Assimilation of Microwave Cloudy Observations over the Rainband of Hurricanes Using a Novel Bayesian Monte Carlo Technique

Isaac Moradi[1,2] Frank Evans[3],
William McCarty[1], Marangelly Cordero-Fuentes[1], Ronald Gelaro[1]
1. GMAO/GSFC/NASA, 2. ESSIC, University of Maryland,
3. U. of Colorado

NOAA STAR Science Forum Seminars,
NCWCP, College Park, MD

September 18, 2019

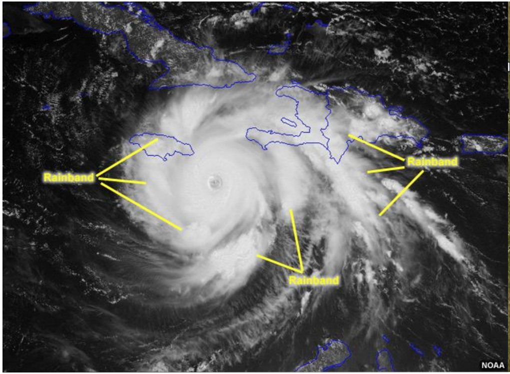
This work is supported by the NASA Data for Operation and Assessment program, grant# NNX17AE89G. Many thanks to NDOA Program Manager, Dr. Tsengdar Lee.

Outline

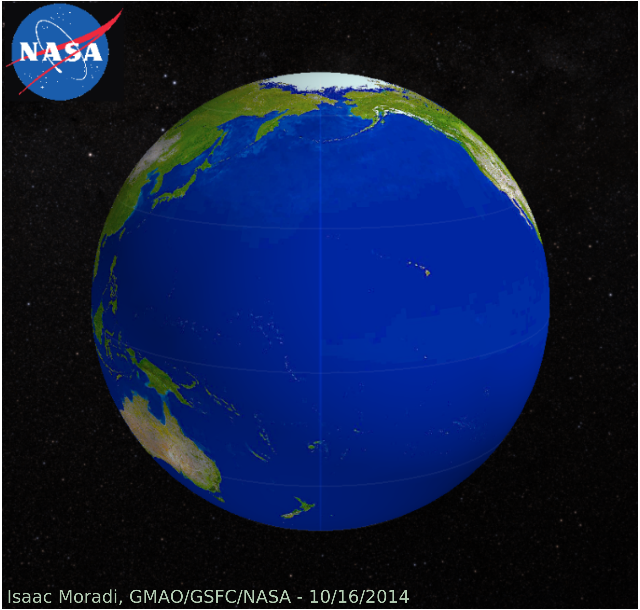
- Definitions
- Satellite Observations
- Motivation of the work
- Bayesian Monte Carlo Integration (BMCI) technique
- Implementation into NASA GEOS
- Results

Why rainbands?

While the eye and eyewall form the core of a hurricane, bulk of the storm is formed outside of the core and creates so called rain-bands. When moving from the center of the storm outward, the intensity of rain and winds decreases passing from one rainband to another.



Polar orbiting vs. low inclination satellites



All-weather radiative transfer calculations

Cost function for 3D-Var Data Assimilation:

$$J(\vec{x}) = \overbrace{\frac{1}{2}(\vec{x}-\vec{x_b})^T \vec{B}^{-1}(\vec{x}-\vec{x_b})}^{J_b} + \overbrace{\frac{1}{2}(H(\vec{x})-\vec{y})^T \vec{R}^{-1}(H(\vec{x})-\vec{y})}^{J_o}$$

Relation between the observations (y) and the forward operator (H) can be expressed as: $y = H(\vec{x}, \vec{p_b}, \vec{p_s}) + \epsilon$

$\vec{x}$ state vector, $\vec{p_b}$ parameters such as shape and size distribution of hydrometers, $\vec{p_s}$ indicates the scattering parameters (e.g., phase function)

$$\frac{dI_\nu}{dx} = -(\alpha_\nu + S_\nu)I_\nu + \alpha_\nu B_\nu(T) + S_\nu J_\nu$$

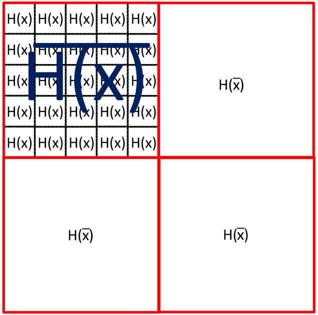
$$J_\nu = \int p_\nu(\Omega) I_\nu d\Omega$$

Limitations of direct assimilation of cloudy radiances

Inaccuracy in the first-guess: the models do not provide a close first guess for cloud parameters or clouds are often displaced.

