Validation of a New Algorithm for Empirical Localization of Observations for Ensemble Kalman Filter Data Assimilation in a Global Atmospheric Model

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Motivation

- The ensemble Kalman filter (EnKF) uses sample statistics from an ensemble model forecast to estimate flow-dependent background error covariance to determine how an observation modifies the background fields (Evensen 1994).
- Small ensembles lead to spurious correlations between observations and state variables, especially for large separations.
- Localization, a technique to 'localize' the impact of an observation to nearby state variables, reduces spurious error correlations.

Definition of Covariance Localization

Given N ensemble increments for observation y, increments for state variable x are:

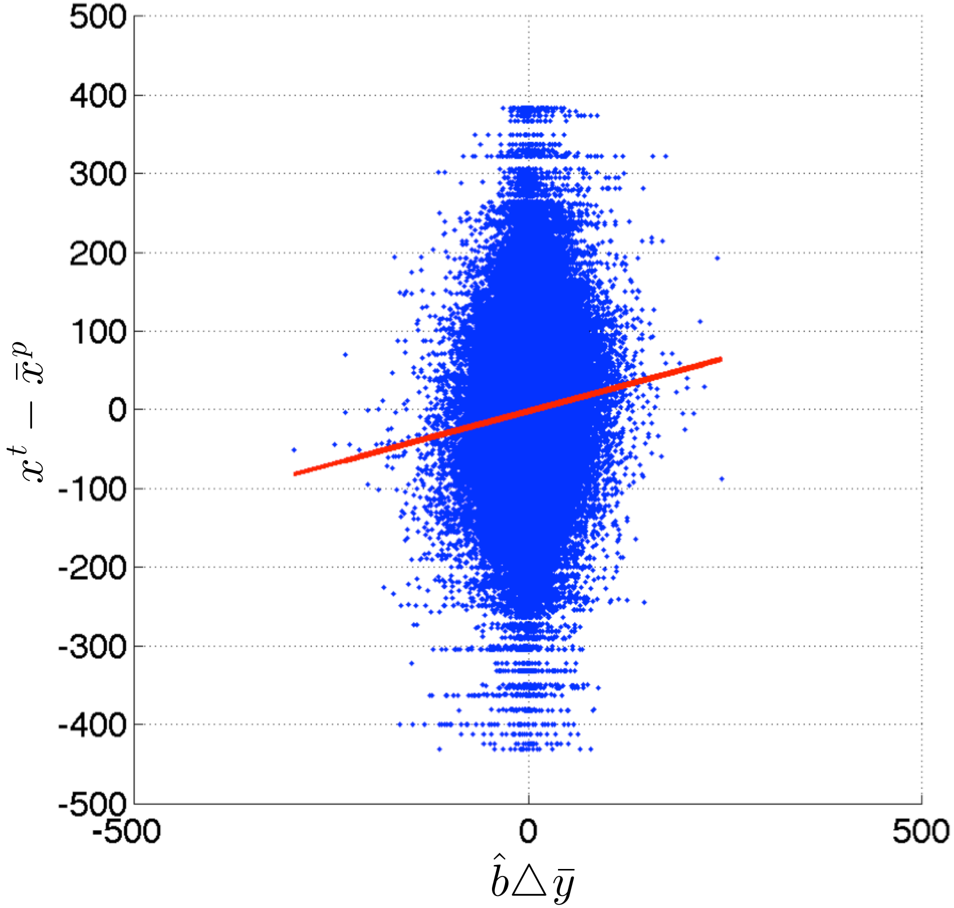
$$\Delta x_n = \alpha \hat{b} \Delta y_n, \quad n = 1, \ldots, N$$

where $\hat{b}$ is a sample regression coefficient,

and α is a localization.

Empirical localization

1. Compute separation between each pair of an observation and a state variable;
2. Divide the set of all pairs into subsets using the separation;
3. Compute the localization for each subset.



The abscissa is the mean observation increment, and the ordinate is the prior mean error. These two quantities are plotted for each pair of a pressure observation and a pressure state variable (blue dots) with separation between (0.45 0.5].

The slope of the least squares fit is the localization α that minimizes the RMS difference between the increments and prior errors:

$$\alpha = \frac{\sum_{k=1}^{K}\left(x_k^t - \bar{x}_k^p\right)\hat{b}_k \Delta\bar{y}_k}{\sum_{k=1}^{K}\left(\hat{b}_k \Delta\bar{y}_k\right)^2}$$

The slope of the least squares fit is also the localization α that minimizes the RMS difference between the posterior ensemble means and true values of the state variable in the subset:

$$J = \sqrt{\sum_{k=1}^{K}(\bar{x}_k^u - x_k^t)^2} = \sqrt{\sum_{k=1}^{K}\left(\bar{x}_k^p + \alpha\hat{b}_k\Delta\bar{y}_k - x_k^t\right)^2}$$

Experimental Design

- An OSSE is conducted using the Data Assimilation Research Testbed (DART) / Community Atmospheric Model (CAM) system (Raeder et al. 2012).
- The forecast model is CAM5 (Neale et al. 2010), the atmospheric component of the Community Earth System Model version 1 (CESM1; Gent et al. 2011).
- The default configuration of the Atmospheric Model Intercomparison Project (AMIP; Gates 1992) protocol is used.
- The model uses a finite volume grid with approximately 2° resolution (94x144), and has 30 vertical levels.

