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大氣科學學系

碩士論文

北臺灣微脈衝差分吸收光達資料分析與同化水
氣及雷達之影響：TAHOPE SOP3 及 IOP3 個案
分析

Analysis of MPD Lidar Data from Northern
Taiwan and the Effects of Humidity and Radar
Data Assimilation : Case Studies of TAHOPE
SOP3 and IOP3

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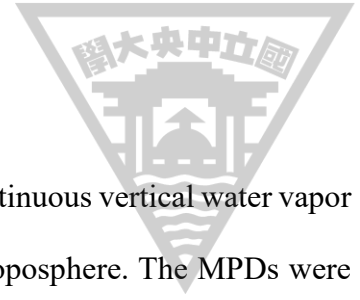
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摘要

微脈衝差分吸收光達(MPD)可提供在對流層低層高時間及高垂直解析度連續水氣剖面觀測資料。在 2022TAHOPE 實驗期間 MPD 被置放於北台灣三個地點：宜蘭、中央大學及新竹。這篇研究第一個目的是利用實驗期間收集的觀測資料分析在夏季不同天氣系統下北台灣的水氣特徵。我們發現在宜蘭是發生午後熱對流事件時水氣會最高。我們還利用 MPD 觀測去計算 500-2000 公尺的總可降水量(TPW)，發現在三個地點的午後熱對流、颱風、低氣壓造成的降水事件中，總可降水量皆可達 22.3mm 以上，而最大值是在宜蘭的午後熱對流事件高達 24.18mm。此外，還去查看水氣跟風場的關係，在宜蘭跟新竹的水氣大小跟風向風速較無關，但在中央大學的測站有發現到當風速越大可以出現較高的水氣。研究的第二個目標是探究同化 MPD 對初始場和降水預報的影響，我們使用 WRF-LETKF 同化系統做了幾組實驗去測試。研究發現同時同化地面測站加上 MPD 的水氣可以得到更好的初始場。在午後熱對流個案中，當同化 MPD 水氣的水平影響半徑設成 48 公里比設成 100 公里在定量降水估計預報更好預測到北台灣及南台灣跟觀測一樣的降雨位置，在 performance diagram 也得到更高的 POD 分數。然而在梅雨個案中，定量降水預報並沒有明顯的改善。研究結果顯示，MPD 所觀測的水氣垂直剖面能有效掌握局部熱力環境；當水平影響半徑設定為 48 公里時，能取得更佳的預報結果，並對中尺度系統產生正面影響。



Abstract

Micropulse Differential Absorption Lidar (MPD) provides continuous vertical water vapor profiles with high vertical and temporal resolution in the lower troposphere. The MPDs were conducted at three sites during Taiwan-Area Heavy rain Observation and Prediction Experiment (TAHOPE). In this study, the first objective is to investigate the water vapor characteristics over northern Taiwan in different weather systems. We found that water vapor at 500m in afternoon cases consistently ranks first or second at three sites. In addition, when calculating Layered Precipitable Water (LPW) using MPD data, the results showed that the highest value of LPW exceeded 24 mm in the afternoon thunderstorm case at Yilan. Furthermore, by examining the diurnal variations, it was found that water vapor in Mei-Yu, afternoon thunderstorm, and typhoon cases was higher during afternoon period (12 to 20 LST). We subsequently conducted several experiments which assimilated reflectivity and radial wind from radar data, water vapor and temperature from surface data, and water vapor profiles from MPDs during different type of severe weather events: afternoon thunderstorm case (SOP3) and Mei-Yu case (IOP3) to examined the impact of assimilating water vapor. WRF-LETKF Radar Assimilation System was used. The result showed that additionally assimilating MPD and surface data provides better thermodynamic environment during both cases. Moreover, the localization of water vapor observed by MPD set to 48km better captured the rainfall area over northern and southern Taiwan in forecast during afternoon thunderstorm case (SOP3) compared to that set to 100km. However, Quantitative Precipitation Forecasts (QPF) had limited improvement in Mei-Yu case. Therefore, the results indicate that humidity profiles observed by MPD can capture the localized thermodynamic environment, leading to better results when the localization is set to 48 km, and having the positive impact on mesoscale system.

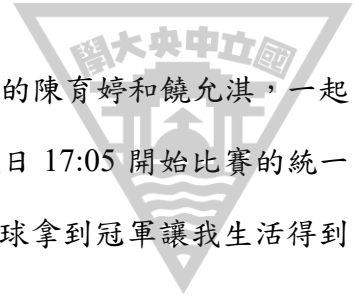


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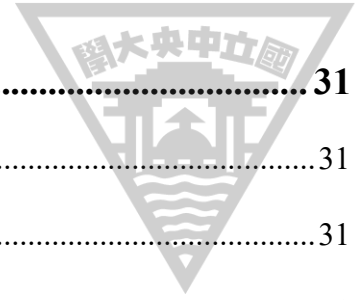
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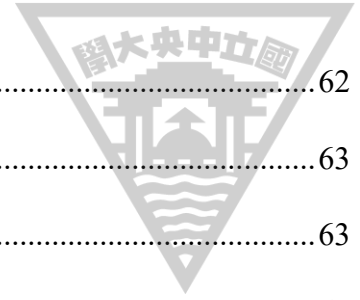


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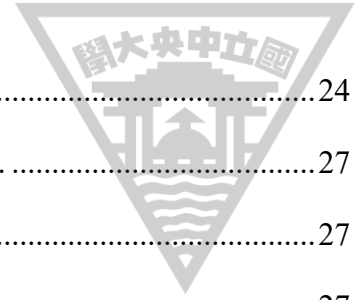
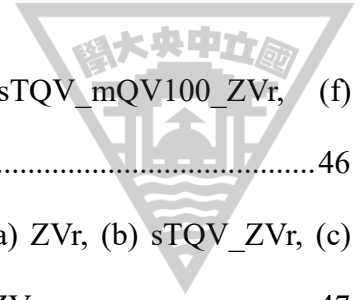


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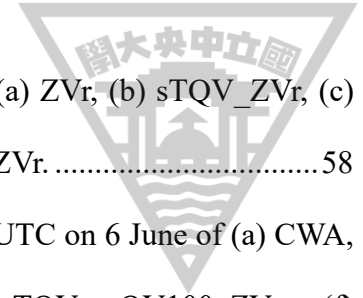
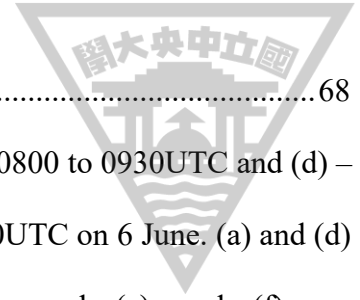
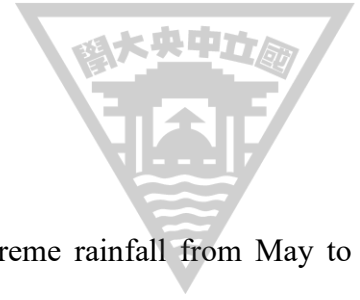


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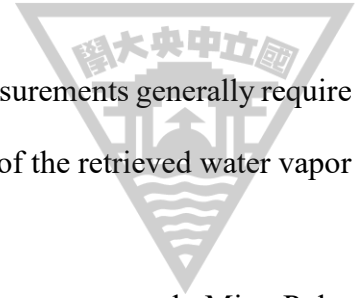


Chapter 1 Introduction

Severe weather occurs frequently in Taiwan and brings extreme rainfall from May to August, including Mei-Yu fronts, tropical cyclones, and afternoon thunderstorms. It is important to improve high-impact weather forecasting skill such as quantitative precipitation forecasting (QPF). Weckwerth et al. (2000) suggested that the average of relative humidity and mixing ratio during storm cases are higher than during no-storm cases. Previous studies have shown that convective systems are associated with abundant water vapor, which plays an important role in their development and maintenance. Therefore, accurate observations of moisture profiles are essential for improving thunderstorm initiation forecasts.

In operational observing network, radiosondes are routinely launched twice daily at 00 and 12 UTC, providing water vapor profile observations from the boundary layer to the mid-troposphere. However, their temporal resolution is limited, making it difficult to capture the rapid evolution of atmospheric moisture associated with severe weather systems. Furthermore, because the radiosonde drifts with the ambient wind during its ascent rather than rising vertically, the measured profiles are not strictly representative of the atmospheric conditions directly above the launch site. In addition, passive remote sensing instruments, such as microwave radiometers, are capable of retrieving atmospheric water vapor profiles. However, their vertical resolution is relatively low.

To overcome the low spatiotemporal resolution, active remote sensing instruments, such as Raman lidar, have been developed to provide continuous water vapor profile observations with high temporal and vertical resolutions. Raman lidar operates by transmitting high-power laser pulses into the atmosphere. The emitted photons interact with atmospheric molecules and undergo Raman scattering, resulting in frequency-shifted backscatter signals. These returned signals are detected by the receiver and subsequently used to retrieve vertical profiles of water

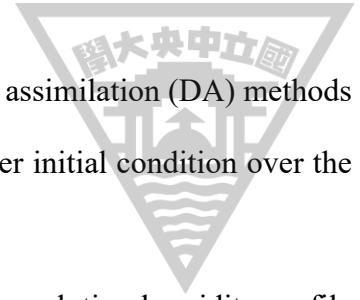


vapor mixing ratio and temperature. Nevertheless, Raman lidar measurements generally require a calibration using radiosonde observations to ensure the accuracy of the retrieved water vapor profiles.

In order to enhance water vapor profiling capabilities and low-cost approach, MicroPulse Differential absorption lidar (MPD) was jointly developed by the National Center for Atmospheric Research (NCAR) and Montana State University (MSU). It emitted high-spectral-fidelity diode lasers of two closely spaced wavelength including one is located near the absorption for water vapor, called online wavelength, and the other is located away from the same absorption feature, called offline wavelength. Since the online and offline wavelengths are closely spaced, the difference between their returned signals is primarily caused by differential water vapor absorption, which can be used to retrieve atmospheric humidity profiles. MPD offers several advantages, including high temporal and spatial resolution of water vapor, while maintaining eye safety through the low-pulse-energy lasers. Furthermore, unlike Raman lidar, MPD retrieves absolute humidity profiles without requiring routine calibration against external instruments, such as radiosondes (Spuler et al. 2015).

Weckwerth et al. (2016) compared the new water vapor micropulse differential absorption lidar with radiosondes, Atmospheric Emitted Radiance Interferometers (AERIs), microwave radiometer profilers (MWRPs), and ground-based global positioning system (GPS) receivers. MPD measurements show high agreement with radiosonde observations between 0.3 and 2 km and with AERI observations between 0.6 and 2 km. The validation results indicate that MPD has the capability to accurately measure vertical water vapor distributions within the boundary layer and performs comparably to other established measurement systems.

Water vapor differential absorption lidar with high temporal and vertical resolutions from the surface to the lower troposphere characterizes the thermodynamic environment of convective systems. Assimilating thermodynamic profiles represents a promising avenue for



enhancing NWP accuracy (Wulfmeyer et al. 2015). Moreover, data assimilation (DA) methods have been used to obtain the optimal analysis and provide the better initial condition over the last two decades.

Previous studies compared the assimilation of high-temporal-resolution humidity profile observations from advanced remote sensing instruments with conventional radiosonde observations to assess their impact on numerical weather prediction. Kay et al. (2022) used Observing System Simulation Experiment (OSSE) to conduct the experiments assimilating convectional observation, radiosonde and MPD data on the convective weather system during the Plains Elevated Convection At Night (PECAN) campaign. They found that assimilating additional MPD data every 15-min during 3-hour DA cycle was more effective at capturing the prediction of convection evolution than assimilating additional radiosondes data only once at the initial assimilation time. Crezee et al. (2025) presented the experiments that assimilated operational observations and water vapor and temperature profiles observed by Raman lidar using the operational model and data assimilation system during a two-week winter period and a two-week summer period. The statistical results revealed that high-frequency assimilation of thermodynamic profiles improved the analysis and forecasts in relative humidity and temperature compared to assimilating collocated radiosonde data updating every 12 hours. So, both studies demonstrated that the assimilation of high-frequency thermodynamic profiles provides more representative initial conditions for forecasts and highlights the potential of deploying a network of water vapor lidars.

Yoshida et al. (2022) used Raman lidar to observe the water vapor exceeding 20 gkg^{-1} when the warm front passed. While assimilating additional water vapor profiles in Mesoscale Convective System contributed to improvements in reproducing the warm frontal surface and enhancing the 6-hour accumulation precipitation forecasts compared with only assimilating operational data. Moreover, assimilating two Raman lidar sites' data produced better forecast

on moisture and horizontal wind fields than assimilating one site data (Yoshida et al. 2024).

During late May to mid-August in 2022, Taiwan-Area Heavy rain Observation and Prediction Experiment (TAHOPE) field campaign was conducted to investigate the large-scale monsoon impacts, mesoscale convective system, landfalling typhoons near Taiwan and clouds physics process. Utilize a dense observational network, including radars and MPD from the United States, as well as radiosondes and operational radars from the Central Weather Administration, to investigate precipitation associated with the Mei-Yu front, afternoon thunderstorms, typhoon, and low-pressure systems. During the field campaign, a total of three MPDs were deployed at different locations across northern Taiwan, collecting more than two months of continuous observations.

The study has two prime objectives. The first objective is analyzed the MPD data under different weather system in summer which usually causes heavy rainfall in Taiwan. The second objective is discussing the impact of data assimilation of high resolution MPD water vapor profiles and water vapor from surface data on an afternoon thunderstorm case and a Mei-Yu front case.

The study is organized as follows. Chapter 2 show the MPD analysis. Chapter 3 describes the two case studies for data assimilation. Chapter 4 includes data assimilation system, observation operator, model configuration, radar data and experimental design. Chapter 5 provides the description of verification methods. Chapter 6 involves results of all the experiments during two different scale cases. Chapter 7 summarizes the results and discusses the future work.



Chapter 2 MPD analysis

2.1 Introduction of MPD during TAHOPE campaign

MPD was conducted at three sites: Yilan, NCU, Hsinchu during TAHOPE 2022 (Fig. 2.1). The data was collected from May 28 2022 to August 12 2022. The MPD observes Absolute Humidity (AH) in unit $[gm^{-3}]$.

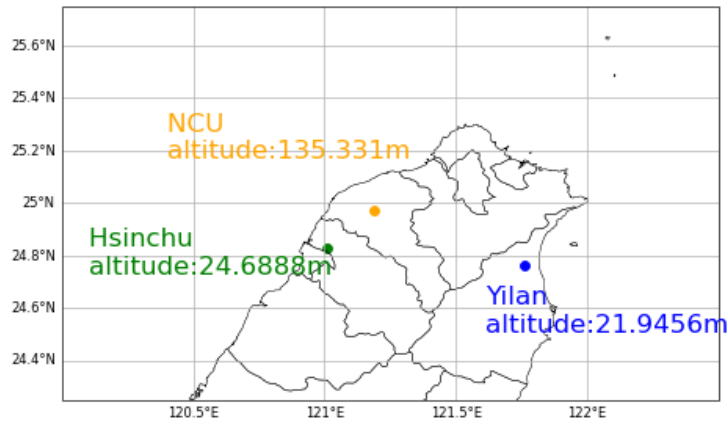


Figure 2.1 MPD sites during TAHOPE campaign.

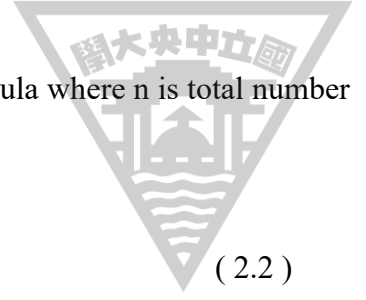
2.2 Results of analysis

2.2.1 Verification method for analysis

In the first part result of MPD analysis, Root Mean Square Error (RMSE) is applied to calculate difference of absolute humidity between MPD and radiosonde data at Hsinchu and Yilan. Transformed from relative humidity, temperature, and pressure observed by radiosonde, the absolute humidity was interpolated to the corresponding levels of MPD, and then the difference could be calculated from the following formula where n is total number of data points.

$$RMSE = \sqrt{\frac{\sum (AH_{MPD} - AH_{sounding})^2}{n}} \quad (2.1)$$

Mean bias is also used to determine whether the MPD data exhibits a wet bias or dry bias



relative to the radiosonde data, calculated using the following formula where n is total number of data points.

$$\text{Mean Bias} = \frac{\sum(AH_{MPD} - AH_{sounding})}{n} \quad (2.2)$$

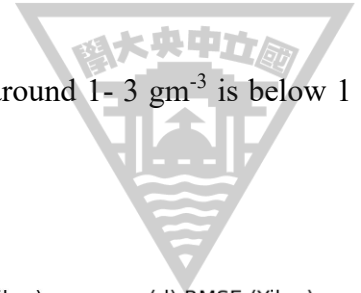
A mean bias value greater than 0 indicates a wet bias, while a value less than 0 indicates a dry bias.

Empirical Orthogonal Function (EOF) and Principal Component (PC) is applied to analysis the vertical structure and time variation of moisture. MPD observations with a 10-min temporal resolution and a 75-m vertical resolution were categorized into different weather systems. The mean profile over the entire TAHOPE observation period was subtracted from each event prior to calculating the covariance matrix for EOF analysis.

$$X(t, h) = \sum_{k=1}^N PC(t, k) \cdot EOF(k, h)$$

2.2.2 Radiosonde comparisons

During TAHOPE, the radiosondes were collocated with MPDs at Yilan and Hsinchu. We interpolated the radiosonde data to the height of MPD, and calculated mean bias and root mean square error (RMSE) of absolute humidity assuming radiosonde data was truth. Fig. 2.2 a and c show wet bias at both Hsinchu and Yilan, respectively. Furthermore, calculating number of samples performed in bottom left picture is 262 and 54 at Hsinchu and Yilan respectively. The highest value of bias was below 500m around 3-4 gm^{-3} at Hsinchu and 2 gm^{-3} at Yilan. RMSE of absolute humidity at Hsinchu above 1000 m is around 1.5 gm^{-3} and the highest value is around 4 gm^{-3} at about 500 m, shown in Fig. 2.2b. On the other hand, RMSE at Yilan is around 1-3 gm^{-3} in Fig. 2.2d. Spuler et al. (2015) also performed MPD compared to radiosonde data,



and they found that higher RMSE of MPD in summer campaign around $1-3 \text{ gm}^{-3}$ is below 1 km which is similar for our results.

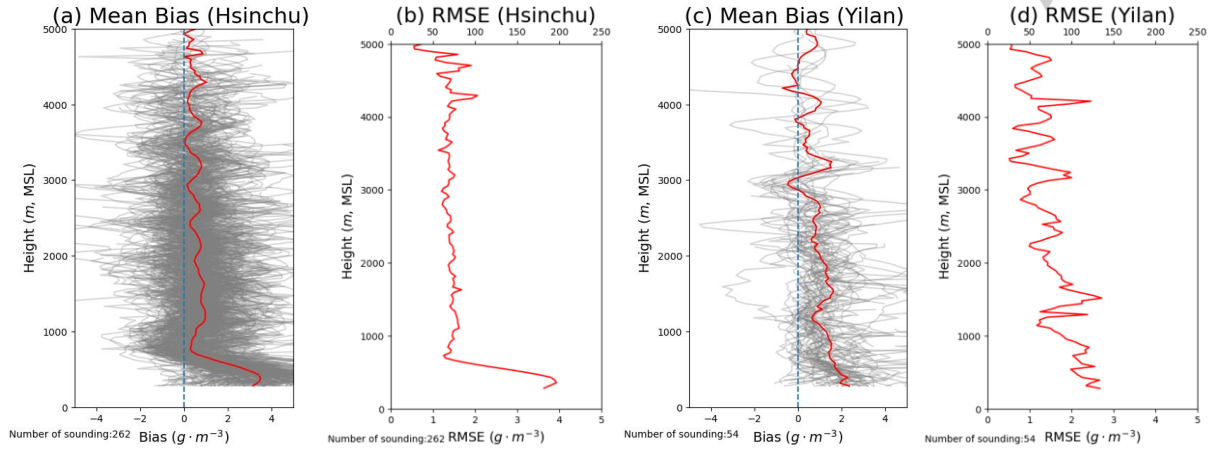


Figure 2.2 absolute humidity Mean bias and RMSE at Hsinchu and Yilan.

2.2.3 Time average of MPD data during different weather system

During TAHOPE experiments, there are total 11 Intensive Observation Periods (IOP) and 8 Special Observation Periods (SOP). For convenience in statistics, the term IOP used hereafter includes both IOP and SOP. Additionally, the IOP could be classified into four types of weather system: Mei-Yu front, afternoon thunderstorm, typhoon, and low pressure, and their occurrence dates are shown in Table 2.1.

Table 2.2 performs average of absolute humidity ranging from 500 m to 1500 m or from 500 to top of the value. Mean of the AH during IOP is higher than during NON-IOP, expect for at NCU from 500 to 1500m. The mean of AH above 500m at Yilan is highest, followed by NCU and Hsinchu. According to (Amzad H. et al 2014), the source of water vapor on June comes from East and South China Sea, so the water vapor over northeastern and southwestern Taiwan is higher than northwestern Taiwan. Our results are in agreement with their findings, indicating that the water vapor at Yilan is higher than that at NCU and Hsinchu.

Fig. 2.3 shows vertical profiles of AH from 500 m to 2000 m averaged over different



weather system. At Yilan, the water vapor during all weather system at 500 m is around 20 gm^{-3} , and the highest water vapor is during afternoon thunderstorm cases while Mei-Yu front's is the lowest. On the other hand, at both NCU and Hsinchu, water vapor in afternoon thunderstorm, typhoon, and low-pressure cases is higher than Mei-Yu front noticeably. Among all weather system, afternoon thunderstorm case consistently ranks first or second at three sites.

Table 2.1 list of weather system occurred during TAHPOE campaign

Weather system	Occurrence date	Total duration (hours)
Mei-Yu front cases	- IOP3 : 6/06 06Z – 6/12 12Z - IOP4 : 6/15 00Z – 6/16 00Z	174
Afternoon thunderstorm cases	- IOP2 : 5/31 00Z – 5/31 12Z - SOP2 : 6/23 00Z – 6/24 00Z - SOP3 : 6/24 00Z – 6/25 00Z - IOP5 : 6/25 00Z – 6/25 15Z - SOP4 : 6/29 00Z – 6/30 00Z - SOP5 : 7/05 00Z – 7/06 00Z - SOP6 : 7/06 00Z – 7/07 00Z - SOP7 : 7/19 00Z – 7/20 00Z - SOP8 : 7/20 00Z – 7/21 00Z - IOP11 : 8/04 00Z – 8/04 12Z	207
Typhoon cases	- IOP6 : 7/01 00Z – 7/04 00Z - IOP7 : 7/05 00Z – 7/05 04Z - IOP8 : 7/13 06Z – 7/16 06Z	148
Low pressure cases	IOP9 : 7/29 00Z – 7/29 12Z	78

	• IOP10 : 8/01 00Z – 8/03 18Z
--	-------------------------------

Table 2.2 average of absolute humidity under two different calculated height during IOP, Non-IOP and whole TAHOPE.

MPD Site	Calculated height	IOP	Non-IOP	TAHOPE
Yilan	0.5 - 1.5 km	17.560	16.974	17.139
	0.5 km - top	13.418	12.543	12.786
NCU	0.5 - 1.5 km	17.196	17.210	17.207
	0.5 km - top	12.302	11.846	11.960
Hsinchu	0.5 - 1.5 km	16.587	16.338	16.405
	0.5 km - top	12.089	11.325	11.522

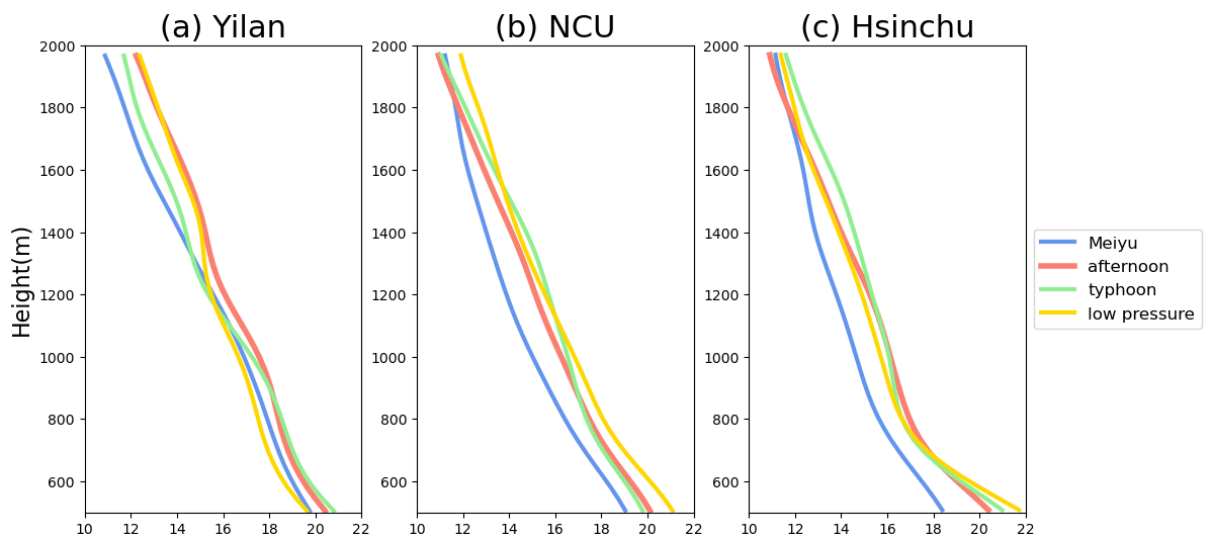


Figure 2.3 vertical profiles of absolute humidity averaged over different weather system at (a) Yilan, (b) NCU, (c) Hsinchu, respectively.

2.2.4 MPD in diurnal variation

We also examined diurnal variation in the water vapor. The day is divided into three time periods: 04-12 UTC (12-20 LST), 12-20 UTC (20-04 LST), 20-04 UTC (04-12 LST). As shown

in Fig. 2.4a, water vapor in Mei-Yu cases at all sites is higher during afternoon period (12-20 LST), followed by midnight period (20-04 LST), morning period (04-12 LST). In afternoon thunderstorm cases and typhoon cases, water vapor is highest during afternoon period (12-20 LST). In contrast, water vapor is highest during morning period (04-12 LST) in low pressure cases.

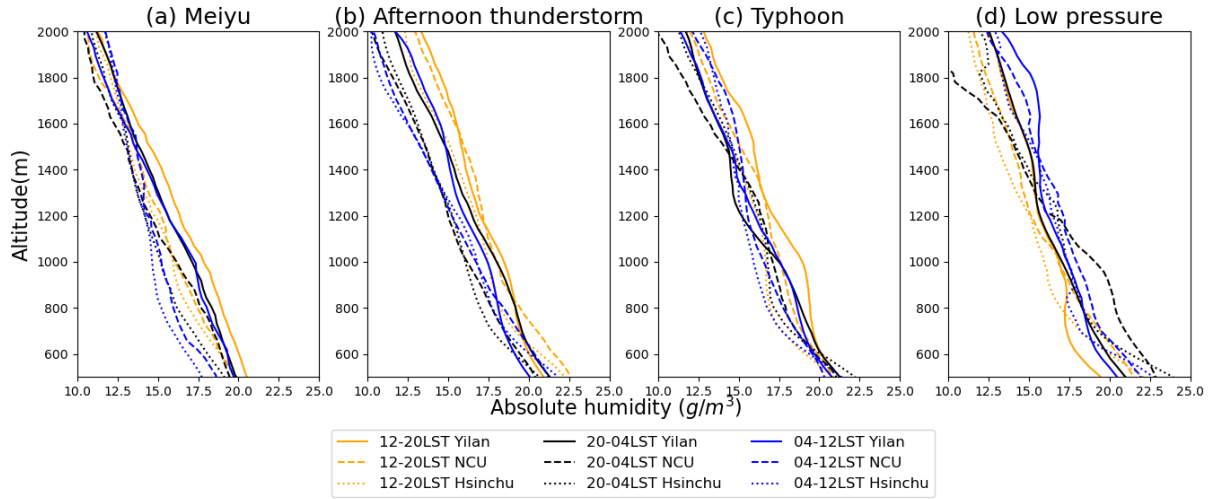


Figure 2.4 Vertical profiles of absolute humidity averaged over different time periods.

