000 UTC 1 September 2008 for Sinlaku; 0000 UTC 25 August 2008 for Ike. Conventional observational data assimilated include radiosonde winds, temperature and specific humidity that are at least 200 km away from the TC center; aircraft winds and temperature; surface pressure data and the Joint Typhoon Warning Center (JTWC) advisory TC position and the National Hurricane Center (NHC) advisory TC position (latitude and longitude of Minimum Sea Level Pressure or MSLP). In

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{flowchart.png}
\caption{Flowchart of WRF/EnKF analysis-forecast cycles.}
\end{figure}
addition, the uncertainty of the JTWC advisory TC position estimates are assumed to be dependent upon the wind speed, and are assigned the following values: 90 km for the maximum sustained wind < 34 knots; 40 km for the wind > 85 knots; and 60 km for intermediate wind (Torn and Snyder, 2012). With more aircraft observations collected in the Atlantic basin, the uncertainty of the NHC advisory TC position estimates is expected to be 25% lower than in the western Pacific basin (empirically determined).

In addition to the conventional observations, the “CTL” experiment also assimilates AMVs from the NCEP operational analysis dataset in a 3-h wide window centered on 0000 UTC, 0300 UTC, etc. All observations in each 3-hour window are assimilated as if they were taken at the center time of the window. The analyses are used to initialize an ensemble of 3-hour forecasts for the next analysis time.
Chapter 3

Influence of Assimilating Atmospheric Motion Vectors

The influence of assimilating geostationary satellite-derived Atmospheric Motion Vectors (AMVs) on WRF/EnKF ensemble analyses and forecasts of Typhoon Sinlaku (2008) is first investigated. Three different groups of AMV data are assimilated in parallel assimilation experiments: CTL – the same dataset that is assimilated in the NCEP operational analysis; CIMSS(h) – hourly datasets processed by CIMSS; and CIMSS(h+RS) – the corresponding Rapid-Scan datasets. The CIMSS(h) dataset comprised an order of magnitude more AMVs than the CTL dataset, and when Rapid-Scan mode was activated the CIMSS(h+RS) dataset offered approximately 5 times more AMVs than CIMSS(h) below 400 hPa. Identical configurations of conventional observations (excluding radiances) were also assimilated in each of the 3 experiments, and no artificial vortex initialization or relocation schemes were used.

Given the promise of AMV data over the ocean and the EnKF data assimilation scheme, it is expected that the assimilation of high-resolution AMVs will improve regional model analyses and forecasts of TC structure and track. In this chapter, an in-depth investigation is performed to demonstrate this concept for Typhoon Sinlaku.
(2008), a widely studied tropical cyclone whose track and structural evolution were difficult to predict.

3.1 Experimental Design

Following section 2.4, two parallel WRF/EnKF experiments are conducted in addition to CTL. The second experiment, denoted “CIMSS(h)” is the same as CTL except that it assimilates the hourly AMVs prepared by CIMSS. A third experiment, denoted “CIMSS(h+RS)”, is the same as CIMSS(h) until the first time that Rapid-Scan data are assimilated on 1800 UTC 10 September 2008, and thereafter all the hourly and quality-controlled Rapid-Scan AMVs are assimilated in a 3-h wide window centered on 0000 UTC, 0300 UTC, etc. A summary of these three experiments is given in Table 3.1.

For the CIMSS(h+RS) experiment, Rapid-Scan AMV datasets are available each hour from 1700 UTC 10 September to 0400 UTC 13 September, with a short gap between 0900-1500 UTC on 12 September. The number of superobbed AMVs assimilated in the CIMSS(h+RS) experiment as a function of analysis time is shown in Fig. 3.1. A sharp increase in the number of observations assimilated after 1800 UTC 10 September 2008 marks the beginning of the inclusion of Rapid-Scan AMVs. Also, a diurnal cycle can be observed from Fig. 3.1 during the inclusion of the Rapid-Scan AMVs, since the major contribution of extra AMVs is from the visible channel (see Figs. 2.6). The majority of the enhanced Rapid-Scan AMVs are below 400 hPa, while the majority of CIMSS hourly AMVs are above 400 hPa.
Table 3.1: WRF/EnKF analyses-forecasts cycles designed to examine the impact of CIMSS hourly and Rapid-Scan AMVs during Typhoon Sinlaku (2008). The analyses cycles update every 3 hours and cover the lifetime of Sinlaku from 0000 UTC 8 September 2008 to 1200 UTC 13 September 2008.

<table>
<thead>
<tr>
<th>Expt</th>
<th>Obs Assimilated</th>
<th>AMVs Assimilated</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTL</td>
<td>Radiosondes u/v/t/q, aircraft</td>
<td>NCEP BUFR dataset</td>
</tr>
<tr>
<td>CIMSS(h)</td>
<td>data u/v/t, surface altimeter</td>
<td>CIMSS hourly dataset</td>
</tr>
<tr>
<td>CIMSS(h+RS)</td>
<td>data and JTWC advisory TC position data.</td>
<td>CIMSS hourly and Rapid-Scan dataset (available from 1800 UTC 10 Sep 2008)</td>
</tr>
</tbody>
</table>

3.2 Influence on Ensemble Analyses

3.2.1 Track and Intensity Analyses

The ensemble mean analyses are first verified on the 27-km domain against the position and intensity estimates from the JMA best track data in which the Dvorak analysis method is utilized on cloud images from the MTSAT satellite. Prior to Sinlaku reaching tropical storm intensity, the ensemble members possessed very broad minima of mean sea level pressure (MSLP), and there was also ambiguity in distinguishing between the low-level circulation maxima associated with Sinlaku and those of neighboring atmospheric features. We therefore consider the analyses from 0000 UTC 9 September 2008 onwards. To track Sinlaku in each of the ensemble members, the GFDL Vortex tracker\(^9\) is used throughout this paper. Between 0000 UTC 9 September and 1200 UTC 10 September, considerable differences exist between the CTL analyses and the CIMSS(h) analyses (Figs. 3.2a-c). The ensemble mean center of Sinlaku in the CTL is too far west of the best track, resulting in track errors above 100 km (Fig. 3.2a, blue line). In contrast, the ensemble mean center in CIMSS(h)

Figure 3.1: Numbers of quality-controlled, superobed AMVs assimilated in CIMSS(h+RS) as a function of analysis time. The sharp increase of AMVs volume from 1800 UTC 10 September marks the beginning of the inclusion of 15-minute CIMSS Rapid-Scan AMVs.

is closer to the best track (although still to the west) with track errors consistently reduced by up to 100 km (Fig. 3.2a, green line). This example also highlights the difficulty in providing accurate analyses of the track when a tropical cyclone is in its early stages. JMAs operational TC analysis uniquely uses an early-stage Dvorak Analysis (EDA) for TCs in generation stage, and the conventional Dvorak analysis for developing or mature TCs. Therefore, it is also worth noting that the error of the JMA best track is likely to be larger in weaker storms than in stronger storms. During the intensification period, the track errors are reduced in both analyses, although the errors in the CTL ensemble members remain larger than those of CIMSS(h). In its mature stage, Sinlaku moved slowly toward northeastern Taiwan from 0000 UTC 11 September to 1200 UTC 13 September with a well-defined center. The mean tracks in the three analyses CTL (blue), CIMSS(h) (green) and CIMSS(h+RS) (red) are very similar at this stage, with errors less than 50 km (Fig. 3.2a).

Prior to the intensification period, the majority of ensemble members in both the CTL and CIMSS(h) analyses exhibit very similar values of minimum MSLP (not
shown). During the intensification between 0000 UTC 9 September and 0000 UTC 10 September, the ensemble mean of the CIMSS(h) MSLP analyses is about 5 hPa too high and that of maximum surface wind speed analyses is about 5-10 m s\(^{-1}\) too weak, but it importantly has a rate of deepening similar and closer to the JMA best track (Figs. 3.2b and c). In contrast, the mean analysis of MSLP and maximum surface wind speed in the CTL experiment is far weaker than that in the JMA best track and does not adequately capture the strength and timing of the deepening. After 0000 UTC 10 September, as Sinlaku enters its mature stage, the mean of the analysis values of MSLP in both the CTL and CIMSS(h) experiments does not approach the best track value of 937 hPa. One possible reason for this inconsistency is that the grid-size of 27 km is not fine enough to adequately resolve the inner core processes associated with the continued deepening. Between 0000 UTC 11 September and 1200 UTC 13 September, Sinlaku continues through its mature stage and then weakens. This is also the period during which the CIMSS(h+RS) experiment is computed. During this period, there are a few times when the ensemble mean MSLP and maximum surface wind speed in CTL analysis is closest to the JMA best track. However, the ensemble mean tracks of CIMSS(h) and CIMSS(h+RS) analyses are more accurate than that of CTL analysis. It is also worth noting that without the Rapid-Scan AMVs assimilated, the mean of the CIMSS(h) analysis values of MSLP and maximum surface wind speed are much weaker than that of CIMSS(h+RS) during this period. Overall, the representation of Sinlaku in the CTL experiment appears less accurate than in both CIMSS experiments for most of the analysis times.

The spread of the analysis ensembles reveals the estimation of the analysis uncertainty. Prior to Sinlaku entering its relatively steady state (1200 UTC 10 September), the CTL analyses have a broad track spread over 122°-127°E (Fig. 3.2d), with a general left bias relative to the best track. As expected, the spread decreases substantially
Figure 3.2: The ensemble mean and spread of (a) track error (km), (b) minimum mean sea level pressure (hPa), and (c) maximum surface wind (m s\(^{-1}\)) of WRF/EnKF analyses CTL, CIMSS(h) and CIMSS(h+RS) as described in Table 2. The track, minimum MSLP, and maximum surface wind are verified against JMA best track data (black). The ensemble track of (d) CTL analyses, (e) CIMSS(h) analyses, and (f) CIMSS(h+RS) analyses. Analysis time is shown by corresponding colors with circle (0000 UTC) and cross (1200 UTC).
as Sinlaku develops a more well-defined center and enters its mature stage. In contrast to the CTL analyses, the CIMSS(h) analyses of the track are more tightly clustered close to the best track, although still with a left-of-track bias (Fig. 3.2e). Fig. 3.2b and Fig. 3.2c reveal that the CIMSS(h) analyses have a smaller spread of MSLP and maximum windspeed than CTL throughout the entire experiment. During the 36 h of intensification, the standard deviation steadily increases from 15 to almost 25 hPa for the CTL analyses. However, the corresponding standard deviation only stays at 8 hPa for the CIMSS(h) analyses. This indicates that the larger uncertainty associated with Sinlaku’s genesis was greatly reduced by the assimilation of CIMSS hourly AMVs. From 0000 UTC 11 September, it is also found that the track spread of CIMSS(h+RS) is fairly close to CIMSS(h), and the MSLP spread of CIMSS(h+RS) gradually increase to 15 hPa at 1200 UTC 13 September (Figs. 3.2a,d-e).

### 3.2.2 Analysis Diagnostics

#### 3.2.2.1 Against Independent Observations

The realism of the WRF/EnKF analyses for the 3 experiments is investigated via a comparison against independent observations that are not assimilated. First, radii of 34-kt winds in the WRF/EnKF analyses are compared against a modified version of the JTWC best track dataset\(^\text{10}\), especially for the early stage of Sinlaku. Fig. 3.3a shows the time-series of radii of 34-kt winds in three WRF/EnKF analyses and radii of 34-kt winds from the modified JTWC best track data in the southeastern quadrant. Performance on the other three quadrants are similar. Prior to 1200 UTC 10

---

\(^{10}\)In the modified version of the best track, several datasets not used in the original JTWC best track are included retrospectively. First, flight-level winds reduced to the surface together with Stepped Frequency Microwave Radiometer (SFMR) winds from reconnaissance aircraft were averaged. Additionally, QuikSCAT and ASCAT imagery and Cooperative Institute for Research in the Atmosphere (CIRA) Advanced Microwave Sounding Unit (AMSU) objective estimates were used to recalculate the wind radii. (Derrick Herndon, CIMSS, personal communication).
September, only a few CTL ensemble members possessed winds exceeding 34-kt, and 34-kt winds were absent in the ensemble mean field.

Comparisons were also performed between the spatial structures of the surface wind fields in the WRF/EnKF analyses and observations from the Quick Scatterometer (QuikSCAT), which was operational in 2008. The 2.5 km resolution wind fields produced by Brigham Young University (BYU) (Halterman and Long, 2006) in a 20° x 20° domain covering the TC are used here. A few passes of QuikSCAT over Sinlaku are close to the analysis time (allowing ± 3 hours difference from analysis time). An example of QuikSCAT sea surface wind image on 0944 UTC 9 September 2008 is shown in Fig. 3.3b. In order to eliminate the impacts of position spread on the spatial structure of wind fields, the 10-meter horizontal wind from CTL and CIMSS(h) ensemble analyses at 1200 UTC 9 September 2008 (Fig. 3.3c-d) are relocated in a storm-centered perspective. The 27-km analysis is not expected to exactly reproduce the features identified in the 2.5-km QuikSCAT image. However, it is evident that the magnitude of the surface wind of the storm are better described by CIMSS(h) analysis. Three further QuikSCAT passes with adequate coverage of Sinlaku at later times (2141 UTC 11 September, 1005 UTC 12 September and 2115 UTC 12 September) are compared with the corresponding WRF/EnKF analyses (not shown). However, given that the three WRF/EnKF analyses produced similar surface wind fields at these later times when Sinlaku was a mature typhoon, no significant differences between the respective 10-meter wind structures were diagnosed.

Vertical profiles of tangential and radial wind in the WRF/EnKF analyses are also compared against targeted dropwindsonde data from Dropsonde Observations for Typhoon Surveillance near the Taiwan Region (DOTSTAR). Only those soundings that are within 30 minutes of the analysis times at which the full ensemble fields were able to be stored (0000 UTC and 1200 UTC) are considered. Four dropwind-
Figure 3.3: (a) Comparison of WRF/EnKF analyses with modified JTWC best track radii (km) of 34-knot wind. Here, only SouthEastern Quadrant (SEQ) is shown. (b) Brigham Young University (BYU) processed QuikSCAT sea surface wind (knot) at 0944 UTC 9 September 2008. Ensemble (shading) mean and (grey contour) spread of 10 m windspeed in a storm-relative framework from (c) CTL analyses and (d) CIMSS(h) analyses at 1200 UTC 9 September 2008.
Figure 3.4: (a) Vertical profiles of (left) tangential wind (m s$^{-1}$) and (right) radial wind (m s$^{-1}$) of the TCs in WRF/EnKF analyses at 0000 UTC 10 September 2008 and DOTSTAR dropsonde (black) deployed 190 km away from Sinlaku at 0006 UTC 10 September 2008. (b) Same as (a), but the analysis time is 0000 UTC 11 September 2008 and the dropsonde is located 420 km away from Sinlaku at 0010 UTC 11 September 2008. Root-mean-square error of tangential and radial wind verified with other dropsondes close to the analyses times are listed in Table 3.2.
sondes deployed fairly close to Sinlaku (about 200 km) on 0006 UTC 10 September, 0015 UTC 10 September, 2339 UTC 9 September and 2355 UTC 9 September 2008 are selected for comparison with the CTL and CIMSS(h) analyses at 0000 UTC 10 September 2008. The vertical profile of tangential and radial wind relative to the TC center from the first of these dropwindsondes is illustrated in Fig. 3.4a alongside those produced by the corresponding WRF/EnKF analyses for CTL (blue) and CIMSS(h) (green). A qualitative inspection reveals that the dropwindsonde profile mostly lies in the middle of the ensembles for both the CTL and CIMSS(h) analyses, although the tangential wind in the dropwindsonde profile does not decay as sharply with height as in the analysis fields. The low-level radial inflow is generally stronger in the CIMSS(h) analyses than in the dropwindsonde data. On the other hand, the low-level radial inflow in the CTL analyses is generally weaker. The spread of the CTL analyses is higher throughout the column. The averaged root-mean-square (RMS) error of the CIMSS(h) tangential wind at this time, verified against the four aforementioned dropsondes, is reduced by over 55% compared with CTL, due to the strengthening of the tangential wind near the core with the assimilation of the extra AMVs (first column of Table 3.2). The RMS error of the radial wind is reduced by about 5% due to the extra AMVs, and a 17% improvement of temperature through the column is also realized. Near 0000 UTC 11 September 2008, another three dropwindsondes about 400-600 km from Sinlaku are selected for verification of the EnKF analyses, with an example shown in Fig. 3.4b. A qualitative comparison (see Table 3.2) indicates that the vertical profile of tangential wind best resembles that of CIMSS(h+RS), compared with CIMSS(h) and CTL. The RMS error of CIMSS(h) and CIMSS(h+RS) estimated tangential wind (radial wind) (temperature) are respectively improved by 28% (34%) (25%) and 36% (38%) (39%) compared with the CTL estimations (Table 3.2). Given that there is already a large number of AMVs in the vicinity of
Table 3.2: Comparison of WRF/EnKF analyses among CTL, CIMSS(h) and CIMSS(h+RS). These statistics are root-mean-square error of estimated tangential, radial winds (m s\(^{-1}\)) and temperature (K) against the profiles from DOTSTAR dropsondes deployed close to the analysis time (allow ± 30 minutes difference from analysis time). At 0000 UTC 10 September 2008, four dropsondes about 200 km from Sinlaku are available. At 0000 UTC 11 September 2008, three dropsondes about 400-600 km from Sinlaku are available.

<table>
<thead>
<tr>
<th></th>
<th>0000 UTC 10 September</th>
<th>0000 UTC 11 September</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vt</td>
<td>Vr</td>
</tr>
<tr>
<td>CTL</td>
<td>10.04</td>
<td>5.22</td>
</tr>
<tr>
<td>CIMSS(h)</td>
<td>4.36</td>
<td>4.96</td>
</tr>
<tr>
<td>CIMSS(h+RS) N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Sinlaku in the CIMSS(h) dataset, the room for improvement due to the addition of Rapid-Scan winds is smaller. Accordingly the reduction of errors of tangential wind, computed by comparing the RMS errors in CIMSS(h+RS) to CIMSS(h), is 12%, and the corresponding error reduction in the radial wind is 7%. The addition of Rapid-Scan winds contributes to a 18% improvement in the temperature through the vertical over CIMSS(h).