Experimental Design

- The data assimilation system is the DART (Anderson et al. 2009) ensemble adjustment Kalman filter (EAKF; Anderson 2001).
- Spatially- and temporally-varying state space adaptive inflation (Anderson 2009) is applied.
- Sampling error correction (Anderson 2012) is used.
- Default localization is Gaspari-Cohn (Gaspari and Cohn 1999) with the vertical distance converted to equivalent radians by normalizing the pressure difference between an observation and a state variable by 1000 hPa .

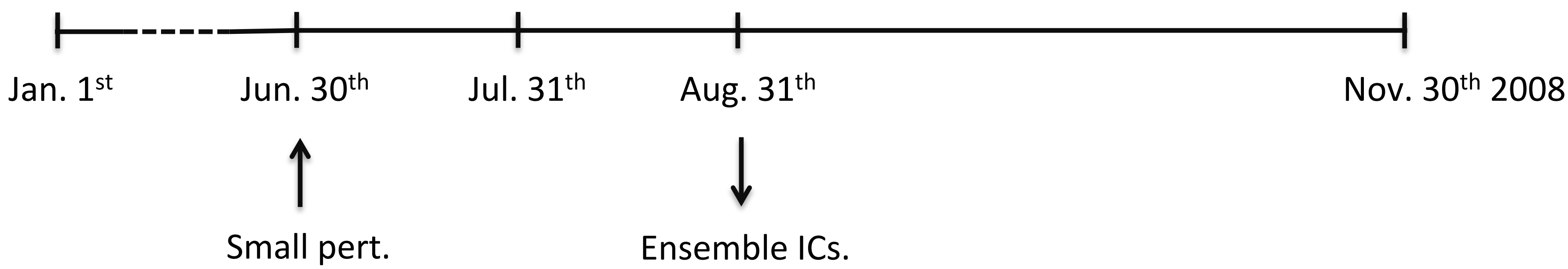
Experimental Design

- The nature run is obtained by advancing the forecast model from an initial condition at 00GMT 1 January 2008 to 12GMT 30 November 2008.
- Synthetic observations of temperature and zonal and meridional winds are generated by adding random draws from a normal distribution with mean 0 and specified observation error variances to spatially interpolated values from the gridded true state.
- Observation error variances are 1 K^2 for temperature and 4 m^2/s^2 for zonal and meridional winds.
- Observations are nearly uniformly distributed in the horizontal (600 profiles on the sphere) and range from 1000 to 5 hPa in the vertical on standard mandatory pressure levels.
- There are 27000 synthetic observations available every 12 hours.

Experimental Design

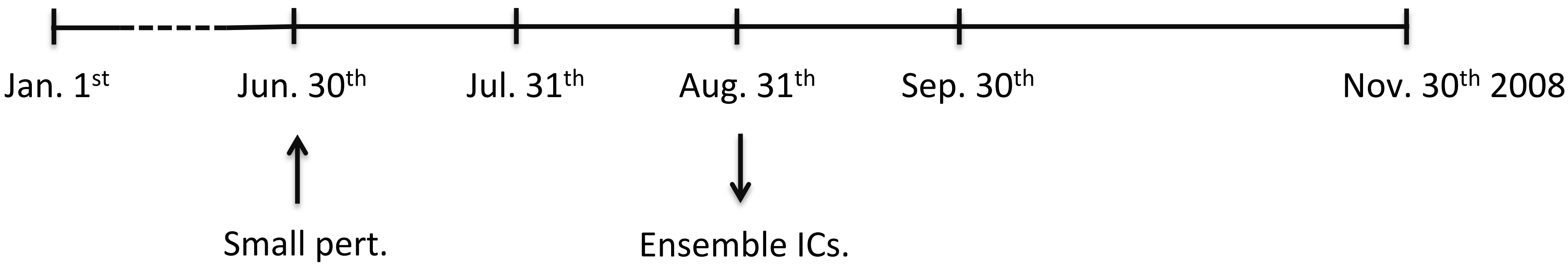
- Adding small perturbations to the temperature field of the true state at 00GMT 30 June 2008 generates N=80 perturbed states.
- These are advanced to 12 GMT 31 July 2008 resulting in N ensemble members that are random draws from the model's climatological distribution.

Experimental Design



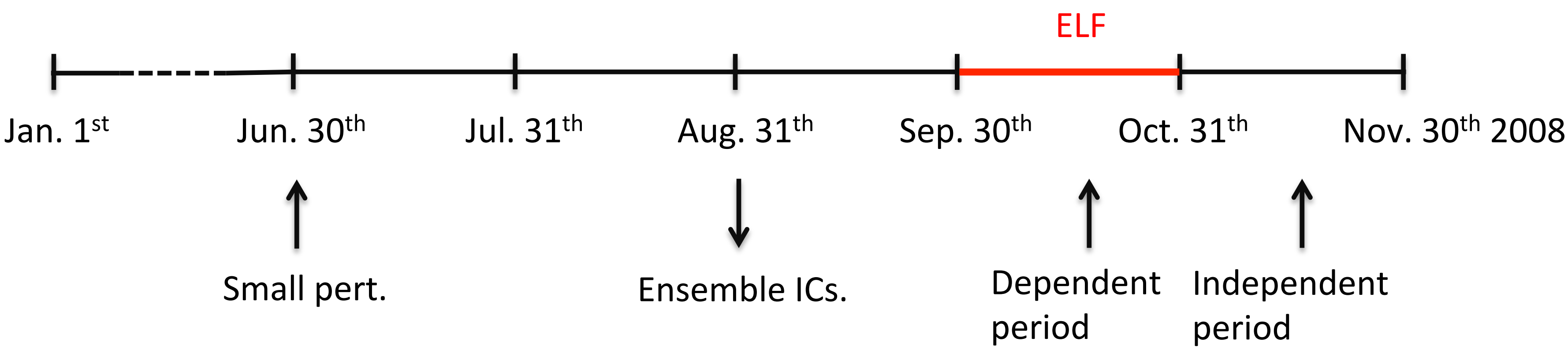
- Synthetic observations are assimilated every 12 hours from 00 GMT 1 August to 12 GMT 31 August 2008.
- Ensemble analyses at 12 GMT August 31 are initial conditions for assimilation experiments.