2.2.5 Relationship between water vapor and wind field

We want to investigate the relationship between water vapor and wind field, so I averaged the absolute humidity between 500 m and 2000 m and categorized it into $<15 \text{ gm}^{-3}$, $15\text{--}17 \text{ gm}^{-3}$, and $>17 \text{ gm}^{-3}$, then plotted these on the corresponding wind direction diagram measured at the surface stations. When the AH increased, there is no significant difference in wind speed which didn't exceed 6 ms^{-1} or wind direction at Yilan (Fig. 2.5a) and Hsinchu (Fig. 2.5c). However, the wind speeds for $\text{AH} < 15 \text{ gm}^{-3}$ group at NCU are generally below 7.5 ms^{-1} , whereas wind speeds between 7.5 and 12 ms^{-1} occur in the higher AH groups, shown in Fig. 2.5b. I suspect this is because NCU is located farther inland and at a higher altitude than the other two stations. Consequently, higher wind speeds ($> 7.5 \text{ ms}^{-1}$) are required to transport larger amounts of moisture to the site.

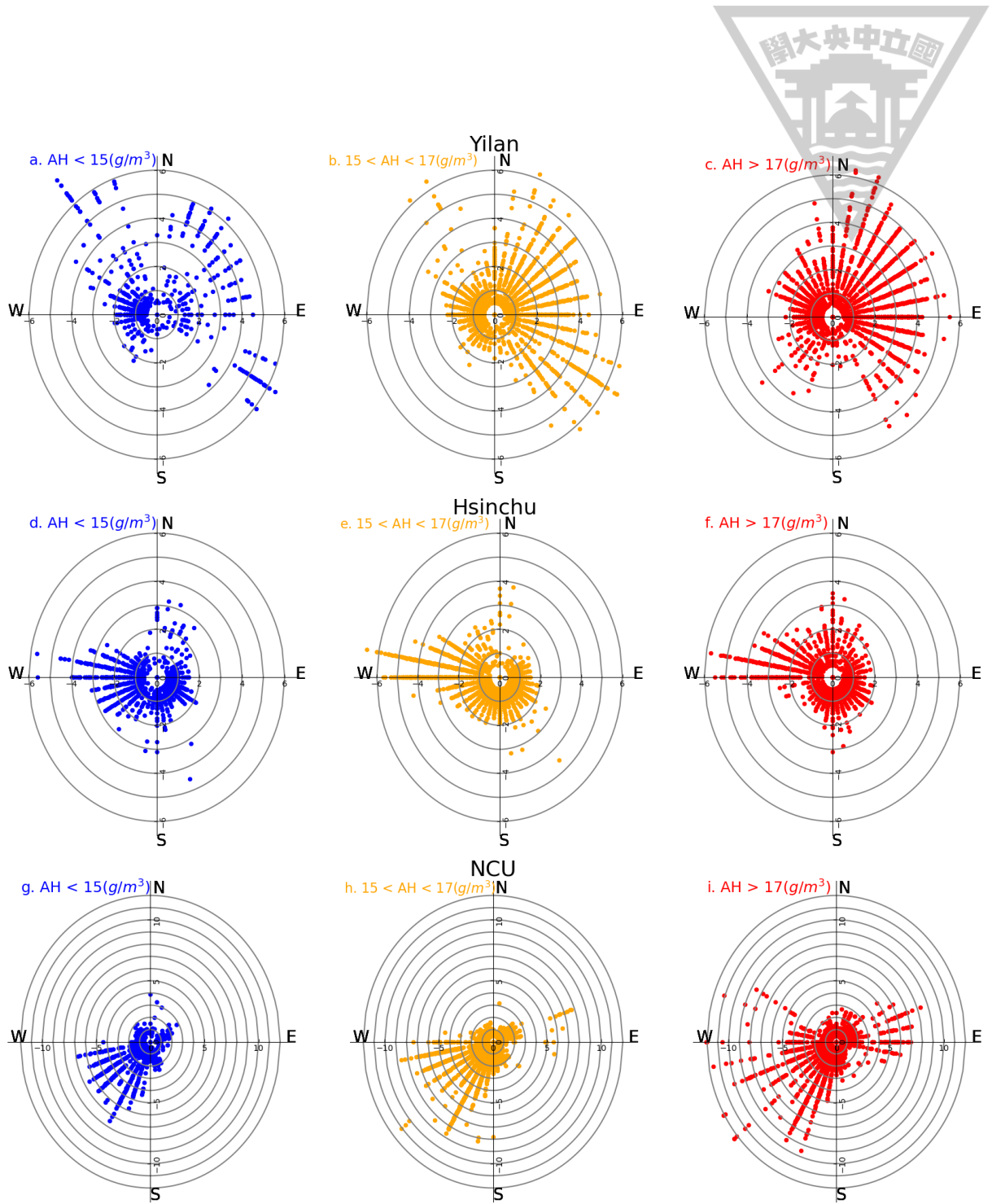


Figure 2.5 Absolute Humidity dots divided into three groups $<15 \text{ gm}^{-3}$, $15\text{--}17 \text{ gm}^{-3}$ and $>17 \text{ gm}^{-3}$ on the corresponding wind direction diagram.

2.2.6 Layered precipitable water(LPW)

We used absolute humidity data from 500 m to 2000 m observed by MPD and applied to Eq. 2.3 to calculate the layered precipitable water (LPW). The highest value at Yilan is

afternoon thunderstorm cases exceeding 24 mm. Furthermore, the LPW during IOP is higher than NON-IOP. The highest LPW at NCU is low pressure cases exceeding 23.5 mm and at Hsinchu is typhoon cases around 22.8 mm. Moreover, the LPW is the lowest during Mei-Yu cases at all three stations.

$$LPW(mm) = \frac{1}{\rho} \int_{500}^{2000} AH \cdot dZ \times 10^3 \quad (2.3)$$

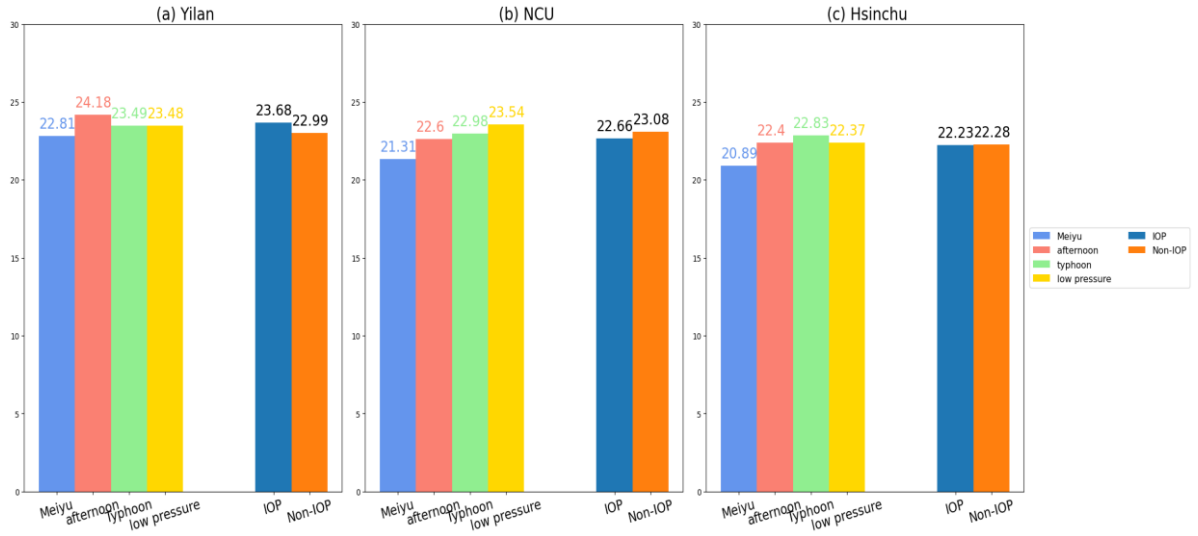
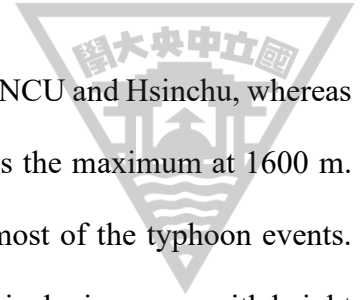


Figure 2.6 Layered Precipitable Water (LPW) in different weather systems.

2.2.7 AH profiles of EOF1

Figs. 2.7-2.10 perform the vertical absolute humidity profiles of first EOF, and corresponding PC1. As mentioned before, each weather event was normalized by subtracting the mean calculated over the entire TAHOPE observation period. Fig. 2.7a shows that water vapor decreases with the height increasing and reach the minimum at 1000m during the positive phase of EOF1 at Hsinchu and NCU, and PC1 exhibits almost positive phase during the whole Mei-Yu cases, which means humidity tended to decrease in Mei-Yu cases (Fig. 2.7b). In the afternoon thunderstorm cases, the EOF1 reveals a coherent increase or decrease in moisture throughout the entire layer over three sites (Fig. 2.8). During the typhoon cases, the EOF1 is



characterized by a layer-wide increase or decrease in moisture over NCU and Hsinchu, whereas over Yilan the moisture anomaly increases with height and reaches the maximum at 1600 m. The time series of PC1 remains in its positive phase throughout most of the typhoon events. During the low-pressure event, the EOF1 loading over NCU and Hsinchu increases with height and reaches a maximum at approximately 1000 m. Above 1000 m, the positive moisture anomaly gradually weakens. However, water vapor increase throughout the entire layer at Yilan. Furthermore, PC1 remains predominantly in the positive phase after August 1, but negative phase on 29 July.

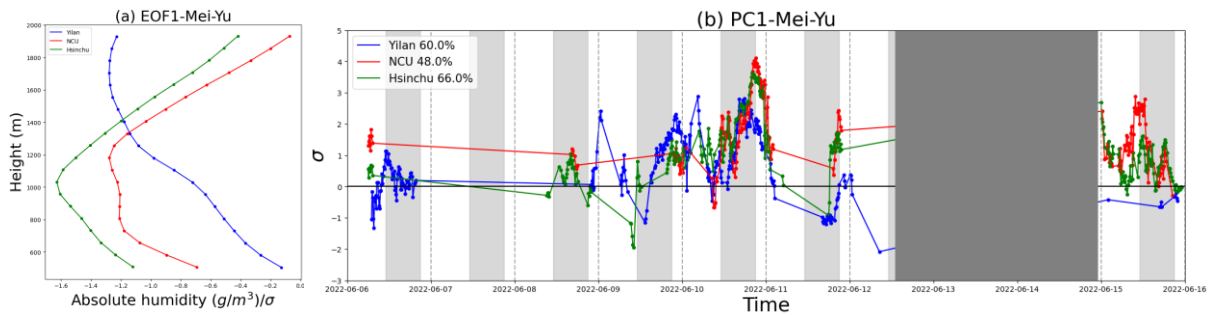


Figure 2.7 The first EOF for absolute humidity in Mei-Yu cases (a) and corresponding time series of PC1 (b). In both pictures, blue line is Yilan, red lines is NCU, and green lines is Hsinchu. The variances are listed in upper left corner of (b). Light gray shading indicates the nighttime from sunset (11 UTC) until sunrise (21 UTC). Dark gray shading masks periods without Mei-Yu events.

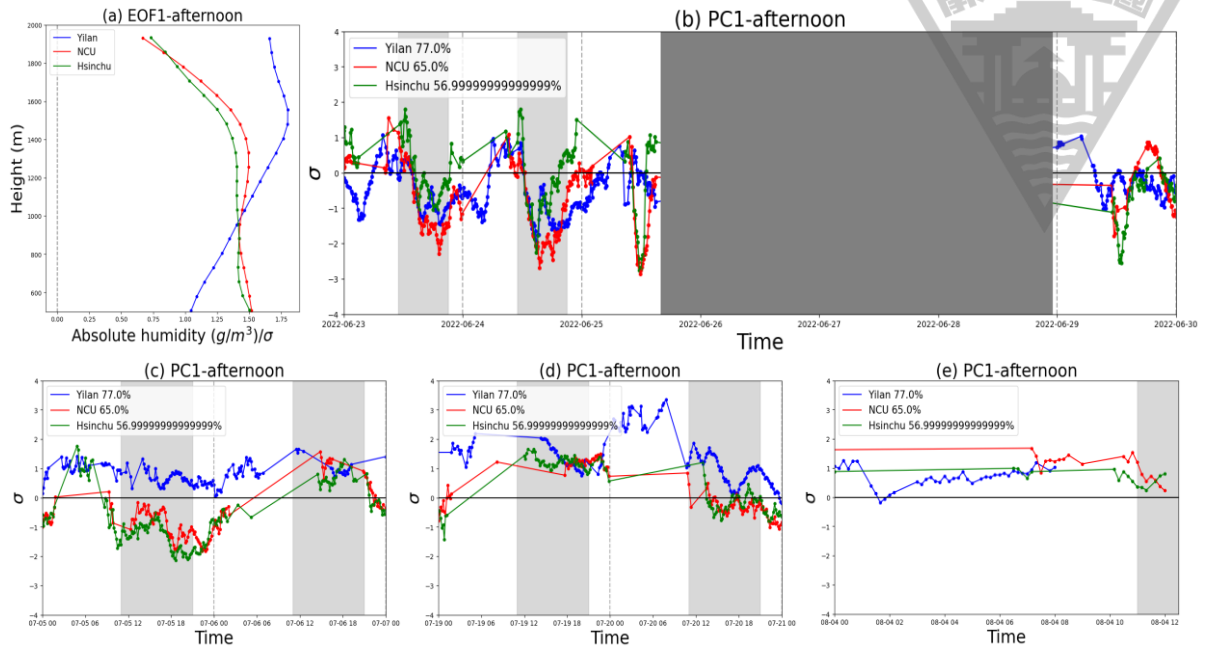


Figure 2.8 The same as Fig. 2.7 but in afternoon thunderstorm cases.

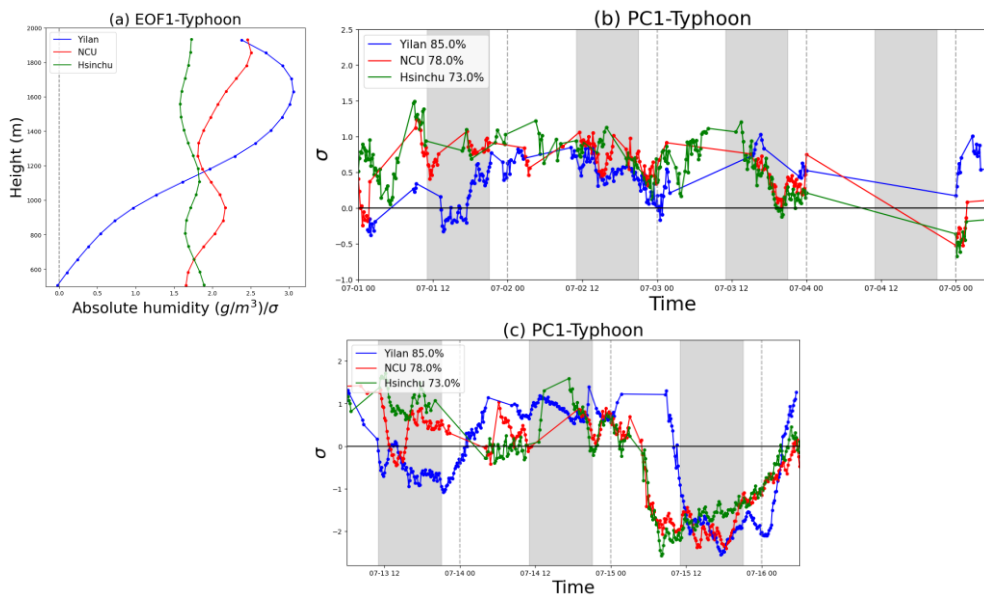


Figure 2.9 The same as Fig. 2.7 but in typhoon cases.

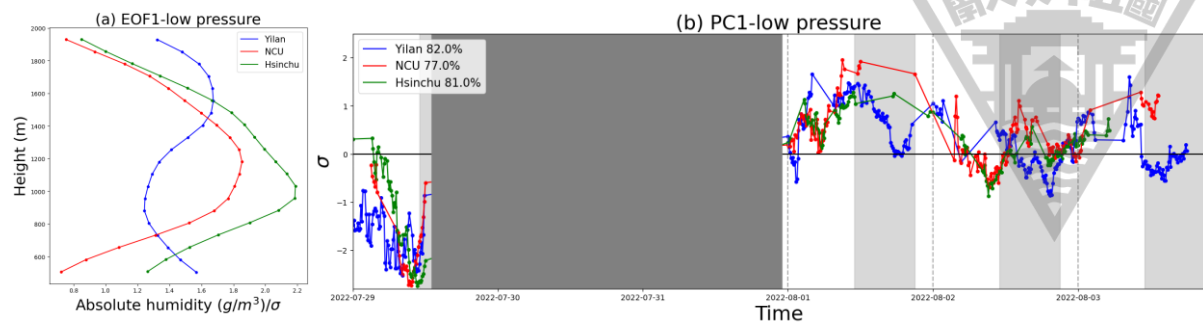


Figure 2.10 The same as Fig. 2.7 but in low pressure cases.



Chapter 3 Case study

3.1 SOP3 - Afternoon Thunderstorm case on 24 June 2022

This case is the third Special Observation Periods #3 (SOP3) during TAHOPE field campaign. Surface map at 06 UTC reveals that Taiwan was under the strong Pacific Subtropical High which is a typical synoptic environment in Taiwan in the summer time (Fig. 3.1). The convective available potential energy (CAPE) observed at Hsinchu at 06 UTC is at a very high value, $4096.4 \text{ m}^2\text{s}^{-2}$, which provides favorable conditions for the development of convective systems (Fig. 3.2). Several local convective cells started to initiate at 0530UTC (1330LST) and continued developing. At 07 UTC (15 LST), several convective cells developed near the mountainous region (Fig. 3.3), and then dissipated at 10 UTC (18 LST).

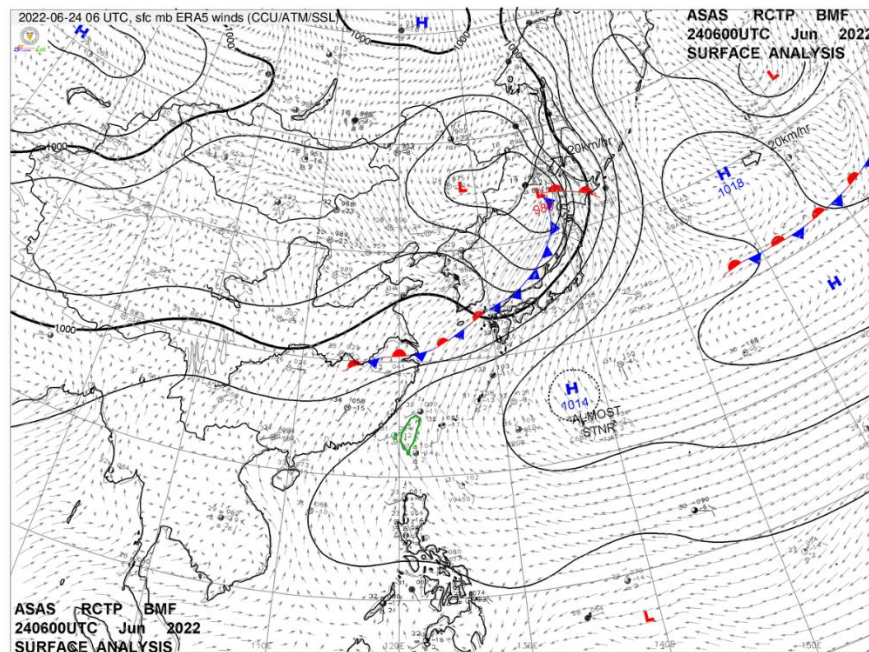


Figure 3.1 weather map at 06 UTC on 24 June 2022.

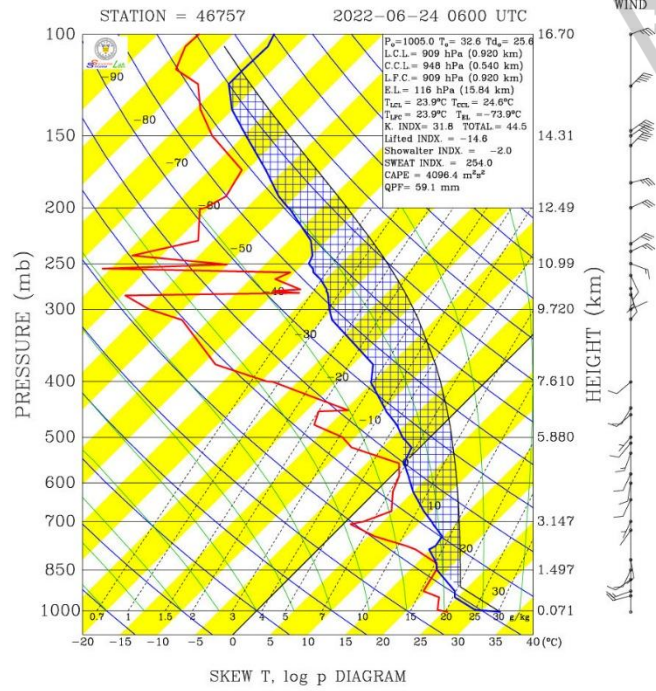


Figure 3.2 Hsinchu sounding profiles at 06 UTC on 24 June 2022.

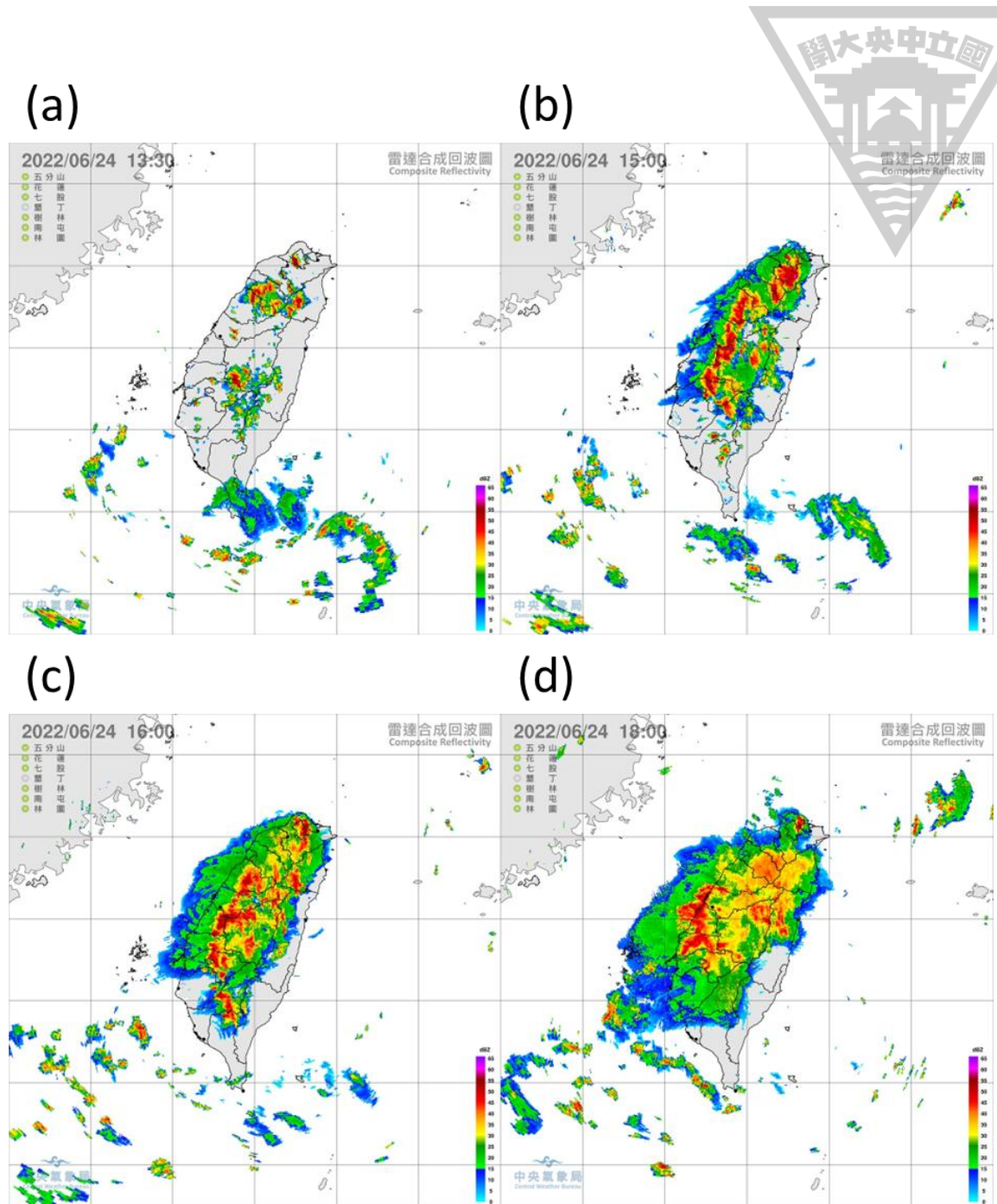


Figure 3.3 Composite reflectivity from CWA at (a) 0530 UTC, (b) 0700 UTC, (c) 0800 UTC and (d) 1000 UTC.

3.2 IOP3 – Mei-Yu case on 6 June 2022

The second objective focused on an extreme rainfall event on the third Intensive Observation Periods #3 (IOP3) during TAHOPE. During IOP3, Taiwan is influenced by Mei-Yu front which usually cause heavy rainfall in summer. The surface weather map showed that

the Mei-Yu front distributed north of Taiwan at 06 UTC (Fig. 3.4), and moved southward over Taiwan at 12 UTC (Fig. 3.5). As a result, Taiwan was affected by the frontal system.