3.2.2.2 Axisymmetric Structure

Given that the 27 km horizontal grid size is not suitable for quantitatively understanding the inner-core structures of the TC, the following analysis diagnostics are instead mostly focused on a qualitative analysis of the broad primary and secondary circulation of the TC, via azimuthally averaged profiles. Fig. 3.5a illustrates the ensemble mean azimuthally averaged tangential wind (black contour), radial wind (shading) and vertical wind (green contour) plus the radius of maximum wind (RMW, grey line) of the CTL and CIMSS(h) analyses at 1200 UTC 10 September. This time is close to the most intense stage of Sinlaku. It had been shown in Fig. 3.2e that the CIMSS(h) analysis is able to capture the rapid intensification in the early stage of
Sinlaku from a tropical storm to a Category-2 typhoon, while the ensemble mean minimum MSLP in the CTL analysis only deepened by about 10 hPa over the same period. The azimuthally averaged profile (Fig. 3.5a) suggests that the lower MSLP in CIMSS(h) is associated with a more intense primary and secondary circulation. A stronger tangential wind with a maximum value of 36 m s\(^{-1}\) situated about 70 km from the center is exhibited in the mean of the CIMSS(h) analyses. This sharp wind maximum is located near 850 hPa, whereas in CTL the broad weak wind is spread almost homogeneously from the top of the boundary layer to about 300 hPa. Also, the low-level radial inflow wind is about two times stronger than CTL ensemble mean analysis at the same time. The azimuthally averaged vertical wind is generally strongest at the uppermost levels, and its mean position is generally aligned with or lies within the average RMW. This analysis time is later chosen as one of the initial times for the 72-h ensemble forecasts.

A day later at 1200 UTC 11 September, the mean analysis of CIMSS(h) still exhibits a stronger tangential wind (maximum value 4 m s\(^{-1}\) larger than the maximum value in CTL), a stronger and more radially tilted structure of vertical wind, and a tighter RMW than the mean analysis of CTL (Fig. 3.5b). Additionally, a stronger low-level outflow at 700 hPa is evident in CIMSS(h). However, it is at this time that the outflow near 100-200 hPa begins to weaken in CIMSS(h). At the same time, with the introduction of the Rapid-Scan AMVs over the previous 18 hours, the mean analysis of CIMSS(h+RS) keeps the general structure as CIMSS(h) does, but with a more pronounced outflow and vertical wind aloft.

Another day later, at 1200 UTC 12 September, the ensemble mean vertical structure in the CTL analyses has now intensified. However, Sinlaku had been slowly weakening over the previous day (Figs. 3.2b-c), and the CIMSS(h) and CIMSS(h+RS) analyses are accordingly not intensifying the vertical structure (not shown).
Figure 3.5: Azimuthally averaged tangential wind (black contour in 2 m s$^{-1}$ interval), radial wind (shading), vertical wind (green contour in 0.05 m s$^{-1}$ interval, maximum 1 m s$^{-1}$) and radius of maximum wind (grey line) at (a) 1200 UTC 10 September 2008, (b) 1200 UTC 11 September 2008.
3.2.2.3 Analysis Increments

To further understand the role of the AMVs as Sinlaku developed from a tropical storm into a category-2 Typhoon during its rapid-intensification period, the structure and magnitude of analysis increments for horizontal wind and temperature fields are examined in a vertical plane that shows the cross section of the TC.

![Mean Increment: V 2008/09/09:00](image)

![Mean Increment: T 2008/09/09:00](image)

Figure 3.6: East-West cross section of meridional wind analysis increments (m s\(^{-1}\), ensemble mean) of (a) CTL and (b) CIMSS(h) at 0000 UTC 9 September 2008. (b) (c) and (d), Same as (a) and (b), but for temperature increment (K, ensemble mean). The overlapped wind barbs are assimilated AMVs ± 500 km from the latitude of the TC center. Grey solid line indicates the location of maximum relative vorticity in each layer.

Even though only a few AMVs are available in CTL (Figs. 3.6a,c), a large number are present in the vicinity of Sinlaku in CIMSS(h) especially in the upper levels...
(Figs. 3.6b,d). At 0000 UTC 9 September, when Sinlaku was a tropical storm, an anticyclonic increment is present to the west of the center and the associated cold increment is evident in CTL (Figs. 3.6a, c). On the other hand, a cyclonic increment throughout the depth of the storm is evident in CIMSS(h), suggesting that the assimilation of the AMVs at that time serves to strengthen the storm in the analysis (Fig. 3.6b). It is worth mentioning that other observation types may also contribute to the increments. For example, the assimilation of the TC positions may contribute to the analyses increments in the lower troposphere. However, by comparing the analysis increments between CTL and CIMSS(h) analyses, the AMVs coverage and quality are the only differences that significantly contribute to the analysis increments.

In addition to the dynamic fields being modified by the assimilation when many AMVs are present, the corresponding thermodynamic fields are also modified. This is evident in the CIMSS(h) analysis at the same time, in which the assimilation of mostly upper-level AMVs produces a moderate but deep warming increment through the troposphere (Fig. 3.6d), consistent with the deep cyclonic increment in Fig. 3.6b.

Similar structures in the analysis increment of meridional wind and temperature fields are evident through 0000 UTC 10 September in CIMSS(h), when analysis increments in CTL first starts to show sign of strengthening. In summary, together with sufficient upper-level AMV coverage in the vicinity of the tropical cyclone, the covariance structure in the EnKF enables the production of a physically consistent modification to the thermodynamic field through the depth of the troposphere.

3.2.2.4 Environmental Wind Fields

In addition to the modification to the storm structure, the effect of assimilating the AMVs on the local environmental flow is now investigated for two representative times, at the 200, 500, and 850 hPa levels. Due to the three-dimensional nature of
(a) the distribution of AMV observations derived from moving clouds and water vapor gradients, (b) the background error covariance in the EnKF, and (c) the propagation of the impact of observations over time, we expect the AMV observations to influence the environmental analysis fields at all levels.

**Analysis Time:** 1200 UTC 9 September 2008

![Figure 3.7](image.png)

**Figure 3.7:** Ensemble mean geopotential height (m) in contour, relative vorticity ($10^{-4}$ s$^{-1}$) in color fill, and wind vector at (a) 200 hPa, (b) 500 hPa, and (c) 850 hPa from CTL analysis at 1200 UTC 9 September 2008. (d)-(f), same as (a)-(c), but for CIMSS(h) analysis at the same time, when the analysis track of CTL has a larger westward departure from JMA best track. Red box highlights the location of the TC.

At 1200 UTC 9 September, when a large group of ensemble members of CTL analyses was found to move the TC erroneously far westward, the most significant difference between the CTL and CIMSS(h) AMV coverage in the near environment of
Sinlaku is in the upper-level anticyclonic outflow (not shown, but similar to Fig. 2.5a and Fig. 2.5b). In Sinlaku itself, the ensemble mean analysis of CTL exhibits relative vorticity of up to $1.5 \times 10^{-4}$ s$^{-1}$ at 850 hPa, and closed isoheight in the vicinity up to 500 hPa. However, no clear center can be identified at 200 hPa in either the geopotential height or relative vorticity fields (Figs. 3.7a-c). On the other hand, the ensemble mean analysis of CIMSS(h) at this time exhibits relative vorticity of up to $2.5 \times 10^{-4}$ s$^{-1}$ at 850 hPa (Fig. 3.7f). A more distinct center associated with stronger vorticity is also visible at both 500 hPa and 200 hPa (Fig. 3.7d-e). At 200 hPa, a larger area of negative vorticity ($-1.5 \times 10^{-4}$ s$^{-1}$) associated with the outflow suggests that the CIMSS(h) analysis possesses a stronger vortex throughout the tropospheric levels (Fig. 3.7d). Differences between the CTL and CIMSS(h) analyses are also evident in the far environment of Sinlaku. They include the short-lived upper-level trough 15° to the north of Sinlaku (visible in both 200 hPa and 500 hPa) and the low-level trough over the Southeast Asian Peninsula. However, the differences are relatively small and their influences on the movement of Sinlaku are very subtle.

Given that the most significant wind difference exists in the vicinity of Sinlaku instead of the far surrounding environment, a local environmental “steering flow” is calculated by averaging the wind vectors over a 1000 x 1000 km domain centered on Sinlaku from 850 hPa to 200 hPa for each analysis time (Fig. 3.8a). By 0000 UTC September 10, the mid-lower tropospheric steering vectors in the CTL analyses exhibit northward to northwestward flows, whereas the steering vectors in the CIMSS(h) analyses are northeastward. This is consistent with the differences in Sinlaku’s motion between the CTL and CIMSS(h) ensemble members in Figs 4d, e. The steering flow weakens by 1200 UTC September 10 in both runs as Sinlaku slows down.

At 1200 UTC 11 September, in addition to the upper-level outflow, the Rapid-Scan AMVs provide enhanced coverage at the middle and lower levels. Additional
Figure 3.8: (a) Height-time diagram of mean steering vectors for the CTL, CIMSS(h), and CIMSS(h+RS) ensemble analyses. The vectors are averaged over a 1000 x 1000 km domain centered on the TC of each individual member. From 0000 UTC 9 September to 1200 UTC 10 September, only steering vectors from CTL and CIMSS(h) are shown. From 0000 UTC 11 September to 1200 UTC 13 September, only steering vectors from CIMSS(h) and CIMSS(h+RS) are shown. Ensemble mean geopotential height (m) in contour, relative vorticity ($10^{-4}$ s$^{-1}$) in color fill, and wind vector at 500 hPa from (b) CIMSS(h) and (c) CIMSS(h+RS) analyses at 1200 UTC 11 September 2008. Red box highlights the location and shape of the subtropical high to the east of Sinlaku.
AMVs are derived in the broad tropical area of clouds and easterly winds far to the southeast of Sinlaku, and further AMVs exist between 400-700 hPa on the southern side of the mid-latitude jet between Korea and Japan, and in the Malaysian and Indonesian regions (not shown, but similar to Fig. 3.5f). At this time, Sinlaku is already a mature TC, and the analysis fields between the CIMSS(h) and CIMSS(h+RS) experiments show similar steering flows throughout the troposphere (Fig. 3.8a). We therefore only show the CIMSS(h) and CIMSS(h+RS) analyses at one level, 500 hPa (Figs. 3.8b-c). The shape and strength of the subtropical ridge to the immediate east of Sinlaku is slightly different between CIMSS(h) and CIMSS(h+RS); however, this difference apparently does not appear to contribute substantially to the steering flows and motion of Sinlaku at this time. In general, from 1200 UTC 11 September onward, the steering vectors are similar between CIMSS(h) and CIMSS(h+RS) analyses throughout the tropospheric layers, with the CIMSS(h+RS) vectors slightly further eastward than the CIMSS(h) vectors above 500 hPa.

3.3 Influence on 72-h Ensemble Forecasts

Given that the WRF/EnKF analyses provide improved representations of track and structure of Typhoon Sinlaku with the assimilation of AMVs, the forecasts initialized from these analyses are expected to produce superior results. Seven different initialization times are chosen as in Table 3.3 to study the influence of assimilating the CIMSS hourly and Rapid-Scan winds on 3-day forecasts. Group one comprises the first 4 initial times: 0000 UTC 9 September, 1200 UTC 9 September, 0000 UTC 10 September and 1200 UTC 10 September (hereafter referred to as FT0900, FT0912, FT1000 and FT1012 respectively). This group is used to compare CTL forecasts versus CIMSS(h) forecasts. Group two comprises the last 3 initial times: 0000 UTC 11 September, 1200 UTC 11 September and 0000 UTC 12 September (FT1100, FT1112
Table 3.3: 72-h ensemble forecasts initialized with WRF/EnKF analyses at different initial times during Typhoon Sinlaku (2008).

<table>
<thead>
<tr>
<th>Case</th>
<th>Forecast Initialization Times</th>
<th>Initial Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>FT0900</td>
<td>0000 UTC 09 September 2008</td>
<td>CTL and CIMSS(h)</td>
</tr>
<tr>
<td>FT0912</td>
<td>1200 UTC 09 September 2008</td>
<td>CTL and CIMSS(h)</td>
</tr>
<tr>
<td>FT1000</td>
<td>0000 UTC 10 September 2008</td>
<td>CTL and CIMSS(h)</td>
</tr>
<tr>
<td>FT1012</td>
<td>1200 UTC 10 September 2008</td>
<td>CTL and CIMSS(h)</td>
</tr>
<tr>
<td>FT1100</td>
<td>0000 UTC 11 September 2008</td>
<td>CTL, CIMSS(h) and CIMSS(h+RS)</td>
</tr>
<tr>
<td>FT1112</td>
<td>1200 UTC 11 September 2008</td>
<td>CTL, CIMSS(h) and CIMSS(h+RS)</td>
</tr>
<tr>
<td>FT1200</td>
<td>0000 UTC 12 September 2008</td>
<td>CTL, CIMSS(h) and CIMSS(h+RS)</td>
</tr>
</tbody>
</table>

and FT1200 respectively). This group is used to compare forecasts from the CTL, CIMSS(h) and CIMSS(h+RS) experiments. For each of these seven initial times, ensemble forecasts are produced for each experiment by integrating the entire 84 ensemble analyses. Consistent with the configuration of the analysis experiment, a fixed outer grid of 27 km resolution and a moving inner grid of 9 km resolution is used for the ensemble forecasts.

For group one, the averaged ensemble mean track error of forecasts initialized with CIMSS(h) stays below 100 km in the first 42 hours and increases up to about 200 km in 72 hours (Fig. 3.9a). The averaged ensemble mean track error of forecasts initialized with CTL begins at about 140 km, and increases to approximately 400 km at 72 h. As an example, the initially large errors and incorrect westward movement in several of the CTL ensemble members for the FT1012 case leads to many of the CTL ensemble members making landfall in central and southern Taiwan, south of the actual track (Fig. 3.9c). On the other hand, the CIMSS(h) ensemble forecast members are generally distributed further to the north, with the best track lying near the mean track. As for the MSLP forecasts, it is first worth noting that the initial MSLP in all CTL and CIMSS(h) is far from the true value, due in part to the coarse grid resolution of the analysis (27 km). As a result, over all four initial times in this
group, the average MSLP errors of the ensemble members are generally decreasing with forecast time for both the CTL and CIMSS(h) experiments (Fig. 3.9b). The errors are clearly smaller for the CIMSS(h) ensemble forecast than for CTL, being approximately 5 hPa more accurate for 72-h forecasts. Additionally, the average 54-72h forecast errors for CIMSS(h) are very low, less than 5 hPa. An example of one of the ensemble forecasts of MSLP is shown in Fig. 3.9d. In the CTL ensemble forecast, many members deepen and reach their peak intensity around 42-48 hours after the initial time, before weakening. In the CIMSS(h) ensemble forecast, the ensemble members deepen less rapidly, due in part to their superior initial structure, and reach a near steady state around 36-42 hours after the initial time. The MSLP in the CIMSS(h) ensemble members remains close to the best track MSLP, and the spread of values is considerably smaller than that in the CTL ensemble forecast.

The forecast track error differences between forecasts initialized with CTL and CIMSS(h) are a combination of initial position errors in earlier lead times and changes of the environmental steering flows at later times. At 0 h, the mean initial position differences between CTL and CIMSS(h) analyses are approximately 70 km (Fig. 3.2a,d-e) where the mean initial position of the CIMSS(h) analyses is shifted more eastward and closer to the best track (Figs. 3.9c). The changes in the environmental steering flows can be explained in part by examining the ensemble mean 500 hPa geopotential height associated with the FT1012 track forecast (Fig. 3.9c). Between 0 h and 24 h, the CTL and CIMSS(h) forecasts of 500 hPa geopotential height associated with the environment of Sinlaku are similar (Fig. 3.10a-b, intermediate times not shown for brevity). By 24 h, the ensemble mean forecast of Sinlaku is a little to the northeast in CIMSS(h) compared with CTL. Concurrently, the subtropical ridge to the immediate east of Sinlaku (5880 m isoheight) exhibits a less westward intrusion which provides less westward steering for Sinlaku (Fig. 3.10b) than is the case with
Figure 3.9: Averaged ensemble mean (solid line) and spread (shading) of (a) track error (km) and (b) RMSE of minimum MSLP (hPa) of 72-h ensemble forecasts over FT0900, FT0912, FT1000 and FT1012 cases. An example of 72-h ensemble forecast (c) track and (d) minimum MSLP (hPa) from FT1012.
CTL. From 48 to 72 h, this westward-intrusive subtropical ridge in CTL continues to provide a stronger westward steering flow to Sinlaku in many ensemble members, leading to those members incurring larger track errors by making landfall in central to southern Taiwan (Figs. 3.10c-d). To confirm this, we also compute local environmental steering vectors by averaging the wind vectors over a 1000 x 1000 km domain centered on the TC of each individual member from 850 hPa to 200 hPa for each 0-72 h forecast initialized with the different analyses (similar to Fig. 3.8a, but for forecast times instead of analysis times). As is evident in Fig. 3.8a for the analysis times, the forecast steering vectors also exhibit a stronger westward component in CTL compared with CIMSS(h), for forecasts of 24 h and beyond (not shown here due to a close similarity to Fig. 3.8a).

