Observation errors

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NWP SAF Training Course
Outline

1. What are observation errors?
2. Estimating observation errors
3. Specification of observation errors in practice
4. Accounting for observation error correlations
5. Summary
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Errors in observations

• Every observation has an error vs the truth:
  – Systematic error
    • Needs to be removed through bias correction (see separate lecture)
  – Random error
    • Topic of this lecture!
Contributions to observation error

**Measurement error**
E.g., instrument noise for satellite radiances

**Forward model (observation operator) error**
E.g., radiative transfer error

**Representativeness error**
E.g., point measurement vs model representation

**Quality control/pre-processing error**
E.g., error due to the cloud detection scheme missing some clouds in clear-sky radiance assimilation
Contributions to observation error

**Measurement error**
E.g., instrument noise for satellite radiances

**Forward model (observation operator) error**
E.g., radiative transfer error

- Are the errors situation-dependent?
- Are the errors correlated (spatially, temporally, between channels)?
- Are the errors systematic (→bias correction)?

**Representativeness error**
E.g., point measurement vs model representation

**Quality control error**
E.g., error due to the cloud detection scheme missing some clouds in clear-sky radiance assimilation
Examples of situation-dependence of observation error

- Cloud/rain-affected radiances: Representativeness error is much larger in cloudy/rainy regions than in clear-sky regions.

- Effect of height assignment error for Atmospheric Motion Vectors:

  ![Diagram showing wind shear and height assignment error](chart.png)

  - Strong shear – larger wind error due to height assignment error
  - Low shear – small wind error due to height assignment error

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Examples of correlated observation error

- Different channels with similar radiative transfer error.
- Different channels with similar error in spatial representativeness.
- Different channels with similar cloud sensitivity in clear-sky assimilation.
- Even instrument noise can be correlated.
Observation error and the cost function

- In data assimilation, observation errors are commonly assumed Gaussian.
- Denoted by the observation error covariance matrix “$R$” in the observation cost function:
  \[
  J(x) = \frac{1}{2} (x - x_b)^T B^{-1} (x - x_b) + \frac{1}{2} (y - H[x])^T R^{-1} (y - H[x])
  \]
- It is often specified through the square root of the diagonals (“$\sigma_o$”) and a correlation matrix (which can be the identity matrix).
Role of observation error

- **R** and the background error **B** together determine the weight of an observation in the assimilation.
- In the linear case, the minimum of the cost function can be found at $x_a$:

\[
(x_a - x_b) = BH^T (HBH^T + R)^{-1} (y - Hx_b)
\]

- **“Large” observation error** $\rightarrow$ **smaller increment**, analysis draws less closely to the observations
- **“Small” observation error** $\rightarrow$ **larger increment**, analysis draws more closely to the observations
Current observation error specification for satellite data in the ECMWF system

• Globally constant, diagonal, dependent on channel only:
  – AIRS, MWHS

• Globally constant, inter-channel error correlations taken into account:
  – IASI, CrIS, ATMS

• Globally constant fraction, dependent on impact parameter; diagonal:
  – GPS-RO

• Situation dependent, diagonal:
  – AMSU-A: dependent on satellite, channel, and RT-model contribution
  – All-sky treatment of MW imagers, MW humidity sounders: dependent on channel and cloud amount
  – AMVs: dependent on level and shear (and satellite, channel, height assignment method)
  – Aeolus: based on physically estimated error for each derived wind
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How can we estimate observation errors?

• Observation errors are *departures from the truth* – which we don’t know.

• We can only *estimate* observation errors. Several methods exist to do this, broadly categorised as:
  
  - **Error inventory:**
    • Based on considering all contributions to the error/uncertainty
  
  - **Diagnostics with collocated observations, e.g.:**
    • Hollingsworth/Lönnberg on collocated observations
    • Triple-collocations
  
  - **Diagnostics based on output from DA systems, e.g.:**
    • O-b statistics
    • Hollingsworth/Lönnberg
    • Desroziers et al 2005
    • Methods that rely on an explicit estimate of B
  
  - **Adjoint-based methods**
Error inventory

- Estimate the error from *physical estimates of all uncertainty* contributions.
- Example: error inventory for IASI

![Graph showing estimated error vs IASI channel index]

