Observed Characteristics of Representation Error

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Can Ensemble Variance Predict Observation Error of Representation?

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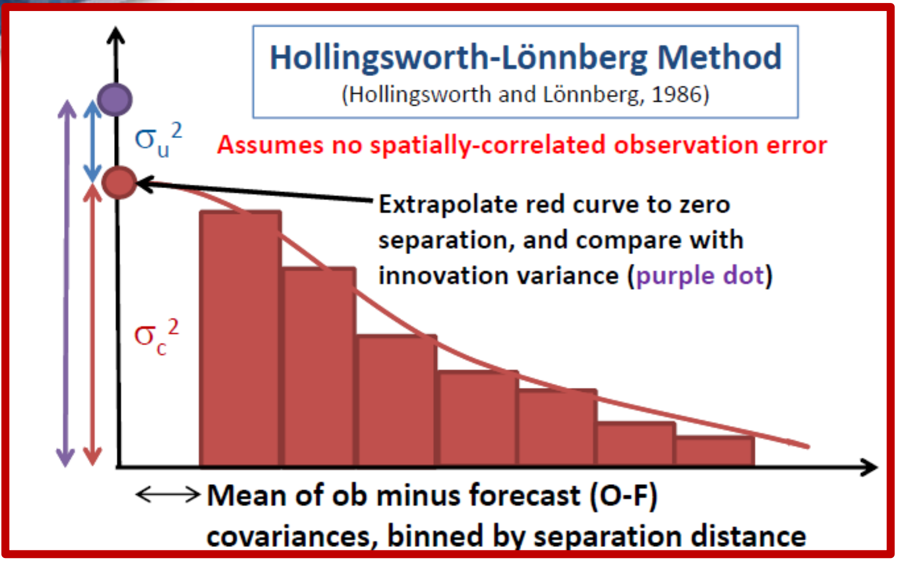
Representation Error

- Arises from the **inability of the forecast model to resolve small-scale properties**:
  - Unresolved processes
  - Boundaries of resolved features
- Results in **incompatibility between coarse model grids and observations**, which observe a higher resolution state.
- Must be accounted for in the **observation error covariance matrix**:
  - The best state that the model can represent is a “smoothed truth”
  - Adding the penalty term to the background error covariance matrix would result in noise once the model is integrated
- Key, if not dominant, contributor to **correlated observation errors**

Estimating Covariance Matrices



$$\left\langle (\vec{O}-\vec{F})(\vec{O}-\vec{A})^T \right\rangle = \mathbf{R}$$

$$\left\langle (\vec{A}-\vec{F})(\vec{O}-\vec{F})^T \right\rangle = \mathbf{HBH}^T$$

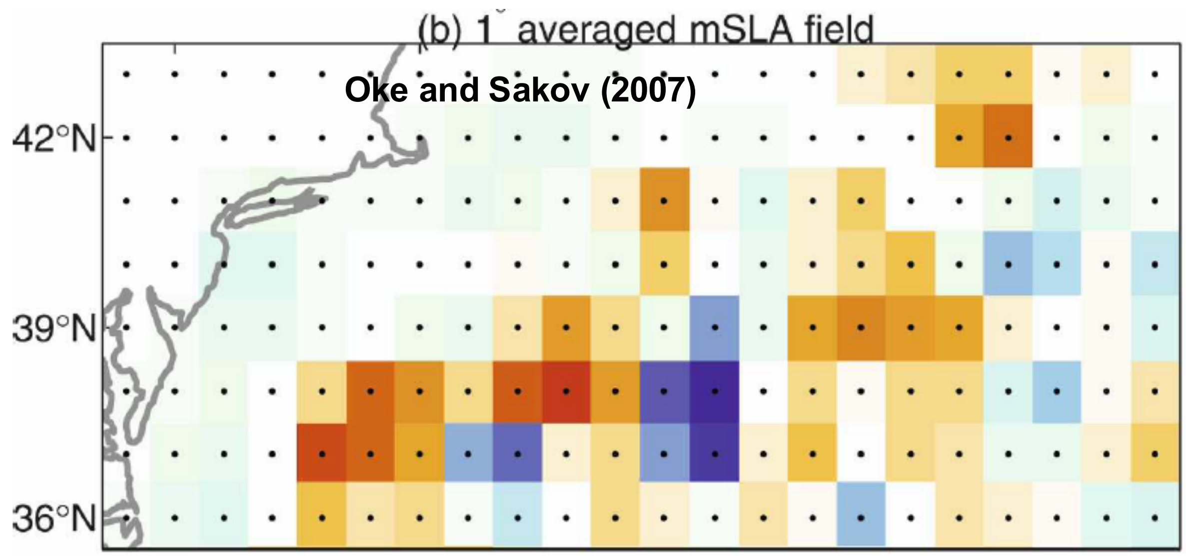
$$\left\langle (\vec{O}-\vec{F})(\vec{O}-\vec{F})^T \right\rangle = \mathbf{R} + \mathbf{HBH}^T$$

1. **Split Observation-minus-Background statistics into observation and background error covariances** (e.g. Rutherford (1972) and Höllingsworth and Lonnberg (1986))
   - Requires a dense observing network
   - Dependent on the chosen correlation function
   - Assumes observation errors are uncorrelated

2. **Iterative procedures based on updating the Kalman gain** (e.g Desroziers and Ivanov (2001), Desroziers et al. (2006))
   - Easy to implement
   - Dependent on prescribed error covariance matrices
   - Iterative procedure may be required

Hodyss and Satterfield (2016) show that when the observation is higher resolution than the model state the Desroziers method and the H-L method have contributions from representation error as well as errors from resolved scales.