Lack of required RT inputs: $\vec{p_s}$ neither provided by the model nor fully measurable thus estimated from limited in-situ/aircraft measurements.

Non-linearity in the forward model: $\vec{x}$ is the mean value of the model variables within grid-box and because H is non-linear: $\overline{H(\vec{x})} \neq H(\bar{\vec{x}})$.



Limitations of direct assimilation of cloudy radiances

Inaccuracy in the first-guess: the models do not provide a close first guess for cloud parameters or clouds are often displaced.

Lack of required RT inputs: $\vec{p}_s$ neither provided by the model nor fully measurable thus estimated from limited in-situ/aircraft measurements.

Non-linearity in the forward model: $\vec{x}$ is the mean value of the model variables within grid-box and because H is non-linear: $\overline{H(\vec{x})} \neq H(\bar{\vec{x}})$.

Simplified RT models: Operational RT models that use a simplified RT framework, such as spherical hydrometeors, which is not appropriate at higher microwave frequencies where ice scattering is important.

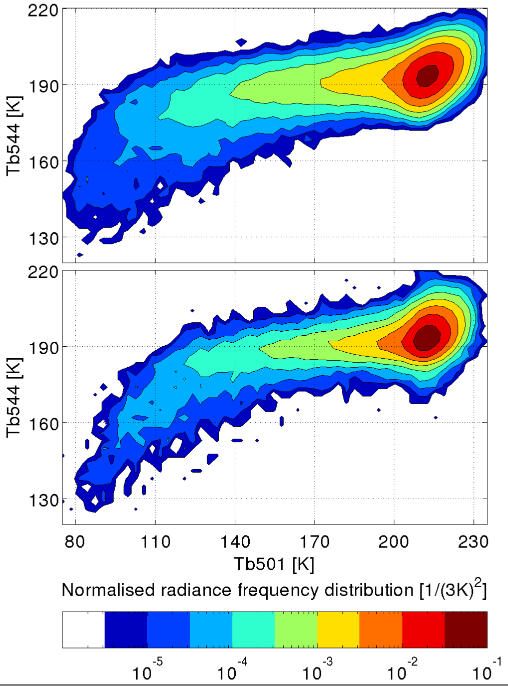
Assuming Gaussian Errors: DA systems assume Gaussian error statistics, examined using the departures, but in the case of cloudy radiances the departures are likely to be non-Gaussian.

The BMCI technique

The BMCI technique can be summarized in three steps:

- generation of a retrieval database of atmospheric state and cloud variables using a-priori information. The database should also include extreme cases as the extrapolation is not allowed.
- the atmospheric state and cloud variables are fed into the RT model to generate the synthetic observations. In addition to the state variables such as temperature, water vapor, and cloud profiles, cloud microphysics and parameterization such as particles' shape and size distribution are also utilized as input.
- real measurements along with the generated database are given to the retrieval package, then the retrieval package will select the cases which are close to the real measurements and integrate them according to the Bayes' theorem to give the estimate of the mean and uncertainty of the state and cloud variables.

Retrieval Database



Rydberg et al., 2009

Some equations behind the BMCI technique

Starting from Bayes' theorem:

$$p_{post}(\vec{x}|\vec{y}) = \frac{p_f(\vec{y}|\vec{x})p_p(\vec{x})}{\int p_f(\vec{y}|\vec{x})p_p(\vec{x})d\vec{x}'} => Posterior = \frac{Likelihood \times Prior}{Marginal\ \ Likelihood}$$

ending with ...

$$\hat{x} = \frac{\sum_i w_i \vec{x}_i}{\sum_i w_i} \qquad w_i = \exp\left(-\frac{1}{2}\chi^2\right)$$

$$\chi^2 = \sum_{j=1}^{M} \frac{[\vec{y}_j - H_j(\vec{x})]^2}{\sigma_j^2}$$

σ is the noise in the measurements.

