

Observation-space localization methods for the maximum likelihood ensemble filter

*Saori Nakashita¹ and Takeshi Enomoto^{2,3}

1. Graduate school of science, Kyoto University
2. Disaster Prevention Research Institute, Kyoto University
3. JAMSTEC APL



Which localization is suitable for nonlinear optimization?

Abstract

We compare localization schemes in the maximum likelihood ensemble filter^[1] (MLEF): two observation-space localizations (OL) and a combination of OL in the horizontal and state-space localization in the vertical (VSL). For nonlinear observations in the simplified atmospheric general circulation model, the OL with global optimization works better than that without optimization or with local optimization owing to a larger cost reduction. Moreover, the OL with global optimization shows comparable performance to VSL for nonlocal observations, suggesting that the global optimization can accommodate nonlinear and nonlocal observations such as satellites.

MLEF

Cost function with control variable transformation :

$$\mathbf{x} = \bar{\mathbf{x}}^f + \mathbf{P}_f^{\frac{1}{2}} \mathbf{w}, [\mathbf{P}_f^{\frac{1}{2}}]_i = \mathbf{p}_i^f = (K - 1)^{-\frac{1}{2}} (\mathbf{x}_i^f - \bar{\mathbf{x}}^f)$$

$$2J = \mathbf{w}^T \mathbf{w} + [\mathbf{y} - H(\mathbf{x})]^T \mathbf{R}^{-1} [\mathbf{y} - H(\mathbf{x})]$$

Analyses are obtained from the optimization of J .

$$\bar{\mathbf{x}}^a = \bar{\mathbf{x}}^f + \mathbf{P}_f^{\frac{1}{2}} \mathbf{w}^{\text{opt}}, \mathbf{P}_a^{\frac{1}{2}} = \mathbf{P}_f^{\frac{1}{2}} [\nabla^2 J(\mathbf{w}^{\text{opt}})]^{-\frac{1}{2}}$$

If H is linear, the analysis is equivalent to ETKF.

Single observation assimilation

Model: SPEEDY^[7] T30L7

Ensemble size: 20

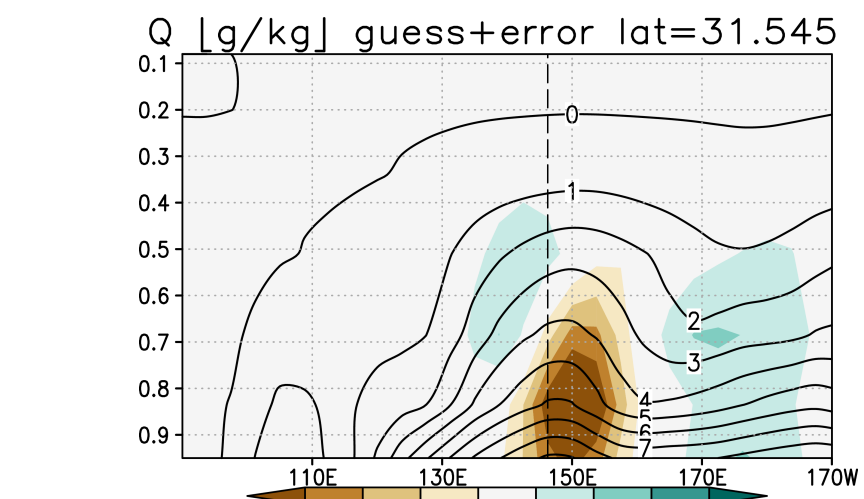
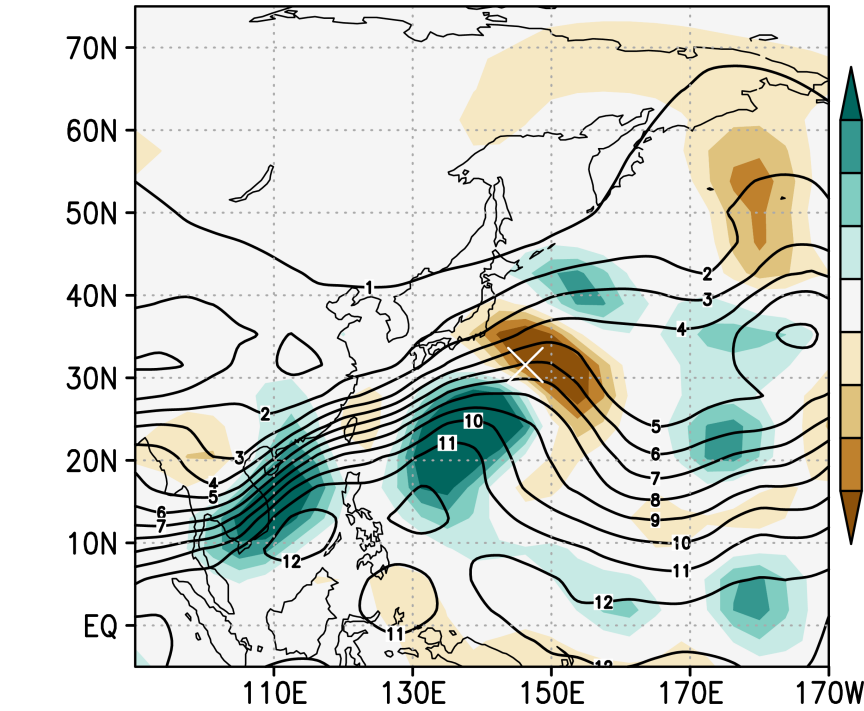
Localization scale:

