Variational Bias Correction for Surface Data Assimilation in a Convective-scale Data Assimilation System

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Outline

1. Introduction
2. Methodology
   - Variational Bias Correction (VarBC)
3. Experiments
4. Bias model performance
5. Verification
6. Conclusion

Data assimilation methods assume unbiased, making bias a key challenge.

The development of Variational Bias Correction (Derber 1989；Dee 2005)

- Update satellite bias correction coefficients every analysis cycle.
- Attributing biases to specific sources and characterize them using model variables.

Application of VarBC (Aulігné et al. 2007；Dee and Uppala 2009)

- VarBC system can quickly respond to instrument changes.
- It can identify biases from multiple sources.

VarBC extend to aircraft observations (Isaksen et al. 2012；Zhu et al. 2015；Gao et al. 2019)

This study aims to **extend VarBC method to surface DA in a convective-scale DA system.**

- Impact of VarBC methods on different precipitation events.
- Analysis of the effects of various bias predictors in the bias model.

Methodology - Variational bias correction (VarBC)

Bias model - estimate biases in observations

$$\boldsymbol{b}(\boldsymbol{x},\beta) = \sum_{i=0}^{n} \beta_i \, \boldsymbol{p}_i(\boldsymbol{x})$$

$\boldsymbol{p}_i$ **: bias predictor**

- Correlated with the bias of observations or model state variables ($\boldsymbol{x}$).

β_i **: bias parameter**

- Updated as the variational cost function is minimized.

3D-Var cost function - bias adjustment during assimilation

$$\begin{aligned} J(\boldsymbol{x},\beta) = {} & (\boldsymbol{x}^b - \boldsymbol{x})^T \boldsymbol{B}_x^{-1} \left(\boldsymbol{x}^b - \boldsymbol{x}\right) \\ & + (\beta^b - \beta)^T \boldsymbol{B}_\beta^{-1} \left(\beta^b - \beta\right) \\ & + [y - \boldsymbol{h}(\boldsymbol{x}) - \boldsymbol{b}(\boldsymbol{x},\beta)]^T \boldsymbol{R}^{-1} [y - \boldsymbol{h}(\boldsymbol{x}) - \boldsymbol{b}(\boldsymbol{x},\beta)] \end{aligned}$$

(1) usual background term

(2) background constraint β

(3) bias-adjusted observation term

Bias model

Temperature:

$$b^{\mathrm{T}} = \beta_0^{\mathrm{T}} * 1 + \beta_1^{\mathrm{T}}\left(\mathrm{H}_{\mathrm{obs}} - \mathrm{H}_{\mathrm{model}}\right) + \beta_2^{\mathrm{T}}\left(T_{\mathrm{s,\,model}} - T_{\mathrm{2,\,model}}\right)$$

constant — elevation difference — proportional to heat flux

Humidity:

$$b^{\mathrm{Q}} = \beta_0^{\mathrm{Q}} * 1 + \beta_1^{\mathrm{Q}}\left(\mathrm{H}_{\mathrm{obs}} - \mathrm{H}_{\mathrm{model}}\right) + \beta_2^{\mathrm{Q}}\left(q_{\mathrm{s,\,obs}}\right) \times 0.3 \times 1000$$

saturation humidity obs

Winds:

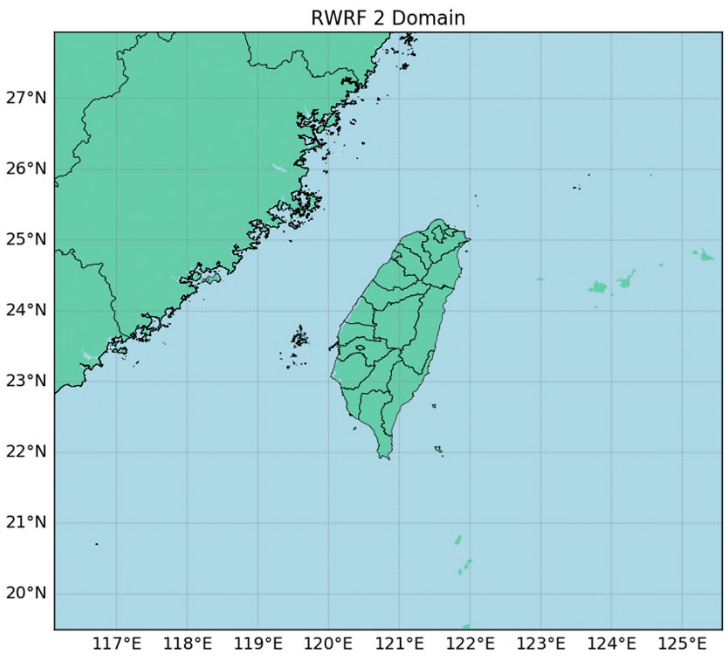
$$b^{\mathrm{U}} = \beta_0^{\mathrm{U}}\left(\frac{\mathrm{U}_{\mathrm{obs}}}{Ws_{\mathrm{obs}}}\right) + \beta_1^{\mathrm{U}}\left(\frac{-Ws_{\mathrm{mod}} * \cos\left(Wd_{\mathrm{mod}}\right)}{std_{\mathrm{U1}}}\right) + \beta_2^{\mathrm{U}}\left(\frac{-\sin\left(Wd_{\mathrm{mod}}\right)}{std_{\mathrm{U2}}}\right)$$

$$b^{\mathrm{V}} = \beta_0^{\mathrm{V}}\left(\frac{V_{\mathrm{obs}}}{Ws_{\mathrm{obs}}}\right) + \beta_1^{\mathrm{V}}\left(\frac{Ws_{\mathrm{mod}} * \sin\left(Wd_{\mathrm{mod}}\right)}{std_{\mathrm{V1}}}\right) + \beta_2^{\mathrm{V}}\left(\frac{-\cos\left(Wd_{\mathrm{mod}}\right)}{std_{\mathrm{V2}}}\right)$$

projection to u, v components — heading bias (wind direction) — airspeed bias (wind speed)

Pourret et al. (2021)

Experiment - CWA convective-scale data assimilation system



Radar **W**eather **R**esearch and **F**orecasting (**RWRF)**

- **Model** : Based on WRF (v3.8.1) and WRF-DA (v4.3.3)
- **Boundary** : NCEP GFS → RWRF 10km
- **Domain** : **2km** (451,451)
- **Eta level** : 52 (top to 20hPa)

	0 hr	0.5 hr	1 hr	1.5 hr	2 hr	half-hour	on the hour
DA	**SFC Radar**	**Radar**	**SFC Radar**	**Radar**	**SFC Radar**	**Radar**	**SFC Radar**
Forecast	**12 hr**		**12 hr**		**12 hr**		**12 hr**

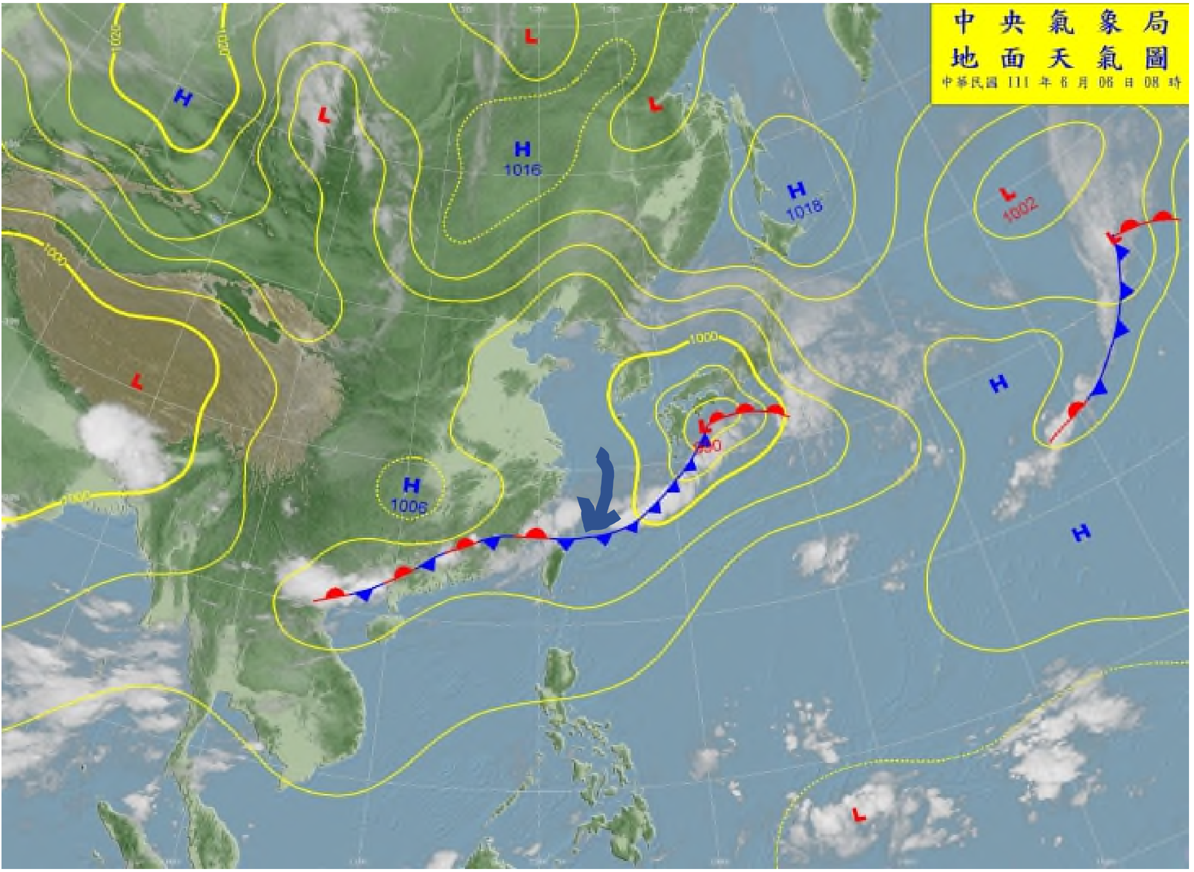
- **Surface DA (Hybrid 3DEnVar):** use VarBC
  ensemble : 42 member
  2m Temperature, 2m humidity, 10m UV winds
  Hourly update

- **Radar DA (3DVar):**
  Reflectivity and Doppler velocity
  Every 30-minute update

Experiment - Case1 Mei-Yu front

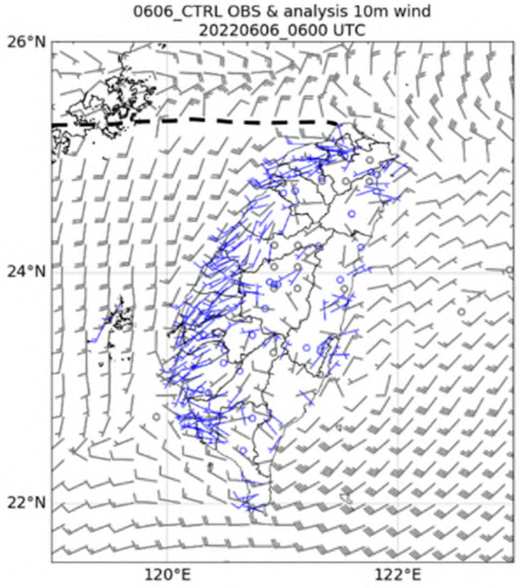
Experiment time：

2022 0606 02 UTC ~ 2022 0608 09 UTC

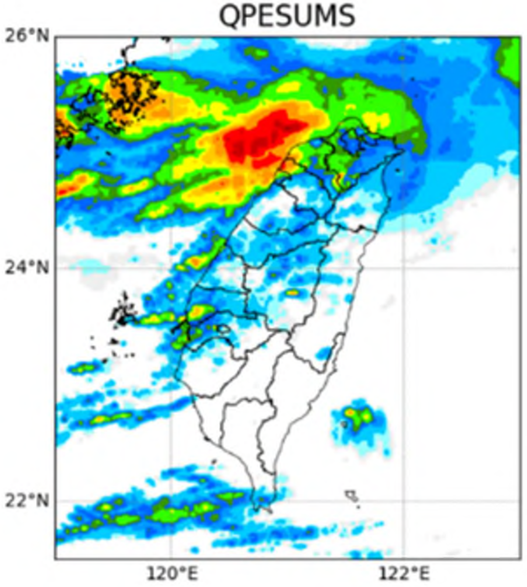


➔ Mei-Yu front passed through, bringing continuous rainfall.