For group two, the averaged ensemble mean track error of CIMSS(h) is again lower than that of CTL with an average improvement of about 50-125 km for 30-72 h forecasts (Fig. 3.11a). However, in the last 24 hours, the averaged track error of CIMSS(h+RS) unexpectedly grows from 200 to 500 km while CTL has a maximum track error of 375 km and CIMSS(h) has a maximum track error of 225 km at 72 h. These results are illustrated with an example of ensemble track forecasts from FT1112 (Fig. 3.11b). While Sinlaku actually recurved toward the northeast after leaving northern Taiwan on 14 September, many of the ensemble members in CTL make landfall in central-to-north Taiwan and then erroneously make another landfall in southeastern China without recurvature. On the other hand, a few of the northern members in CIMSS(h) demonstrate their potential to recurve after 48 hours without making landfall in either Taiwan or southeastern China beforehand.

Furthermore, all of the members in CIMSS(h+RS) initially travel close to the best track and then recurve toward the northeast without making landfall in Taiwan, followed by a subsequent rapid track towards the northeast which amplifies the
Figure 3.10: Averaged ensemble mean 500 hPa geopotential height of ensemble forecasts initialized with (blue) CTL and (green) CIMSS(h) analyses at 1200 UTC 10 September 2008: (a) 0h, (b) 24h, (c) 48h, and (d) 72h lead time. Color fill denotes the 500 geopotential height difference between ensemble mean of forecasts initialized with CTL and CIMSS(h).
Figure 3.11: Averaged ensemble mean (solid line) and spread (shading) of (a) track error (km) of 72-h ensemble forecasts over FT1100, FT1112, and FT1200 cases. An example of 72-h ensemble forecast (b) track from FT1112.

Figure 3.12: Mean steering vectors for the CIMSS(h) and CIMSS(h+RS) ensemble forecasts initialized at 1200 UTC 11 September 2008. The vectors are averaged over a 1000 x 1000 km domain centered on the TC of each individual member.
forecast errors at 72 hours. The capture of the recurvature is an important issue in the track forecast of Sinlaku, especially when Sinlaku left Taiwan and was on its way towards Japan. Unfortunately, the recurvature in the CIMSS(h+RS) members was premature.

For the same case (FT1112), the differences between the environmental 500 hPa geopotential height fields in the CIMSS(h) and CIMSS(h+RS) analyses are very subtle from 1200 UTC 11 September onward (as mentioned in Section 3b.4). The same is true for their respective forecasts up to 18 hours, and the interpretation is unclear. Instead, the time-height diagram of local environmental steering vectors is presented in Fig. 3.12. The difference between the averaged local environmental steering vectors in the CIMSS(h) and CIMSSS(h+RS) ensemble forecasts becomes clear in the middle and upper troposphere from 24 h onward. These vectors in the CIMSS(h) forecasts are northwestward to northward, whereas the steering vectors in the CIMSS(h) forecast are northeastward. This is consistent with the premature recurvature found in ensemble forecast tracks of CIMSS(h+RS). In other words, by 24 h, the influence of the Rapid-Scan AMV data on the mid-latitude flow has begun to influence the track forecasts. At later times, an examination of the 500 hPa geopotential height fields shows that the track of Sinlaku begins to be influenced by a deeper mid-latitude trough to its north in the CIMSS(h+RS) forecasts (not shown).

3.4 Summary and Discussions

Compared against the CTL analyses, the CIMSS(h) analyses were mostly superior in depicting the initial storm positions, and the timing of the early intensification of Sinlaku. The more accurate initial intensification rate corresponded directly with a stronger three-dimensional primary and secondary circulation, and a tighter vortex with a sharper wind maximum during the period prior to Sinlaku reaching peak inten-
sity (1200 UTC 10 September). Comparisons with a modified best track, independent QuikSCAT ocean surface winds and vertical wind profiles from dropwindsondes also suggested that the CIMSS(h) analyses were more consistent with observations than the CTL analyses during the same period. Furthermore, the larger quantity of AMV data in CIMSS(h) allowed the EnKF to produce more dynamically and thermodynamically consistent analysis increments through the depth of Sinlaku in its developing stage. Finally, during the same period, the influence of assimilating the hourly AMV data on the analyses was most pronounced in the TC and its near environment, and less so in the far environment. On the negative side, the peak intensity was not reached in any of the analysis ensemble members in either experiment, likely due to the 27 km resolution on the assimilation grid. The CIMSS(h) analysis ensemble also exhibited an unappealingly low spread in the intensity, which was clearly insufficient when compared with the error. After Sinlaku had reached peak intensity, the vertical profiles of tangential wind, radial wind and temperature in the CIMSS(h) analyses remained more consistent with available dropwindsonde profiles than CTL, but other improvements were less clear.

Given that the MTSAT Rapid-Scan mode was activated after Sinlaku had reached its peak intensity and was in a relatively steady state, the impact of adding Rapid-Scan AMV data on the TC structure analyses was not expected to be as substantial as compared with CIMSS(h). However, some minor improvements are noted. First, the CIMSS(h+RS) analyses produced average minimum MSLP and maximum surface wind values closer to the best track. Additionally, the vertical profiles of tangential wind, radial wind and temperature were respectively 12%, 7% and 18% superior to CIMSS(h) when evaluated against 3 dropwindsonde profiles. Finally, the assimilation of the Rapid-Scan AMV data made some subtle changes to the TC structure in the analyses, and minor changes to the local and remote environmental fields.
The 0-72 h WRF ensemble forecasts initialized with CIMSS(h) analyses outperformed the forecasts initialized with CTL data in both track and intensity. The averaged ensemble mean forecast track error of CIMSS(h) initialized forecasts were found to be 100-150 km smaller than CTL initialized forecasts. During the 36-h period in which TC Sinlaku was intensifying, the MSLP errors for 30-72 h forecasts initialized during this period were on average reduced by at least 50%. During the 24-h period after TC Sinlaku had reached peak intensity and the Rapid-Scan AMV data were available, the CTL and many of the CIMSS(h) ensemble members tended to predict an erroneous landfall in mainland China. In contrast, the CIMSS(h+RS) ensemble members predicted recurvature away from mainland China, although unfortunately prematurely. The influence of assimilating the Rapid-Scan AMV data on the track forecasts was very subtle, with initially small differences in the CIMSS(h+RS) versus CIMSS(h) analyses leading to large differences in the forecasts 2-3 days later.

While some results from this case study are promising, a larger sample of TC cases will be necessary in order to evaluate the consistency of the forecast impacts provided by the enhanced AMV data. Furthermore, understanding where the TC analyses are benefiting most from the enhanced AMV information can lead to potential targeting scenarios, such as activating and directing Rapid-Scan operations. In Chapter 4, the relative importance of specific horizontal and vertical subsets of enhanced AMVs on TC analyses and forecasts will be investigated via several parallel data-denial assimilation experiments. The influence of assimilating subsets of enhanced AMVs on Hurricane Ike (2008) will also be presented in Chapter 4.
Chapter 4

Understanding the Contributions of Assimilating Subsets of Atmospheric Motion Vectors

Given the findings from the past decade of forecast impact experiments for selected sets of satellite and aircraft observations (summarized in a WMO report by Majumdar et al. 2011b), one may expect that the assimilation of AMVs in selected tropospheric layers or locations relative to the TC center would be particularly important for improving analyses and forecasts of TC track, structure or intensity. For example, Yamaguchi et al. (2009) and Aberson et al. (2011) showed that in selected case studies, the assimilation of dropwindsonde observations in targeted areas around the TC can result in improved track forecasts. Similarly, Harnisch and Weissmann (2010) found that dropwindsondes deployed in the vicinity of the TC are more useful for near-term track forecasting than those in the farther synoptic environment. Kieu et al. (2012) investigated the relative roles of AMVs located within the 300-100 hPa versus 800-300 hPa layers, and found that despite the relatively small number of AMVs between 800-300 hPa, the track forecast is more sensitive to the AMVs in this layer. However, the impact on TC structure and intensity is not emphasized in these studies. We suggest
a better understanding of the impact of assimilating AMV datasets by identifying regions and locations of assimilated AMV data that improves forecast of TC track, intensity and structure the most. Findings from this study can lead to informed decisions regarding observing system assessments and deployments. For example, this information could impact potential targeting scenarios, such as activating and focusing satellite Rapid-Scan operations, or directing aircraft assets.

We quantify the impact of assimilating subsets of enhanced AMV data on mesoscale ensemble forecasts of TCs, via six parallel observing system experiments (OSE) that assimilate the following: all AMVs; only AMVs near the TC (within 1000 km radius of the TC); only AMVs in the domain exterior to this region; and all AMVs but with each of three selected tropospheric layers removed. The two TC cases, Typhoon Sinlaku (2008) and Hurricane Ike (2008) are examined.

4.1 Experimental Design

For Sinlaku, six parallel 3-hourly WRF/EnKF experiments are initialized on 0000 UTC 1 September 2008, a week prior to its formation. The corresponding six parallel WRF/EnKF experiments for Hurricane Ike are initialized on 0000 UTC 25 August 2008, again a week prior to its formation.

In addition to the conventional observations, the first experiment (denoted “ALL”) assimilates all of the available enhanced AMVs produced by CIMSS in a 3-h wide window centered on 0000 UTC, 0300 UTC, etc. All observations in each 3-hour window are assimilated as if they were taken at the central time of the window (no time adjustments). The analyses are used to initialize an ensemble of 3-hour forecasts for the next analysis time. The second (third) experiment, denoted “Interior” (“Exterior”) is the same as ALL except that it assimilates the enhanced AMVs only within (outside) 1000 km radius from the TC center. The size of 1000 km is chosen as ap-
Figure 4.1: The spatial distribution of superobbed AMVs assimilated in “HALL” experiment (a) at 0000 UTC Sep 11 2008 near the most intensified stage of Sinlaku, and (b) at 1200 UTC Sep 4 2008 close to Ike reached its strongest stage. The black circle is centered at the JMA best track location of Sinlaku (yellow star) at the time of the analysis and it marks the 1000 km radius. As in (a)-(b), (c)-(d) are superobbed AMVs assimilated in “RSALL” experiment. (e) The spatial distribution of assimilated radiosondes and not assimilated but verified dropwindsondes for the duration of Sinlaku. (f) is the same as (e), but for the duration of Ike.
Table 4.1: WRF/EnKF cycled analyses-forecasts experiments designed to understand the contribution of assimilating subsets of CIMSS hourly and Rapid-Scan AMVs during Typhoon Sinlaku (2008) and Hurricane Ike (2008). The analyses experiments cover the lifetime of Sinlaku from 0000 UTC 8 September 2008 to 1200 UTC 13 September 2008, and the lifetime of Ike from 0000 UTC 1 September 2008 to 0000 UTC 10 September 2008. To differentiate hourly and Rapid-Scan experiments, “H” is added to the name of the experiments which assimilate CIMSS hourly AMVs, and “RS” is added to the Rapid-Scan experiments.

<table>
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<th>Expt</th>
<th>Conventional Obs</th>
<th>CIMSS AMVs Assimilated</th>
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<tr>
<td>ALL</td>
<td>Radiosondes u/v/t/q, aircraft data</td>
<td>All AMVs</td>
</tr>
<tr>
<td>Interior</td>
<td>Only AMVs within 1000 km radius of TC center</td>
<td></td>
</tr>
<tr>
<td>Exterior</td>
<td>Only AMVs outside 1000 km radius of TC center</td>
<td></td>
</tr>
<tr>
<td>noLL</td>
<td>Eliminate all lower-level (LL) AMVs (700-999 hPa)</td>
<td></td>
</tr>
<tr>
<td>noML</td>
<td>Eliminate all mid-level (ML) AMVs (350-700 hPa)</td>
<td></td>
</tr>
<tr>
<td>noUL</td>
<td>Eliminate all upper-level (UL) AMVs (100-350 hPa)</td>
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proximate to the upper limit of the filter radius of 1200 km that the GFDL vortex initialization method proposed in Kurihara and Bender (1993) to separate the TC flow from the environmental flow. The fourth to sixth experiments are the same as ALL except that they eliminate AMVs between 150-350 hPa; 350-700 hPa; and 700-999 hPa, respectively. These experiments are named “noUL” (no upper-layer AMVs), “noML” (no middle-layer AMVs), and “noLL” (no lower-layer AMVs) respectively. The six parallel experiments were conducted for “Hourly” AMVs for both tropical cyclone cases, and repeated for ‘Rapid-Scan’ AMVs where available for Sinlaku (after its rapid intensification), and through the entire period of Ike. It is important to note that the “Hourly” and “RS” AMV datasets are treated separately in this study, even though for much of the time in these two TC cases they were simultaneously
available. This results in a total of 24 (6 denial experiments; 2 AMV datasets; 2 TC cases) parallel experiments; a summary is given in Table 4.1.

As shown in Fig. 4.1, AMVs are grouped into upper-, middle-, and lower-tropospheric layers and highlighted with colors corresponding to the experimental design. A black circle centered on the location of the TC (yellow star) indicates the separation between interior and exterior AMVs. From Table 4.2, it is first worth noting that the interior AMVs represent approximately 10% of the total number of AMVs in both TC cases. Second, as seen in Fig. 4.1a and b, most of the hourly AMVs are at the upper-layers (73% upper / 11% middle / 16% lower for Sinlaku and 56% upper / 10% middle / 33% lower for Ike). The greater % with Sinlaku relative to Ike is due to the image sampling. The 15-min. interval available from GOES for Ike is much better for tracking shorter-lived, low-level cumulus than the 30-min. interval from MTSAT during Sinlaku, especially for the VIS AMVs. Third, the activation of Rapid-Scan mode increases the number of AMVs for all subsections as expected (e.g. Figs. 4.1c and d), but the percentages between the three layer subsets become more comparable, more so for Sinlaku than for Ike (31% upper / 40% middle / 29% lower for Sinlaku and 48% upper / 24% middle / 28% lower for Ike). The shorter image intervals allows for better tracking of low and mid-level clouds, with the jump from 30- to 15-minute scans having a bigger impact with Sinlaku than the 15- to 7.5 minute images for the Ike Rapid-Scan. Finally, the distribution of AMVs by layer in the interior section is comparable to the distribution of AMVs by layer over the whole domain.

The distribution of radiosondes (assimilated) and dropwindsondes (not assimilated, and only within 100-1200 km from TC centers) is illustrated for Sinlaku and Ike in Figs 4.1e and f, respectively.
Table 4.2: Time-averaged percentages of different subsets of assimilated superobbed AMVs in the WRF/EnKF system for Typhoon Sinlaku (2008) and Hurricane Ike (2008). Rapid-Scan AMVs are shown in boldface. Upper-levels, mid-levels, lower-levels, and interior follow the definitions in Table. 4.1. The first column is the averaged number of superobbed AMVs in “ALL” and “Interior” experiments.

<table>
<thead>
<tr>
<th>AMVs (#)</th>
<th>ALL Levels(%)</th>
<th>Upper-Levels(%)</th>
<th>Mid-Levels(%)</th>
<th>Lower-Levels(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Typhoon Sinlaku (2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALL 2413/5302</td>
<td>100/100</td>
<td>73.1/30.6</td>
<td>11.2/40.5</td>
<td>15.7/28.9</td>
</tr>
<tr>
<td>Interior 237/560</td>
<td>9.8/10.6</td>
<td>71.1/37.6</td>
<td>7.0/31.6</td>
<td>21.9/30.8</td>
</tr>
<tr>
<td>Hurricane Ike (2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALL 2253/3991</td>
<td>100/100</td>
<td>56.4/47.7</td>
<td>9.9/23.7</td>
<td>33.7/28.6</td>
</tr>
<tr>
<td>Interior 245/428</td>
<td>10.9/10.7</td>
<td>58.7/54.8</td>
<td>6.1/15.4</td>
<td>35.2/29.8</td>
</tr>
</tbody>
</table>

4.2 Analysis Results from 6 Assimilation Experiments

4.2.1 Assimilation Performance

The performance of the EnKF assimilation is first evaluated, via examining the prior and posterior winds at radiosonde locations in the environment of both TCs. It is worth noting that even if a given observation is successfully assimilated in one experiment, it may be rejected in another experiment and vice versa. In order to perform statistics that directly reflect the quality of the assimilation, only the observations which were assimilated in both experiments should be contributed to the summary statistics. To ensure this, a diagnostic tool developed by DART is designed to select only those observations that are commonly assimilated in parallel experiments.
Figure 4.2: The time-averaged vertical profiles of (a) root-mean-square error, (b) bias and (c) total spread of prior (colored solid lines) and posterior (dashed lines) for zonal wind (m s$^{-1}$) from the six “H” experiments verified with the radiosonde observations illustrated in Fig. 4.1e during Sinlaku. (d) The number of commonly assimilated radiosondes in the six “H” experiments.

Figure 4.3: As in Fig. 4.2, but for prior and posterior from the six “RS” experiments verified with the radiosonde observations illustrated in Fig. 4.1f during Ike.

In Figs. 4.2 and 4.3, vertical profiles of the root-mean-square error (RMSE), bias, and total spread$^{11}$ of zonal wind are calculated based on the common observations.

$^{11}$i.e. the square root of sum of ensemble variance and observation-error variance (Raeder et al., 2012)
For the radiosondes in the Sinlaku domain, the time-averaged RMSE of zonal wind is reduced by around 1 m s\(^{-1}\) from prior to posterior in each of the six “H” experiments (Fig. 4.2a). The low bias in the lower troposphere is significantly reduced in the posterior, as is the slight high bias in the upper troposphere (Fig. 4.2b). The total spread is also reduced after assimilation (Fig. 4.2c). The RMSE and total spread are generally largest in the upper troposphere. In terms of the individual experiments, “HInterior” and “HnoLL” have slightly larger prior RMSE from middle to lower levels than the other experiments, and the prior “HInterior” and “HnoUL” are found to have larger total spread aloft. “HInterior” also has the largest total spread through the entire column, and the total spread of “HnoLL” (“HnoUL”) is relatively large in lower levels (upper levels). This indicates that without the assimilation of exterior AMVs, the prior ensemble members are less accurate and more uncertain in estimating the environmental flows in all layers. Furthermore, by excluding lower-level (upper-level) AMVs, the 3-hour prior ensemble forecast provides less confident or accurate estimations of the lower-level (upper-level) environmental flow. The corresponding results for the meridional flow are very similar and are not shown here.

