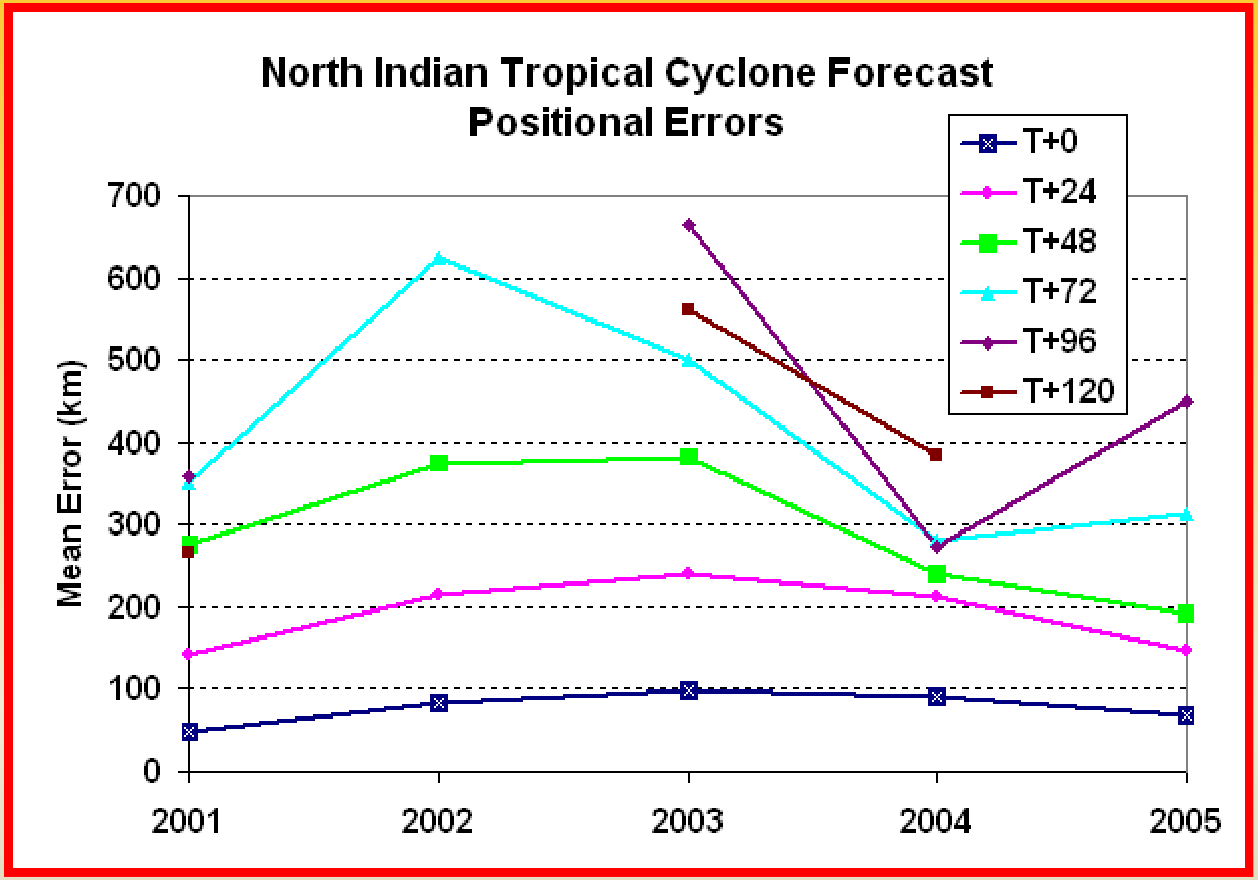
Towards a multi-satellite radiance assimilation in regional models for track forecasting of tropical cyclones

Prof. C. Balaji
Heat Transfer and Thermal Power Laboratory
Department of Mechanical Engineering
Indian Institute of Technology Madras, Chennai

Tropical cyclones in the North Indian Basin



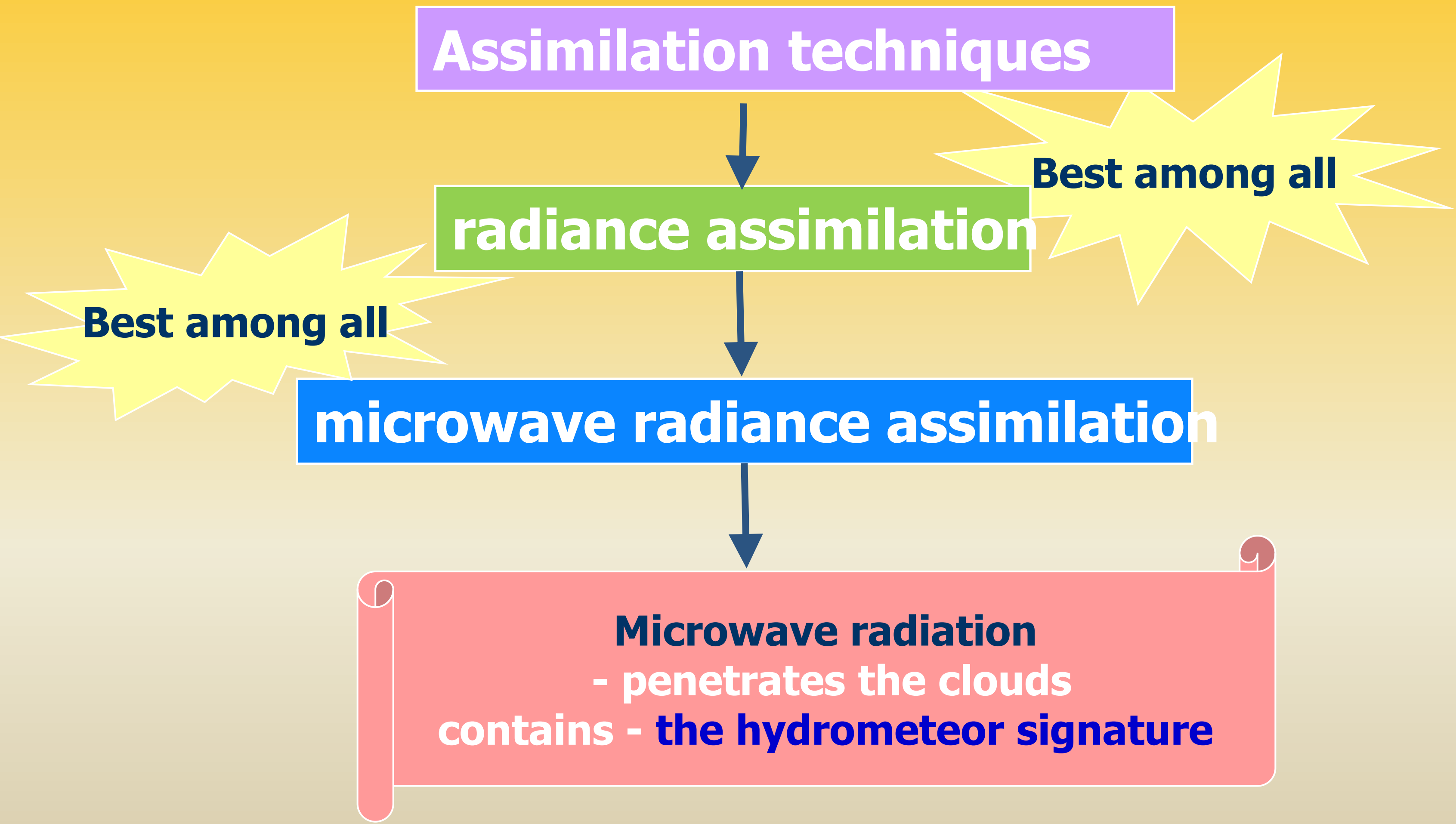
Source: UK Met office web site

Dramatic increase in computing power!
No dramatic reduction in track errors!
There is a need for sophisticated methods.

Strategy for dramatic reduction in track errors

- Forecasting – An initial value problem
- Assimilation:
  - direct injection of observations from satellite into numerical calculations
  - can be continuously done (even at 1 hour intervals for e.g.) - errors do not build up
  - only way to improve short term forecasting

Microwave radiance assimilation



Theory of radiance assimilation

From microwave radiation model

P(x/Y)=P(Y/x)* P(x)

$$P\left(y/x\right) \approx \exp\left[-\frac{1}{2}(y_{obs}-y_{sim}(x))^{T}(O+F)^{-1}(y_{obs}-y_{sim}(x))\right]$$

$$P\left(x\right) \approx \exp\left[-\frac{1}{2}(x-x_{b})^{T}B^{-1}(x-x_{b})\right]$$

From forecasting model

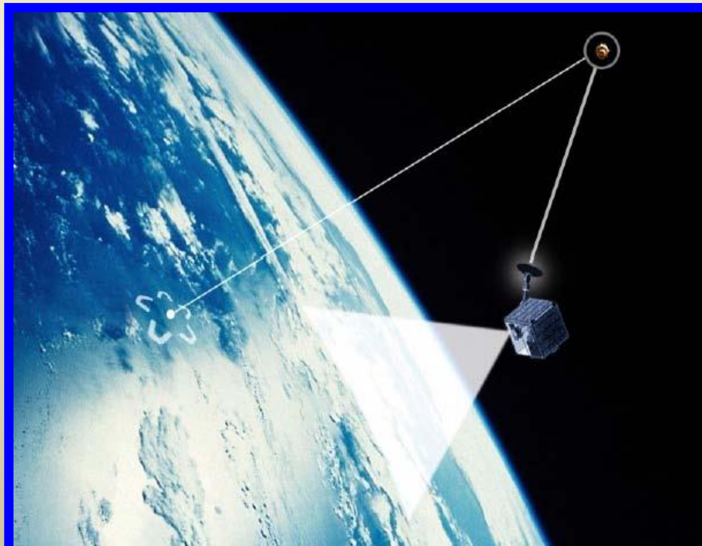
Theory of radiance assimilation (contd.)

- Maximizing P(x/Y) analogous to minimizing –ln P(x/Y)
- -ln P(x/Y) – Cost function or objective function in the parlance of optimization
- Optimization accomplished by using calculus based / non-calculus based techniques

Key challenges in assimilation

- **High dimensional inverse problem** as

- satellite outputs are radiances
- numerical weather model works with atmospheric variables like temp, humidity, hydrometeor in a multilayered atmosphere
- Satellite radiances – 5 channels x 2 polarizations = 10 signals
- Parameters to be retrieved (typical) – 14 layers x 4 parameters/layer = 56



Key challenges in assimilation

- A powerful radiative transfer model (forward model) for simulating top of the atmosphere microwave radiances in a precipitating atmosphere.

- Specification of prior information (comes from the mesoscale model)

- A robust and fast optimization (retrieval) algorithm

- A fast forward model (for rapidity in assimilation)

Advanced research WRF (ARW)

- A widely used community mesoscale model developed by National Center for Atmospheric Research (NCAR)
- Fifth generation mesoscale model (MM5)
- Can be used for both research and operational applications
- Has its own data assimilation system that will (supposed to!) advance both understanding and improve the prediction of meso scale weather systems.

Governing equations

- The Numerical Weather Prediction models uses the following four basic equations with hydrostatic assumption or non-hydrostatic equation.
    1. Continuity equation
    2. Momentum conservation equation
    3. Thermodynamic energy equation
    4. Equation of state for an ideal gas

- “Equations of atmospheric dynamics” - basic form of Eulerian equations of fluid motion

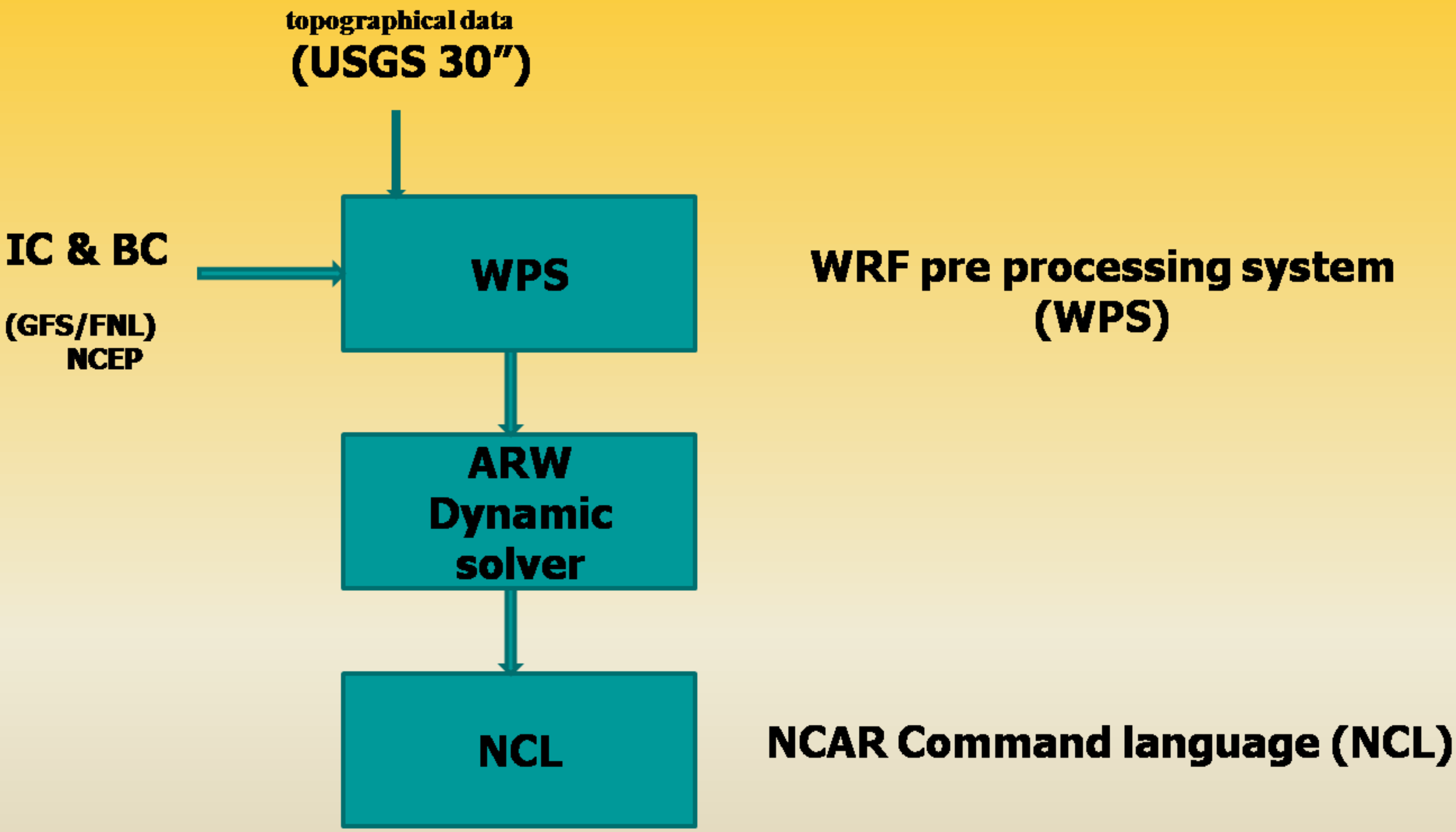
- The ARW dynamics solver integrates the compressible, non-hydrostatic Euler equations.
- The equations are cast in flux form using variables that have conservation properties, following the philosophy of Ooyama (1990).
- The equations are formulated using a terrain-following mass vertical coordinate (Laprise, 1992) called as sigma (σ) coordinate.

Features of ARW model

- Horizontal grid : Arakawa C grid staggering
- Time Integration: Time-split integration using a 3rd order Runge-Kutta scheme with smaller time step for acoustic and gravity-wave modes
- Spatial Discretization: 2nd to 6th order advection options in horizontal and vertical
- Earth’s Rotation: Full Coriolis terms included
- Nesting: One-way, two-way and moving nests

- Mapping to Sphere:
  - Three map projections
  - Lambert-conformal
  - Mercator
  - Polar stereographic
- Model Physics:
  - Microphysics
  - Cumulus parameterizations
  - Planetary boundary layer physics
  - Land surface physics
  - Atmospheric radiation physics
  - Long wave schemes
  - Short wave schemes

Model run


topographical data
(USGS 30”)
IC & BC
(GFS/FNL)
NCEP
WPS
WRF pre processing system
(WPS)
ARW
Dynamic
solver
NCL
NCAR Command language (NCL)

Sensitivity study of ARW model parameterizations in tropical cyclones

Main Objectives

- To analyze the impact of various physics parameterizations in propagation and intensity of tropical cyclone

- To find out the best combination of physics schemes for predicting track and intensity of cyclone in North Indian Ocean

- This experiment is conducted by choosing a several physics parameterization schemes, then analyzing the impact of the particular parameterization in track and intensity.

