Assimilation of satellite microwave observations in the rainband of hurricanes using Bayesian Monte Carlo Technique

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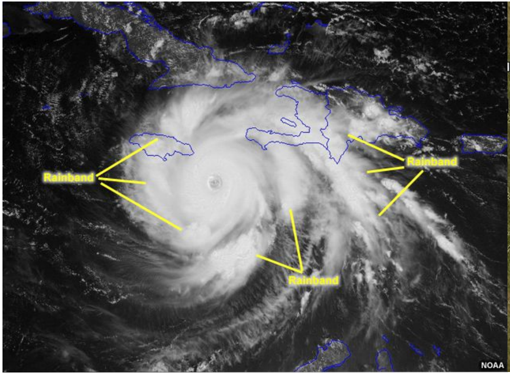
Outline

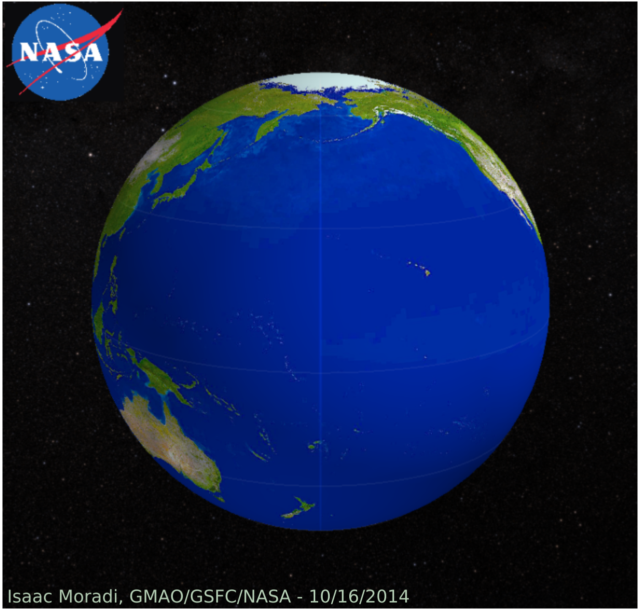
- Definitions
- Satellite Observations
- Motivation of the work
- Bayesian Monte Carlo Integration (BMCI) technique
- Implementation into NASA GEOS
- Results

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)

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

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

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

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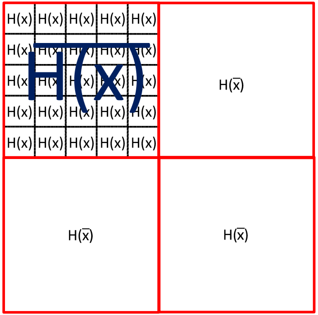

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Assuming Gaussian Errors: DA systems assume Gaussian error statistics, examined using the departures, but in the case of cloudy radiances the departures are likely to be non-Gaussian.

The BMCI technique

The BMCI technique can be summarized in three steps:

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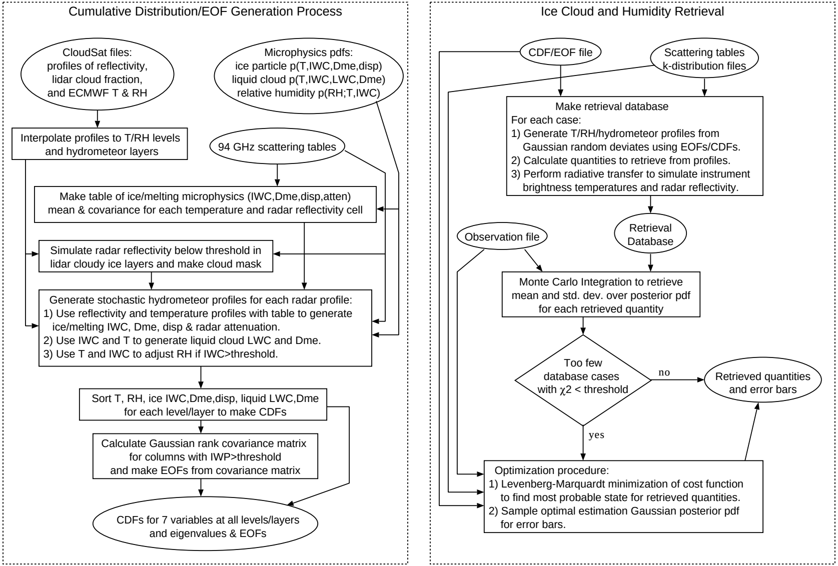
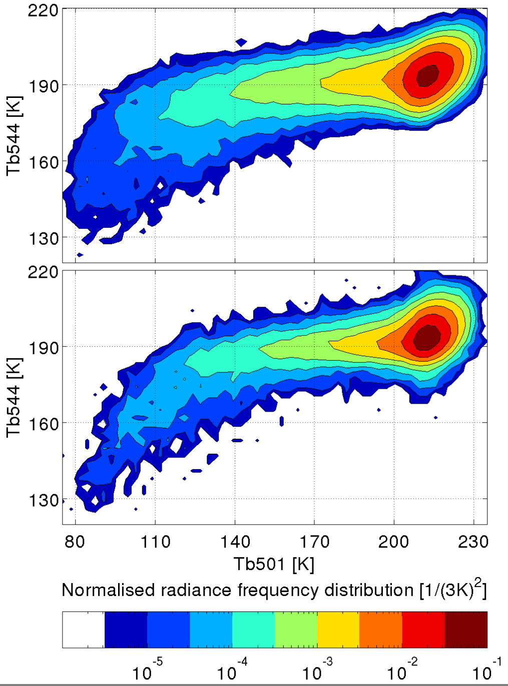
- real measurements along with the generated database are given to the retrieval package, then the retrieval package will select the cases which are close to the real measurements and integrate them according to the Bayes' theorem to give the estimate of the mean and uncertainty of the state and cloud variables.