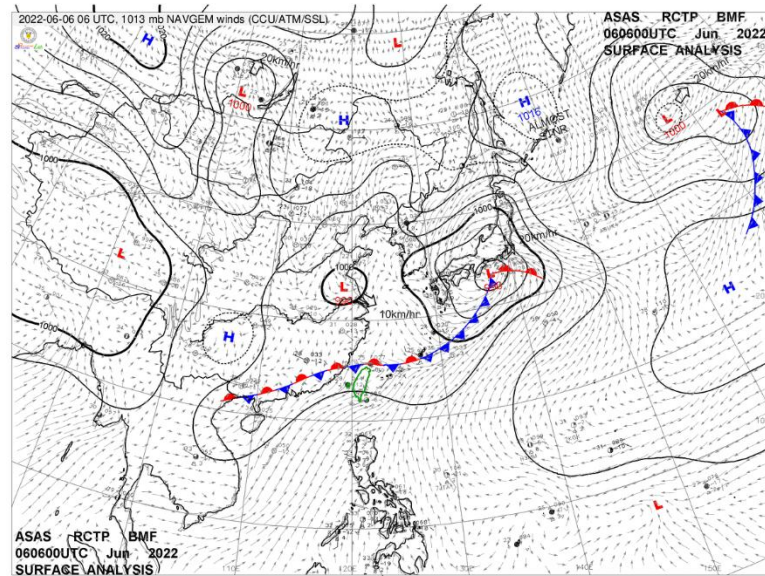


Figure 3.4 surface map at 06 UTC on 6 June 2022.

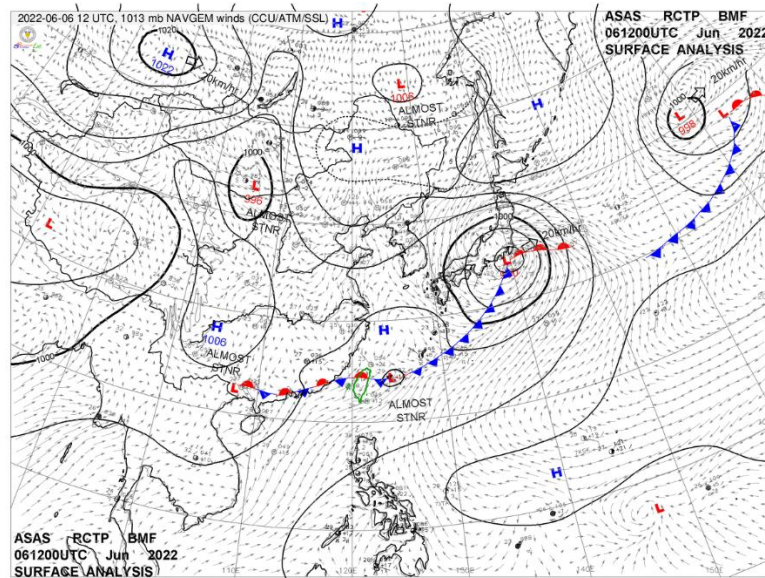
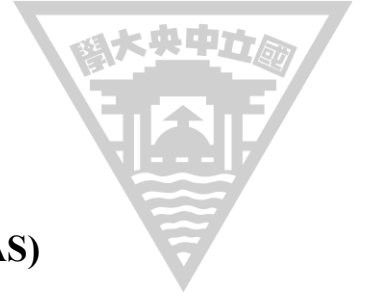


Figure 3.5 surface map at 12 UTC on 6 June 2022.

The sounding at Pengjia Islet at 06 UTC revealed the CAPE value reached $2280 \text{ m}^2\text{s}^{-2}$, which is favorable for convection development (Fig. 3.6).



Chapter 4 Methodology

4.1 WRF-LETKF Radar Assimilation System (WLRAS)

This study used WRF-LETKF Radar Assimilation System (WLRAS) developed by Tsai et al.(2014). This system integrates radar observations with model outputs using the Local Ensemble Transform Kalman Filter (LETKF) to improve quantitative precipitation nowcasting. LETKF is a type of deterministic EnKF which was proposed by Ott et al. (2004), and the full algorithm was first described in Hunt et al. 2007. Ensemble mean and ensemble perturbation are updated separately in LETKF which means estimating the state variables and their uncertainty, respectively, by using the following matrix formula.

$$\bar{\mathbf{x}}_a = \bar{\mathbf{x}}_b + \mathbf{X}_b \bar{\mathbf{w}} \quad (4.1)$$

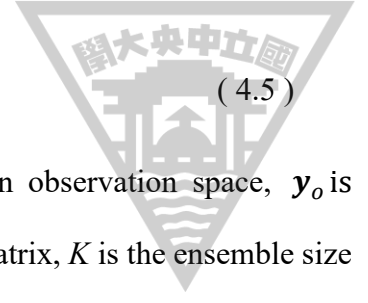
$$\mathbf{X}_a = \mathbf{X}_b \mathbf{W} \quad (4.2)$$

$\bar{\mathbf{X}}$ is column vector containing mean state of model variable while $\mathbf{X}$ is perturbation matrix of k th column corresponding to k th ensemble member. The subscripts a and b mean analysis and background, respectively. In short, analysis mean increment and analysis perturbations are derived from the linear combination of background perturbations. Each model grid point is individually processed at the LETKF analysis step, and the localization process selects the background field and observation information within the localization radius around each point. $\bar{\mathbf{w}}$ and $\mathbf{W}$ represent the weighting coefficients vector and matrix that can be expressed as formula as follows :

$$\bar{\mathbf{w}} = \tilde{\mathbf{P}}_a \mathbf{Y}_b^T \mathbf{R}^{-1} (\mathbf{y}_o - \bar{\mathbf{y}}_b) \quad (4.3)$$

$$\mathbf{W} = [(\mathbf{K} - 1) \tilde{\mathbf{P}}_a]^{1/2} \quad (4.4)$$

where $\tilde{\mathbf{P}}_a$ is the analysis error covariance in ensemble space, computed as



$$\tilde{\mathbf{P}}_a = [(\mathbf{K} - 1)\mathbf{I}/\rho + \mathbf{Y}_b^T \mathbf{R}^{-1} \mathbf{Y}_b]^{-1} \quad (4.5)$$

$\bar{\mathbf{y}}_b$ and $\mathbf{Y}_b$ are background ensemble mean and perturbation in observation space, $\mathbf{y}_o$ is observation, $\mathbf{R}$ is observation error covariance, $\mathbf{I}$ is the identity matrix, K is the ensemble size and ρ is a multiplicative covariance inflation factor (Anderson, 2001). Moreover, ρ was set as empirical value of 1.08 and $\mathbf{R}$ is diagonal matrix assuming the error independence between observations.

The advantages of LETKF including that the background error covariances are flow-dependent which is more representative than the static background covariance, it doesn't need the tangent linear model and adjoint model which could significantly reduce computational cost and expense, and some nonlinear issues are managed by full utilization of the nonlinear model and nonlinear observation operator.

4.2 Observation Operator

LETKF requires observation operator to transform model variable in model space into observational space so that they can be calculated with observations. The operator performs both spatial interpolation and variable conversion. During the spatial interpolation process, the operator identifies the eight grid points closest to the observation location and interpolates the model variables from eight points to the observation point by inverse distance weighting. The observations variable used in this study comprise radial wind (V_r), radar reflectivity (Z), Absolute humidity, water vapor mixing ratio(q_v), and temperature(T). The conversion of V_r follows the method of Sun and Crook (1997) by model variable of u , v , w and terminal velocity V_t on the radar beam as

$$V_r = \frac{x}{r}u + \frac{y}{r}v + \frac{z}{r}(w - V_t) \quad (4.6)$$

$$r = \sqrt{x^2 + y^2 + z^2} \quad (4.7)$$

where x , y and z are the Cartesian coordinates with origin at the radar site. V_t is derived assuming a Marshall-Palmer drop size distribution (DSD; Marshall and Palmer 1948) as

$$V_t = 0.54(p_{sfc}/\bar{p})^{0.4}(\rho_a q_r)^{0.125} \quad (4.8)$$

where p_{sfc} is surface pressure, $\bar{p}$ is the base-state pressure, ρ_a is the air density, and q_r is the rain mixing ratio. As mentioned before, under the assumption of a Marshall–Palmer drop size distribution, the operator of Z based on Dowell et al. (2011) is computed by summing up the rain, snow and graupel as

$$Z = Z_r + Z_s + Z_g \quad (4.9)$$

$$Z_r = 3.63 \times 10^9 (\rho_a q_r)^{1.75} \quad (4.10)$$

$$Z_{s-dry} = 2.79 \times 10^8 (\rho_a q_s)^{1.75}, (T \leq 0^\circ C) \quad (4.11)$$

$$Z_{s-wet} = 1.21 \times 10^{11} (\rho_a q_s)^{1.75}, (T > 0^\circ C) \quad (4.12)$$

$$Z_g = 1.12 \times 10^9 (\rho_a q_g)^{1.75} \quad (4.13)$$

where q_r , q_s , and q_g represent mixing ratio of rain water, snow, and graupel, respectively. Z_s is further categorized into dry snow ($T \leq 0^\circ C$) and wet snow ($T > 0^\circ C$).

The operator of absolute humidity observed by MPD follow as

$$Qv = \frac{\rho_w}{\rho_a} \quad (4.14)$$

$$\rho_a = \frac{P}{R_d T (1 + \frac{Qv}{R_d/R_v})} \quad (4.15)$$

$$R_v = 461.5 (J \cdot kg^{-1} \cdot K^{-1}), R_d = 287.05 (J \cdot kg^{-1} \cdot K^{-1}) \quad (4.16)$$

Where ρ_w is absolute humidity, ρ_a is the density of dry air, Qv is water vapor mixing ratio, P is pressure (Pa), T is temperature (K), and $R_d(R_v)$ is gas constant for dry (moisture) air. To convert absolute humidity to water vapor mixing ratio, temperature and pressure data were



obtained from the NCEP reanalysis and interpolated to the same vertical levels as the MPD observations.

4.3 Model Configuration

This study applied Weather Research and Forecasting (WRF) version 3.9.1 to simulate the afternoon thunderstorm case and Mei-Yu case. The three nesting domains (Fig. 4.1) include 325x271 grid points with a 15-km horizontal resolution (D01), 496x466 grid points with a 3-km horizontal resolution (D02) and 550x550 grid points with 1-km horizontal resolution (D03). Total 52 eta levels with 10-hPa model top were set in vertical resolution. Initial conditions and boundary conditions are provided by National Centers for Environmental Prediction (NCEP) Final analysis (FNL) with a 0.25° resolution. The Goddard Cumulus Ensemble microphysical scheme (GCE) (Tao et al. 1989; Tao et al. 2003) was implemented. The Grell-Devenyi scheme was applied in domain one (D01). The 50 ensemble members were perturbed by WRFDA CV3 in D01 and nest down to D02 and D03. The data assimilation was performed in D03 and propagated through upscaling.

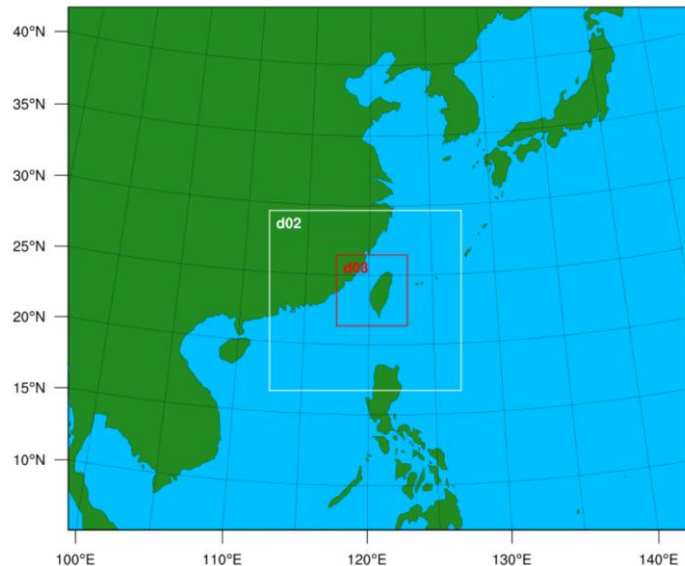
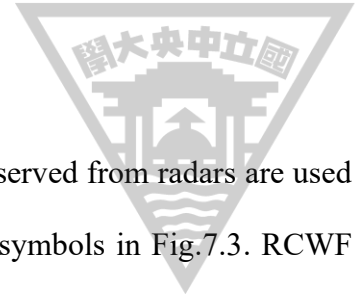


Figure 4.1 WRF model domain setting.

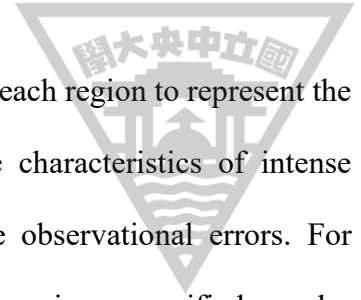


4.4 Radar data

As mentioned before, reflectivity (Z) and radial wind (V_r) observed from radars are used for data assimilation, with their locations marked by red triangle symbols in Fig.7.3. RCWF and RCCG from the CWA, SPOL from National Center for Atmospheric Research (NCAR) and Taiwan Experimental Atmospheric Mobile Radar (TEAM-R) from the Radar Meteorology Laboratory (RaMeLa) at National Central University (NCU) are applied to assimilate radar data in this study. Their locations are plotted in Fig. 4.3. During TAHOPE, RCWF scanned with 15 elevation angles ($0.5^\circ, 0.9^\circ, 1.3^\circ, 1.8^\circ, 2.4^\circ, 3.1^\circ, 4.0^\circ, 5.1^\circ, 6.4^\circ, 8.0^\circ, 10.0^\circ, 12.0^\circ, 14.0^\circ, 16.7^\circ$ and 19.5°), RCCG scanned with 9 elevation angles ($0.5^\circ, 1.4^\circ, 2.4^\circ, 3.4^\circ, 4.3^\circ, 6.0^\circ, 9.9^\circ, 14.6^\circ$ and 19.5°), SPOL scanned with 10 elevation angles ($0.5^\circ, 1.0^\circ, 1.5^\circ, 2.0^\circ, 3.0^\circ, 4.0^\circ, 5.0^\circ, 7.0^\circ, 9.0^\circ, 11.0^\circ$, and TEAM-R scanned with 10 elevation angles ($0.5^\circ, 1.5^\circ, 2.4^\circ, 3.4^\circ, 4.3^\circ, 6.0^\circ, 9.9^\circ, 14.6^\circ$ and 19.5°). During SOP3, only assimilated Z and V_r from RCWF, RCCG and SPOL because TEAM-R didn't use PPI to scan in that period.

Before data assimilation, the radar data must be eliminated non-meteorological signals through quality control (QC). This study used RAKIT developed by RaMeLa in NCU. For all the dual-polarization radar, the first step is unfolding Φ_{DP} (Φ_{DP}). In the second step, data points with $RhoH$ (ρ_{hv}) smaller than 0.8 (0.85 for RCWF) and standard deviation of Φ_{DP} larger than 15 (10 for RCWF) are identified as non-meteorological signals and subsequently removed. After that, unfolding V_r were implemented.

Since radar observations have a much higher spatial resolution than the model grid for data assimilation, the data is necessary to reduce resolution. This procedure helps prevent overfitting, reduces computational cost, and better satisfies the assumption of spatially uncorrelated observation errors in the data assimilation system. There are two approaches for reducing the resolution : data thinning and superobbing. In data thinning, a thinning distance comparable to the model grid spacing is specified, and the observations are distributed into corresponding

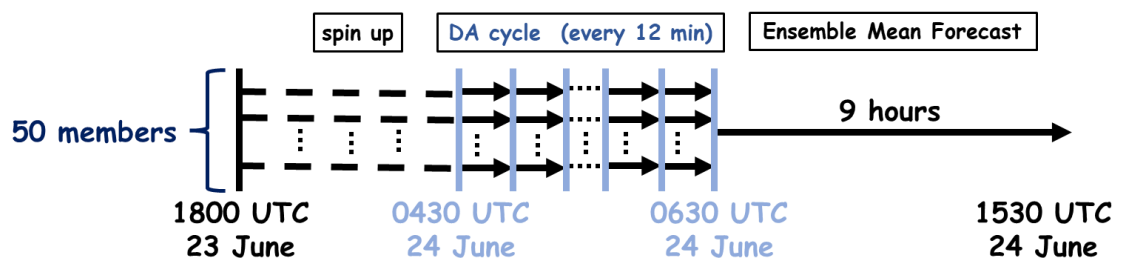


sampling regions. One observation is then randomly selected from each region to represent the observational information. Although this method can retain the characteristics of intense convective features, the random sampling process may increase observational errors. For superobbing, radial data are first selected based on azimuth angle using a specified angular interval. Along each selected azimuth, observations are then grouped into bins with a prescribed spacing. Finally, Gaussian weighting is applied to the observations within each bin to compute a representative value. Superobbing is applied in this study, the data were processed using a resolution of 2° in azimuthal direction and 2 km in radial direction.

4.5 Experimental design

Fig. 4.2. shows the data assimilation flow chat in two cases. Spin-up of 50 ensemble members is necessary to product the background. The spin-up time in afternoon thunderstorm case is 10.5 hours and in Mei-Yu case is 12 hours. After spin-up process, subsequently data assimilation cycle was implemented for two hours. The radar data, surface data, and MPD data were assimilated every 12 minutes, and their locations are shown in Fig 4.3. Fig. 4.3 and 4.4 are MPD data used for data assimilation during SOP3 and IOP3 respectively. When the data assimilation cycle ended, the analysis of ensemble mean was applied to run 9-hours deterministic forecasts.

(a)



(b)

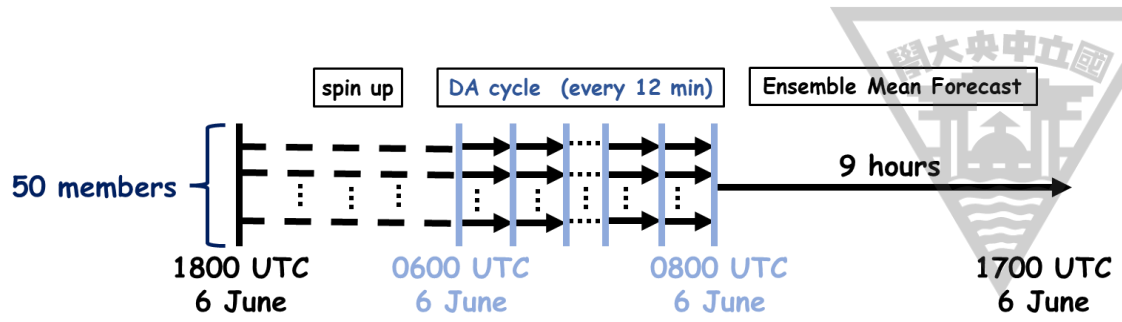


Figure 4.2 flow chat for all experiments during (a) SOP3, (b) IOP3.

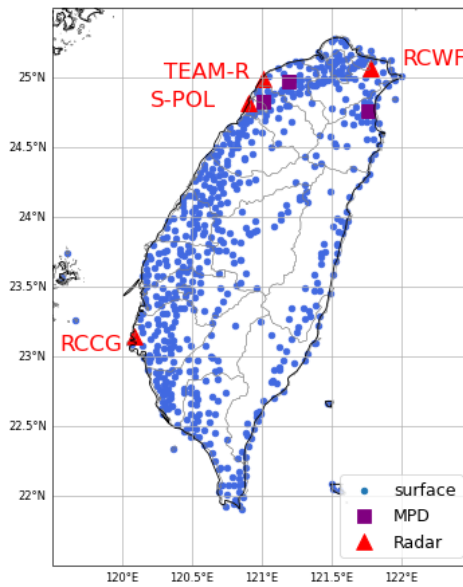


Figure 4.3 the locations of assimilated observations for two cases.

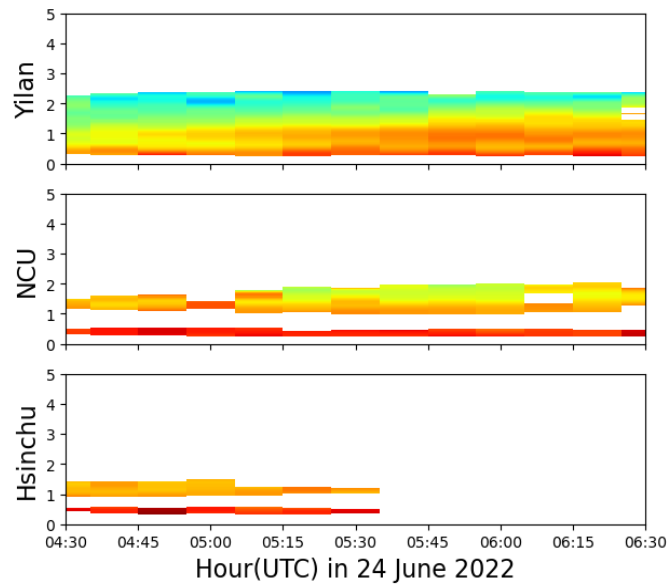


Figure 4.4 MPD data used for data assimilation during SOP3.

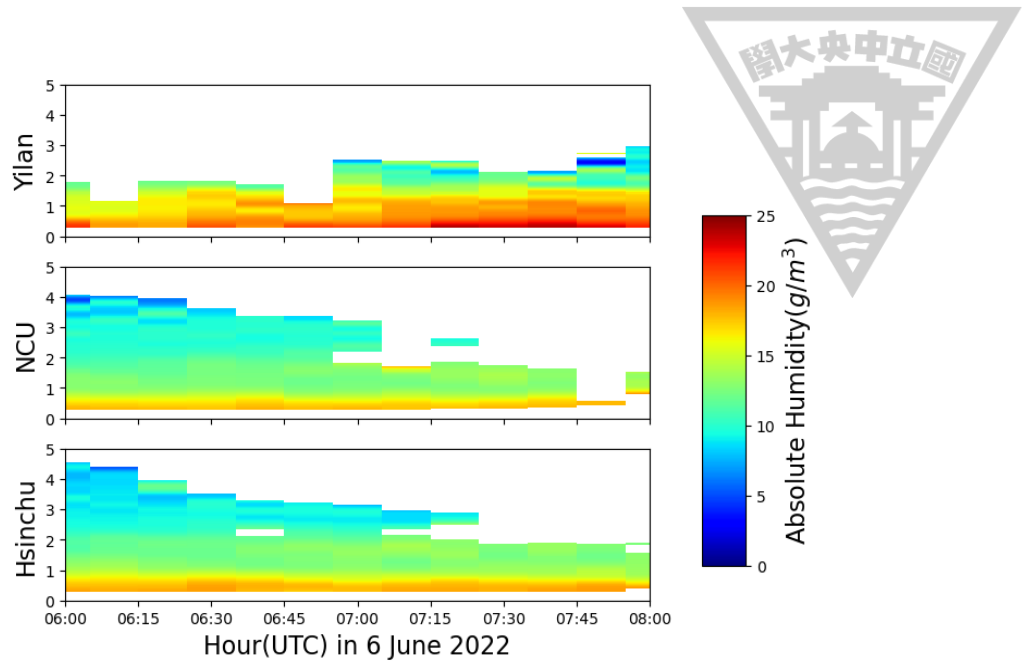


Figure 4.5 MPD data used for data assimilation during SOP3.

Table 4.1. lists the model variables updated by the observation data, localization, and the inflation factors. Table 4.2. lists the assimilated observation variables and their error set up in data assimilation process. In the data assimilation, all the observation variables updated all the model variables.

Table 4.1 Localization radius (km) and inflation factor set in the WLRAS

Variable	U	V	W	PH	T	QVAPOR	QCLOUD	QRAIN	QICE	QSNOW	QGRAUP
Horizontal localization radius(km)	36	36	12	12	12	48/100	24	12	24	12	12
Vertical localization radius(km)	4										
Inflation	1.08										

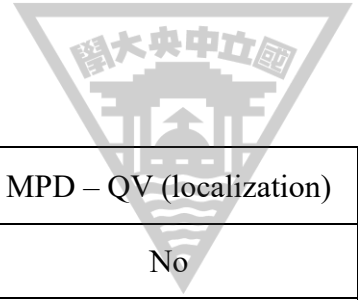


Table 4.2 observation error set up in the data assimilation

Variable	Reflectivity (Z)	Radial wind (Vr)	Temperature (T)	Water vapor mixing ratio (QV)
error	5dBz	3m/s	1K	1g/kg

Table 4.3. shows the conducted experiments in afternoon thunderstorm case and Mei-Yu case. The conducted experiments are the same in both cases. ZVr experiment assimilated reflectivity(Z) and radial wind (Vr) from radar data. sTQV_ZVr experiment where the lowercase 's' represents surface data assimilated temperature and water vapor mixing ratio from surface data and radar data. mQV100_ZVr experiment where the lowercase 'm' represents MPD data and '100' means localization of water vapor from MPD set to 100km assimilated water vapor from MPD and radar data. Because we treated the water vapor profiles observed by the MPD as having large-scale characteristic similar for those of radiosondes. Consequently, the localization set to 100km. sTQV_mQV100_ZVr experiment assimilated surface data, MPD data and radar data. Due to MPD with high temporal and spatial resolution, we regard it as more local feature. Therefore, sTQVmQV48_ZVr experiment where localization of water vapor of MPD set to 48km as surface data was conducted. Surface data and MPD data were assimilated simultaneously to obtain the analysis, after which radar data were assimilated. The differences between sTQV_ZVr and ZVr can be used to investigate the impact of assimilating surface station observations. The comparison of sTQV_ZVr and sTQV_mQV100_ZVr, sTQVmQV48_ZVr examines the impact of assimilating additional MPD data. The comparison of sTQV_mQV100_ZVr and sTQVmQV48_ZVr discusses the influence of MPD data.

Table 4.3 Data assimilation experiments during afternoon thunderstorm case (SOP3) and Mei-



Yu case (IOP3).

EXP	Radar – Z, Vr	Surface – T,QV	MPD – QV (localization)
ZVr	Yes	No	No
sTQV_ZVr	Yes	Yes	No
mQV100_ZVr	Yes	No	Yes (100km)
sTQV_mQV100_ZVr	Yes	Yes	Yes (100km)
sTQVmQV48_ZVr	Yes	Yes	Yes (48km)



Chapter 5 Verification Methods

This chapter describes the validation used on the variable in analysis and forecast quantitatively.

5.1. Root Mean Square Error (RMSE)

RMSE verify the difference between background or analysis and observation during data assimilation cycle to examine whether analysis is closer to assimilated observation. Model variables in model space are interpolated to observational space and convert to observation variables through the observation operators, and subsequently applied to the following formula.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} (X_i - O_i)^2}{N}} \quad (5.1)$$

X_i is the background or analysis in observation grids and O_i is the observations.

5.2. Mean Bias

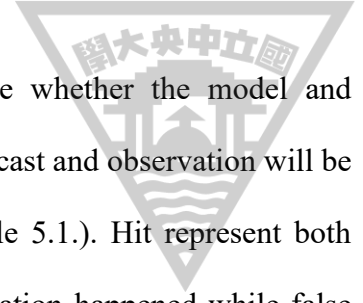
Mean bias is used to investigate the bias of final analysis compared to observations. Model variables in model space are interpolated to observational space and convert to observation variables through the observation operators, and subsequently applied to the following formula.

$$Mean\ Bias = \frac{\sum_{i=1}^{i=N} (X_i - O_i)}{N} \quad (5.2)$$

X_i is the background or analysis in observation grids and O_i is the observations.