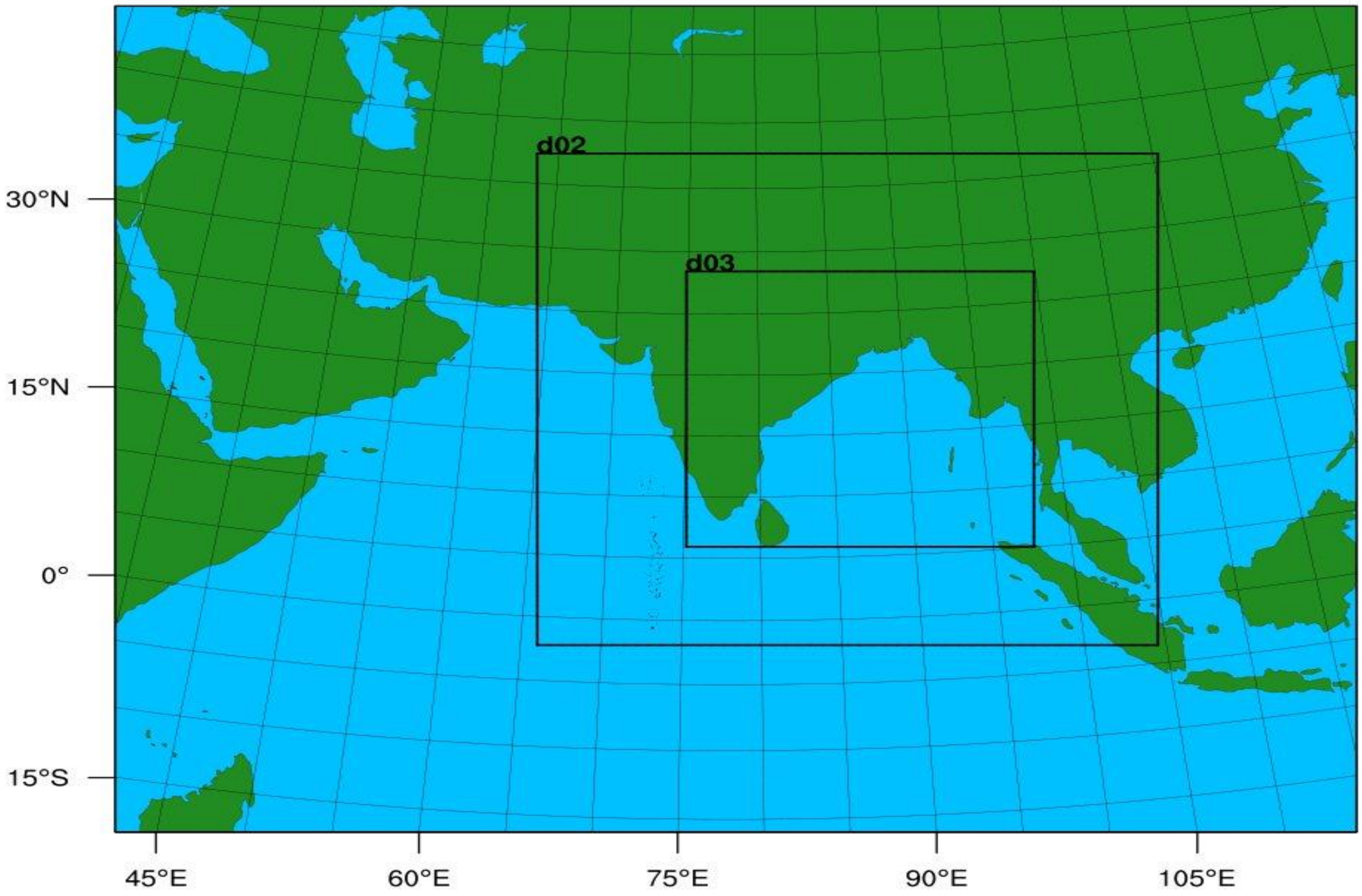
- Sensitivity studies initiated with the tropical cyclone Jal
- Two experiments conducted – one to find the best schemes for track prediction and other for intensity.
- Totally 56 experiments conducted to find out best set of physics schemes for track and intensity prediction.

Track experiments

- Numerical experiments conducted with various physics parameterization available in ARW model.

- The best scheme selected - based on the propagation of simulated track and RMS errors with respect to JTWC observation data.

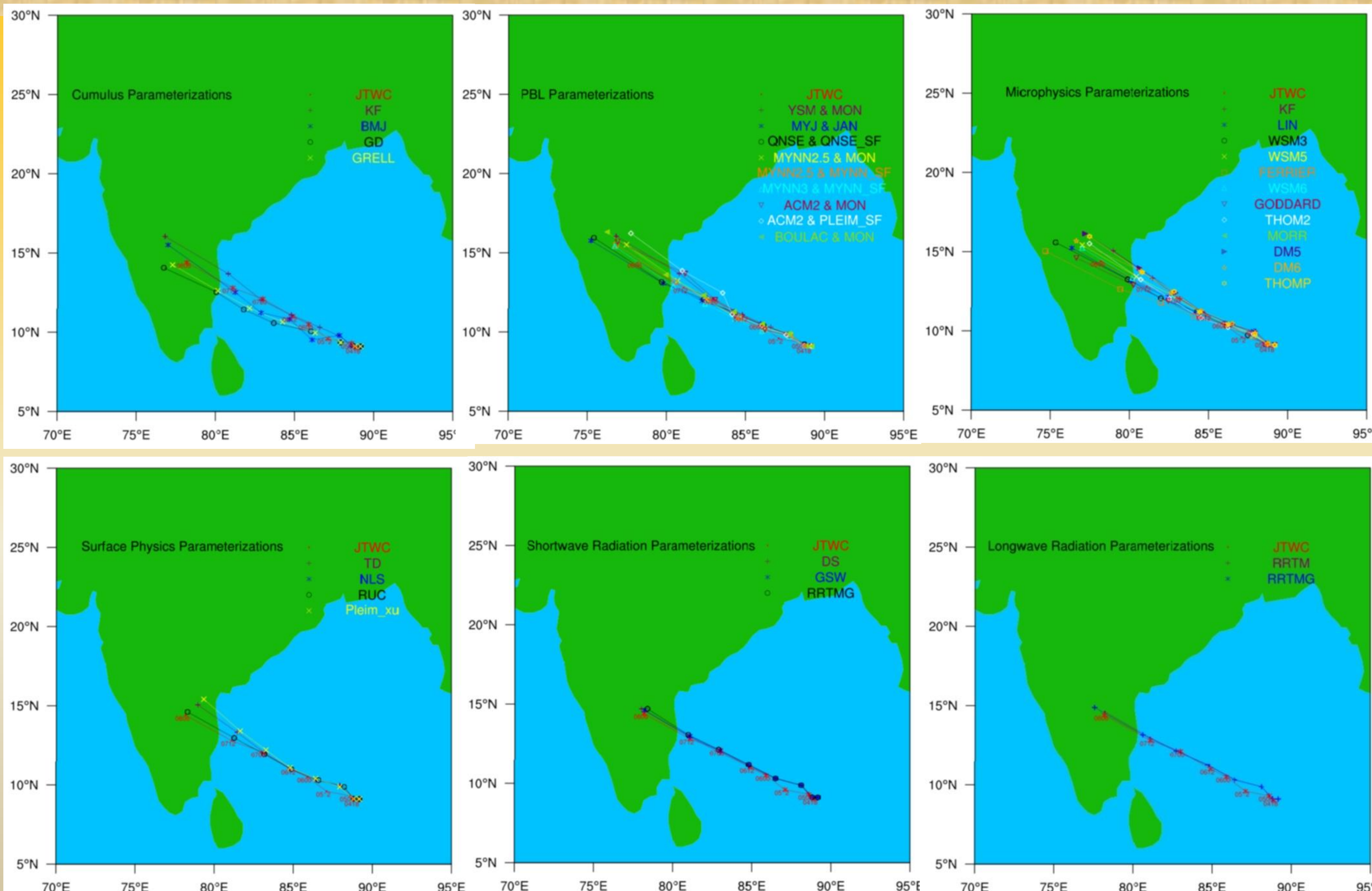
Model Domain



Model Domain

Map projection	Lambert conformal mapping
Central point of the domain	78 E, 16 N
No of domains	3 (one coarse and two nested), two way nesting.
No of vertical layers	27 sigma levels
Horizontal grid distance	90 km, 30 km, 10 km for domain 1,2,3 respectively
Time step	270 sec, 90 sec, 30 sec for domain 1,2,3 respectively
No of grid points	101 (E-W), 85 (S-N) in domain 1 151 (E-W), 151 (S-N) in domain 2 250 (E-W), 250 (S-N) in domain 3

Track propagation of cyclone JAL



Track error with JTWC observation

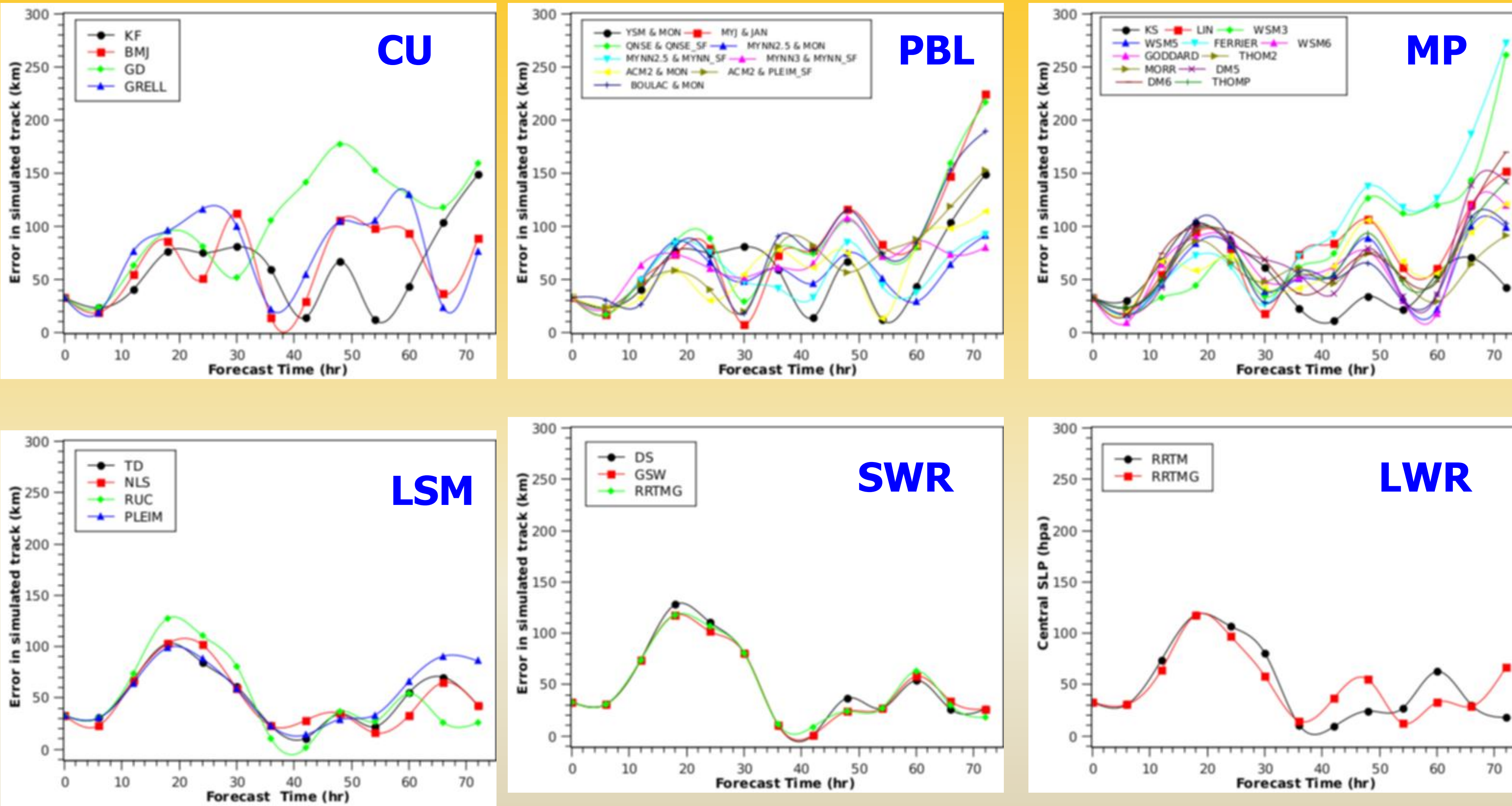


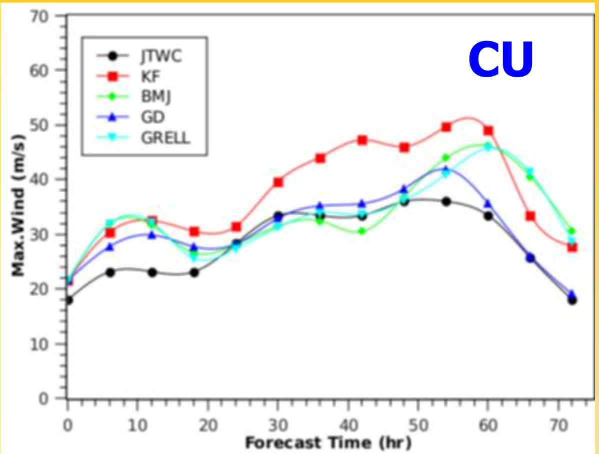
Figure.2

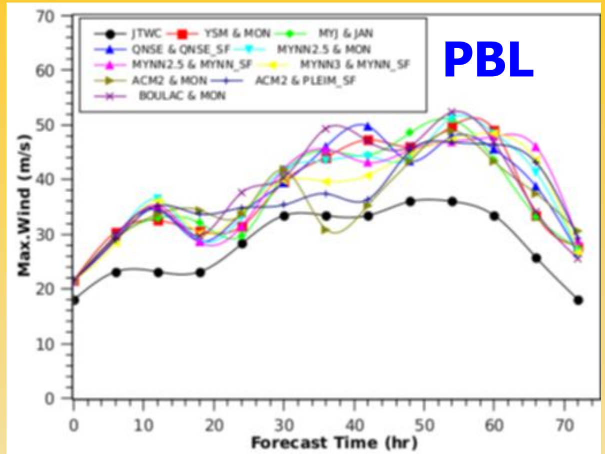
Best set of physics options and corresponding RMS track errors

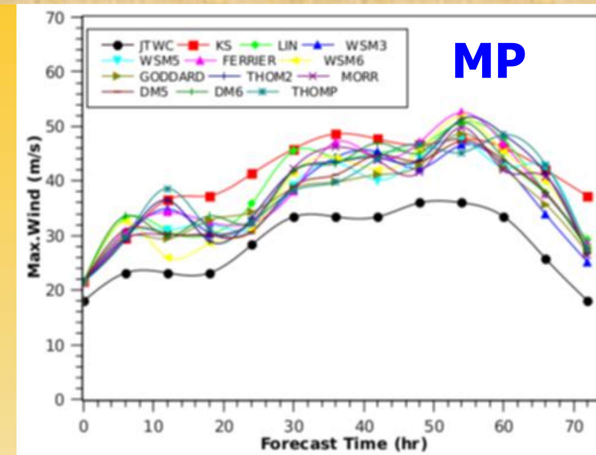
S.no	Model physics	schemes
1	Cumulus parameterization	Kain-Fritsch(new Eta) scheme (KF)
2	Planetary boundary layer	MYNN2.5 level TKE (MYNN2.5)
3	Microphysics	Kessler scheme (KS)
4	sf_ sfclay_ physics	Monin-Obukhov scheme (MON)
5	Surface land physics	RUC land-surface model (RUC)
6	Long wave Radiation Physics	rrtm scheme (RRTM)
7	Shortwave Radiation Physics	rrtmg scheme (RRTMG)

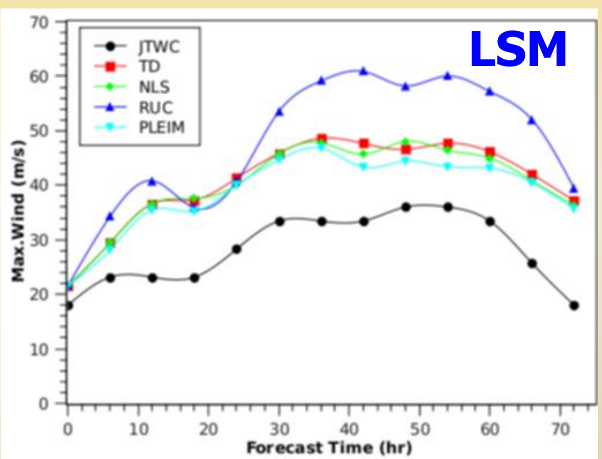
Time (hr)	6	12	18	24	30	36	42	48	54	60	66	72	RMS error
Error (km)	31	74	118	107	81	11	9	24	27	63	30	18	61

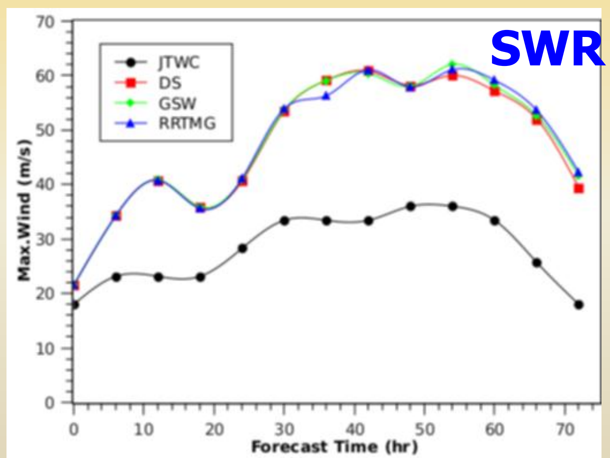
Maximum sustained wind speed with best set of physics option

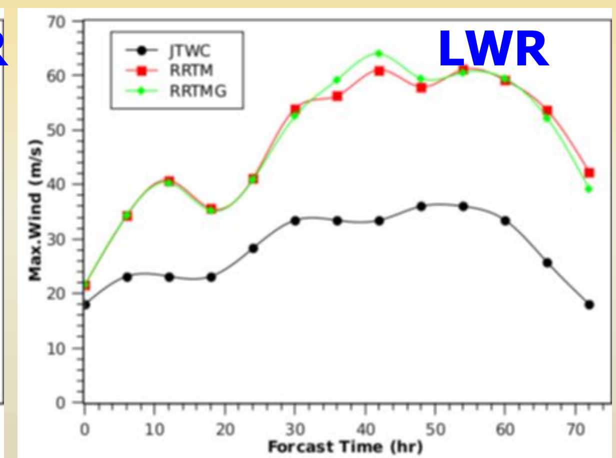










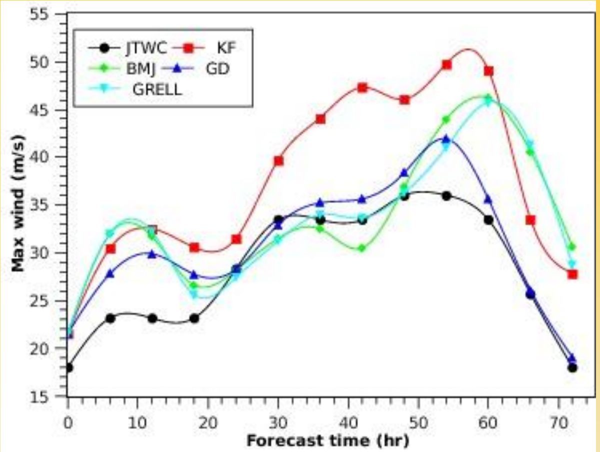


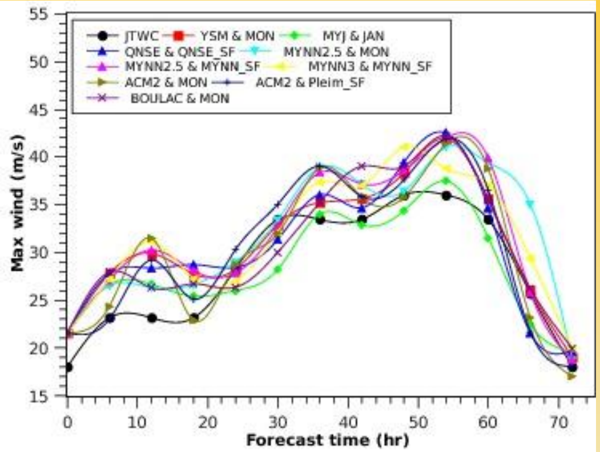
Key observations

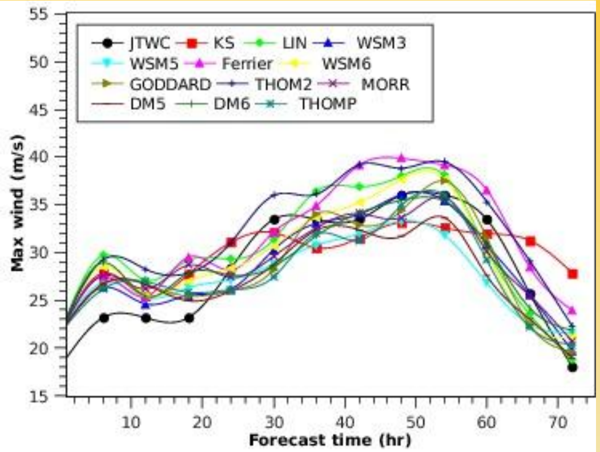
- Best set of physics options with respect to track error over predicts the intensity of the cyclone (For example, Jal).

