A posteriori diagnosis tools for improved data assimilation system performance

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Abstract

The information content of atmospheric measurements in data assimilation systems (DASs) is closely determined by the representation of the model and observation error statistics. Evaluation of short-range forecast error sensitivities to observation error variance and innovation-weight parameters provides guidance to improve the system performance. A case study is presented for various observing instruments assimilated in NASA's GEOS. Statistical analysis of data assimilation products indicates that, in general, increasing the observation weight would improve the forecast skill.

Research Objectives

Optimal assimilation of high-resolution satellite data in NASA's GEOS requires an improved representation of observational error statistics. This study presents the following diagnosis tools for DAS optimization:

1. *A posteriori* estimates to observation error covariance for radiances assimilated in NASA's GEOS with emphasis on hyper-spectral instruments
2. *A priori* estimates to the forecast error impact from tuning observation error variance and innovation weight parameters in the DAS
3. Identification of high-impact geographical regions with increased forecast error sensitivity

Results are shown for analyses valid at 00UTC June 2014 and 6hr forecasts.

1 *A posteriori* observation error variance

Observation error variance σ_o^2 assigned in the DAS is often over conservative (Figure 1). For each observation type, estimates $\tilde{\sigma}_o^2$ of the true σ_o^2 are obtained *a posteriori* from the statistical expectation of observed minus analysis $\mathbf{d_a^o}$ and observation minus background (innovations) $\mathbf{d_b^o}$ as [2]:

$$(\tilde{\sigma}_o^2) = \mathbf{E}\left[(\mathbf{d_a^o})^{\mathbf{T}}(\mathbf{d_b^o})\right] \tag{1}$$

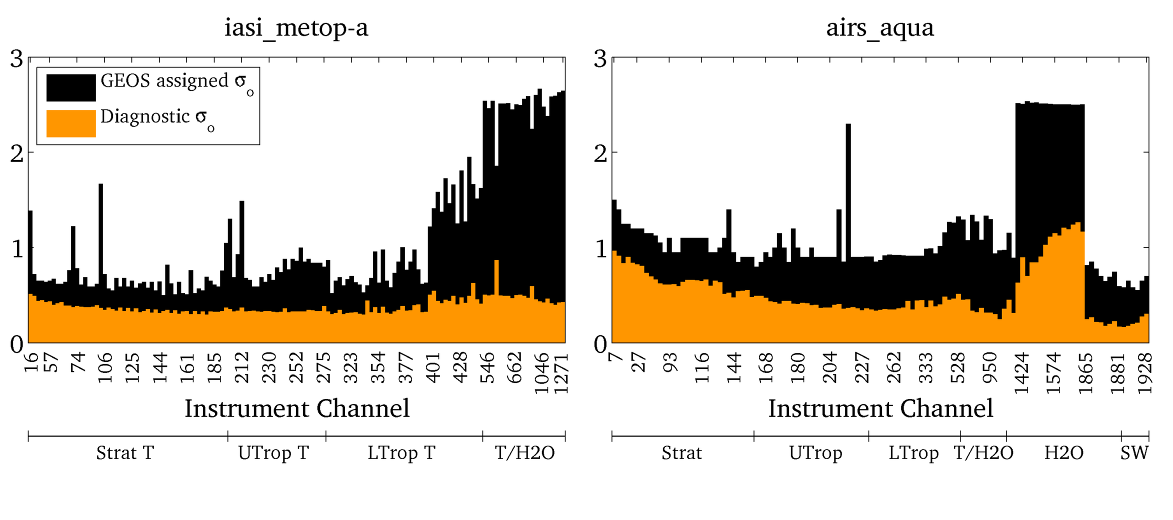

Figure 1: *GEOS assigned σ_o and diagnostic estimates $\tilde{\sigma}_o$ (K) for IASI (left) and AIRS (right) instruments. The a posteriori estimates indicate that the assigned σ_o values are overly conservative.*

Departure of $\tilde{\sigma}_o^2$ from σ_o^2 assigned in the DAS can be described with an observation error variance weight parameter ($\mathbf{s_o}$):

$$\mathbf{s_o} = \frac{\tilde{\sigma}_\mathbf{o}^2}{\sigma_\mathbf{o}^2} \tag{2}$$

where $\mathbf{s_o} = \mathbf{1}$ represents the status quo configuration.

