Estimation of Forecast Sensitivity to Observations within KIAPS-LETKF data assimilation system

Ji-Sun Kang*, Byoung-Joo Jung*, Youngsoon Jo*, and Yoichiro Ota#

*Korea Institute of Atmospheric Prediction Systems (KIAPS)
#Japanese Meteorological Agency (JMA)
KIAPS-LETKF data assimilation system has been developed for cubed-sphere grid model (e.g. NCAR CAM-SE, KIAPS-GM now being developed).

- We have examined the KIAPS-LETKF system in various simulation experiments, and have successfully assimilated real data (conventional data from NCEP prepbufr) into the system.
  
  "Posters of Dr. Jung and Ms. Jo"

- Now, (AMSU-A and IASI) radiance data assimilation using RTTOV and GPS RO data assimilation using ROPP are in progress.

- We also would like to estimate observation impact using EFSO technique introduced by Kalnay et al. (2012) within KIAPS-LETKF.
Ensemble Forecast Sensitivity to Observations (EFSO)

- Estimating forecast sensitivity to observations, without TLM/ADJ of the model
  - Kalnay et al. (2012) has introduced a simple formula to estimate forecast sensitivity to observations, within an ensemble data assimilation cycle.
  - Ota et al. (2013) has applied the method of Kalnay et al. (2012) to NCEP GFS-EnSRF data assimilation system and has shown promising results.

We decided to implement this method to KIAPS-LETKF system

Fig. 2. Estimated average 24-hour forecast error reduction contributed from each observation type (moist total energy, J kg\(^{-1}\)). (a) represents the total error reduction and (b) represents error reduction per observation.

(Ota et al. 2013)
Ensemble Forecast Sensitivity to Observations (EFSO)

- Forecast error reduction is defined as
  \[ J = e_{t|0}^T C_{jj} e_{t|0} - e_{t|-6}^T C_{jj} e_{t|-6} \]
  - Here, \( e_{t|0} = \bar{X}_{t|0} - X_t \), \( e_{t|-6} = \bar{X}_{t|-6} - X_t \) (\( X_t \) should be the best estimate of true atmosphere), and \( C_{jj} \) is a total moist energy norm.

- EFSO formula introduced by Kalnay et al. (2012)
  \[
  (\Delta e^2)_{j,l} = \frac{1}{K-1} \left( \delta y_0 \right)_l \left[ \rho_j R^{-1} Y_0^{a T} \left( X_{t|0}^{f T} \right)_j C_{jj} \left( e_{t|0} + e_{t|-6} \right)_j \right]_l,
  \]
In order to estimate observation impact at time $t$, forecast fields valid at $t+\tau$ are used.

- Observation impact tends to be advected and diffused as a result of atmospheric flow during the forecast hours.

- We need to localize information.

Kalnay et al. (2012) shows different results from several localization functions.

- As $\tau$ increases, no localization case gives better performance.
Localization Function in Kalnay et al. (2012)

- NoLoc gives better results than other localization function cases (NL-loc and CL-loc) as the forecast lead time increases.
- NL-loc is not feasible for real case due to too much computational cost, but CL-loc has significant underestimation.
- Therefore, we would like to try modifying localization function not only moving the center but also changing the radius of the function.
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- Therefore, we would like to try modifying localization function not only moving the center but also changing the radius of the function.

Table 2: Same as Table 1 but with 10 ensemble members and localization when indicated