5.3. Forecast Skill Scores

Quantitative Precipitation Estimation and Segregation Using Multiple Sensors (QPESUMS) obtained from Central Weather Administration (CWA) is used to validate the 9-hours QPF with probability of detection (POD), success ratio (SR), false alarm ratio (FAR), threat score (TS) and bias. The observation points within Taiwan area are calculated with the



closest model grid points. The thresholds are set to determine whether the model and observations reach the specified criterion. The events between forecast and observation will be categorized into four types based on the contingency table (Table 5.1.). Hit represent both observation and forecast were occurred. Miss means only observation happened while false alarm represent that forecast predicted but not actually occurred. After classified into four scenarios, the forecast skill scores can be calculated with the following formulas.

$$POD = \frac{Hit}{Hit+Miss} \quad (5.3)$$

$$FAR = \frac{False\ Alarm}{Hit+False\ Alarm} \quad (5.4)$$

$$SR = \frac{Hit}{Hit+False\ Alarm} = 1 - FAR \quad (5.5)$$

$$TS = \frac{Hit}{Hit+Miss+False\ Alarm} \quad (5.6)$$

$$Bias = \frac{Hit+False\ Alarm}{Hit+Miss} = \frac{POD}{SR} \quad (5.7)$$

POD measures how many observed events are successfully detected. If every observed event is detected, the value of POD equals to 1. FAR represents how many forecasted events are not observed. If all the forecasted events are not observed, the value of FAR equals to 1. SR is opposite of FAR and indicates the proportion of forecasts that are actually correct. TS means how many observed or forecasted events are observed and detected simultaneously. When the value of TS equals to 1, the model successfully forecasts all the observations. Bias is the ratio between forecasted events and observed events, and the value is from 0 to infinity. Bias larger than 1 represents the model overforecasting, while bias value less than 1 indicates underforecasting. The information of POD, SR, TS and bias can be performed in the performance diagram with SR as the X-axis and POD as the Y-axis (Roebber 2009). When points near to the upper right corner is better performance.

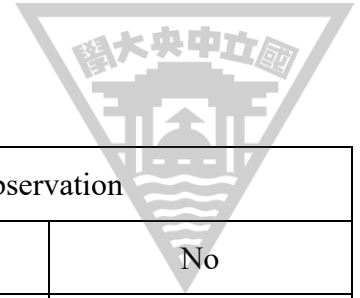
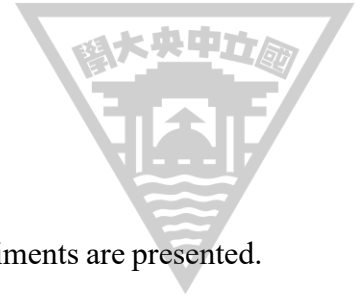


Table 5.1 Contingency Table

Contingency Table		observation	
		Yes	No
Forecast	Yes	Hit	False Alarm
	No	Miss	Correct Negative



Chapter 6 Results of data assimilation

In this section, the analysis and forecast result of all the experiments are presented.

6.1 section is results in afternoon thunderstorm case, and 6.2 section is results in Mei-Yu case.

6.1. Afternoon thunderstorm case

6.1.1. Performance during DA cycling

The RMSE of water vapor mixing ratio, temperature and absolute humidity during DA cycling are showed in Fig. 6.1. RMSE of water vapor (Fig. 6.1) assuming surface data is truth presents that the experiments assimilating water vapor from surface data get lower error at 0630 UTC than at 0430 UTC. In contrast, the RMSE of temperature in all experiments increased at 0630 UTC compared to 0430 UTC (Fig. 6.1.b). RMSE of absolute humidity assuming three MPDs is truth shows the experiments assimilating MPD data decreased error at 0630UTC. The results indicate assimilating MPD data and surface data could obtain the better water vapor field on the initial condition.

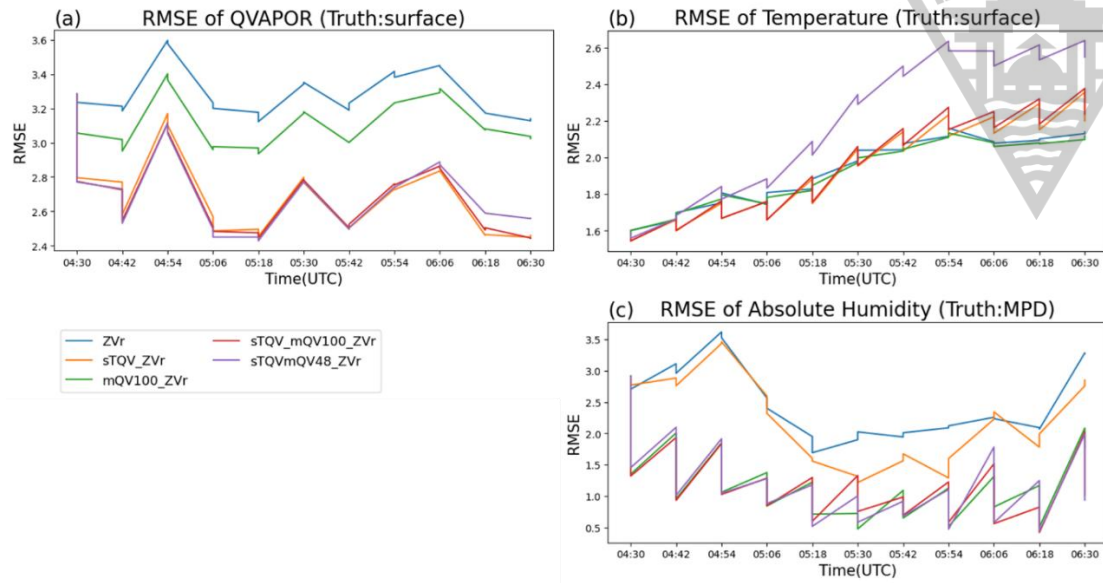


Figure 6.1 RMSE of all the experiments during data assimilation cycling compared to (a) surface water vapor, (b) surface temperature, (c) absolute humidity of MPD for the afternoon thunderstorm case.

6.1.2. Observation – Analysis of water vapor at 0630 UTC

Fig. 6.2. shows the difference between observation and the experiments of water vapor mixing ratio at 1st eta level height. ZVr and mQV100_ZVr experiments which didn't assimilate surface data perform large error and underestimation compared to the other experiments (Fig. 6.2. a, c) and RMSE are around 3g/kg (Table 6.1). sTQV_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr decrease the error and overestimate in somewhere underestimate over middle Taiwan (Fig. 6.2. b,d,and e). Therefore, RMSE of them decreased to 2.5 gkg⁻¹.

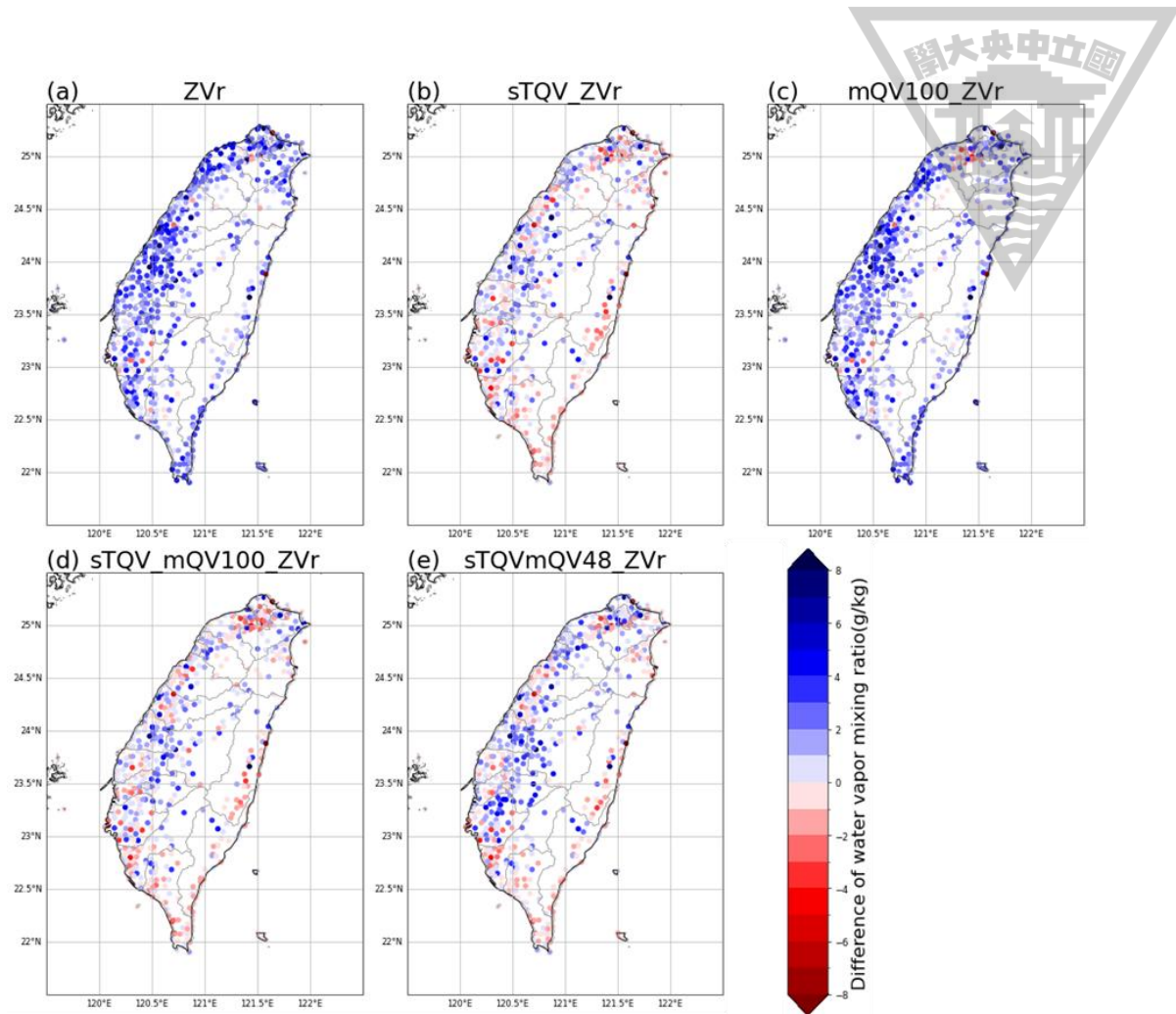


Figure 6.2 observation minus analysis of water vapor at 0630 UTC during SOP3 for
 (a) ZVr, (b) sTQV_ZVr, (c) mQV100_ZVr, (d) sTQV_mQV100_ZVr, (e)
 sTQVmQV48_ZVr.

Table 6.1 RMSE and Bias of water vapor at 0630UTC during SOP3.

EXP	RMSE	Bias
ZVr	3.139	-1.910
sTQV_ZVr	2.459	-0.056
mQV100_ZVr	3.025	-1.733

sTQV_mQV100_ZVr	2.443	-0.059
sTQVmQV48_ZVr	2.559	-0.358

6.1.3. Observation – Analysis of temperature at 0630 UTC

All the experiments underestimate over southern Taiwan and overestimate in Taipei basin (Fig. 6.3), while sTQVmQV48_ZVr decrease overestimation in Taipei basin (Fig. 6.3.e). Table 6.2. shows RMSE of most of the experiments is about 2.2 K.

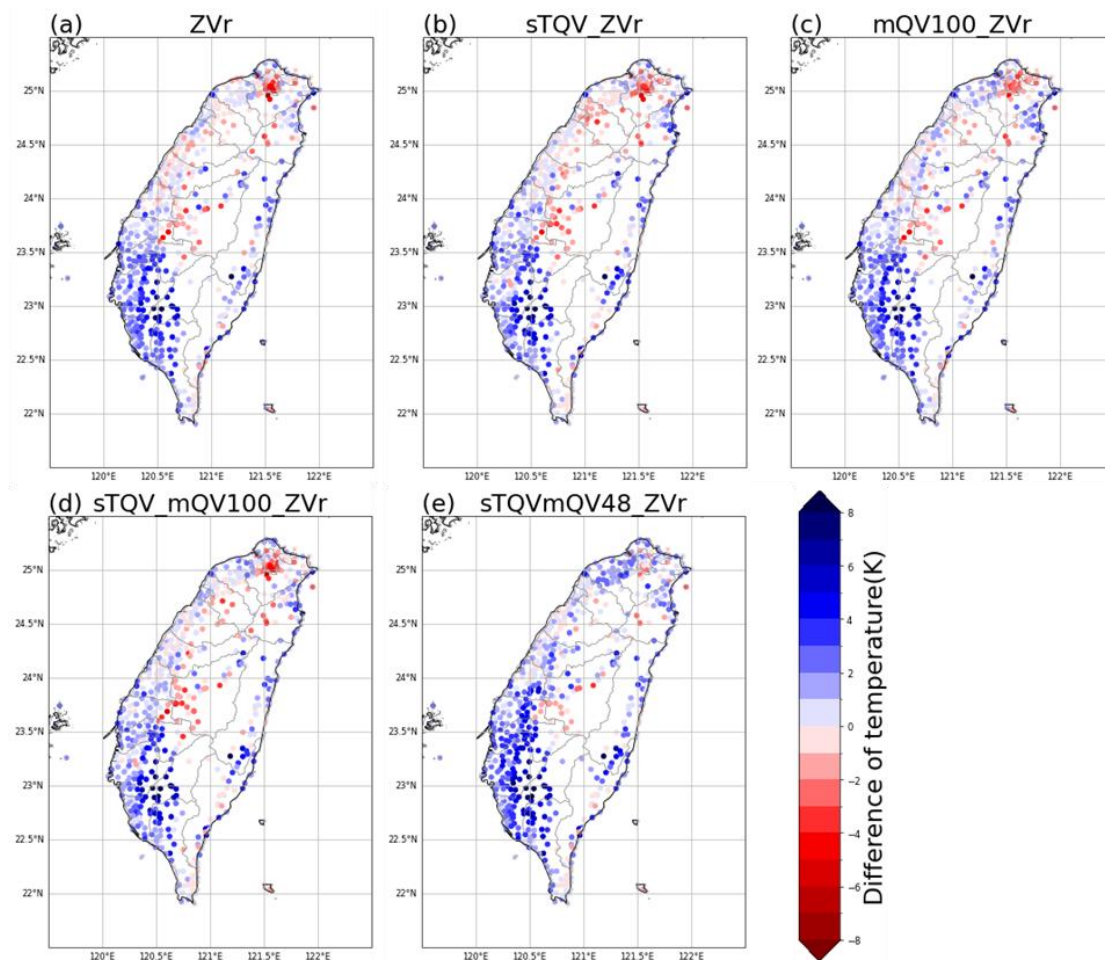
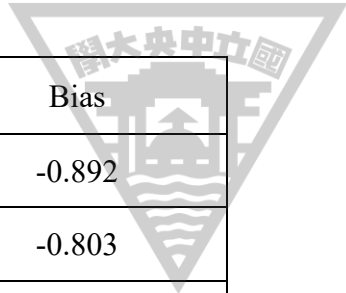


Figure 6.3 observation minus analysis of temperature at 0630 UTC.

Table 6.2 RMSE and Bias of temperature at 0630 UTC during SOP3

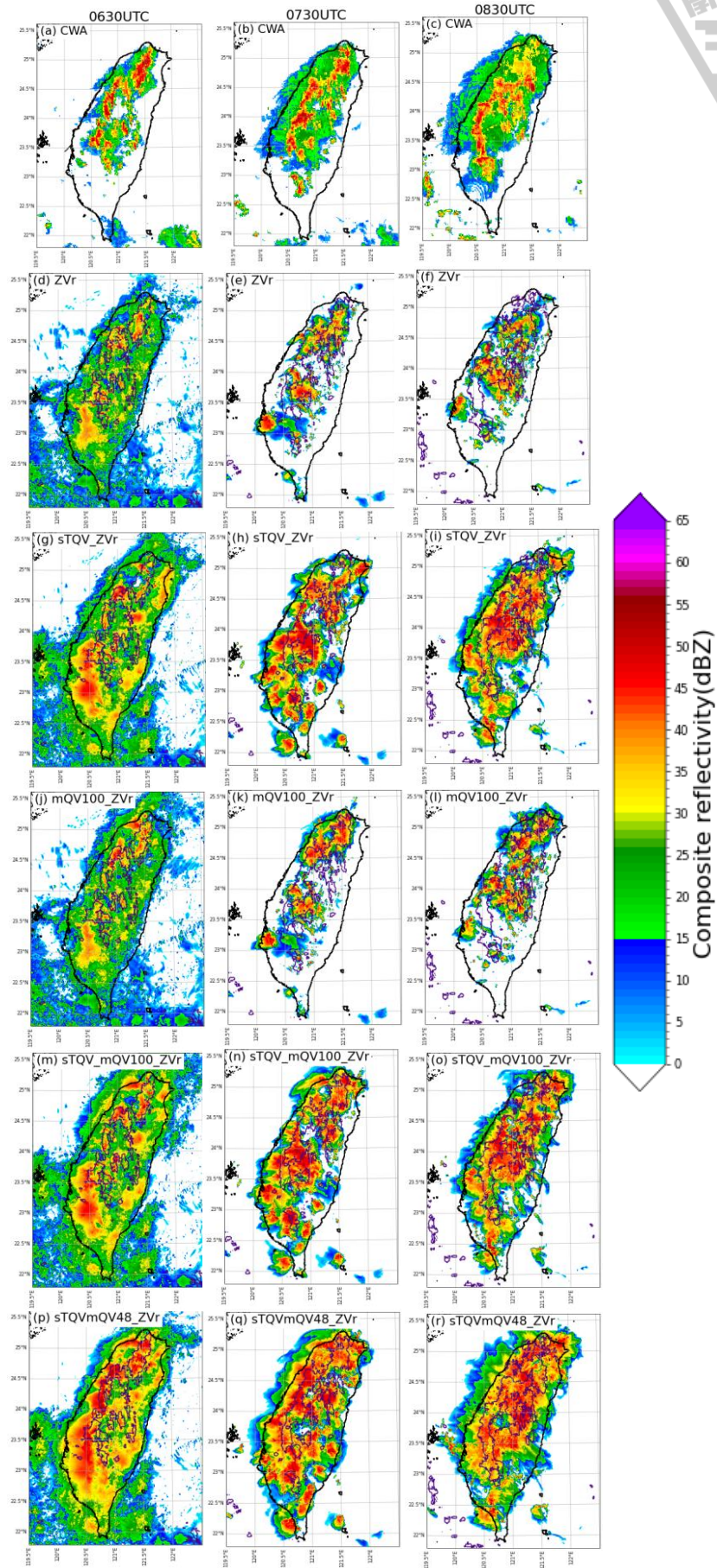


EXP	RMSE	Bias
ZVr	2.140	-0.892
sTQV_ZVr	2.202	-0.803
mQV100_ZVr	2.119	-0.988
sTQV_mQV100_ZVr	2.239	-0.873
sTQVmQV48_ZVr	2.551	-1.653

6.1.4. Composite reflectivity

Fig. 6.4. d, g, j, m, p show the composite reflectivity in final analysis while Fig. 6.4. e, f, h, i, k, l, n, o, q, r perform that in forecast. The composite reflectivity from CWA shows stronger convection zone in northern and central Taiwan at 0630UTC (Fig. 6.4.a), and new convective cells located in southern Taiwan at 0730UTC (Fig. 6.4.b). At 0830UTC, the stronger convective cells in northern Taiwan dissipated while the stronger convective cells in central and southern Taiwan continued to develop (Fig. 6.4.c). The solid purple lines on the pictures of experiments represent reflectivity of CWA greater than 30dBZ. ZVr (Fig. 6.4. d,e,f) only captures the convection zone in northern Taiwan at 0630UTC and at 0730UTC, but didn't capture the strong convection cells in southern Taiwan. After additional assimilating surface data, it reveals the stronger convection zone in southern Taiwan but near to the coastal region at 0630UTC, and dissipated at 0830UTC (Fig. 6.4. g,h,i). Assimilating MPD and radar data has the same distribution with ZVr experiment (Fig. 6.4. j,k,l). The convection zone in northern Taiwan at 0730UTC lasted longer and more accurate position in sTQV_mQV100_ZVr (Fig. 6.4. n) compared to sTQV_ZVr. Assimilating additional MPD and its localization set to 48km perform similar distribution to CWA at 0630UTC, and continued

developing until 0830UTC. Although the convection zone in southern Taiwan exhibited near the coastal area at 0630UTC, it moved closer to the mountainous area similar for the observation at 0730 UTC and continued to develop until 0830 UTC (Fig. 6.4. p,q,r).



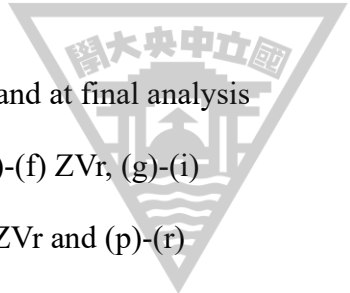


Figure 6.4 Composite reflectivity from (a)-(c) CWA observations and at final analysis time(0630UTC), prediction time (0730 and 0830 UTC) for (d)-(f) ZVr, (g)-(i) sTQV_ZVr, (j)-(l) mQV100_ZVr, (m)-(o) sTQV_mQV100_ZVr and (p)-(r) sTQVmQV48_ZVr. The solid purple lines represent reflectivity of CWA greater than 30dBZ.

6.1.5. Absolute humidity profiles at 0630 UTC

Figure 6.5 shows the absolute humidity vertical profiles of MPD, background (green line) and analysis (red line) at 0630UTC at three sites respectively. The analysis results in ZVr and sTQV_ZVr don't get better performance relative to background results. The other experiments (mQV100_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr) assimilating MPD data improve the vertical moisture at NCU and Yilan compared to background.

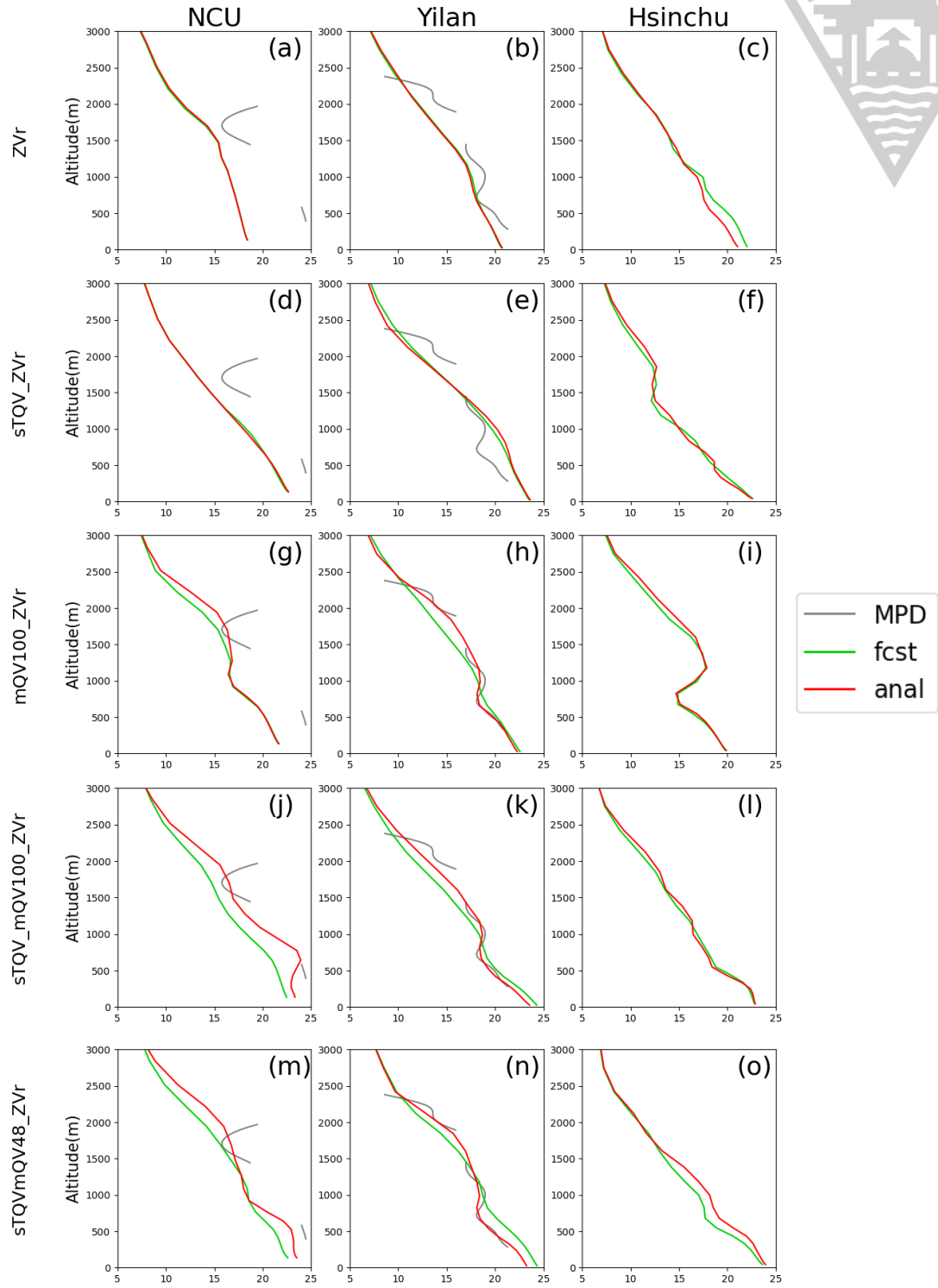
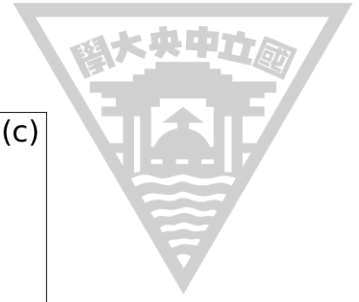
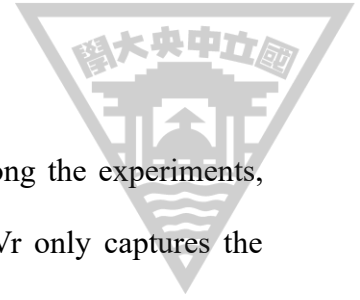


Figure 6.5 absolute humidity vertical profiles compared to three MPD sites at 0630

UTC for (a)-(c) ZVr, (d)-(f) sTQV_ZVr, (g)-(i) mQV100_ZVr, (j)-(l)

sTQV_mQV100_ZVr and (m)-(o) sTQVmQV48_ZVr.



6.1.6. Rainfall forecast

Fig. 6.6 shows the 3 hours accumulated precipitation. Among the experiments, ZVr performs largest underestimation (Fig. 6.6.b). mQV100_ZVr only captures the rainfall area in the Taipei basin and Miaoli (Fig. 6.6.d). The spatial distributions of rainfall in sTQV_ZVr and sTQV_mQV100_ZVr are highly similar, except for slight differences in the Taoyuan mountainous region (Fig. 6.6. c,e). sTQVmQV48_ZVr captures the rainfall in the Miaoli region similar for the observation, which is not captured by the other experiments. Moreover, the rainfall area over southern Taiwan in sTQVmQV48_ZVr is located closer to the mountainous region (Fig. 6.6f), consistent with the observation. In comparison, sTQV_ZVr and sTQV_mQV100_ZVr place the rainfall area closer to the coast.

