Estimation of satellite observation impact on numerical weather forecast using adjoint-based method

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Background

- Recently, the number of observations used in a data assimilation system is increasing enormously. Because it is not clear that all of these observations are always beneficial to the performance of the NWP, it is important to evaluate the effect of observations on these forecasts.
- Traditionally, the impact of observations has been assessed with **observation system experiments** (OSEs). The OSEs require **much computational resources.**
- The alternative way to evaluate the impact of observations on the forecast is the **adjoint-based method**, introduced by Baker and Daley (2000).
- The adjoint-based observation impact can simultaneously evaluate the observation impact for all dataset, with lesser computation compared to OSEs, by using the **adjoints of DA** and **forecast system**.
- In this study, the impact of observation on the forecast is evaluated by the adjoint-based method in a global (UM) modeling and analysis system.

Forecast sensitivity to observation

δR is measure of forecast error reduction [e.g. energy norm]

$$\delta R = (\mathbf{x}^{fa} - \mathbf{x}^{t})^T \mathbf{C}(\mathbf{x}^{fa} - \mathbf{x}^{t}) - (\mathbf{x}^{fb} - \mathbf{x}^{t})^T \mathbf{C}(\mathbf{x}^{fb} - \mathbf{x}^{t})$$

$$\frac{\partial R}{\partial \mathbf{y}} = \frac{\partial \mathbf{x}_a}{\partial \mathbf{y}} \frac{\partial R}{\partial \mathbf{x}_a}$$

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}(\mathbf{y} - h(\mathbf{x}_b))$$

Sensitivity to the analysis → $\frac{\partial R}{\partial \mathbf{x}_a}$

Analysis sensitivity to observation → $\frac{\partial \mathbf{x}_a}{\partial \mathbf{y}} = \mathbf{K}^T = \mathbf{R}^{-1}\mathbf{H}(\mathbf{B}^{-1} + \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H})^{-1}$

$$\begin{aligned} < \frac{\partial R}{\partial \mathbf{x}_a}, \delta \mathbf{x}_a > &= < \frac{\partial R}{\partial \mathbf{x}_a}, \mathbf{x}_a - \mathbf{x}_b > \\ &= < \frac{\partial R}{\partial \mathbf{x}_a}, \mathbf{K}(\mathbf{y} - h(\mathbf{x}_b)) > \\ &= < \mathbf{K}^T \frac{\partial R}{\partial \mathbf{x}_a}, (\mathbf{y} - h(\mathbf{x}_b)) > \\ &= < \frac{\partial R}{\partial \mathbf{y}}, \delta \mathbf{y} > \end{aligned}$$

Forecast impact :

$$\delta R = \frac{\partial R}{\partial \mathbf{y}}(\mathbf{y} - h(\mathbf{x}_b))$$

Experimental design

- Period
  - 2011. 6. 1. 00 UTC ~ 2011. 8. 31. 00 UTC [Summer months]
    2011. 12. 1. 00 UTC ~ 2012. 2. 29. 00 UTC [Winter months]
  - **24hour forecast, evaluate on 00, 06, 12, and 18 UTC**

- Model configuration
  - KMA UM N512 (vn7.7) and 4D-Var N144 (vn27.2)
  - Dry TE norm (projected on sfc to 150 hPa) + simple moisture physics