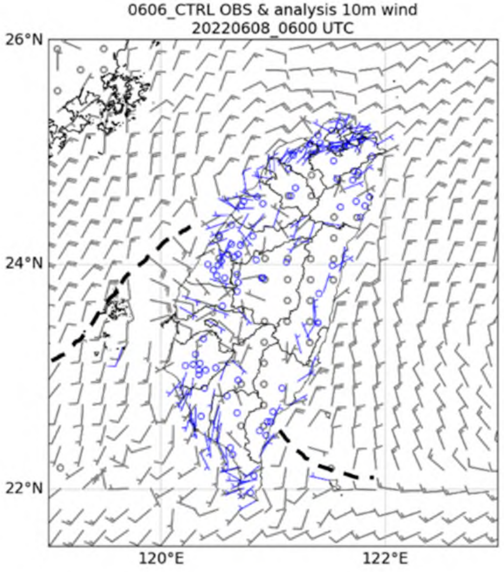
0606 06 UTC



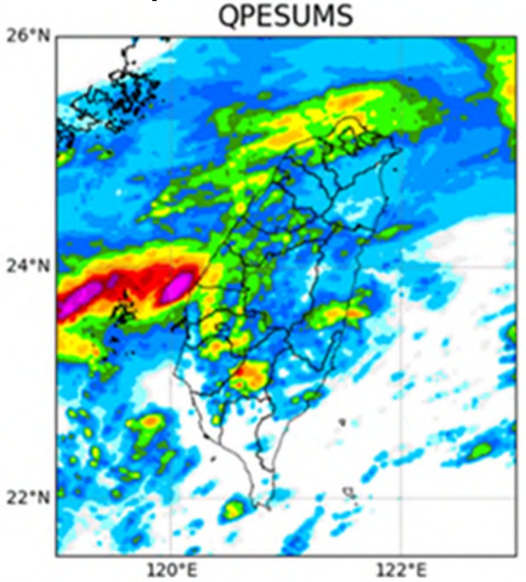
6hr Precipitation 0606 06-12 UTC

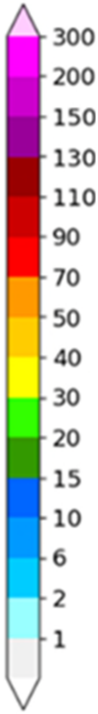


0608 06 UTC

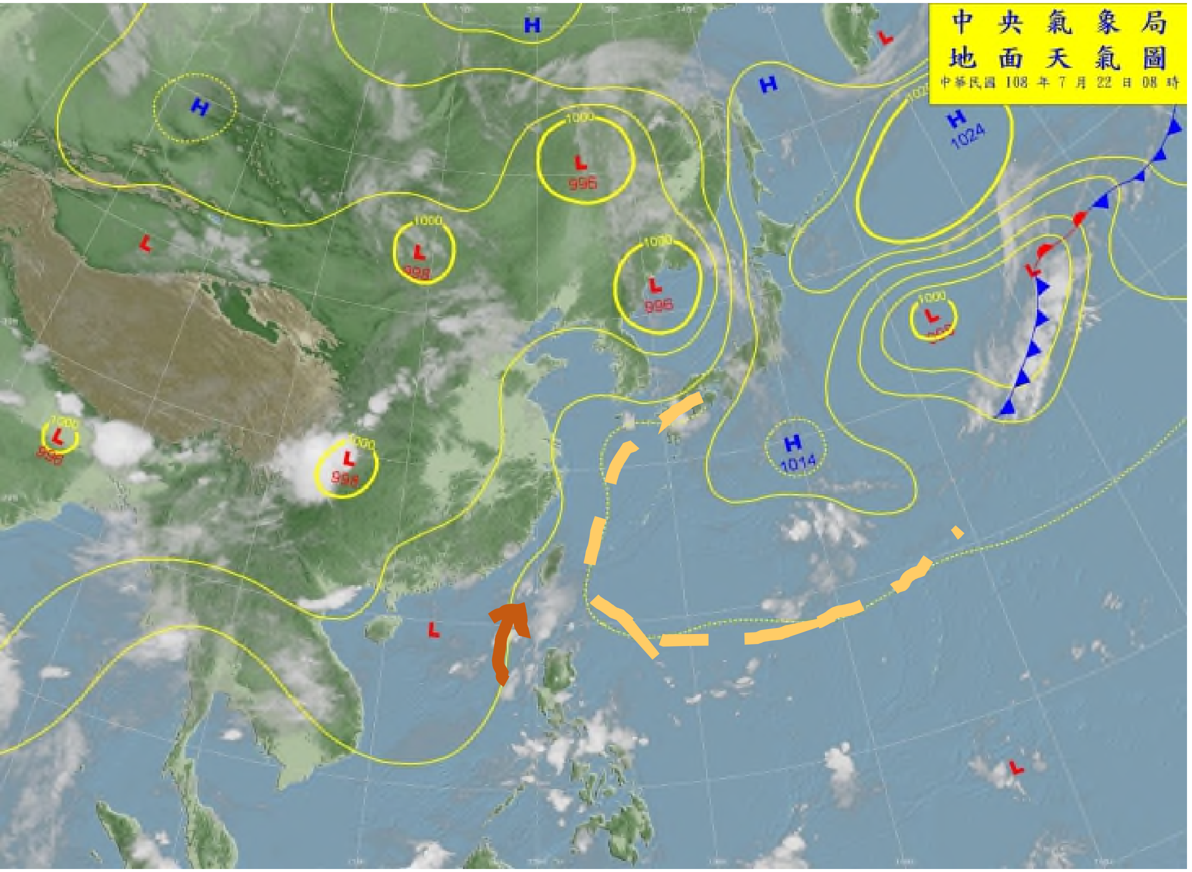


6hr Precipitation 0608 06-12 UTC

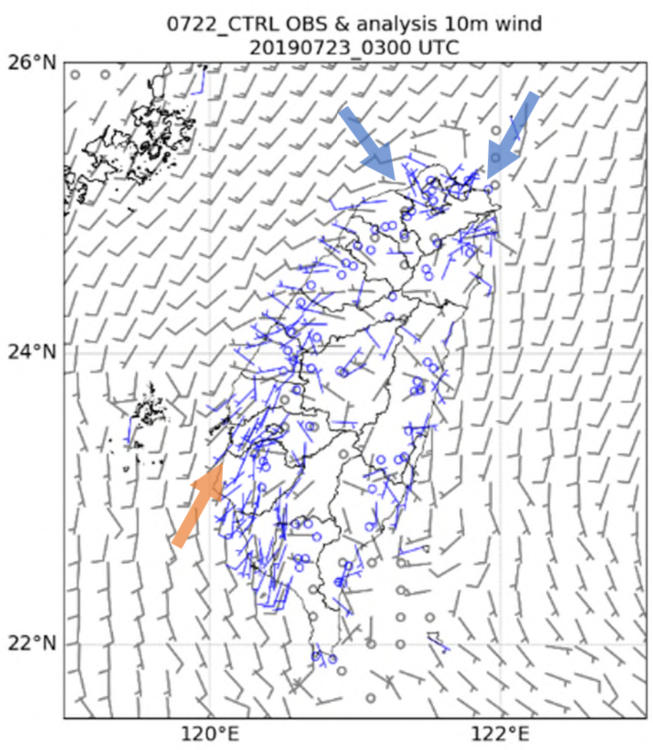




Experiment time：
2019 0722 01 UTC ~ 2019 0723 18 UTC

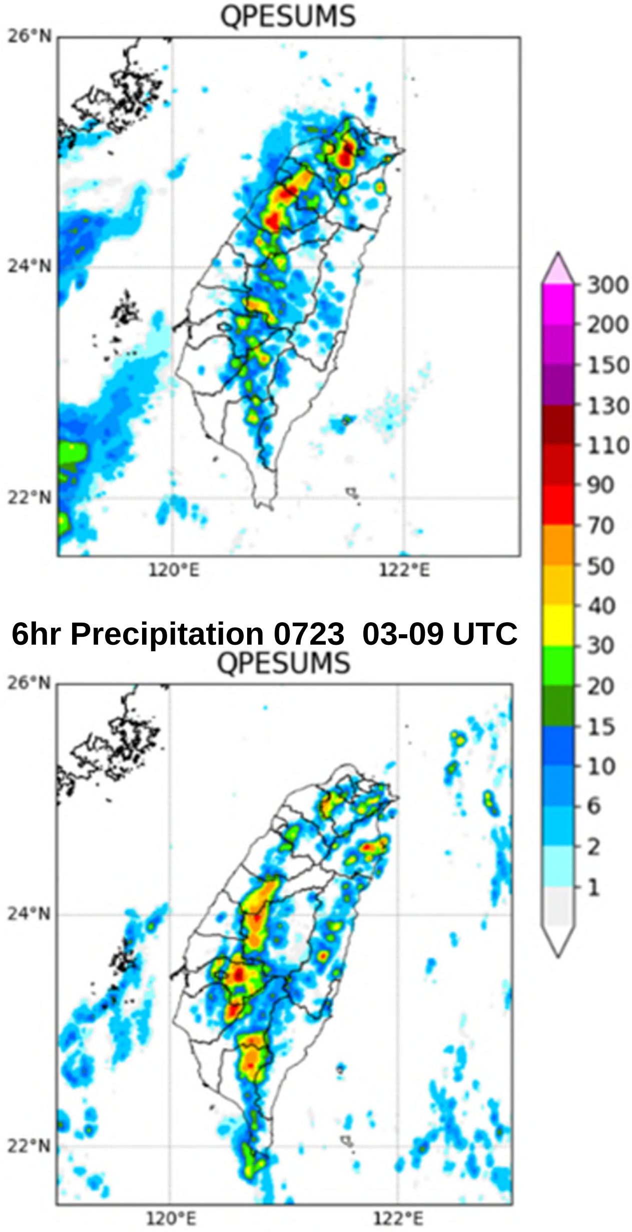


0723 03 UTC



6hr Precipitation 0722 03-09 UTC

6hr Precipitation 0723 03-09 UTC



➔ High pressure extends westward, prevailing southwest winds.
➔ Stable synoptic weather conditions.

Experiment - setting

- **Case1** ： 2022 0606 02 – 0608 09 UTC **(Mei-Yu front)**

  (1) 0606_ CTRL (no use VarBC)
  (2) 0606_SfcBC (use VarBC)

- **Case 2** ： 2019 0722 01 – 0723 18 UTC **(afternoon thunderstorm)**

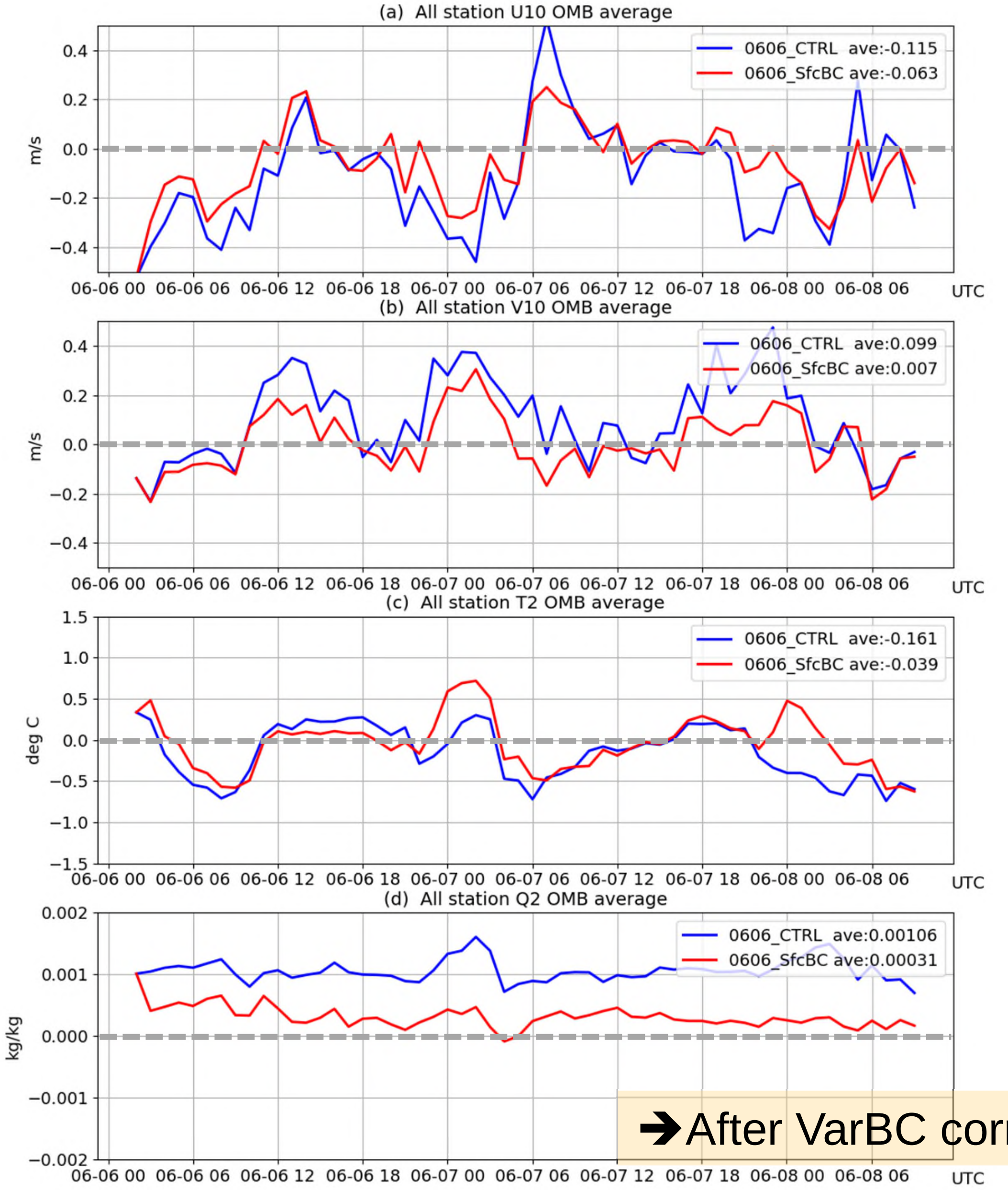
  (1) 0722_ CTRL (no use VarBC)
  (2) 0722 _SfcBC (use VarBC)

➔ Investigating the differences and effects of VarBC in different rainfall events.

