Cloud/precipitation assimilation at NASA GSFC

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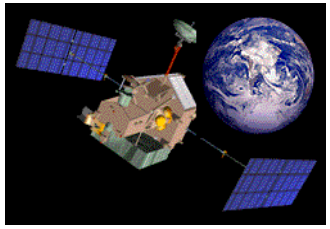
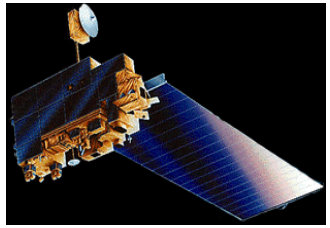



GCSS Panel Meeting, NASA GISS, New York City, 21-23 September 2004

Main points of the talk

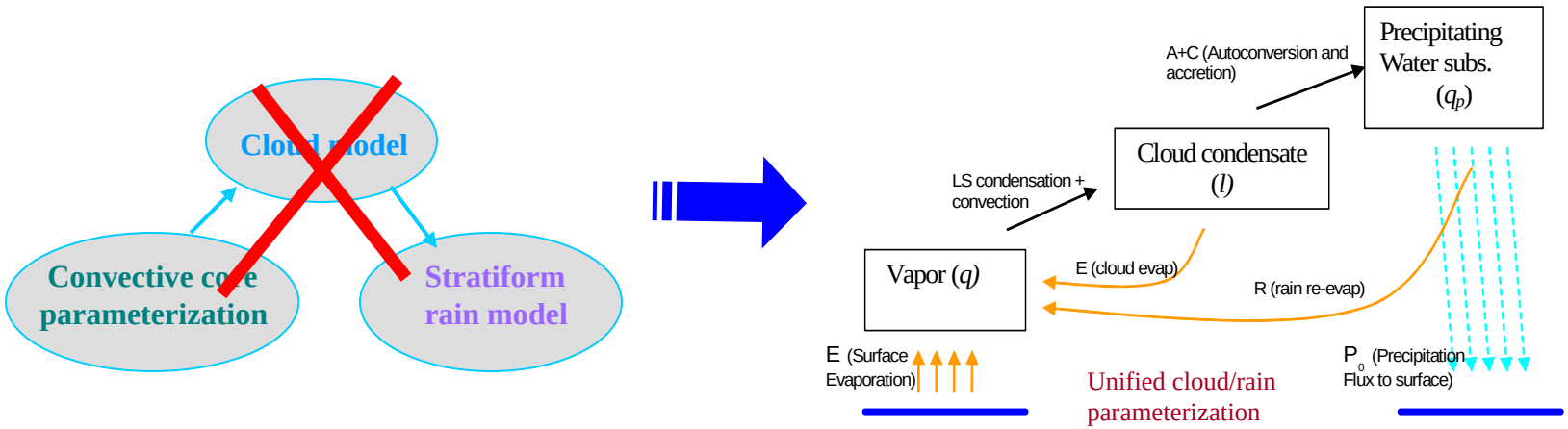
- Shouldn't model clouds in isolation from precipitating processes
  - a unified approach to cloud/rain modeling & assimilation
- Key issues in global cloud/precipitation assimilation
  - data impact and usage depend upon how well we can model cloud/precipitation processes
  - need for advanced assimilation techniques
- Given a sound cloud/precipitation parameterization framework, data assimilation could offer a new pathway to estimating empirical parameters within observation uncertainties
- Role of CRM in guiding cloud/precipitation parameterization and assimilation research

A unified approach to cloud/precipitation assimilation

- Systematic errors in model clouds may represent not only errors in "cloud parameterizations" but also errors in detrained liquid/ice from convective processes or in the background humidity field (which is linked to convective detrainment and circulations in the tropics).

- Similarly, one cannot effectively address errors in rain and latent heating profiles without considering entrainment/detrainment of cloud condensates and other cloud-scale processes.

- GEOS-5 global model uses a single unified cloud/rain parameterization with precipitating condensates generated from cloud condensates, dictating the combined use of cloud/rain information in data assimilation.

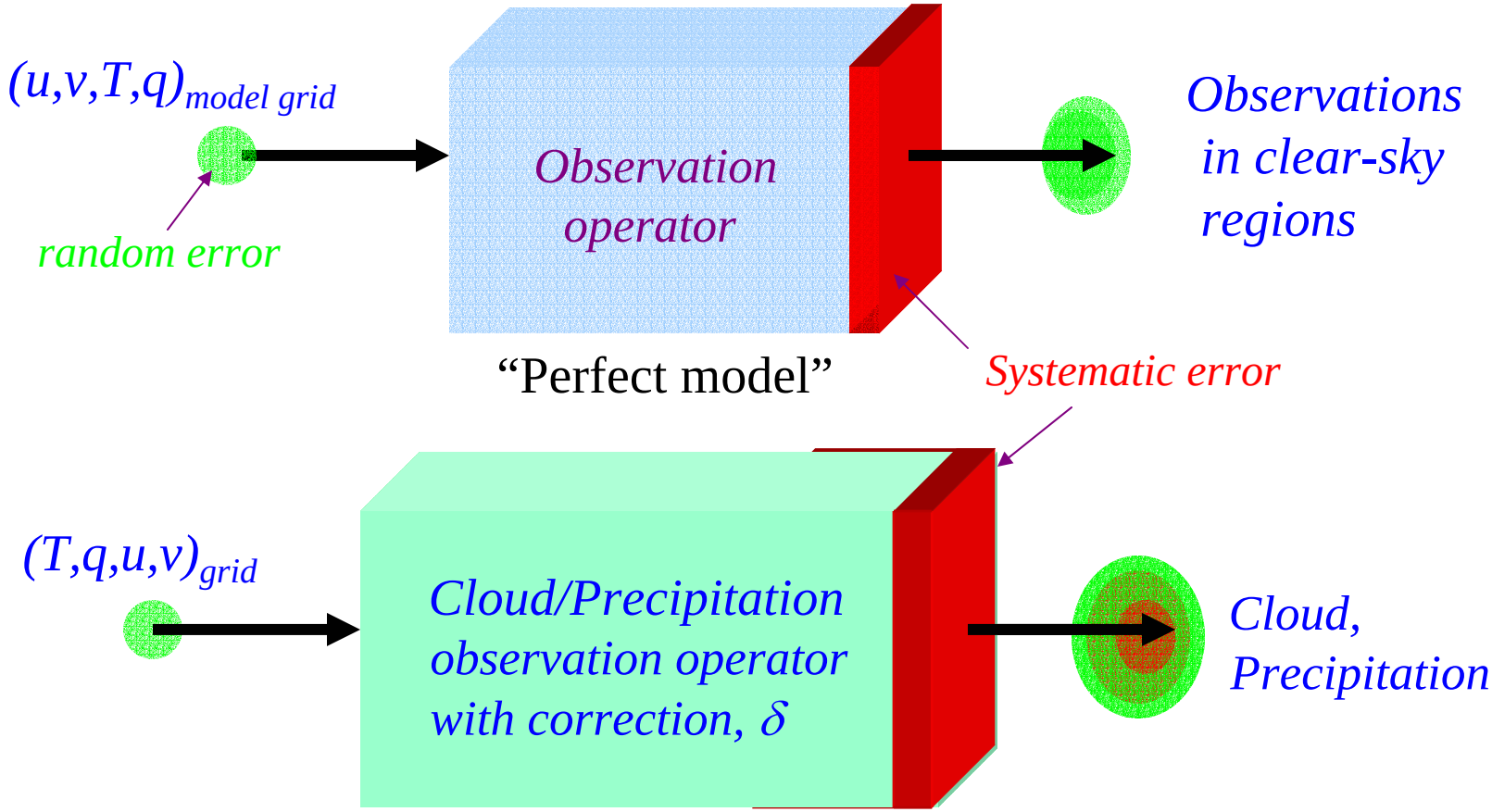


Why exploring new pathways in cloud/rain assimilation?

- Conventional data assimilation algorithms are based on the assumption that the underlying observation and model error statistics are random, unbiased, stationary, and normally distributed.
- But model clouds and precipitation are derived from parameterized moist physics, which can have large systematic errors. Unless these (largely unknown) systematic model errors are accounted for in the assimilation procedure, one will always make sub-optimal use of these data.
- A basic problem is that the observation operators for clouds, rain, and latent heating are not as accurate as those for conventional data or observables in clear-sky regions.

What is an observation operator?

It relates an observable to model state variables (u,v,T,q, etc.)



Developing procedures to make online estimation and correction of biases in observation operators to make effective use of cloud and precipitation data

Focused research areas at NASA GFSC

- Exploring ways to make effective use of cloud/precipitation data in the presence of model biases:
  - Relaxing the "perfect model" assumption to *estimate and empirically correct for biases in observation operators* to assimilate
    - » Variational assimilation of rainfall, latent heating, and cloud data using the forecast model as a weak constraint
  - Using observation-constrained CRM simulations to guide parameterization improvement and choices of control variables for variation assimilation
    - » Identify deficiencies in parameterizations to guide selection of control variables for variational assimilation and investigate the feasibility of direct assimilation of radiances
  - 1D ensemble data assimilation
    - » Unified framework for handling IC and model errors.

Cloud/rain assimilation using model as a weak constraint

Precipitation information

(TMI, SSM/I, AMSR-E)

- *Assimilation of surface rain using moisture time-tendency correction as the control variable*
- *Assimilation of convective and stratiform latent heating profiles using parameters in cloud and convective schemes as control variables*

(GEOS-3)

Cloud information

(ISCCP, SSM/I, MODIS)

- *Assimilation of cloud fraction, optical depth, and SSM/I cloud liquid water path using cloud parameters as control variables*

(GEOS-4)

GEOS-5

Single cloud/rain parameterization with precipitating condensates generated from cloud condensates

Variational continuous assimilation (VCA) of surface rain

- *Assimilation of 6h surface rain accumulation using a 6h-mean moisture tendency correction as the control variable and applying the correction continuously over a 6h analysis window to achieve dynamical consistency*

A 1+1D observation operator (H) based on a 6h time-integration of a column model of moist physics with large-scale forcing prescribed from "first guess"

