Study of the impact of combined TMI-PR retrieved rainy observations in regional weather forecast models in an ensemble Bayesian framework

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Abstract

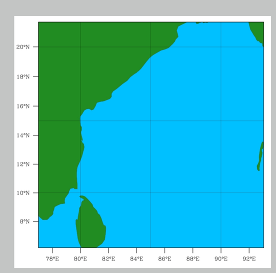
A new ensemble based algorithm has been developed that assimilates the vertical rain structure retrieved from combined microwave radiometer and radar measurements in a regional weather forecast model, by employing a Bayesian framework. The goal of the study is to evaluate the capability of the proposed technique to improve track prediction of tropical cyclones that originate in the North Indian Ocean.

Advanced Weather Research and Forecast (ARW)

The model domain is shown in Figure 1. It has one coarse domain consists of 291 x 291 grids points with 6 km resolution and covers 3 to 25 N and 77 to 93 E

Cumulus parameterization	Grell-Devenyi ensemble scheme (GD)
PBL	Mellor-Yamada-janjic(Eta) TKE
Micro physics	WRF Single Moment 3-class simple ice
urface layer physics	Monin-Obukhov (janjic Eta) scheme (JAN)
Land Surface model	Pleim-Xu scheme (PLEIM)
Long wave Radiation Physics	Rapid Radiative Transfer Model (RRTM
Shortwave Radiation Physics	Rapid Radiative Transfer Model for Global (RRTMG)

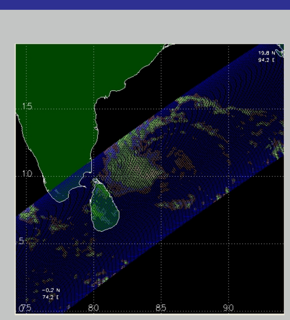
Physics parameterizations schemes used in this study



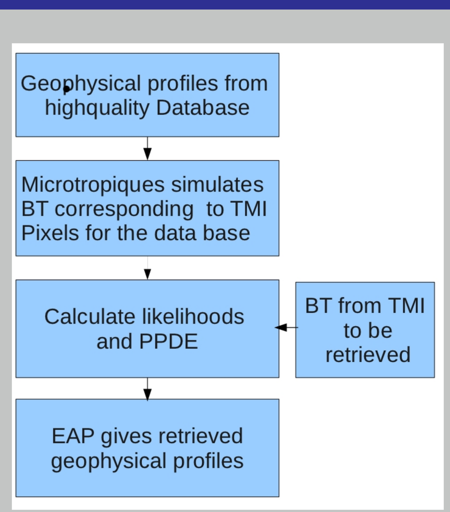
Model Domain

Data used for assimilation

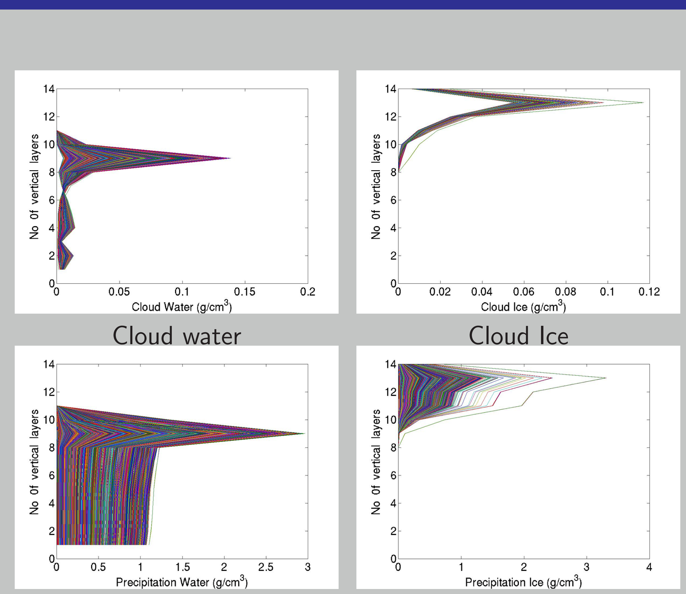
The TRMM Microwave Image(TMI) 1B11(10.65, 19.35, 21, 37, and 85.5 GHz) brightness temperature (BT) data are used to retrieve hydrometeors profiles that are assimilated simultaneously.



