Analysis of Predictability Improvement due to the Enhancement of Observation Error for the GK-2A Infrared Channels in Data Assimilation

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The All-Sky Radiance (ASR) data from geostationary satellites are important for improving initial conditions in numerical modeling through data assimilation, as it provides dense spatio-temporal atmospheric information over a wide area. Accurately applying the error information inherent in observations is essential for enhancing its effectiveness of satellite data assimilation. In this study, we calculated an observation error model for the ten infrared radiation channels of the Advanced Meteorological Imager (AMI) on the GEO-KOMPSAT-2A (GK-2A) for the summer season using the standard deviation of the brightness temperature observation minus background (O-B) as a function of the cloud impact parameter (Ca). The normalized brightness temperature of O-B probability density function is scaled such that it more closely approximates a normal distribution. For data assimilation experiments, we used the Community Radiative Transfer Model (CRTM) as the satellite observation operator and applied the 3-dimensional variational data assimilation method of the Weather Research and Forecasting Model Data Assimilation. When applying the adjusted observation error model for summer precipitation cases in the Korean peninsula, both the analysis and forecast fields improved compared to a prescribed constant error value. The best rainfall forecast performance was observed in the linear model, which followed the normal distribution better than the high-order regression observation error model. This is thought to be due to the observation error in the linear model saturates more gradually, allowing for consideration of a wider variability of Ca, i.e., a more detailed spatial distribution of cloud impact. Meanwhile, the assimilation results of Clear-Sky Radiance (CSR), excluding cloud area information, were compared to analyze the additional effects of cloud-precipitation area information during ASR assimilation. Further, we plan to assimilate both the water vapor channel ASR and the surface-sensitive channel CSR to improve the cloud detection algorithm, quality control, and refine surface parameter estimates for enhanced predictability.

Key words: GK-2A infrared channels, data assimilation, observation error, precipitation forecast

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Introduction

Research Background

- All-Sky Radiance (ASR) information from geostationary satellites such as GEOKOMPSAT 2A (GK-2A) is crucial for improving initial fields in numerical weather prediction.
- Considering the complex error characteristics of ASR, properly prescribing observation errors is essential for the successful assimilation of ASR.
- Okamoto et al. (2014) suggested assigning an observation error with standard deviation (STD) of brightness temperature (BT) observation minus background (O-B) departure as a function of the symmetric cloud effect parameter, C_A.

$$C_A = \frac{|B - B_{clr}| + |O - B_{clr}|}{2}$$

B: Background BT simulated as all−sky
B_{clr}: Background BT simulated as clear−sky
O: Observation BT of all−sky

Research Goal

- Establishing observation error models for the GK-2A AMI infrared (IR) channels.
- Investigating the impact of different observation error models in the assimilation experiments for summertime precipitation cases.
- Examining the effects of including all hydrometeors (cloud, rain, ice, snow, and graupel) as a control variable in the observation error model and data assimilation.

Data and Methods

Modeling and Assimilation Systems

* Community Radiative Transfer Model (CRTM) as an observation operator

❑ Weather Research and Forecasting Model (**WRF**) & WRF Data Assimilation (**WRFDA**) 3D-VAR

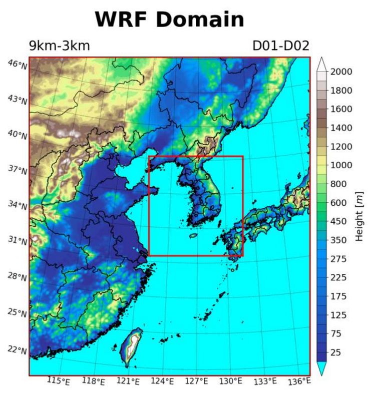

Fig. 1. WRF domain

Table 1. WRF model configuration

WRF_V4.2.1	D01	D02
Resolution	9 km	3 km
Grid #	301 x 341 x 60	301 × 319 × 60
Microphysics	WDM 6-class scheme	
Radiation	Rapid Radiative Transfer Model longwave radiation scheme	
	Dudhia shortwave radiation scheme	
Cumulus	Multiscale Kain–Fritsch scheme	
Surface Layer	Revised MM5 Monin-Obukhov scheme	
Land-surface	Unified Noah land-surface model	
PBL	Yonsei University Scheme	
I.C & B.C	NCEP GDAS/FNL 0.25 Degree Global Tropospheric Analyses	

