Overview on Cloud and Precipitation Assimilation in Gridpoint Statistical Interpolation (GSI) System

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NASA GMAO/ GESTAR

Acknowledgement:

Ricardo Todling, and Amal Akkaraoui, Jinjun Jin, Will McCarty, Ron Gelaro, and many others in NASA GMAO

Fuzhong Weng, John Derber, Daryl Kleist,, Yanqiu Zhu, Emily Liu, Andrew Collard, and Jeff Whitaker in NOAA

Gridpoint Statistical Interpolation (GSI) System

- 3D-Var analysis algorithm developed by NOAA NCEP to replace SSI as new generation global/regional unified analysis system. Became operational as NOAA Global DA System in May 2007.

- Collaboration with NASA GMAO started circa 2005 with GSI replacing PSAS soon after.

- Since early days, the number of groups involved in GSI development has increased substantially to groups such as NOAA/ESRL/GSD and NCAR/ESSL/MMM. Community software distribution is handled by NCAR/DTC.

Hybrid Variational-Ensemble Analysis System

Incorporate ensemble perturbations directly into variational cost function through extended control variable.

… Lorenc (2003), Buehner (2005), Wang et. al. (2007), etc.

$$J(d\mathbf{z}) = \frac{1}{2}\delta\mathbf{z}^T[\beta_s\mathbf{B}_s + \beta_e\mathbf{B}_e]^{-1}\delta\mathbf{z} + \frac{1}{2}(\mathbf{d} - \mathbf{H}\delta\mathbf{z})^T\mathbf{R}^{-1}(\mathbf{d} - \mathbf{H}\delta\mathbf{z})$$

$$d\mathbf{z} = \beta_s\delta\mathbf{x} + \beta_e\sum_{m=1}^{M}\alpha_m \circ \delta\mathbf{x}_m^e$$

β_s & β_e: weighting coefficients for fixed and ensemble covariance respectively

$\mathbf{B}_s$: static background error covariance

$\mathbf{B}_e$: ensemble background error covariance

α_m e:xtended control variable

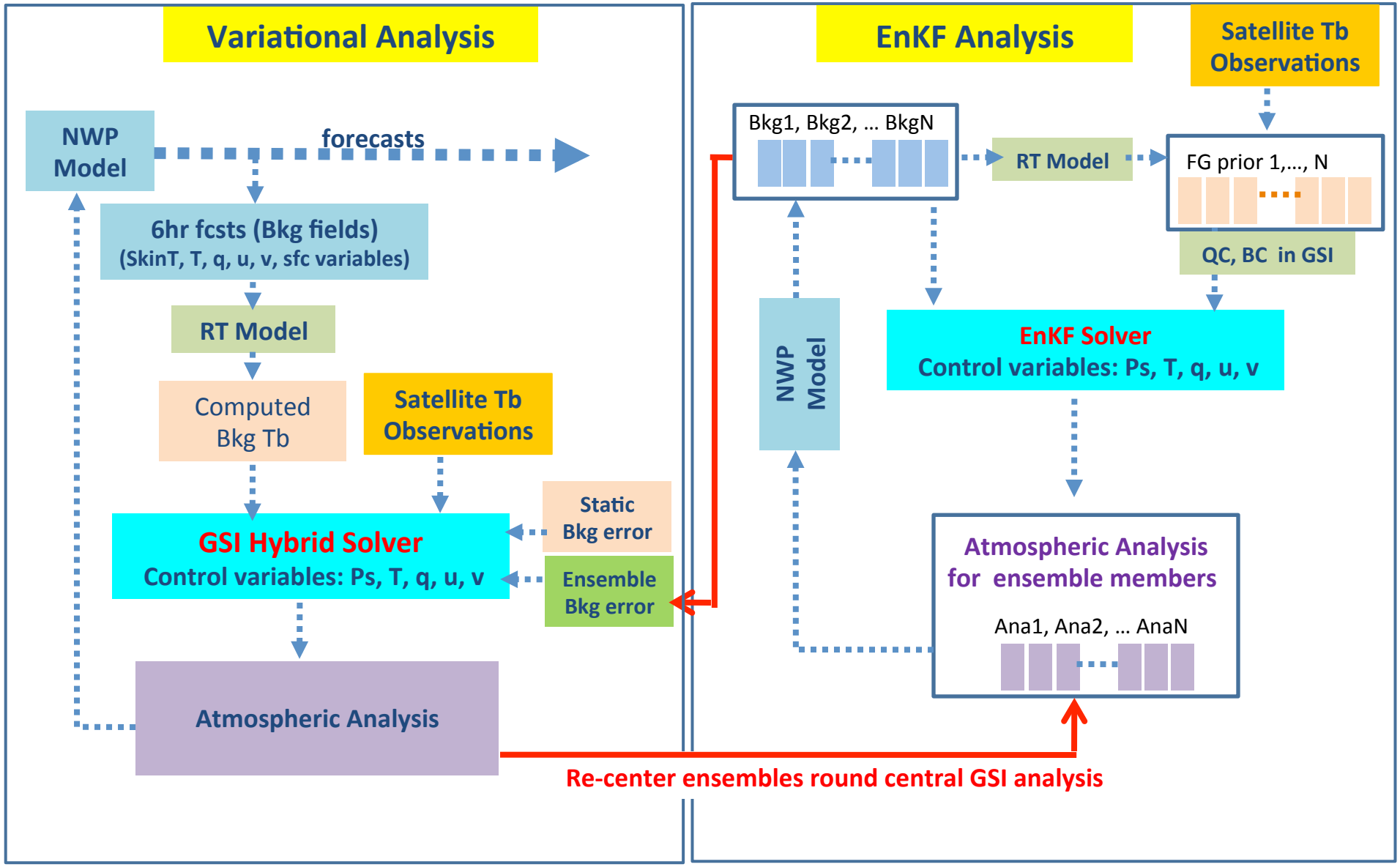
δx_m^e: m-th ensemble perturbation created from the m-th member background state x_m

d: observation residual vector ($d=y-h(x_g)$) where h is observation operator

H: linearized observation operator h

GSI-based Analysis Systems

Hybrid system (Ensemble DA + Variational DA)

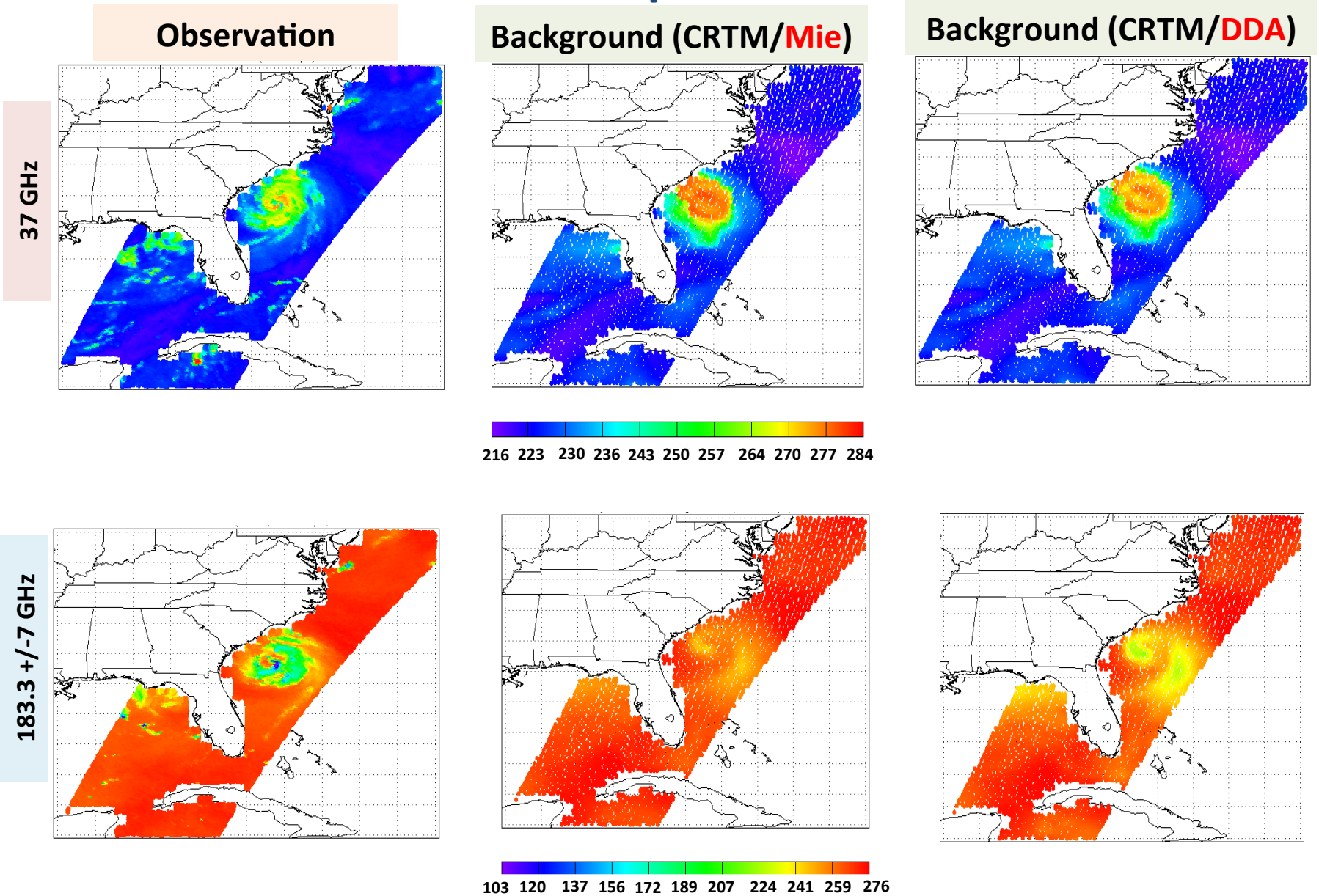


Extended components in GSI for All-Sky Radiance DA

X_b = Background (first-guess)	Added cloud liquid (ql), cloud ice(qi), rain(qr), snow(qs)
x_a = Analysis	Added ql, qi, qr, qs
O = Observations	New QC gross checks to keep cloud and precipitation affected radiance data
B = Background Error Covariance	Added static B and EnKF B for ql, qi, qr, and qs
R = Observation Error	Assigned observation errors for all-sky GMI radiance data. R is function of cloud amount. (Geer et al. ECMWF)
H = Observation Operator	Evaluate/Enhance CRTM performance in regions with precipitation
Bias correction : Variational Bias Correction (VarBC)	Bias correction predictors in VarBC: constant, lapse rate, lapse rate^2 to correct air-mass related biases.

- GMAO's efforts are focused on all-sky MW imagers (e.g. GPM Microwave Imager).
- NCEP's efforts are focused on non-precipitating cloudy AMSU-A data.
- So far, developments have focused on utilizing microwave data over ocean only.

Observation Operator: CRTM



Hurricane Arthur (3 July 2014)

Observation Operator: CRTM

- **For now, cloud optical parameters are given to CRTM users as a cloud coefficient file.**
  - It is not flexible for users to test with different scattering parameter databases and different particle size distributions.
  - JCSDA is currently working on making cloud optical parameter related codes as modules to allow the flexibility for users.

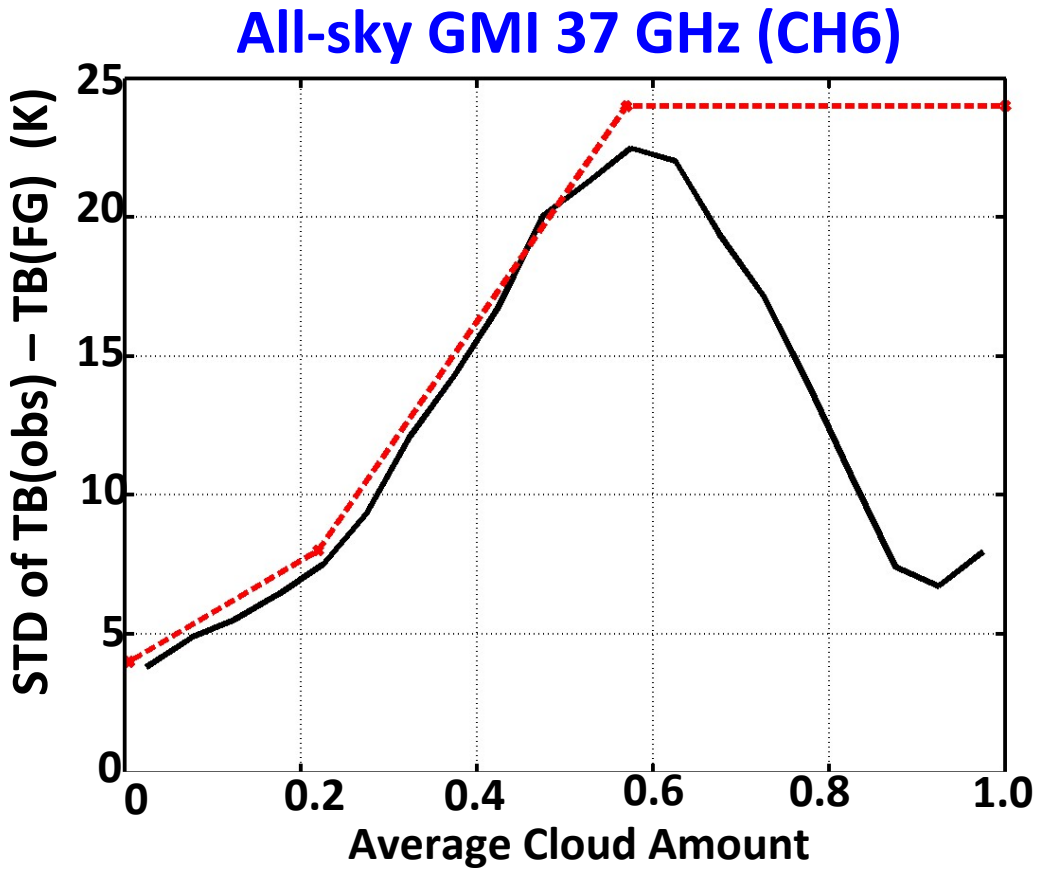
- **Cloud fraction capability which will be available in CRTM (Paul van Delst talk yesterday)**

- **Moisture physics schemes will be upgraded in global model (e.g. two moment microphysics scheme in GEOS-5)**

- **We expect all these will contribute simulated background brightness temperatures much closer to observations and reduce observation errors.**