Estimating Representation Error

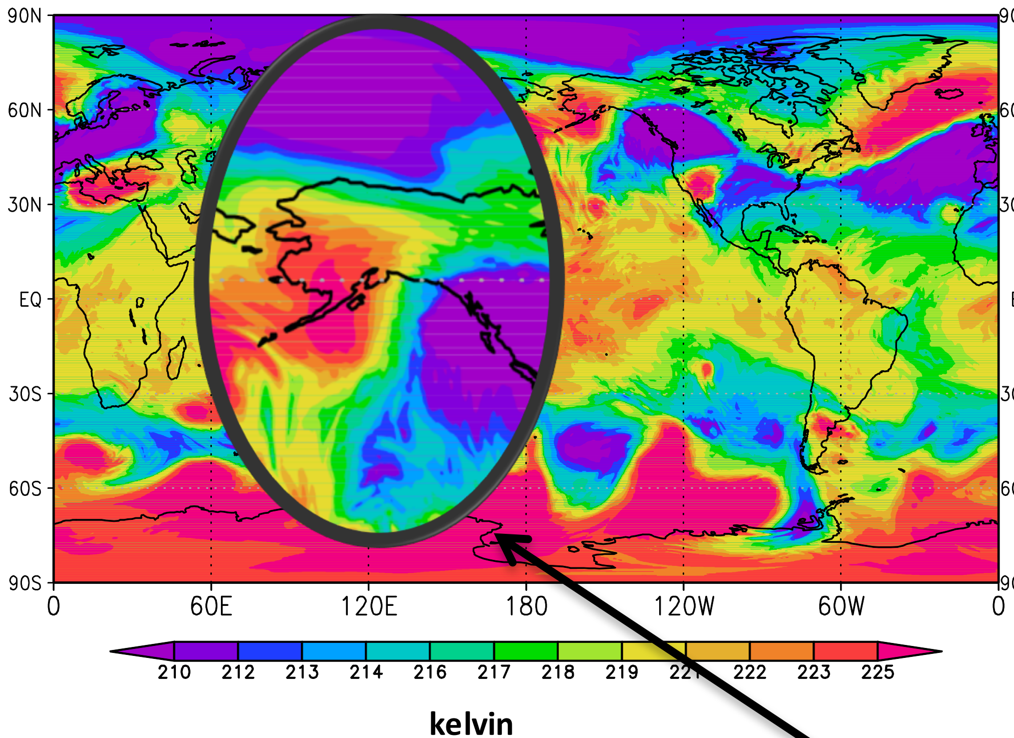


3. Observation based methods to calculate representation error (e.g. Forget and Wunsch (2007), Oke and Sakov (2007))

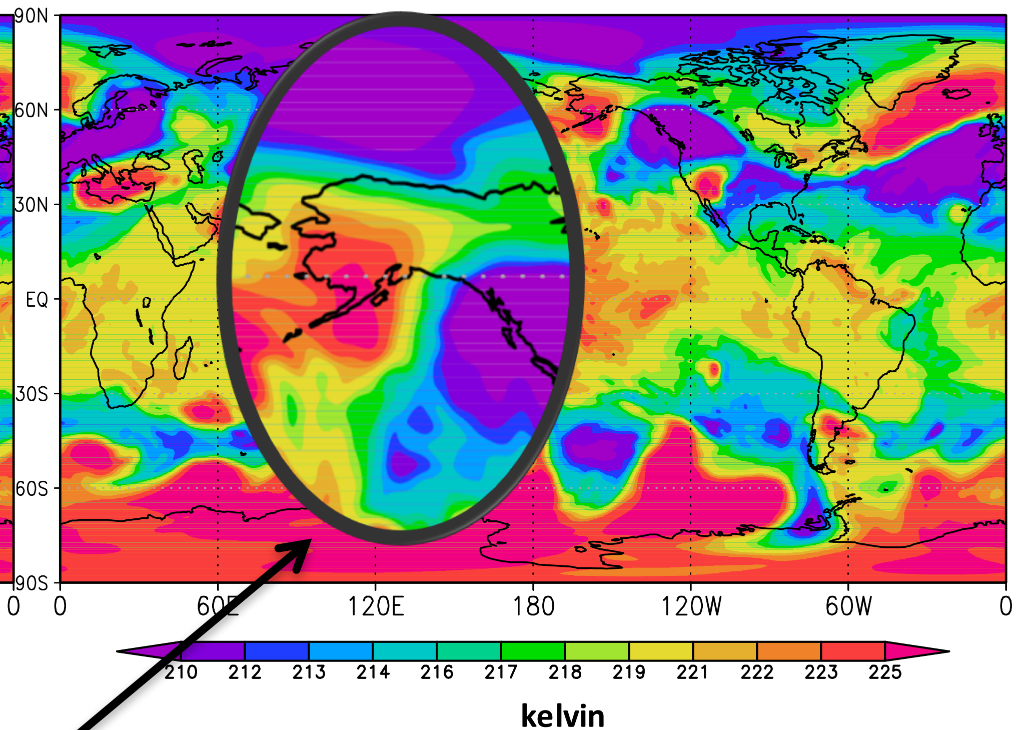
- Average observation data to model resolution and interpolate back to high resolution grid to compute differences
- Ideally, we would like a continuous field, which observations cannot provide (using a spectral filter was discussed by Mitchell and Daley (1997) and Liu and Rabier (2002))
- ***effective spectral resolution*** of a particular model may be smaller than the spectral resolution of the model due to diffusion or model error terms which may act to smooth the field

Error of Representation

200 hPa temperature 1 Jan 2015
ECMWF analyses 32km resolution



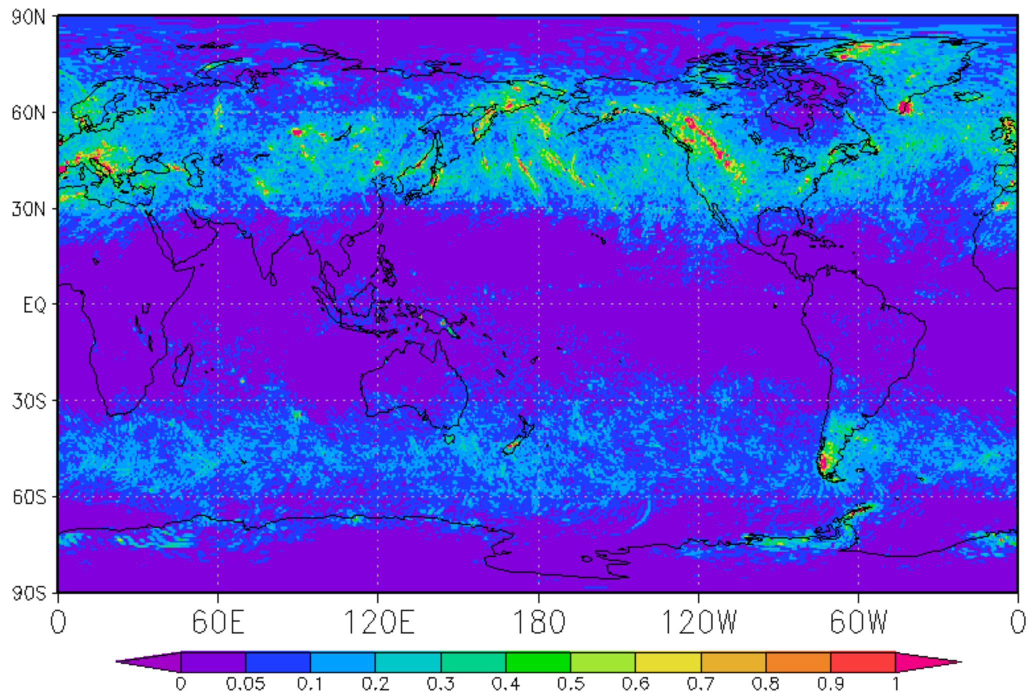
200 hPa temperature 1 Jan 2015
Filtered ECMWF analyses 125 km resolution



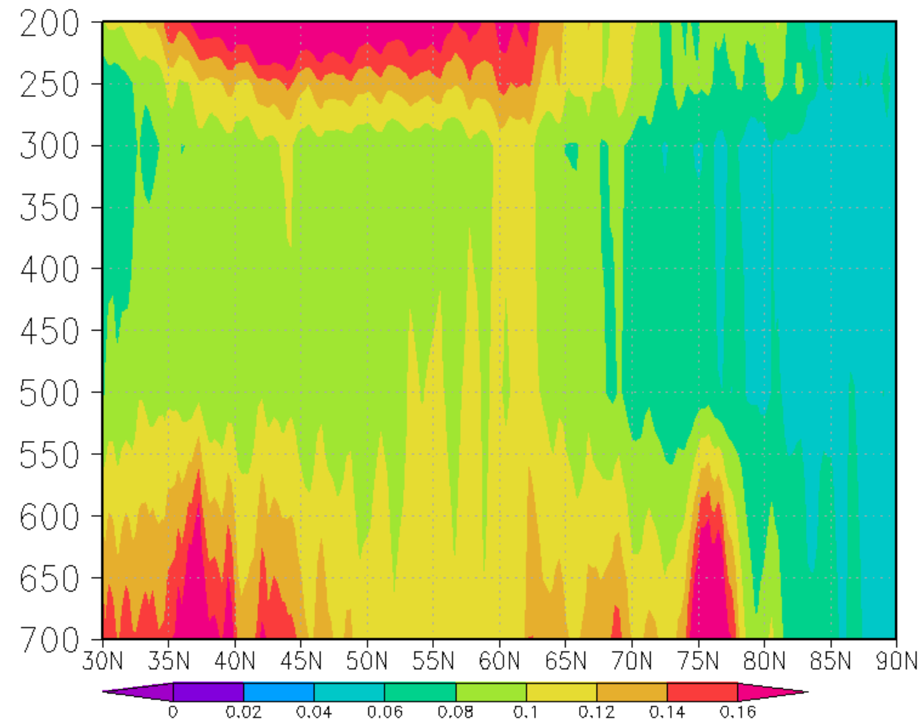
Filtering acts to smooth features

Error Variance due to spectral truncation of ECMWF analyses

Error Variance due to Spectral Truncation. Shown for temperature.



