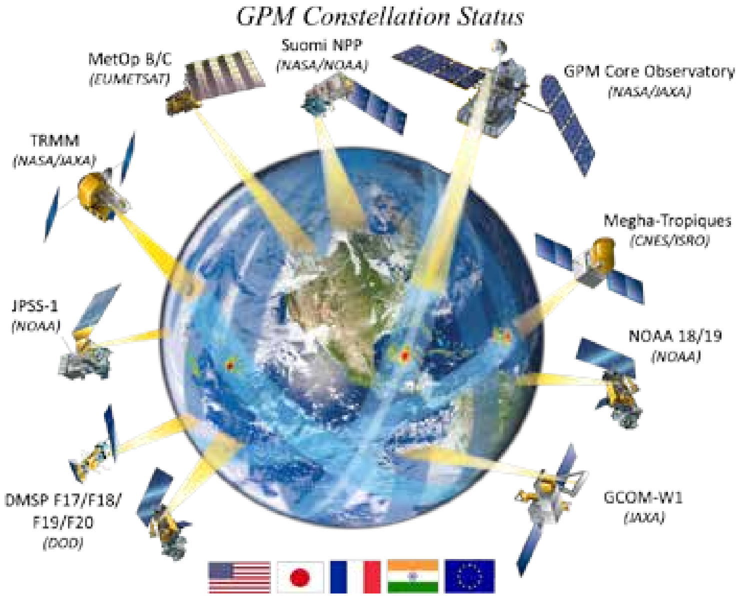
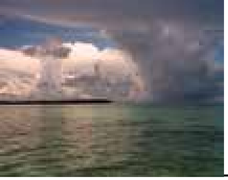
Passive Microwave (Rainfall) Algorithms

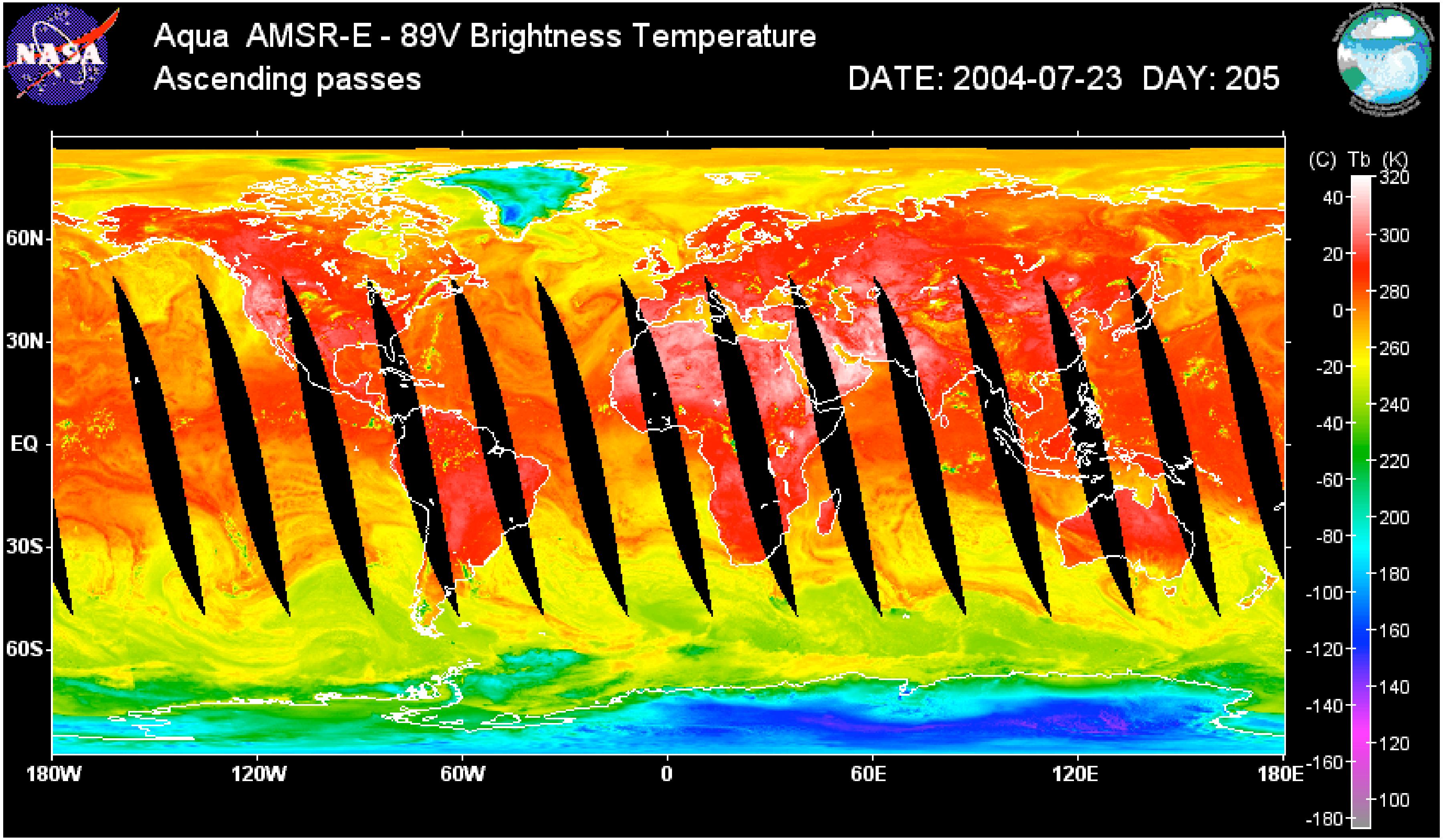


Christian Kummerow
Colorado State Univ.

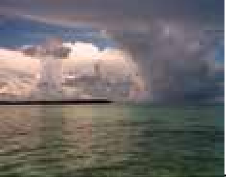
7th Workshop of International Precipitation Working Group
November 18, 2014
Tsukuba, Japan



Passive Microwave Remote Sensing



http://nsidc.org/data/amsre/data_summaries



Microwave Radiation

Plank Function:

$$B_\lambda(T) = \frac{2hc^2}{\lambda^5\left[e^{\frac{hc}{k\lambda T}} - 1\right]}$$

Rayleigh-Jeans Approximation:

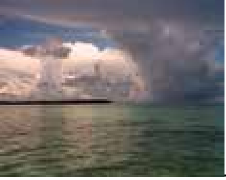
$$B_\lambda(T) = \frac{2ckT}{\lambda^4}$$

Observed Radiance:

$$I_\lambda = \varepsilon_\lambda \cdot B_\lambda(T)$$

Observed Brightness Temperature:

$$Tb_\lambda \propto \varepsilon_\lambda \cdot T$$



Microwave Radiation

$$\varepsilon_{ocean} \approx 0.5$$

$$\varepsilon_{land} \approx 0.9$$

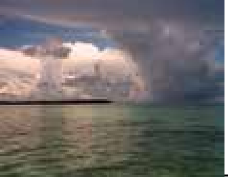
$$\varepsilon_{ice} \approx 0.5$$

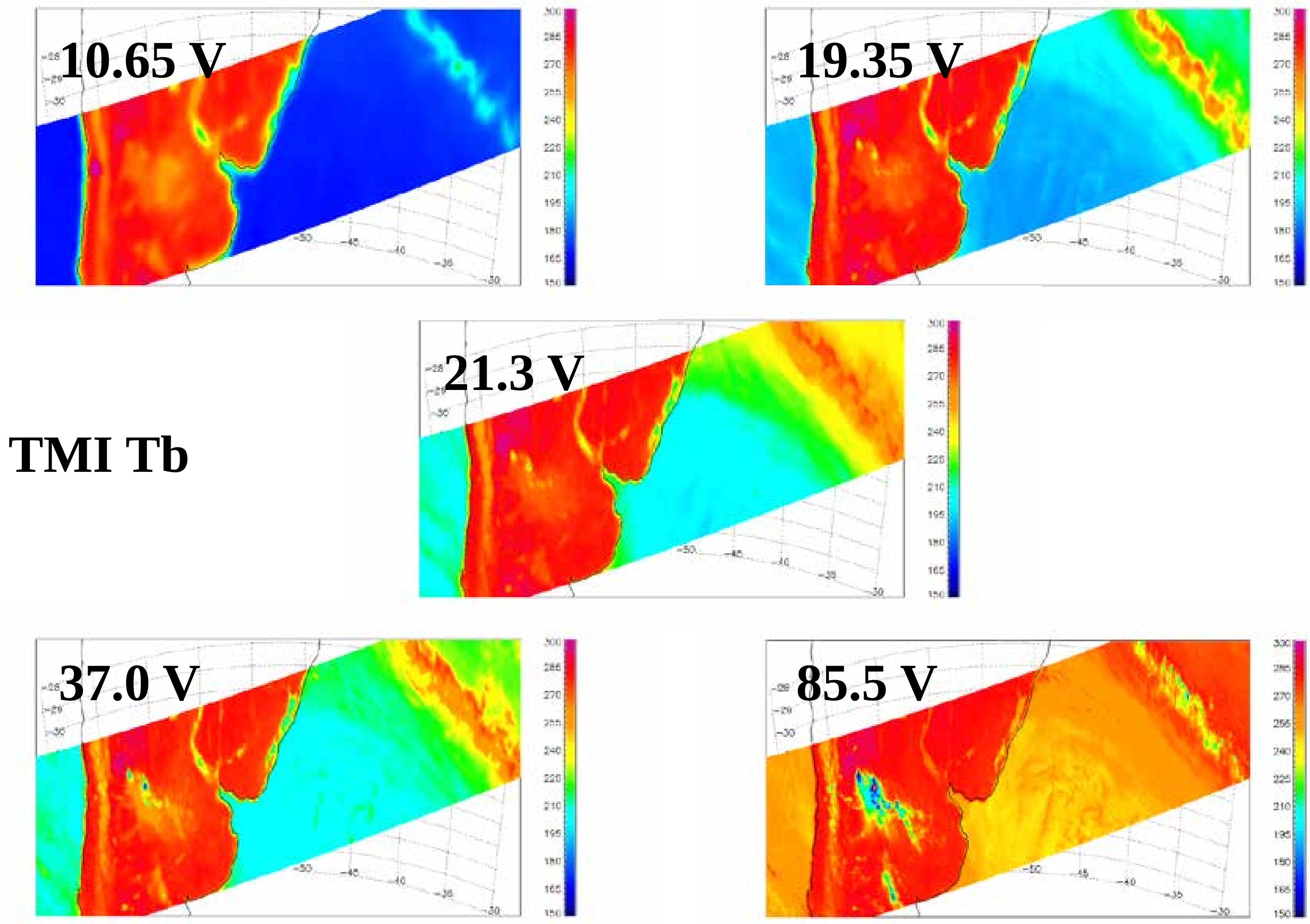
Water is a strong absorber/emitter in microwave regime

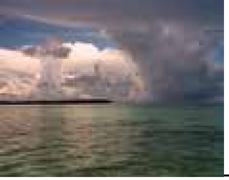
Snow/ice crystals do not absorb, but scatter radiation

