Improving CRM Physics Within the Data Assimilation Framework

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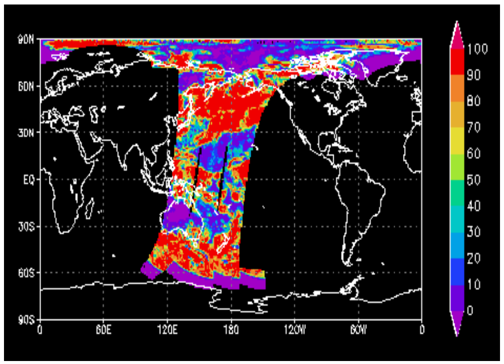
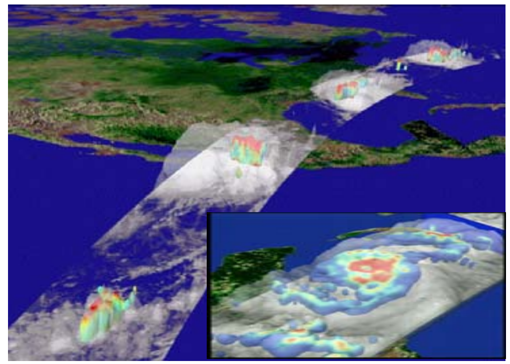
A new paradigm for model improvement: Motivation

- Using cloud/precipitation information from satellites to evaluate CRM simulations and identify model deficiencies.



Cloud information: MODIS, CloudSat/CALISPO/A-Train



Precipitation information: TRMM, AMSR, SSMI, *GPM*

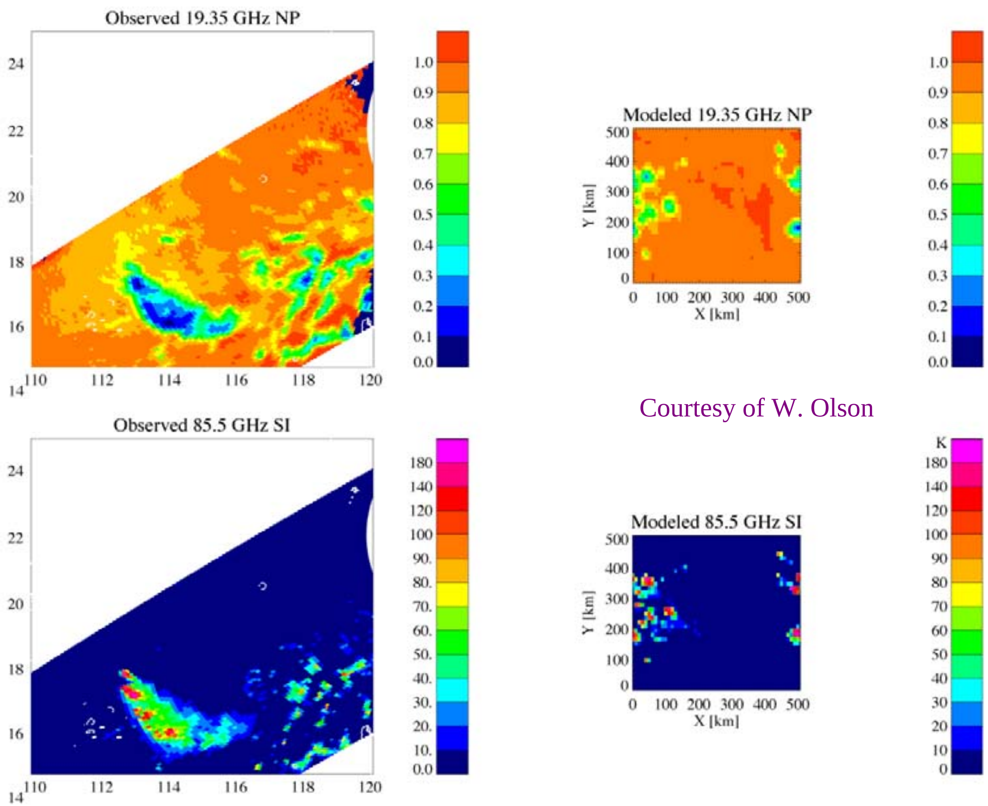
Microphysical properties of cloud and precipitation processes are becoming increasingly available from new satellite sensors

- Estimating model physics parameters in the presence of *unbiased* environmental states –

  moving away from parameter estimation in simulated states (*which can be - and usually are - biased*) to optimizing semi-empirical physical parameters w.r.t. “unbiased” observed/analyzed states within the framework of data assimilation.

