Assimilation of Microwave Cloudy Radiances into NASA GEOS Model Using a Novel Bayesian Monte Carlo Technique

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Outline

Definitions

Motivation of the work

Bayesian Monte Carlo Integration (BMCI) technique

Implementation into NASA GEOS

Results

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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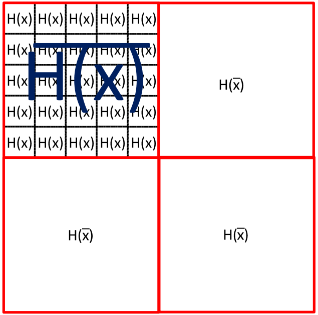

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Assuming Gaussian Errors: DA systems assume Gaussian error statistics, examined using the departures, but in the case of cloudy radiances the departures are likely to be non-Gaussian.

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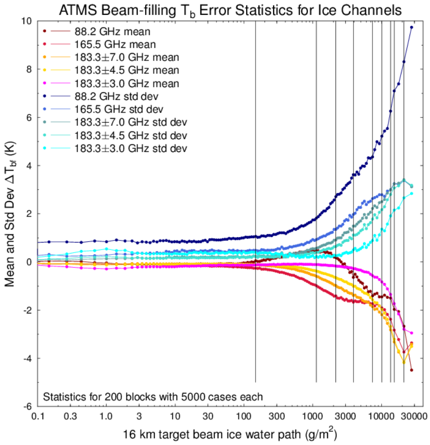
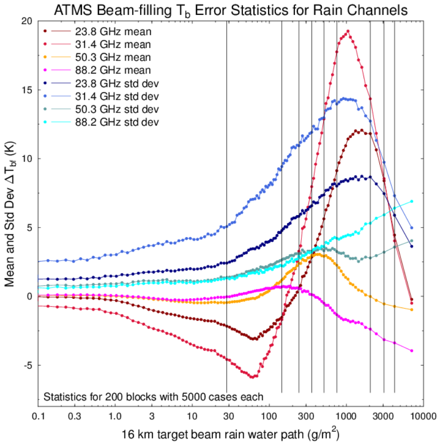
- real measurements along with the generated database are given to the retrieval package, then the retrieval package will select the cases which are close to the real measurements and integrate them according to the Bayes' theorem to give the estimate of the mean and uncertainty of the state and cloud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

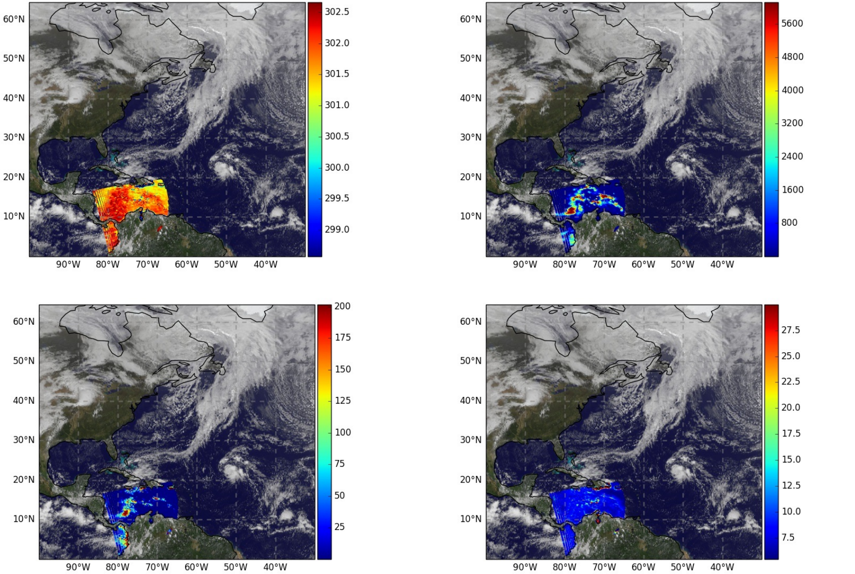
Beam filling

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.

