Improving Afternoon Thunderstorm Prediction over Taiwan through 3DVar-Based Radar and Surface Data Assimilation

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Outline

1. Introduction
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   - 4 questions
2. Description of cases, observational data, and verification methods
3. Designation of convective-scale data assimilation system
4. Experimental design
5. Results
   - Evaluation of the 10-day experiments (6/29 ~ 7/8)
   - Case study (7/6)
6. Summary – To answer the 4 questions

1. Introduction

a. Paper review

- **The characteristics of afternoon thunderstorms (ATs) in Taiwan**

  (1) The intensity can reach 131 mm/hr. (Miao and Yang 2020)

  (2) The storms initiate at the ridge and propagate downslope.

  (Jou 1994; Johnson and Bresch 1991; Chen et al. 2007; Lin et al. 2011)

- **The key factors in AT initiation and development**

  (1) Land-sea breeze and local circulation are influential in AT initiation.

  (Chen and Li 1995; Johnson and Bresch 1991; Lin et al. 2011; Chang et al. 2017)

  (2) Cold pool and outflow boundary is critical in AT development.

  (Hirt et al. 2020; Rotunno et al. 1988)

  (3) The diurnal surface observation variations are apparently different in days with and without AT development.

  (Lin et al. 2011)

1. Introduction

a. Paper review

- **The issues on operational nowcasting for ATs**

(1) Initial condition accuracy has large impacts on the model predictability.

(Sokol and Zacharov 2012; Sun et al. 2012; Tong et al. 2016)

(2) Radar observations are assimilated through Rapid Update Cycles (RUC; Benjamin et al. 2004), which is proved beneficial.

(Sun et al. 2010; Sun and Crook 1998)

(3) Surface observations assimilation is challenged by the mismatch of terrain height between the model and observations.

(Pu et al. 2013; Deng and Stull 2007)

1. Introduction

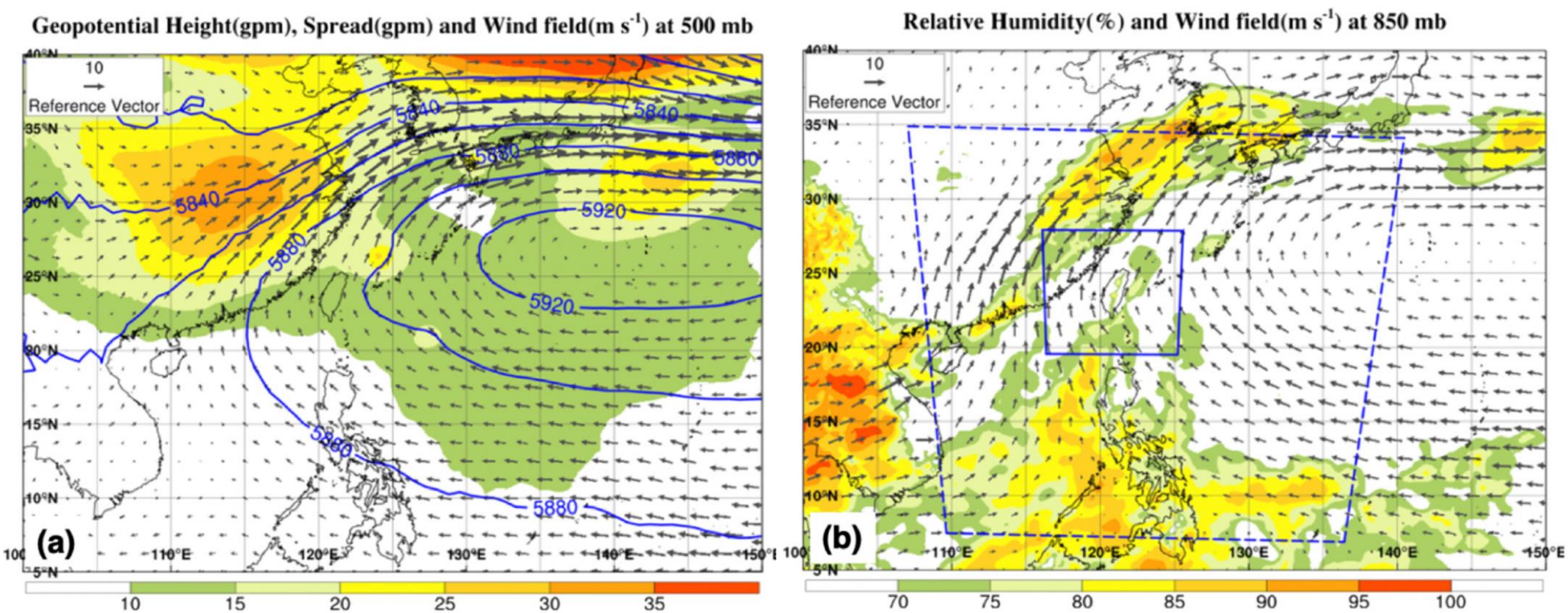
b. Four questions in this paper

1) Is the designation of the RUC strategy combined with a blending scheme (Yang 2005) effective in the nowcasting system?
2) Can surface data assimilation contribute positively to AT prediction under the complex geography of Taiwan island?
3) What is the relative importance between radar and surface observation to AT prediction? Does their combination add additional value?
4) Can we increase the AT forecast lead time in the morning through data assimilation? If so, which type of observation is more critical?

2. Description of cases, observational data, and verification methods

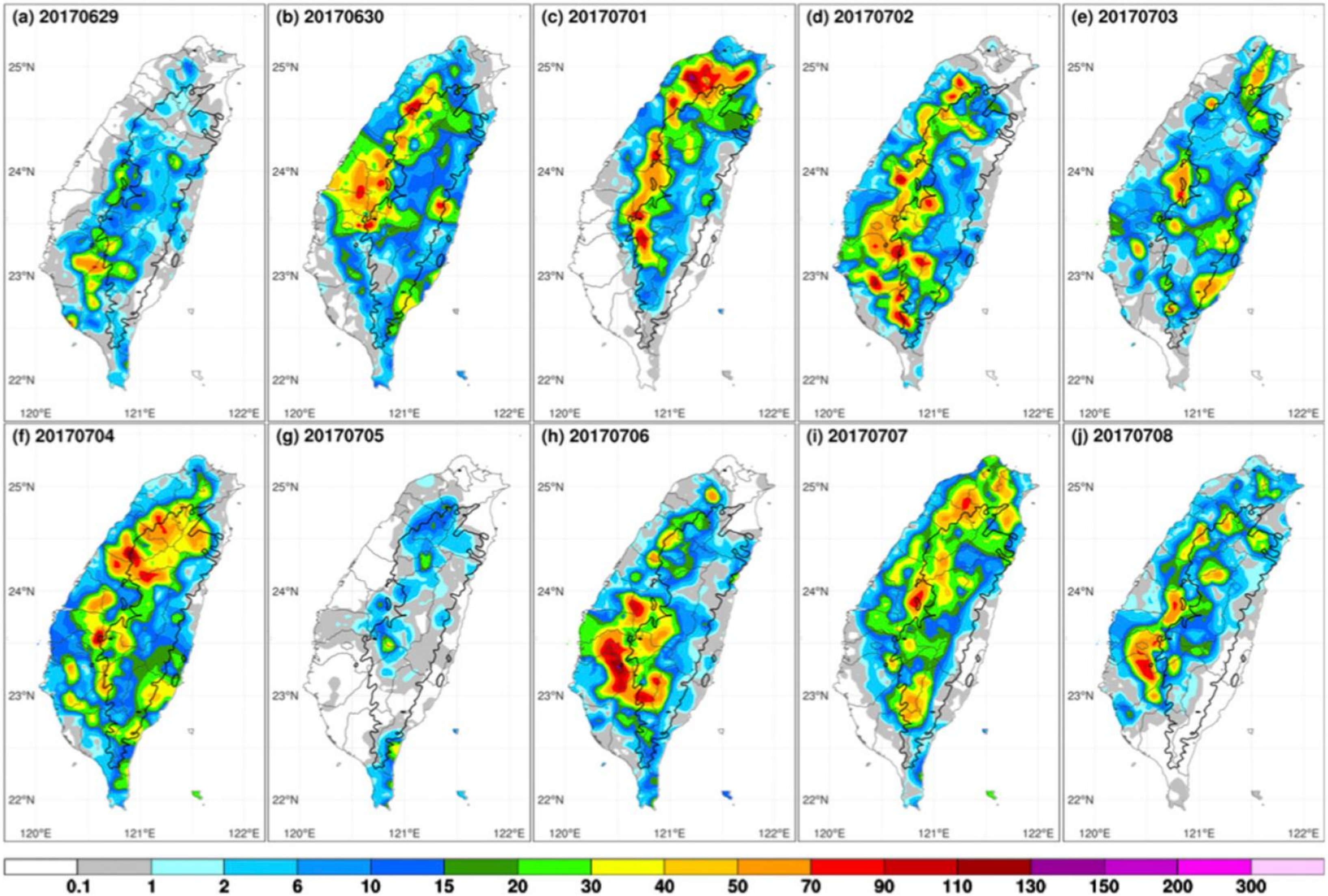
a. Consecutive afternoon thunderstorms – 29 June 2017 ~ 8 July 2017 (10 days)

- Taiwan was dominated by subtropical high.
- Typhoon Nanmadol passed east Taiwan.
- Disturbances around Taiwan could push moist air over land.



2. Description of cases, observational data, and verification methods

a. Consecutive afternoon thunderstorms – 29 June 2017 ~ 8 July 2017 (10 days)



2. Description of cases, observational data, and verification methods

a. Consecutive afternoon thunderstorms – 29 June 2017 ~ 8 July 2017 (10 days)

