Observation impact in East Asia and western North Pacific regions using WRF-FSO system

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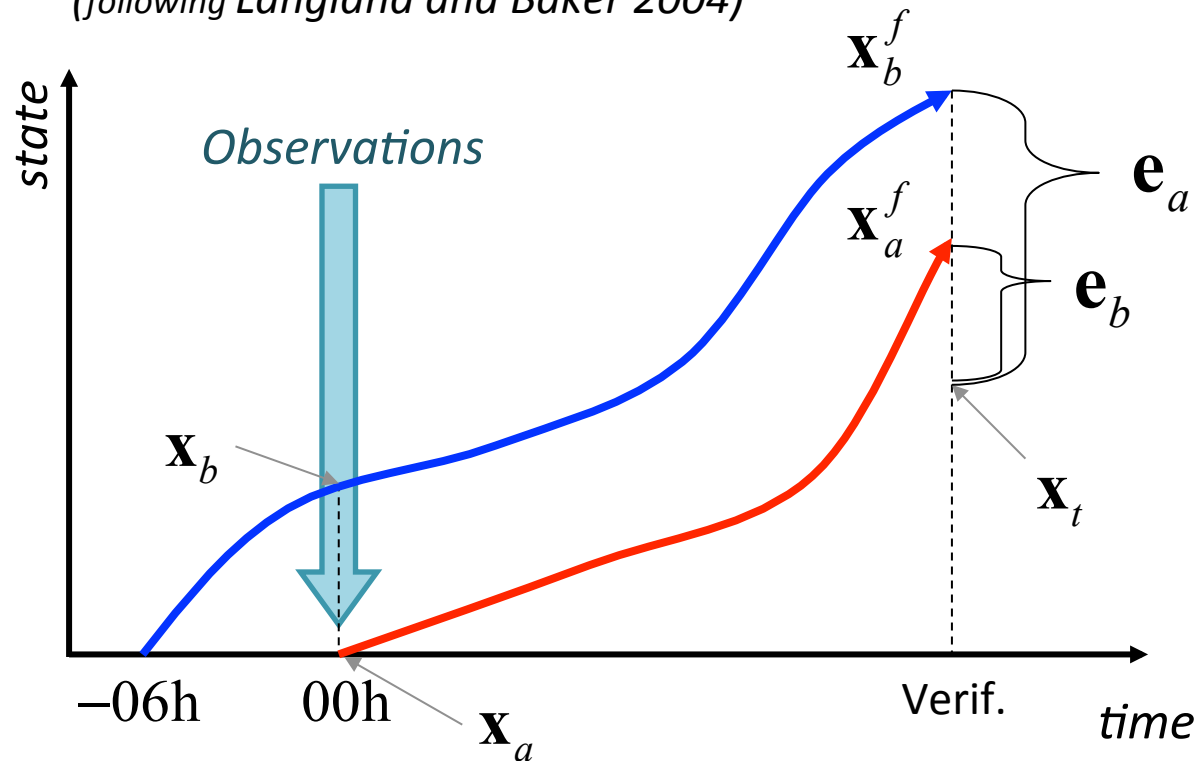**Korea Institute of Atmospheric Prediction Systems (KIAPS)**
(재)한국형수치예보모델개발사업단

- In numerical weather prediction (NWP), the initial condition of a forecast model is given by **an analysis field** from a data assimilation (DA) system, which is a mixture of background fields and observations with weights of their error statistics.

- Recently, the amount of observations rapidly increases, especially due to satellite observations. For optimal use of observations and forecast skill improvement, it is important to evaluate and monitor the impact of observations in the NWP system.

- Traditionally, the impact of given observations has been assessed with **observation system experiments** (OSEs; Atlas 1997, Masutani et al. 2010).

- In OSEs, new analysis is made by adding (or subtracting) specific observations to (from) the reference set of observations in DA system. Then, the impact of given observations can be evaluated by comparing the forecast integrated from a new analysis with that from a reference analysis.

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- However, OSEs require **much computational resources** as the whole DA and forecast system should be independently performed for several months.

- The alternative way to evaluate the impact of observations on the forecast is the **adjoint-based observation impact method**, first introduced by Barker and Daley (2000) in the context of adaptive observation.

- The adjoint-based observation impact can **simultaneously** evaluate the observation impact for all dataset, with lesser computation compared to OSEs, by using the **adjoint of DA system** as well as the **adjoint of forecast system**. Also, the impact can be easily grouped with its subset.

- Langland and Baker 2004, Langland 2004, Cardinali 2009, Gelaro and Zhu 2009, Gelaro et al. 2010…

- In this study, the adjoint-based observation impact is evaluated in East Asia, using version 3.3 of WRF-FSO system (Auligne 2010).