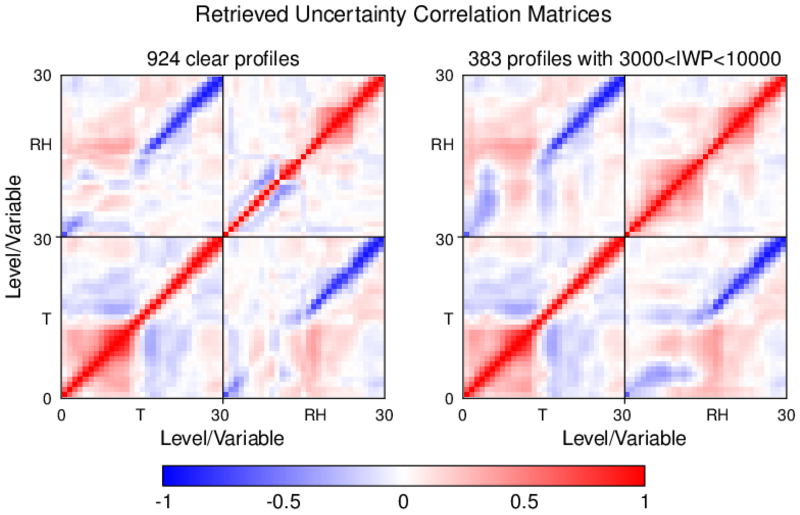




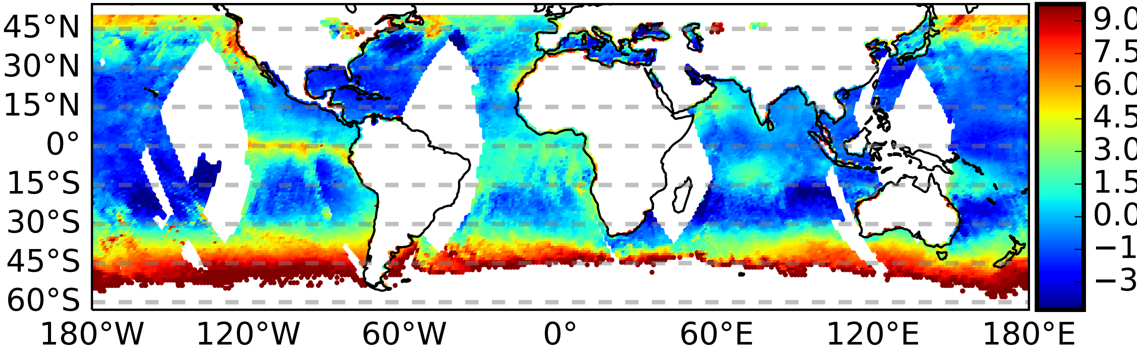
Top: SkinTemp (left), IWP (right), Bottom: Rain WP (left), Surface Wind Speed (right)



