Accounting for Infrared Sounder Correlated Observation Errors in the GSI

Kristen Bathmann(1), Ricardo Todling(2) & Andrew Collard(1)

(1)I.M. Systems Group at NCEP/EMC,
(2)Global Modeling and Assimilation Office, NASA Goddard Space Flight Center

Kristen.Bathmann@noaa.gov

Introduction

Numerical weather prediction requires precise initial conditions to provide an accurate forecast. The true state of the atmosphere, which is unknown, can be estimated by combining observations with short range forecasts, or model background. This estimate, called the analysis, can then be used as an initial condition. Determining the analysis depends not only on the observations and background, but also on their errors.

At the National Center for Environmental Prediction (NCEP), data assimilation is executed with the Gridpoint Statistical Interpolation (GSI). Satellite observations from the Infrared Atmospheric Sounding Interferometer (IASI) and the Atmospheric Infrared Sounder (AIRS) provide a wealth of observations and have both been proven to be extremely beneficial to numerical weather prediction. In the GSI, 616 IASI channels and 281 AIRS channels are used, of which 165 from IASI and 117 from AIRS are actively assimilated. From IASI, this set includes longwave upper and lower temperature sounding channels, longwave window channels, and ozone channels. From AIRS, this includes upper and lower temperature sounding channels, longwave window channels, water vapor channels, and a few shortwave window and temperature channels.

Inter-channel error correlations are not accounted for within the GSI, however they are known to exist. The purpose of this study is to ultimately enhance the specification of observation errors in the operational GSI by improving their estimates and by properly accounting for these inter-channel error correlations.

Theory and Methods

The goal of data assimilation is to determine the analysis state $\mathbf{x}^a$ that minimizes a cost function

$$J(\mathbf{x}) = \frac{1}{2}(\mathbf{x}-\mathbf{x}^b)^T\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^b) + \frac{1}{2}(\mathbf{y}^o - H(\mathbf{x}))^T\mathbf{R}^{-1}(\mathbf{y}^o - H(\mathbf{x})) \quad (1)$$

where $\mathbf{x}^b$ denotes the background state, $\mathbf{B}$ the background error covariance matrix, H the nonlinear observation operator, $\mathbf{y}^o$ the observations and $\mathbf{R}$ the observation error covariance matrix.

In current NCEP operations, $\mathbf{R}$ is assumed to be diagonal, and does not account for inter-channel correlations. To estimate the full $\mathbf{R}$, the Desroziers diagnostic is used. This method assumes that observation and background errors are uncorrelated and are perfectly specified in the analysis. For a pair of analysis and background departures (observation minus guess), denoted by A and B respectively, the error covariance is given by the expected value

$$\mathbf{R} = E[(A)^T B].$$

For channels r and c of IASI or AIRS, this means that inter-channel error covariances can be estimated by computing

$$\mathbf{R}_{r,c} = \frac{1}{p}\sum_{k=1}^{p} A_{k,r}B_{k,c} - \frac{1}{p^2}\sum_{k=1}^{p} A_{k,r}\sum_{k=1}^{p} B_{k,c} \quad (2)$$

where p denotes the size of a set of departure pairs.

Experimental Setup and Considerations

The Desroziers diagnostic in (2) is used to compute observation error covariance matrices for IASI and AIRS over all surface types. Here, departure pairs are made for observations that are actively assimilated and are within 60 minutes and 25 kilometers of one another.

Correlation matrices computed from April 4, 2014 to June 7, 2014 for both instruments are shown below.