900 km (H), 0.1 ln p (V)

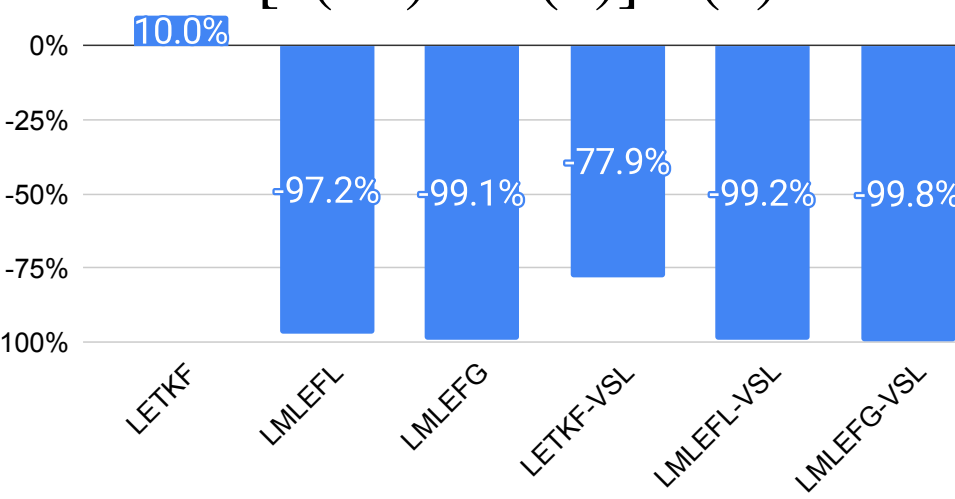
Observation
(146.3E, 31.5N):