Correlated observation errors

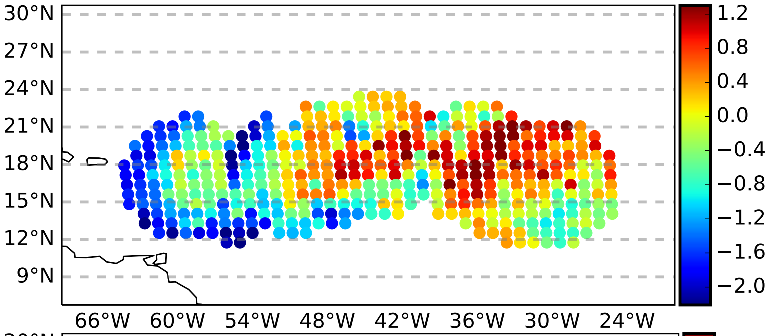


SST Analysis

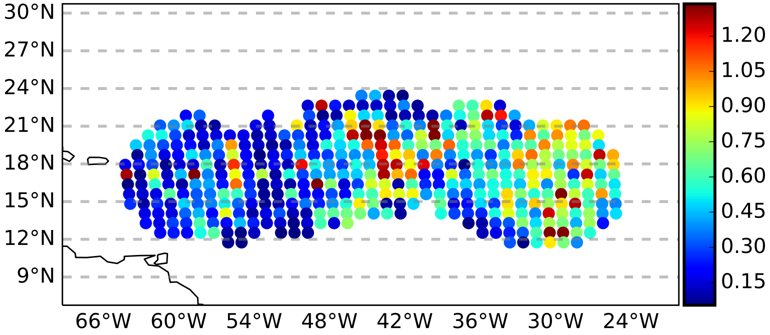


SST Analysis

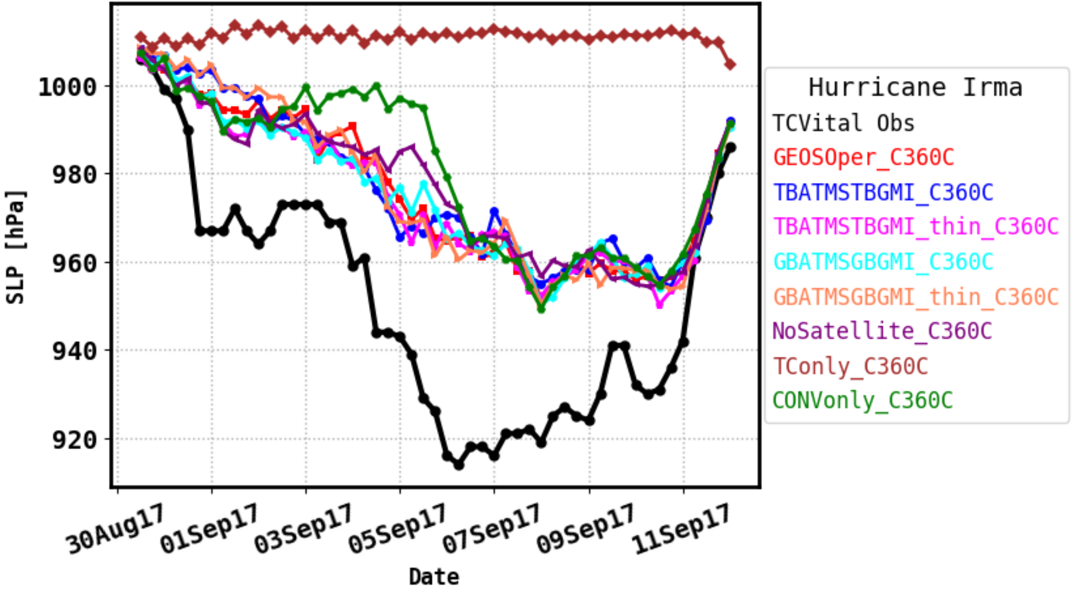
Mean