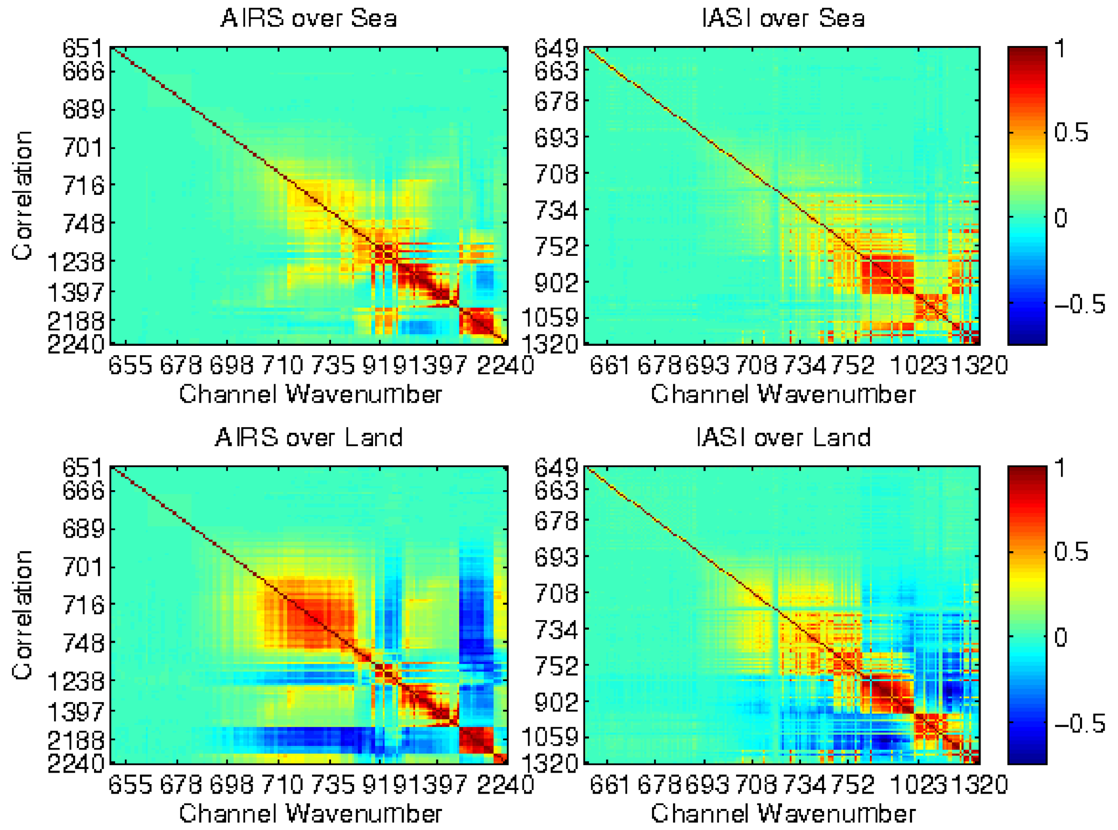

Figure 1: Diagnosed observation error correlation matrices for AIRS (left) and IASI (right) over water (top) and land (bottom) surfaces.

Reconditioning

The condition number of a matrix, K, is defined as the ratio of its largest eigenvalue to its smallest. Minimizing the cost function in (1) requires the computation of $\mathbf{R}^{-1}$ which can be expensive if $\mathbf{R}$ is poorly conditioned (K is large). To recondition $\mathbf{R}$, first the smallest eigenvalues are set equal to λ_{min}/K_1, where $K_1 = 150$ for AIRS and $K_1 = 200$ for IASI. Next, the diagonal of $\mathbf{R}$ is inflated by a small standard deviation σ:

$$\mathbf{R}_{r,r} = \left(\sqrt{\mathbf{R}_{r,r}} + \sigma\right)^2.$$

The value of σ is chosen to give $\mathbf{R}$ a condition number of approximately 40.