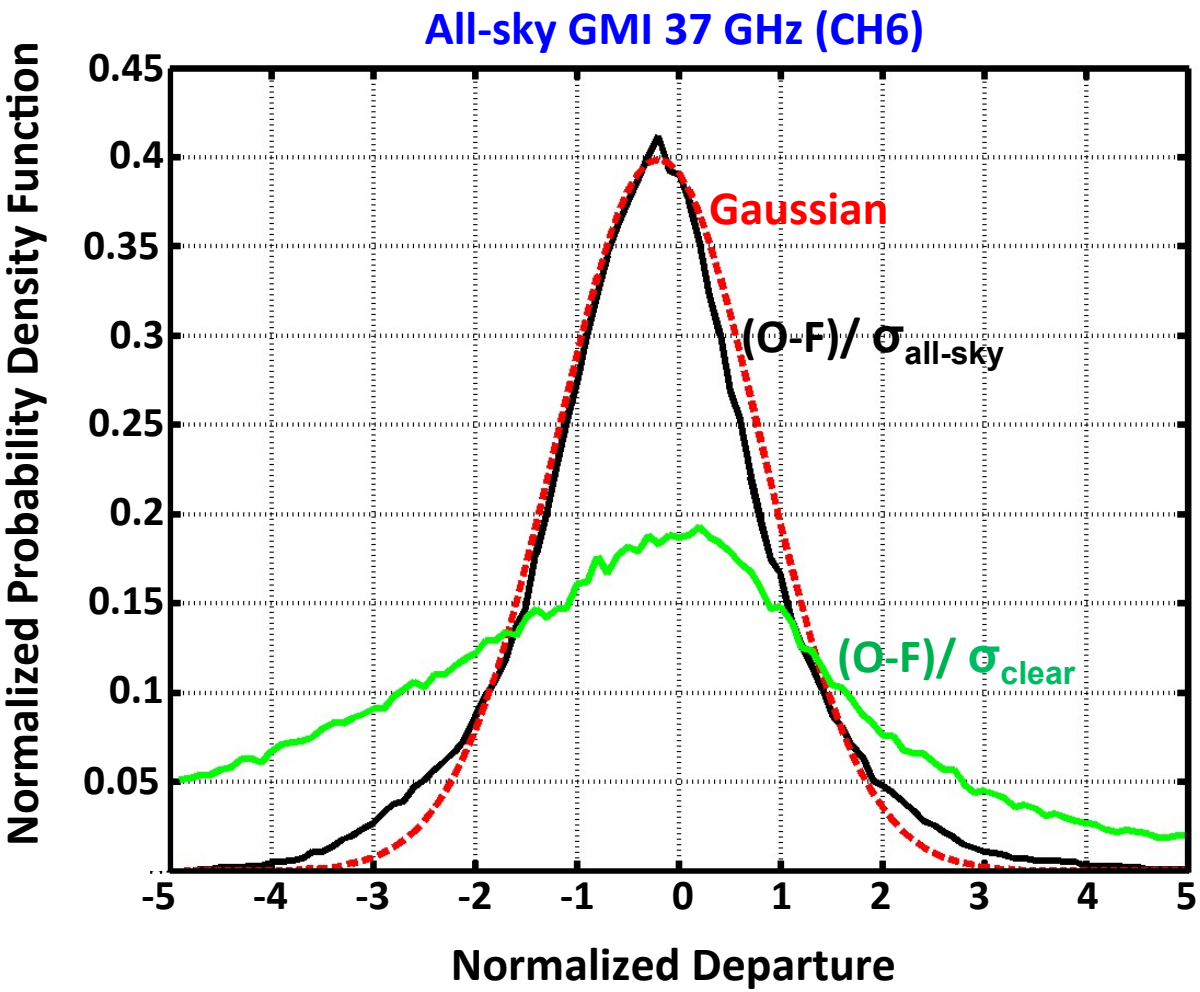
Observation Errors for All-Sky GMI

- Observation error is defined as a function of cloud amount. (Geer et al.@ ECMWF)
- Smaller errors in clear sky and larger errors in cloudy and precipitation situation



Mean of observed and first-guess(FG) cloud amount derived from 37 GHz polarization difference

First-guess Departure (Observed Tb – Bkg Tb)



Cloud dependent observation errors help distributions to be more Gaussian.

Why analyzing clouds and precipitation?

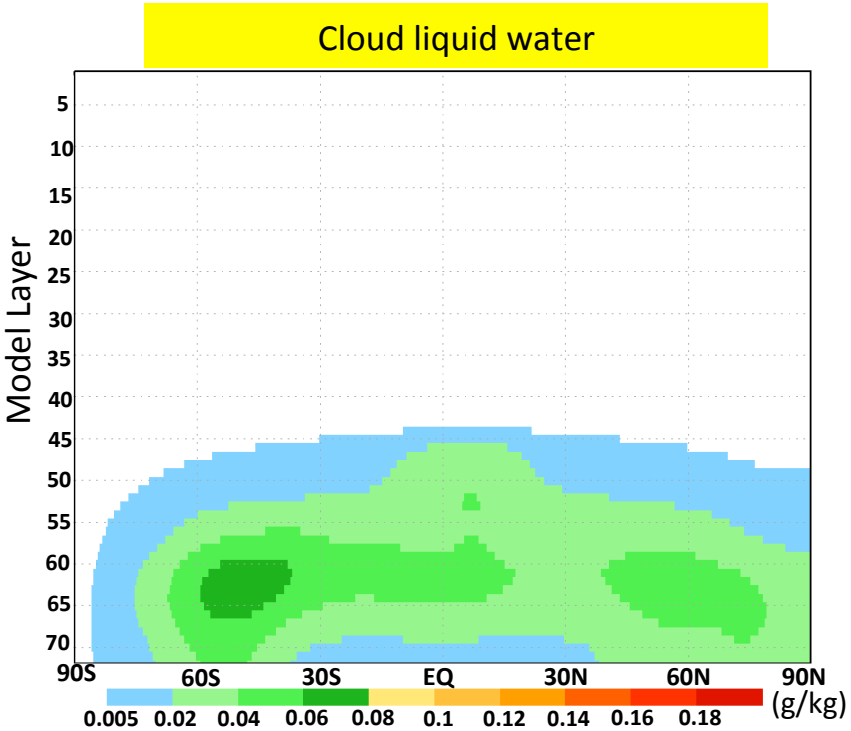
• **All-sky assimilation not taking cloud and precipitation as part of the control vector is likely to introduce inconsistencies in the increments of temperature and humidity.**

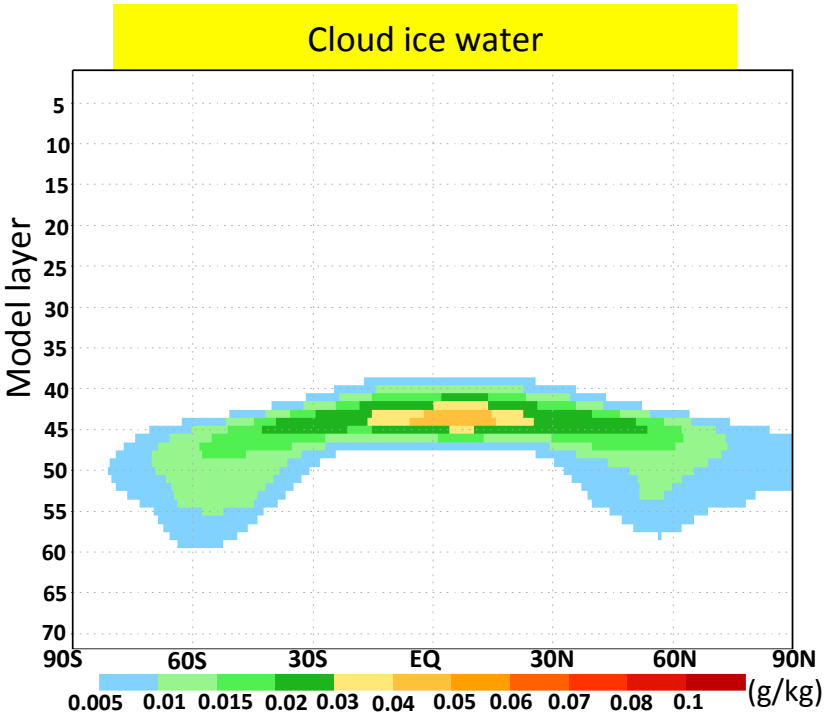
For example,
Large clouds/precipitation in the observations, smaller clouds/precipitation in background fields .
→ Large positive first-guess departures in lower microwave channels
→ Result in adjusting q or T analysis fields if clouds/precipitation are not allowed to change

• **However, taking cloud and precipitation into account requires difficult specification of background error variances for these variables.**

Static Background Error (B)

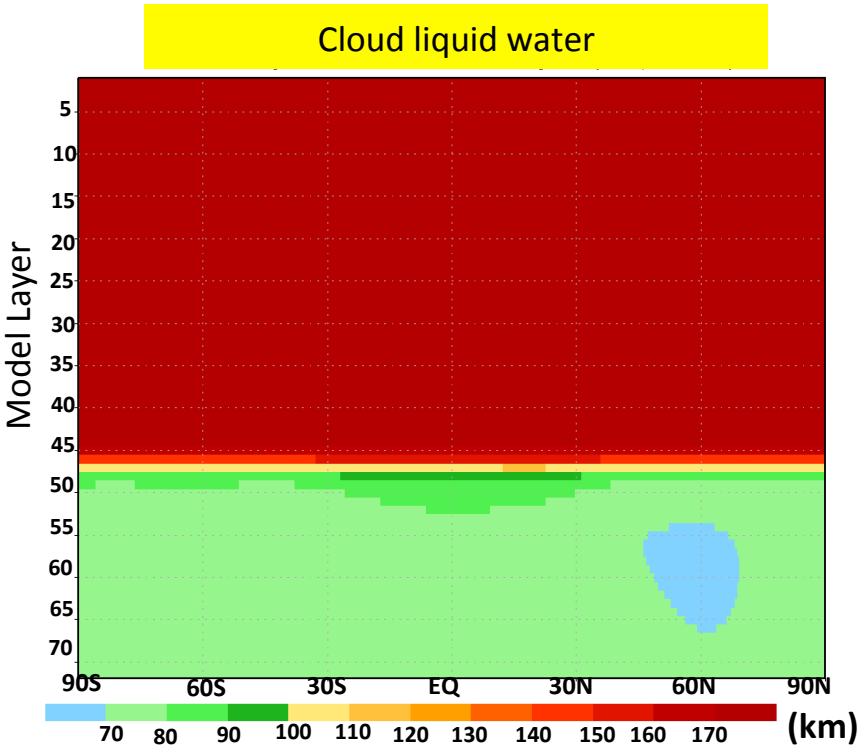
• Based on NMC Method (Parrish and Derber 1992): Use differences between 24-hour and 48-hour forecasts that are valid for the same time as a proxy for background error

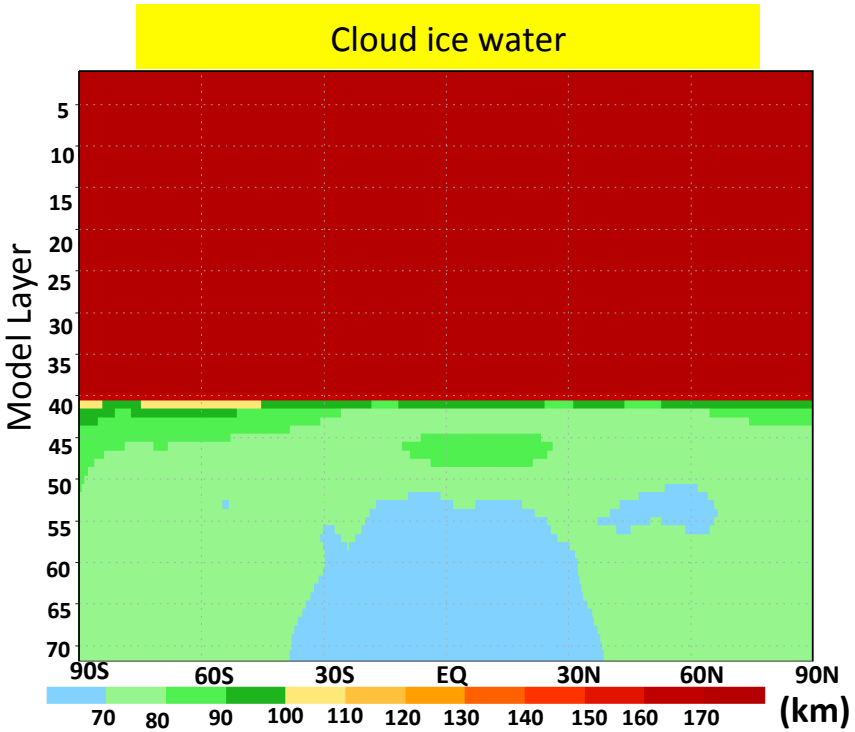




- **NASA GEOS-5 24hr and 48hr forecasts. (~ 1 year long data base used)**
- **Generally smooth patterns**
- **ql maximum error (~0.08 g/kg) in lower troposphere near SH storm track**
- **qi maximum error (~0.06 g/kg) near tropical tropopause**