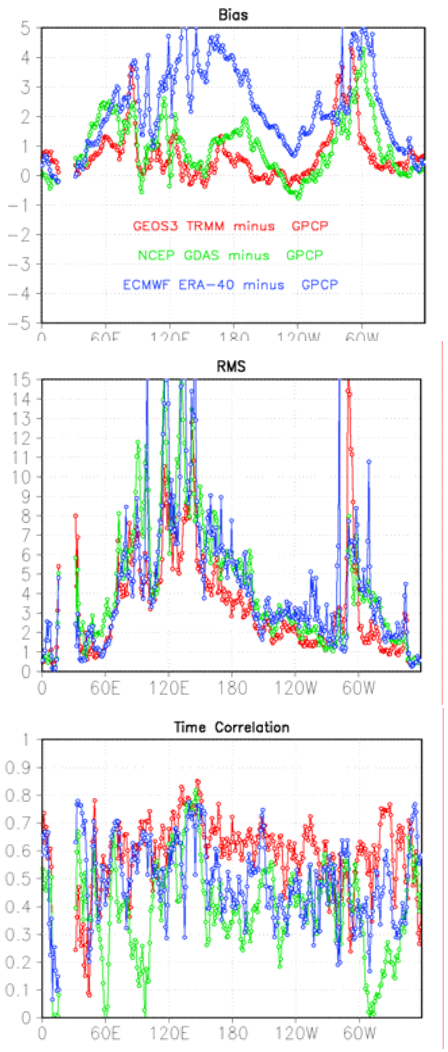
Minimizing the cost function:

$$J(x) = (x)^T \boldsymbol{P}^{-1} (x) + (y^o - \boldsymbol{H}(x))^T \boldsymbol{R}^{-1} (y^o - \boldsymbol{H}(x))$$

- model tendency correction: x
- logarithm of observed rain rate: y^o
- logarithm of model rain estimate: $\boldsymbol{H}(x)$
- error covariance of prior estimate: $\boldsymbol{P}$
- logarithm of relative observation error variance: $\boldsymbol{R}$

- *Estimate and correct for biases in model's moisture tendency every 6h (width of the analysis window) to minimize the discrepancy in 6h rain between the model and observations.*

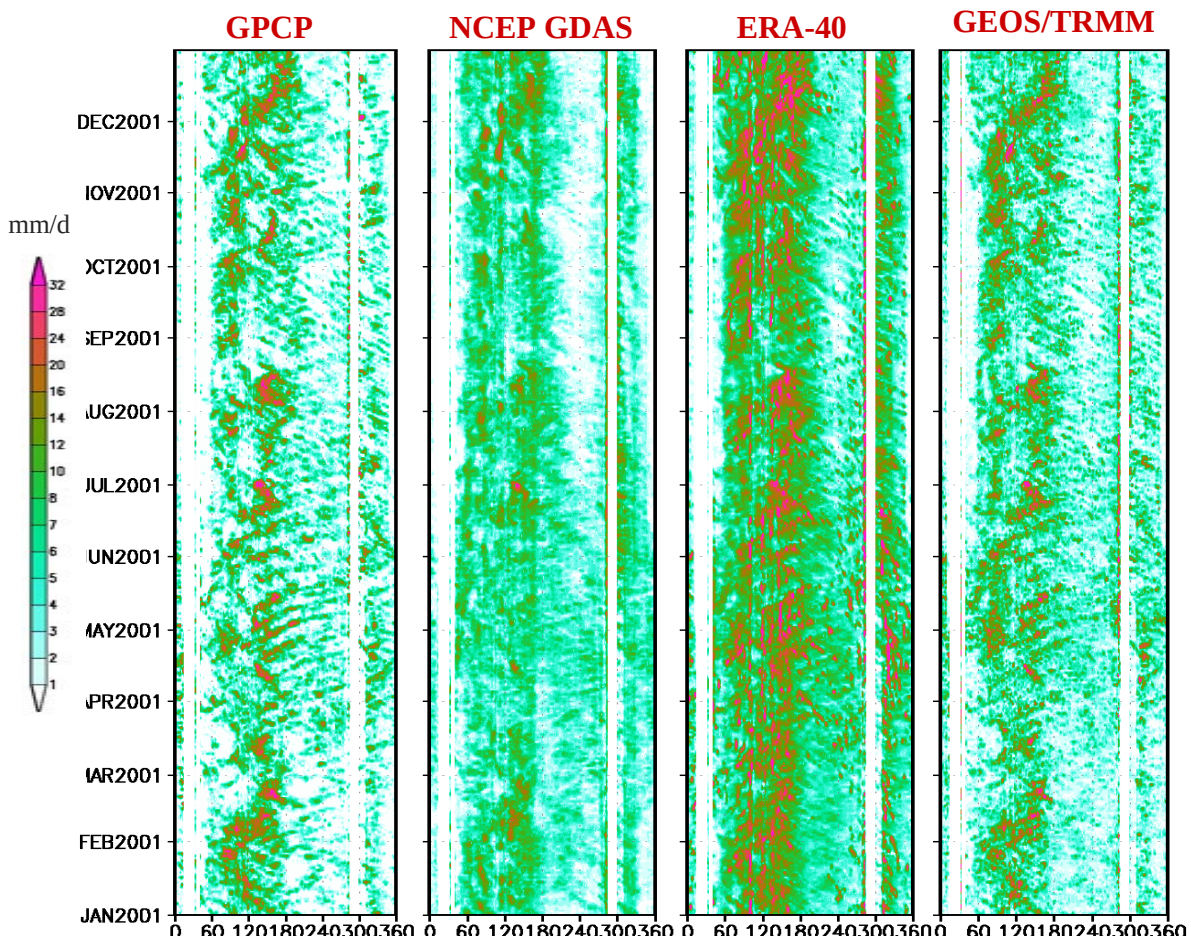
Impact of VCA rainfall assimilation on GEOS-3 analysis



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

GEOS = Goddard Earth Observing System

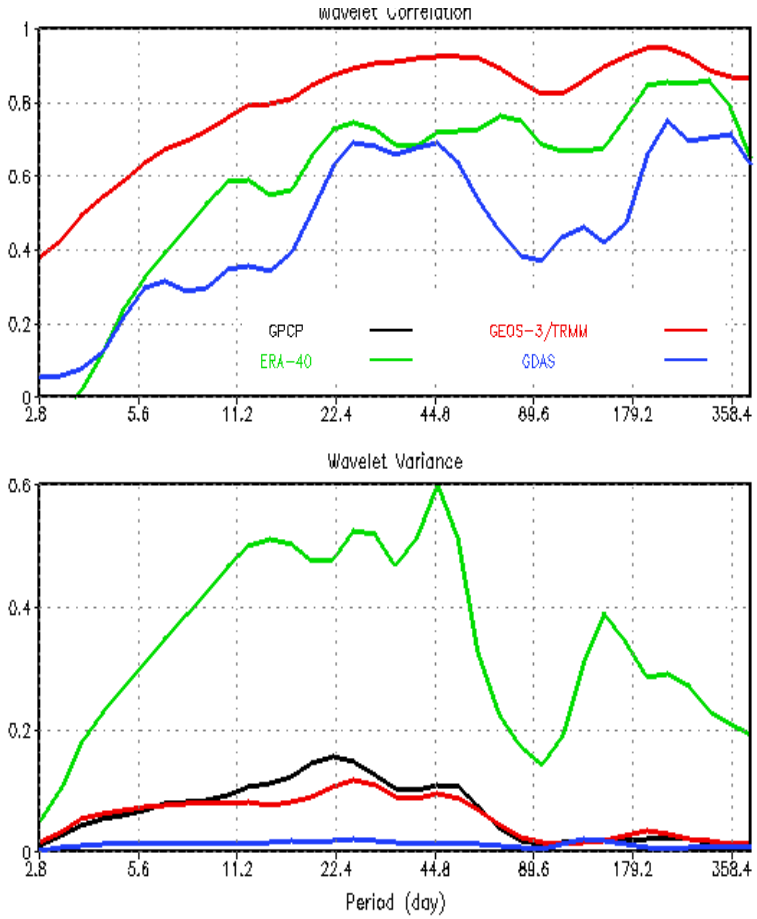
Replicating observed propagation and intensity of tropical rainfall systems and intraseasonal oscillation



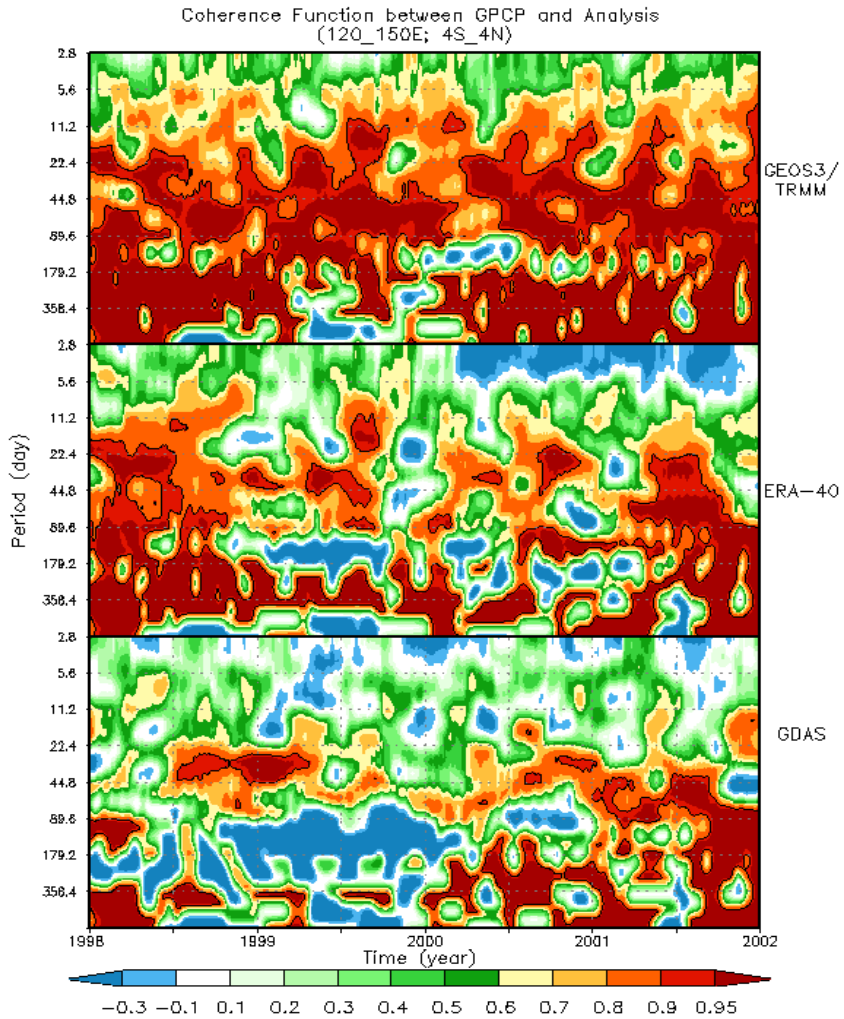
MJO in precipitation over tropical oceans (10N-10S) 2001

Improved temporal and spatial variability in GEOS-3 analysis

Avg. Precipitation (120-150E, 4S-4N)
(Morlet analysis)