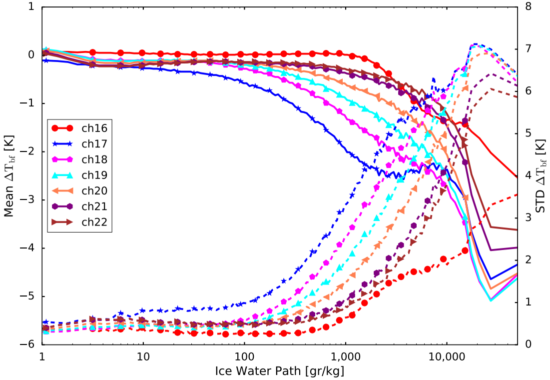
Improvements to the BMCI Retrievals

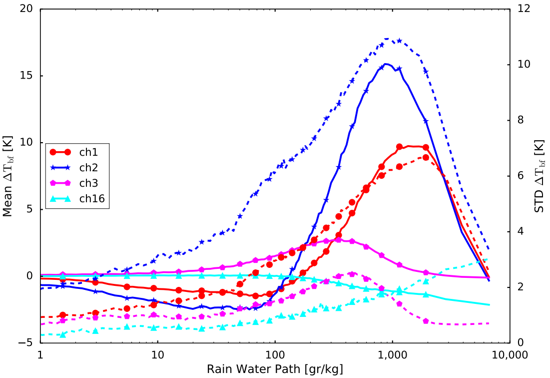
Some major enhancements to the original system developed for airborne radars:

- Adding temperature profile retrieval capability as well as the ocean skin temperature and near surface wind speed
- Computing ice particle scattering properties at new frequencies and generating new scattering tables
- Implementing the FASTEM microwave ocean surface emissivity model, both forward and adjoint, in the BMCI code
- Modifying the original CloudSat reflectivity profile based CDF/EOF program to also use GPM Dual-frequency Precipitation Radar (DPR) reflectivity profiles
- Analyzing in situ warm cloud and rain microphysical data from the Hurricane Research Division (HRD) and generating stochastic profiles of warm liquid cloud profiles
- Modifying the CDF-EOF algorithm to allow for clear layers using a hydrometeor masking procedure for ice, rain, and liquid cloud

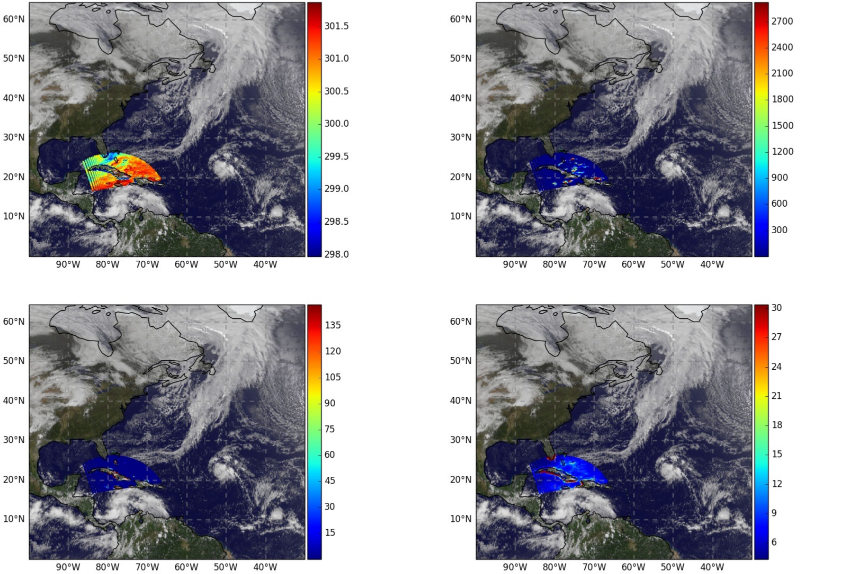
Beam filling

Beam filling was calculated as the difference between the brightness temperatures weighted according to an elliptical Gaussian beam pattern and Tbs calculated using the average profiles. The profiles were generated with 5km resolution using stochastic statistics derived from GPM DPR and central profiles IWP and rain rate.

