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

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

TROPICS Applications Meeting

October 23, 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
- 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)

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

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

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.

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.

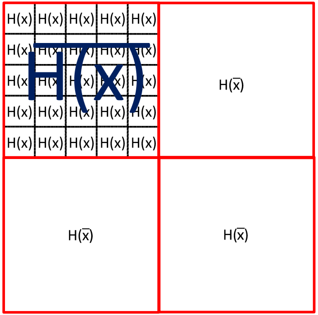
Lack of required RT inputs: $\vec{p_s}$ neither provided by the model nor fully measurable thus estimated from limited in-situ/aircraft measurements.

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.

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 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.

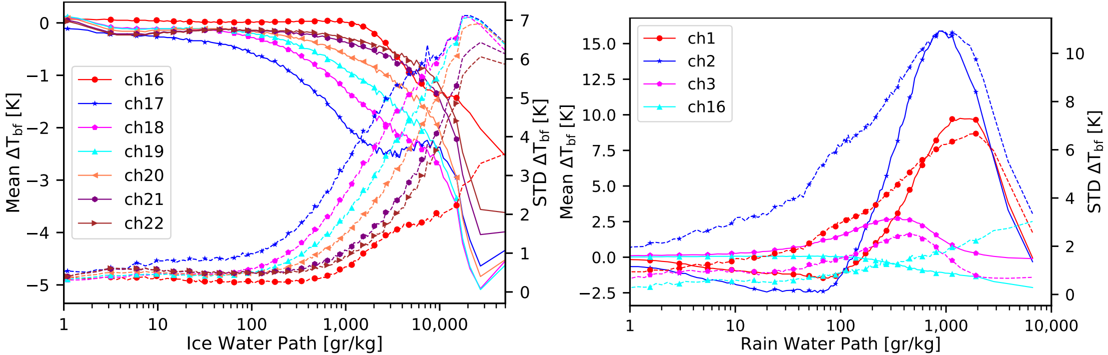
The BMCI technique

The BMCI technique can be summarized in three steps:

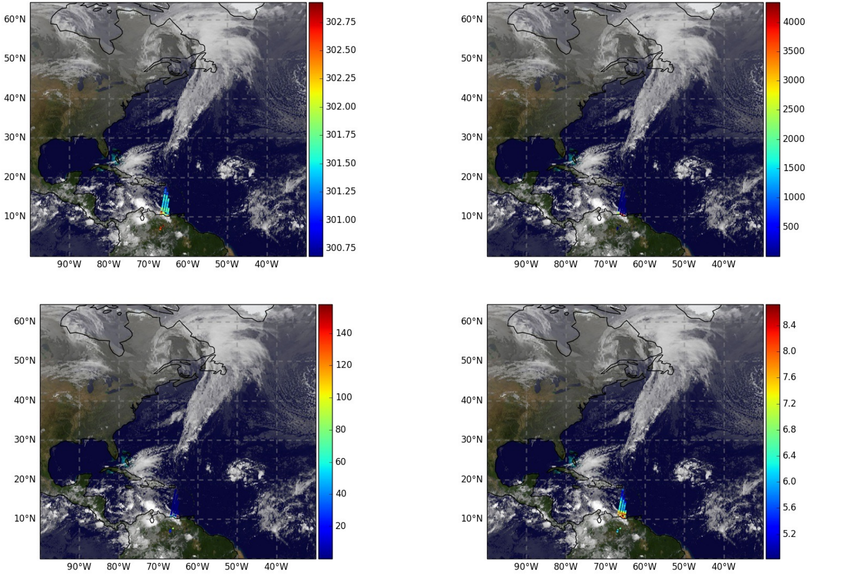
- generation of a retrieval database of atmospheric state and cloud variables using a-priori information. The database should also include extreme cases as the extrapolation is not allowed.
- the atmospheric state and cloud variables are fed into the RT model to generate the synthetic observations. In 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.