❑ DA Experimental setup

Table 2. Experiment configurations

Experiment Name	Assimilated Data	Cloud Control Variables	BT Observation Error
CSR_LinE (Qcr)	Conventional + GK-2A CSR: WV Ch 8 / 9 / 10	Total Water (Qc, Qr)	Linear (piecewise)
ASR_ConE (Qcr)	Conventional + GK-2A ASR: WV Ch 8 / 9 / 10		Constant (O-B STD)
ASR_LinE (Qcr)			Linear (piecewise)
ASR_HirE (Qcr)			Higher-order regression
Same 4 experiments (Qcrisg)	*Same*	Qc, Qr, Qi, Qs, Qg	*Same* for LinE but ConE & HirE modeled with Qcrisg

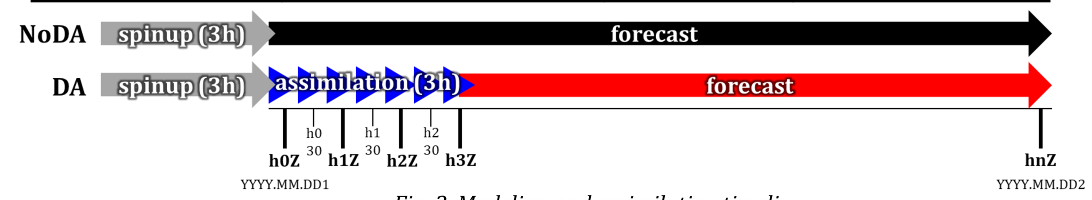

Fig. 2. Modeling and assimilation timeline

Assimilated Data & QC

- **Data**
  - ✓ Conventional data (sondes, wind profilers, AWS, GK-2A AMV)
  - ✓ GK-2A AMI water vapor (WV) channels (Ch8/9/10) CSR / ASR
- **ASR data QC (Okamoto, 2017)**
  - ✓ if (C_A > 3K) && (|O-B| > 1.8* C_A) ⇒ QC BAD
- **Cloud Control Variables**

Table 3. Cloud Control Variable Options

① Qcr	Use total water (WV+cloud liquid water+rain water) control variable
② Qcrisg	Use individual hydrometeor control variables with hard-coded error covariances

Case

- Stationary front developed with convective cells along the west coast of the Korean Peninsula
- 2019.07.25.0300 ~ 2019.07.26.1200 UTC

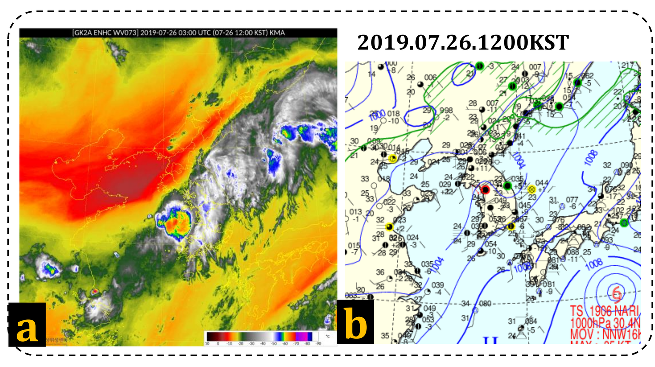

Fig. 3. (a) GK-2A AMI Ch10 BT and (b) surface synoptic weather map at 2019.07.26.0300 UTC