For the corresponding profiles in the “RS” experiments for Ike (Fig. 4.3a-c), several similar results to Figs. 4.2a-c are evident except that the six profiles are more tightly clustered, and there is a stronger wind bias in the upper troposphere which may largely be due to differences between the mid-latitude flows captured by the radiosondes in the two domains. Comparing Fig. 4.2d and Fig. 4.3d, the commonly assimilated radiosonde observation number in each vertical layer is also very similar between the Sinlaku and Ike cases. In summary, the error statistics of these two groups of assimilation experiments, which are calculated based on almost the same sample size, have demonstrated similar characteristics and a satisfactory assimilation performance.
4.2.2 Initial Analyses: TC Position and MSLP

The ensemble mean analyses are first verified on the 27-km domain against the best track position and MSLP estimates from the JMA and NHC for Sinlaku and Ike, respectively. For Sinlaku, only the analyses from 0000 UTC 9 September 2008 onward are verified, given the ambiguity in locating the center prior to Sinlaku reaching tropical storm status. For Ike, only the analyses from 0000 UTC 3 September 2008 onward are verified, due to the proximity of Ike to the eastern boundary of the domain at earlier times.\textsuperscript{12}

4.2.2.1 Sinlaku

The ensemble mean TC positions, position errors and spread, and MSLP and MSLP spread of the ensemble analyses from the six “H” experiments during Sinlaku are presented in Figs. 4.4a-c. During the early stage of Sinlaku (0000 UTC 9 September), all the analyses are shifted westward of the JMA Best Track positions (Fig. 4.4a) with an average error of around 140 km (Fig. 4.4b). It is noteworthy that the JTWC advisory TC position data were rejected in the first few assimilation cycles beginning from 0000 UTC 8 September. As mentioned before, the representation of Sinlaku in the 3-h WRF forecast is rather weak prior to 0000 UTC 9 September so that the prior observation operator was not able to locate the center. Without prior estimates of storm centers, no observation increment of storm center is available for the analysis update. Despite that AMVs were assimilated during the period when the advisory TC position data were rejected, improvement in reducing the TC position errors is limited because near-storm AMVs are mostly depicting upper-levels outflows and therefore

\textsuperscript{12}Since Ike took a steady westward track through its life cycle, the domain selected to include all relevant atmospheric features through this period was necessarily large. Due to computational limitations, the eastern boundary was selected to be less than 1000 km from the center of Ike prior to 1200 UTC 2 September 2008, and therefore only limited enhanced AMV data were assimilated in the vicinity of Ike in its earliest stage.
Figure 4.4: (a) Ensemble mean initial TC positions of analyses from the six parallel “H” experiments for the duration of Sinlaku. (b) Ensemble mean and spread of (d) initial TC position error (km) and (c) minimum mean sea-level pressure (mb). (d)-(e) are similar to (b)-(c), but for analyses from the six parallel “RS” experiments. JMA best track is plotted in grey color in (a),(c), and (e). The corresponding ensemble mean initial TC positions, TC position error and minimum MSLP of CTL analyses in Wu et al. (2014) are plotted in orange.
may be less accurate to infer the storm surface center. The mean position errors in five of the experiments then drop to 30 km after 0000 UTC 10 September and remain below 50 km at later times (the advisory TC position data are no longer rejected). The only exception is the “HExterior” experiment where the mean position errors reduce much slower and stay above 50 km until 0000 UTC 11 September. From 0000 UTC 11 September onward, the mean positions errors from the six ‘H analyses stay below 50 km and “HnoLL” has the smallest and very steady mean errors of 20 km. Interestingly, the “HnoLL” AMVs comprise 22% of interior AMVs, which is larger than 7% of the interior middle-level AMVs (see Table. 4.2), and it will be intuitive to suspect that the position errors may increase more by withholding the “HnoLL” AMVs than the “HnoML”. However, the opposite is true and a possible reason is the interior lower-level AMVs are asymmetrically distributed and therefore may act to pull the TC off center.

After the Rapid-Scan AMVs became available from 1800 UTC 10 September, the EnKF analyses of “HALL” were utilized to initiate the first cycles of the six parallel “RS” experiments at this time. The mean position errors from the six “RS” analyses at later times are also illustrated in Fig. 4.4d. The mean errors of “RSALL” are found to be slightly smaller than that of “HALL” when both of their errors are well below 40 km. Unlike in the “H” group, the mean position errors between “RSnoUL”, “RSnoML”, and “RSnoLL” are closer to each other, which is most likely due to their more comparable AMV proportions.

The ensemble mean MSLP is very similar among the six parallel experiments prior to 1200 UTC 10 September (Fig. 4.4c). However, although most of the experiments still show a steady intensification of Sinlaku over the following two days, there is less intensification on average in the “HExterior” and “HnoUL” analyses. These results indicate that the assimilation of AMVs within the general realm of the TC vortex
can have an important influence on both the position and MSLP analyses of Sinlaku, and that the upper-layer AMVs in particular are important to the MSLP analyses. From 0000 UTC 11 September, the mean MSLP of the six “RS” analyses is shown in Fig. 4.4e. Unlike the mean position errors, there is much more variability between the “RS” analyses, especially 0000 UTC 12 September onward.

Examining the spread of the analysis ensembles is a way to estimate the analysis uncertainty. In Figs. 4.4b-c, not only do the “HExterior” and “HnoUL” ensemble mean possess less accurate analysis TC position and MSLP, but their ensemble spread is larger, particularly for “HExterior”. This result supports the findings above that without the vortex-domain AMVs, and to a lesser extent the upper-layer AMVs, the analyses are not only less accurate but also more uncertain in estimating the TC position and MSLP. The same situation is found in Fig. 4.4d-e where larger ensemble spreads are also associated with “RSExterior” and “RSnoUL”, and the spread is found to be larger than the same cases in the “H” group.

4.2.2.2 Ike

Since the Rapid-Scan mode of GOES-EAST was activated during the full lifetime of Ike, the two groups (“H” and “RS”) of six parallel experiments are available for the entire duration of the assimilation experiments. In general, the analysis differences between the “H” and “RS” results are mostly not significant for Ike, which is not that surprising given their similar AMV quantities (Table 4.2). Note that both “HALL” and “RSALL” are neither the best nor the worst matches to the best position in their groups. Unlike in Sinlaku, the “Exterior” experiment at times yields the smallest ensemble mean position errors (see Figs. 4.5b,d). Curiously, “Interior” analyses have larger errors initially, and “Exterior” errors grow after 0000 UTC 8 September. This is evident in both “H” and “RS” groups. This is potentially related to structural
Figure 4.5: As in Fig. 4.4, but for analyses from the six parallel “H” experiments (a-c) and “RS” experiments (d-e) for the duration of Ike. NHC best track is plotted in grey color in (a),(c), and (e). Again, the orange lines represent the corresponding CTL analyses for TC Ike.
changes in Ike after it made its first landfall on Cuba around 0000 UTC 8 September. Ike's circulation doubled in size (from 150 km to 300 km according to 34-kt wind radii) perhaps making it more resolvable by the AMV winds within the “Interior” domain. In both the “H” and “RS” experiments, the ensemble mean position errors of “ALL”, “noLL”, “noML”, and “noUL” analyses have similar evolutions, and it is not clear which analysis overall is most compromised when a particular layer of AMVs is removed.

In Figs. 4.5c,e, none of the “H” or “RS” ensemble mean MSLP estimates are close to the best track MSLP, likely due to the limited model resolution. Despite this 20 hPa discrepancy, the ensemble mean MSLP estimates of “HInterior” and “RSInterior” are closest to the best track values prior to the landfall on Cuba on 8 September, despite the larger initial position errors noted earlier. Unlike in Sinlaku, the “HnoUL” (“RSnoUL”) analyses are no longer the weakest, but they still have relatively larger spread, especially prior to September 8th. It is also noteworthy that the “RSnoLL” shows a 1-day delay in the September 6-7 intensification while the other analyses show gradual intensification. This delay of intensification is not seen in the corresponding “HnoLL” analyses, and could be due to the increased coverage of LL vectors produced by the rapid-scans. After September 8, as Ike makes landfall over Cuba, the six analyses in the “H” and “RS” groups have relatively small differences in the MSLP.

Overall, for Ike, the effects of removing subsets of the AMV data from the assimilation experiments are more subtle than for Sinlaku. The exterior AMVs are important in the reduction of position error during Ike’s west-southwestward progress towards Cuba, and the interior AMVs appear more important during and after landfall over Cuba when Ike’s size broadens. In contrast to Sinlaku, in the case of Ike the lower-layer AMVs serve to improve the analyses especially with RS.
4.2.2.3 Discussion

In general, the AMVs provide an improvement to the initial analyses of Sinlaku, but the results are more mixed for Ike. Part of this may be due to the fact that Ike had very good storm information provided by the NHC, which was successfully used in the EnkF assimilation process. On the other hand, TC positions for Sinlaku are initially over 1 deg off from the Best Track for all the ‘H’ AMV experiments, while the advisory positions are 20-30km off, yet the CTL (no CIMSS AMVs) has similar initial position errors to the “H” analyses. Certainly the model resolution of 27 km accounts for some of the precision variability (especially noted in the MSLP analyses), but this also raises the question of near core assimilation when there is 1) a lot of data that might not be horizontally or vertically symmetric in their distribution about the TC center (AMVs), and 2) TC advisory information of varying quality.

In the “H” experiments for Sinlaku in particular, the noLL is probably the best overall for initial position. What relatively few LL AMVs there are near Sinlaku are asymmetrically distributed and may therefore skew the TC off center. The RS LL AMVs are much more prevalent, and provide more complete (symmetric) coverage, with better initial positioning results. In contrast, the ML and UL AMV coverage is more consistent over/around the storm, and therefore the results are more consistent between the H and “RS” experiments. Also, for TCs at various stages, the AMV distributions can act in different ways to represent their contributions to the TC structure and near environments. These findings therefore provide suggestions for the data assimilation community on what specific attributes of AMVs may be more beneficial at improving the initial analyses of TCs and their near-environments if there is priority in data selection or observation weighting.
4.2.3 Verification against Dropwindsonde Data

Vertical profiles of the ensemble mean storm-relative wind are verified against independent dropwindsonde observations less than 1000 km radius from the TC center. Prior to computing the mean, the wind profile in each ensemble member is first computed relative to the TC center in that member. Dropwindsondes were released in the core region of Sinlaku during the Tropical Cyclone Structure (TCS-08) / THORPEX Pacific Asian Regional Field Campaign (T-PARC), and by NOAA in and near Ike. Only those dropwindsondes within 30 min of the analysis times at which the full ensemble fields were able to be stored (0000 and 1200 UTC) are considered, and are listed in Table 4.3. 17 dropwindsondes, which were all released close to Sinlaku’s peak intensity, are selected in an annulus between 100-650 km from the center of Sinlaku (see Fig. 4.1e) with about half of those providing data above 650 hPa, up to 150 hPa. 14 dropwindsondes are selected in an annulus between 100-1100 km from the center of Ike (see Fig. 4.1f), with all but 2 sampling up to at least 200 hPa. Several other dropwindsondes deployed less than 100 km from the TC center are excluded due to our inability to represent the inner-core dynamics with the 27 km grid spacing. Remote dropwindsondes outside the TC are also not considered.

For Sinlaku, the RMSE of tangential wind between 1000-200 hPa lies between 2-5 m s$^{-1}$ for most of the experiments, except for “HExterior” and “HnoUL” where the RMSE lies between 3.5-8 m s$^{-1}$ (Fig. 4.6a). There is a corresponding negative (weak) bias in the lower troposphere in all the data denial experiments, though this bias is nullified in “HALL” (Fig. 4.6b). The RMSE of radial wind between 1000-200 hPa ranges between 3.5-8 m s$^{-1}$ over all the six experiments, with the largest of these errors still evident in “HExterior” (throughout the depth) and “HnoUL” (above 600 hPa) (Fig. 4.6d). A positive bias of radial wind up to 2 m s$^{-1}$ is evident below 700 hPa, especially for “HExterior”, “HnoLL” and “HnoUL” (Fig. 4.6e). In the upper
Table 4.3: Dropwindsondes selected for analyses verification (allow ± 30 minutes difference from analysis time) during Typhoon Sinlaku (2008) and Hurricane Ike (2008). Dropwindsondes that are less than 100 km from the TC are not included.

<table>
<thead>
<tr>
<th>Flight</th>
<th>Height (mb)</th>
<th>Analyses Times</th>
<th>#</th>
<th>Distance from TC (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Typhoon Sinlaku (2008)</strong></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>DOTSTAR Astra</td>
<td>150</td>
<td>0000 UTC 10 Sep 2008</td>
<td>5</td>
<td>256/243/184/172/175</td>
</tr>
<tr>
<td>DOTSTAR Astra</td>
<td>150</td>
<td>0000 UTC 11 Sep 2008</td>
<td>4</td>
<td>601/602/450/258</td>
</tr>
<tr>
<td>NOAA P3</td>
<td>650</td>
<td>0000 UTC 11 Sep 2008</td>
<td>5</td>
<td>645/540/459/371/328</td>
</tr>
<tr>
<td>USAF C130</td>
<td>700</td>
<td>1200 UTC 11 Sep 2008</td>
<td>3</td>
<td>197/144/100</td>
</tr>
</tbody>
</table>

| **Hurricane Ike (2008)** |             |                      |   |                       |
| USAF C130      | 200         | 0000 UTC 07 Sep 2008 | 2 | 962/1158             |
| NOAA G4        | 150         | 0000 UTC 07 Sep 2008 | 2 | 640/790              |
| NOAA G4        | 150         | 1200 UTC 07 Sep 2008 | 2 | 952/1114             |
| NOAA G4        | 150         | 0000 UTC 08 Sep 2008 | 3 | 488/366/506          |
| NOAA G4        | 150         | 1200 UTC 08 Sep 2008 | 3 | 759/911/1022         |
| NOAA P3        | 700         | 0000 UTC 10 Sep 2008 | 2 | 103/186              |

troposphere, the negative bias in “HnoUL” contributes to large errors. The ensemble spread of tangential and radial wind between 1000-200 hPa is tightly clustered near 2 m s\(^{-1}\) with little vertical variation in four of the experiments (Figs.4.6c, f). The two exceptions, “HnoUL” and “HExterior”, have larger spread, consistent with the vertical profiles of RMSE in Figs. 4.6a,d, and also the larger position and MSLP spread in Figs. 4.4d,e.

For the “RS” analyses of Ike, the vertical profiles of RMSE, bias, and spread of the tangential and radial winds are more tightly clustered in the 6 experiments than for Sinlaku. The averaged profile of RMSE of tangential wind ranges between approximately 2-4 m s\(^{-1}\) (Fig. 4.7a), considerably smaller than for Sinlaku (Fig. 4.6a). In contrast to the Sinlaku case, the average tangential wind bias for Ike is small and positive in the lower troposphere, and consistently negative (too weak) and of magnitude 2 m s\(^{-1}\) above 700 hPa (Fig. 4.7b). The radial wind exhibits a positive bias throughout the column (Fig. 4.7e), suggesting too weak an inflow and too strong
Figure 4.6: The averaged vertical profiles of (a) root-mean-square error, (b) bias, and (c) spread of estimated tangential winds (m s$^{-1}$) relative to the TC center in the six “H” analyses verified with the 17 dropwindsondes during Sinlaku. As in (a)-(c), but for radial winds (m s$^{-1}$) in (d)-(f).
Figure 4.7: As in Figs. 4.6a-f, but for estimated tangential winds and radial winds (in $m s^{-1}$) relative to the TC center in the six “RS” analyses verified with the 14 dropwindsondes during Ike.
an outflow in the ensemble analyses. One potential reason for the tighter clustering in Ike is the larger number of assimilation steps compared with Sinlaku which helped the solutions to converge, given the longer duration of investigation for Ike.

The ensemble spread of both the tangential and radial wind profiles in the 6 parallel experiments is also smaller and more tightly clustered for Ike than for Sinlaku, not exceeding 2.5 m s\(^{-1}\) through the column. The spread is largest in “RSExterior” and “RSnoLL”, and is especially consistent with the largest RMSE in these two experiments below 800 hPa.

Overall, the error characteristics of the tangential and radial wind profiles show some differences between the Sinlaku and Ike cases, though with some common results. The assimilation of AMVs in the interior region, and at the upper levels is particularly important for reducing errors, biases and ensemble spread through the tropospheric column. The assimilation of lower-tropospheric AMVs serves to improve the lower-tropospheric analyses.

4.2.4 Azimuthally Averaged Structure

A qualitative analysis of the ensemble mean and spread of the primary and secondary circulation of the TC via azimuthally averaged profiles is conducted for the six “H” and “RS” parallel analyses for Sinlaku and Ike respectively at selected times. In addition to the tangential, radial and vertical winds, the radius of maximum wind (RMW) and maximum tangential wind are included. For Sinlaku, the six “H” analyses on 1200 UTC 11 September are presented in Fig. 4.8, at the time when Sinlaku had reached its maximum intensity and was in a steady state. The azimuthally averaged tangential wind speed in the ensemble mean of “HExterior” and “HnoUL” is weak compared with “HALL” (Fig. 4.8a). This is also evident in Fig. 4.8b where the maximum tangential wind does not exceed 35 m s\(^{-1}\) in either “HExterior” or
“HnoUL”, whereas the maximum value exceeds 45 m s\(^{-1}\) in the other four analyses. The ensemble spread in both “HExterior” and “HnoUL” is also relatively large. In most analyses, the ensemble mean RMW is a little less than 100 km through the column, and its slope is not steep (80-100 km from 1000-200 hPa) in most analyses. The spread of RMW is tight in many cases, except for “HExterior” and the upper levels of “HnoUL”. We therefore deduce that the assimilation of interior AMVs is responsible for reducing the uncertainty in estimating the RMW and also the maximum tangential wind.