Bias model performance – OMB stations average

➔ If no bias, OMB average will be close to 0

Case 1 ：Mei-Yu



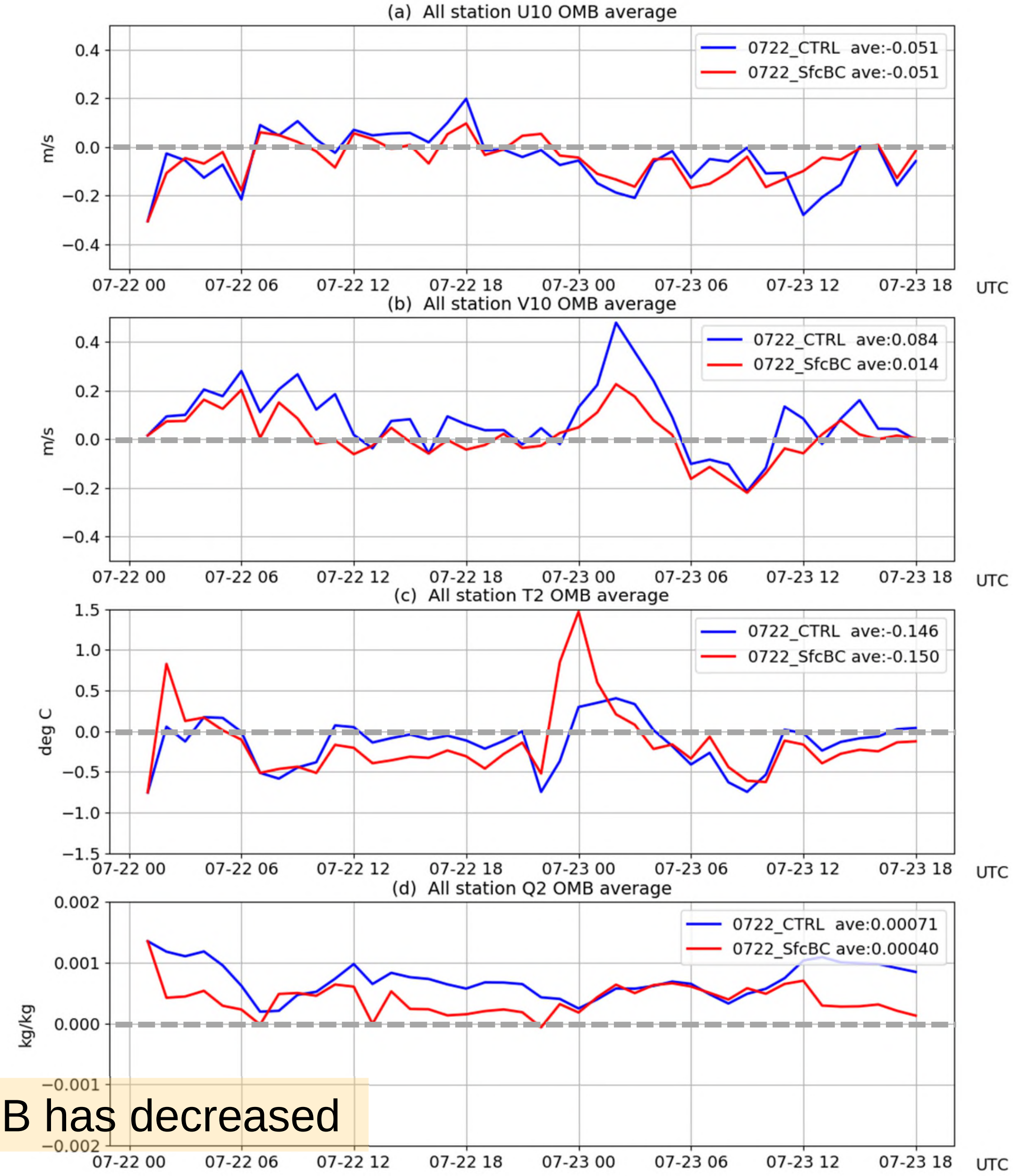
U10

V10

T2

Q2

Case 2 ：thunderstorm

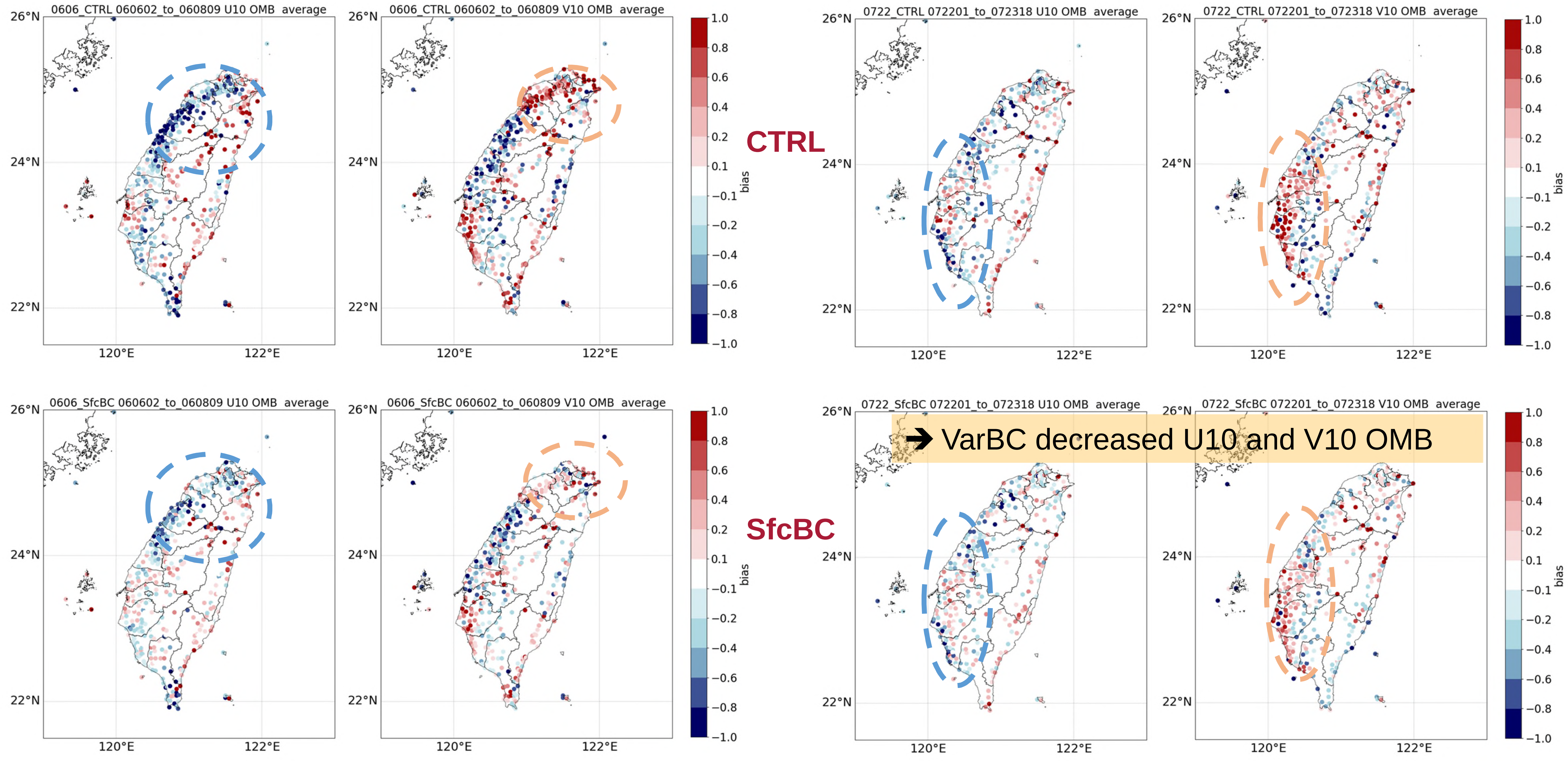


➔After VarBC correction, OMB has decreased

Bias model performance – **U10 and V10** OMB time average

U10 Case 1 : Mei-Yu V10

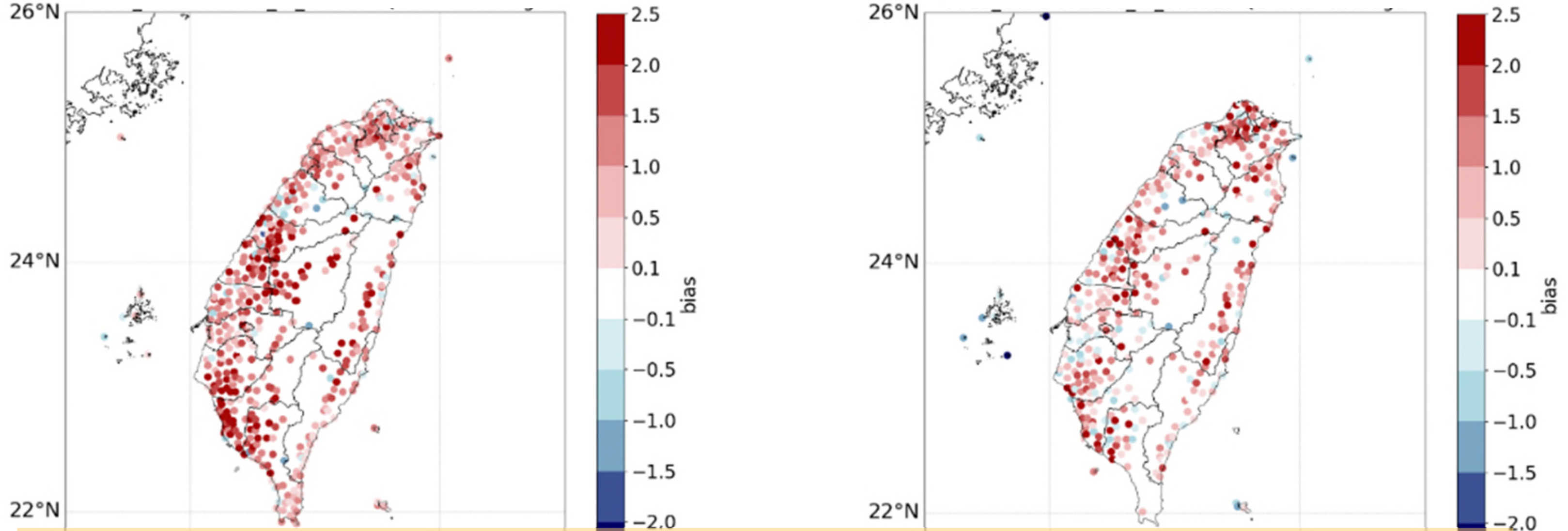
U10 Case 2 : thunderstorm V10



Bias model performance – **Q2** OMB time average

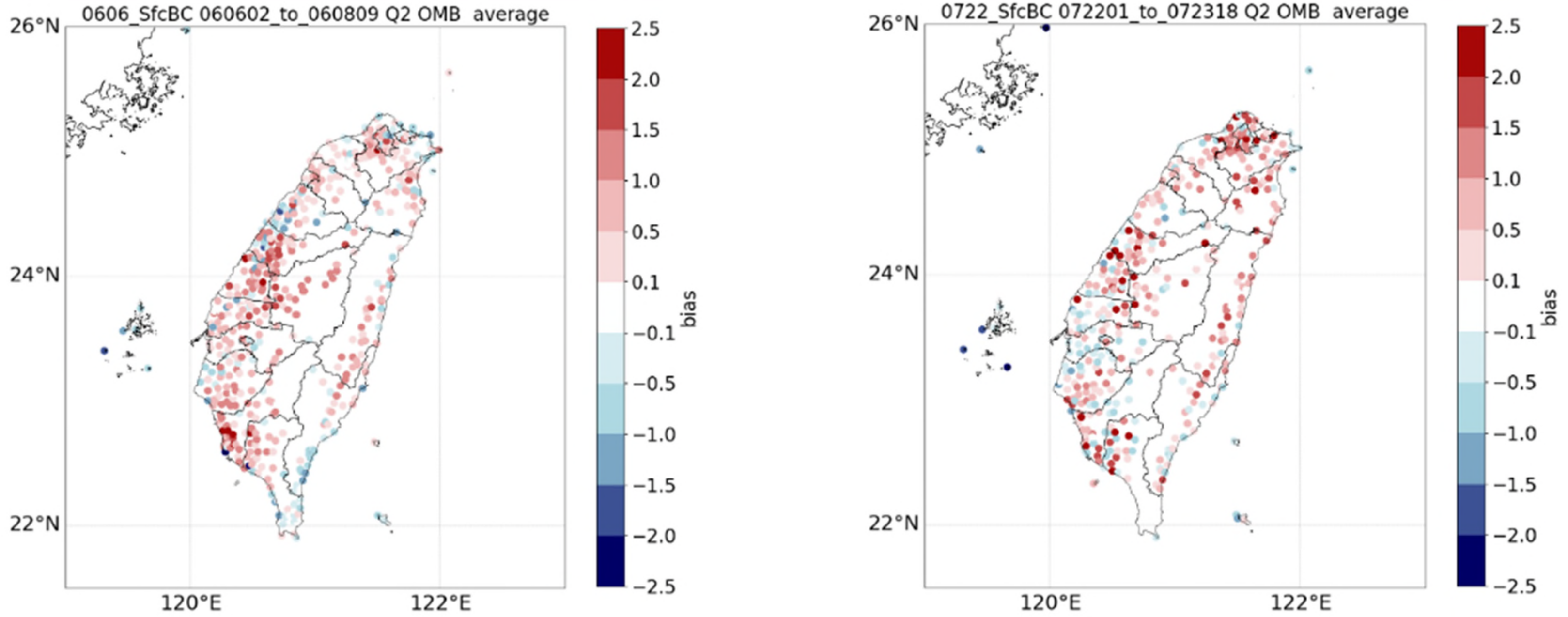
Case 1 ：Mei-Yu **Case 2 ： thunderstorm**

CTRL



➔ Q2 bias in both cases is consistent, with a **wet bias** across Taiwan.

SfcBC

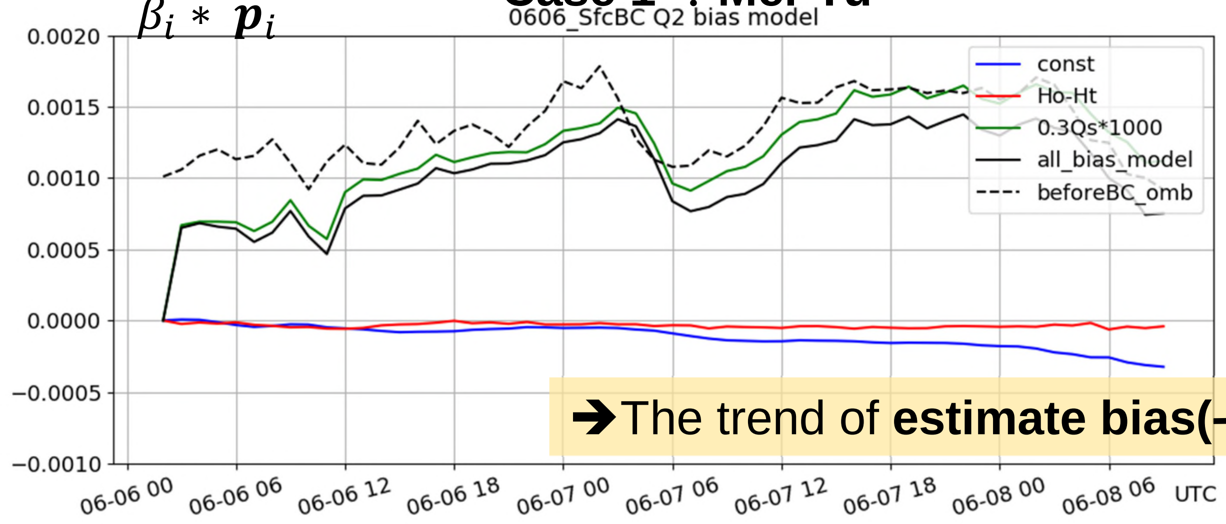


Bias model performance - Q2

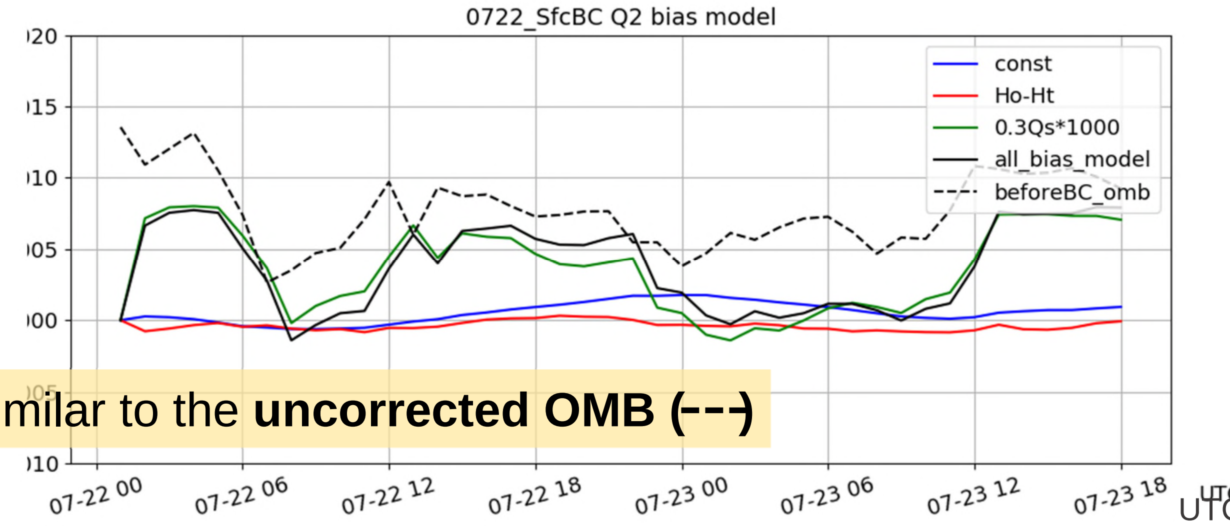
$$b^{Q} = \beta_0^{Q} + \beta_1^{Q}\left(\mathrm{H_{obs}} - \mathrm{H_{model}}\right) + \beta_2^{Q}\left(q_{s,\,obs}\right) * 300$$

