Assimilation of all-weather GMI and ATMS observations into HWRF

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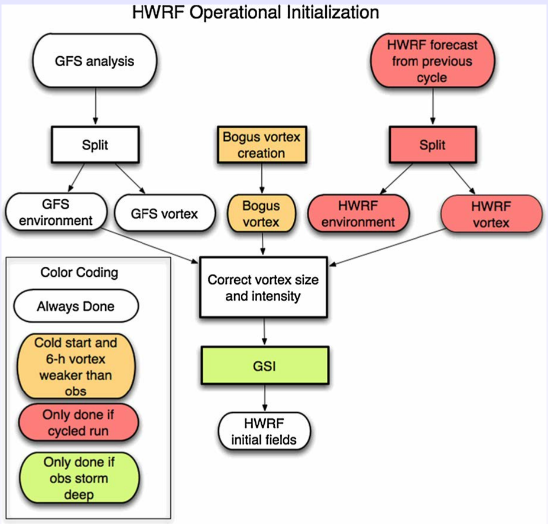
Summary

We propose a novel Bayesian Monte Carlo Integration (BMCI) technique to retrieve the profiles of temperature, water vapor, and cloud liquid/ice water content from microwave cloudy measurements in the presence of tropical cyclones (TCs). These retrievals then can either be directly used by meteorologists to analyze the structure of TCs or be assimilated to provide accurate initial conditions for the NWP models. The technique is applied to the data from the Advanced Technology Microwave Sounder (ATMS) onboard Suomi National Polar-orbiting Partnership (NPP) and Global Precipitation Measurement (GPM) Microwave Imager (GMI).

HWRF


HWRF Operational Initialization

GFS analysis
HWRF forecast from previous cycle
Split
Bogus vortex creation
Split
GFS environment
GFS vortex
Bogus vortex
HWRF environment
HWRF vortex
Color Coding
Always Done
Cold start and 6-h vortex weaker than obs
Only done if cycled run
Only done if obs storm deep
Correct vortex size and intensity
GSI
HWRF initial fields

Overview of the HWRF system configured for operation in the Atlantic basin (Image credit: NOAA DTC). The HWRF initial condition is generated using NOAA GFS global forecast, HWRF 6-hr forecast (when available), and the storm message from the National Hurricane Center (NHC).

Direct Radiance Assimilation

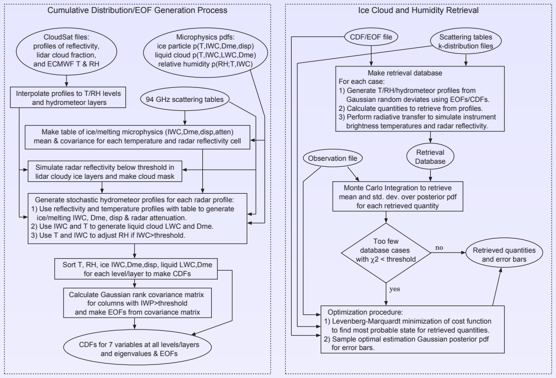
Variational data assimilation minimizes the difference between observations ($\vec{O}$) and the first guess ($H(\vec{x})$, H is the forward operator applied to the control vector $\vec{x}$). The relation between the observations (O) and the forward operator (H) can be expressed as:

$$O = H(\vec{x}, \vec{p_b}, \vec{p_s}) + \epsilon$$

where $\vec{p_b}$ represents parameters such as shape and size distribution of hydrometers, $\vec{p_s}$ indicates the scattering parameters (e.g., phase function) that are required by the forward operator (RT model) but are not provided by the NWP model. Several limitations exist including:

- $H(\vec{x})$ is the mean signature because $\vec{x}$ is the mean value of the model variables within the volume element of the model and because H is a non-linear function then $\overline{H(\vec{x})} \neq H(\bar{\vec{x}})$.
- The NWP models tend not to make a close first guess for cloud parameters required by the RT model or clouds are often displaced in the NWP simulations .
- The scattering parameters are neither provided by the model nor fully measurable in the real world thus are estimated from limited in-situ and aircraft measurements with limited accuracy.
- RT models that are used operationally use a simplified RT framework, such as spherical hydrometeors, which is not appropriate at higher microwave frequencies where ice scattering is important.
- DA systems assume Gaussian error statistics which is normally examined using the histograms of the departures. However, in the case of cloudy radiances the departures are likely to be non-Gaussian.

The BMCI Technique

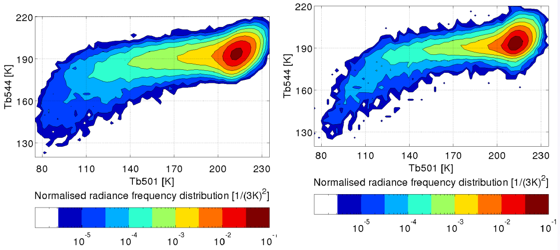

Cumulative Distribution/EOF Generation Process

CloudSat files: profiles of reflectivity, lidar cloud fraction, and ECMWF T & RH
Microphysics pdfs: ice particle p(T,IWC,Dme,disp) liquid cloud p(T,IWC,LWC,Dme) relative humidity p(RH;T,IWC)
Interpolate profiles to T/RH levels and hydrometeor layers
94 GHz scattering tables
Make table of ice/melting microphysics (IWC,Dme,disp,atten) mean & covariance for each temperature and radar reflectivity cell
Simulate radar reflectivity below threshold in lidar cloudy ice layers and make cloud mask
Generate stochastic hydrometeor profiles for each radar profile:
1) Use reflectivity and temperature profiles with table to generate ice/melting IWC, Dme, disp & radar attenuation.
2) Use IWC and T to generate liquid cloud LWC and Dme.
3) Use T and IWC to adjust RH if IWC>threshold.
Sort T, RH, ice IWC,Dme,disp, liquid LWC,Dme for each level/layer to make CDFs
Calculate Gaussian rank covariance matrix for columns with IWP>threshold and make EOFs from covariance matrix
CDFs for 7 variables at all levels/layers and eigenvalues & EOFs

Ice Cloud and Humidity Retrieval

CDF/EOF file
Scattering tables k-distribution files
Make retrieval database
For each case:
1) Generate T/RH/hydrometeor profiles from Gaussian random deviates using EOFs/CDFs.
2) Calculate quantities to retrieve from profiles.
3) Perform radiative transfer to simulate instrument brightness temperatures and radar reflectivity.
Observation file
Retrieval Database
Monte Carlo Integration to retrieve mean and std. dev. over posterior pdf for each retrieved quantity
Too few database cases with $\chi 2$ < threshold
no
Retrieved quantities and error bars
yes
Optimization procedure:
1) Levenberg-Marquardt minimization of cost function to find most probable state for retrieved quantities.
2) Sample optimal estimation Gaussian posterior pdf for error bars.

A schematic description of the BMCI technique. First, a retrieval database is developed which includes CDFs and EOFs of profiles of temperature, humidity, median mass equivalent sphere diameter (D_{me}) and cloud ice and liquid water content. This database is then used to retrieve the profiles of atmospheric state variables from the observations (Image credit: F. Evans).



Simulated versus real observations of the Odin SMR. Depicts show the relations between simulated (left) and real (right) observations from two different Odin channels (Image credit: P. Eriksson).

! The project is still in early stage and more results will be presented at AMS Annual Meeting.

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https://gmao.gsfc.nasa.gov/