$$\int_{\sigma=0.95}^{\sigma=0.51} \ln Q \, d\sigma$$

Q [g/kg] guess+error sig=0.835

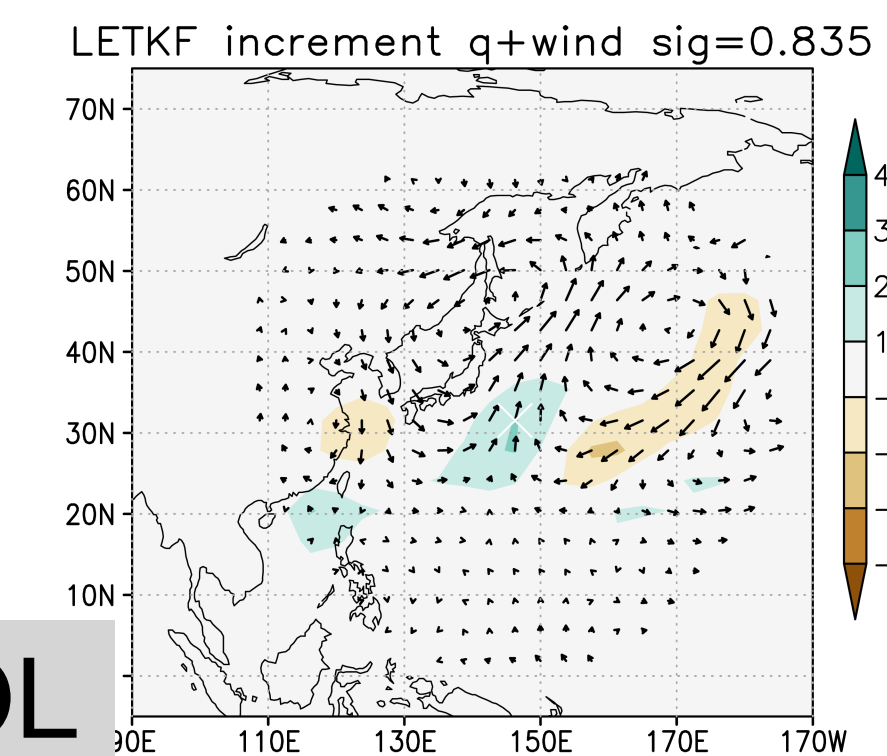


$[J(\mathbf{w}^a) - J(0)]/J(0)$



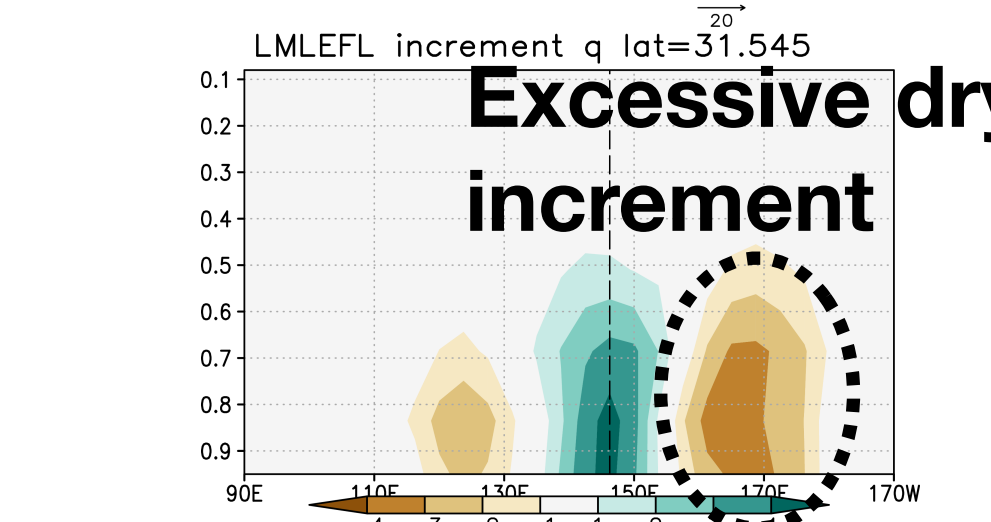
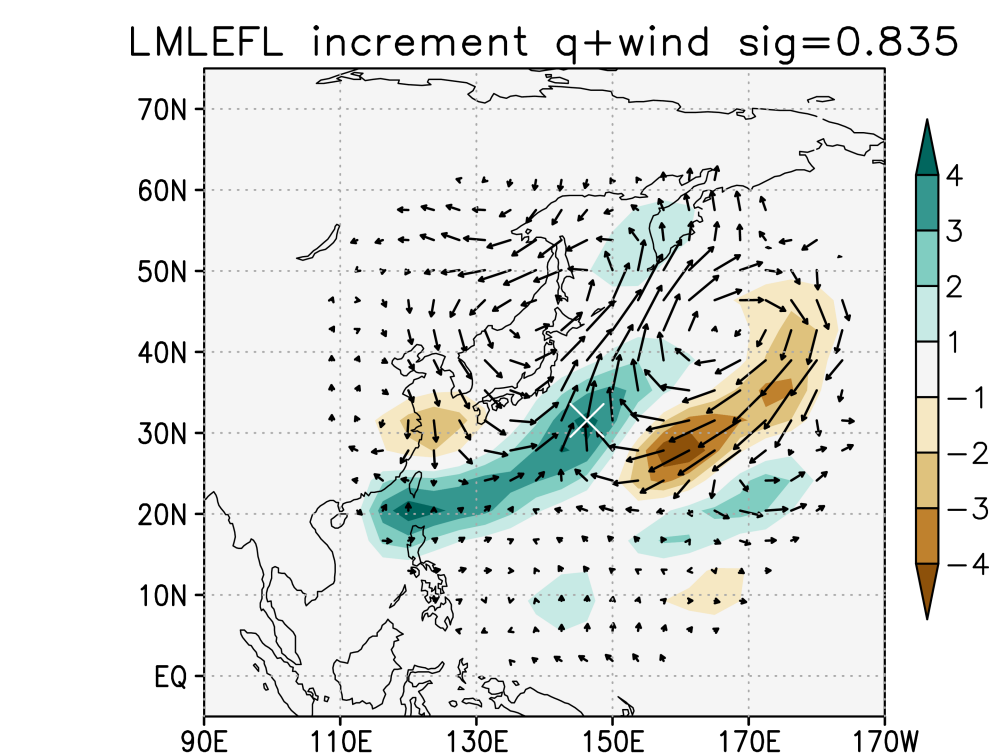
More effective with VSL

