



Assimilating OLCI and MODIS NIR calibrated Precipitable Water Vapor (PWV) to improve weather forecasting performance

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Introduction

Description of WRF data assimilation experiment

Evaluation results

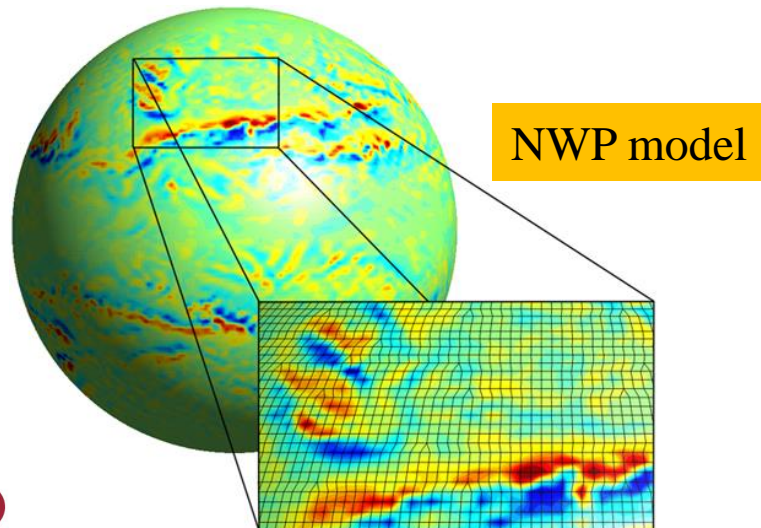
- WRF PWV evaluation results
- WRF rainfall forecasting success rate
- WRF rainfall forecast skill scores
- WRF rainfall spatial pattern

Conclusions

Introduction: Weather forecasting & data assimilation



- ❑ Numerical Weather Prediction (NWP) model uses math equations to forecast weather based on current atmosphere state (“**initial value**”)
- ❑ **Weather forecasting is an “initial value” problem !!!**
(Abbe, C., 1901; Bauer, P. , et. al., 2015; Jankov, I. et. al., 2022)
- ✓ **Data assimilation** aims to **improve** the quality of “**initial value**” to obtain better forecasting results.



Why assimilating water vapor?

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- ❑ Water vapor plays an important role in **formation of clouds and rainfall.**

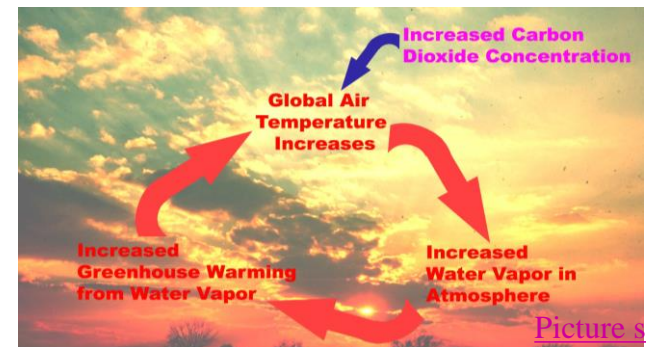
(Benevides, P, et. al., 2015; Padullés, R., et. al., 2022)

- ❑ Distribution and variation of water vapor significantly **affects other meteorological parameters, such as temperature.**

(Sherwood, S. C., et al., 2010; Inomata, Y., et. al., 2021)



[Picture source](#)



[Picture source](#)

- ❑ It has been widely demonstrated that **assimilating accurate water vapor data** can improve the initial fields and further **leads to a better forecasting performance**, such as:

- **higher rainfall forecast skill scores**
- **better humidity forecasting fields**
- **more accurate forecast of tropical cyclone intensity**
- ...

Current research status of NIR water vapor assimilation



- ❑ **Very limited** studies has been focusing on satellite-based **NIR water vapor assimilation**.

(Chen et al., 2008 and Saunders 2021)

- ❑ U.K. Meteorological Office (Met Office) is **the first one in the world** successfully assimilating **Sentinel-3 (3A launched 2016; 3B launched 2018) OLCI NIR PWV** into the global NWP model **since May 2022**.

- ❑ Dr. Roger Saunders (2021) from Met Office demonstrated that assimilating OLCI NIR PWV **made positive contribution to the Met Office's global NWP model in forecast scores**.

Saunders, R. (2021). Assimilation of OLCI total column water vapour in the Met Office global numerical weather prediction system. *Meteorological Applications*, 28(5), e2029.

Our work in NIR water vapor assimilation



❑ To the best of our knowledge, our group is the **2nd one** to assimilate Sentinel-3 OLCI NIR PWV, and the **first one** to assimilate OLCI NIR PWV into a **regional NWP model**.

- ❑ We assimilated Sentinel-3 OLCI NIR PWV over the South China into the WRF model for March and June 2020. Our results showed:
- ✓ PWV forecasting accuracy for the first 12-h after assimilation is improved by **3.1% for March; 4.4% for June**
 - ✓ For June 2020, after assimilating OLCI NIR PWV, the **POD** and **CSI** scores can improve up to **0.024** and **0.017**, respectively.

Gong, Y., Liu, Z., Chan, P. W., & Hon, K. K. (2023). Assimilating Sentinel-3 All-Sky PWV Retrievals to Improve the WRF Forecasting Performance Over the South China. *Journal of Geophysical Research: Atmospheres*, 128(8), e2022JD037979.

Our work about GNSS PWV assimilation

We assimilated **GNSS PWV** and radiosonde data over the South China into the WRF:

❑ **Improvement in PWV forecasting accuracy:**

- WRF+GNSS(A) (assimilation of 76 GNSS): **11.6%**
- WRF+GNSS(B) (assimilation of 213 GNSS): **14.5%**
- WRF+RS (assimilation of 23 radiosonde): **2.9%**
- WRF+GNSS(A)+RS (assimilation of 213 GNSS + 23 radiosonde): **14.8%**

❑ **Rainfall forecasting performance for the first 6-h after assimilation:**

- **POD score improvement** under rainfall threshold of 0.1 mm, 5 mm, 10 mm, 15 mm, and 20 mm are up to **0.041, 0.078, 0.080, 0.079, and 0.075**, respectively.
- **CSI score improvement** under rainfall threshold of 0.1 mm, 5 mm, 10 mm, 15 mm, and 20 mm are up to **0.036, 0.057, 0.048, 0.045, and 0.040**, respectively.
- **ETS score improvement** under rainfall threshold of 0.1 mm, 5 mm, 10 mm, 15 mm, and 20 mm are up to **0.036, 0.057, 0.047, 0.044, and 0.039**, respectively.

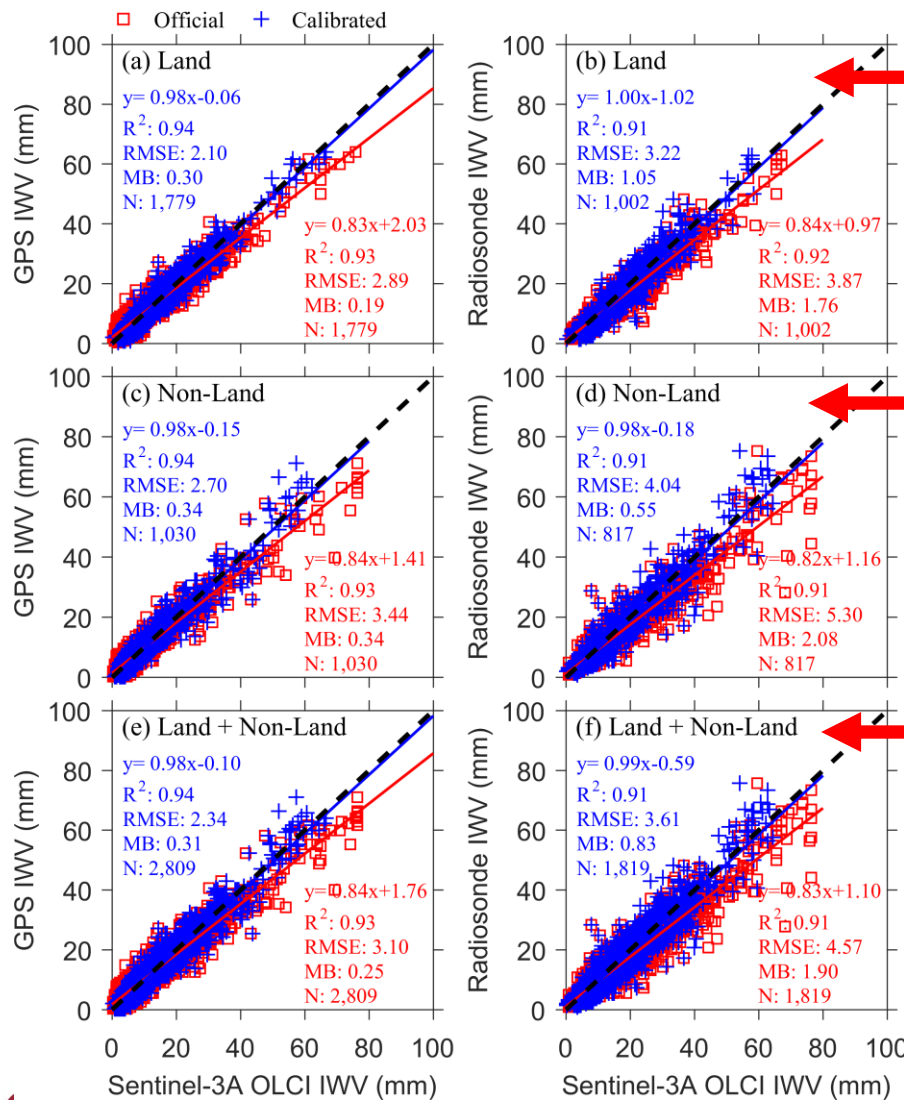
Gong, Y., Liu, Z., Chan, P. W., & Hon, K. K. (2023). Assimilating GNSS PWV and radiosonde meteorological profiles to improve the PWV and rainfall forecasting performance from the Weather Research and Forecasting (WRF) model over the South China. *Atmospheric Research*, 286, 106677.