Experimental Design



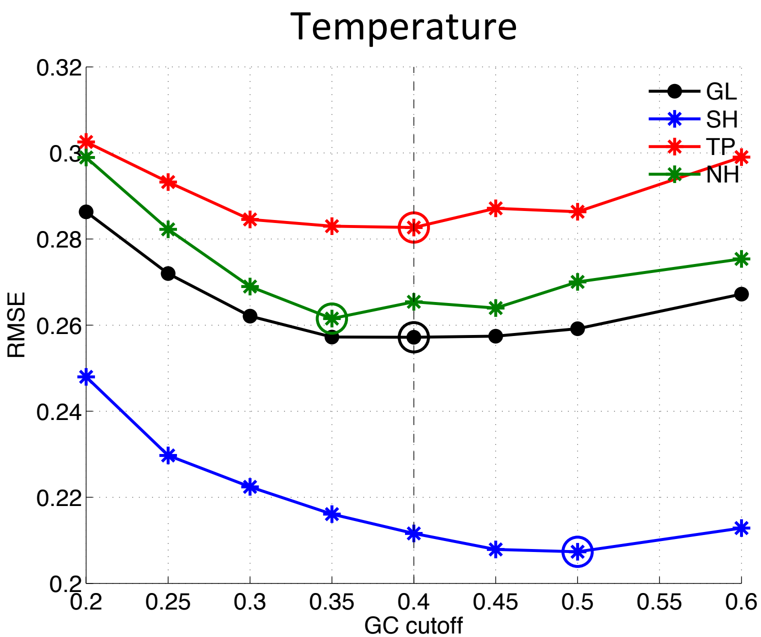
- From 12 GMT 31 August 31 to 12 GMT 30 September 30 2008, assimilation experiments are conducted to find the optimal value GC halfwidth.
- 10 days are discarded to eliminate transients; the last 20-days are used.

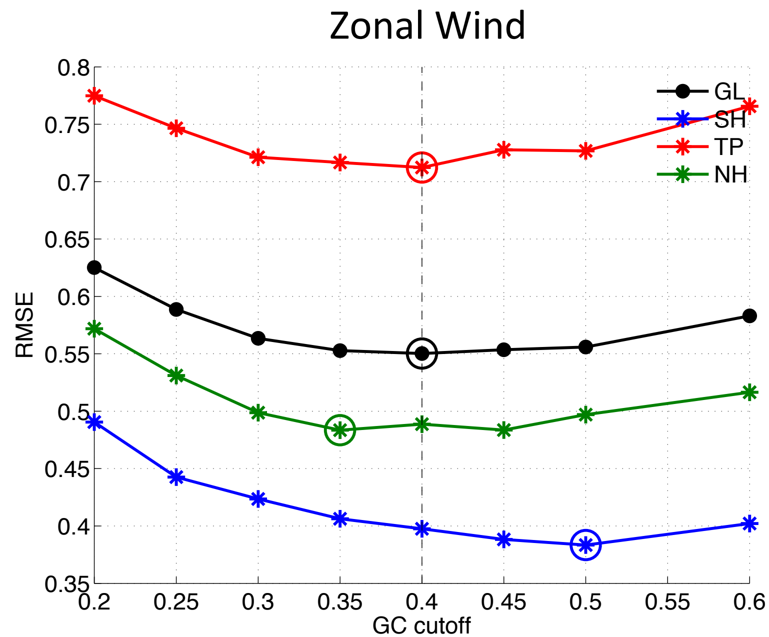
Experimental Design



- An assimilation experiment with GC halfwidth 0.2 (GC0.2) is conducted from 12 GMT 31 August 31 to 12 GMT 30 November.
- Results from second month (October) are used to compute ELFs.
- Additional assimilation experiments using the computed ELFs also start at 12 GMT 31 August.
- ELFs are iteratively computed by using the output of an OSSE in which the previously constructed ELF is applied (Anderson and Lei 2013).