No optimization:
little modification

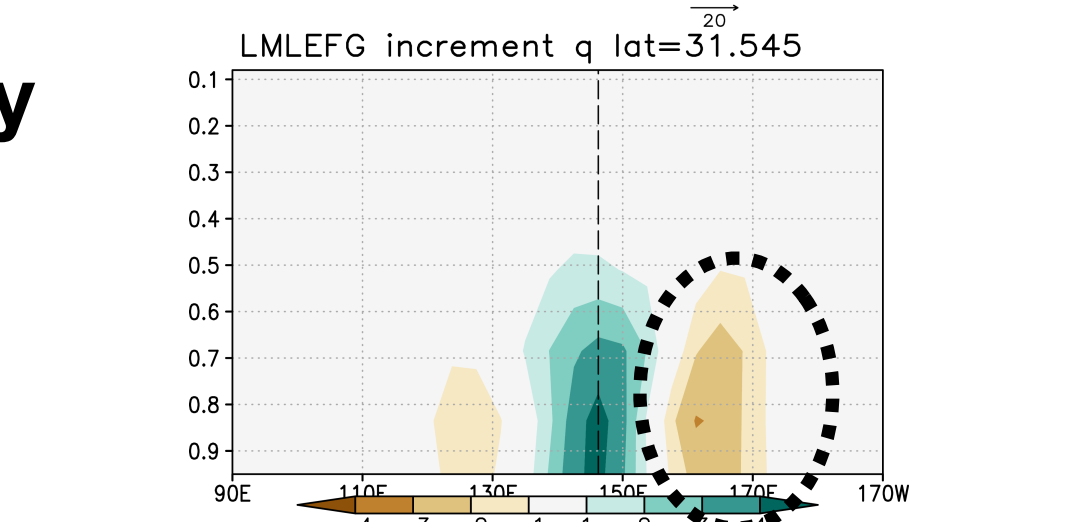
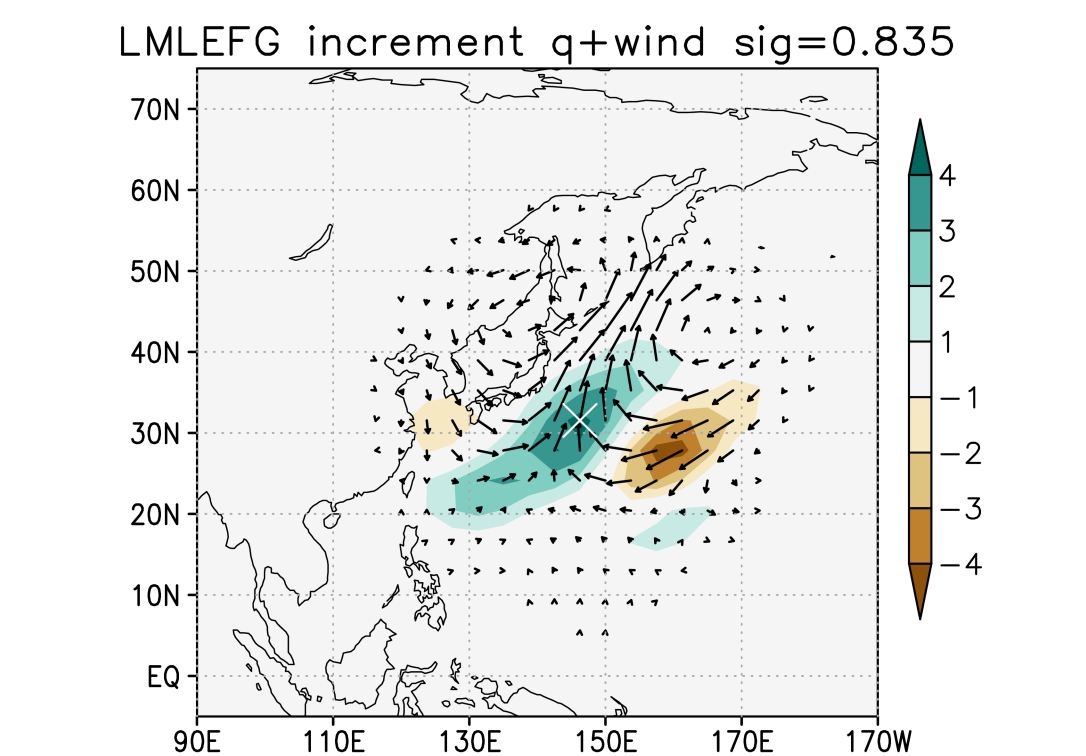