2 Innovation-weight parameterization

Direct tuning of the gain operator $\mathbf{K}$ can be done by introducing the innovation-weight parameter $\mathbf{s_b}$ into the analysis equation:

$$\mathbf{x_a}(\mathbf{s_b}) = \mathbf{x_b} + \mathbf{K}\left[\mathbf{s_b} \circ (\mathbf{y} - \mathbf{H}\mathbf{x_b})\right] \tag{3}$$

where $\mathbf{y} - \mathbf{H}\mathbf{x_b}$ is the innovation vector and $\mathbf{s_b} = \mathbf{1}$ represents the status quo configuration.

3 Forecast error sensitivity and impact

The forecast score can be defined as a short-range forecast error measure[1]:

$$e(\mathbf{x^a}) = \left(\mathbf{x_f^a} - \mathbf{x_f^v}\right)^{\mathbf{T}} \mathbf{C}\left(\mathbf{x_f^a} - \mathbf{x_f^v}\right) \tag{4}$$

where $\mathbf{x_f^a}$ is the model forecast at verification time t_f initiated from $\mathbf{x^a}$, $\mathbf{x_f^v}$ is the verifying analysis at t_f, which serves as a proxy to the true state $\mathbf{x_f^t}$, and $\mathbf{C}$ is a diagonal matrix of weights that gives the forecast score units of energy per unit mass.

3.1 Sensitivity to σ_o^2-weight parameters

Forecast error sensitivity to the observation error variance parameter $\mathbf{s_o}$ is:

$$\frac{\partial e}{\partial \mathbf{s_o}} = [\mathbf{H}\mathbf{x^a} - \mathbf{y}] \circ \frac{\partial e}{\partial \mathbf{y}} \tag{5}$$

where $\mathbf{x^a}$ is the analysis state in the *status quo* DAS and

$$\frac{\partial e}{\partial \mathbf{y}} = \mathbf{K}^{\mathrm{T}} \frac{\partial e}{\partial \mathbf{x^a}} \tag{6}$$

is the forecast error sensitivity to observations that is obtained by applying the adjoint-DAS operator $\mathbf{K}^{\mathrm{T}}$ to the forecast error sensitivity to analysis. [1]

A note on sensitivity guidance:

- Positive σ_o^2-weight sensitivities identify observation system components that may benefit from reducing the assigned observation error variance.
- Negative σ_o^2-weight sensitivities identify observation system components that may benefit from increasing the assigned error variance.

3.2 Sensitivity to innovation-weight parameters

The forecast error sensitivity to innovation-weight parameters $\mathbf{s_b}$ is defined as the element-wise product between the innovation vector and observation sensitivity:

$$\frac{\partial e}{\partial \mathbf{s_b}} = \left[\mathbf{y} - \mathbf{H}\mathbf{x^b}\right] \circ \frac{\partial e}{\partial \mathbf{y}} \tag{7}$$

In general, the forecast error s_o- and s_b-sensitivities are anti-correlated.

In the case study presented here the forecast error displays positive sensitivity to observation error variance weight factor and negative sensitivity to innovation weight factor (Figure 2).

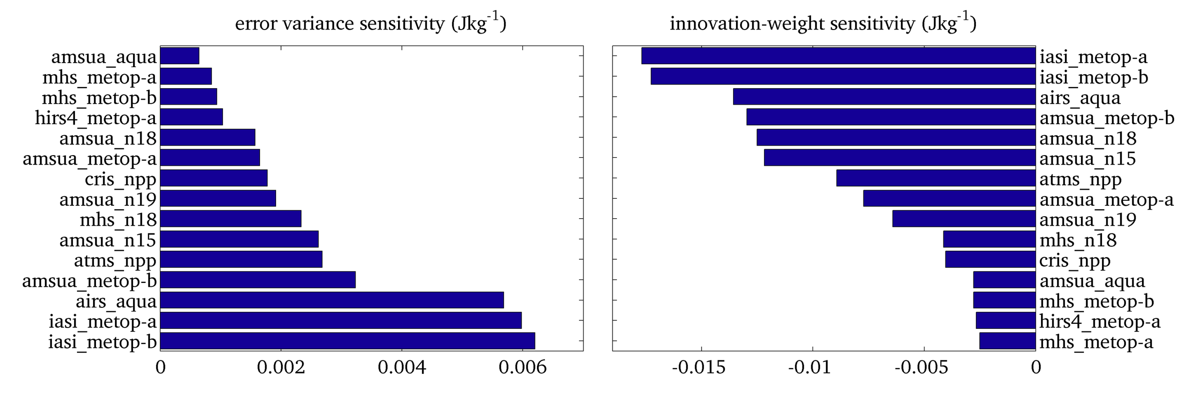

Figure 2: *Observation system components that exhibit large forecast error sensitivities to observation error variance (left) and innovation weight parameters (right). Increasing the weight of information provided by the radiances would improve the forecast skill.*