Enhanced frequency-time coherence
between GPCP and GEOS-3 analysis

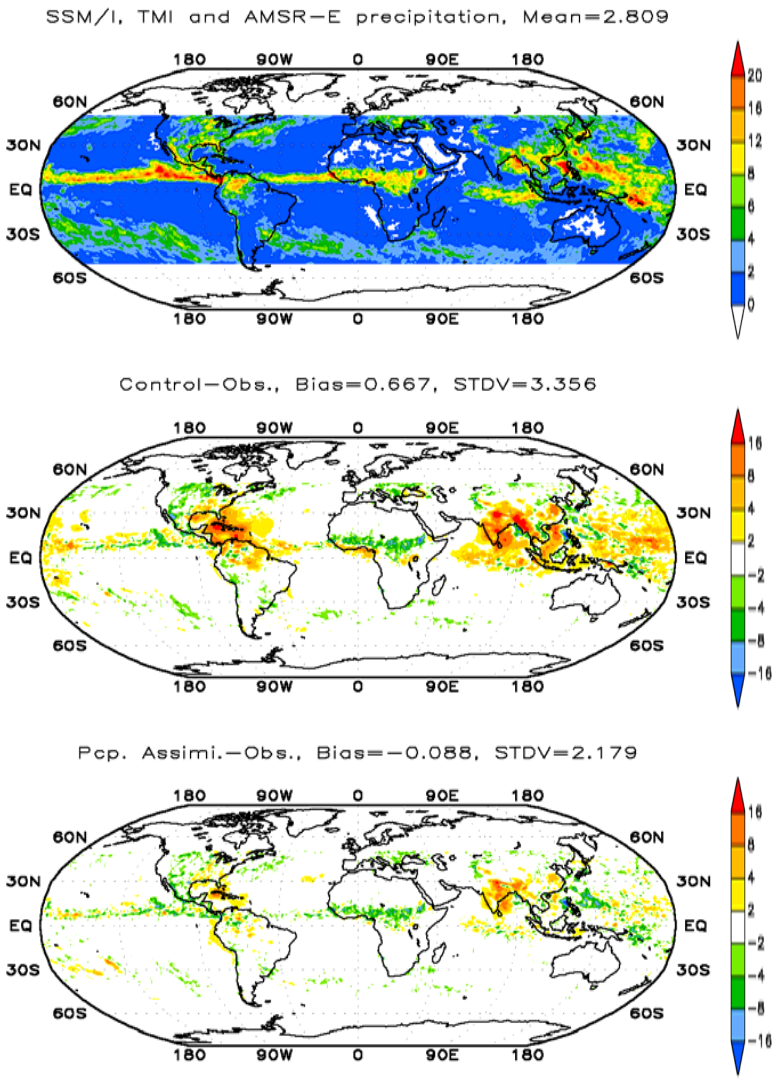


An atmospheric analysis dynamically consistent with observed rainfall variability

Improved TOA radiation using TMI, SSM/I & AMSR-E rain

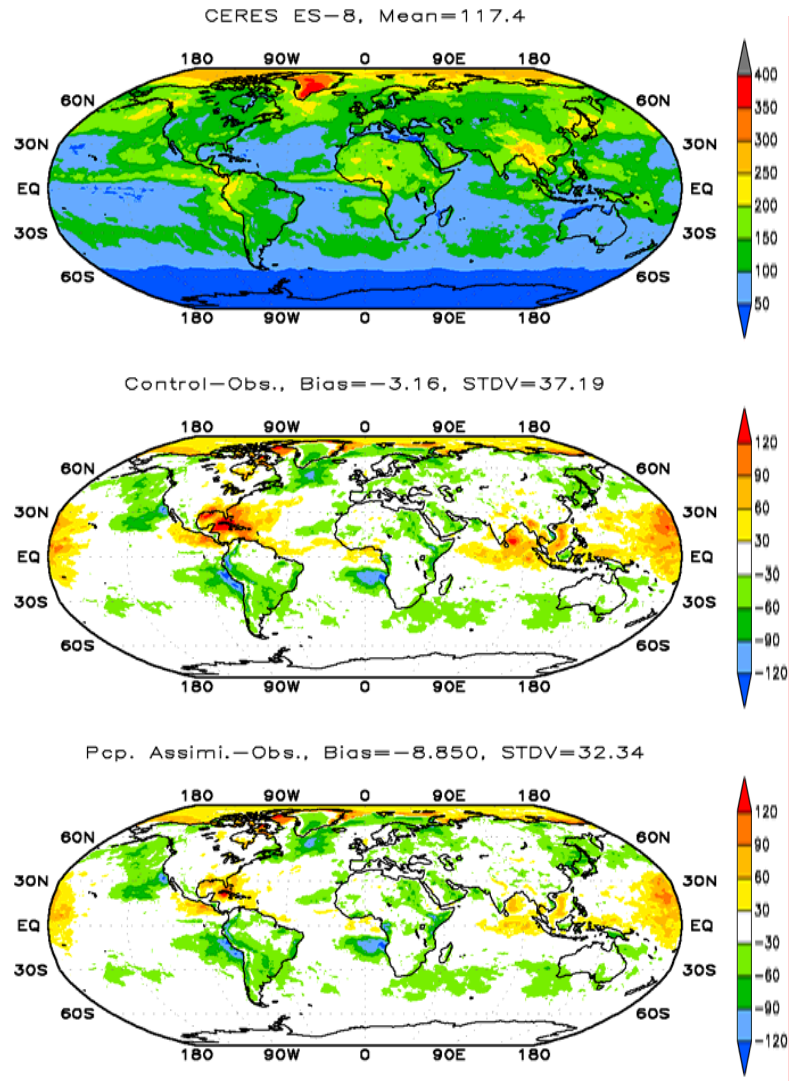
Precipitation July 2002

mm/d



OSR July 2002

W/m^2



Impact on wind and humidity analyses

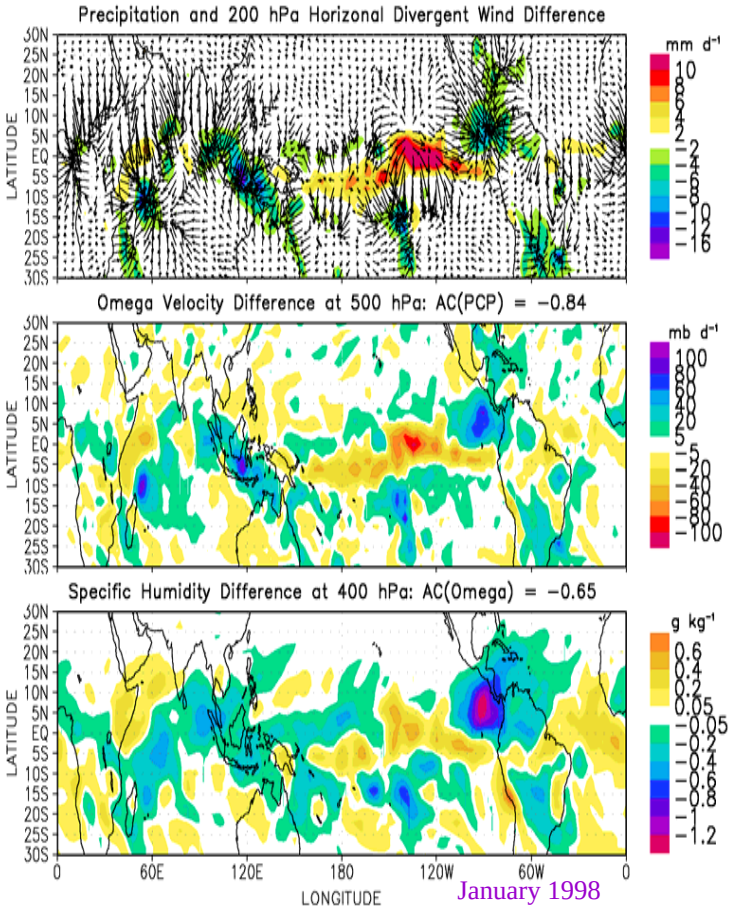
Improved latent heating patterns and large-scale motion fields leading to improved upper-tropospheric humidity (verified against TOVS brightness temperature)

GEOS(TMI+SSM/I PCP+TPW) minus GEOS(CONTROL)

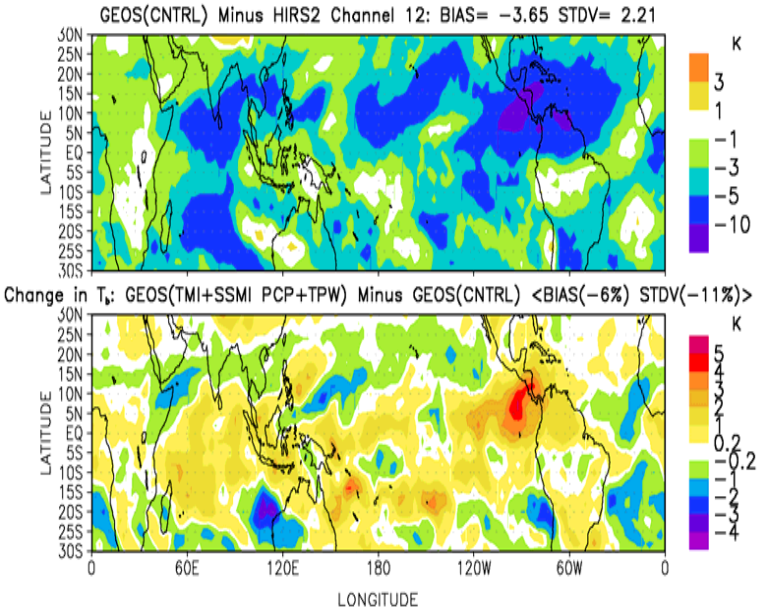
Surface rain & Horizontal div. wind at 200 hPa