RMSE for Different GC Halfwidths



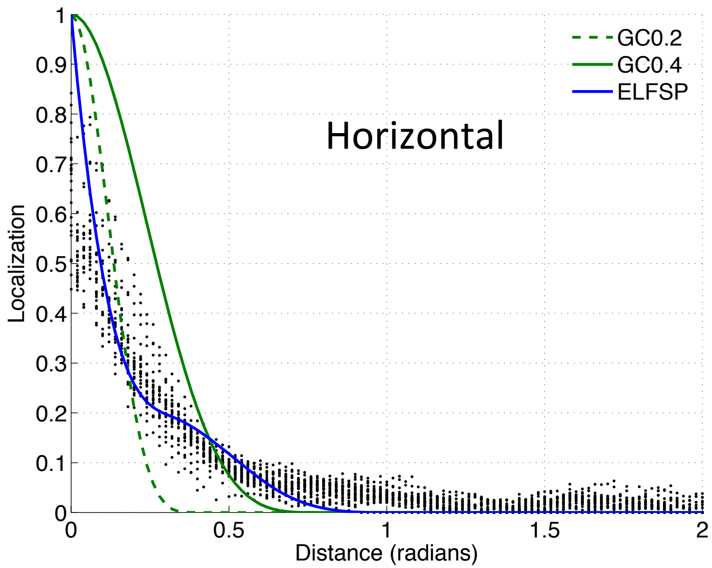


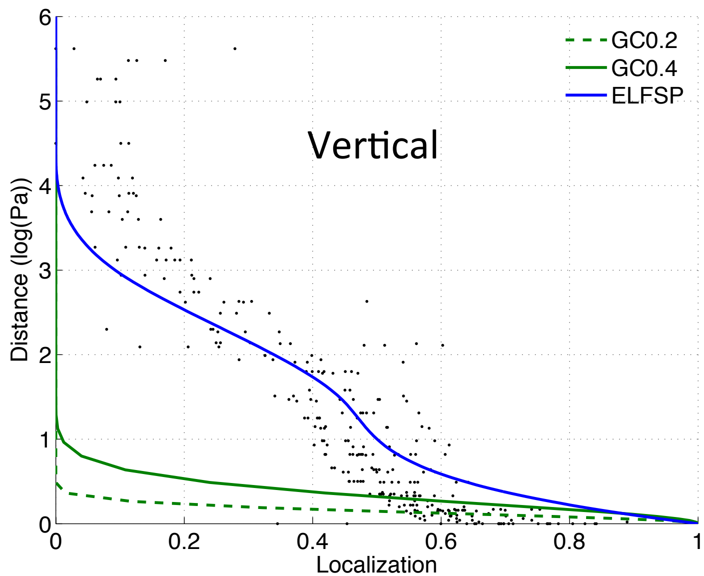
RMSEs for temperature and zonal wind are averaged globally (GL), in the southern hemisphere (SH), tropics (TP) and northern hemisphere (NH).

GC0.4 has smallest globally averaged RMSE, so 0.4 is chosen as the best halfwidth.

Some RMSEs computed for SH, TP and NH separately are smallest for other halfwidths; tuning the GC halfwidth is complex.

Horizontal and Vertical Empirical Localization Functions





Empirical localizations (black dots) are computed separately for temperature, zonal and meridional winds at ten levels (30 dots per separation).

A z-test is used to assess the significance of the empirical localization.

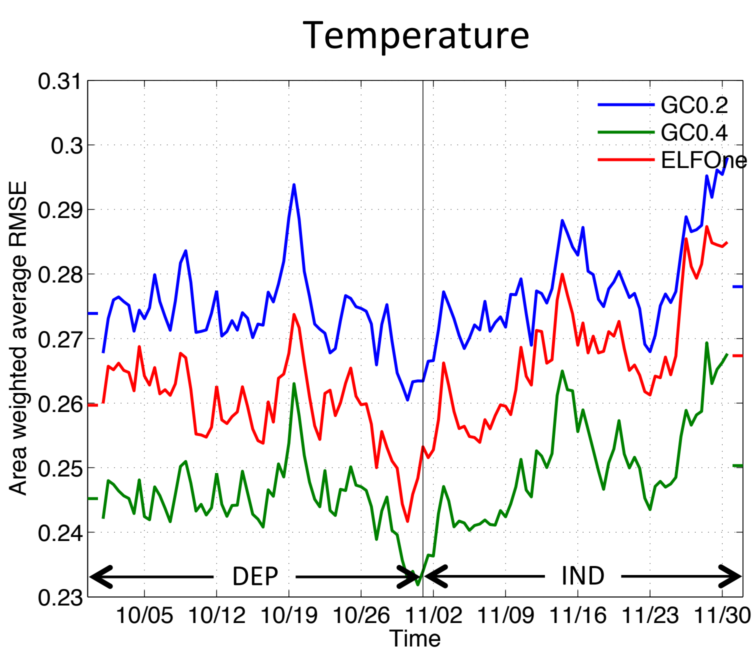
A cubic spline (blue line) is applied to the empirical localization to produce the final localization function (ELFSP).

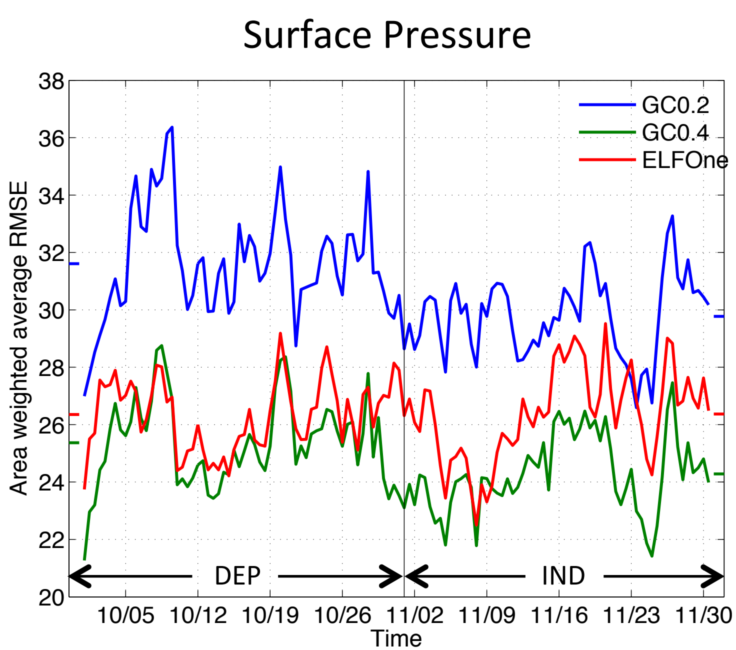
The horizontal ELFSP is smaller than the GC0.2 and GC0.4 at small separations and has a wider tail than GC0.2 and GC0.4.