Case 1 ： Mei-Yu

$\beta_i * \boldsymbol{p}_i$

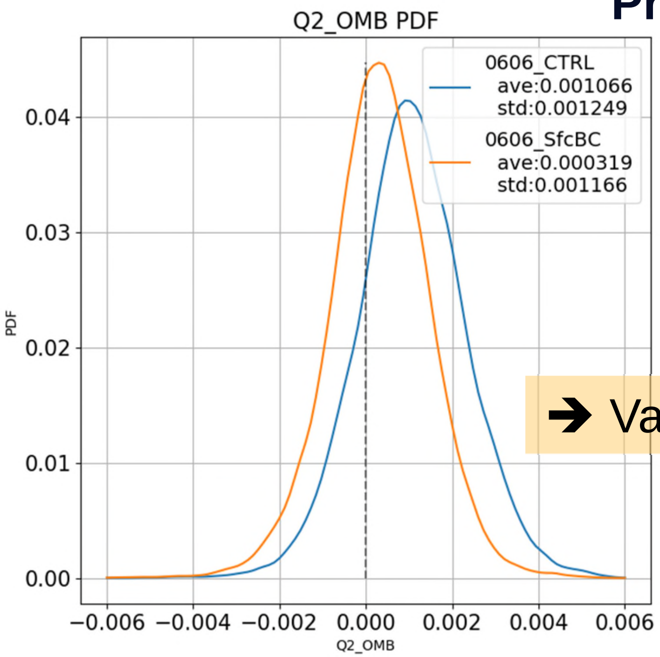


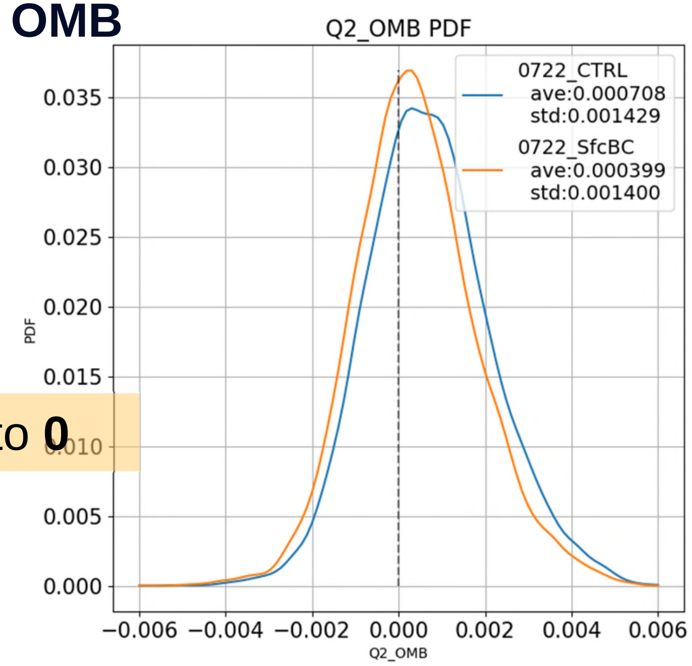
Case 2 ： thunderstorm



➔The trend of **estimate bias(—)** similar to the **uncorrected OMB (---)**

Probability density function Q2 OMB





➔ VarBC can bring Q2 OMB closer to **0**

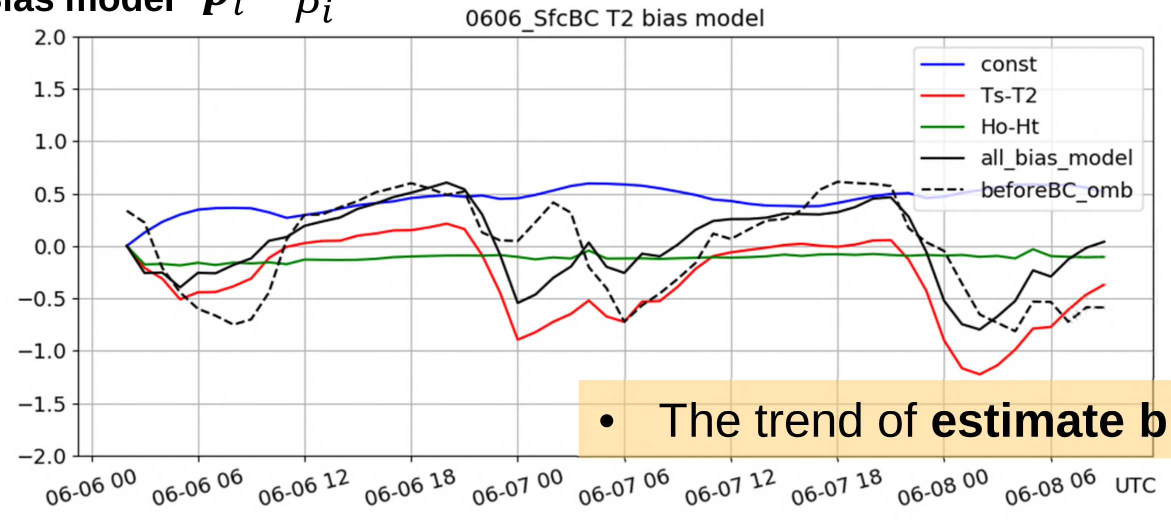
Bias model performance - **T2**

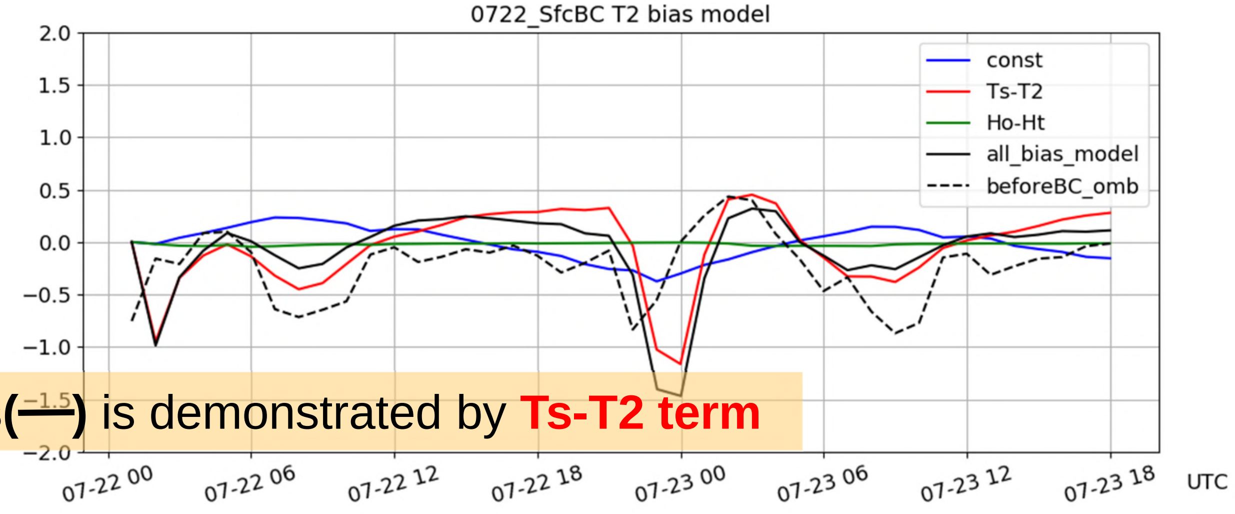
$$b^{T} = \beta_0^{T} + \beta_1^{T}(\mathrm{H_{obs}} - \mathrm{H_{model}}) + \boldsymbol{\beta_2^{T}}(T_{s,\,model} - T_{2,\,model})$$

Case 1 ：Mei-Yu

Case 2 ：thunderstorm

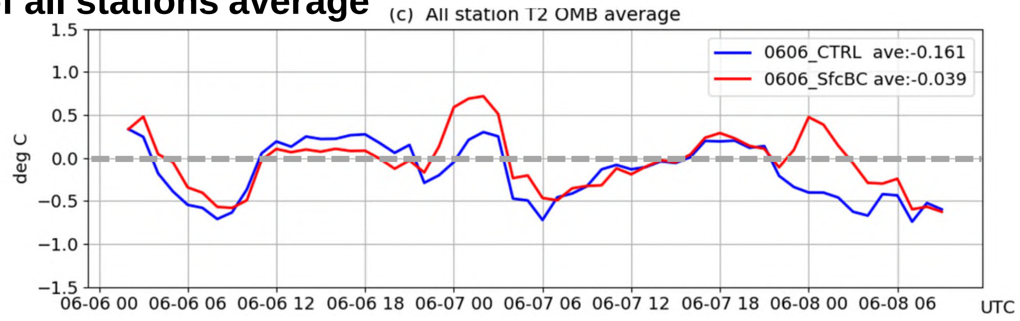
Bias model $p_i * \beta_i$

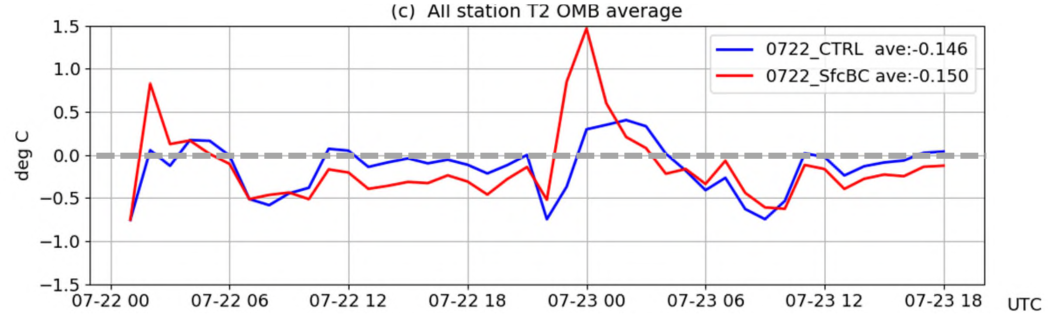




- The trend of **estimate bias(—)** is demonstrated by **Ts-T2 term**

OMB of all stations average





Case 1：

- Estimate bias generally match uncorrected OMB.

Case 2：

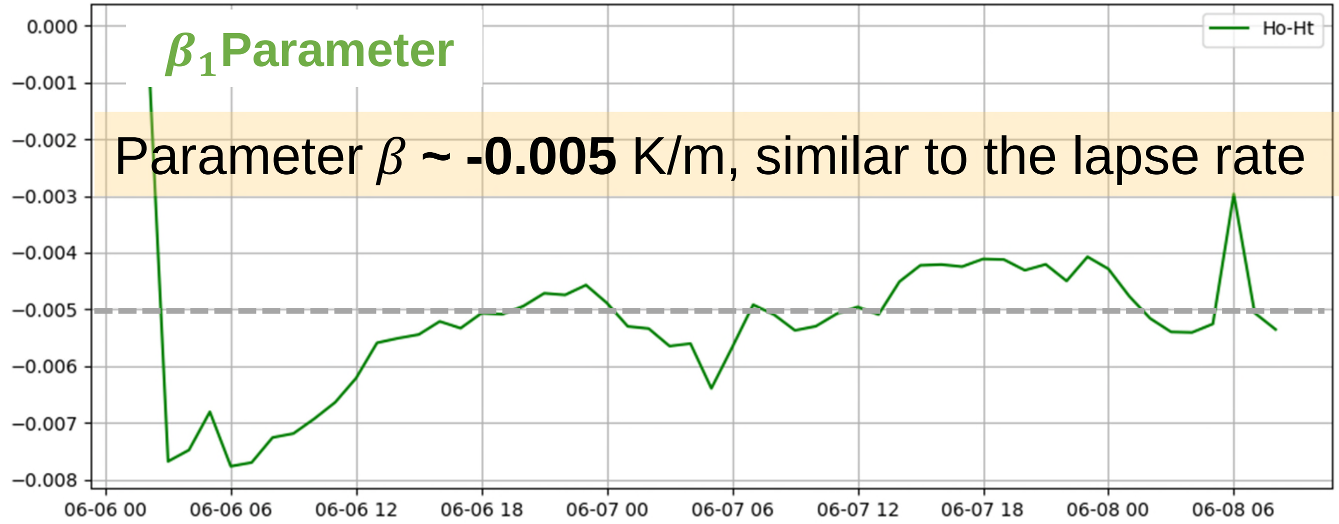
- TsT2 term can’t fully represent the diurnal cycle, making it ineffective in correcting T2 OMB.

Bias model performance - **T2**

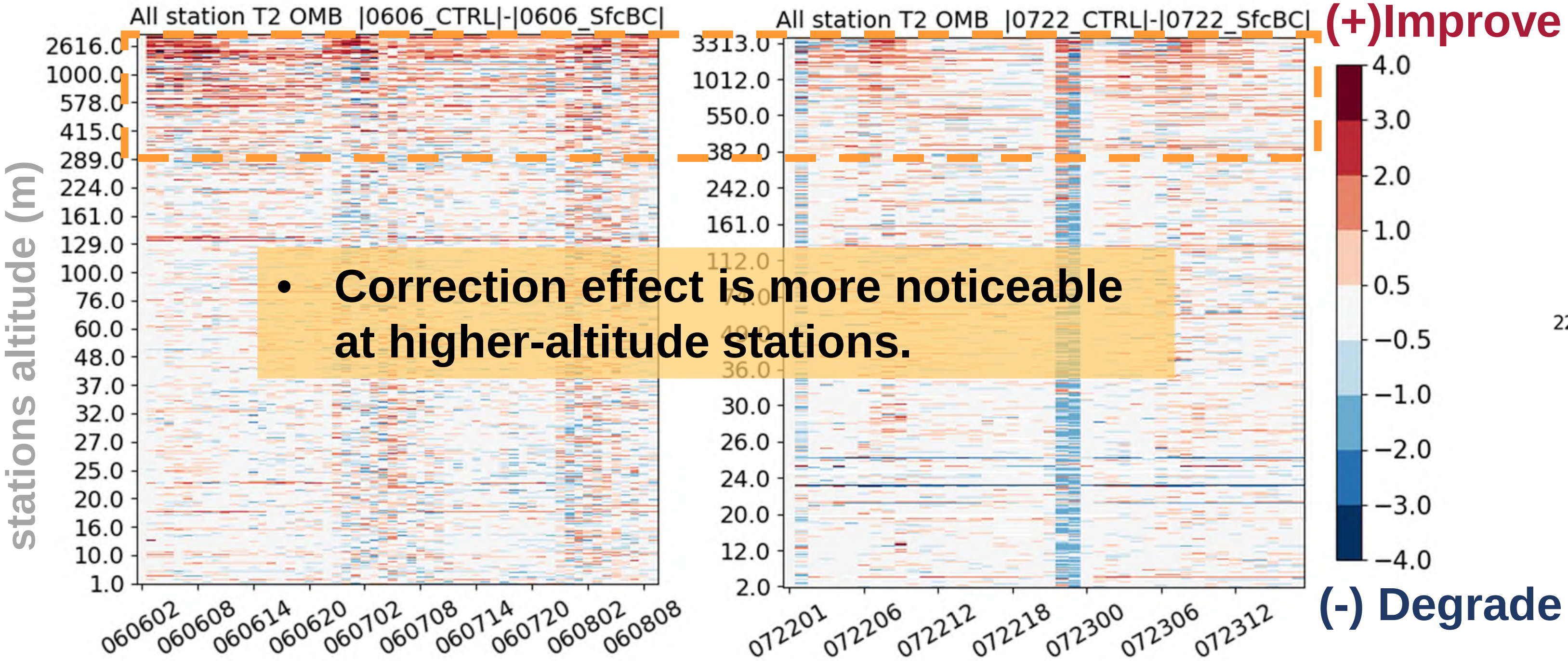
$$b^{T} = \beta_0^{T} + \beta_1^{T}(H_{obs} - H_{model}) + \beta_2^{T}\left(T_{s,\,model} - T_{2,\,model}\right)$$

β_1 **Parameter**

Parameter β ~ **-0.005** K/m, similar to the lapse rate

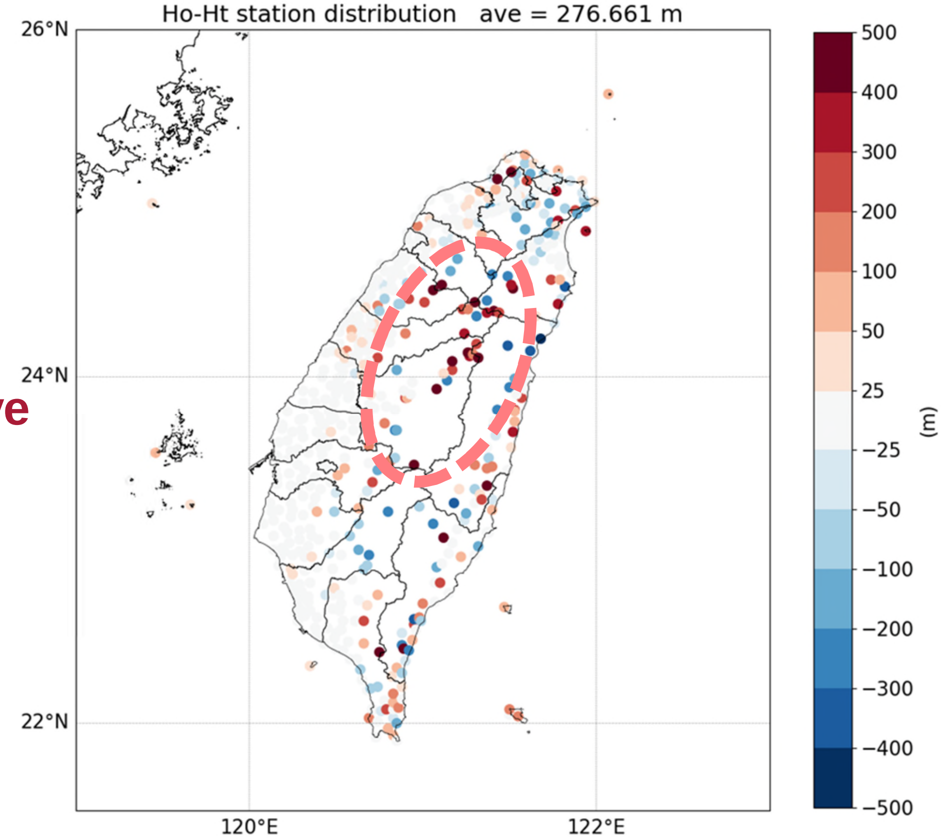


All station T2 OMB |CTRL| – |SfcBC|



- **Correction effect is more noticeable at higher-altitude stations.**

p_1 **Ho-Ht**



Verification

Model verification

- Use each analysis field as the true to verify the forecast field

Observation verification

- Zenith Total Delay (ZTD)
- QPESUMS

Mean Error

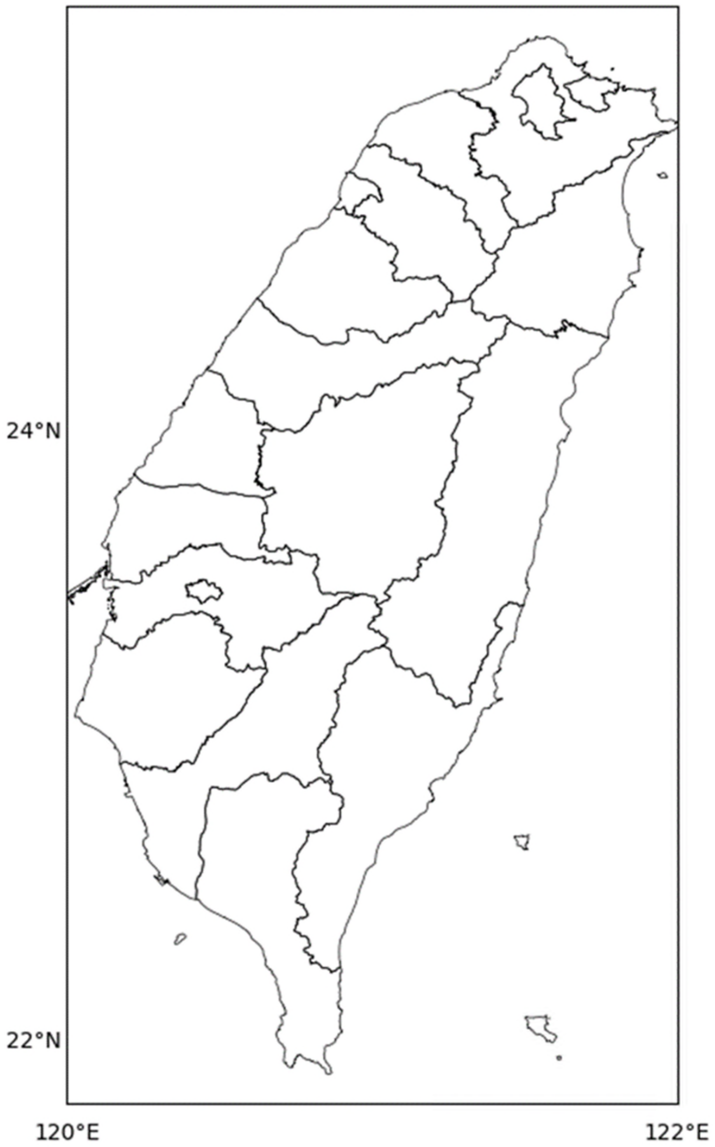
$$ME = \frac{1}{n}\sum_{i=1}^{n}(obs - fcst)$$