Comparing the vertical profiles of “HALL” with “HnoLL”, “HnoML” and “HnoUL”, the assimilation of upper-level AMVs has a significant influence on the profile of the maximum tangential wind. An examination of the radial wind structure reveals that “HExterior” and “HnoUL” are again showing much weaker lower-level inward flows and upper-level outward flows (Fig. 4.8c). Additionally, a region of low-level outflow centered on 80 km radius and 700 hPa is evident in “HALL”, “HInterior”, “HnoLL”, and “HnoML”, with the strongest speed of 6 m s\(^{-1}\) in “HALL” and lower mean values in the other three analyses. This low-level outflow is not perceptible (at least in the azimuthally-averaged perspective) in the ensemble mean of “HExterior” and “HnoUL”, though a local patch of ensemble spread of up to 2 m s\(^{-1}\) near the same location is identifiable in both cases. Given that “HExterior” and “HnoUL” exhibit a relatively weak lower-level inflow and upper-level outflow in the radial wind profile, it is not surprising that the vertical wind is also weak (figure not shown). The same vertical profiles (as Fig. 4.8, but not shown here due to similarity) were produced for the parallel six “RS” analyses at the same time. The ensemble mean of tangential and radial wind profiles in the six “RS” analyses are more comparable, except for “RSExterior” still being slightly weaker. The ensemble spread of tangential wind profiles in “RSExterior” and “RSnoUL” are still the largest but with smaller magnitudes than
(a) Tangential Wind (m/s)

(b) RMW (km) and Max. Tangential Wind (m/s)
Figure 4.8: Ensemble mean (contour) and spread (colorfill) of azimuthally averaged (a) tangential wind (m s$^{-1}$), (b) radius of maximum wind (blue) and maximum tangential wind (red in 10 m s$^{-1}$), and (c) radial wind (m s$^{-1}$) of the six “H” analyses at 1200 UTC 11 September during Sinlaku.
the corresponding ensemble spread in “HExterior” and “HnoUL”. It is worth noting that the decrease in the ensemble spread of tangential wind is largely associated with smaller spread of RMW in “RSExterior” and “RSnoUL”, and less with the spread of maximum tangential wind.

Very similar features are observed in Ike, but with less pronounced differences between the six analyses (not shown). The ensemble mean and spread of tangential wind, RMW, maximum tangential wind, and radial wind are much more alike between the six “H” analyses. Slightly larger ensemble spread in the profiles of maximum tangential wind and upper-level outflow is still evident in “HExterior”. For radial wind profiles, in addition to “RSExterior”, “RSnoLL” also has rather weak upper-layer outflows while larger spread is found mostly associated with “RSExterior” and “RSnoUL”.

These results corroborate the previous verification against dropwindsonde data in concluding that the interior and upper-layer AMVs are especially important for modifying the primary and secondary circulation. In addition to the interior and upper-layer AMVs, lower-layer AMVs are also found to be important in resolving the tangential and radial wind structure in the lower troposphere, and thereby to improving storm positions and intensity. This is mostly evident in the “RS” analyses and it may be (as discussed previously) that lower-layer AMV coverage can be significantly improved from the activation of Rapid-Scan, and thereby creating a more homogeneously distributed dataset around the TC core.

### 4.3 WRF Ensemble Forecasts

To assess model TC track and intensity forecast impact from the various AMV modifications to the initial analyses, 84-member ensemble forecasts are produced for each experiment by integrating the ensemble analyses with the same configuration as in the
Table 4.4: 72-h ensemble forecasts initialized with WRF/EnKF analyses at different initial times during Typhoon Sinlaku (2008) and Hurricane Ike (2008). The ensemble forecasts initialized at 0000 UTC 8-10 September for Hurricane Ike (2008) are extended to 120-h to cover the landfall in southern Texas, US.

<table>
<thead>
<tr>
<th>Forecast Initialization Times</th>
<th>Initial Conditions</th>
</tr>
</thead>
<tbody>
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<td></td>
</tr>
<tr>
<td>0000 UTC 09 September 2008</td>
<td>H: ALL, Interior, Exterior, noLL, noML and noUL</td>
</tr>
<tr>
<td>0000 UTC 10 September 2008</td>
<td>H: ALL, Interior, Exterior, noLL, noML and noUL</td>
</tr>
<tr>
<td>0000 UTC 11 September 2008</td>
<td>H&amp;RS: ALL; RS: Interior, Exterior, noLL, noML and noUL</td>
</tr>
<tr>
<td>1200 UTC 11 September 2008</td>
<td>H&amp;RS: ALL; RS: Interior, Exterior, noLL, noML and noUL</td>
</tr>
<tr>
<td>0000 UTC 12 September 2008</td>
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<tr>
<td>Hurricane Ike (2008)</td>
<td></td>
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<td>H&amp;RS: ALL</td>
</tr>
<tr>
<td>0000 UTC 10 September 2008</td>
<td>H&amp;RS: ALL</td>
</tr>
</tbody>
</table>

analysis experiment, together with a vortex-following inner grid of 9-km resolution. For Sinlaku, two periods are focused upon (Table 4.4): 1) 0000 UTC 9-11 September, comparing the six “H” 3-day ensemble forecasts; 2) 0000 UTC 11 September, 1200 UTC 11 September and 0000 UTC 12 September, which specifically examines the re-curvature in the track from the six “RS” 3-day ensemble forecasts. For Ike, six different initialization times are selected to focus on two periods (Table 4.4): 1) 0000 UTC 5-8 September, comparing the six “H” 3-day ensemble forecasts and the six “RS” 3-day ensemble forecasts; 2) 0000 UTC 8-10 September, which specifically examines 5-day ensemble forecasts for the “HALL” and “RSALL” experiments during a period of operational model forecast uncertainty, and up to Ike’s landfall in Texas.
4.3.1 3-day Forecasts of Sinlaku: 9-11 September

The ensemble mean track error of “HALL”, averaged over the three forecasts initialized on 00 UTC 9-11 September, is notably lower than that from the denial experiments “HInterior” and “HExterior” (Fig. 4.9a). “HInterior” begins with a relatively small track error compared with “HExterior”, but exceeds “HExterior” after 18 hours and reaches 345 km in 3 days. Combining this with earlier findings on the impacts of the various sub datasets on the initial analyses of TC structure, this result suggests that the interior AMVs are especially important for initializing the TC structure and its initial motion, while the exterior AMVs are particularly influential on the environmental steering flow that influences the forecast track especially beyond 1 day. The range of 3-day ensemble member track errors in “HALL” is slightly lower than that in “HInterior”, while “HExterior” exhibits a very large range.

“HALL” also has the lowest ensemble mean MSLP error throughout most of the 3-day forecasts (Fig. 4.9b). “HExterior” begins with a large mean error and range of errors, which gradually reduce with time. Interestingly, the mean error of the 34 kt wind radii, averaged over all quadrants, is lower for both “HInterior” and “HExterior” than “HALL” (Fig. 9c), although the range of errors is narrowest for “HALL”. All forecasts have a larger storm than the observed one. Note: Several datasets not used in the original JTWC best track are included retrospectively in our analysis of TC Sinlakus wind radii. These include special reconnaissance aircraft flight-level winds reduced to the surface together with Stepped Frequency Microwave Radiometer (SFMR) surface winds, and satellite-based scatterometer surface wind estimates.

The ensemble mean track error of “HALL” is also lower than those of “HnoLL”, “HnoML” and “HnoUL” (Fig. 4.9d). “HnoLL” and “HnoML” have very similar track errors, while “HnoUL” has the largest track errors. The track error spread is very similar between the four cases, compared with Fig. 4.9a. The error of minimum MSLP
Figure 4.9: Averaged ensemble mean (solid line) and spread (shading) of (a) track error (km), (b) error of minimum MSLP (hPa), and error of 34-Knot wind radii of 72-h ensemble forecasts initialized with “HALL”, “HInterior”, and “HExterior” analyses at 0000 UTC 9-11 September. As in (a)-(c), but for 72-h ensemble forecasts initialized with “HALL”, “HnoLL”, “HnoML”, and “HnoUL” analyses in (d)-(f). Double-headed arrows on the right-hand side of each subfigure are estimated ensemble spread of the track error (left), error of minimum MSLP (middle), and error of 34-knot wind radii (right) for the listed cases in the 72nd hour. The arrows are color-coded as the label suggests.
in Fig. 4.9e is a tight cluster with “HALL” slightly better than the three experiments in which a layer of AMVs is denied (Fig. 4.9e). A tighter clustering is also found for 34 kt wind radii (Fig. 4.9f).

4.3.2 3-day Forecast of Sinlaku: 11-12 September

This set of forecasts focuses on Sinlaus track forecasts with respect to Taiwan landfall, and the subsequent recurvature, using the RS datasets (although “HALL” is included as a reference dataset). For the initial time of 0000 UTC 11 September (Fig. 10), all forecasts are premature in turning Sinlaku towards Taiwan, with the RSExterior providing the worst track forecast. The ensemble mean track forecasts in “RSALL”, “RSnoLL”, and “RSnoUL” then show signs of early recurvature back to the north beginning from 42 h. In contrast, “HALL”, “RSInterior”, and “RSExterior” move Sinlaku more westward towards southeastern China after making landfall over northern Taiwan (Figs. 4.10a, b).

Considering the forecasts initialized on 1200 UTC 11 September, “RSALL” and “RSExterior” really pick up the impending recurvature to the northeast, albeit about 36 hours too soon. “HALL” and “RSInterior” continue to move Sinlaku westward towards southeastern China (Fig. 4.10c). All of the other “RS” forecasts show recurvature to varying degrees, (Fig. 4.10d). For forecasts initialized 12 h later on 0000 UTC 12 September, “HALL” and “RSInterior” now show a late recurvature, while the other ensemble mean forecasts suggest recurvature (Figs. 4.10e, f).

These results demonstrate the high sensitivity in the track forecasts during this period. To better understand the different forecast track behaviors, a local environmental steering flow at pressure levels between 850-200 hPa is calculated at each forecast time by averaging the ensemble mean wind vectors over a 1000 x 1000 km² domain centered on the TC of each individual member. The “RSALL”, “RSExterior”
and "RSInterior" forecasts initialized on 1200 UTC 11 September (Fig. 4.10g) clearly show steering differences, with "RSInterior" appropriately showing more westward steering vectors. "RSExterior" are similar to those in "RSALL" except for above 500 hPa, where "RSALL" exhibits a more northeastward motion from 24 h to 48 h, likely leading to the earlier and more pronounced recurvature. The corresponding steering vectors for "RSALL", "RSnoUL", "RSnoML" and "RSnoLL" remain similar through the first few 12 hours of the forecast (Fig. 4.10h). By 24 h, the steering vectors in "RSnoML" begin to depart from the remaining three vectors in the mid-upper troposphere, showing a more northward steering while the remaining three are more north-eastward consistent with the premature recurvature seen in the forecast tracks. The steering vectors for the same initialization time (1200 UTC 11 September) are now visualized via difference fields of 500 hPa geopotential height. First, both "RSInterior" and "RSnoML" weaken the trough to the north of Sinlaku compared with "RSALL", leading to less of an northeastward steering flow (Figs. 4.11a, d). Also, the location of the 5880 m contour to the east of Sinlaku is found to be further westward in "RSInterior", "RSExterior", "RSnoLL" and "RSnoML", compared with "RSALL", which leads to a more westward track in the data denial experiments. On the other hand, there is minimal difference in the vicinity of Sinlaku between the 500 hPa geopotential heights in "RSnoUL" and "RSALL" (Fig. 4.11e). At 48h (Figs. 4.11f-j), the difference field in 24 h is amplified and is consistent with the steering vector profiles in Figs. 4.10g-h, and the motion of Sinlaku.

In this case of high track sensitivity to environmental steering, very different track forecasts result from the different AMV datasets denied in the assimilation experiments.
Figure 4.10: Ensemble mean track of ensemble forecasts initialized with (a) “HALL”, “RSALL”, “RSInterior”, and “RSExterior” analyses; (b) with “HALL”, “RSALL”, “RSnoLL”, “RSnoML”, “RSnoUL” analyses at 0000 UTC 11 September. As in (a)-(b), but for ensemble forecasts initialized at 1200 UTC 11 September in (c)-(d), and for ensemble forecasts initialized at 0000 UTC 12 September in (e)-(f). (g) Mean steering vectors for ensemble forecasts in (c). The vectors are averaged over a 1000 x 1000 km² domain centered on the TC of each individual member. (h) is similar to (g), but for ensemble forecasts in (d).
Figure 4.11: Ensemble mean 500-hPa geopotential height of 24-h forecasts initialized with “RSALL” (blue) and (a) “RSInterior”, (b) “RSExterior”, (c) “RSnoLL”, (d) “RSnoML”, and (e) “RSnoUL” (red) analyses at 1200 UTC 11 September. Color fill denotes the 500-hPa geopotential height difference between the blue and red contours. As in (a)-(e), but for 48-h forecasts in (f)-(j).
4.3.3 3-day Forecasts of Ike: 5-8 September

The average forecast errors for Ike during 5-8 September (4 time periods) exhibit different characteristics to those for Sinlaku. In contrast to Fig. 4.9, neither “HALL” nor “RSALL” consistently possess the lowest average errors in track or MSLP as compared with their data denial counterparts (Fig. 4.12). In general, the “H” tracks are better than their “RS” counterparts, while the “RS” MSLP forecast errors are slightly superior. As suggested by Fig. 4.12a, “HALL” starts with a slightly larger mean track error than “HExterior”, but thus reverses after 36 hours. This is also the case for “RSALL” and “RSExterior”, but with a more pronounced difference (see Fig. 4.12d), and the “RSALL” track error remains slightly larger than that of “RSExterior” until 66 hours. In contrast to the ensemble forecasts for Sinlaku, the growth rate of track error in “Interior” tends to be close to that of “ALL”, except for being approximately 10-20 km larger (both “H” and “RS”).

Considering the MSLP mean forecast errors, “Interior” outperforms “ALL” for the entire forecast period (in both “H” and “RS”) with a small range in ensemble errors (Fig. 4.12b,e). The MSLP error of “Exterior” gradually departs from “ALL” and “Interior” with growing ensemble spreads. Figs. 4.12c,f suggest “Interior” has generally larger 34 kt wind radii errors in both the “H” and “RS” experiments. The “Exterior” forecasts for both the “H” and “RS” groups provide the best mean errors, but also have the largest ensemble error spreads.

As was the case in Sinlaku (Fig. 4.9d), “noUL” in both “H” and “RS” groups for Ike has the largest track errors and range for the entire forecast length, compared with “ALL”, “noML” and “noLL” (Fig. 4.12g,j). Curiously, “noML” performs the best for track forecasts, especially in the “RS” set of runs. While AMVs tend not to be overly abundant in this layer of the troposphere, this result suggests some sensitivity. In fact, it was found in Sears and Velden (2012) that AMV quality generally deteriorates
Figure 4.12: As in Fig. 4.9a-f, but for averaged ensemble mean and spread of 72-h ensemble forecasts initialized with “HALL”, “HInterior”, and “HExterior” (in a-c), “RSALL”, “RSInterior”, and “RSExterior” (in d-f), “HnoLL”, “HnoML”, and “HnoUL” (in g-i), “RSnoLL”, “RSnoML”, and “RSnoUL” (in j-l) analyses at 0000 UTC 5-8 September for Ike case.
in the middle levels due to uncertain vector height assignments. Since Ike was a well-developed vortex during this period, the steering flow was deep with a strong influence from the mid levels (Velden 1991). Taking out the mid-level AMVs in this case actually helps improve the track forecast.

It is interesting to find that there are more variations in “H” group in terms of MSLP errors than “RS” group where results are more tightly clustered (Fig. 4.12h,k). Comparing to the interior and exterior AMV data denial experiments (Figs. 4.12c,f), less significant changes to the storm size errors are found between forecasts initialized with different tropospheric layers removed, especially in “RS” group. One exception is that the 34-knot wind radii errors in “HnoLL” are slightly larger, even though this experiments MSLP errors yielded the best results. In this case, taking out the hourly low-level AMVs created a stronger and bigger TC. It is worth pointing out that the average NHC best track uncertainty estimates for 34 kt wind radii is about 55 km, even with assistance from satellite and aircraft observations (Landsea and Franklin, 2013).

In order to understand how the differences between the steering flows in the data denial experiments change the forecast tracks, we further examine the ensemble forecasts initialized on 0000 UTC 6 September, which includes Ike’s unexpected turn to the southwest and first landfall in Cuba on September 7. The “H” and “RS” track forecasts are relatively similar, so only the “RS” group is presented. Fig. 4.13a “RSInterior” (“RSExterior”) has the worst (best) track forecast, and “RSALL”, “RSnoLL”, “RSnoML” and “RSnoUL” lie in between. To investigate this further, the 18-h ensemble forecasts (around the time the track forecasts really diverge) in Figs. 4.13b-f show the corresponding 500-hPa geopotential height differences between “RSALL” and the other five experiments. “RSInterior” shows a substantially weaker westward extension of the ridge just north of Cuba, which would promote a more northerly
track as seen in Fig. 4.13a. On the other hand, the small height differences just
to the north of Ike in “RSExterior” and “noML” suggest a little stronger ridge and
would promote the more southerly tracks seen in Fig. 4.13a.

4.3.4 5-day Forecast of Ike: 8-10 September

The forecasts of Ike during this period presented a substantial challenge to NHC, given
the run-to-run inconsistency in the operational models’ predictions of the landfall
location in the United States (Brennan and Majumdar, 2011). Here, we compare the
5-day “HALL” and “RSALL” track predictions over the same period.