Omega velocity at 500 hPa

Specific humidity at 400 hPa

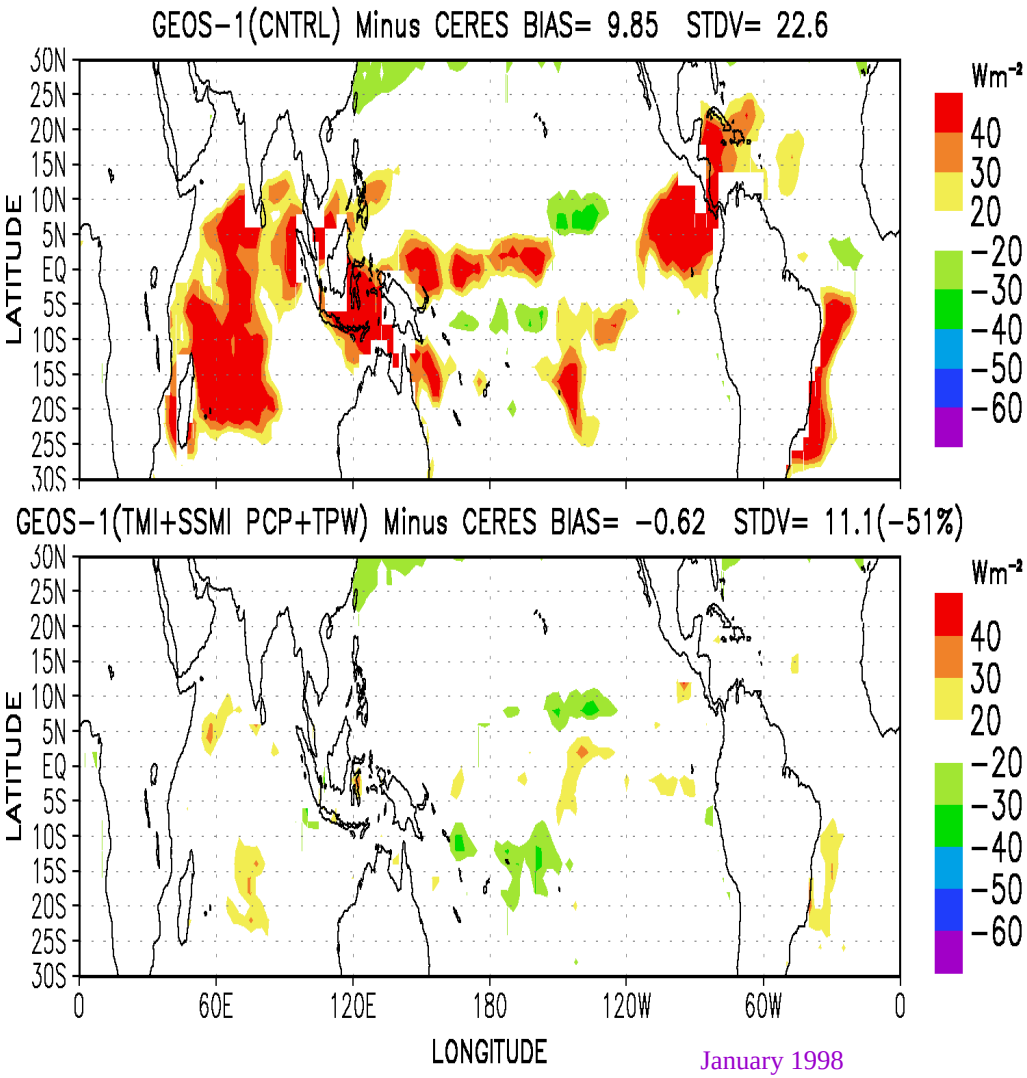


Verification: HIRS2 Channel 12 Brightness Temperature



- GEOS control has a moist/cold bias relative to HIRS2 channel 12 (top)
- Rainfall assimilation leads to a drier upper-troposphere & reduces the err.std.dev by 11%

Improved cloud radiative forcing verified against CERES



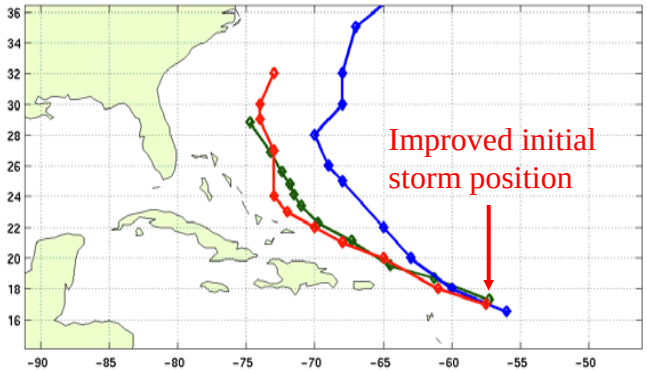
- 94% reduction in bias
- 51% reduction in error std dev

Precipitation assimilation enables the system to make better use of cloud information

Impact of precipitation assimilation (continued)

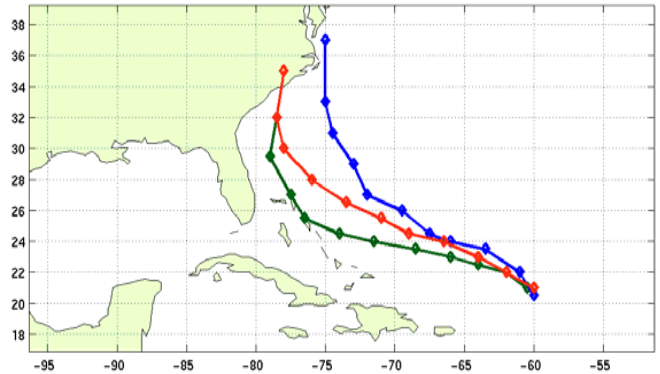
Bonnie

5-day track forecast from 12UTC 8/20/98

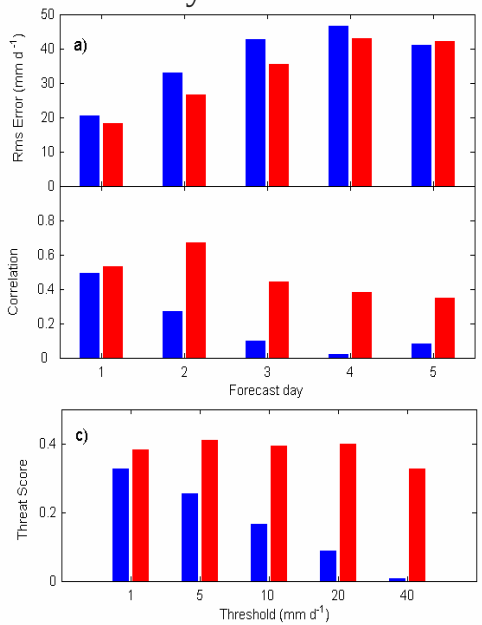


Floyd

5-day track forecast from 00UTC 9/11/99



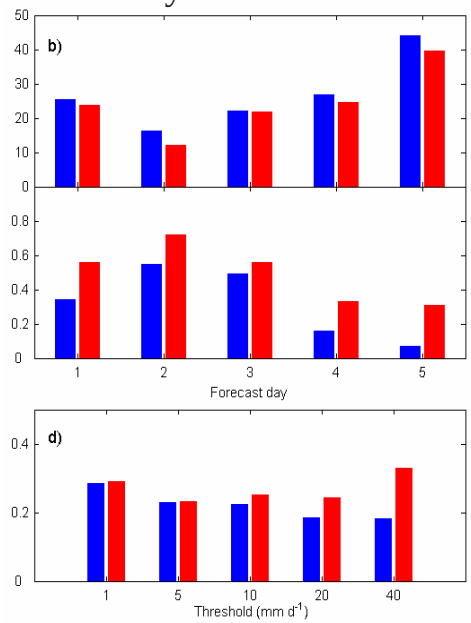
5-day rain forecast



Blue: No rainfall data in IC
Red: With rainfall data in IC
Green: NOAA "best track"

Hou et al. 2004:
MWR, August issue.

5-day rain forecast



TMI latent heating assimilation via parameter estimation

Assimilation of accurate latent heating vertical structure is expected to improve the horizontal divergent winds in the tropics

- *Seek further improvements through assimilation of 6h TMI GPROF convective and stratiform latent heating profiles* $Q_1 = L_V(c-e) - \frac{\partial \overline{\omega' s'}}{\partial p}$ *using model's moist physics parameters as control variables:*

  - convective adjustment time (P1) and critical RH for condensation (P2) for $Q_{convective}$
  - fraction of detrained liquid for anvil rain (P3) and ratio of water/ice in anvil rain (P4) for $Q_{stratiform}$

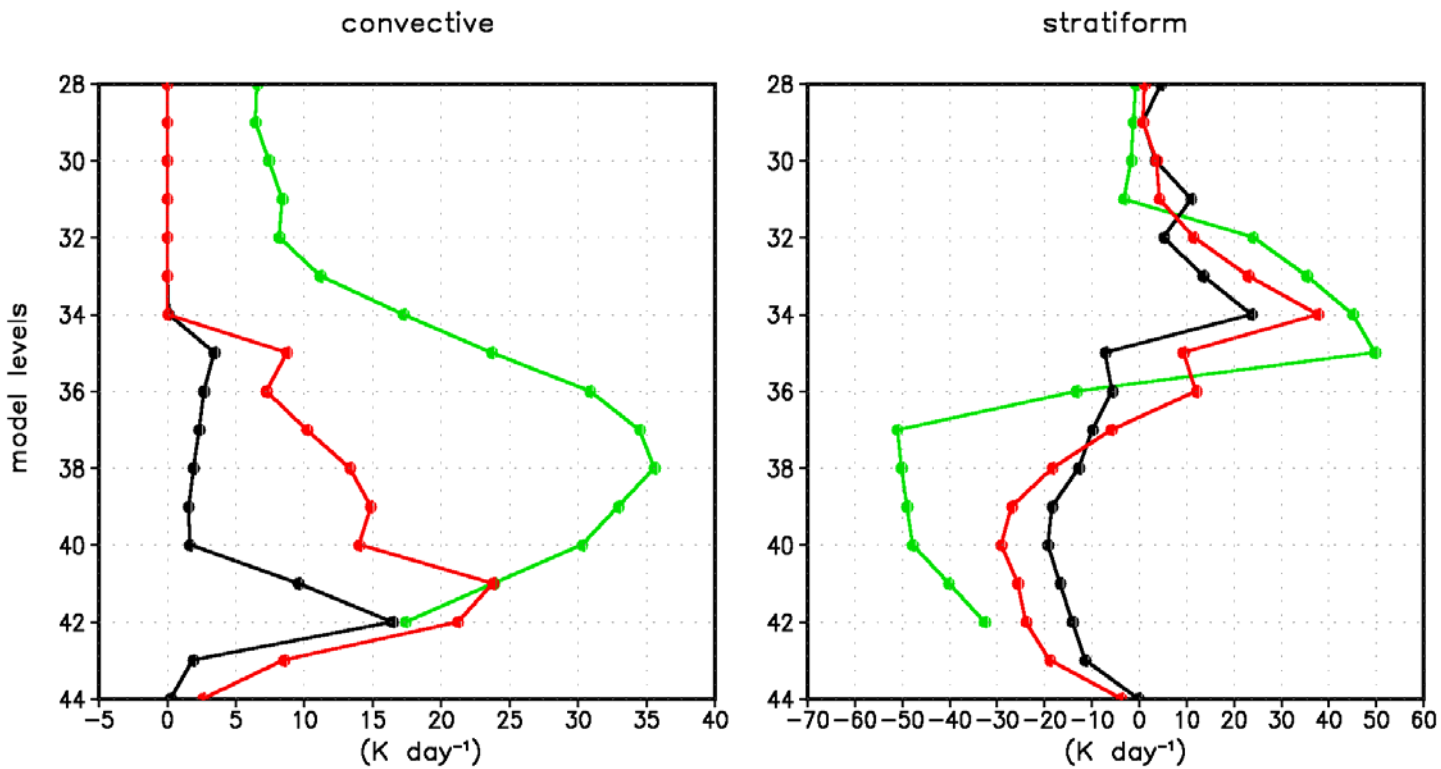
A 1+1D observation operator $Q(x)$ based on a 6h time-integration of a column model of moist physics with large-scale forcing prescribed from "first guess"

Minimizing the cost function:

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

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

Impact on C/S latent heating profiles



Example at a single 1° x 1° model grid

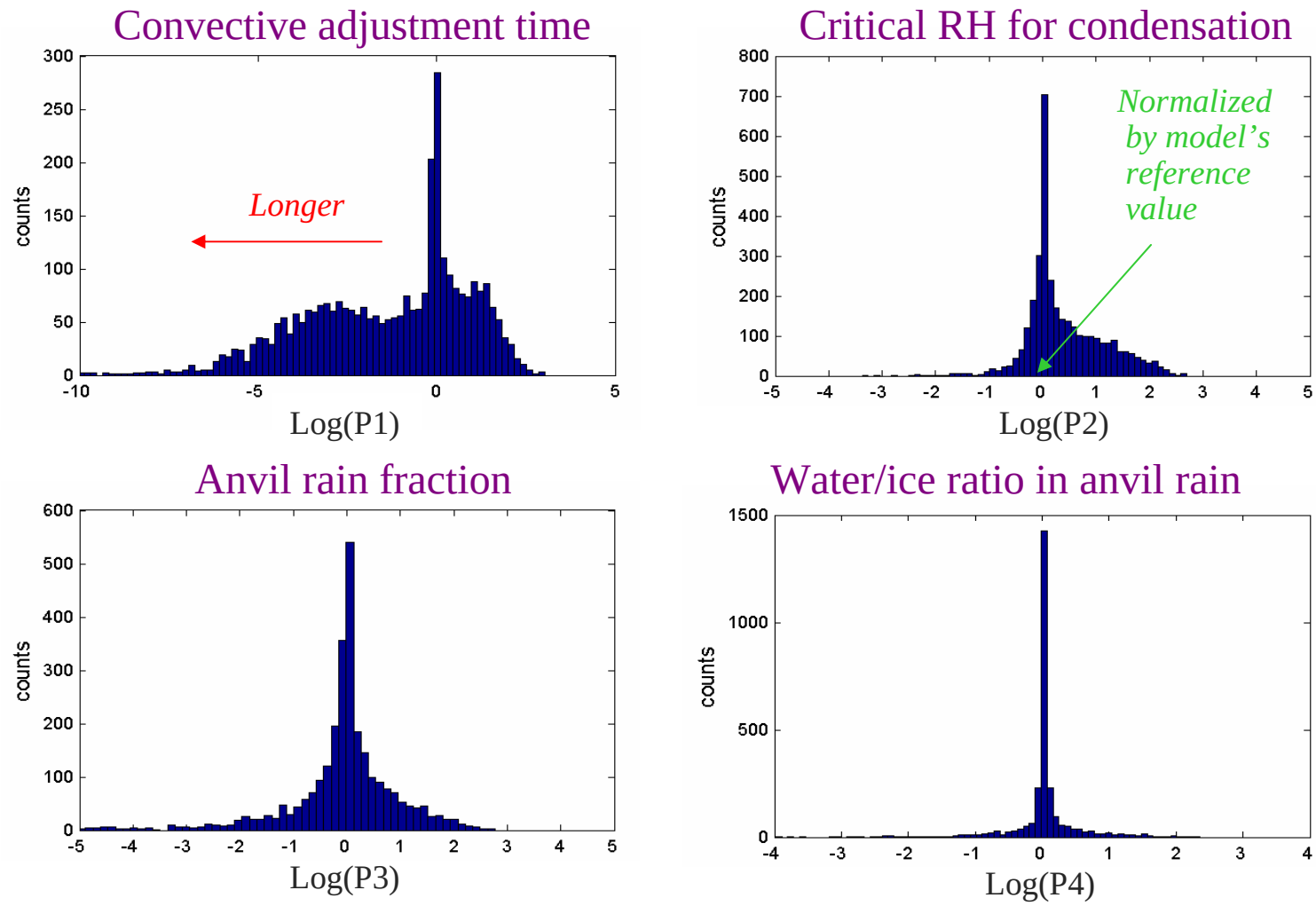
Green: TMI latent heating retrieval

Black: Model first guess

Red: 4-parameter minimization solution

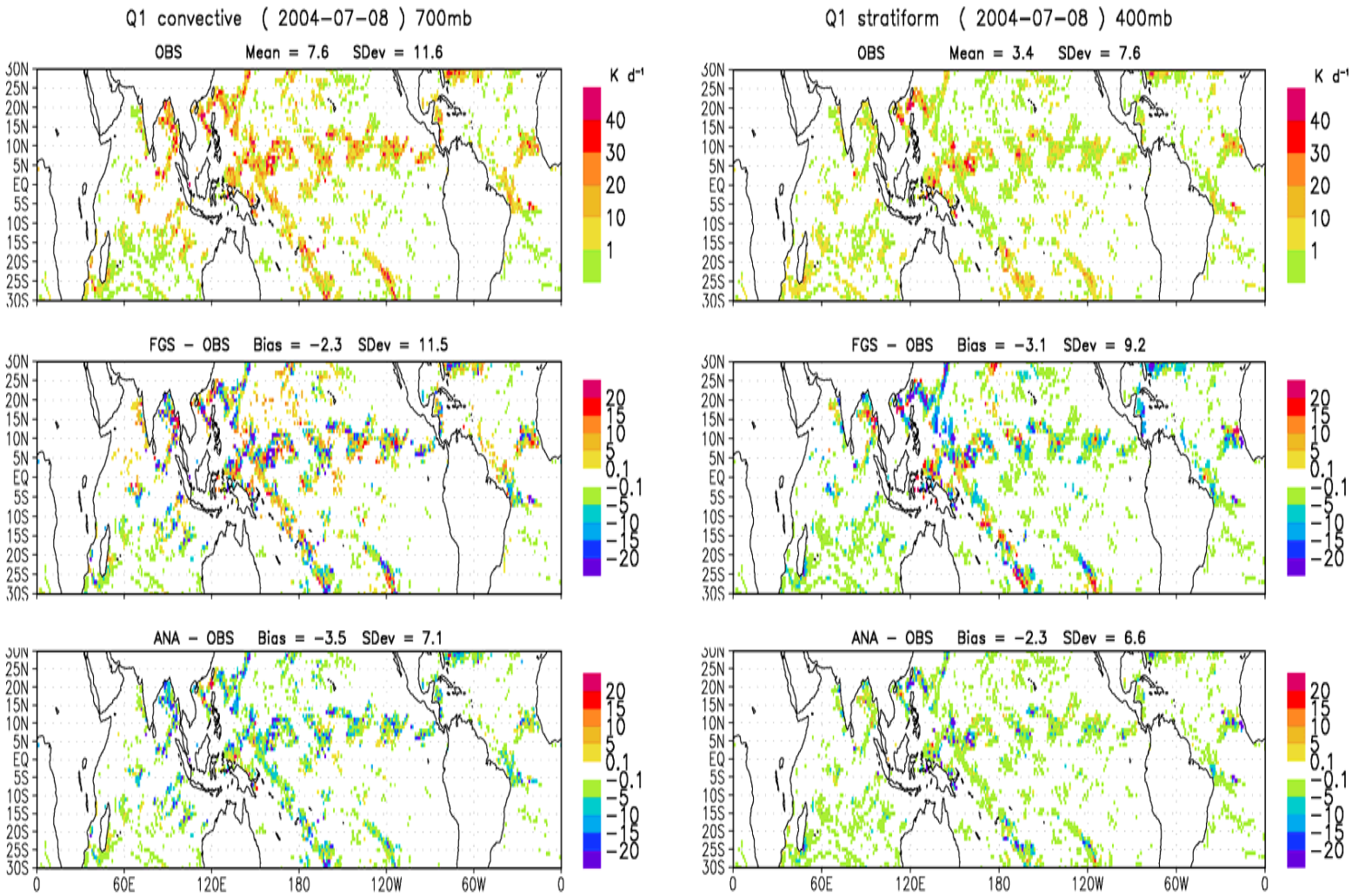
Final matching of the vertically integrated latent heating with observations is handled through the assimilation of surface rainfall using the VCA procedure

New pathway for improving moist physics schemes



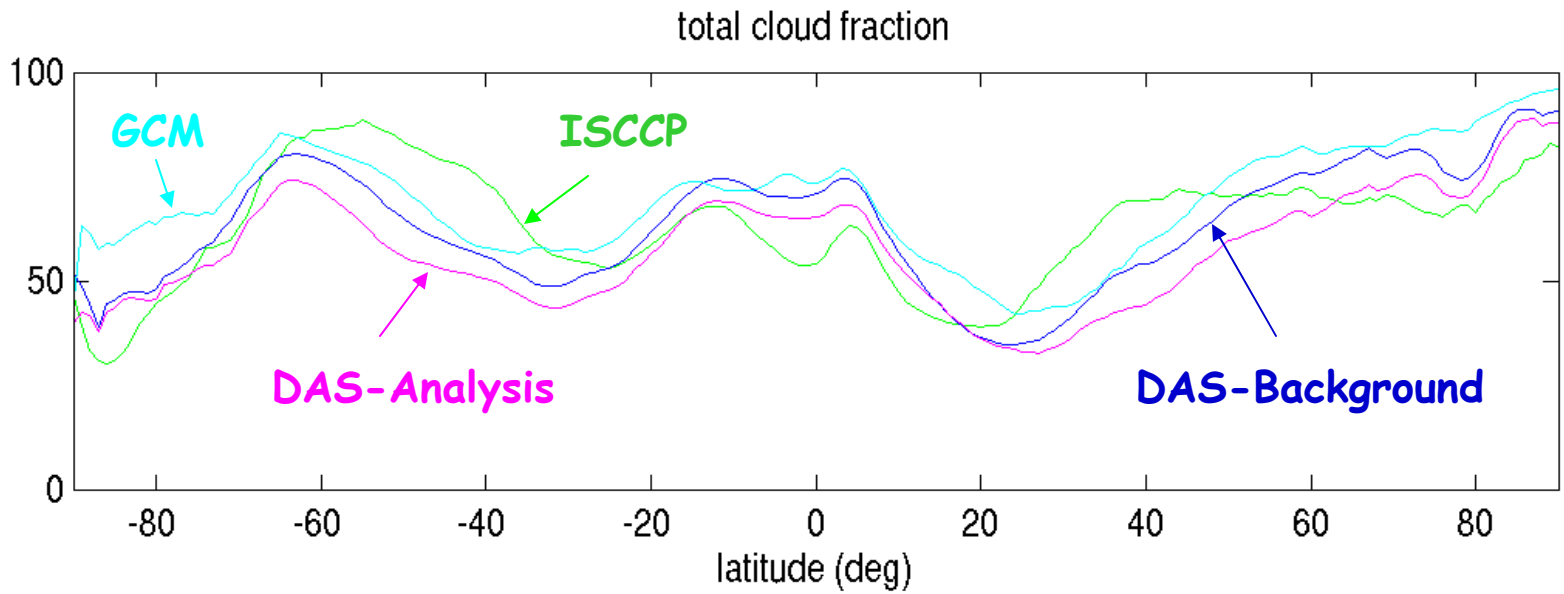
State-dependent parameters and/or stochastic parameterizations?