<table>
<thead>
<tr>
<th></th>
<th>6 h</th>
<th>12 h</th>
<th>1 d</th>
<th>2 d</th>
<th>3 d</th>
<th>5 d</th>
<th>7 d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth</td>
<td>-23 (0)</td>
<td>-32 (0)</td>
<td>-56 (0)</td>
<td>-121 (2)</td>
<td>-213 (6)</td>
<td>-582 (27)</td>
<td>-1144 (47)</td>
</tr>
<tr>
<td>Analysis</td>
<td>-25 (0)</td>
<td>-31 (0)</td>
<td>-51 (0)</td>
<td>-115 (2)</td>
<td>-206 (6)</td>
<td>-570 (27)</td>
<td>-1126 (46)</td>
</tr>
<tr>
<td>(4-ADJ)</td>
<td>-21 (0)</td>
<td>-25 (0)</td>
<td>-39 (0)</td>
<td>-77 (1)</td>
<td>-132 (4)</td>
<td>-344 (17)</td>
<td>-627 (52)</td>
</tr>
<tr>
<td>(5-OLD) Noloc</td>
<td>-12 (0)</td>
<td>-14 (0)</td>
<td>-24 (1)</td>
<td>-50 (3)</td>
<td>-69 (4)</td>
<td>136 (22)</td>
<td>1163 (65)</td>
</tr>
<tr>
<td>(6-NEW) Noloc</td>
<td>-32 (0)</td>
<td>-39 (0)</td>
<td>-62 (1)</td>
<td>-133 (4)</td>
<td>-227 (6)</td>
<td>-574 (41)</td>
<td>-1220 (80)</td>
</tr>
<tr>
<td>(5-OLD) Fxloc</td>
<td>-25 (0)</td>
<td>-30 (0)</td>
<td>-47 (0)</td>
<td>-89 (2)</td>
<td>-117 (4)</td>
<td>-9 (9)</td>
<td>486 (29)</td>
</tr>
<tr>
<td>(6-NEW) Fxloc</td>
<td>-28 (0)</td>
<td>-33 (0)</td>
<td>-50 (0)</td>
<td>-86 (2)</td>
<td>-106 (4)</td>
<td>-125 (11)</td>
<td>-162 (29)</td>
</tr>
<tr>
<td>(6-NEW) NL-loc</td>
<td>-24 (0)</td>
<td>-24 (0)</td>
<td>-47 (0)</td>
<td>-107 (2)</td>
<td>-178 (4)</td>
<td>-422 (27)</td>
<td>-788 (57)</td>
</tr>
<tr>
<td>(6-NEW) CL-loc</td>
<td>-28 (0)</td>
<td>-33 (0)</td>
<td>-54 (0)</td>
<td>-99 (2)</td>
<td>-151 (5)</td>
<td>-284 (18)</td>
<td>-462 (30)</td>
</tr>
</tbody>
</table>

\[ J = e_{t|0}^T C_{jj} e_{t|0} - e_{t|6}^T C_{jj} e_{t|6} \]

(6-NEW): \( (\Delta e)^2 \) = \[ \frac{1}{K-1} \left( \delta y_0 \right)_{t} \left[ \rho_j \mathbf{R}^{-1} \mathbf{Y}_0 \left( \mathbf{X}_{t|0}^T \right) C_{jj} \left( e_{t|0} + e_{t|6} \right) \right] \]
How large the localization scale should be?

- We have estimated a time mean of nonlinear localization function (NL-Loc) of Kalnay et al. (2012).

As forecast lead time gets longer, the center of the localization function has been shifted. Also, *localization scale* gets remarkably larger!

(Kalnay et al. 2012)
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Fig. 5. Example of the evolution of the localization function with two methods. (a) Localization function with the non-linear incremental evolution (NL-loc); and (b) localization function moving with constant group velocity (CL-loc).
We have reproduced the table as shown in the previous slide and compare our estimation with a different localization function.

Results show that **WdLoc consistently outperforms ClLoc and NILoc** when the forecast lead time is greater than 6 hour.

– NILoc takes too long (~four times slower than others)

Thus, we conclude that localization scale changes the results significantly. In order to improve the result, we need to consider more sophisticated localization function in terms of its **width**.
Simple Experiment with Lorenz 40-var model

- We have reproduced the table as shown in the previous slide and compare our estimation with a different localization function.