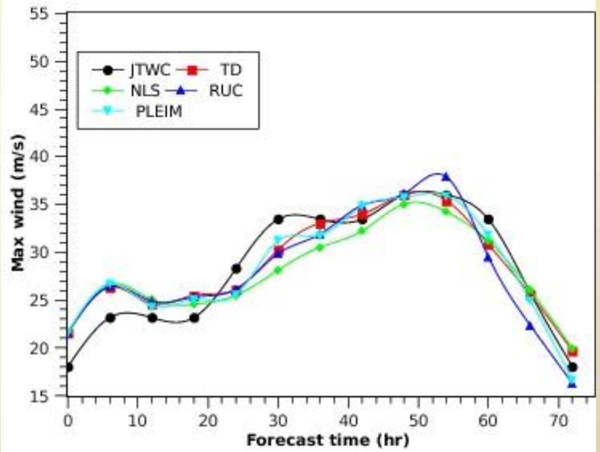
- Hence, further experiments conducted for determining best set of physics schemes for intensity prediction.

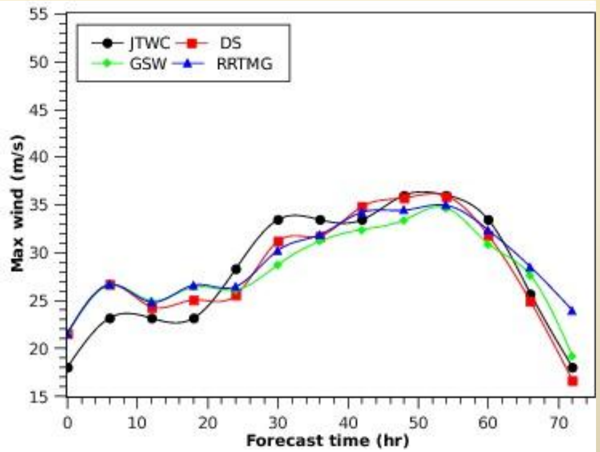
Maximum sustained wind speed

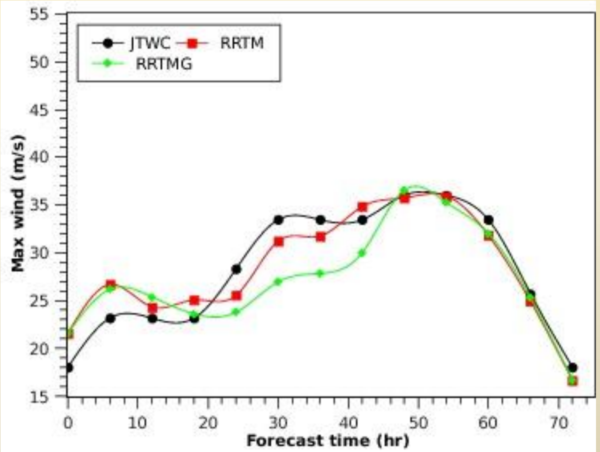










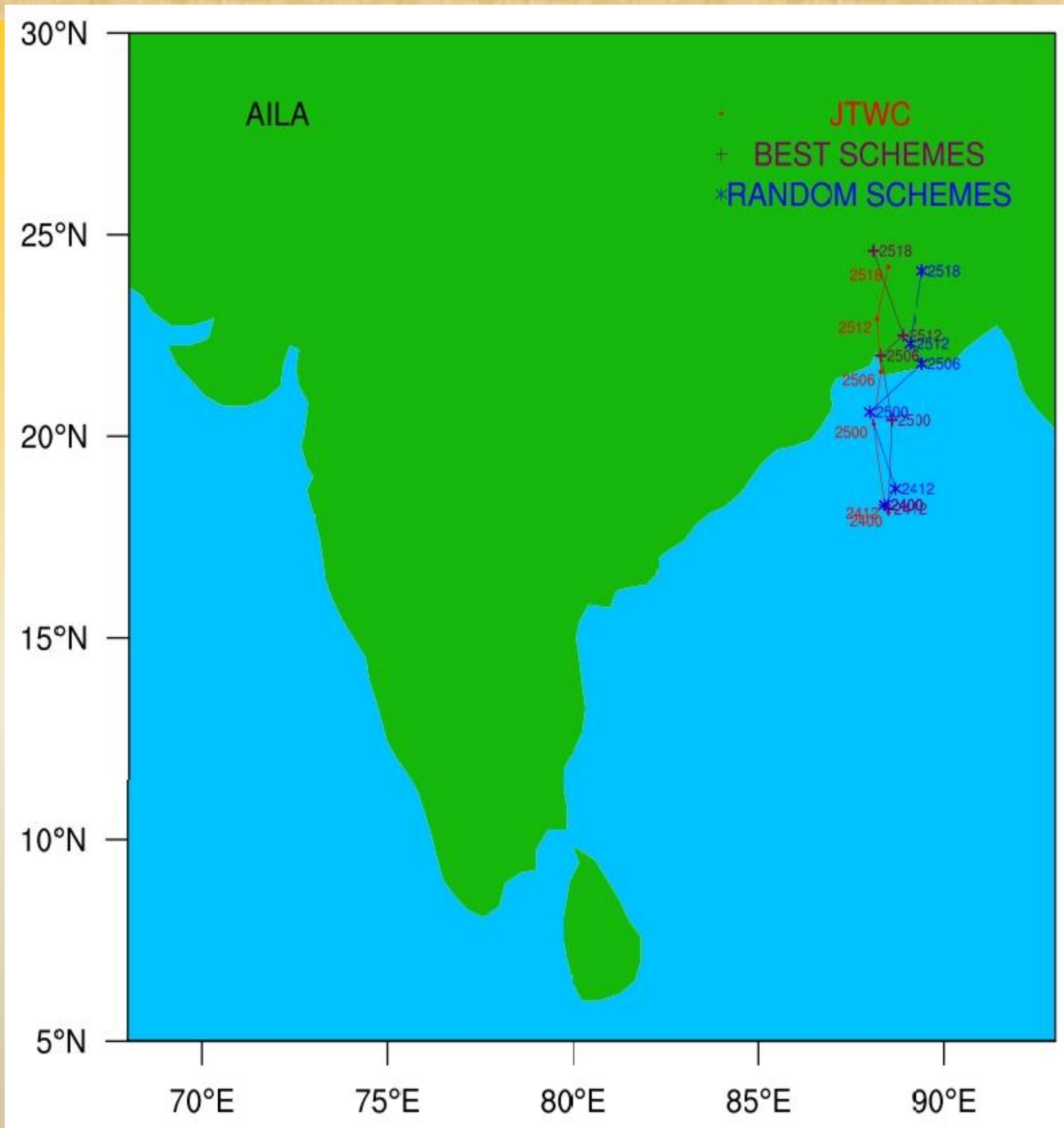


Best set of physics options and corresponding RMS error for intensity prediction

S.no	Model physics	schemes
1	Cumulus parameterization	Grell-Devenyi ensemble scheme (GD)
2	Planetary boundary layer	Mellor-Yamada-janjic(Eta) TKE scheme (MYJ)
3	Microphysics	WSM 3-class simple ice scheme (WSM3)
4	sf_ sfclay_ physics	Monin-Obukhov (janjic Eta) scheme (JAN)
5	Surface land physics	Pleim-Xu scheme (PLEIM)
6	Long wave Radiation Physics	rrtm scheme (RRTM)
7	Shortwave Radiation Physics	Dudhia scheme (DS)

Time (hr)	6	12	18	24	30	36	42	48	54	60	66	72	RMS error
Error (m/s)	3.5	1.2	1.9	2.8	2.3	1.7	1.4	0.3	0.1	1.6	0.8	1.4	1.8

Cyclone Aila



Time (hr)	Random schemes	Best schemes
0	28.1	28.1
6	81.9	107.9
12	50.4	10.9
24	32.7	53.5
30	126.2	44.8
36	115.8	87.6
42	97.1	60.8
RMS Error	90.4	68.3

Formulation of optimization problem

$$J = J_b + J_{obs}$$

$$J_{(x)} = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2}(y - Hx)^T R^{-1}(y - Hx)$$

$J_{(x)} = \text{Cost function}$

$x = \text{Analysis variable (or) state vector } (n)$

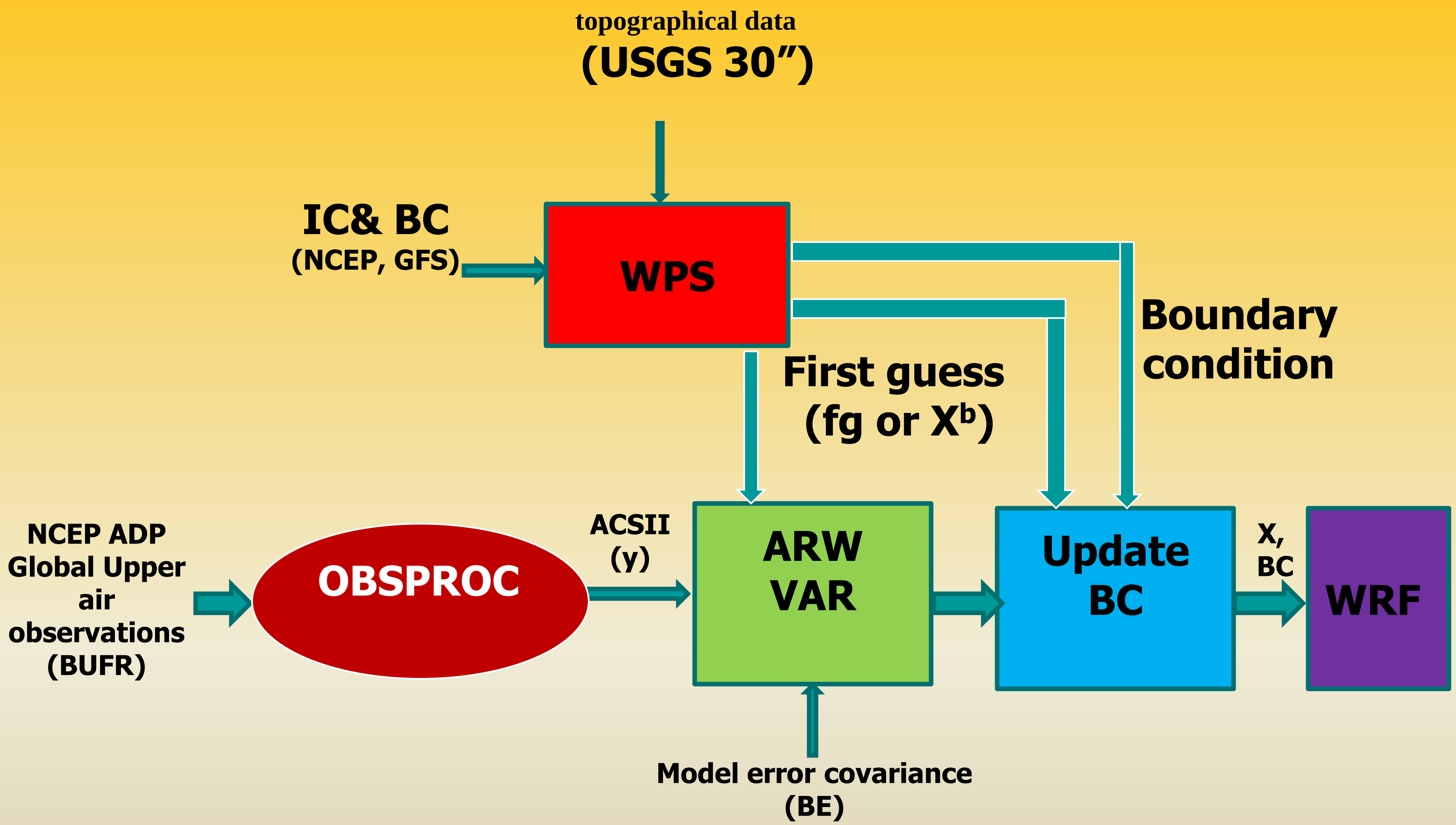
$x_{\text{b}} = \text{Back ground error (or) first guess } (n)$

$B = \text{Back ground error covariance matrix } (n\ x\ n)$

$y = \text{Observations } (m)$

$H = \text{Model operator} (mxn)$

$R = \text{Observation error covariance } (m\ x\ m)$



WPS : WRF Preprocessing system

OBSPROC : Observational preprocessor

NCEP ADP Global Upper air Observational Weather Data (ds 351.0)

- Air Temperature
- Dew point temperature
- Geopotential height
- Pressure
- Wind direction and speed

Aircraft

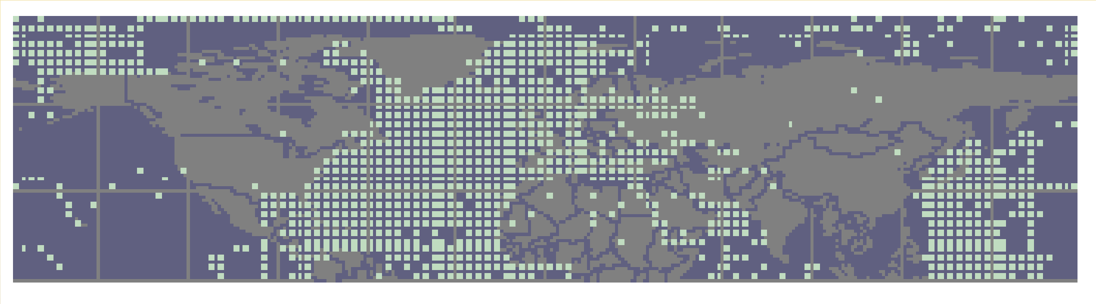
- Dropwinsonde
- Manual AIREP format aircraft data
- Manual PIREP format aircraft data
- Automated AMDAR format ASDAR/ACARS aircraft data
- Automated MDCRS ACARS aircraft data (from ARINC)
- Flight level reconnaissance aircraft data
- European ASDAR/ACARS Data Acquisition System (E-ADAS) aircraft data
- Automated MDCRS ACARS aircraft data (from ARINC via AFWA)
- Automated TAMDAR aircraft data (from NOAA/ERSL/GSD MADIS)
- Automated Canadian ASDAR/ACARS aircraft data
- Automated TAMDAR-PenAir aircraft data
- Automated TAMDAR-Chautauqua aircraft data

Land Station

- Rawinsonde - fixed land
- Rawinsonde - mobile land

Roving Ship

- Rawinsonde - ship



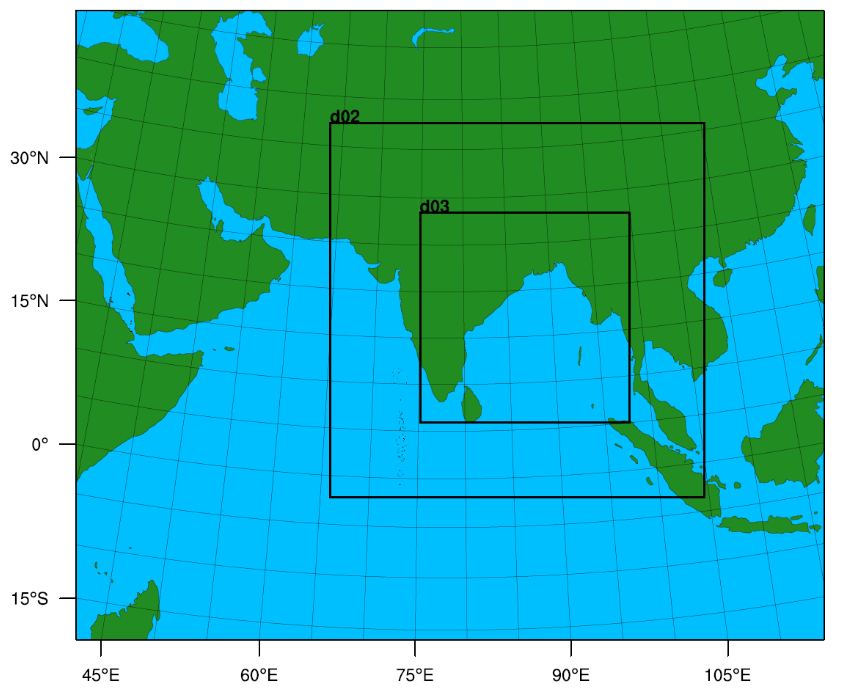
Satellite

- GOES/NESDIS infrared derived cloud motion - high density (from NESDIS server, originally in OPARCH format)
- GOES/NESDIS water vapor imager derived cloud motion (from NESDIS server, originally in OPARCH format)
- GOES/UW-CIMSS visible derived cloud motion
- GOES/NESDIS picture triplet derived cloud motion (from NESDIS server, originally in modified OPARCH format)
- GOES/NESDIS infrared derived cloud motion
- GOES/NESDIS water vapor imager derived cloud motion
- GOES/NESDIS visible derived cloud motion
- GOES/NESDIS picture triplet derived cloud motion
- INSAT/KALPANA/India infrared derived cloud motion
- INSAT/KALPANA/India visible derived cloud motion
- INSAT/KALPANA/India water vapor derived cloud motion