Results

BT Observation Error Models for GK-2A AMI WV channels

* Calculated with 6h of WRF-CRTM simulations over 2020-08

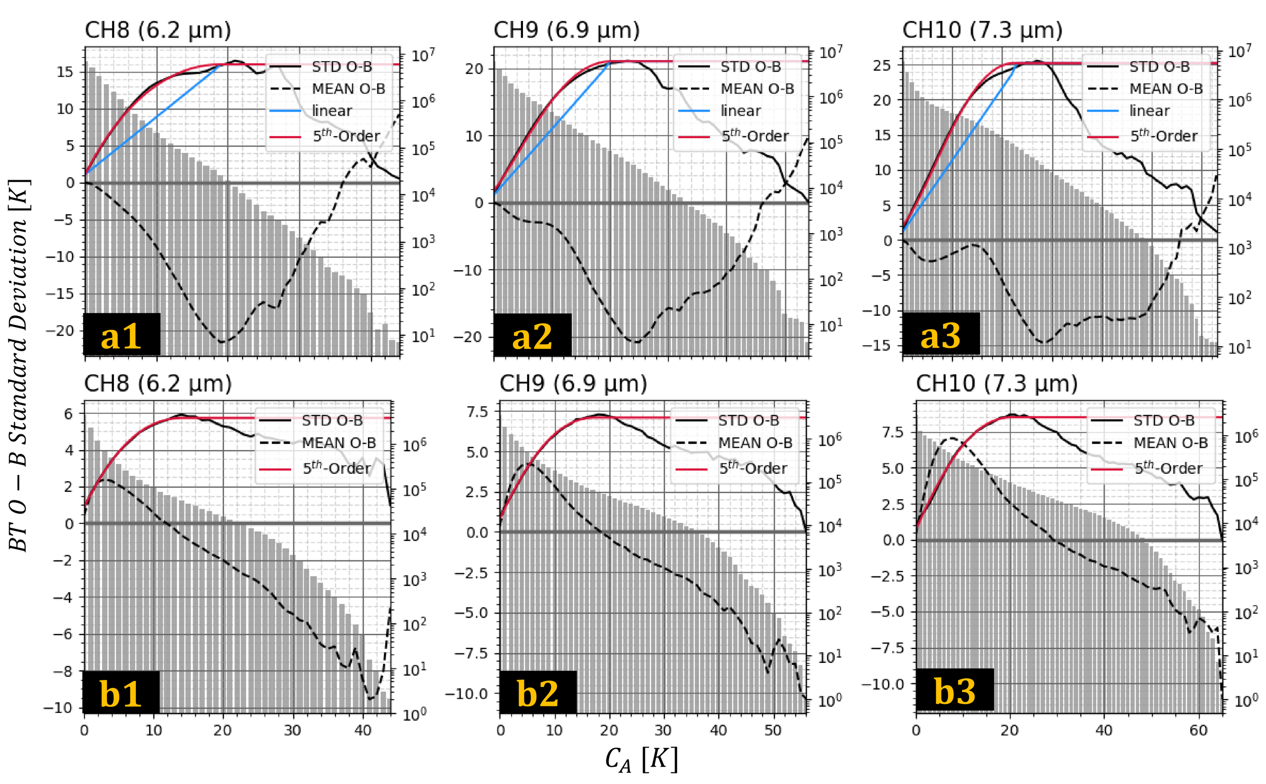

Fig. 4. (Black) GK-2A BT O-B mean (dashed line) and STD (solid line), (Red) Higher-order regression and (Blue) linear model with the number of data points (grey bar) at each C_A bin. (a1)~(a3) errors modeled with total water (Qr & Qc), and (b1)~(b3) with all hydrometeors as a control variable. Column 1 to 3 corresponds to each WV IR channel (Ch 8 ~ 10)

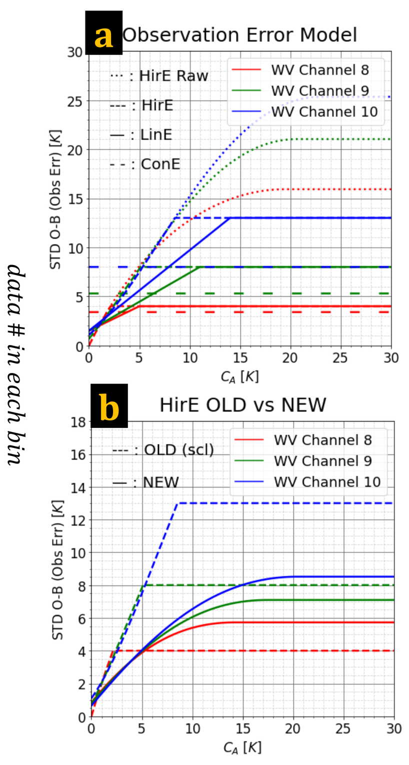

Fig. 5. BT error models for GK-2A WV channels (red: Ch 8, green: Ch 9, blue: Ch 10). (a) Qcr error models and (b) Qcr vs Qcrisg HirE model

