Assimilation of GMI and ATMS observations in the rainbands of hurricanes

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Many thanks to NDOA Program Manager, Dr. Tsengdar Lee.

Overview

- Due to limitations in directly assimilating microwave cloudy observations in the rain-bands of hurricanes, a new technique named Bayesian Monte Carlo Integration (BMCI) is introduced.
- The BMCI technique is used to retrieve T, q, wind speed and several other parameters from microwave radiances.
- These retrievals can be either directly used by forecasters to evaluate the structure of hurricanes or be assimilated into NWP models.

Limitations of direct assimilation of cloudy radiances

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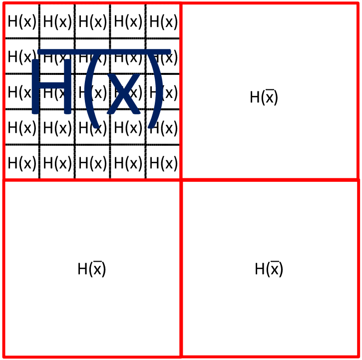

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Assuming Gaussian Errors: DA systems assume Gaussian error statistics, examined using the departures, but in the case of cloudy radiances the departures are likely to be non-Gaussian

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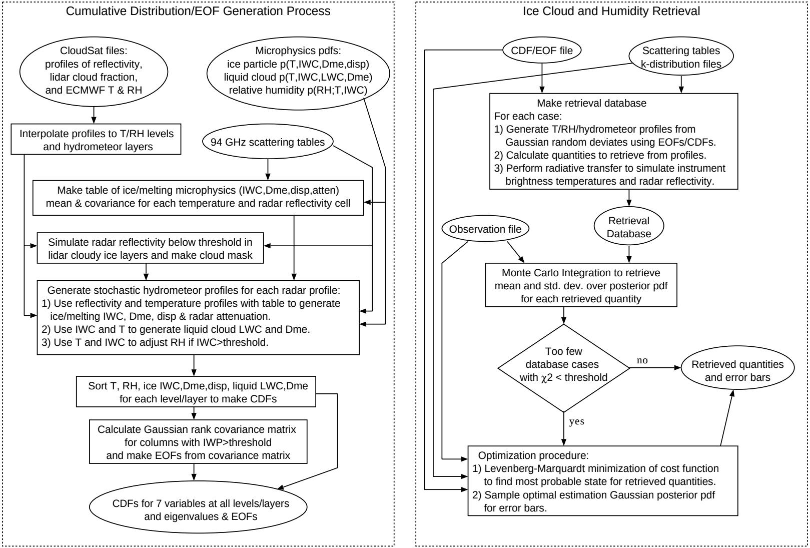
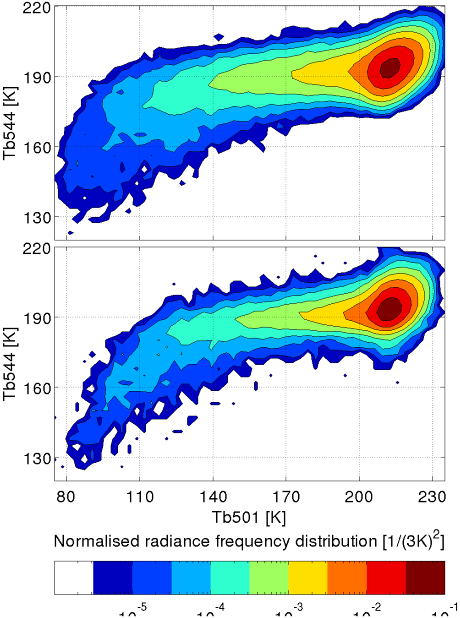
- real measurements along with the generated database are given to the retrieval package, then the retrieval package will select the cases which are close to the real measurements and integrate them according to the Bayes' theorem to give the estimate of the mean and uncertainty of the state and cloud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

BMCI technique



Evans et al., 2012

Retrieval Database



Rydberg et al., 2009

The BMCI technique

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

The retrieved values for atmospheric or cloud state ($\hat{x}$) can be computed by integrating over the posterior pdf:

$$\hat{x} = \int \vec{x} p_{post}(\vec{x}|\vec{y})dx$$

$$\hat{x} = \frac{\sum_i x_i p_f(\vec{y}|\vec{x_i})}{\sum_i p_f(\vec{y}|\vec{x_i})}$$