Beam filling

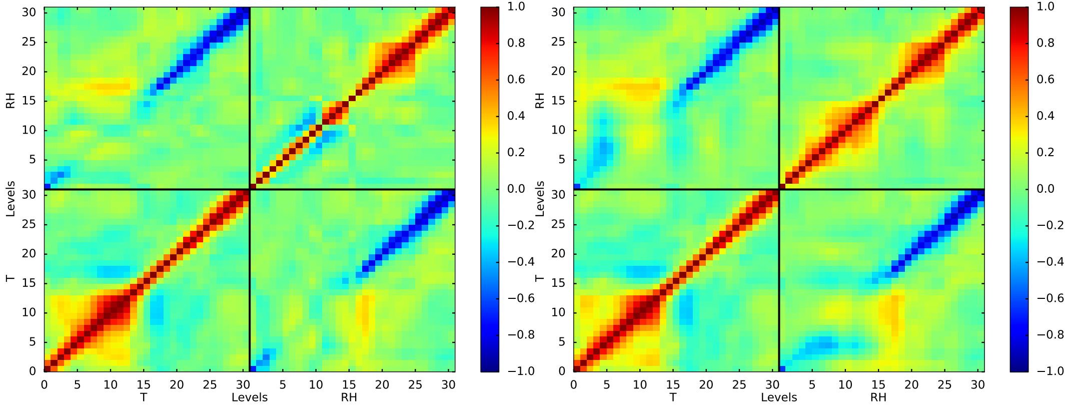
Beam filling was calculated as the difference between the brightness temperatures weighted according to an elliptical Gaussian beam pattern and Tbs calculated using the average profiles. The profiles were generated with 5km resolution using stochastic statistics derived from GPM DPR and central profiles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



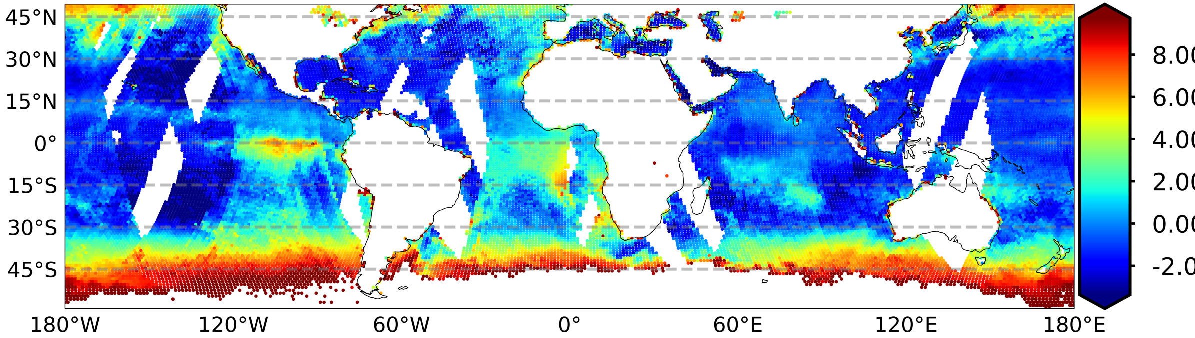
Top: SkinTemp (left), IWP (right), Bottom: Rain WP (left), Surface Wind Speed (right)