Official and Calibrated Sentinel-3A OLCI Water Vapor

IWV: integrated water vapor

MB: mean bias

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Land (clear sky)

2.89 mm → 2.11 mm (GPS) 27.34%

3.87 mm → 3.22 mm (radiosonde) 16.80%

Non-Land (non-clear sky):

3.44 mm → 2.70 mm (GPS) 21.51%

5.30 mm → 4.04 mm (radiosonde) 23.77%

Land + Non-Land (all sky):

3.10 mm → 2.34 mm (GPS) 24.52%

4.57 mm → 3.61 mm (radiosonde) 21.01%

Xu, J., & Liu, Z. (2023a). A Back Propagation Neural Network-Based Calibration Approach for Sentinel-3 OLCI Near-Infrared Water Vapor Product. *IEEE Geoscience and Remote Sensing Letters*, 20, 1-5.

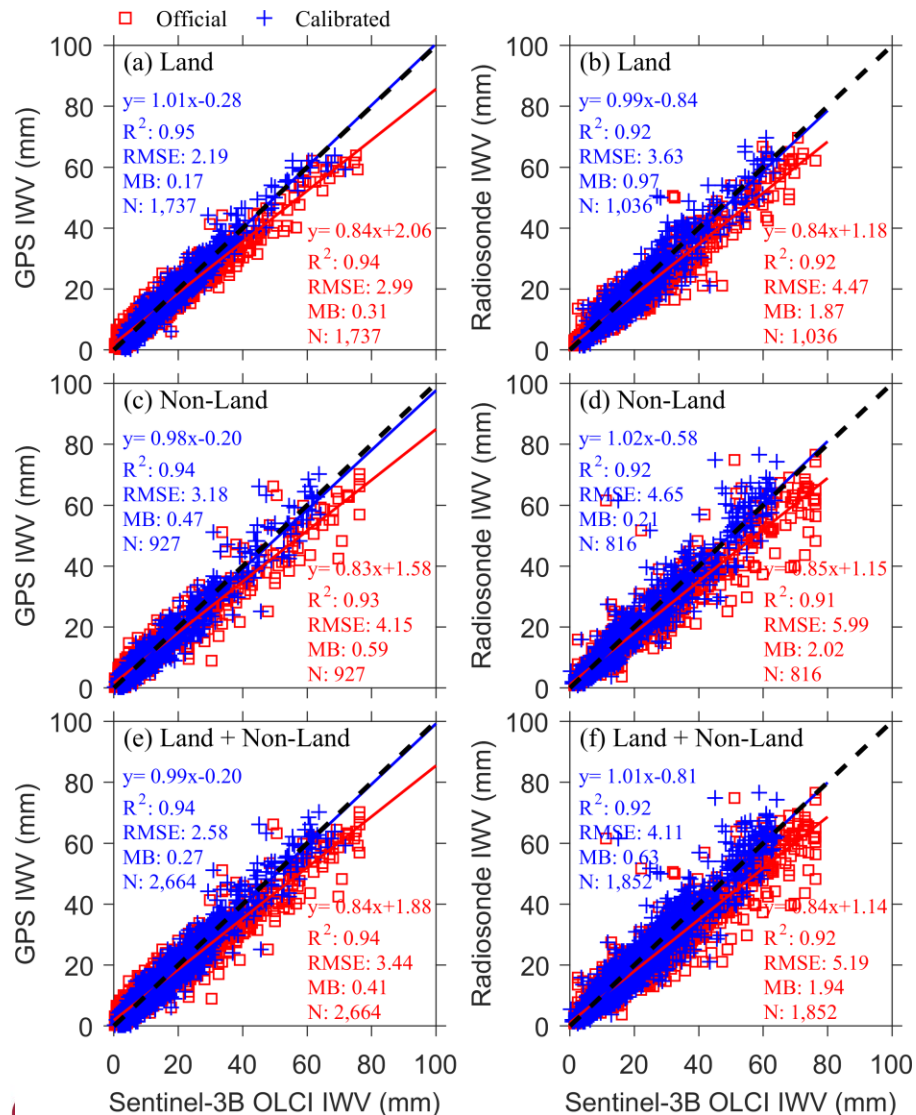
Official: red square Calibrated: blue +

Official and Calibrated Sentinel-3B OLCI Water Vapor

IWV: integrated water vapor

MB: mean bias

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Land (clear sky):

2.99 mm → **2.19 mm** (GPS) **26.76%**

4.47 mm → **3.63 mm** (radiosonde) **18.79%**

Non-Land (non-clear sky):

4.15 mm → **3.18 mm** (GPS) **23.37%**

5.99 mm → **4.65 mm** (radiosonde) **22.37%**

Land + Non-Land (all sky):

3.44 mm → **2.58 mm** (GPS) **25.00%**

5.19 mm → **4.11 mm** (radiosonde) **20.81%**

Xu, J., & Liu, Z. (2023a). A Back Propagation Neural Network-Based Calibration Approach for Sentinel-3 OLCI Near-Infrared Water Vapor Product. *IEEE Geoscience and Remote Sensing Letters*, 20, 1-5.

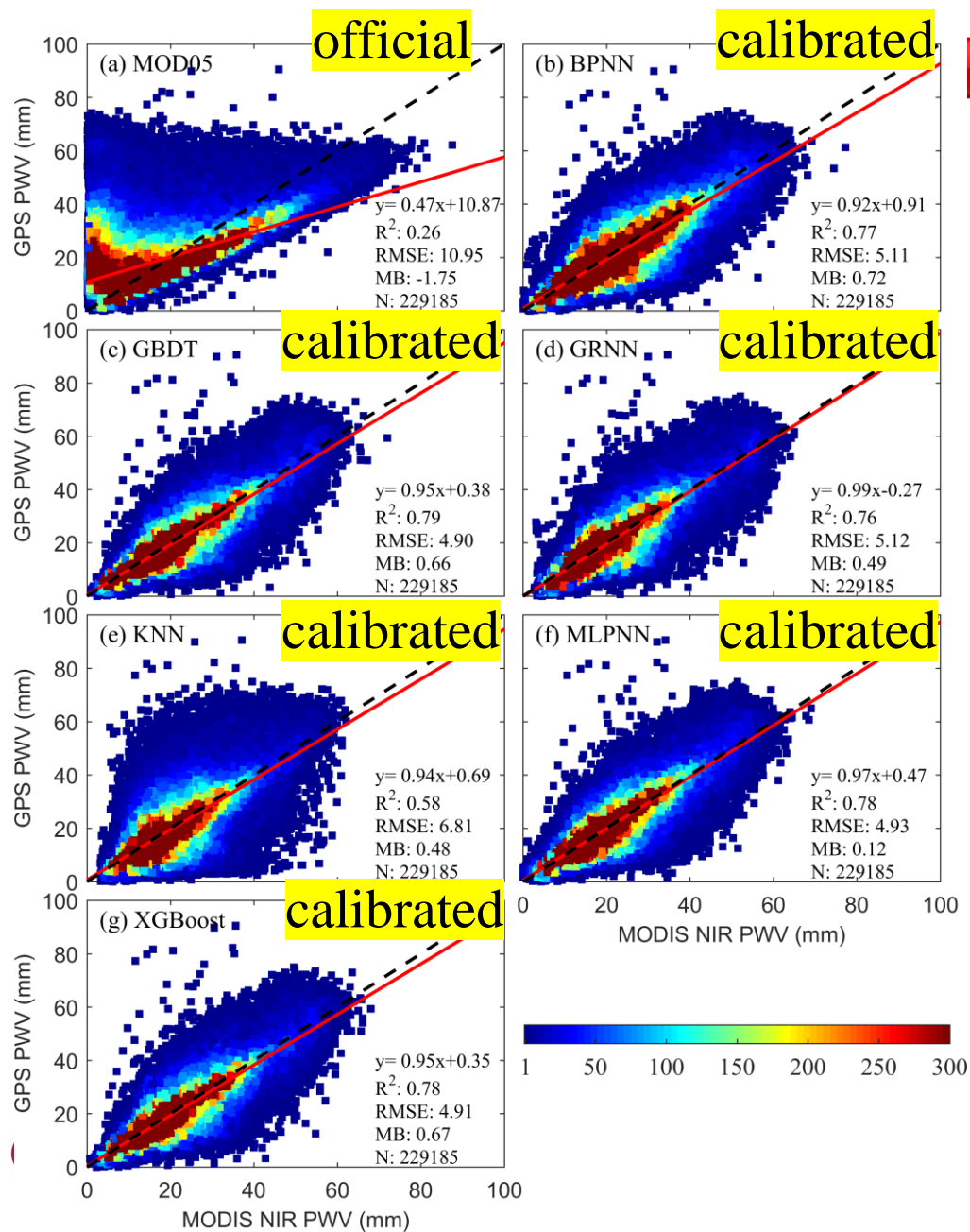
Official: red square Calibrated: blue +

Official and Calibrated Terra MODIS Water Vapor

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PWV: precipitated water vapor
 MB: mean bias

- All-sky RMSE:
- **10.95 mm (official)** → **~ 5.00 mm (calibrated)**
- **~54.00%** ↓



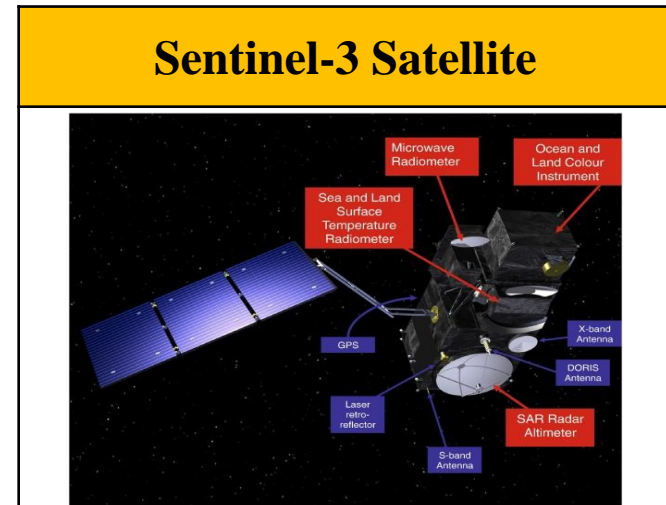
Xu, J., & Liu, Z. (2023b). Improving the Accuracy of MODIS Near-Infrared Water Vapor Product Under all Weather Conditions Based on Machine Learning Considering Multiple Dependence Parameters. IEEE Transactions on Geoscience and Remote Sensing, 61, 1-15.