Absorption & scattering increase with frequency

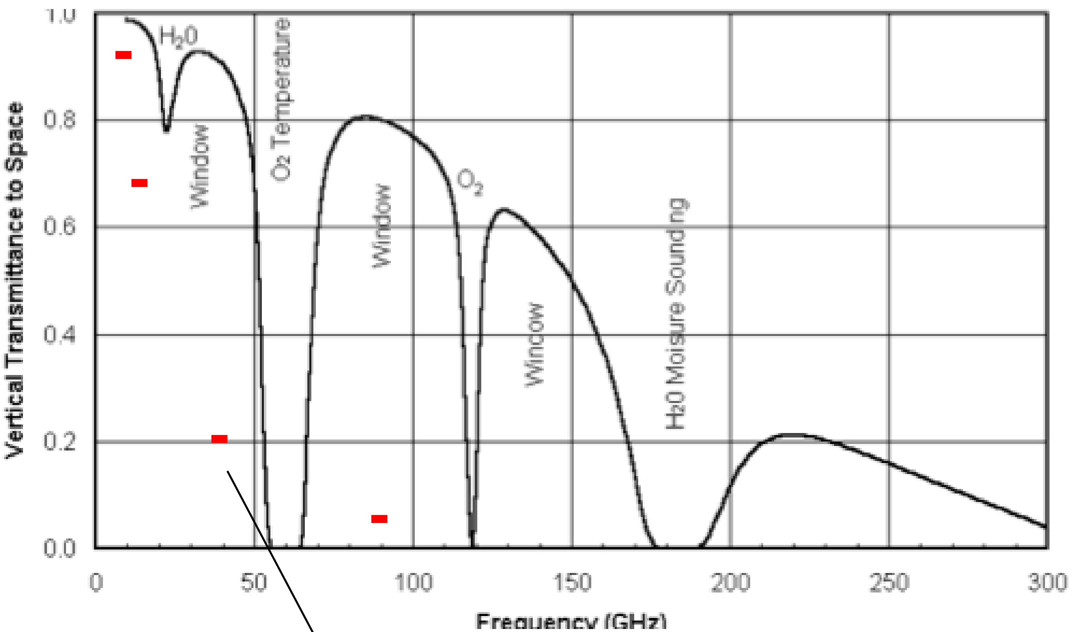
Microwave Radiation

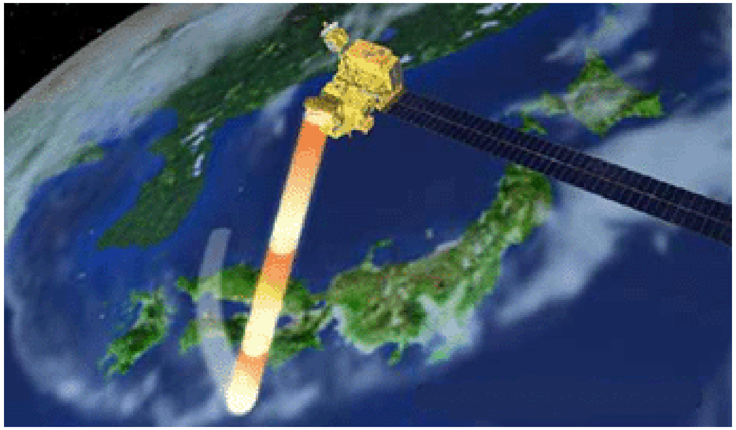




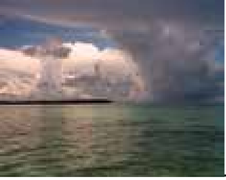


Gas Absorption

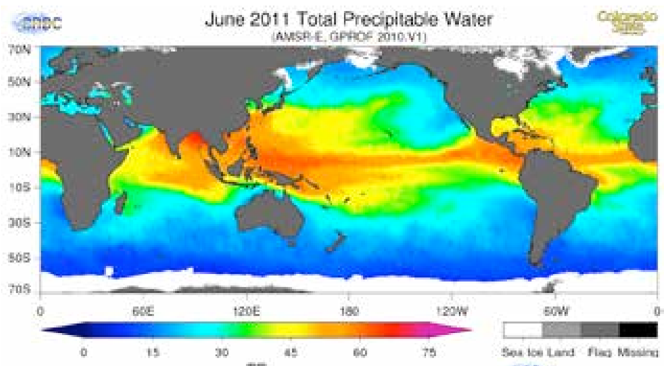




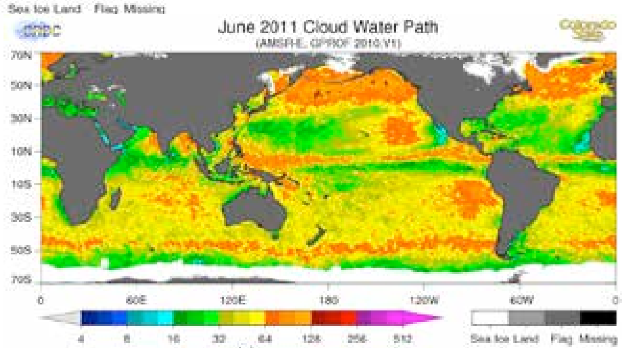
5 mm/hr rain at 37 Ghz



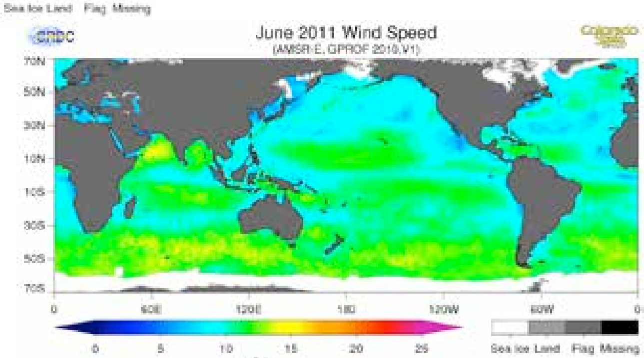
Physical retrievals - Oceans



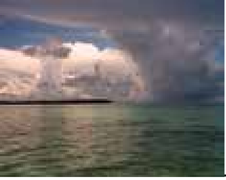
Water Vapor



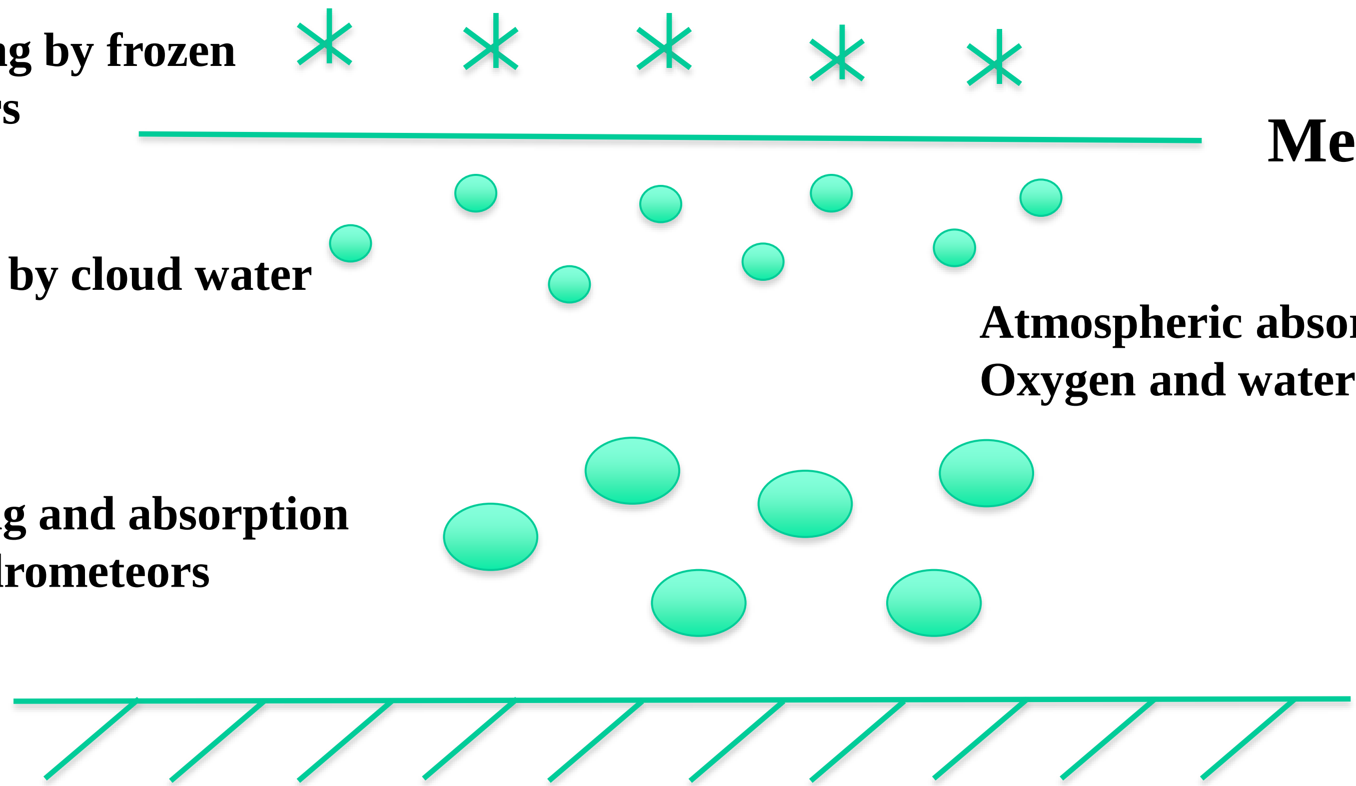
Cloud Water



Wind



Absorption, Emission, & Scattering



Mie scattering by frozen hydrometeors

Melting layer

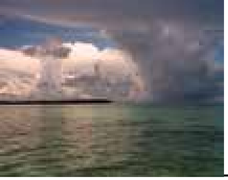
Absorption by cloud water

Atmospheric absorption by Oxygen and water vapor

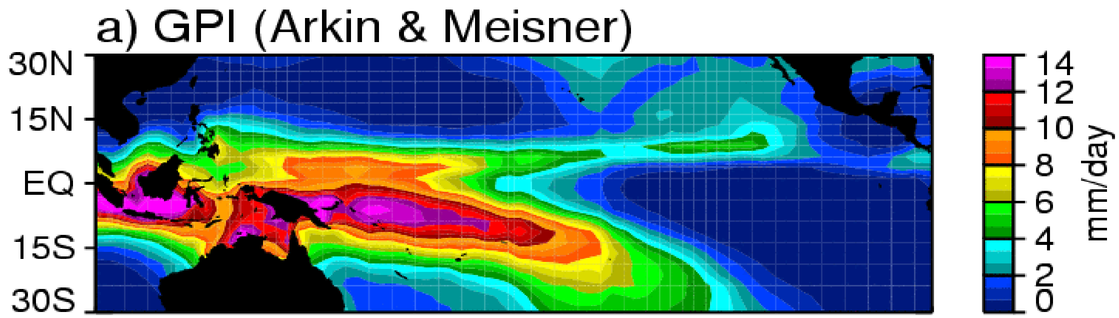
Mie scattering and absorption by liquid hydrometeors

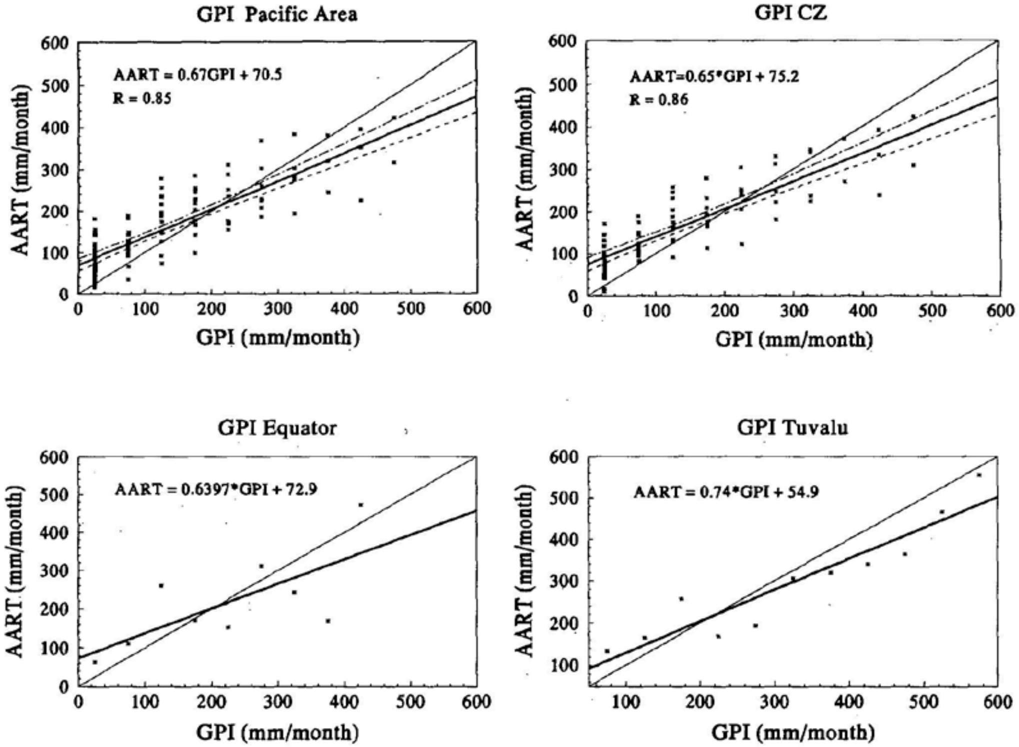
Surface emissivity: **Salinity, SST, wind speed, foam**

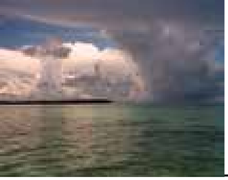
Soil type, soil moisture, vegetation



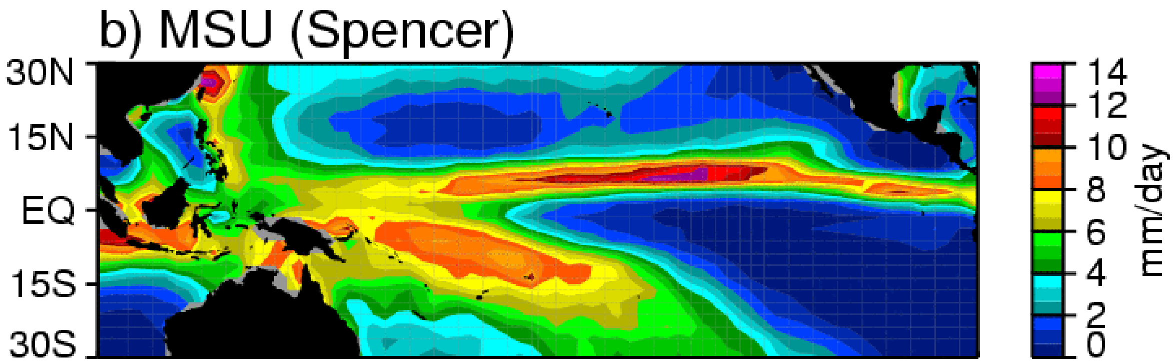
GPI


a) GPI (Arkin & Meisner)
30N
15N
EQ
15S
30S
14
12
10
8
6
4
2
0
mm/day

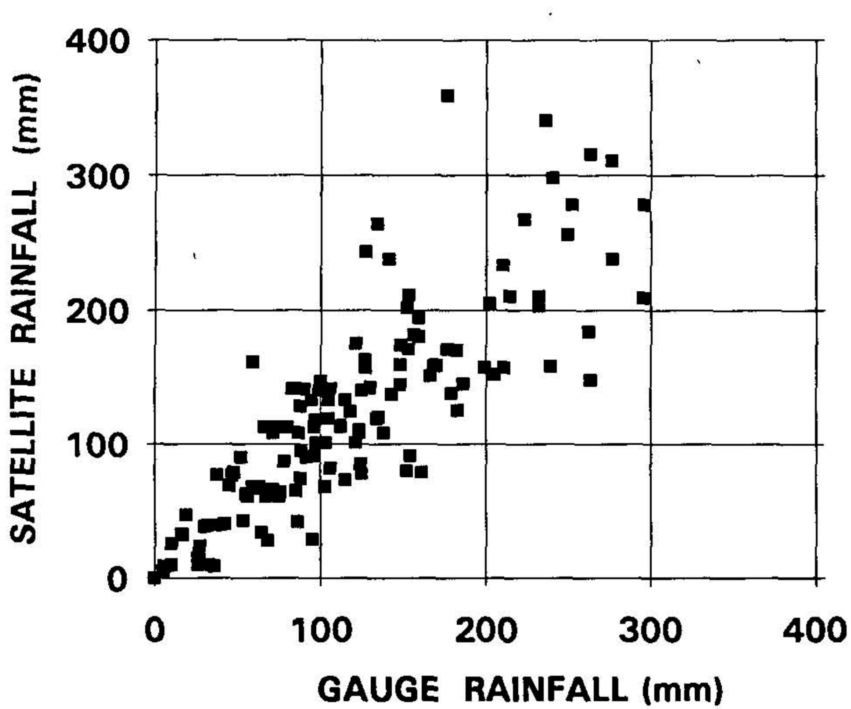

GPI Pacific Area
AART = 0.67GPI + 70.5
R = 0.85
AART (mm/month)
GPI (mm/month)
GPI CZ
AART=0.65*GPI + 75.2
R = 0.86
AART (mm/month)
GPI (mm/month)
GPI Equator
AART = 0.6397*GPI + 72.9
AART (mm/month)
GPI (mm/month)
GPI Tuvalu
AART = 0.74*GPI + 54.9
AART (mm/month)
GPI (mm/month)