Global and east Asia domain

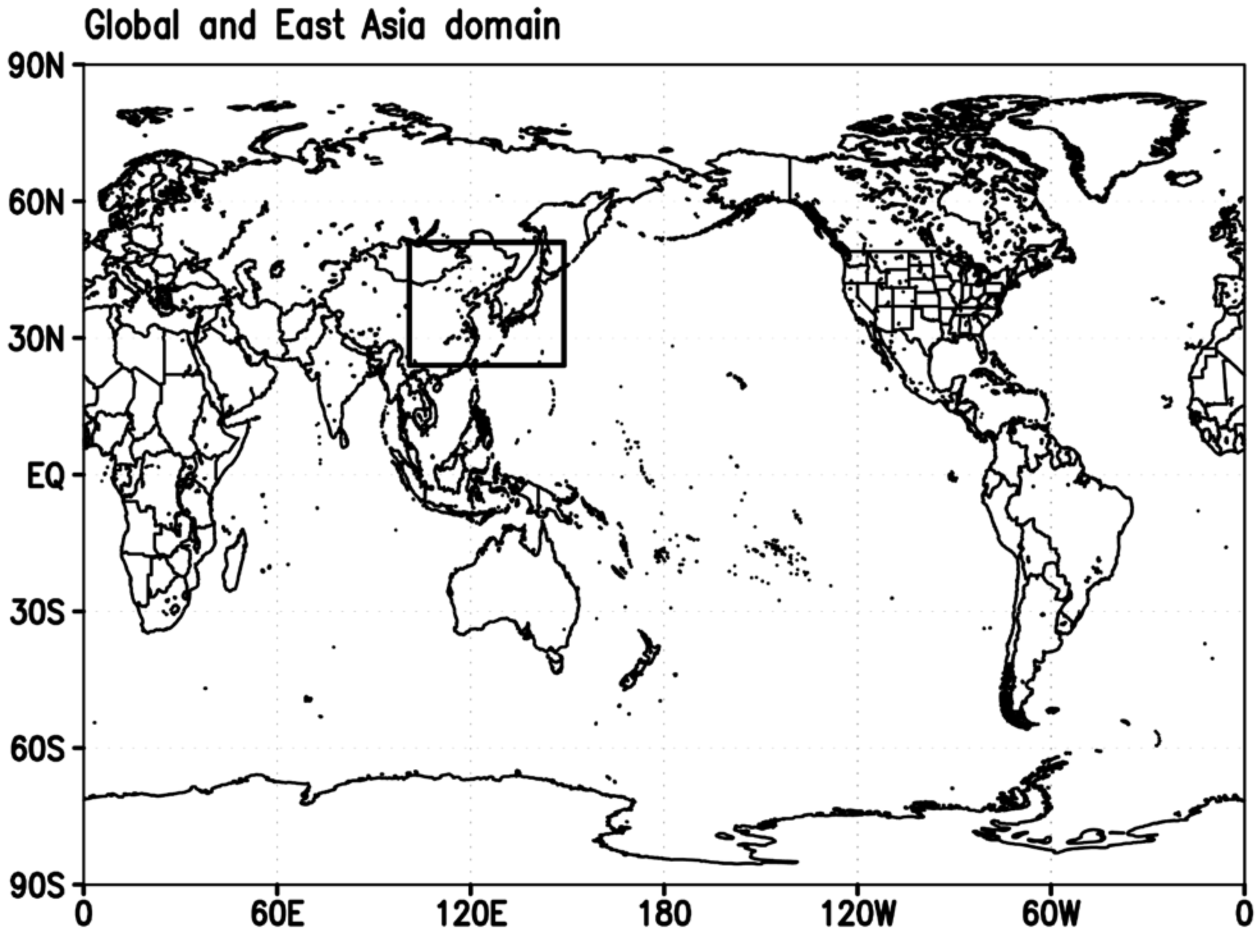


Fig. 1. Global and east Asian domain (black solid box).

Forecast error reduction

$$\delta R = (\mathbf{x}^{fa} - \mathbf{x}^{t})^{T}\mathbf{C}(\mathbf{x}^{fa} - \mathbf{x}^{t}) - (\mathbf{x}^{fb} - \mathbf{x}^{t})^{T}\mathbf{C}(\mathbf{x}^{fb} - \mathbf{x}^{t})$$

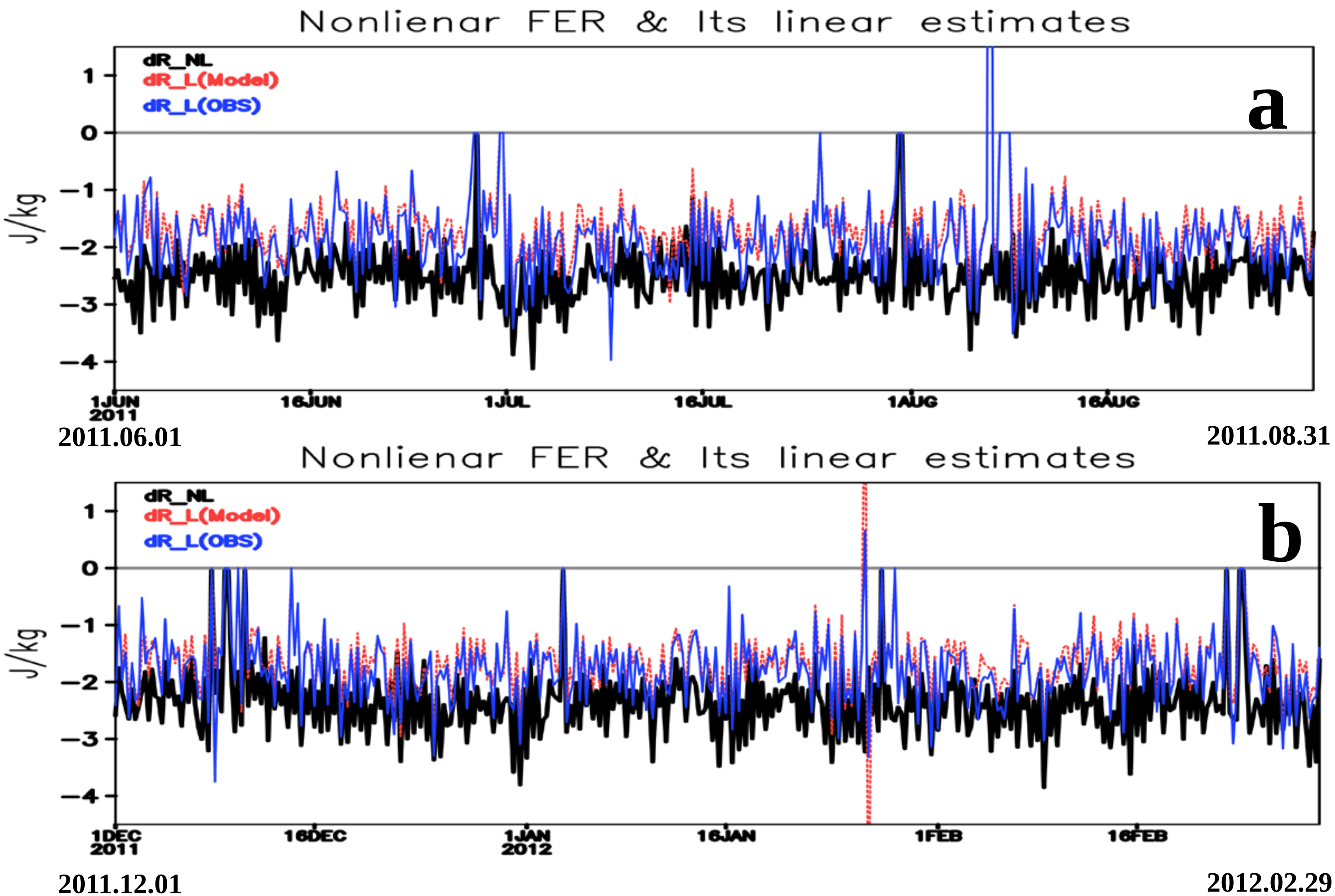


Fig. 2. Nonlinear forecast error reduction (black line) and its linear estimation in model space (red line) and in observation space (blue line) for analysis time in (a) summer and (b) winter months.