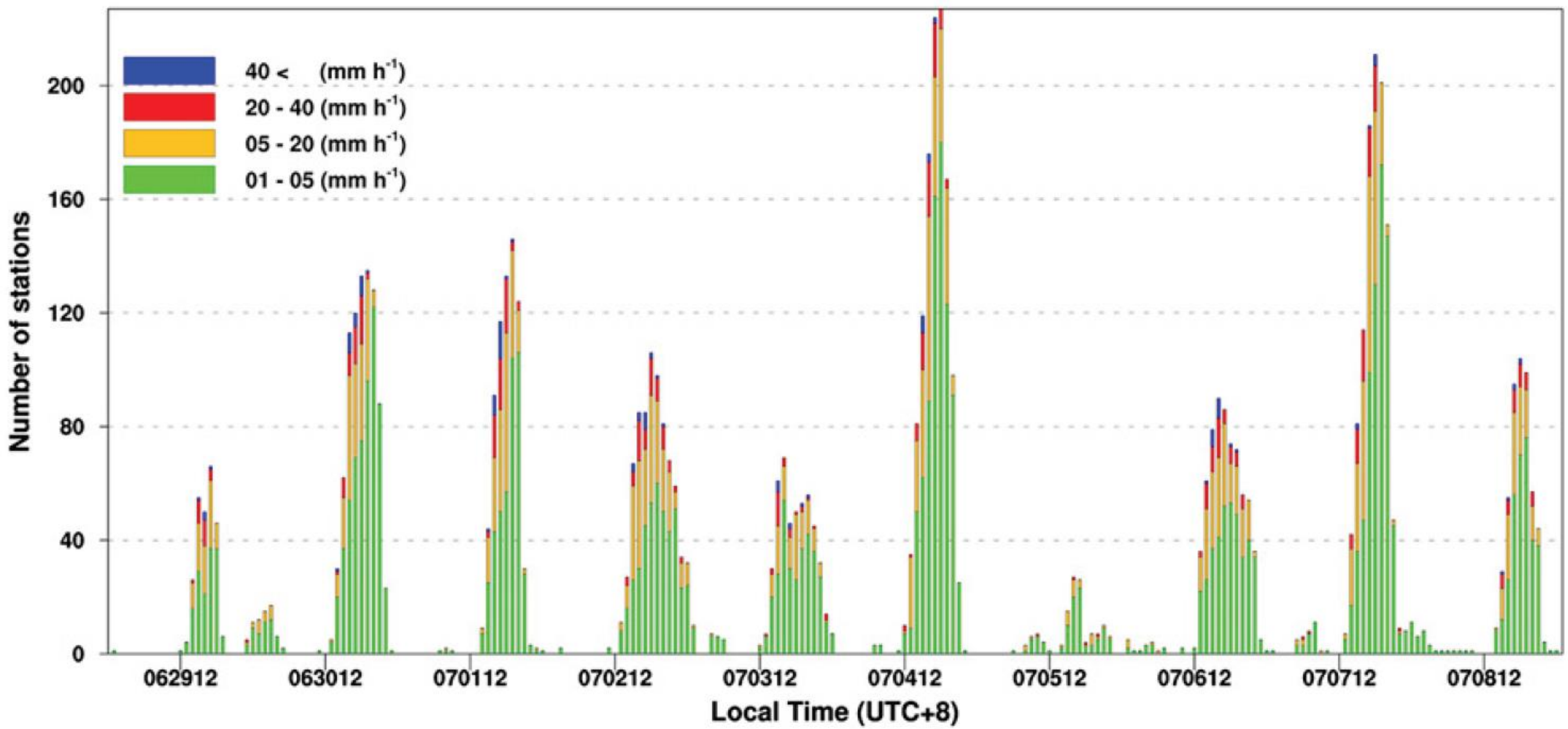
- **AT life cycle**

  Initiated between 1300 ~ 1400

  Matured between 1500 ~ 1700

  Dissipated after 1800

- **Short life span – about 6hr**
- **High rainfall intensity – 40 mm/hr**



2. Description of cases, observational data, and verification methods

b. Surface and radar observations

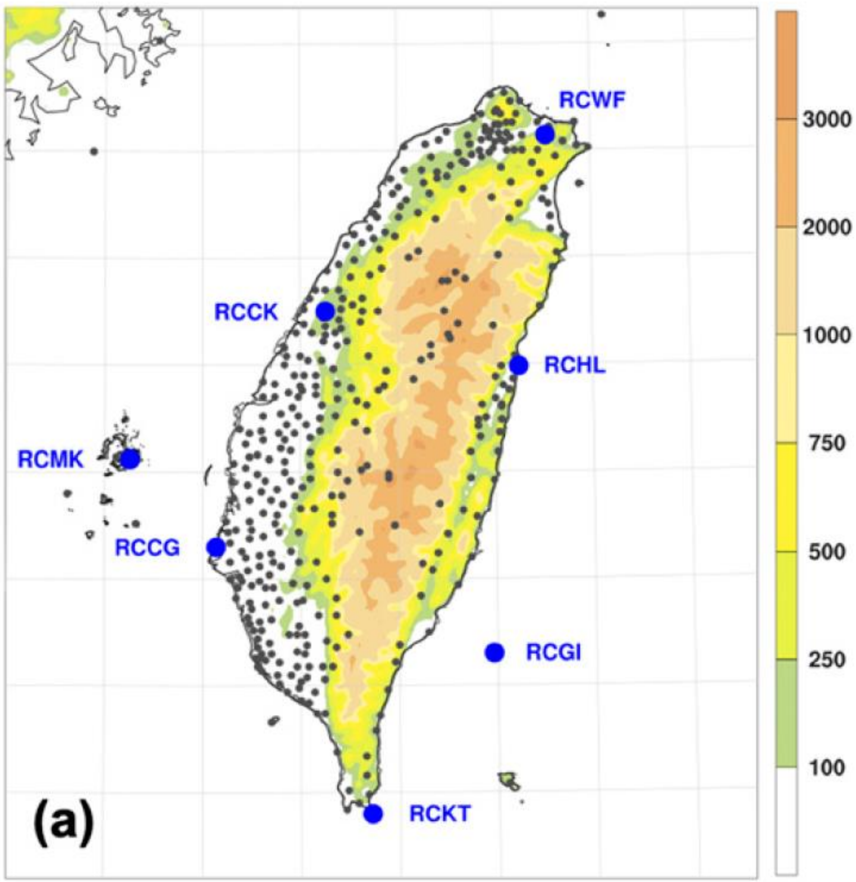
- **Surface observations**

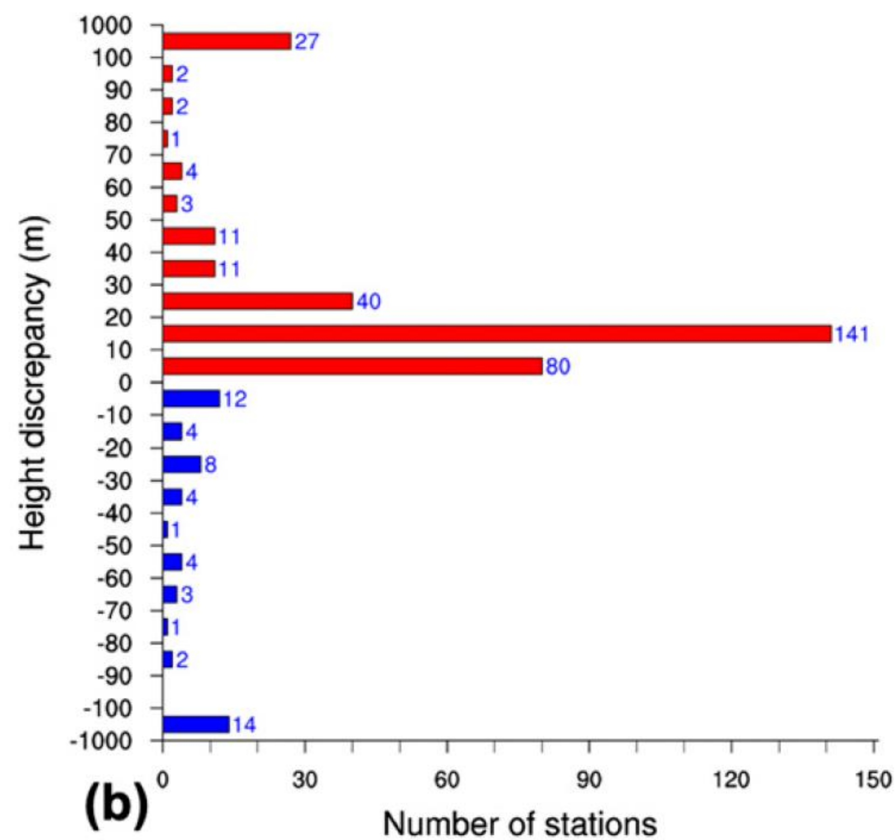
  375 surface stations

  U, V, P, T, RH are assimilated

- **Height discrepancy correction**

  Stations with height mismatch > 100 m were removed





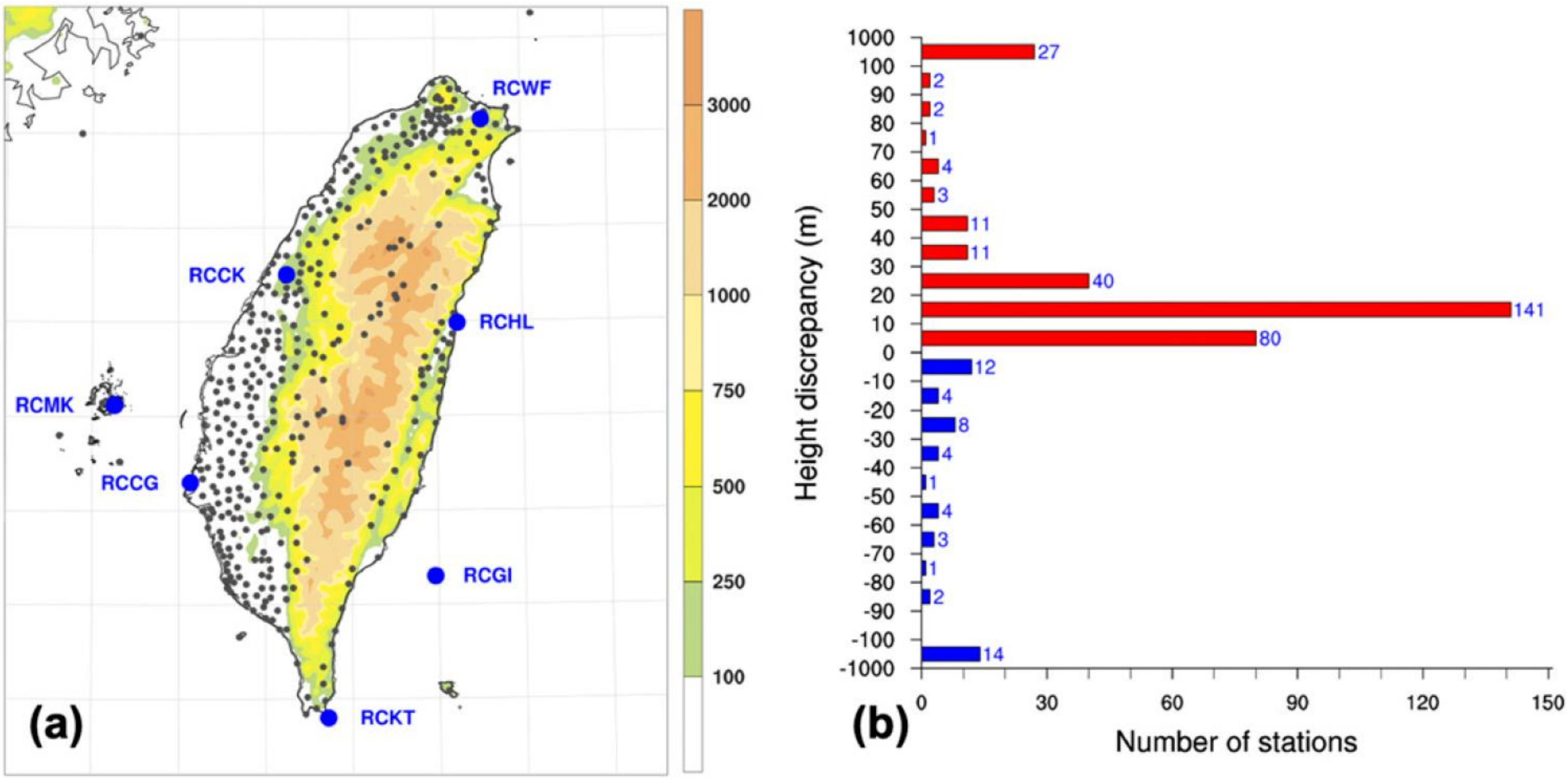
2. Description of cases, observational data, and verification methods

b. Surface and radar observations

- **Radar observations**

  Radial wind and reflectivity are assimilated

  Reflectivity → mixing ratio of rain, graupel, and snow (Wang et al. 2013)



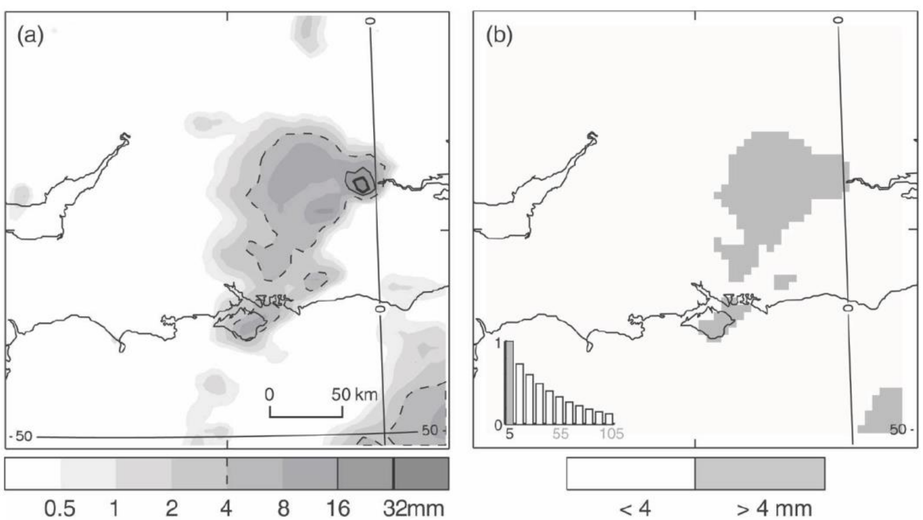
2. Description of cases, observational data, and verification methods

c. Verification methods

- **Verification of quantitative precipitation forecast (QPF)**

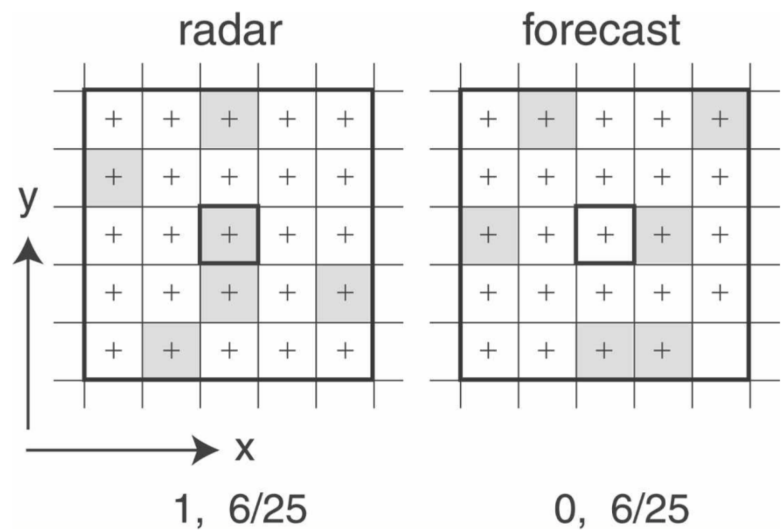
  Neighborhood-based **fractions skill score** (**FSS**; Roberts and Lean 2008) is used

[Step 1]: Decide the threshold



(Roberts and Lean 2008, Fig. 1)