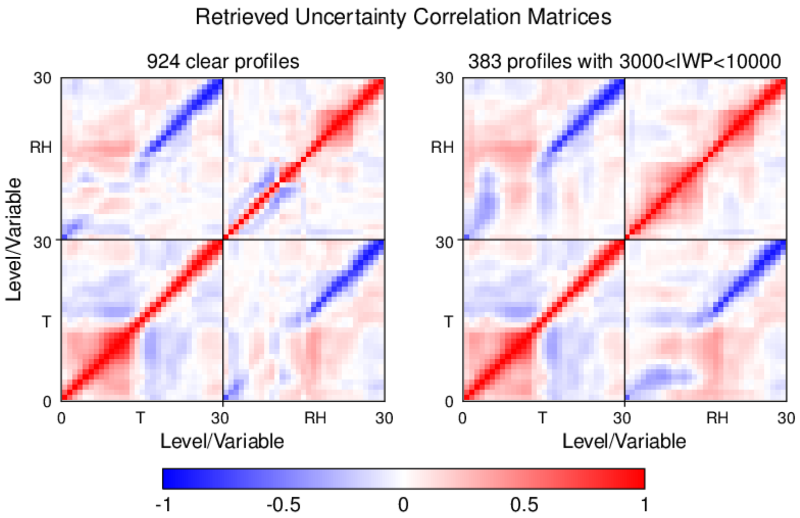




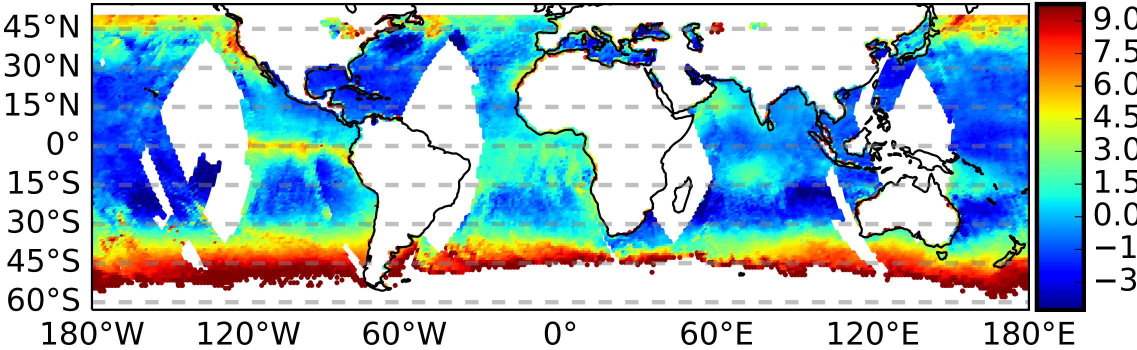
Top: SkinTemp (left), IWP (right), Bottom: Rain WP (left), Surface Wind Speed (right)