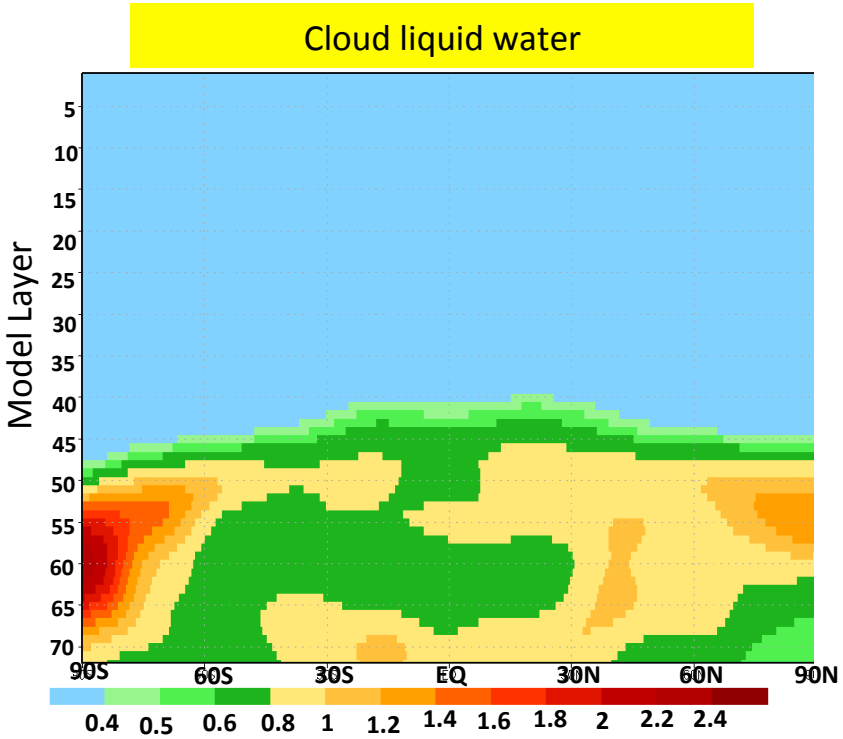
Static B: Horizontal Correlation Length

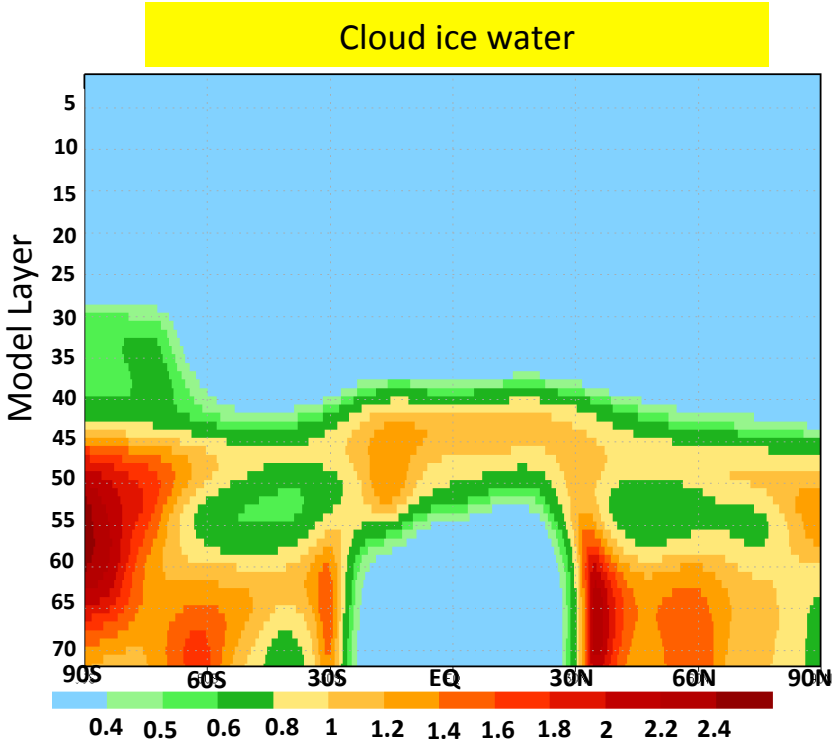




Almost constant in troposphere (70~90 km)

Static B: Vertical Correlation Length

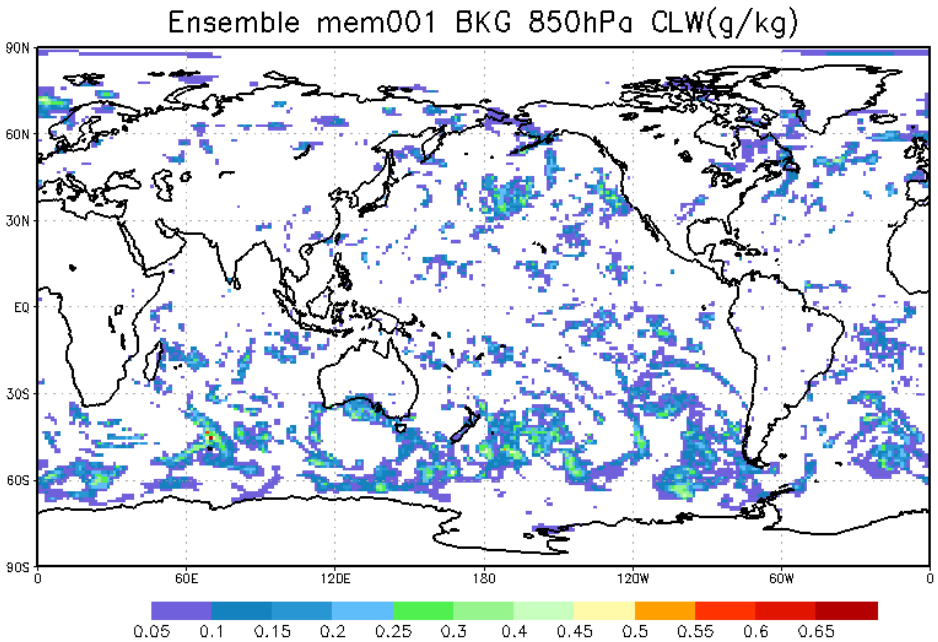




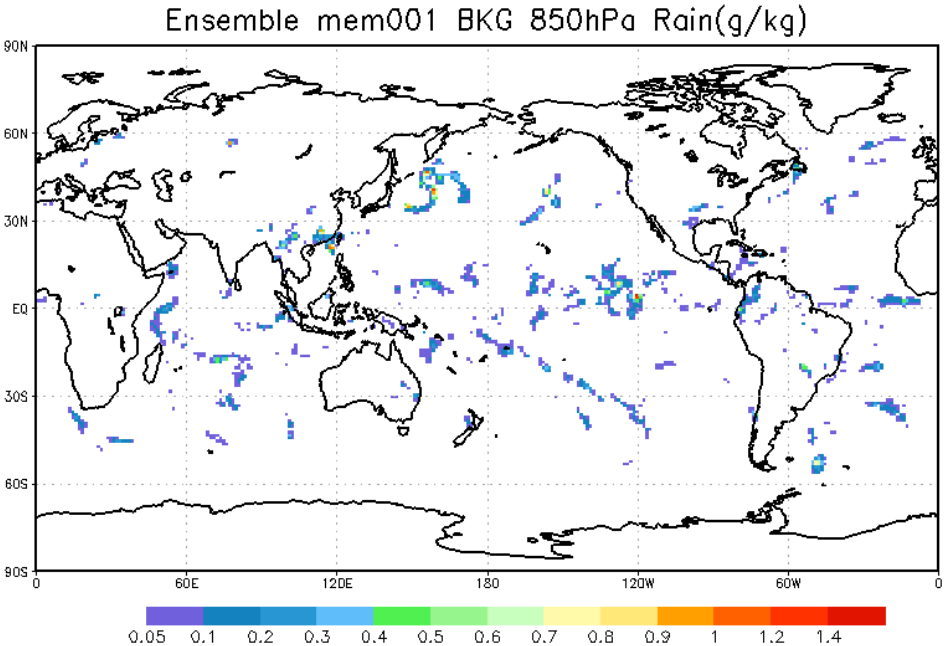
- Unit : number of vertical layers
- More variability in vertical correlation length than horizontal correlation length
- liquid cloud: less than 1 layer in most of the area except polar regions
- ice cloud: 1~2 layers most of the area

Ensemble B: Clouds and precipitation

Cloud Liquid Water



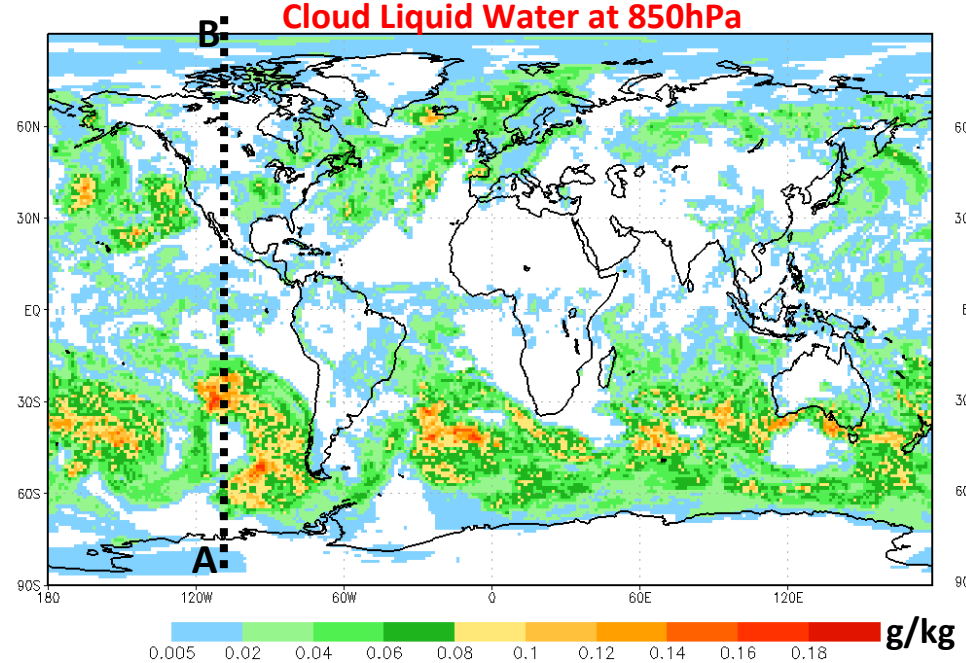
Rain Water



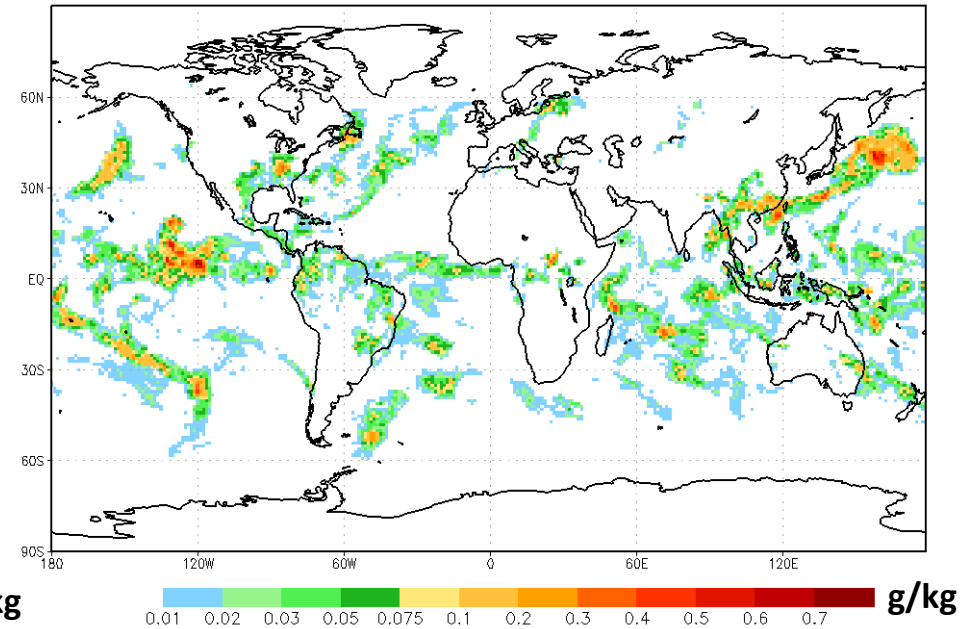
- 32 ensemble members from NASA GMAO's GEOS-5 system
- Horizontal: 1-deg (Ensemble bkg), 25 km (forecasts); Vertical: 72-levels
- Upcoming GMAO system:
  - *Horizontal: 0.5-deg (ensemble bkg), 12 km (forecasts);
  - *Vertical: 137-levels