OL

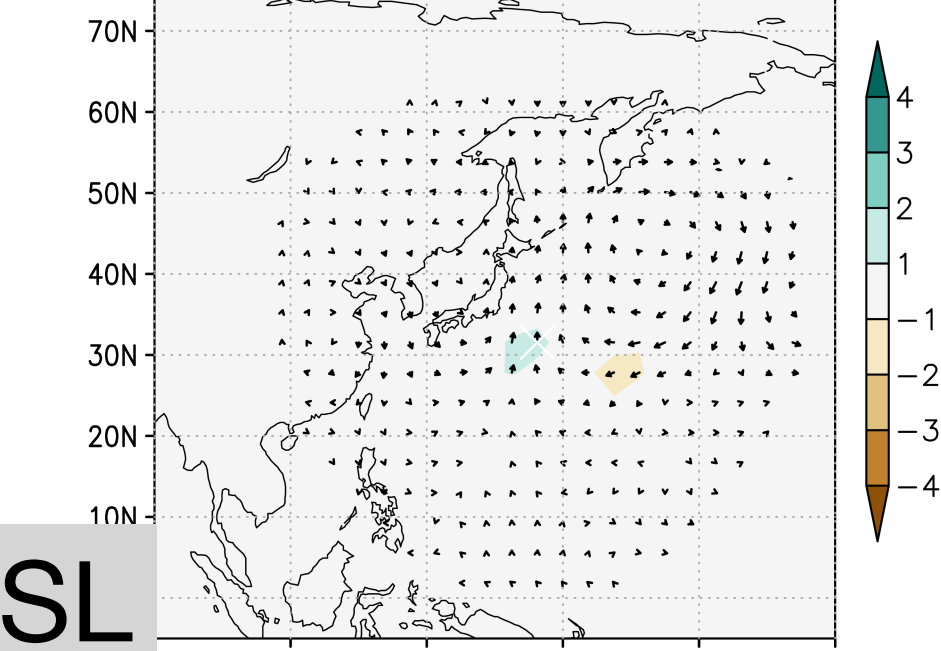
Local optimization:
broad impact



Global optimization:
severe localization

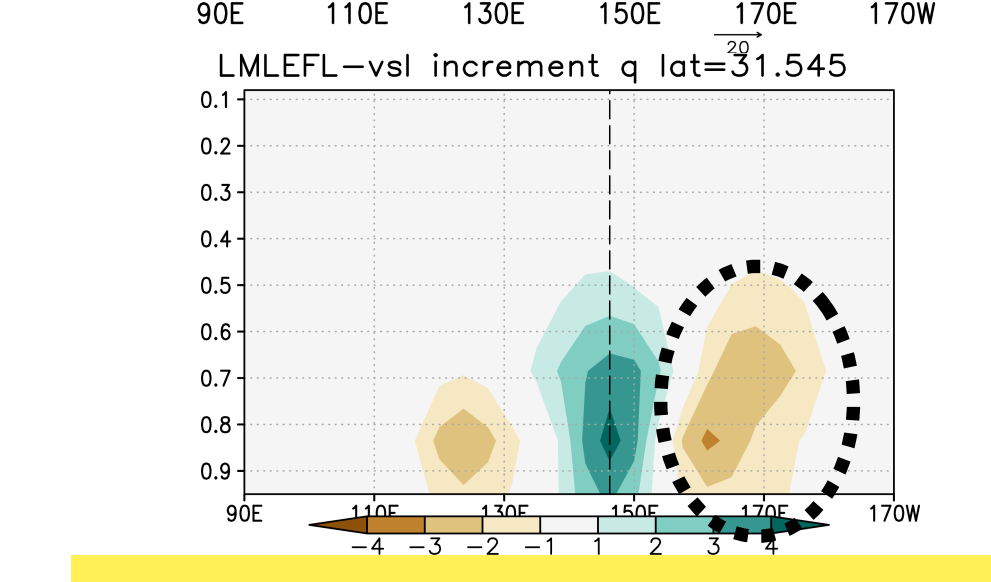
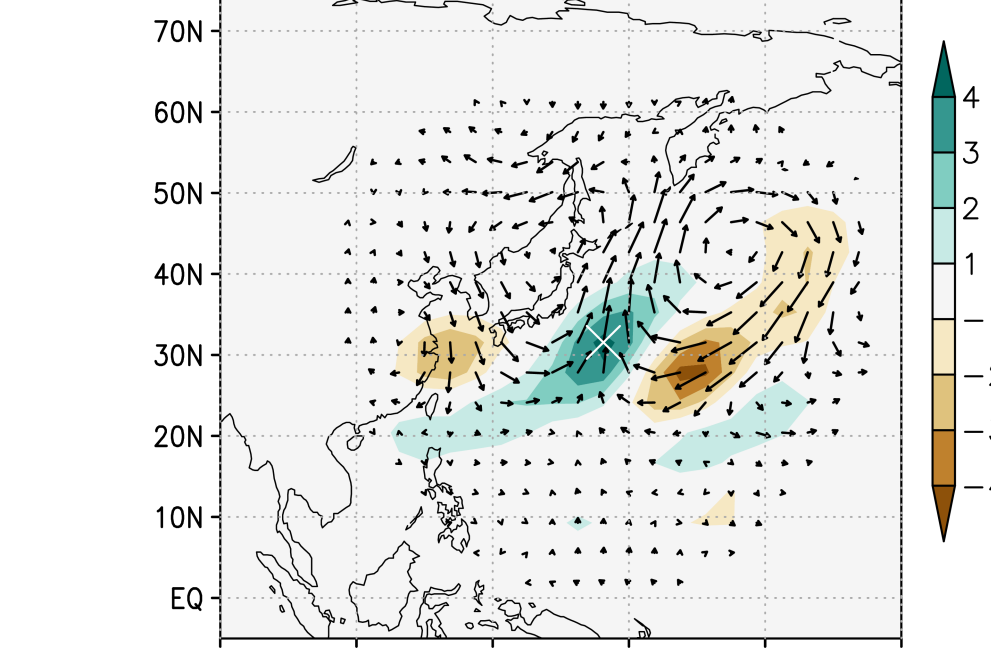