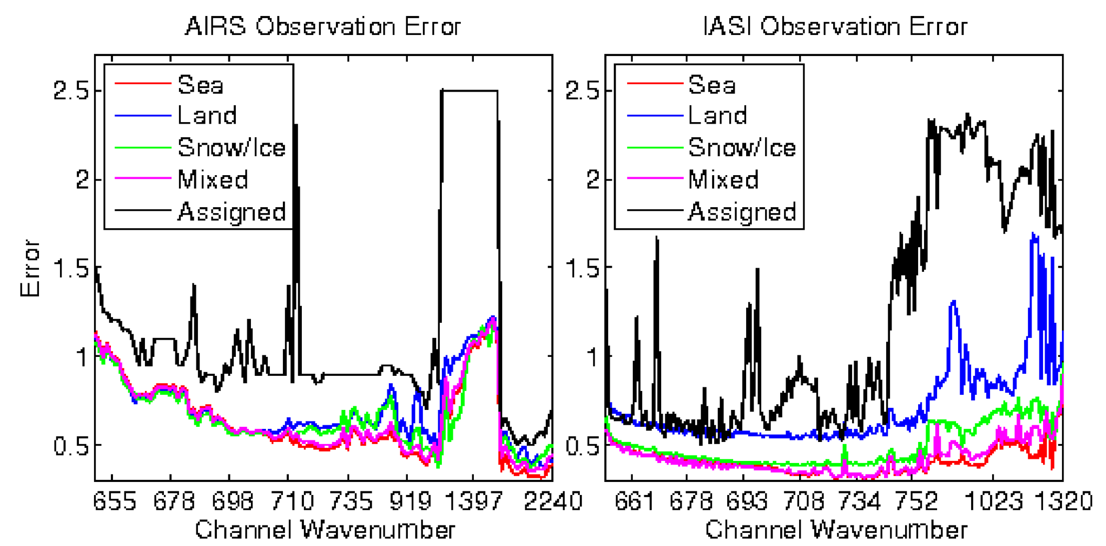

Figure 2: Diagnosed observation errors for AIRS (left) and IASI (right) after reconditioning, compared to the assigned errors.

Results

Full observation error covariances for AIRS and IASI were used globally in a two month long assimilation experiment using the Global Forecast System (GFS). This Full **R** experiment is compared to a control experiment using Diagonal **R**.

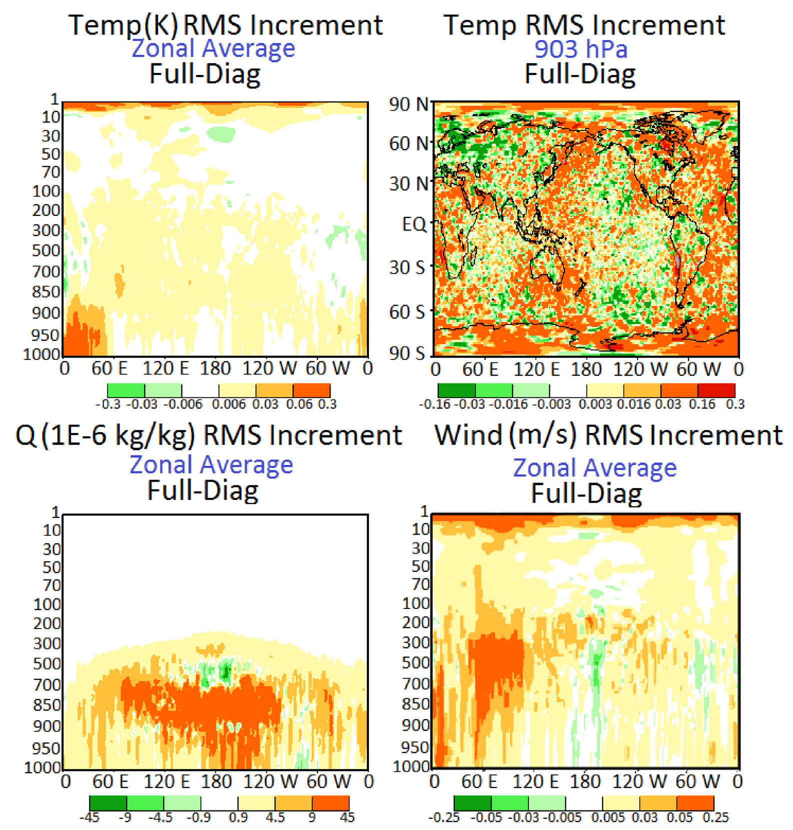

Figure 3: Analysis RMS increment differences between the Full **R** and Diagonal **R** experiments.