Introduction of OLCI

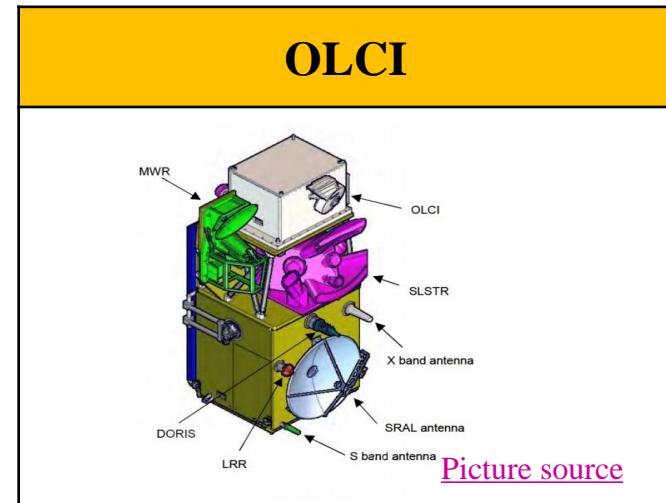


❑ The **Ocean and Land Colour Instrument (OLCI)** instrument aboard **Sentinel-3** satellites:

<p>Bands used in OLCI near-infrared (NIR) water vapor retrieval</p>	<p>❑ Absorption bands</p> <ul style="list-style-type: none"> • O19 (centered at 900 nm) • O20 (centered at 940 nm) <p>❑ Window band</p> <ul style="list-style-type: none"> • O18 (centered at 885 nm)
<p>Spatial resolution</p>	<p>300 m</p>
<p>Temporal resolution</p>	<p>around 4 days of global coverage revisit time for one Sentinel-3 satellite.</p>
<p>Accuracy of water vapor measurements</p>	<p>PWV RMSE:</p> <ul style="list-style-type: none"> • Raw: 3.10 to 4.44 kg/m² • Calibrated: 2.34 to 2.58 kg/m² <p>(Xu and Liu, 2023a)</p>



Picture source



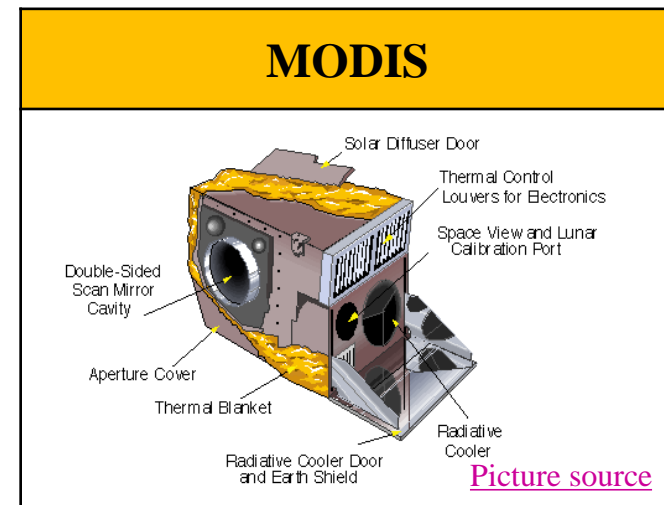
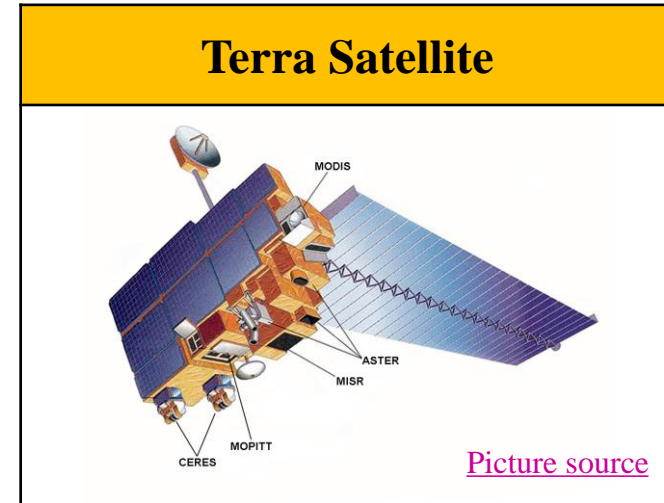
Picture source

Introduction of MODIS



❑ The **Moderate Resolution Imaging Spectroradiometer (MODIS)** instrument aboard **Terra** satellite:

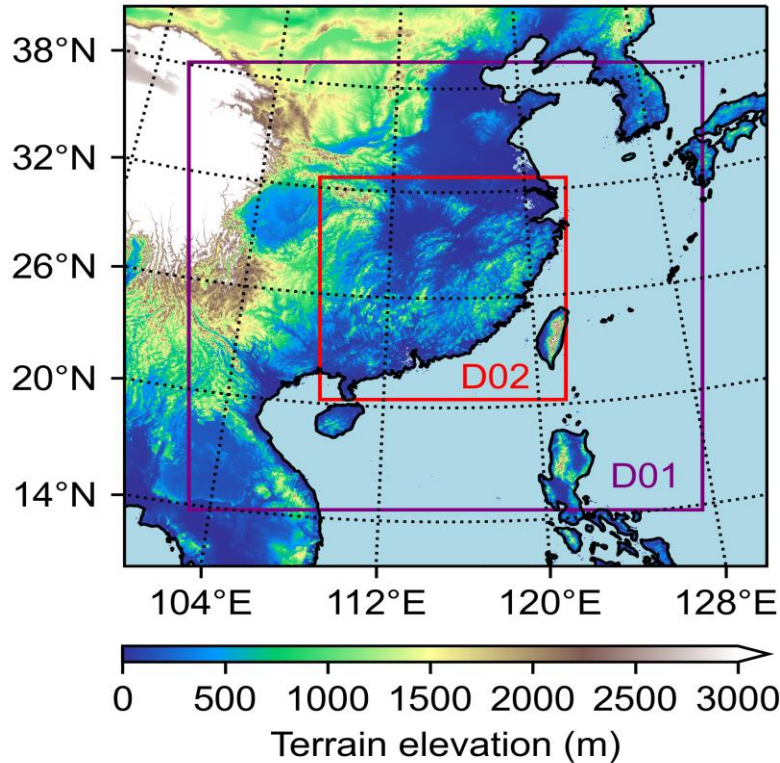
<p>Bands used in MODIS NIR water vapor retrieval</p>	<p>❑ Absorption bands:</p> <ul style="list-style-type: none"> • band 17 (centered at 905 nm) • band 18 (centered at 936 nm) • band 19 (centered at 940 nm) <p>❑ Window bands</p> <ul style="list-style-type: none"> • band 2 (centered at 865 nm) • band 5 (centered at 1240 nm)
<p>Spatial resolution</p>	<p>1 km</p>
<p>Temporal resolution</p>	<p>1-2 days of global coverage revisit time</p>
<p>Accuracy of water vapor measurements</p>	<p>PWV RMSE:</p> <ul style="list-style-type: none"> • Raw: 10.95 kg/m² • Calibrated: 4.90 kg/m² <p>(Xu and Liu, 2023b)</p>



Design of WRF data assimilation experiment



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- Two two-way WRF nested domains
- Grid spacing
 - Domain 01 (D01): 15 km
 - **Domain 02 (D02): 3 km**
- 36 vertical levels

WRF scheme	Data assimilated
WRF_NoDA	-
WRF+OLCI_Raw	OLCI raw PWV
WRF+OLCI_Cal	OLCI calibrated PWV
WRF+MODIS_Raw	MODIS raw PWV
WRF+MODIS_Cal	MODIS calibrated PWV
WRF+OLCI+MODIS_Cal	Both OLCI calibrated PWV and MODIS calibrated PWV

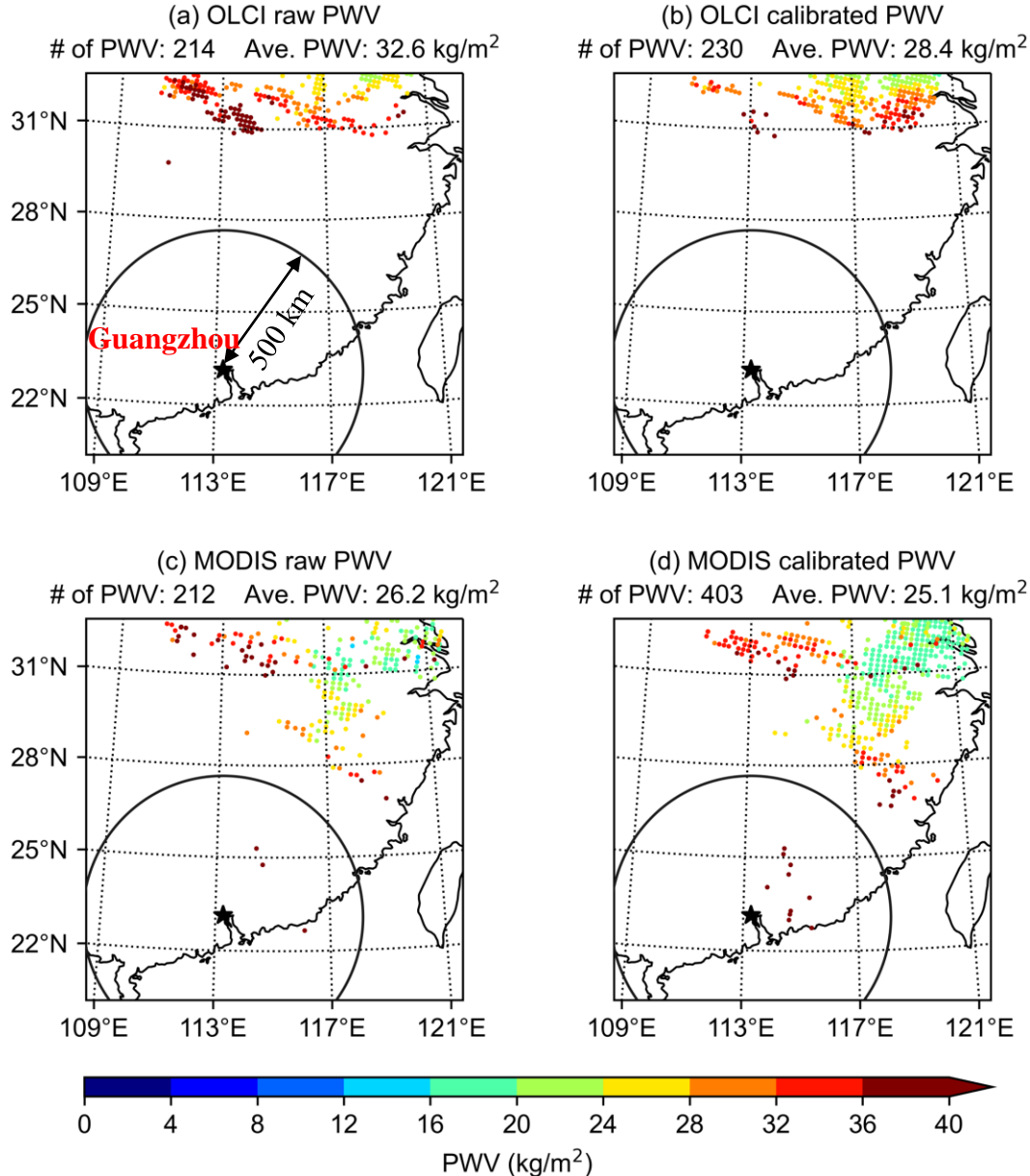
- Raw PWV: PWV from official product
- **Calibrated PWV**: PWV calibrated using the method proposed by Xu and Liu (2023a) & Xu and Liu (2023b)