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(*following* *Langland and Baker 2004*)

$$e_a = \left(\mathbf{x}_a^f - \mathbf{x}_t\right)^T \mathbf{C}\left(\mathbf{x}_a^f - \mathbf{x}_t\right)$$

$$e_b = \left(\mathbf{x}_b^f - \mathbf{x}_t\right)^T \mathbf{C}\left(\mathbf{x}_b^f - \mathbf{x}_t\right)$$

$\mathbf{C}$: *Dry total energy norm*
(Rabier et al. 1996 , Palmer et al. 1998, Zou et al. 1997)

The difference between the errors is due to assimilation of observations at 00 UTC.

$$\Delta\mathbf{e} = \mathbf{e}_a - \mathbf{e}_b$$

$\Delta\mathbf{e} < 0,$ forecast error is reduced !

$\Delta\mathbf{e} > 0,$ forecast error is increased !

How to estimate the obs. impact?

- Nonlinear forecast model $\quad\mathbf{x}^f = \mathbf{m}\left(\mathbf{x}^0\right)$
- Tangent linear model $\quad\quad \delta\mathbf{x}^f = \mathbf{M}\,\delta\mathbf{x}^0 \quad\quad \mathbf{M} = \partial\mathbf{m}/\partial\mathbf{x}$
- Definition of forecast measure $\quad R = f\left(\mathbf{x}^f\right)$

✓ $\dfrac{\partial R}{\partial \mathbf{x}^o} = \mathbf{M}^T \dfrac{\partial R}{\partial \mathbf{x}^f}$ ***Forecast sensitivity to analysis (model I.C.)***

Adjoint of TL model

✓ $\mathbf{x}_a = \mathbf{x}_b + \mathbf{K}\mathbf{d}$ ***(simplified) Analysis system***

✓ $\dfrac{\partial R}{\partial \mathbf{y}} = \mathbf{K}^T \dfrac{\partial R}{\partial \mathbf{x}_a} = \mathbf{K}^T \mathbf{M}^T \dfrac{\partial R}{\partial \mathbf{x}^f}$ ***Forecast sensitivity to observation***

Adjoint of TL model

Adjoint of DA

✓ $\delta R = \left\langle \dfrac{\partial R}{\partial \mathbf{y}}, \mathbf{d} \right\rangle = \left\langle \mathbf{K}^T \dfrac{\partial R}{\partial \mathbf{x}_a}, \mathbf{d} \right\rangle$ ***Observation impact estimation***
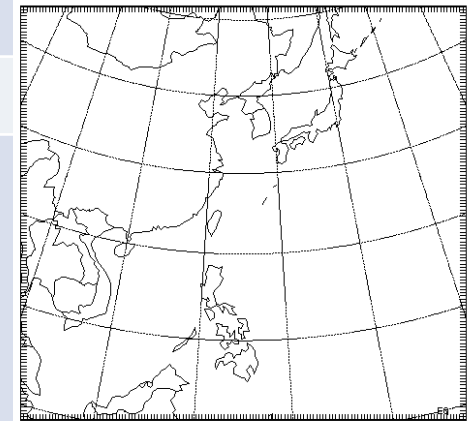
$\mathbf{K}^T = \mathbf{R}^{-1}\mathbf{H}\mathbf{A}$ A is estimated by using leading eigenpairs from Lanczos algorithm (Golub and Van Loan 1996, Tremolet 2008)
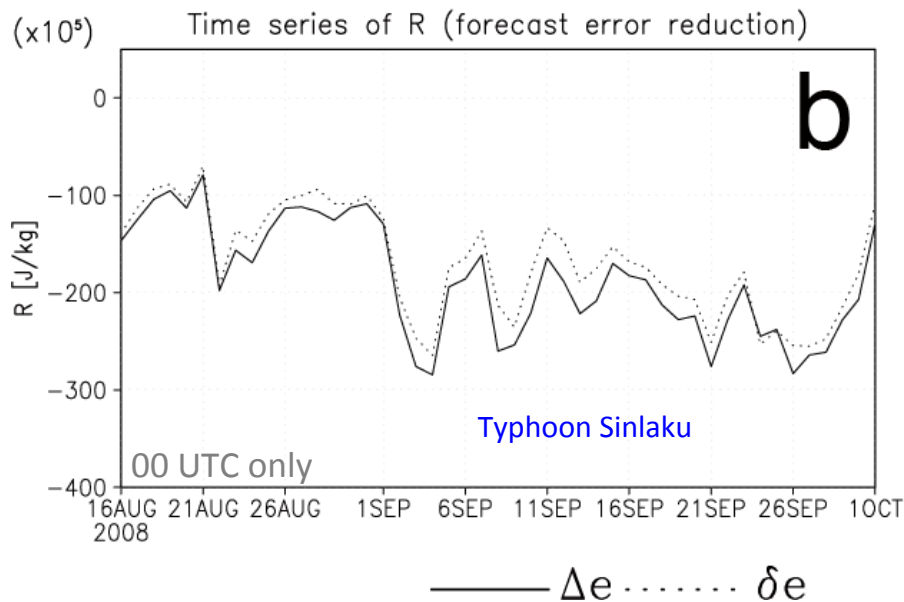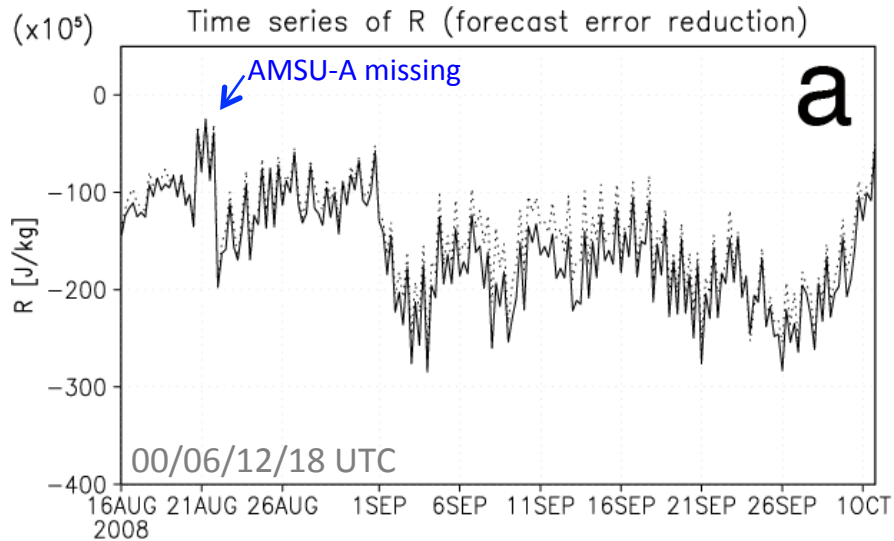
$R \equiv \Delta\mathbf{e}$