Most of the operational numerical forecasts initialized at 0000 UTC 9 September
took Ike south of the best track (GFS track forecasts are blue lines in Fig. 4.14), while
the corresponding forecasts initialized at 0000 UTC 10 September brought Ike back
towards its actual landfall in southeastern Texas (Brennan and Majumdar, 2011). In
contrast, we find that the ensemble means of our “HALL” and “RSALL” ensemble
forecasts initialized on 0000 UTC 9 September were more accurate, while the corre-
sp dumping forecasts initialized on 0000 UTC 10 September took Ike further south
towards the Texas-Mexico border (Fig. 4.15a). For the 0000 UTC 9 September ensem-
ble forecasts, the rapid-scan AMVs (“RSALL”) produce an excellent track forecast.
“HALL” begins to depart from “RSALL” after 2 days, with stronger southwestward-
pointed steering vectors vs. GFS analyses above 500 hPa (red vectors inside the black
box of Figs. 4.15b, c). The corresponding steering vectors a day later are now both
indicating this phenomenon.

To further assess the behavior of these forecast tracks, the 500 hPa geopotential
heights of the “HALL” and “RSALL” forecasts valid at 0600 UTC 12 September
are compared against the corresponding NCEP GFS analyses. For the forecasts
initialized on 0000 UTC 9 September, the 5940-m contours in “HALL” (red contours
Figure 4.13: (a) Ensemble mean track forecasts initialized with “RS” analyses at 0000 UTC 6 September for Ike case. The orange bar in (a) denotes the 18-h point in the track. Ensemble mean 500-hPa geopotential height of 18-h forecasts initialized with “RSALL” (blue) and (b) “RSInterior”, (c) “RSExterior”, (d) “RSnoLL”, (e) “RSnoML”, and (f) “RSnoUL” (red) analyses at 0000 UTC 6 September. Color fill denotes the 500-hPa geopotential height difference between the blue and red contours.
Figure 4.14: Ensemble mean track of forecasts initialized with “HALL” (green) and “RSALL” (red) analyses at 0000 UTC 9-10 September for Ike case and corresponding 120-h GFS track forecast (blue) initialized at 0000 UTC 9 September (GFS09: square) and 0000 UTC 10 September (GFS10: triangle). The black-dash box highlights the track forecast differences between GFS and “HALL” and “RSALL” cases near Ike’s final landfall in southeastern Texas.

in Fig. 4.16a) shows the northwestern edge of the Atlantic subtropical ridge to the northeast of Ike is well-aligned with its counterpart in the corresponding/validating NCEP GFS analysis (blue contour). On the other hand, in the forecasts initialized on 0000 UTC 10 September and valid at the same time (Fig. 4.16b), the northwestern edge of the ridge in “HALL” is shifted further to the southwest which acts to push Ikes forecast track further westward. Essentially, the same situation is found between “RSALL” forecasts initialized on 10 September and valid at the same time.
Figure 4.15: (a) Similar to Fig. 4.14, but replace GFS forecast track with GFS analysis track. Black-dash box in (a) highlights the times between 0000 UTC 10 September and 0000 UTC 14 September (72 hours) in which the two forecasts (red and green) both cover but in different forecast lead times. (b) Mean steering vectors of forecasts initialized with “HALL” analyses at 0000 UTC 9 September (red) and at 0000 UTC 10 September (green) as function of forecast times for that 72 hours. As in (b), but (c) is for forecasts initialized with “RSALL” analyses. X-axis label in blue is for mean steering vectors calculated from GFS analysis (blue), and the other two X-axis labels are colored for corresponding forecasts.
Figure 4.16: Ensemble mean 500-hPa geopotential height of (a) 78-h forecasts initialized with “HALL” (red) analysis at 0000 UTC 9 September and GFS analysis (blue) valid at 0600 UTC 12 September. As in (a), but is 54-h forecasts initialized with “HALL” (red) analysis at 0000 UTC 10 September and GFS analysis valid at the same time in (b). Colorfill denotes the 500-hPa geopotential height difference between the blue and red contours. Cyan boxes highlight the location of the northwestern edge of the ridge to the northeast of Ike.
4.4 Summary and Discussions

In summary, our findings show that the direct assimilation of AMVs provides an improvement to the initial analyses of Sinlaku, but the results are more mixed for Ike. In addition to the impact of the various AMV subsets on TC initial analyses, the performance of 3-day ensemble forecasts initialized with the modified analyses is also evaluated. For Sinlaku during its early stage (9-11 September), the interior AMVs are found to be important for accurately initializing the TC structure and accordingly its initial motion, while the exterior AMVs influence the track forecasts beyond 1 day via improved representation of the environmental flow. A larger range of track errors in the ensemble is evident when interior AMVs are not assimilated. The upper-layer AMVs are particularly crucial in reducing the track errors. The interior AMVs reduce errors in the forecasts of MSLP over 3 days, and 34 kt wind radii over 1 day. There is no clear signal in the forecasts of MSLP and 34 kt wind radii when the AMVs in different layers are removed. For the subsequent stage of Sinlaku, between 11-12 September, the focus turned to track recurvature which was more carefully investigated in Wu et al. (2014). Our study shows that the AMVs from Rapid-Scans influence the steering flow correctly leading to forecast recurvature, albeit somewhat prematurely. This case presents a very sensitive situation, as interior AMVs, and AMVs at different layers produce substantially different forecast tracks.

The conclusions for the ensemble forecasts of Ike are not so clear, and are not entirely consistent with those of Sinlaku. For Ike, more similarities are evident between the forecasts from which Hourly versus Rapid-Scan winds are assimilated. This is perhaps expected, since unlike the Sinlaku case, the number of AMVs is not too different between Hourly and Rapid-Scan datasets. AMV observations in the exterior are particularly necessary to improve the track forecasts, and AMVs in all three layers exert a modest influence on the track forecast. Curiously, “noML” performs
the best for track forecasts, especially in the “RS” set of runs. While AMVs tend not to be overly abundant in this layer of the troposphere, AMV quality generally deteriorates in the middle levels due to uncertain vector height assignments. Since Ike was a well-developed vortex during this period, the steering flow was deep with a strong influence from the mid levels. Taking out the suspect mid-level AMVs in this case where the background steering flow is already good actually helps improve the subsequent track forecasts. Within 5 days of Ike’s landfall over northeastern Texas, the two WRF ensemble track forecasts examined with AMVs exhibit some variability, as did the operational numerical track forecasts issued at that time. The Rapid-Scan AMVs offer some improvement in one forecast case, but none in the other.

Commonalities in the findings between Sinlaku and Ike include the following: 1) interior AMVs are important for analyses and forecasts of MSLP, 2) excluding upper-layer AMVs generally results in larger track errors and ensemble spread, 3) compared with denying interior or exterior AMVs, withholding AMVs in different tropospheric layers has less impact on the forecasts of 34 kt wind radii, 4) without the assimilation of interior and upper-layer AMVs, the largest ensemble spreads are found in forecast track, MSLP and 34 kt wind radii, and 5) withholding the middle-layer AMVs can improve the track forecasts.

With only two tropical cyclones considered in this study, it is not suitable to generalize the conclusions. However, some insights are found, that could influence future scenarios that involve the targeted acquisition and assimilation of high-density AMV observations in TC events.

The frequent observational data with broad coverage over the TC and its surrounding environment lead to the assumption that the assimilation of AMVs derived from geostationary platforms is beneficial to TC initial position and intensity and their forecasts. This has been presented and discussed in both Chapter 3 and 4. In
the following chapter, the impact of assimilating satellite-derived observations from polar-orbiting platforms is discussed. The focus of the discussion is also switched from derived wind vectors to derived temperature and moisture observations, including those from satellite sounding profiles and integrated moisture surface observations.
Chapter 5

Improving the Assimilation of Temperature and Moisture Soundings and Total Precipitable Water

Previous chapters have discussed the influence of assimilating geostationary satellite-derived AMVs on TC analyses and forecasts by comparing parallel experiments that assimilate different AMV datasets (Chapter 3), and by conducting data-denial experiments for further understandings on the relative importance of the horizontal and vertical subsets of AMV datasets (Chapter 4). The current chapter switches to the use of polar-orbiting satellite derived observations and attempts to improve the assimilation of the observations on TC structure and environment under the mesoscale configuration. Polar-orbiting satellites comprise the majority of observations assimilated into current operational NWP centers worldwide. With many advanced instruments mounted on polar-orbiting satellites, observations including high-resolution soundings of temperature and moisture, ocean surface wind, precipitation and water vapor related products are the principal source of dynamic and thermodynamic information over the tropical oceans where conventional in-situ observations are limited. A
demonstration of the role of satellite data assimilation in the forecast of Hurricane Sandy (2012) by McNally et al. (2014) has highlighted the importance of assimilating polar-orbiting satellite observations in making accurate track forecast in 4-5 days lead time.

In the current chapter, observations including derived temperature and moisture soundings from the AMSU-AIRS product and the CIMSS research product and total precipitable water data from AMSR-E are utilized. Several parallel experiments are conducted to explore the influence of assimilating the aforementioned observations for Typhoon Sinlaku during its rapid-intensification and subsequent landfall in northern Taiwan.

5.1 Bias Correction on Soundings and Experimental Design

The quality and biases of satellite retrievals are two essential factors prior to the assimilation of satellite data. The accuracy of satellite retrievals can be affected by uncertainties and discrepancies in various retrieval algorithms between different satellites (Derber and Wu, 1998). Pu and Zhang (2010) compared total of 181 dropwindsonde observations from two field experiments, the NASA African Monsoon Multidisciplinary Analyses (NAMMA) over the eastern Atlantic Ocean and the THORPEX Pacific Asian Regional Campaign (T-PARC) over the tropical oceans with collocated AMSU-AIRS temperature and moisture soundings for Tropical Storm Debby (2006) and Typhoon Jangmi (2008). They found that while the AMSU-AIRS temperature profiles are slightly biased and are in good agreement with dropwindsonde observations near the TC environment, the AMSU-AIRS moisture profiles exhibit large dry bias over the tropical oceans where the TCs developed. The assimilation of AMSU-
AIRS products after their bias correction was then able to improve the simulation of Debby’s development.

In Pu and Zhang (2010), a total of 672 dropwindsondes were deployed during NAMMA (197) and TPARC (475) for the duration of Tropical Storm Debby (2006) and Typhoon Jangmi (2008), and only 67 and 114 matched profiles were found within maximum time difference of 2 h and maximum horizontal distance of 100 km from the collocated AMSU-AIRS soundings. These 67 and 114 matched profiles were then used for their bias correction Pu and Zhang (2010). To perform robust statistics for bias correction, a larger sample of matched profiles between the biased data (AMSU-AIRS soundings) and the ground truth (here, dropwindsondes) is required. The CIMSS AIRS dataset is known for its higher horizontal resolution and many more vertical levels in the sounding profiles. The spatial coverage of the CIMSS AIRS soundings is then largely reduced to compromise the better vertical and spatial resolution. It is difficult to acquire a good number of the matched profiles between the CIMSS AIRS soundings and dropwindsondes deployed during Typhoon Sinlaku (2008) for statistical significance. An alternative solution is the use of indirect ground truth.

The European Centre for Medium-Range Weather Forecasting (ECMWF) operationally provides high-resolution forecasts up to 10 days every 6 hour with 91 vertical levels and 0.25-degree spatial resolution. Taking the highly variant environment near TCs into account, CIMSS AIRS soundings that are located within ±1 hour difference from the ECMWF 6-hourly analysis (0-h forecast) are considered for the comparison. Due to the orbital design of Aqua satellite, its revisit times at the same day and same locations within the domain of interest are close to 0600 UTC and 1800 UTC. The ECMWF analysis valid at these two times are interpolated to the locations of the CIMSS AIRS soundings that are within ±1 hour difference from 0600 UTC and 1800 UTC respectively.
5.1.1 Bias Correction with ECMWF Analysis and Dropwindsonde Observations

Biases associated with the ECMWF forecast model and their data assimilation system also introduce errors in the analysis product. To alleviate this potential error, a total of 149 dropwindsonde temperature and moisture profiles deployed in T-PARC for the duration of Sinlaku are compared with the collocated ECMWF 91 level analysis data. In Fig. 5.1a, the ECMWF temperature profile is close to the dropwindsonde for most pressure levels, except for the slight warm bias between 300 and 600 mb. The ECMWF specific humidity profile as in Fig. 5.1b is found to be moister than dropwindsonde values above 750 mb. To correct the warm and moist biases, the 149 dropwindsonde profiles and the collocated ECMWF analysis data are interpolated onto 10 pressure levels, 1000, 925, 850, 700, 600, 500, 400, 300, 250, and 200 mb. A linear regression relationship is derived for both temperature and moisture profiles at each level between the collocated ECMWF analysis data and dropwindsonde profiles. This linear relationship is then used to correct the ECMWF analysis data to generate the “bias-corrected” ECMWF analysis (hereafter, BC-ECMWF analysis). The bias correction procedure ensures the biases between the ECMWF analysis data and dropwindsonde observations are adjusted while the spatial features in the ECMWF analysis data are preserved in BC-ECMWF analysis.

The BC-ECMWF analysis data are now used to correct the CIMSS AIRS soundings at co-locations. In Fig. 5.2a, the CIMSS AIRS soundings are found to be slightly colder than the BC-ECMWF analysis data above 750 mb and below 900 mb. The high correlation and R² (≥ 0.8) also suggest that bias correction based on the linear regression relationship has a large potential benefit for the soundings. A dry bias below 700 mb is found in the CIMSS AIRS specific humidity profiles (Fig. 5.2b). The correlation coefficients are well above 0.7 for most levels, but lower than the corre-
Figure 5.1: Averaged (a) temperature (K) and (b) specific humidity (g/kg) profiles over 149 collocated dropwindsondes (red) and ECMWF analysis data (black) during Typhoon Sinlaku (2008). Open circle and cross represents the correlation coefficient, $r$, and coefficient of determination, $R^2$, between the collocated data.

The corresponding values in the temperature profiles. In the specific humidity profiles, the much smaller $R^2$ also indicate the linear relationships are about 10-20% less representative than the linear relationships found in the temperature profiles. With lower correlation and $R^2$ values, the linear bias correction is expected to be less effective for specific humidity profiles.

Figs. 5.3 and 5.4 show the scatterplots of collocated points between BC-ECMWF and CIMSS AIRS temperature and specific humidity sounding profiles respectively. Similar to the bias correction procedure between the collocated dropwindsondes and ECMWF analysis data, the sounding profiles are grouped into 10 pressure levels. The linear relationship found in each group applies to the collocated points in the group.
Due to the low quality of retrieved soundings at upper levels, the bias correction is only performed for sounding profiles up to 200 mb.

### 5.1.2 Experimental Design

In addition to CTL (the same from Chapter 3), five parallel experiments that assimilate soundings from standard AIRS products and CIMSS AIRS products are prepared. The first experiment, AMSU-AIRS TQ, assimilates temperature and specific humidity soundings from the AMSU-AIRS products, and the second experiment, CIMSS-AIRS TQ, assimilates temperature and specific humidity soundings from the CIMSS AIRS products. The third experiment, BCCIMSS-AIRS TQ, assimilates temperature and specific humidity soundings from the bias-corrected CIMSS AIRS products based on
Figure 5.3: Scatterplots of collocated points between BC-ECMWF temperature analysis and CIMSS AIRS temperature soundings (K) at each level. The linear regression relationship, number of data points, averaged bias, and correlation coefficient (r) and coefficient of determination (R$^2$) of each scatterplot are listed in the upper-left corner. The light green line describes y=x and the red line describes the linear regression relationship.

ECMWF analysis. The fourth (fifth) experiment in which specific humidity (temperature) from CIMSS-AIRS TQ is excluded is prepared, and named CIMSS-AIRS T (CIMSS-AIRS Q). A summary of these WRF/EnKF experiments is given in Table 5.1.

5.2 Selected Results from Ensemble Analyses

The EnKF assimilation performance is first evaluated via vertical profiles of prior and posterior temperature, specific humidity, and horizontal winds at radiosonde locations in the environment of TC from the analyses of CTL, AMSU-AIRS TQ, CIMSS-AIRS TQ, and BCCIMSS-AIRS TQ (Figs. 5.5-5.7).
Figure 5.4: Same as Fig. 5.3, but for specific humidity (g/Kg).

5.2.1 Performance of EnKF Assimilation

Figure 5.5: The time-averaged vertical profiles of (a) root-mean-square error, (b) bias and (c) total spread of prior (colored solid lines) and posterior (dashed lines) for temperature (K) from the AIRS experiments verified with the radiosonde observations. (d) The number of commonly assimilated radiosondes in each experiment.
Table 5.1: Similar to Table 4.1, this table summarizes the WRF/EnKF cycled analyses-forecasts experiments for the understanding of the influence of assimilating the AIRS soundings during Typhoon Sinlaku (2008).