- Two short-term WRF forecasts during a heavy rainfall event: **May 20 to 21, 2020 at Guangzhou area**:
 - 03 UTC to 24 UTC May 20, 2020
 - 03 UTC to 24 UTC May 21, 2020

Distribution of OLCI and MODIS PWV

assimilated for May 20 to 21, 2020

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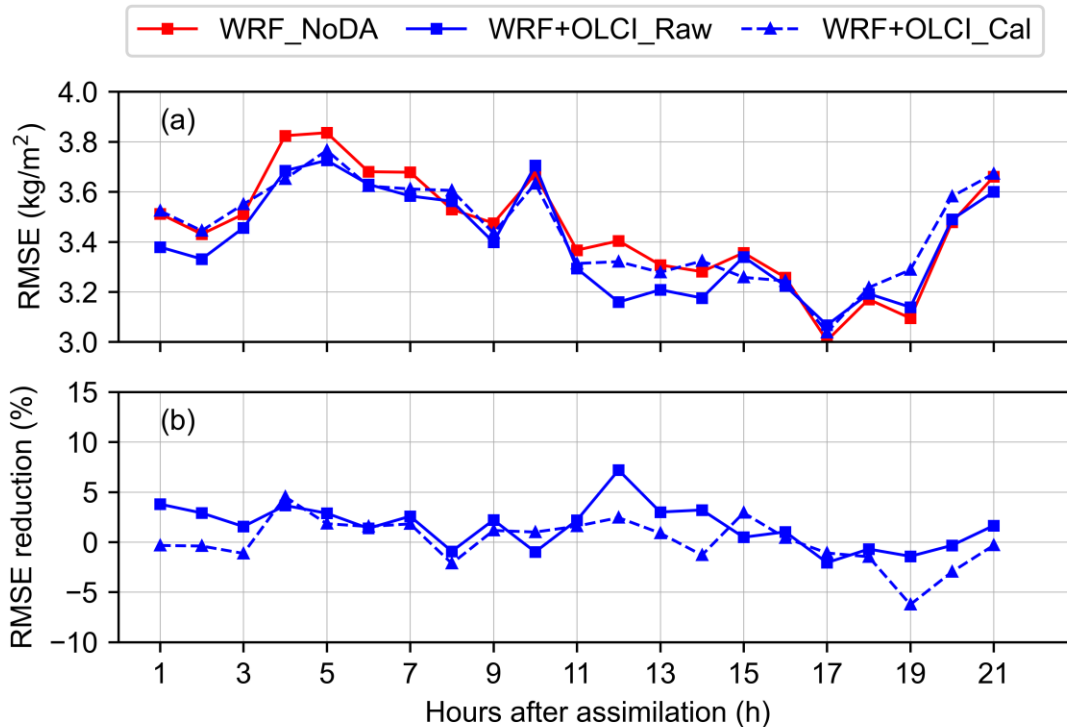


- **OLCI and MODIS PWV were mainly located at the north part of inner domain**
- **Mean value of calibrated PWV is lower than that of raw PWV.**

WRF PWV vs GNSS PWV

RMSE and RMSE reduction (1/4)

RMSE and RMSE reduction of WRF PWV



OLCI

Maximum/Average PWV RMSE reduction

WRF scheme	Max./Ave. reduction
WRF+OLCI_Raw	7.2% / 1.6%
WRF+OLCI_Cal	4.5% / 0.1%

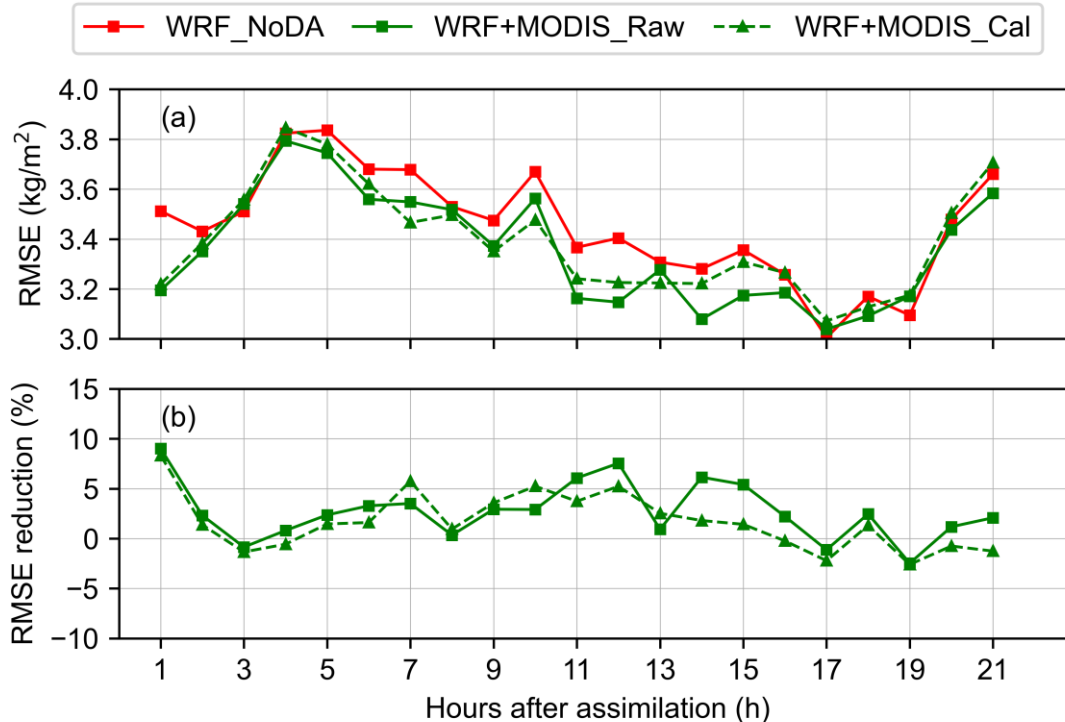


❖ **RMSE of WRF PWV** ↓ after assimilation

WRF PWV vs GNSS PWV

RMSE and RMSE reduction (2/4)

RMSE and RMSE reduction of WRF PWV



MODIS

Maximum/Average PWV RMSE reduction

WRF scheme	Max./Ave. reduction
WRF+MODIS_Raw	9.0% / 2.7%
WRF+MODIS_Cal	8.3% / 1.7%

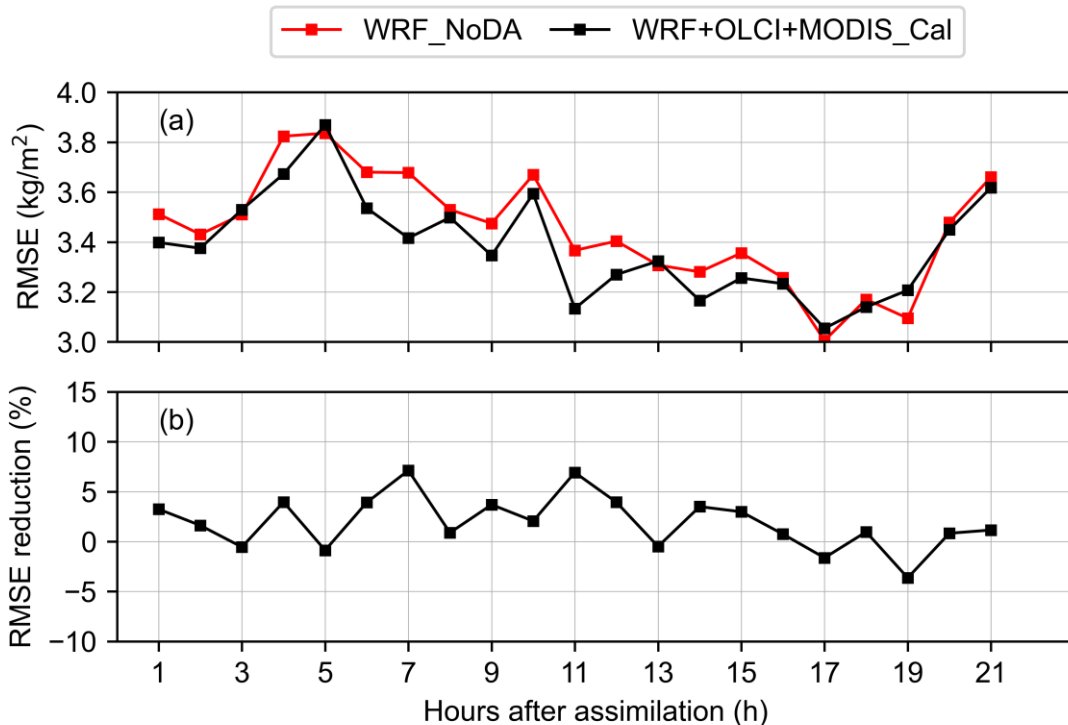


RMSE of WRF PWV ↓ after assimilation

WRF PWV vs GNSS PWV

RMSE and RMSE reduction (3/4)