[Step 2]: Decide the radius

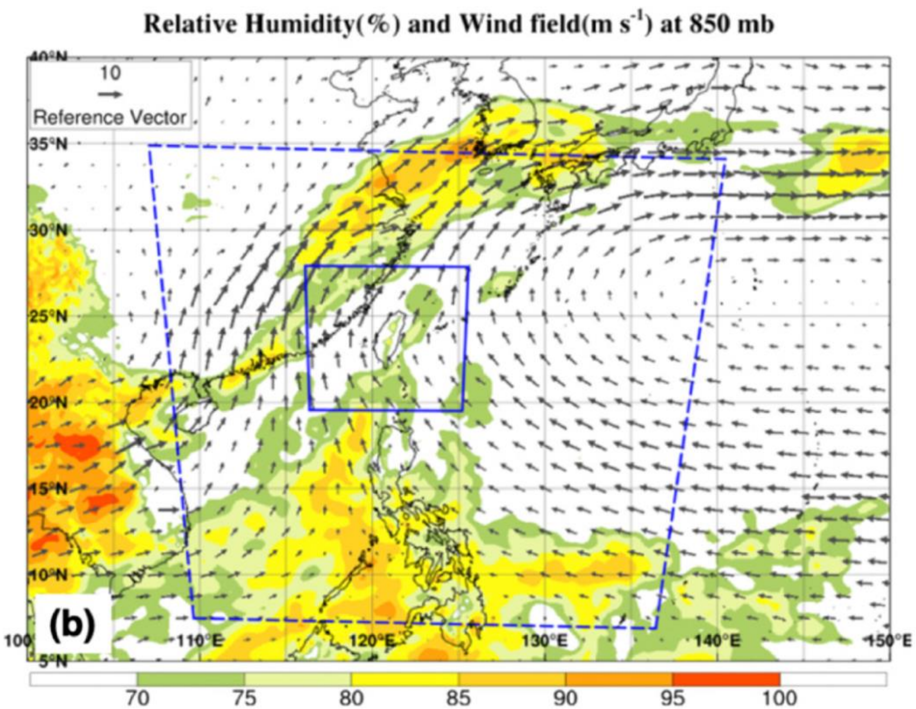


(Roberts and Lean 2008, Fig. 2)

$$(Perfect)\ \ \mathbf{1 \leq \mathit{FSS} \leq 0}\ \ (No\ skill)$$

3. Designation of convective-scale data assimilation system

a. Configuration of the numerical model



- **Global reanalysis data:**

  NCEP GFS 0.25° analysis
- **10-km** mesh (- - - -): 301 x 301
- **2-km** mesh (———): 451 x 451
- **Vertical layers**:

  52 sigma levels

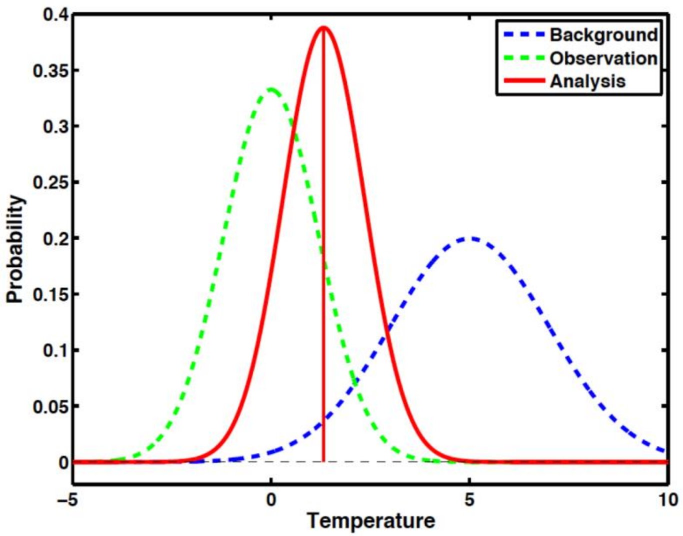
  model top at 20 hPa
- **Both domain are independent (NOT nested)**

PBL scheme	Microphysics scheme	Shortwave and longwave scheme	Cumulus scheme (10-km mesh)
YSU	**Goddard**	**RRTMG**	**Kain-Fritsch**

3. Designation of convective-scale data assimilation system

b. Configuration of data assimilation system (3D-Var)

- **Concept of 3D-Var** (Guo-Yuan Lien, Data Assimilation Course 2020)



(Guo-Yuan Lien, Data Assimilation Course 2020)

$$L_{\sigma_b}\left(T \| T_b\right) = p_{\sigma_b}\left(T_b | T\right) = \frac{1}{\sqrt{2\pi}\sigma_b} e^{-\frac{(T_b - T)^2}{2\sigma_b^2}}$$

$$L_{\sigma_o}\left(T \| T_o\right) = p_{\sigma_o}\left(T_o | T\right) = \frac{1}{\sqrt{2\pi}\sigma_o} e^{-\frac{(T_o - T)^2}{2\sigma_o^2}}$$

$$\max_T L_{\sigma_b,\sigma_o}\left(T \| T_b, T_o\right) = \frac{1}{2\pi\sigma_b\sigma_o} e^{-\frac{(T_b - T)^2}{2\sigma_b^2} - \frac{(T_o - T)^2}{2\sigma_o^2}}$$

$$\boxed{J\left(T\right) = \frac{\left(T_b - T\right)^2}{2\sigma_b^2} + \frac{\left(T_o - T\right)^2}{2\sigma_o^2}}$$

- **3D-Var cost function**

$$J(\mathbf{x}) = J_b + J_o = \frac{1}{2}(\mathbf{x} - \mathbf{x}^b)^{\mathrm{T}} \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}^b) + \frac{1}{2}(\mathbf{y} - \mathbf{y}^o)^{\mathrm{T}} \mathbf{O}_i^{-1} (\mathbf{y} - \mathbf{y}^o)$$

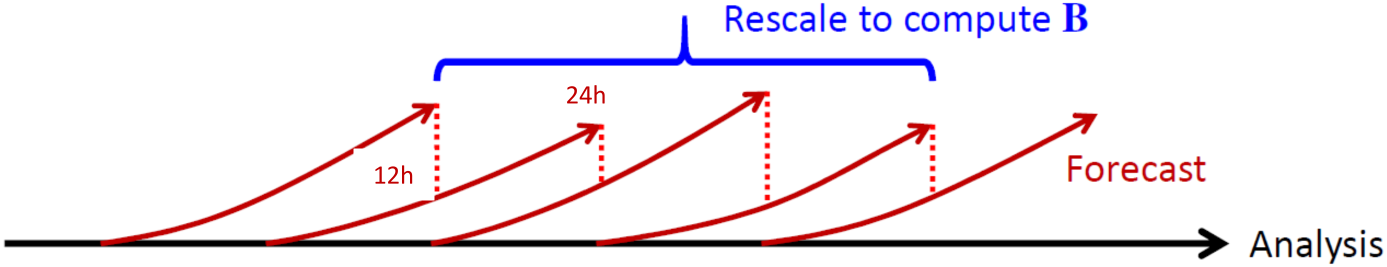
B: Background error covariance (BEC)

O: Observation error covariance

3. Designation of convective-scale data assimilation system

b. Configuration of data assimilation system (3D-Var)

- **To obtain Background Error Covariance (BEC) --- NMC method**



$$\mathbf{B} \approx \alpha E\left\{\left[\mathbf{x}_f^{24\,\mathrm{h}} - \mathbf{x}_f^{12\,\mathrm{h}}\right]\left[\mathbf{x}_f^{24\,\mathrm{h}} - \mathbf{x}_f^{12\,\mathrm{h}}\right]^T\right\}$$

(Guo-Yuan Lien, Data Assimilation Course 2020)

- **Prescribed observation error**

Surface observation	Observation error	Gross check
Wind	$1.5\ \mathrm{m\,s^{-1}}$	$4.5\ \mathrm{m\,s^{-1}}$
Temperature	1 k	1.5 k
Surface pressure	100 Pa	300 Pa
Relative humidity	10%	10%

3. Designation of convective-scale data assimilation system

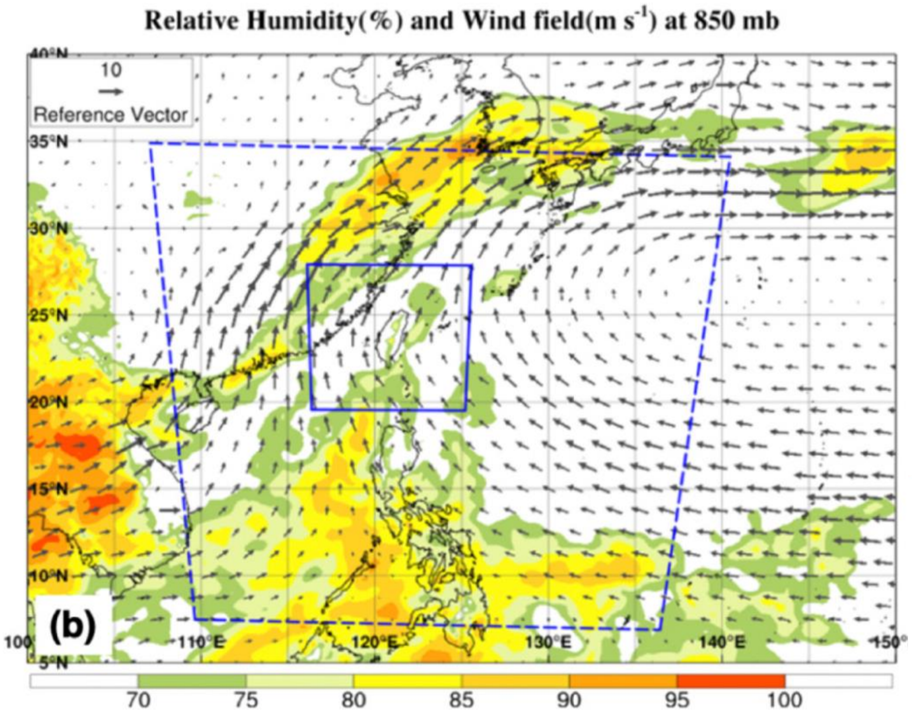
b. Configuration of data assimilation system (3D-Var)

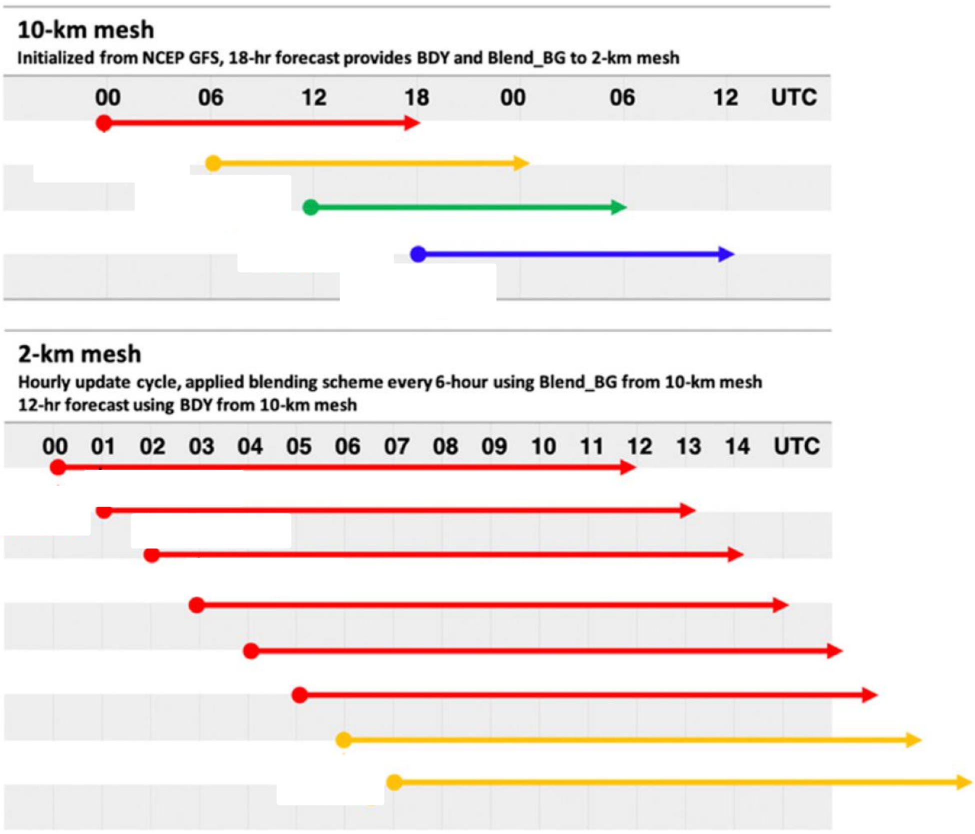
- **Single observation tests by laying pseudo observations at the lowest level**

Model variable	Control variables	Innovation	Analysis increment	*e*-folding length	
				Horizontal (km)	Vertical (eta levels)
U component	*U* component	$3\,m\,s^{-1}$	$1.91\,m\,s^{-1}$	24	14
V component	*V* component	$3\,m\,s^{-1}$	$1.92\,m\,s^{-1}$	20	15
Temperature	Temperature	2 K	0.55 K	22	8
Surface pressure	Surface pressure	300 Pa	98 Pa	34	x
Water vapor mixing ratio	Pseudo–relative humidity	$20\,g\,kg^{-1}$	$5.3\,g\,kg^{-1}$	22	9