Impact on Q_c and Q_s at maximum heating levels



Reduction of error std dev by ~ 30%. Scheme minimizes the vertically-integrated RMS error in heating profile. It does not guarantee bias reductions at all levels

Cloud assimilation: Motivation



Mid-latitude clouds are not replicated by the GCM either in climate simulations or short-term forecasts (DAS-Background). The problem is made worse with assimilation of observed moisture data into the analysis (DAS-Analysis).

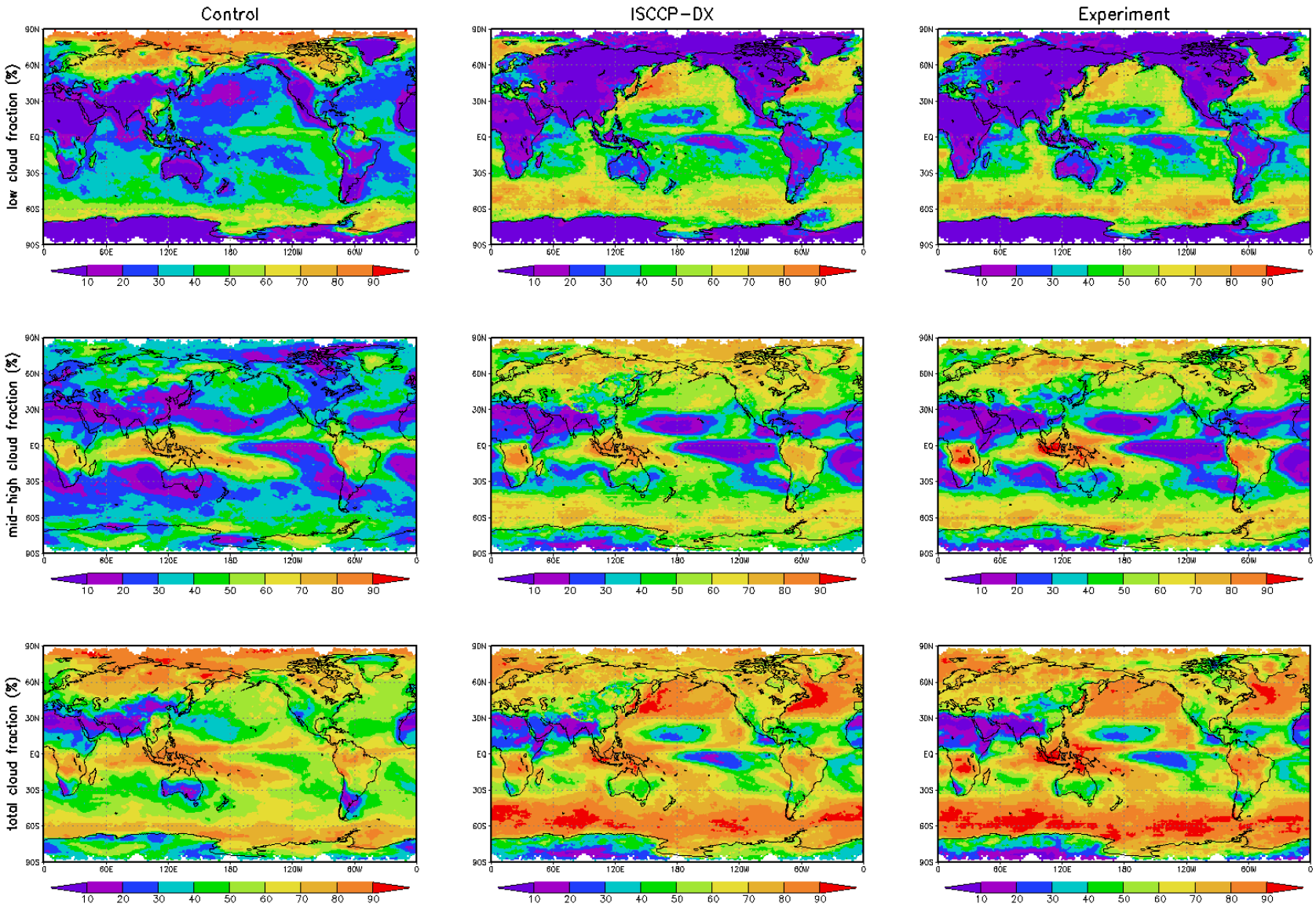
GCM cloud cover parameterization is typically tuned globally (e.g., via a critical relative humidity) to the model's moisture fields to give reasonable TOA fluxes in climate simulations. Assimilation of observed moisture data in the analysis breaks this tuning.

Cloud assimilation via parameter estimation

Estimation of empirical cloud parameters to improve the treatment of unresolved sub-grid-scale moisture variability, microphysical details, and cloud overlap.

- Developing variational algorithms to assimilate
  - ISCCP-DX cloud fraction and optical depth
  - SSM/I cloud liquid water path
  - *MODIS cloud fraction and optical depth*
- Control variables:
  - *Critical RH* plus a parameter governing the functional dependence of cloud fraction on RH* (CCM3 physics generalized to a 2-parameter, S-shaped $f(RH^*, \alpha)$)
    - » Big improvement in LW cloud radiative forcing
  - *Reference LWC value in CCM3 cloud water scheme* for cloud liquid water
    - » Further improvements in the tropics
  - *Effective cloud overlap* parameter in CCM3 physics for cloud optical depth
    - » Minimizing errors in SW cloud radiative forcing