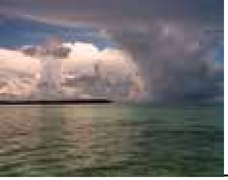
MSU



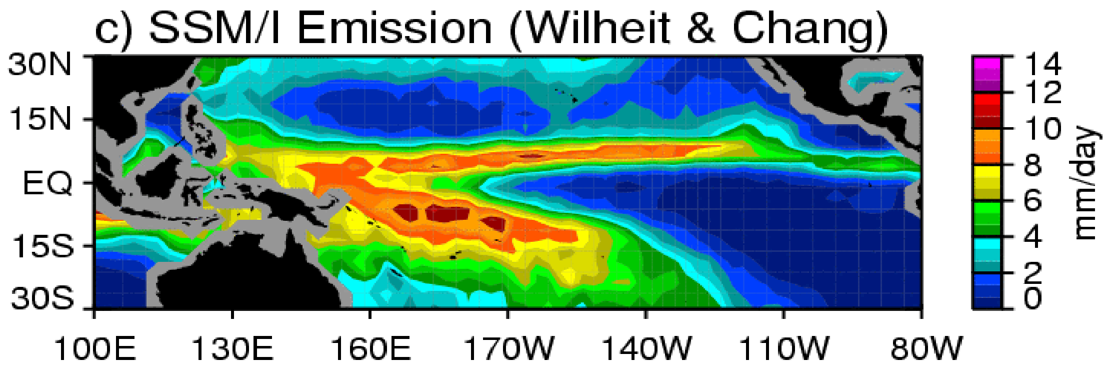
b) MSU (Spencer)
30N
15N
EQ
15S
30S
14
12
10
8
6
4
2
0
mm/day



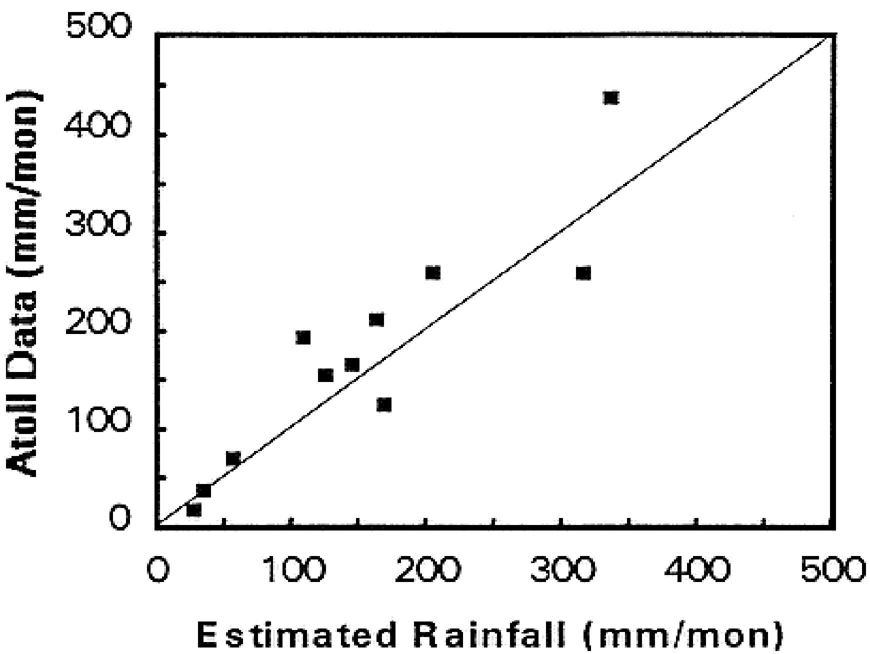
400
300
200
100
0
SATELLITE RAINFALL (mm)
0
100
200
300
400
GAUGE RAINFALL (mm)



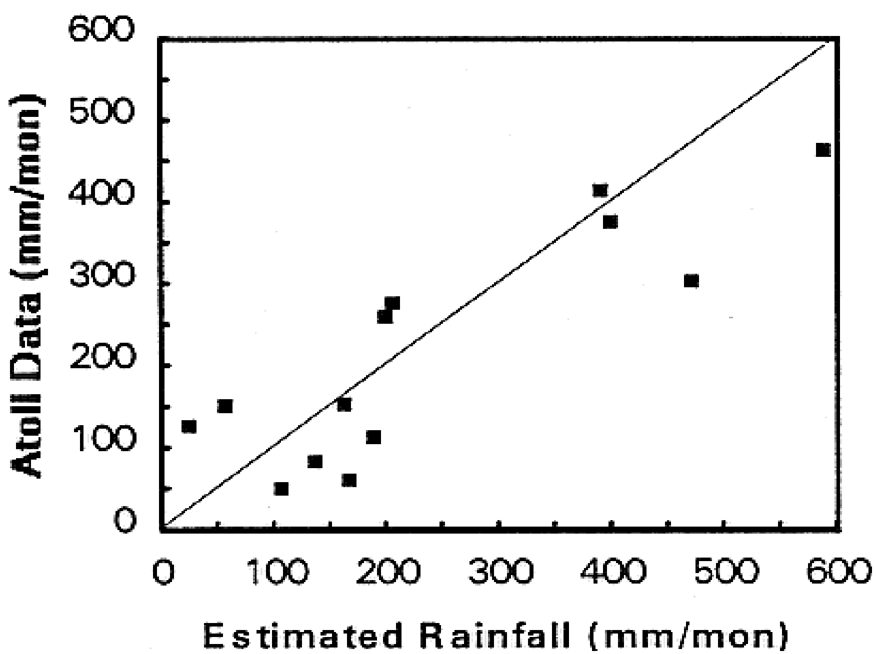
SSM/I

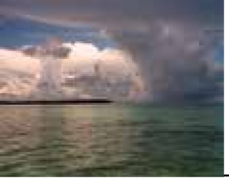


Sept. 1987



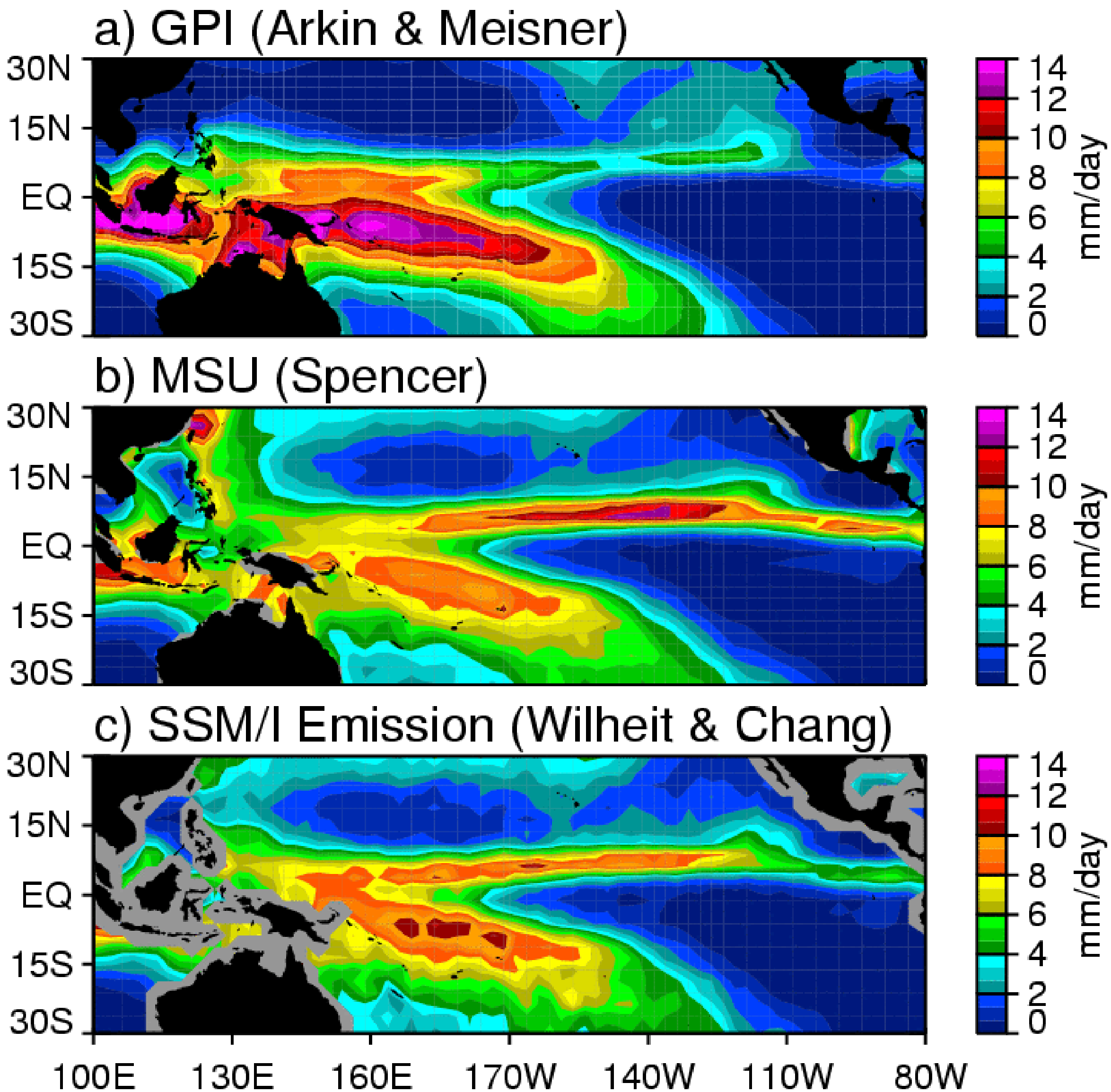
JAS, 1987



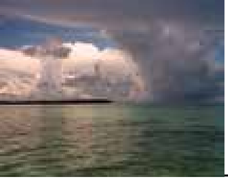


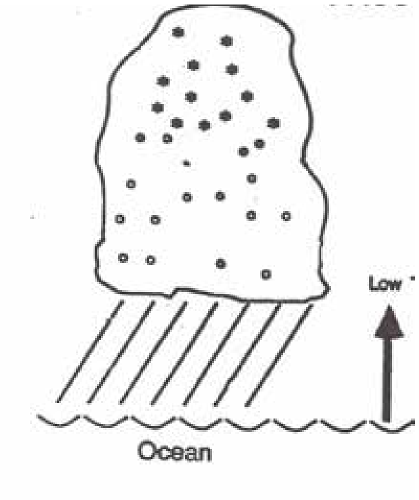
Satellite Rainfall Biases

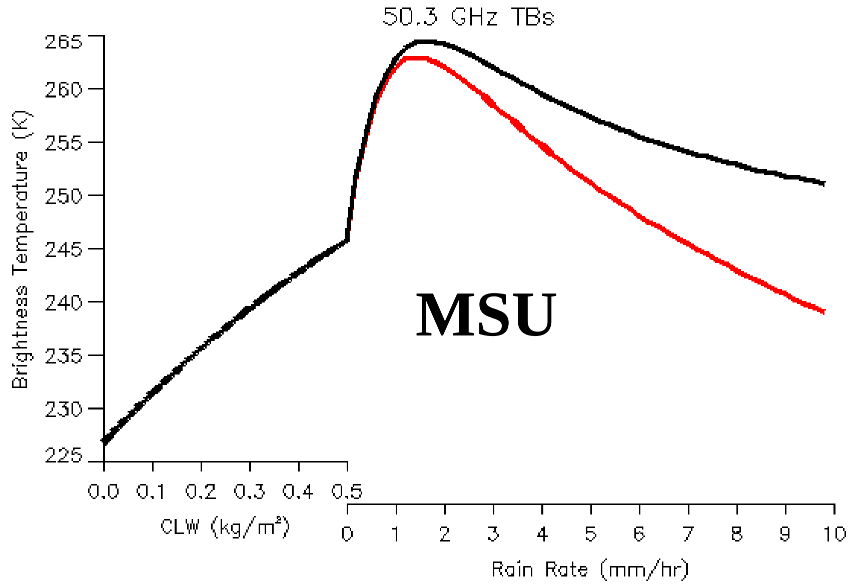
Mean DJF Rainfall (1987 – 1996)