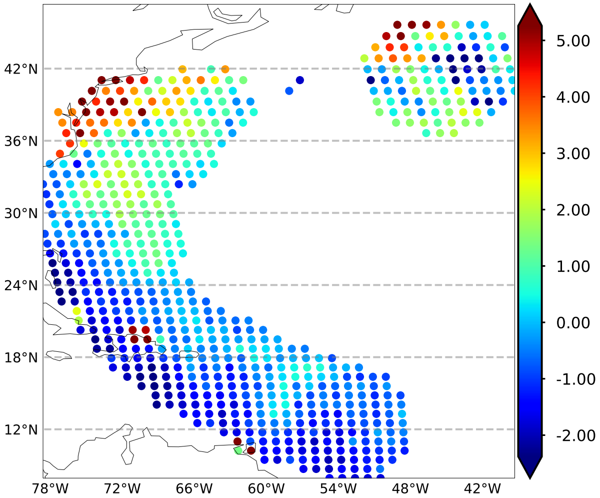
Correlated observation errors

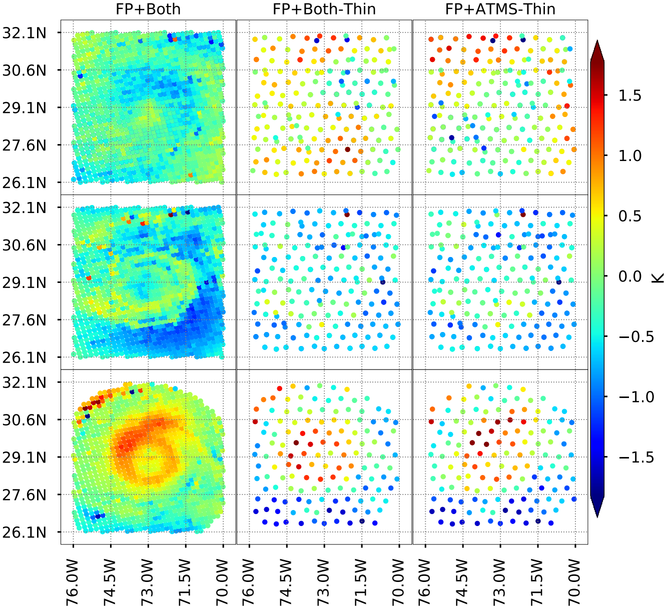


SST Analysis

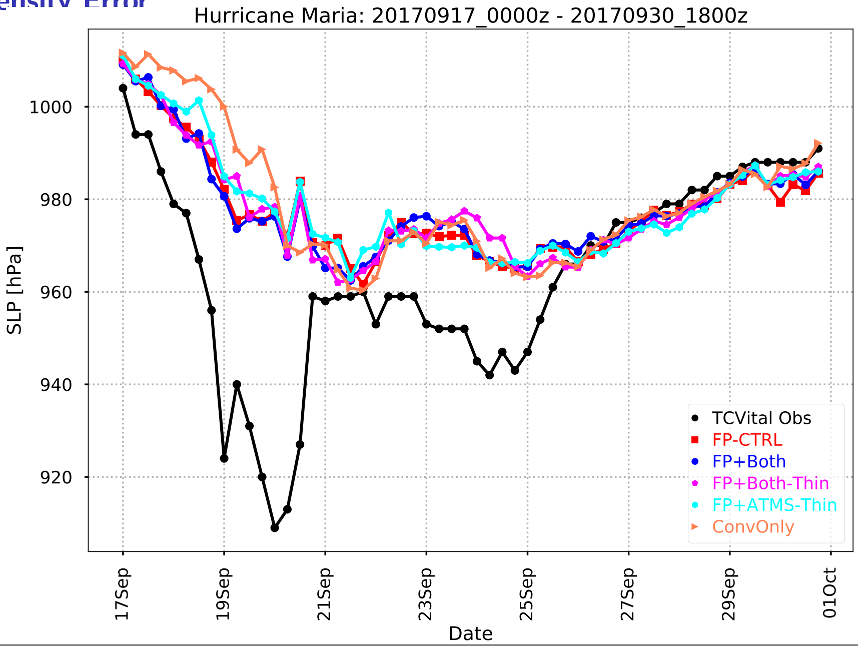


SST Analysis

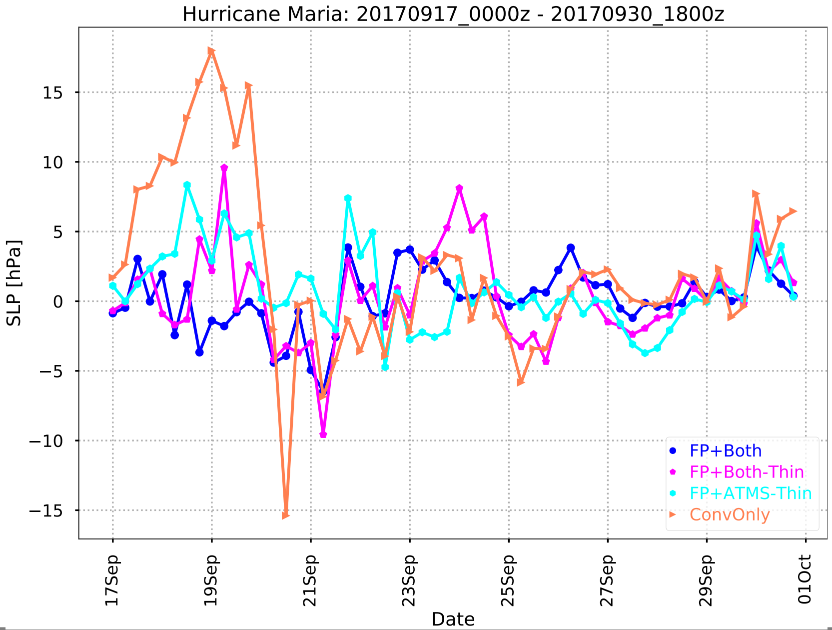



FP+Both
FP+Both-Thin
FP+ATMS-Thin
32.1N
30.6N
29.1N
27.6N
26.1N
76.0W
74.5W
73.0W
71.5W
70.0W
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
K