3.3 *A priori* impact of tuning observation error variance

An *a priori* forecast impact estimate of adjusting σ_o^2 to $\tilde{\sigma}_o^2$ is given by:

$$\delta e = \frac{\partial e}{\partial \mathbf{s}_o} \circ \delta \mathbf{s}_o = \frac{\partial e}{\partial \mathbf{s}_o} \circ \left(\frac{\tilde{\sigma}_o^2}{\sigma_o^2} - 1\right) \tag{8}$$

Impact estimates indicate that, in general, tuning the observation error variance improves forecast skill (Figure 3). Note that some instruments channels, such as AIRS short-wave temperature soundings (1897 to 1928), benefit from increasing the observation error variance. DAS performance may be optimized, therefore, by tuning individual channels rather than instruments as a whole.

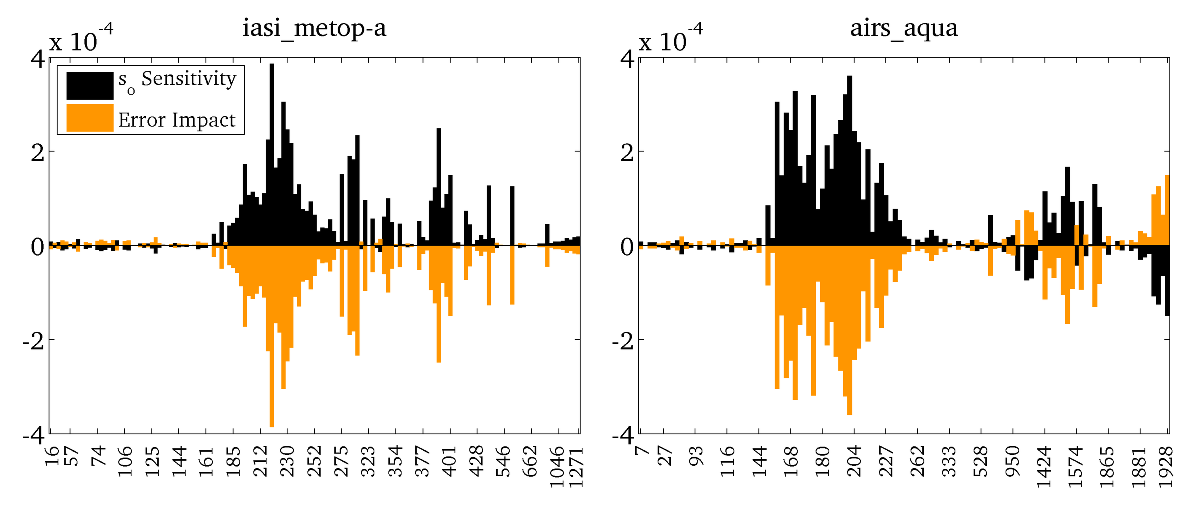

Figure 3: *Forecast error sensitivity and a priori impact estimates for IASI (METOP-A) and AIRS (Aqua) instruments. The guidance is that for most channels, forecasts will benefit from reducing the assigned σ_o values.*

Error variance sensitivity and subsequent forecast error impacts are not globally uniform. The AIRS instrument, for example, is highly sensitive in the tropics over the East Pacific (Figure 4). Spatially variable tuning of weight parameters may enhance forecast error reduction.