Retrieval algorithm



Flow chart of the algorithm developed for hydrometeor retrieval



Cloud water Cloud Ice Precipitation water Precipitation Ice

Empirical Orthogonal Functions (EOF)

- Extracting shape information from a database (from the NCEP GFS data 2010 Nov 06 00 UTC, i/c for control run) through the covariance matrix.
- Calculating principal components of this covariance matrix by performing an eigenvalue analysis.
- Generating synthetic profile by using random number vectors and eigenvectors and eigenvalues of principal components.

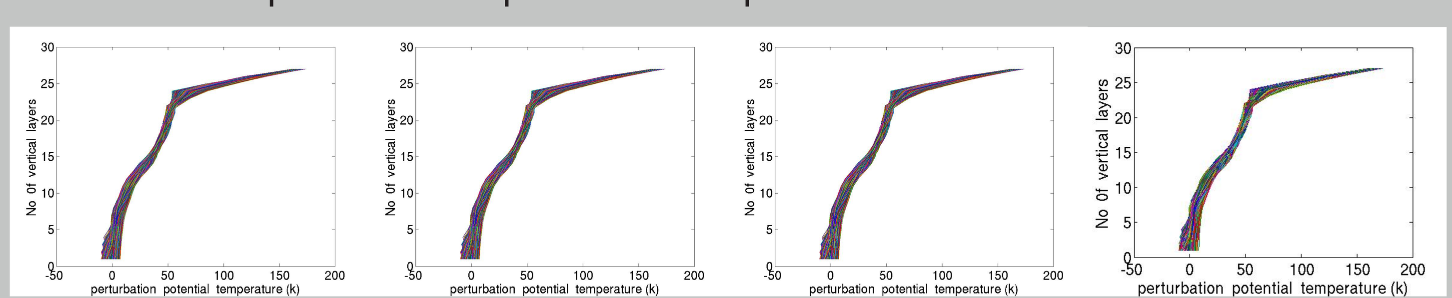
$$\mathbf{X_{perturbed}} = \mathbf{X_{unperturbed}} + \sum_{v=1}^{N} \zeta_v \sqrt{\lambda_v} \phi_v$$

ζ_v is a normal random number and $\mathbf{X_{unpertubed}}$ is the vector of initial conditions obtained from NCEP.The details of generating synthetic profiles avilable in Tatarskaia et al.[1].

Variables perturbed

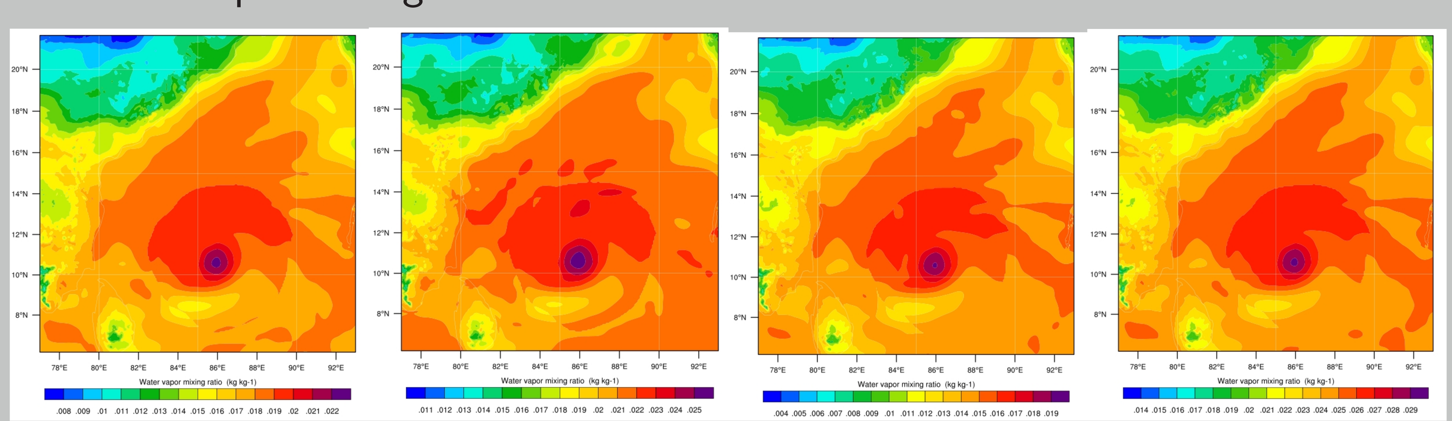
Perturbation geopotential $(\phi, \mathbf{m^2/s^2})$, Perturbation potential temperature $(\theta, \mathbf{k})$, X-wind(U, m/s) and Y-wind velocity$(\mathbf{V, m/s})$, Water Vapor mixing ratio $(\mathbf{q_v, kg/kg})$