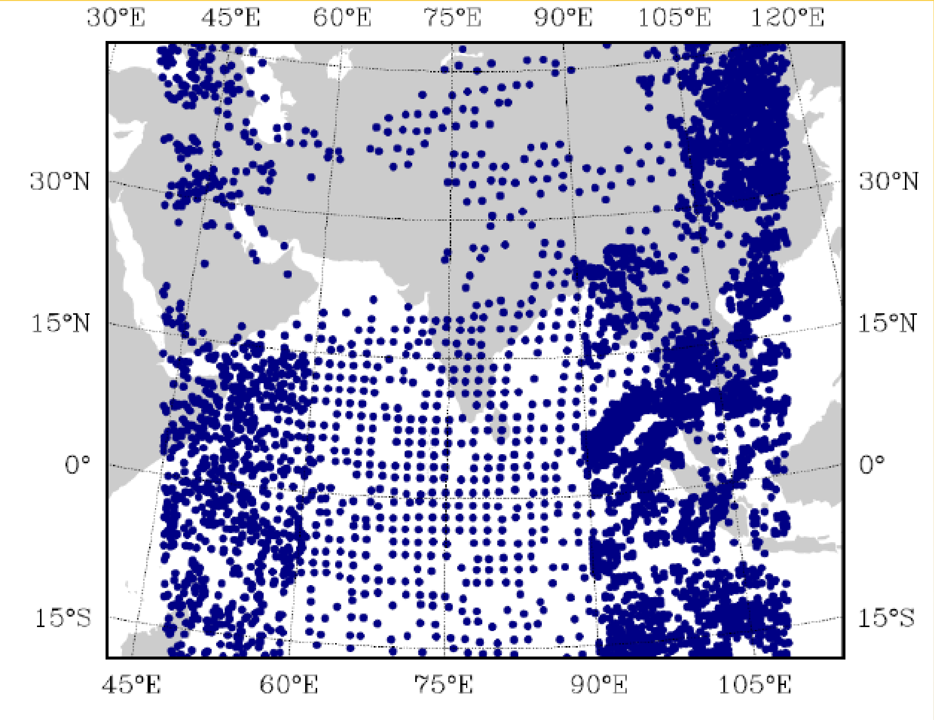
•GMS/GMS/MTSAT/JMA infrared derived cloud motion - low density
•MTSAT/JMA visible derived cloud motion - low density
•GMS/MTSAT.JMA water vapor imager derived cloud motion - low density
•GMS/MTSAT/JMA infrared derived cloud motion
•GMS/MTSAT/JMA visible derived cloud motion
•GMS/MTSAT/JMA water vapor imager derived cloud motion
•METEOSAT/EUMETSAT infrared derived cloud motion - low density, time frequency
•METEOSAT/EUMETSAT visible derived cloud motion - low density, time frequency
•METEOSAT/EUMETSAT water vapor imager derived cloud motion - low density, time frequency
•METEOSAT/EUMETSAT infrared derived cloud motion
•METEOSAT/EUMETSAT visible derived cloud motion
•METEOSAT/EUMETSAT water vapor imager derived cloud motion
•AQUA/TERRA MODIS infrared derived cloud motion
•AQUA/TERRA MODIS water vapor imager derived cloud motion

Source
http://dss.ucar.edu/datasets/ds351.0/metadata/detailed.html

Model Domain

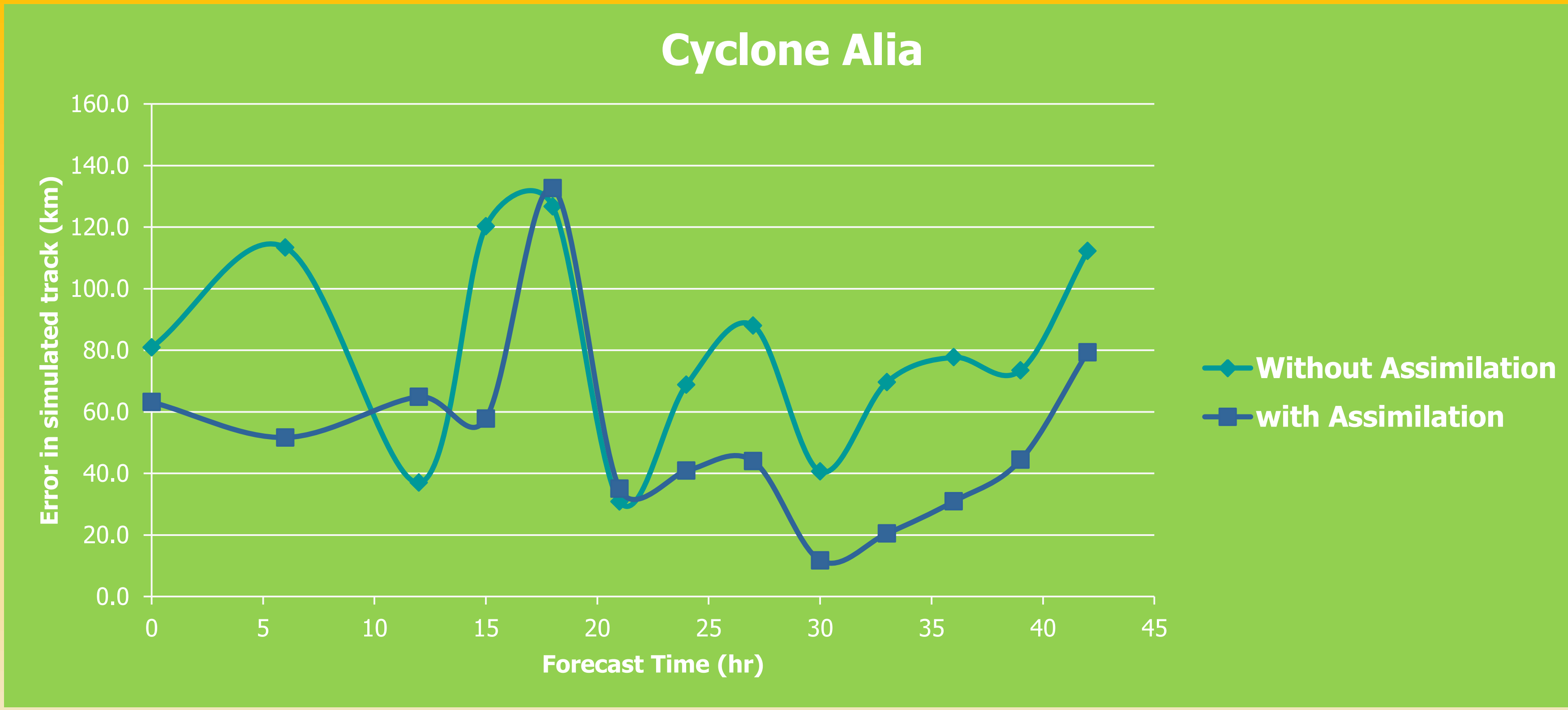


Available observations

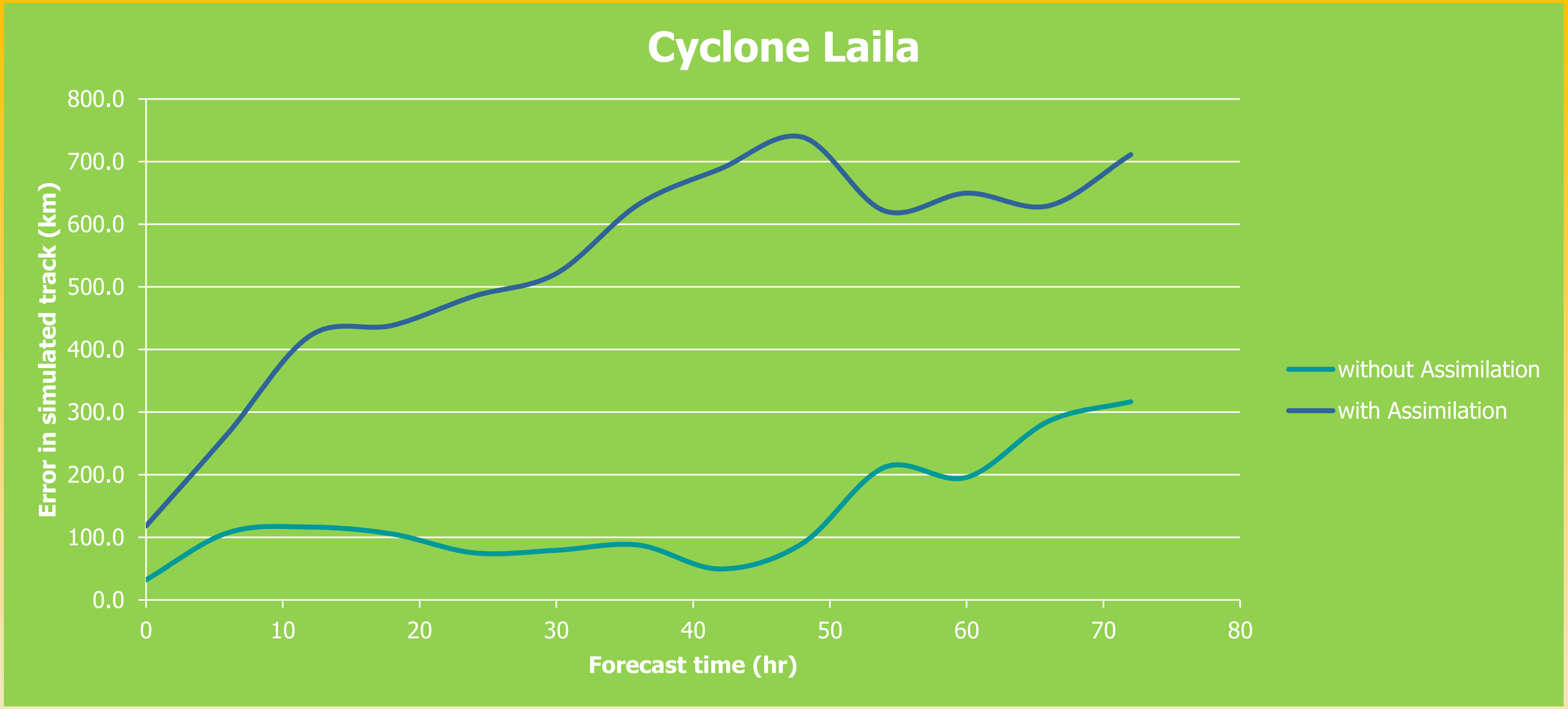


Acronyms

UW-CIMSS: University of Wisconsin Cooperative Institute for Meteorological Satellite Studies
NESDES: National Environmental Satellite, Data, and Information Service
GOES: Geostationary Operational Environmental Satellite
GMS: Geostationary Meteorological Satellite
MTSAT: Multi-functional Transport Satellite
JMA: Japan Meteorological agency
EUMETSAT: European Organization for the Exploitation of Meteorological Satellites
MODIS: Moderate Resolution Imaging Spectroradiometer
MDCRS: Meteorological Data Collection and Reporting System
ACARS: Aircraft Communications Addressing and Reporting System
TAMDAR: Troposphere Airborne Meteorological Data Reporting
MADIS: Meteorological Assimilation Data Ingest System



Time (hr)	0	6	12	18	24	30	36	42	RMS Error(km)
Without Assimilation	**80.9**	**113.4**	**37**	**126.7**	**68.7**	**40.6**	**77.7**	**112.2**	**87.9**
With Assimilation	**63.2**	**51.7**	**64.9**	**132.6**	**40.9**	**11.8**	**30.9**	**79.3**	**68.4**



Time (hr)	0	6	12	18	24	30	36	42	48	54	60	66	72	RMS Error(km)
Without Assimilation	**32.2**	**107.5**	**116.4**	**105.4**	**75.2**	**79.3**	**87.7**	**49.5**	**90.4**	**211.8**	**195.8**	**285.5**	**316.6**	**159.9**
With Assimilation	**118. 1**	**266.4**	**422**	**438.5**	**485.3**	**521.4**	**631.5**	**688.6**	**739.1**	**621.4**	**649.7**	**629.5**	**711.1**	**561**

DA with inbuilt options

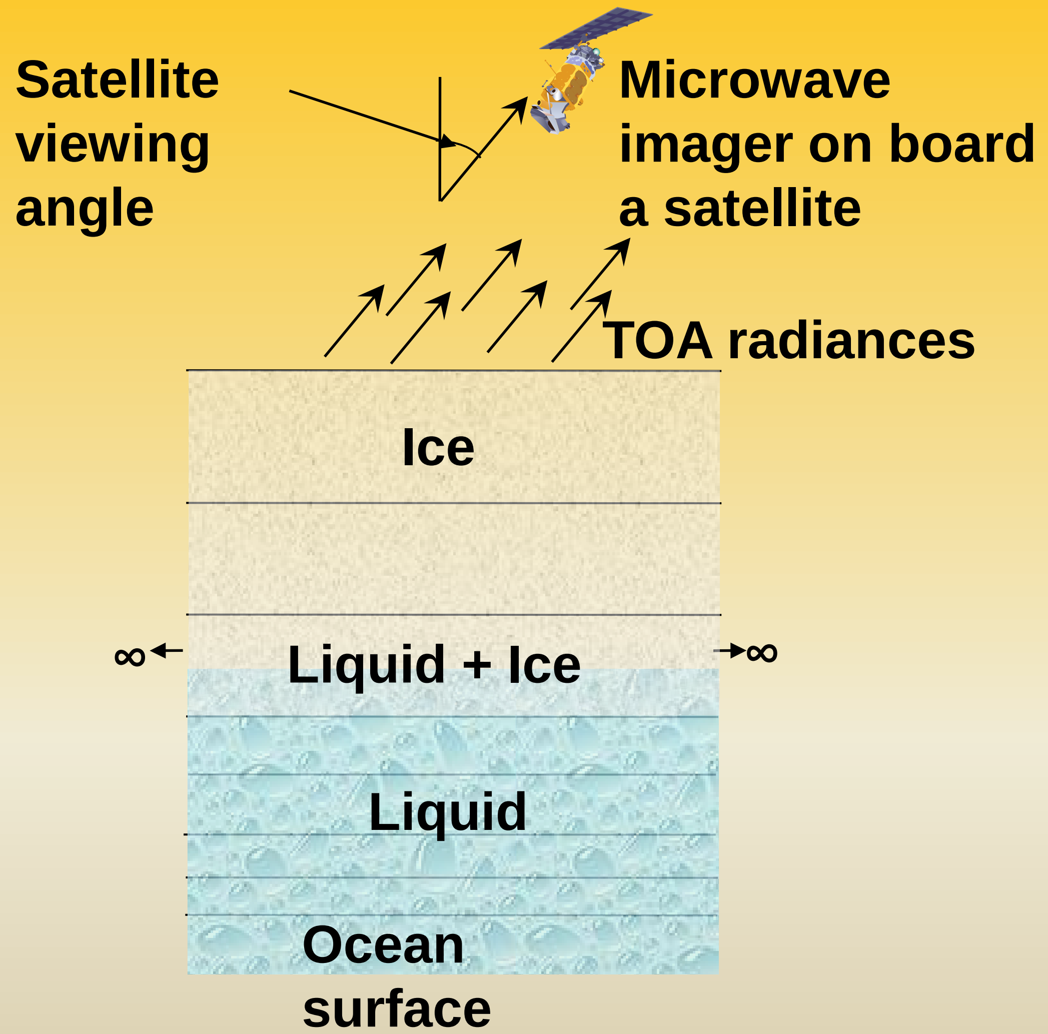
- Success with DA using upper air observations into ARW has been mixed and sporadic.

- The key to get a better skill of track forecast lies in getting the hydrometeors right.