The BMCI technique



Evans et al., 2012

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.

Some references ...

Several Papers from Frank Evans
University of Colorado
http://nit.colorado.edu/mwcirrus/submmcirrus.html

Bayesian Monte Carlo
Carl Edward Rasmussen and Zoubin Ghahramani
Gatsby Computational Neuroscience Unit
University College London
http://mlg.eng.cam.ac.uk/zoubin/papers/RasGha03.pdf

Monte Carlo Integration in Bayesian Estimation
Avinash Kak
Purdue University
https://engineering.purdue.edu/kak/Tutorials/MonteCarloInBayesian.pdf

Improvements to the BMCI Retrievals

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

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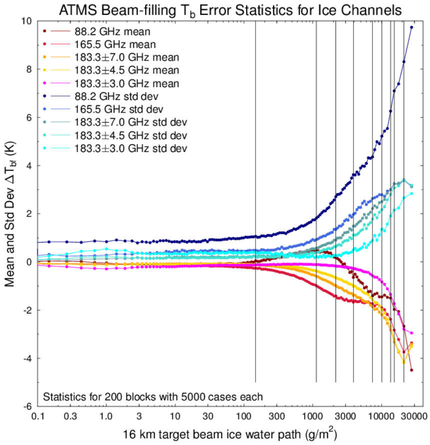
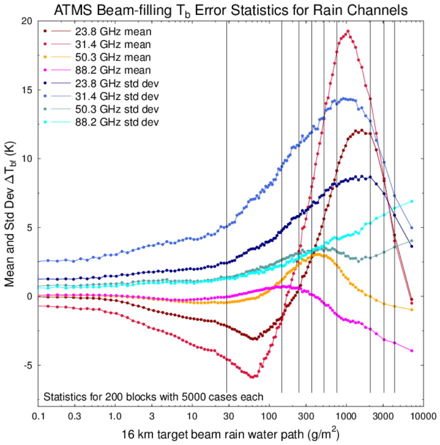
- Modifying the CDF-EOF algorithm to allow for clear layers using a hydrometeor masking procedure for ice, rain, and liquid cloud

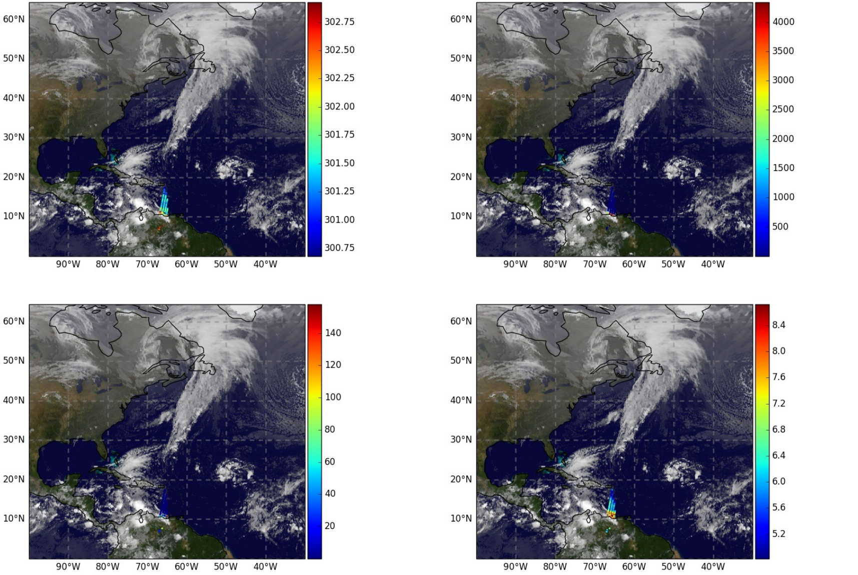
Beam filling

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.