LETKF-vsl increment q+wind sig=0.835

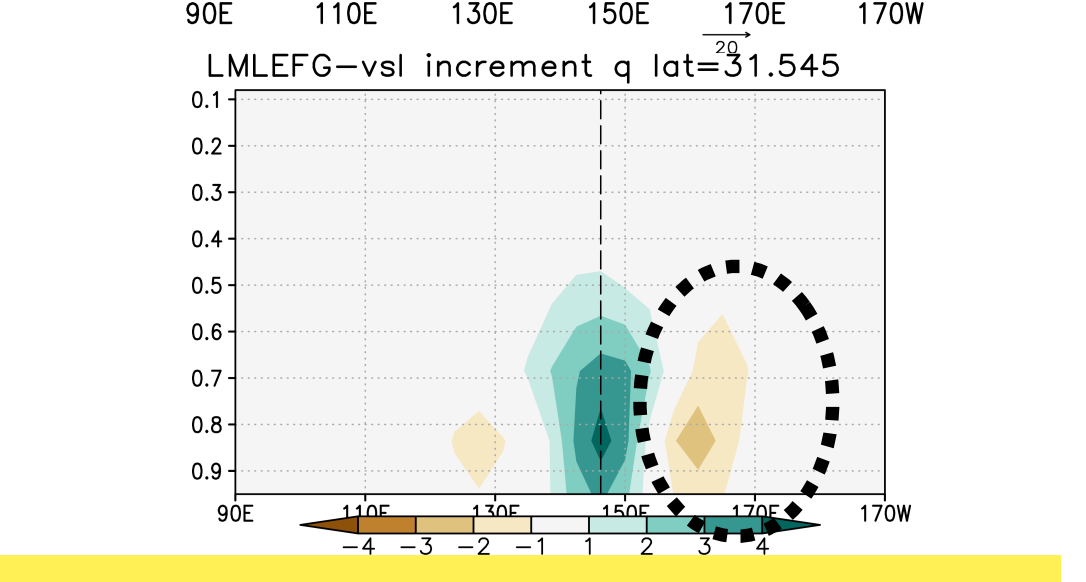
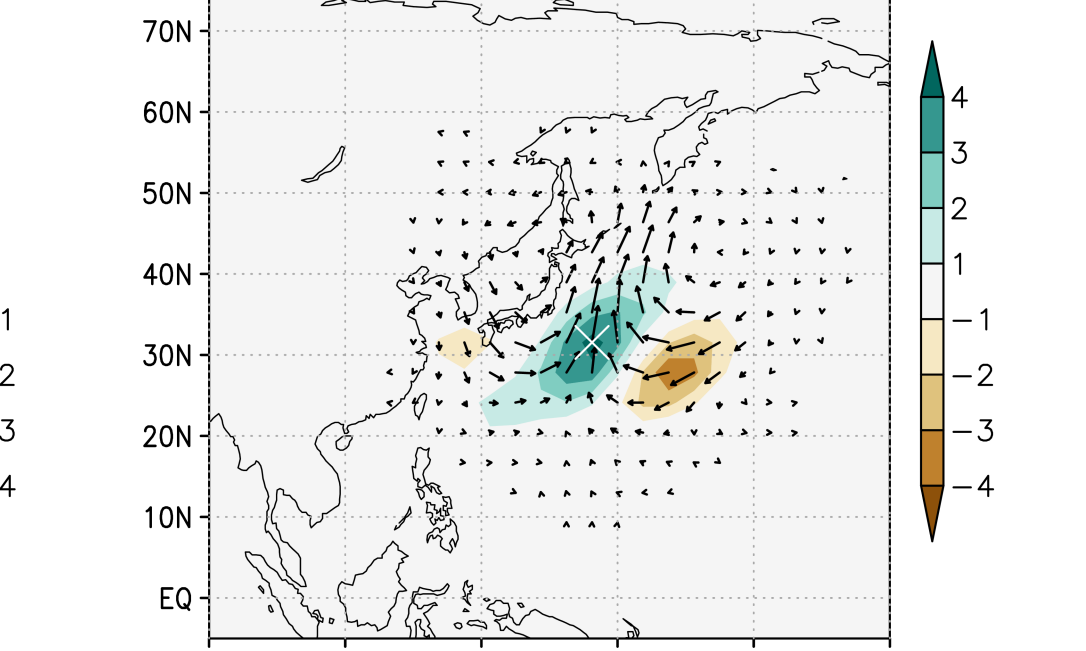