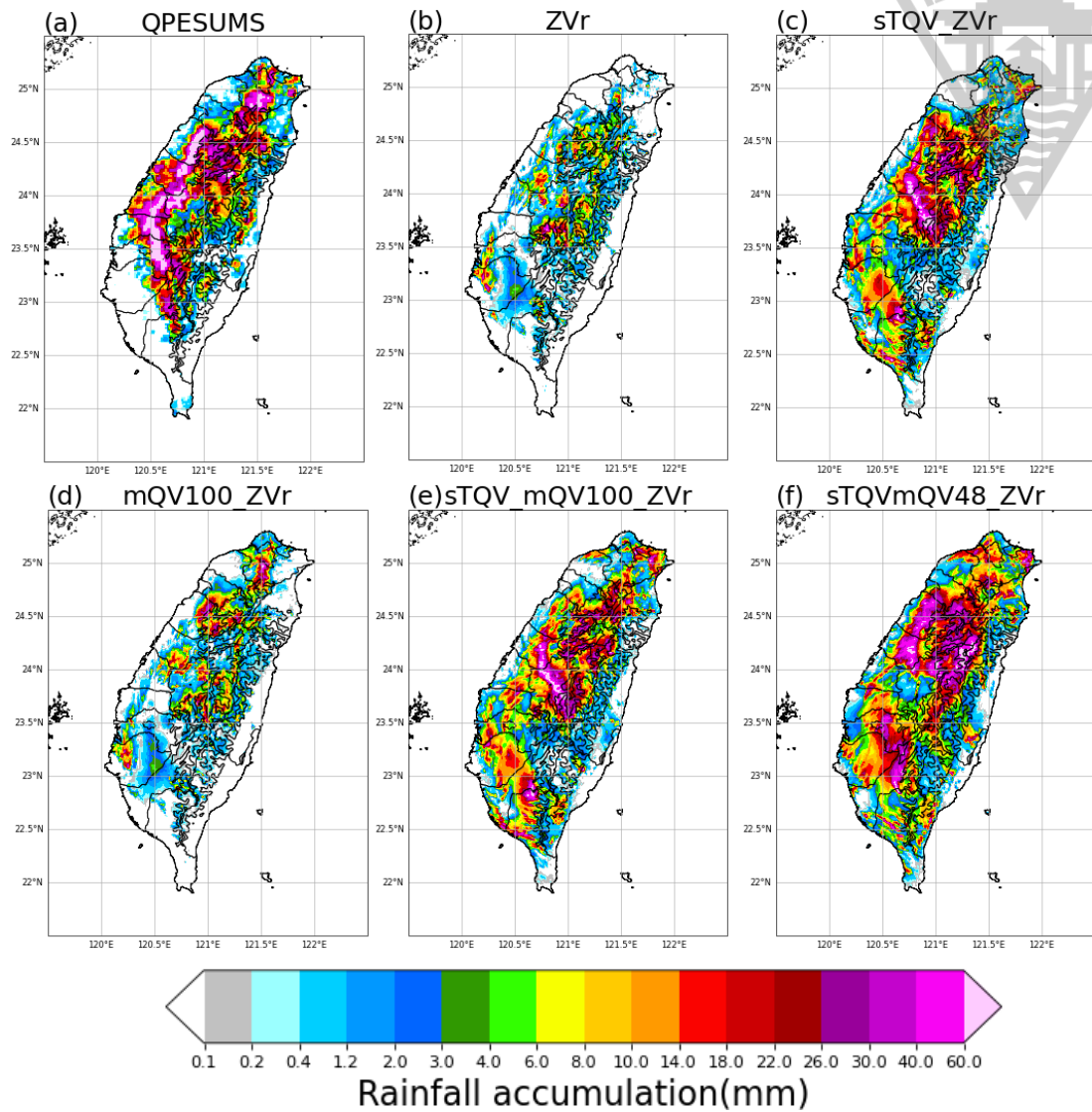


Figure 6.6 3 hours accumulated precipitation from 0630 to 0930UTC on 24 June of (a) CWA, (b) ZVr, (c) sTQV_ZVr, (d) mQV100_ZVr, (e) sTQV_mQV100_ZVr, (f) sTQVmQV48_ZVr.

Fig. 6.7 shows the 6 hours accumulated precipitation. The performance distributes the same rainfall pattern to 3 hours accumulated precipitation. sTQVmQV48_ZVr reveals the better rainfall performance closer to the observation.

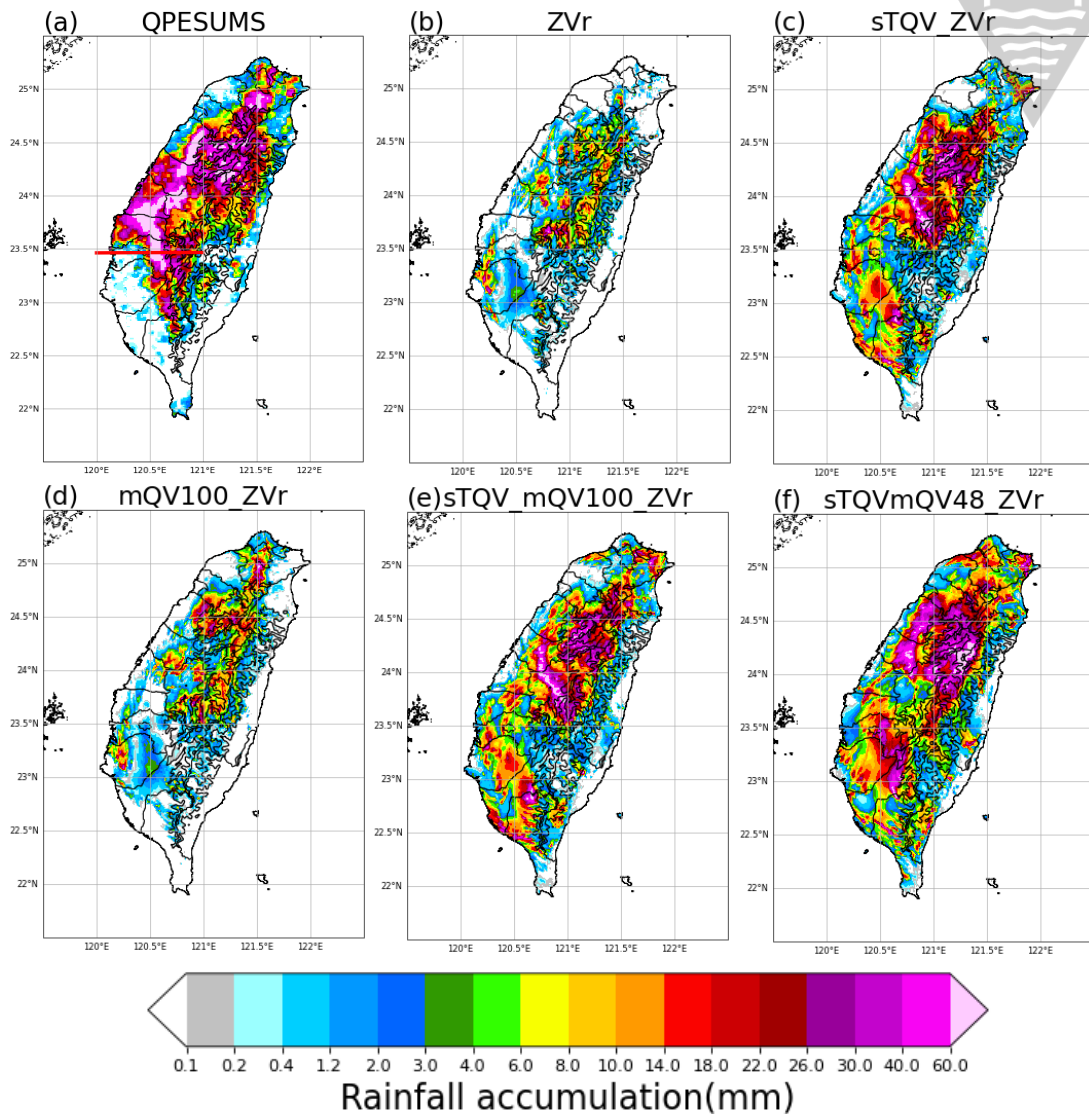


Figure 6.7 6 hours accumulated precipitation from 0630 to 1230 UTC on 24 June of (a) CWA, (b) ZVr, (c) sTQV_ZVr, (d) mQV100_ZVr, (e) sTQV_mQV100_ZVr, (f) sTQVmQV48_ZVr.

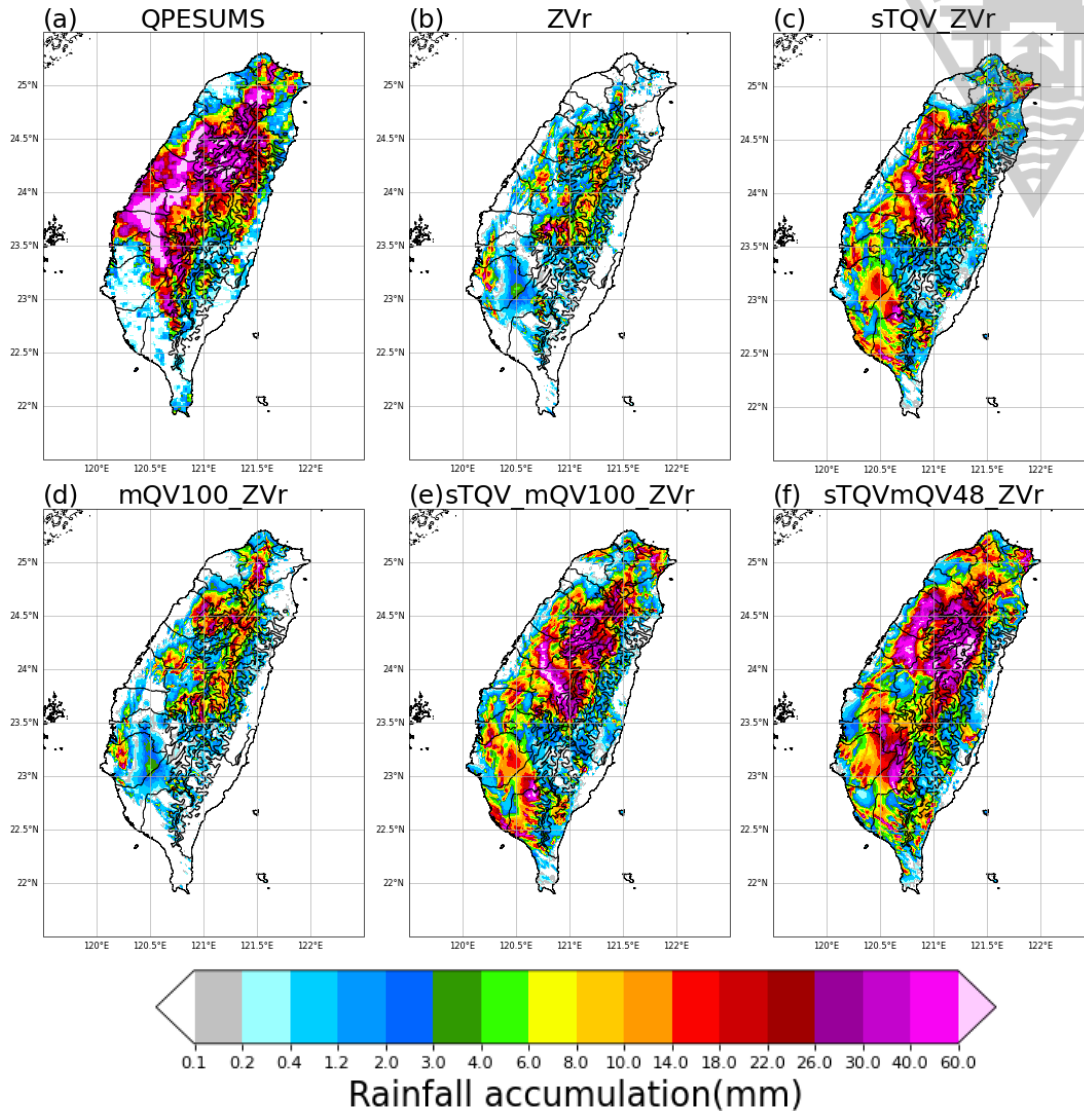


Figure 6.8 9 hours accumulated precipitation from 0630 to 1230UTC on 24 June of
 (a) CWA, (b) ZVr, (c) sTQV_ZVr, (d) mQV100_ZVr, (e) sTQV_mQV100_ZVr, (f)
 sTQVmQV48_ZVr.

6.1.7. Divergence

In Figs. 6.9, the pronounced low-level convergence over the Taipei basin is observed in all the experiments, while that in the Miaoli only presented in sTQVmQV48_ZVr leading to the rainfall in this region. Moreover, sTQVmQV48_ZVr exhibits convergence in the southern Taiwan closer to the mountain region associated with the

rainfall in this region while sTQV_ZVr and sTQV_mQV100_ZVr distribute that near the coastal region.

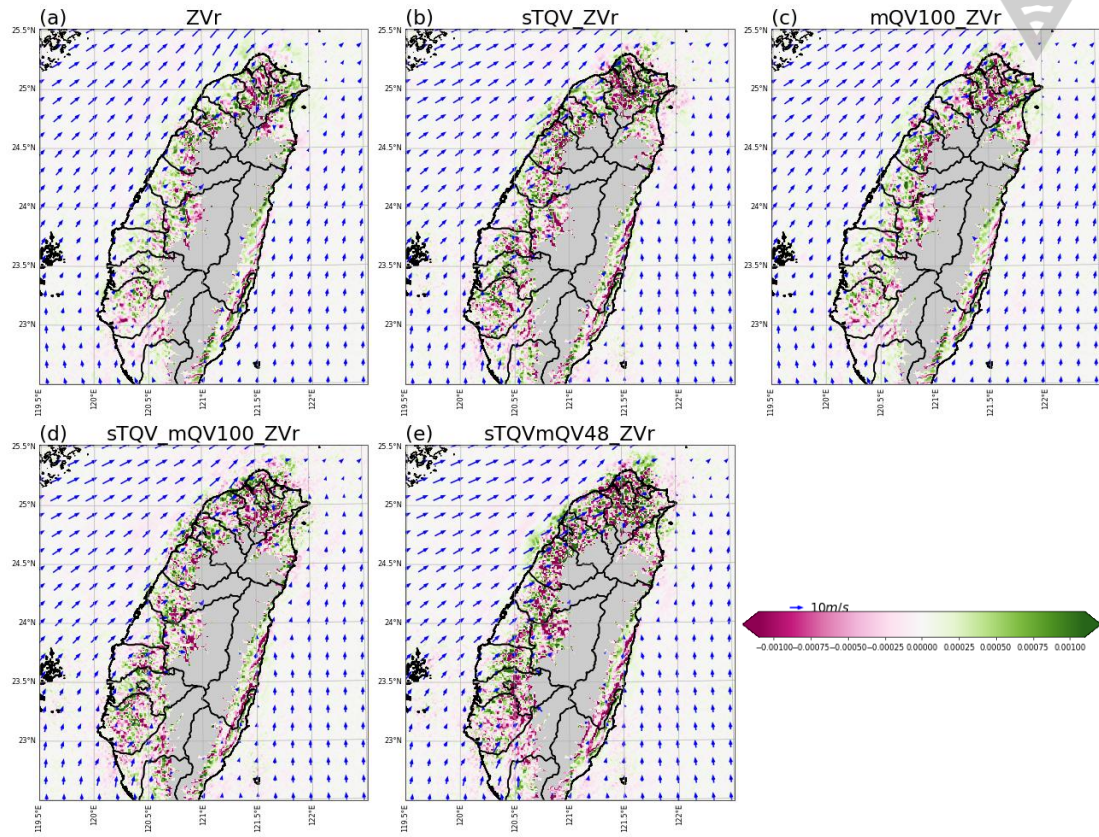
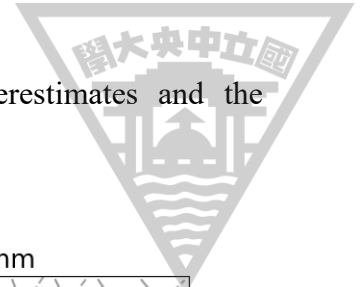


Figure 6.9 900-hPa divergence at 0630 UTC during SOP3 for (a) ZVr, (b) sTQV_ZVr, (c) mQV100_ZVr, (d) sTQV_mQV100_ZVr, (e) sTQVmQV48_ZVr.

6.1.8. Performance diagrams

Fig. 6.10 plots the performance diagram of 1 to 9 hours accumulated rainfall evaluated at four different rainfall thresholds. At all thresholds, ZVr gets the lowest scores, followed by mQV100_ZVr. sTQV_ZVr and sTQV_mQV100_ZVr exhibits quite the same performance at all thresholds. sTQVmQV48_ZVr obtains higher POD scores compared to the other experiments at all threshold. At 1mm threshold,



sTQV_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr overestimates and the scores of 6 hours and 9 hours perform better than the other times.

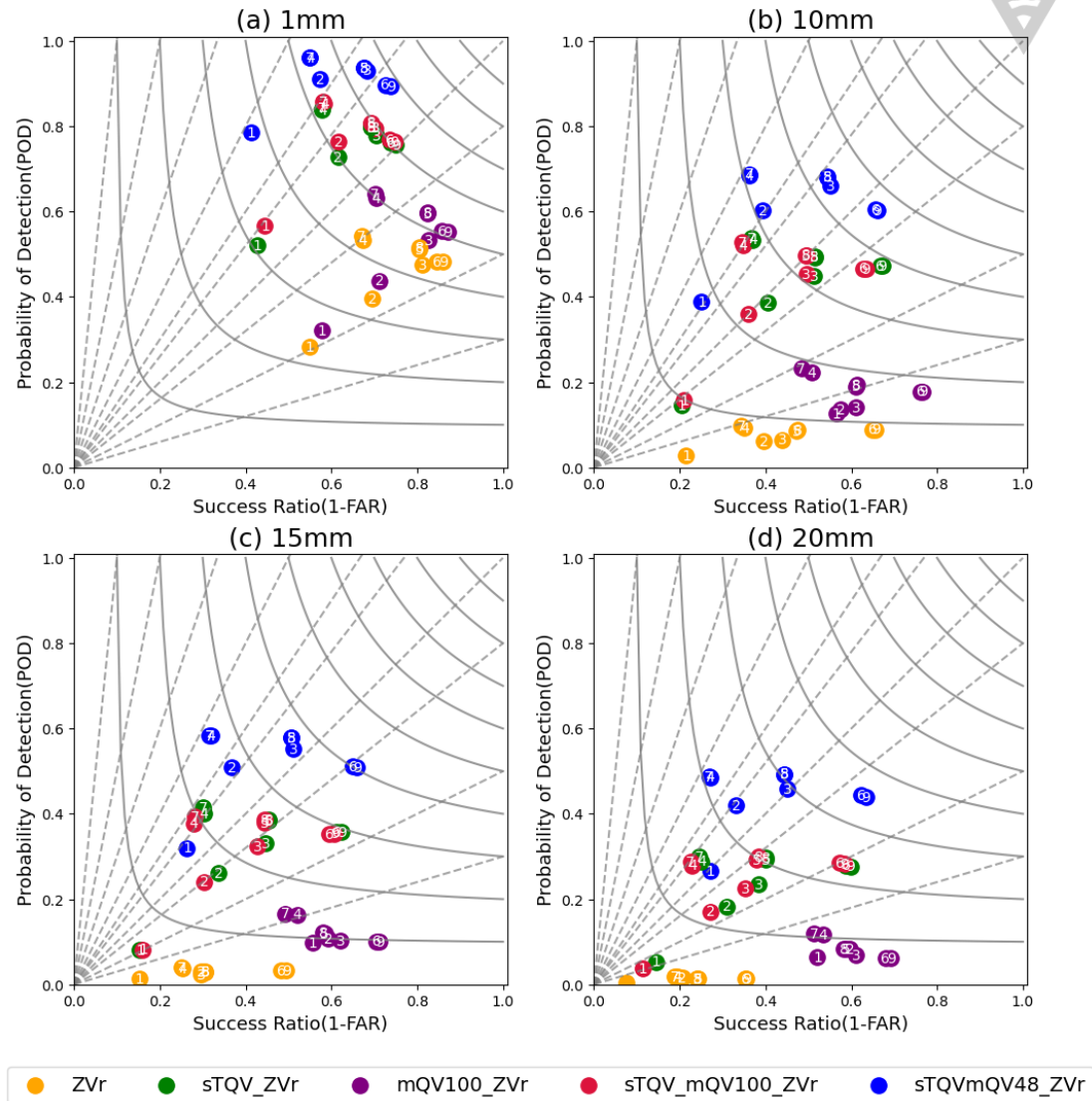


Figure 6.10 Performance diagrams of 1 to 9 hours accumulated rainfall in afternoon thunderstorm case.

6.1.9. Cross section of water vapor at 0630UTC

Fig 6.11 shows cross section of water vapor through the red line in Fig. 6.7a. ZVr and mQV100_ZVr distribute smaller water vapor below 1000m compared to the other experiments. sTQV_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr perform



higher qv_{vapor} below 1000m but only $sTQVmQV48_ZVr$ appears low-level convergence led to rainfall at longitude 120.5° (Fig. 6.7f) while the others don't show convergence and precipitation.

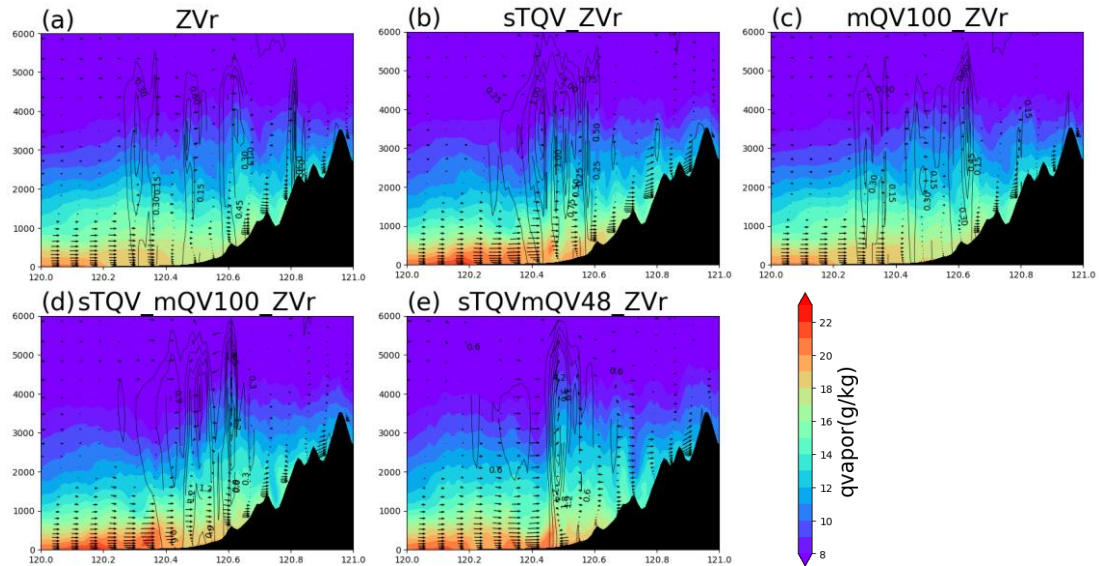


Figure 6.11 Cross section of water vapor mixing ratio (color fill; g kg^{-1}), rain water mixing ratio (black contour; g kg^{-1}), and horizontal wind (vector; m s^{-1}) for (a) ZVr, (b) $sTQV_ZVr$, (c) $mQV100_ZVr$, (d) $sTQV_mQV100_ZVr$, (e) $sTQVmQV48_ZVr$ through the red line in Figure 6.6a at 0630 on 24 June 2022.

6.1.10. Mechanism of MPD impact on the southern Taiwan

Based on the results presented above, assimilating additional MPD data improves the rainfall forecasts over southern Taiwan and the Miaoli region. In this section, we discuss how the three MPDs from northern Taiwan propagate their impact to the southern Taiwan. Fig. 6.12(a) shows the difference of 900hPa water vapor and horizontal wind for $sTQVmQV48_ZVr$ minus $sTQV_ZVr$ at 1st DA cycle (0430 UTC). Higher water vapor concentrations are observed over Tainan in $sTQVmQV48_ZVr$

compared to sTQV_ZVr, and then we plotted the cross section along the blue arrow. Fig. 6.12b shows a southward wind anomaly in sTQVmQV48_ZVr relative to sTQV_ZVr, which indicates that assimilating additional MPD data modifies the wind field. Therefore, the result suggests that the southerly wind may transport the water vapor from northern to southern Taiwan.

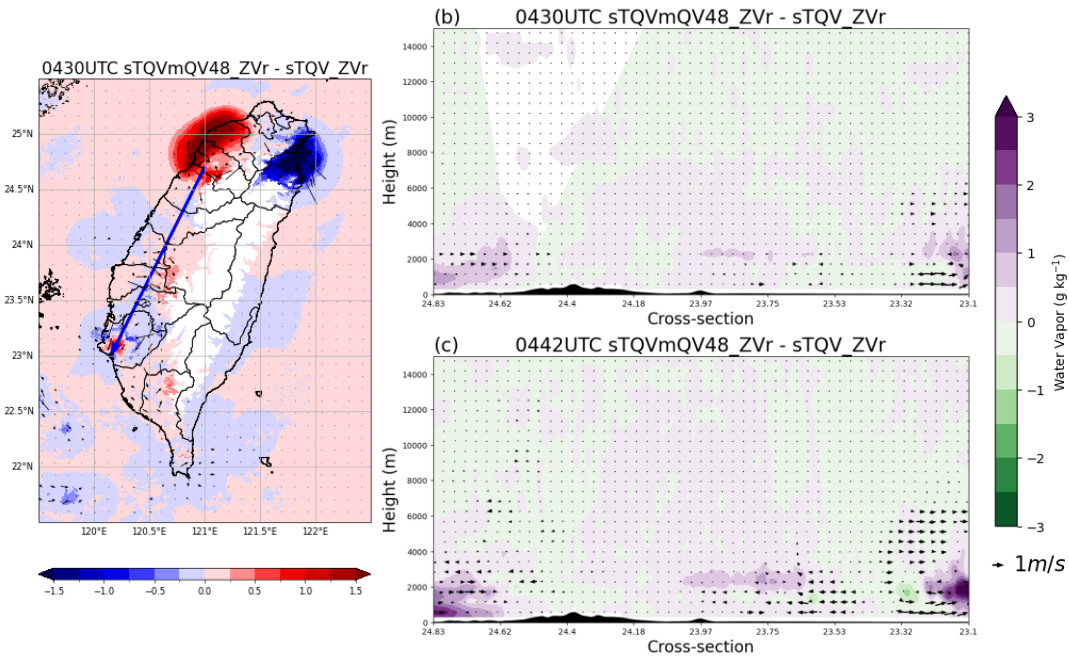


Figure 6.12 (a) difference of 900-hPa water vapor (shading) and horizontal wind field at 0430 UTC in sTQVmQV48_ZVr minus sTQV_ZVr. (b), (c) The vertical cross sections of (a) along the blue arrow at 0430 and 0442 UTC, respectively.

6.2. Mei-Yu case

6.2.1. Performance during DA cycling

The RMSE of water vapor mixing ratio, temperature and absolute humidity during DA cycling are showed in Fig. 6.13. RMSE of water vapor assuming surface data is truth presents that the experiments assimilating water vapor from surface data get lower error at 0630 UTC than at 0430 UTC. In contrast, the RMSE of temperature in the

experiments that assimilated surface data slightly increased at 0630 UTC compared to 0430 UTC (Fig. 6.13.b). RMSE of absolute humidity assuming three MPDs is truth shows the experiments assimilating MPD data decreased error at 0630 UTC. The results indicate assimilating MPD data and surface data could obtain the better water vapor field on the initial conditions.