- Instrument noise (information from data providers)
- Radiative transfer error (difficult…)
- Spatial representativeness error (e.g., through high vs low-resolution simulations)
- Cloud detection error (e.g., using simulations of cloudy radiances)
- Total error

(Courtesy Hyoung-Wook Chun, Reima Eresmaa)
Error inventory

- Estimate the error from **physical estimates of all uncertainty** contributions.
- Example: error inventory for IASI

![Graph showing total error correlation]

- Very useful to **understand** error contributions.
- **How realistic** is each estimate?
Error inventory and physical observation error models

• Other applications of an inventory approach:
  – Physical error models: propagate parameter uncertainty through observation operator/retrieval
  – Useful for identifying leading contributors of observational uncertainty
  – Basis for “observation error models” to capture situation-dependence of observation errors

An observation error model for the height assignment uncertainty could be:
\[ \sigma_{HA} = f(\Delta p, \text{shear in background}) \]
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    - Methods that rely on an explicit estimate of B
  
  - **Adjoint-based methods**
Departure-based diagnostics

• Several methods have been developed that are based on departures from data assimilation systems (ie o-b, o-a).

• If observation errors and background errors are uncorrelated then:

\[
\text{Cov}[(y - H[x_b]),(y - H[x_b])] = H B_{\text{true}} H^T + R_{\text{true}}
\]

• In this case, stdev(o-b) is an upper bound for \(\sigma_o\).

• Statistics of background departures give information on observation and background error combined. To separate the two, we need to make assumptions (which may or may not be true).
Departure-based observation error diagnostics: Methods that rely on an estimate of the background error

• **Basic assumptions:**
  
  – Background and observation error are *uncorrelated.*
  
  – We have a **reliable estimate of the background error**, for instance:

    • Background error is small: \[ R = \text{Cov}[(y - H[x_b]), (y - H[x_b])] - HBH^T \]

    • Or: we “know” \( HB_{\text{true}}^T \) from the assimilation system:

      \[ R = \text{Cov}[(y - H[x_b]), (y - H[x_b])] - H B_{\text{true}}^T \]
Departure-based observation error diagnostics: Hollingsworth/Loennberg method (I)

• **Basic assumption:**
  – Background errors are spatially correlated, whereas observation errors are not.
  – This allows to separate the two contributions to the variances of background departures.

• **Recipe:**
  – Take a large database of pairs of departures and bin by distance between the observations.
  – Calculate covariance of departures for each bin.

• **Drawback:**
  – Not reliable when observation errors are spatially correlated.
Departure-based observation error diagnostics: Hollingsworth/Loennberg method (II)

• Similar methods have been used with differences between two sets of **collocated observations**:
  
  – Example: AMVs collocated with radiosondes (Bormann et al 2003).
    
  • Radiosonde error assumed spatially uncorrelated.
Departure-based observation error diagnostics: Desroziers diagnostic (I)

• **Basic assumptions:**
  – Assimilation process can be adequately described through linear estimation theory.
  – Weights used in the assimilation system are consistent with true observation and background errors.

• Then the following relationship can be derived:

\[ R = Cov[d_a, d_b] \]

with \( d_a = (y - H[x_a]) \) (analysis departure)

\( d_b = (y - H[x_b]) \) (background departure)

(see Desroziers et al. 2005, QJRMS)

• **Consistency diagnostic** for the specification of \( R \). Increasingly used to estimate \( R \).
Departure-based observation error diagnostics: Desroziers diagnostic (II)

• Very easy to use – all ingredients readily available in an assimilation system.
• Can be applied iteratively.

• It *will give incorrect estimates* if its assumptions are violated (as with any method!).

• For real assimilation systems, the limits of applicability of the diagnostic for estimating observation errors is still subject of research.
Some points on departure-based diagnostics

• All departure-based diagnostics rely on assumptions (which may or may not be true):
  – Assume we know the background error characteristics → remove B
  – Assume a certain structure of the errors → Hollingsworth/Lönnberg
  – Assume weights used in the assimilation system are accurate → Desroziers diagnostic
• All diagnostics additionally assume that the error in the observations and background are uncorrelated.