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Modeling system	WRF v3.3 WRFPLUS v3.3	Full physics Dry physics
Analysis system	WRFDA v3.3	3dvar BES with NMC method
Domain	141 x 131 (45 km) v41	
Lateral B.C.	NCEP Final Analysis	
Observations	Surface (SYNOP, SHIPS, BUOY, METAR) Upper-air (sound, PILOT, PROFL) Aircraft (AIREP) Surface GPS (GPSPW) Ocean surface wind (QSCAT) Atmospheric motion vector (GEOAMV) Radiance (AMSU-A from 4 satellites)	Ch5-9, CRTM, VarBC
Period	From 16 August to 1 October 2008 (~ 6 week)	Typhoon season, T-PARC

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Time series of R (forecast error reduction) — panel a (00/06/12/18 UTC), AMSU-A missing; panel b (00 UTC only), Typhoon Sinlaku. Legend: —— Δe ······ δe

- Δe < 0
- Assimilation of observations reduces the forecast error.
- δe agrees well with Δe (variability and magnitude).

- δe slightly underestimates Δe.
  - Neglected moist physics in ADJM
  - Linear assumption
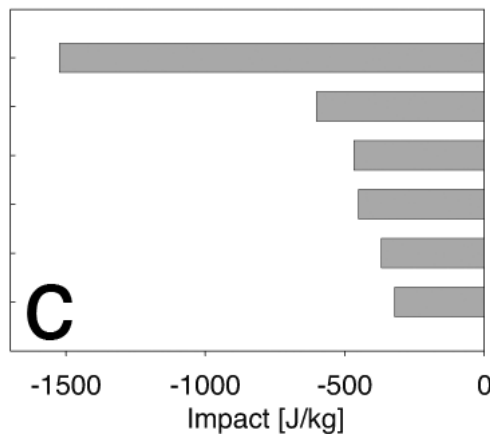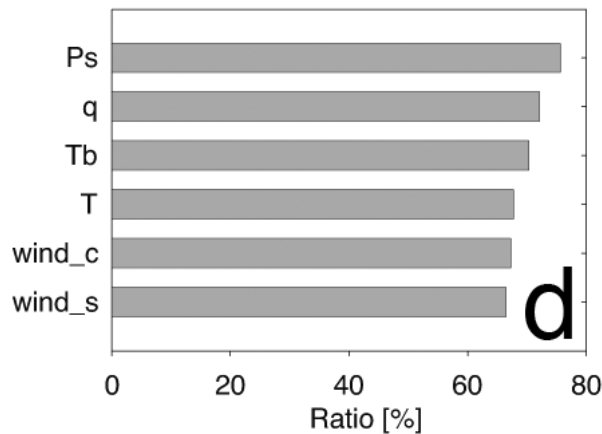 - Approx.-formula of forecast error reduction.

Time-averaged obs. impact
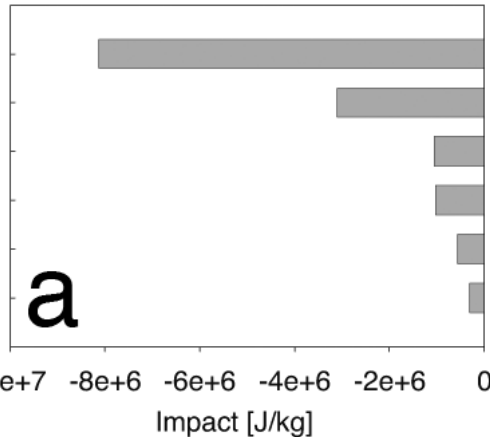
Obs. number
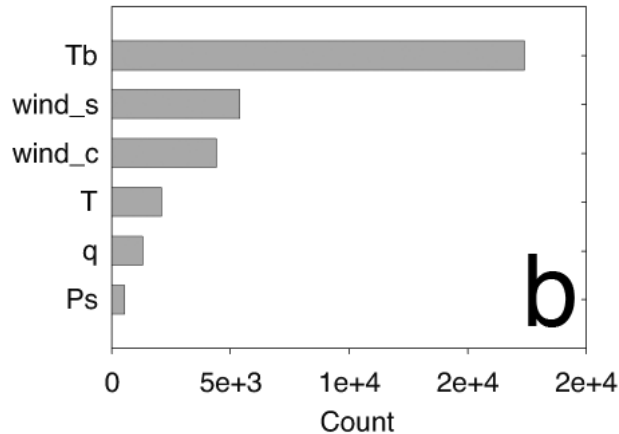
Normalized obs. impact