obs minus forecast



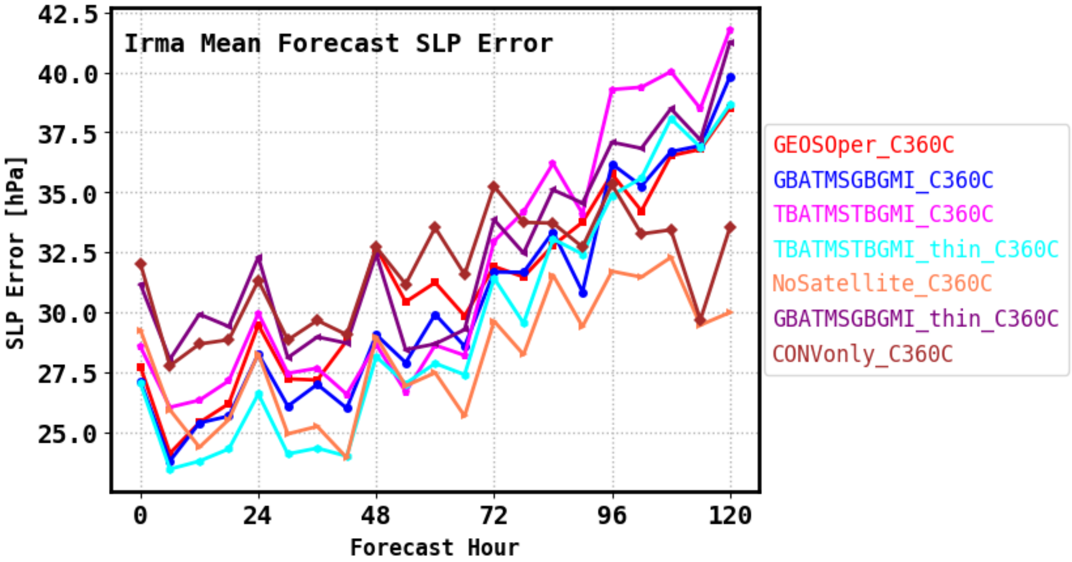
Std
obs minus forecast



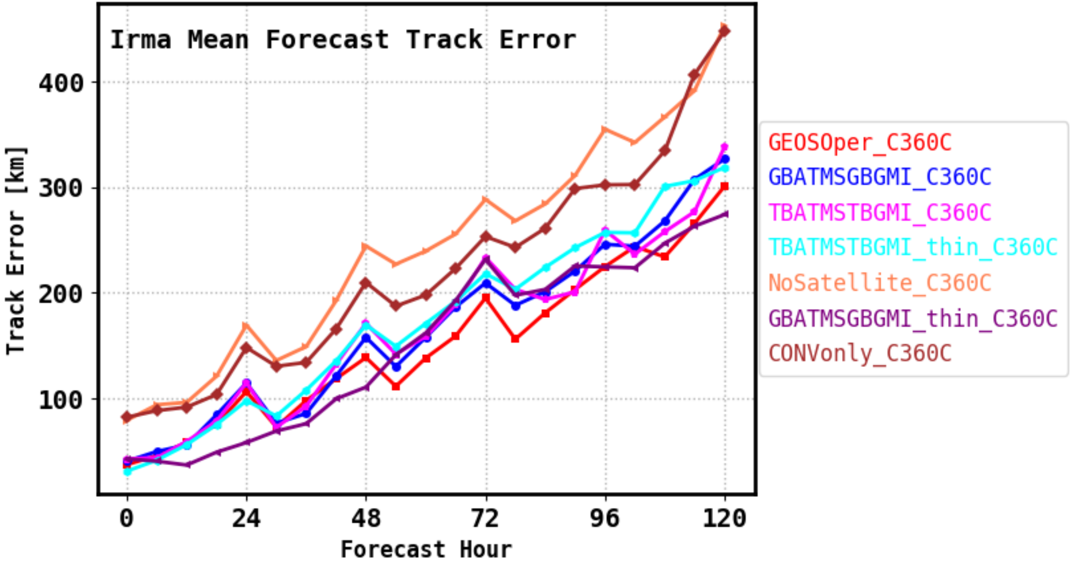
Analysis Intensity Error



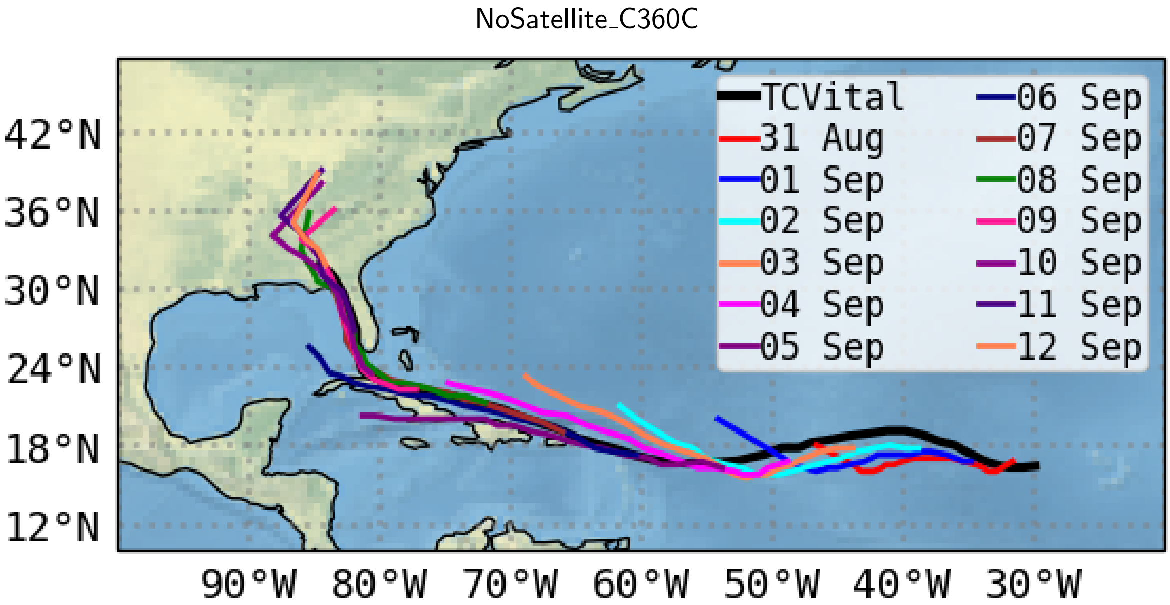