PDF of Normalized O-B BT

$$OMB' = \frac{(OMB - \overline{OMB})}{STD_{OMB}}$$

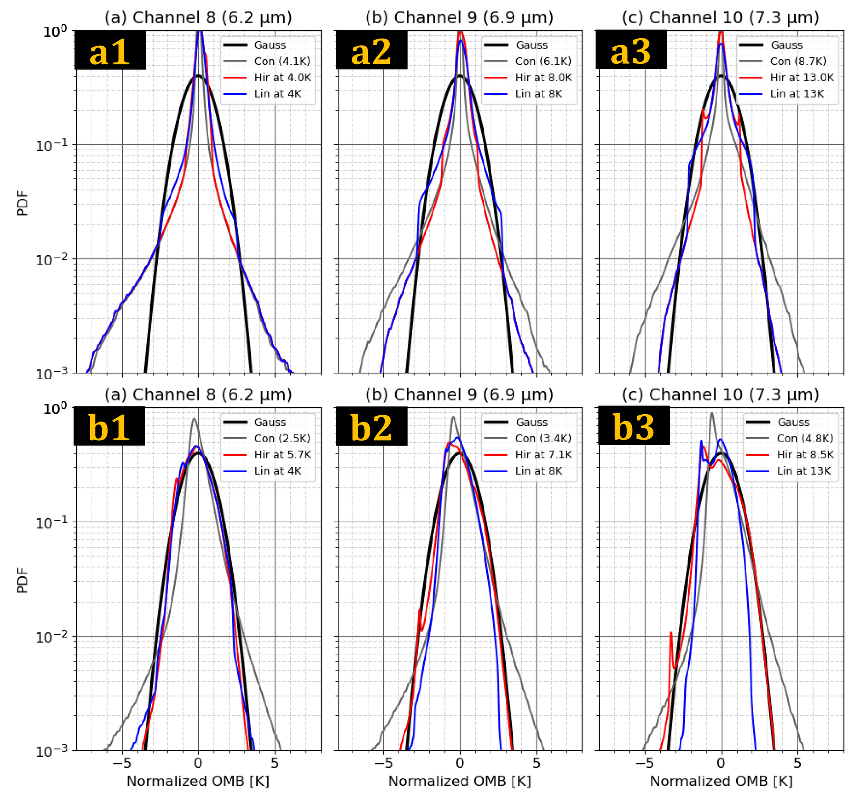

Fig. 6. Probability density distribution of normalized O-B (OMB') for (a1, b1) Ch 8, (a2, b2) Ch 9, (c) Ch 10 (a3, b3) with normal distribution (black), ConE (grey), LinE (blue), and HirE (red). Normalized with (a) Qcr and (b) Qcrisg error models.

- Maximum O-B BT STD increases as the channel goes from 8 (upper) to 10 (lower).
- BT modeling with Qcrisg reduces overall O-B STD with better Gaussian-shaped O-B BT distribution.

Changes in the Analysis (at the last DA cycle)

- Observation errors can reflect the scene-dependent O-B characteristics when modeled by C_A.
- Convective signals over the Yellow Sea are pronounced in all Qcr DA experiments, which are somewhat excessive than the real system.
- In Qcrisg DA experiments, background BT followed the observation BT more closely, therefore reducing the strong spurious convection over the Yellow Sea.