Issues in matching observations with simulations

SCSMEX Obs vs. GCE - 2241 UTC 20 May 1998



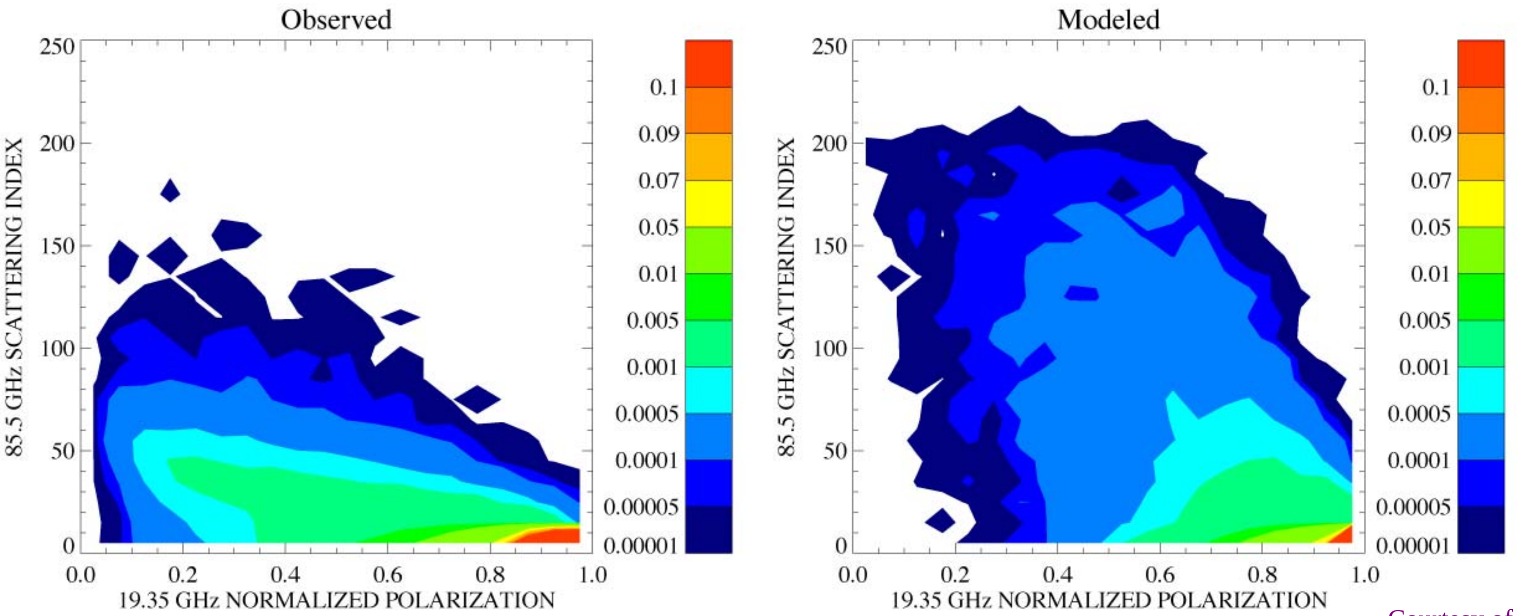
Courtesy of W. Olson

- Cloud and precipitation processes are highly variable in space and time
- Observations are temporally and spatially discrete.
- Matching observational snapshots with instantaneous model states is difficult due to the stochastic nature of these processes and model biases.

key premise: In terms of the effect of cloud microphysics on large-scale processes, accurate simulation at cloud pixel scales is not as important as correct simulation of aggregated cloud properties.