Ensemble spread for clouds and precipitation

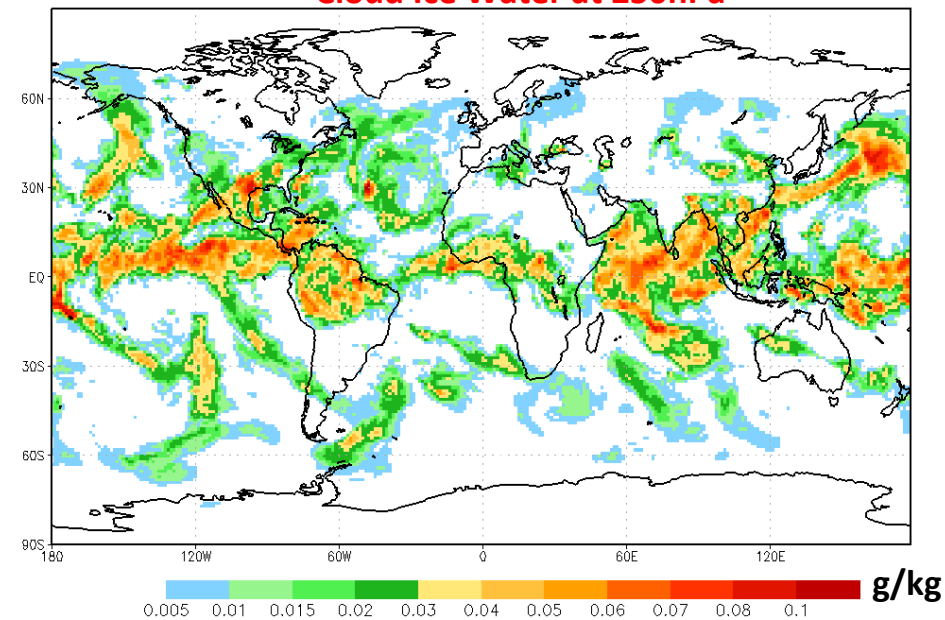
Cloud Liquid Water at 850hPa



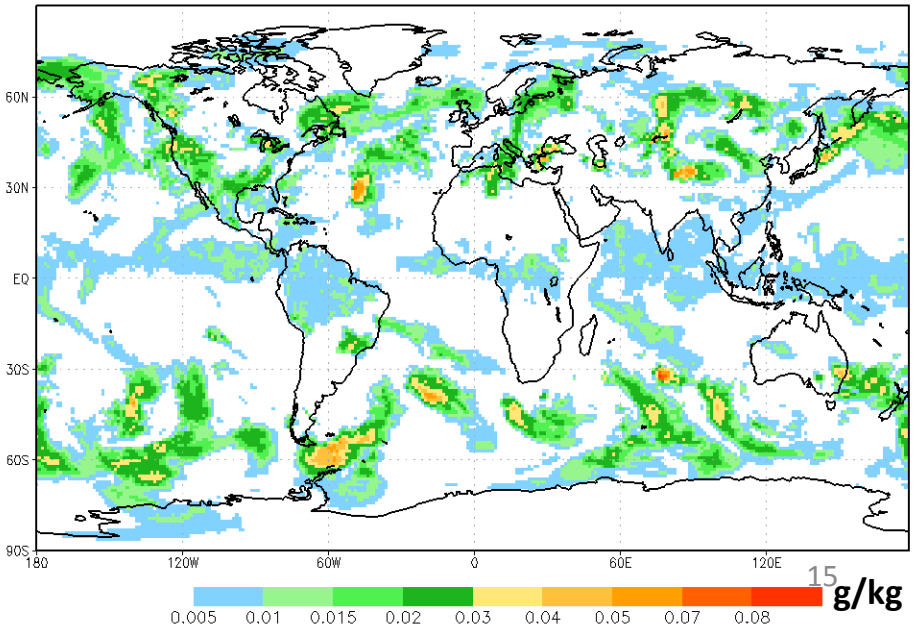
Rain Water at 850hPa



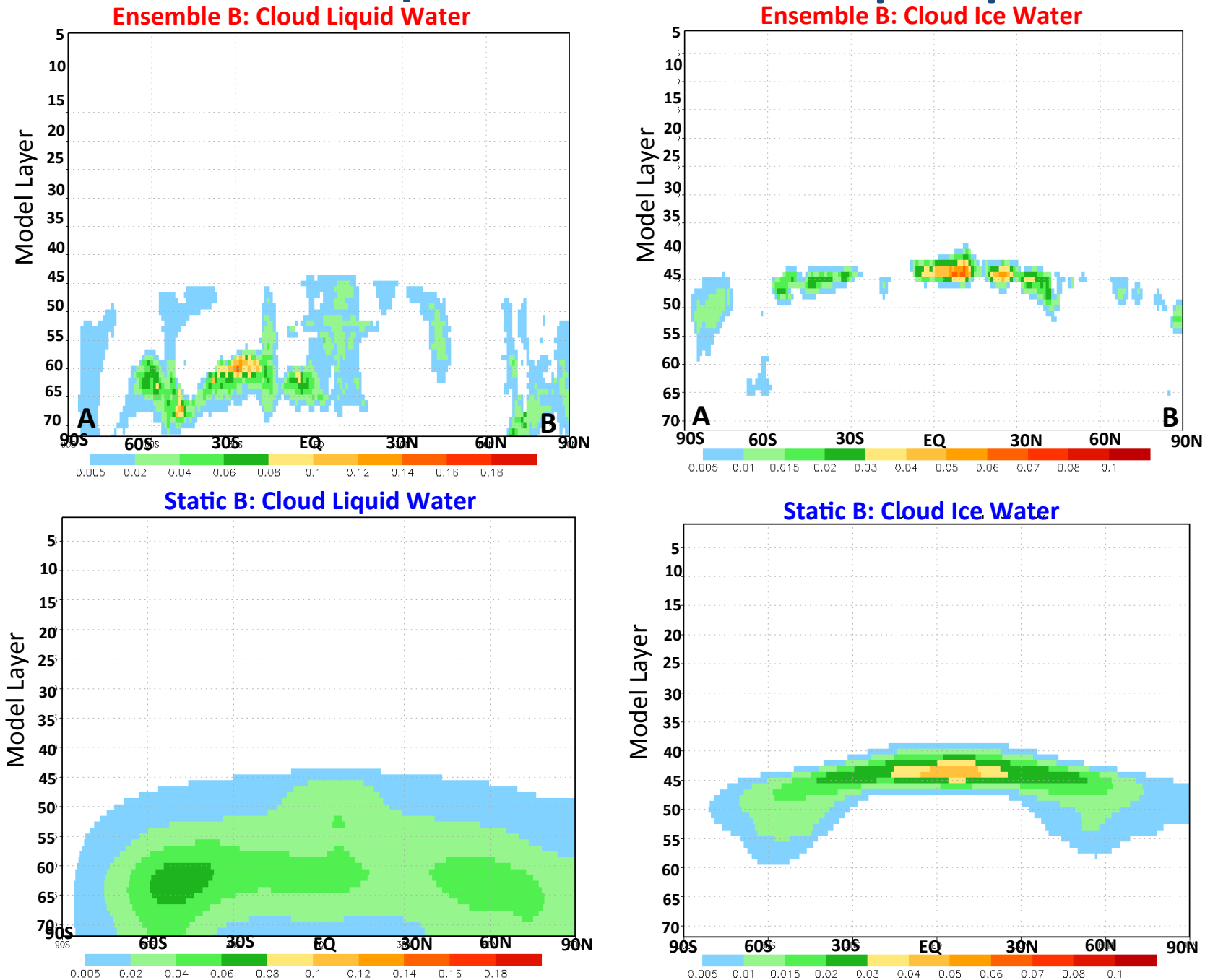
Cloud Ice Water at 250hPa



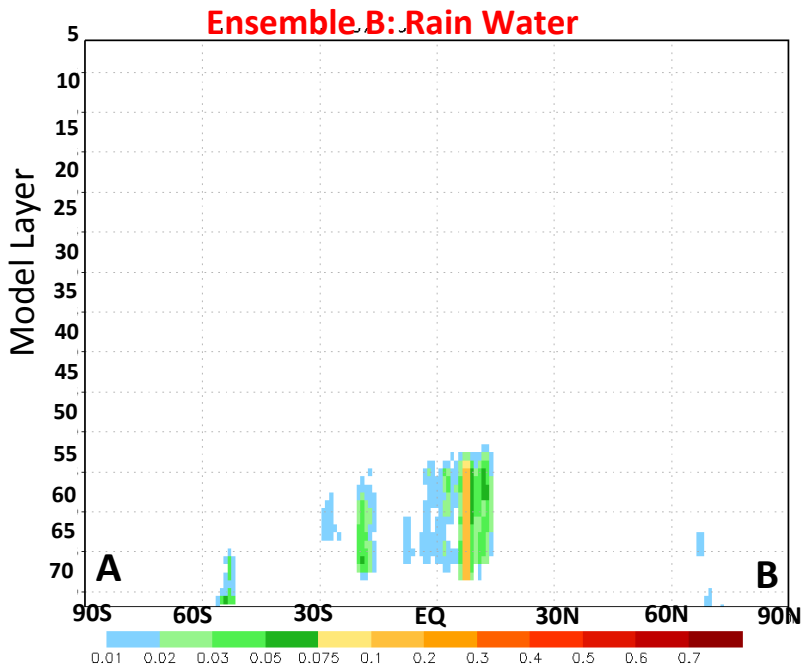
Snow Water at 350hPa

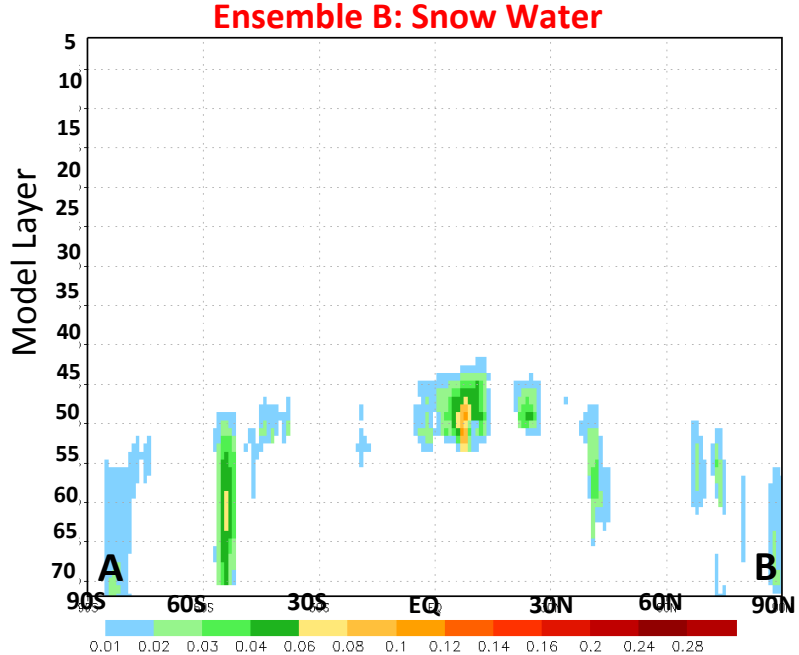


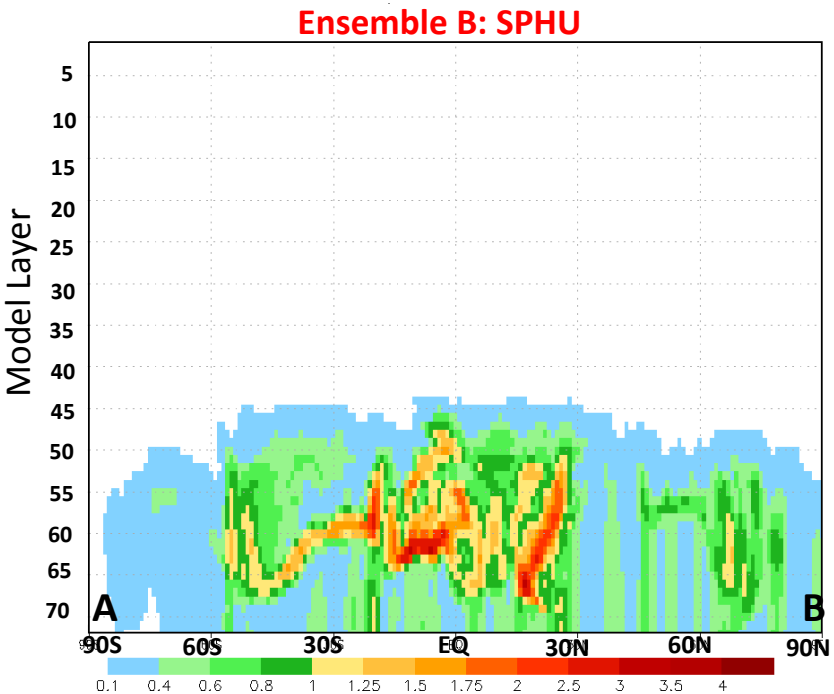
Ensemble spread for clouds and precipitation