Fraction of beneficial obs.

- Satellite obs. has the largest *total* impact.
- Impact for momentum variables is larger than that for mass/humidity variables.

- *Total* impact is (partly) related to number.

- Conv. wind has the largest impact *per* one obs.
  - Consistent with recent studies (WMO, 2012)
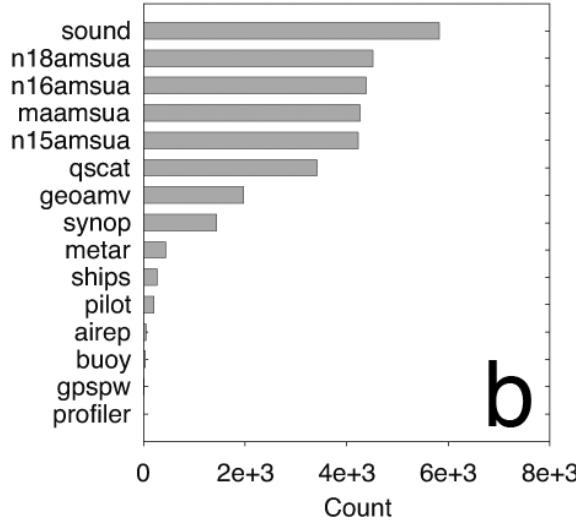- Ps has follows ~ more large-scale information (Bengtsson 1980, Compo et al. 2011)

Time-averaged obs. impact — Impact [J/kg]
Obs. number — Count
Normalized obs. impact — Impact [J/kg]
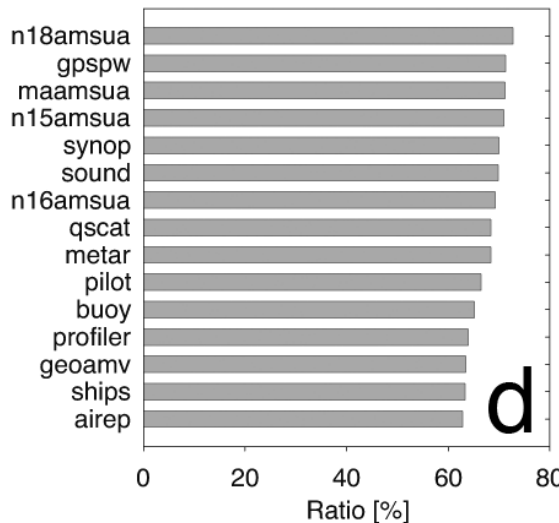Fraction of beneficial obs. — Ratio [%]
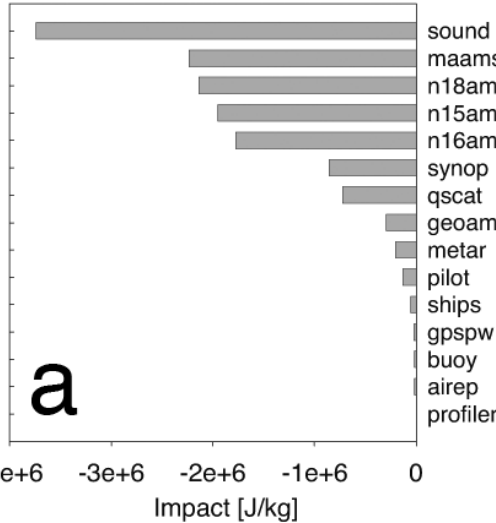
- SOUND has the largest *total* impact
- and AMSU-A, SYNOP, QSCAT, GEOAMV

- GPSPW has the largest impact *per* one obs.
- SYNOP has larger impact per obs. than AMSU-A from one satellite.
- Impact per obs. for QSCAT and GEOAMV is quite small.