Statistical-based matching of cloud/rain properties

19 GHz NP vs. 85 GHz SI Histograms
(SCSMEX 30-Day Period)



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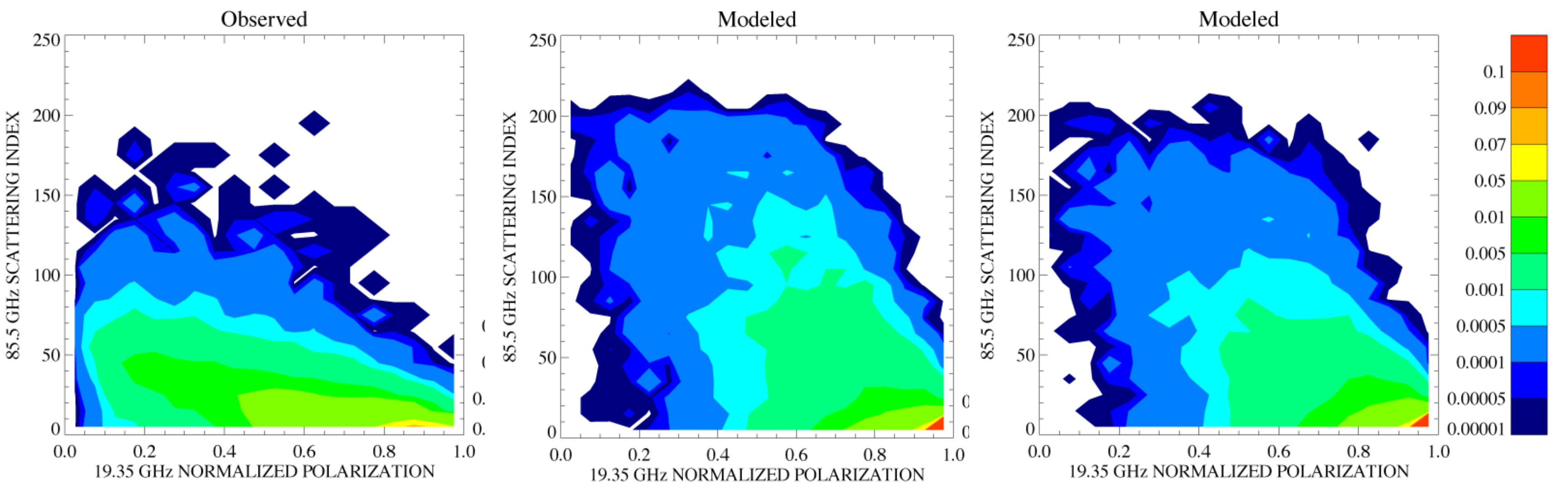
Model simulations show higher values of 85 GHz SI and 19 GHz NP, indicative of intense convection without a lot of areal coverage.

(NP ~ 1-f, where f = fraction of significant rain within the footprint)

Sensitivity to model parameters

19 GHz NP vs. 85 GHz SI Histograms
(30-Day SCSMEX simulations with and without graupel growth due to snow collection)



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Parameter estimation to minimize discrepancies between the observed and modeled statistics within the data assimilation framework

Example: A variational procedure to minimize the functional:

$$J(x) = (x-x^b)^T \mathbf{P}^{-1} (x-x^b) + \{Q^o - Q(x)\}^T \mathbf{R}^{-1} \{Q^o - Q(x))\}$$

- model parameters: $x = (P1,P2,P3,P4)$
- observed statistics: Q^o
- model statistics: $Q(x)$
- error covariance of prior estimate: $\mathbf{P}$
- observation error variance: $\mathbf{R}$

Cloud/rain assimilation using the forecast model as a weak constraint

- Conventional data assimilation algorithms do not address errors arising from model deficiencies - they assume that the model is essentially perfect and that the first-guess is reasonably accurate.
- The goal of assimilation of cloud/rain or any non-state variables in this perfect-model framework is to improve estimates of the state variables - u, v, T, q, etc.
- In reality, uncertainties in model physics parameters can be the dominant source of errors in cloud and precipitation fields.
- The "weak constraint" approach relaxes the perfect-model assumption and uses cloud/rain information to make online estimation and correction of errors arising from model physics.