4. Experimental Design – NODA, CNTL, SFC, RADAR, SFC_RADAR

a. Forecast strategy for NODA

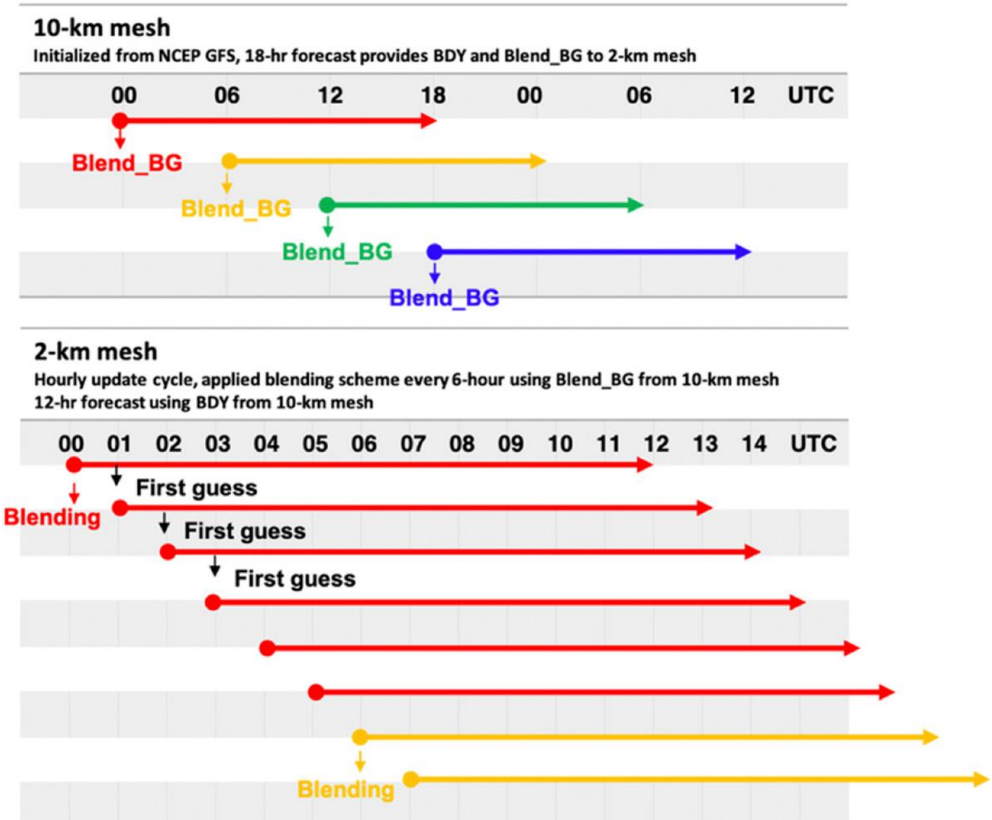




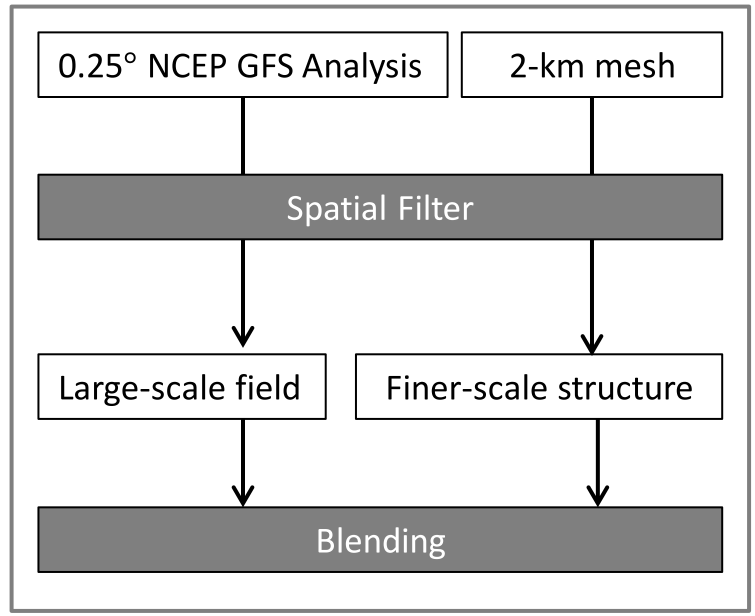
Expt	Radar DA	SFC DA	Blending scheme	First guess	Boundary condition
NODA	N	N	N	Downscale from 10-km forecast	Downscale from 10-km forecast
CNTL	N	N	Y	1-h forecast from previous run	
SFC	N	Y	Y		
RADAR	Y	N	Y		
SFC_RADAR	Y	Y	Y		

4. Experimental Design – NODA, CNTL, SFC, RADAR, SFC_RADAR

b. Forecast strategy for CNTL, SFC, RADAR, SFC_RADAR



Blending scheme



Expt	Radar DA	SFC DA	Blending scheme	First guess	Boundary condition
NODA	N	N	N	Downscale from 10-km forecast	Downscale from 10-km forecast
CNTL	N	N	Y	1-h forecast from previous run	
SFC	N	Y	Y		
RADAR	Y	N	Y		
SFC_RADAR	Y	Y	Y		

5. Results

a. Evaluation of the 10-day experiments – Surface wind and temperature

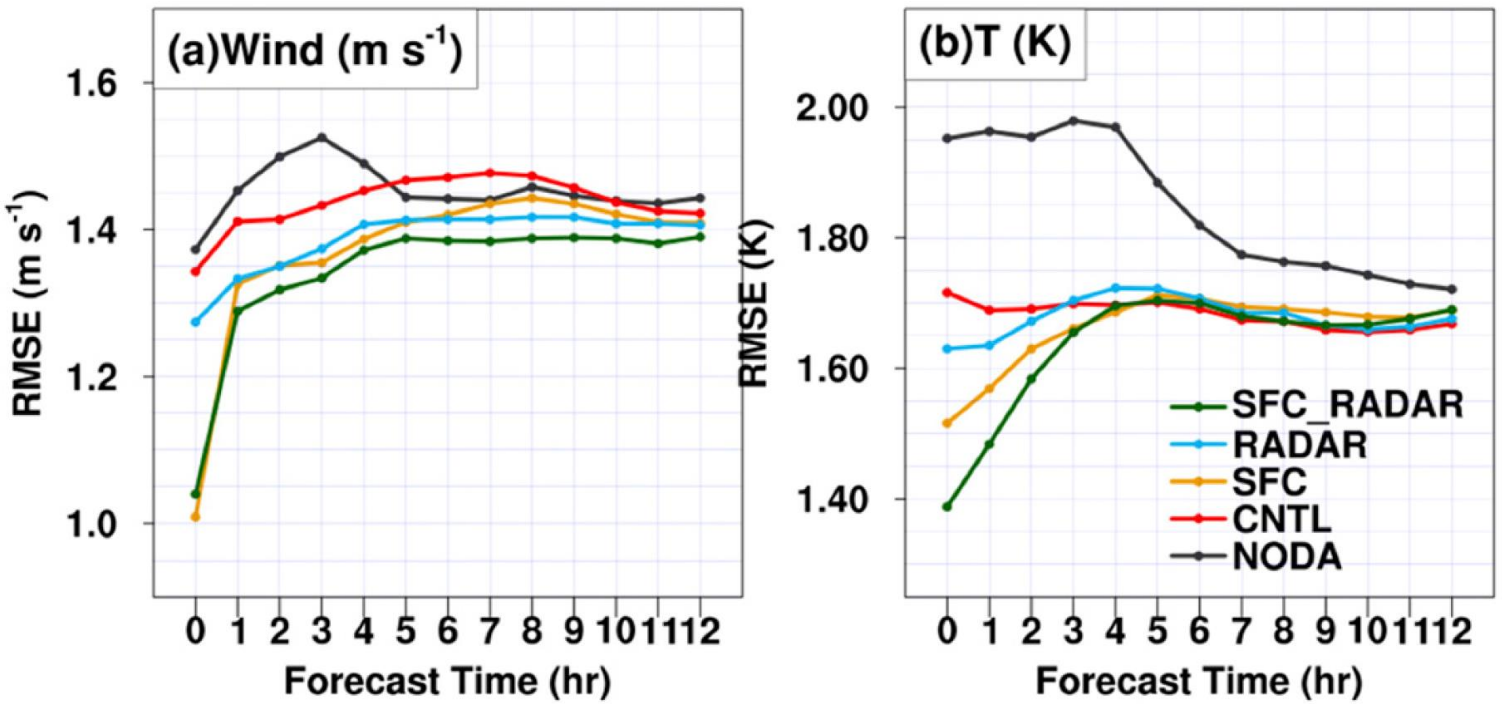
① NODA has spin-up problem due to downscale interpolation

② CNTL performs better than NODA

→ cycling strategy prevent imbalanced initial condition

③ SFC_RADAR > SFC > RADAR > CNTL > NODA

④ SFC_RADAR and SFC have 1h spin-up issue

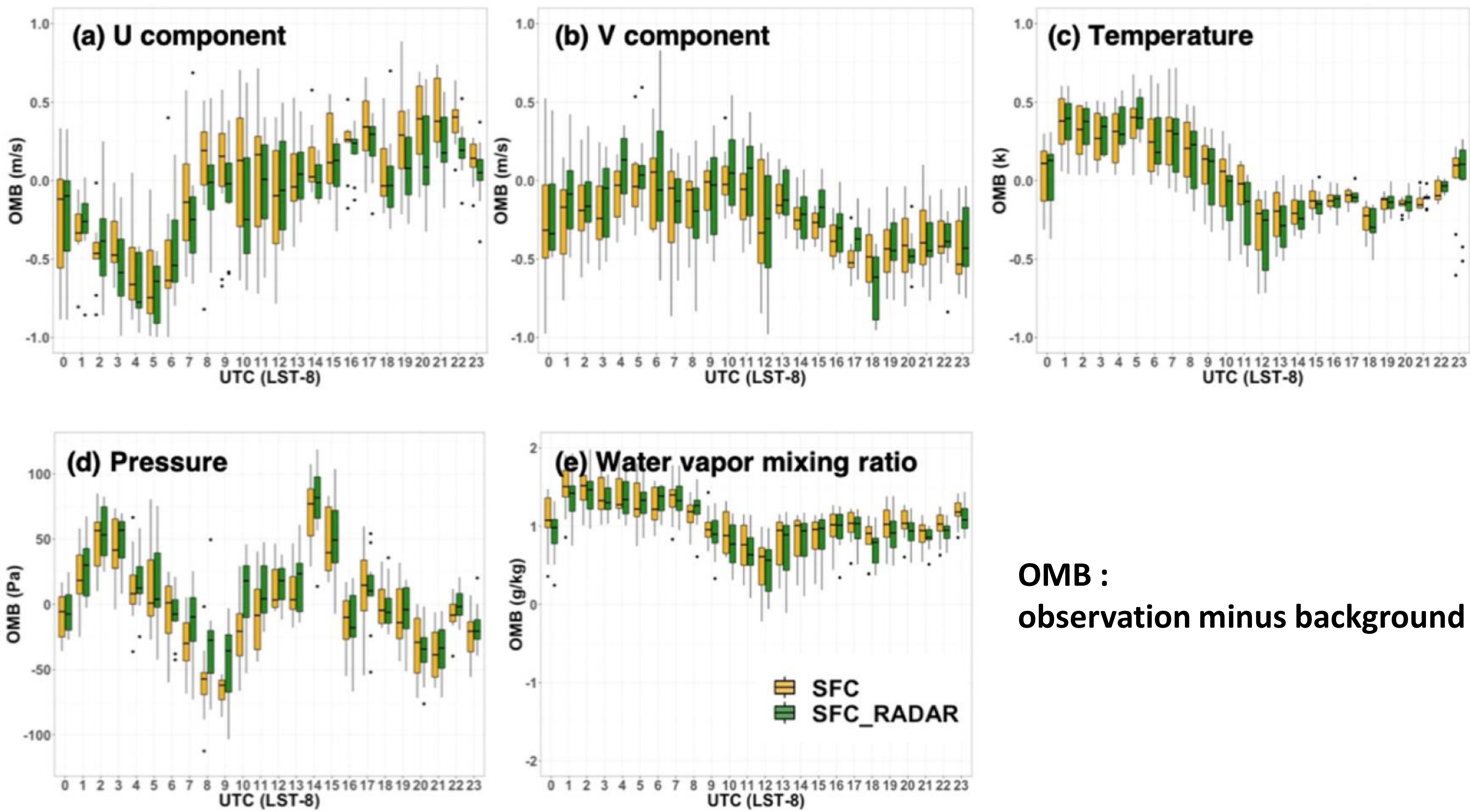


5. Results

a. Evaluation of the 10-day experiments –10-day-averaged hourly innovation vectors