The vertical ELFSP is much broader than the GC0.2 and GC0.4.

The horizontal and vertical ELFSPs are used in a subsequent OSSE (ELFOne).

Global average RMSE for GC0.2, GC0.4 and ELFOne

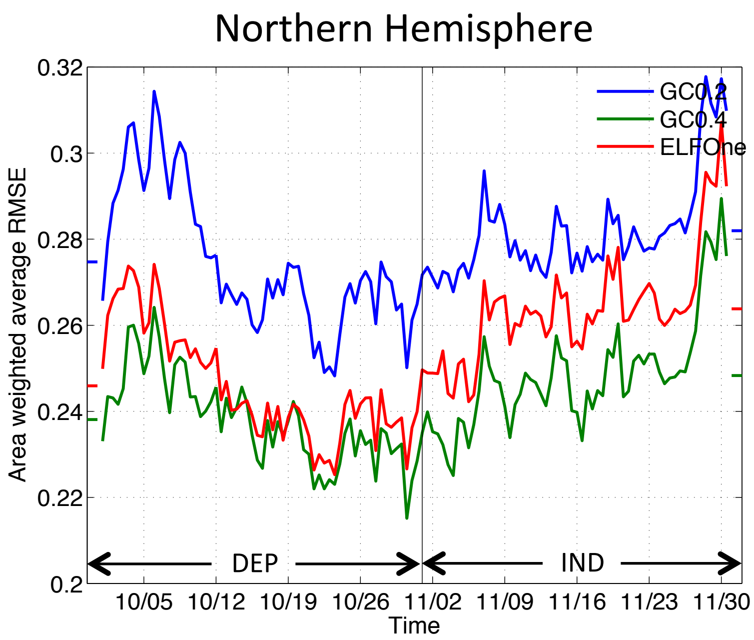


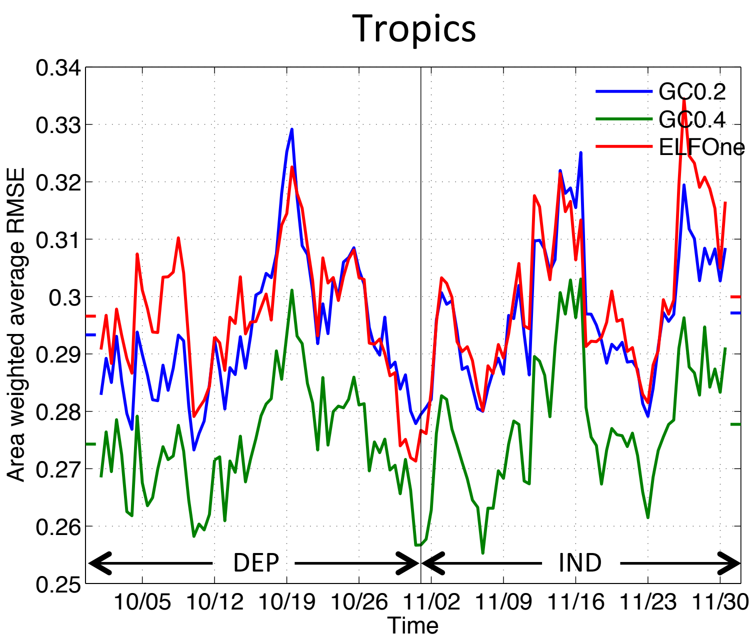


ELFOne has smaller temperature RMSE than GC0.2, but larger RMSE than GC0.4, the best GC.

ELFOne has smaller surface pressure RMSE than GC0.2, and slightly larger RMSE than GC0.4.