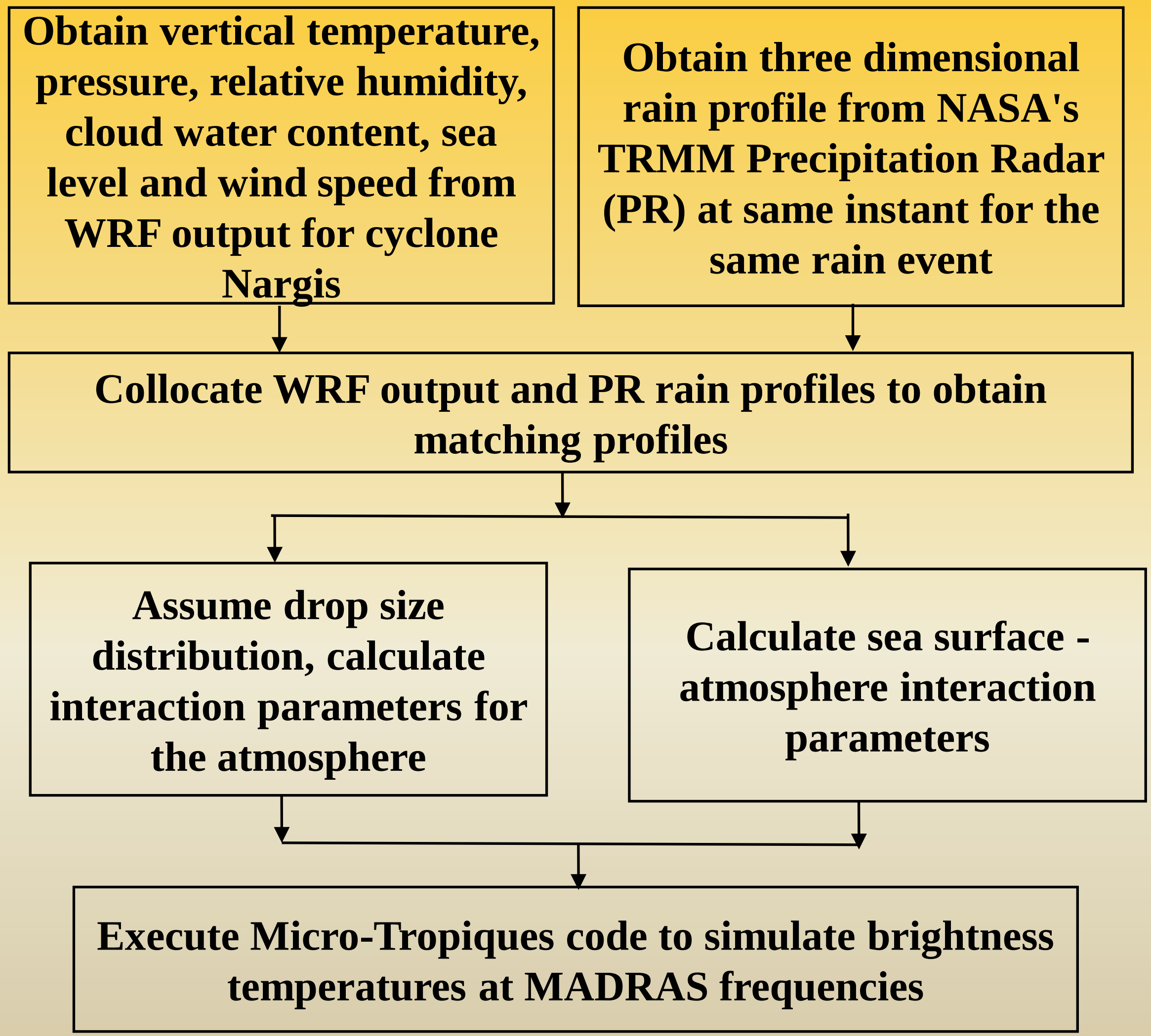
- Hydrometeor representation is the “Achilles Heel” in the WRF model.

Retrieval of cloud and rain profiles using microwave observations – The radiative part of the story

Schematic of layered plane parallel atmosphere



A brief overview of the forward model used in the present work



Channels of MADRAS and their related mission objectives

Frequency (GHz)	Polarisation	Pixel size	
18.7	H+V	≤ 40 km	Rain above oceans
23.8	V	≤ 40 km	Integrated water vapour
36.5	H+V	≤ 40 km	Liquid water in clouds, rain above sea
89	H+V	≤ 10 km	Convective rain areas over land and sea
157	H+V	≤ 6 km	Ice at cloud tops

Following, Evans and Stephens (1991)

$$\mu \frac{dI}{d\tau}(\tau,\mu,\phi) = -I(\tau,\mu,\phi) + \frac{\omega}{4\pi}\int_0^{2\pi}\int_{-1}^{1} P\left(\mu,\phi;\tilde{\mu},\tilde{\phi}\right) d\tilde{\mu}\, d\tilde{\phi} + (1-\omega)\, B(T)\begin{bmatrix}1\\0\\0\\0\end{bmatrix}$$

where

I	**diffuse radiance field**
P	**scattering matrix**
B	**Planck's blackbody function**
ω	**single scattering albedo**
τ	**optical depth**
μ	**cosine of the zenith angle**
ϕ	**azimuth angle**

Bayesian Retrieval Algorithm

* Database – Randomly chosen set of Parameters in possible range & corresponding pre-calculated vector of simulated values
* Integrates over the points in the database with Bayes theorem
* Bayes theorem

$$p_{post}(x|y) = \frac{p_f(y|x)\; p_{pr}(x)}{\int p_f(y|x)\; p_{pr}(x)\, dx}$$

$p_{post}(x|y)$ -Posterior Probability Density Function

$p_f(y|x)$ -Conditional Probability Density Function

$p_{pr}(x)$ -Prior Probability Density Function

x - State Vector

y - Vector of Observations

$Z_j(x)$ – Vector of Simulated values

* Retrieval Parameter

$$x_{ret} = \frac{\int x\; p_f(y|x)\; p_{pr}(x)\, dx}{\int p_f(y|x)\; p_{pr}(x)\, dx} \rightarrow x_{ret} = \frac{\sum_i x_i\; p_f(y|x_i)}{\sum_i p_f(y|x_i)}$$

- Retrieved Parameter

$$x_{ret} = \frac{\sum_{i=1}^{N_{data}} w_i \, x_i}{\sum_{i=1}^{N_{data}} w_i}$$

x_i – Database profile

N_{data} – Number of Database data

- Calculate the weight (w_i) for each profile based on Normal distribution of database values over measurement

$$w_i = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{RMS_i}{2\,\sigma^2}\right]$$

σ – Gaussian of standard deviation

- Calculate the RMS error for each database profile

$$RMS_i = \frac{\sum_{j=1}^{N_{channel}} w_j \, \chi_j^2}{\sum_{j=1}^{N_{channel}} w_j}$$

w_j - Weights for each measurement

$N_{channel}$ - Number of Measurements

- For each channel, calculate the difference between simulated and measured quantity

$$\chi_j = \left(y_j - Z_j\right)$$

Principal Difficulties

- Simulations with artificial profiles cannot be done indiscriminately (this means ***prior profiles are not easily forthcoming***!)
- High dimensionality of the problem – 56 output parameters to be retrieved from 9 input parameters!
- Stochastic optimization inevitable!

Retrieval of rainfall

Forward Problem:

To Find: Brightness Temperatures at given frequencies - 9

Known : Atmospheric Constituents
[rain rate – 14 , ice content – 14, cloud Liquid content –14, Cloud Ice–14]

Inverse Problem:

To Find: Atmospheric Constituents
[rain rate – 14 , ice content – 14, cloud Liquid content –14, Cloud Ice–14]

Known: Brightness Temperatures at given frequencies - 9 [Satellite measured Data]

Parameter retrieval - Raining Atmosphere – 14 Layers

Forward Problem – Polarized Microwave Model using Adding & Doubling Method

Inverse Problem – Bayesian Retrieval Algorithm, Artificial Neural Network

Data base:

Number of Data for Training = 43000
Number of Data for Testing = 7000

TOGA COARE Experiments

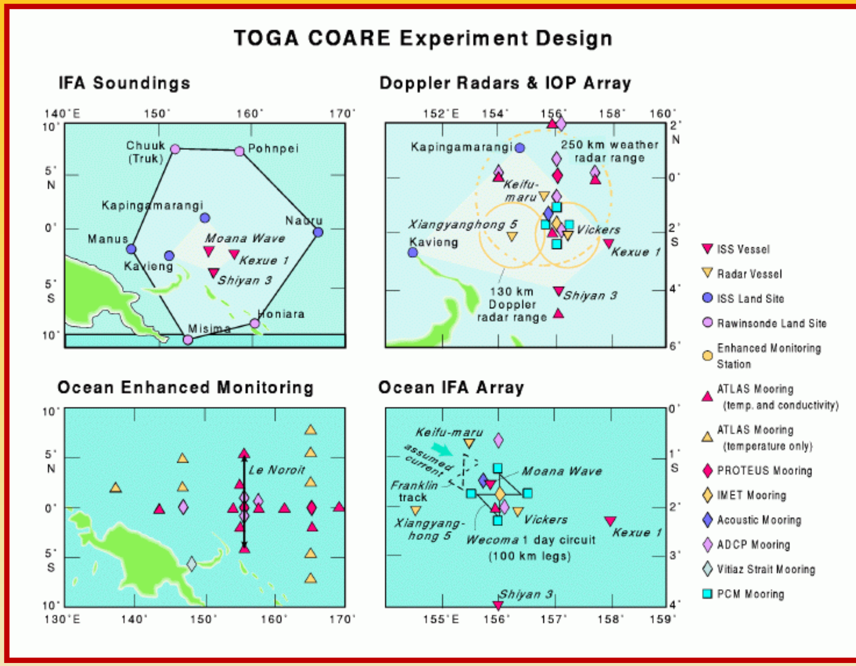
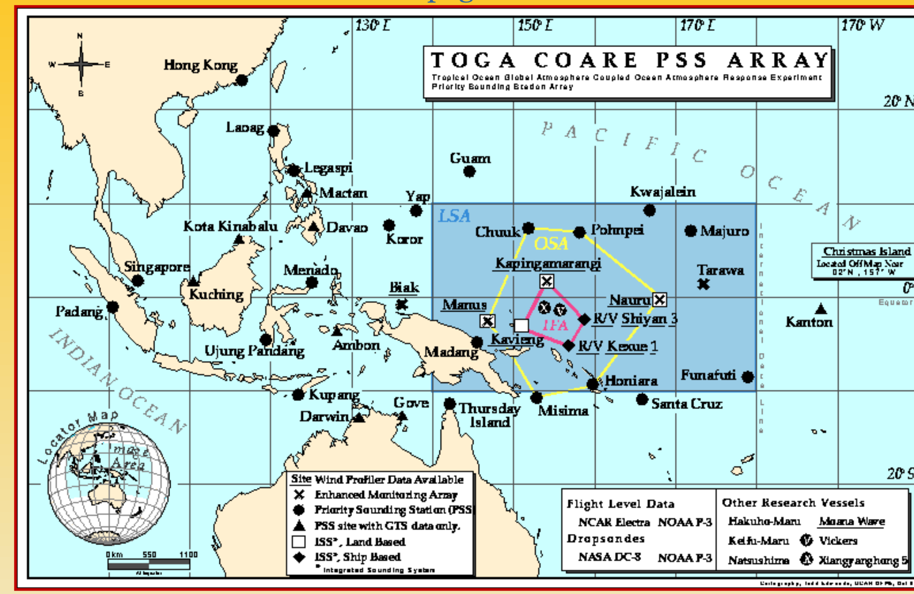


Illustration: NASA webpage



Prior Knowledge: TRMM-TMI Profiles

Key novelty : *Populate the Bayesian with data from previous cyclones*

TRMM -TMI Profiles
of
Tropical Cyclones

Polarized
Microwave Forward
Model

Brightness Temperatures at various ***Frequencies*** and ***Polarizations***

Database for Precipitation Retrieval

TRMM -TMI Profiles
of
Tropical Cyclones

Brightness Temperatures at various ***Frequencies*** and ***Polarizations***

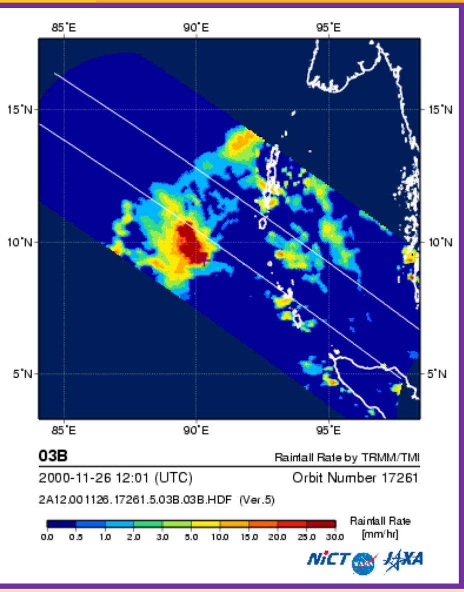
Philosophical underpinning of the approach

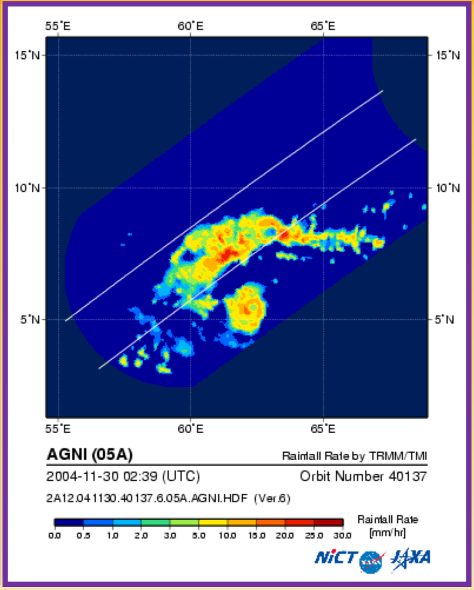
- Hydrometeor profiles to be used as input come from a once already retrieved data set for similar events, wherein output was titrated against input!

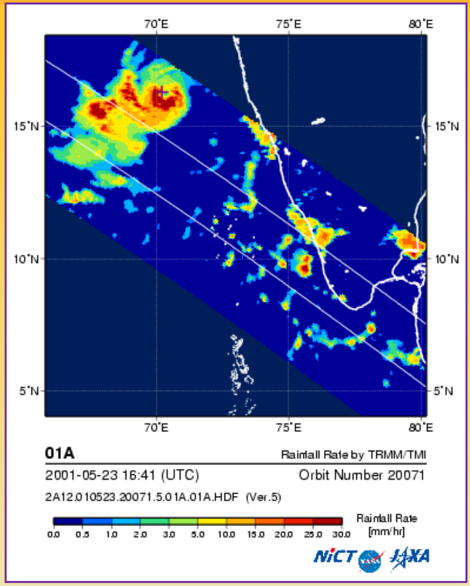
- Retrieval with this set of profiles carries more physics than the original set of profiles (that came from a numerical model + limited measurements)!

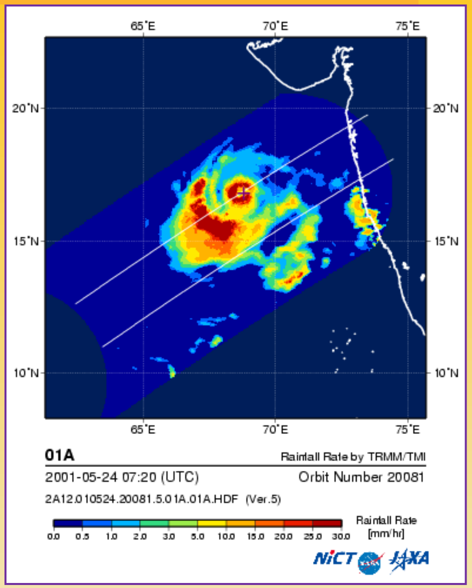
  (***A conjecture we are yet to verify!***)

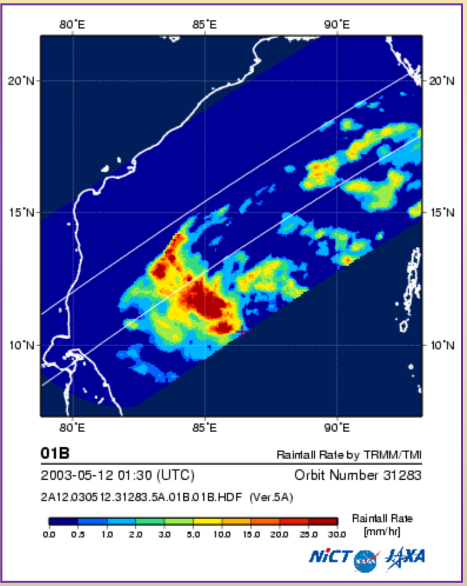
Snapshot of snapshots!