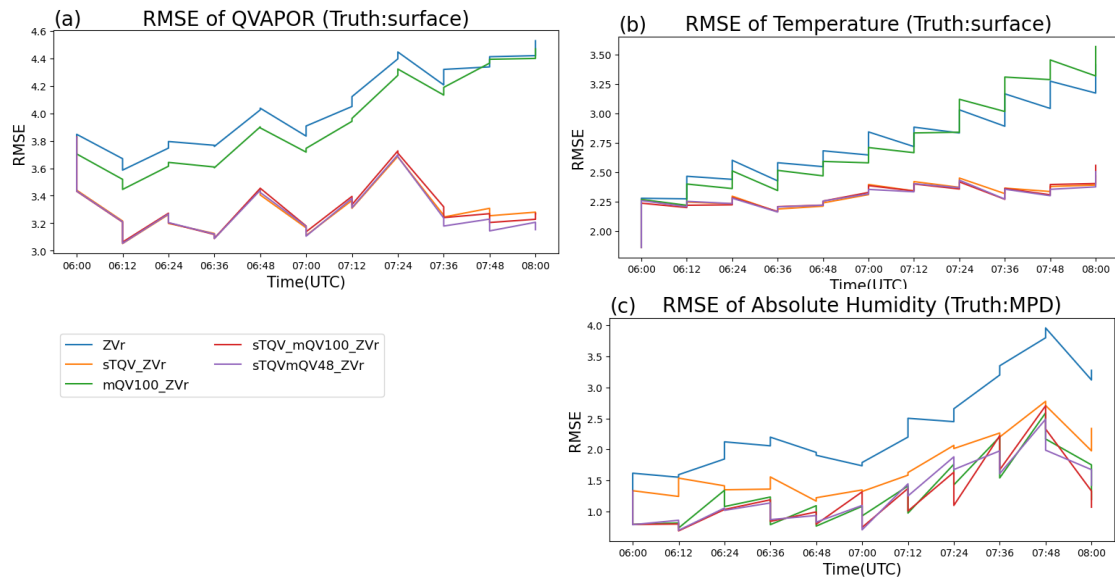


Figure 6.13 RMSE of all the experiments during data assimilation cycling compared to (a) surface water vapor, (b) surface temperature, (c) absolute humidity of MPD for the Mei-Yu case.

6.2.2. Observation – Analysis of water vapor at 0800 UTC

All the experiments underestimate over western Taiwan. Assimilating additional surface data reduce the errors in southern Taiwan (Figs. 6.14. b, d, e). The RMSE of ZVr and mQV100_ZVr is around 4.5, the others are about 3.2 (Table 6.3). Thus, after

assimilating surface data and MPD data the errors were reduced.

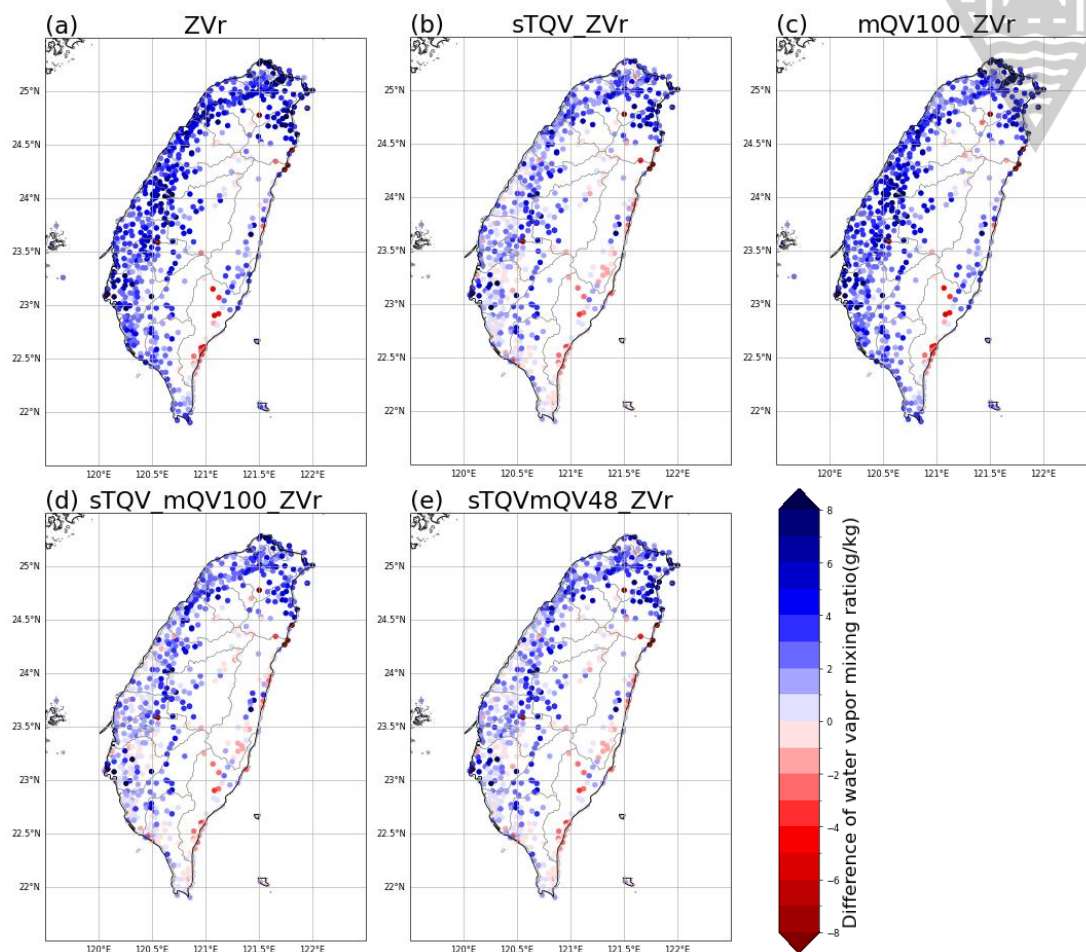


Figure 6.14 observation minus analysis of water vapor at 0800 UTC for the Mei-Yu case.

Table 6.3 RMSE and Bias of water vapor at 0800 UTC during IOP3

EXP	RMSE	Bias
ZVr	4.529	-3.319
sTQV_ZVr	3.268	-1.523
mQV100_ZVr	4.469	-3.125
sTQV_mQV100_ZVr	3.271	-1.535
sTQVmQV48_ZVr	3.153	-1.500



6.2.3. Observation – Analysis of temperature at 0800 UTC

ZVr and mQV100_ZVr experiments which didn't assimilate surface data perform large error and underestimation compared to the other experiments (Fig. 6.15. a, c). Their RMSE is about 3.5K while the others are around 2.5K, shown in Table 6.4. sTQV_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr reduce error at all surface station (Fig. 6.15. b, d, e).

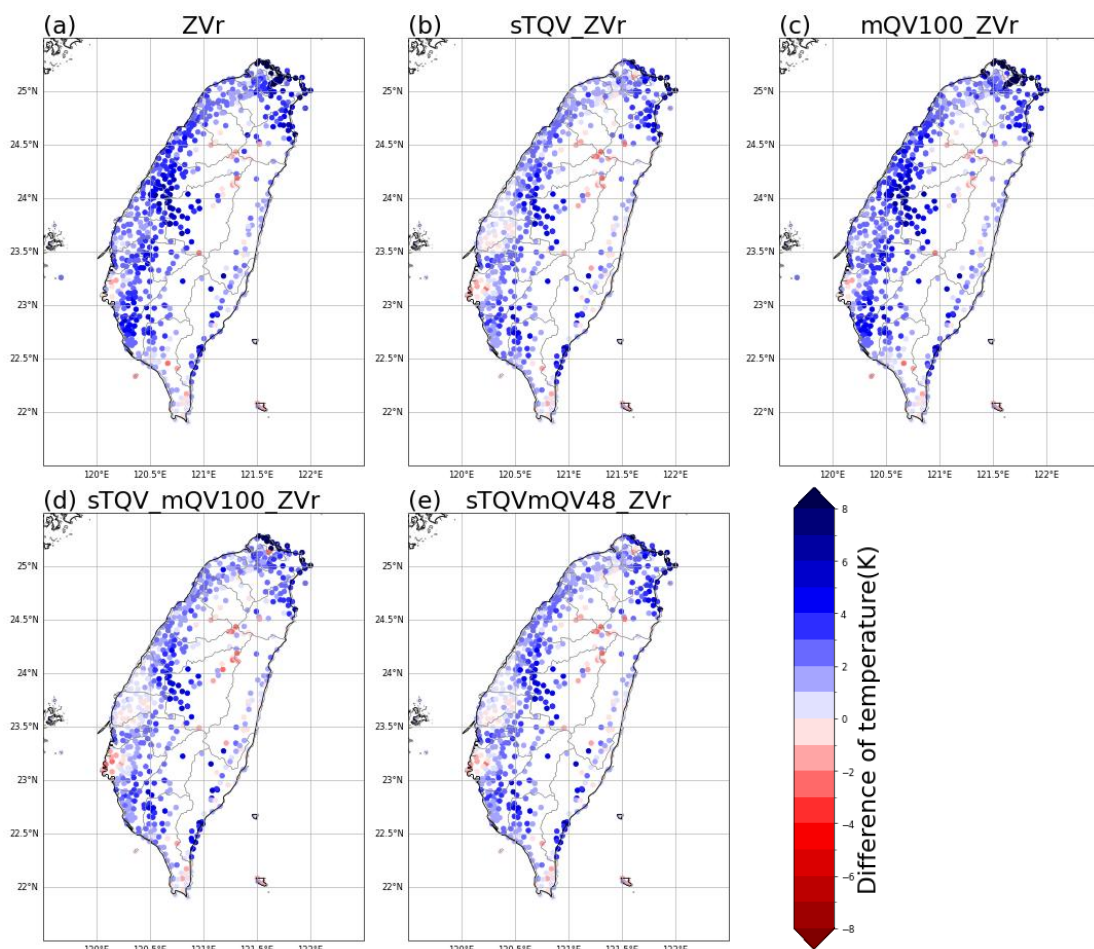
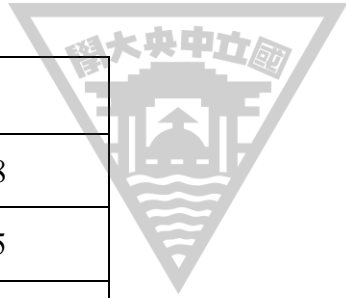


Figure 6.15 observation minus analysis of temperature at 0800 UTC for the Mei-Yu case.

Table 6.4 RMSE and Bias of temperature at 0800UTC during IOP3.



EXP	RMSE	Bias
ZVr	3.412	-2.768
sTQV_ZVr	2.469	-1.795
mQV100_ZVr	3.568	-2.766
sTQV_mQV100_ZVr	2.560	-1.809
sTQVmQV48_ZVr	2.507	-1.784

6.2.4. Absolute humidity vertical profiles at 0800 UTC

Figure 6.16 shows the absolute humidity vertical profiles of MPD, background (green line) and analysis (red line) at 0800UTC at three sites respectively. Compared with the background, the analysis from ZVr and sTQV_ZVr exhibit larger discrepancies from the MPD observations between 500m to 1500m at Hsinchu. Analysis of mQV100_ZVr shows improved agreement with MPD between 1000m to 1500m at NCU (Fig. 6.16 g), below 1000m at Yilan (Fig. 6.16 h) and below 1500m at Hsinchu (Fig. 6.16 i) compared to background. Analysis of sTQV_mQV100_ZVr is closer to MPD below 900m at Yilan (Fig. 6.16 k) and matches the observations almost perfectly below 800m at Hsinchu (Fig. 6.16 l). Analysis of sTQVmQV48_ZVr exhibits much better agreement with the MPD observations from 1200 to 1500m and below 700m at Yilan (Fig. 6.16 n), and below 1400m at Hsinchu (Fig. 6.16 o).

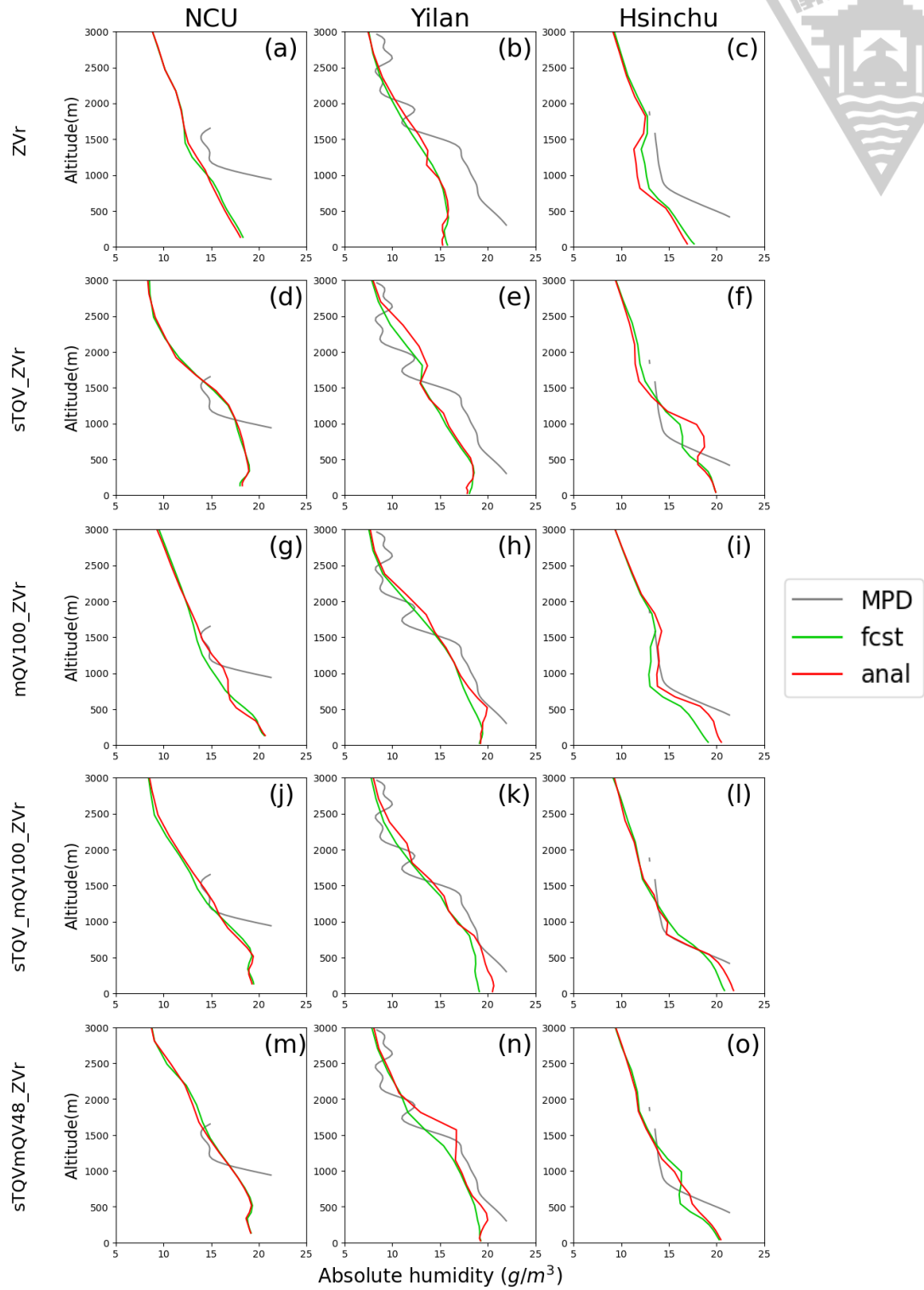
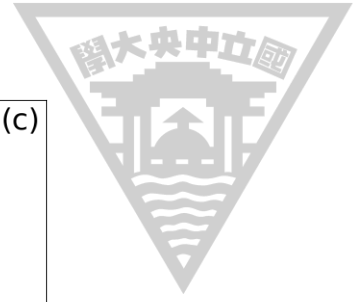


Figure 6.16 absolute humidity vertical profiles compared to three MPD sites at 0800

UTC for (a)-(c) ZVr, (d)-(f) sTQV_ZVr, (g)-(i) mQV100_ZVr, (j)-(l)

sTQV_mQV100_ZVr and (m)-(o) sTQVmQV48_ZVr.



6.2.5. Composite reflectivity

The composite reflectivity from CWA shows two southwest-to-northeast-oriented convective lines, which is along northwestern coast of Taiwan and the other is over northern Taiwan at 0800UTC (Fig. 6.17.a), and continued developing at 0900UTC (Fig. 6.17.b), eventually merging at 10UTC (Fig. 6.17.c). Fig. 6.17 d-r present the results of the experiments and the solid purple lines overlaid on the pictures represent reflectivity of CWA greater than 30 dBZ. All the experiments capture the left part of convective line at 0800UTC (Fig. 6.17.d,g,j,m, and p), but dissipated over northern Taiwan and distributed northwest of Taiwan at 0900 and 1000UTC. All the experiments reveal convective cells over central Taiwan closer to observation at 0800 and 0900 UTC.

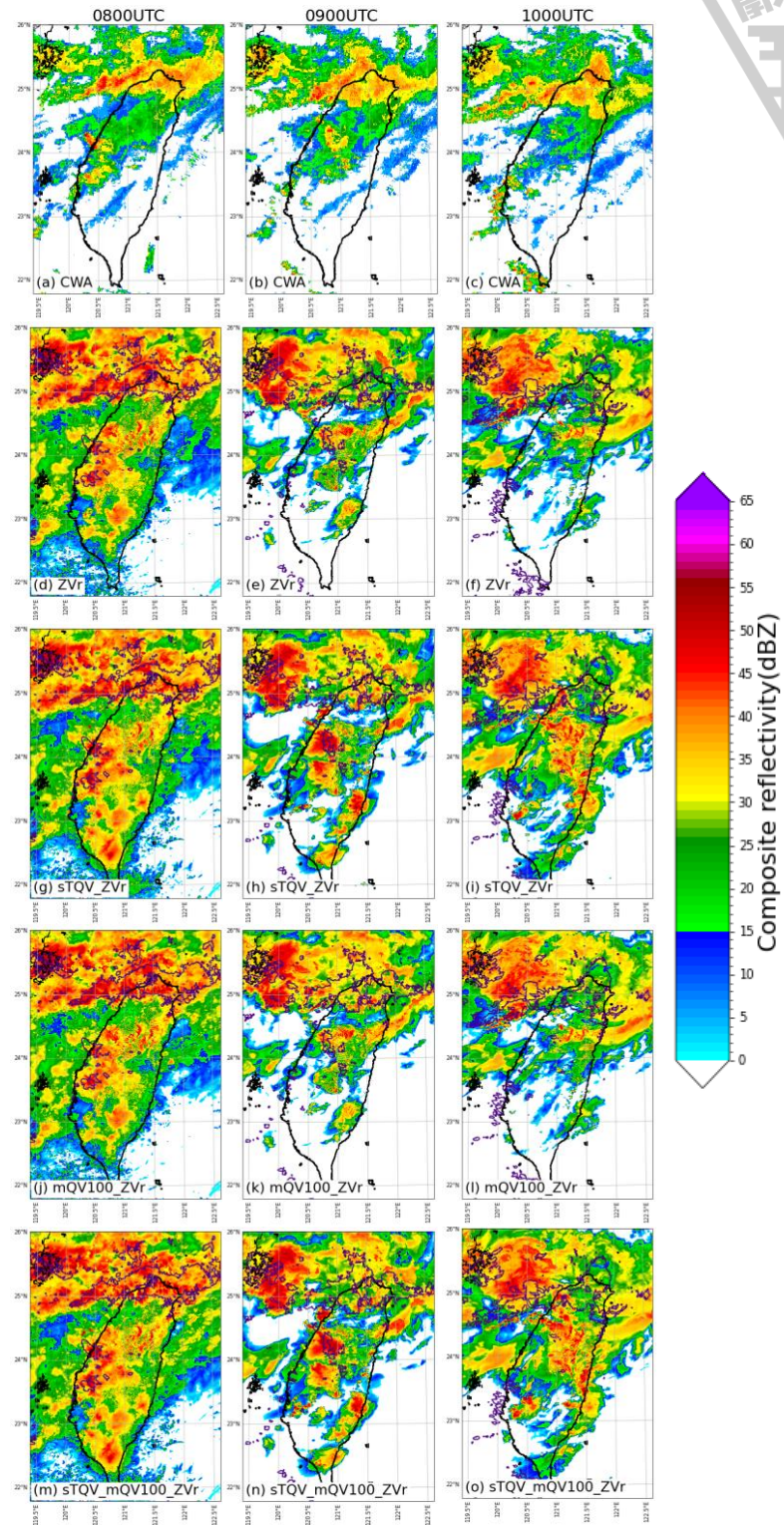


Figure 6.17 Composite reflectivity from (a)-(c) CWA observations and at final analysis time (0800 UTC), prediction time (0900 and 1000 UTC) for (d)-(f) ZVr, (g)-(i) sTQV_ZVr, (j)-(l) mQV100_ZVr, (m)-(o) sTQV_mQV100_ZVr and (p)-(r)



sTQVmQV48_ZVr. The solid purple lines represent reflectivity of CWA greater than 30dBZ.

6.2.6. Divergence

In Figs 6.18, all the experiments distribute similar location of the low-level convergence over northern Taiwan.

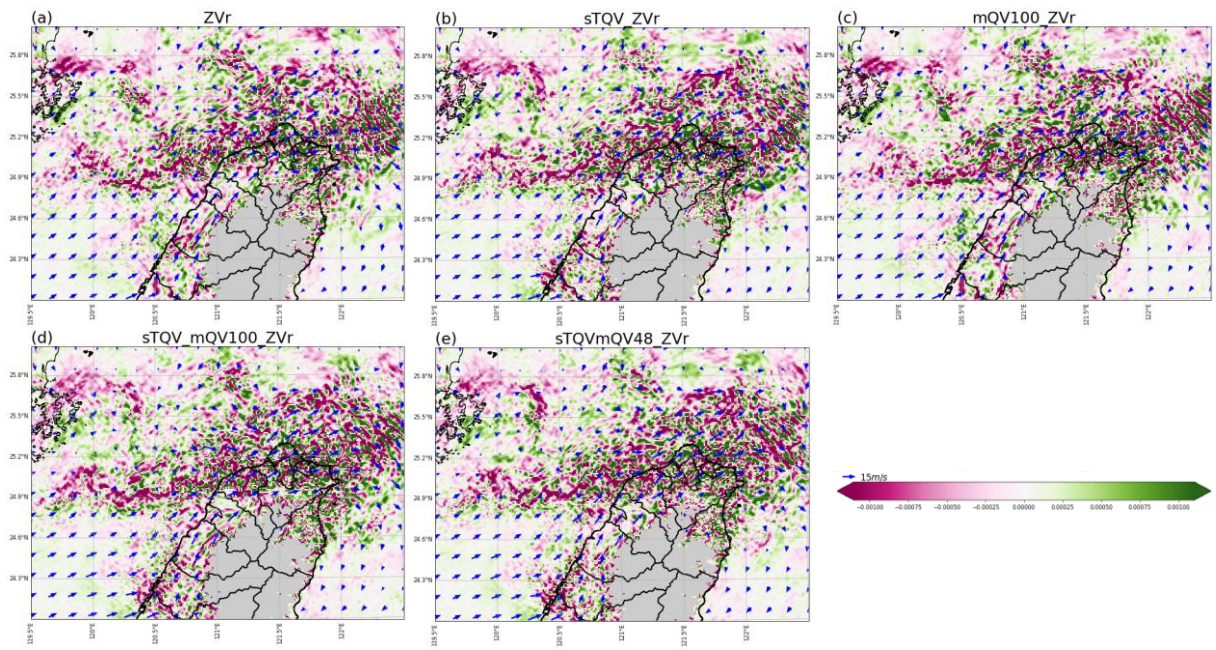


Figure 6.18 divergence at 900hPa at 0800 UTC during IOP3 for (a) ZVr, (b) sTQV_ZVr, (c) mQV100_ZVr, (d) sTQV_mQV100_ZVr, (e) sTQVmQV48_ZVr.

6.2.7. Rainfall forecast

The 3-hour accumulated precipitation from QPESUMS exhibits maximum rainfall area in northern Taiwan (Fig. 6.19a). ZVr shows the prominent underestimation (Fig. 6.19b). The heavy rainfall simulated by mQV100_ZVr is concentrated over northern Taiwan, but the intensity is lower than observation (Fig. 6.19d). The maximum rainfall area of sTQV_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr occur over central Taiwan and distributes the same rainfall pattern over northern and southern Taiwan (Fig.

6.19 c,e,f).

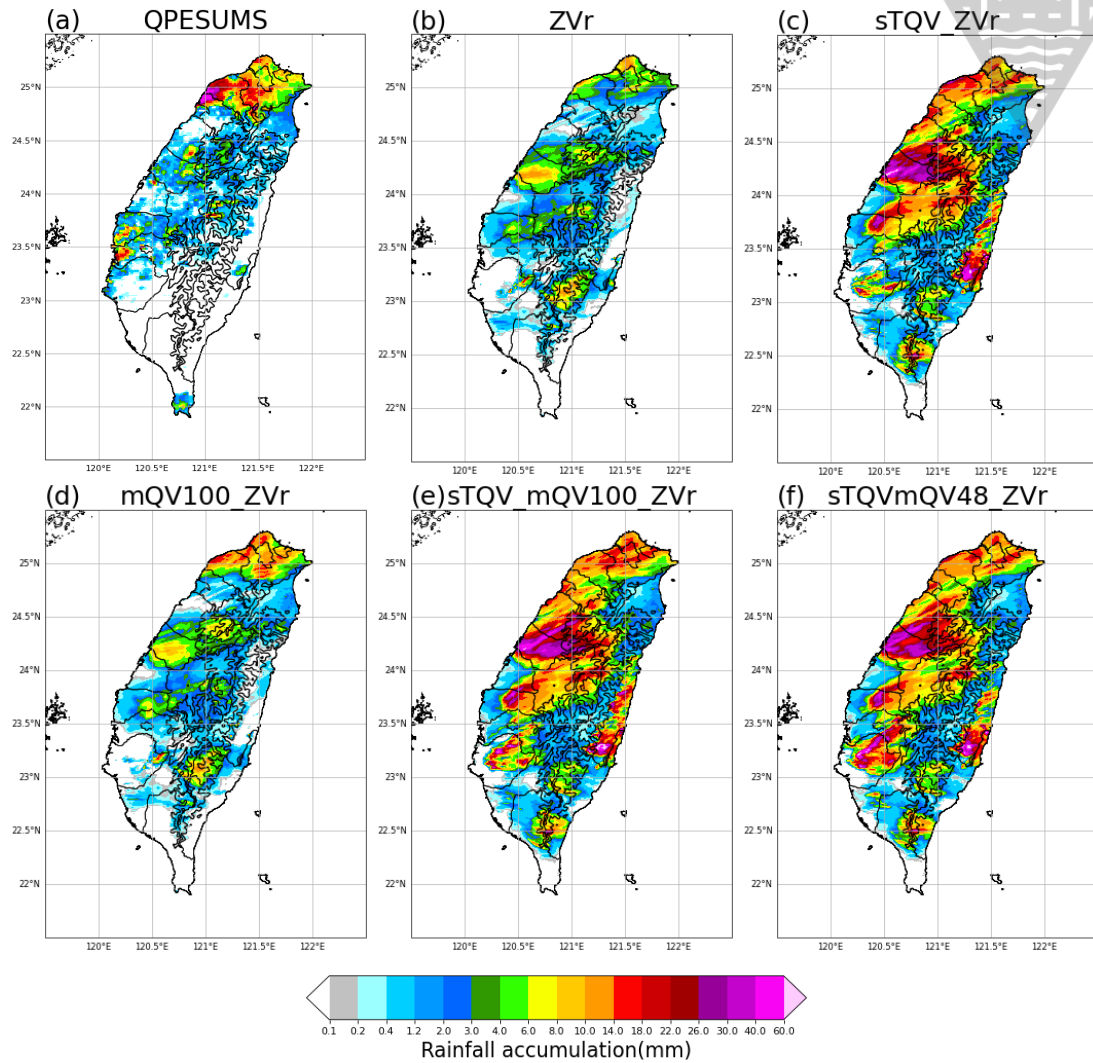


Figure 6.19 3 hours accumulated precipitation from 0800 to 1100 UTC on 6 June of
(a) CWA, (b) ZVr, (c) sTQV_ZVr, (d) mQV100_ZVr, (e) sTQV_mQV100_ZVr, (f)
sTQVmQV48_ZVr.