RMSE and RMSE reduction of WRF PWV



OLCI+MODIS

Maximum/Average PWV RMSE reduction

WRF scheme	Max./Ave. reduction
WRF+OLCI+MODIS_Cal	7.1% / 1.9%



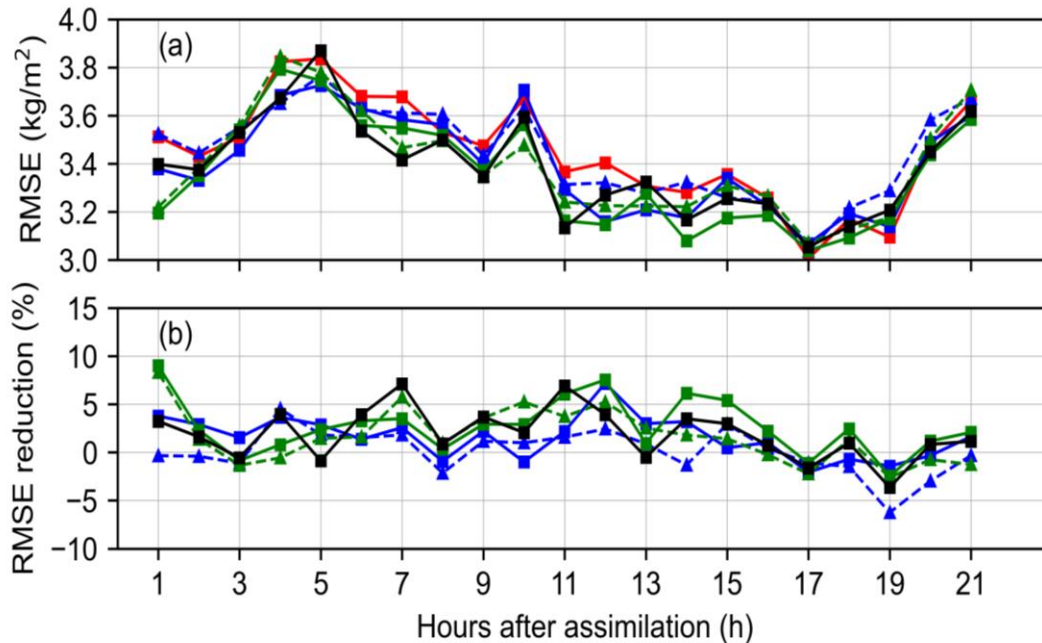
❖ **RMSE of WRF PWV** ↓ **after assimilation**

WRF PWV vs GNSS PWV

RMSE and RMSE reduction (4/4)

RMSE and RMSE reduction of WRF PWV

—■— WRF_NoDA
 —■— WRF+OLCI_Raw
 - -▲- WRF+OLCI_Cal
—■— WRF+MODIS_Raw
 - -▲- WRF+MODIS_Cal
 —■— WRF+OLCI+MODIS_Cal



Maximum/Average PWV RMSE reduction

WRF scheme	Max./Ave. reduction
WRF+OLCI_Raw	7.2% / 1.6%
WRF+OLCI_Cal	4.5% / 0.1%
WRF+MODIS_Raw	9.0% / 2.7%
WRF+MODIS_Cal	8.3% / 1.7%
WRF+OLCI+MODIS_Cal	7.1% / 1.9%



RMSE of WRF PWV ↓ after assimilation

WRF PWV vs GNSS PWV

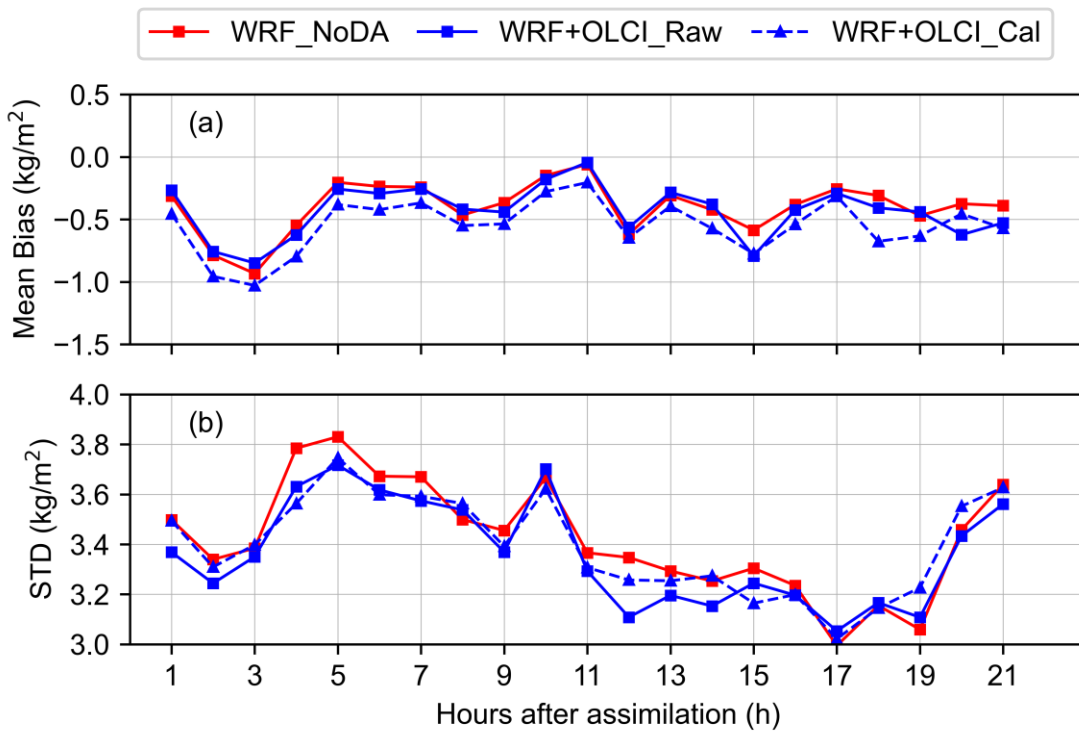
Bias and STD (1/4)



mean bias and standard deviation (STD) of PWV difference between WRF and GNSS

OLCI

Average STD of PWV difference between WRF and GNSS



STD of PWV difference between WRF and GNSS ↓ after assimilation

WRF scheme	Ave. STD (kg/m ²)
WRF_NoDA	3.42
WRF+OLCI_Raw	3.36
WRF+OLCI_Cal	3.40

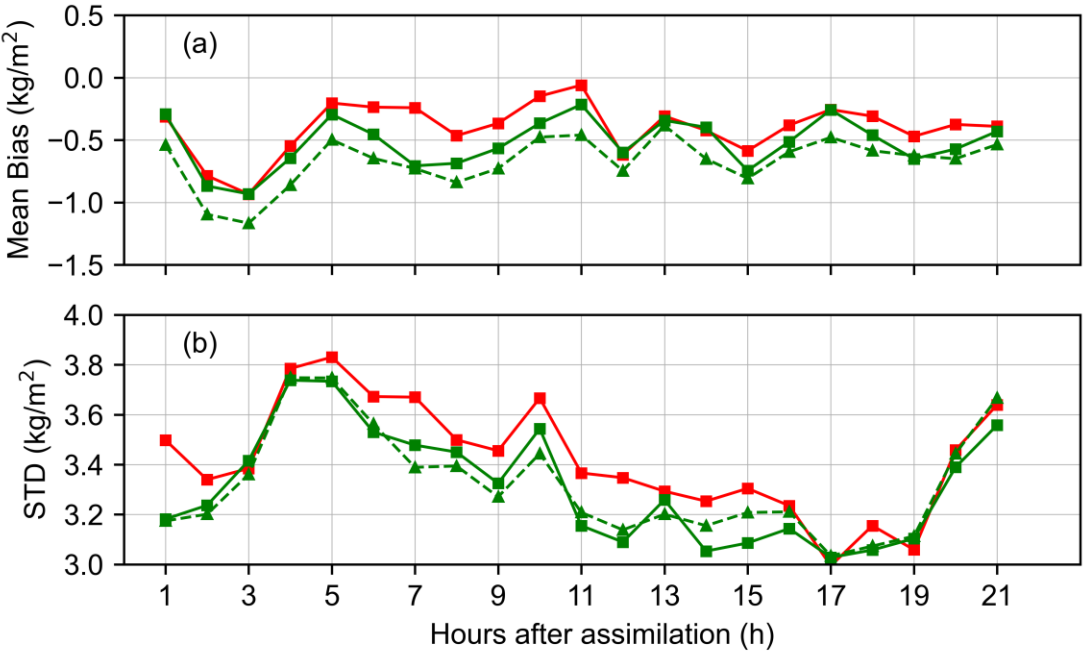
WRF PWV vs GNSS PWV

Bias and STD (2/4)



□ mean bias and standard deviation (STD) of PWV difference between WRF and GNSS

—■— WRF_NoDA —■— WRF+MODIS_Raw -▲- WRF+MODIS_Cal



❖ STD of PWV difference between WRF and GNSS ↓ after assimilation

MODIS
Average STD of PWV difference between WRF and GNSS

WRF scheme	Ave. STD (kg/m ²)
WRF_NoDA	3.42
WRF+MODIS_Raw	3.31
WRF+MODIS_Cal	3.32

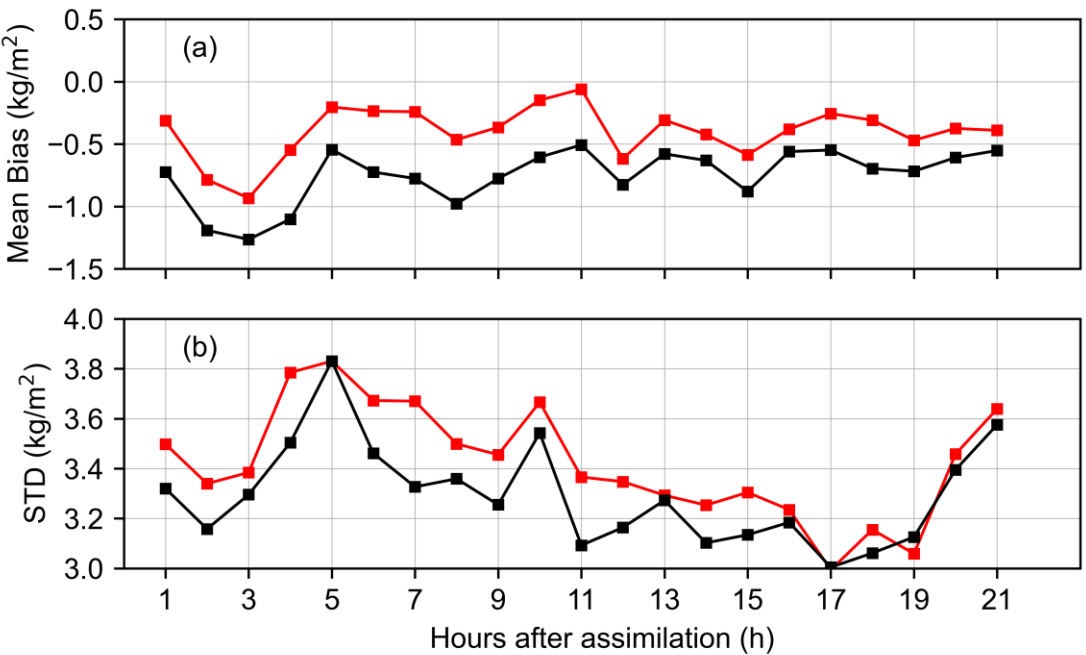
WRF PWV vs GNSS PWV

Bias and STD (3/4)



