The effect of NWP model bias on radiance bias correction schemes

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From James Cameron

Operational:
• in Global model, March 2016
• in UKV, July 2017.

Bias predictors:
• as old scheme (2 thicknesses) +
• orbital bias predictors for SSMIS

Bias halving time: 2 days

Impact – VERY LARGE!:
• T+24 H500 RMSE vs analysis: -7.1% in NH and -5.9% in SH
• Improved (O-B) fits, e.g. 2-6% improved fit to ATMS
The bias correction problem in DA

- Standard DA theory assumes observations are unbiased
- … or that they are bias-corrected ahead of the DA

- Bias correction is necessary for assimilation of radiances
- … for biases in the observations and/or their operators

- Two types of observation in DA:
  - “Anchor” observations, assumed unbiased
  - may have been pre-corrected (e.g. sondes)
  - may still contain biases
  - Observations to be bias-corrected within the DA system

HOWEVER …
What is the purpose of observation bias correction in DA?

- To remove biases between observations and NWP fields (backgrounds or analyses)
- To improve NWP analyses and forecasts
Types of bias correction scheme used within DA systems

Bias correction schemes can:

- attempt to remove biases:
  - relative to background, or
  - relative to analysis

- be “static” (one-off), or
- iterated to convergence
  (e.g. variational bias correction, VarBC)
Bias correction literature

- “Static” bias correction (against background)
  - Eyre, ECMWF TM 176, 1992
  - Harris and Kelly, QJRMS, 2001

- VarBC (correction against analysis)
  - Derber and Wu, MWR, 1998
  - Dee, ECMWF Workshop, 2004; Dee, QJRMS, 2005

- “Off-line scheme” (like VarBC, but correcting v. background)
  - Auligné et al., QJRMS, 2007

- General papers on biases in DA and forecast model bias
  - Dee and da Silva, QJRMS, 1998; Dee, QJRMS, 2005
This study

- An attempt to understand scientific differences between Met Office old “static” scheme and new VarBC scheme
- Uses a very simple system (one variable)
- Explores the role of anchor observations
- Explores the role of model bias

For details see:

This study – key result

• Bias correction of observations is not “passive”. …

• … In the presence of model bias, bias-correcting a greater proportion of observations pulls the analysis away from the anchor observations and towards the model bias

→ Consequences for how we should do bias correction in future
Very simple assimilation system: the analysis step

- One scalar analysis variable
- Scalar observations in same space as analysis

Analysis, at \( n^{th} \) step:

\[
x_{a,n} = w_b x_{b,n} + w_1 y_{1,n} + w_2 y_{2,n}
\]

\( x_{a,n} = \) analysis, \( x_{b,n} = \) background
\( y_{1,n} = \) anchor observations, \( y_{2,n} = \) observations to be bias-corrected
\( w_j = \) analysis weights – general, not necessarily optimal, but …

\[
w_b + w_1 + w_2 = 1
\]
Very simple assimilation system: the error model

Biases and random errors:

\[ x_{j,n} = x_{t,n} + b_j + \varepsilon_{j,n} \]

\[ y_{j,n} = y_{t,n} + b_j + \varepsilon_{j,n} \]

\[ b_a = w_b b_b + w_1 b_1 + w_2 b_2 \]
Very simple assimilation system: the forecast step and its bias

**Forecast model**

\[ x_{b,n+1} = x_{f,n} = x_{a,n} + \delta x_{m,n} \]

**Forecast increment**

\[ \delta x_{m,n} = \delta x_{t,n} + \delta b_{m,n} + \delta \epsilon_{m,n} \]

Forecast model bias:

- a relaxation towards state \( x_{m,n} \), which has bias \( b_{m} \)
- where the relaxation rate is \( \alpha \).

\[ \delta b_{m,n} = \alpha (x_{m,n} - x_{a,n}) \]

\[ b_{b,n+1} = (1- \alpha)b_{a,n} + \alpha b_{m} \]

bias propagation in time
In asymptotic limit, and assuming anchor obs unbiased, with a static bias correction scheme (correcting against background):

\[
\frac{b_b}{b_m} = \frac{\gamma}{\gamma + w_1}, \quad \frac{b_a}{b_m} = \frac{\gamma(1 - w_1)}{\gamma + w_1}
\]

- \(b_b\): background bias
- \(b_a\): analysis bias relative to anchor obs
- \(b_m\): model bias
- \(w_1\): weight of anchor observations
- \(\gamma\): a model relaxation rate, \(\gamma = \frac{\alpha}{1 - \alpha}\)

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In asymptotic limit, and assuming anchor obs unbiased, with $\text{VarBC}$ (correcting against analysis):

$$
\frac{b_b}{b_m} = \frac{\gamma(1-w_2)}{\gamma(1-w_2) + w_1}
$$

$$
\frac{b_a}{b_m} = \frac{\gamma(1-w_1-w_2)}{\gamma(1-w_2) + w_1}
$$

$w_2$ weight of bias-corrected observations

***

So we now have 4 equations for bias as a fraction of model bias:

- for background bias, and for analysis bias
- correcting against background, and correcting against analysis
This study – parameters used

Baseline values – to mimic Met Office global NWP system

- **Total observation weight**, $\frac{\text{Tr}(W)}{p} \approx 1 - \left\{ \frac{\text{E}(J_{of})}{\text{E}(J_{oi})} \right\}^{0.5}$
  
  where $W$ is matrix of obs weights, dimension $p$, $\text{Tr}(\ldots)$ = trace, $\text{E}(\ldots)$ = expected value,
  $J_{if}$ = VAR initial observation cost,
  $J_{of}$ = VAR final observation cost.