① **Pressure and temperature have diurnal cycle**

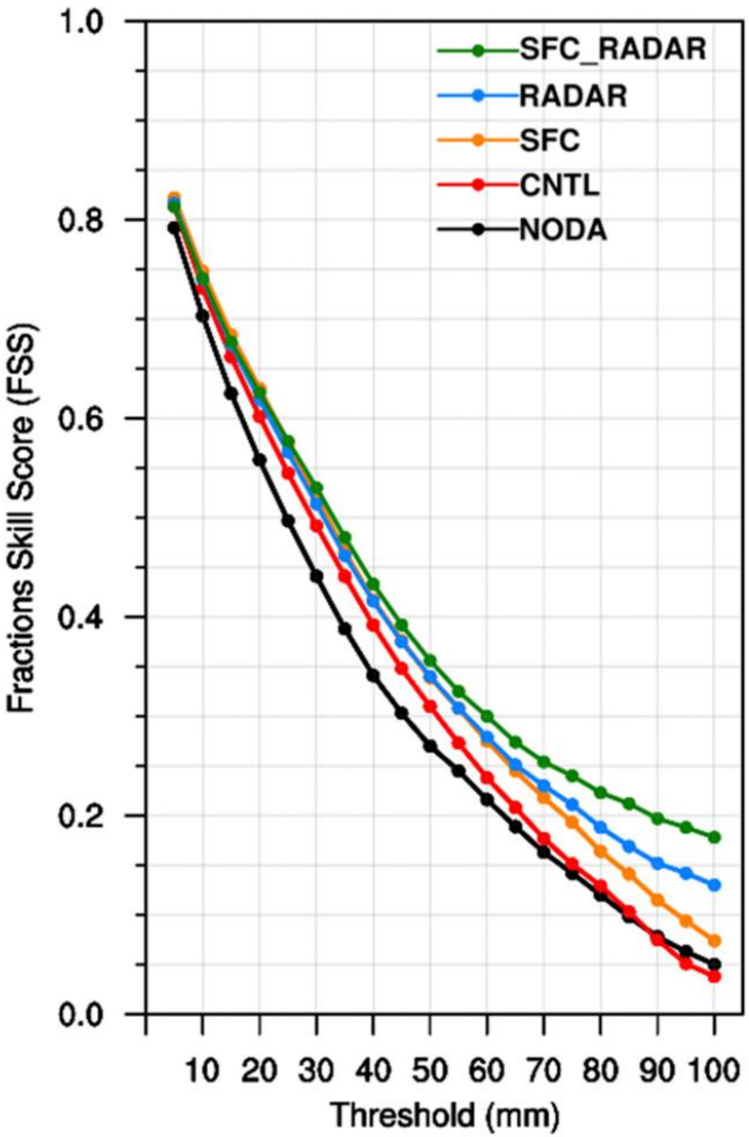
② **The model has dry bias**



OMB :
observation minus background

5. Results

a. Evaluation of the 10-day experiments – 12h accumulated precipitation



① SFC_RADAR > RADAR > SFC > CNTL > NODA

② RADAR ≈ SFC for small rainfall (< 60 mm)

③ RADAR > SFC for heavy rainfall (> 60 mm)

5. Results

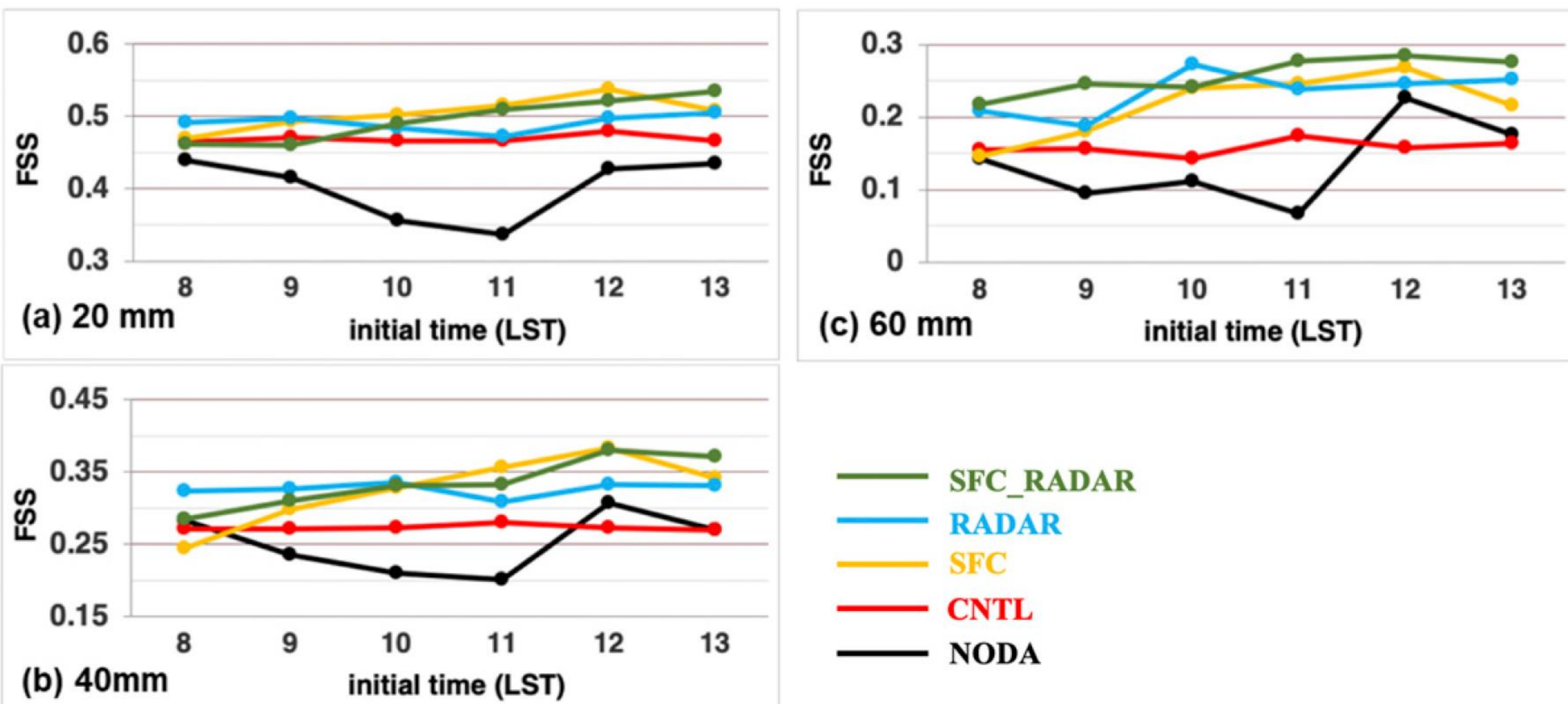
a. Evaluation of the 10-day experiments – 1300~1700 accumulated precipitation

① **CNTL performs better than NODA**

→ cycling strategy prevent imbalanced initial condition

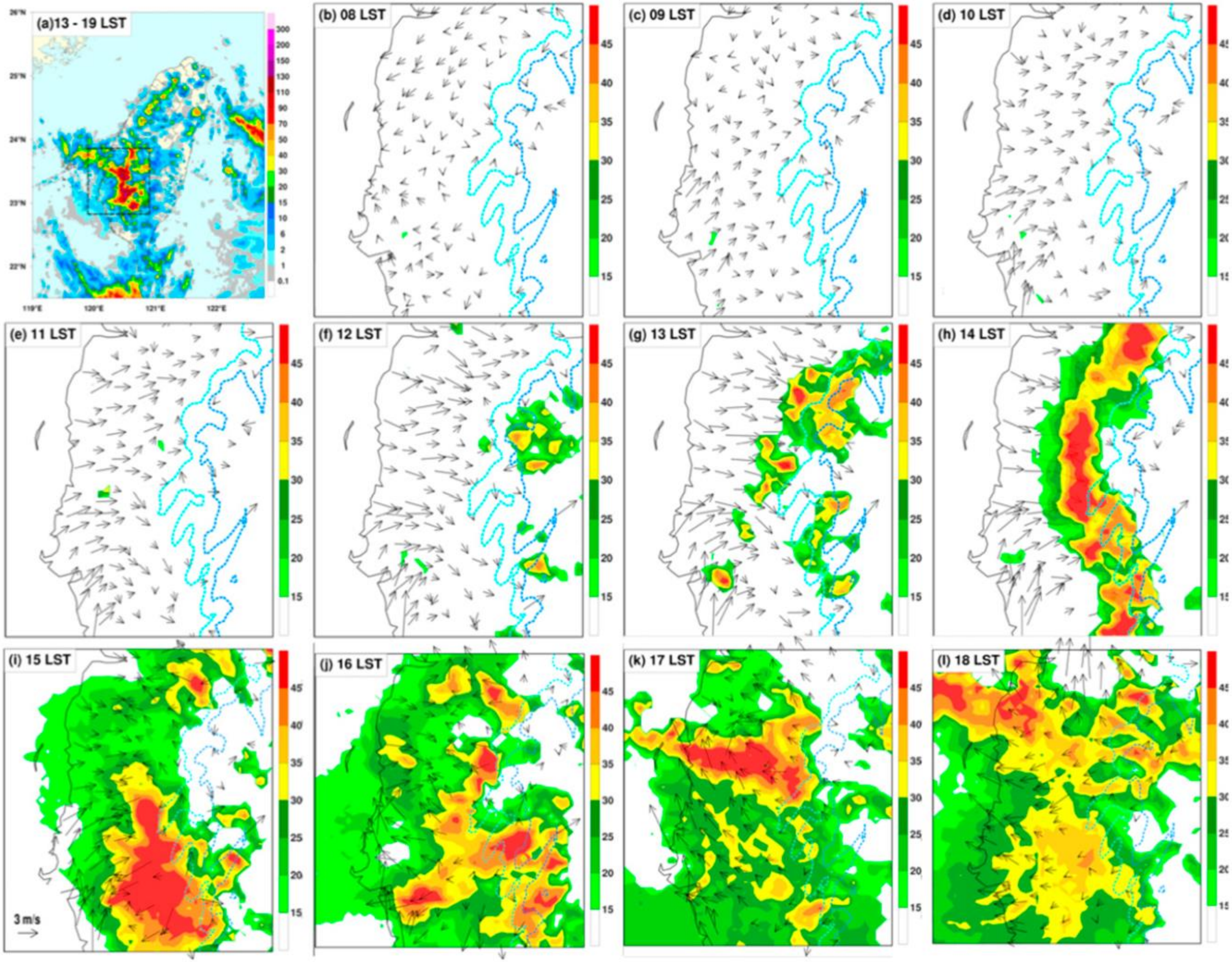
② **FSS in SFC and SFC_RADAR increase as lead time decrease**

