

A Quality Control Study of NOAA MIRS Cloudy Retrievals during Hurricane Sandy

Steven J. Fletcher

Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, CO, USA

EMAIL: Steven.fletcher@colostate.edu



Abstract

Cloudy radiances present a difficult challenge to data assimilation (DA) systems, through both the nonlinear radiative transfer behaviors as well as the complex hydrometer interactions required to resolve the clouds and precipitation. In most DA systems the hydrometers are not control variables due to many limitations. The National Oceanic and Atmospheric Administration's (NOAA) Microwave Integrated Retrieval System (MIRS) is producing products from the Suomi-NPP ATMS satellite sensor when the scene is cloud and precipitation affected. We present a test case from Hurricane Sandy in October 2012.

As a quality control study we compare the retrieved water vapor content with the first guess and the analysis from the NOAA Gridpoint Statistical Interpolation (GSI) system during the lifetime of Hurricane Sandy. The assessment involves the gross error check system against the first guess with different values for the observational error's variance to see if the difference is within three standard deviations. We also compare against the final analysis at the relevant cycles to see if the products which have been retrieved through a cloudy radiance are similar, given that the GSI system does not assimilate cloudy radiances yet.

Microwave Integrated Retrieval System (MIRS)

- is an iterative, physically based 1DVAR retrieval algorithm,
- $J(X) = \frac{1}{2}(X - X_0)^T B^{-1}(X - X_0) + \frac{1}{2}(Y^m - Y(X))^T E^{-1}(Y^m - Y(X))$
- where X_0 and B are the mean vector and error covariance of the state. X that is being retrieved. Y^m are the measurements while $Y(X)$ is the forward operator that maps the guess state to the brightness temperatures and E is the observational error covariance matrix.
- Forward operator is the Community Radiative Transfer Model (CRTM)
- The solution to the cost function above is found through using an iterative solver to the problem:

$$\frac{\partial J(X)}{\partial X} = 0$$

Which then leads to the background-departure-based solution as $\Delta X_{n+1} = \{BK_n^T(K_nBK_n^T + E)^{-1}\}[(Y^m - Y(X_n)) + K_n\Delta X_n]$

- Parameters that are retrieved:
 1. Temperature
 2. Moisture
 3. Atmospheric hydrometeor profiles
 4. Skin surface temperature
 5. Emissivity vector

Quality Control

As part of most operational NWP DA systems there is a form of quality control measure which screens the observations that are eligible to be assimilated to ensure that they are within a set distance from the current *first guess* of the true state. This is referred to as the gross error check, defined as

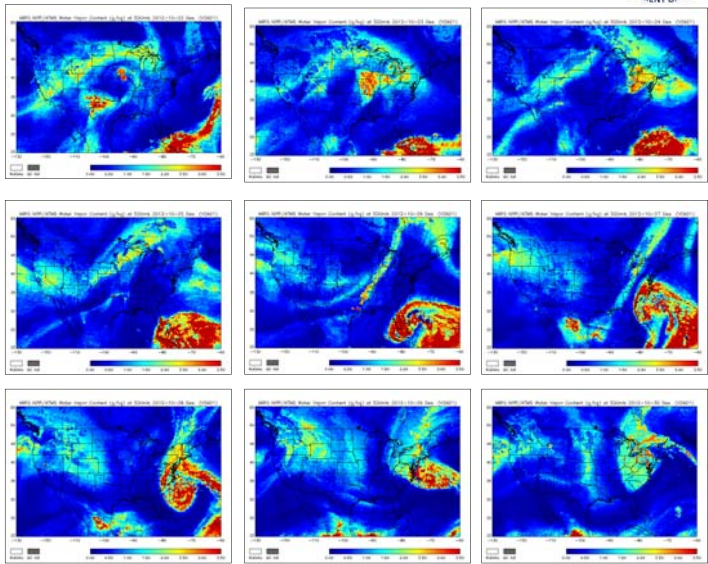
$$\frac{|Y^m - h(x_{fg})|}{\sigma} < 3$$

where σ is the approximation to the observational error standard deviation.

In the experiments that will perform the actual measurements will be the retrieved temperature and moisture products from MIRS given the brightness temperature from ATMS and the $h(x)$ will be the first guess and the analysis for the equivalent fields from the GSI system for the equivalent fields.

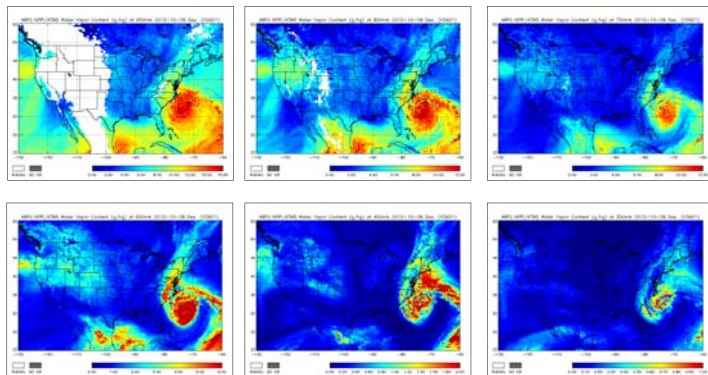
The reason for this is to assess the impact of the hybrid system from the first guess and the analysis compared to the retrieved products, which introduced flow dependencies and possible non-linear flows into the background error covariances compared to the static covariances used in the MIRS retrieval.

MIRS uses a logarithmic transform for retrieving the humidity field. This implies that the humidity field is being treated like a lognormal random variable, and as such we shall be able to compare a Holm transform approach against the median found from the logarithmic transform approach.



Temporal ↑

Vertical ↓



Hybrid Variational-Ensemble Data Assimilation

During May 2012 the National Center for Environmental Prediction (NCEP) implemented an operational version of a hybrid data assimilation system which has the following cost function to minimize:

$$J(x'_f, \alpha) = \beta_f \frac{1}{2}(x'_f)^T B^{-1}(x'_f) + \beta_e \frac{1}{2}\alpha^T L^{-1}\alpha + \frac{1}{2}(y - Hx'_f)^T R^{-1}(y - Hx'_f)$$

$$x'_f = x'_f + \sum_{k=1}^K (\alpha_k \circ x'_k), \quad \frac{1}{\beta_f} + \frac{1}{\beta_e} = 1$$

β_f, β_e : weighting coefficients for fixed and ensemble covariance x'_f : (total increment) sum of increment from fixed/static and ensemble α_k : extended control variable; x'_k : ensemble perturbation L : correlation matrix [localization on ensemble perturbations]

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