200 hPa

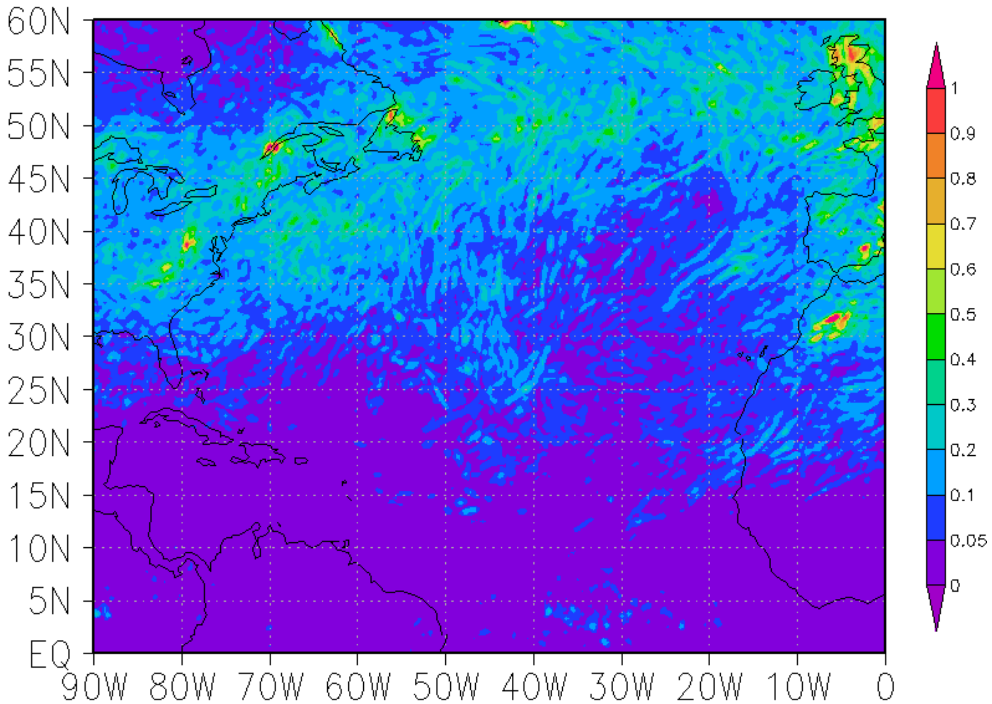


Zonal average

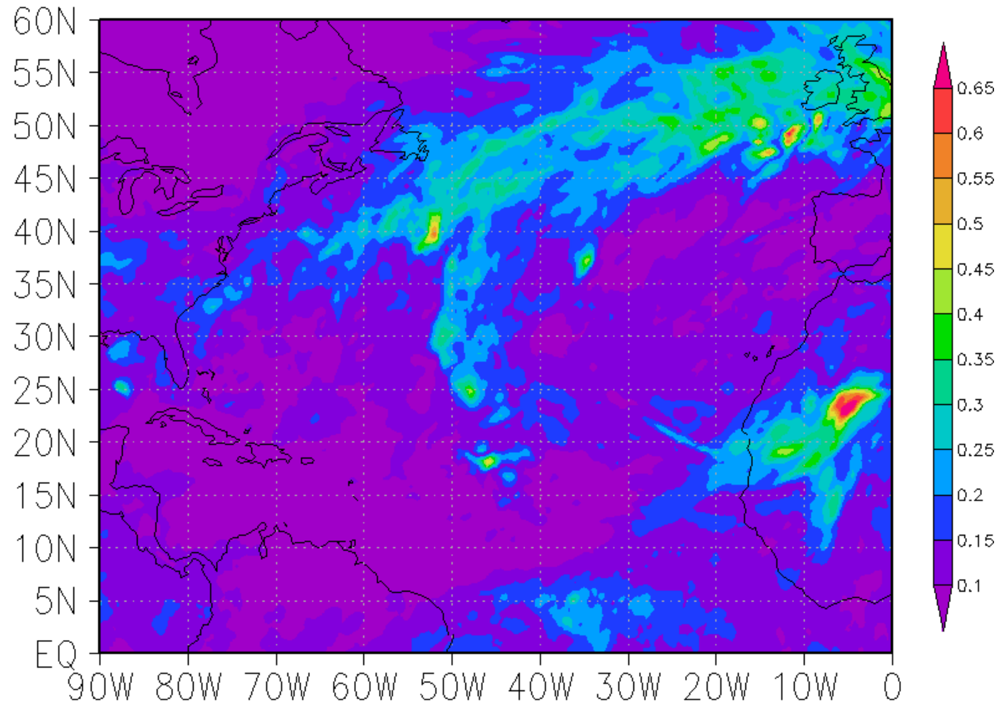
Shown for January 2015

Comparison with ensemble variance

Temperature shown for January 2015



Error Variance due to Spectral Truncation of ECMWF deterministic forecast

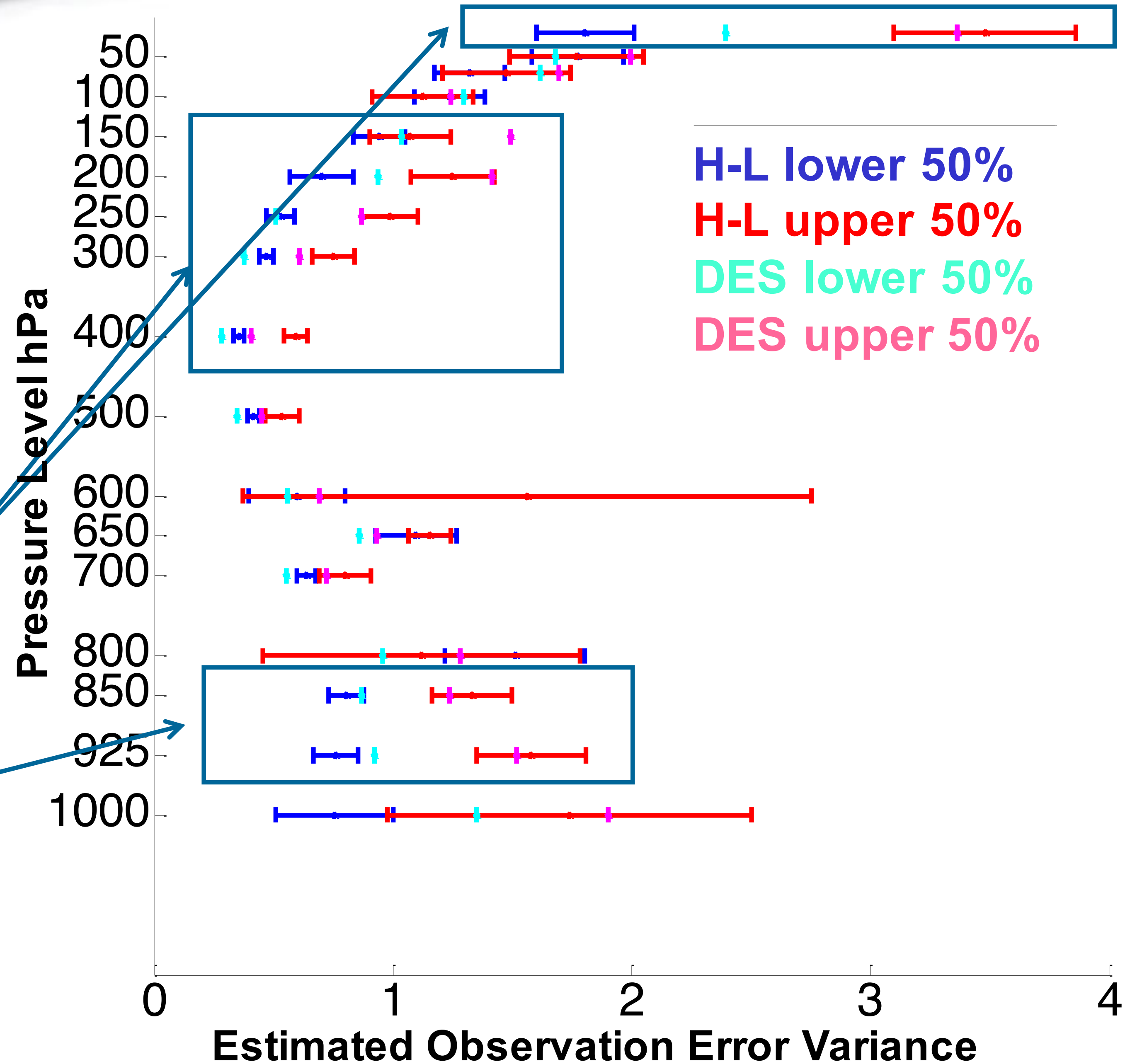


Time averaged ECMWF Ensemble Variance

Is Representation Error Dependent on Ensemble Variance?

- We apply both the H-L and Desroziers methods to two equally populated subsets of data based on ensemble variance.
- We use the NAVGEM ensemble and model background and restrict the observation type to temperature measurements from Vaisala RS92 radiosondes to limit the influence of spatial variation of instrument error, correlation, errors from observation operator, and bias.

Binning by ensemble variance

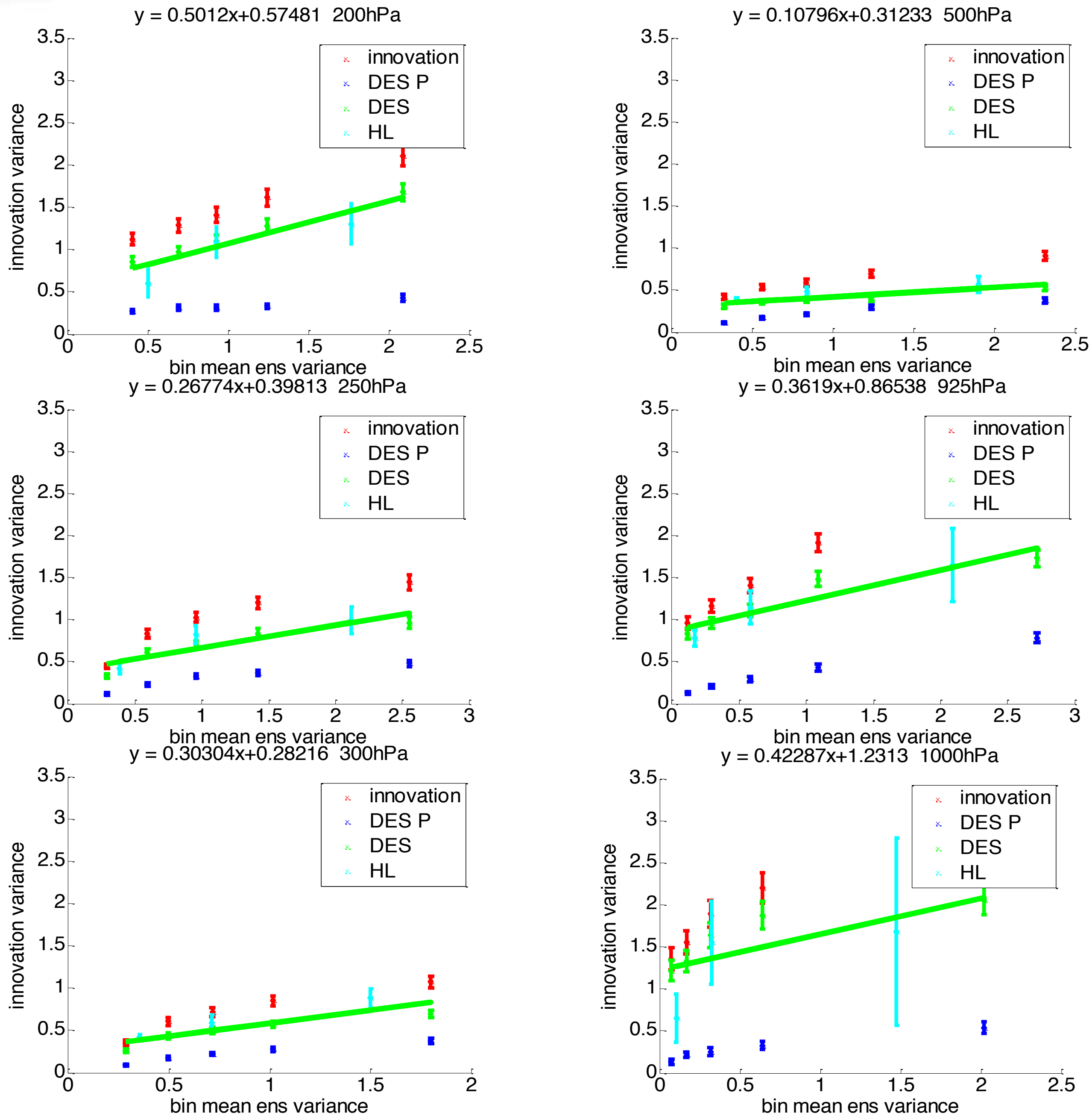


Boxes indicate levels at which both methods result in estimated observation error variance values that are dependent on ensemble variance

Accounting for Representation Error

Results for NAVGEM temperatures

A regression based method would allow us to prescribe a static error, as is currently done in the observation covariance model, and also allow for representation error to vary as a function of ensemble variance.