③ **FSS in CNTL and RADAR remain constant as lead time decrease**



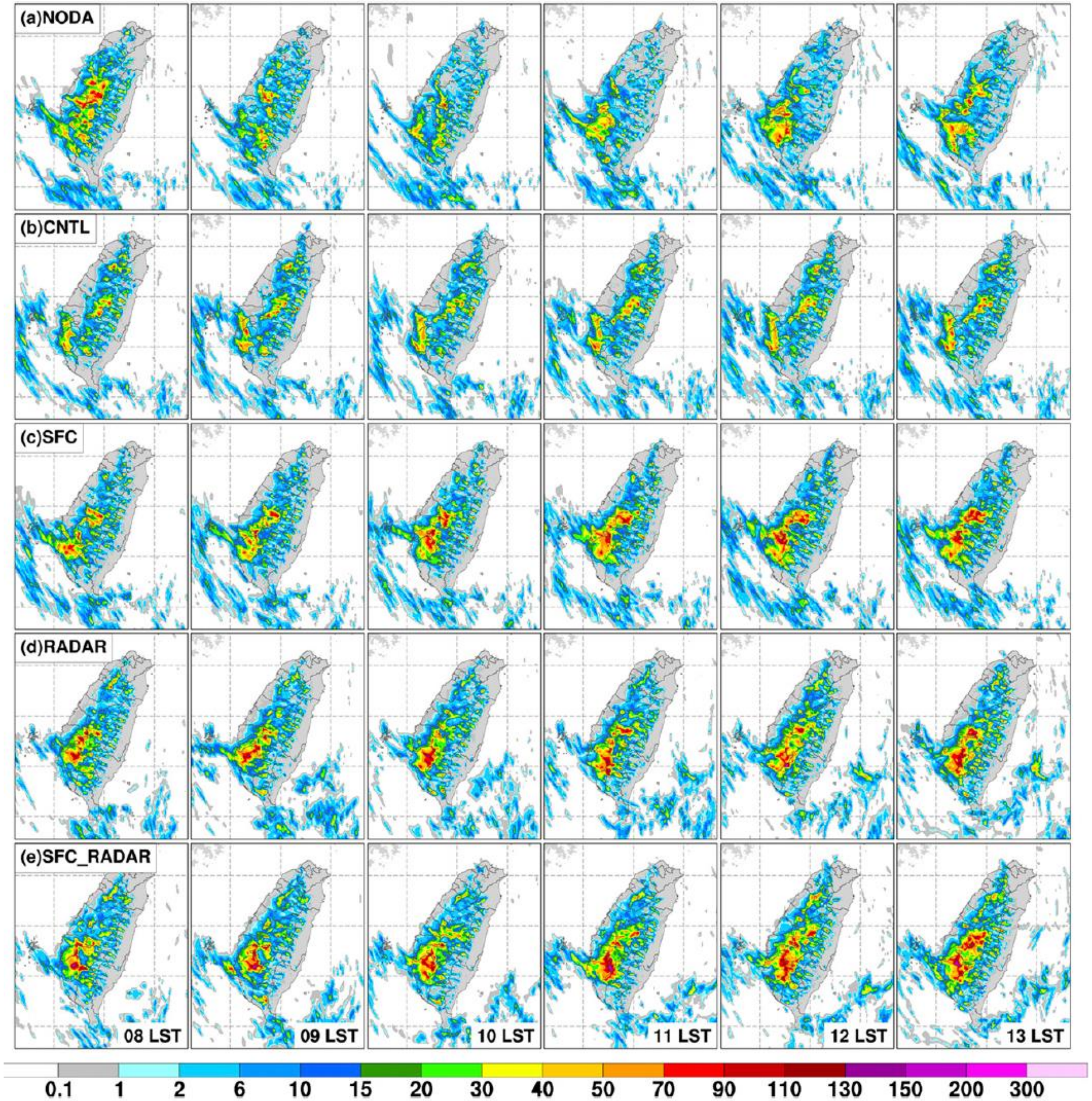
5. Results

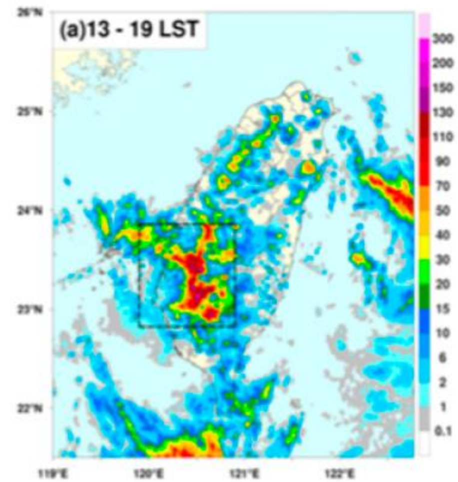
b. Case study – AT in June 6



5. Results

b. Case study – 6h accumulated precipitation from 1300~1900

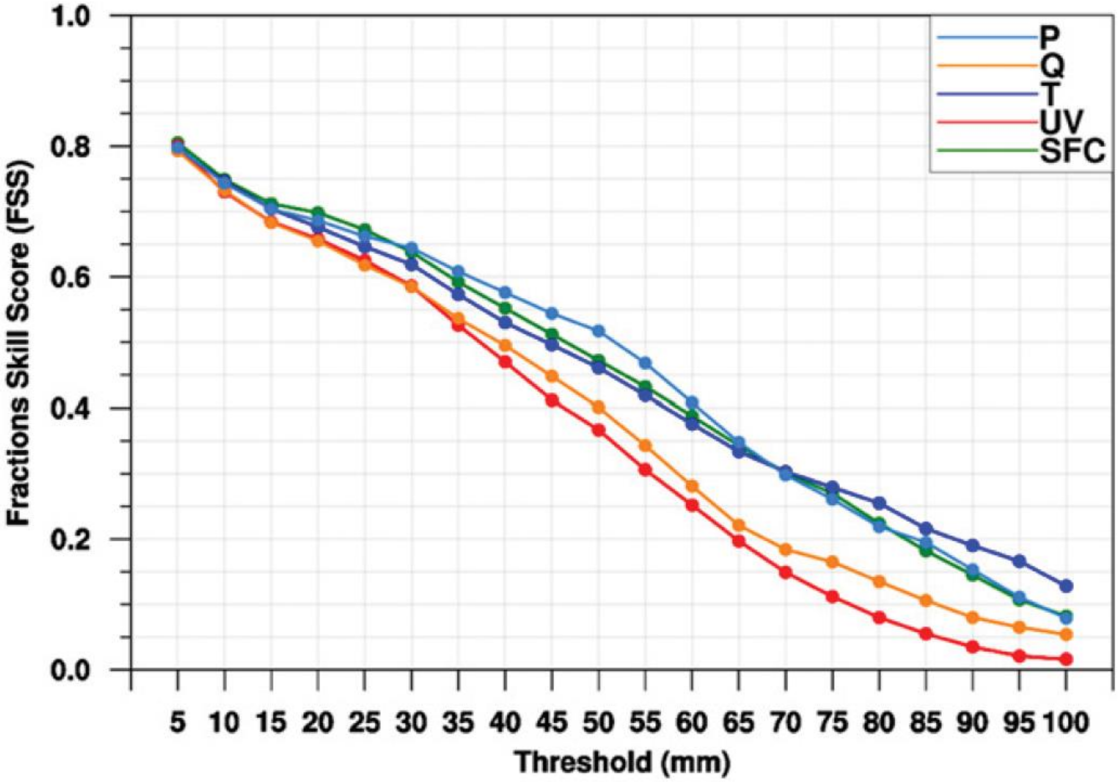




5. Results

b. Case study – test the relative importance of the variables

- **One of the variables was excluded in assimilation**



Low-level wind (UV) and **water vapor field (Q)** were critical in predicting AT

5. Results