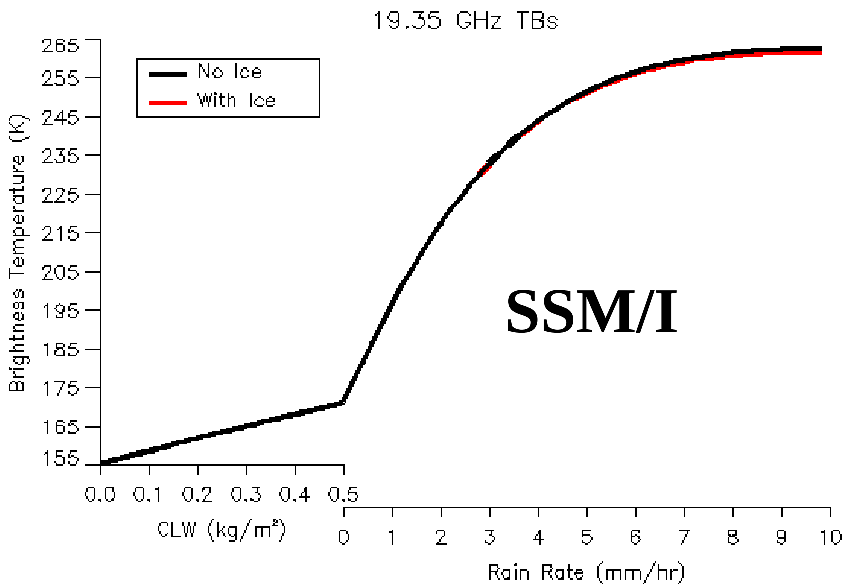


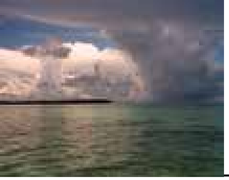
Relationship between Tb and Rainfall



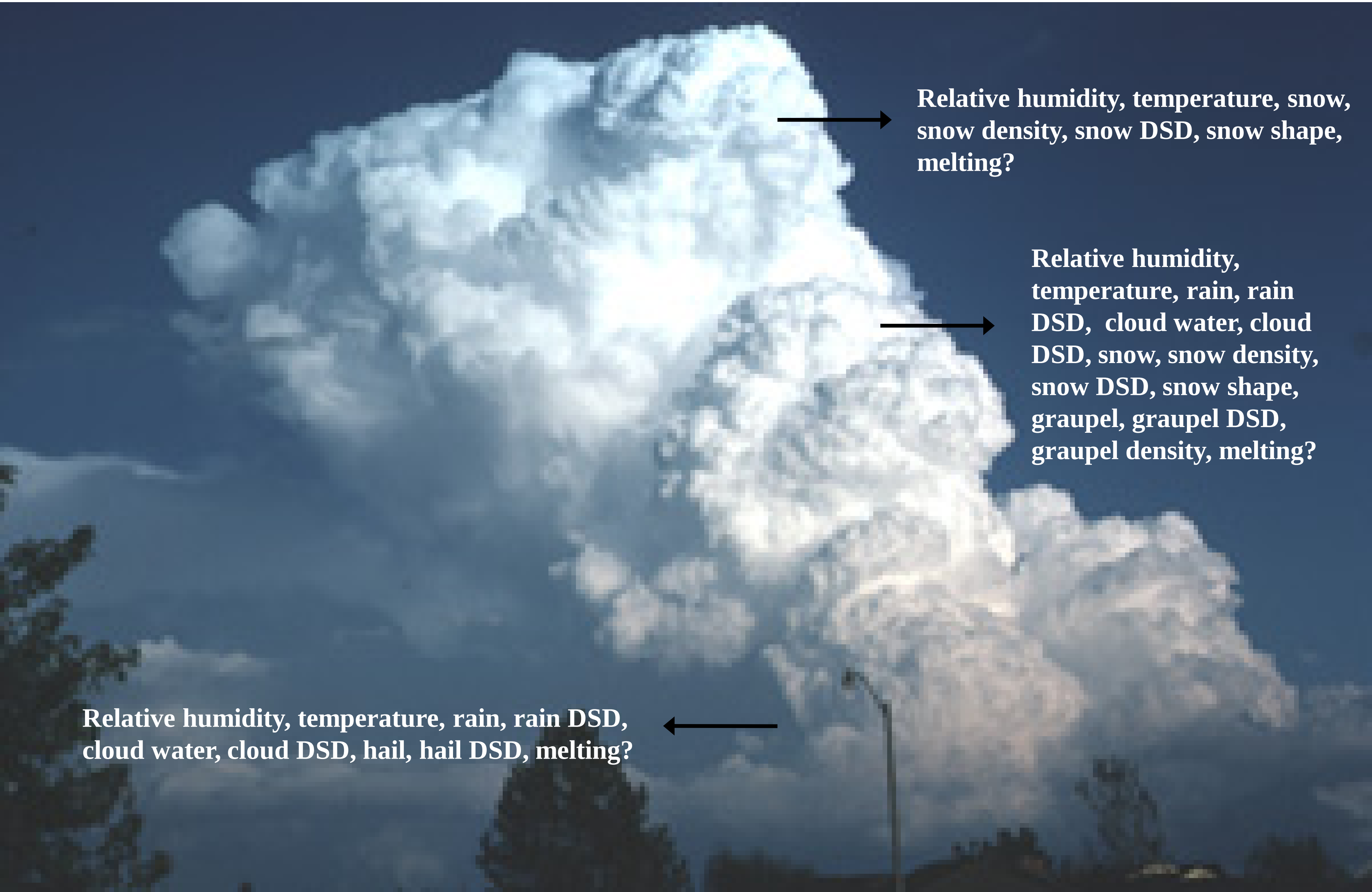


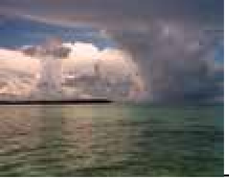




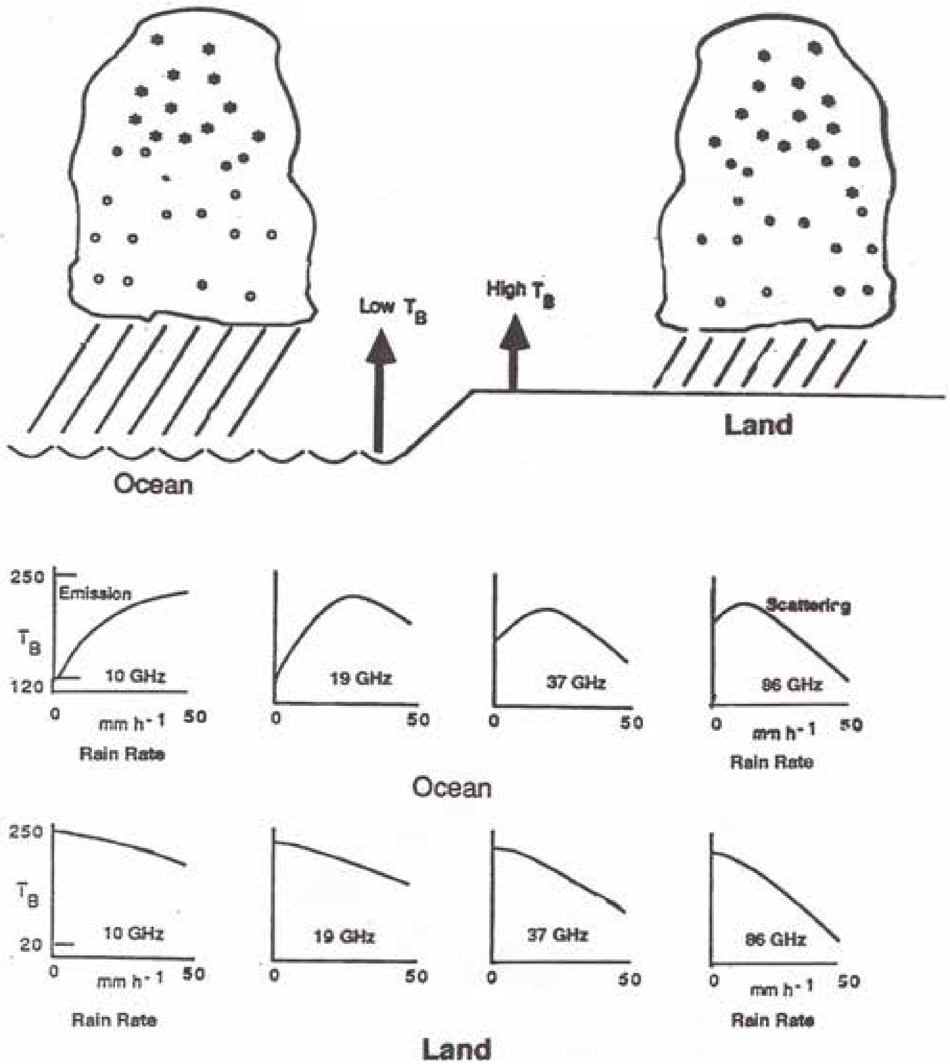


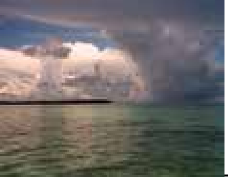
Real Clouds are Complicated





Passive Microwave Signatures (Ocean vs Land)





Rainfall Algorithms

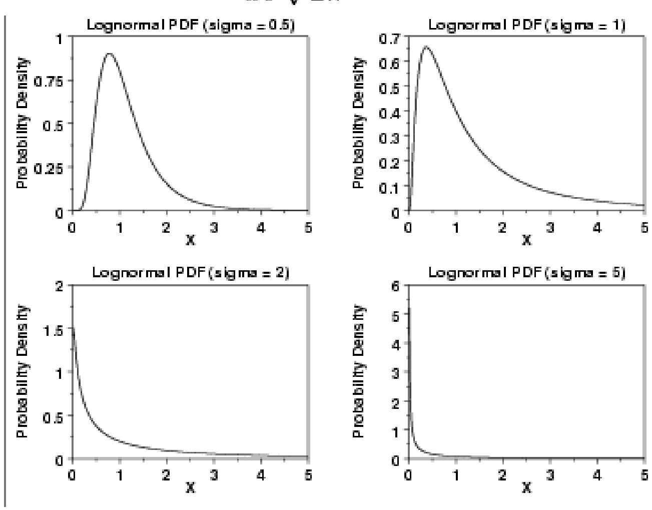
Under-constrained Solutions

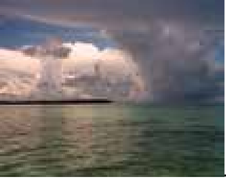
Ocean vs Land (Emission vs Scattering)

Mixed Lognormal PDF of Rain (Rain – NoRain)

Inter-satellite Consistency

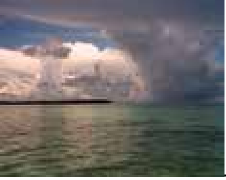
$$f_X(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}, \quad x > 0$$



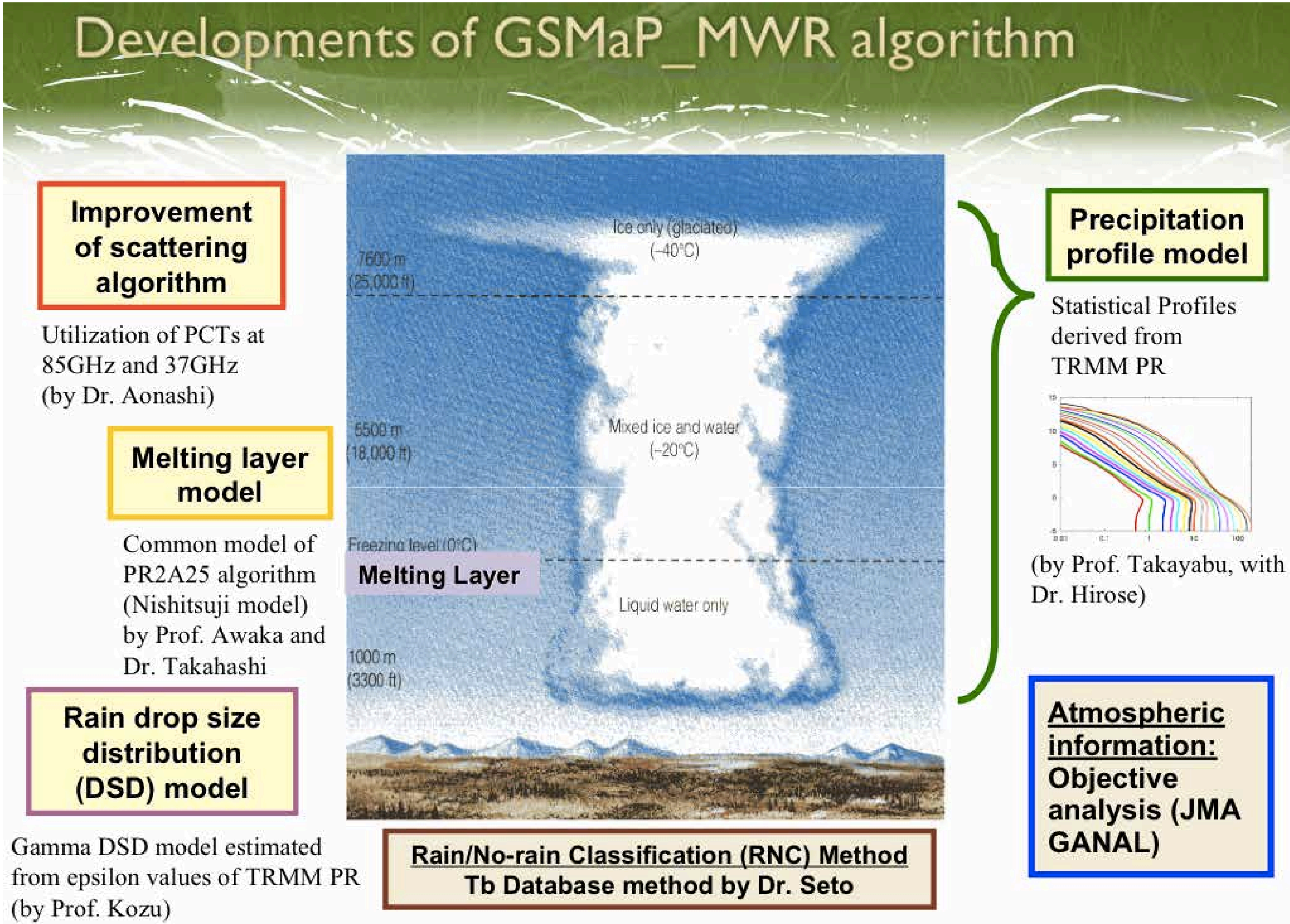


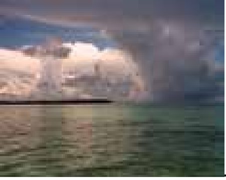
Types of Algorithms - Regression

- **Need to construct a cloud w. various rain rates**
- **Need to decide what to vary with rain and what to vary independently (co-variance)**
- **Generally need to decide if raining or not raining before applying regression.**
- **Because of poor knowledge of land background, use only high frequency scattering signal. Mask cold surfaces.**



Types of Algorithms - Regression





Minimum Variance Framework

$$y = f(x, b)$$

$$\Phi = (y - f(x,b))$$

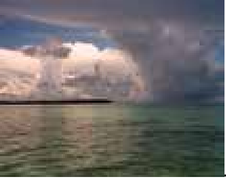
$y =$ Observed Brightness Temperatures (Tbs)

$x =$ State Vector (precipitation water)

$b =$ Forward Model Parameters (SST, total precipitable water, surface wind speed, integrated cloud liquid water, ice particles)

$f =$ Forward Model (operates on x and b)

Goal: Minimize F (e.g. **find *x* that yields forward computed Tbs which agree with observed Tbs**



Optimal Estimation Framework

$$y = f(x,b) + \varepsilon_b + \varepsilon_y$$

$y =$ **Observed Brightness Temperatures (TBs)**

$\varepsilon_b,\ \varepsilon_y =$ **Error Term (model parameter, measurement error)**

$x =$ **State Vector (total precipitable water, TPW;**

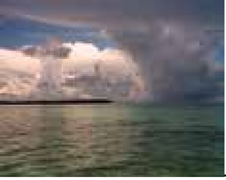
s urface wind speed, WIND;

i ntegrated cloud liquid water, LWP)

$b =$ **Forward Model Parameters (i.e. Scale Height, Lapse Rate, SST)**

$f =$ **Forward Model (operates on x and b)**

***Goal*: Find x that yields forward computed TBs which agree with observed TBs within allotted error range**



Optimal Estimation

$$y = f(x,b) + \varepsilon_b + \varepsilon_y$$

Minimize cost function:

$$\Phi = \underbrace{(y - f(x,b))^{\mathbf{T}} S_Y^{-1} (y - f(x,b))}_{\textbf{TERM 1}} + \underbrace{(x - x_A)^{\mathbf{T}} S_A^{-1} (x - x_A)}_{\textbf{TERM 2}}$$

Minimize Differences between Observed and Simulated TBs

$S_Y =$ **Errors in Measurements and Model**

***No Off-Diagonal Elements**

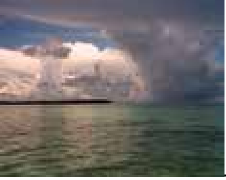
***1-2% Error for Each TB Channel**

Minimize Differences between *a priori* and retrieved states

$S_A =$ **Errors in** x_a

***No Off-Diagonal Elements**

***50-100% Error for *a priori* TPW, WIND and LWP**



Minimization

- Equate Gradient ∇_x of Cost Function Φ to zero.

- Solution x is found in an iterative manner using $\nabla_x \Phi$ in Framework analogous to Newton's Method.