Vertical structure of perturbation potential temperature



Unperturbed GFS random sample 1 random sample 2 random sample3

First level water vapor mixing ratio



Unperturbed GFS random sample 1 random sample 2 random sample3

Observation operator

$$P_{sat} = 61.078 \left(\frac{7.5T - 2048.625}{T - 25.85} \right)$$
$$P_v = RH \times \frac{P_{sat}}{100}$$
$$P_{air} = P - P_v$$
$$\rho = 100 \left(\frac{P_d}{R_d \times T} + \frac{P_v}{R_v \times T} \right)$$

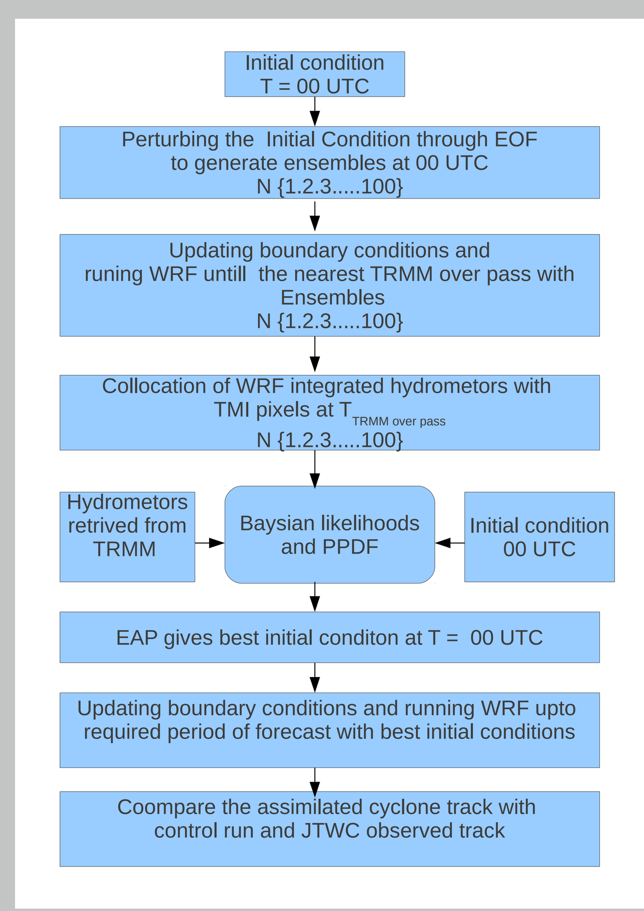
where
P_{sat} is saturation pressure,
P_v is vapor pressure,
P_d is dry air pressure
R_v is gas constant of vapor**(461.495)**
$(R_d)$is gas constant of dry air**(287.058)**.

If height $\leq$ 5km	$CLW = 1000 \times Q_c \times \rho$	$CI = 0$
If height $\geq$ 5km	$CI = 1000 \times Q_c \times \rho$	$CLW = 0$
If height $\leq$ 5km	$PW = 1000 \times Q_r \times \rho$	$PI = 0$
If height $\geq$ 5km	$PI = 1000 \times Q_r \times \rho$	$PW = 0$

Data Assimilation Methodology

Bayesian likelihood

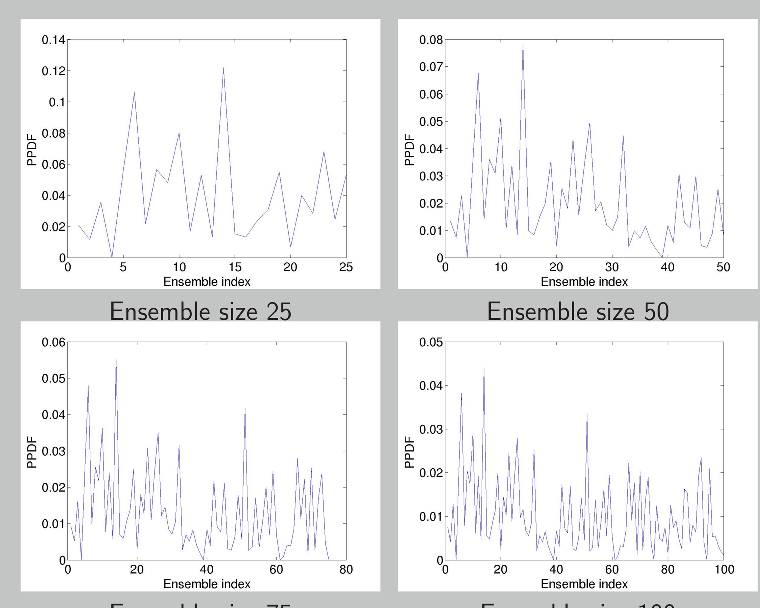
$$L_{(ensemble)} = \exp \left[-\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{14} \sum_{k=1}^{4} \left(\frac{HM(k)_{ret:i,j} - HM(k)_{ens:i,j}}{HM(k)_{ret:i,j} - HM(k)_{ctr:i,j}} \right)^2 \right]$$