Forecast Intensity Error



Forecast Track Error



Irma Track in GEOS-5 Forecast



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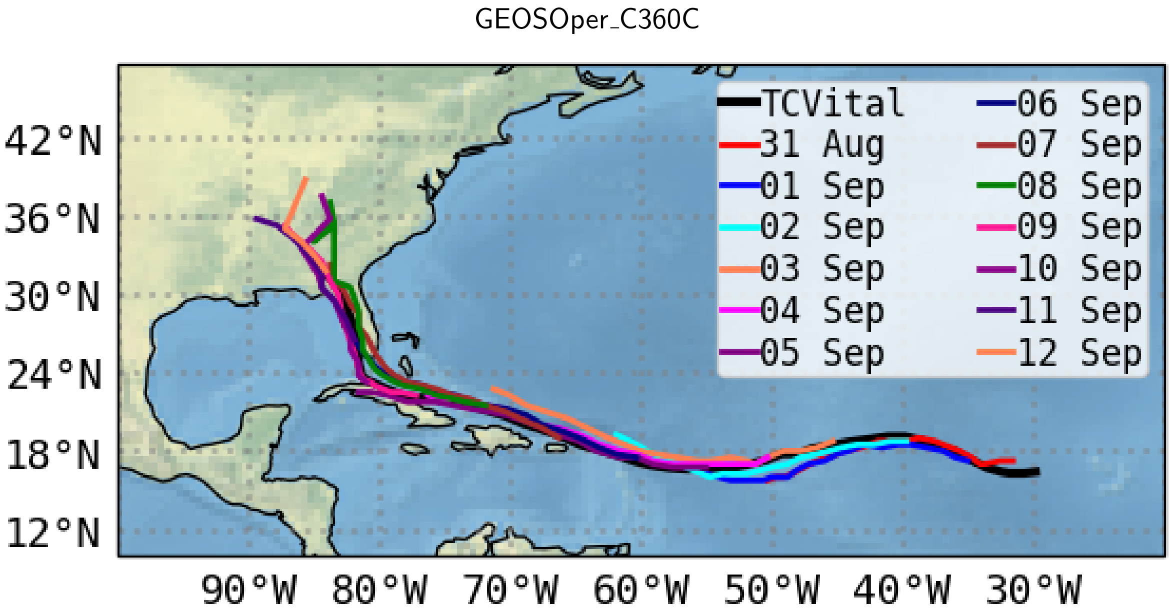