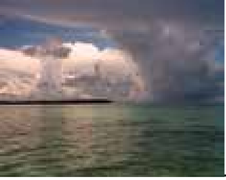
$$x_{i+1} = x_i + (S_a^{-1} + K_i^T S_y^{-1} K_i)^{-1} [K_i^T S_y^{-1} (y - f(x_i, b)) - S_a^{-1} (x_i - x_a)]$$

where $K = \dfrac{df}{dx}$

Solution x $\longrightarrow$ $K \quad S_a \quad S_y$

Retrieval Error (S_X) $\longrightarrow$ $(S_a^{-1} + K_i^T S_y^{-1} K_i)^{-1}$

****Details on Optimal Estimation Methodology Can Be Found Rodg**



MIRS Concept

Variational Assimilation Retrieval (1DVAR)

CRTM as forward operator, validity-> clear, cloudy and precip conditions

Emissivity spectrum is part of the retrieved state vector

Algorithm valid in all-weather conditions, over all-surface types

Cloud & Precip profiles retrieval (no cloud top, thickness, etc)

EOF decomposition

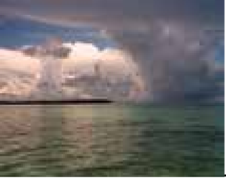
Sensor-independent

Highly Modular Design

Flexibility and Robustness

Selection of Channels to use, parameters to retrieve

Modeling & Instrumental Errors are input to algorithm



Cost Function Minimization

- Cost Function to Minimize:

$$\boxed{J(X)=\left[\frac{1}{2}(X-X_0)^T\times B^{-1}\times(X-X_0)\right]+\left[\frac{1}{2}\left(Y^m-Y(X)\right)^T\times E^{-1}\times\left(Y^m-Y(X)\right)\right]}$$

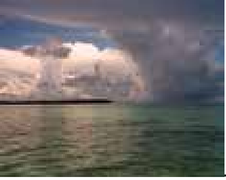
- To find the optimal solution, solve for: $\frac{\partial J(X)}{\partial X}=J'(X)=0$
- Assuming Linearity $y(x)=y(x_0)+K\left[x-x_0\right]$
- This leads to iterative solution:

$$\boxed{\Delta X_{n+1}=\left\{\left(B^{-1}+K_n^T E^{-1} K_n\right)^{-1} K_n^T E^{-1}\right\}\left[\left(Y^m-Y(X_n)\right)+K_n\Delta X_n\right]}$$

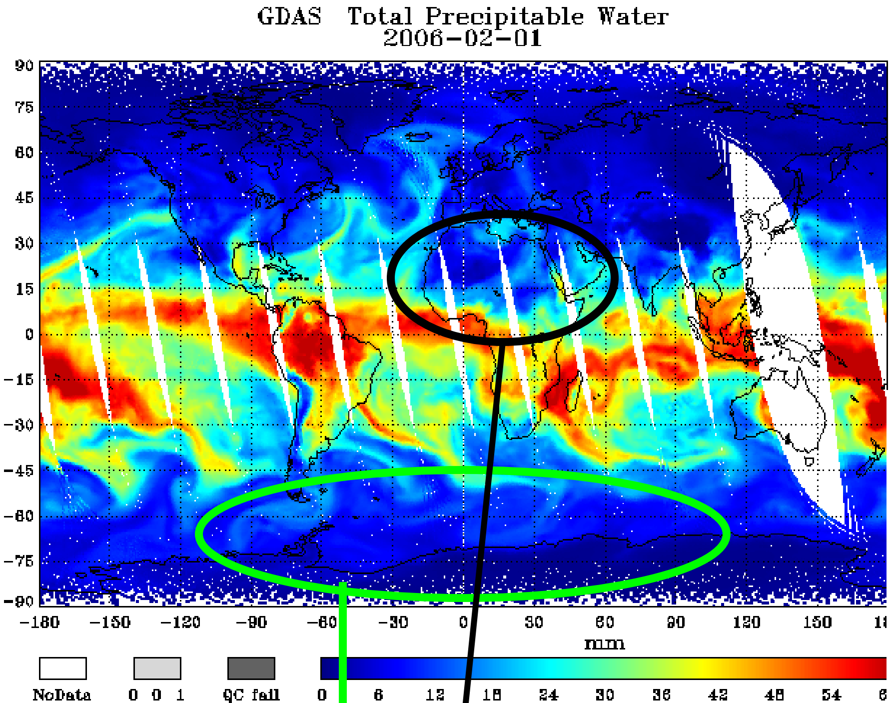
$$\boxed{\Delta X_{n+1}=\left\{B K_n^T\left(K_n B K_n^T+E\right)^{-1}\right\}\left[\left(Y^m-Y(X_n)\right)+K_n\Delta X_n\right]}$$

More efficient
(1 inversion)

Preferred when nChan << nParams (MW)

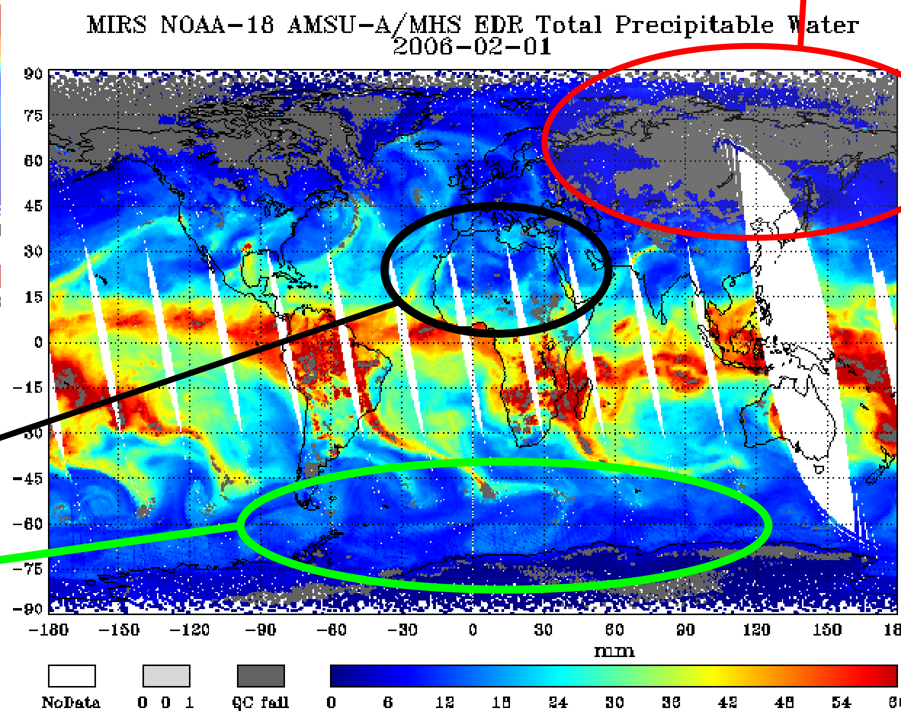


Microwave TPW Extended over Land



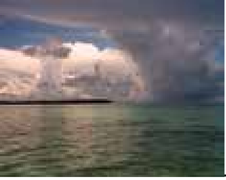
GDAS Analysis

snow-covered surfaces need better handling

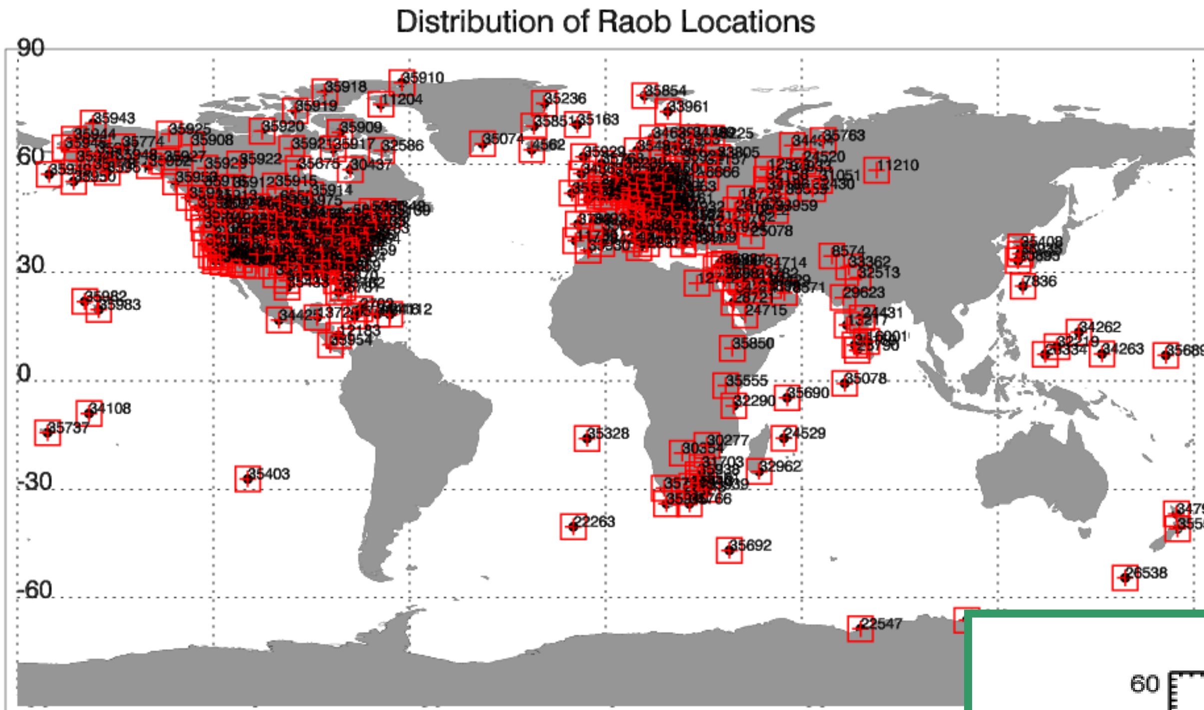


Retrieval over sea-ice and most land areas capturing same features as GDAS

MIRS Retrieval

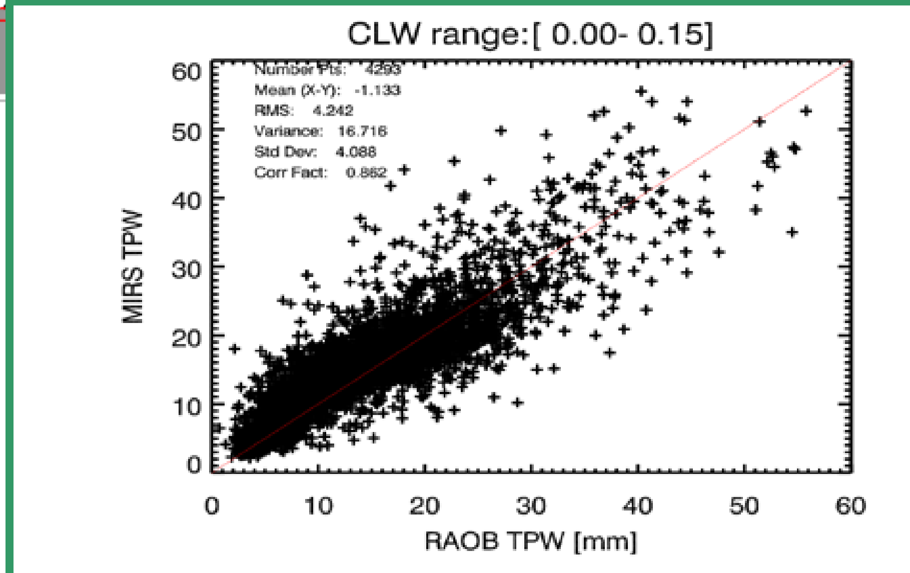


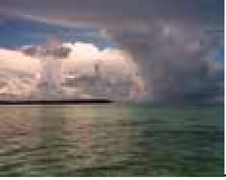
TPW Retrieval over Land



Bias: -1.13 mm

Corr. Factor: 0.86





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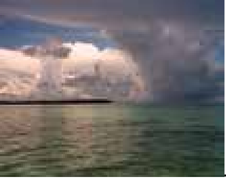
***No Off-Diagonal Elements**

***50-100% Error for *a priori* TPW, WIND and LWP**



Bayesian Retrieval Retrieval

Simplified Bayesian retrieval with assumption that pdf's of both hydrometeor profiles and observations are realistic and representative: $P(\mathbf{R}\,|\,\mathbf{T_b}) \propto P(\mathbf{R}) \times P(\mathbf{T_b}\,|\,\mathbf{R})$

Expected value hydrometeor profile

$$E(\mathbf{w}_j) = \frac{\sum_i \mathbf{w}_i J_i}{\sum_i J_i}, \quad i = 1, n$$

Expected value of errors

$$E(\acute{\mathbf{o}}^2_{\mathbf{w}}) = \frac{\sum_j [\mathbf{w}_j - E(\mathbf{w}_j)]^2 J_j}{\sum_j J_j}, \quad j = 1, n$$

Cost-function

$$J_i = \exp\left\{ -\frac{1}{2} \left[\mathbf{tb}^o - \mathbf{tb}(\mathbf{w}_i)\right]^T (\mathbf{O}+\mathbf{S})^{-1} \left[\mathbf{tb}^o - \mathbf{tb}(\mathbf{w}_i)\right] \right\}$$

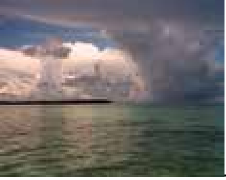
Observed TB-vector

Simulated TB-vector

Observation & modelling error covariance matrix

Quality control:

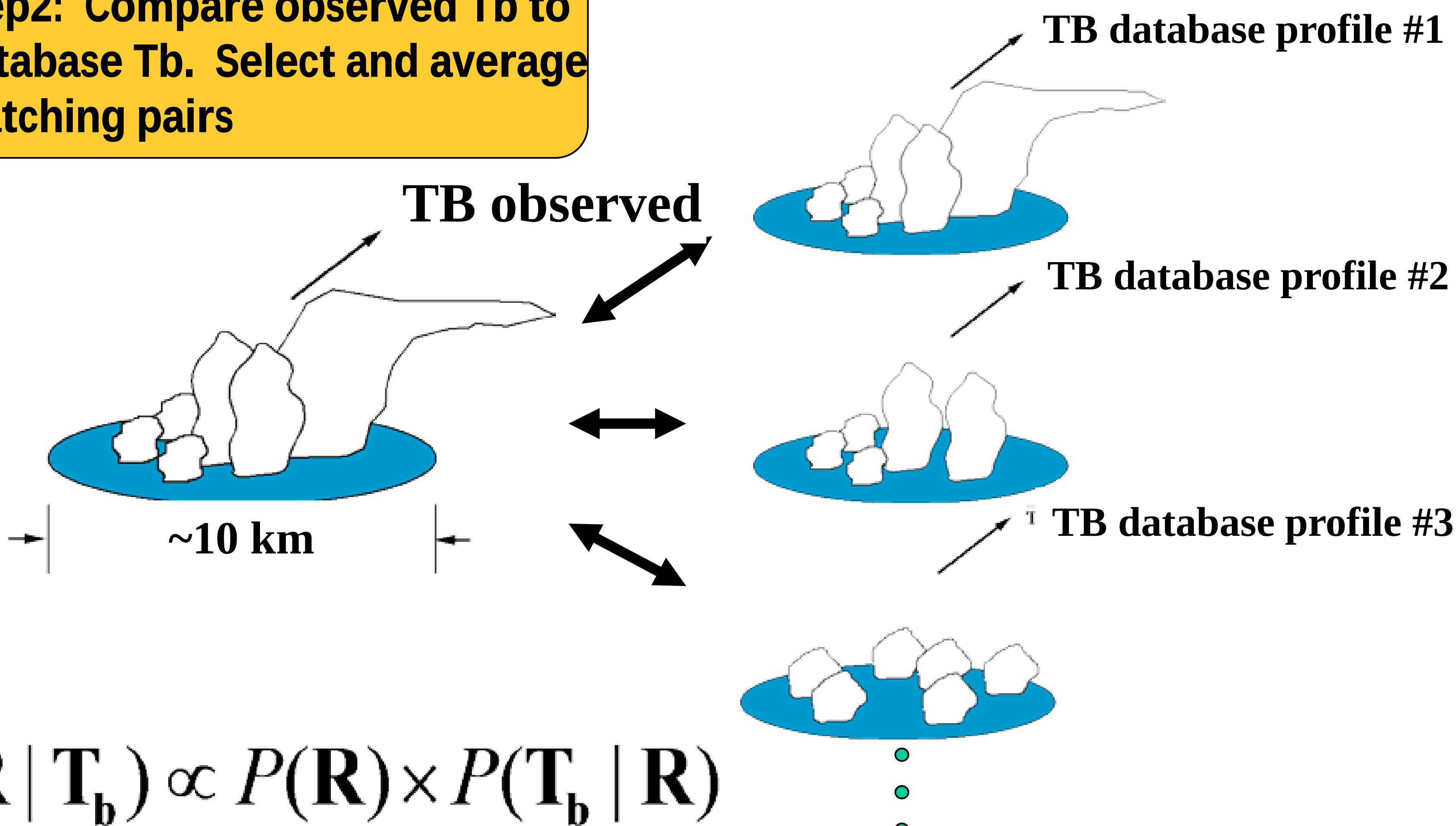
1) Only take profiles with $|\mathbf{tb}_o - \mathbf{tb}(w_i)| < 20$ K;
2) Assume uncorrelated errors (2-5 K);
3) Perform bias-correction using TB-pdf medians/modes.



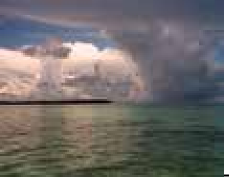
The GPM radiometer algorithm

Step 1: Use TRMM/GPM Satellite to derive set of "Observed" profiles that define an a-priori database of possible rain structures.

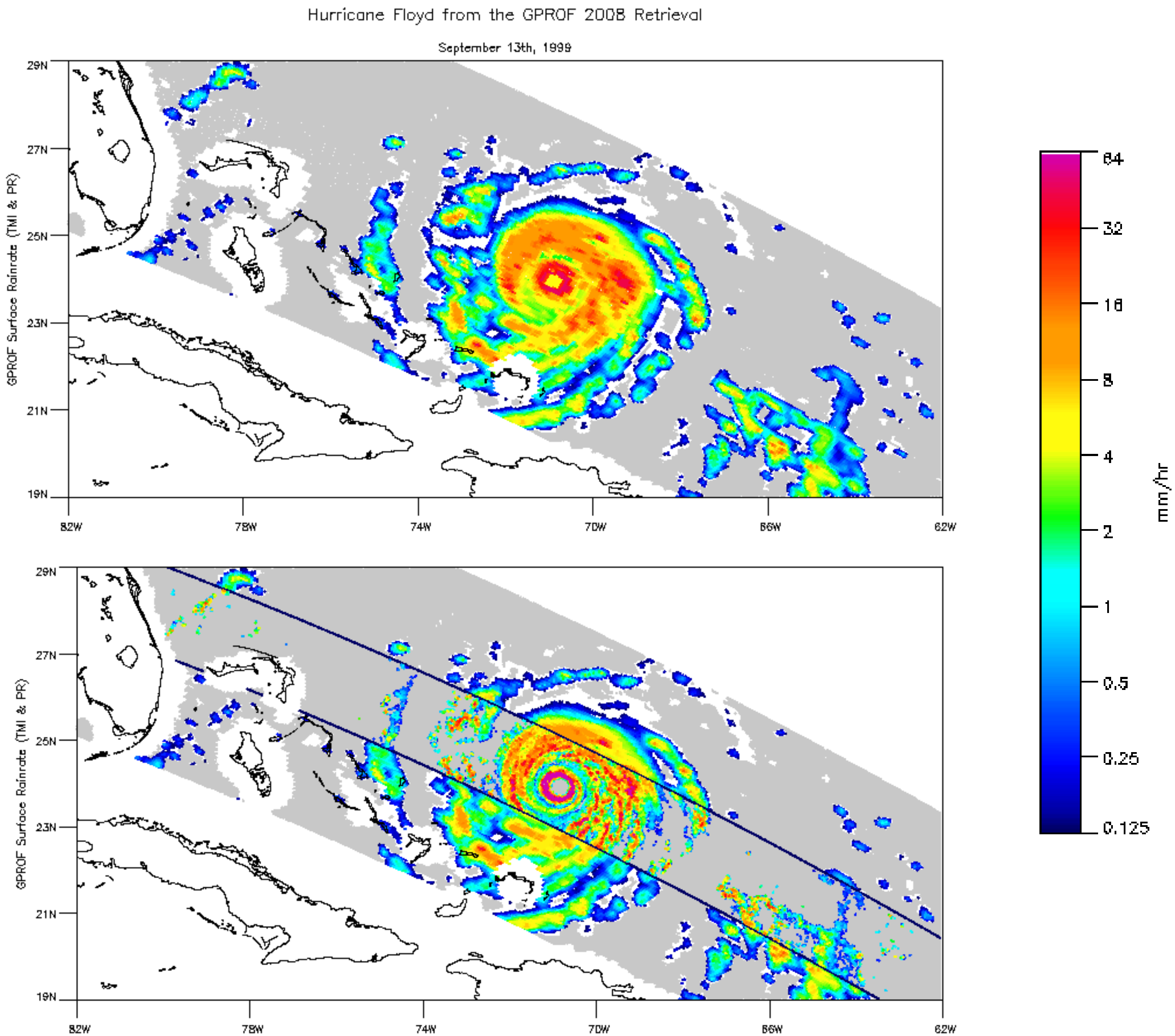
Step2: Compare observed Tb to Database Tb. Select and average matching pairs

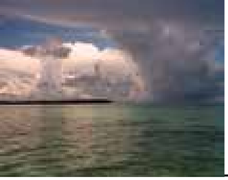


$$P(\mathbf{R}\,|\,\mathbf{T_b}) \propto P(\mathbf{R}) \times P(\mathbf{T_b}\,|\,\mathbf{R})$$