The variance (error) of the posterior pdf is calculated as:

$$\sigma_x^2 = \int (x - \hat{x})^2 p_{post}(\vec{x}|\vec{y})dx$$

The BMCI technique

The conditional pdf can be defined using the probability density of the measured vectors for any given atmospheric state (j channel number):

$$P(\vec{y}|\vec{x}) = \prod_{j=1}^{m} \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{[\vec{y_j} - H_j(\vec{x})]^2}{2\sigma_j^2}\right)$$

σ is the noise in the measurements and $\hat{x}$ now can be calculated as:

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

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

Improvements to the BMCI Retrievals

We have made a significant progress on enhancing the BMCI retrieval system and adding new functionalities to the code. Some of the major enhancements to the code are as follows:

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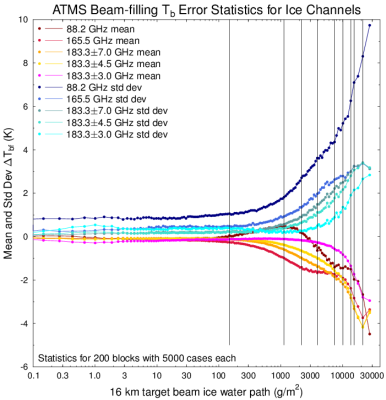
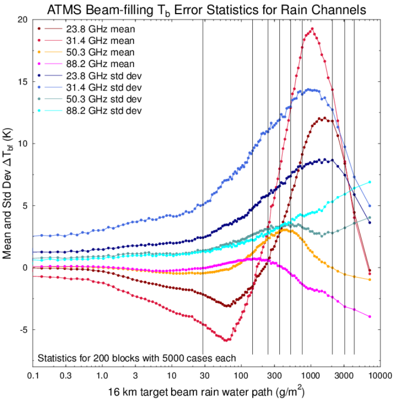
- Modifying the CDF-EOF algorithm to allow for clear layers using a hydrometeor masking procedure for ice, rain, and liquid cloud
- Modifying the 1D Bayesian retrieval program to input the new CDF-EOF a priori file and generate consistent profiles of temperature, relative humidity, and ice particle, raindrop, and cloud droplet size distribution parameters to use in the Bayesian profile retrievals.

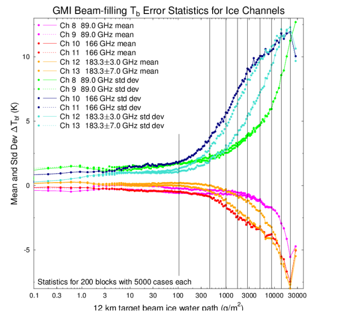
Beam filling

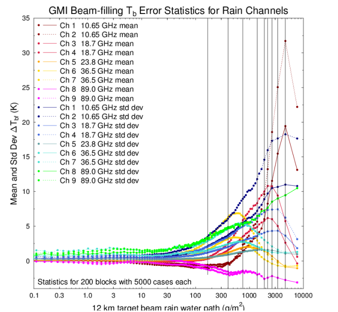
Beam filling was calculated as the difference between the brightness temperatures weighted according to an elliptical Gaussian beam pattern and Tbs calculated using the average profiles. The profiles were generated with 5km resolution using stochastic statistics derived from GPM DPR and central prof

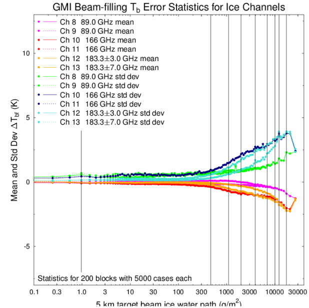


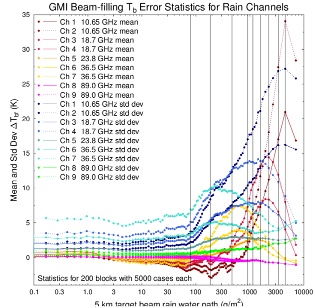


Beam filling – GMI instrument









Selected Hurricanes

Hurricane Sandy CloudSat overpassed it on October 27, 2012

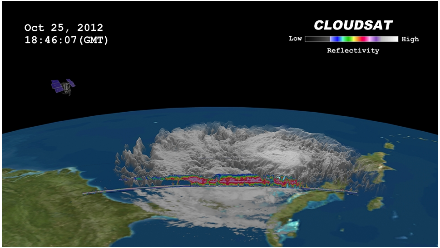
Hurricane Iselle CloudSat overpassed the hurricane on August 4, 2014