<table>
<thead>
<tr>
<th></th>
<th>6 h</th>
<th>12 h</th>
<th>1 d</th>
<th>2 d</th>
<th>3 d</th>
<th>5 d</th>
<th>7 d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth</td>
<td>-23.4</td>
<td>-32.4</td>
<td>-56.06</td>
<td>-121.76</td>
<td>-214.38</td>
<td>-584.14</td>
<td>-1139.08</td>
</tr>
<tr>
<td>Analysis</td>
<td>-24.96</td>
<td>-30.74</td>
<td>-51.12</td>
<td>-115.06</td>
<td>-206.76</td>
<td>-572.46</td>
<td>-1121.2</td>
</tr>
<tr>
<td>FxLoc</td>
<td>-28.28</td>
<td></td>
<td>-33.54</td>
<td>-50.12</td>
<td>-86.46</td>
<td>-107.82</td>
<td>-124.52</td>
</tr>
<tr>
<td>NoLoc</td>
<td></td>
<td>-38.62</td>
<td>-62.48</td>
<td>-133.68</td>
<td>-227.8</td>
<td>-582.82</td>
<td>-1224.4</td>
</tr>
<tr>
<td>NlLoc</td>
<td></td>
<td>-24.4</td>
<td></td>
<td>-47.54</td>
<td>-107.26</td>
<td>-177.9</td>
<td>-416.3</td>
</tr>
<tr>
<td>WdLoc</td>
<td>-28.38</td>
<td></td>
<td>-33.54</td>
<td>-57.5</td>
<td>-118.98</td>
<td>-201.1</td>
<td>-509.34</td>
</tr>
</tbody>
</table>

- Results show that **WdLoc** consistently outperforms **ClLoc** and **NlLoc** when the forecast lead time is greater than 6 hours.
  - NlLoc takes too long (~four times slower than others)

- Thus, we conclude that localization scale changes the results significantly. In order to improve the result, we need to consider more sophisticated localization function in terms of its width.
Findings from Lorenz model experiments

- Tuning width of localization function with respect to forecast lead time changes results significantly.
  - Use of greater localization scales for longer forecast lead time improves the estimation of EFSO

- In more realistic system, it is not easy to define climatological localization scales as the case of Lorenz
  - We have considered several ways to tune the localization scales adaptively.
- **Moving the center of localization functions**
  - *without changing a localization scale*
  - “The coefficient that multiplies the average horizontal wind is tuned”

  ![Diagram](image)

  

\[
\begin{align*}
\Delta x &= u \Delta t \Rightarrow d\text{lon} \\
\Delta y &= v \Delta t \Rightarrow d\text{lat}
\end{align*}
\]

Information at the forecast time, collected for estimating an impact of the observation at A

\[
(\Delta e^2)_{j,l} = \frac{1}{K - 1} (\delta y_0)_l \left[ \rho_j R^{-1} Y_0^a \left( X_{t|0}^T \right)_j C_{jj} \left( e_{t|0} + e_{t|-6} \right)_j \right]_l,
\]

- Since it already computes displacement in zonal and meridional directions, we may use those values for the width of localization function
- Changing localization scale based on the moving distance
  - Circular shape of localization function as a standard
  - Its radius is defined by $r + \sqrt{\Delta x^2 + \Delta y^2}$

Information at the forecast time, collected for estimating an impact of the observation at A

$$\left(\Delta e^2\right)_{j,l} = \frac{1}{K-1} \left(\delta y_0\right)_l \left[ \rho_j R^{-1} y_0^a \left( X_{i|0}^T \right)_j C_{ji} (e_{i|0} + e_{i|-6})_j \right]_l,$$

(Kang et al. 2014, in prep.)
Various localization functions for EFSO – (1)

- Changing localization scale based on the moving distance
  - Circular shape of localization function as a standard
  - Its radius is defined by \( r + \sqrt{\Delta x^2 + \Delta y^2} \)

- Computational burden is increased a lot...