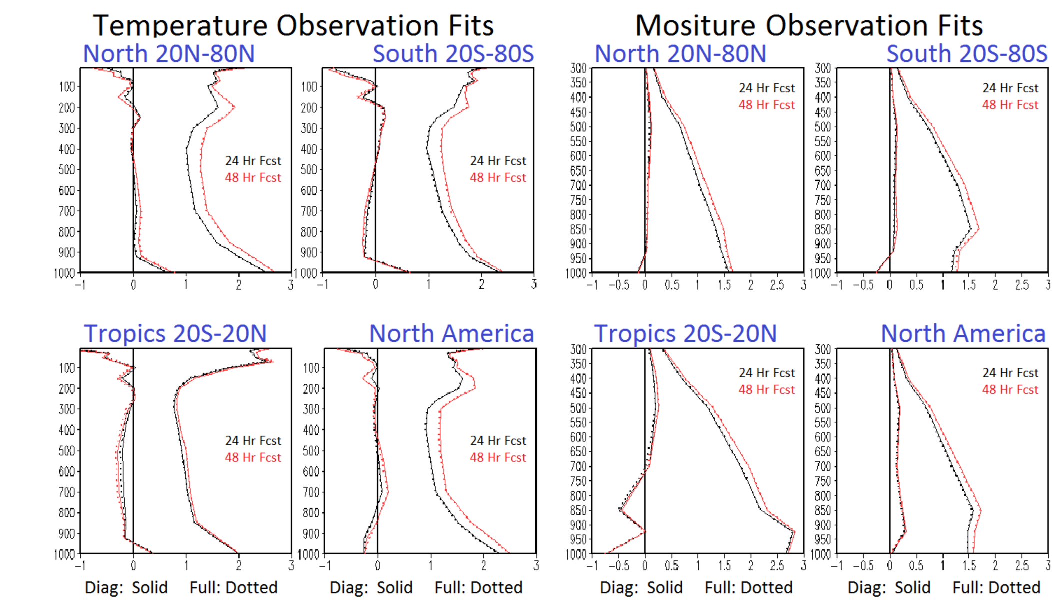

Figure 4: The forecast fit to temperature (left) and humidity (right) observations.

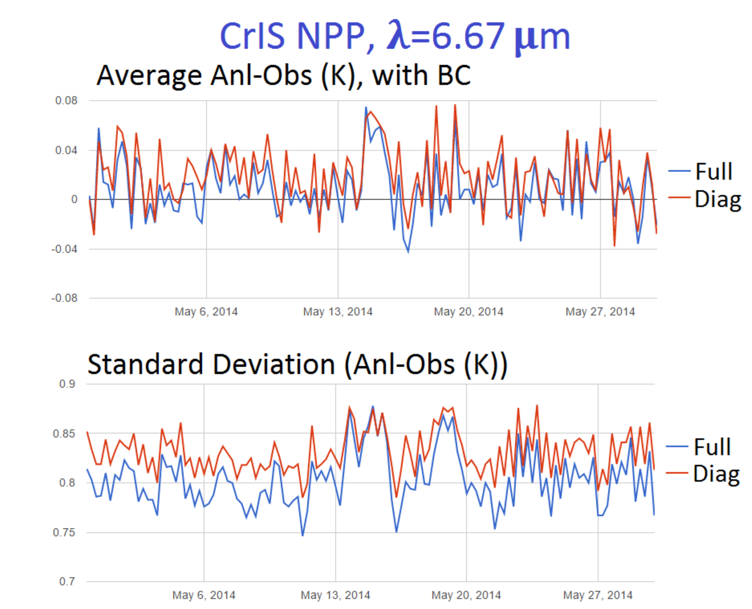

Figure 5: The analysis fit to a passive Cross-track Infrared Sounder (CrIS) humidity sounding channel. The background fit (not shown) is similar.