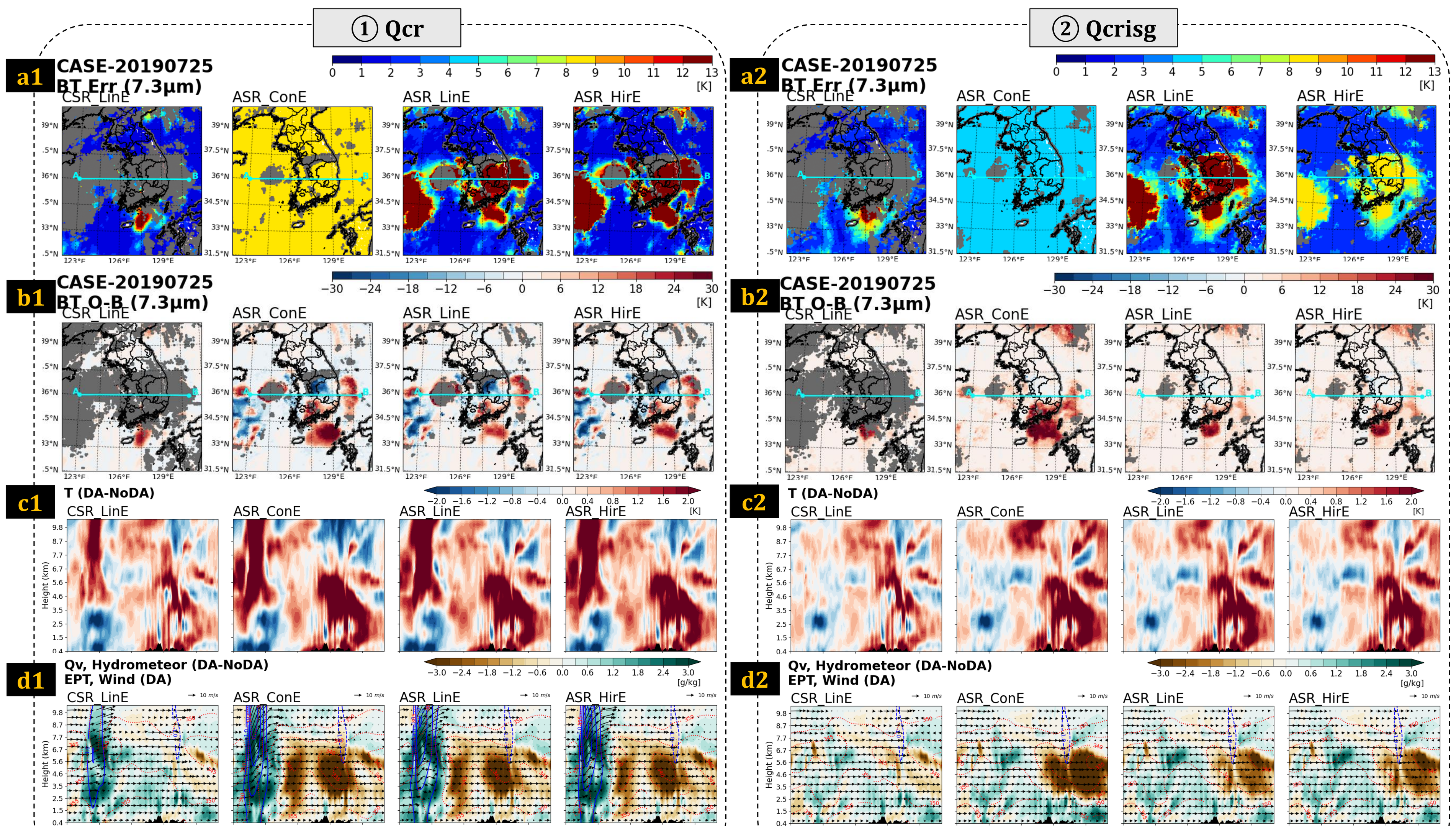

*Fig. 7. (a) Observation error and (b) O-B distribution of AMI Ch10 BT. Analysis departures from NoDA (DA-NoDA): (c) Temperature (shading), (d) WV mixing ratio (shading) and hydrometeor (blue contour). Analysis values of equivalent potential temperature (EPT) (red contour) and winds (vector) are also presented in (d). Control variable setting: **(Left:1) Qcr** and **(Right:2) Qcrisg***

Improvements of Precipitation Forecast Score

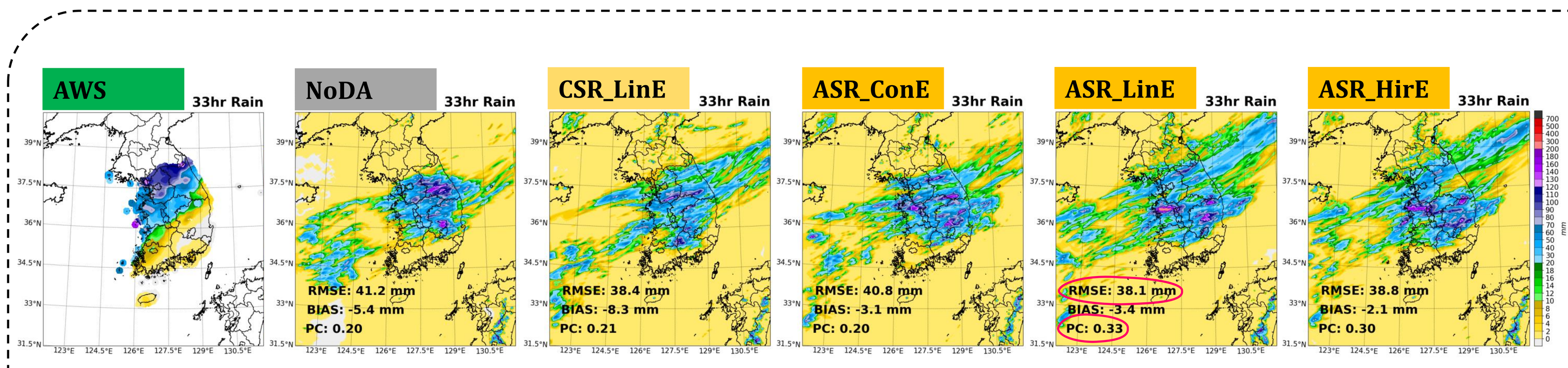

*Fig. 8. Total accumulated rainfall during the forecast times (Control variable setting: **Qcrisg**)*