Summary

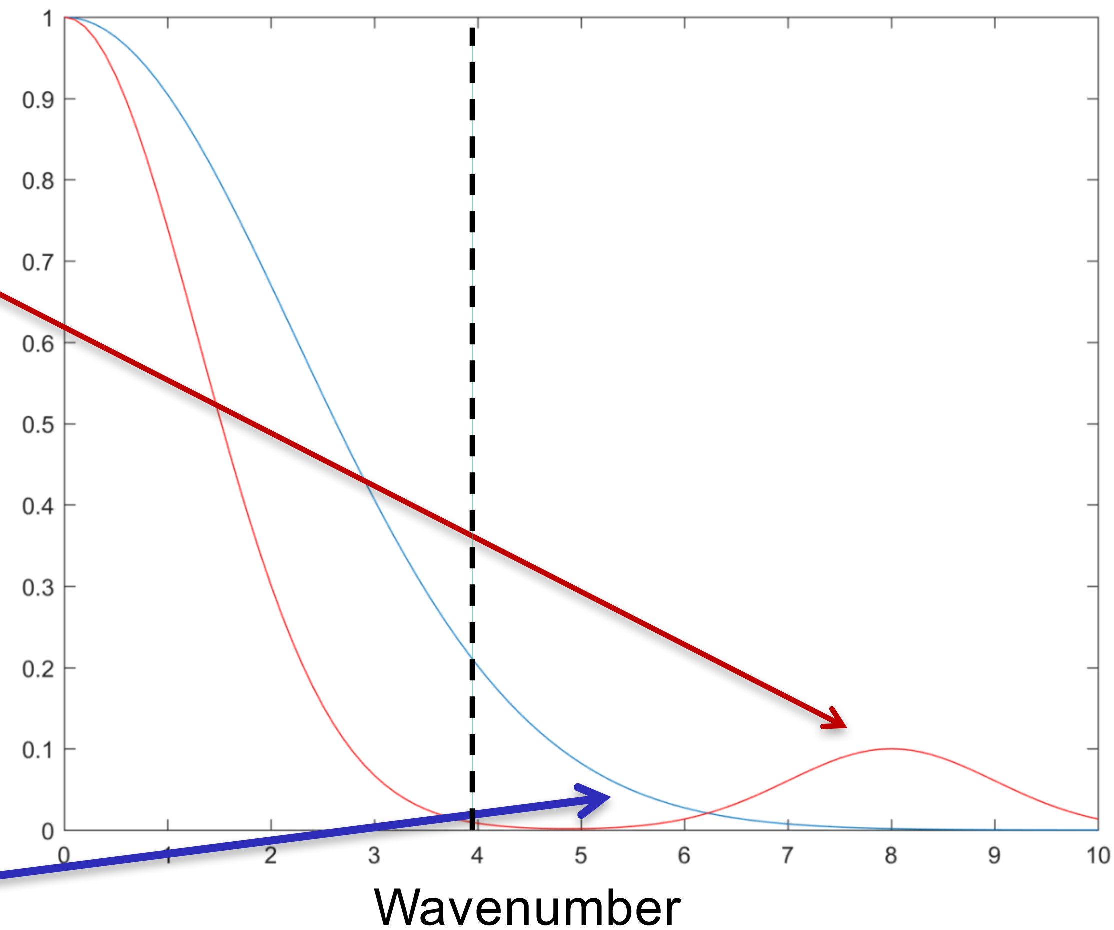
- We then examined fluctuations in estimated observation error variances when the Desroziers and H-L methods are applied to subsets of innovations based on binning by ensemble variance.
- Our comparison of the two methods demonstrates that deficiencies in the estimation methods cannot explain such fluctuations.
- Regions of these fluctuations are in qualitative agreement with maps of variances due to spectral truncation.
- Our study indicates that the ensemble variance could be used as a predictor of representation error. The relative benefit of a flow dependent versus static form are the subject of current work.
- This procedure is general enough to be applied to other observation types, although potential spatial variations in instrument error as well as correlated errors need to be accounted for.

Extra Slides

Example Spectrums

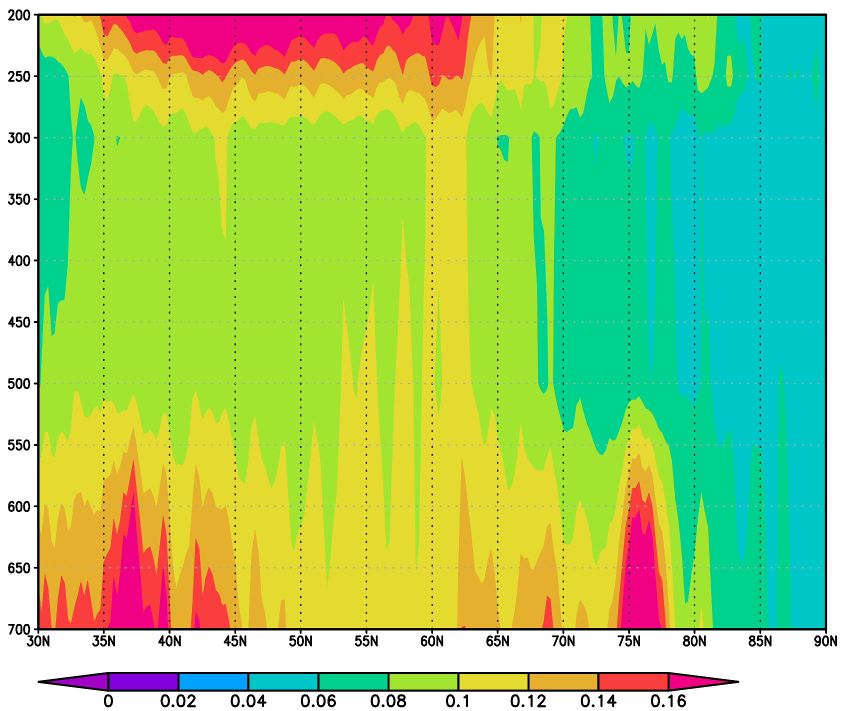
If our coarse resolution model truncated the spectrum at wavenumber 4 it would be entirely missing the “small-scale” processes creating the peak at wavenumber 8.

If we truncate at wavenumber 4, we will remove a substantial portion of the tail of the feature represented by the blue curve. This results in a misrepresentation of the feature and what we believe to be a key contributor to error of representation.