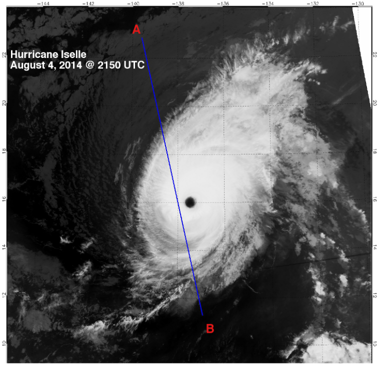
Hurricane Amanda CloudSat overpassed Hurricane Amanda on May 25, 2014

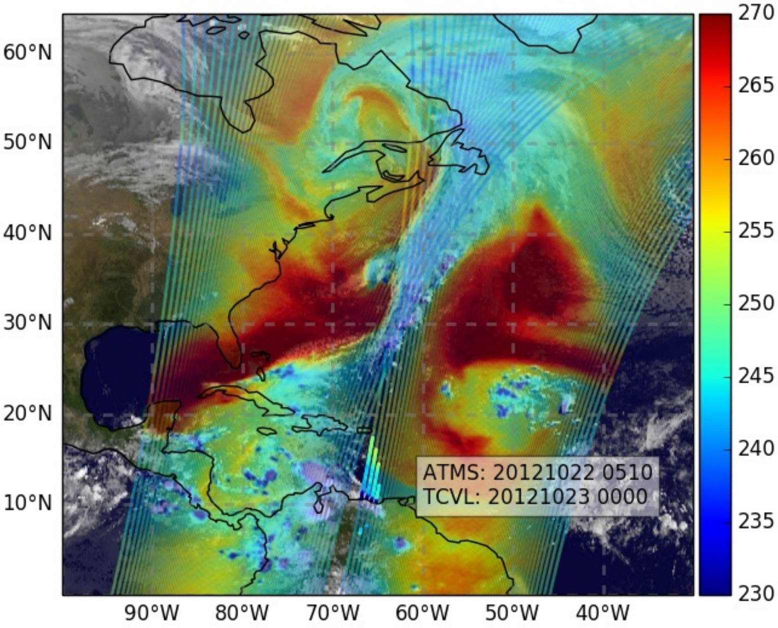
Hurricane Joaquin In an early stage of the formation of Hurricane Joaquin, on September 29, 2015, CloudSat passed over the center of the hurricane in the Caribbean.

Image credit:

`cloudsat.atmos.colostate.edu`






60°N
50°N
40°N
30°N
20°N
10°N
90°W
80°W
70°W
60°W
50°W
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270
265
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255
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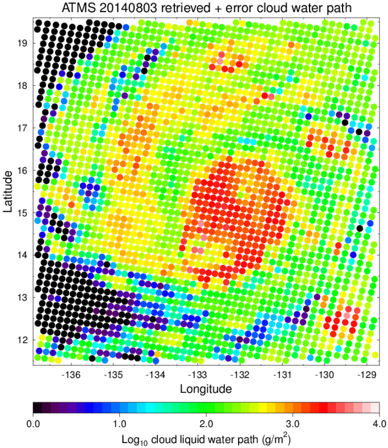
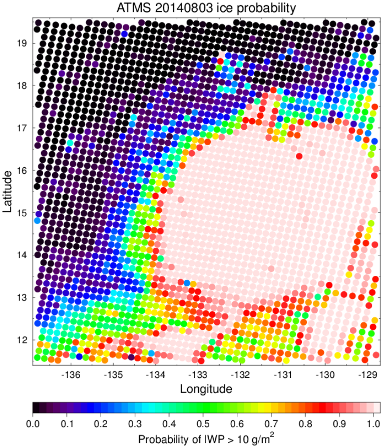
245
240
235
230
ATMS: 20121022 0510
TCVL: 20121023 0000