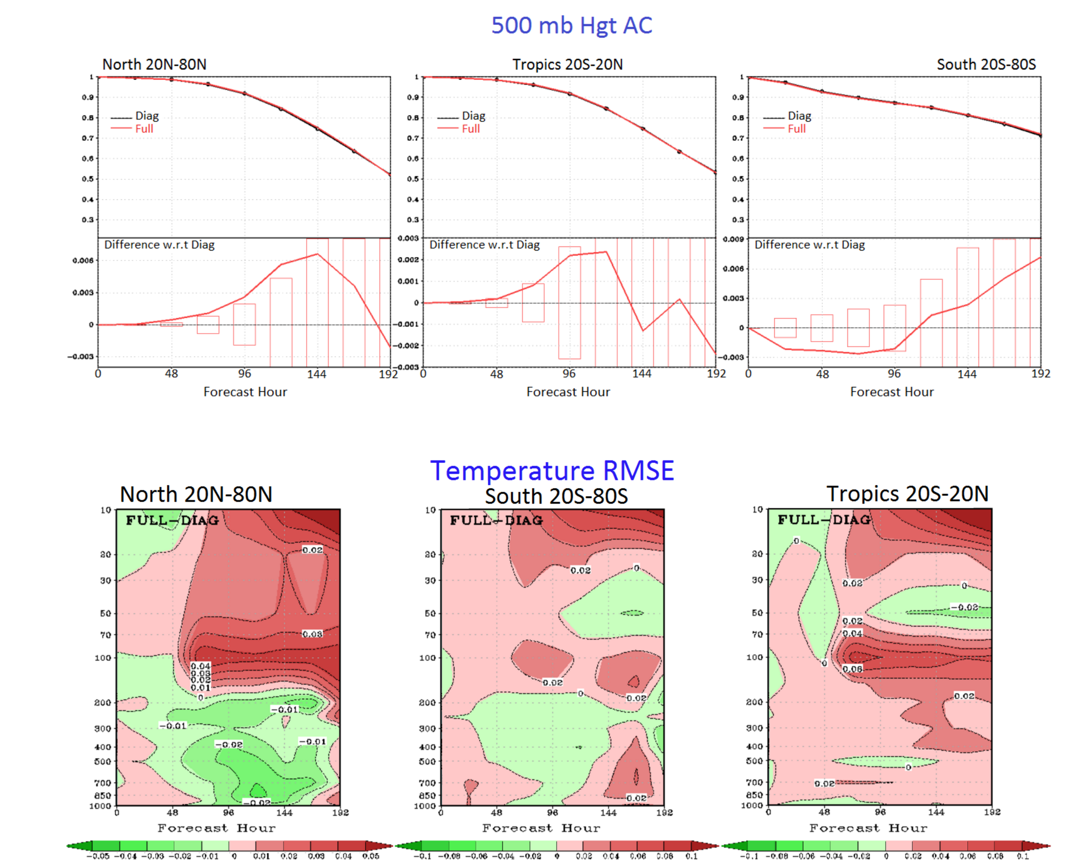

Figure 6: The 500 mb Height Anomaly Correlation (top) and temperature RMSE differences between the Full **R** and Diagonal **R** experiments (bottom).

Conclusions

- Inter-channel observation error correlations exist for IR instruments, and the currently assigned errors are much larger than the diagnosed values.
- Overall, using fully correlated observation error covariances for AIRS and IASI improved the fit to numerous observation types, including temperature and humidity. The fits to various channels from CrIS and other satellite instruments were also improved.
- Analysis increments are increased by using a full error covariance matrix, however, forecast impacts are generally neutral.

Forthcoming Research

Upcoming research will focus on:

- Optimizing the forecast impact by tuning the reconditioning parameter σ
- Studying the impact of each instrument separately, as well as the treatment of different surface types,
- Using full covariances for CrIS.

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