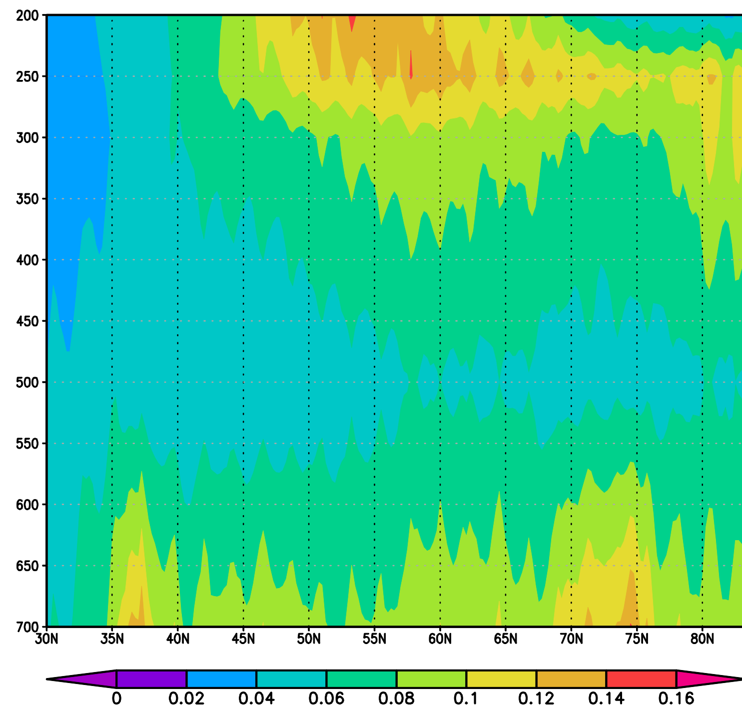


Error Variance due to spectral truncation of ECMWF analyses

Zonally averaged Error Variance due to Spectral Truncation



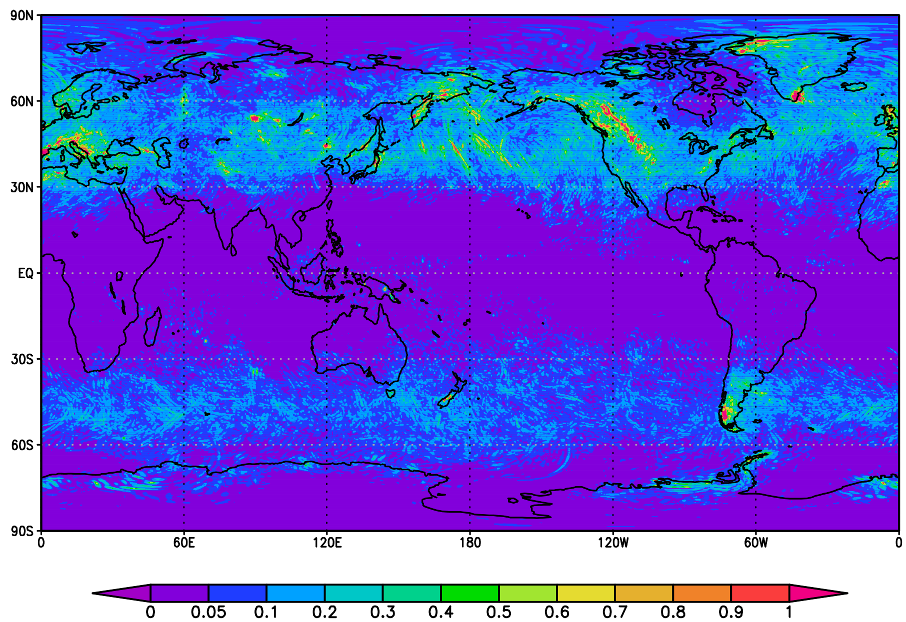
Jan 2015



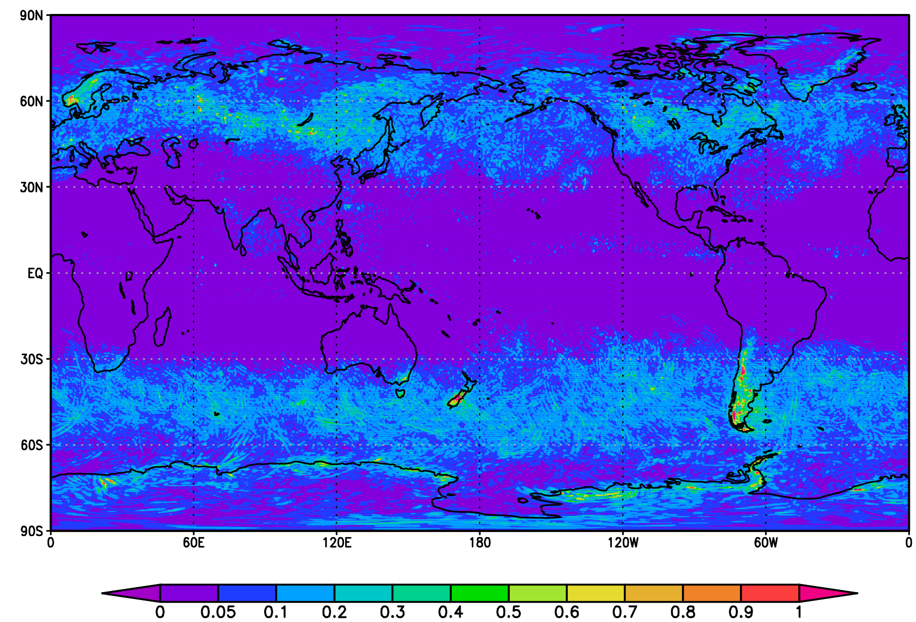
July 2013

Error Variance due to spectral truncation of ECMWF analyses

Error Variance due to Spectral Truncation at 200hPa



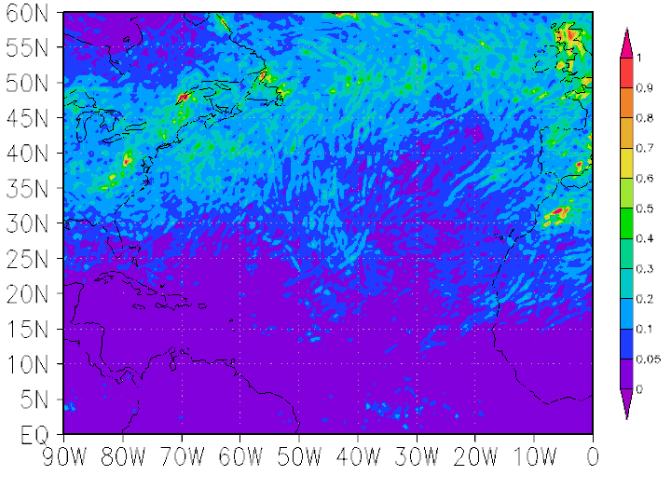
Jan 2015



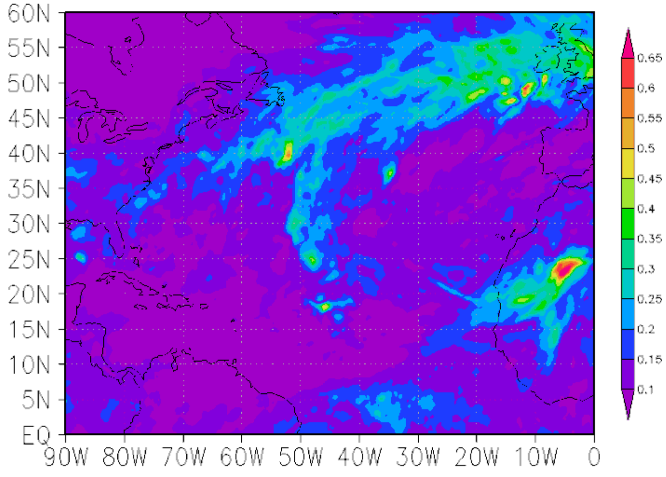
July 2013

Comparison with ensemble variance

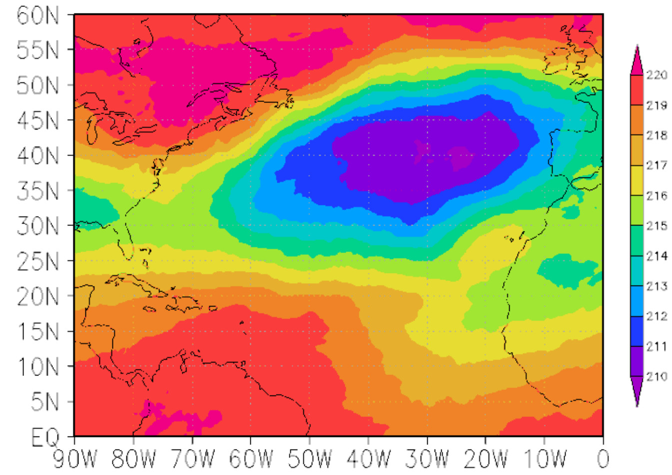
Shown for January 2015



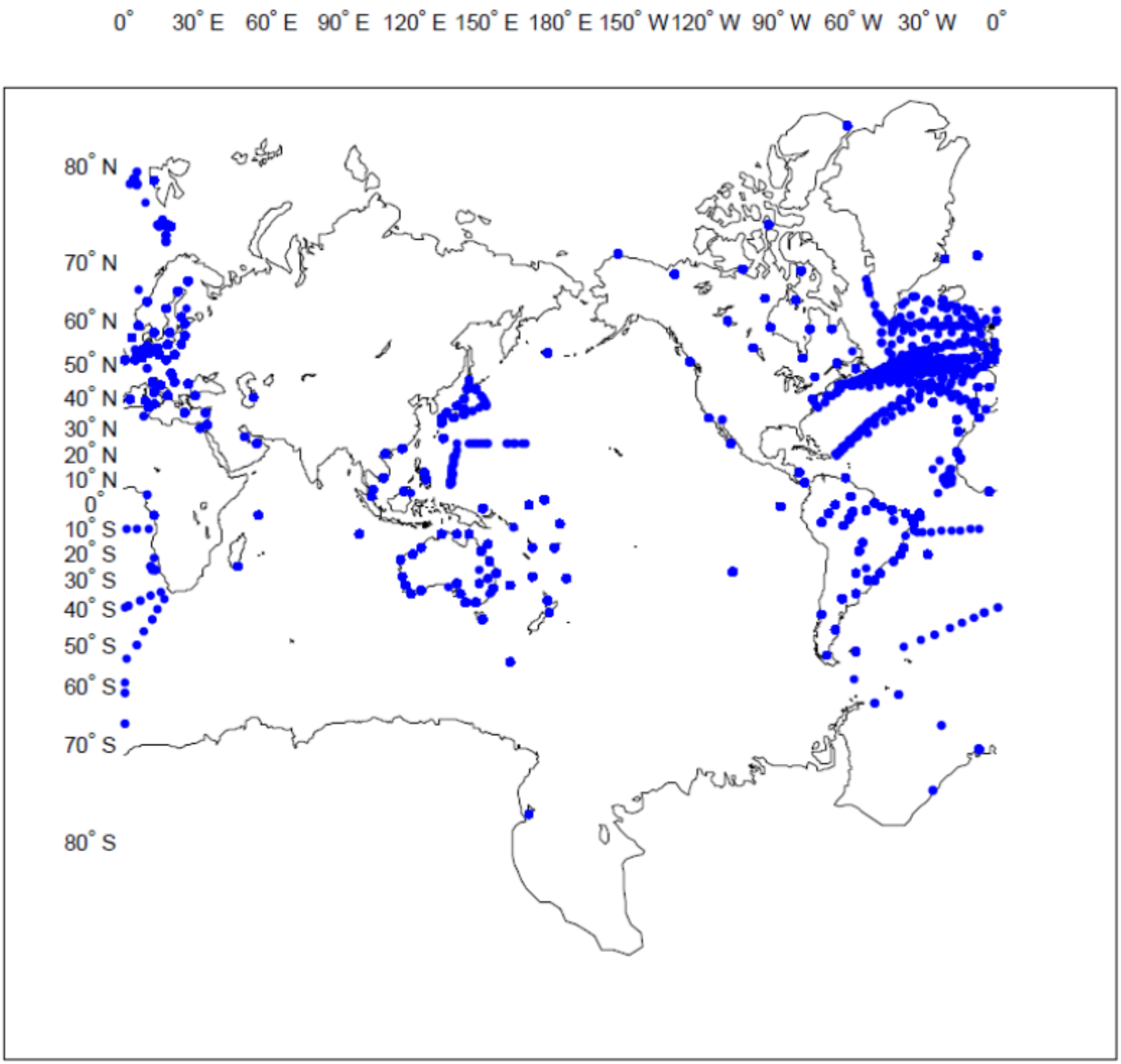
Error Variance due to Spectral Truncation of ECMWF deterministic forecast for Temperature at 200hPa



