# A review of the evolution of setting observation errors in satellite DA

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with material from many people



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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 Dick Dee's talk)

#### Random error

- Mostly assumed Gaussian in DA.
- Denoted by the observation error covariance matrix "**R**" in the observation cost function:

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

• Often specified through the square root of the diagonals (" $\sigma_o$ ") and a correlation matrix (which can be the identity matrix).

## Contributions to observation error

#### **Measurement error**

E.g., instrument noise for satellite radiances

### Representation error (e.g., Janjić et al 2017)

#### Forward model (observation operator)

error E.g., radiative transfer error



#### **Representativeness error**

E.g., point measurement vs model representation





## Contributions to observation error

#### Representation error (e.g., Janjić et al 2017)



## Observation error specification 20 years ago

- R diagonal, one constant number per channel/level
- Thin data, to avoid spatial error correlations

#### • Prevailing wisdom: Make $\sigma_o$ large

- To counter-act remaining error correlations
- To stay away from the danger zone



### Assigning observation errors matters

#### AMSU-A observation error revision at ECMWF, 37r2, 2011

#### Impact on Z500 RMSE



Estimated error [K]



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## Increased sophistication of observation error assignment

• Current observation error setting at ECMWF reflect two main strands of recent development in observation error modelling:

## Situation-dependent observation errors:

- AMSU-A: dependent on satellite, channel, cloudiness, surface emissivity error
- All-sky error model for MW imagers, MW humidity sounders: dependent on channel and cloud amount
- AMVs: dependent on level and wind shear (and satellite, channel, height assignment method)
- Aeolus: based on physically estimated error for each derived wind

Observation errors with inter-channel error correlations taken into account (globally constant):

- IASI, CrIS
- ATMS
- WV channels from geostationary imagers

## Outline

- 1. Introduction
- 2. Situation-dependent observation errors
- 3. Correlated observation errors
- 4. Error inventories and closure studies
- 5. Summary

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1. Introduction

#### 2. Situation-dependent observation errors

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## Situation-dependence of observation errors

- Observation errors can be situation-dependent, particularly the contributions from representation error.
- To account for this, observation errors are modelled as a function of situation-dependent parameters.





## Situation-dependence of observation errors: Example: surface-related errors

(e.g., English et al 2008; Lawrence et al 2015; etc)

Contributions from emissivity and skin-temperature errors to forward-modelling for surface-sensitive radiances:

$$dI = \epsilon \tau \delta T_s + ((T_s - T)\tau + (T - T_c)\tau^2)\delta\epsilon$$

 $\sigma_0^2 = (\sigma_{O NeDT})^2 + (dI)^2$ 







Situation-dependence of observation errors: Example: All-sky assimilation

(e.g., Geer and Bauer 2011; Okamoto et al 2014; Harnisch et al 2016)

Representation error larger in cloudy regions: observation error modelled as function of cloud indicator; observation error model derived from stdev(o-b)





## Some remarks on modelling situation-dependent observation errors

- Current approaches aim to identify and model the main situation-dependent contributions, based on physical considerations
  - Models are mostly specified based on observation departure statistics (stdev(o-b)), with ad-hoc assumptions on the behaviour of background errors.
    - How valid are the underlying assumptions on background errors?
    - Scope for more independent specification of error sources?
- What situation-dependent variations are we currently missing?
  - E.g., convective vs stratiform clouds in all-sky; larger errors in H for obs at the end of 4D-Var window?
  - What level of sophistication is useful and desirable for situation-dependent observation errors? What can
    we model reliably?

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## **Observation error correlations**

- Representation error is likely to be correlated between different observations, e.g.:
  - An error in cloud detection is likely be similar for other channels with similar cloud-sensitivity in clear-sky assimilation.
  - A radiative transfer error is likely to be similar for spectrally-similar channels.
  - A height-assignment error for AMVs is likely to be similar for neighbouring AMVs derived from a similar cloud.
- And even instrument noise can be correlated between channels:



ATMS instrument noise correlation, from independent instrument characterisation.



## Estimating spatial error correlations for AMVs

(e.g., Bormann et al 2003)

- Estimated using a Hollingsworth/Lönnberg approach:
  - Use pairs of collocated AMVs & radiosondes.
  - Assume errors in radiosondes uncorrelated.

## Correlations between AMV/radiosonde differences



## Estimating inter-channel error correlations for hyper-spectral IR observations

**B1** 

1

**B1** 

LN conding

(e.g., Garand et al 2007)

- Estimated using a Hollingsworth/Lönnberg approach: ٠
  - Use pairs of o-b for AIRS.
  - Assume AIRS observation errors are spatially • uncorrelated.
- Possible source of error correlation:
  - Cloud detection
  - Spatial representativeness •
  - Radiative transfer

#### 123 100 **B4** 98 80 **B**3 71 60 **B**2 40 39

**B2** 

Wwindow

channels

39

**B**3

sounding

Humidity

98

71

**B4** 

SW channels

123

18

20

#### Diagnosed error correlations for AIRS [%]



## Estimating inter-channel error correlations for hyper-spectral IR observations and the Desroziers diagnostic

index

Channel

(e.g., Desroziers et al 2005)

#### Basic assumptions:

- Linear estimation theory; errors in observation and background uncorrelated.
- Weights used in the assimilation system are consistent with true observation and background errors.
- Then the following relationship can be derived:

 $\mathbf{R} = Cov[\mathbf{d}_a, \mathbf{d}_b]$ 

with  $\mathbf{d}_a = (\mathbf{y} - \mathbf{H}[\mathbf{x}_a])$  (analysis departure)

 $\mathbf{d}_b = (\mathbf{y} - \mathbf{H}[\mathbf{x}_b])$  (background departure)

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• **Consistency diagnostic** for the specification of **R**. Increasingly used to estimate **R**.