BMCI Retrievals





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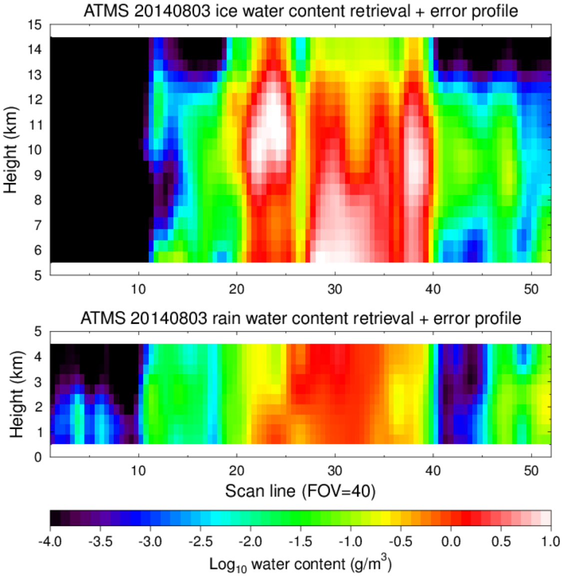

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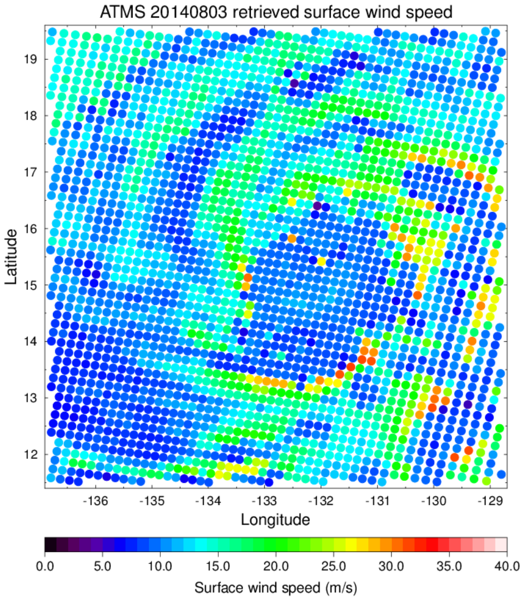