Correlated observation errors

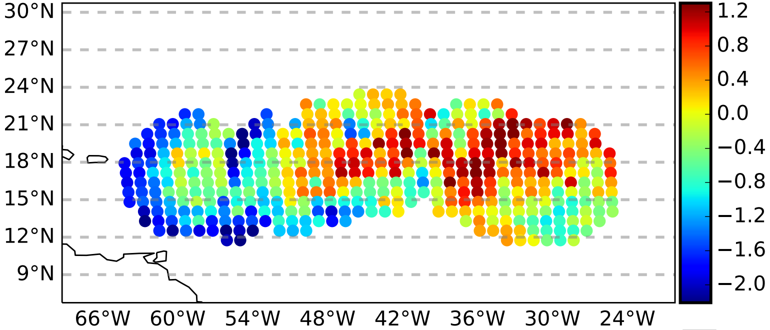


SST Analysis

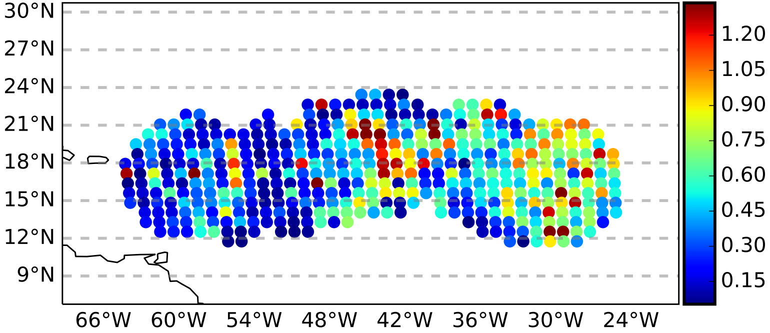


SST Analysis

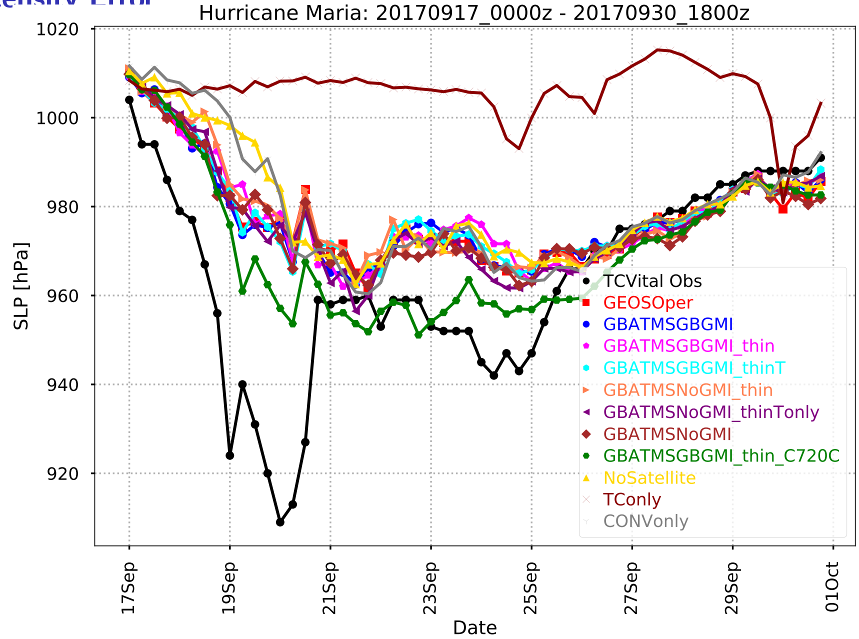
Mean
obs minus forecast



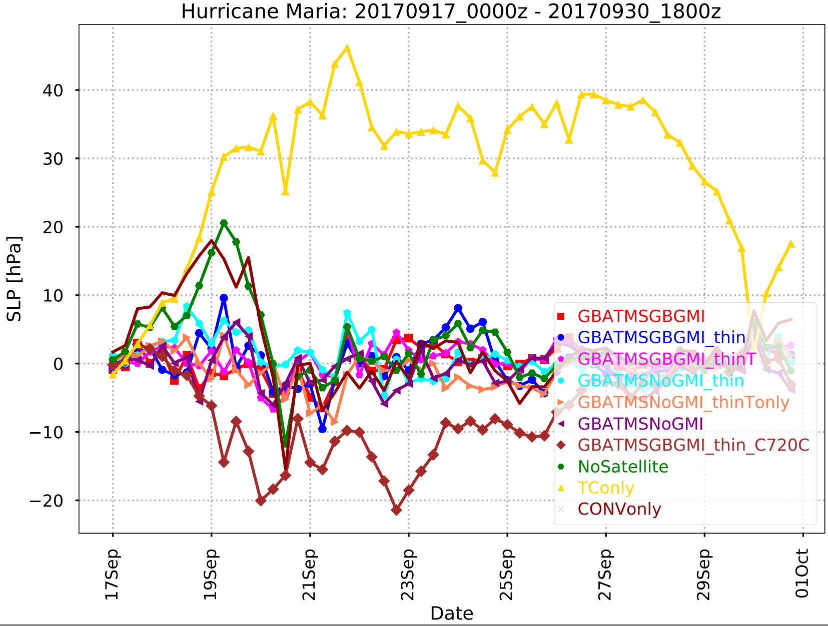
Std
obs minus forecast



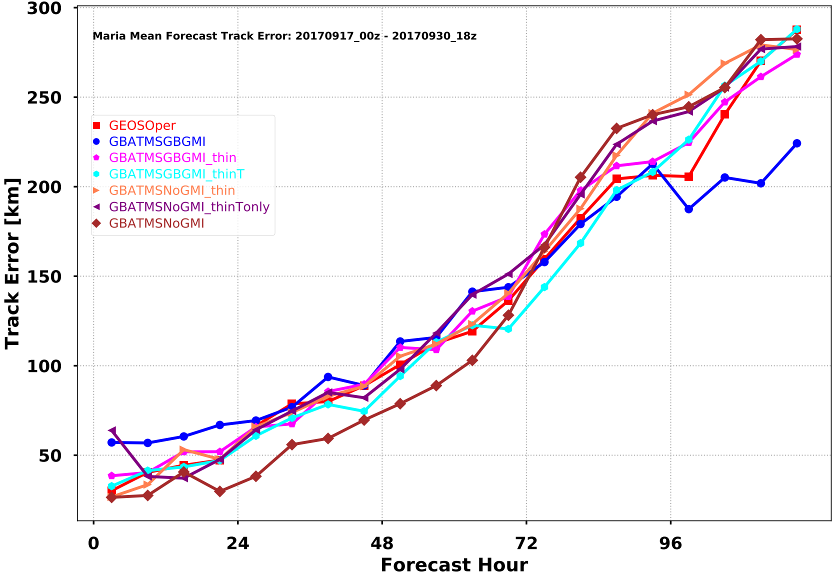
Analysis Intensity Error



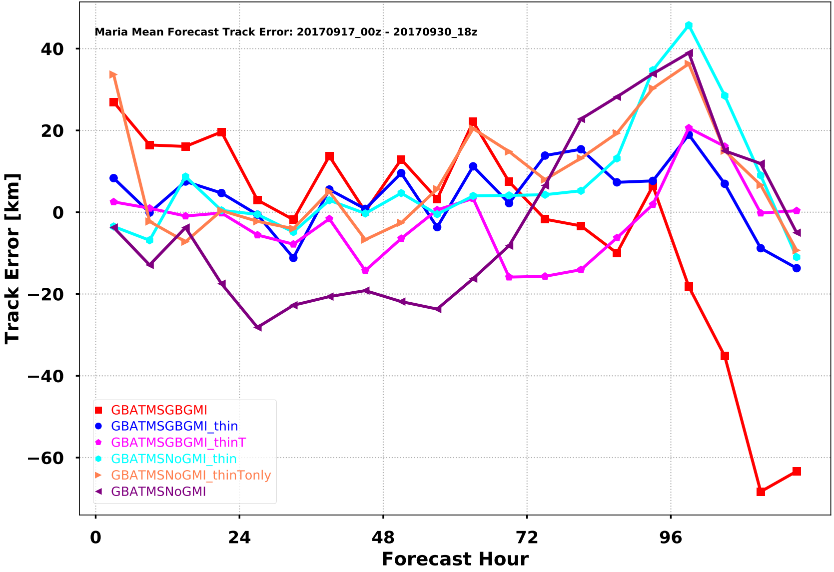
Forecast Intensity Error