  For Met Office global 4D-Var, $\frac{J_{if}}{J_{of}} \approx 0.6$-$0.7$,

  and so $\frac{\text{Tr}(W)}{p} \approx 0.2$

- **FSOI results** $\rightarrow w_1 \approx w_2 \rightarrow w_1 = w_2 = 0.2$

- **Model relaxation time** $\approx 3$ days $\rightarrow \gamma = 0.1$ (per DA cycle)
Asymptotic behaviour: no weight to anchor observations
Asymptotic behaviour: baseline weights

Bias correction vs background

$w_1 = 0.2, w_2 = 0.2$

- anchor obs
- analysis
- background
- model bias

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Asymptotic behaviour: reduced weight to anchor observations
At convergence:

varying relative weight of anchor obs

Vary $w_1$ with

$w_1 + w_2 = 0.4$

and $\gamma = 0.1$

baseline
At convergence: varying total weight of observations

Vary $w_1$ with $w_1 = w_2$ and $\gamma = 0.1$
At convergence: varying model relaxation rate

Vary $\gamma$ with $w_1 = w_2 = 0.2$
Some findings (1)

• In asymptotic limit, **biases in background and analysis** are **weighted averages of model bias and bias in anchor observations**, when correcting against background or against analysis.

• When **more** observations are bias-corrected, less weight is given to anchor observations and **more** weight to model bias.

• This effect is less pronounced when correcting v. analysis (VarBC) than when correcting v. background … but difference is small.

• In VarBC, effect of model bias is realised quickly; …

• …in static scheme not fully realised, or only through repeated application of scheme.
Some findings (2)

• Baseline values used in this scheme are intended to be representative of Met Office global NWP system

→ background/analysis bias is ~0.3 of model bias ! …

• … but much variation expected within model domain – according to observation density, fraction of anchor observations, height, model variable
Implications and questions

- Effect of adding more and more radiances
- Role of radio occultation
- Bias correction of radiosondes?
- Choice of bias predictors?
  - Avoid predictors for which variables have large model biases, particularly if they change rapidly, e.g. LST or cloud
- Choice of radiances used to compute bias correction coeffs.?
  - Take care with radiances affected by land surface or cloud
- Need for improved bias correction strategies?
Conclusions

• In the absence of model bias, bias correction of observations is relatively straightforward.

• **Radiance bias correction is not “passive” – it reinforces model bias.**

• VarBC is less affected by model bias than an equivalent scheme attempting to remove bias relative to the background,

• … but difference is small compared with model bias itself.

• With baseline values used here background / analysis biases are ~0.3 of model bias – larger than expected.

• **As relative weight of anchor observations decreases, effect of model bias on background/analysis bias increases**

  → important implications for observation bias correction strategies.
Thank you! Questions?
A very simple assimilation system (4)

Combining these equations →

\[ b_b = b_a + \alpha (b_m - b_a) = (1 - \alpha) b_a + \alpha b_m \]

→

\[ b_b = \frac{\gamma b_m + w_1 b_1 + w_2 b_2}{\gamma + w_1 + w_2} \]

\[ b_a = \frac{\gamma (1 - w_1 - w_2) b_m + (1 + \gamma)(w_1 b_1 + w_2 b_2)}{\gamma + w_1 + w_2} \]

where \( \gamma = \frac{\alpha}{1 - \alpha} \)
Special case – no model bias

No model bias: $\alpha = \gamma = 0$:

$$b_a = b_b = \frac{w_1 b_1 + w_2 b_2}{w_1 + w_2}$$

If also, $w_2 = 0$

$$b_a = b_b = b_1$$

Bias correction strategy:

- introduce observations $y_2$ into DA system passively: $w_2 = 0$
- monitor bias in $y_2$ against background: $c_2 = b_2 - b_b$
- bias-correct $y_2$: $y_2^* = y_2 - c_2$

These bias-corrected observations will now have bias:

$$b_2^* = b_2 - c_2 = b_b = b_a = b_1$$

PERFECT!!!
Effects of model bias (1)

With a **static bias correction scheme**, after 1\textsuperscript{st} application:

using (O-B) statistics $\rightarrow$

\[ c_2 = b_2 - b_b = b_2 - \frac{\gamma b_m + w_1 b_1 + w_2 b_2}{\gamma + w_1 + w_2} \]

In principle, you can stop here.

*** But we tend to repeat the process in an ad hoc manner ***

If you repeat the process to convergence:

$\rightarrow$

\[ b_b = \frac{\gamma b_m + w_1 b_1 + w_2 b_2}{\gamma + w_1 + w_2} \]

If $b_1 = 0$, $\rightarrow$

\[ \frac{b_b}{b_m} = \frac{\gamma}{\gamma + w_1} \]

\[ \frac{b_a}{b_m} = \frac{\gamma (1 - w_1)}{\gamma + w_1} \]

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