Observation impact

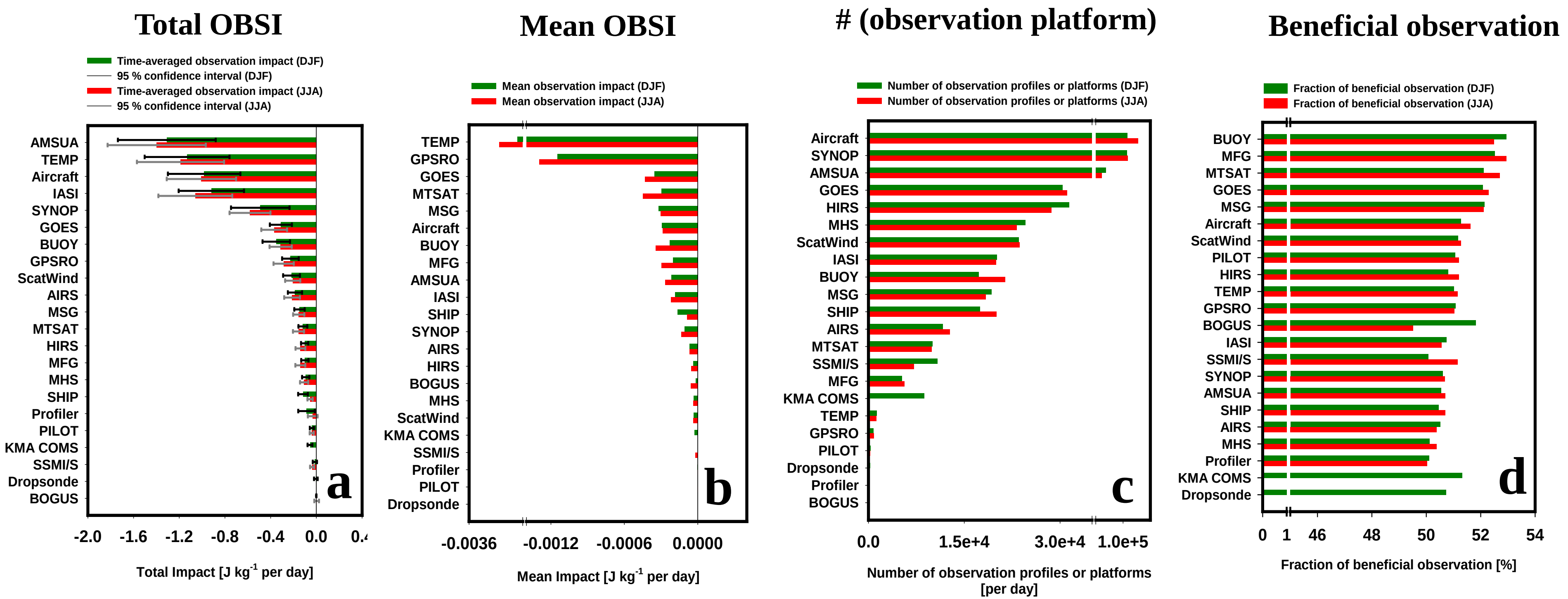


Fig. 3. Time-averaged statistics (mean and 95 % confidence interval) stratified by each observation type for (a) total observation impact, (b) mean observation impact, (c) number of observation profiles or platforms, and (d) fraction of beneficial observation in summer (JJA) and winter (DJF) months in the global region.