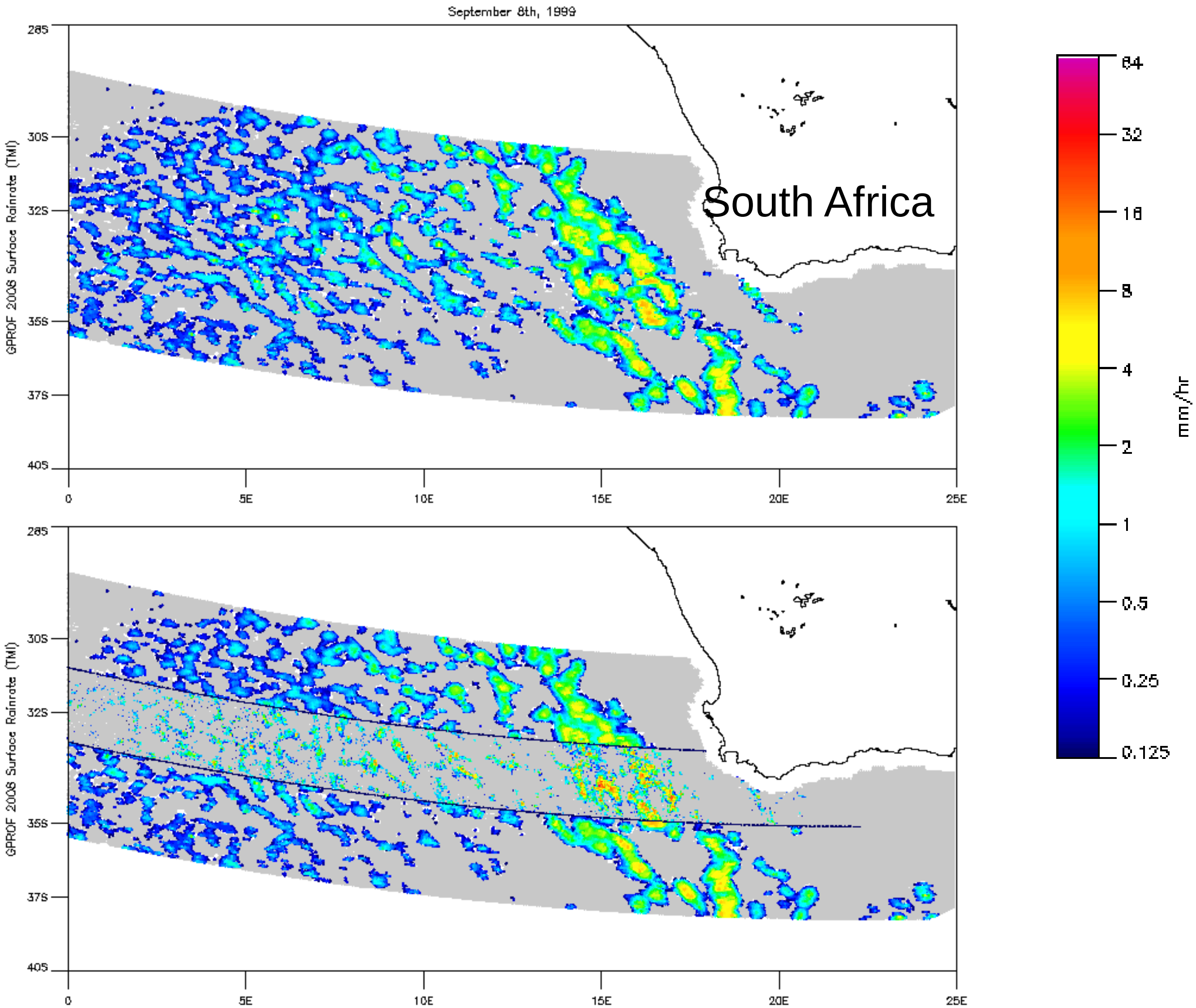


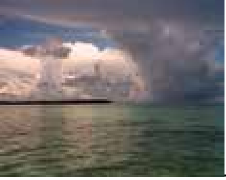
GPROF 2010 w. ideal database



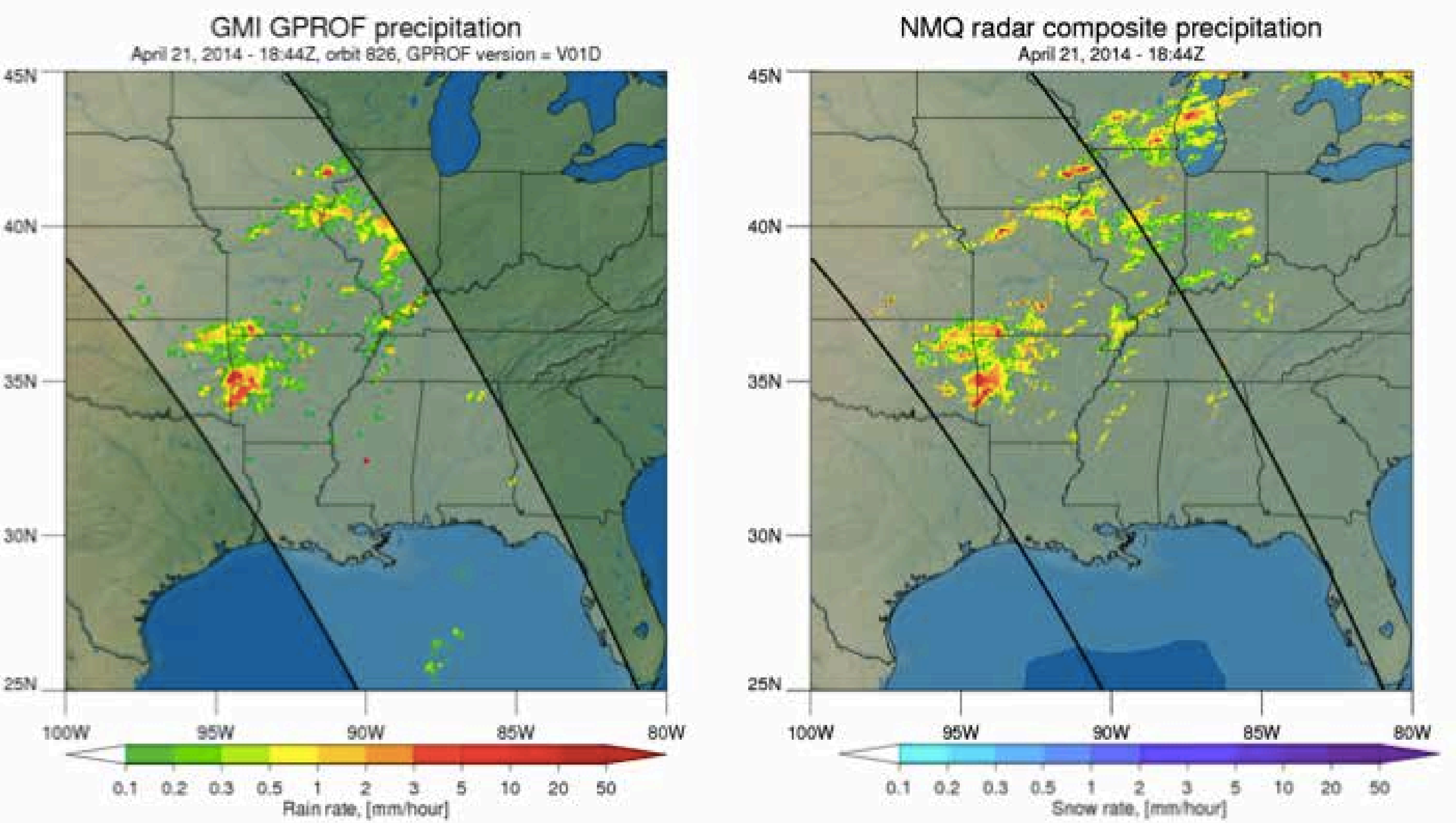


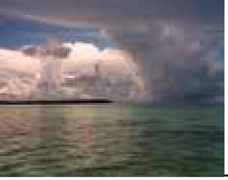
GPROF 2010 w. ideal database



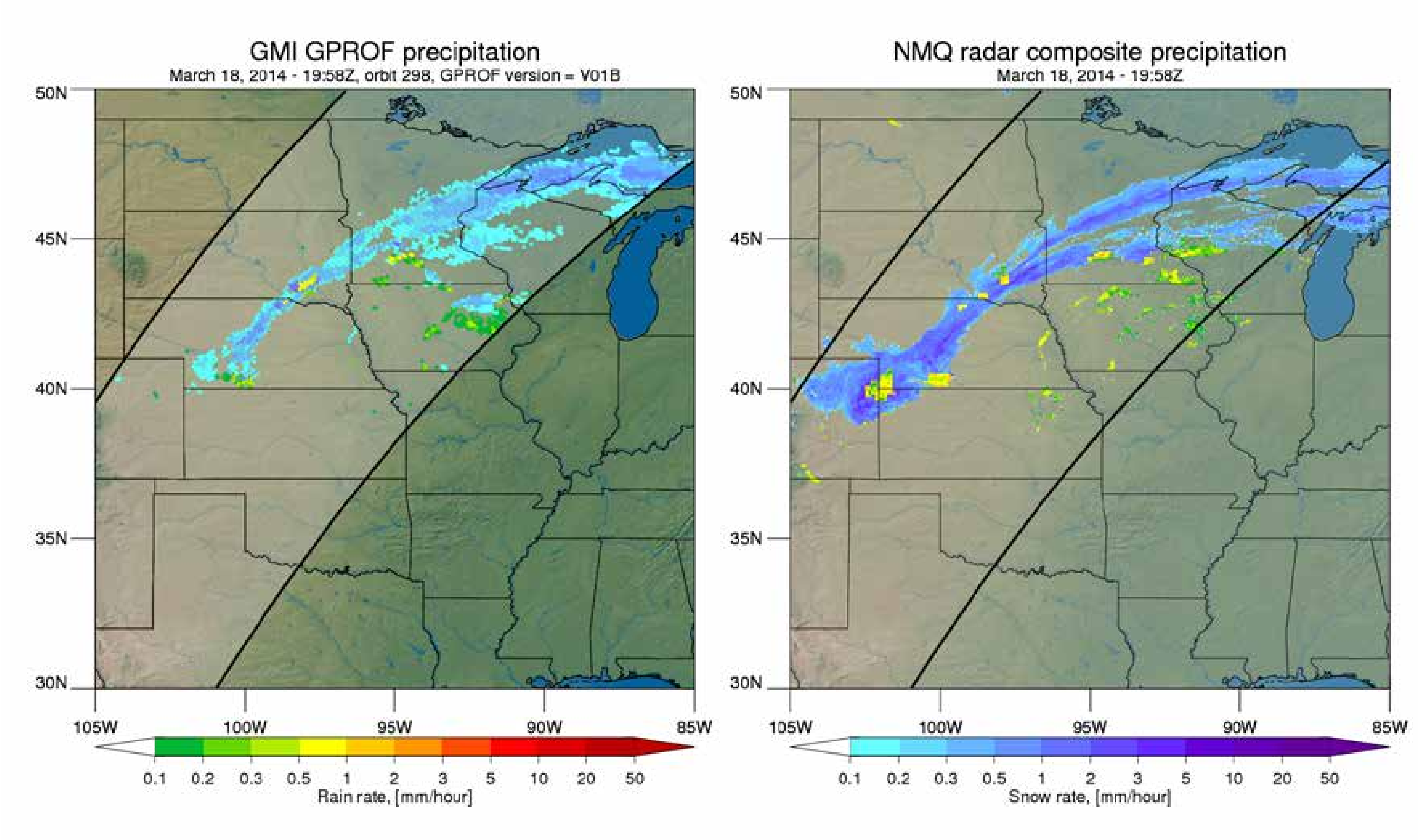


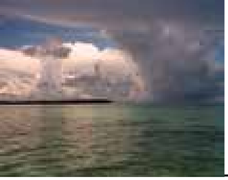
GMI Rainfall



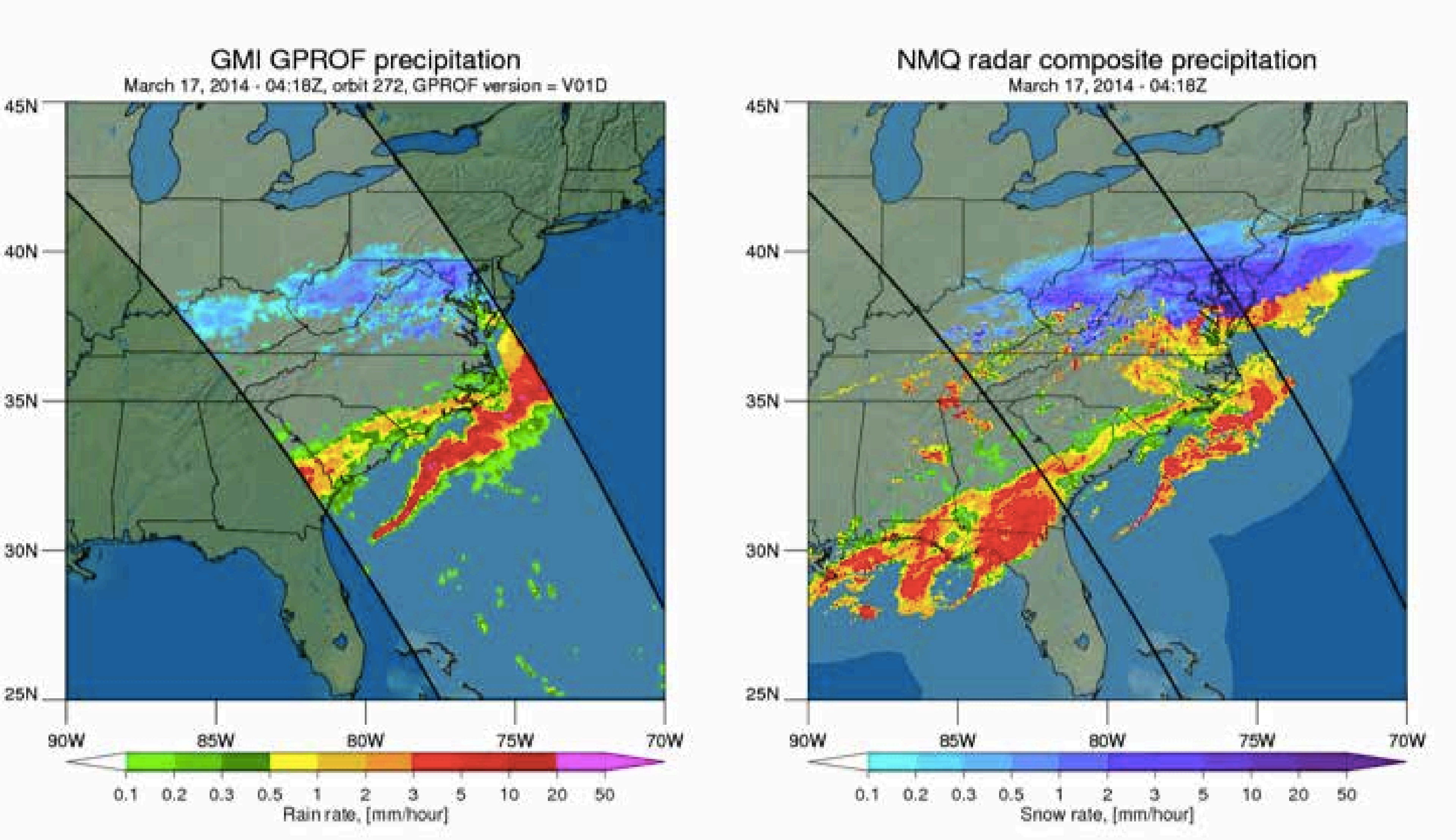


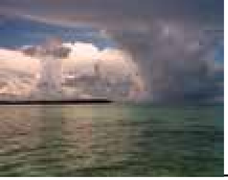
Snow over the United States



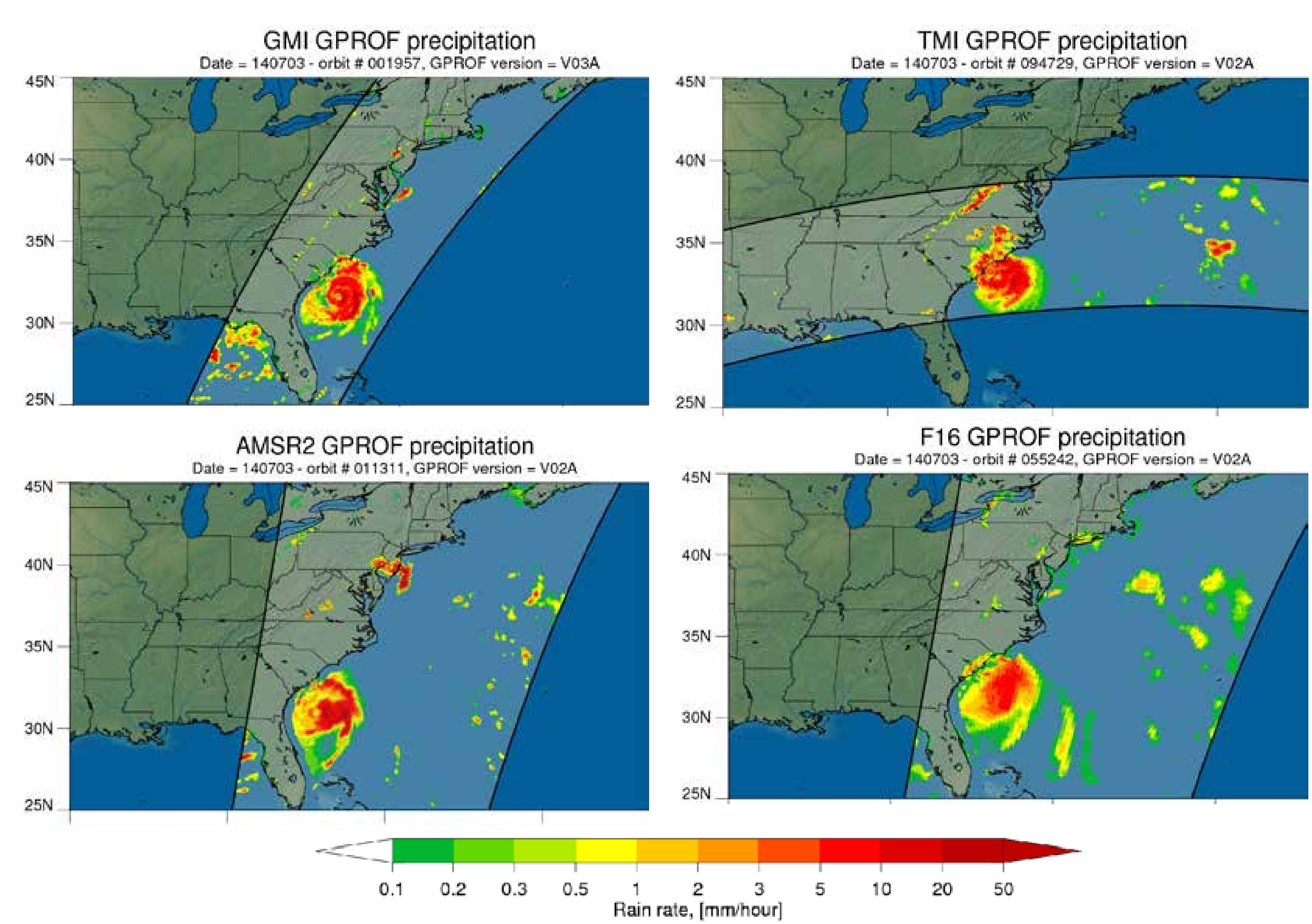


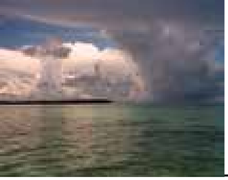
GPROF - GMI V01D (PPS)





*Hurricane **Arthur***



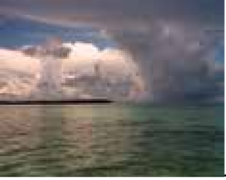


GPROF 2014 V1- V4

Ocean – Same as TRMM. GMI and other sensor databses were computed from physically consistent database of TRMM PR and TMI. Colder regions extended by artificially lowering the freezing level of TRMM observed profiles. Tested for SSMI and AMSR-E before GMI. (Sarah Ringerud, Dave Randel)

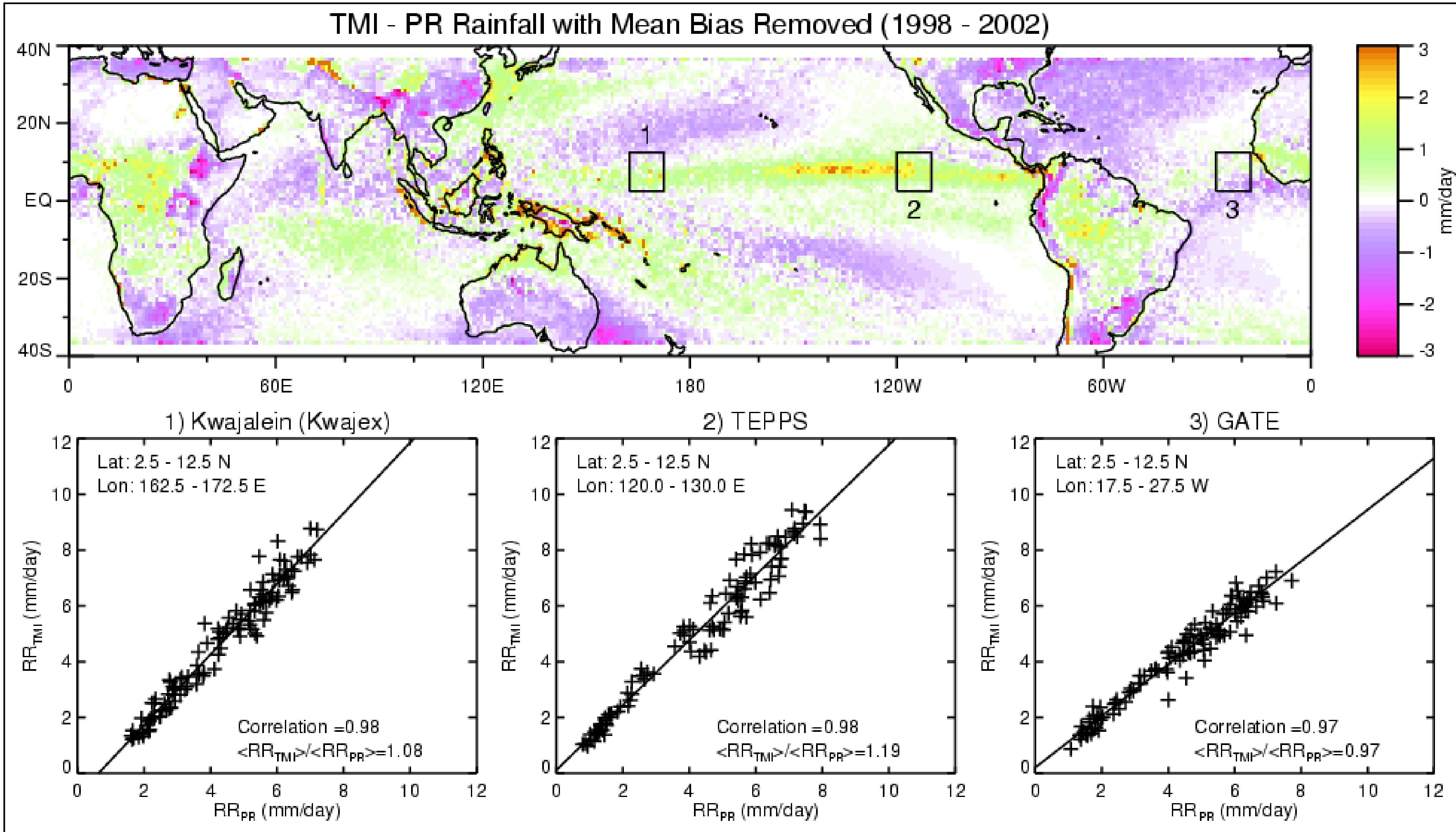
Land – Fundamentally changed algorithms from TRMM. Used surface radar over US (NMQ) to construct databases of observed surface rain and sensor Tb for each radiometer. GMI currently running with SSMIS database. (Pierre Kirstetter, Nai-Yu Wang/Ralph Ferraro)