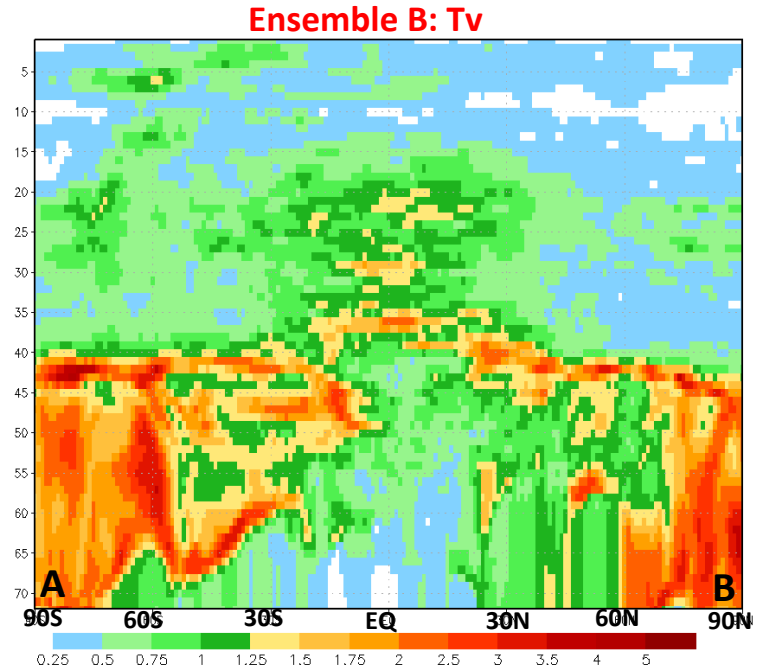


Ensemble Spread for Clouds and Precipitation

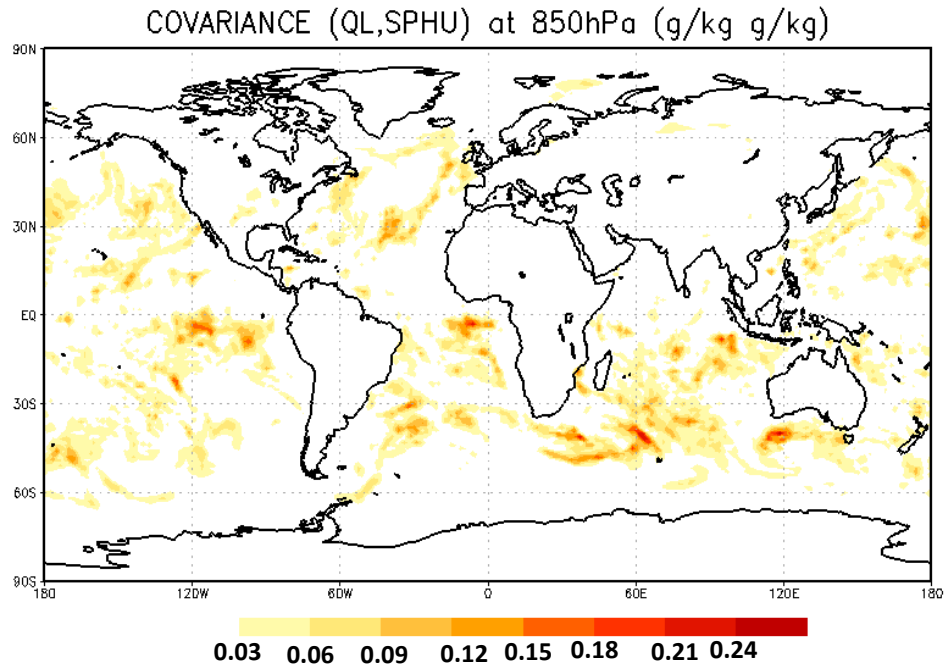


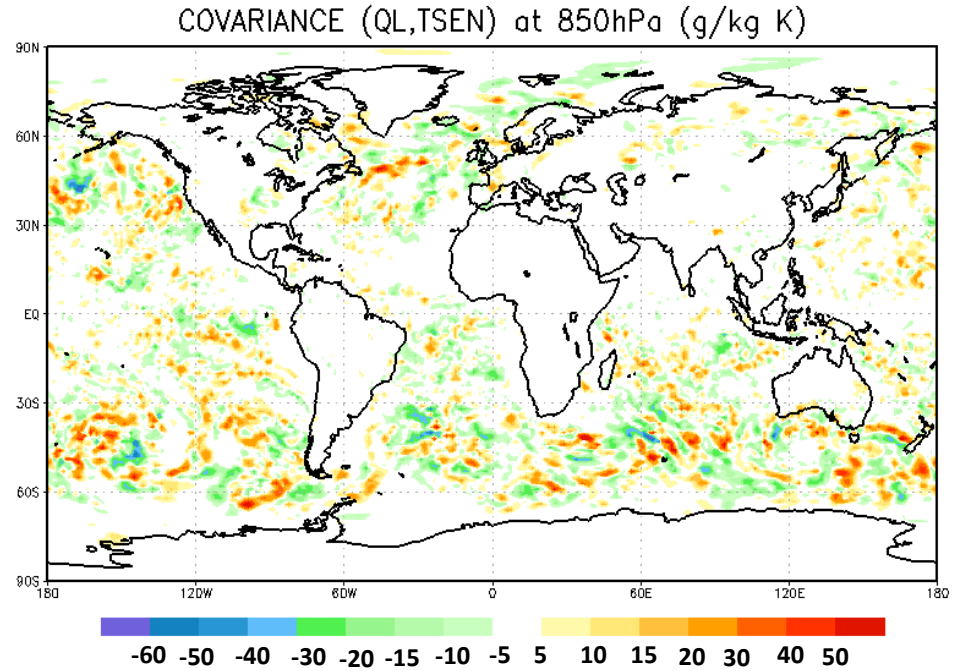






Covariance among different variables in Ensembles

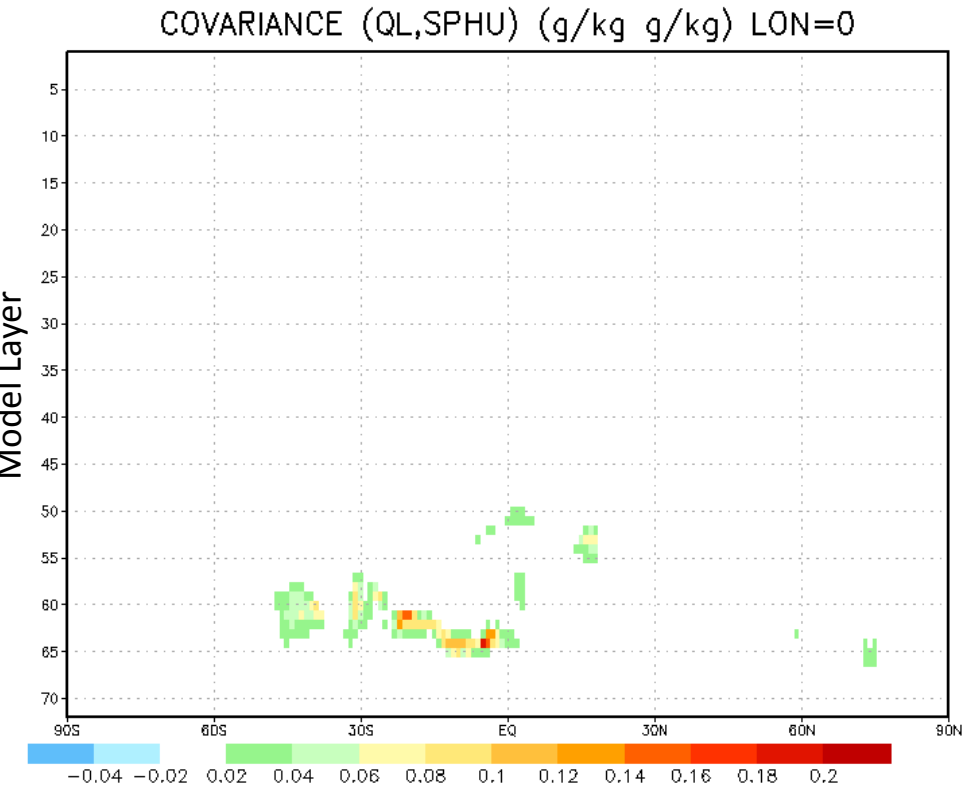


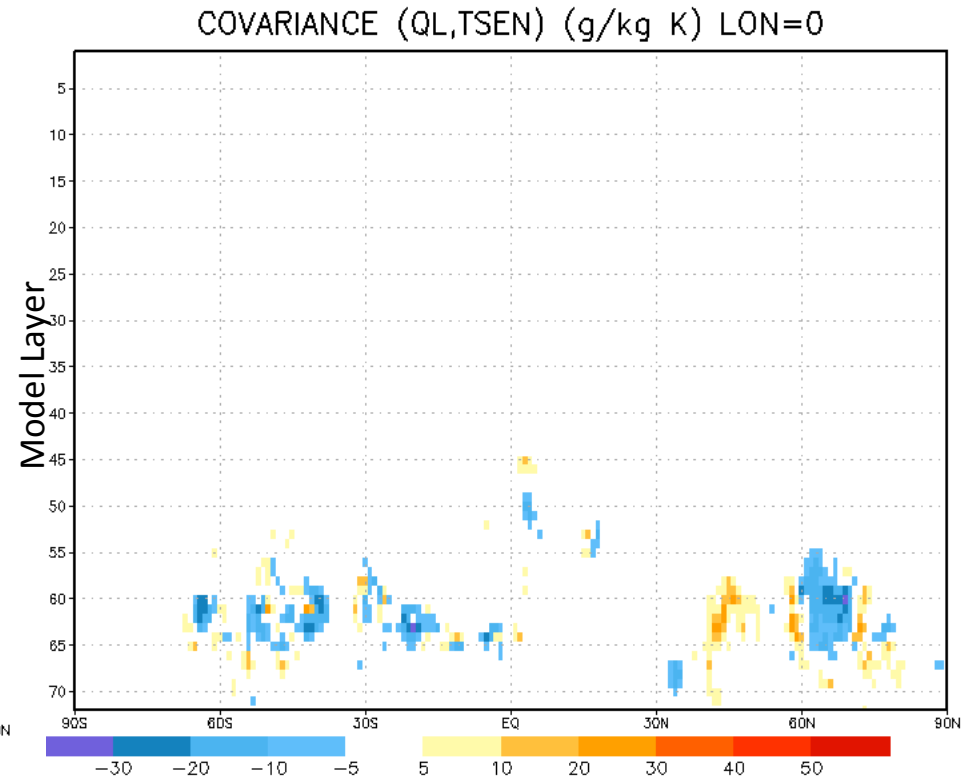


CLW and specific humidity: **positive** covariance

CLW and sensible temperature: positive and negative covariance mixed

Covariance among different variables in Ensembles



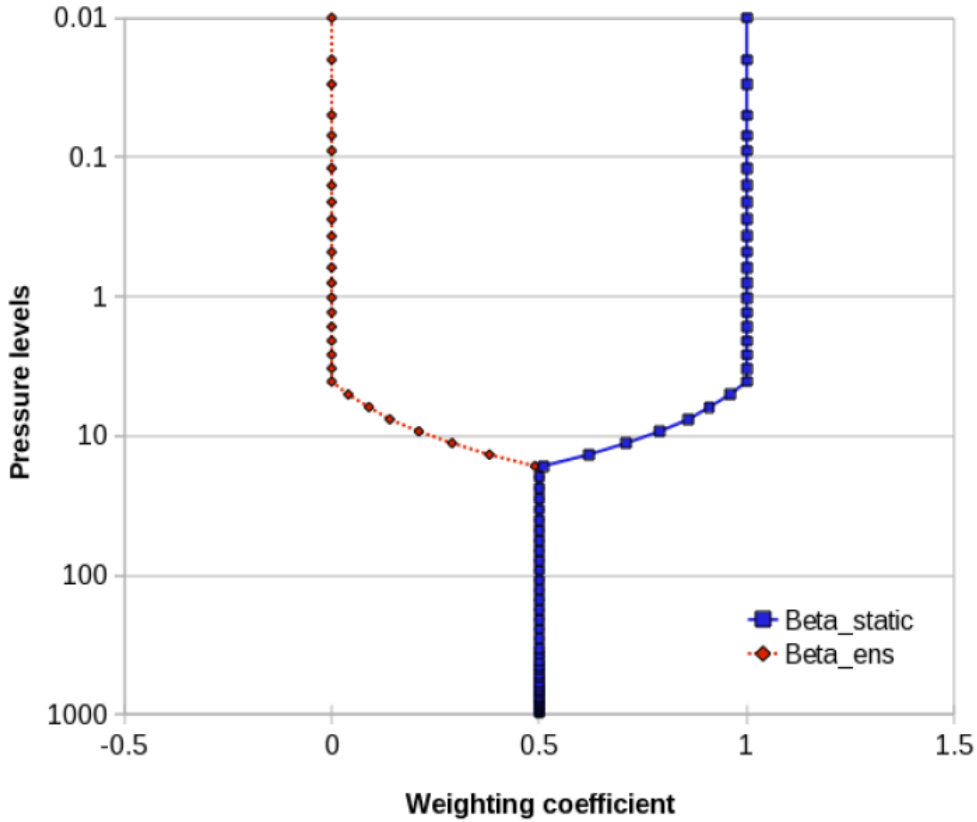


CLW and specific humidity:
positive covariance

CLW and sensible temperature:
positive and negative covariance mixed

Contribution from the ensemble B and Static B

In Hybrid GSI system used in NASA GMAO

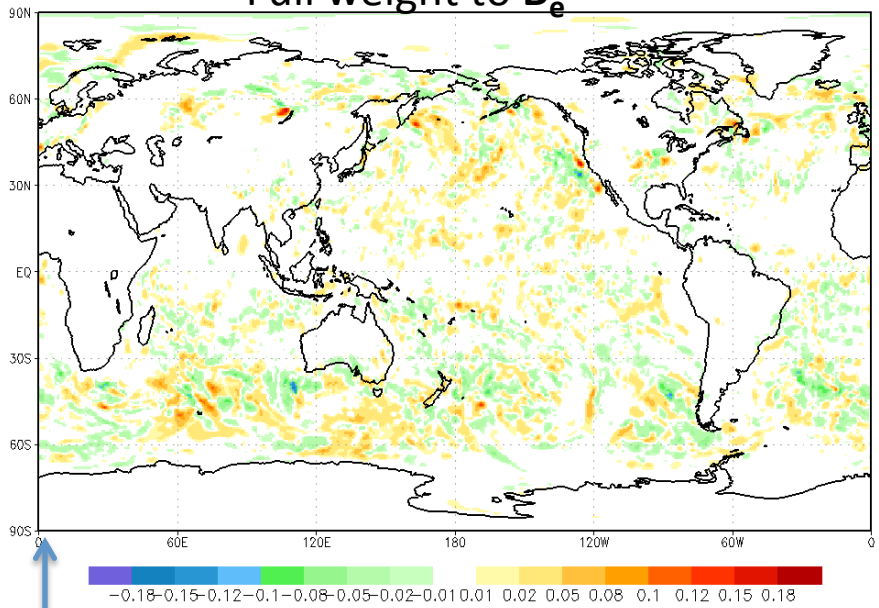


Courtesy: Ricardo Todling & Amal El Akkraoui (GMAO)

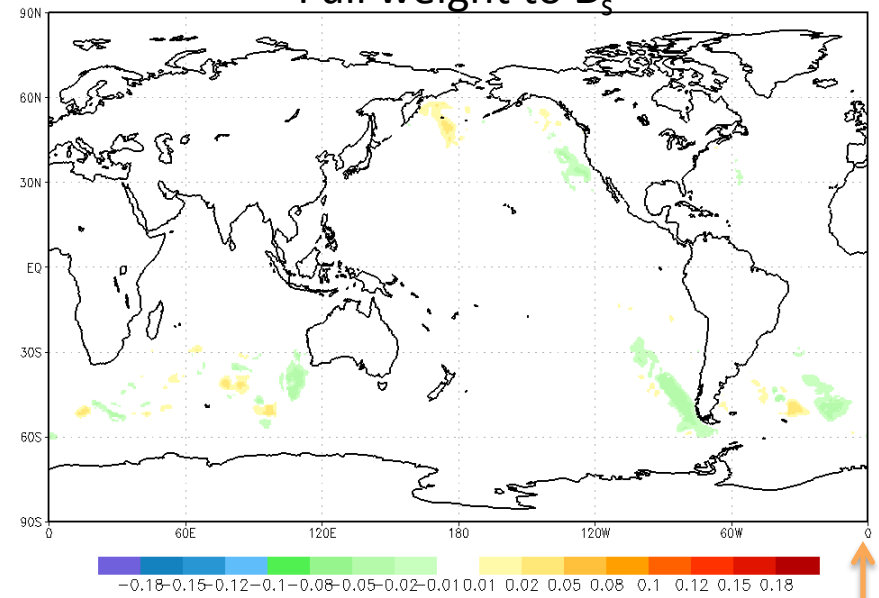
- Equal weights to each background error covariance term up to 20hPa.
- Above this level, full weight is given to the static background error covariance matrix.

Cloud Liquid Water Analyses from GSI

Full weight to $\mathbf{B_e}$

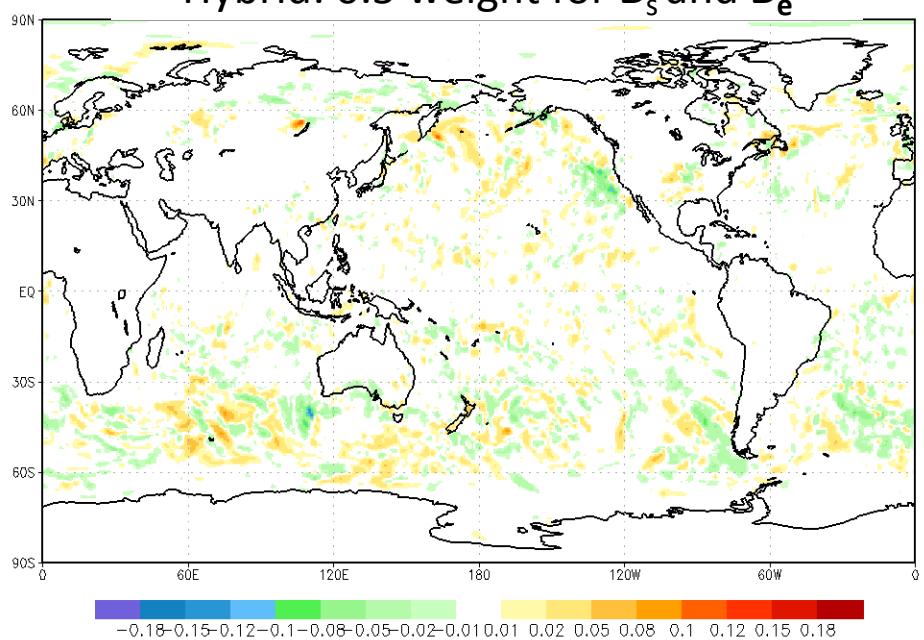


Full weight to $\mathbf{B_s}$



GMI + other observations data can generate cloud/ precipitation increments ghrough Be.