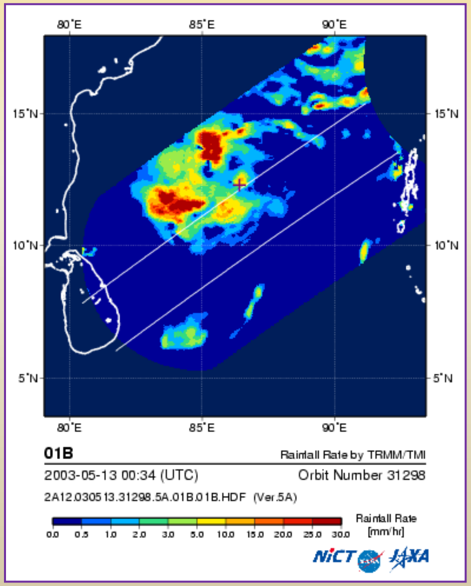


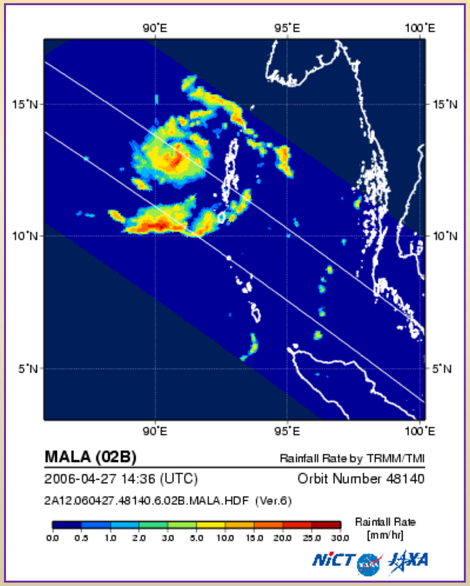


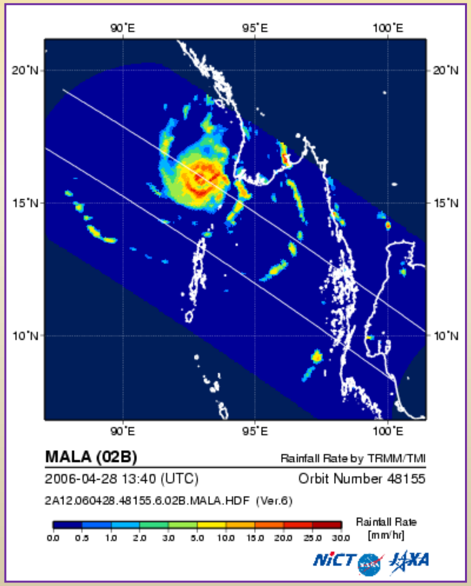




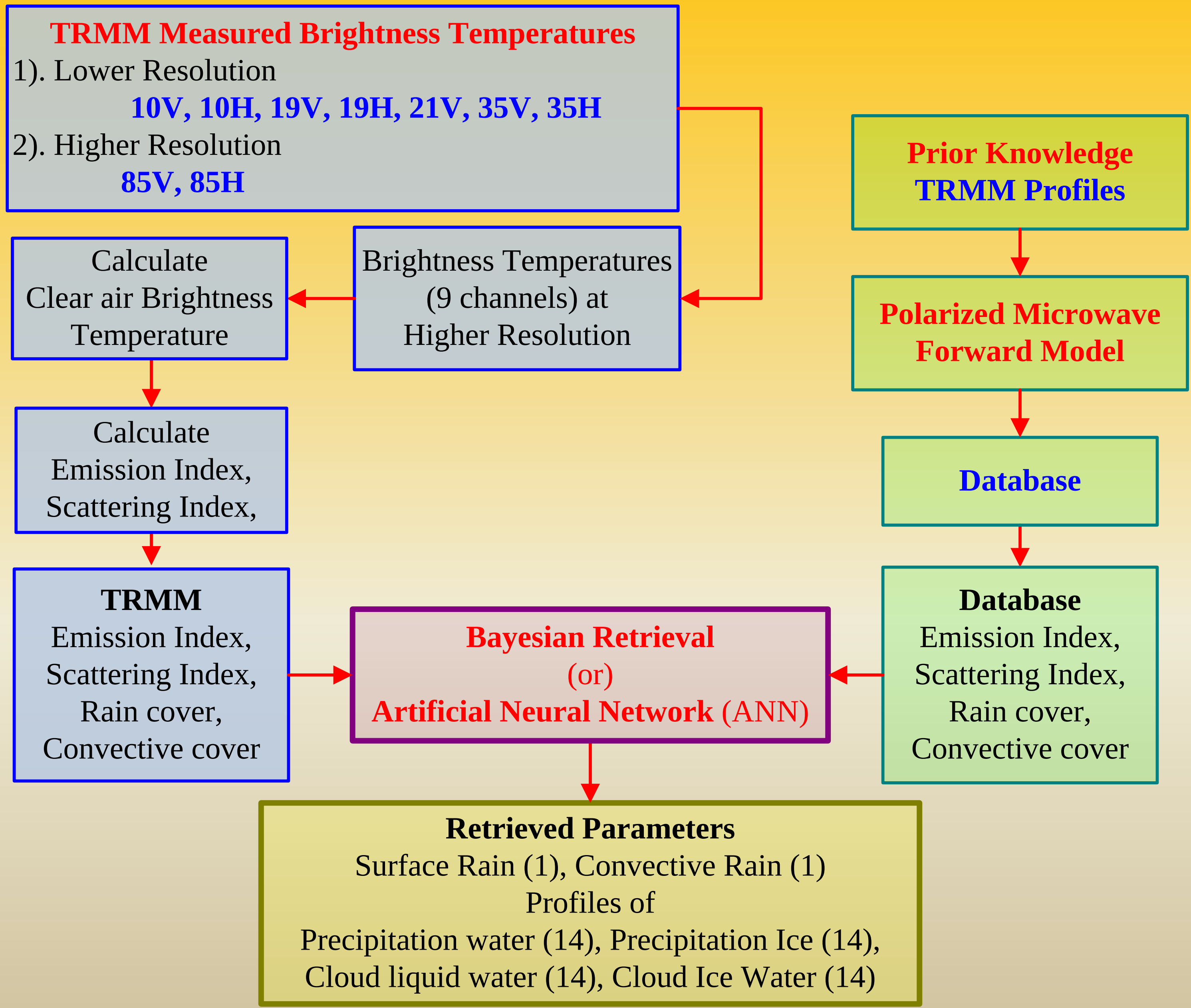








Precipitation Retrieval Algorithm



Emission and Scattering Indices

$$\text{Emission Index } 1 = \left[\frac{T_{B,10H} - T_{B,10V}}{T_{B,clear,10H} - T_{B,clear,10V}} \right]$$

$$\text{Emission Index } 2 = \left[\frac{T_{B,19H} - T_{B,19V}}{T_{B,clear,19H} - T_{B,clear,19V}} \right]$$

$$\text{Emission Index } 3 = \left[\frac{T_{B,36H} - T_{B,36V}}{T_{B,clear,36H} - T_{B,clear,36V}} \right]$$

$$\text{Emission Index } 4 = \left[\frac{T_{B,85H} - T_{B,85V}}{T_{B,clear,85H} - T_{B,clear,85V}} \right]$$

$$\text{Scattering Index } 1 = \left(\frac{T_{B,36H} - T_{B,36V}}{T_{B,clear,36H} - T_{B,clear,36V}} \right) T_{B,36H} + \left(1 - \frac{T_{B,36H} - T_{B,36V}}{T_{B,clear,36H} - T_{B,clear,36V}} \right) 273.0 - T_{B,36H}$$

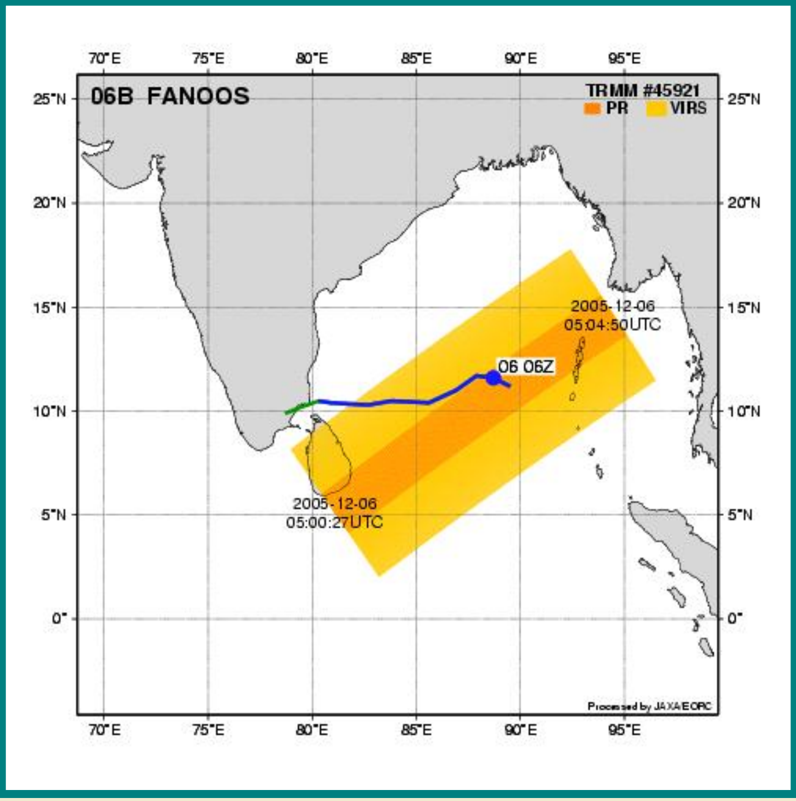
$$\text{Scattering Index } 2 = \left(\frac{T_{B,85H} - T_{B,85V}}{T_{B,clear,85H} - T_{B,clear,85V}} \right) T_{B,85H} + \left(1 - \frac{T_{B,85H} - T_{B,85V}}{T_{B,clear,85H} - T_{B,clear,85V}} \right) 273.0 - T_{B,85H}$$

Based on the work of G.W.Petty

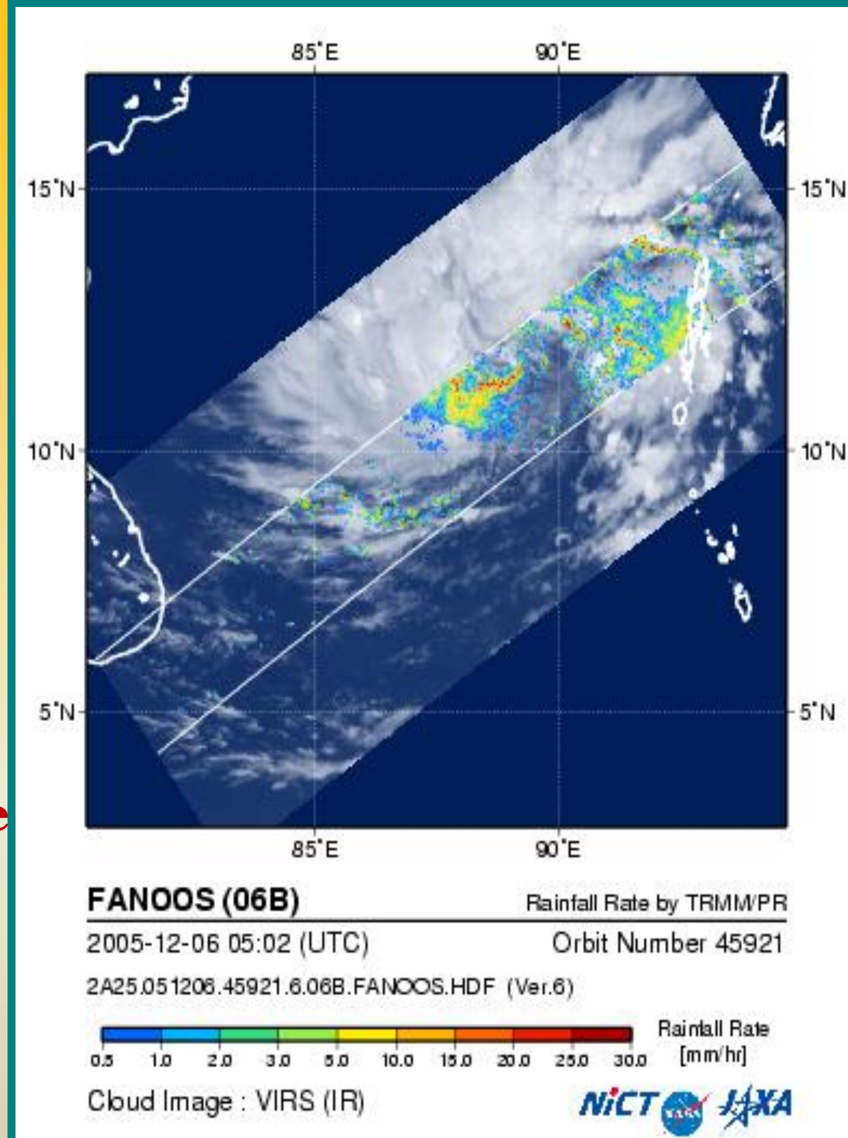
Retrieval of Rainfall:

Application to Tropical Cyclone (<u>FANOOS</u>, December 2005)

Tropical Cyclone FANOOS - Data



Rainfall Rate & Cloud Image



JAXA/EORC Tropical Cyclone Database

Date/Time:	Dec 06,2005 05:02 (UTC)
Satellite/Sensor:	PR, VIRS, TMI
Orbit Number:	45921
Lat/Lon:	2 N – 18 N 81 E – 98 E

Inverse Problem– Inputs

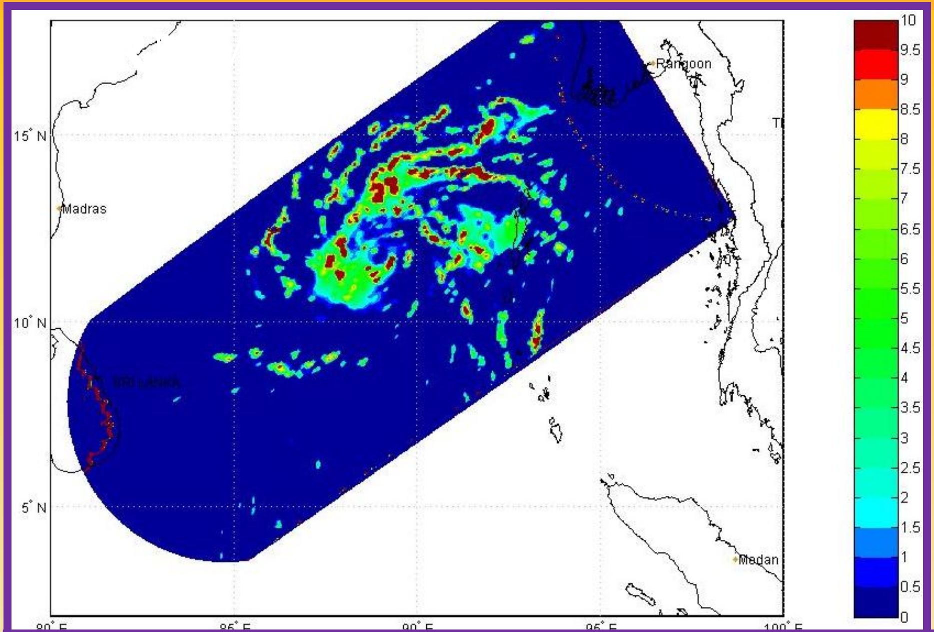
- ✯ Number of Layers: **14**
- ✯ Frequencies: 10.7, 19.4, 21.3, 37.0, 85.5 GHz,
- ✯ *TRMM-TMI Measured* Vertical, Horizontal Polarized Brightness Temperatures
- ✯ Total No. of Database Profiles over ocean surface: **43000**

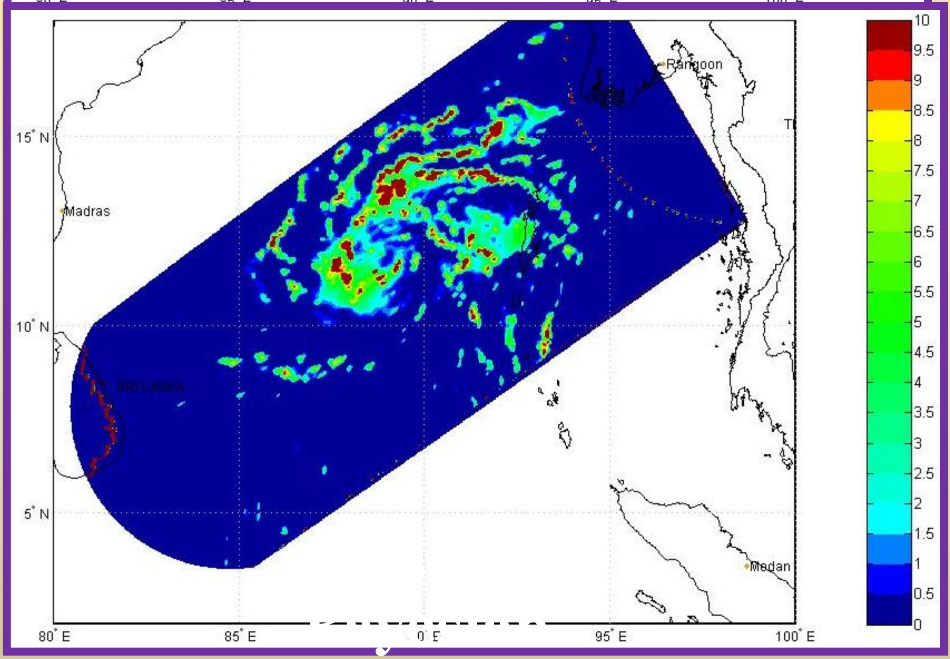
Output:

Profiles of Liquid Cloud, Ice Cloud & Hydrometeors (Liquid & Ice phase)

- Ground Rain rate

Ground Rain rate – Comparison with TRMM-TMI





Improving accuracy of radiative transfer simulations – collocative strategy

Inputs:

From numerical weather prediction model

Pressure, hPa
Temperature, K
Relative humidity, %
Sustained wind speed, m/s
Sea surface temperature, K
Cloud contents, g/m^3

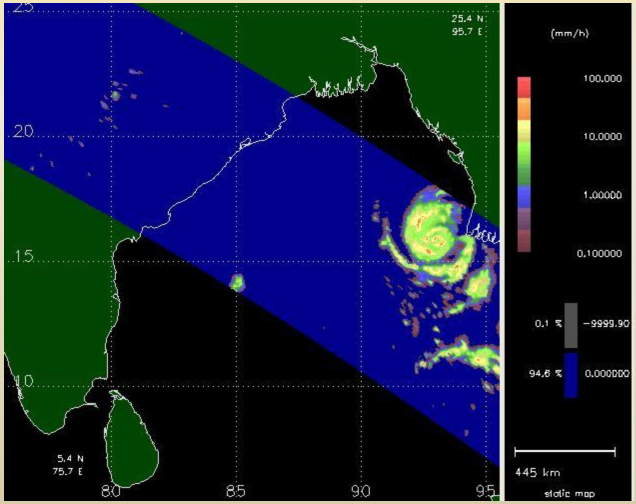
From observation from NASA's TRMM Precipitation Radar

Precipitating Water, mm/hr
Precipitating ice, mm/hr

Inputs are collocated at TRMM PR's resolution of 5 km

Cyclone Nargis

- ARW v3.1.1 model used for getting vertical profiles.
- The NCEP FNL data used as initial and boundary conditions, in this study May 2, 2008 at 00 UTC is used as the initial condition and six hours boundary condition up to 06 UTC.



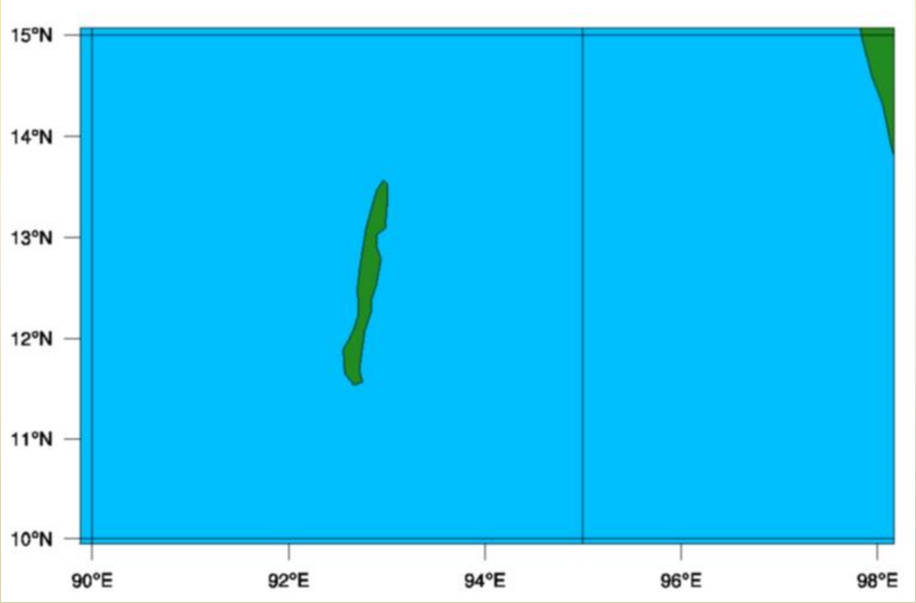
TRMM covered the region on May 2, 2008.