<table>
<thead>
<tr>
<th>Expt</th>
<th>Common Obs</th>
<th>AIRS Soundings Assimilated</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTL</td>
<td>Radiosondes u/v/t/q, aircraft data,</td>
<td>None</td>
</tr>
<tr>
<td>AMSU-AIRS TQ</td>
<td>u/v/t, surface altimeter data, JTWC/NHC advisory TC position data, and NCEP BUFR AMVs.</td>
<td>AMSU-AIRS Temperature and Specific Humidity Soundings</td>
</tr>
<tr>
<td>CIMSS-AIRS TQ</td>
<td>Similar to CIMSS-AIRS TQ, but with Bias-Corrected Soundings</td>
<td></td>
</tr>
<tr>
<td>BCCIMSS-AIRS TQ</td>
<td>Same as BCCIMSS-AIRS TQ, but excludes Specific Humidity Soundings</td>
<td></td>
</tr>
<tr>
<td>BCCIMSS-AIRS Q</td>
<td>Same as BCCIMSS-AIRS TQ, but excludes Temperature Soundings</td>
<td></td>
</tr>
</tbody>
</table>

The assimilation performance is evaluated via comparing the error statistics of temperature, specific humidity, and horizontal winds at radiosonde locations estimated by CTL, AMSU-AIRS TQ, CIMSS-AIRS TQ, and BCCIMSS-AIRS TQ. Another two experiments, in which the specific humidity and temperature profiles are denied respectively, BCCIMSS-AIRS T and BCCIMSS-AIRS Q, are discussed later. The reduction of time-averaged RMSE temperature profiles (about 0.25 K from prior to posterior) suggests the assimilation (Fig. 5.5a). CTL is found to have smaller RMSE than AMSU-AIRS TQ and CIMSS-AIRS TQ, especially from 500 hPa and above. After the linear bias correction, the RMSE of BCCIMSS-AIRS TQ is smaller and most evident from 700 hPa and above. The bias profile of BCCIMSS-AIRS TQ is also closer to zero (Fig. 5.5b) while the bias profiles of AMSU-AIRS TQ and CIMSS-AIRS TQ are large in middle and upper levels. In general, BCCIMSS-AIRS TQ and CTL have similar bias profiles, and the biases are slightly smaller in BCCIMSS-AIRS TQ profiles. The total spread profiles of temperature are a tight cluster and the reduction is found subtle in posterior (Fig. 5.5c).
The corresponding profiles for specific humidity are examined and illustrated in Fig. 5.6. RMSE reduction is also evident from prior to posterior (Fig. 5.6a). While the profiles are tightly clustered, especially in the upper levels, the RMSE of CIMSS-AIRS TQ is found slightly larger than the rest of the experiments. In the bias profiles, CIMSS-AIRS TQ also exhibits large dry biases in middle to lower levels while the rest of the experiments are either slightly moist or fairly close to zero (Fig. 5.6b). The total spread of specific humidity profiles reveals very subtle differences between each experiment in both prior and posterior profiles (see Fig. 5.6c).

![Figure 5.6](image)

**Figure 5.6:** Similar to Fig. 5.5, but for specific humidity (g/Kg).

In addition to temperature and moisture, profiles of RMSE and bias are also examined for horizontal winds (due to similarity, only zonal wind is shown here). Note that the bias correction was performed on temperature and specific humidity profiles of CIMSS AIRS dataset. The assimilation of these bias-corrected temperature and specific humidity profiles has shown improved horizontal wind analysis with reduced the wind speed RMSE and bias as well. The RMSE is reduced by $\sim 1$ m s$^{-1}$ from prior to posterior (Fig. 5.7a). CTL has the smallest RMSE in each level and AMSU-
AIRS TQ have largest RMSE above 400 hPa, although the RMSE of CIMSS-AIRS TQ is largest in most of the levels below 400 hPa. In Fig. 5.7b, profiles of biases are within \( \pm 1 \text{ m s}^{-1} \) in each experiment with negative bias in the lower levels and positive biases in the upper levels. The bias of CIMSS-AIRS TQ is found to be largest than the rest of the experiments. Similar to the temperature total spread profiles (Fig. 5.5c), the uncertainty of estimating zonal wind is reduced by \( \sim 0.5 \text{ m s}^{-1} \) from prior to posterior. The total spread of AMSU-AIRS TQ prior temperature profiles has highest uncertainty throughout the vertical level, and exceptionally higher above 250 hPa. The prior total spread profiles of CTL and CIMSS-AIRS TQ are slightly smaller than that of AMSU-AIRS TQ, and the bias corrected BCCIMSS-AIRS TQ has the smallest uncertainty at all levels.

![Figure 5.7: Similar to Fig. 5.5, but for zonal wind (m s\(^{-1}\)).](image)

### 5.2.2 Verification with Dropwindsonde Observations

The 27-km ensemble analyses from CTL and the five parallel AIRS experiments are further evaluated via verifying the vertical profiles of storm-relative temperature,
specific humidity, and tangential and radial winds with independent dropwindsondes (not assimilated) less than 1200 km from the TC center (Fig. 5.8). The temperature RMSE profiles of CTL, CIMSS-AIRS TQ, BCCIMSS-AIRS TQ, BCCIMSS-AIRS T, and BCCIMSS-AIRS Q have similar vertical structure with RMSE ranging from 0.7 to 1.7 within 1000-2000 hPa while AMSU-AIRS TQ has distinct temperature RMSE profile with largest errors beyond 2 K above 350 hPa. In Fig. 5.8b-d, the specific humidity, tangential wind, and radial wind RMSE profiles of AMSU-AIRS TQ also exhibit larger errors, and the RMSE profiles of CTL, CIMSS-AIRS TQ, BCCIMSS-AIRS TQ, BCCIMSS-AIRS T, and BCCIMSS-AIRS Q are a tight cluster.

The impacts of bias correction are more evident in the profiles of temperature and tangential and radial winds, and less so in specific humidity profiles (CIMSS-AIRS TQ vs. BCCIMSS-AIRS TQ). Nevertheless, the RMSE profiles of BCCIMSS-AIRS TQ and CTL are similar in general. It is found that assimilating the additional bias-corrected CIMSS AIRS temperature and moisture soundings has slight improvement in the vicinity of TC. As one would expect from comparing BCCIMSS-AIRS T and BCCIMSS-AIRS Q, temperature RMSE increases when temperature soundings are withheld and specific humidity RMSE becomes larger when specific humidity soundings are withheld.

Ensemble mean analyses of CTL, AMSU-AIRS TQ, and BCCIMSS-AIRS TQ are discussed in more detail here. In Figs. 5.9a-c, 850 hPa temperature and MSLP show that while the MSLP is comparable between CTL, AMSU-AIRS TQ, and BCCIMSS-AIRS TQ, AMSU-AIRS TQ is much colder in the vicinity of Sinlaku. Similar to the temperature field, AMSU-AIRS TQ is also found drier than CTL and BCCIMSS-AIRS TQ analyses in the vicinity of TC when Sinlaku is under rapid-intensification (Figs. 5.9d-f). The west-east cross-section along TC center in Figs. 5.9g-i also suggest AMSU-AIRS TQ having less organized 3-dimensional wind structure. These findings
Figure 5.8: The time-averaged vertical profiles of root-mean-square error for (a) temperature, (b) specific humidity, (c) tangential wind, and (d) radial wind from the AIRS experiments verified with the dropwindsondes observations.

in Fig. 5.9 and the vertical profiles of dropwindsondes suggest that the assimilation of standard AIRS sounding profiles results in weak, dry, and cooler TC during its intensification period.

5.3 Selected Results from Ensemble Forecasts

Short-term ensemble forecasts with the full ensemble are produced for each experiment by integrating the 84 ensemble analyses to 72 hours. To be consistent with the ensemble analyses, the short-term forecast follows the same WRF configuration as was done in the assimilation experiment, together with a vortex-following inner grid of 9-km. Three initial times are selected: 1200 UTC, on each day of 9-11 September 2008 to understand the influence of assimilating AIRS soundings on short-term forecasts of Sinlaku.
Figure 5.9: Ensemble mean 850 hPa temperature (colorfill) and MSLP (contour) of (a) CTL, (b) AMSU-AIRS TQ, and (c) BCCIMSS-AIRS TQ analyses at 0000 UTC 10 September 2008. (d)-(f), similar to (a)-(c), but for ensemble mean 950 hPa water vapor mixing ratio (colorfill) and wind vector. (g)-(i), similar to (a)-(c), but for west-east cross-section of horizontal divergence (colorfill) and meridional wind (contour) along the TC center.
Ensemble mean errors of track, MSLP (intensity), and 34-knot wind radii (size) averaged over the 3 forecast cases are summarized in Fig. 5.10a-c. AMSU-AIRS TQ has the lowest averaged track errors, but weakest intensity. In comparison to CTL, CIMSS-AIRS TQ has larger track errors (20 km in average). The initial MSLP errors are slightly lower but quickly converge to that of CTL after 24 hours. After the bias correction, BCCIMSS-AIRS TQ exhibits smaller track errors than CIMSS-AIRS TQ and CTL, but still slightly larger track errors than AMSU-AIRS TQ. The impact of assimilating bias-corrected CIMSS AIRS soundings on intensity is more perceptible after 24 hours onward. Both BCCIMSS-AIRS T and BCCIMSS-AIRS Q
have larger track forecast errors than BCCIMSS-AIRS TQ. Withholding the temperature profiles, BCCIMSS-AIRS Q, results in worse track forecasts than withholding the specific humidity profiles. On the contrary, withholding the temperature profiles improves the initial MSLP forecasts up to 36 hours. It is also found that withholding the specific humidity profiles of bias-corrected CIMSS AIRS soundings has slightly negative impact on MSLP forecasts. In Fig. 5.10c, AMSU-AIRS TQ produces smaller storm than observed while CTL, CIMSS-AIRS TQ, BCCIMSS-AIRS TQ and its denial experiments all produce slightly larger storms in average.

5.4 Summary of the Selected Results

The AIRS temperature and specific humidity sounding profiles from the AMSU-AIRS product and CIMSS research product are assimilated into the WRF/EnKF data assimilation system for the case of Typhoon Sinlaku (2008). The CIMSS AIRS sounding profiles are provided with better vertical and spatial resolution but limited spatial coverage due to the use of high-resolution pixels and AIRS hyperspectral IR channels only. On the other hand, the AMSU-AIRS product provides soundings with broad spatial coverage but coarser spatial and vertical resolution by using both AIRS IR and AMSU MW channels.

A linear bias correction is performed on the CIMSS AIRS soundings with the 91 level 0.25 x 0.25 degree ECMWF analyses that are corrected by 149 collocated dropwindsonde observations. The two parallel experiments, AMSU-AIRS TQ and BCCIMSS-AIRS TQ, have shown distinct TC structure. During the rapid-intensification period of Sinlaku, AMSU-AIRS TQ produces dry and cold environment in the vicinity of storm. The wind structure is also less organized than CTL. BCCIMSS-AIRS TQ is found to be comparable to CTL with less pronounced structural differences. Short-range ensemble forecasts also suggest ensemble forecasts initialized by AMSU-
AIRS TQ result in more accurate track forecasts but weak storm intensity while forecasts initialized by BCCIMSS-AIRS TQ exhibit less accurate track forecasts but more intensified storm.

![Figure 5.11: Same as Fig. 5.1, but for averaged profiles over collocated BC-ECMWF analysis data and the AMSU-AIRS soundings.](image)

Note that no bias correction is performed on the AMSU-AIRS soundings. In Fig. 5.11a, the averaged temperature profiles are slightly colder than the collocated BC-ECMWF analysis data. Dry biases are also visible in the lower tropospheric layers (below 600 mb in Fig. 5.11b). These biases associated with the AMSU-AIRS soundings may be responsible for producing a dry and cold storm in Figs. 5.9b,e, and h. While both the correlation and coefficient of determination are high between the temperature collocated points, these two coefficient are much lower between the specific humidity collocated points (Fig. 5.11). Performing the linear bias correction
on the AMSU-AIRS soundings is possible to correct the cold bias, but is less likely to correct the dry bias in lower levels.

Given the fundamental differences including 1) spatial resolution, 2) horizontal coverage, and 3) potential biases introduced by different retrieval algorithms between the AMSU-AIRS and CIMSS AIRS products, it is unclear and not necessary to conclude whether one is superior to the other on improving the analyses and forecasts of Typhoon Sinlaku. Without further investigations, the puzzle regarding whether spatial resolution or the horizontal coverage plays a more important role in improving the TC structure and track forecasts also remains unsolved. Nevertheless, this study suggests that assimilating the CIMSS AIRS temperature and moisture soundings has positive impacts on improving TC structure, and the assimilation of the AMSU-AIRS soundings generates a more accurate TC track.

### 5.5 Preliminary Results from the TPW Assimilation Experiments

In addition to the experiments that assimilate AIRS soundings, two more parallel experiments are prepared to understand the impacts of assimilating TPW data on TC analyses and forecasts (Table 5.2).

**Table 5.2:** Similar to Table 5.1, this table summarizes the WRF/EnKF cycled analyses-forecasts experiments for the understanding of the influence of assimilating the AMSR-E TPW during Typhoon Sinlaku (2008).

<table>
<thead>
<tr>
<th>Expt</th>
<th>Common Obs</th>
<th>TPW Assimilated</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTL</td>
<td>Radiosondes u/v/t/q, aircraft data u/v/t, surface altimeter data, JTWC/NHC advisory TC position data, and NCEP BUFR AMVs.</td>
<td>None</td>
</tr>
<tr>
<td>AMSR-E TPW</td>
<td>AMSR-E Standard L2 Total Precipitable Water</td>
<td></td>
</tr>
<tr>
<td>BCAMSR-E TPW</td>
<td>Similar to AMSR-E TPW, but with Bias-Corrected TPW</td>
<td></td>
</tr>
</tbody>
</table>
The AMSR-E standard level 2 TPW products are selected. The strong emissivity from the background of land inhibits the retrieval quality of TPW over land surface. In this study, only TPW products over ocean are utilized. TPW is related to the atmospheric moisture profile via

\[ TPW = \frac{\int_{p_{\text{bottom}}}^{p_{\text{top}}} q_v dp}{\rho g} \]  

where \( q_v \) is water vapor mixing ratio, \( p \) is pressure, \( \rho \) is atmospheric density, and \( g \) is gravitational acceleration. The TPW is usually integrated from the surface to 200 hPa, where the atmosphere becomes very dry.

The BC-ECMWF analysis data is again used to bias correct the AMSR-E TPW at co-locations with the linear regression method utilized in Section 5.1. Very high correlation \( r \geq 0.96 \) and \( R^2 \) are found between the collocated points regardless of the small averaged bias ( -0.01 cm in Fig. 5.12). The single linear fit in Fig. 5.12 is found to be less representative for TPW values above 6 cm. It is likely that the higher TPW values are associated with the vicinity of the TC.

Given the fact that a) the averaged bias is small and 2) the single linear fit is insufficient for larger TPW values, the impact from bias correction is expected to be minor. In Fig. 5.13a, the difference between RMSE profiles of temperature before and after bias correction are subtle. The impact from the linear bias correction is more visible in the specific humidity profiles in which the BCAMSR-E TPW has slightly lower RMSE than AMSR-E TPW (Fig. 5.13b).

In comparison to CTL, the assimilation of AMSR-E TPW regardless of bias correction produces more accurate TC primary and secondary wind structure and temperature (not below 700 mb) and moisture profiles (Figs. 5.13a-d). The impact of assimilating the AMSR-E TPW data is positive and slightly more promising than re-
results from assimilating the AMSU-AIRS and CIMSS-AIRS soundings in the vicinity of the TC.

The west-east cross-section through the TC center also reveals a more intensified and moist storm after the assimilation of AMSR-E TPW data regardless of the linear bias correction (Fig. 5.14). As mentioned previously, Fig. 5.13 and Figs. 5.14b-c together conclude that the single linear bias correction on TPW has a subtle impact on the TC structure. Finally, the results from Chapter 3, 4, and 5, and the impact of assimilating AMSR-E TPW on short-range forecasts are discussed in the next chapter in concluding the overall assimilation experiments.

Unlike AMVs and AIRS soundings, TPW is a vertically-integrated surface observation that describes the amount of water between the surface and the top of the troposphere. Preliminary results suggest that assimilating the AMSR-E TPW data produces a more intensified storm regardless of bias correction. Before the linear bias...
Figure 5.13: Similar to Fig. 5.13, but for the AMSR-E TPW experiments.

Figure 5.14: West-east cross-section of ensemble mean water vapor mixing ratio (colorfill), relative vorticity (black contour), and temperature (red contour) along the TC center.

correction, the impact on temperature structure in the vicinity of Sinlaku is more pronounced than the impact on moisture structure.
Figure 5.15: Spatial distribution of AMSR-E TPW data that is (a) within and (b) outside the 1000 km radius of the center of Sinlaku. (c)-(d), similar to Fig. 5.12, but for the collocated points in (a) and (b) respectively.

It is found that the single linear fit to the entire collocated points between AMSR-E TPW data and the BC-ECMWF analysis data throughout the domain of interest may not represent the majority of high TPW values that are associated with the TC (see Fig. 5.15a). The collocated points are separated by their geographical distances to the center of Sinlaku as seen in Figs. 5.15a-b. For collocated points that are within 1000 km of Sinlaku (interior), the AMSR-E TPW data has an average of 0.12 cm moist bias over the BC-ECMWF analysis. In Fig. 5.15c, the linear relationship changes from $y = 0.90x + 0.53$, where all collocated are included, to $y = 0.68x + 1.74$, where only the interior collocated points are included. While the correlation and $R^2$ (0.84 and 0.71 respectively) are slightly lower than the values when all collocated
points are counted (0.96 and 0.93 respectively), the linear bias correction can be a potential correction to the moist-biased AMSR-E data in the vicinity of TC. Outside the vicinity of the TC, the average bias between the collocated points is as small as -0.04 cm, and $y = 0.93x + 0.40$ well describes the linear relationship between collocated points with very high $r$ and $R^2$ (Fig. 5.15d).

Given the bias-sensitivity in the vicinity of TC, the future work regarding the use of TPW data may involve dividing the domain of interest to TC interior and exterior and then apply the linear bias corrections respectively.
Chapter 6

Summary and Future Directions

The research in this dissertation has investigated the influence of assimilating satellite-derived observations on mesoscale analyses and forecasts of tropical cyclone track and structure with the WRF/EnKF data assimilation system. Detailed discussions and conclusions regarding the impacts of assimilating AMVs, AIRS temperature and moisture soundings, and AMSR-E TPW were provided in Chapter 3 and 4, and 5 respectively. In this chapter, an overall summary of the results including all the assimilation experiments is given.