The 6-hour accumulated precipitation from QPESUMS exhibits maximum rainfall area at coastal region of Hsinchu and Miaoli and mountain area in central Taiwan (Fig. 6.20a). ZVr shows maximum rainfall region at northwest corner of Taiwan (Fig. 6.20b). mQV100_ZVr simulated heavy rainfall at coastal region of Taipei and Taoyuan (Fig. 6.20d). The maximum rainfall area of sTQV_ZVr, sTQV_mQV100_ZVr and

sTQVmQV48_ZVr distributes the same rainfall pattern over northern Taiwan but overpredicts many area, with the intensity slightly lower than observation.

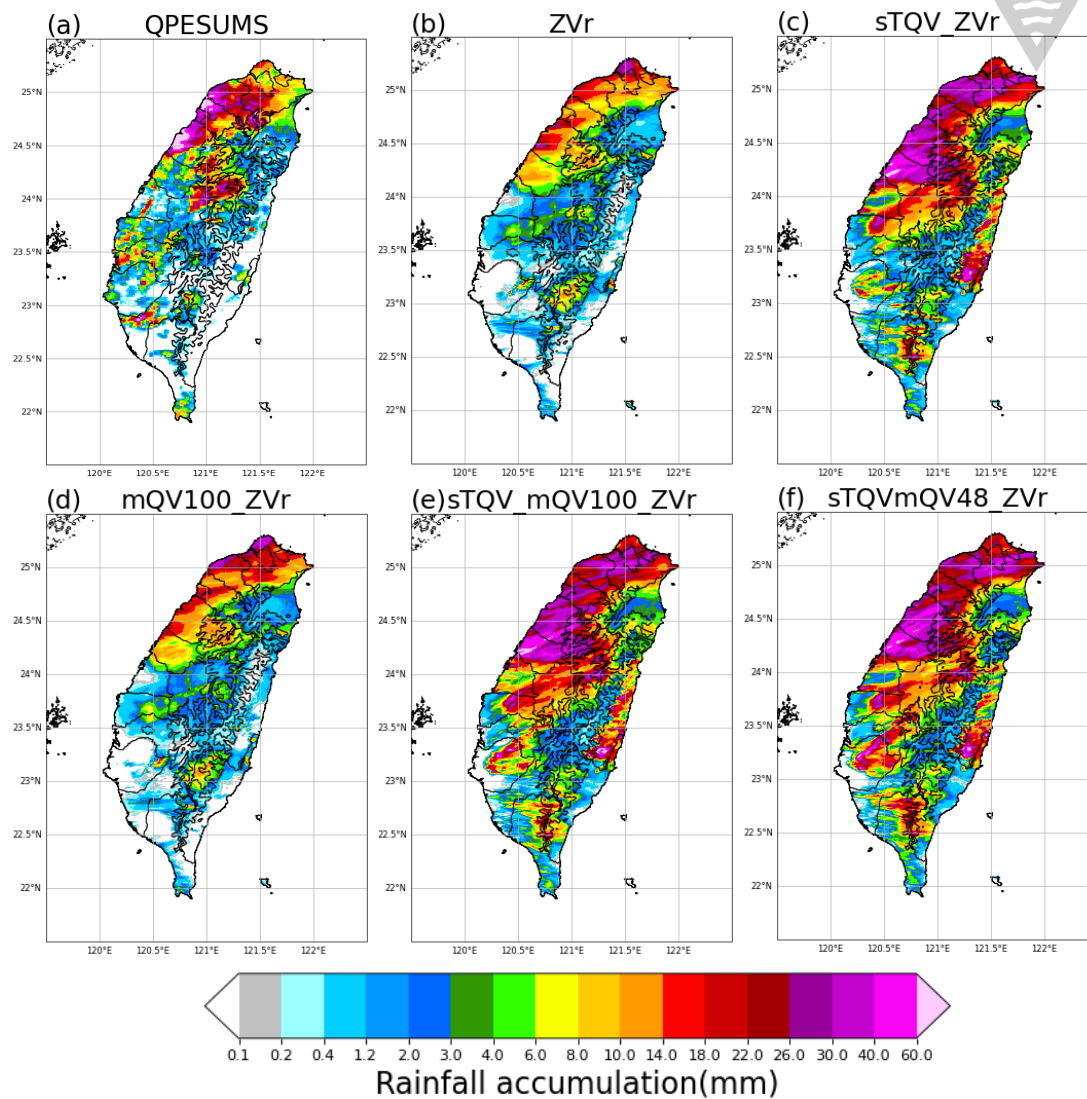


Figure 6.20 6 hours accumulated precipitation from 0800 to 1400UTC on 6 June of
 (a) CWA, (b) ZVr, (c) sTQV_ZVr, (d) mQV100_ZVr, (e) sTQV_mQV100_ZVr, (f)
 sTQVmQV48_ZVr.

The 9-hour accumulated precipitation from QPESUMS exhibits heavy rainfall over northern Taiwan and mountain area in central Taiwan (Fig. 6.21a). The intensity of ZVr and mQV100_ZVr underestimates compared to the observation. sTQV_ZVr,

sTQV_mQV100_ZVr and sTQVmQV48_ZVr capture the same rainfall pattern with the observation but overpredict the rainfall areas including coastal region of Taichung and Changhua and some regions in southern and eastern Taiwan.

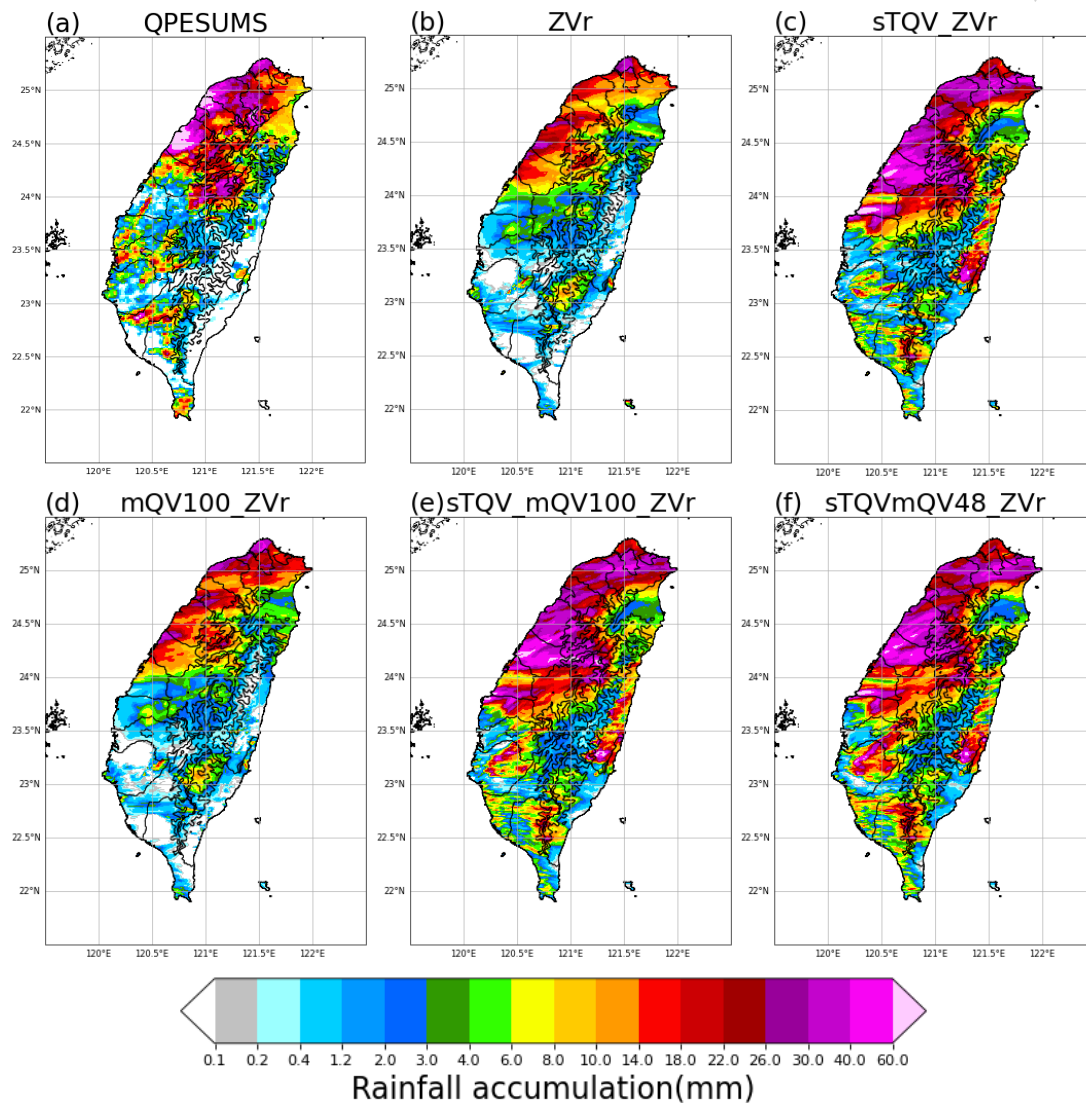
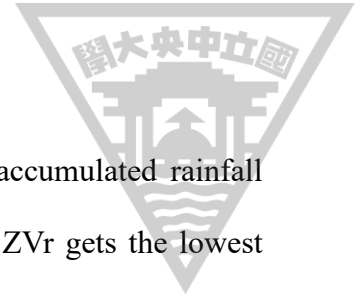


Figure 6.21 9 hours accumulated precipitation from 0800 to 1700UTC on 6 June of (a) CWA, (b) ZVr, (c) sTQV_ZVr, (d) mQV100_ZVr, (e) sTQV_mQV100_ZVr, (f) sTQVmQV48_ZVr.



6.2.8. Performance diagram

Fig. 6.22 plots the performance diagram of 1 to 9 hours accumulated rainfall evaluated at four different rainfall thresholds. At all thresholds, ZVr gets the lowest scores, followed by mQV100_ZVr. sTQV_ZVr, sTQV_mQV100_ZVr and sTQVmQV48_ZVr exhibits quite the same performance and positive bias at all thresholds. sTQVmQV48_ZVr obtains higher POD scores compared to the other experiments only at 1mm threshold.

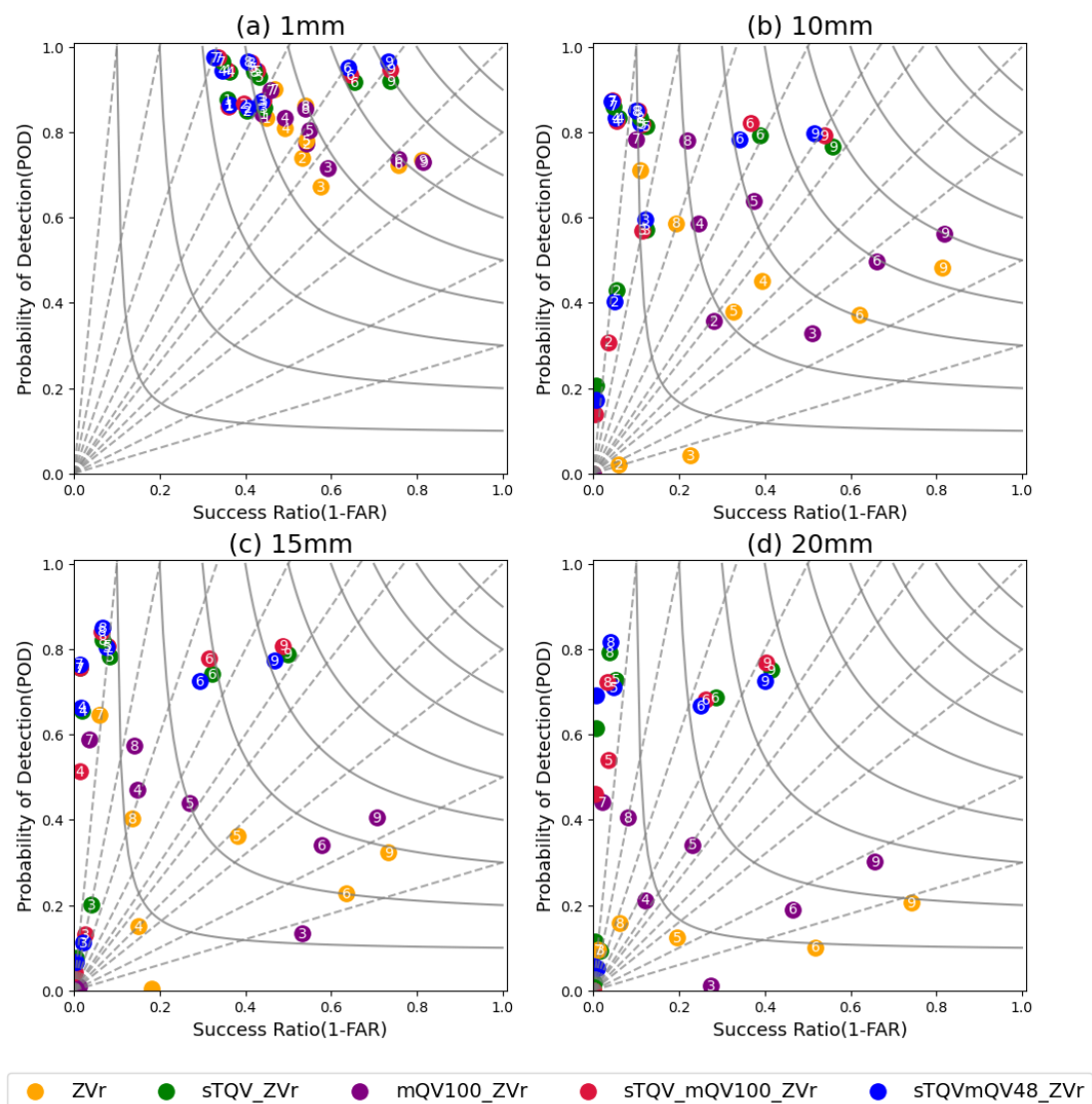


Figure 6.22 Performance diagrams of 1 to 9 hours accumulated rainfall in Mei-Yu



case

6.3. Sensitivity experiment I

In the previous section, we show the results that assimilated water vapor mixing ratio transformed from MPD, but the variable observed by MPD is absolute humidity. Thus, we conducted the experiment assimilating MPD in absolute humidity and localization set to 100km compared to original sTQV_mQV100_ZVr experiment assimilating in water vapor mixing ratio during SOP3 (6.3.1 section) and IOP3 (6.3.2 section).

Table 6.5 the experiments conducted in sensitivity test I during SOP3 and IOP3.

EXP	Radar – Z,Vr	Surface – T,QV	MPD variable (localization)
sTQV_mAH100_ZVr	Yes	Yes	Absolute humidity (100km)
sTQV_mQV100_ZVr	Yes	Yes	Water vapor (100km)

6.3.1. Results during SOP3

Figure 6.23 performs observation minus analysis at 0630UTC. sTQV_mAH100_ZVr decreases the error in Taipei, northeast corner of Taiwan and coastal region of Hsinchu and Miaoli. Their difference between two experiments is shown in Fig. 6.24. The RMSE of both experiments is around 2.44, and bias is about -0.1 (Table 6.6).

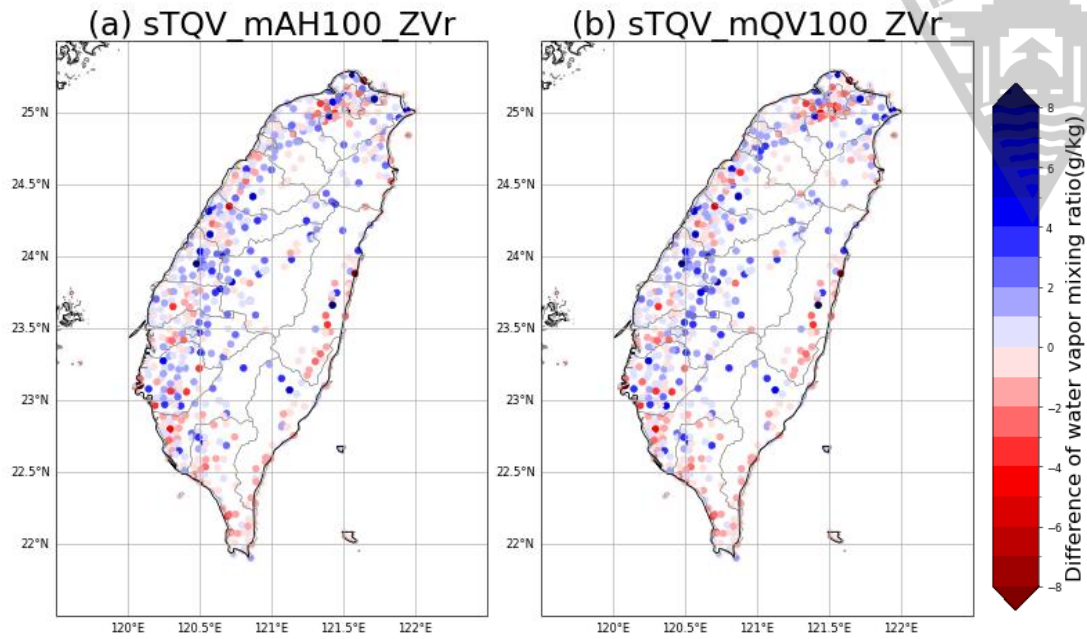


Figure 6.23 observation minus analysis of water vapor at 0630 UTC at 1st eta level during SOP3 for (a) sTQV_mAH100_ZVr and (b) sTQV_mQV100_ZVr.

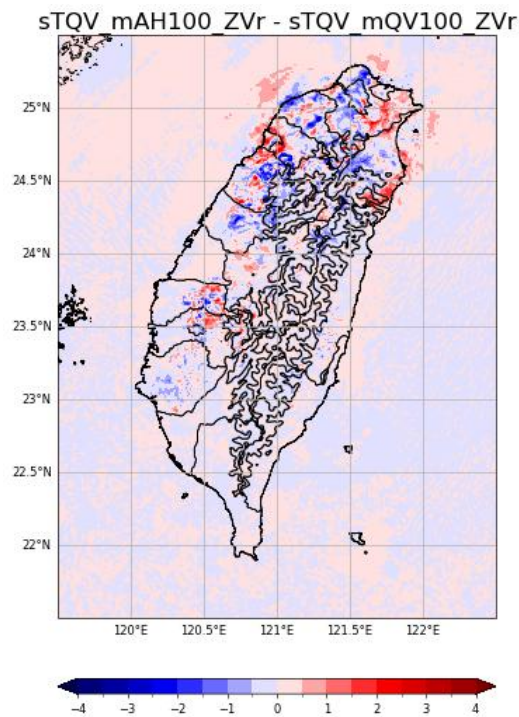


Figure 6.24 difference of water vapor in sTQV_mAH100_ZV minus sTQV_mQV100_ZVr at 0630 UTC at 1st eta level.

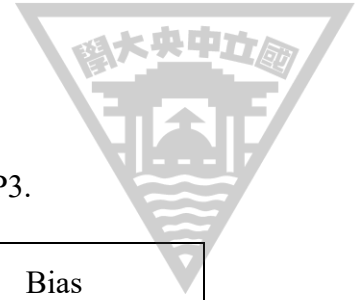


Table 6.6 RMSE and Bias of water vapor at 0630UTC during SOP3.

EXP	RMSE	Bias
sTQV_mAH100_ZVr	2.434	-0.098
sTQV_mQV100_ZVr	2.443	-0.059

Figure 6.25 reveals the 3 hours and 6 hours accumulated precipitation in both experiments, and their differences are shown in Fig. 6.26. Compared with sTQV_mQV100_ZVr, sTQV_mAH100_ZVr produces less rainfall in mountain area of north Taiwan and more rainfall in northeastern corner of Taiwan, resulting in larger discrepancies from the observations.

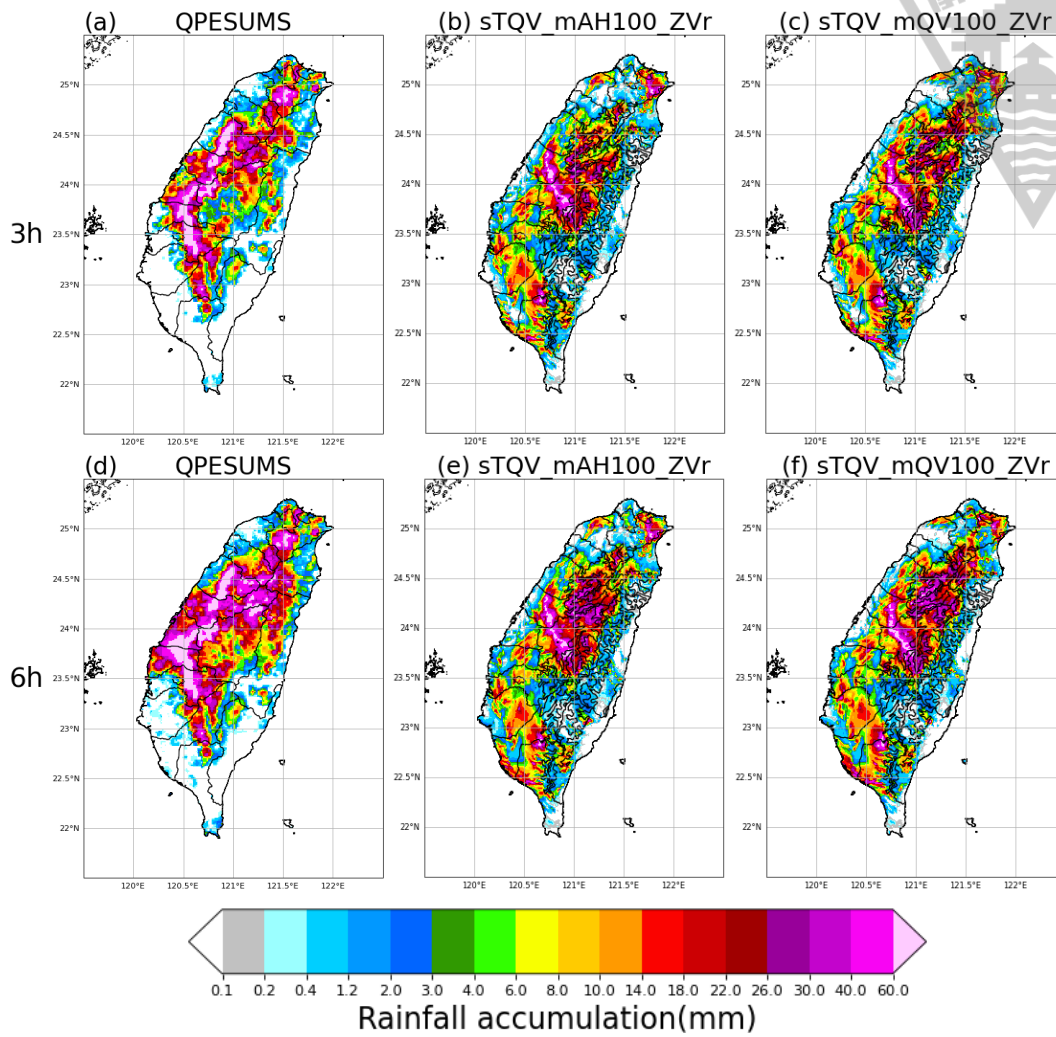


Figure 6.25 (a) – (c) show 3 hours accumulated precipitation from 0630 to 0930 UTC and (d) – (f) show 6 hours accumulated precipitation from 0630 to 1530UTC on 24 June. (a) and (d) are QPESUMS, (b) and (e) are sTQV_mAH100_ZVr, and (c) and (f) are sTOV_mQV100_ZVr.

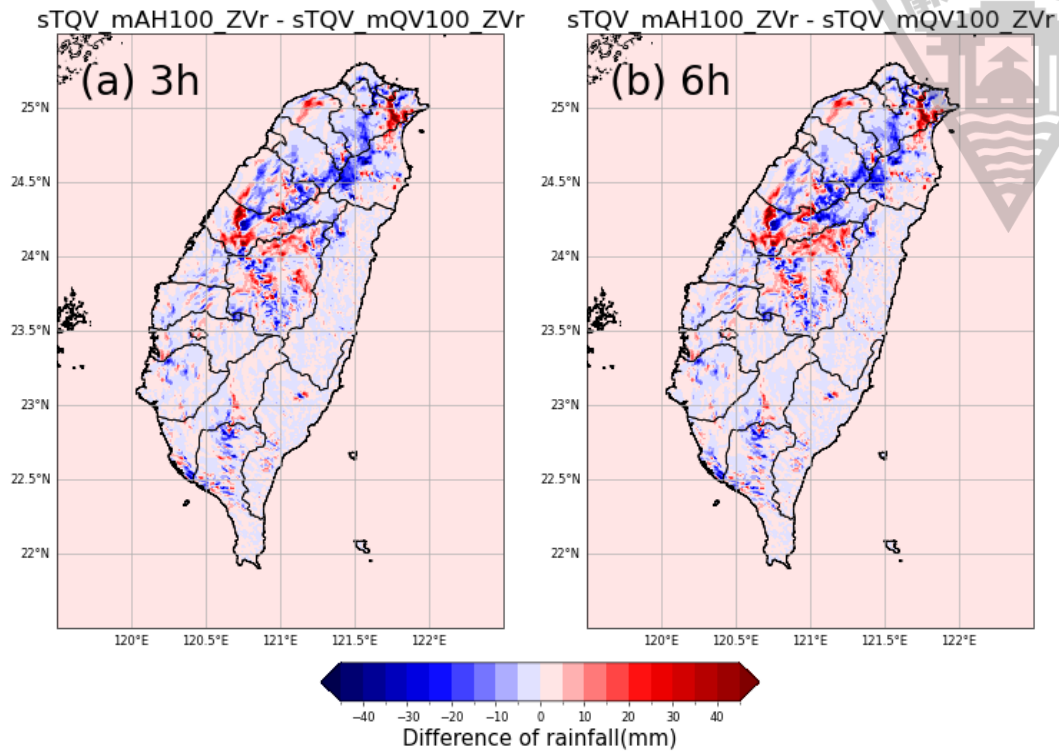


Figure 6.26 difference of (a) 3 hours (b) 6 hours accumulated precipitation in sTQV_mAH100_ZV minus sTQV_mQV100_ZVr during SOP3.

6.3.2. Results during IOP3

Fig. 6.27 performs observation minus analysis at 0800UTC and Fig. 6.28 reveals the difference of water vapor in sTQV_mAH100_ZV minus sTQV_mQV100_ZVr at 0800UTC. sTQV_mAH100_ZV simulates more water vapor over northern Taiwan, leading to less error compared to sTQV_mQV100_ZVr.