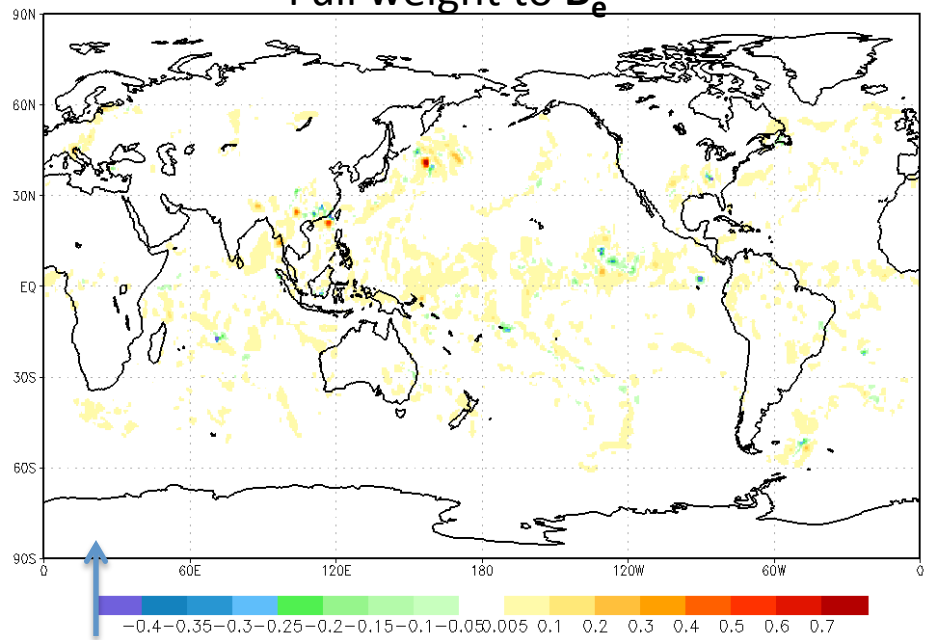
Hybrid: 0.5 weight for $\mathbf{B_s}$ and $\mathbf{B_e}$



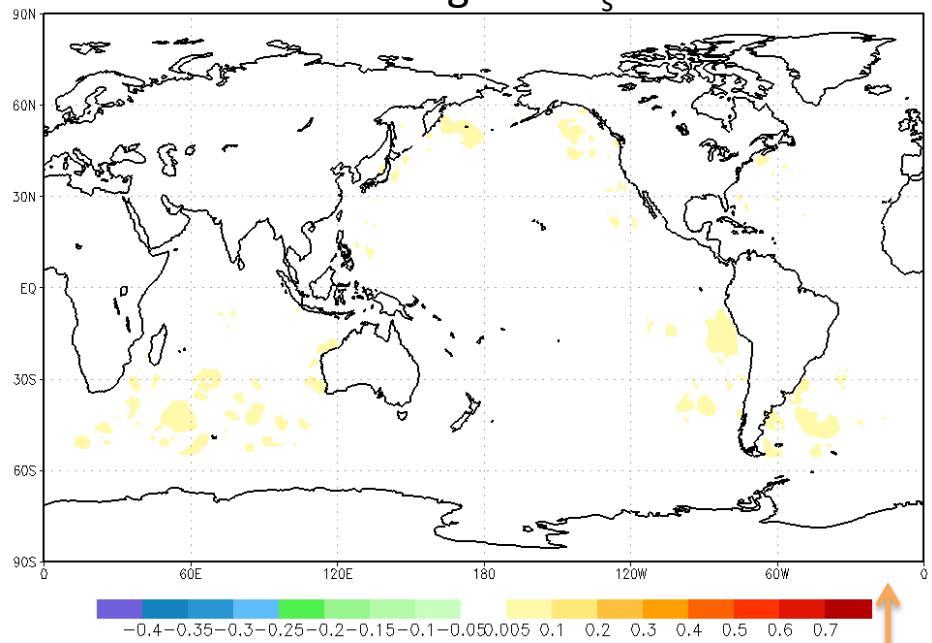
Only all-sky GMI data which can generate non-zero cloud and precipitation jacobians create increments.

Rain Water Analyses from GSI

Full weight to $\mathbf{B_e}$



Full weight to $\mathbf{B_s}$



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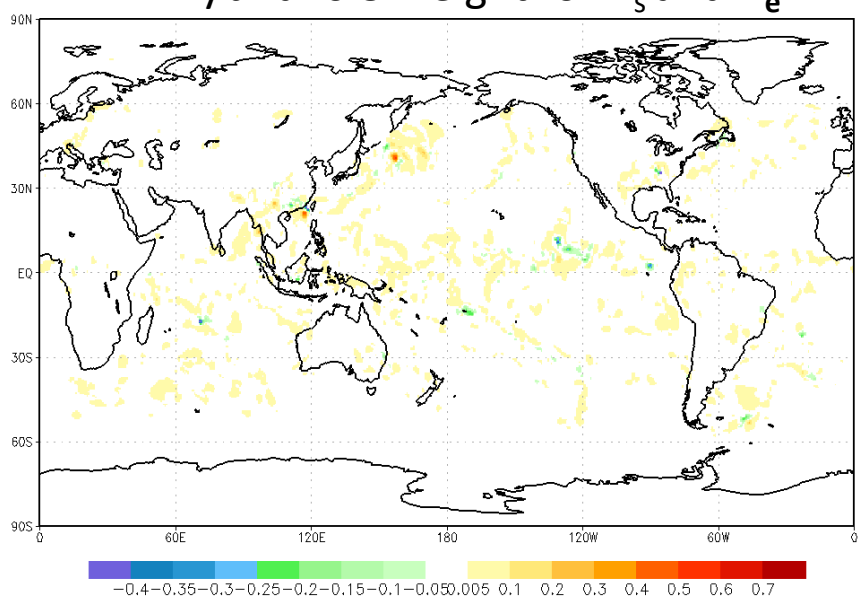


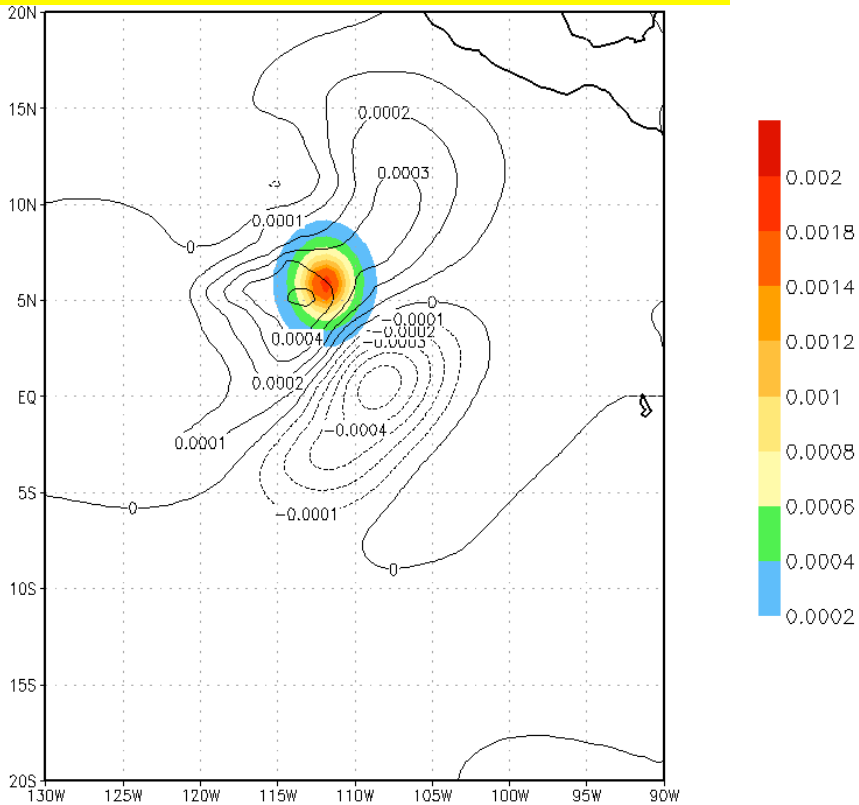
Only all-sky GMI data which can generate non-zero cloud and precipitation jacobians create increments.

Single point observation test

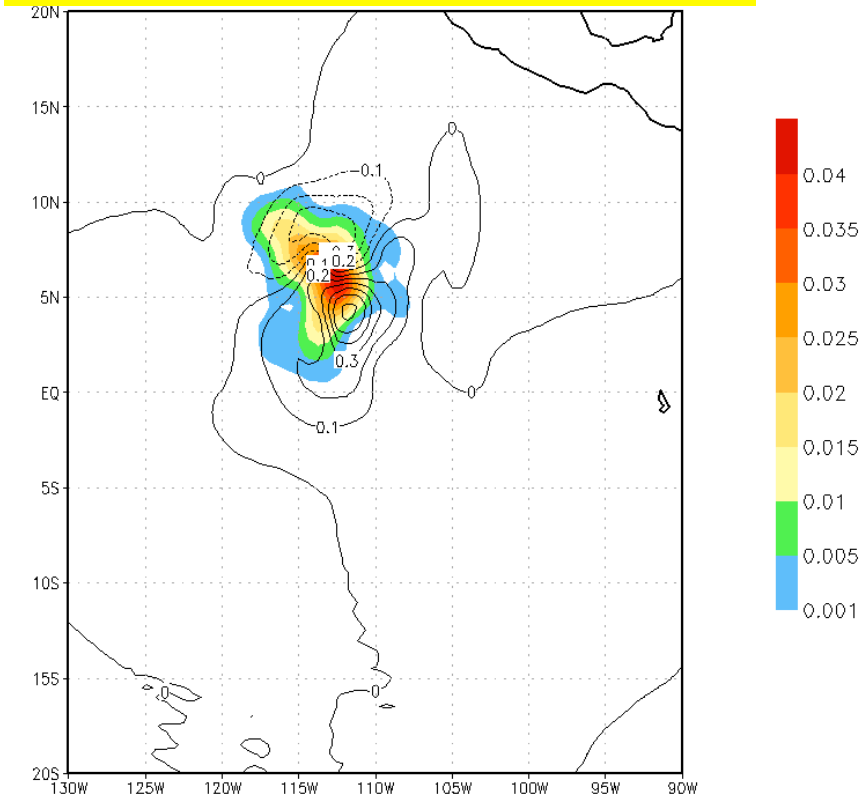
- Single point observation of GMI 9 channels' Tbs are used.
- Observed CLWP >> Bkg CLWP

Snow water (shade) and v-wind analysis(contour) increments at 500hPa

Full weight to $\mathbf{B_s}$



Full weight to $\mathbf{B_e}$



Bkg Error Covariance from Ensembles:

Question: Does it help moisture fields be balanced?

- Single point observation of GMI 9 channels' Tbs are used.
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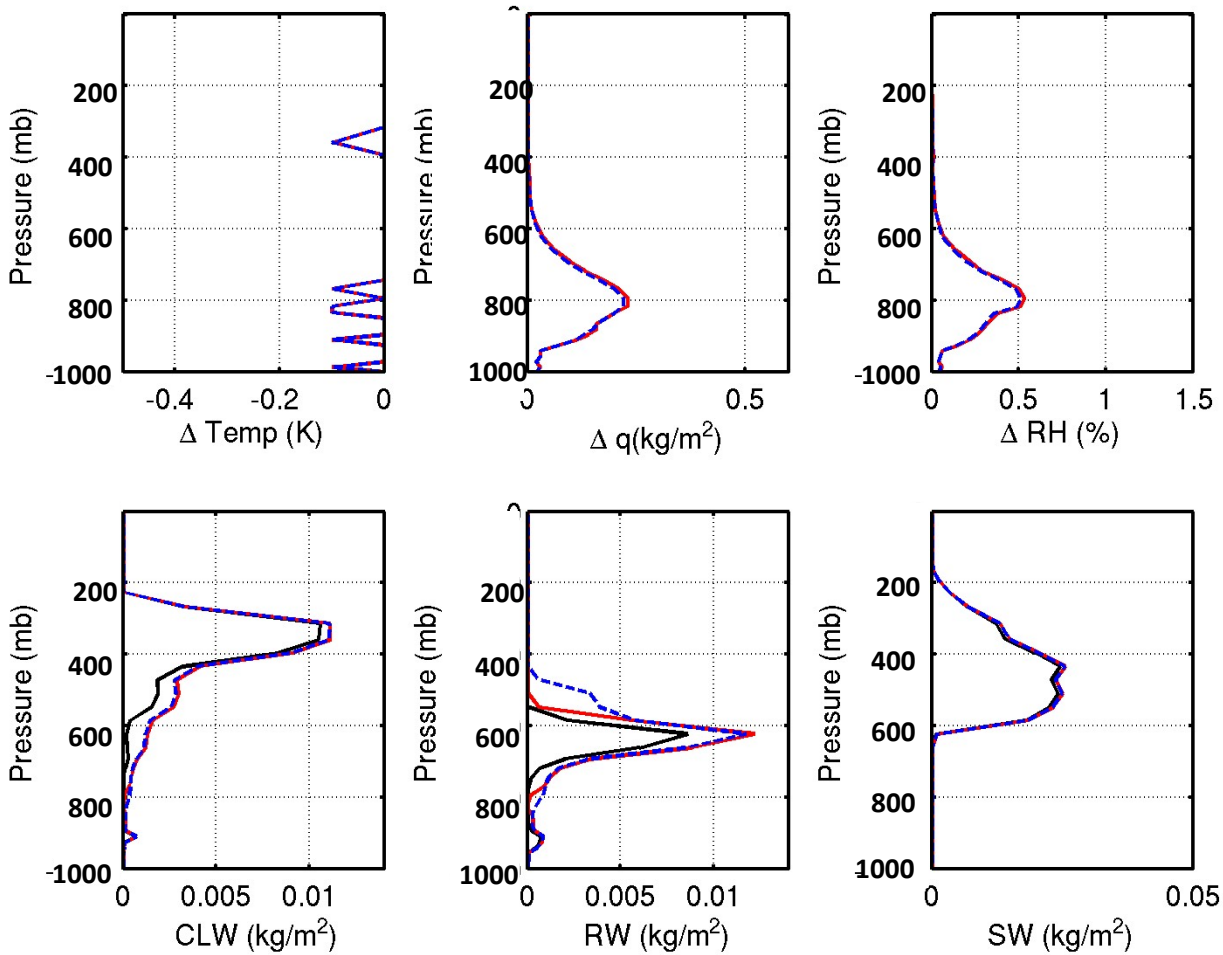
1st outerloop
2nd outerloop