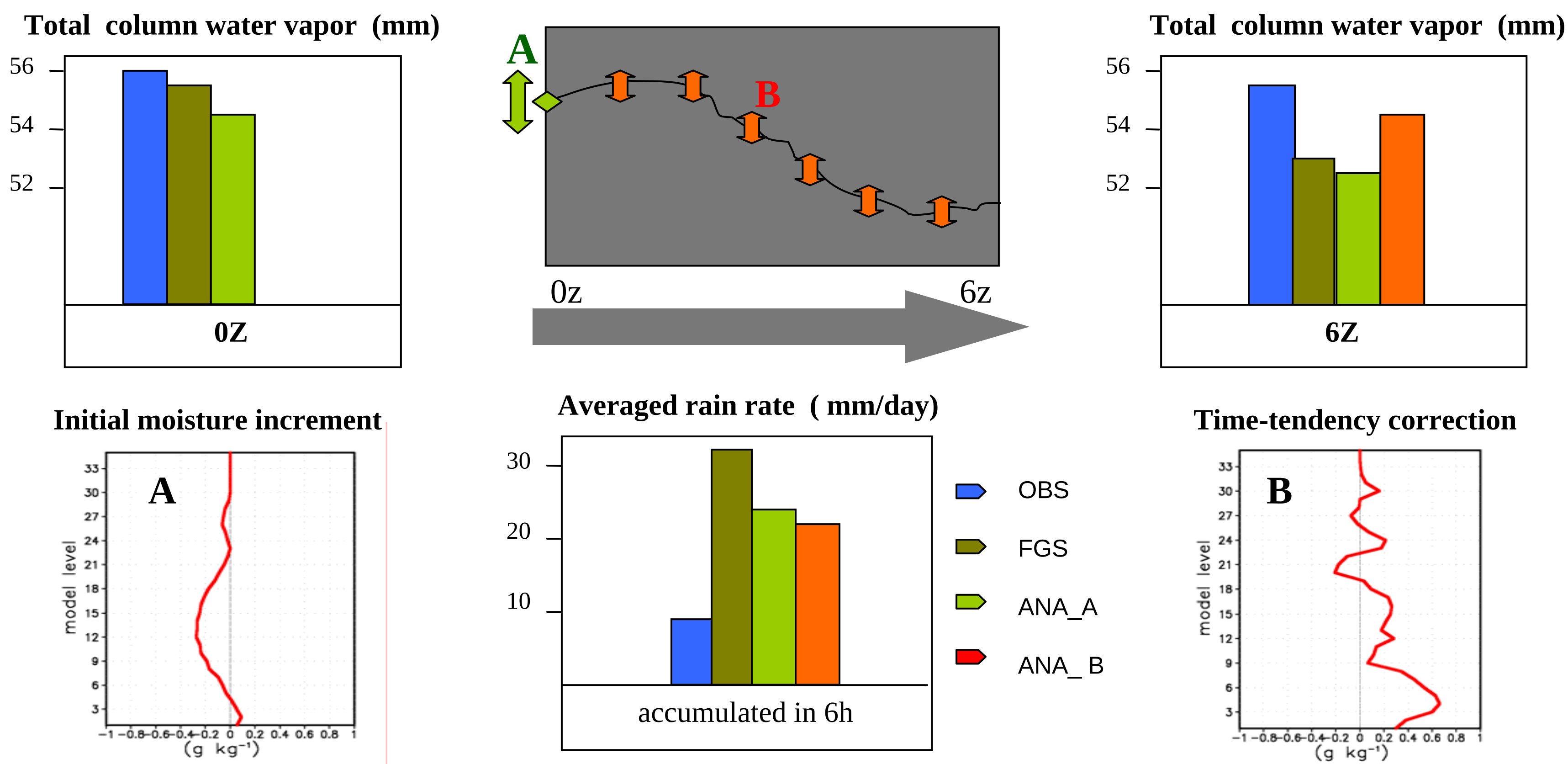
Perfect model assumption vs. model error correction: An example

1+1D (column + time) variational assimilation of 6h rain accumulation

Forecast initialized with moisture consistent with the observed TCWV produces excessive rain over 6h, leading to a dry bias in the final moisture field.

Method A: adjustment of initial moisture profile assuming a perfect model

Method B: continuous correction of time-tendency of moist processes



Rain/clouds assimilation in the presence of moist physics errors by adjusting initial conditions can *degrade analyses of other variables.*