- ASR_LinE and ASR_HirE gave the overall best scores with the magnitude and patterns of total & hourly accumulated rainfall, both in Qcr and Qcrisg DA experiments.
- Small convective rain cells at the western coast and the rain band peak near 38°N were better simulated in ASR_LinE and ASR_HirE.
- By including all hydrometeors as control variables, background BT was closer to the observation BT (e.g. spurious convection at the west diminishes) ⇒ PC at initial forecast time increased.

* Improvement rate = $\frac{DA - NoDA}{NoDA} \times 100$ (%)   * Major rainfall period

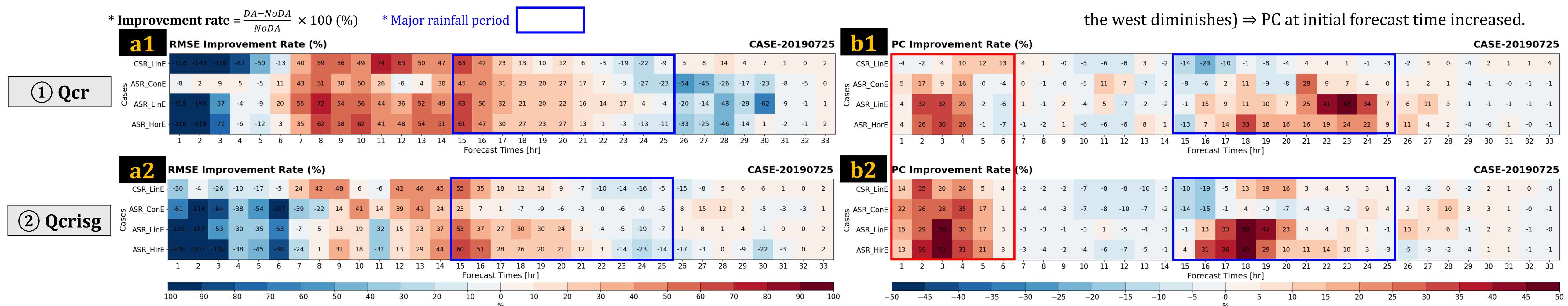

*Fig. 9. Score improvement rate of (a) Root Mean Square Error (RMSE) and (b) Pattern Correlation (PC) compared to NoDA. Red colors indicate better predictability. Control variable setting: **(Upper:1) Qcr and (Lower:2) Qcrisg***

Summary & Future Work

Summary

- ASR observation error models for the three GK-2A AMI water vapor channels have been calculated as a function of symmetric cloud effect parameter and additional scaling process have been applied in Qcr experiments to achieve more Gaussian.
- Error modeling with Qcrisg gave normalized O-B PDF closer to the Gaussian distribution than Qcr, without additional scaling.
- We conducted ASR assimilation experiments for summertime precipitation cases and compared the effects of each model, by applying constant, linear, and higher-order regression observation error models.
- Overall, there were improvements of both methods in data assimilation with the analysis and forecast fields for ASR_LinE and ASR_HirE, showing superiority over prescribing constant observation errors in the all-sky regime.
- Assimilating ASR showed better verification statistics than CSR, which implies the benefit of ingesting information in cloudy areas, when the increased uncertainties can be properly treated.
- Including all individual hydrometeors as a control variable simulates BT closer to the observations, which leads to better PC scores at the initial forecast times.

Future Work

- Further case studies with various weather systems are needed to draw more generalized conclusions about the effectiveness of different observation error models.
- Additional QC procedures may be suggested to retain as many observations as possible with more stable DA adjustment.
- Constructing the observation error models for the surface-sensitive IR channels in GK-2A AMI as well, we aim to assimilate more information near the surface, taking into account the high sensitivities to clouds in these channels.

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