→ similar OMB average

Root Mean Squared Error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(obs - fcst)^2}$$

Verification range
(21.8-25.4°N, 120-122°E)



Model verification : **Case 1 Mei-Yu**

$$ME = \frac{1}{n}\sum_{i=1}^{n}(fcst - ana)$$

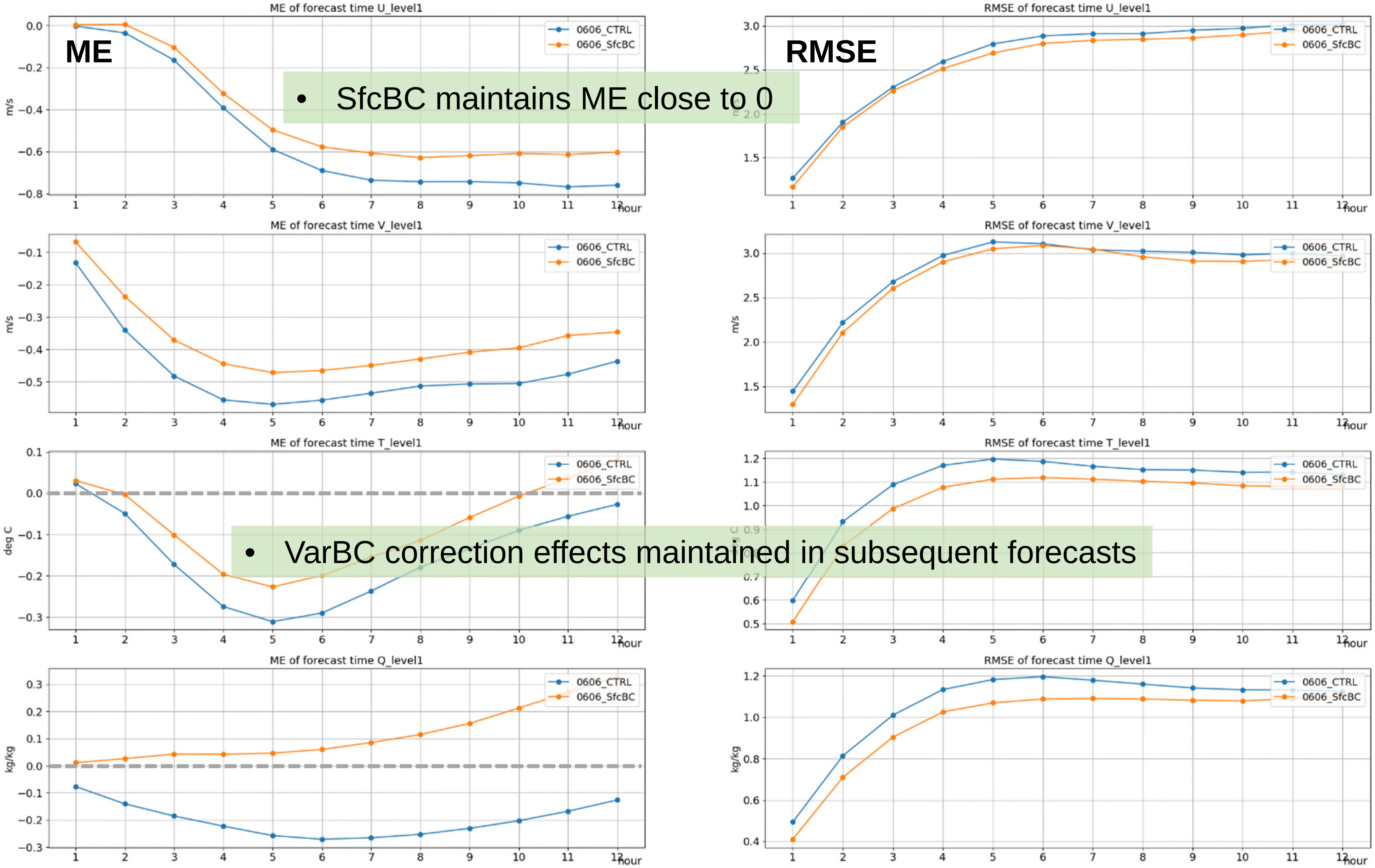
Forecast length

U_level1

V _level1

T _level1

Q _level1



- SfcBC maintains ME close to 0

- VarBC correction effects maintained in subsequent forecasts

Model verification : **Case 2 thunderstorm**

$$ME = \frac{1}{n}\sum_{i=1}^{n}(fcst - ana)$$

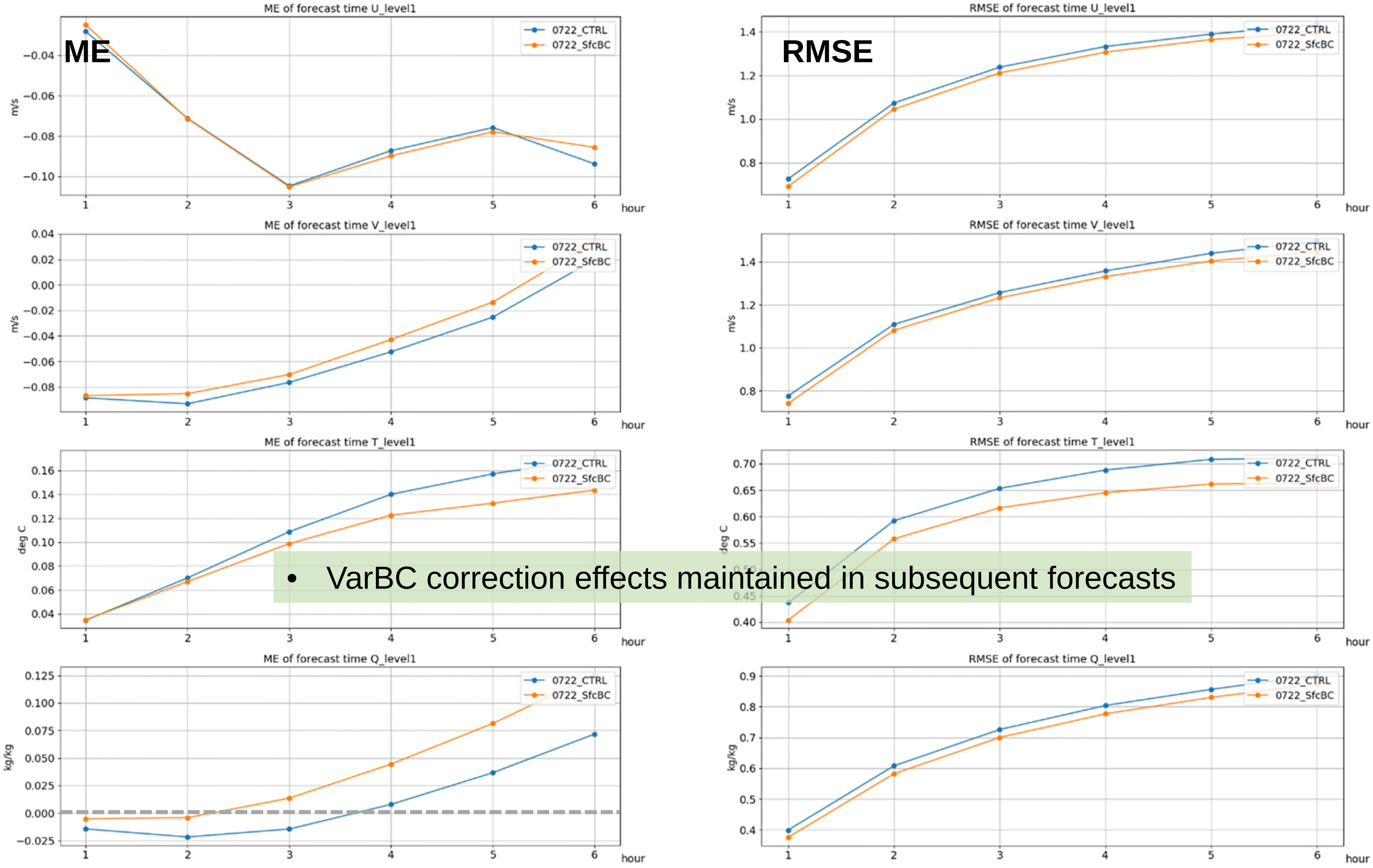
Forecast length

U_level1

V _level1

T _level1

Q _level1



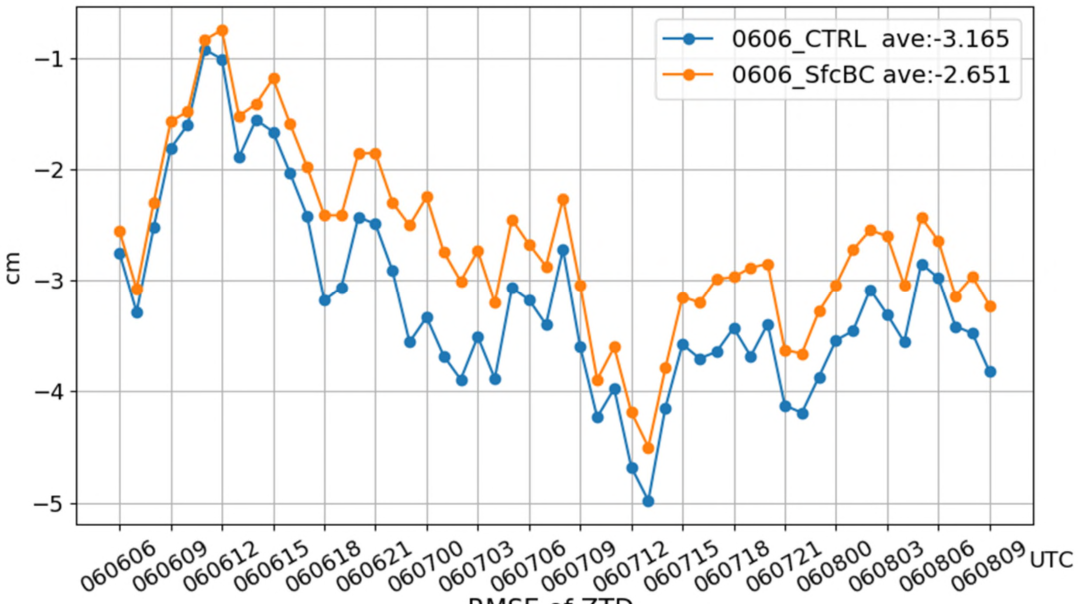
- VarBC correction effects maintained in subsequent forecasts

Observation verification : **ZTD**

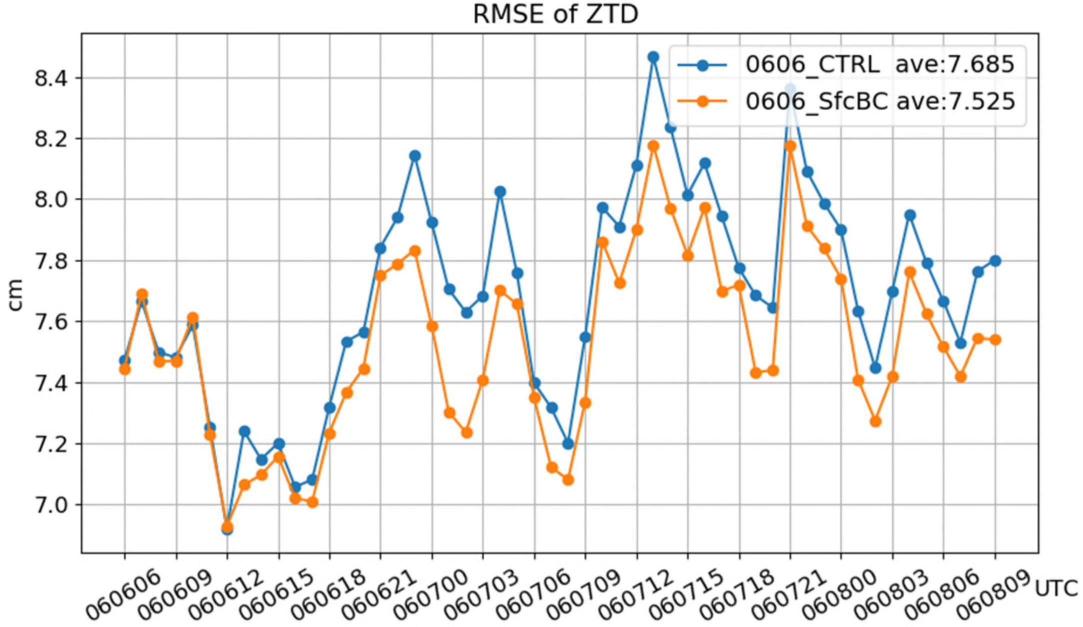
$$ME = \frac{1}{n}\sum_{i=1}^{n}(obs - fcst))$$