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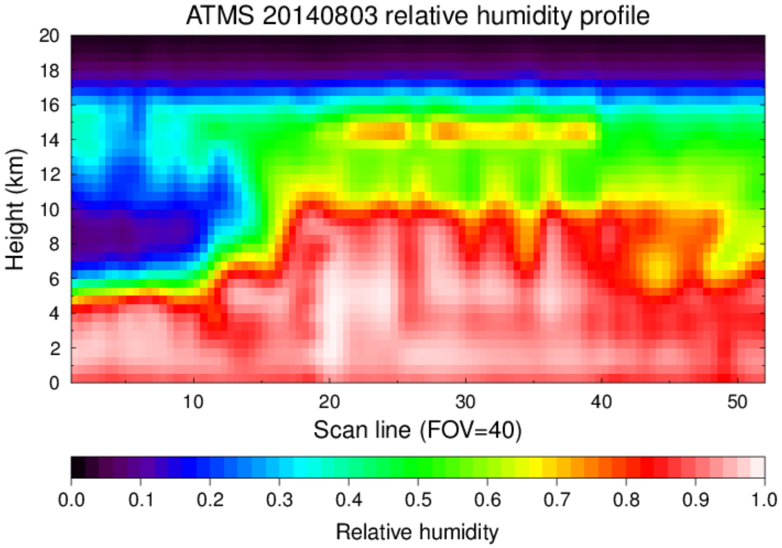
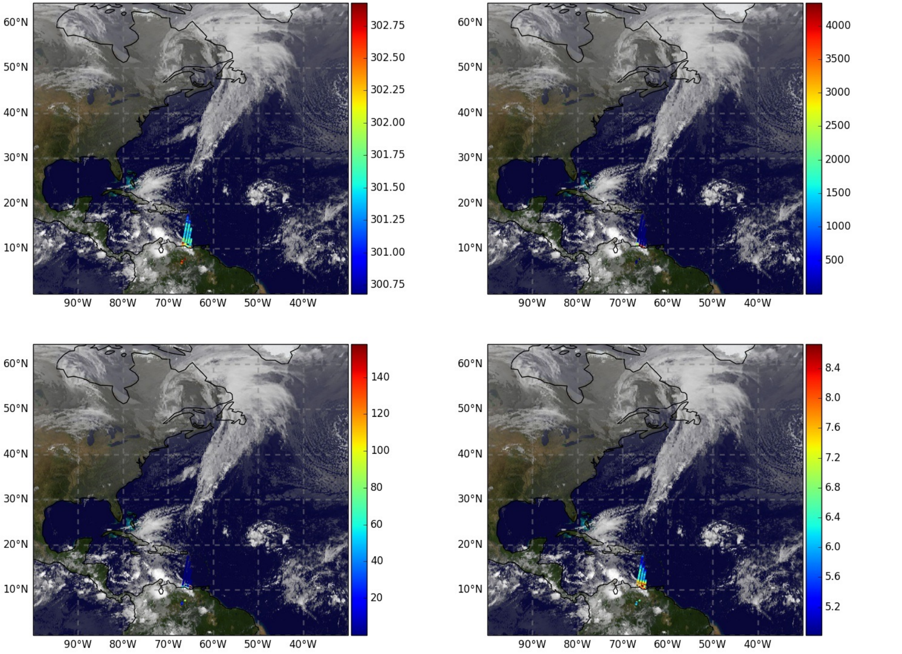
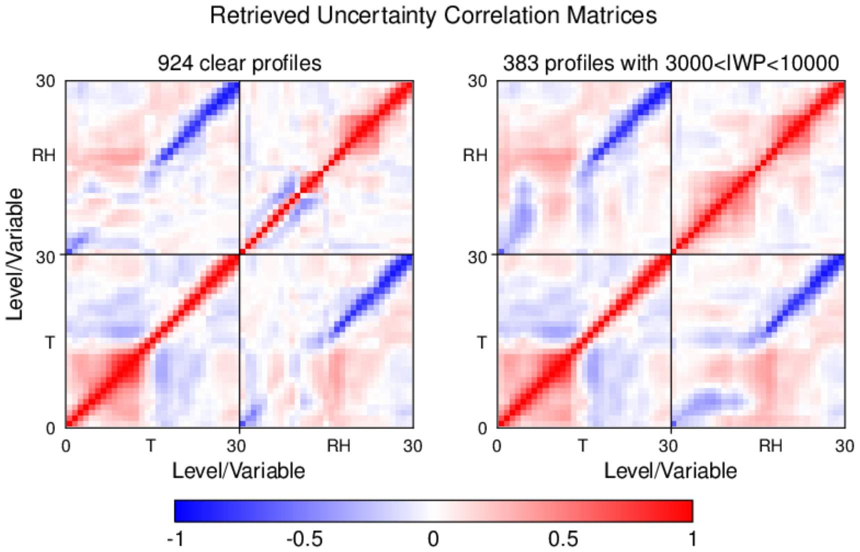


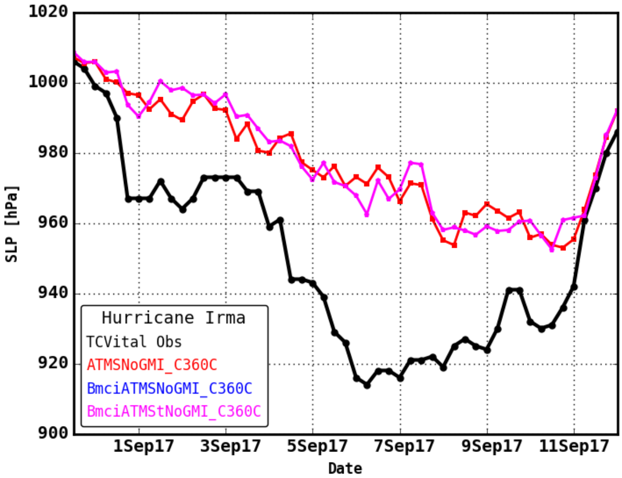
Top: SkinTemp (left), IWP (right), Bottom: Rain WP (left), Surface Wind Speed (right)