VSL

LMLEFL-vsl increment q+wind sig=0.835



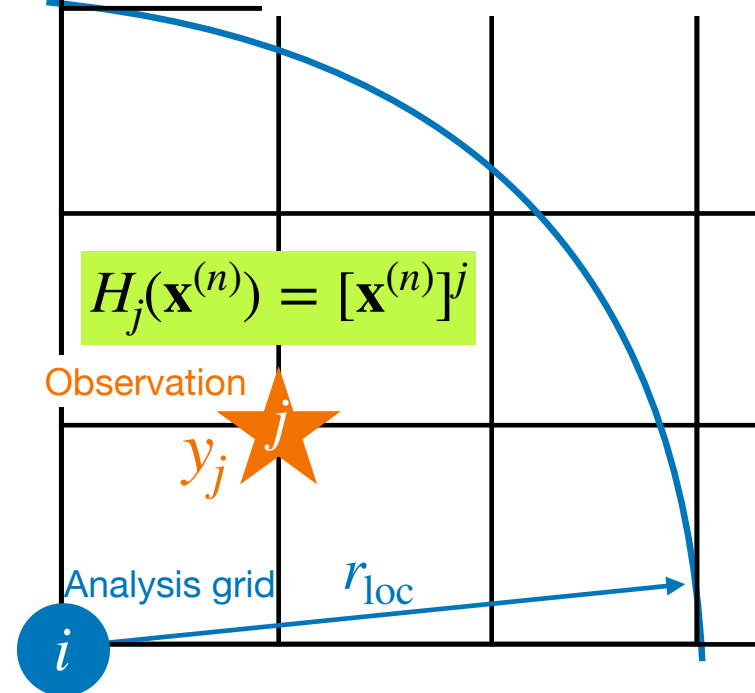
LMLEFG-vsl increment q+wind sig=0.835



VSL and global OL ameliorates negative dry increment.

Optimization with OL

Consider local cost at n -th iteration.



$$J_i^{(n)} = \frac{1}{2} \mathbf{w}_i^{(n)\top} \mathbf{w}_i^{(n)} + \frac{1}{2} [\mathbf{y} - H(\mathbf{x}^{(n)})]^\top \mathbf{R}_i^{-1} [\mathbf{y} - H(\mathbf{x}^{(n)})]$$

$$\nabla_{\mathbf{w}} J_i^{(n)} = \mathbf{w}_i^{(n)} - \mathbf{Z}_i^{(n)\top} \mathbf{R}_i^{-1/2} [\mathbf{y} - H(\mathbf{x}^{(n)})]$$

$$\mathbf{Z}_i^{(n)} = \mathbf{R}_i^{-1/2} [H(\mathbf{x}^{(n)} + \mathbf{X}_f) - H(\mathbf{x}^{(n)})]$$

\mathbf{w} around y_j are required to update $H_j(\mathbf{x})$, which prevents independent analysis of OL.

Global optimization (LMLEFG)
Update $\mathbf{x}^{(n)}$ globally in each iteration^[2,3]. This is equivalent to minimizing $\sum_i J_i$.

Local optimization (LMLEFL)
Update $[\mathbf{x}^{(n)}]^j$ by $\mathbf{w}_i^{(n)}$ assuming locally constant weights^[4]. J_i are minimized independently.

Vertical state-space localization

A square root of vertically localized \mathbf{P}_f is constructed by modulated ensemble^[5,6]:

$$\mathbf{P}_{loc}^{\frac{1}{2}} = [\dots, \text{Diag}(\mathbf{p}_i^f) \mathbf{L}_v^{\frac{1}{2}}, \dots]$$

The augmented ensemble size becomes $K \times N_v$ (number of vertical layers). The K analysis ensemble for each vertical column is obtained from the modified gain formulation^[6].