Case 1 ：Mei-Yu

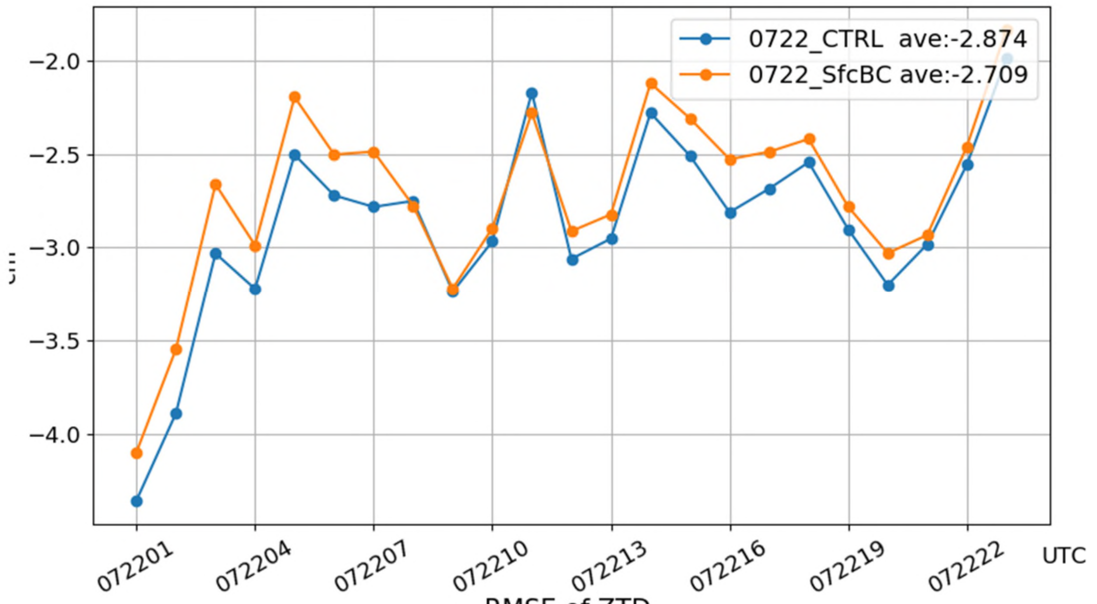
ME

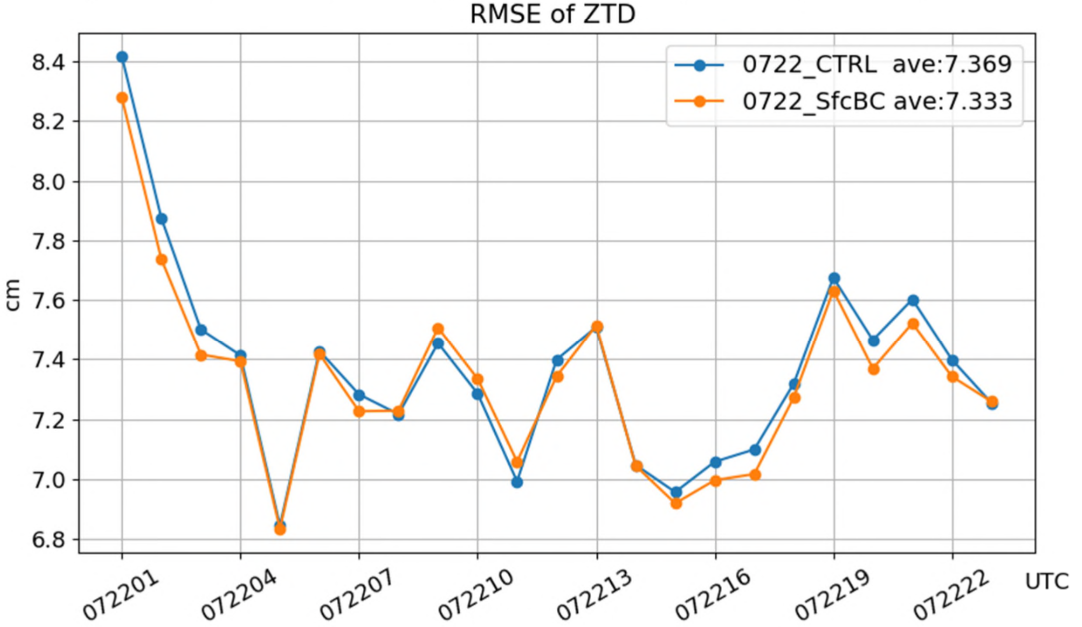


RMSE



Case 2 ： thunderstorm





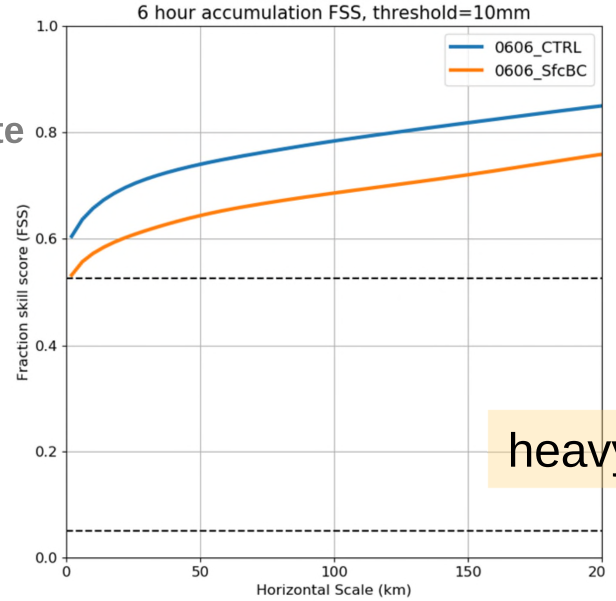
Observation verification : **QPESUMS**

Threshold=10mm

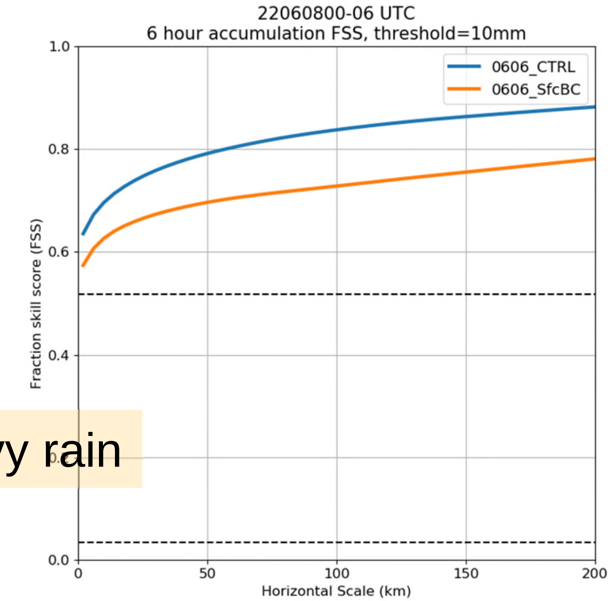
Case 1 ： Mei-Yu

6hr accumulate rainfall

0607 00-06 UTC



0608 00-06 UTC

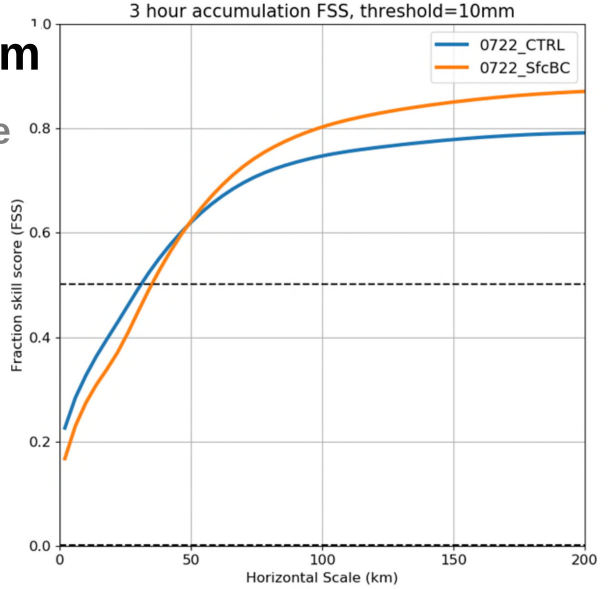


heavy rain

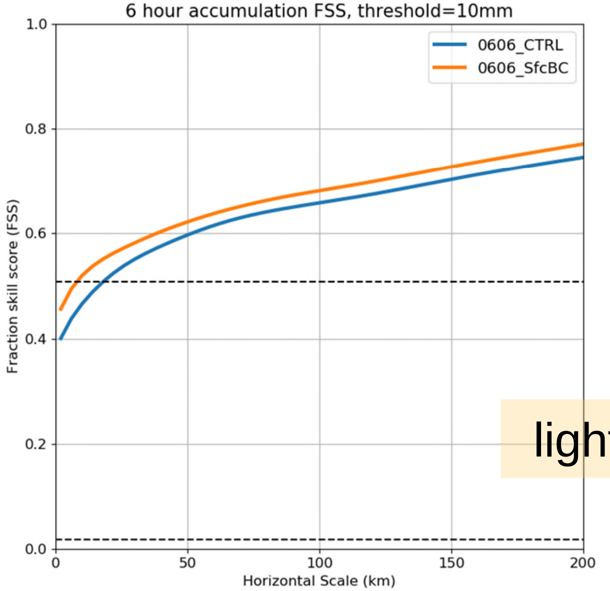
Case 2 ： thunderstorm

3hr accumulate rainfall

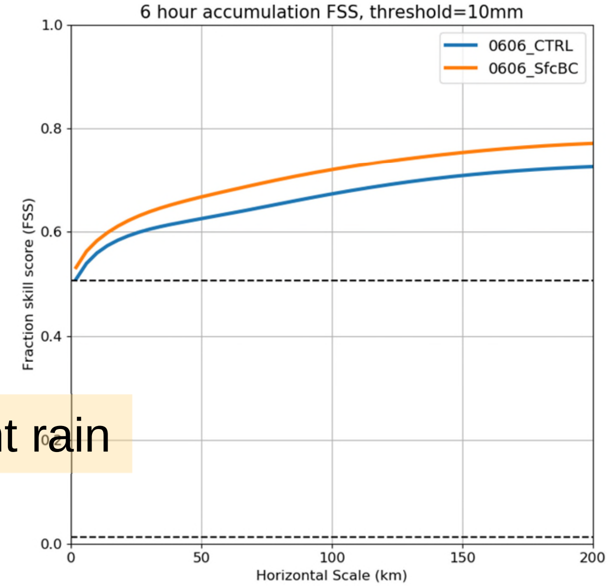
0722 04-07 UTC



0606 18-00 UTC

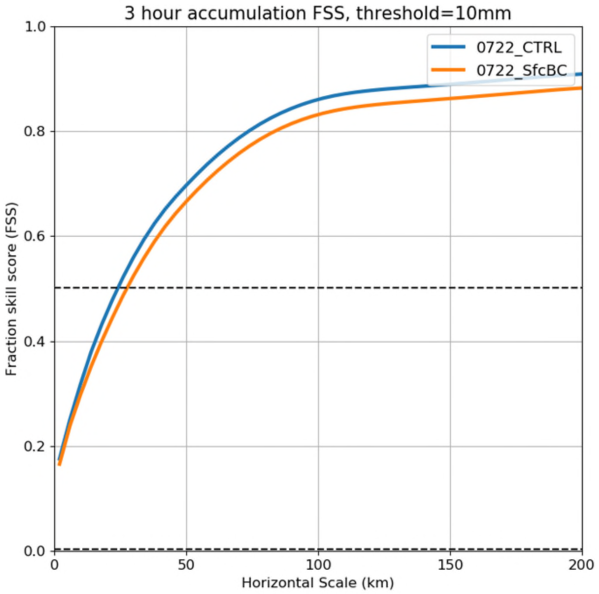


0607 12-18 UTC



light rain

0723 04-07 UTC



Discussion – Impact of no **anchor data**

Traditional VarBC uses anchor data to identify bias sources.

- Without anchor data, the system may overcorrect observations, making results dependent on the model.
- Lack of anchor data can lead to model drift.

This study applies VarBC **without anchor data**.

- It corrects biases in both observations and the model.
- Background-dependent corrections better match model needs.
- The adjustments are applied to diagnostic variables.
- Reduced correction amounts help stabilize the model.

→ Positive impacts are noticeable even without anchor data.

- **Bias model performance**
  1. **With surface VarBC, overall OMB average decreased.**

     Reduce Q2 OMB noticeable positive bias.

     Reduce local OMB of U10 and V10 .
  2. **T2 bias model reasonable corrections.**

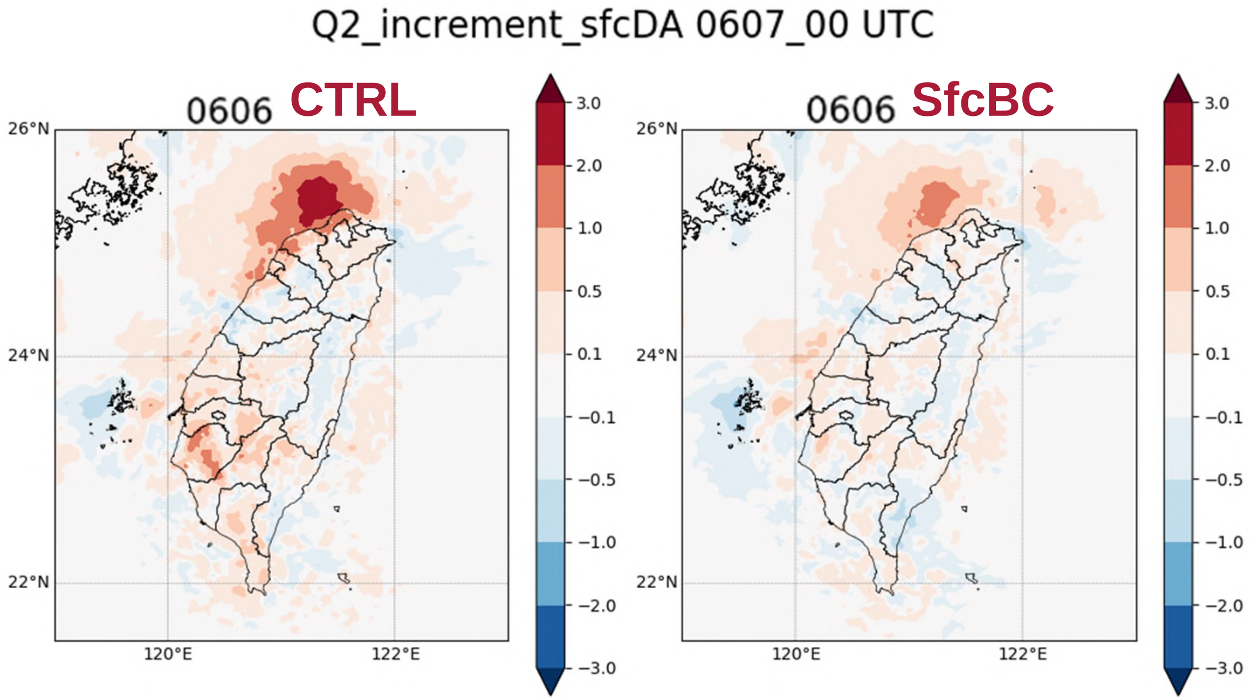
     TsT2 term： capture bias of diurnal cycle.

     HoHt term： correct T2 bias from altitude differences.
- **Verification**
  1. **VarBC can improve both the analysis field and subsequent forecasts.**
  2. **Model verification**：VarBC can bring forecasts closer to the analysis field.
  3. **Independent verification**： VarBC reduces overestimated water vapor.