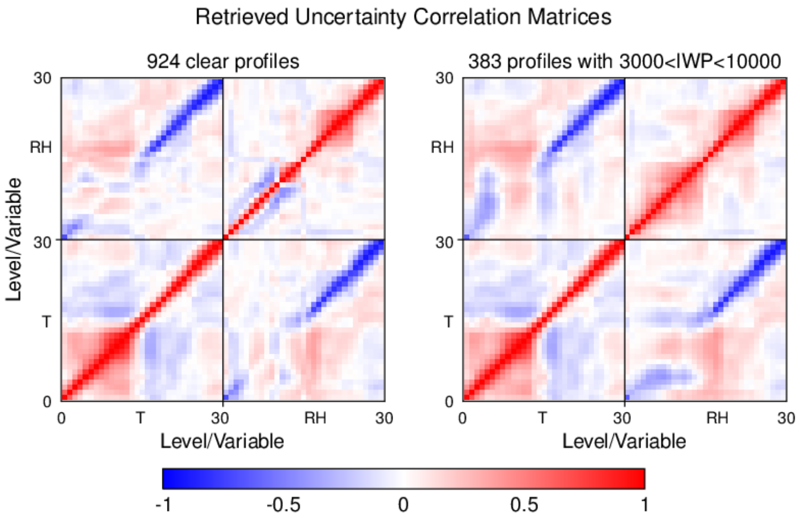




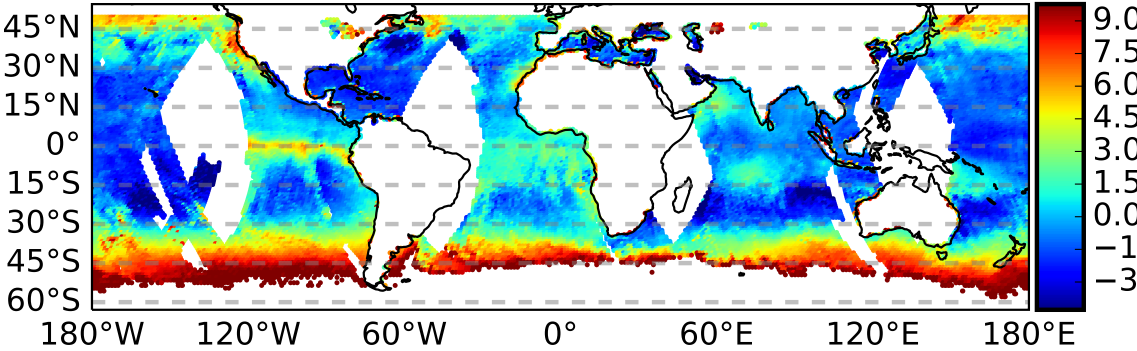
Top: SkinTemp (left), IWP (right), Bottom: Rain WP (left), Surface Wind Speed (right)