Weak-constraint experiments with GEOS global DAS

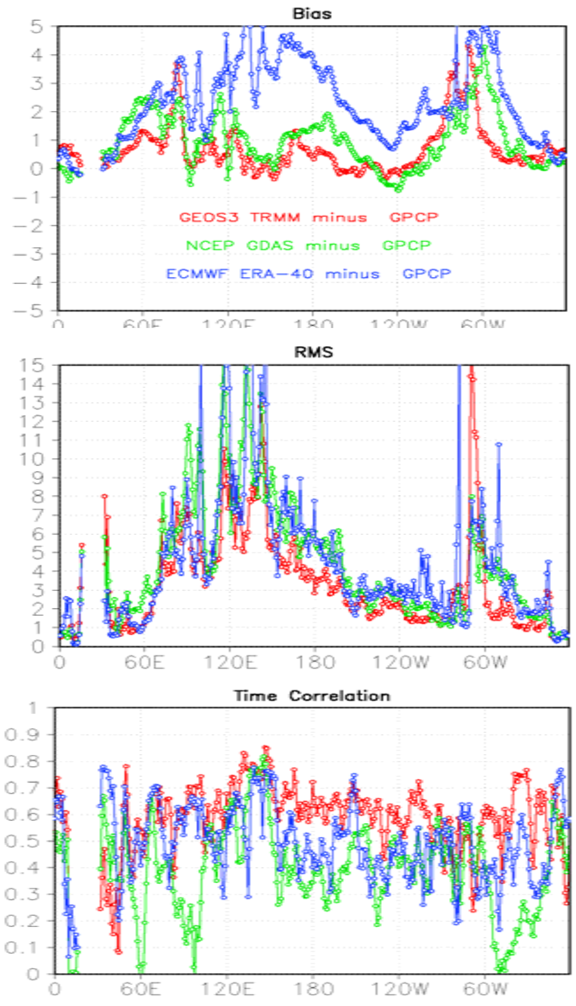
- Variational continuous assimilation (VCA) of 6h surface rain accumulation using moisture tendency correction as a control variable
  - 1+1D observation operator based on 6h time-integration of the column model of moist physics with prescribed large-scale forcing
  - Online estimation and correction for 6h-mean moisture tendency error
  - Moisture tendency correction applied continuously over the 6h analysis window to achieve dynamical consistency

- Variational assimilation of 6h convective/stratiform latent heating profiles using empirical parameters in the moist physics as control variables
  - Used in conjunction with rainfall assimilation to seek further improvements
  - Estimating empirical parameters consistent with *analyzed* rather than *simulated* atmospheric states - and accounting for sub-grid-scale variability not captured in conventional parameterization schemes

- Variational assimilation of cloud fraction and optical depth from ISCCP and MODIS using empirical cloud parameters as control variables
  - Estimation of empirical cloud parameters to improve the treatment of unresolved sub-grid-scale moisture variability, microphysical details, and cloud overlap.