Time averaged ECMWF Ensemble Variance for Temperature at 200hPa

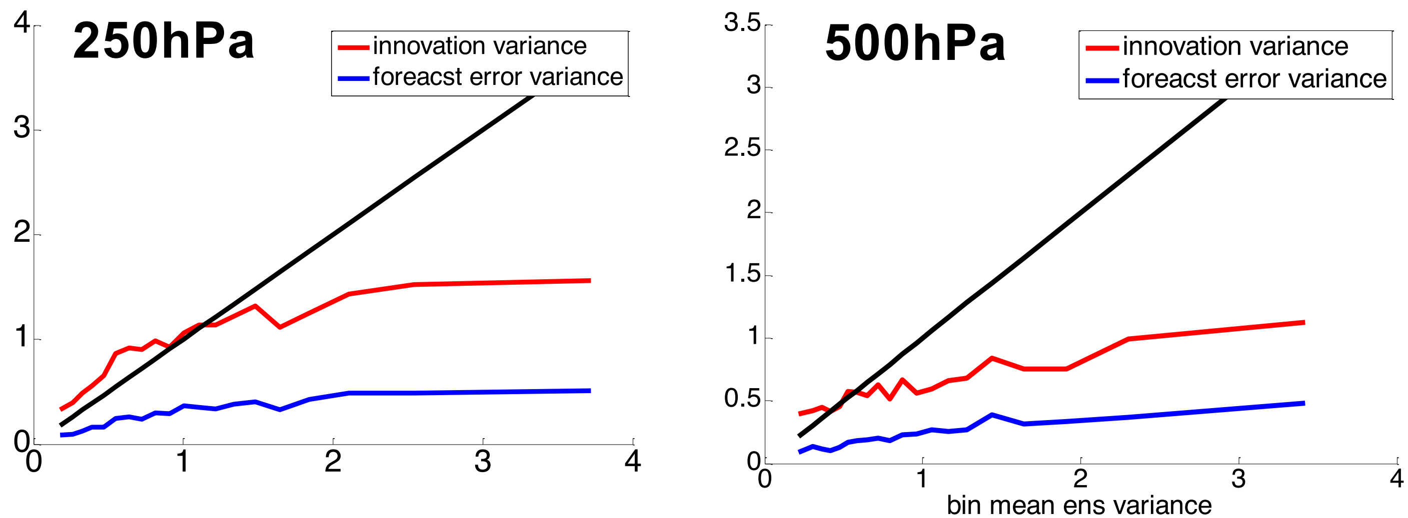


Time averaged ECMWF 200hPa Temperature

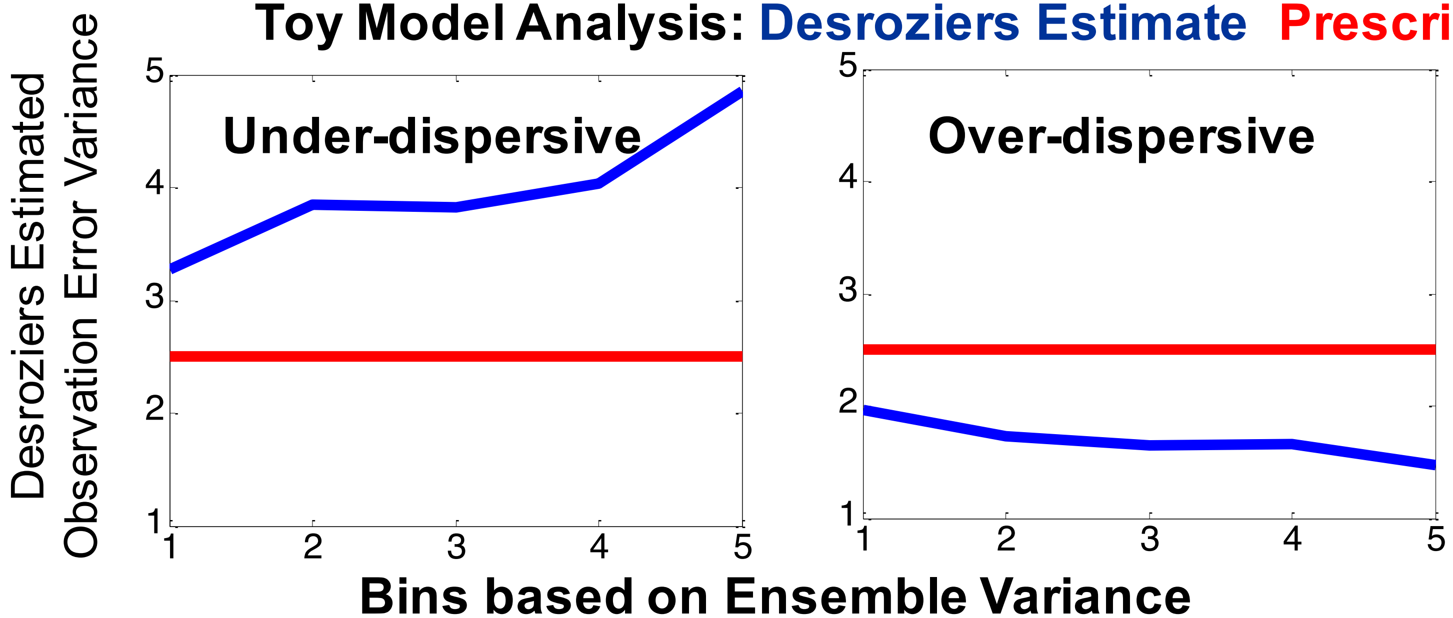

0° 30° E 60° E 90° E 120° E 150° E 180° E 150° W 120° W 90° W 60° W 30° W 0°
80° N
70° N
60° N
50° N
40° N
30° N
20° N
10° N
0°
10° S
20° S
30° S
40° S
50° S
60° S
70° S
80° S

What is the impact of ensemble dispersion?