Observation impact

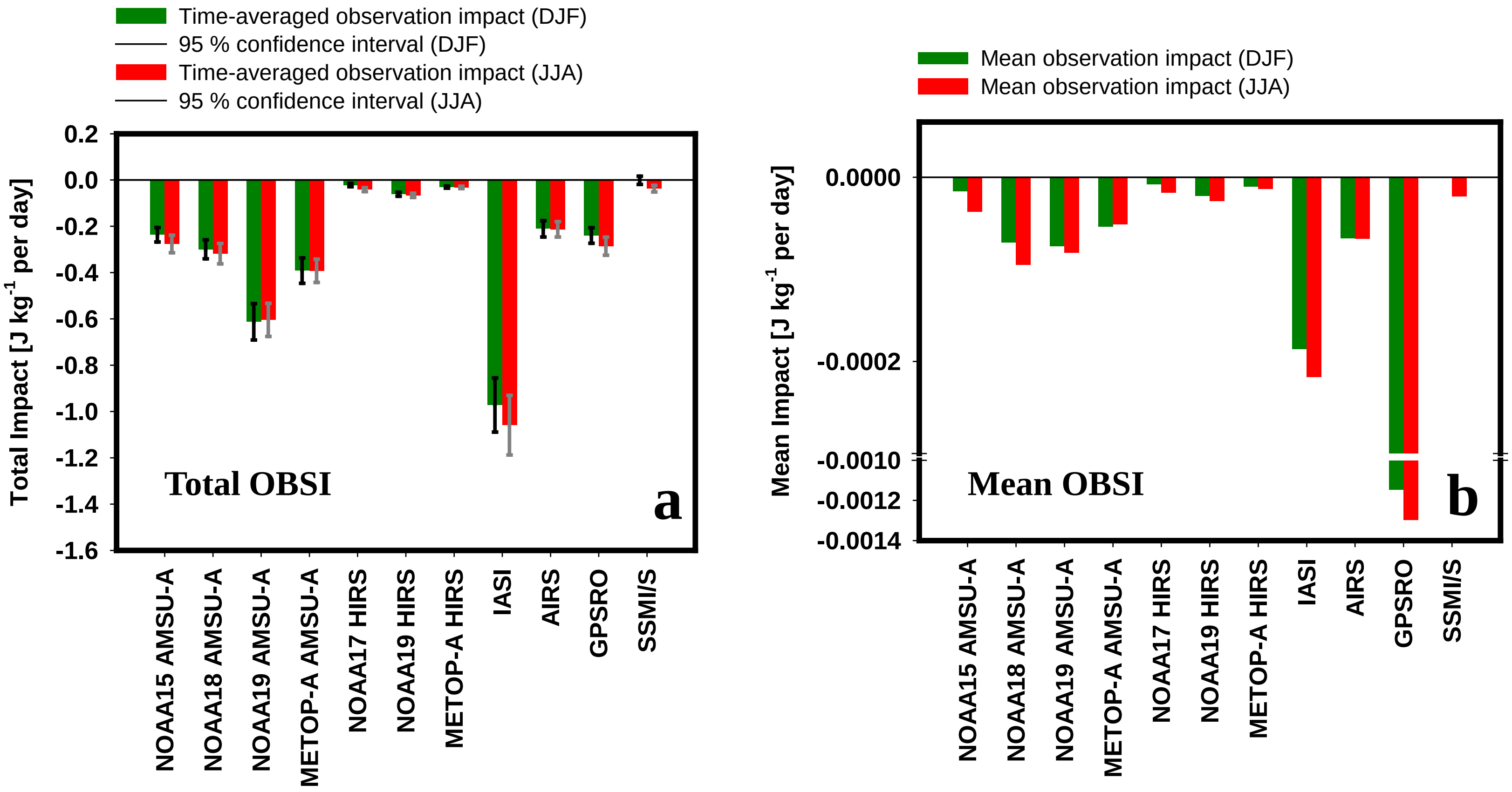


Fig. 4. Time-averaged statistics (mean and 95 % confidence interval) stratified by sounder-type satellite observation assimilated for (a) total observation impact, (b) mean observation impact in summer (JJA) and winter (DJF) months in the global region.

Observation impact

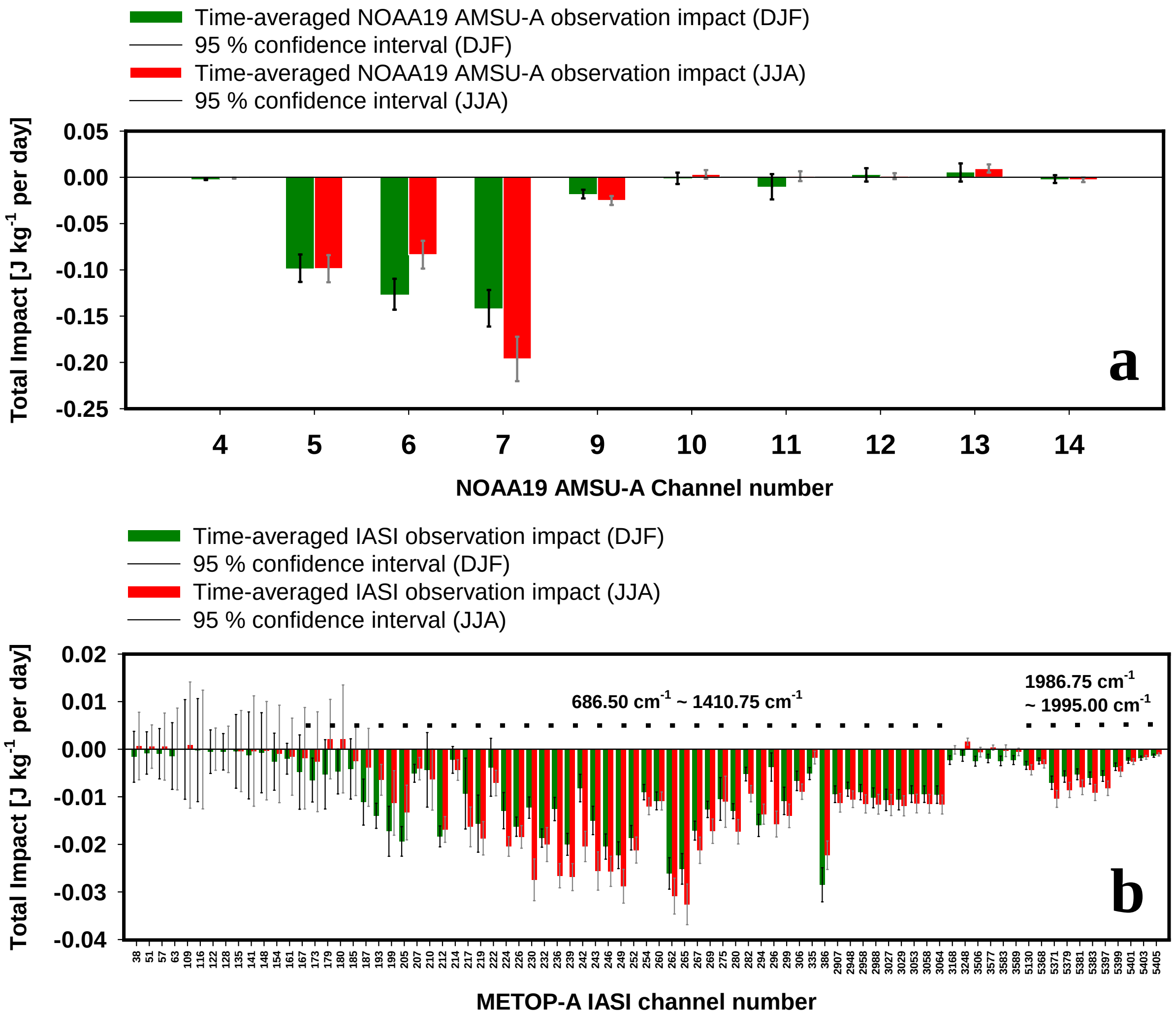


Fig. 5. Time-averaged statistics (mean and 95 % confidence interval) stratified by (a) NOAA 19 AMSU-A and (b) METOP-A IASI channel assimilated for total observation impact in summer (JJA) and winter (DJF) months in the global region. The wave length range corresponding to large observation impact is indicated by the dashed line.