Correlated observation errors



SST Analysis

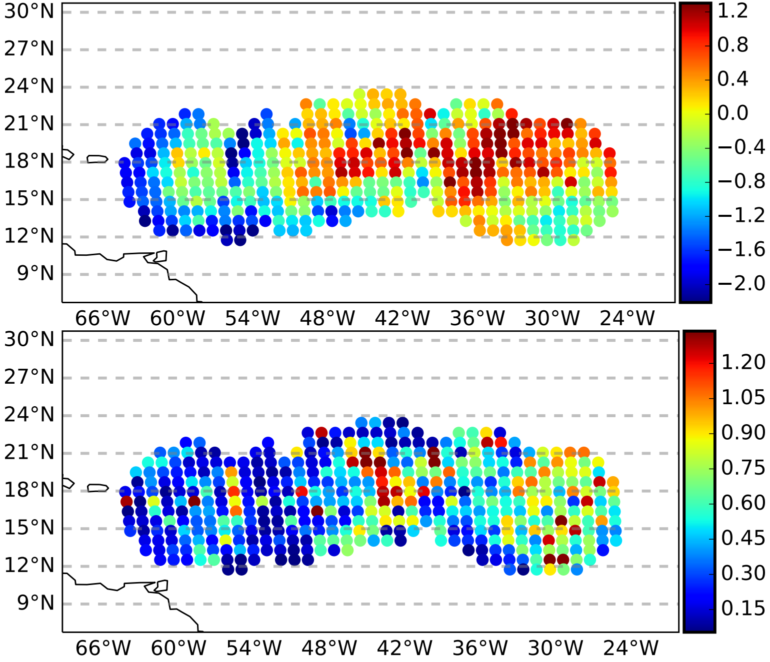


National Aeronautics and Space Administration

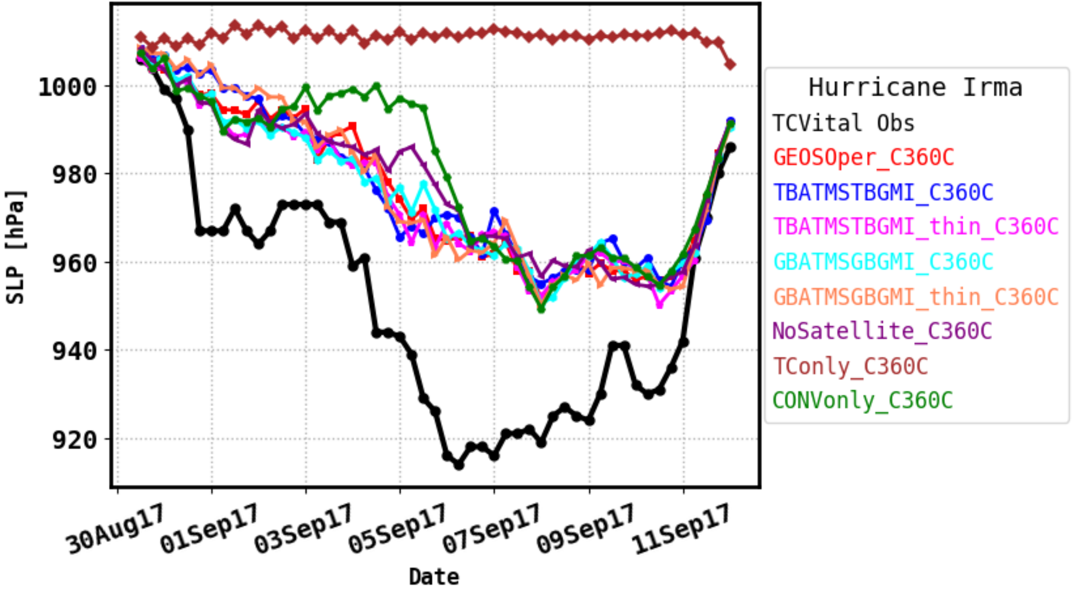
SST Analysis

Mean
obs minus forecast

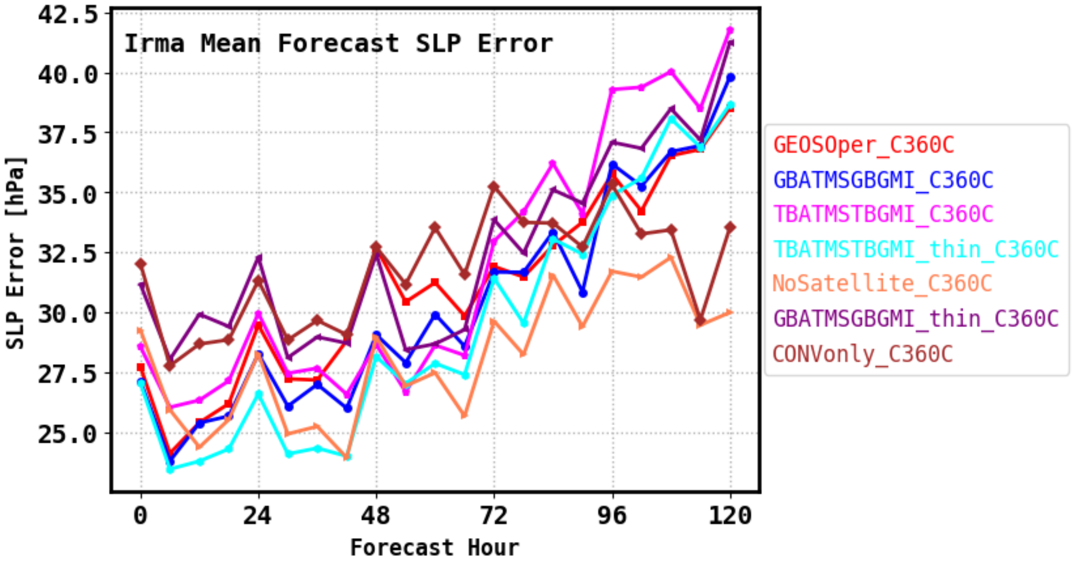
Std
obs minus forecast