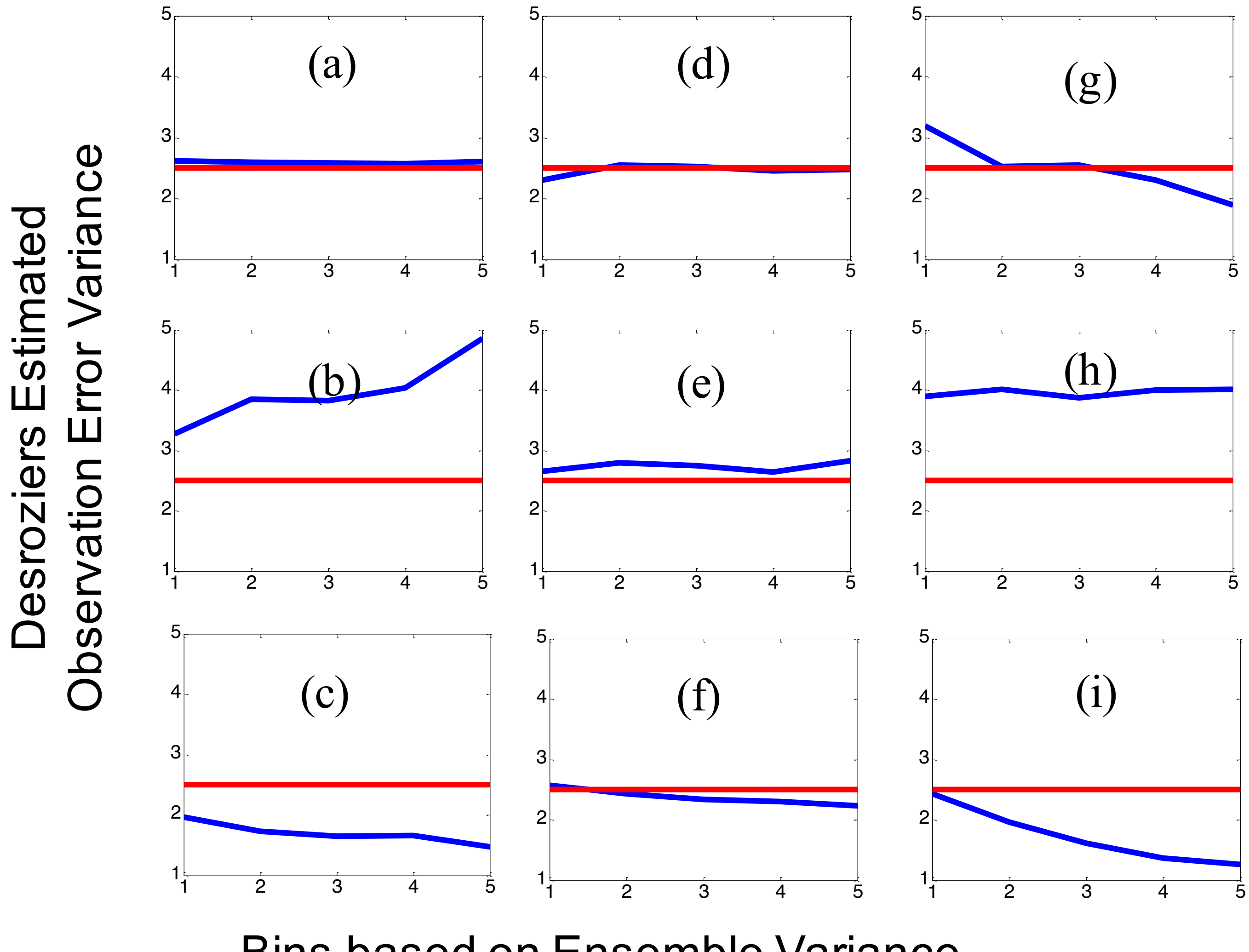
Results for NAVGEM temperatures

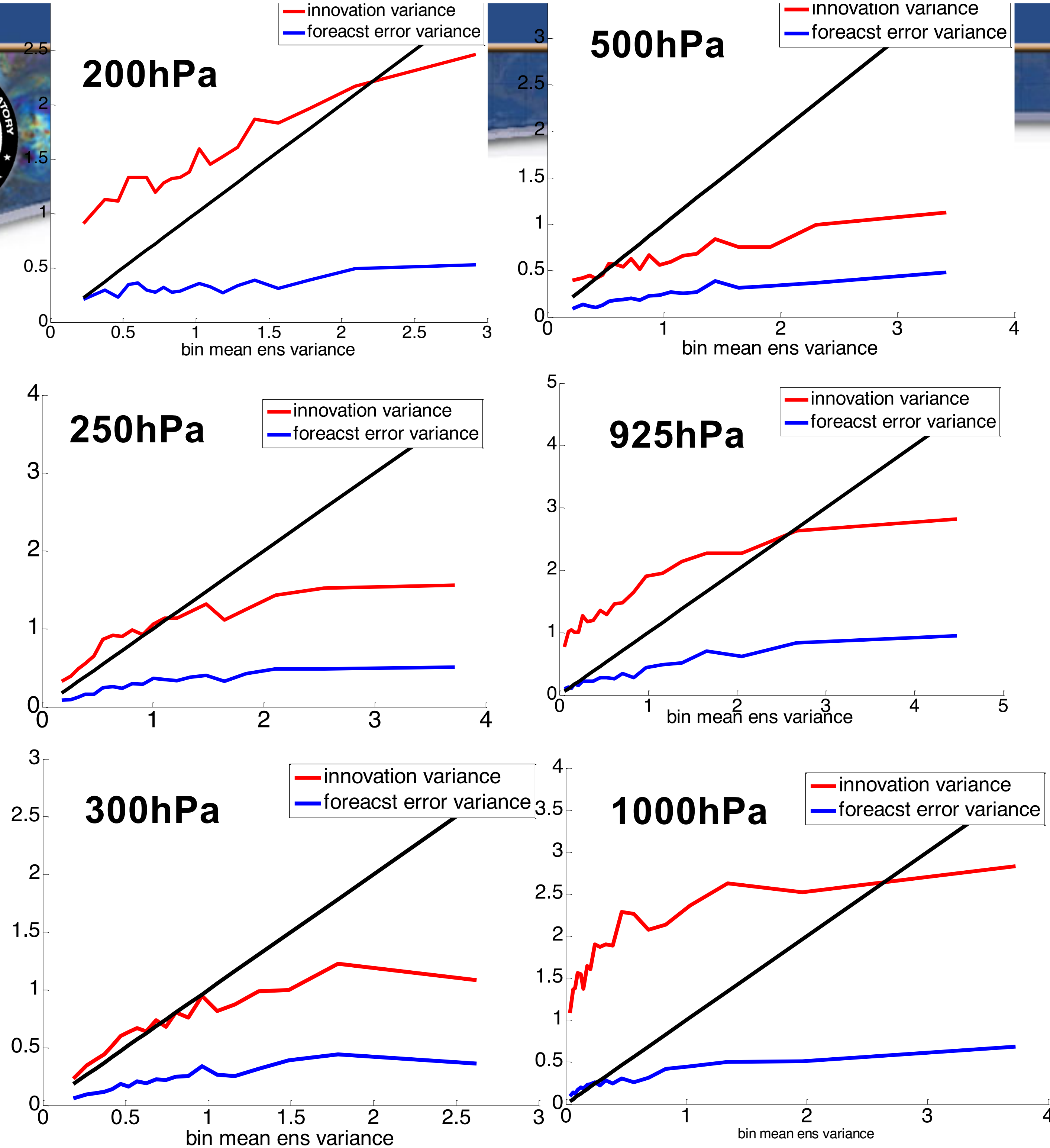


Toy Model Analysis: Desroziers Estimate Prescribed



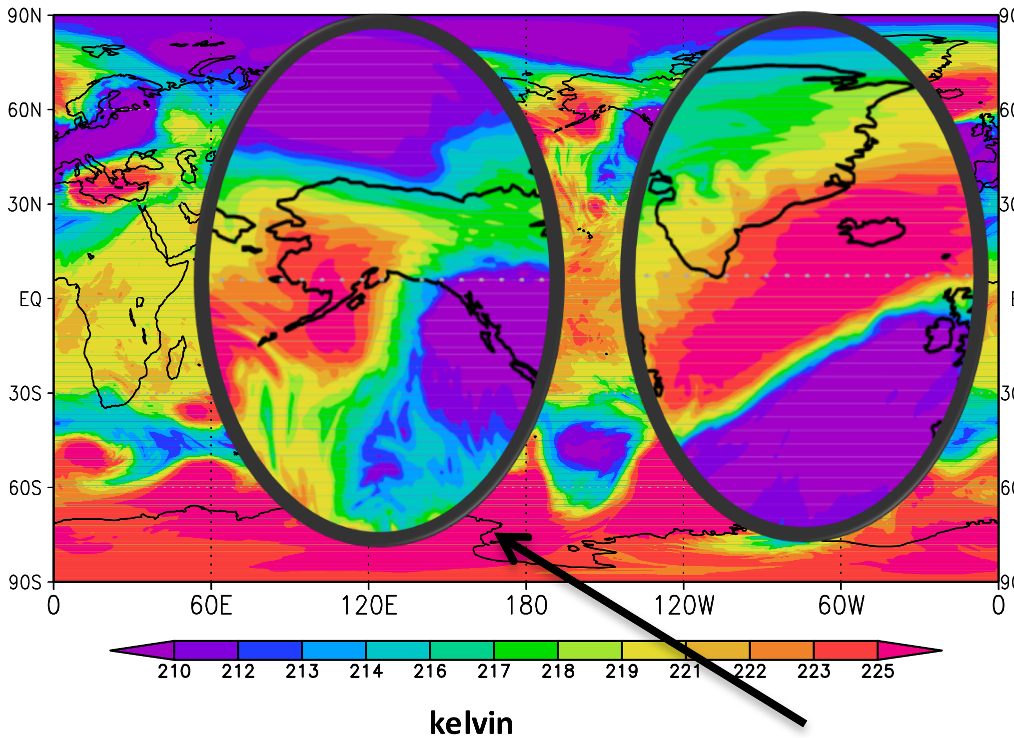
The **Desrozier diagnostic (blue)** and the **prescribed observation error variances (red)** for a) a perfectly dispersive ensemble (a=1) b) an under dispersive ensemble a=0.2 and c) an over dispersive ensemble (a=2). (d-f) repeat (a-e) with reduced day to day variation of forecast error variance. (g-i) repeat (a-c) with reduced ensemble size.



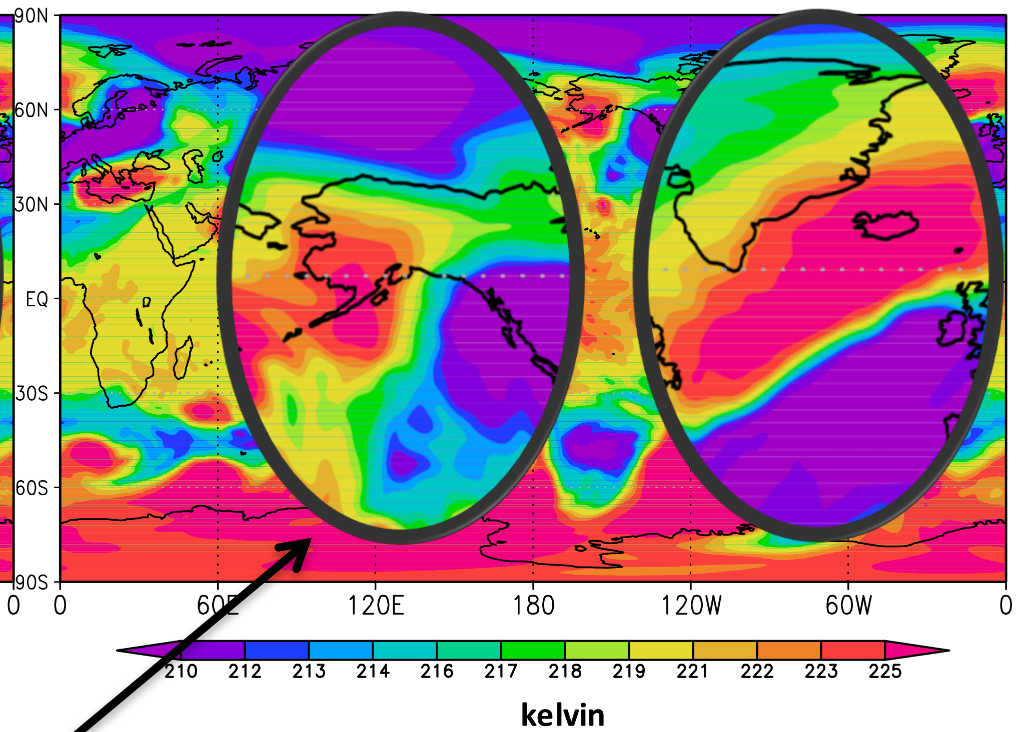

200hPa
500hPa
250hPa
925hPa
300hPa
1000hPa
innovation variance
foreacst error variance
bin mean ens variance