□ **mean bias and standard deviation (STD)** of PWV difference between WRF and GNSS

—■ WRF_NoDA —■ WRF+OLCI+MODIS_Cal



❖ **STD** of PWV difference between WRF and GNSS ↓ after assimilation

OLCI+MODIS

Average STD of PWV difference between WRF and GNSS

WRF scheme	Ave. STD (kg/m ²)
WRF_NoDA	3.42
WRF+OLCI+MODIS_Cal	3.29

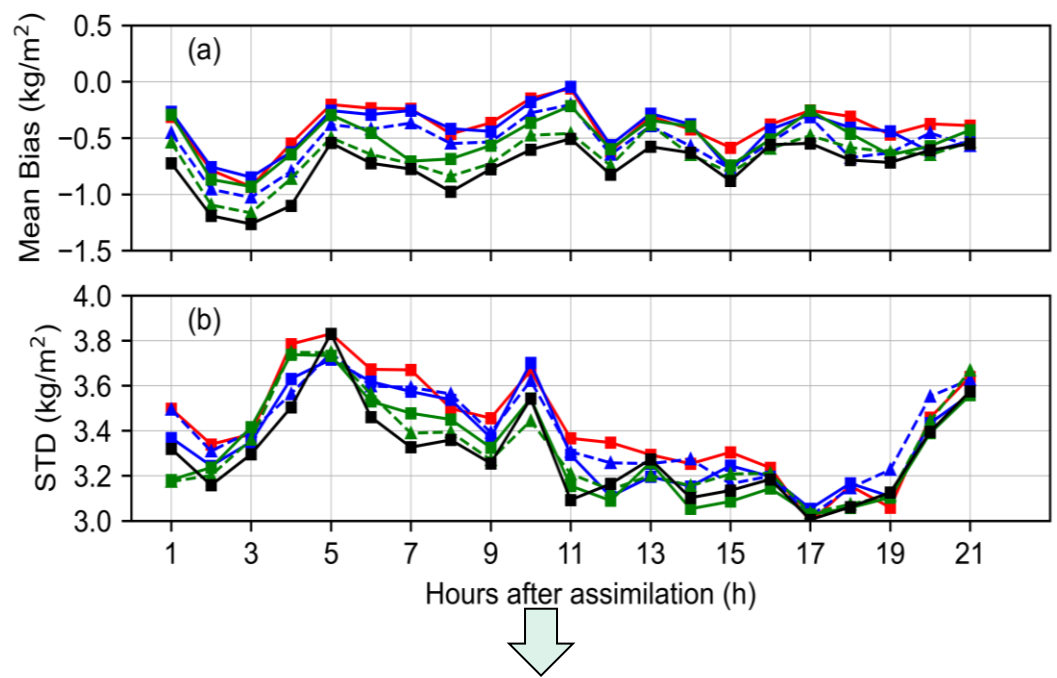
WRF PWV vs GNSS PWV

Bias and STD (4/4)



□ mean bias and standard deviation (STD) of PWV difference between WRF and GNSS

■ WRF_NoDA ■ WRF+OLCI_Raw - - WRF+OLCI_Cal
■ WRF+MODIS_Raw - - WRF+MODIS_Cal ■ WRF+OLCI+MODIS_Cal



❖ STD of PWV difference between WRF and GNSS ↓ after assimilation

Average STD of PWV difference between WRF and GNSS

WRF scheme	Ave. STD (kg/m ²)
WRF_NoDA	3.42
WRF+OLCI_Raw	3.36
WRF+OLCI_Cal	3.40
WRF+MODIS_Raw	3.31
WRF+MODIS_Cal	3.32
WRF+OLCI+MODIS_Cal	3.29

WRF vs meteorological stations rainfall observations for whole inner domain

(a) WRF_NoDA

Met. station	N	L	M	H
N	40.4%	4.7%	0.5%	0.5%
L	16.3%	15.1%	3.7%	4.1%
M	1.2%	2.3%	0.7%	2.2%
H	0.5%	3.2%	1.3%	3.3%

(b) WRF+OLCI_Raw

Met. station	N	L	M	H
N	41.0%	4.2%	0.5%	0.4%
L	16.2%	14.8%	4.2%	4.1%
M	1.1%	2.4%	0.8%	2.0%
H	0.4%	3.1%	1.3%	3.6%

(c) WRF+OLCI_Cal

Met. station	N	L	M	H
N	40.9%	4.0%	0.6%	0.5%
L	16.5%	14.8%	3.7%	4.2%
M	0.8%	2.5%	0.9%	2.1%
H	0.4%	3.0%	1.4%	3.5%

(d) WRF+MODIS_Raw

Met. station	N	L	M	H
N	40.7%	4.4%	0.7%	0.3%
L	16.0%	15.0%	3.3%	4.2%
M	1.0%	2.7%	0.5%	2.1%
H	0.5%	3.1%	1.3%	3.5%

(e) WRF+MODIS_Cal

Met. station	N	L	M	H
N	40.8%	4.2%	0.8%	0.3%
L	16.3%	14.4%	3.4%	4.6%
M	1.0%	2.4%	0.8%	2.1%
H	0.5%	3.0%	1.6%	3.3%

(f) WRF+OLCI+MODIS_Cal

Met. station	N	L	M	H
N	40.6%	4.3%	0.7%	0.5%
L	16.5%	15.3%	3.3%	4.1%
M	1.1%	2.4%	0.7%	2.3%
H	0.4%	3.1%	1.4%	3.5%

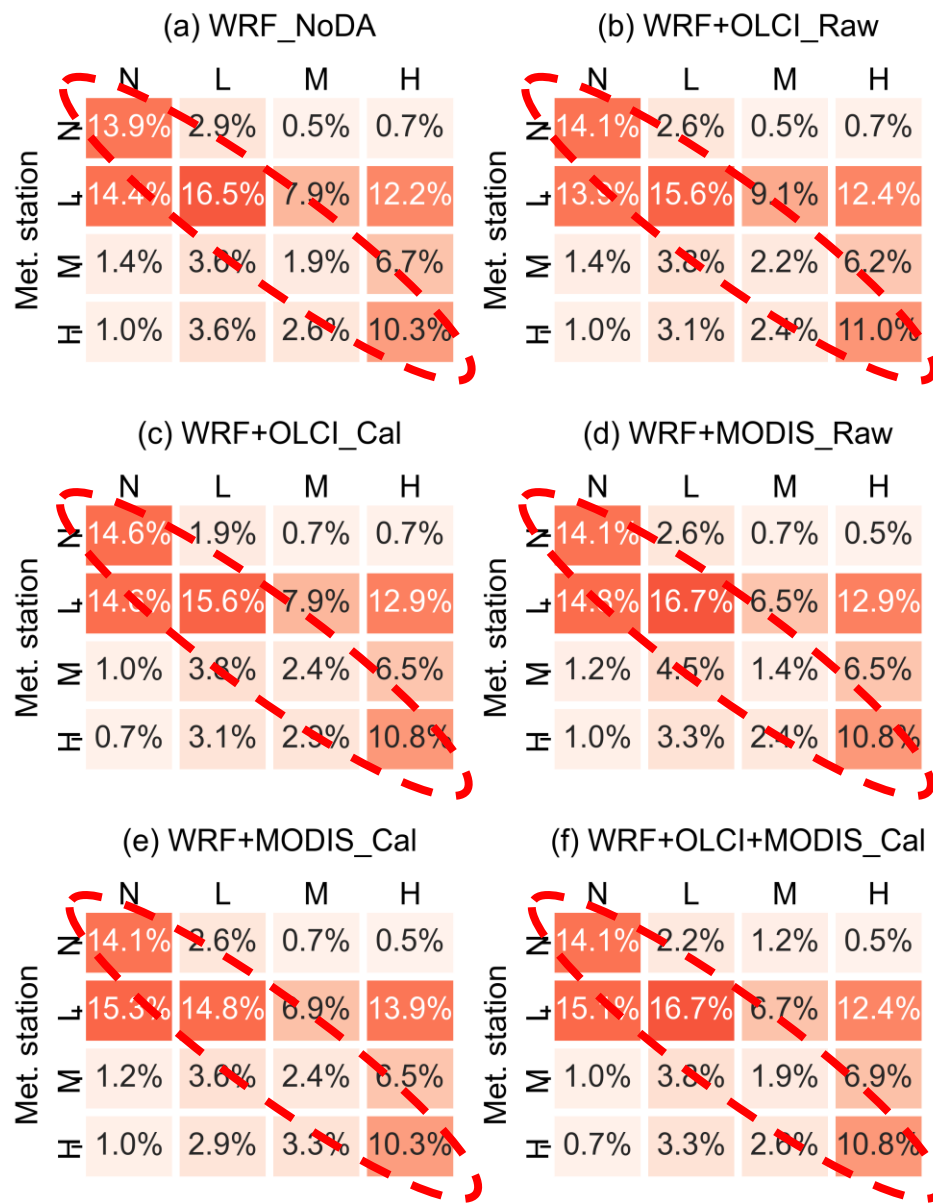
- ☐ 12-h accumulated rainfall
- N: no rainfall (0.1 mm)
- L: light rainfall (0.1 to 10 mm)
- M: moderate rainfall (10 to 20 mm)
- H: heavy rainfall (> 20 mm)

WRF overall rainfall success rate

WRF scheme	Success rate
WRF_NoDA	59.5%
WRF+OLCI_Raw	60.2% ↑
WRF+OLCI_Cal	60.1% ↑
WRF+MODIS_Raw	59.7% ↑
WRF+MODIS_Cal	59.4% ↓
WRF+OLCI+MODIS_Cal	60.1% ↑

WRF vs meteorological stations' rainfall observations for Guangzhou area

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- ☐ 12-h accumulated rainfall
- N: no rainfall (0.1 mm)
- L: light rainfall (0.1 to 10 mm)
- M: moderate rainfall (10 to 20 mm)
- H: heavy rainfall (> 20 mm)
- Guangzhou area: within 500 km to Guangzhou