Improved cloud fraction

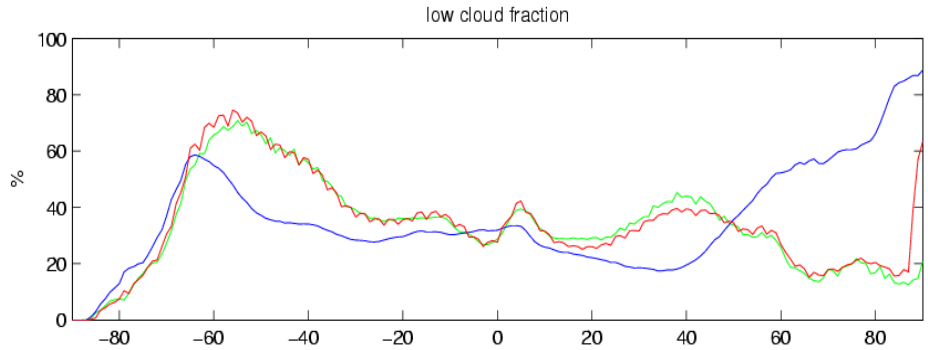


P. Norris & A. da Silva

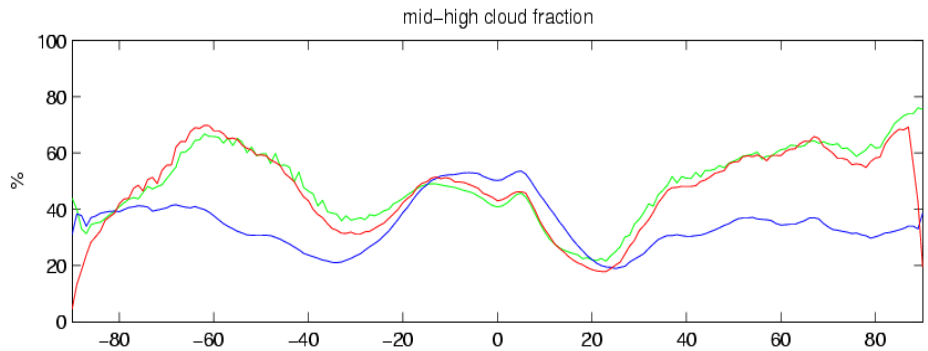
DJF 2000

Improved cloud fraction

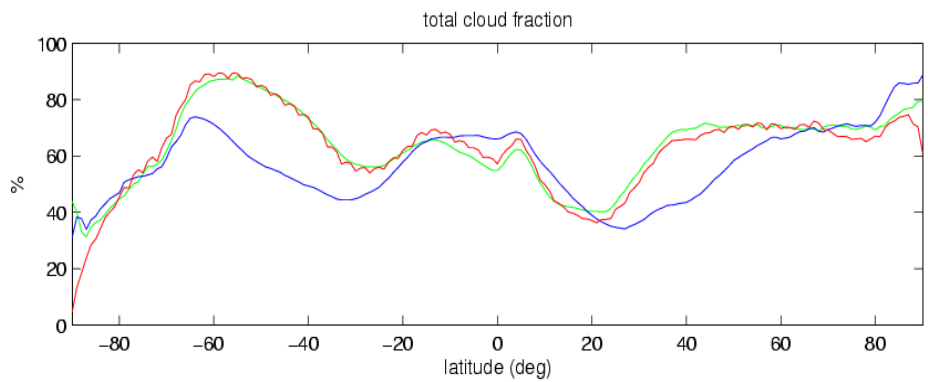
LOW



MID-HIGH



TOTAL

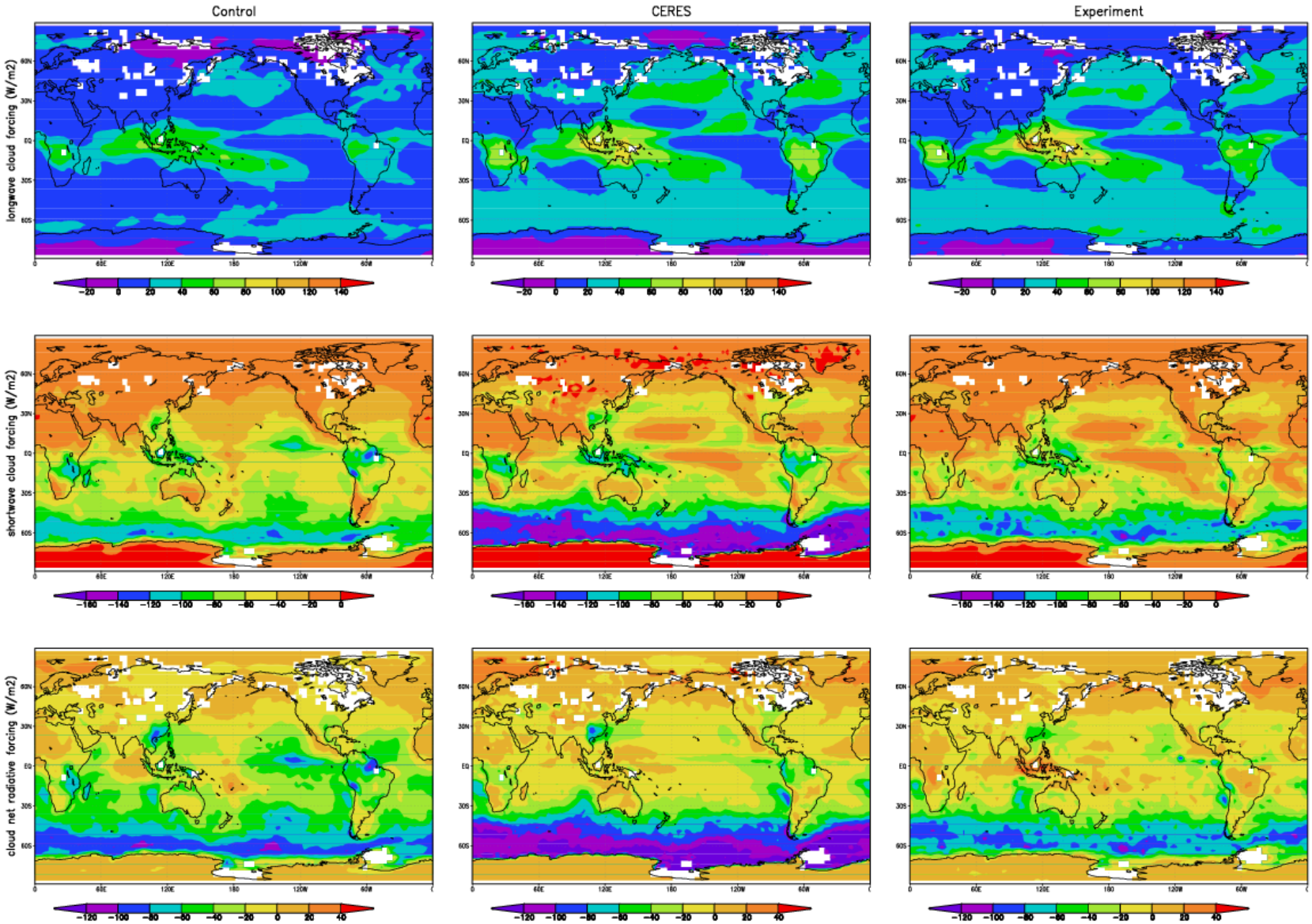


Green: CERES

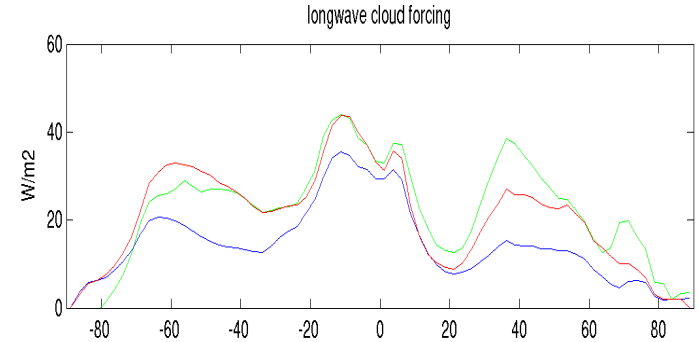
Blue: Control

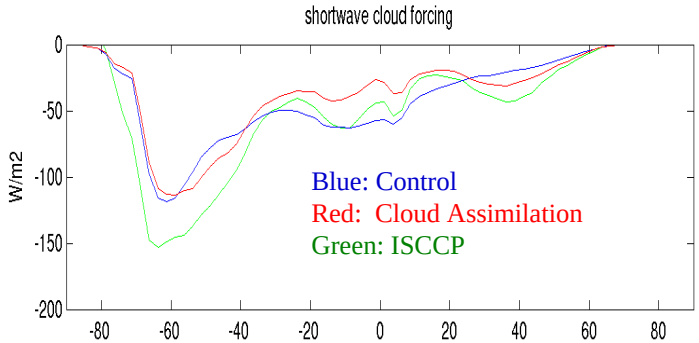
Red: Cloud Assimilation

Improved TOA cloud radiative forcing (CERES verification)

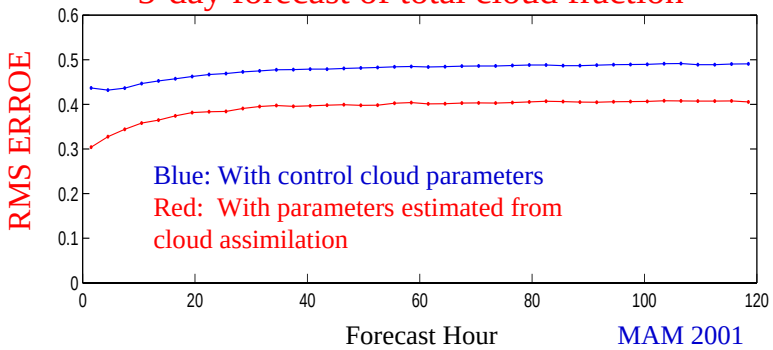


Impact of cloud assimilation



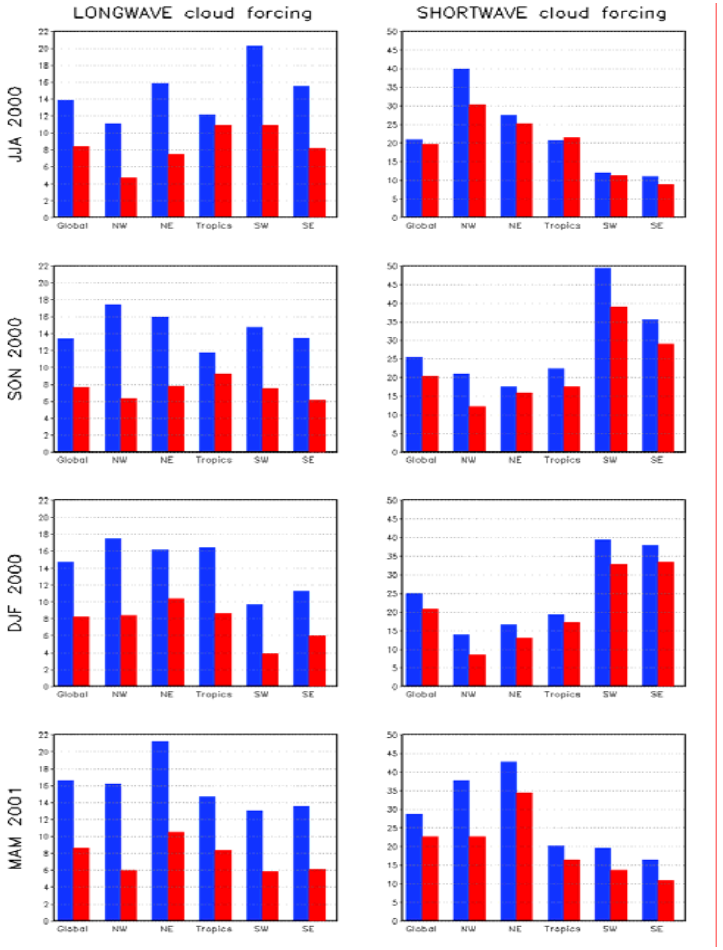


5-day forecast of total cloud fraction



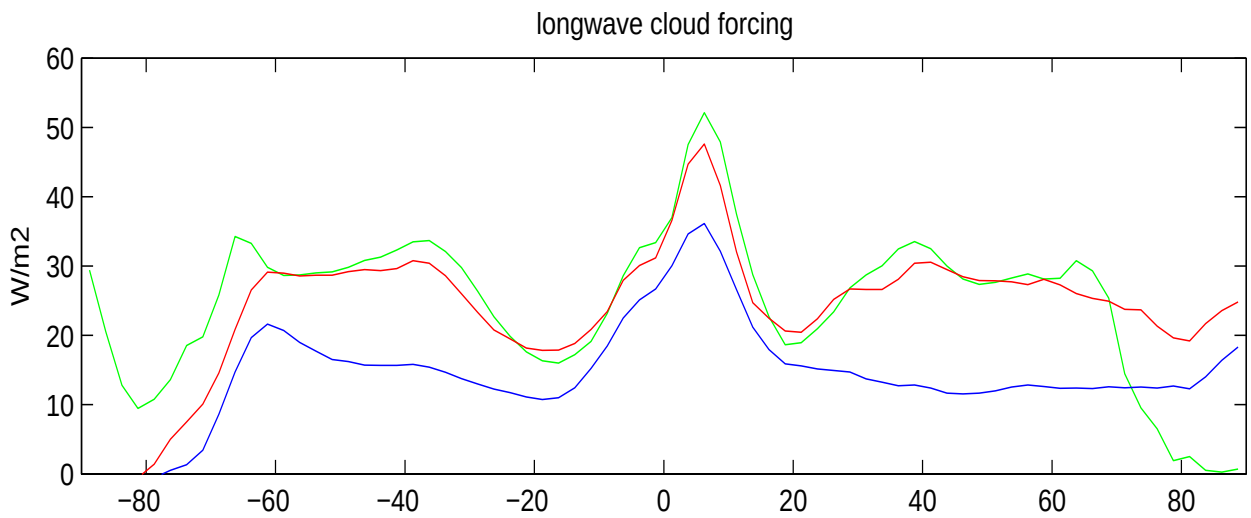
MAM 2001

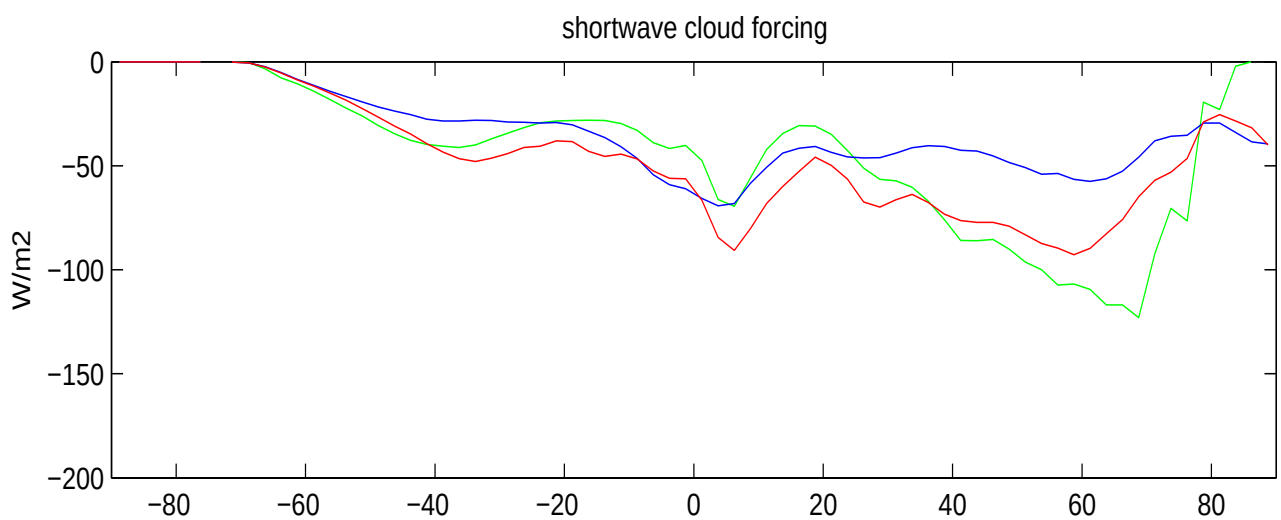
Reduced RMS error in cloud-radiative forcing verified against CERES