Observation impact in the east Asia region

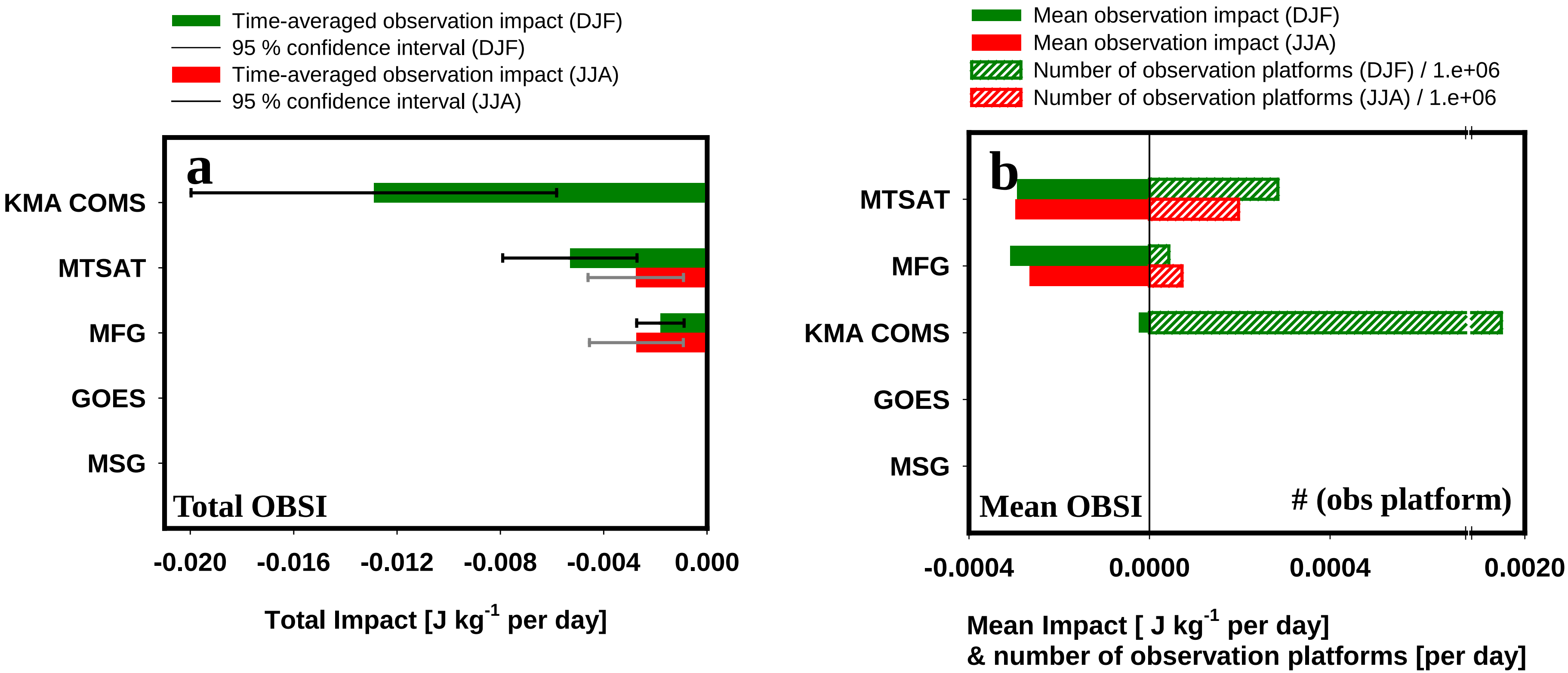


Fig. 6. Time-averaged statistics (mean and 95 % confidence interval) stratified by imager type for (a) total observation impact, (b) mean observation impact and number of observation platforms at summer (JJA) and winter (DJF) months in the east Asia region. In Fig. 12b, number of observation platforms is normalized by $1*10^6$. At summer (JJA) months, the COMS observation is not assimilated.

Summary

- The linear δR underestimates the nonlinear δR (75% in summer and 80% in winter), similar to Langland and Baker (2004).

- The magnitude of δR depends on the number of observational data assimilated. The impact of each observation does not change depending on season.

- For the global region, the impact of AMSUA is largest, followed by Temp, AIRCRAFT, IASI, Synop, GOES, Buoy, GPSRO, ScatWind, etc.

Sensitivity to error covariance parameters

Courtesy of Daescu and Todling (2010)

Define: $\delta \mathbf{B} = \delta s^b \mathbf{B} \quad \delta \mathbf{R}_i = \delta s_i \mathbf{R}$

Sensitivity to background error covariance weighting	➡	$$\frac{\delta R}{\delta s^b} = [\mathbf{y} - h(\mathbf{x}_a)]^T \frac{\delta R}{\delta \mathbf{y}}$$
Sensitivity to observation error covariance weighting	➡	$$\frac{\delta R}{\delta s_i^o} = [h_i(\mathbf{x}_a) - \mathbf{y}_i]^T \frac{\delta R}{\delta \mathbf{y}_i}$$

y Observation **B Background error covariance**

$\mathbf{x_b}$ Background **R Observation error covariance**

$\mathbf{x_a}$ Analysis *h* **Observation operator**

Experimental design

- Period

  - 2012. 7. 1. 00 UTC ~ 2012. 7. 31. 18 UTC [To estimate the error covariance parameter]

    2012. 8. 1. 00 UTC ~ 2012. 8. 31. 18 UTC [To verify the additional forecast error reduction]

  - **24 hour forecast, evaluate on 00, 06, 12, 18 UTC**

- Model configuration
  - KMA UM N512 (vn7.7) and 4D-Var N144 system (vn27.2), before Hybrid-system
  - **Dry total energy norm** (projected on sfc to 150 hPa) + simple moisture physics

- Observation
  - Surface : Synop, Ship, Buoy
  - Sonde : TEMP (radiosonde), PILOT, Wind profiler, Dropsonde
  - Aircraft : AMDAR, AIREP
  - Satwind : GOES (+ MODIS, AVHRR), KMA (COMS), JMA, MSG, Meteosat
  - ATOVS : NOAA 15~19, MetOp2 (i.e., MetOp-A)
  - Scatwind, SSMIS, AIRS, IASI, GPSRO

