Correlated Observation Errors in Data Assimilation

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Outline

• Observation Errors
• Errors of Representativity
• Experimental Results
• Summary
Observation Errors

- Observation errors assumed uncorrelated in data assimilation
Observation Errors

- Observation errors assumed uncorrelated in data assimilation

- Observation errors in real data are found to be correlated
  (Stewart et al, 2009, 2012; Bormann et al, 2010; Waller et al, 2013.)

Observation Error Covariance Matrix
Observation Errors

- Observation errors assumed uncorrelated in data assimilation

- Observation errors in real data are found to be correlated
  (Stewart et al, 2009, 2012; Bormann et al, 2010; Waller et al, 2013.)

- Using observation error correlations in data assimilation is shown to improve the analysis
  (Stewart et al, 2010, 2012; Weston, 2012.)
Observation Errors

Four main sources of observation errors:
Research Aims

- Investigate the *structure* and properties of *representativity* errors (this talk)

- *Estimate* and *incorporate correlated observation errors* in ensemble data assimilation (see poster of Joanne Waller)
Errors of Representativity

Data assimilation combines observations with a model prediction.

Observations can contain information at smaller scales than the model can resolve.

Errors of representativity are the result of small scale information in observations being incorrectly represented in the model.
Structure of Static Representativity Error

Liu & Rabier (2002)  *QJRMS*
Experiments

Assumption: Model state is a truncation of a high resolution ‘true’ state.

True states are temperature and humidity from MetO UKV (1.5 km) model. Truncation is $\times 8$ ($\sim 12$ km grid). Observed at all model grid points.

Two cases -

- Case 1: cloudy/ convection
- Case 2: slow tracking deep depression
Data – Case 1

Temperature and specific humidity fields at 749 hPa
### Representativity Error Variances - Case 1

<table>
<thead>
<tr>
<th>Experiment Number</th>
<th>Truncation</th>
<th>Number of Observations ($p$)</th>
<th>Observation type</th>
<th>Temperature RE variance ((K)$^2$)</th>
<th>Humidity RE variance ((kg/kg)$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>32</td>
<td>32</td>
<td>Direct</td>
<td>$4.81 \times 10^{-3}$ (0.7%)</td>
<td>$1.51 \times 10^{-3}$ (1.9%)</td>
</tr>
<tr>
<td>1.2</td>
<td>32</td>
<td>32</td>
<td>Uniform</td>
<td>$2.71 \times 10^{-3}$ (0.4%)</td>
<td>$1.08 \times 10^{-3}$ (1.3%)</td>
</tr>
<tr>
<td>1.3</td>
<td>32</td>
<td>32</td>
<td>Gaussian</td>
<td>$8.99 \times 10^{-4}$ (0.1%)</td>
<td>$3.80 \times 10^{-4}$ (0.5%)</td>
</tr>
<tr>
<td>1.4</td>
<td>32</td>
<td>16</td>
<td>Direct</td>
<td>$4.81 \times 10^{-3}$ (0.7%)</td>
<td>$1.51 \times 10^{-3}$ (1.9%)</td>
</tr>
<tr>
<td>1.5</td>
<td>64</td>
<td>64</td>
<td>Direct</td>
<td>$2.13 \times 10^{-3}$ (0.3%)</td>
<td>$4.04 \times 10^{-4}$ (0.5%)</td>
</tr>
</tbody>
</table>

Representativity error (RE) variances for temperature and natural logarithm of specific humidity at 749 hPa for Case 1. The values in brackets compare the RE variance to the high-resolution data variance.
Representatvity Error Correlation Structure

Figure 2. Representatvity error correlations between observation center points for Case 1 at 749hPa with truncation to 32 points (12km resolution) with every model grid point observed using direct (solid line) and Gaussian-weighted (dashed line) observations. a) Temperature b) ln(Specific humidity)
Results - Case 1

(a) Temperature (K)  
(b) log(Specific humidity) (kg/kg)

Standard Deviations of Representativity Errors
Results - Case 2

Standard Deviations of Representativity Errors

(a) Temperature (K)  
(b) log(Specific humidity) (kg/kg)
Conclusions

Errors of representativity:

• are correlated and state and time dependent;
• are reduced by increasing model resolution or increasing observation length scale;
• vary with height throughout the atmosphere;
• are more significant for humidity than temperature;
• depend only on distance between observations and not the number.

Limitations and Extensions

Diagnosing correlated observation errors using this technique is **not feasible** in practice.

- Spectral covariance of truth is unknown
- Operators not invertible
- Error covariances are static

Now developed a **new** method for diagnosing and incorporating **time-dependent observation error covariances** in an ensemble Kalman filter. Gives improved analysis. (See poster of Joanne Waller.)

References

• Waller JA. 2013. Using observations at different spatial scales in data assimilation for environmental prediction, PhD thesis, University of Reading.
Aims: enable discussion and exchange of expertise between stakeholders on

- Methods for finding and approximating observation error correlation matrices
- Methods for efficiently implementing correlated observation errors in data assimilation systems

Outcome: better value from available observations