Temperature RMSE averaged in NH and TP



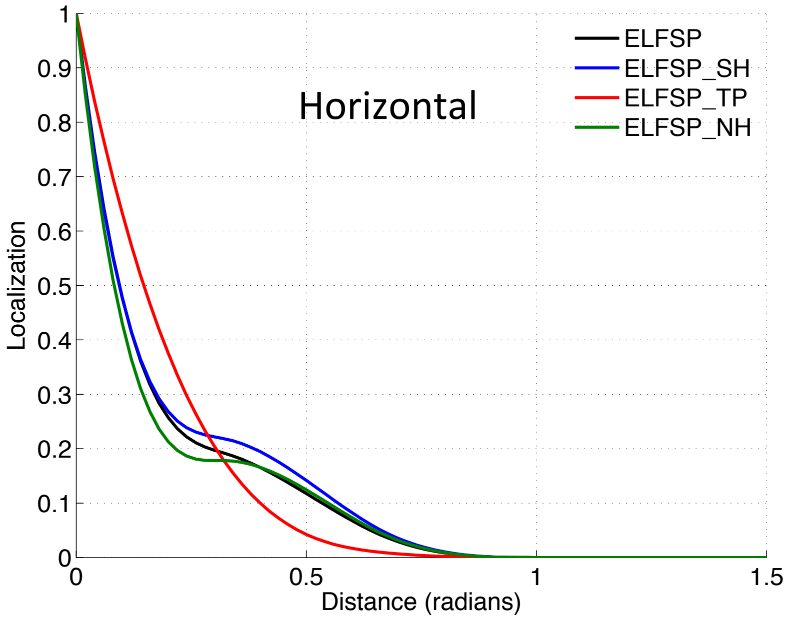


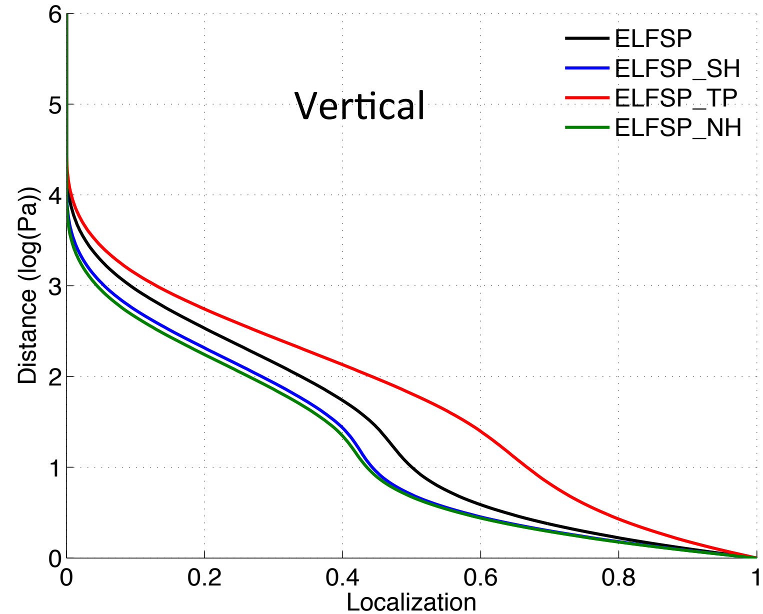
ELFOne has smaller temperature RMSE than GC0.2 in NH and SH.

ELFOne has larger temperature RMSE than GC0.2 in TP.

Improvements of ELFOne over GC0.2 are mainly in SH and NH.

Horizontal and Vertical ELFs varying by region





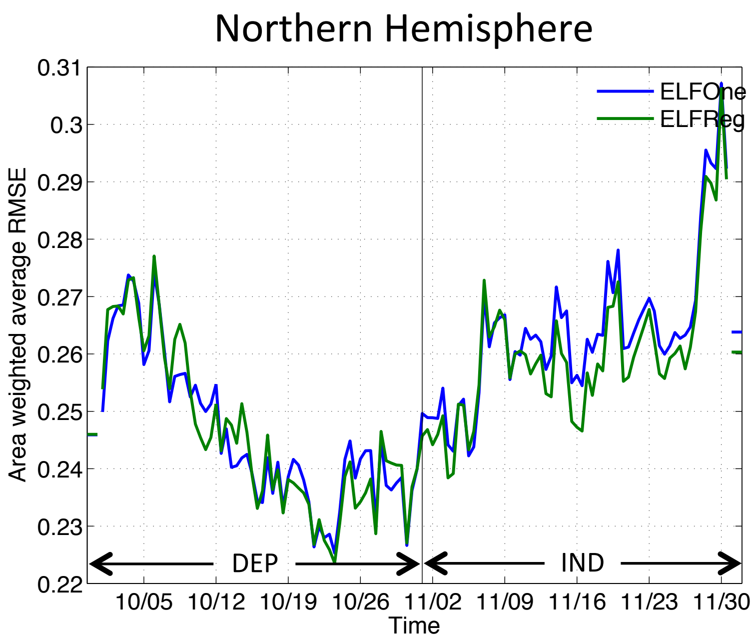
Horizontal and vertical ELFSPs are computed for the SH, TP and NH separately.

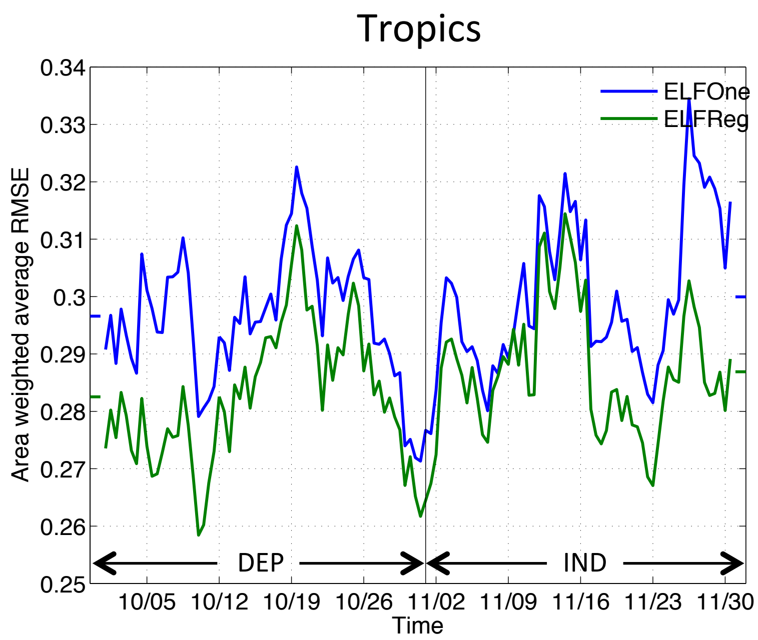
The horizontal ELFSP_SH and ELFSP_NH have similar shape to the global ELFSP. The horizontal ELFSP_TP has a more compact tail than the ELFSP, ELFSP_SH and ELFSP_NH.

The vertical ELFSP_SH and ELFSP_NH are similar with smaller magnitude than the global ELFSP. The vertical ELFSP_TP is broader than the global ELFSP.

Horizontal and vertical ELFSPs varying by region are used in a subsequent OSSE (ELFReg).