6.1 Comparison between Satellite Datasets

The spatial and temporal availability of the satellite observations used in this work have fundamental differences largely owing to the satellite platforms and retrieval algorithms, from which these derived observations originate. The spatial distribution of satellite-derived observations including CIMSS hourly AMVs, AMSR-E TPW, AMSU-AIRS and CIMSS AIRS soundings in 3-hour assimilation interval is illustrated in Fig. 6.1. The distributions of AMSR-E TPW and AMSU-AIRS soundings are almost identical because AMSR-E and AIRS are both carried on NASA’s Aqua satellite.
Figure 6.1: 1-day spatial distribution of (a) CIMSS hourly AMV dataset, (b) AMSR-E TPW, (c) standard AIRS soundings, and (d) CIMSS AIRS soundings observations. Observations are grouped into 3-hour assimilation interval centered at 00Z, 03Z, etc.
Table 6.1: 3-hourly assimilated observation counts within 1000 km of Sinlaku averaged over the entire assimilation period (8-13 September, 2008)

<table>
<thead>
<tr>
<th>Obs</th>
<th>00Z</th>
<th>03Z</th>
<th>06Z</th>
<th>09Z</th>
<th>12Z</th>
<th>15Z</th>
<th>18Z</th>
<th>21Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>CIMSS hourly AMV</td>
<td>331</td>
<td>254</td>
<td>293</td>
<td>174</td>
<td>211</td>
<td>160</td>
<td>210</td>
<td>182</td>
</tr>
<tr>
<td>Standard AIRS soundings</td>
<td>0</td>
<td>19</td>
<td>253</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>339</td>
<td>0</td>
</tr>
<tr>
<td>CIMSS AIRS soundings</td>
<td>0</td>
<td>1</td>
<td>37</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>49</td>
<td>0</td>
</tr>
<tr>
<td>AMSR-E TPW</td>
<td>0</td>
<td>20</td>
<td>180</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>183</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 6.1 further summarizes the observation counts in the interior of storm, within 1000 km radius of the center of Sinlaku, in a 3-hour assimilation interval. The spatial coverage of the CIMSS hourly AMV dataset is continuous and almost homogeneous over the storm interior. On the other hand, the spatial coverage of AMSR-E and AIRS over the storm interior only occurs twice per day (06Z and 18Z in northwestern Pacific basin). Nevertheless, it is noteworthy that the observation counts in the storm interior are comparable to the CIMSS hourly AMV datasets. Note that one single sounding is more than a data point. Each sounding contains vertical profiles of atmospheric thermal structure.

Fig. 6.2 compares the performance of 72-h ensemble forecasts from the experiments previously discussed individually in Chapter 3, 4, and 5. The assimilation of CIMSS hourly AMVs produces more accurate track and intensity forecasts than CTL and most of the other experiments, but it tends to generate larger storms. The assimilation of AMSU-AIRS soundings produces better track forecasts, comparable to forecasts initialized with the assimilation of CIMSS hourly AMVs, but it generates much weaker storms. The assimilation of bias-corrected CIMSS AIRS soundings improves the intensity forecasts, however, the improvement over CTL is subtle and only perceptible from 30 hours onward. Unlike the improvements seen in the AMSR-E TPW analyses, ensemble forecasts initialized with the assimilation of AMSR-E TPW have poor track forecasts, but good short-range intensity forecasts up to 48 hours.
The results also suggest that the impacts on forecast track, intensity, and size are not well correlated. There is no particular single case that simultaneously improves all three metrics (i.e. TC track, intensity, and size). Table 6.2 summarizes the correlation coefficients between pairs of the three error metrics that are computed by 72-h ensemble forecasts initialized with CTL, AMSU-AIRS TQ, BCCIMSS-AIRS TQ, AMSR-E TPW, and CIMSS HAMV analyses. These error metrics are absolute values so that errors of intensity and size do not suggest stronger (weaker) and larger (smaller) storm, rather, they signify the inaccuracy compared to observed values.

In Table 6.2, the correlation coefficients are all very small ($r \leq 0.2$). The correlation between track and intensity errors and the correlation between size and intensity errors are especially weak ($r \leq 0.1$ for most cases). The correlation coefficients between track and size errors are slightly larger ($\approx 0.16$), but are still considered statistically weak. This statistical analysis shows that there is low consistency between improvements in track, intensity, and size forecasts. Improving track forecasts does not guarantee the improvement in intensity or size forecasts, and vice versa.
Table 6.2: The correlation coefficients ($r$) between ensemble forecast errors for each assimilation experiment. The first column lists $r$ between track errors and intensity errors, the second column lists $r$ between track errors and size errors, and the last column lists $r$ between size errors and intensity errors respectively for the five forecast experiments as shown in Fig. 6.2.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Track vs. Intensity</th>
<th>Track vs. Size</th>
<th>Size vs. Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTL</td>
<td>-0.03</td>
<td>0.15</td>
<td>0.16</td>
</tr>
<tr>
<td>AMSU-AIRS TQ</td>
<td>0.02</td>
<td>0.15</td>
<td>0.01</td>
</tr>
<tr>
<td>BCCIMSS-AIRS TQ</td>
<td>-0.11</td>
<td>0.17</td>
<td>0.03</td>
</tr>
<tr>
<td>AMSRE-TPW</td>
<td>0.01</td>
<td>0.17</td>
<td>0.08</td>
</tr>
<tr>
<td>CIMSS HAMV</td>
<td>-0.09</td>
<td>0.16</td>
<td>0.04</td>
</tr>
</tbody>
</table>

While future operational data assimilation aims to include as many observations that are available, one of the original goals of this research is to suggest what combination of observational datasets are most likely to produce the desirable performance - an overall improvement in TC track, intensity, and structure (size) forecasts. The simple statistical test (Table 6.2) shows that the results do not provide any definitive conclusion on the combination of datasets that will provide significant improvement in TC forecasts. Based on Chapters 3-5 and Fig. 6.2, the assimilation of AMV has shown the most promising results regarding the desirable performance. With sufficient computing resources, it is expected the impact of assimilating AMVs will dominate the performance when all satellite-derived observations are assimilated at the same time.

### 6.2 Scientific Questions and Hypotheses Reviews

The scientific questions and hypotheses are listed again and discussed briefly below:

**Reviews of the Scientific Questions:**

- How are the model states modified when each satellite-derived dataset is assimilated?
• Have the short-range ensemble forecasts improved with improved analyses through assimilating satellite-derived observations?

• If the answer is yes, how long do the forecasts retain the influence of assimilated data in terms of TC track, intensity, and storm size forecasts?

• Given that polar-orbiting satellite observations are less frequent and more sparse in the vicinity of TCs in comparison to geostationary satellite observations, what is their values in mesoscale TC data assimilation?

The assimilation performance is evaluated by verifying with co-located independent observations such as dropwindsonde wind and temperature profiles and best track data that has TC location, intensity, and size information. In addition, qualitative and quantitative comparisons between the CTL and parallel assimilation experiments are also addressed in Chapters 3-5 respectively. While the verification is mostly taken in the vicinity of TC, the modification to the TC environment from the assimilation is also discussed via examining the 500 hPa geopotential height field and deep-layer (850 to 200 mb) area-averaged steering flow.

The assimilation of CIMSS hourly AMV data has improved the primary and secondary circulation of TC Sinlaku and its initial intensity. The analysis increment in Fig. 3.6 also reveals a physically consistent modification to the corresponding thermodynamic fields throughout troposphere. Furthermore, the results of data-denial experiments suggest the assimilation of interior and upper-layer AMVs is especially responsible for the improvement of TC structure and initial position. The evolution of area-averaged steering flow indicates TC Sinlaku track is highly sensitive to environmental steering, with very different track forecasts resulting from the different AMV datasets denied in the assimilation experiments.

The assimilation of bias-corrected CIMSS-AIRS soundings has little impact on TC circulation and slightly positive impact on the temperature and moisture fields in
the vicinity of TC. The AMSU-AIRS experiment has shown degraded TC structure, both dynamically and thermodynamically, that is very likely due to the obvious cold and dry biases in AMSU-AIRS soundings. The preliminary results from the AMSR-E TPW experiments have shown promising improvements in TC thermal and dynamical structure regardless of the linear bias correction based on the ECMWF analysis dataset.

Reviews of the Hypotheses:

1. With broad spatial coverage and good quality, the enhanced AMVs provide better representations of the upper-level wind structure and the environmental steering flows. The assimilation of the enhanced AMVs should lead to more accurate analyses and further improve track and intensity forecasts. This hypothesis is examined in both Chapter 3 and 4 and is found valid. In Chapter 3, the comparison between CIMSS(h) (or CIMSS(h+RS)) to CTL reveals how the assimilation of enhanced AMVs result in more accurate TC structure analyses and subsequent improved TC track and intensity forecasts. Parallel data-denial experiments further identify the interior and upper-layer AMVs are especially crucial for maintaining the TC structure and initial position. Ensemble forecasts initialized with the denial experiments also confirm that without assimilating interior or upper-layer AMVs the ensemble errors of track, intensity, and size forecasts are larger and the ensemble uncertainties are higher as well.

2. Temperature and moisture soundings with high vertical resolution and microwave TPW data in the vicinity of TC are critical for representing the environment, in particular when it is favorable for TC development. The assimilation of these data should improve the forecast of TC intensity change, especially during rapid intensification.
This hypothesis is examined in Chapter 5 and requires further investigations before it can be passed. The assimilation of AMSU-AIRS soundings (without bias correction) shows a weaker storm while the assimilation of bias-corrected CIMSS-AIRS soundings shows some improvement in the TC structure, albeit subtle. While the obvious dry and cold biases were identified in the AMSU-AIRS soundings, the linear bias correction is likely to improve the performance of the assimilation of AMSU-AIRS soundings. However, the linear dependence between the AMSU-AIRS humidity profiles and the BC-ECMWF analyses collocated points are rather weak, and the potential to correct the cold bias is lower and may require further work to separate the soundings into TC and non-TC regions. Preliminary results from the AMSR-E TPW assimilation experiments suggest positive impact on TC structure analyses. However, the short-range forecasts exhibit the largest TC track errors.

3. Given that dynamic datasets such as the enhanced AMVs has higher spatial and temporal availability than thermodynamic datasets, it is anticipated that the assimilation of dynamic satellite-derived data will dominate the impacts of the analyses and forecasts on the TC structure and environment.

This hypothesis is examined in Chapter 3, 4, and 5 and appears to be valid under the framework of this dissertation research. Hyperspectral soundings and TPW data (thermodynamic datasets) that are originated from polar-orbiting satellites are relatively few and less frequent than observations derived from geostationary satellites. The AIRS temperature and moisture soundings and the AMSR-E microwave TPW data are available only twice per day while the CIMSS AMV datasets are available hourly and even more frequent when Rapid-Scan mode is activated.
6.3 Implications for Data Assimilation for Tropical Cyclones

Chapter 3 and 4 together suggest that high temporal and spatial AMVs derived from geostationary satellites have contributed to improving not only the environmental steering flow but also the description of TC structure. The increased density and coverage of AMVs over the storm interior along with the more frequent assimilations are beneficial to mesoscale numerical TC forecasts for both track and intensity. Furthermore, it is found that the interior and upper-layer AMVs have more potential to improve the accuracy and certainty of estimating TC track and structure and therefore provide suggestions for the data assimilation community on what specific attributes of AMVs may be more beneficial at improving the initial analyses of TCs and their near-environments if there is priority in data selection or observation weighting.

The discussion of the impacts from between AMSU-AIRS and CIMSS-AIRS sounding datasets is more than answering to a multiple choice question that simply asks which dataset is superior to another. It involves multiple issues including whether data coverage or data resolution is more important and how do the different combinations of sounding coverage and resolution influence the subsequent TC track, intensity, and structure (size) forecasts. Observed from the results in Chapter 5, the findings suggest the high-resolution temperature and moisture soundings have positive impacts on TC wind and thermal structure. The impacts are subtle and are likely due to the low frequent data availability. By combining AMSU microwave channels, the additional information from microwave radiance improves the sounding spatial coverage but reduces the sounding resolution. The assimilation of these soundings with broad coverage shows improved TC track forecasts but degraded TC intensity forecasts without applying any bias correction. The overall results from the sounding
assimilation experiments in Chapter 5 demonstrate the importance of having satellite-derived soundings with both broad spatial coverage and higher horizontal and vertical resolution for TC applications.

6.4 Future Research Directions

As the title of the dissertation suggests, the goal is to understand the influence of the assimilation of satellite-derived observations on TC mesoscale analyses and forecasts. A broad topic like this involves various aspects that require expertise in satellite data, numerical modeling, data assimilation, and TC dynamics. While advancement and improvement of each component is taking place along the work of this research, here, the author presents only some of such topics that are directly related to this study.

- As proxies for local horizontal winds, the enhanced AMV dataset are provided with estimated errors (EE) that reflect the errors associated with the ever-changing flows. However, in order to have equivalent configurations as CTL experiments, AMV observation errors are assigned according to NCEP operational guide, which has much larger errors than the EE that comes with the enhanced AMV dataset and has no reflection of the error of the day. The process of superobbing also loses fine flow features by averaging over observations within a pre-defined prism. Ideally, the introduction of flow-dependent observation errors (i.e. the use of EE) and a data assimilation scheme which accounts for error correlations should alleviate the issues and more optimally exploit the use of the densely-distributed satellite-derived observations.

- The less frequent refresh rate of polar-orbiting satellite has limited the coverage and density of data over TC and its surrounding environment. The assimilation of the derived products including soundings and surface observations such as
TPW has shown improved analyses of TC initial positions and MSLP. However, the improvement over noDA (i.e. CTL) is subtle. Evidence in Chapter 5 has shown that bias correction on CIMSS AIRS soundings is capable of reducing the RMSE of temperature and moisture profiles estimated at both radiosonde and dropwindsonde locations. It is anticipated that bias correction on standard AIRS soundings, especially those in the vicinity of TC, has potential to improve the temperature and moisture analyses at dropwindsonde locations, and furthermore reduce intensity forecast errors.

While the launch of hyperspectral sounders onboard geostationary satellites is one of the ideal approaches to improve the satellite sounding coverage, accuracy, resolution, and frequency at the same time, it may be many more years ahead before the standard products become available. The assimilation of satellite radiances, especially in cloudy condition and moist atmosphere, is an alternative approach to satellite soundings for TC data assimilation.

- Due to limited computing resources, data assimilation is only performed on the larger domain of 27 km grid size in this study. To compromise the rather coarse resolution, a vortex-following 9 km inner nest is introduced in the forecast step to allow the information from finer domain to feed back onto the coarser domain. On the other hand, the horizontal dimension of the superob prism within which the satellite-derived observations are averaged is chosen to be rather large and reflecting more than 3 times the model grid size (90 x 90 km). There are no well-documented rules regarding the choice of superob prism size based on the model configurations. The prism size of about 2 times the model grid size is empirically preferred in current data assimilation community. This is because by averaging the densely distributed observations within a prism that is 2 times
the model grid size guarantees that the superob features can be resolved by model, and the superobs are also able to retain the finest features.

- Increasing the grid resolution of forecast models has shown to improve the TC intensity and structure forecasts in recent mesoscale modeling. Data assimilation performed on much finer domains may further improve the use of high-resolution satellite data and therefore provide better representation of the TC structure, especially features in near core region that are crucial to TC intensity change.

- It is noted that the model uncertainties are not properly accounted for in EAKF embedded in DART. Boundary layer and microphysics parameterizations and land surface schemes are known sources of large uncertainties. Ensemble data assimilation without proper consideration of model uncertainties may suffer from insufficient ensemble spread, which can lead to poor analyses and forecasts. While the under-dispersiveness can be alleviated by adaptively inflating the ensemble spread, techniques to represent model uncertainties have been proposed, including multi-physics approach and stochastic kinetic-energy backscatter scheme (SKEBS). A Multi-physics approach aims at sampling over different physics packages while SKEBS perturbs ensemble members by a stochastic forcing term to represent the effects of missing subgrid-scale fluctuations. Both methods have shown more reliable and skillful ensemble analyses and improved short-range forecasts in mesoscale ensemble prediction system with WRF-DART.

Due to the observation data availability and limitations on computing resources, the investigation is only performed on two TC cases. Despite the limited TC cases, Typhoon Sinlaku and Hurricane Ike are the most challenging cases for operational
models to predict in the northwestern Pacific and north Atlantic basins in 2008 respectively. Conclusions drawn from this study should not be generalized until more TC cases are examined.

6.5 Final Remarks

While this study investigates the use of high-resolution satellite-derived observations to understand their impacts on mesoscale TC numerical prediction, a more comprehensive mesoscale analysis for TC forecast that includes other aspects of NWP is still needed. Satellite observations play a huge role in NWP and TC forecasts. The prediction of tropical cyclones, a multi-scale weather system, requires both in-situ and satellite observations to improve our understanding of its fine structure and embedded environment. It has been shown that in addition to high-resolution satellite observations, the assimilation of TC advisory latitude and longitude is critical to TC initial position estimates, especially during genesis and early development stage.

There are many fundamental differences between satellite observations and given that this study uses only two TC cases and several assimilation experiments, it is difficult to conclude which satellite platforms and what kinds of satellite observations are more beneficial. Further investigations are necessary to device optimal strategies for assimilating satellite observations that would improve TC forecasts. Nevertheless, this study recommends the use of observations with high temporal frequency, broad spatial coverage, and greater proximity of TCs for overall improvement of TC track and structure under the mesoscale configuration. That is to say, the development of a continuous monitoring polar-orbiting and geostationary satellite constellations is essential to improve TC prediction.

Finally, precipitation is another important aspect of TC dynamics and forecasts, but it is beyond the scope of this study. Recent developments in satellite instruments
(e.g. The Global Precipitation Measurement mission) and advanced radiative transfer modeling increases the possibility to use satellite data under all weather conditions. More useful information regarding the TC inner core and rainband structure is expected to improve our understanding of TC evolution and intensity change that are crucial to accurate forecasts.
References