- 60 ~80 % of obs. are beneficial. ($\delta e < 0$)
  - greater than previous studies
  - 50-54% in Gelaro et al. (2010)
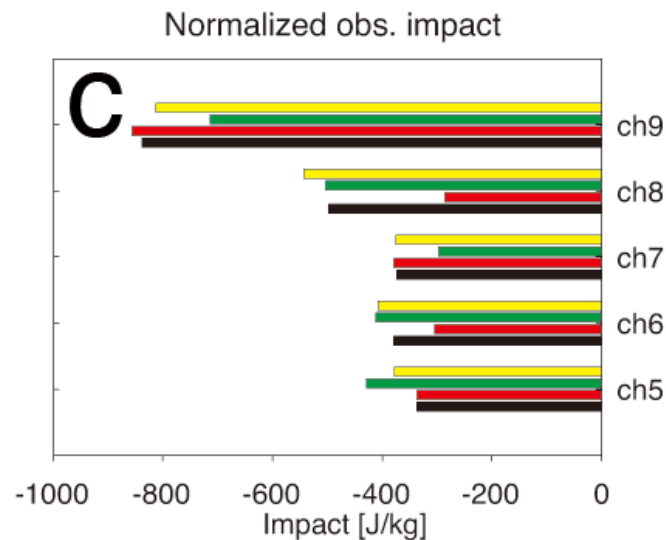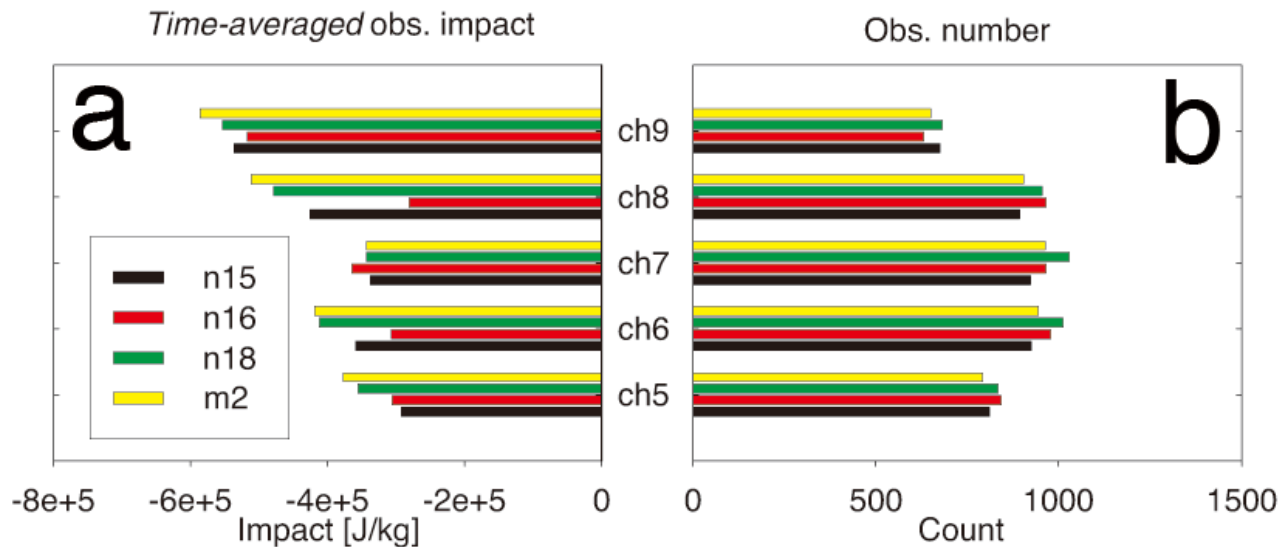 - Slightly more than half in Kunii et al. (2012)

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Time-averaged obs. impact

Obs. number

Normalized obs. impact
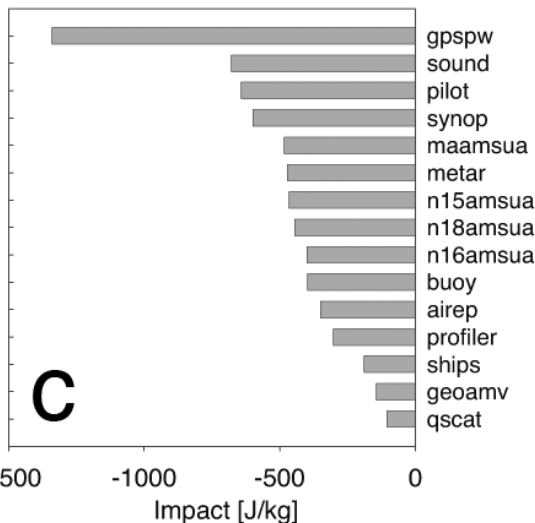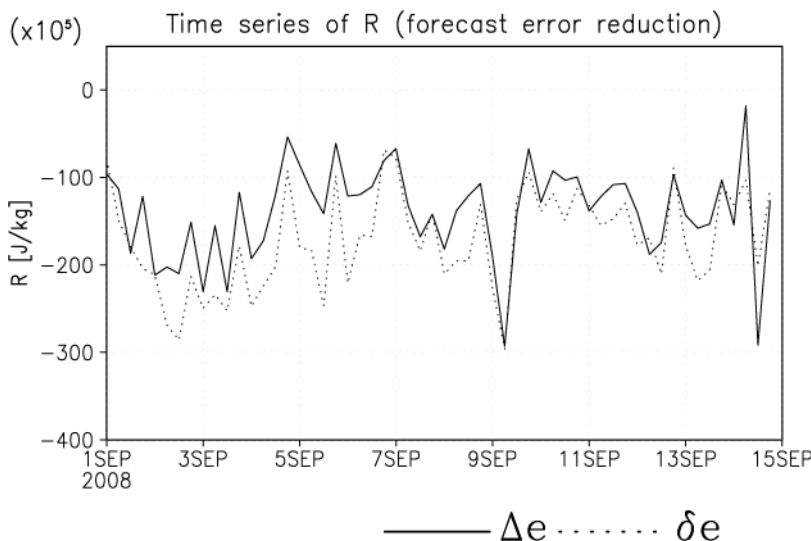
- Ch9 has the largest impact. ~ upper trop.