Temperature RMSE averaged in NH and TP



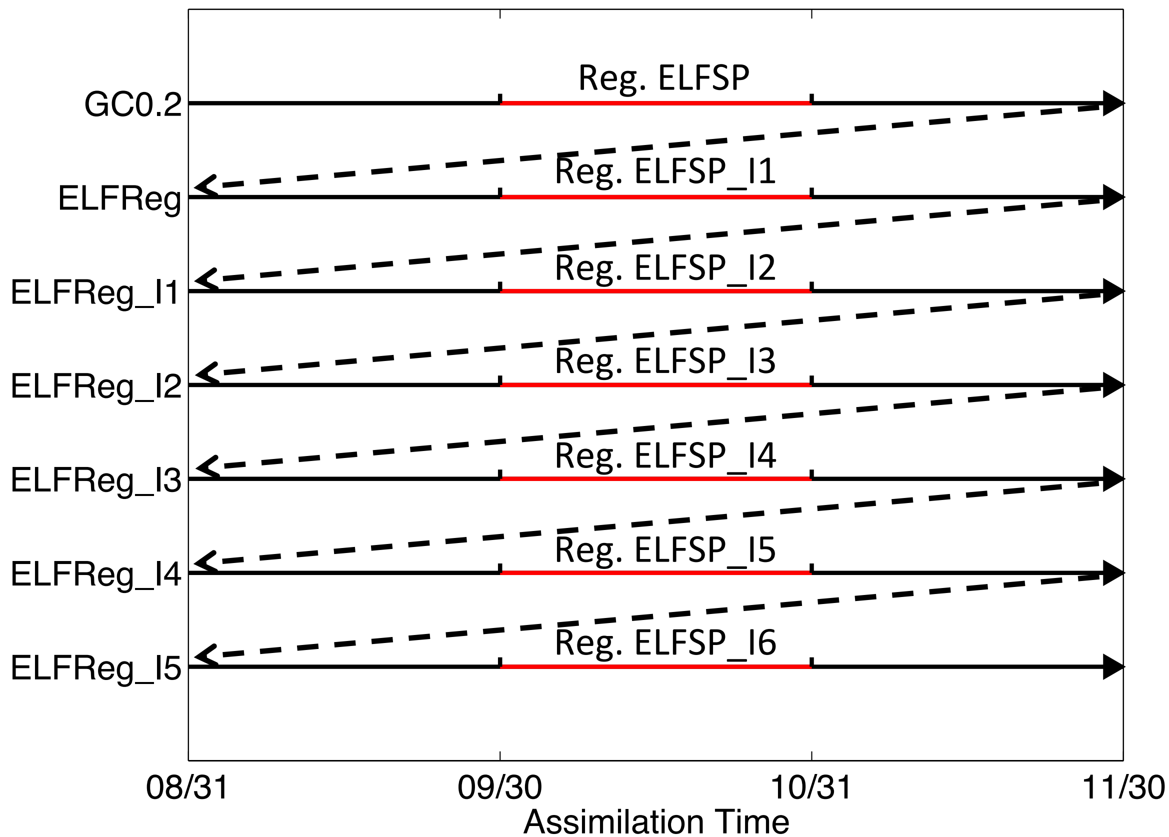


ELFReg has slightly smaller temperature RMSE than ELFOne in NH and SH.

ELFReg has smaller temperature RMSE than ELFOne in TP.

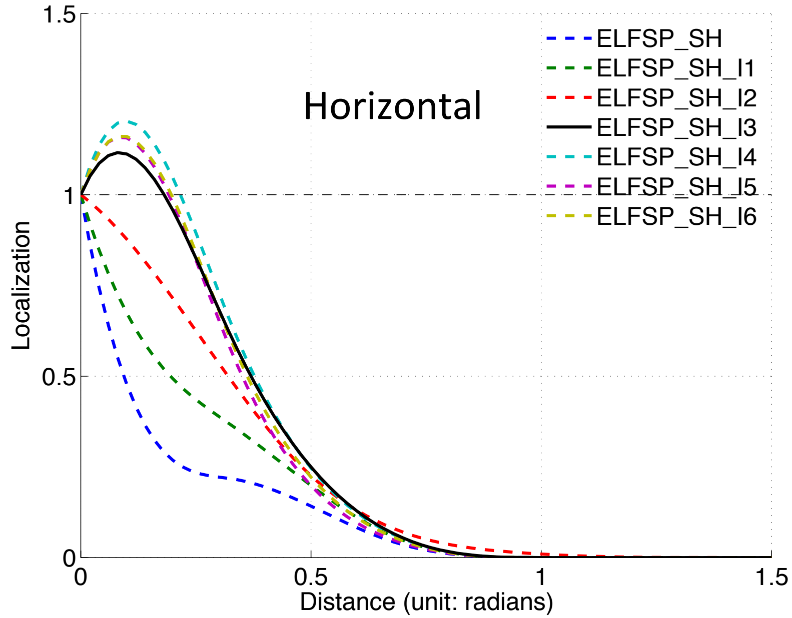
ELFReg has smaller globally averaged RMSE than ELFOne.