Flow chart of the new ensemble based assimilation algorithm developed in this study

posterior probability density function(PPDF)

$$P_{(ensemble_i)} = \frac{L(ensemble_i)}{\sum_{j=1}^{N} L(ensemble_j)}$$



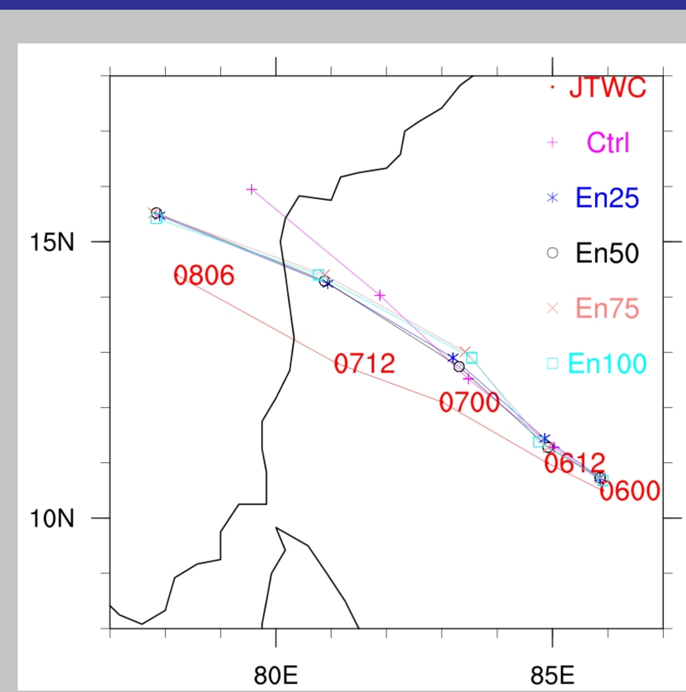
Ensemble size 25 Ensemble size 50 Ensemble size 75 Ensemble size 100

PPDF of Ensemble sensitivity study

Results

Time UTC	Forecast hour	ctrl	En25	En50	En75	En100
600	0	20.5	26.4	26.4	26.4	26.4
606	6	29.5	24.4	29.5	37.9	46.4
612	12	33.8	47.3	25.9	33.8	37.6
618	18	68.6	44.0	58.6	54.0	63.5
700	24	70.8	40.6	53.7	49.8	45.0
706	30	99.9	102.8	89.2	86.3	99.9
712	36	161.2	146.8	139.5	147.8	152.9
718	42	171.8	156.3	151.0	186.3	169.7
806	54	228.4	190.8	183.2	193.6	194.4
	24hr Avg	44.6	36.5	38.8	40.4	43.8
	54hr Avg	98.3	86.6	84.1	90.6	92.9

Error in track (km) in the ensemble sensitivity study



Track propagation in the Ensemble sensitivity study

Conclusions

- From the ensemble sensitivity study, it was seen that the assimilation can reduce track errors up to **12%** in a 54 hr forecast and up to **18.16%** in a 24hr forecast with an ensemble family size of 25.
- This study mainly demonstrated the efficacy Monte Carlo ensemble based Bayesian assimilation algorithm for track reduction with a NWP model.
- Further studies are required to accurately assess the real impact of this assimilation algorithm in cyclone predictions that can be applied in a variety of situations.

References

[1].M.S. Tatarskaia, R.J. Lataitis, B.B. Stankov, and V.V. Tatarskii. "A numerical method for synthesizing atmospheric temperature and humidity profiles", Journal of Applied Meteorology, 37(7):718-729, 1998.

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