WRF overall rainfall success rate

WRF scheme	Success rate
WRF_NoDA	42.6%
WRF+OLCI_Raw	42.8% ↑
WRF+OLCI_Cal	43.3% ↑
WRF+MODIS_Raw	43.1% ↑
WRF+MODIS_Cal	41.6% ↓
WRF+OLCI+MODIS_Cal	43.5% ↑

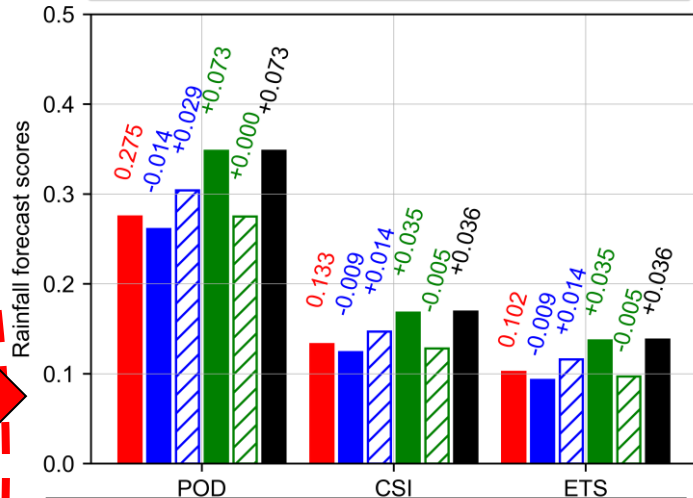
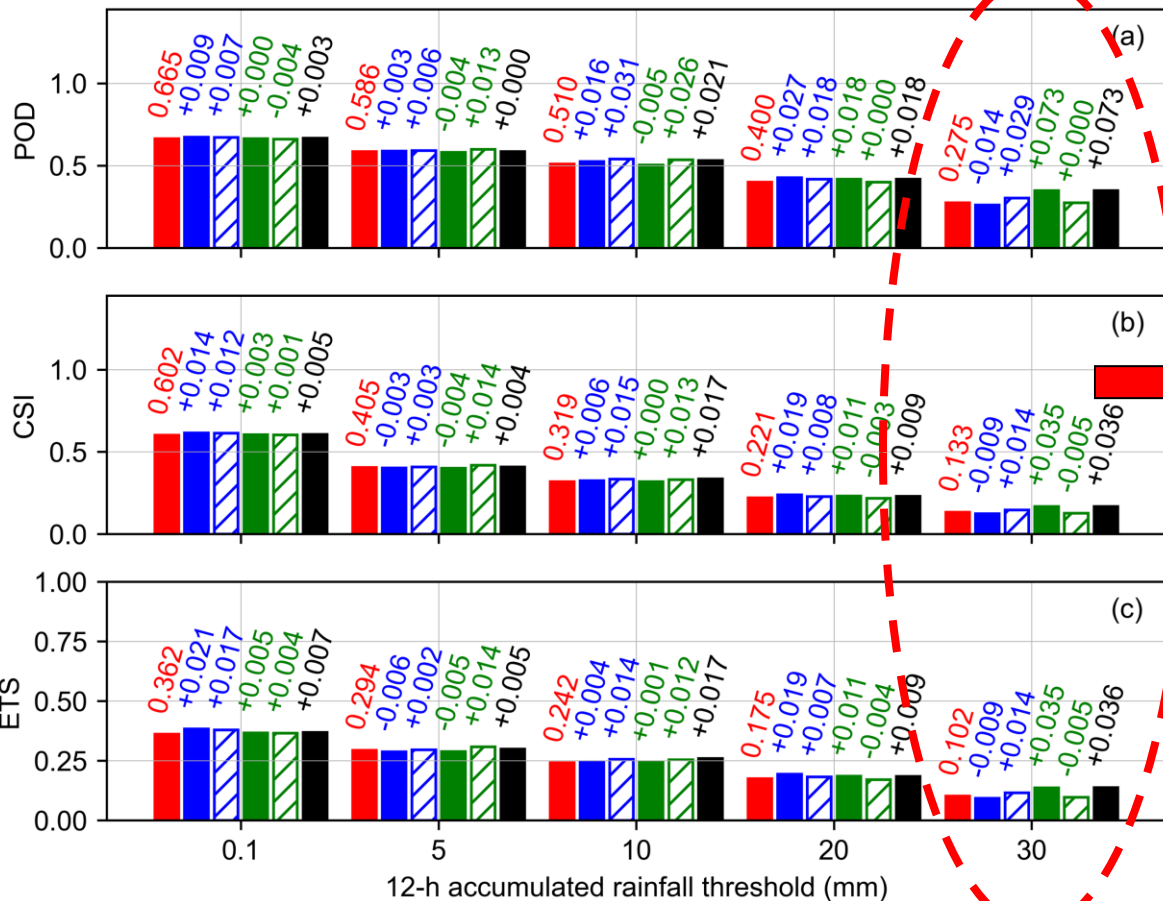
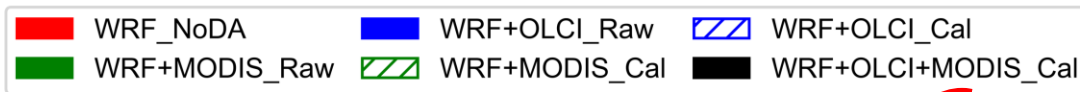
WRF rainfall forecast score (1/2)

– for whole inner domain



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☐ The 12-h accumulated (the first 12 h after data assimilation) rainfall forecast skill scores for the **whole inner domain** for May 20 and 21, 2020.



POD, CSI, and ETS scores are improved by up to **0.073**, **0.036**, and **0.036**, respectively for **30 mm** of rainfall threshold.

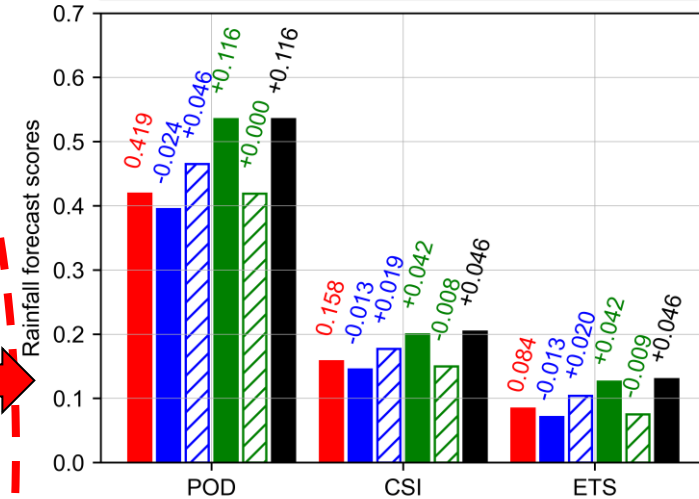
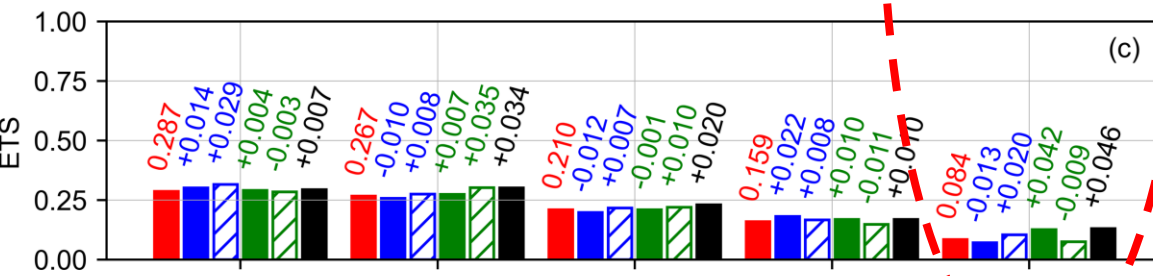
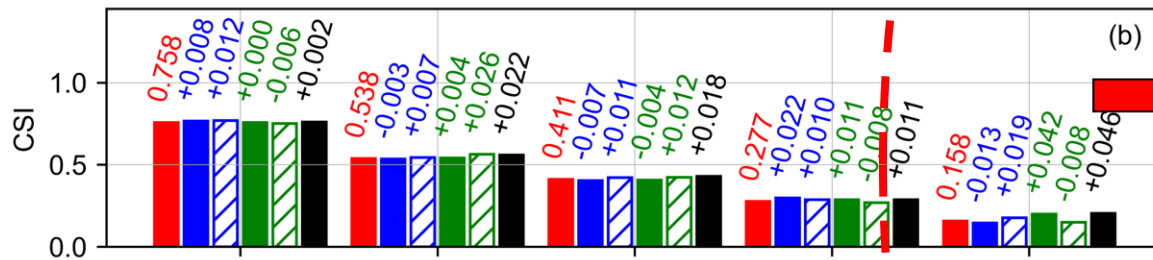
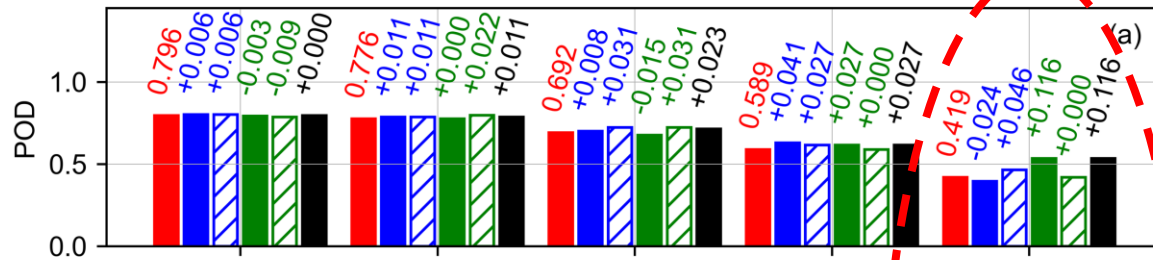
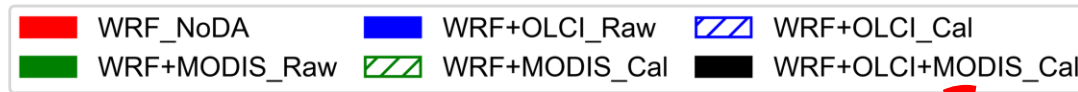
WRF rainfall forecast score (1/2)

– for Guangzhou area



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☐ The 12-h accumulated (the first 12 h after data assimilation) rainfall forecast skill scores for the **Guangzhou area (within 500 km to Guangzhou)** for May 20 and 21, 2020.