b. Case study – Wind and precipitable water vapor (PWV) between CNTL and SFC

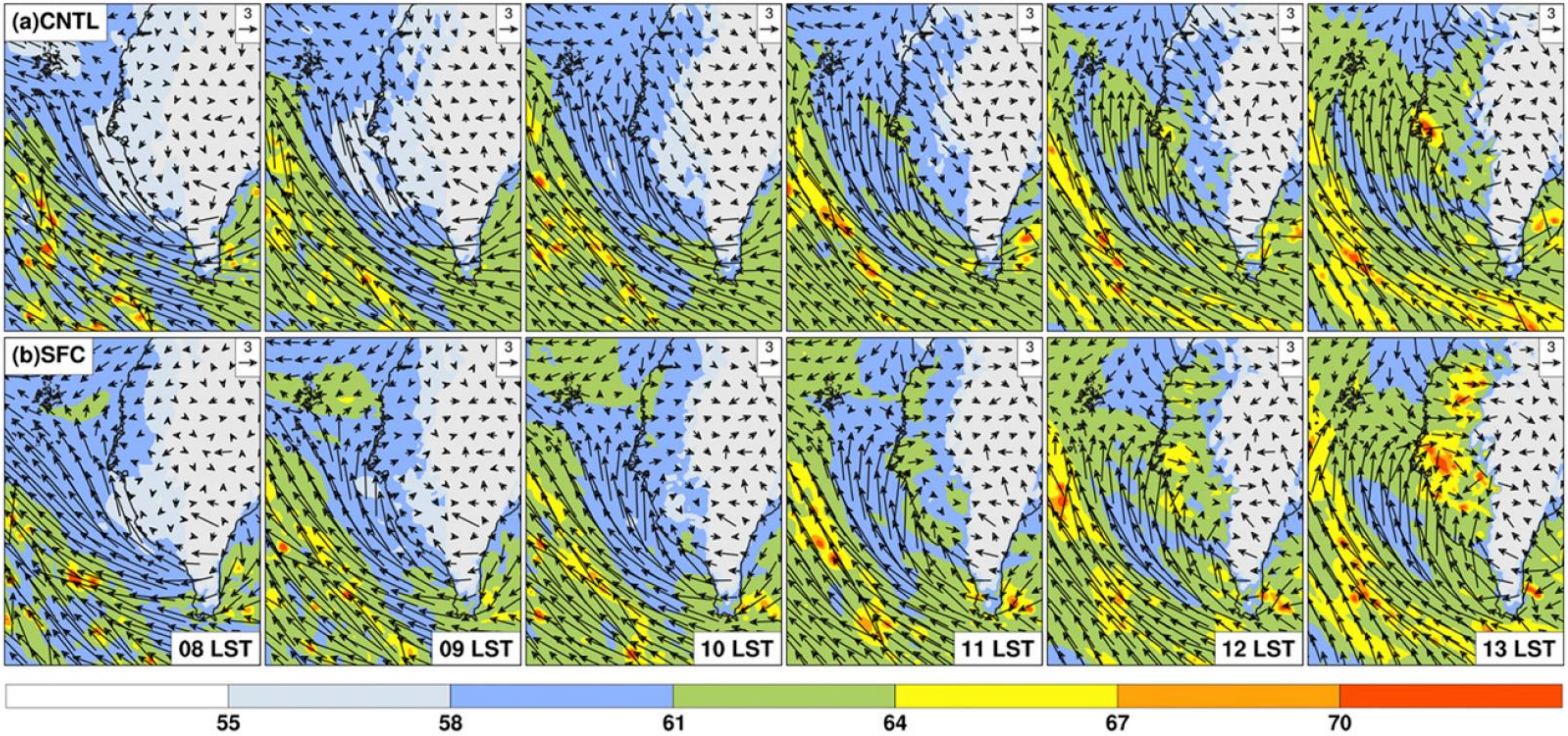
- **Before 09 LST**

  CNTL and SFC are similiar

- **After 10 LST**

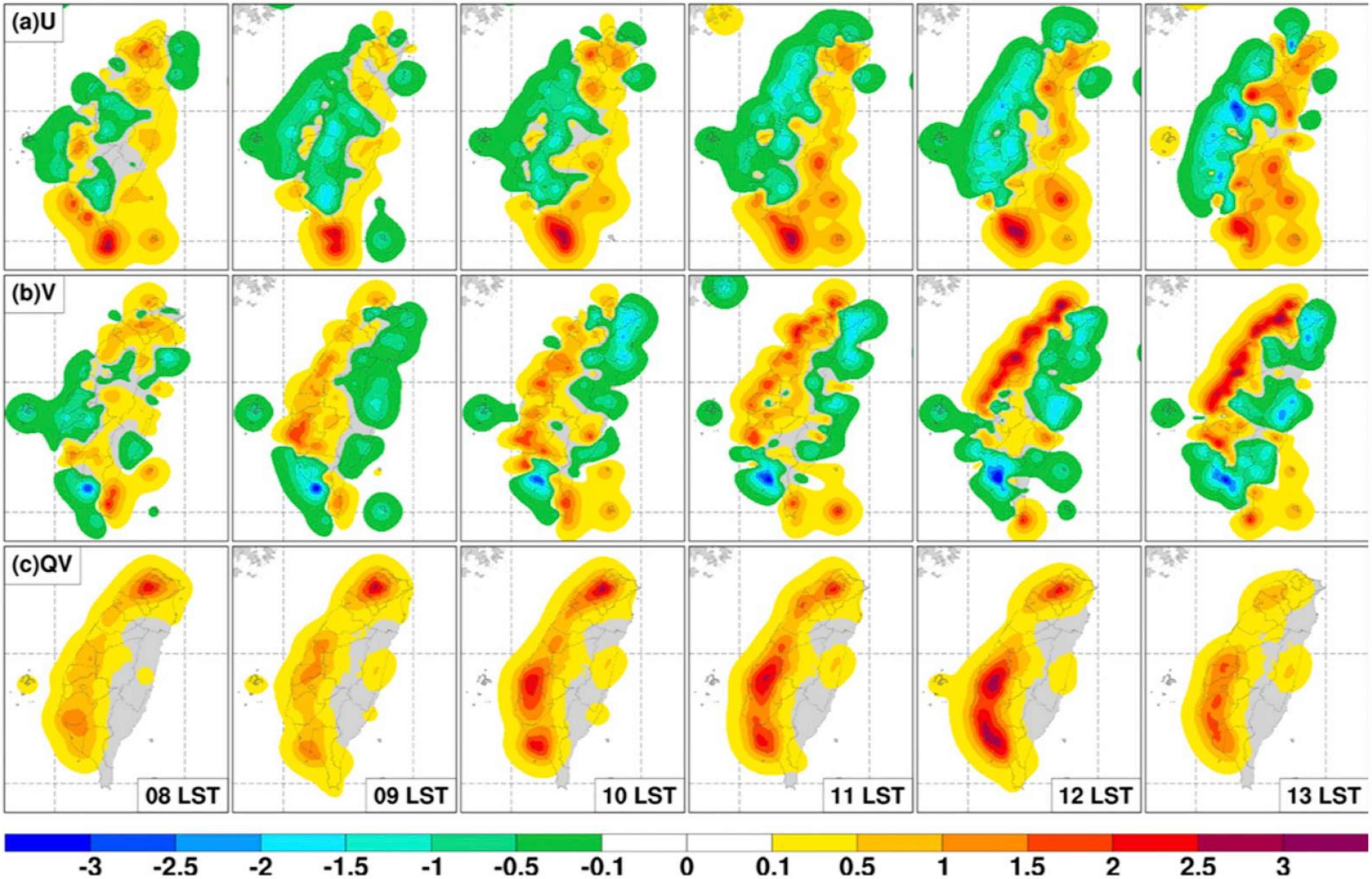
  SFC had more inland wind component

  SFC had more precipitable water vapor over land



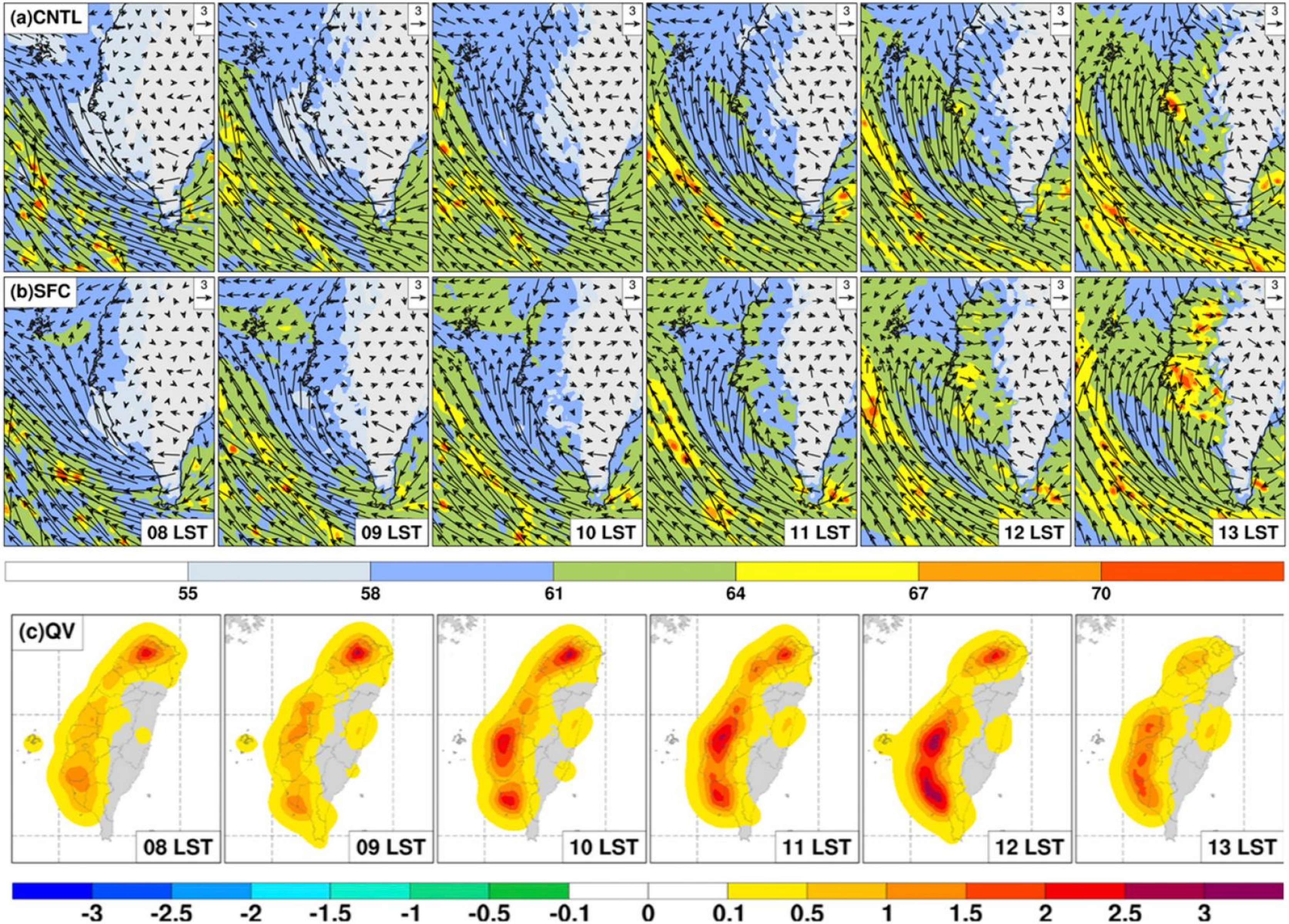
5. Results

b. Case study – Analysis increment of U, V, and QV



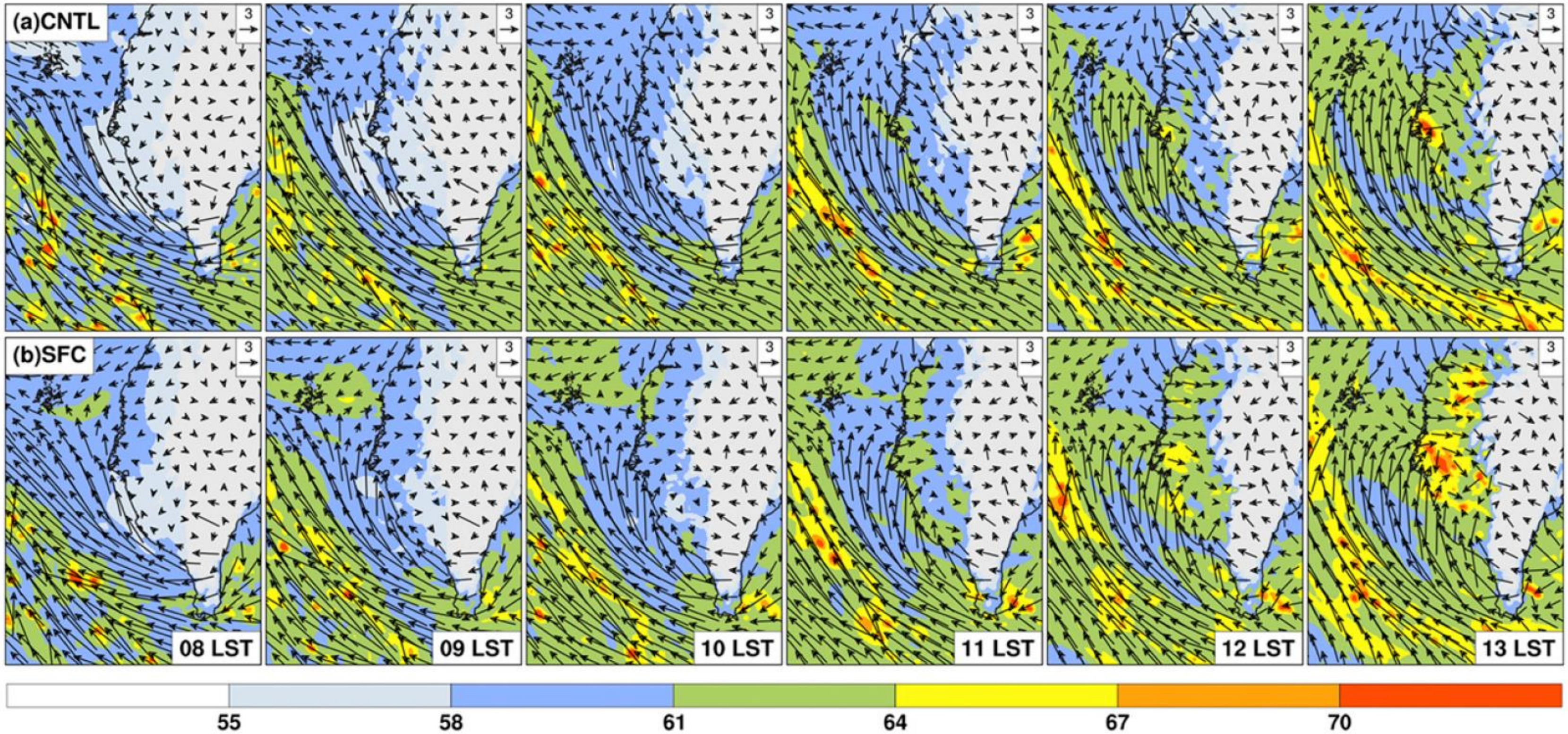
5. Results

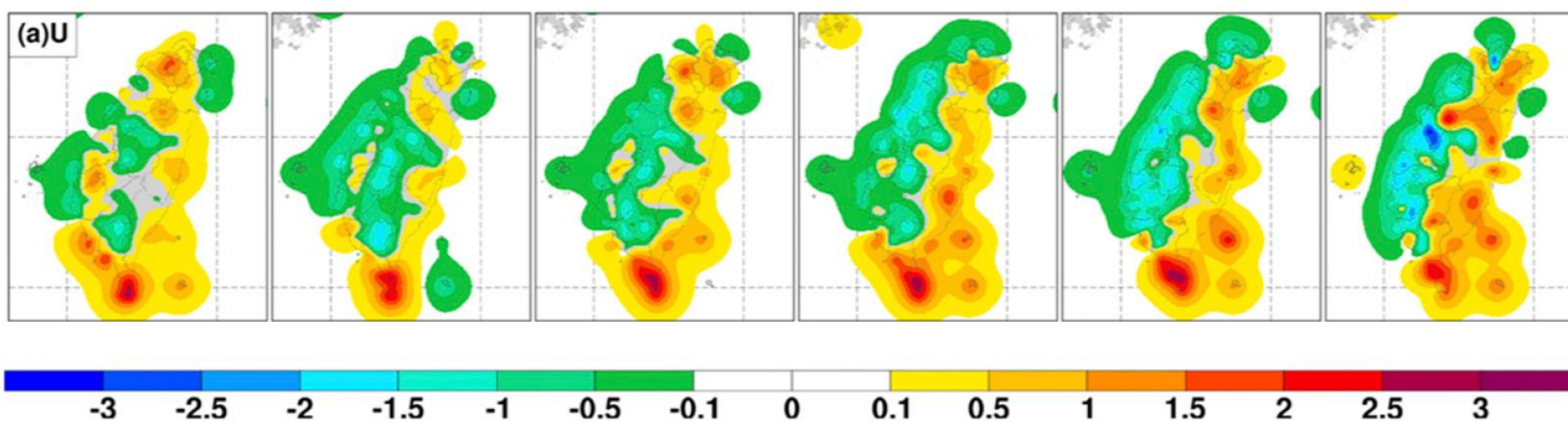
b. Case study – Analysis increment of QV