• Before applying any diagnostic, think about whether the assumptions are likely to be true.
• It is best to use several diagnostics to avoid misleading estimates due to violated assumptions.
• Diagnostics do not tell you where the error comes from.
  – Additional physical understanding of the error sources will be beneficial → error inventory.
  – Diagnostics can be used together with physical error models.
Examples of applying observation error diagnostics: AMSU-A

Diagnostics for $\sigma_o$
Examples of applying observation error diagnostics: AMSU-A

Inter-channel error correlations:

Hollingworth/Loennberg

Desroziers
Examples of applying observation error diagnostics: AMSU-A

Spatial error correlations:

- **Channel 5**
  - Red line: Desroziers method
  - Blue line: Background error method

- **Channel 7**
  - Red line: Desroziers method
  - Blue line: Background error method
Examples of applying observation error diagnostics: IASI

Diagnostics for $\sigma_0$
Examples of applying observation error diagnostics: IASI

Inter-channel error correlations
Examples of applying observation error diagnostics: IASI

Inter-channel error correlations

Humidity
Ozone
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How do I specify observation errors in practice?

- Observation error diagnostics or error inventories can provide guidance for observation error specification in DA, including on:
  - *Relative size* of observation and background errors
  - Presence of observation *error correlations*
  - *Situation-dependence* of observation errors

- **But:**
  - Estimates might have short-comings (violated assumptions).
  - Observation errors specified in assimilation systems often need to be *simplified*:
    - Observation error covariance is often *assumed to be diagonal or globally constant*.
  
  → *Assumed* observation errors may need *adjustments* compared to estimated ones.
Too large assumed observation errors tend to be safer than too small ones. Why?

Consider a linear combination of two estimates $x_b$ and $y$:

$$x_a = \alpha x_b + (1 - \alpha) y$$

The error variance of the linear combination is:

$$\sigma_a^2 = \alpha^2 \sigma_b^2 + (1 - \alpha)^2 \sigma_o^2$$

The optimal weighting (ie minimum $\sigma_a$) is:

$$\alpha = \frac{\sigma_o^2}{\sigma_b^2 + \sigma_o^2}$$

**Danger zone:** Too small assumed $\sigma_o$ will lead to an analysis worse than the background when the (true) $\sigma_o > \sigma_b$. Assuming an inflated $\sigma_o$ will never result in deterioration.
What to do when there are error correlations?  
Option 1: Thinning

• If the observations have **spatial error correlations, but these are neglected** in the assimilation system, assimilating these observations too densely can have a **negative effect**.

• **Pragmatic solution 1**: Select one observation within a “thinning box”.

• See Liu and Rabier (2003), QJRMS: “Optimal” thinning when $r \approx 0.15-0.2$

• Using **fewer** observations gives **better** results!

• (But we lose out on information on smaller scales.)

![Diagram showing analysis error vs. observation interval](image-url)
What to do when there are error correlations?
Option 2: Inflation

- If the observations have *error correlations, but these are neglected* in the assimilation system, assimilating them can have a *negative effect*.

- **Pragmatic solution 2**: Use larger $\sigma_o$ than expected (“*Error inflation*”).

- **Neglecting error correlation with no inflation** can result in an analysis that is *worse* than the background!

- Note: Background departure statistics for other observations are a useful indicator to tune observation errors.
What to do when there are error correlations? Combining thinning and inflation

- In case of spatial error correlations, thinning and inflation can be used together.
- Example: Use of AMSU-A in the Environment Canada system (Bedard et al. 2019, ITSC-22)
  - Optimal inflation factor is larger with less thinning.

Impact on vertically averaged global 48-hour forecast error
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Accounting for error correlations

• Accounting for observation error correlations is an area of active research.

• Efficient methods exist if the error correlations are restricted to small groups of observations (e.g., *inter-channel error correlations*).
  
  – E.g., calculate $R^{-1} (y - H(x))$ without explicit inversion of $R$, by using Cholesky decomposition (algorithm for solving equations of the form $Az = b$).
  
  – Used operationally for IASI, CrIS and ATMS at ECMWF (and elsewhere)

• Accounting for *spatial error correlations* is technically more difficult in variational algorithms, though methods are being developed.
What is the effect of error correlations?