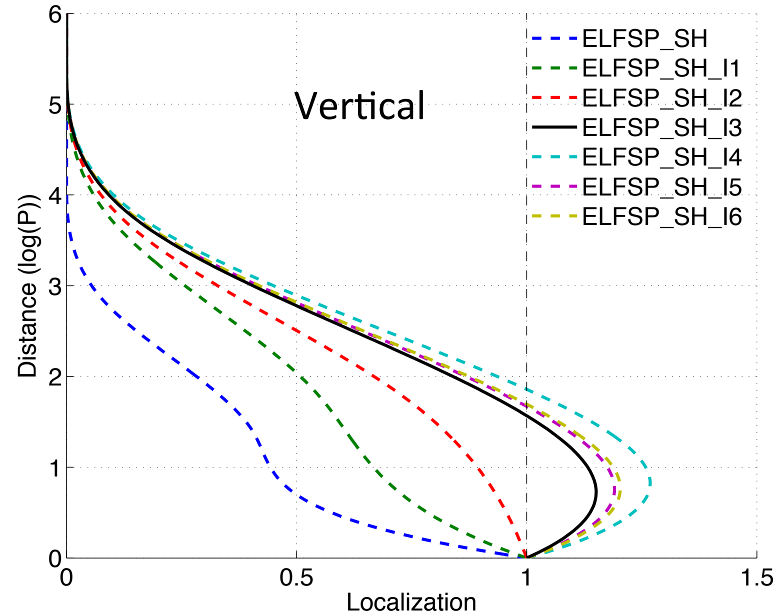
Convergence of the ELFSPs



Five OSSEs (ELFReg_I#, #=1,…,5) are conducted iteratively. Each OSSE uses the regional ELFSPs computed from the output of the previous OSSE.

Convergence of the ELFSPs





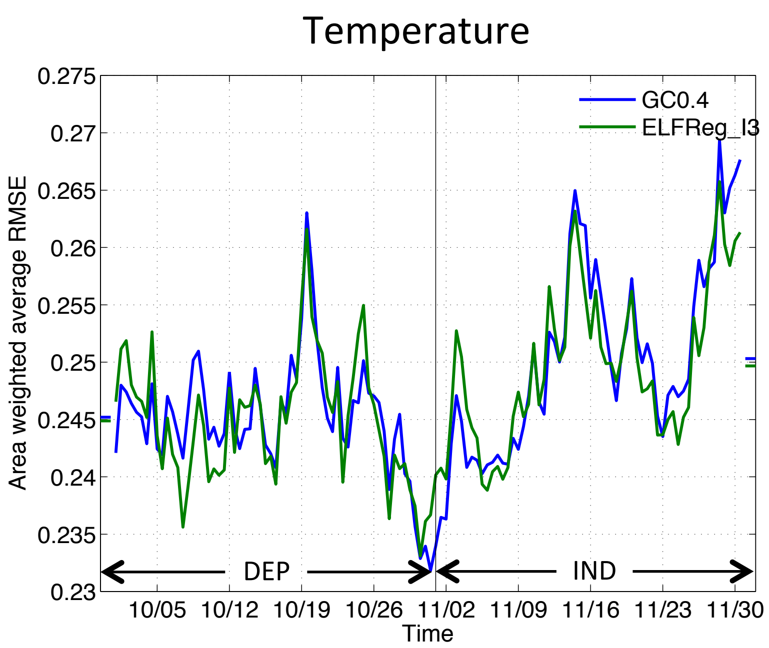
The ELFSP_SHs becomes larger with iterations.

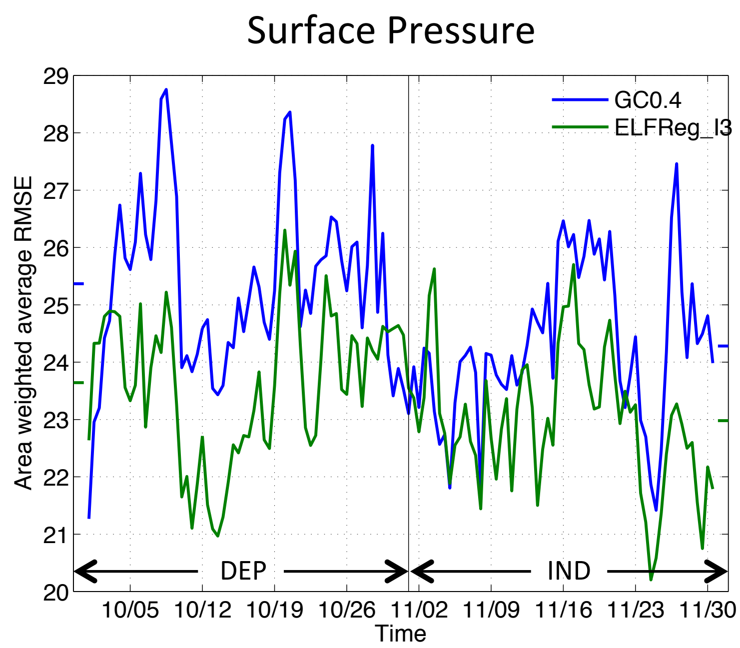
The ELFSP_SHs appear to have mostly converged after 3 iterations.

The ELFSP_SHs from iterations 3 to 6 are larger than 1.0 at small separations. This indicates insufficient spread and the empirical localization acts as an inflation.

Empirical localization values larger than 1.0 are set to 1.0 when used in an OSSE.

Global average RMSE for GC0.4 and ELFReg_I3





ELFReg_I3 produces slightly smaller temperature RMSE than GC0.4.

ELFReg_I3 has significantly smaller surface pressure RMSE than GC0.4

Conclusions

- ELFOne, which uses the ELFSPs computed from the output of an OSSE using GC localization with halfwith 0.2 radians, has smaller RMSE than GC0.2, mainly due to error reduction in SH and NH.
- ELFReg that uses the ELFSPs varying with regions has advantages over ELFOne, especially in TP.
- The ELFSPs appear to have converged after 3 iterations.
- The converged ELFSPs generally lead to significantly smaller RMSE for temperature, zonal and meridional winds than GC0.4 in the dependent verification period, and similar RMSE to GC0.4 in the independent verification period. The converged ELFSPs have significantly smaller RMSE of surface pressure than GC0.4.

THANK YOU!