Blue: Control Red: Cloud Assimilation

Preliminary MODIS cloud assimilation





Green: CERES

Blue: Control

Red: Cloud Assimilation

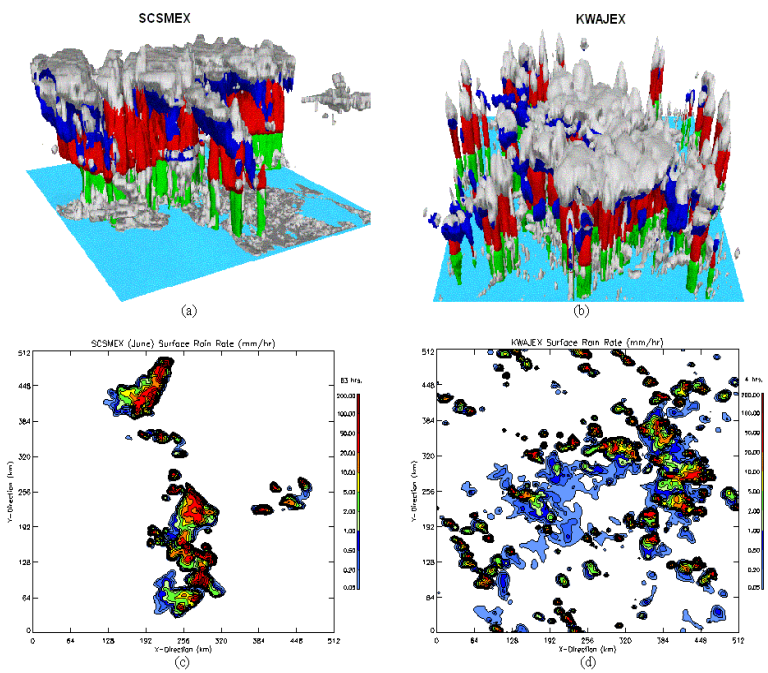
Issues and challenges in cloud assimilation

- Attribution of sources of model errors is risky: Need better physical understanding of model deficiencies for guidance.
- Issues arising from averaging over model grids of nonlinear sub-grid scale processes.
- Validation of cloud data – e.g., uncertainties in cloud-top height and effective radius estimates in the presence of multi-layer clouds.
- Compatibility between radiative transfer code used in retrievals and assimilation models.
- Physical and sampling compatibility between measurements and model quantities.

CRM need to provide benchmarks for investigating some of these issues

Bridging the gap between satellite observations and global models

Using cloud/radiation/precipitation observations to evaluate and improve CRM microphysics:



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)

- Access CRM's ability to bridge the gaps in *physics* and *spatial scales* between global systems and satellite observations:

  - Do CRM simulations driven by large-scale forcing from global analysis replicate observed microphysical cloud properties, DSD, and radiances from region to region?

- Develop techniques to assimilate cloud/precipitation information (and their statistical properties) in cloud-scale models including the direct use of level-1 radiance measurements. Examine the feasibility of radiance assimilation in cloudy and rainy regions using moist physics parameterized in terms of the grid-averaged state.

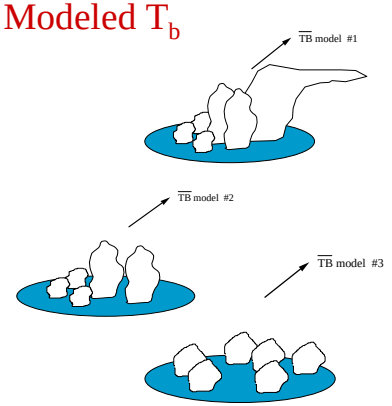
CRM as an interpreter of satellite observations

Using observation-constrained CRM realizations of moist processes to guide parameterization improvement and the choice of control variables in variational cloud/precipitation assimilation.

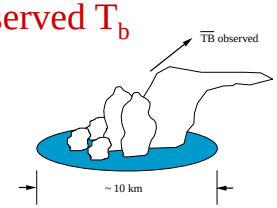
A Bayesian rain estimate from MW T_b

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

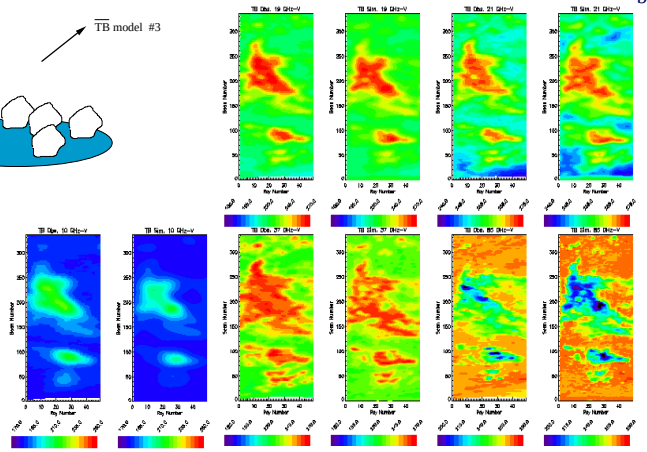
Modeled T_b



Observed T_b

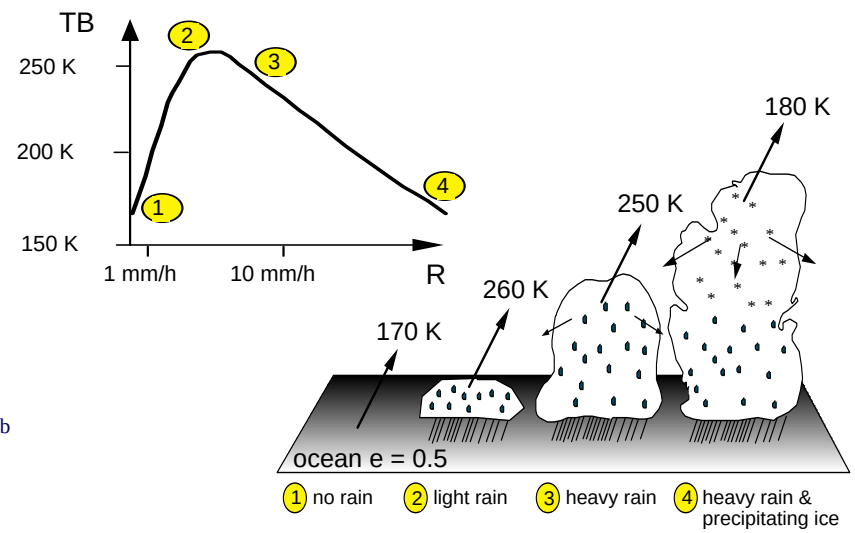


Simulated vs. TMI observed T_b



Courtesy of W. Olson

Microwave radiance at 37 GHz



Example: Ensemble of CRM simulations of moist processes which are radiatively consistent with MW radiances in raining areas

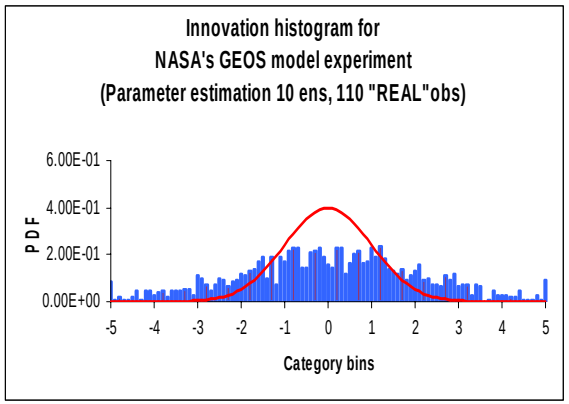
Ensemble techniques for cloud/precipitation assimilation

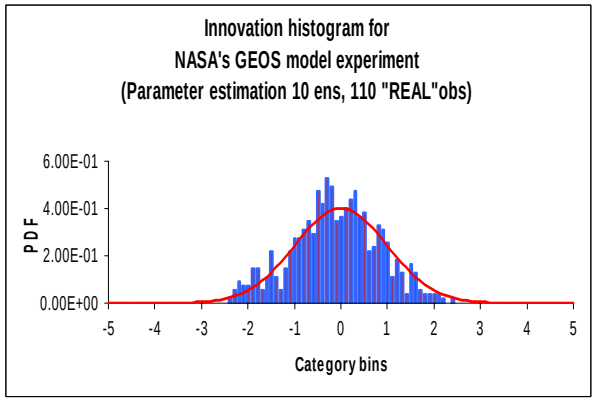
- EnsDA is a promising strategy for assimilating observables with nonlinear observation operators that may have significant errors:
  - no tangent linear or adjoint model
  - unified framework for treating initial-condition and model errors
  - direct estimation and update of flow-dependent analysis and forecast error covariances

- GSFC/CSU collaboration on EnsDA using GEOS-5 column model of unified cloud/rain physics (*with D. and M. Zupanski*)
  - variational solution to obtain a maximum likelihood estimate (equivalent to EnsKF/KS)
  - augmented control variables to address IC and systematic model errors

GSFC/CSU ensemble data assimilation experiments

- "Fraternal twin" experiment with prescribed IC and model errors to examine
  - algorithm's ability to estimate the partition of forecast error statistics due to IC errors and model errors
  - detecting systematic model errors
  - benefits of direct estimation and updating of flow-dependent forecast error covariances
  - parametric ranges in ensemble size, width of analysis window, and error magnitudes for obtaining useful estimates





Sensitivity of innovation statistics to prescribed observation error

↑

The only input!

Summary and Plans

- Effective use of cloud/precipitation information in global data assimilation poses a special challenge because parameterization schemes can have large systematic errors, which must be addressed in the assimilation procedure:
  - Using the forecast model as a weak constraint
  - Cloud/precipitation assimilation offering a new pathway to estimating empirical parameters in moist physics schemes (within observational uncertainties and consistent with analyzed atmospheric states)
  - Using observation-constrained CRM simulations of moist processes to identify deficiencies in moist physics schemes and guide the selection of control variables in variational assimilation of cloud/rain information (- with CRM forced by the same large-scale flows)
  - Addressing IC and model errors within the EnsDA framework

Summary and Plans (continued)

- Observation-driven CRM studies:
  - Using cloud/precipitation observations to evaluate CRMs
  - Developing methods to assimilate statistical properties of precipitation and clouds in CRMs
  - Incorporating observed subgrid-scale pixel information into a PDF-based statistical parameterization of subgrid-scale variability – i.e., evolving towards statistical cloud/rain parameterizations and assimilation techniques for global systems

Linking to GCSS

* Looking to GCSS community to provide sound scientific basis to help model & algorithm developers to make intelligent choices in data assimilation research and applications

* Coordination, priorities, and timely feedback will be key considerations in attempting more direct engagements at the working level between GCSS and model developers