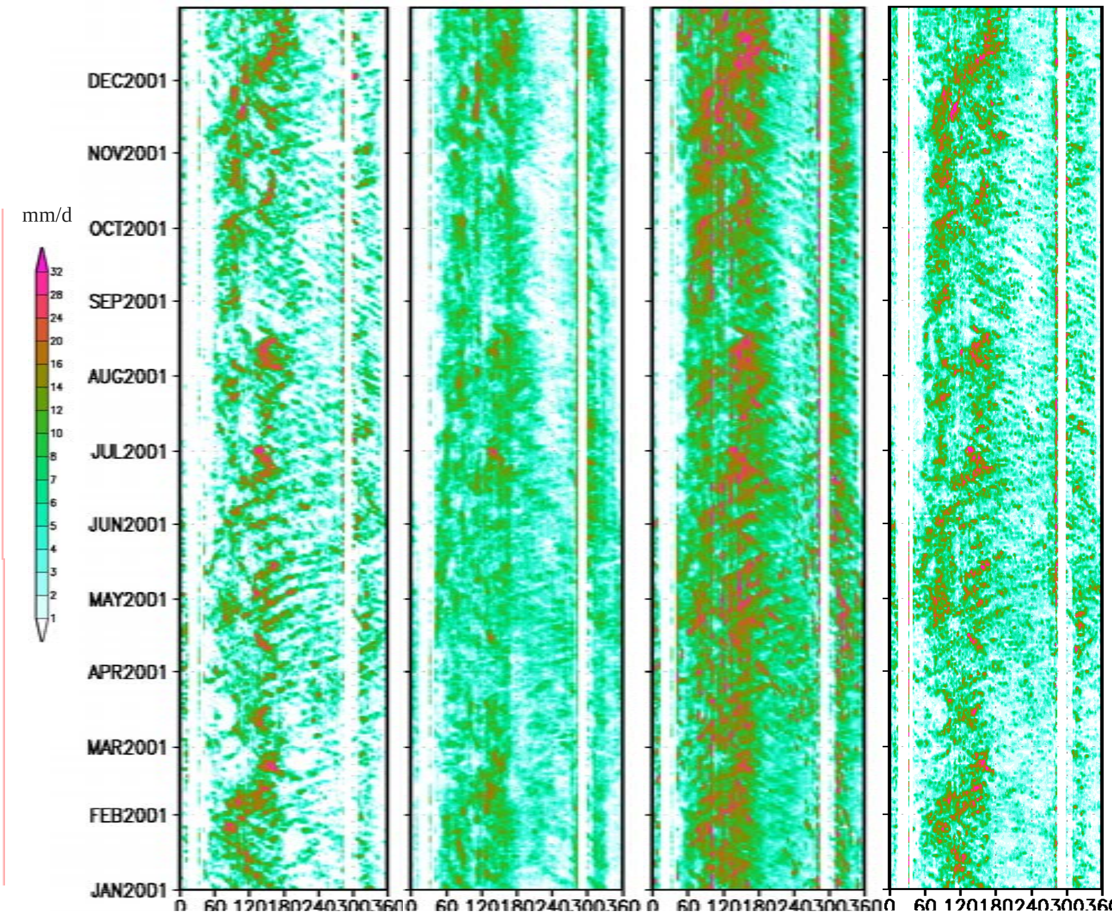
GEOS = Goddard Earth Observing System

Impact of VCA scheme on precipitation analysis



Rain error reduction (30N-30S, ocean)

MJO signals in precipitation over tropical oceans (10N-10S): January-December 2001

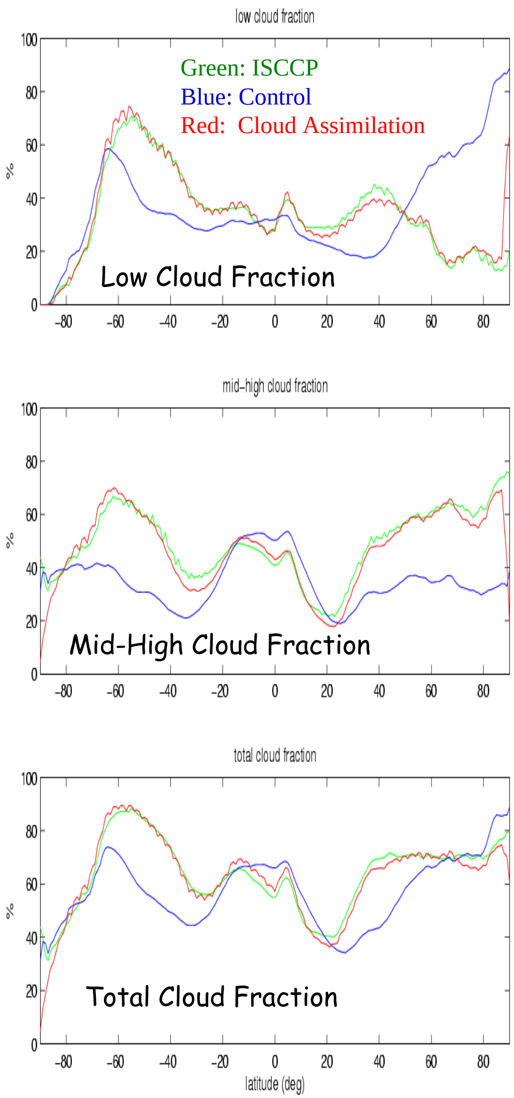


Precipitation assimilation using the VCA procedure reduces biases in rainfall analysis and improves temporal and spatial patterns of tropical rain systems.