- Inconsistent with Gelaro et al. (2010) ~ ch5-7
- Due to different configuration, low model top, norm definition

- There is a large forecast error in the upper trop.
- Forecast error in the upper trop. is over-emphasized in terms of energy.
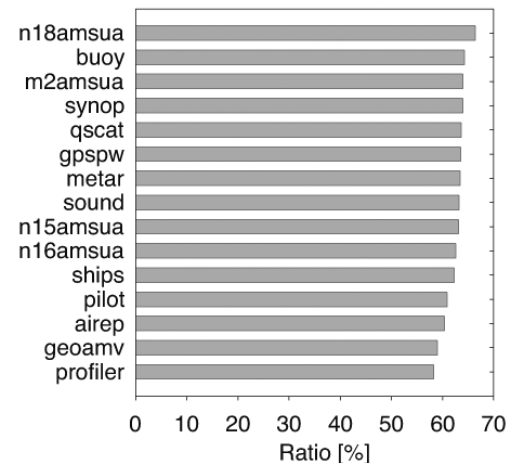
- Observation impact on **24 hour** forecast error reduction
- 2 weeks (from 1 to 14 September 2008)

- Overall, the result is consistent with that of the 6 hour Exp.
- The major rankings of obs. variables/types are not changed.
- Except Ps, the beneficial fraction is reduced by ~6%.