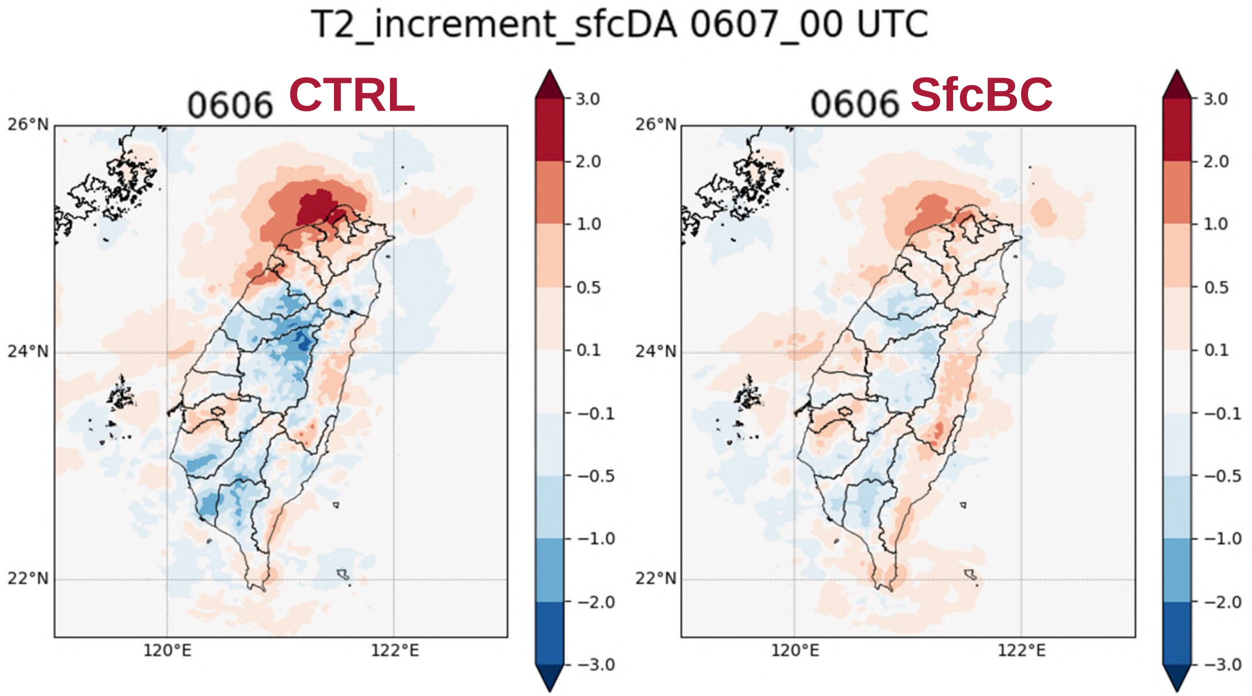
Thanks for listening

Results – **Case 1 : Mei-Yu** Q2 and T2 increment

Q2

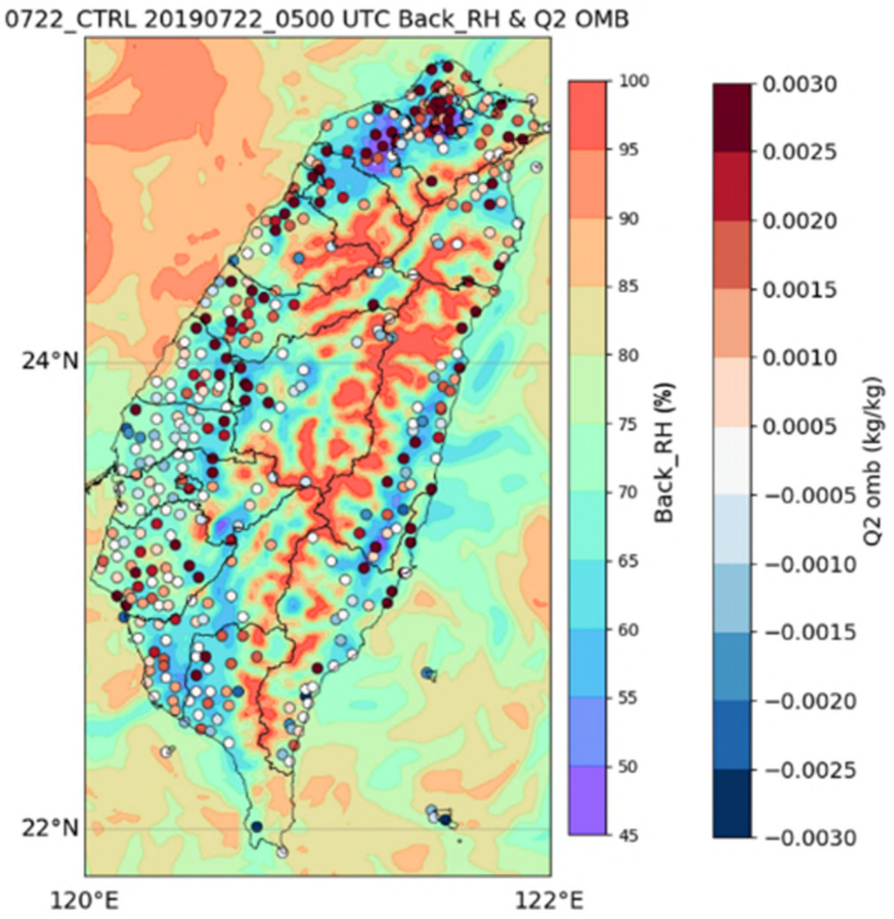


T2

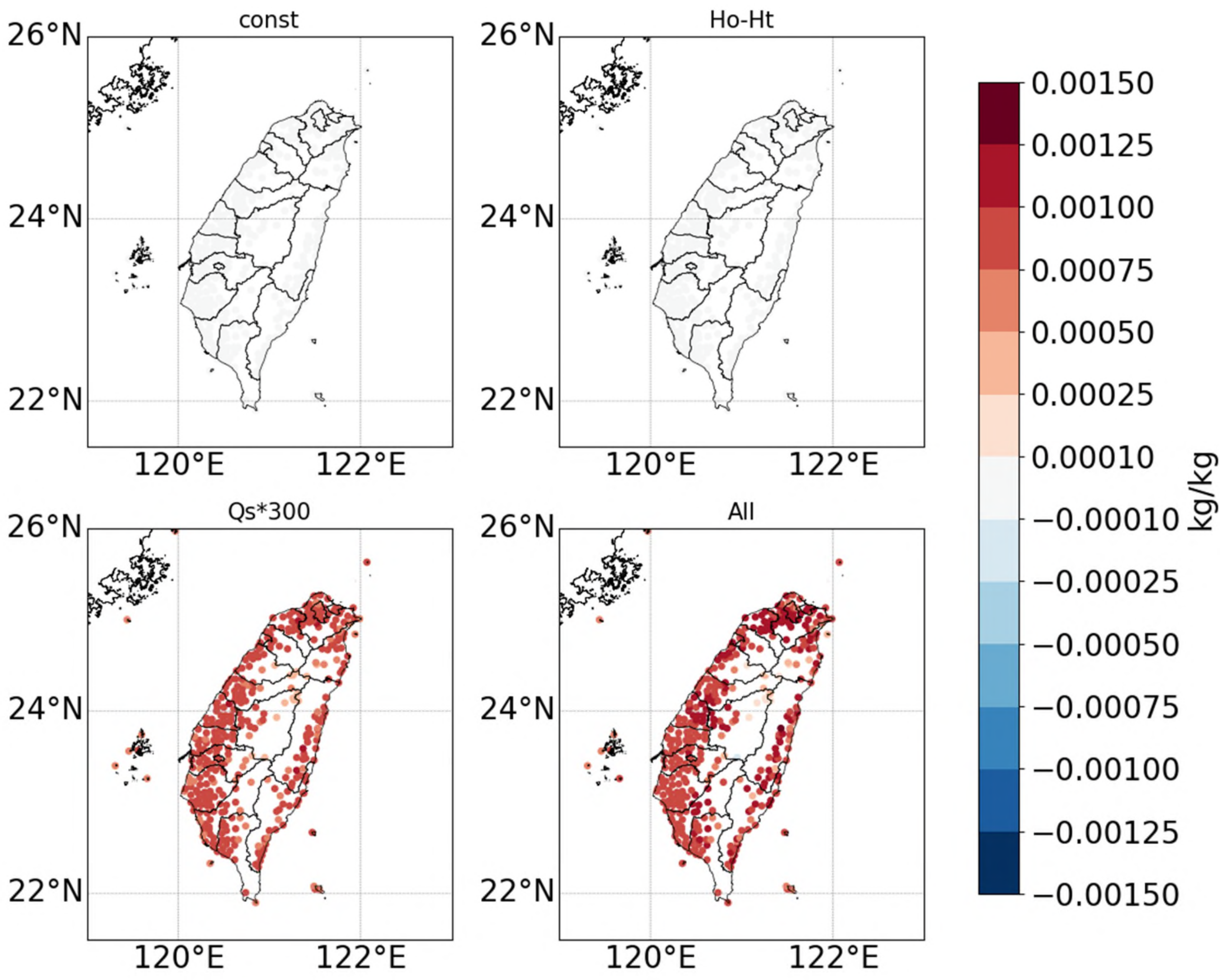


- After VarBC correction, increment decreased.
- Improve model stability.
- The effect of VarBC on surface DA is reasonable.

Results – **Case 2 : thunderstorm** Q2 bias model each term



0722 05UTC_SfcBC Q bias model pred*para

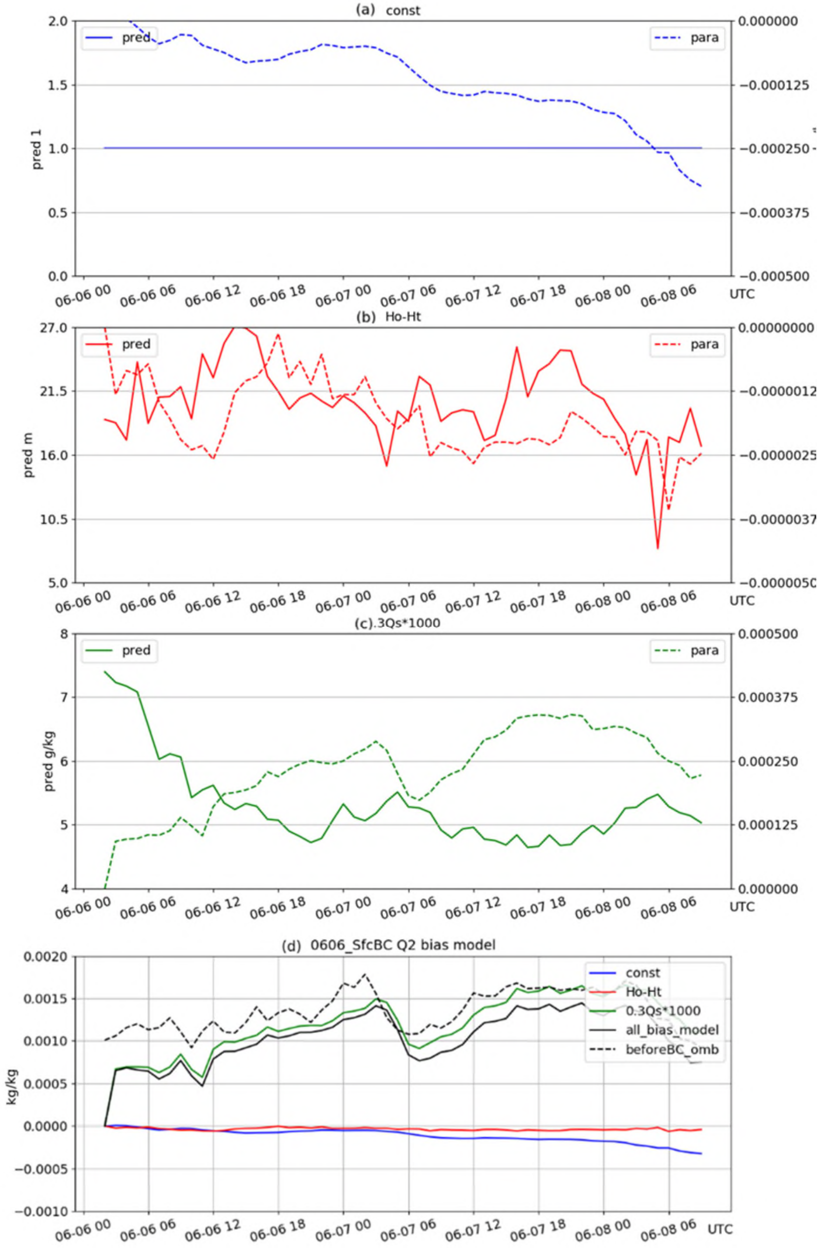


➔ Local rainfall causes irregular OMB distribution.

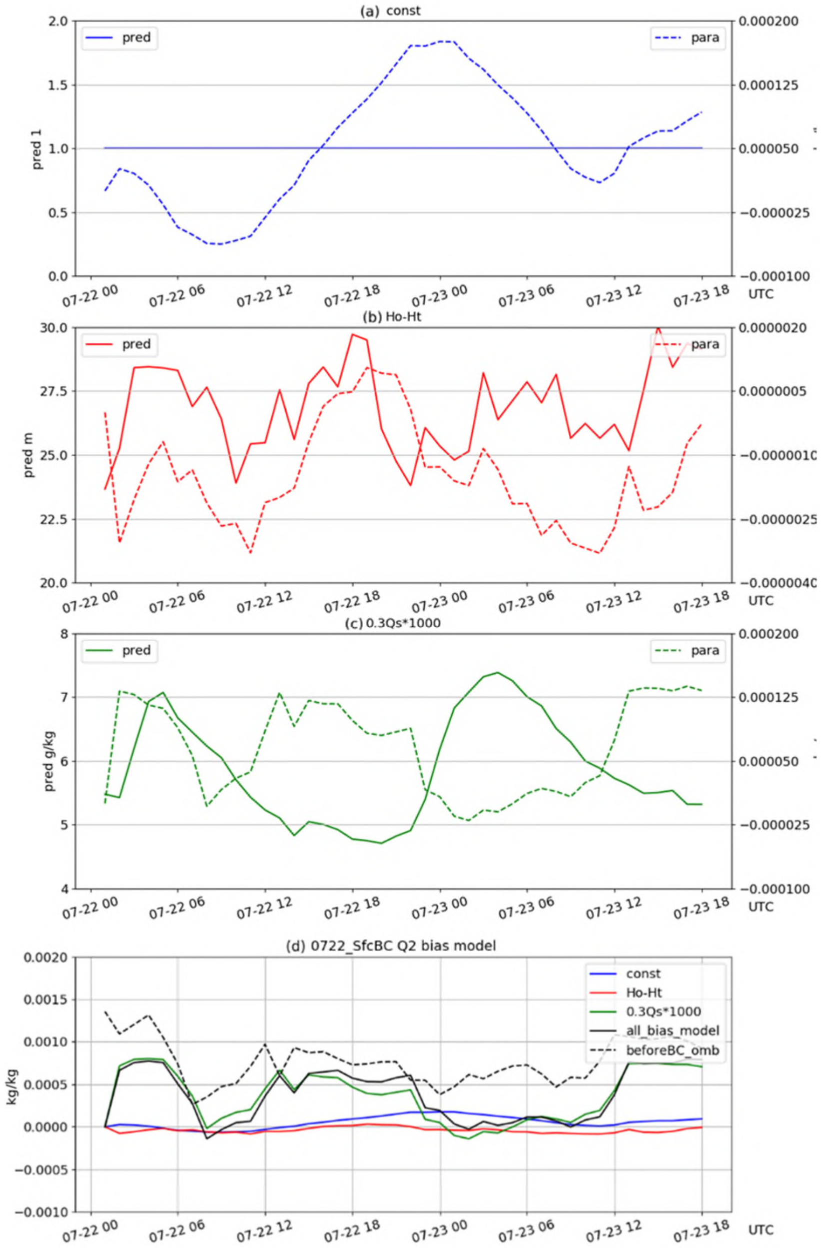
➔ Qs term mainly corrects the overall positive bias.