Forecast Track Error

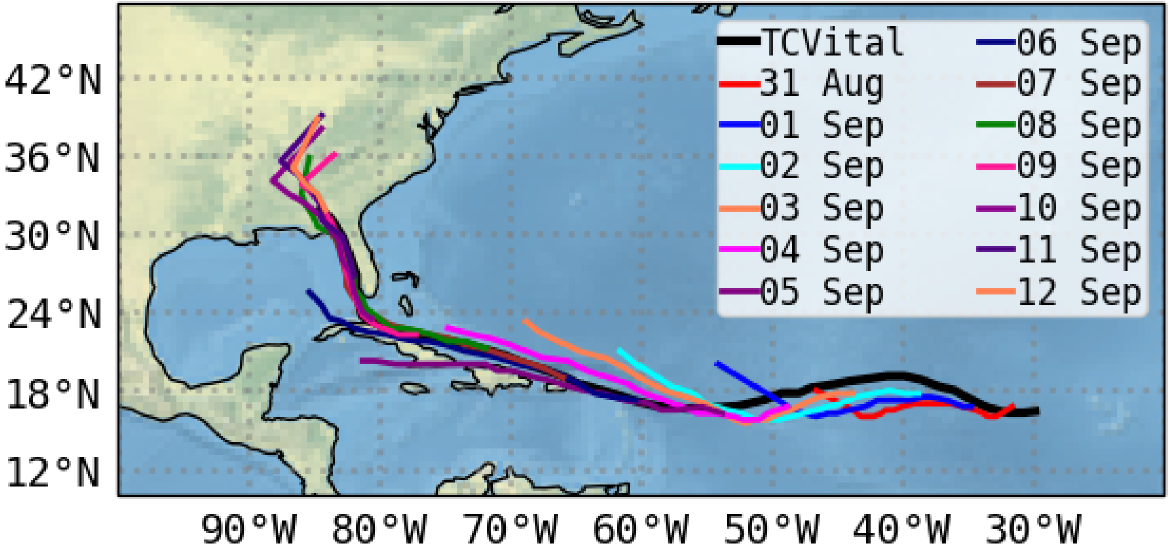


Forecast Track Error vs. GEOS operational run



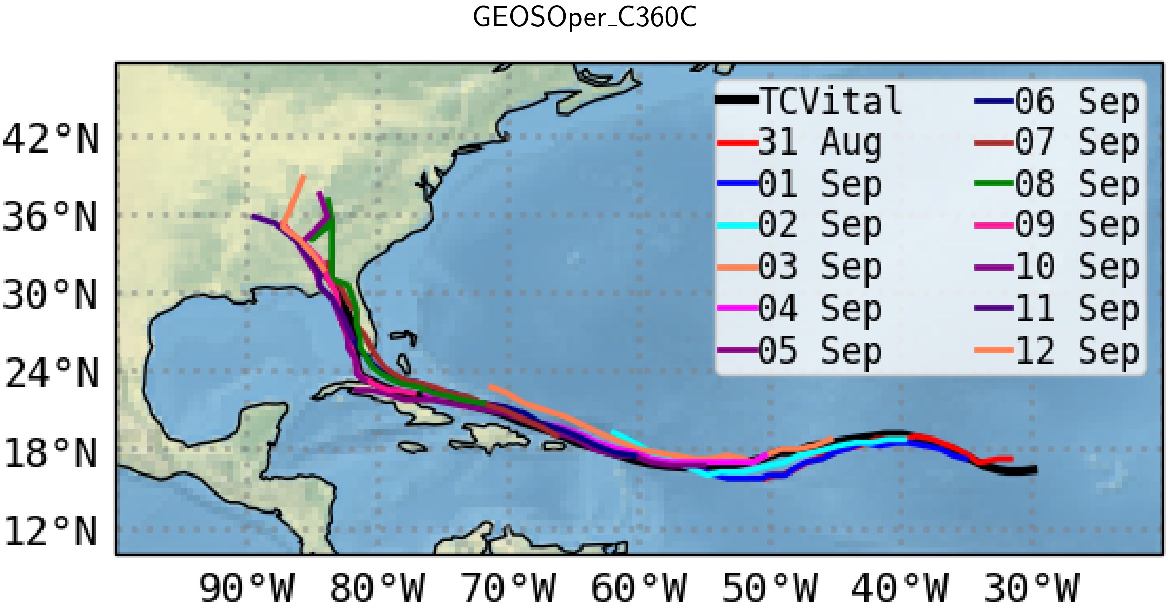
Irma Track in GEOS-5 Forecast

NoSatellite_C360C

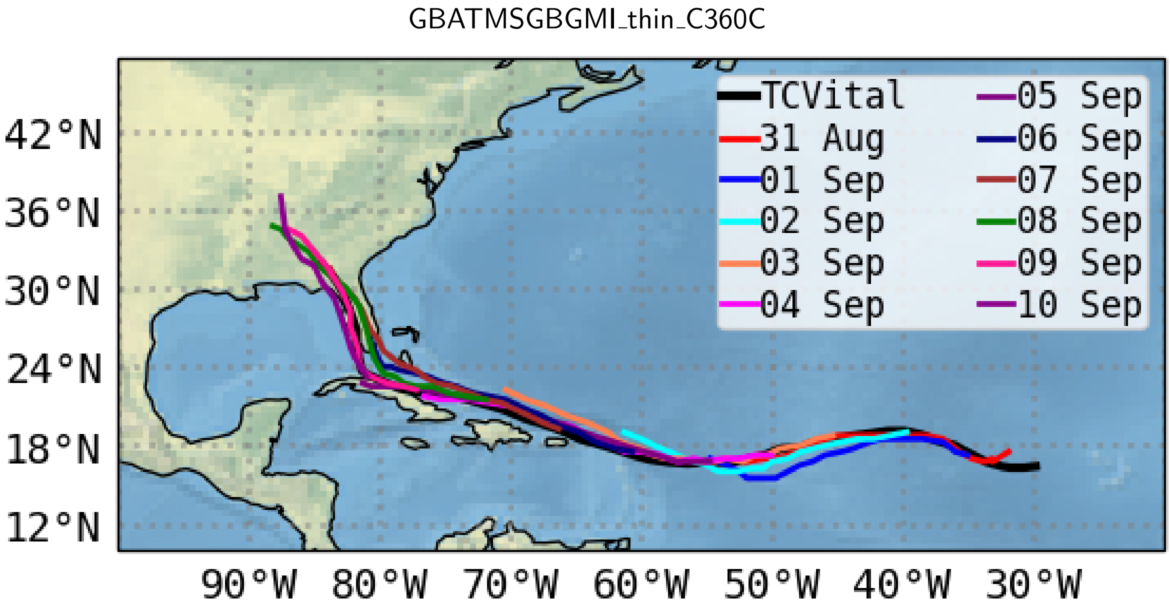


National Aeronautics and Space Administration

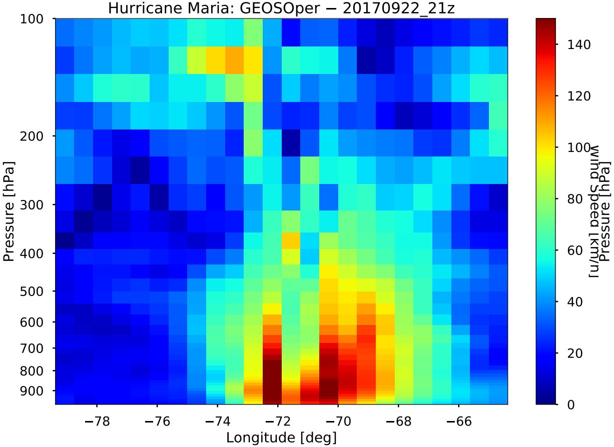
Irma Track in GEOS-5 Forecast



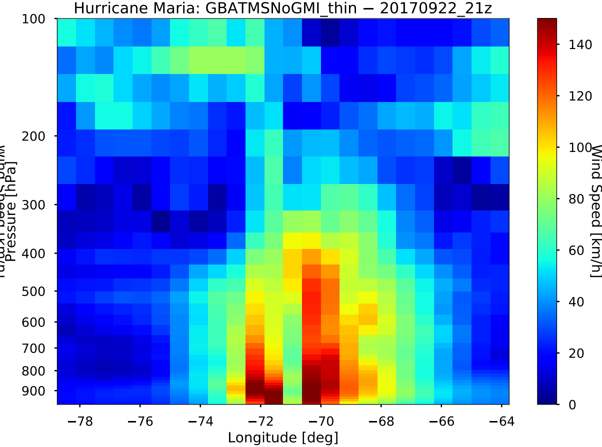
Irma Track in GEOS-5 Forecast