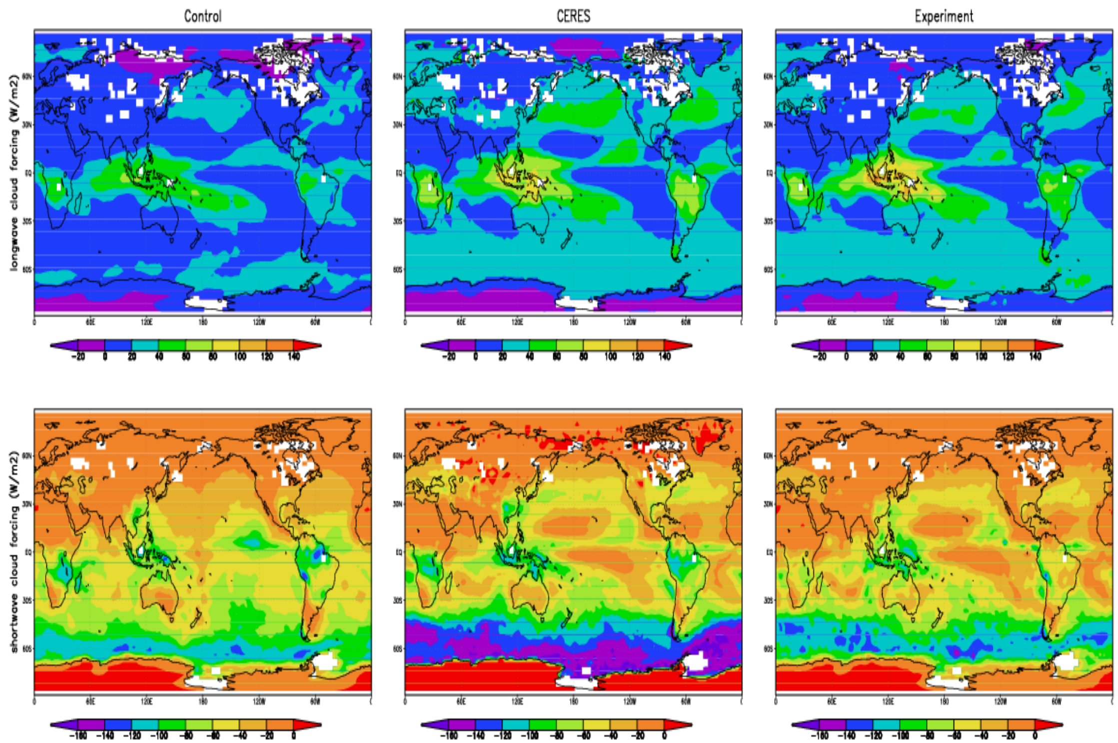
GEOS = Goddard Earth Observing System

Assimilation of ISCCP cloud fraction/optical depth and SSM/I cloud LWP

Improved Cloud Fraction



Improved TOA radiation verified against CERES

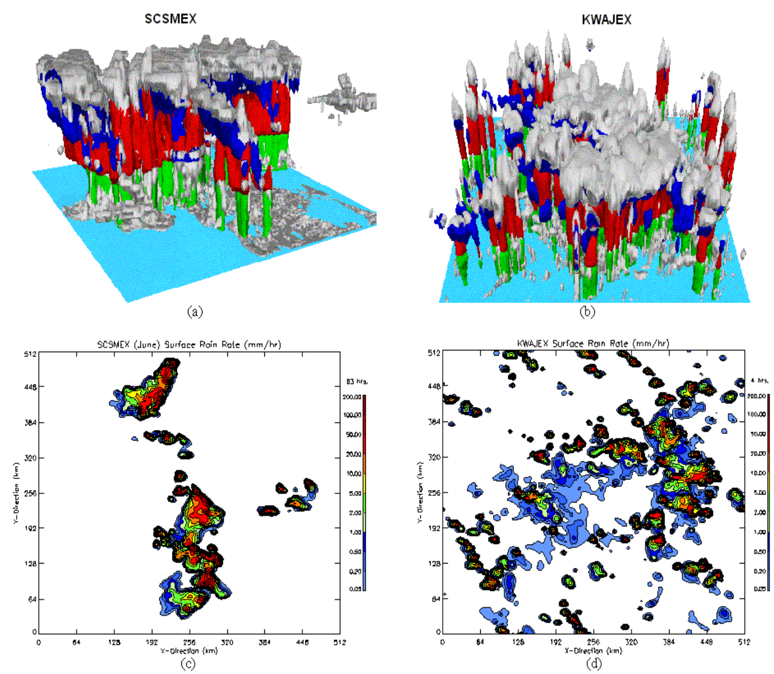


Courtesy of P. Norris

Control variables

- Critical RH* and the functional dependence of cloud fraction on RH (CCM3 physics generalized to a 2-parameter, S-shaped f(RH*, α))
- Reference LWC value in cloud water scheme for cloud liquid water
- Effective cloud overlap parameter for cloud optical depth