If errors \textit{are correlated} and we \textit{assume no error correlations}, we assign…

- … an error that is \textit{too small} for features along the blue direction (mean-like features), leading to over-weighting of the observations. Hence inflation helps.
- … an error that is \textit{too large} for features along the red direction (gradient-type features).
What is the effect of error correlations?

Uncorrelated error

\[
R = \begin{pmatrix}
1 & 0 \\
0 & 1
\end{pmatrix}
\]

Correlated error

\[
R = \begin{pmatrix}
1 & 0.8 \\
0.8 & 1
\end{pmatrix}
\]

Similarly, when we account for observation error correlations we tell the assimilation system that…

… departures that are similar for different observations are more likely due to errors in the observations.

… departures that are different for different observations are less likely due to errors in the observations.
Example: Assimilation of a IASI spectrum (I)

Assimilate a single IASI spectrum,
• assuming no error correlations,
• assuming diagnosed error correlations ($\sigma_o$ unchanged in both cases).

Obs-background departure (all channels assimilated)
Example: Assimilation of a IASI spectrum (I)

Assimilate a single IASI spectrum, 
• assuming no error correlations, 
• assuming diagnosed error correlations ($\sigma_o$ unchanged in both cases).

Similar departures → increments reduced with error correlations taken into account
Example: Assimilation of a IASI spectrum (II)

Assimilate a single IASI spectrum,
• assuming no error correlations,
• assuming diagnosed error correlations ($\sigma_o$ unchanged in both cases).

Different departures $\rightarrow$ increments *increased* with error correlations taken into account.
Example: Assimilation of a IASI spectrum (II)

Assimilate a single IASI spectrum,
• assuming no error correlations,
• assuming diagnosed error correlations ($\sigma_o$ unchanged in both cases).

Introducing error correlations will change the weighting of the observations in a situation/depature-dependent way.

Different departures $\rightarrow$ increments *increased* with error correlations taken into account.
Effect of accounting for error correlations in the assimilation of IASI

Most centres now take inter-channel error correlations into account for the assimilation of hyperspectral IR data.
Some points on accounting for observation error correlations

• Accounting for observation error correlations is an **active area of research**.
• **Benefits** have been **demonstrated** at many centres for the assimilation of hyperspectral IR data.
• Note:
  – Assuming error correlations puts **more weight on differences between observations**. Are these differences reliable? How reliable are **inter-channel calibration/bias correction**?
  – Are the **estimates of error correlations reliable**?
  – Accounting for observation error correlations can affect the **conditioning** of the assimilation and lead to slower convergence.
  – Error correlation matrices **may need adjustments** (“re-conditioning”, inflation).
• How important it is to account for error correlations may additionally depend on the structure of the background error.
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Summary

• Assigned observation and background errors determine how much weight an observation receives in the assimilation.

• For satellite data, “true” observation errors are often correlated (spatially, in time, between channels, etc) and situation-dependent.

• Careful use of departure-based diagnostics can provide guidance on the setting of observation errors.

• Diagonal observation errors are still widely assumed for many observations, and thinning and error inflation are used to counter-act the effects of error correlations.

• “Observation error models” are used to account for situation-dependence of observation errors.

• Accounting for observation error correlations has become more common in the last few years and is an active area of research.
Further reading


• Bormann and Bauer (2010): Estimates of spatial and inter-channel observation error characteristics for current sounder radiances for NWP, part I: Methods and application to ATOVS data. QJRMS, 136, 1036-1050.

• Bormann et al. (2010): Estimates of spatial and inter-channel observation error characteristics for current sounder radiances for NWP, part II: Application to AIRS and IASI. QJRMS, 136, 1051-1063.


• Desroziers et al. (2005): Diagnosis of observation, background and analysis error statistics in observation space. QJRMS, 131, 3385-3396.


• Liu and Rabier (2003): The potential of high-density observations for numerical weather prediction: A study with simulated observations. QJRMS, 129, 3013-3035.

Vacancies for EUMETSAT Research Fellowships at ECMWF

• **All-sky assimilation of radiances from microwave instruments in NWP**
  – Up to 5-year contract
  – Deadline 16 March 2020

• **Assimilation of geostationary radiances in NWP**
  – Up to 3-year contract
  – Deadline 16 March 2020

For more information see:
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Or
https://www.ecmwf.int/en/about/jobs/jobs(ecmwf)