5. Results

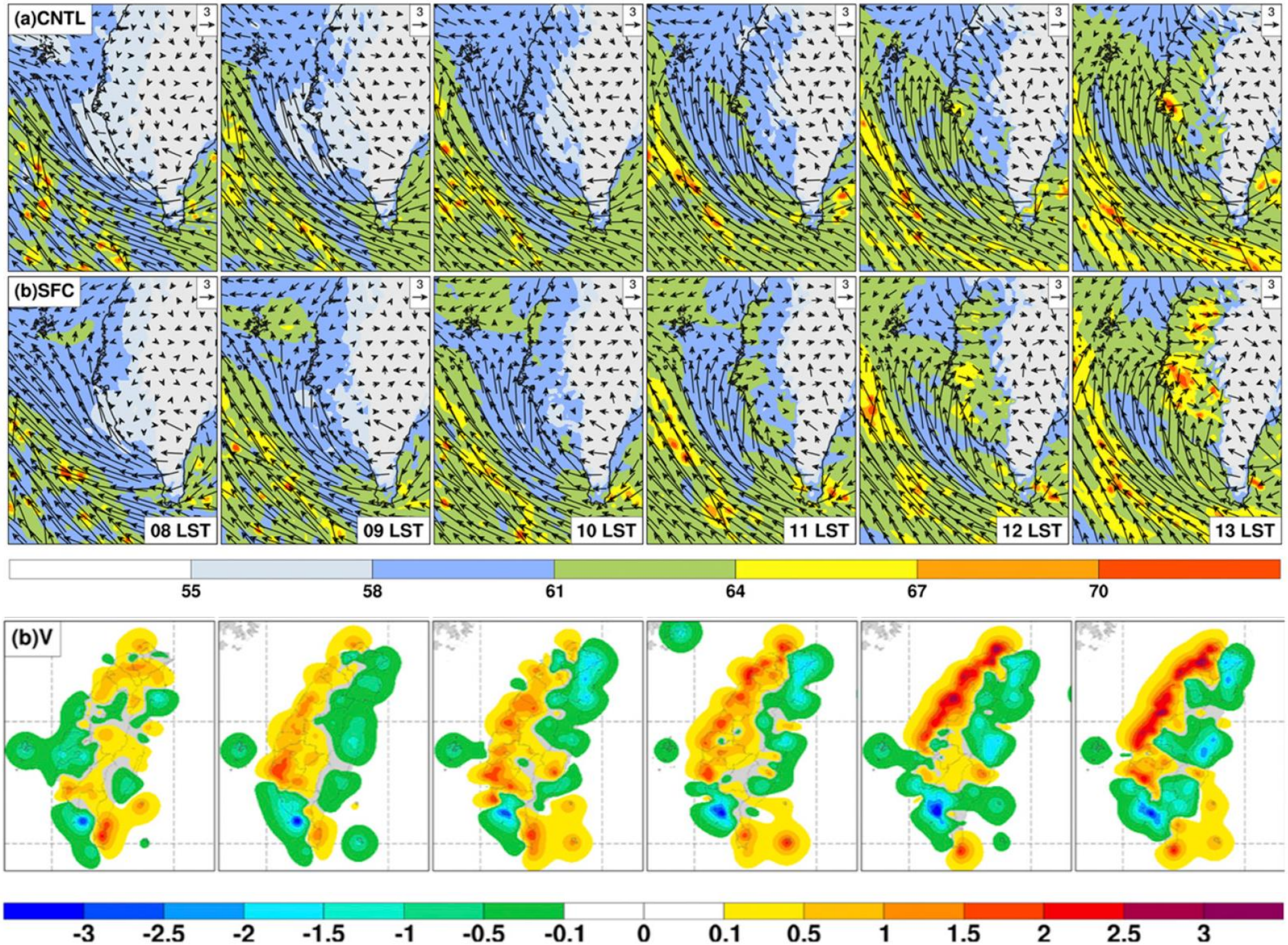
b. Case study – Analysis increment of U





5. Results

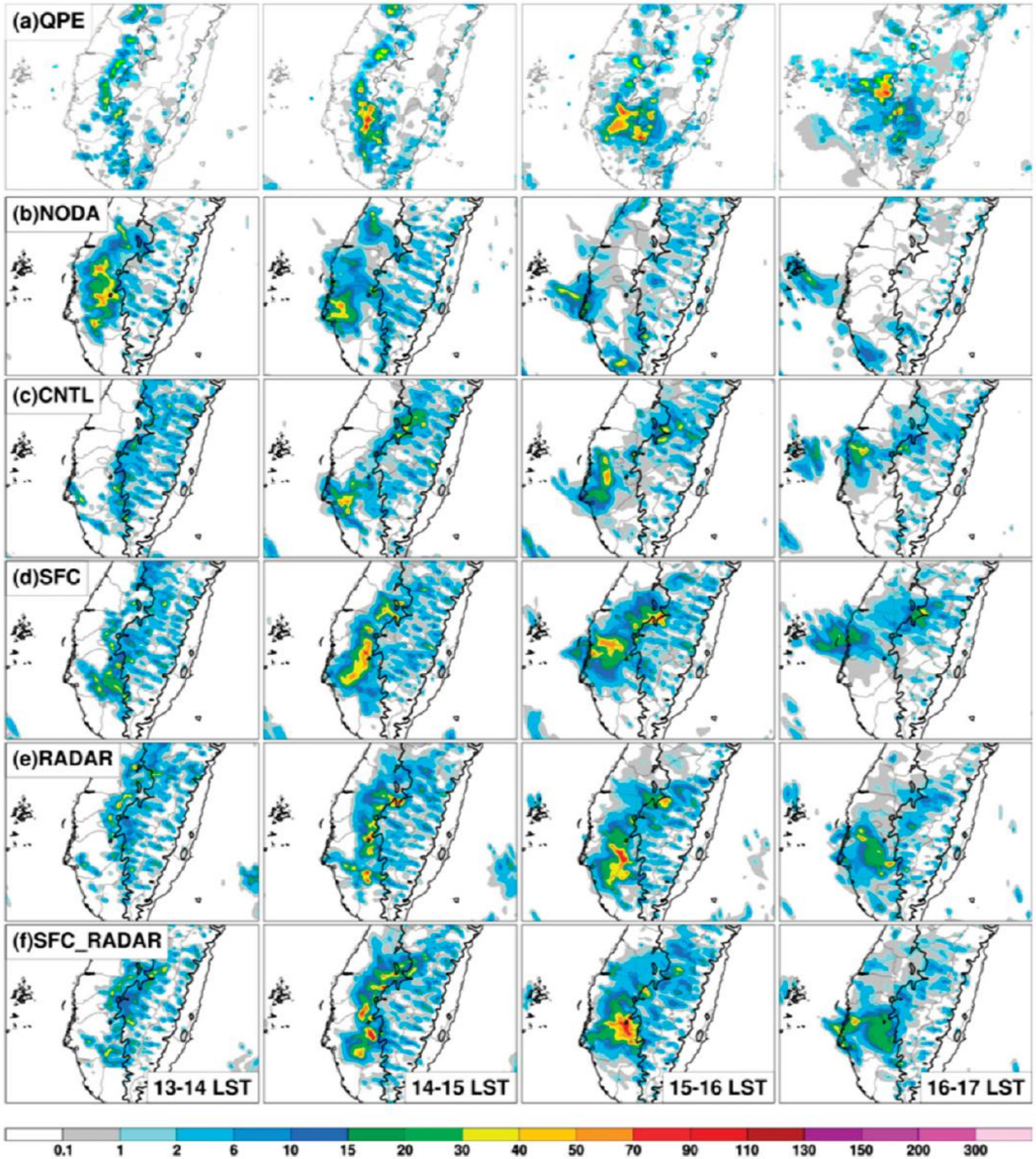
b. Case study – Analysis increment of V



5. Results

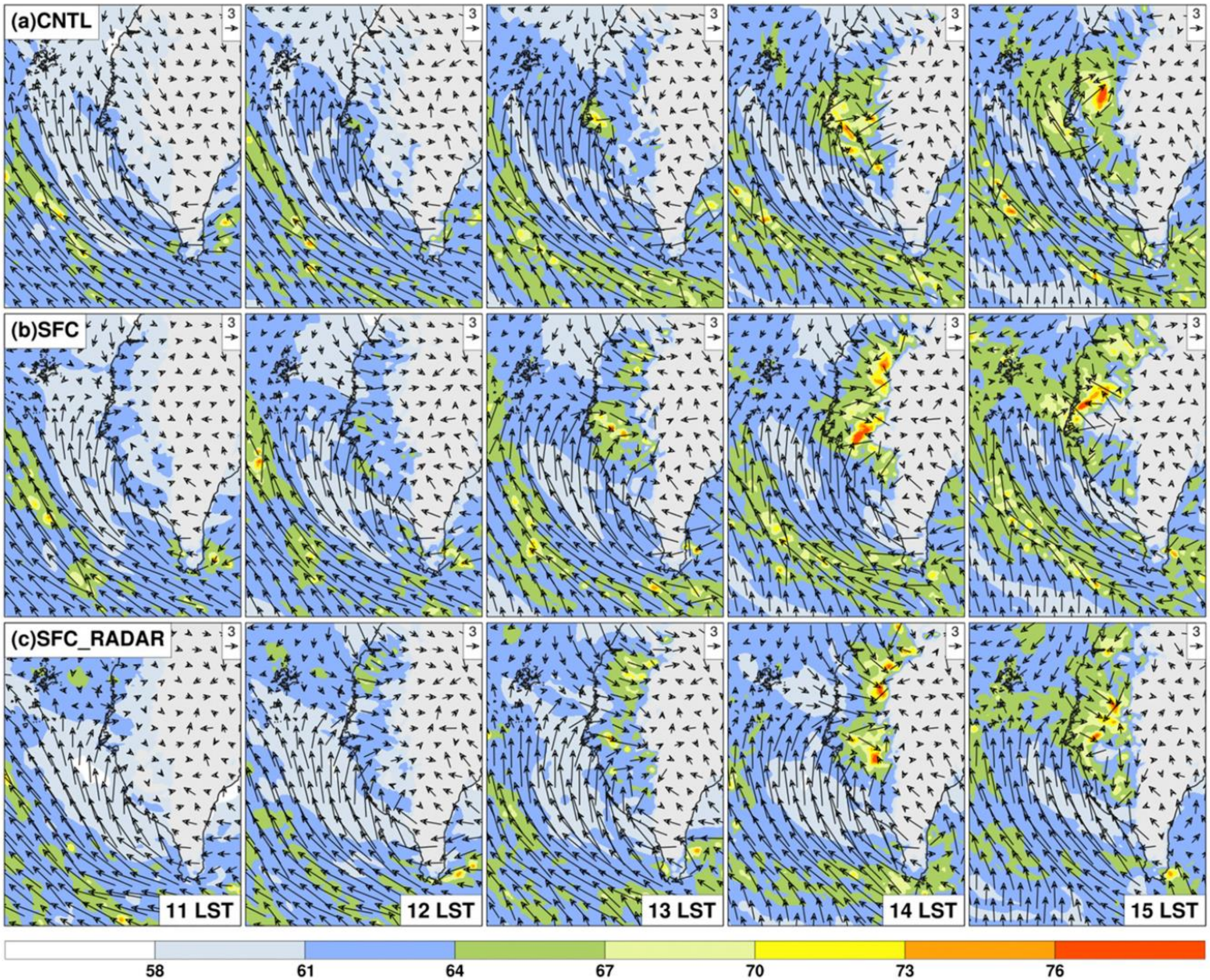
b. Case study

- **Hourly accumulated rainfall**
- **Initiated at 1100 LST**



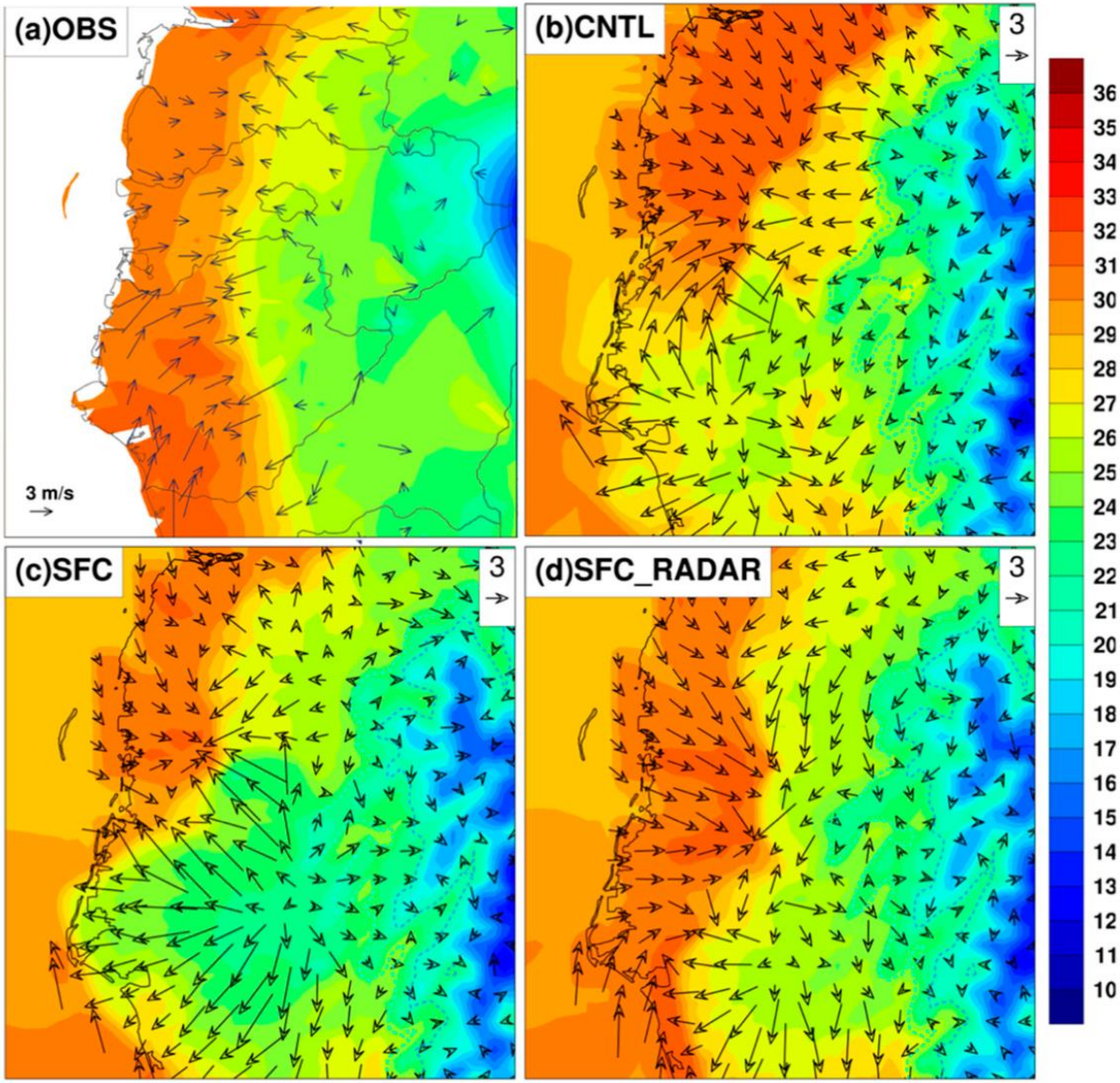
5. Results

b. Case study – Wind and precipitable water vapor between 3 experiments



5. Results

b. Case study – Surface wind and temperature at 1500 LST



6. Summary

1) Is the designation of the RUC strategy combined with a blending scheme effective in the nowcasting system?

- Comparing CNTL with NODA, RUC can mitigate model spin up resulting from downscale interpolation, which is detrimental for nowcasting.
- Comparing CNTL with NODA, blending scheme can handle model accumulated errors properly.

2) Can surface data assimilation contribute positively to AT prediction under the complex geography of Taiwan island?

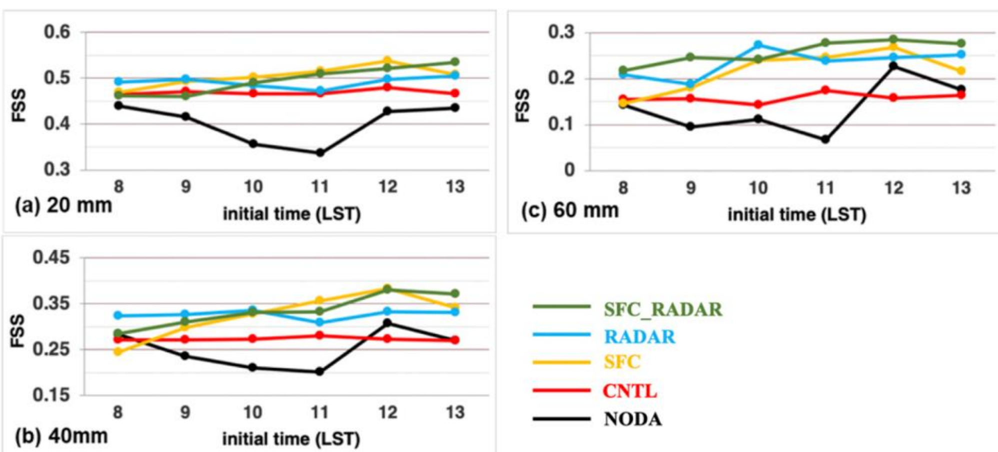
- Surface variables and QPF are both improved in SFC compared to CNTL.
- Assimilating relative humidity (RH) and wind (U,V) are more important than temperature (T) and pressure (P) in QPF.
- However, the skill to forecast AT development is not improved.

6. Summary

3) What is the relative importance between radar and surface observation to AT prediction? Does their combination add additional value?

- Surface observations can correct model near-surface errors every hour, which provides more accurate near-surface features for the subsequent AT.
- Radar observations can provide more accurate first guess throughout the current cycling strategy.
- SFC_RADAR performs the best in both surface variables and QPF.

4) Can we increase the AT forecast lead time in the morning through data assimilation? If so, which type of observation is more critical?



- Radar observations can not improve FSS when lead time decrease.
- Surface observations can provide more accurate information for the following AT.