PDF-based assimilation of cloud properties to improve CRM physics and simulations



3D GCE model-simulated cloud hydrometeor mixing ratios. White: cloud water/ice, Blue: snow, Green: rain water, Red: graupel. Surface rain rate (bottom) in mm h^{-1} resembling radar observations. (Courtesy of W.-K. Tao)

- Assimilate the PDF's of cloud-affected reflectivity/radiance measurements - and/or retrieved cloud properties - in the Goddard Cumulus Ensemble (GCE) model: e.g.,
  - CloudSat radar reflectivity
  - MODIS cloud properties
- Investigate sensitivities of PDF's of cloud measurements/properties to semi-empirical model parameters (e.g., parameters of cloud particle size distributions) to identify the control variables for variational assimilation.
- Use precipitation observations from TRMM, AMSR-E, and/or SSM/I to verify model improvement.

Expected results

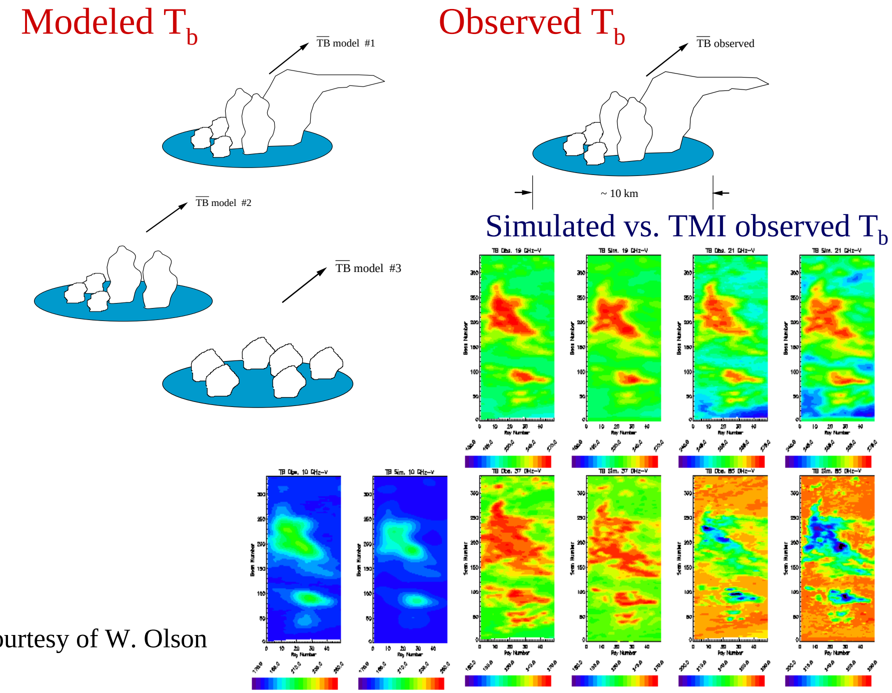
- CRM simulations consistent with observed cloud statistics *and* the large-scale environment

- Parameter estimation under a range of climatic conditions and geographic locations provides insights into cloud/precipitation microphysical processes

- Using cloud-constrained GCE simulations as the data base for PMW retrievals in rainy areas moves a step closer to providing a cloud/rain-constrained CRM benchmark for understanding moist processes and evaluating model parameterizations.

A Bayesian rain estimate from MW T_b

$$E[R]=\sum_k R_k \frac{\exp\left\{-0.5\left(\mathbf{TB_M}(R_k)-\mathbf{TB_O}\right)^T \mathbf{O_{TB}}^{-1}\left(\mathbf{TB_M}(R_k)-\mathbf{TB_O}\right)+C\right\}}{\hat{N}}$$



Courtesy of W. Olson

Physical rain retrieval based on CRM cloud ensemble simulations that are radiatively compatible with MW radiances in rainy areas

Closing remarks

- Attribution of sources of model errors is risky:

  - Parameter adjustments should not depend solely on parameter sensitivity, but should be guided by physical understanding of model deficiencies whenever possible.

  - It is crucial to seek independent confirmation that the adjustments are doing the right thing.

- Parameter estimation can *improve* the model only within the limits of a given physics formulation. But it can be a powerful tool for diagnosing model deficiencies using observations.