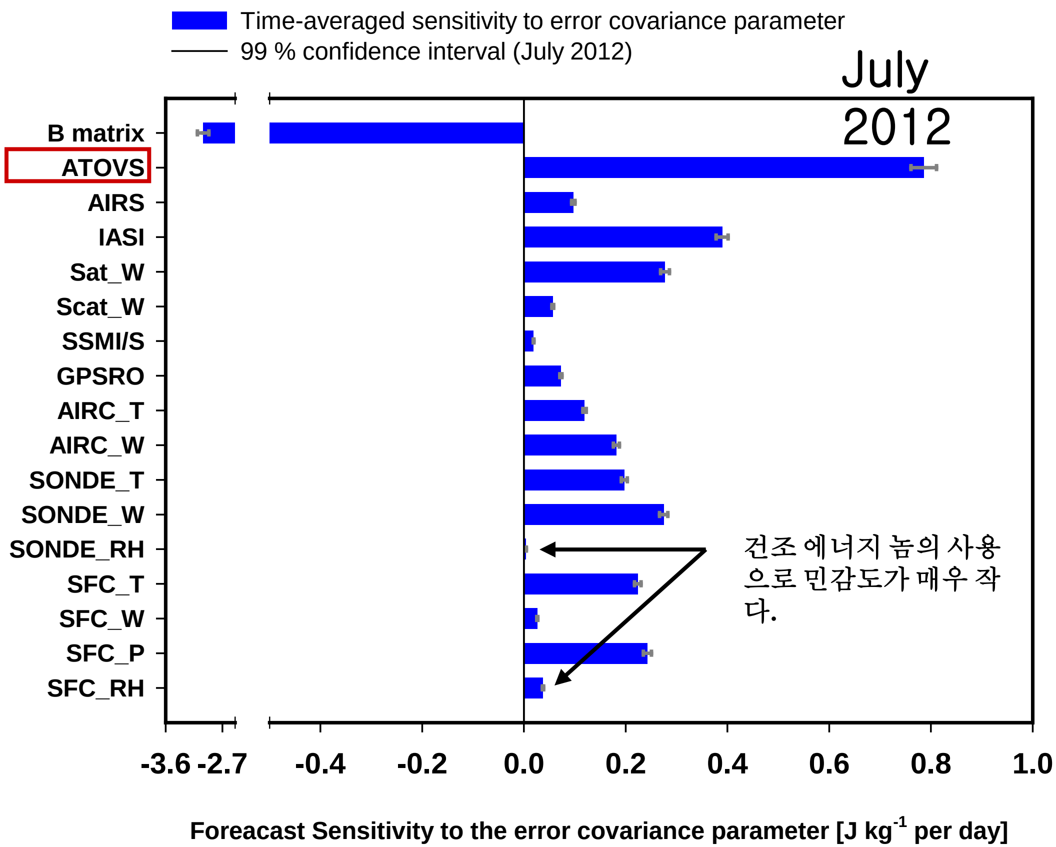
Statistics of Forecast sensitivity to error covariance parameter

$$\delta R = R(\mathbf{B}+\delta\mathbf{B},\mathbf{R}+\delta\mathbf{R}) - R(\mathbf{B},\mathbf{R})$$

$$\approx \delta R_b + \sum_i \delta R_i^o = \left\langle \left(\frac{\delta R}{\delta s_b}, \frac{\delta R}{\delta s_i^o} \right), \left(\delta s_b, \delta s_i^o \right) \right\rangle$$

δR	(Linear) forecast error reduction
δR/δs	Sensitivity to error parameters
δs	Error covariance parameter (weighting)

관측 종



Error covariance parameter

$$\delta R = R(\mathbf{B}+\delta\mathbf{B},\mathbf{R}+\delta\mathbf{R}) - R(\mathbf{B},\mathbf{R})$$

$$\approx \delta R_b + \sum_i \delta R_i^o = \left\langle \left(\frac{\delta R}{\delta s_b}, \frac{\delta R}{\delta s_i^o} \right), \boxed{\left(\delta s_b, \delta s_i^o \right)} \right\rangle$$

δR	(Linear) forecast error reduction
δR/δs	Sensitivity to error parameters
δs	Error covariance parameter (weighting)

When every potential outlier (> 3 sigma) is rejected:

July 2012

	B matrix	ATOVS	IASI	AIRS	SAT_W
August	0.3000	-0.7238	-1.0467	-0.3746	-0.5235
	SCAT_W	**GPSRO**	**SSMI/S**	**SONDE_T**	**SONDE_W**
August	0.2183	-0.6425	-2.0419	-0.9712	-0.4131
	SONDE_RH	**SFC_P**	**SFC_T**	**SFC_W**	**SFC_RH**
August	-0.9745	-0.7905	-0.5636	-0.7638	0.2676
	AIRC_T	**AIRC_W**	**Rejection rate**		
August	-0.3410	-1.2261	**7/124 (5.6 %)**		

