Evaluating the Analysis/Forecast System Using Observation-Impact

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Is there something **wrong** with MODIS AMVs?

**Clustered Detrimental Observations!**

Regions (black boxes) with clusters of **detrimental (red)** observations.

Case: Feb/06/2012 18Z  
Color: 06hr MTE impact (J/kg)  
Size: Magnitude of impact

**Detrimental episodes monitored w/EFSO**

**Detrimental episodes** in some observing systems.  
**MODIS polar winds** is one of the contributors.  
**Powerful QC monitoring for every system!**

Chen, T.-C., K. Bhargava, T. Yoshida, and E. Kalnay, 2018: New applications of advanced data assimilation to improve models and observations. Naval Research Laboratory

We will get back to this.
Assume initial forecast errors grow exponentially, with initial state defined by the DA background (6-hr forecast from previous analysis).

Forecast error grows from $e_{b0}$ to $e_{b24}$ along forecast background trajectory.

DA reduces initial error to $e_{a0}$ and forecast error evolves to $e_{a24}$ along analysis trajectory.
6-hourly analysis cycles April-June 2013

How does ob-impact change as high-quality pseudo-obs are assimilated and improve the analysis/forecast system?
Global Model Experiment: ECMWF Pseudo-raobs assimilated in NAVGEM

assimilate regular observations

Ob-Impact -7.7689

Trajectory curves are synthetic and are for illustrative purposes only. Final-time represents mean 24-hr error across all analysis cycles, relative to verifying analysis.
Global Model Experiment: ECMWF Pseudo-raobs assimilated in NAVGEM

Assimilate regular observations
assimilate reg. obs. + ECMWF pseudo-obs.

Ob-impact reduced by 15.6% when analysis is improved
What about the impact of each individual observation?

The observations $y$ influence the forecast error $e_f$ through translation of the innovation into an analysis increment by DA, and the evolution of the increment through the forecast by NWP:

$$(y, x_b) \rightarrow x_a \rightarrow x_f \rightarrow e_f$$

You can follow this process through the adjoint of these operators to obtain the sensitivity of $e_f$ with respect to each observation in $y$:

$$\begin{pmatrix} \frac{\partial e_f}{\partial y} \\ \frac{\partial e_f}{\partial x_b} \end{pmatrix} \text{DA}^T \frac{\partial e_f}{\partial x_a} \text{NWP}^T \frac{\partial e_f}{\partial x_f}$$

The impact of the observation $y_i$ is the product of the sensitivity to $y_i$ and $y_i$’s innovation:

$$i_i = \left( \frac{\partial e_f}{\partial y_i}, y_i - H(x_b) \right)$$
Comparison between observations and across centers is tricky...

Why does **NRL** get more impact out of their **AMVs**?
When assimilating ECMWF analysis temperatures into the NAVGEM, an apparent warm-bias at polar latitudes is corrected, and observation-impact of AMVs decreases. This is a response to the interaction between model bias, thermal wind balance, and observation of high-latitude winds by AMVs.

AMVs have higher impact because the NAVGEM analysis is biased.
Current NAVGEM assimilation promotes bias at high latitudes.
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\[ \mathbf{BC} \]

\[ \mathbf{x}_b \rightarrow \mathbf{y}_{\text{rad}}: (\mathbf{y}, \mathbf{x}_b) \]

biased    biased    biased
Current NAVGEM assimilation promotes bias at high latitudes.

\[ X_b \rightarrow y_{\text{rad}} : (y, X_b) \rightarrow X_a \]

偏态 biased
Experimental NAVGEM assimilation

\[ X_b : (y |_{\text{noBC}}, X_b) \rightarrow X_{b2} \rightarrow y_{\text{rad}} : (y, X_b) \rightarrow X_a \]

biased

less biased

less biased

less biased
Kalnay et al. have identified MODIS polar AMVs as an observation-type that routinely does **more harm than good** on the 6-hr GEFS forecast, using an ensemble-based approximation to the adjoint-derived observation-impact.
Further, they cite a **tendency** of MODIS wind observations to be **detrimental** when the zonal-wind innovation is positive.

The conclusion reached by Kalnay et al. is that the **observations themselves must be formulated incorrectly**, particularly for observations expressing a positive zonal-wind innovation.
This view is further enforced by demonstrating that removing the detrimental observations improves the forecast into mid-range, demonstrating that the signal they have identified is real and relevant to the forecast.

While I won’t argue with the reality of the signal, I question its source. It’s not the observations.
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\[
(y, x_b) \xrightarrow{\text{DA}} x_a \xrightarrow{\text{NWP}} x_f \xrightarrow{\text{Eval.}} e_f
\]
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\[
\begin{align*}
\text{DA} & \quad \xrightarrow{\text{NWP}} \quad \text{Eval.} \\
X_b & \quad \longrightarrow \quad X_a \quad \longrightarrow \quad X_f \quad \longrightarrow \quad e_f
\end{align*}
\]

Corrupt observations will carry through the system and raise the forecast error through “garbage in, garbage out”
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Poor assimilation of good observations can likewise raise the forecast error
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**Poor assimilation** of good observations can likewise raise the forecast error

**Poor NWP** from a properly configured analysis can also raise the forecast error
Corrupt observations will carry though the system and raise the forecast error through "garbage in, garbage out"

Poor assimilation of good observations can likewise raise the forecast error

Poor NWP from a properly configured analysis can also raise the forecast error
If the observations were corrupt, then the impact of those observations should be detrimental regardless of the DA and NWP used to produce a forecast.

MODIS AMVs are beneficial in every other system they’ve been tested in:

ECMWF: Beneficial

JMA: Beneficial

UKMet: Beneficial
Pressed for a guess, I would anticipate that the problem is in the GDAS’s assimilation of high-latitude AMVs, which may produce anomalously beneficial impact in the NAVGEM and anomalously detrimental impact in the GFS for roughly the same reason: bad assumptions during assimilation.
2000 “Surprise Snowstorm”

Hurricane Joaquin (2015)