Wind speed (km/h) profiles

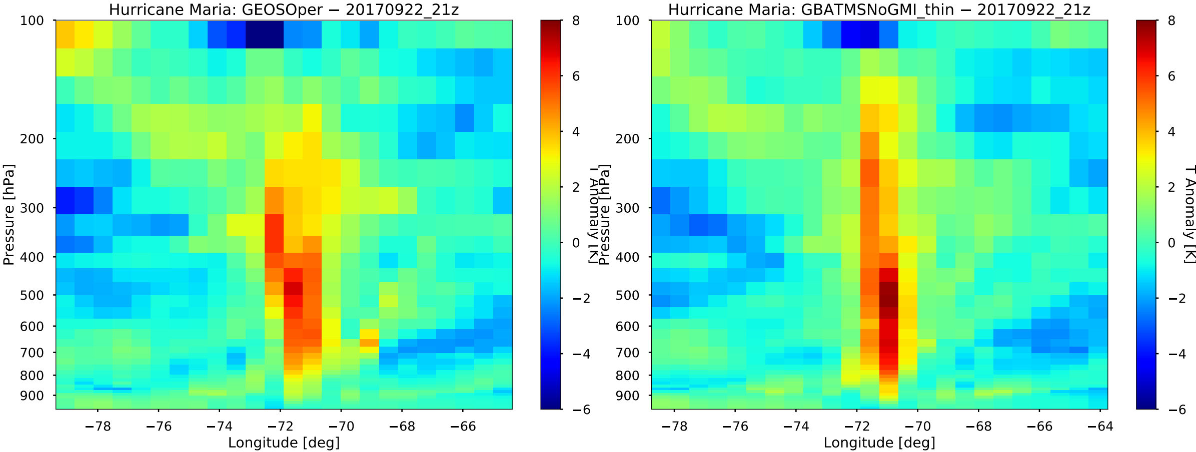


GEOSOper_C360C



GBATMSGBGMI_thin_C360C

Temperature anomaly



GEOSOper_C360C

GBATMSGBGMI_thin_C360C

Conclusions

- Conventional data assimilation schemes cannot properly assimilate satellite radiances in the rainband of tropical cyclones due to inaccuracy in RT scattering parameters as well as inaccuracy in the first guess provided by NWP models
- A new technique is proposed that does not depend on the minimization of the cost function.
- Preliminary results from BMCI technique are encouraging but require extensive validation, though validation itself is challenging
- These retrieved profiles are valuable for both analyzing the structure of the hurricanes as well as to provide more accurate initial conditions for the NWP models


Thank you for your attention!