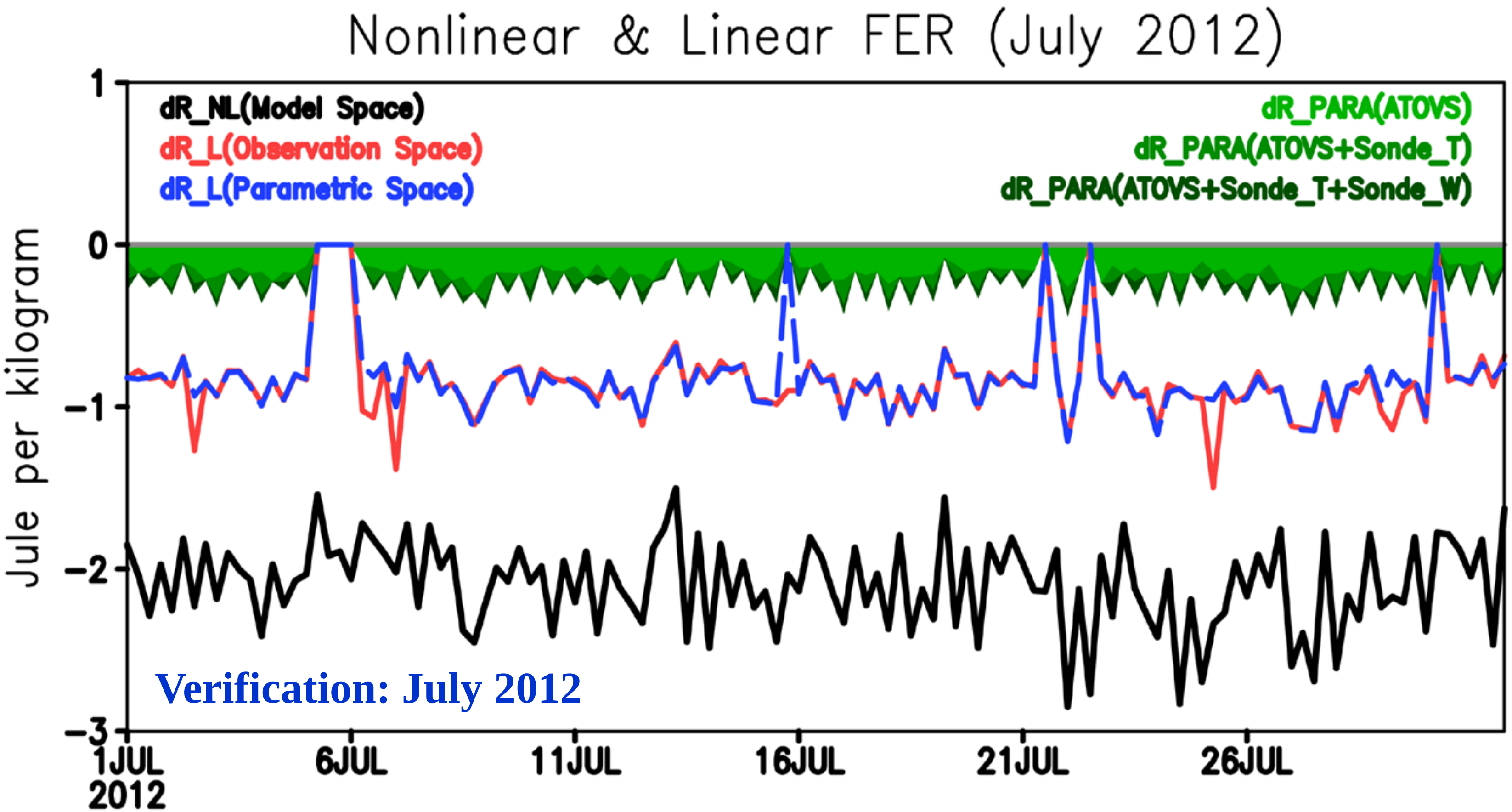
~ Tuning variable not used for DA system

Forecast error reduction

$$\delta R = R(\mathbf{B}+\delta\mathbf{B}, \mathbf{R}+\delta\mathbf{R}) - R(\mathbf{B}, \mathbf{R})$$

$$\approx \delta R_b + \sum_i \delta R_i^o = \left\langle \left(\frac{\delta R}{\delta s_b}, \frac{\delta R}{\delta s_i^o} \right), \left(\delta s_b, \delta s_i^o \right) \right\rangle$$

δR	**(Linear) forecast error reduction**
δR/δs	**Sensitivity to error parameters**
δs	**Error covariance parameter (weighting)**