Correlated observation errors

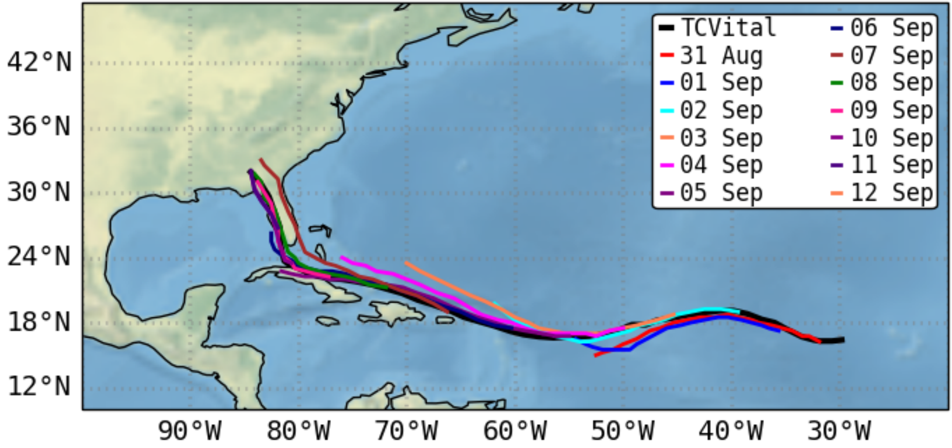


Data Assimilation Results - Intensity

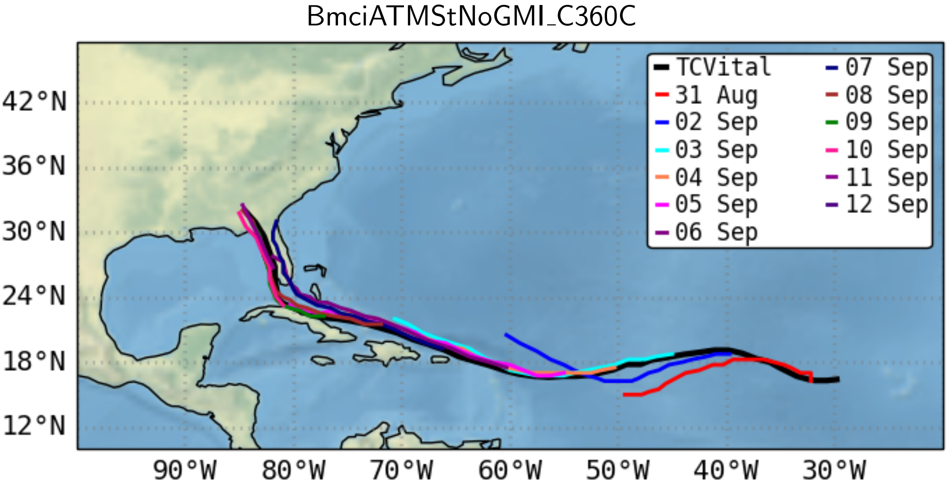


Data Assimilation Results - Track

ATMSNoGMI_C360C



Data Assimilation Results - Track and Intensity Error



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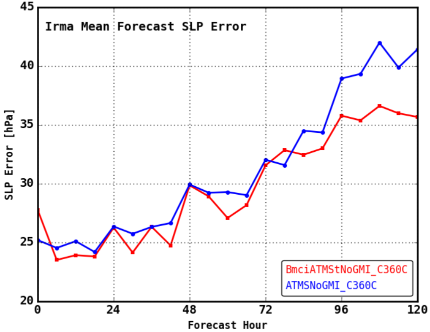

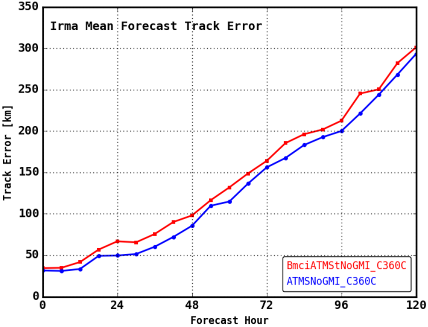

Conclusions

- 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!

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