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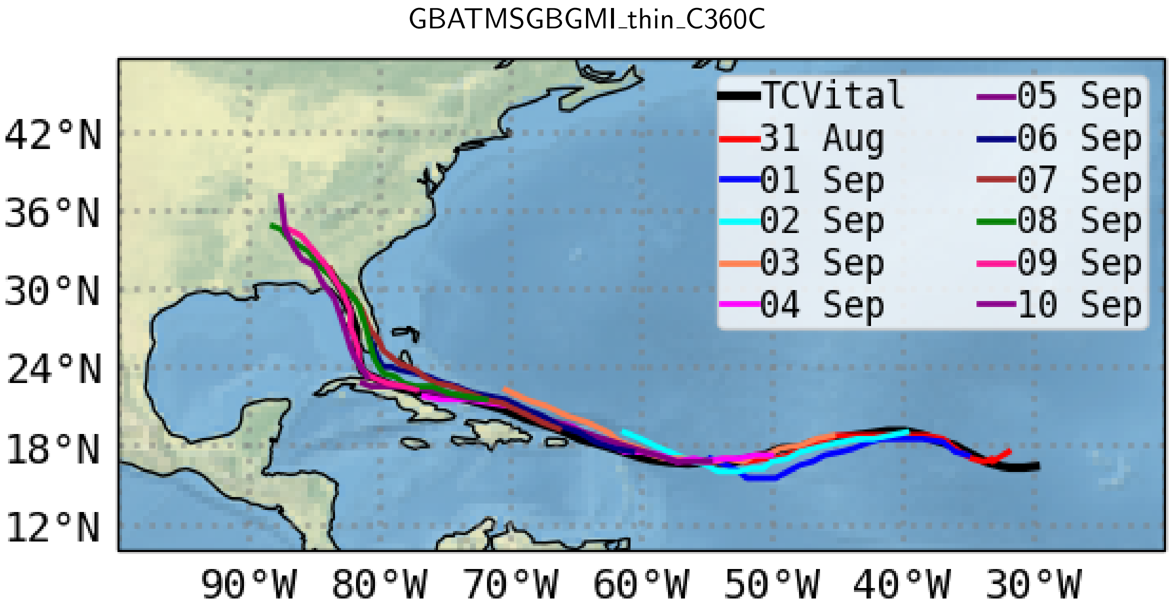
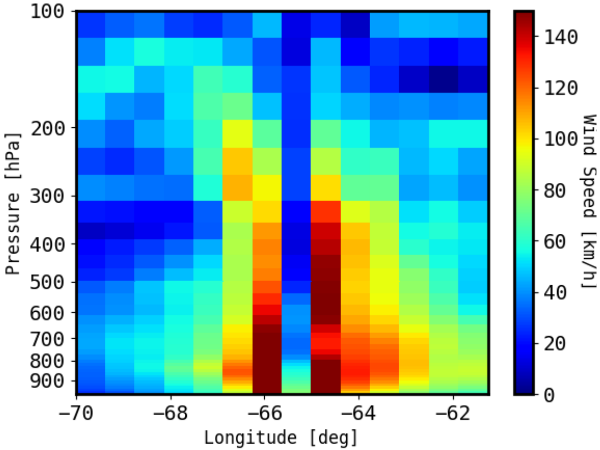
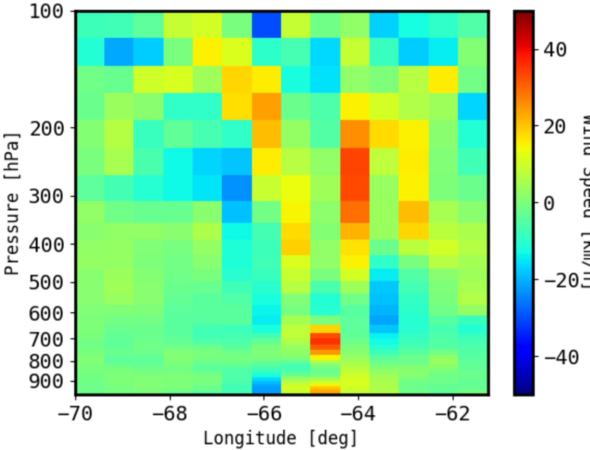


Wind speed (km/h) profiles



GEOSOper_C360C



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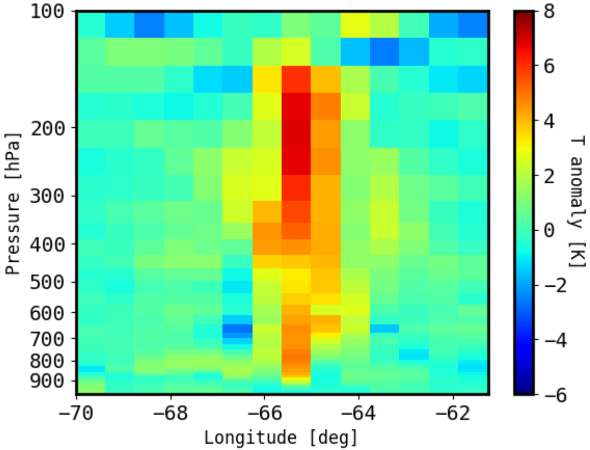
Temperature anomaly



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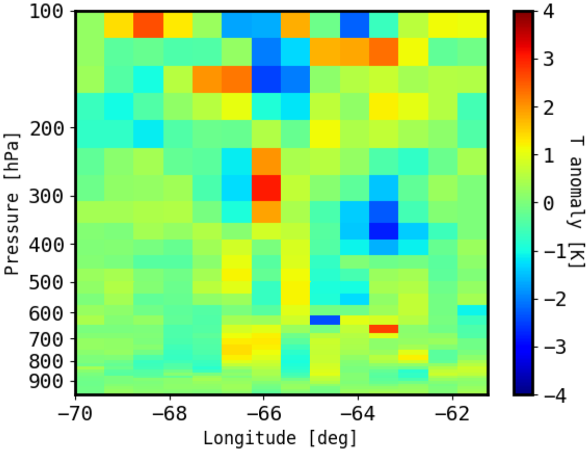

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Conclusions

- 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!