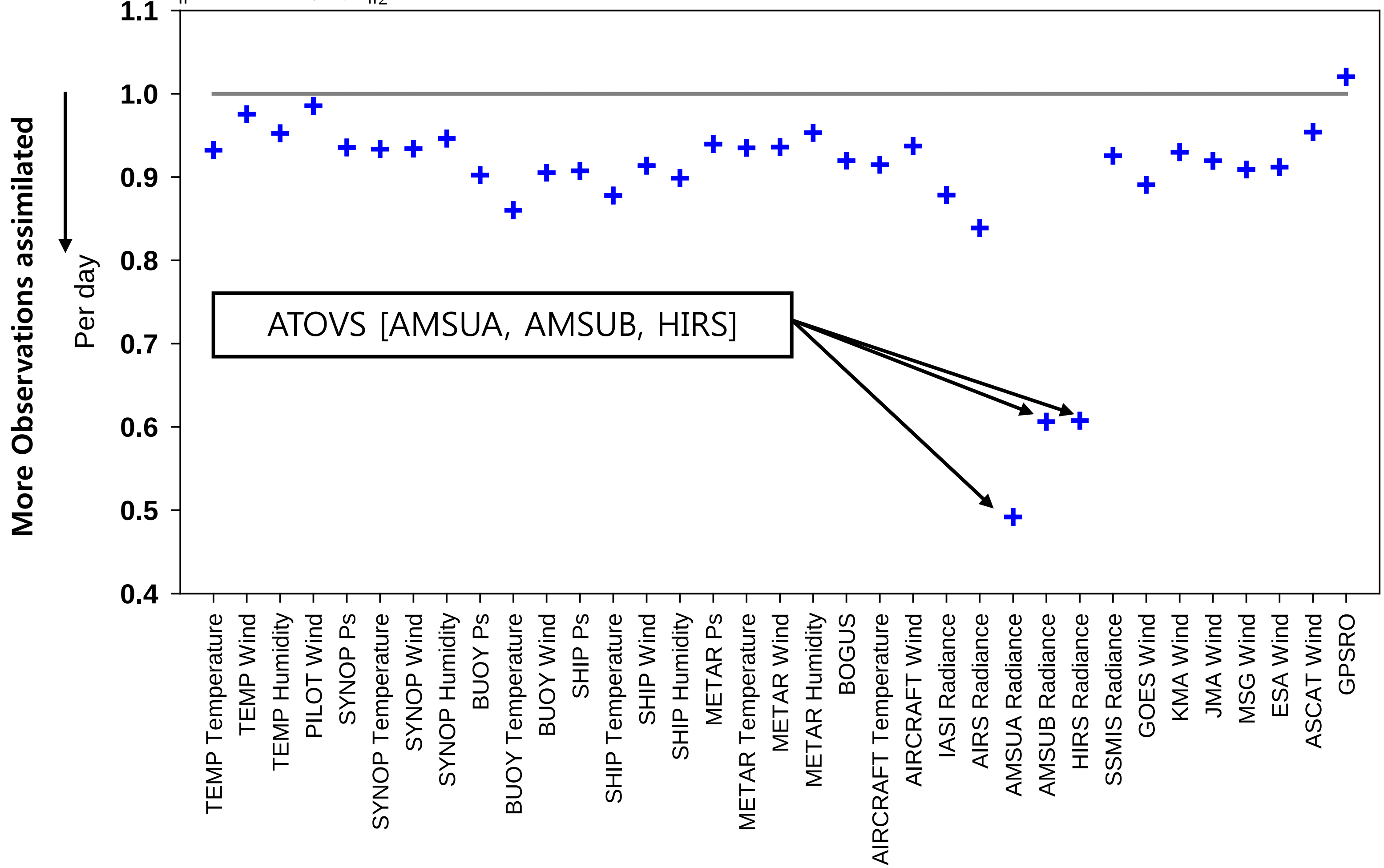
Verification : Observation residual

L2-norm

$$\frac{\left\| \mathbf{y} - h(\mathbf{x}_a(\hat{\sigma})) \right\|_2}{\left\| \mathbf{y} - h(\mathbf{x}_a(\sigma)) \right\|_2}$$

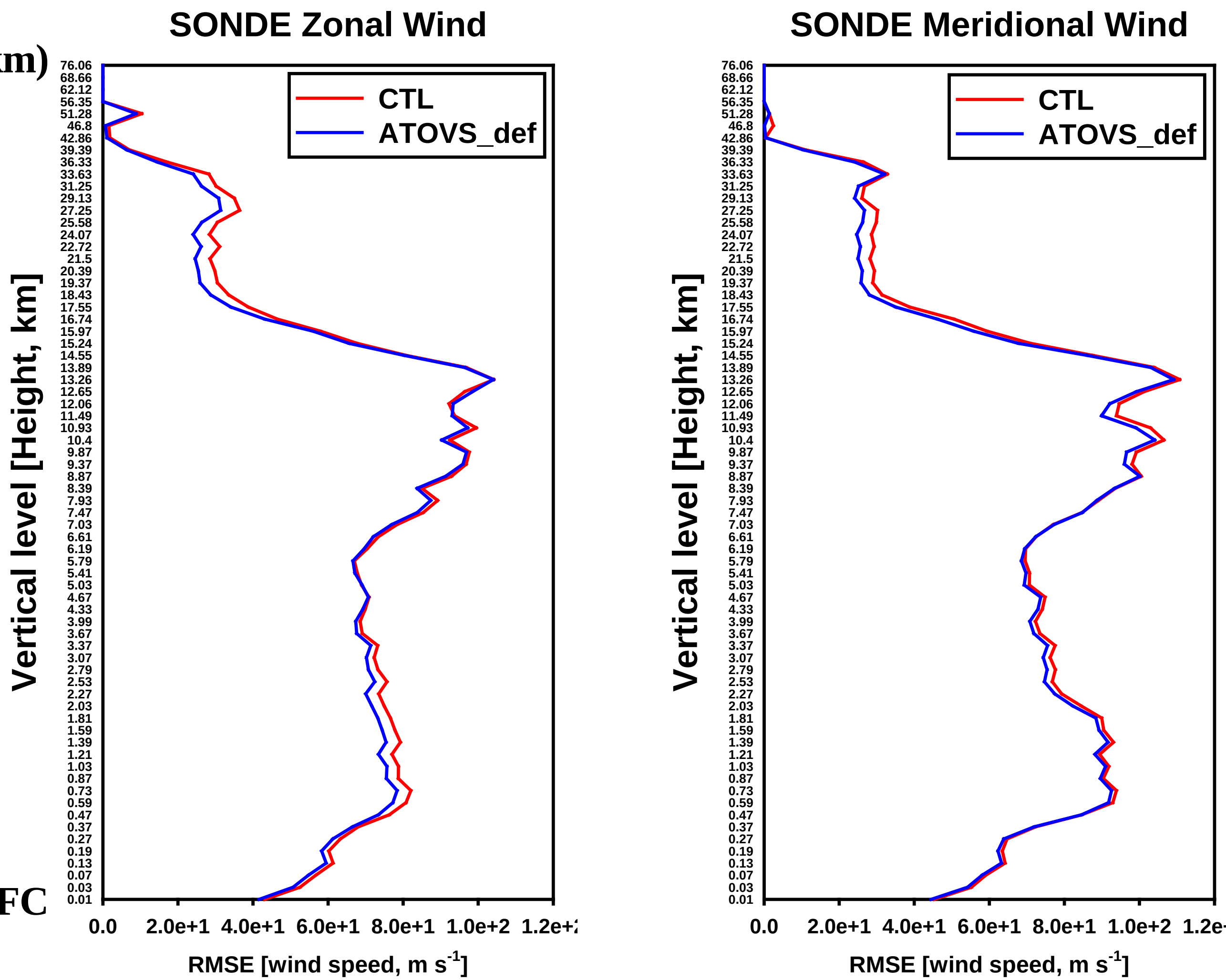
Time-averaged $||y-h(x_a)||_2$ in ATOVS_def / Time-averaged $||y-h(x_a)||_2$ in CTL

Average 10.62% residual reduction



Verification : Forecast error (time-average) in the observation space

Top (76 km)



SFC

August 2012

Summary

- This study calculated the forecast sensitivity to error covariance parameter (Daescu and Todling 2010) for July 2012, and proposed the optimized error covariance by using the multiple linear regression. The modified error covariance was applied to the forecast trajectory during August 2012, and the forecast errors using the modified error covariance were evaluated in the observation and model space.

- The multiple linear regression analysis for the sensitivity to error covariance parameter suggested that the ATOVS observation (i.e., AMSU-A, AMSU-B and HIRS) error needs to be decreased by 72.38 % when the background error covariance is increased by 30 %. It is indicated that the more ATOVS observation must be assimilated in the numerical model, compared to the current operational system.

- According to the verification for August 2012 period, the more ATOVS observation assimilated in the model decreased the distance between the forecast and the observation in the observation space.

Thank you