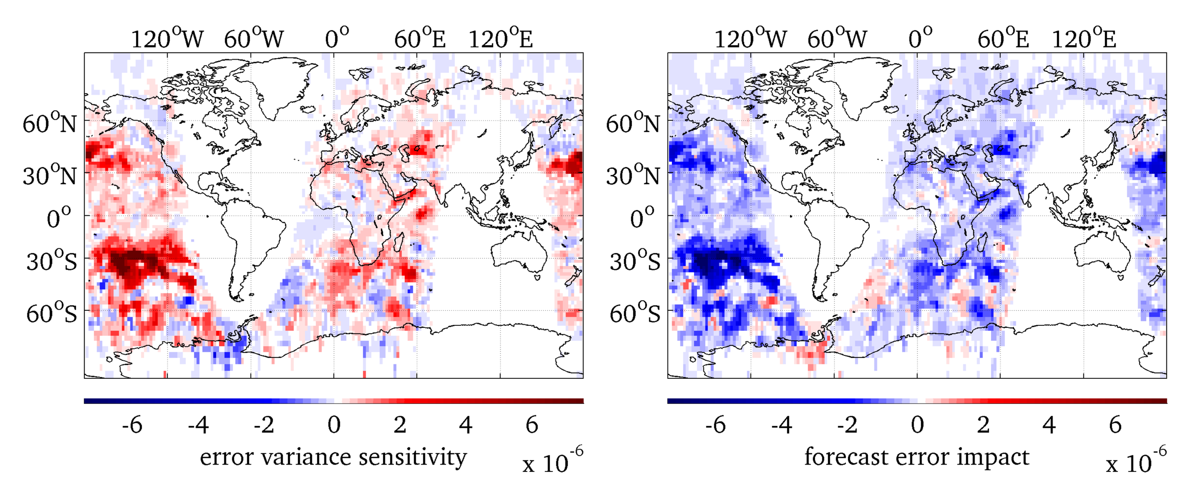

Figure 4: *Geographic distribution of σ_o sensitivity (left) and forecast error impact (right) for AIRS long-wave CO_2 channels 156 to 256 assimilated in GEOS.*

4 Conclusions

- *A posteriori* consistency analysis suggests the assigned observation error variance is overly conservative in the GEOS.
- Adjoint-DAS sensitivity guidance indicates that, in general, increasing the observation weight would improve the forecast skill.
- Despite general trends error sensitivities are not uniform among instrument channels nor geographical locations, which may impair the forecast performance of error covariance tuning procedures.
- Therefore, novel adaptive tuning approaches that account both for instrument characteristics and the variability of forecast errors in the time/space domain are necessary.

5 Forthcoming Research

This case study examined *a posteriori* diagnosis tools for optimizing NASA's GEOS by tuning observation error variance and innovation-weight parameters. Diagnosis tools have also been developed to account for observation error correlations (Figure 5). Future research will examine: 1.) *A posteriori* guidance for tuning observation and background error covariance in GEOS and 2.) Adaptive error covariance tuning experiments to validate *a priori* forecast error impact estimates.

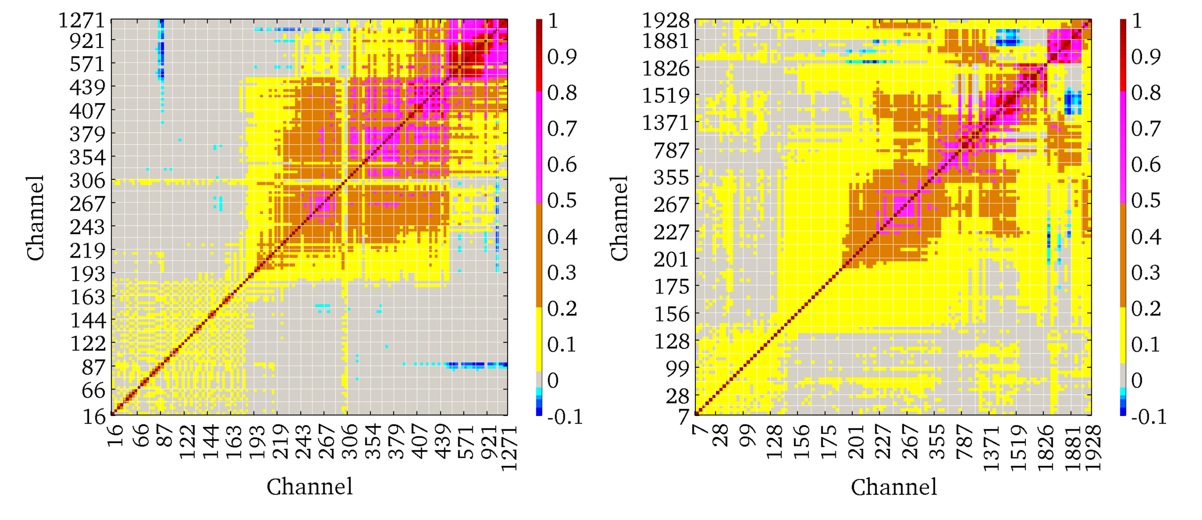

Figure 5: *Inter-channel correlations for IASI (left) and AIRS (right) instruments. For both instruments airs water vapour channels exhibit strongest correlations*

References

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