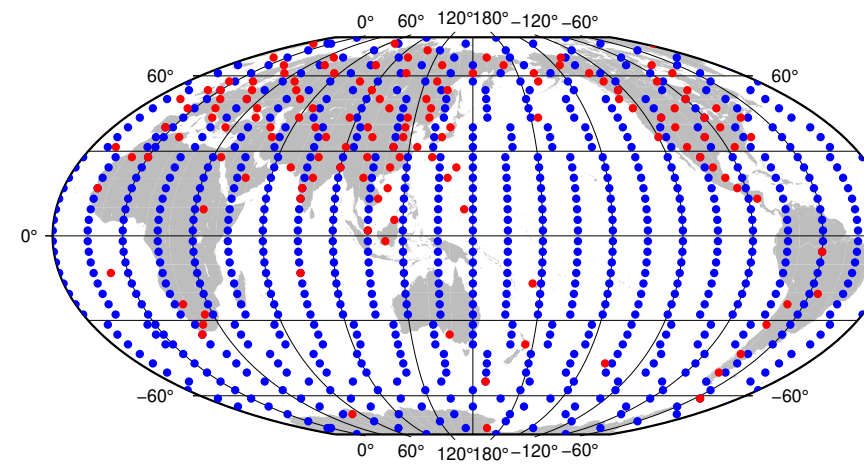
References

[1] Zupanski, M. 2005: *MWR*, 133, 1710–1726.
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 [8] Miyoshi, T. 2011: *MWR*, 139, 1519–1535.

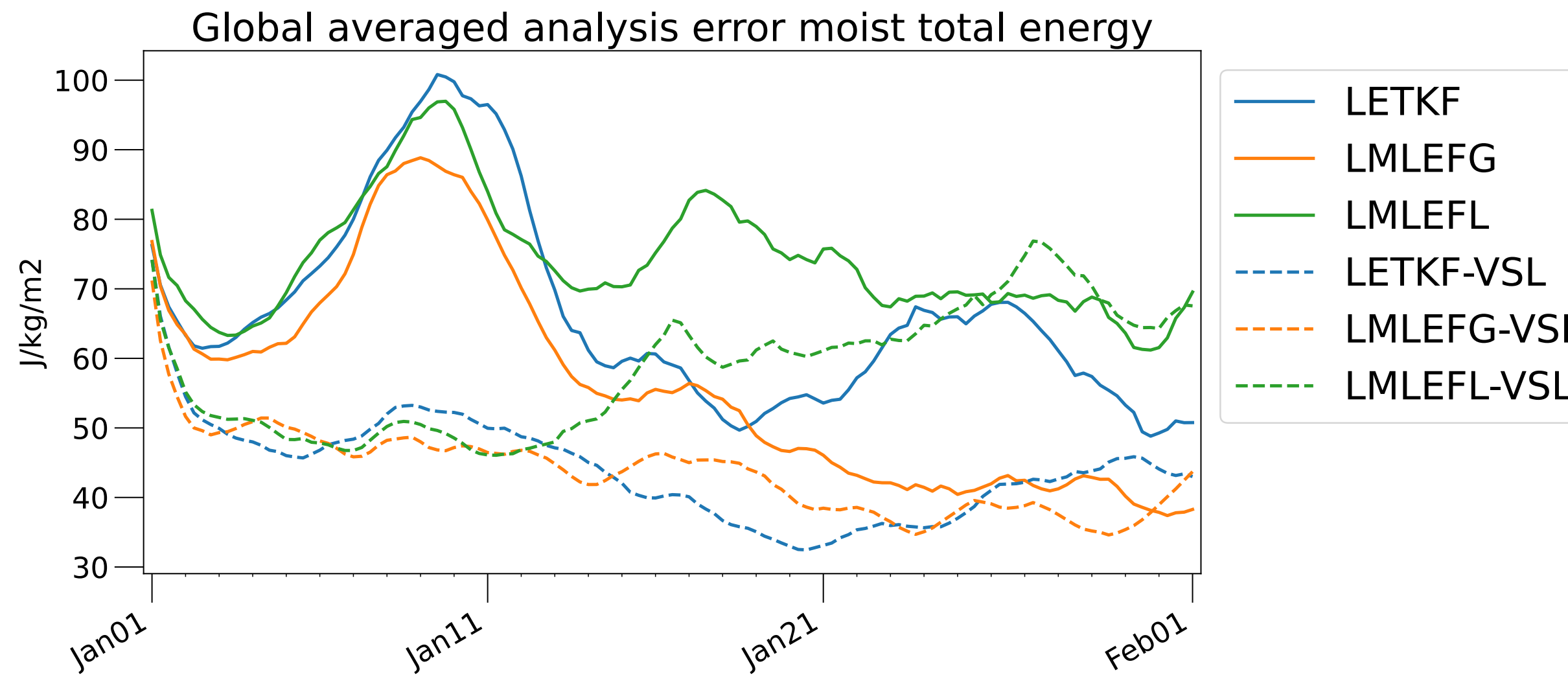
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Cycling experiments

Inflation: adaptive multiplicative^[8]
 Experimental period: January
 Cycling interval: 6 hours



Observations
Linear (139): U, V, T (7 levels), Q (4 levels), Ps
Nonlinear (748) $\int \ln Q \, d\sigma$



- VSL shows better performance than OL in the early cycles.
- The global optimization with OL reaches comparable quality to VSL in later cycles.
- The local optimization may deteriorate the analysis in the dense observed area.