Assimilation of calibrated PWV outperforms that of raw PWV for 5 mm and 10 mm of rainfall threshold.

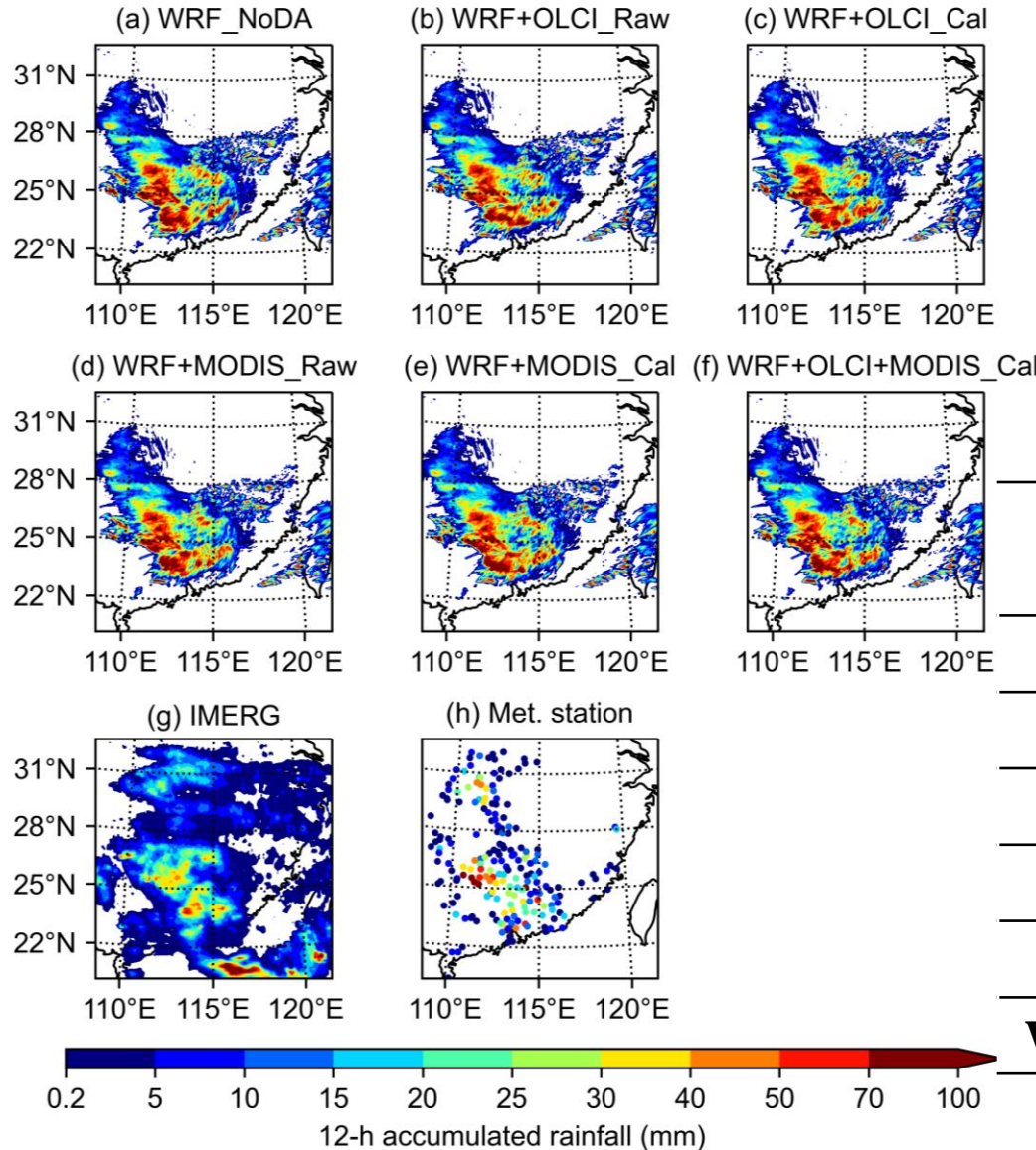
12-h accumulated rainfall threshold (mm)

WRF rainfall forecasting spatial pattern (May 20, 2020)



12-h (03 to 15 UTC) accumulated rainfall pattern on **May 20, 2020**

Correlation between WRF and IMERG rainfall grid product/Meteorological stations



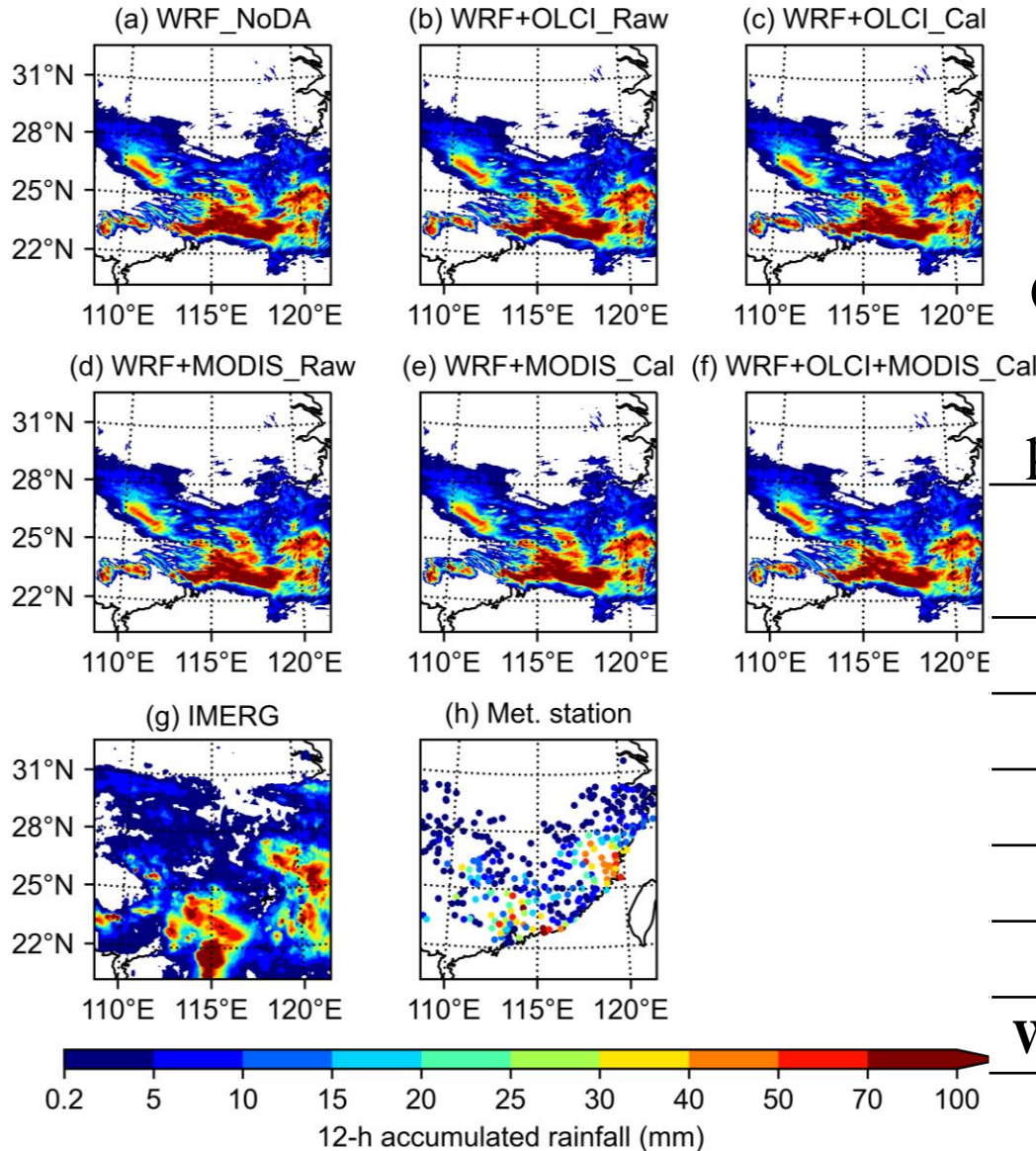
WRF scheme	Correlation IMERG/Met.
WRF_NoDA	0.272/0.485
WRF+OLCI_Raw	0.293/0.478
WRF+OLCI_Cal	0.292/0.458
WRF+MODIS_Raw	0.279/0.473
WRF+MODIS_Cal	0.274/0.436
WRF+OLCI+MODIS_Cal	0.279/0.470

WRF rainfall forecasting spatial pattern (May 21, 2020)



☐ 12-h (03 to 15 UTC) accumulated rainfall pattern on **May 21, 2020**

Correlation between WRF and IMERG rainfall grid product/Meteorological stations



WRF scheme	Correlation IMERG/Met.
WRF_NoDA	0.169/0.289
WRF+OLCI_Raw	0.162/0.277
WRF+OLCI_Cal	0.173/0.278
WRF+MODIS_Raw	0.168/0.310
WRF+MODIS_Cal	0.167/0.273
WRF+OLCI+MODIS_Cal	0.166/0.304

❑ PWV forecasting results:

- WRF PWV forecasting RMSE is reduced by up to **2.7%** for the first 21 h after assimilation

❑ Rainfall forecasting success rate:

- For the whole inner domain: **improved by 0.7%** from 59.5% to 60.2%
- For Guangzhou area: **improved by 0.9%** from 42.6% to 43.5%
- Assimilation of both OLCI calibrated PWV and MODIS calibrated PWV has the **highest rainfall forecasting success rate** for Guangzhou area.

❑ Rainfall forecast skill score:

- For whole inner domain: improves **POD by 0.073; CSI by 0.036; ETS by 0.036**
- For Guangzhou area: improves **POD by 0.116; CSI by 0.046; ETS by 0.046**

Thank you



DEPARTMENT OF
LAND SURVEYING AND GEO-INFORMATICS

土地測量及地理資訊學系

PolyU Micro-LARGE

**Assimilating OLCI and MODIS NIR
calibrated Precipitable Water Vapor (PWV)
to improve weather forecasting performance**

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August 11, 2023

第五届全国中尺度气象学论坛
August 09 to 12, 2023, in Ningxia



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2023/24

HONG KONG



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 \approx **US\$ 3,470/month**
- **No tuition**