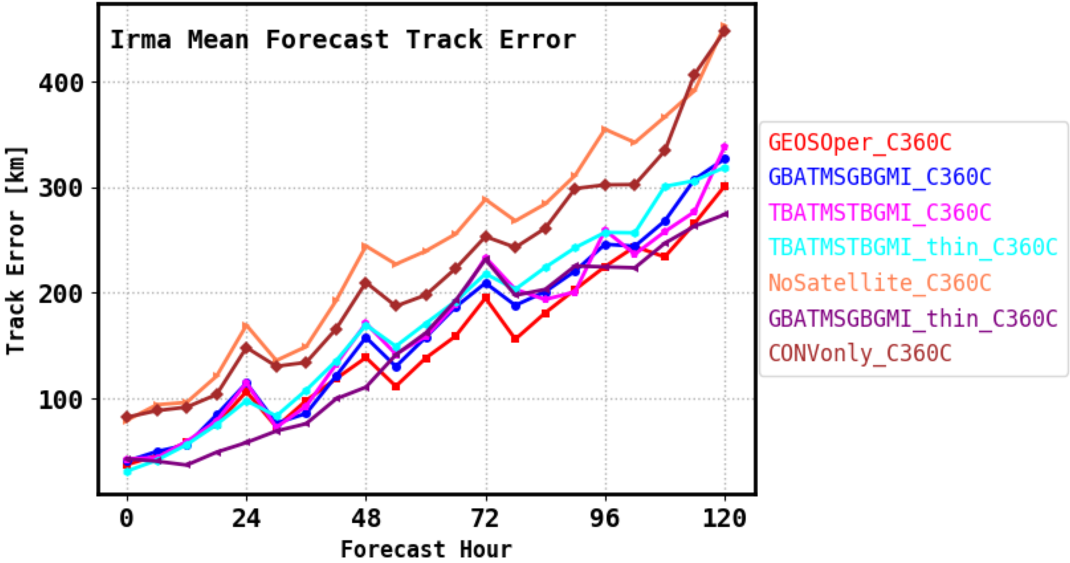
Analysis Intensity Error



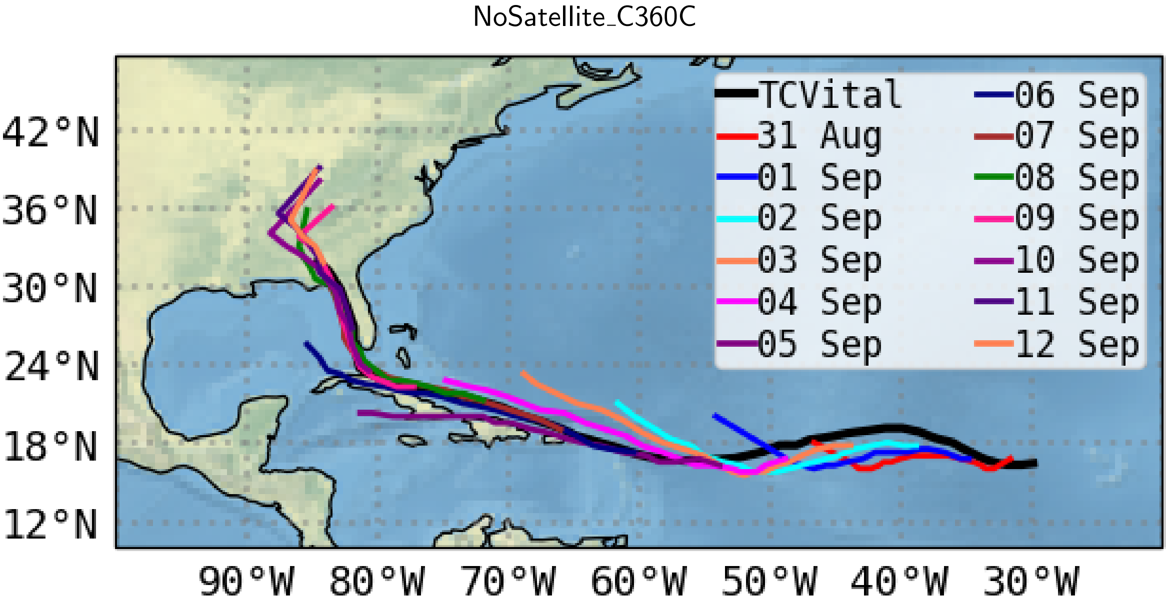
Forecast Intensity Error



Forecast Track Error



Irma Track in GEOS-5 Forecast



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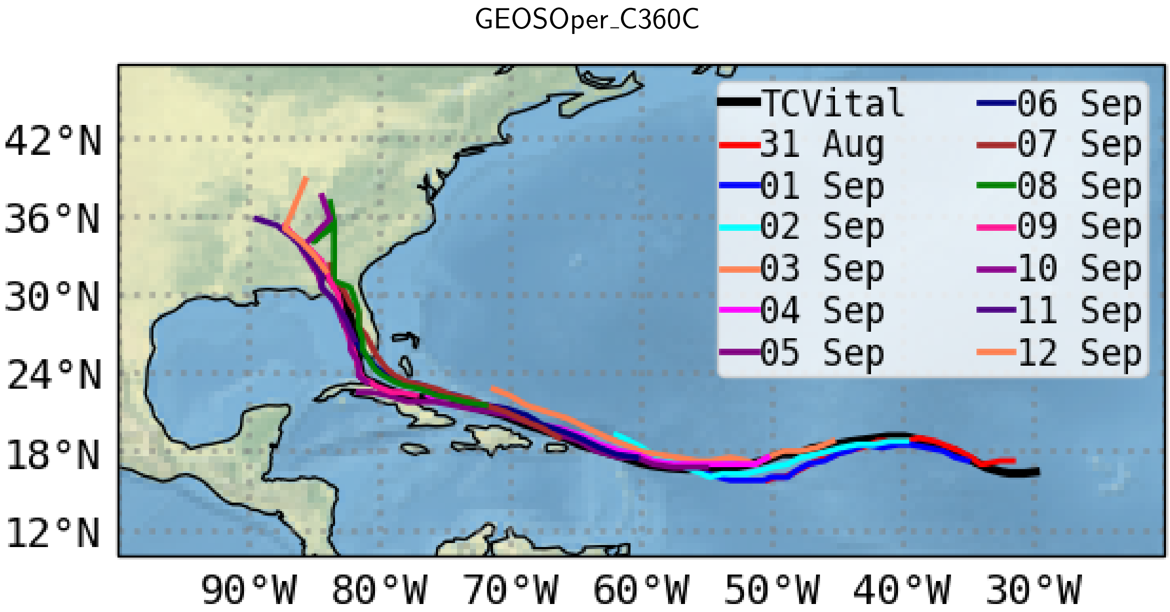