Error of Representation

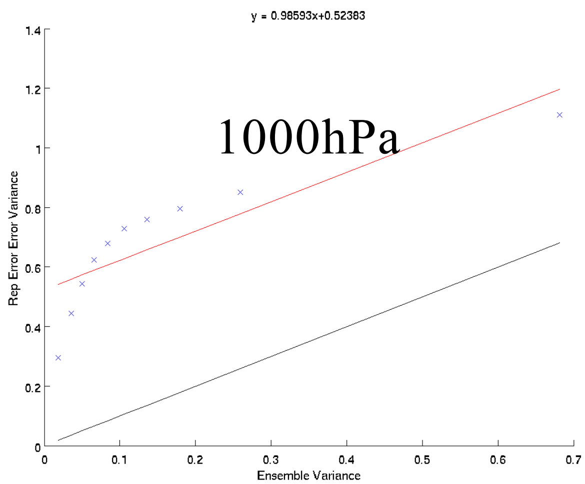
200 hPa temperature 1 Jan 2015
ECMWF analyses 32km resolution

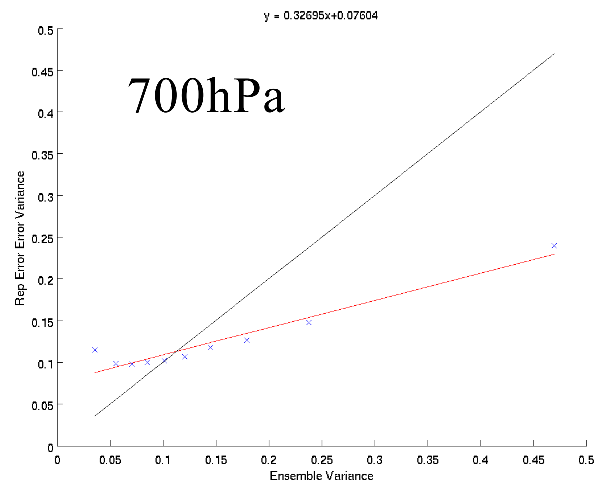


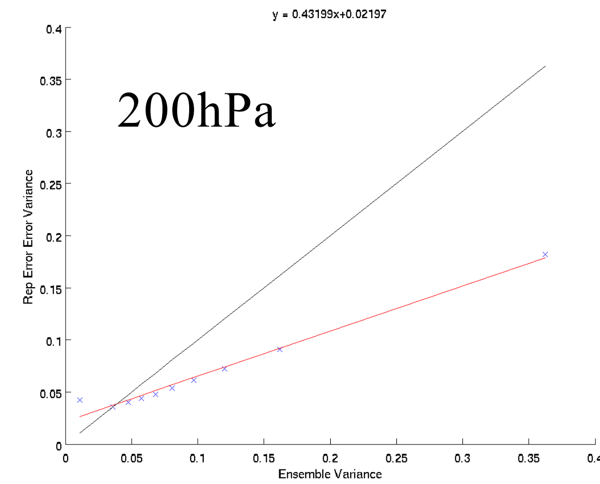
200 hPa temperature 1 Jan 2015
Filtered ECMWF analyses 125 km resolution

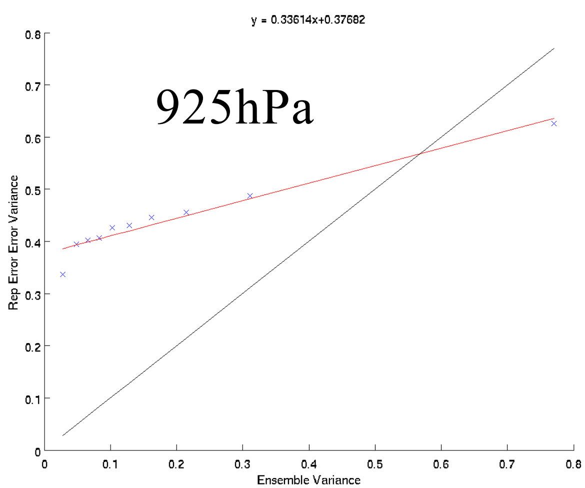


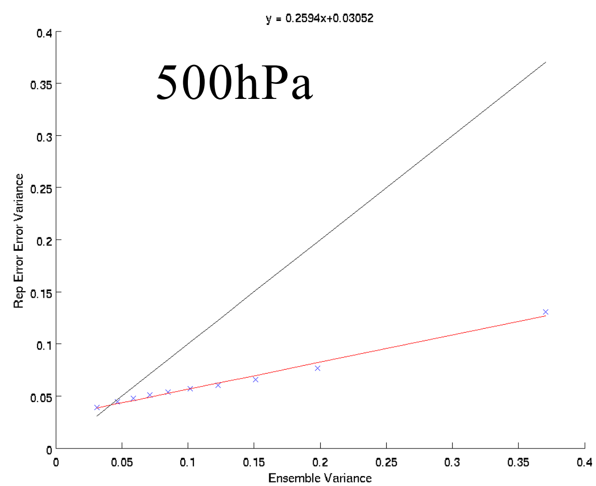
Filtering acts to smooth features

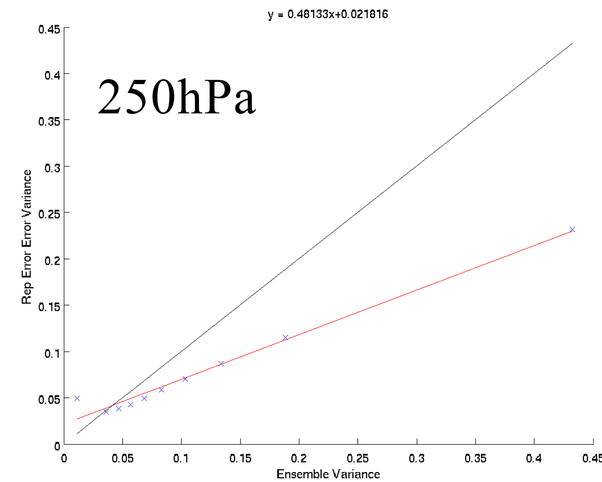

y = 0.98593x+0.52383
1000hPa
Rep Error Error Variance
Ensemble Variance

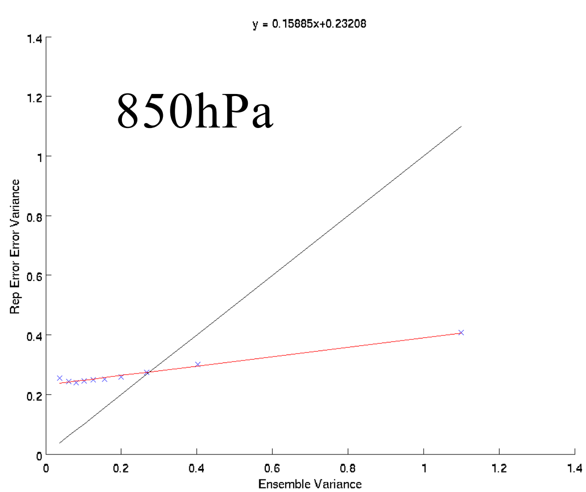

y = 0.32695x+0.07604
700hPa
Rep Error Error Variance
Ensemble Variance

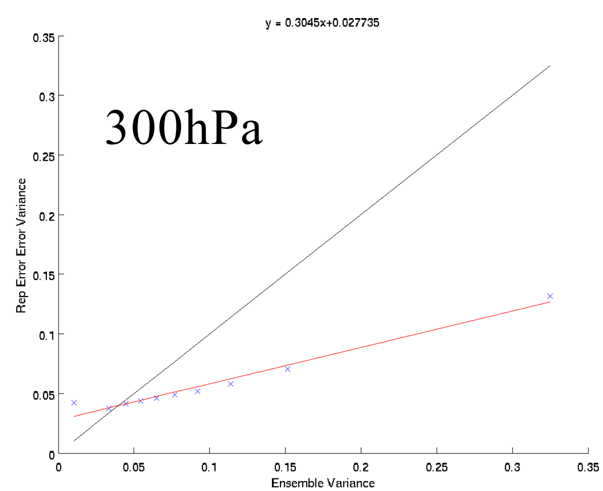

y = 0.43199x+0.02197
200hPa
Rep Error Error Variance
Ensemble Variance


y = 0.33614x+0.37682
925hPa
Rep Error Error Variance
Ensemble Variance


y = 0.2594x+0.03052
500hPa
Rep Error Error Variance
Ensemble Variance


y = 0.48133x+0.021616
250hPa
Rep Error Error Variance
Ensemble Variance


y = 0.15885x+0.23208
850hPa
Rep Error Error Variance
Ensemble Variance


y = 0.3045x+0.027735
300hPa
Rep Error Error Variance
Ensemble Variance