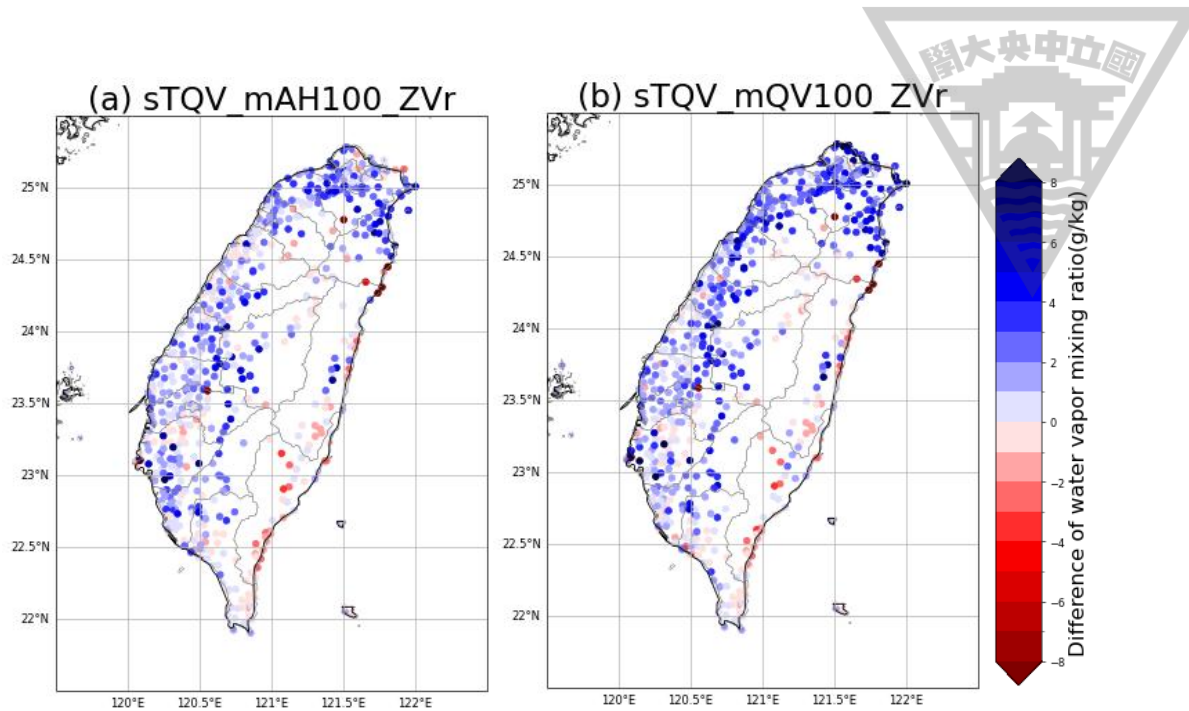


Figure 6.27 observation minus analysis of water vapor at 0800UTC at 1st eta level during IOP3 for (a) sTQV_mAH100_ZVr and (b) sTQV_mQV100_ZVr.

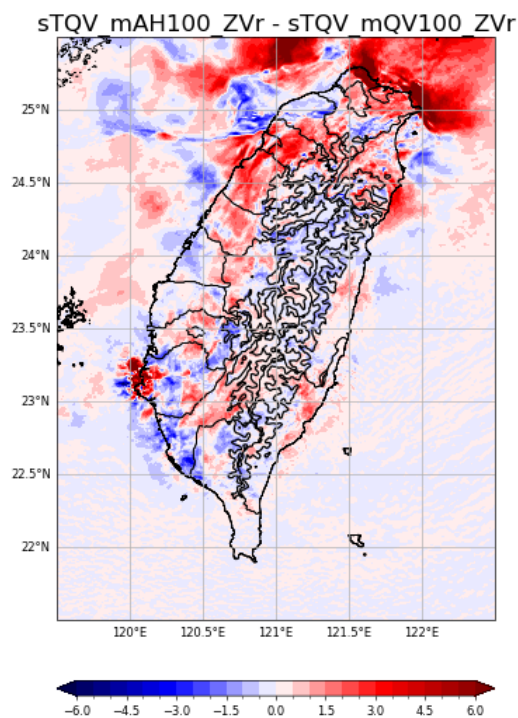


Figure 6.28 difference of water vapor in sTQV_mAH100_ZVr minus sTQV_mQV100_ZVr at 0800UTC at 1st eta level.

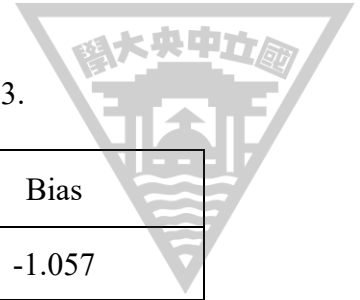


Table 6.7 RMSE and Bias of water vapor at 0800UTC during IOP3.

EXP	RMSE	Bias
sTQV_mAH100_ZVr	2.903	-1.057
sTQV_mQV100_ZVr	3.271	-1.535

Fig 6.29 presents 3 hour and 9 hour accumulated precipitation during IOP3. sTQV_mAH100_ZVr exhibited the wrong position and lower value of maximum rainfall in observation (Fig. 6.29b,e). However, sTQV_mQV100_ZVr demonstrated the higher intensity of the rainfall in northern Taiwan but overpredicted in central Taiwan. Fig. 6.30 shows the difference of the precipitation, revealing that the intensity of the precipitation in sTQV_mAH100_ZVr is weaker than sTQV_mQV100_ZVr.

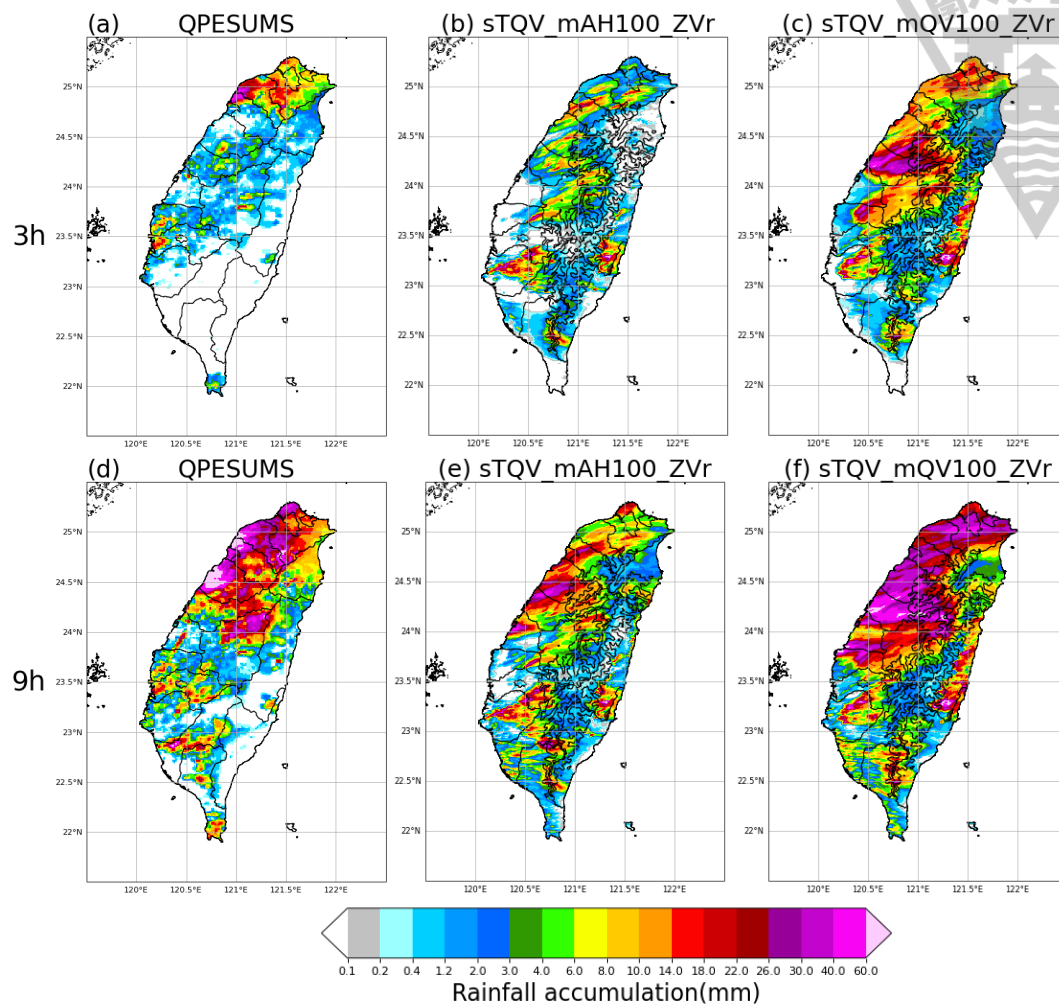


Figure 6.29 (a) – (c) show 3 hours accumulated precipitation from 0800 to 0930UTC and (d) – (f) show 9 hours accumulated precipitation from 0800 to 1700UTC on 6 June. (a) and (d) are QPESUMS, (b) and (e) are sTQV_mAH100_ZVr, and (c) and (f) are sTQV_mQV100_ZVr.

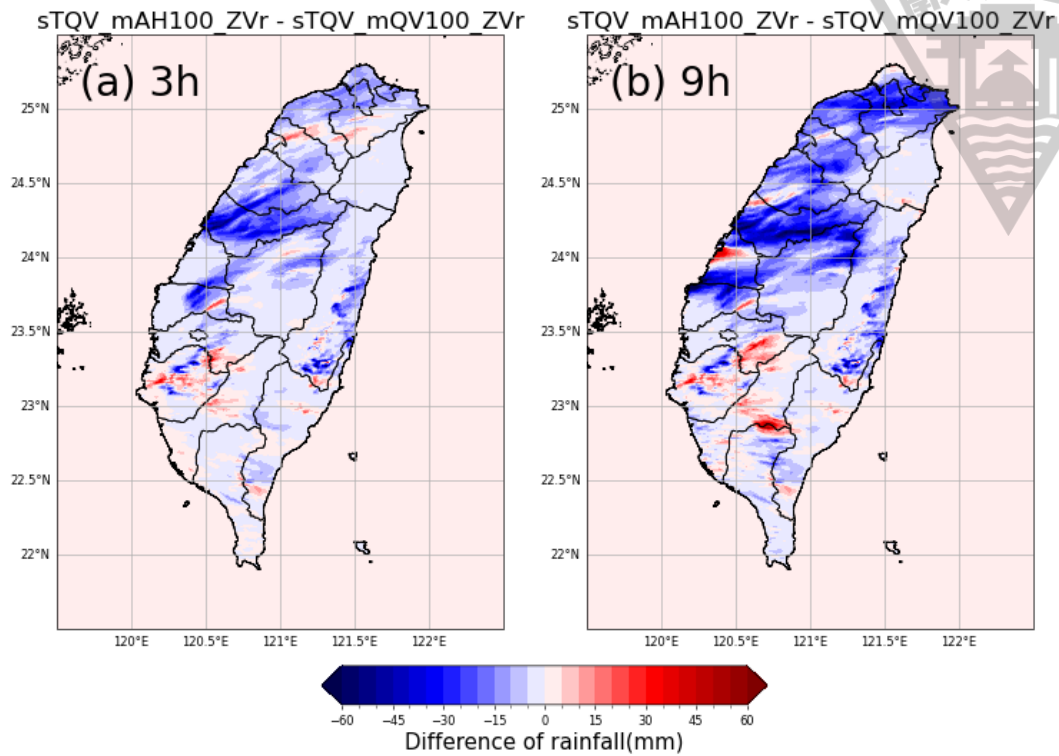


Figure 6.30 difference of (a) 3 hours (b) 6 hours accumulated precipitation in sTQV_mAH100_ZV minus sTQV_mQV100_ZVr during IOP3.

6.4. Sensitivity experiment II

In this section, we want to examine assimilating the water vapor profiles only above 500m. According to 2.2.2 section, MPD comparisons with the radiosondes produces higher error below 500m, so we conducted the new experiment: sTQVmQV48_a500_ZVr (Table 6.8) which only assimilated MPD data above 500m compared to sTQVmQV48_ZVr experiment assimilating all-height MPD data during SOP3.

Table 6.8 experiments conducted in sensitivity test II during SOP3.

EXP	Radar – Z,Vr	Surface – T,QV	MPD – QV (localization) range
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sTQVmQV48_a500_ZVr	Yes	Yes	Yes (48km) - above 500m
sTQVmQV48_ZVr	Yes	Yes	Yes (48km) - all height

Figure 6.31 shows Observation – Analysis of water vapor at 0630UTC at 1st eta level. sTQVmQV48_a500_ZVr has larger underestimation in Hsinchu region compared to sTQVmQV48_ZVr. Their difference is shown in Fig. 6.32. While the experiment which didn't assimilate water vapor below 500m performs less water vapor in coastal region of Hsinchu and Taipei but higher in north of Taipei basin. These two experiments exhibit comparable RMSE and bias value (Table 6.9).

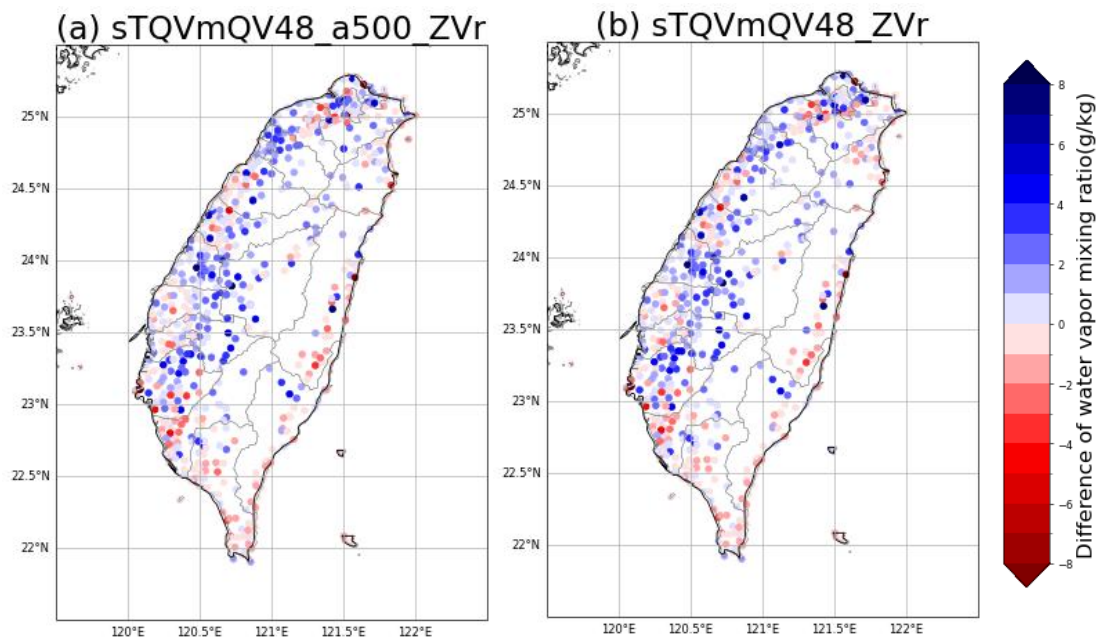


Figure 6.31 Observation – Analysis of water vapor at 0630UTC at 1st eta level in (a) sTQVmQV48_a500_ZVr, (b) sTQVmQV48_ZVr.

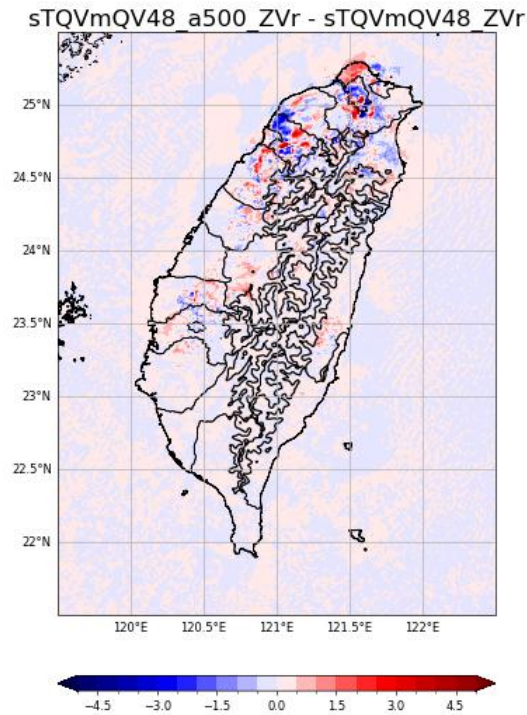


Figure 6.32 difference of sTQVmQV48_a500_ZV minus sTQVmQV48_ZVr at 0630UTC at 1st eta level.

Table 6.9 RMSE and Bias of water vapor at 0630UTC during SOP3.

EXP	RMSE	Bias
sTQVmQV48_a500_ZVr	2.555	-0.334
sTQVmQV48_ZVr	2.559	-0.358

Fig. 6.33 presents 3 hours and 6 hours accumulated precipitation in both experiments. sTQVmQV48_a500_ZVr reveals larger rainfall in coastal region of Hsinchu and northeast corner of Taiwan, but the pattern is inconsistent with the observations. In the other hand, sTQVmQV48_a500_ZVr decreases the rainfall over coastal region of Taoyuan, which matches the QPESUMS. Their difference of accumulated precipitation is shown in Fig. 6.34.

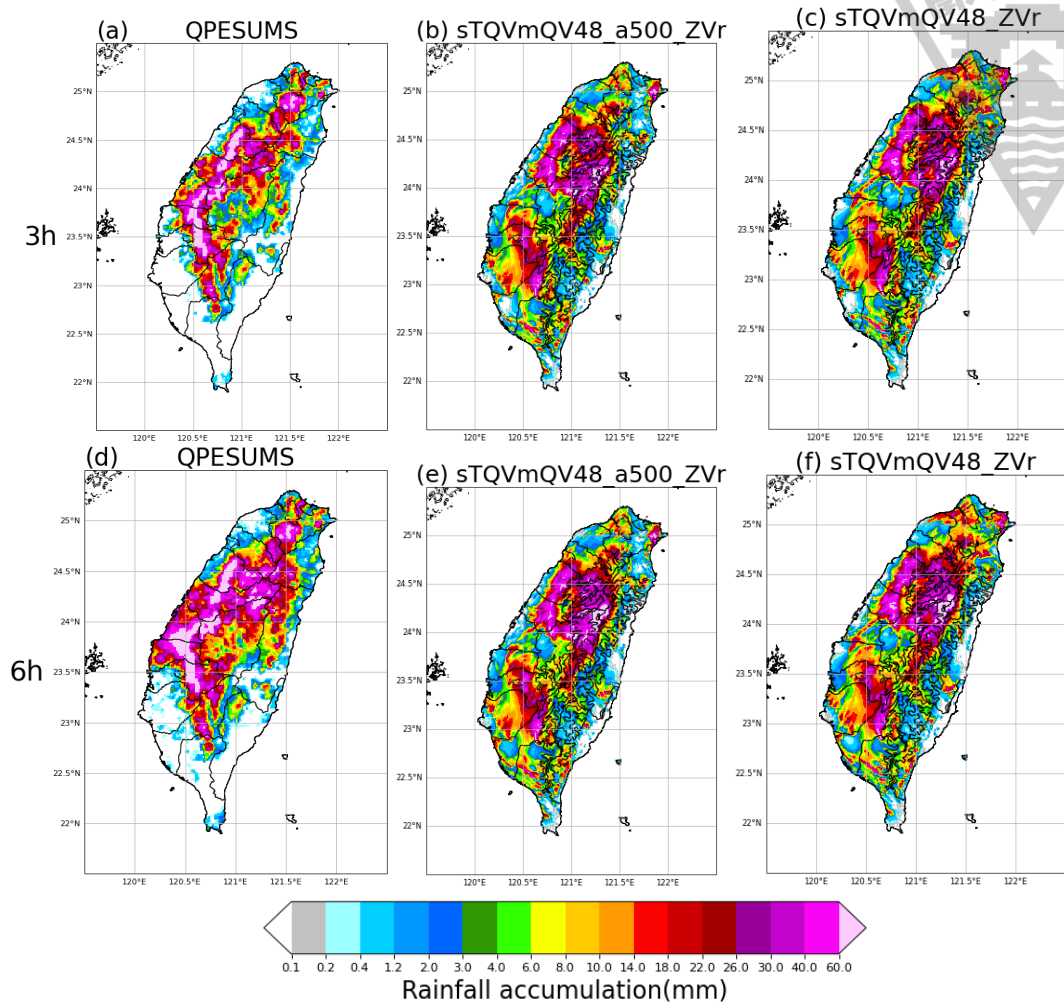


Figure 6.33 (a) – (c) show 3 hours accumulated precipitation from 0630 to 0930UTC and (d) – (f) show 6 hours accumulated precipitation from 0630 to 1530UTC on 24 June. (a) and (d) are QPESUMS, (b) and (e) are sTQVmqV48_a500_ZVr, and (c) and (f) are sTQVmqV48_ZVr.

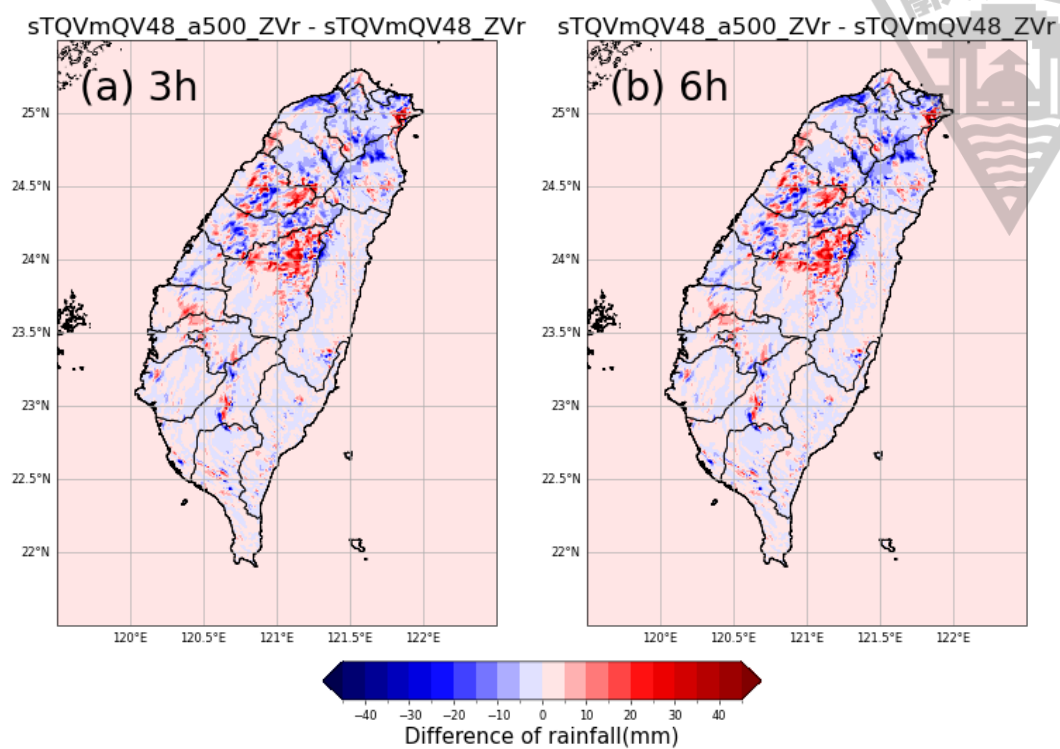


Figure 6.34 difference of (a) 3 hours (b) 6 hours accumulated precipitation in
sTQVmQV48_a500_ZV minus sTQVmQV48_ZVr.



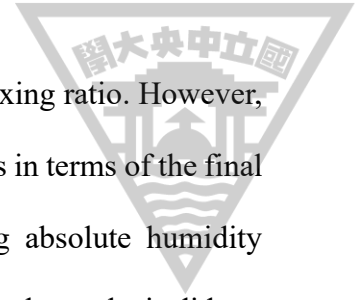
Chapter 7 Conclusions and future works

7.1. Conclusions

Three MPDs were conducted during TAHOPE campaign, collecting data from May 28 to August 12 2022. Therefore, we examined the water vapor characteristics in northern Taiwan. We found out that absolute humidity and LPW in afternoon thunderstorm cases is the highest among all weather systems. Moreover, the water vapor in Mei-Yu, afternoon thunderstorm, typhoon cases is the highest during afternoon period. The larger wind speed exceeding 7.5 ms^{-1} led to higher water vapor at NCU because it's located at higher altitude and more inland area. EOF analysis can identify the differences in the vertical moisture variability associated with different weather events relative to the mean conditions during the entire TAHOPE campaign.

To investigate the impact of assimilating MPD and surface data on the initial condition and forecasts. Assimilating water vapor of MPD and surface data which provide three-dimensional mapping of the water vapor field provide better thermodynamic environment during both cases. The assimilation of MPD data modifies the wind field, which indirectly alters the moisture distribution over southern Taiwan. When the localization of MPD set to 48 km improves rainfall forecast in afternoon thunderstorm compared to 100 km. However, improvement is limited in the Mei Yu case. Consequently, higher spatiotemporal resolution of MPD represent more local thermodynamic environment leading to better results when the localization is within 48 km, and having a more positive impact on mesoscale systems like afternoon thunderstorm case but is limited in large scale system like Mei-Yu case.

In the sensitivity test I, we examined the impact of assimilating MPD data in

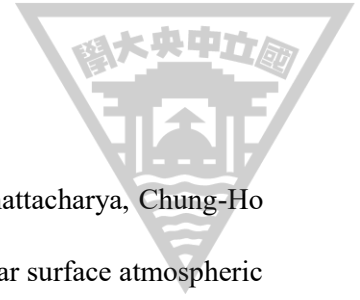


different variable including absolute humidity and water vapor mixing ratio. However, no significant differences were found between the two experiments in terms of the final analysis and rainfall forecasts for SOP3. In IOP3, assimilating absolute humidity reduced the RMSE by about 0.3; nevertheless, this improvement in the analysis did not translate into better quantitative precipitation forecast (QPF). In sensitivity test II, despite excluding water vapor observations below 500 m from the assimilation, the final analysis and QPF showed results similar to those from the experiment assimilating water vapor observations at all heights.

7.2. Future works

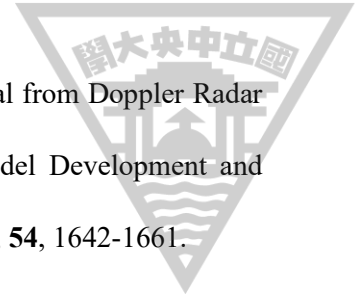
In this study, we investigated the positive impact of MPD in the afternoon thunderstorm case. To further assess the assimilation benefits of MPD observations for afternoon thunderstorm, future work should evaluate additional convective cases to determine whether similar positive impacts can be consistently achieved. Although the positive impact of MPD assimilation was limited in the 6 June 2022 Mei-Yu case, more case studies are needed before a robust conclusion can be drawn regarding the effectiveness of MPD observations for Mei-Yu events.

Based on the results of Chapter 2, higher water vapor was also observed in typhoon and low-pressure cases. Therefore, future work should investigate the impacts of MPD assimilation on these weather systems to further assess its applicability and forecasting benefits.

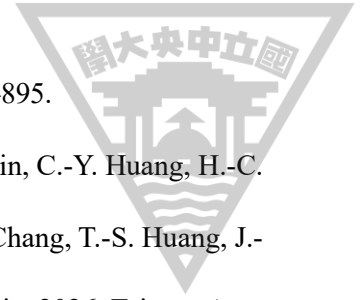


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