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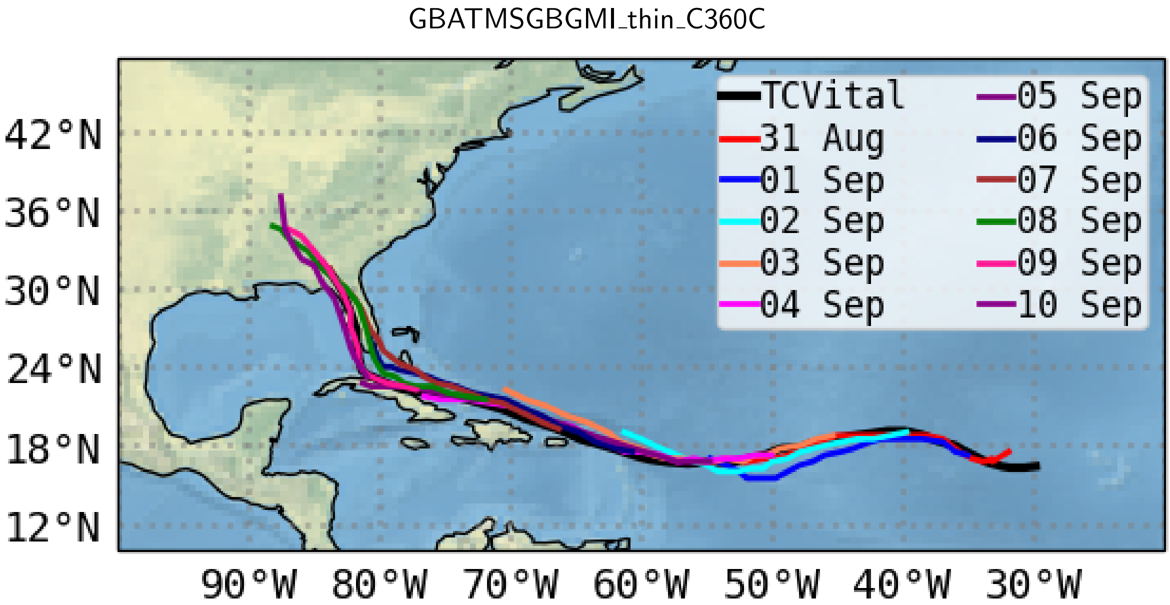