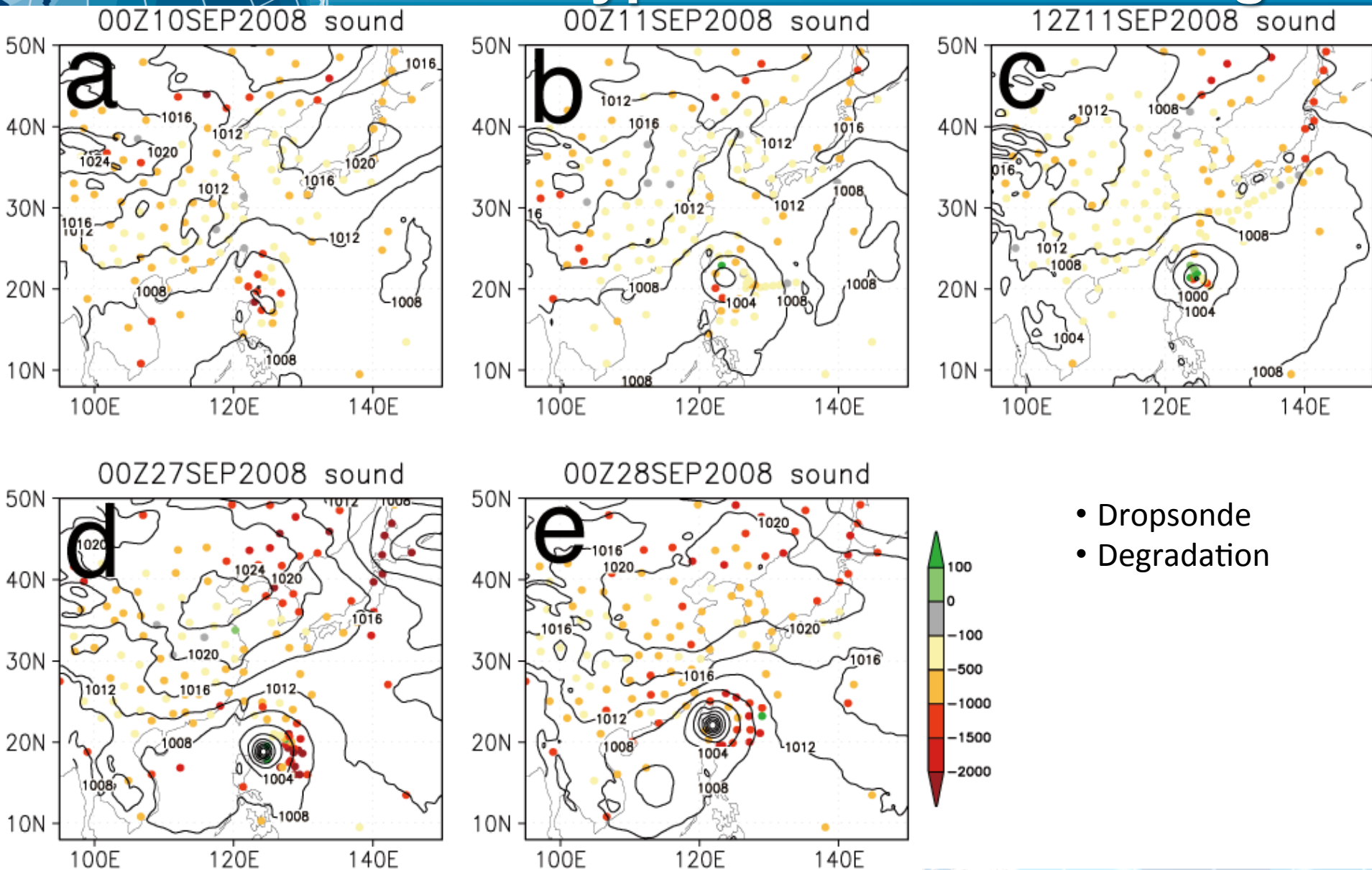 - This implies that the verifying analysis is partly correlated with the assimilated obs.
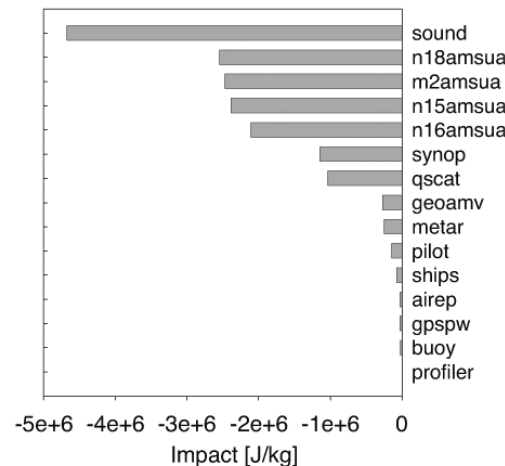
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- Dropsonde
- Degradation
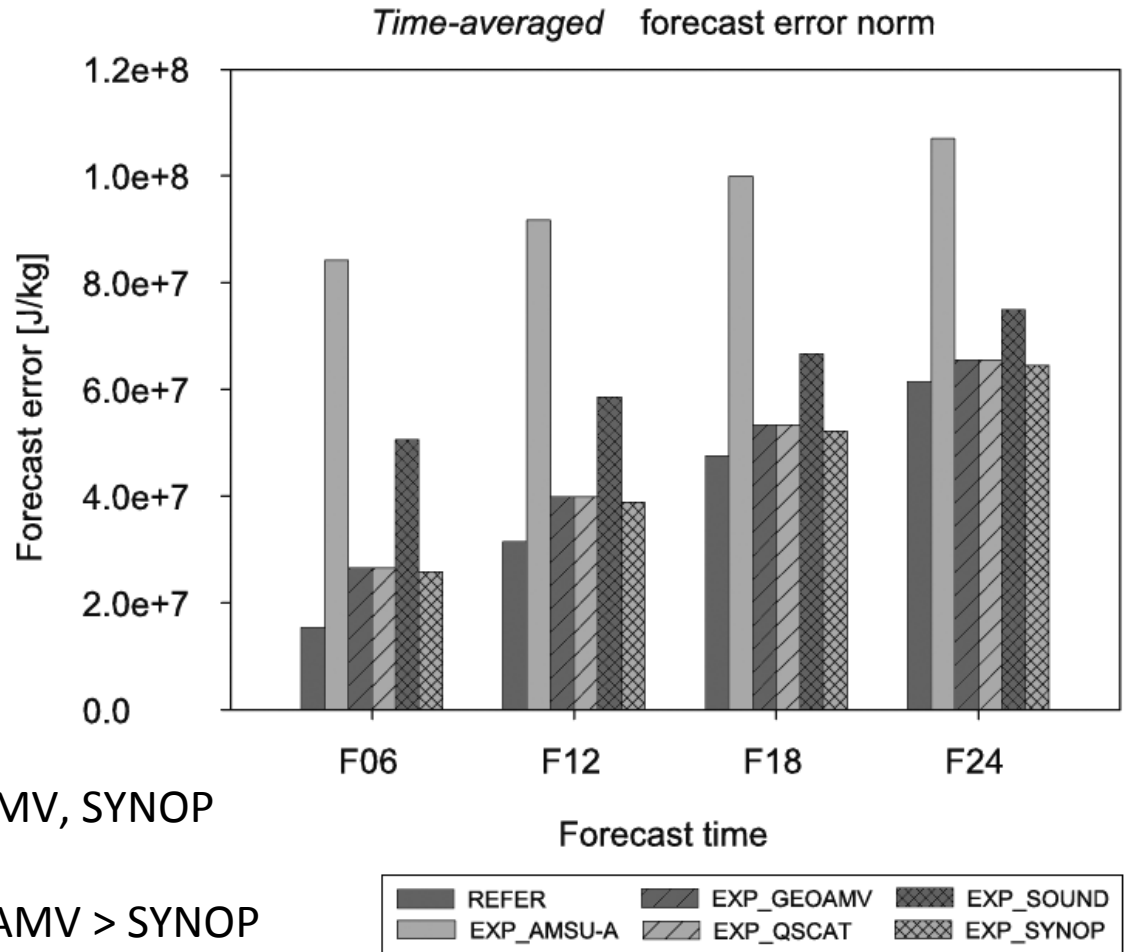
- Sensitivity to the error covariance parameters (Daescu and Todling 2010)
- Based on Le Dimet et al. (1997) and Daescu (2008)
- Result implies that the background error covariance is over-estimated,
  while the observation error variance is under-estimated.