## Diagnosed error correlations for IASI (Stewart et al 2009, 2014)



 $\rightarrow$  Sarah Dance's talk on error diagnostics <sup>19</sup>

## Estimating inter-channel error correlations for hyper-spectral IR observations and the Desroziers diagnostic



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Diagnosed error correlations for IASI (Stewart et al 2009, 2014)

1206.00

1409.25

120

1990.00

- 0.75

- 0.5

0.25

-0.5

-0.75

0.25 0 0 value -0.25 0

 $\rightarrow$  Sarah Dance's talk on error diagnostics 20 Estimating inter-channel error correlations for hyperspectral IR: Different diagnostics, similar results

(Bormann et al 2010)







Estimating inter-channel error correlations for hyperspectral IR: Different diagnostics, similar results

(Bormann et al 2010)





Channel number



Wavenumber [cm-

- 0.9

0.85

0.8

0.75

0.7

0.65

0.6

0.55

0.5

0.45

0.4

0.35

0.3

0.25

0.2

0.15

0.1

0.05

-0.05

- 0



## What is the effect of error correlations?



Compared to diagonal errors, *positive error correlations imply*...

- ... *larger errors* for features along the blue direction (mean-like features).
- ... *smaller errors* for features along the red direction (differencee-type features).

### Example: error correlations for IASI

Eigenvalues of the error correlation matrix:





## Example: Assimilation of a single 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 single IASI spectrum (II)

Assimilate a single IASI spectrum,

- assuming no error correlations,
- assuming diagnosed error correlations ( $\sigma_0$  unchanged in both cases).



"Different" departures → increments *increased* 



## Effect of accounting for inter-channel error correlations in the assimilation of IASI



### Accounting for inter-channel error correlations in the assimilation

- Now widely used at operational centres, for hyperspectral IR, geostationary imager radiances, ATMS, etc.
- E.g., Weston et al (2014), Bormann et al (2016), Campbell et al (2017), Weston and Bormann (2018), Burrows (2018), Bathmann and Collard (2020), ...
- $\rightarrow$  Fiona Smith's talk on the status of R for hyperspectral IR



#### Verification v Observations

Verification v Analyses



Weston et al (2014)

## Accounting for spatial error correlations

- Less work has been done on accounting for spatial error correlations in NWP, partly as it is *technically more difficult in variational frameworks*.
- But recent activity in several areas (→ *talks by Koji Terasaki, Oliver Guillet, Joël Bédard*)
  - First operational application in Met Office UKV system for radial winds from Doppler radar (Simonin et al 2019):



Accounting for spatial error correlations allows beneficial assimilation of radar winds with less thinning.

Particular interest for regional models, to *improve small-scale representation*.

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Some further points on accounting for observation error correlations

- Accounting for 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.
- The importance of accounting for error correlations may additionally depend on the structure of the **background error**.

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## Contributions to observation error



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error E.g., radiative transfer error



#### Representativeness error

E.g., point measurement vs model representation







## Error inventory

(e.g., Chun et al 2015)

 Idea: Estimate the observation error from estimates of <u>all</u> uncertainty contributions.

• Example: error inventory for IASI



## Error inventory

(e.g., Chun et al 2015)

- Idea: Estimate the observation error from estimates of <u>all</u> uncertainty contributions.
- Example: error inventory for IASI







## Error inventory ... and closure studies

• How do the separate error estimates compare to the total (observation + background) error estimate from observation departures?

#### • <u>Here:</u> Combined observation error estimate alone is (mostly) <u>larger</u> than stdev(o-b).

- Overestimation of error contributions?
- Correlations between background and observation errors (e.g., cloud detection error)?





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## Summary

- A lot of progress in specifying observation errors in recent years; *more aspects of observation error are being taken into account*.
  - Situation-dependence of observation errors increasingly taken into account, based on physical considerations paired with departure statistics.
  - Inter-channel error correlations are now widely accounted for, using results of departure-based diagnostics with some adjustments to specify R.
  - Accounting for *horizontal error correlations* is emerging.
  - Continue to see *significant benefit* for forecast skill from better specifications of observation errors.
- Most sophistications of observation error modelling are based on departure statistics in one way or another.
  - Stdev(o-b), Hollingsworth/Lönnberg, Desroziers, Cov(o-b) HBH<sup>T</sup>; collocated observations/triple collocations
  - All rely on a *range of assumptions*, which may or may not be true.
  - Sometimes *adjustments* are necessary (inflation/reconditioning), sometimes they aren't.
  - Error inventories can instead shed light on the dominant sources of error, and they can bring further independent information to error modelling.

## Some thoughts for the working groups

- A lot of progress in specifying observation errors in recent years with increased sophistication.
  - But what level of (further) sophistication is useful/desirable?
    - Limitations in the available estimates for specifying R
    - Maintainability of error modelling responding to changes in the size of error contributions
- What tools do we have to estimate observation errors and how well do they cover our needs?
  - How can we make more use of uncertainty characterisation beyond departure-based diagnostics (e.g., instrument characterisation, metrological approaches, etc)?
- When do observation error correlations matter?
  - Compare, for instance, success of taking inter-channel error correlations into account for hyper-spectral IR vs the diagonal observation error modelling in successful MW all-sky assimilation (where representation error is huge and correlated).
- What aspects of observation error modelling may become more important in the future?
  - E.g., due to higher-resolution analyses; observations with higher temporal resolution; Earth system approaches