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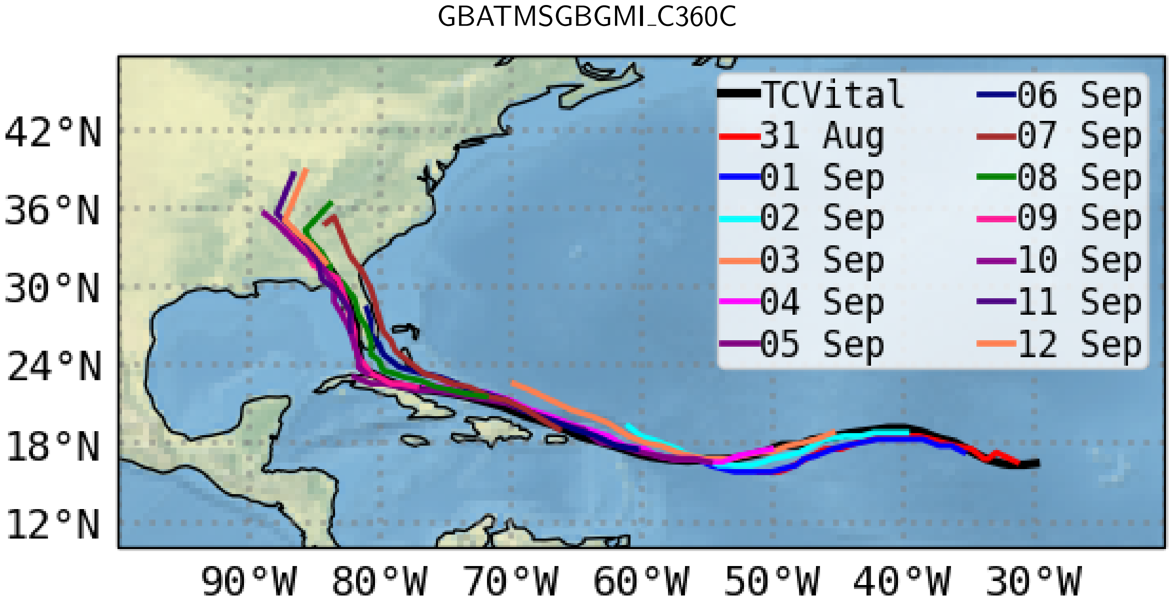
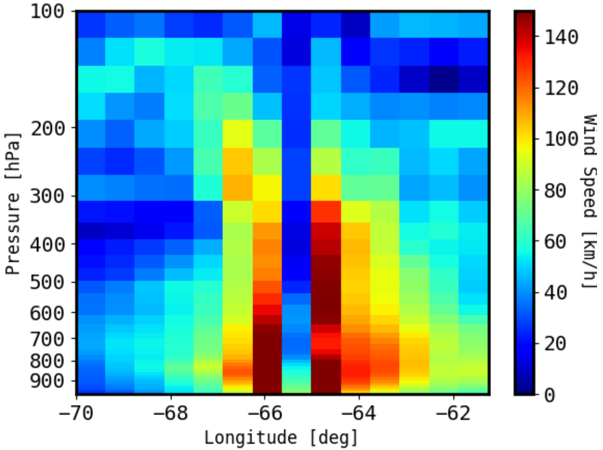
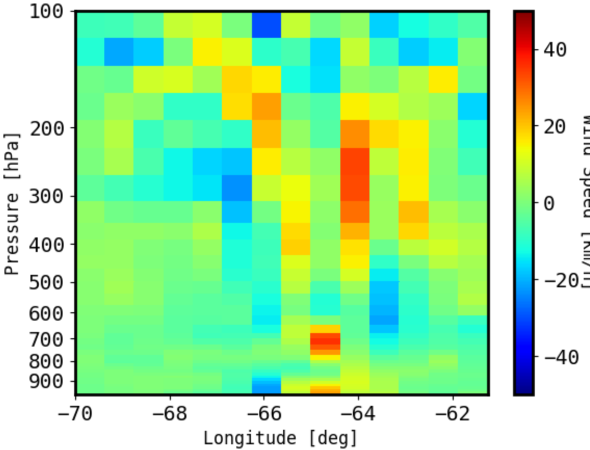


Wind speed (km/h) profiles

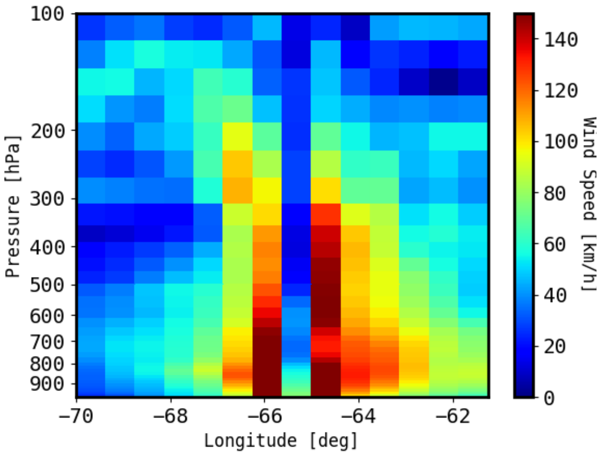


GEOSOper_C360C

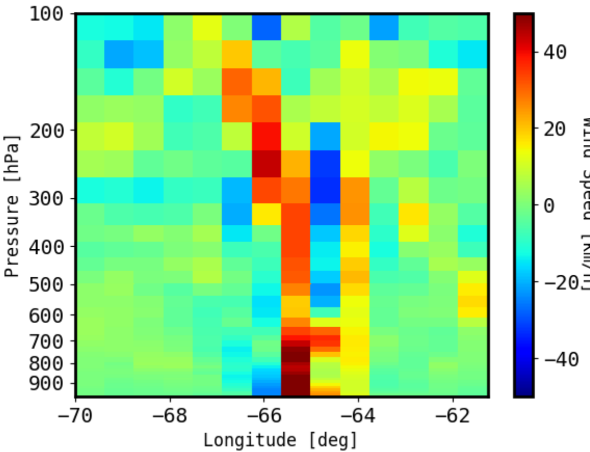


GBATMSGBGMI_thin_C360C

Wind speed (km/h) profiles



GEOSOper_C360C



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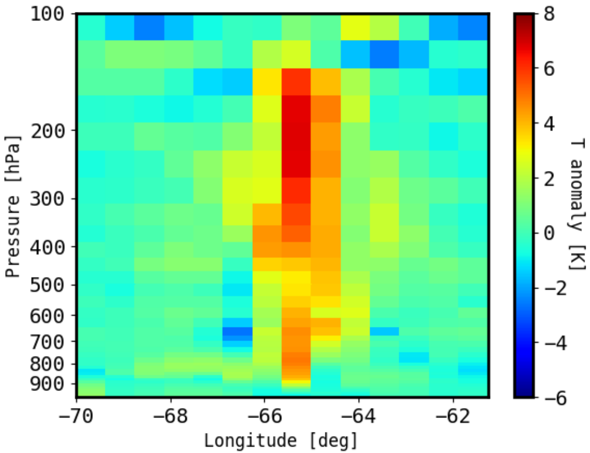
Temperature anomaly