Full weight to $\mathbf{B}_s$



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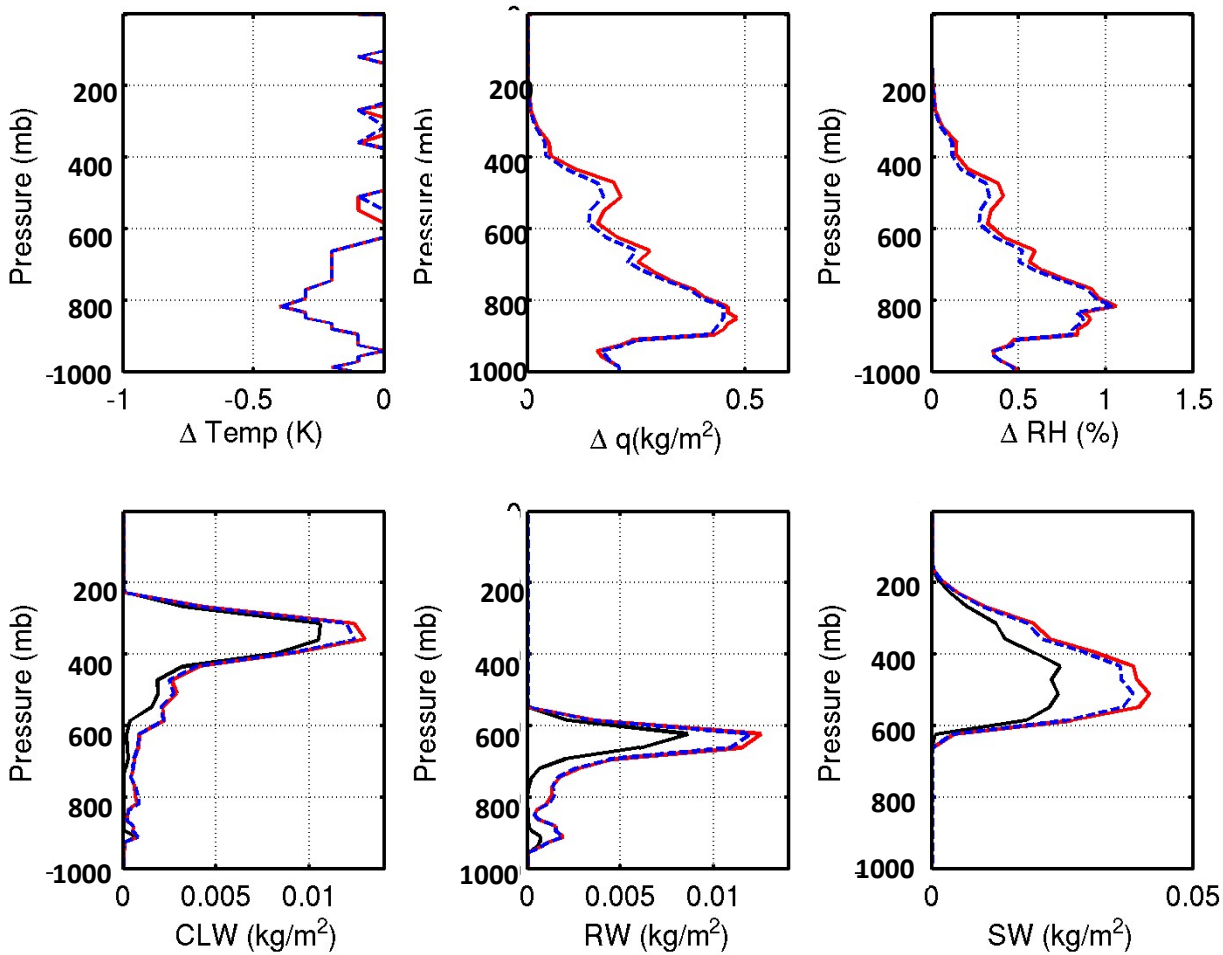

Bkg Error Covariance from Ensembles:

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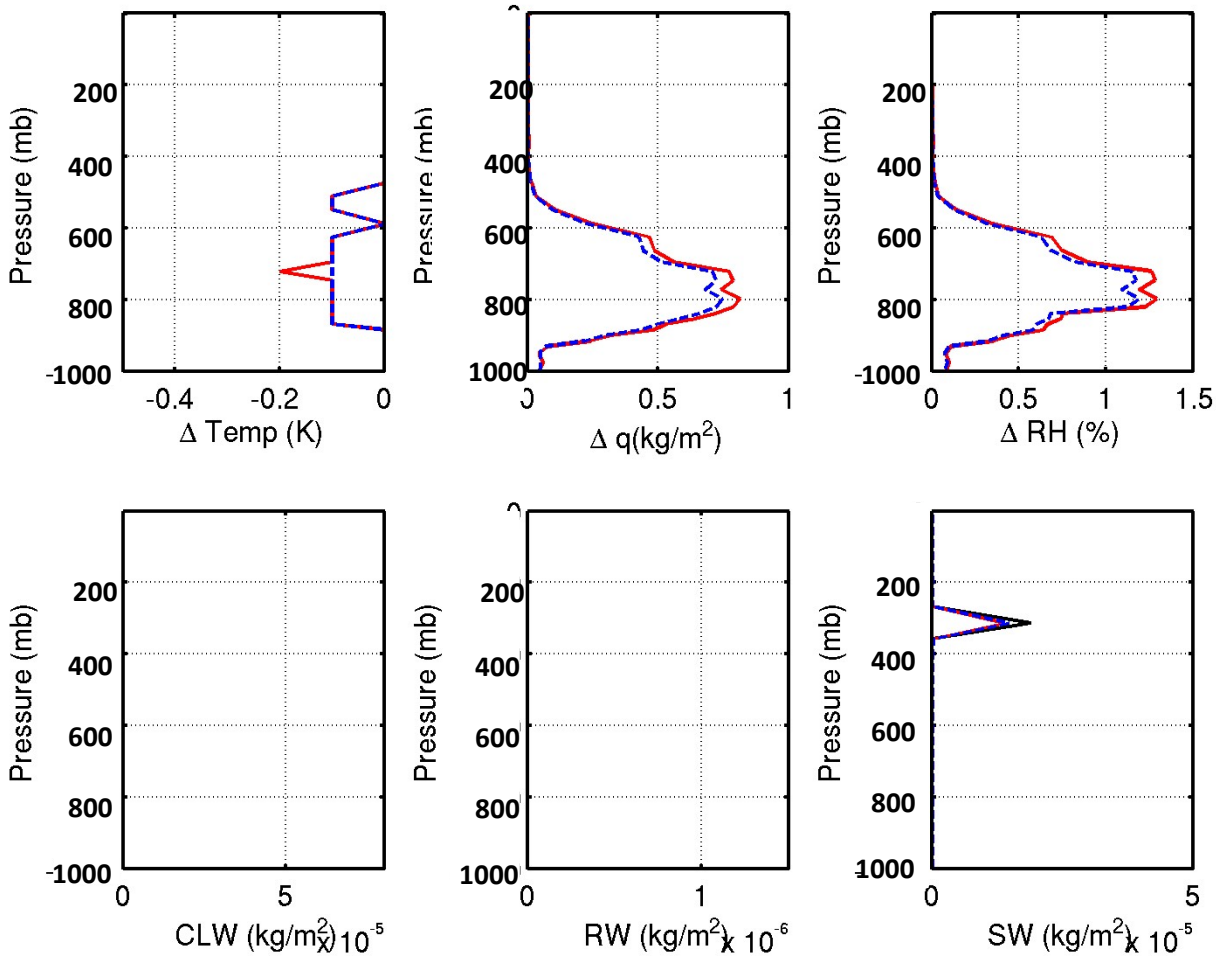
- Observed CLWP > 0, No CLW in background.

1st outerloop
2nd outerloop

Full weight to $\mathbf{B_s}$



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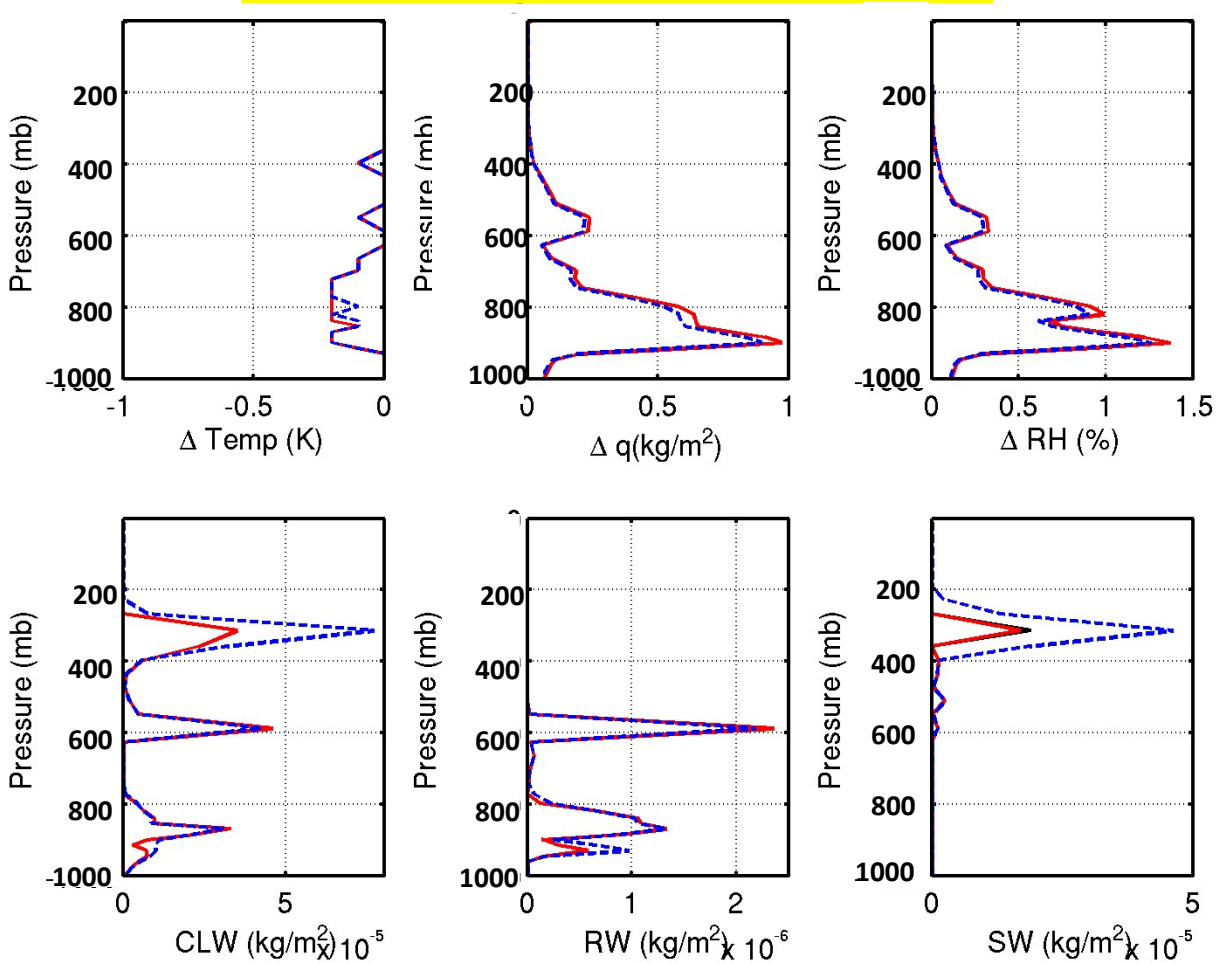
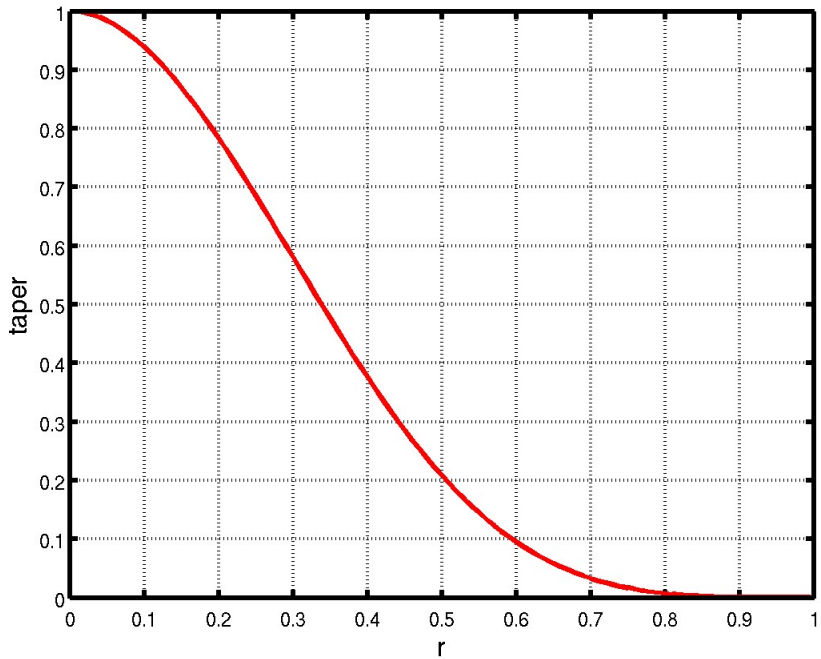


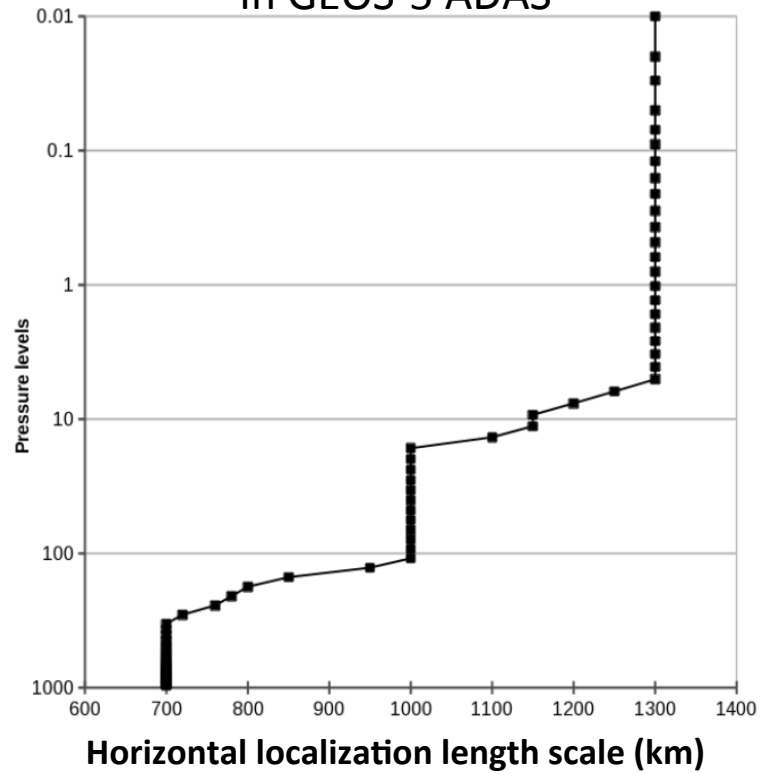
Covariance Localization

- To adjust noisy background error covariances caused by using small ensemble.
- Currently using two functions in GSI: One defining Gaspari and Cohn (1999, QJRMS) localization function and the other one to smoothly blend parameter values defined separately for NH, SH, and TRO.
- Currently using same localization scale for all observations. May need different localization for cloud and precipitation sensitive observations.