Orbit no: 59603
Max surface rain rate: 30 mm/hr

Domain:
10^o N – 15^o N, 90^o E and 97.5^o E

Model Domain

- The model domain cover a part of Bay of Bengal bounded by 10° N to 15° N and 90 ° E to 98° E with 5 km x 5km of horizontal resolution.
- 115 grid points in North-South and 181 grid points in West-East.



Physics and Dynamics

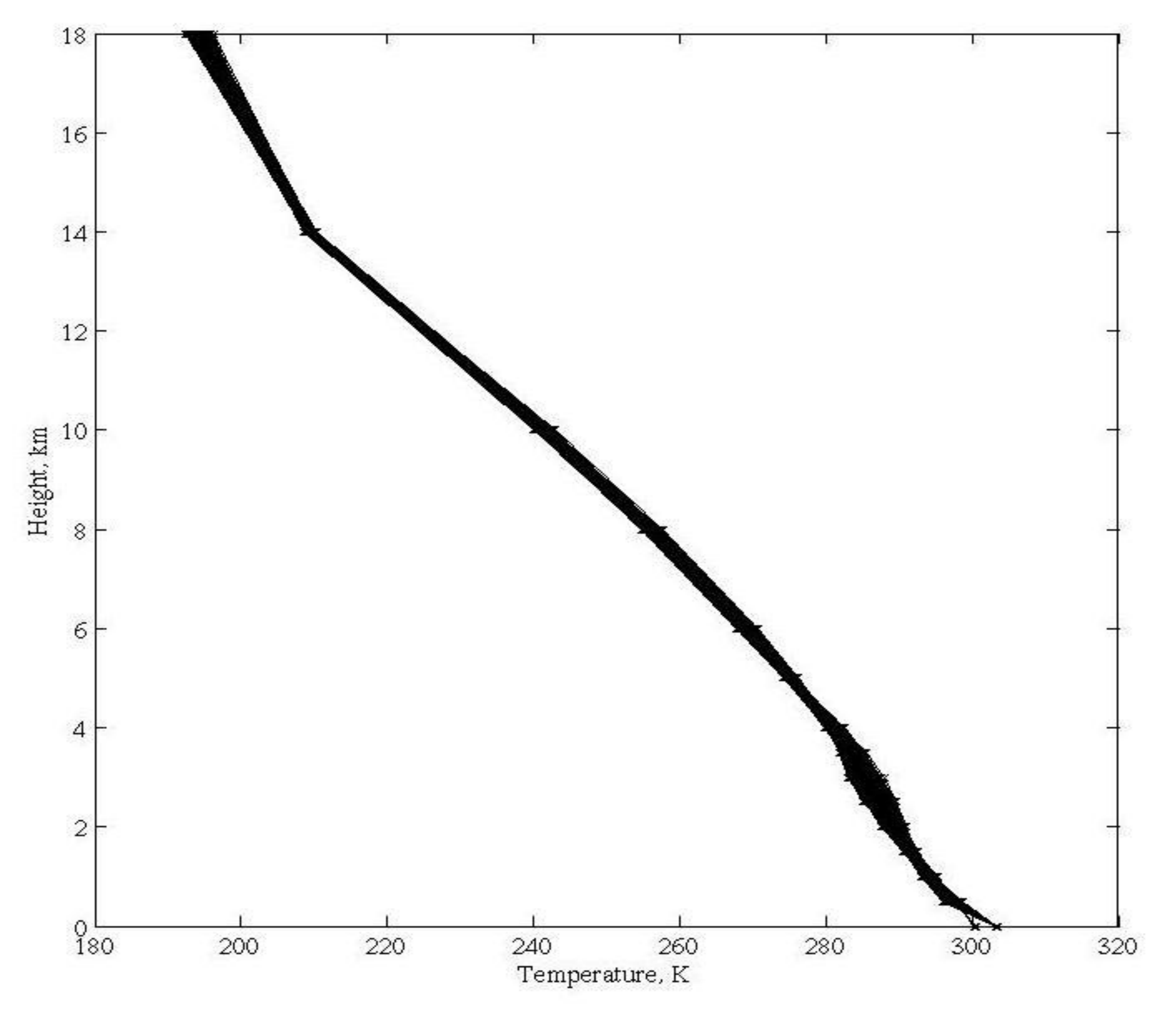
Equation	Nonhydrostatic
Time integration scheme	Third-order Runge-Kutta scheme
Integration time step	15 sec
Horizontal grid system	Arakawa-C grid
Map projection	Mercator
Microphysics	WSM 3 simple ice scheme
Radiation parameterizations	RRTM (long wave radiation), Dudhia (short wave radiation)
Cumulus parameterization	Grell-Devenyi ensemble
PBL parameterization	YSM scheme
Surface layer parameterization	Monin-Obukhov scheme, Thermal diffusion scheme

Obtaining atmospheric variables from WRF output

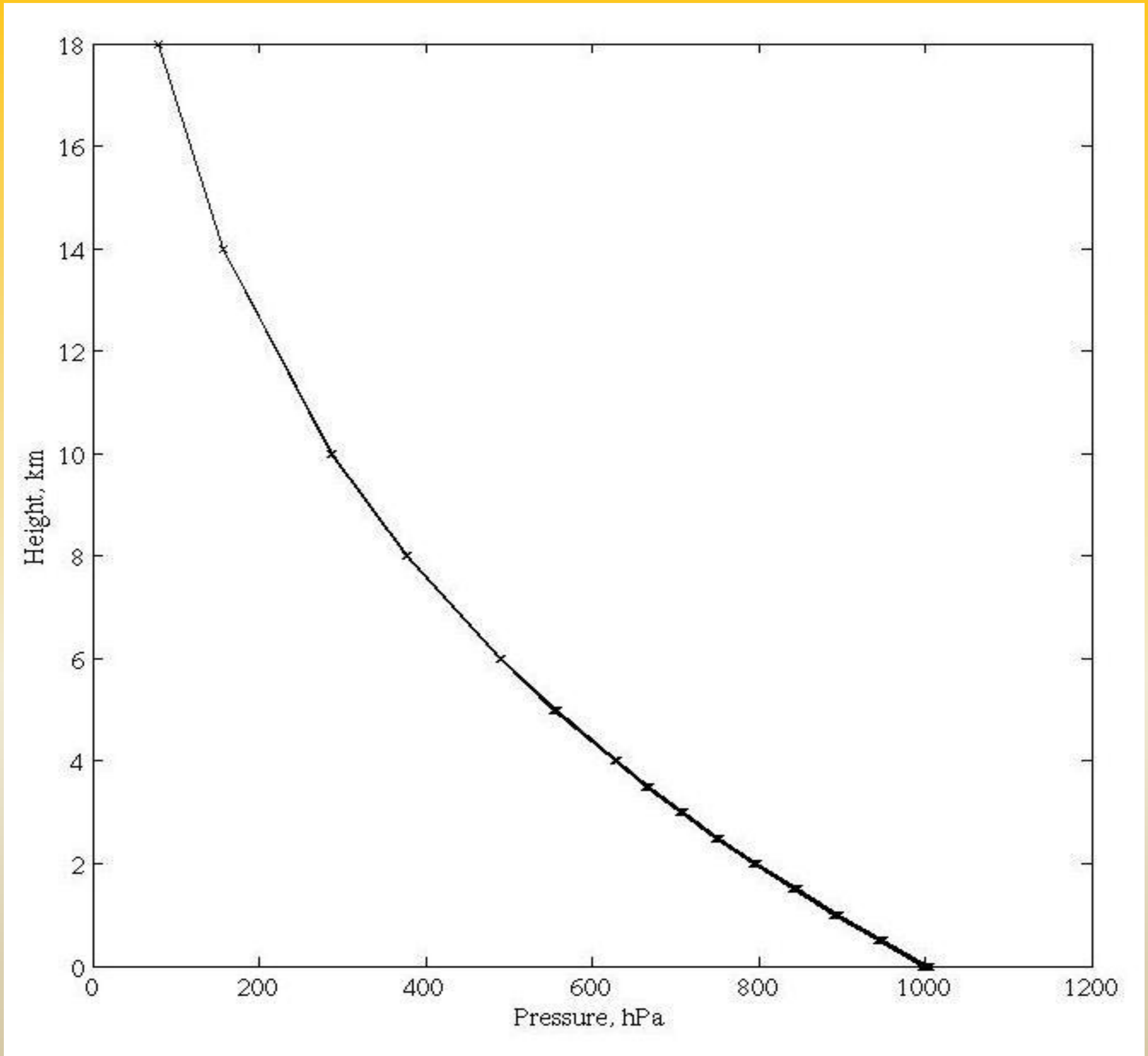
The ARW model was run for a time period of six hours with a time step of 15 seconds and the following variables are taken from wrf output of May 2, 2008 at 01 UTC.

- Sea level pressure (SLP) in hpa,
- Sea surface temperature (SST) in K,
- Relative humidity at a height of 2m (%),
- Wind speed at 10 m height (m/s),
- Vertical profiles of
  - Pressure (hpa)
  - Temperature (K)
  - Relative humidity (%)
  - Cloud water mixing ratio (g/kg)

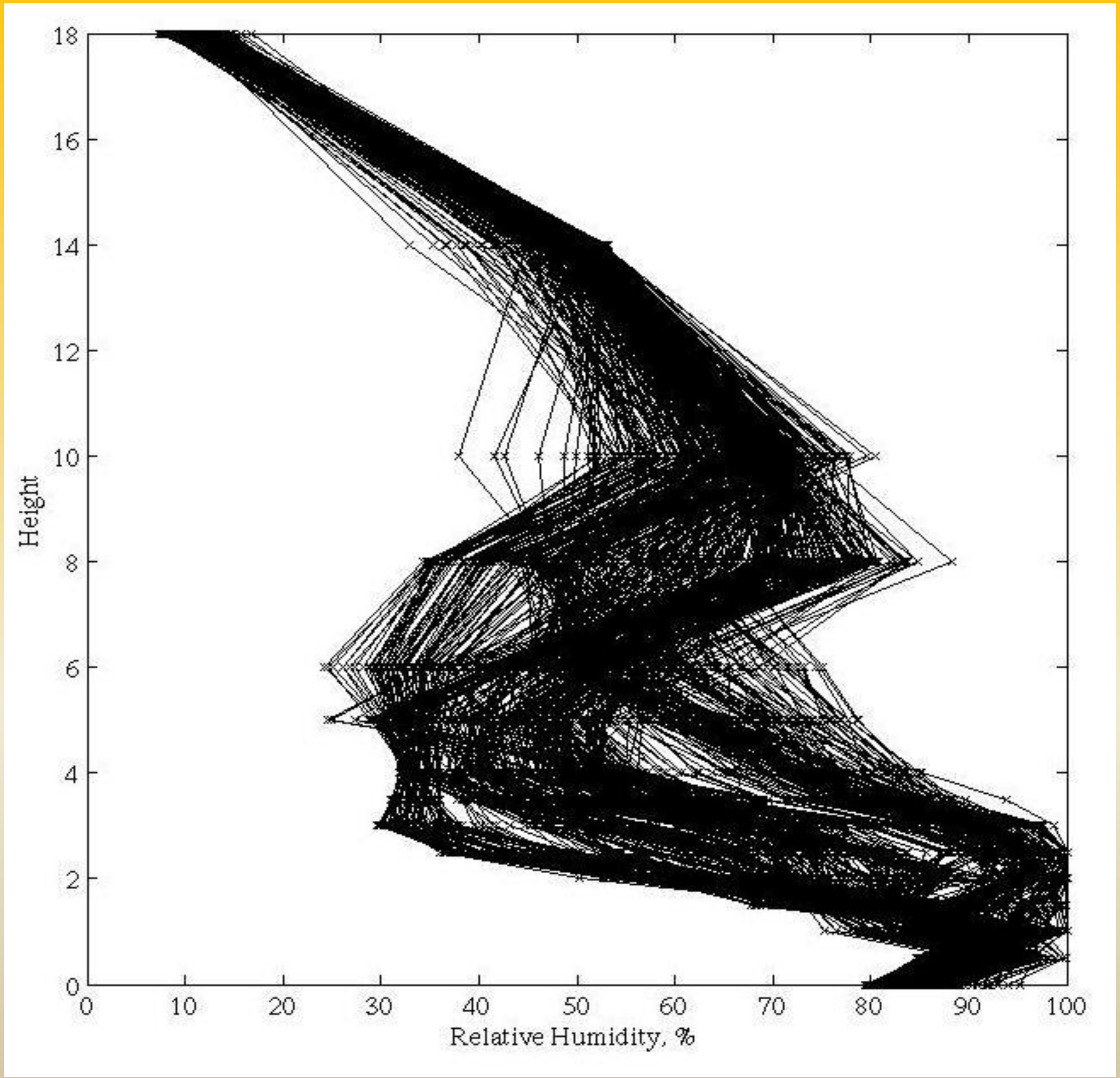
Temperature profiles obtained from WRF model output



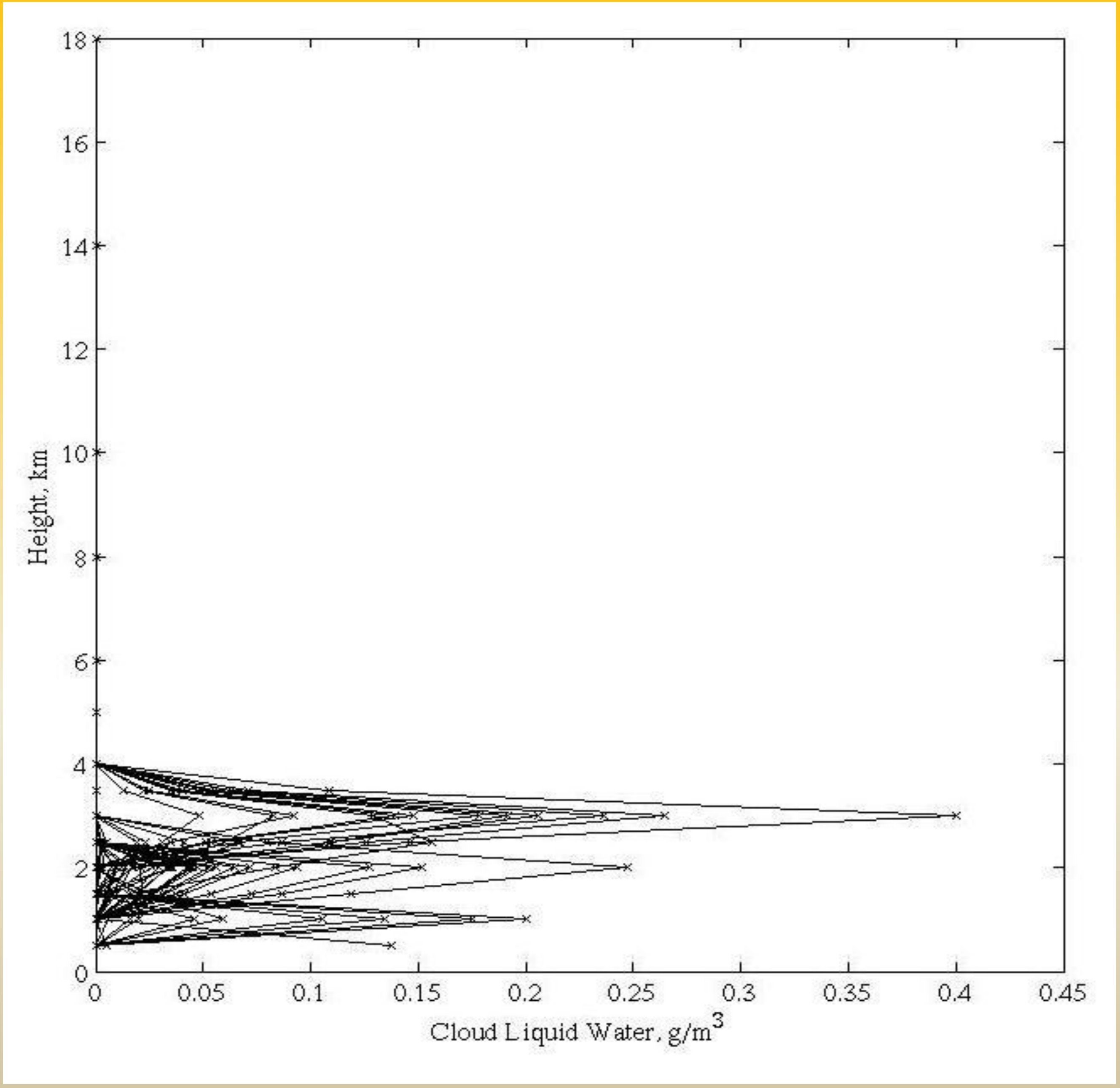
Pressure profiles obtained from WRF model output