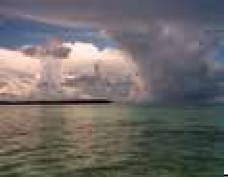
Cold Sfc – Used AMSR2/MHS with CloudSat rain & MMF for physically consistent database. All sensors use AMSR2+MHS channels (Mark Kulie, Karen Mohr, Toshio Matsui)



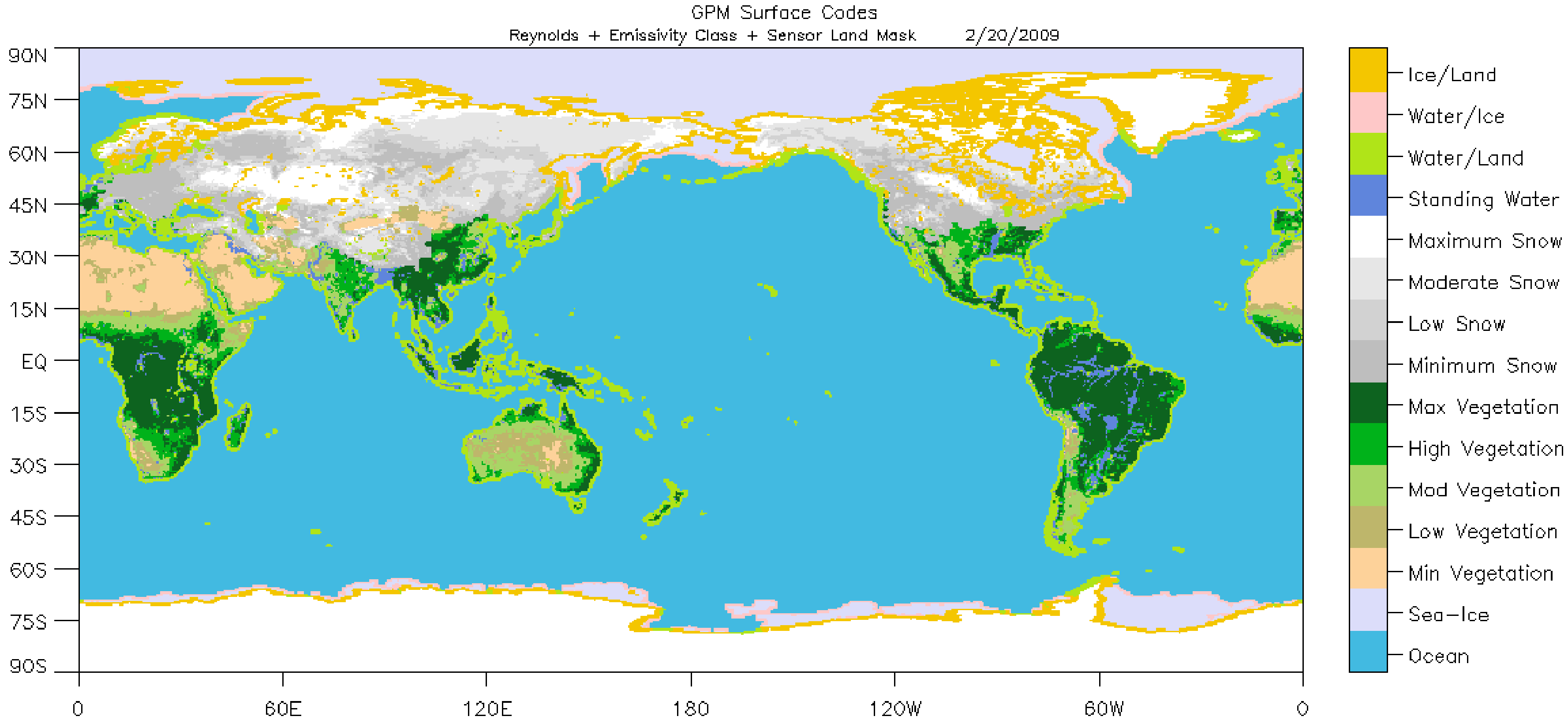
PR/TMI Rainfall Differences

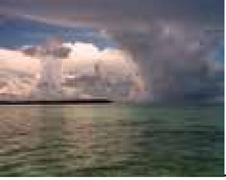
5-year mean Radar (2A25) - Radiometer (2A12)

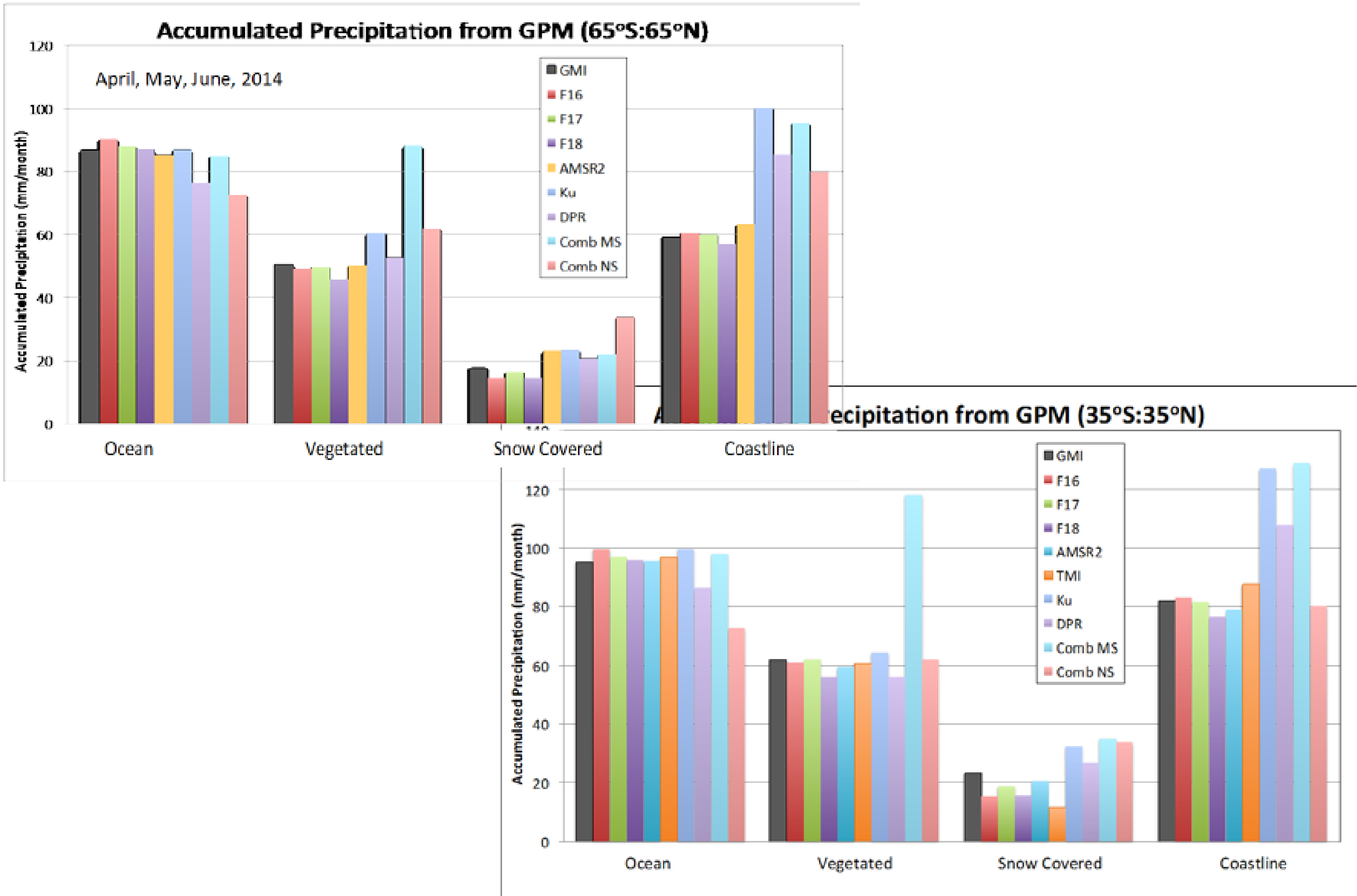




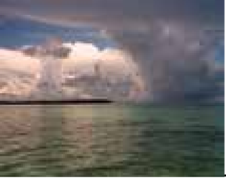
Surface types





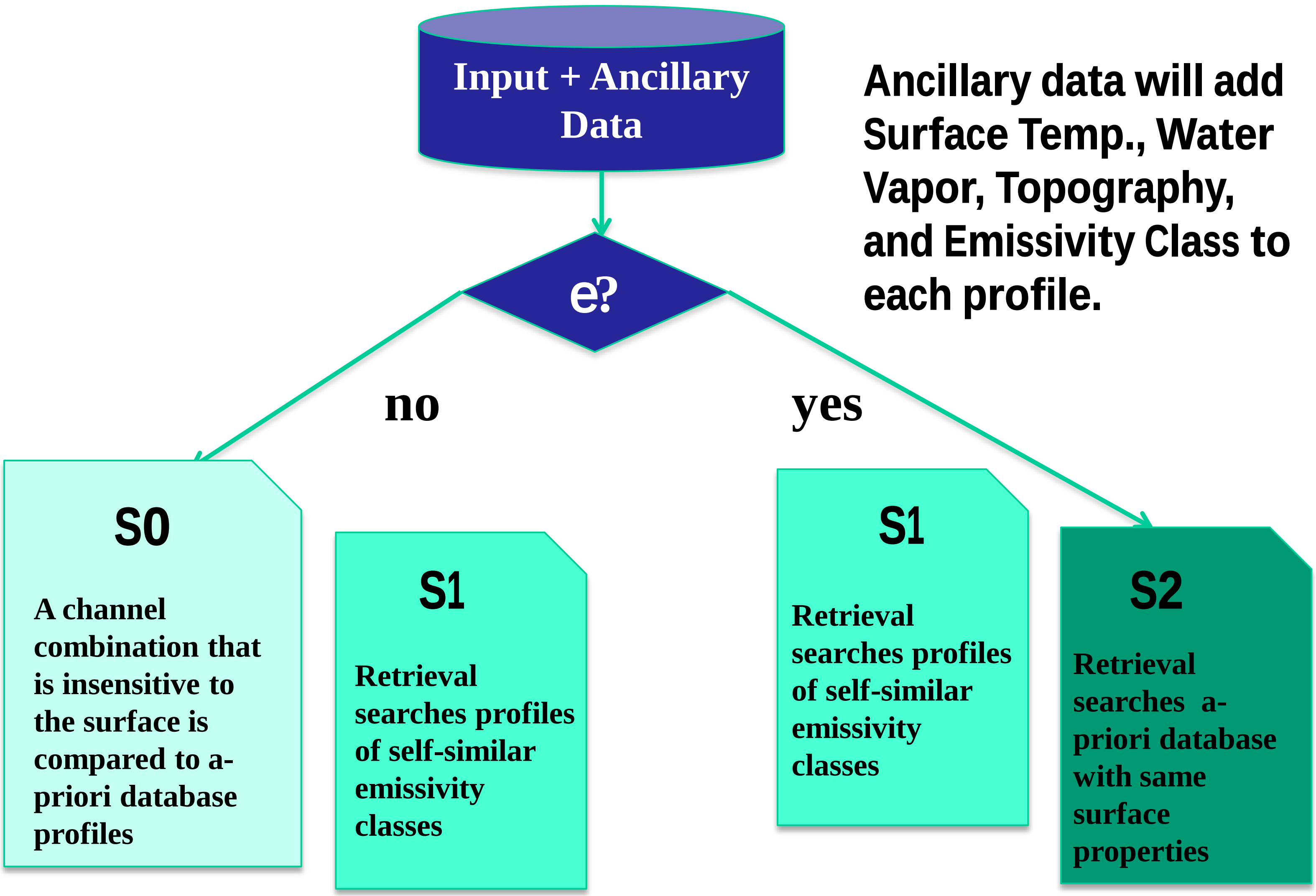


Accumulated Precipitation from GPM (65°S:65°N)
April, May, June, 2014
Accumulated Precipitation (mm/month)
0
20
40
60
80
100
120
GMI
F16
F17
F18
AMSR2
Ku
DPR
Comb MS
Comb NS
Ocean
Vegetated
Snow Covered
Coastline
ecipitation from GPM (35°S:35°N)
Accumulated Precipitation (mm/month)
0
20
40
60
80
100
120
GMI
F16
F17
F18
AMSR2
TMI
Ku
DPR
Comb MS
Comb NS
Ocean
Vegetated
Snow Covered
Coastline



The Retrieval Algorithm

Retrievals to search only subset of database with similar ancillary values



Ancillary data will add Surface Temp., Water Vapor, Topography, and Emissivity Class to each profile.

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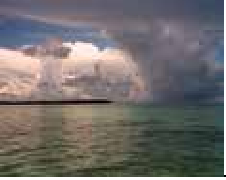

Ancillary Data - Topography

Elevation

1 km global elevation from GLOBE, Sampled to 1/10 of a degree (12 km).
Includes standard deviation of elevation within the sampled 10X10 footprint.