- \( \Delta x \) and \( \Delta y \) tend to be very much different
  - Suppose a jet region: \( \Delta x >> \Delta y \)

Information at the forecast time, collected for estimating an impact of the observation at A

\[
(\Delta e^2)_{j,l} = \frac{1}{K-1} \left( \delta y_0 \right)_l \left[ \rho_j R^{-1} Y_0^a \left( X_{l|0}^T \right)_j C_{jj} \left( e_{l|0} + e_{l|6} \right)_j \right]_l,
\]
Various localization functions for EFSO – (2)

- Changing localization scale based on the moving distance of x- and y-direction separately
  - Elliptic shape of localization function based on $\Delta X$ (dlon) and $\Delta Y$ (dlat)

- Computational cost is less than the previous treatment although it’s costly than Ota et al. (2013)

Information at the forecast time, collected for estimating an impact of the observation at A

(Kang et al. 2014, in prep.)
KIAPS-LETKF system implemented to NCAR CAM-SE model

- Resolution: ne16np4 (~2.5°) with 30 levels (~2hPa top)
- Observing System Simulation Experiments (OSSEs)
  - Sonde, surface Ps, and AIRS T and q retrieval data

Impact of localization strategies

- Compute $J = e_{t|0}^T C_{j,j} e_{t|0} - e_{t|-6}^T C_{j,j} e_{t|-6}$ at every model grid point, $J_m$
- Compute the same $J$, but at the observation space with different localization functions, $J_o$
- Compare global mean of $J_m$ and $J_o$
  - NO EFSO formula incorporated!
  - Assuming perfect FSO formula (w.r.t. truth), we can see the impact of localization function only.
As expected, forecast error reduction ($J_m$) becomes greater as the forecast lead time gets longer.

We will see how the estimations obtained at the observation space ($J_o$) with different localization methods look.
**J_m vs. J_o with different localization functions (τ=6hr)**

Jm vs. Jo (MOIST) w.r.t. TRUTH [tau=6hr]

<table>
<thead>
<tr>
<th></th>
<th>Jm</th>
<th>Jo_FxLoc</th>
<th>Jo_MV_Ota</th>
<th>Jo_MVnew</th>
<th>Jo_MVelp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time mean</td>
<td>-0.663</td>
<td>-0.773</td>
<td>-0.717</td>
<td>-0.735</td>
<td></td>
</tr>
</tbody>
</table>

(τ= 6hr)

**Perfect formula of J**

(No EFSO formula, but different localization strategies)
$J_m$ vs. $J_o$ with different localization functions ($\tau=24$hr)

**Jm vs. Jo (MOIST) w.r.t. TRUTH**

<table>
<thead>
<tr>
<th></th>
<th>$J_m$</th>
<th>$J_o_{FxLoc}$</th>
<th>$J_o_{MV_Ota}$</th>
<th>$J_o_{MV_new}$</th>
<th>$J_o_{MV_elp}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time mean</strong></td>
<td>-0.824</td>
<td>-0.920</td>
<td>-0.934</td>
<td>-0.873</td>
<td>-0.883</td>
</tr>
</tbody>
</table>

(No EFSO formula, but different localization strategies)
**J_m vs. J_o with different localization functions (τ=60hr)**

Jm vs. Jo (MOIST) w.r.t. TRUTH [tau=60hr]

<table>
<thead>
<tr>
<th></th>
<th>Jm</th>
<th>Jo_FxLoc</th>
<th>Jo_MV_Ota</th>
<th>Jo_MVnew</th>
<th>Jo_MVelp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time mean</td>
<td>-1.49</td>
<td>-1.69</td>
<td>-1.62</td>
<td>-1.55</td>
<td>-1.57</td>
</tr>
</tbody>
</table>

(τ= 60hr)

Perfect formula of J

(No EFSO formula, but different localization strategies)
Different strategies of localization function for estimating EFSO have been investigated.

- We have shown that tuning localization scales gives positive impact on the result, using Lorenz model and OSSEs with KIAPS-LETKF.
- OSSEs of KIAPS-LETKF system will also quantify how much EFSO estimates can be degraded by imperfect forecast error estimates (due to imperfect analysis), EFSO formula, etc.
- We are generating EFSO estimates now and will analyze the results carefully.

We will test this technique in KIAPS-LETKF with real data (conventional data, AMSU-A and IASI radiance data, and GPS RO data), which are in progress.