Results – **Q2** OMB of station average

Case 1 ：Mei-Yu



Case 2 ： thunderstorm

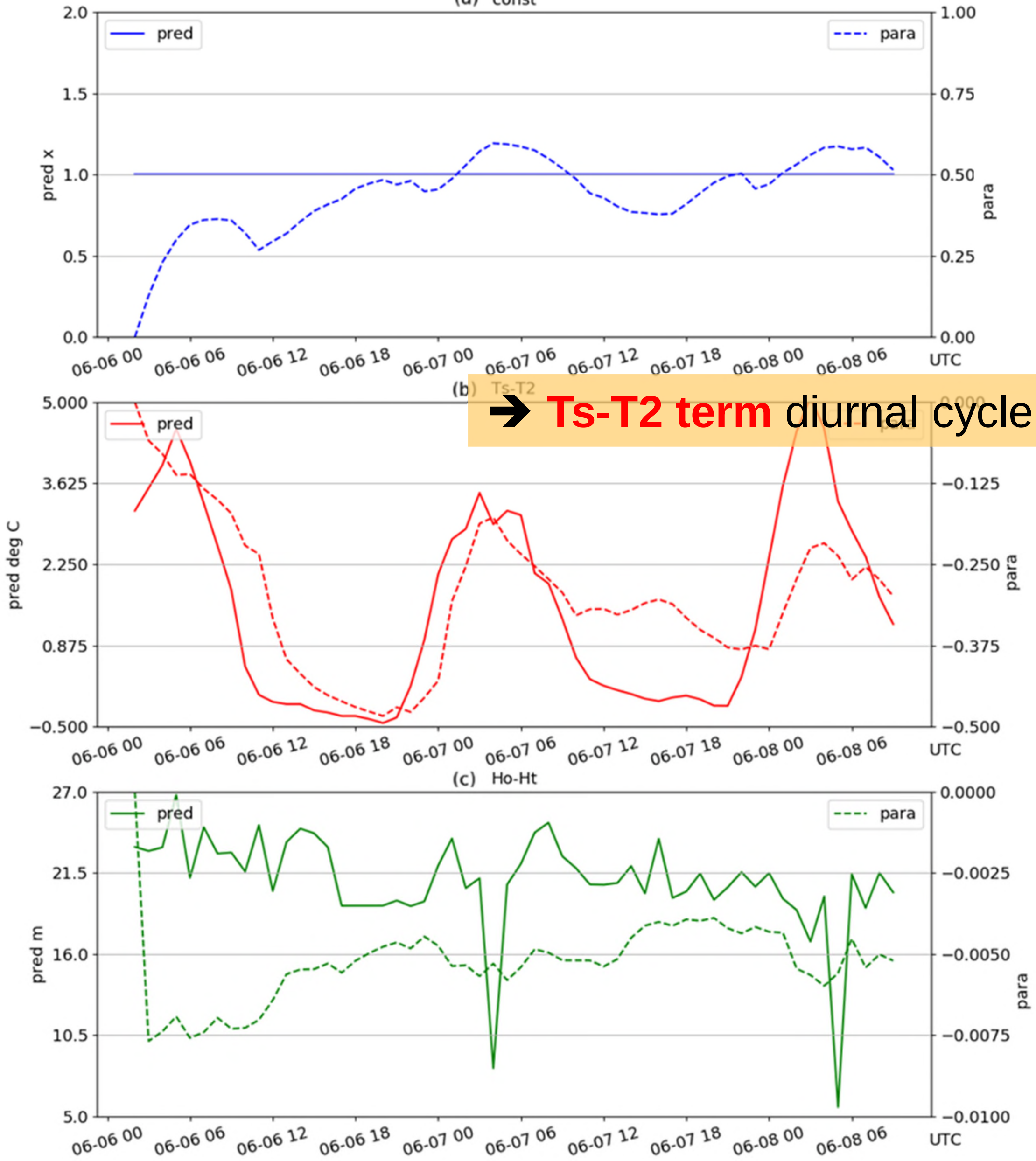


Results – T2 bias model

$$b^{T} = \beta_0^{T} + \beta_1^{T}(\mathrm{H_{obs}} - \mathrm{H_{model}}) + \boldsymbol{\beta_2^{T}}\left(\boldsymbol{T}_{s,\,\mathrm{model}} - \boldsymbol{T}_{2,\,\mathrm{model}}\right)$$

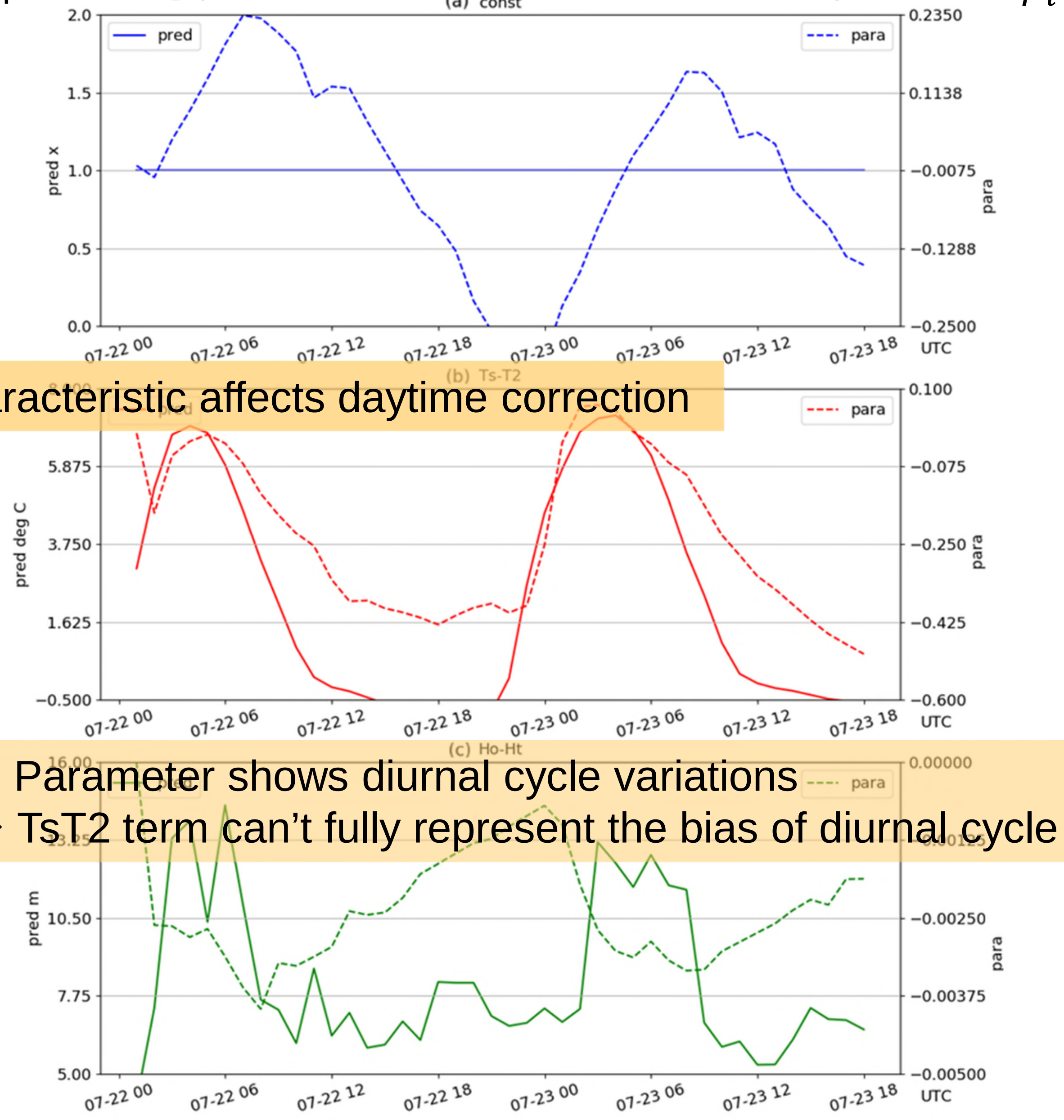
Case 1 : Mei-Yu

predictor $\boldsymbol{p}_i$ parameter β_i



Case 2 : thunderstorm

predictor $\boldsymbol{p}_i$ parameter β_i



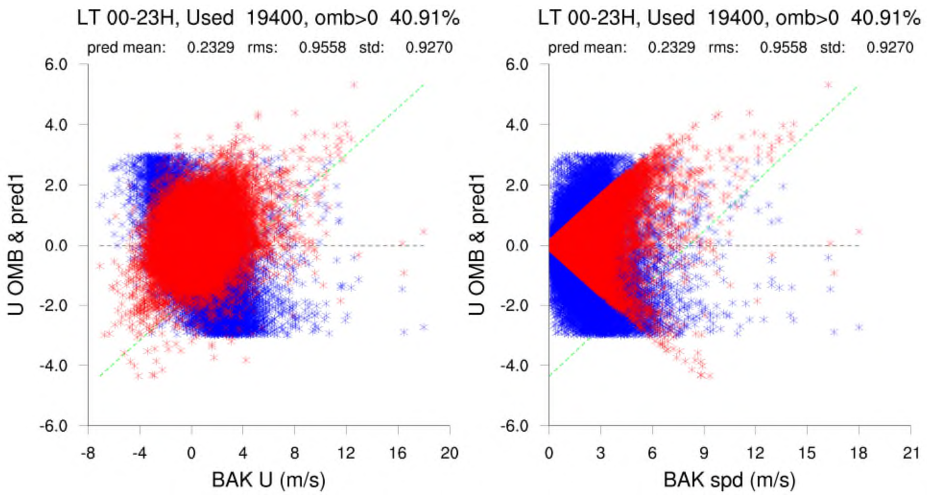
➔ **Ts-T2 term** diurnal cycle characteristic affects daytime correction

- Parameter shows diurnal cycle variations

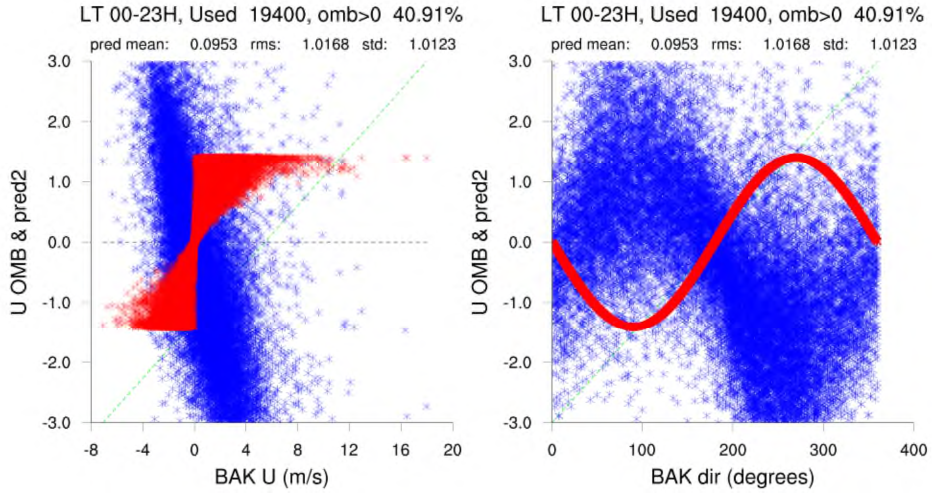
➔ TsT2 term can't fully represent the bias of diurnal cycle

Results – VarBC **U10 & V10** bias model

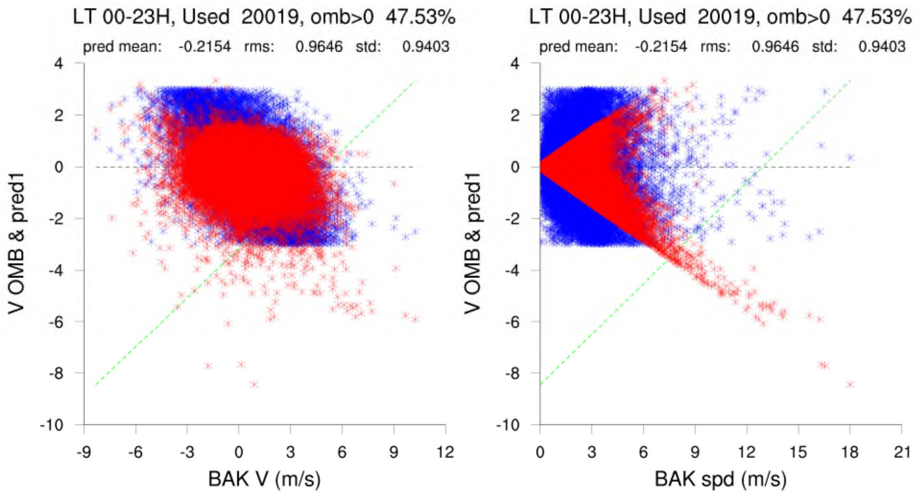
U10 $p_{u1} = -ws * \ cos(wd)/\sigma_{pu1}$



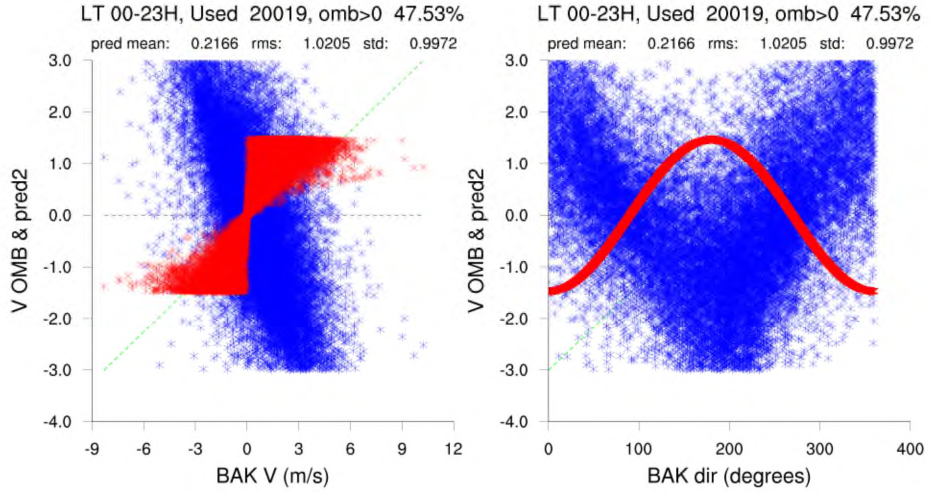
$p_{u2} = -sin(wd)/\sigma_{pu2}$



V10 $p_{v1} = ws * \ sin(wd)/\sigma_{pv1}$



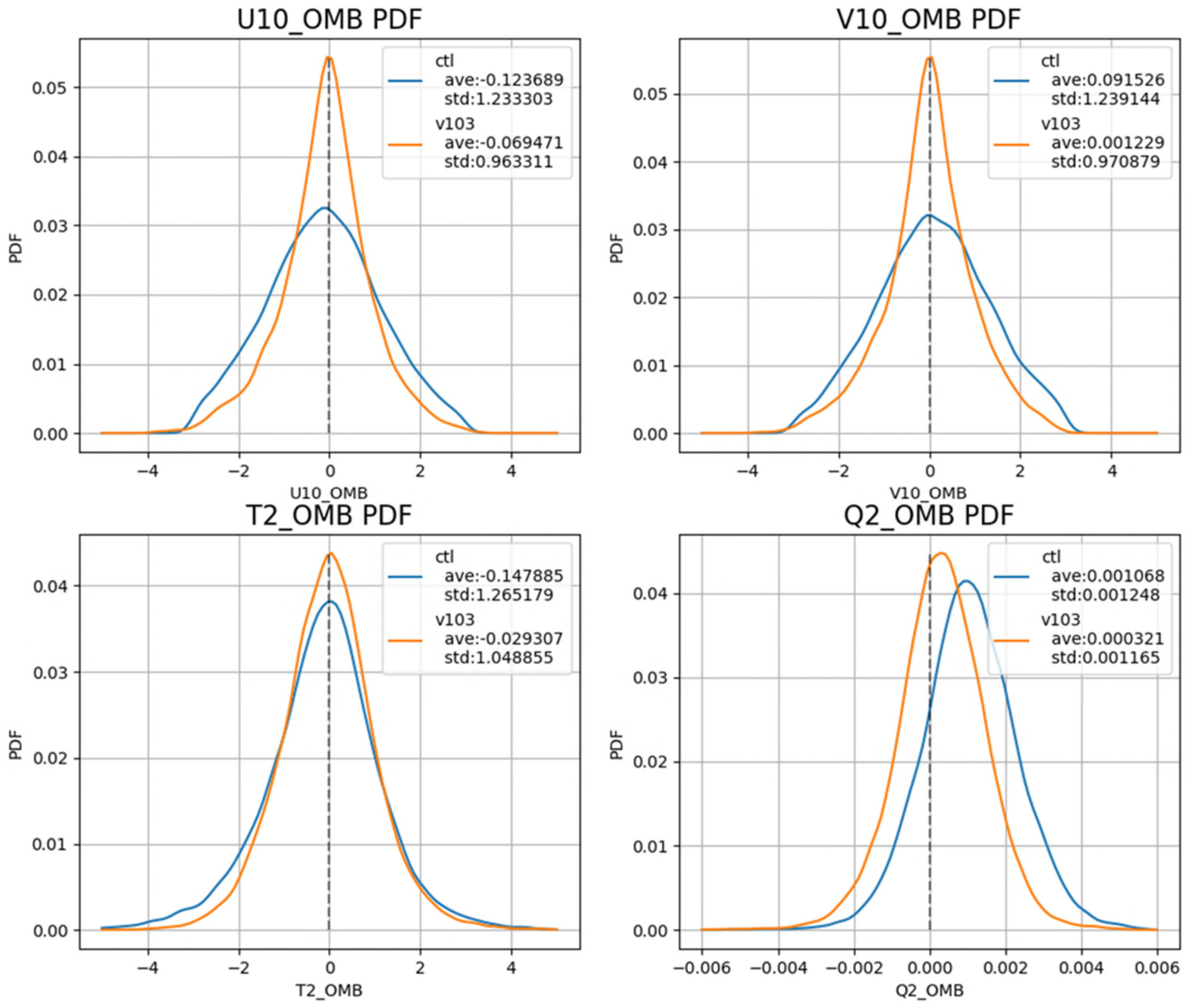
$p_{v2} = -cos(wd)/\sigma_{pv2}$



➔在predictor 2 與U、V背景場有高度負相關

Results – PDF

Case 1 ：Mei-Yu



Case 2 ： thunderstorm