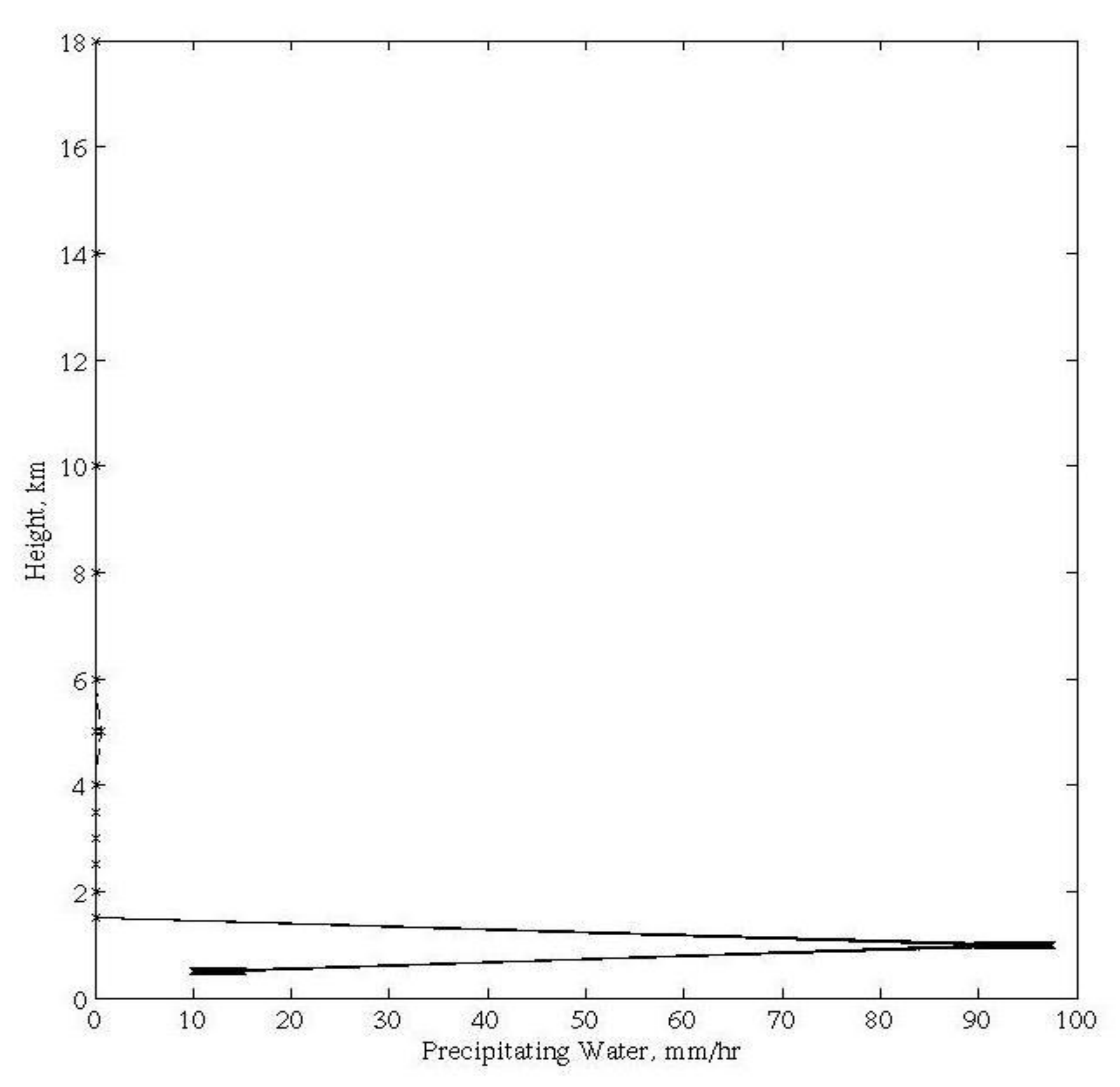
Relative Humidity profiles obtained from WRF model output



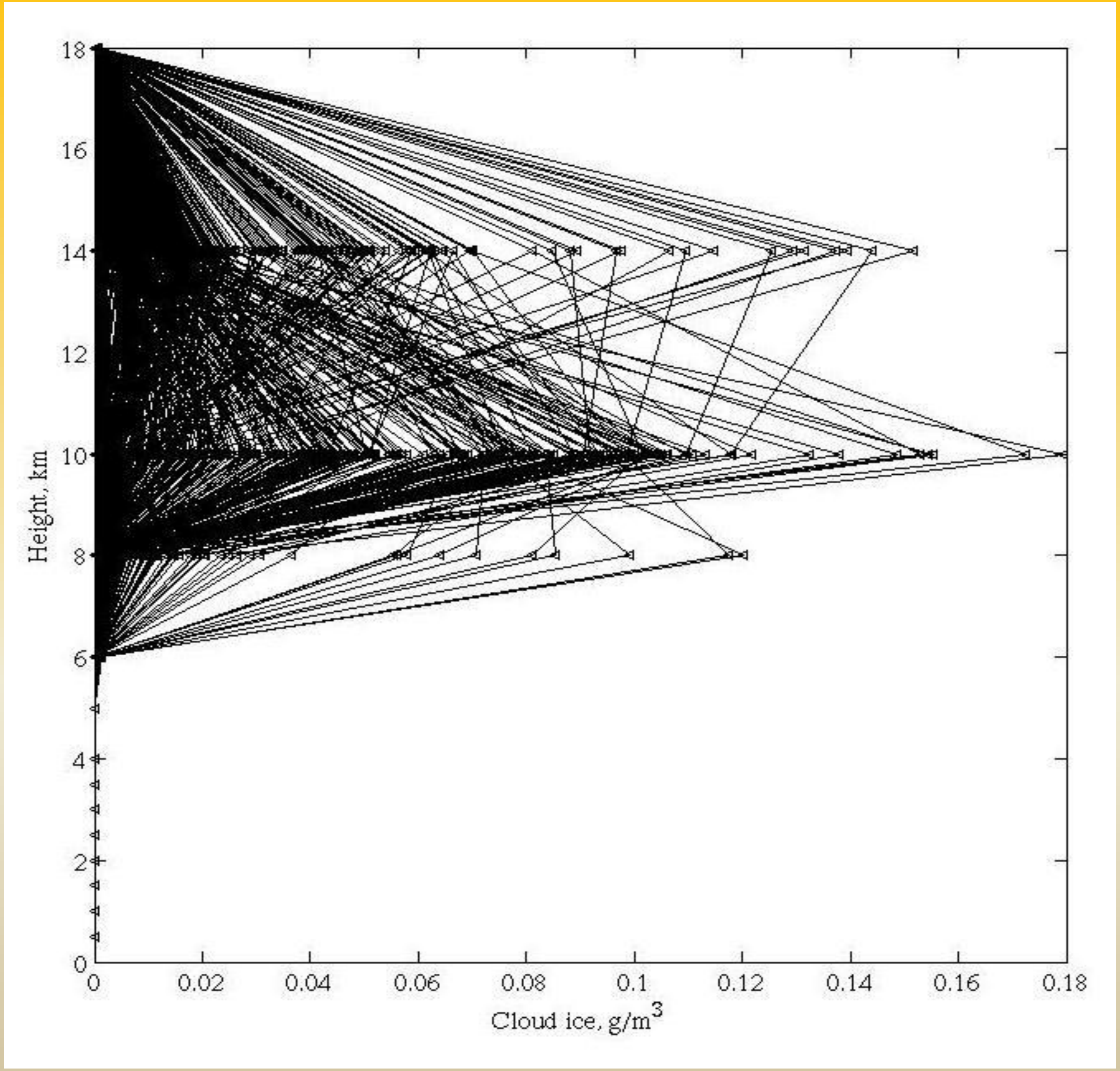
Cloud Liquid Water profiles obtained from WRF model output



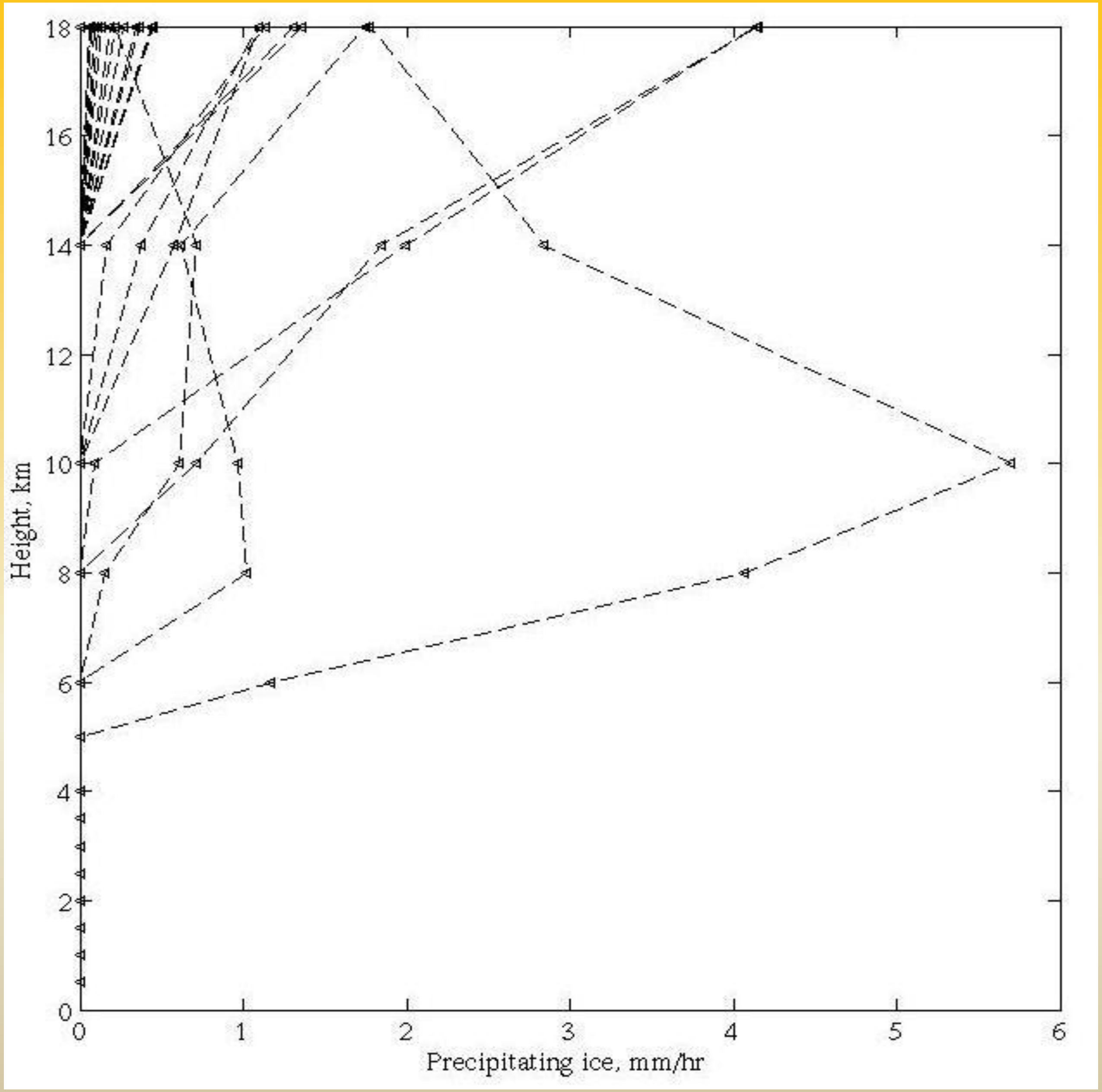
Rain profiles obtained from NASA's TRMM Precipitation Radar



Cloud Ice profiles obtained from WRF model output



Precipitating Ice profiles obtained from NASA's Precipitation Radar



Generation of database

Retrieval algorithms such as ANN data driven

Atmosphere divided into 14 layers of unequal spacing

P, T, RH, SST, WS, CLW, CI generated for Cyclone Nargis using WRF model output

PR, PI obtained from NASA's TRMM Precipitation Radar for same event

Inputs are collocated at common footprint size of PR (~5km)

A collocated data base is generated with about 440 profiles

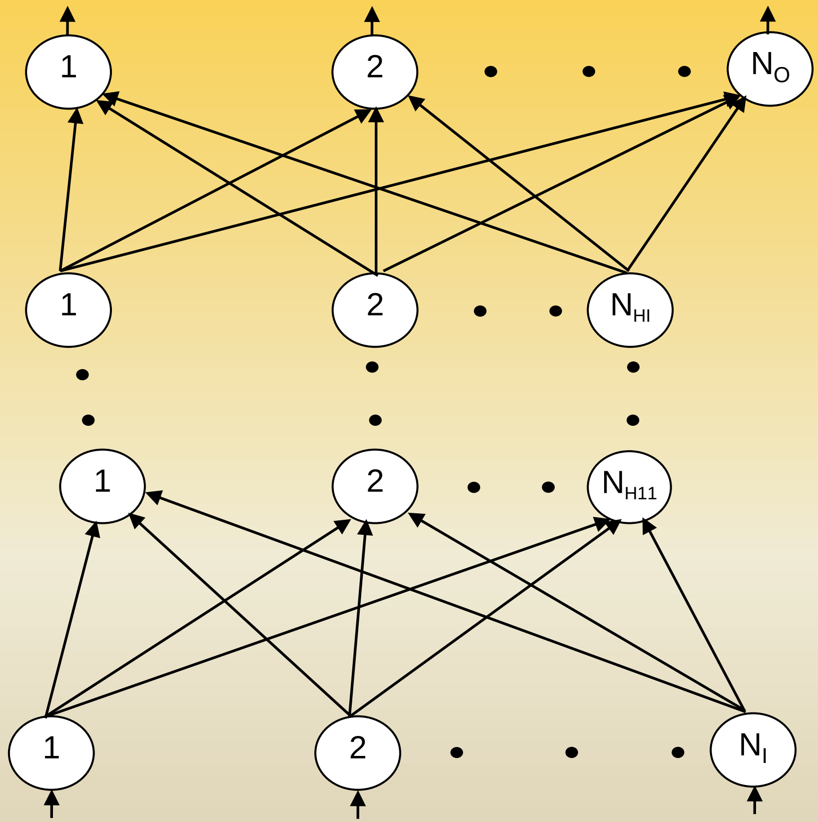
Brightness Temperatures are simulated using Micro-Tropiques at MADRAS frequencies of the Megha-Tropiques satellite

Neural Network based Fast Forward model for Radiative Transfer Simulations

- Radiation modeling of raining atmosphere is complex due to scattering process
- In-house VRTE takes 6 seconds to simulate brightness temperatures for a given cloud scene i.e. every pixel
- For comparison, the TMI onboard TRMM satellite makes a measurement of about 116 profiles per second!
- Need to speed up computational time involved in forward calculations for real time processing of satellite images

ANN as a Fast Forward Model

9 brightness temperatures corresponding to 5 frequencies, 2 polarizations of MADRAS imager of MeghaTropiques



102 inputs

9 outputs

Pressure (14+sea level), Temperature (14+SST), Humidity (14+sea level), CLW, CI, PW, PI in 14 vertical layers, sustainable wind speed

The output of hidden layer neurons are calculated using

$$y_j = F\left(\sum_{i=1}^{n} w_{ij}\, x_i\right)$$

where F is transfer function given by sigmoidal function

$$F = \frac{1}{1+e^{-x}}$$

Value of ‘F’ lies between 0 and 1. Hence output values are normalized using following expression

$$\theta = \frac{T_{f,p} - T_{f,p,\min}}{T_{f,p,\max} - T_{f,p,\min}}$$

‘f’ refers to frequency
‘p’ refers to polarization
min / max refers to minimum / maximum

Extreme values of input parameters:

Parameter	Min	Max
Wind speed, m/s	0.4	13.6
Pressure, hPa	77.77	1013.55
Temperature, K	191.33	304.18
Relative Humidity (%)	0	100
CLW, g/m^3	0	0.5
PW, g/m^3	0	1.362
CI, g/m^3	0	0.129
PI, g/m^3	0	1.184

The output of output layer neurons are calculated once output of hidden layer neurons are evaluated, using linear activation function given by

$$\boxed{o_j = \sum_{i=1}^{n} w_{ij} x_i}$$

The objective of the training phase of network is to arrive at the set of weights which will minimize the difference between simulated outputs and the target values.

Performance of various network architectures: Neuron independent study

Architecture	R^2								
102-5-9	0.9985	0.9995	0.9985	0.9964	0.9995	0.9989	0.9985	0.9993	0.9993
102-10-9	**0.9997**	**0.9998**	**0.9996**	**0.9997**	**0.9999**	**0.9998**	**0.9998**	**0.9998**	**0.9998**
102-15-9	0.9998	0.9998	0.9997	0.9998	0.9999	0.9999	0.9999	0.9999	0.9998
102-20-9	0.9999	0.9998	0.9995	0.9996	0.9999	0.9999	0.9999	0.9998	0.9998
102-25-9	0.9998	0.9999	0.9996	0.9996	0.9999	0.9999	0.9998	0.9999	0.9999
102-30-9	0.9999	0.9999	0.9995	0.9996	0.9999	0.9997	0.9996	0.9998	0.9998
102-35-9	0.9998	0.9998	0.9997	0.9984	0.9999	0.9997	0.9996	0.9988	0.9992
102-40-9	0.9998	0.9998	0.9996	0.9996	0.9999	0.9999	0.9998	0.9998	0.9999
102-45-9	0.9998	0.9998	0.9997	0.9996	0.9999	0.9998	0.9999	0.9999	0.9999
102-50-9	0.9998	0.9998	0.9997	0.9996	0.9999	0.9999	0.9999	0.9999	0.9999

Back propagation network toolbox in commercial software MATLAB used for training and testing the network performance

Out of 12,968 profiles, 9901 profiles (~76%) correspond to snapshots of cyclones originated between 2003 – 2009 is used for training the network

Remaining 3,067 profiles (~24%) correspond to snapshots of cyclones originated in 2010 are used for testing purposes

Work in progress

- Integrating microwave radiance assimilation into WRF in a Bayesian framework.
- Fast RT model for this is already ready.
- For training and testing the approach TRMM data to be used.
- Integrating IR radiances with GOES data and Kalpana data with fast RT model for IR (also ready).
- Fine tune the suite of algorithms for maximizing forecast skill.
- Set up a framework to assimilate MT and INSAT 3D data

In house computing facility at IIT Madras

Mini super computer
Cray CX1

Technical specifications

Speed	488.7 Gflops based on High performance Linpack benchmark
No of Nodes	6 (1 master node + 5 compute nodes)
Total no of CPU	12 CPUs (2 CPUs per node)
Total no of core	72 Cores (2 cores per CPU; 12 cores per node)
Processor	Intel Xeon six cores WX5660 2.80 GHz 12M 6.4 GT/sec
Memory	72 x 4 GB DDR3 1333 MHz Total memory : 288 GB (48 GB per nodes)
Hard Drive	250 GB 7.2K RPM SATA 2.5” Internal Fixed hard Drive in each nodes. 4 TB External hard drive (4 x 1 TB 7.2 RPM SATA 3 Gbps)
Operating system	Red hat Linux
Compiler	Gfortran, Intel

Additional computational facilties at IIT Madras

- We also use the Vega cluster with 2048 cores available at IIT Madras (because of heavy load on this CRAY is a much better option for us as it is dedicated).

Thank You