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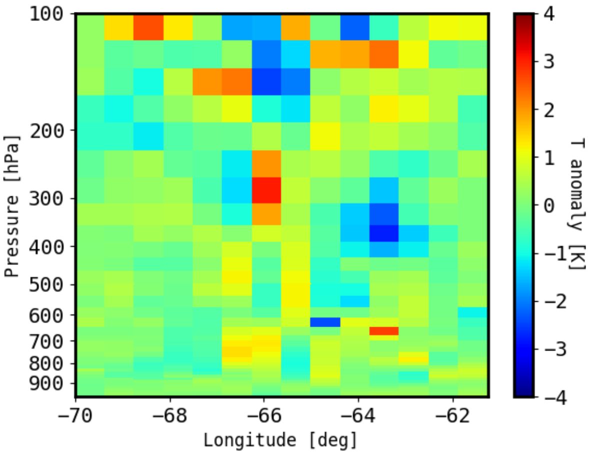

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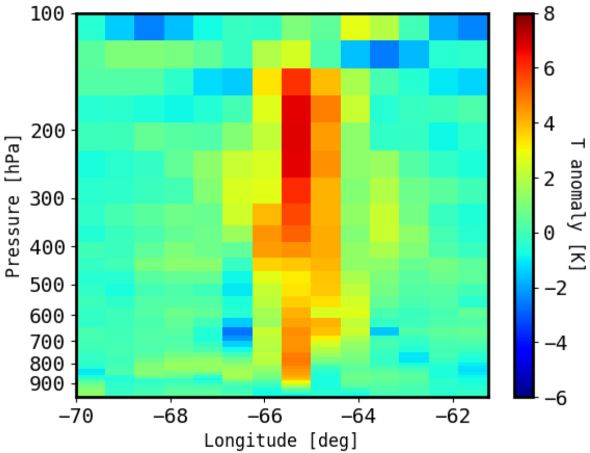

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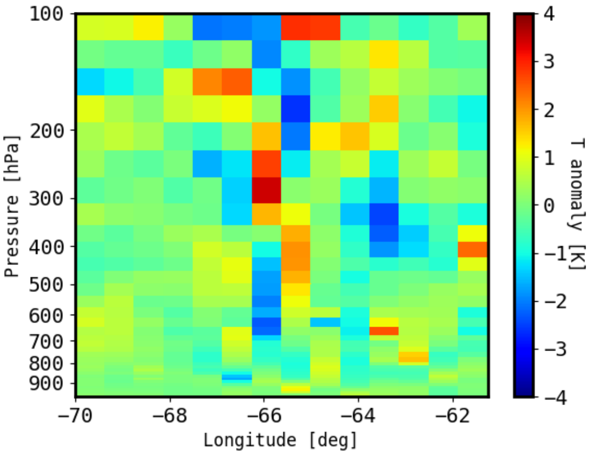
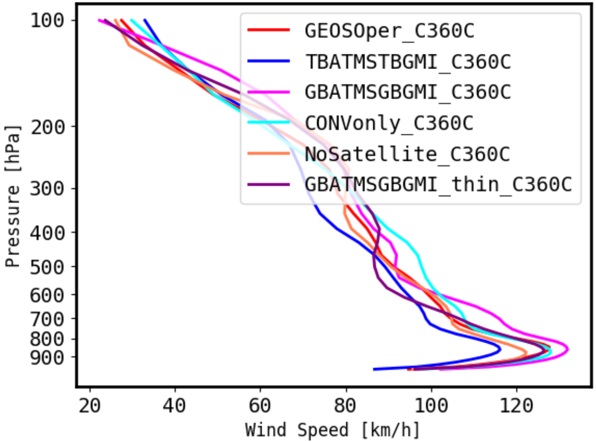
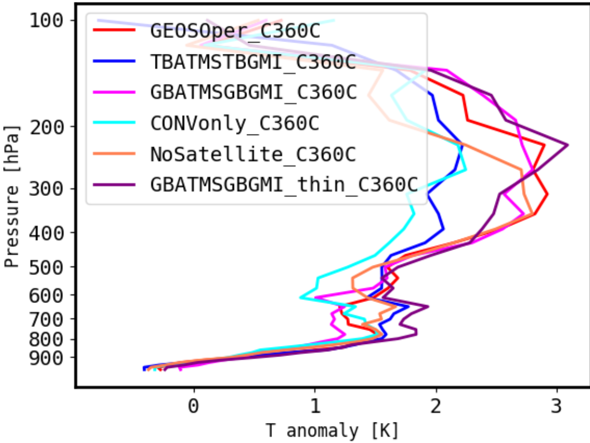


GBATMSGBGMI_C360C

Wind Speed [km/hr] – 2deg band



Wind speed (km/hr)



Temperature anomaly (K)

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!