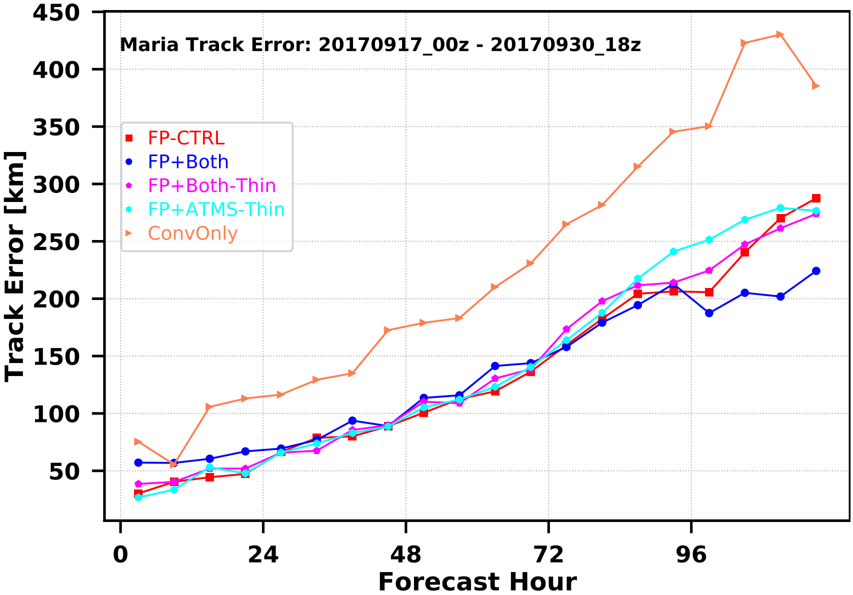
Analysis Intensity Error



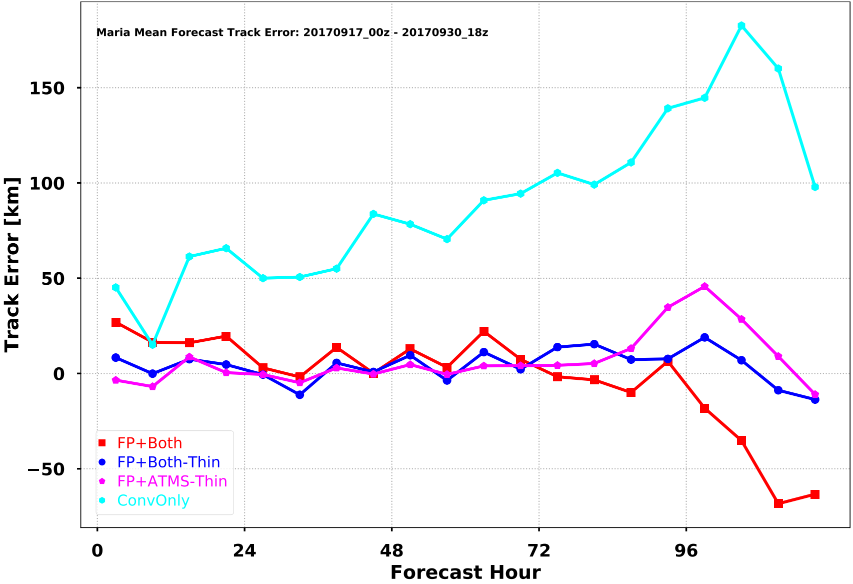
Forecast Intensity Error

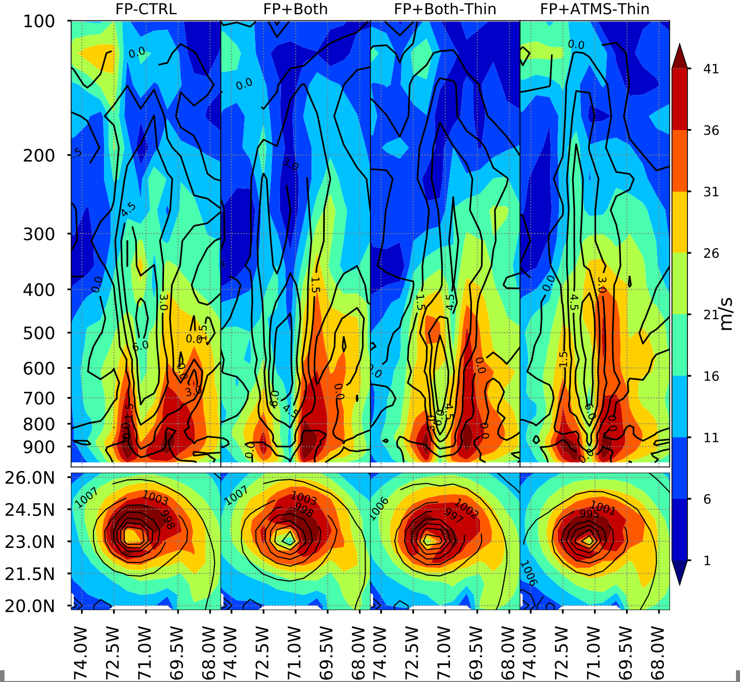


Forecast Track Error



Forecast Track Error vs. GEOS operational run




FP-CTRL
FP+Both
FP+Both-Thin
FP+ATMS-Thin
100
200
300
400
500
600
700
800
900
26.0N
24.5N
23.0N
21.5N
20.0N
74.0W
72.5W
71.0W
69.5W
68.0W
41
36
31
26
21
16
11
6
1
m/s

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!