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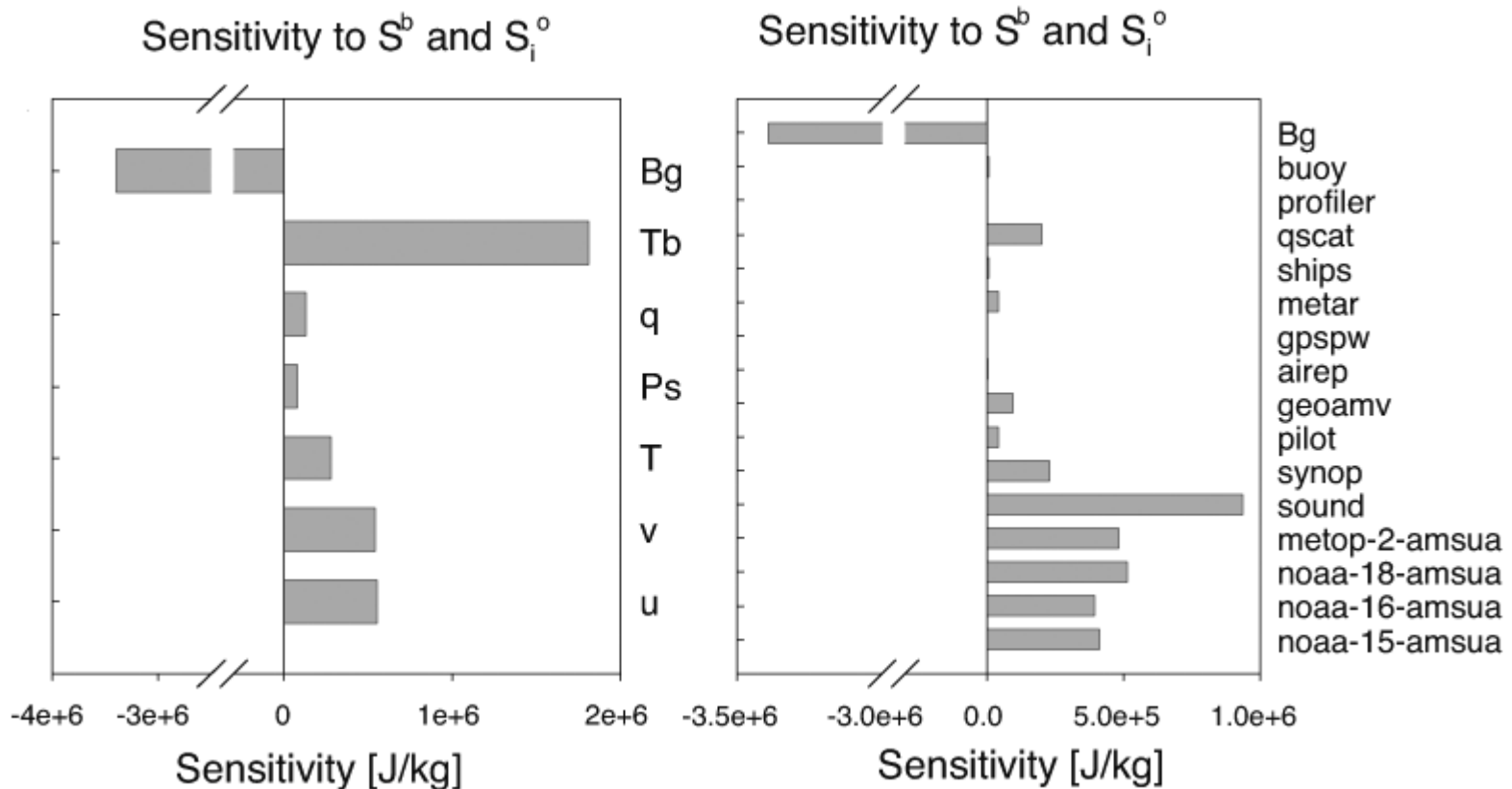
Observing System Experiments

Time-averaged forecast error norm

OSE impact

AMSU-A > SOUND > QSCAT, GEOAMV, SYNOP

Adjoint-based impact

AMSU-A > SOUND > QSCAT > GEOAMV > SYNOP

Qualitatively similar result for major obs. Types
Consistent with Gelaro and Zhu (2009) and Caldinali (2009)

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- The observation impact can be simultaneously assessed in a routine manner with FSO.

- Interpretation is not straightforward.
  - Observation with $\delta e > 0$ may be due to problems with quality control, observation operator, surface emissivity, bias in background field,,,

- FSO can give a comprehensive information on how the observing systems affect the overall forecast skill of the NWP systems.

- Issues...
  - Validity of linear assumption (forecast lead time)
  - Effect of moist linear physics
  - Choice of norms
  - Effect of lateral boundary

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