Gaspri & Cohn Localization Function



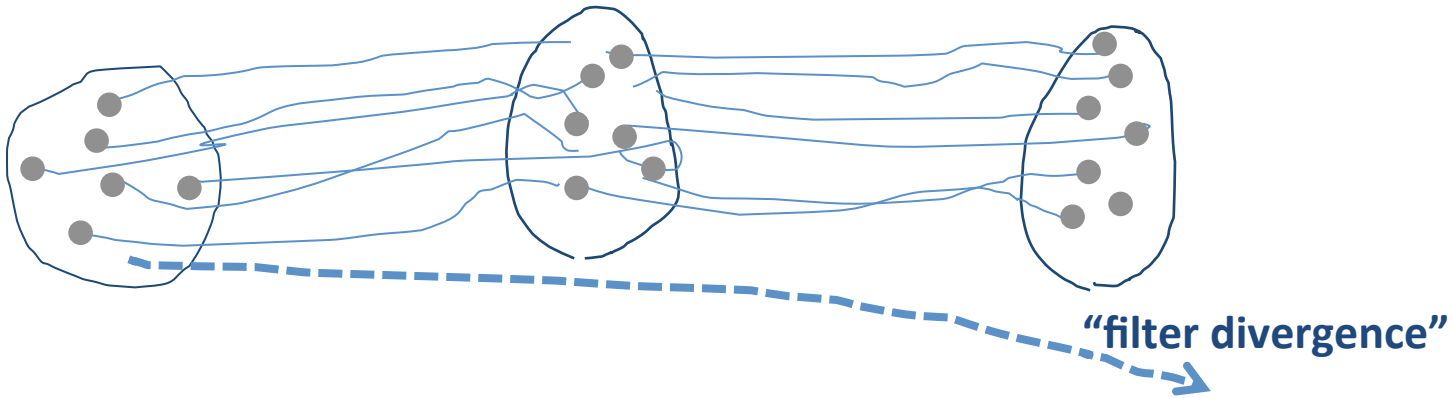
In GEOS-5 ADAS



Courtesy: Ricardo Todling & Amal El Akkraoui

Error Covariance Inflation

• Ensemble of solutions drifts away from true solution. During data assimilation, small variance in background forecasts causes data assimilation to ignore influence of new observations.

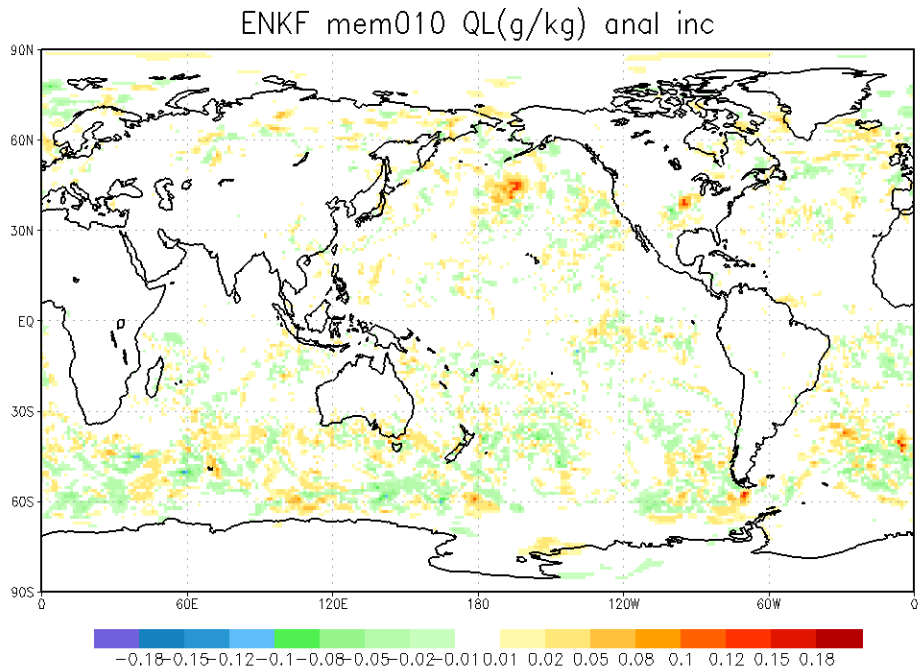


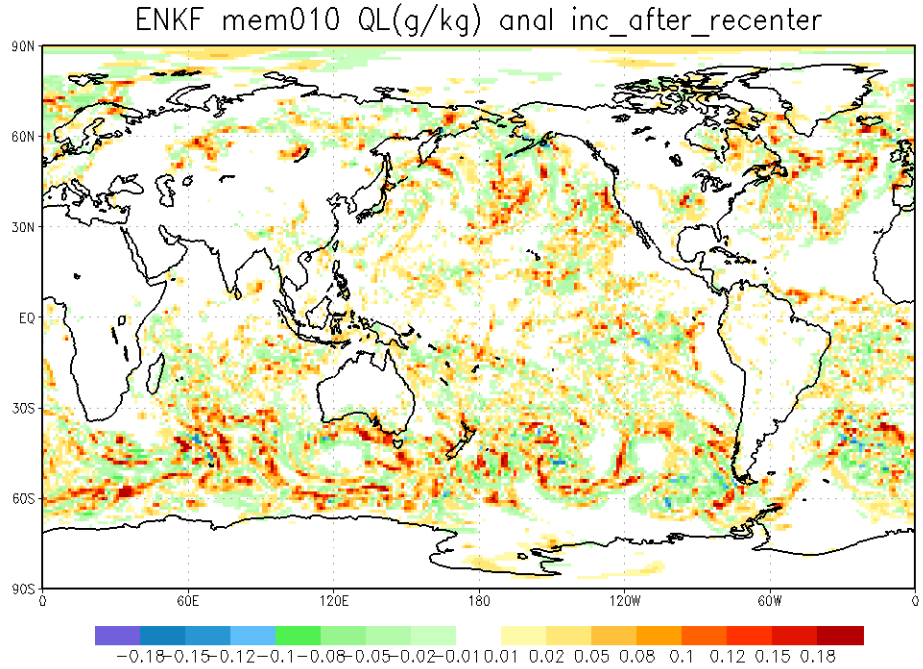
• Possible remedies

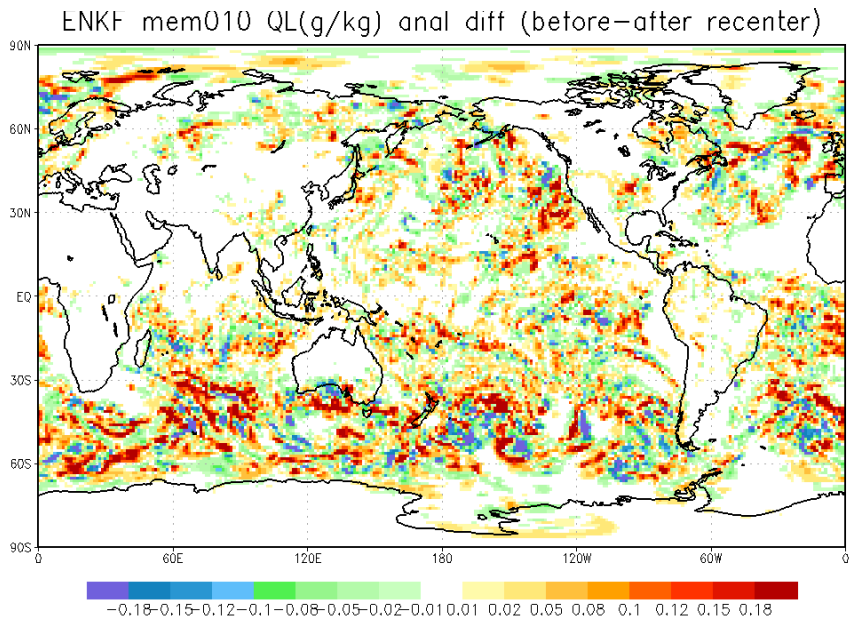
- higher-resolution model, more members,
- multiplicative inflation and additive inflation
- Integrate stochastic noise (perturbed physics)

Courtesy: Thomas Hamill

Cloud analyses in ensembles before and after recentering



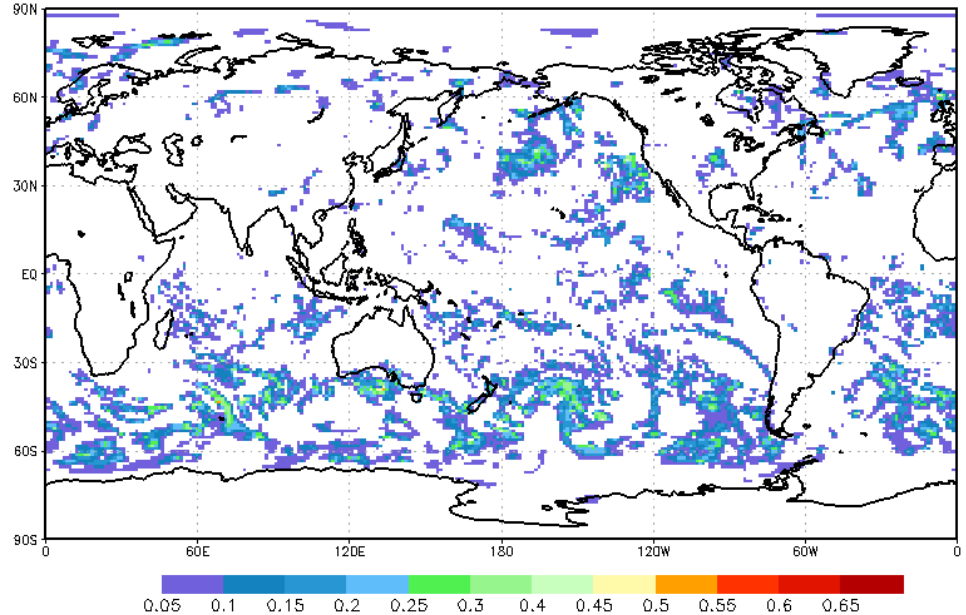




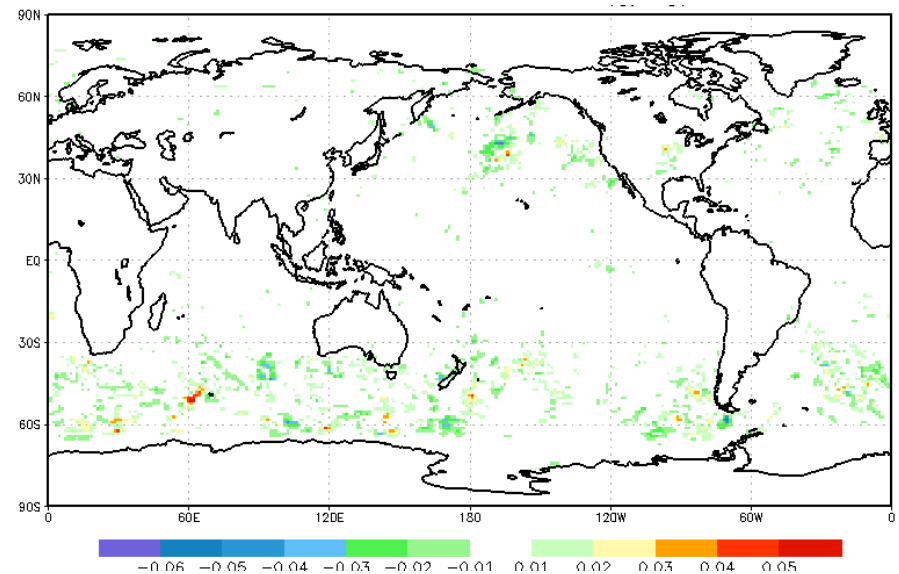
Resolution difference in ensembles and central backgrounds. We expect improving ensemble resolution will mitigate this problem.

Sequential DA: Is the analysis sensitive to the ordering of data assimilated?

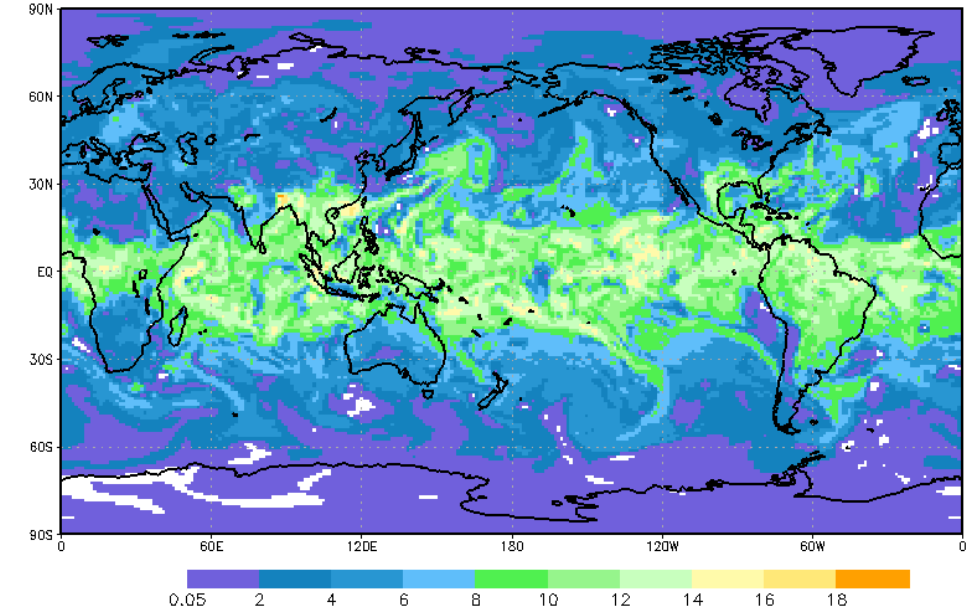
850 hPA CLW analysis (Assigned Order)



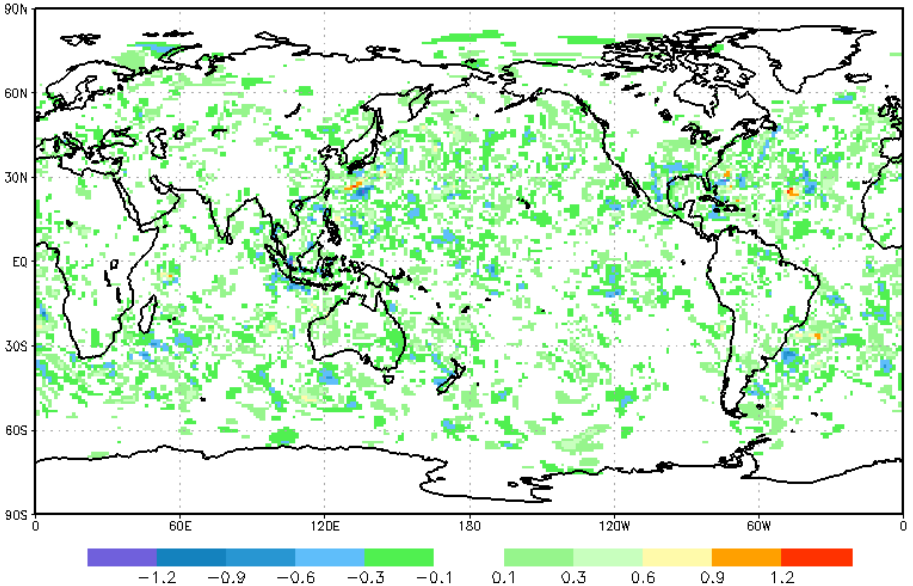
CLW analysis (Assigned) – CLW analysis (Random Order)



850 hPA SPHUanalysis (Assigned Order)



SPHU analysis (Assigned) – SPHU analysis (Random Order)



More Thoughts/Questions

- **Putting cloud analysis increments back to model as forcing.. What benefits and risks can we expect?**

- **Issues related to insufficient microphysics parameters required for radiative transfer computation**

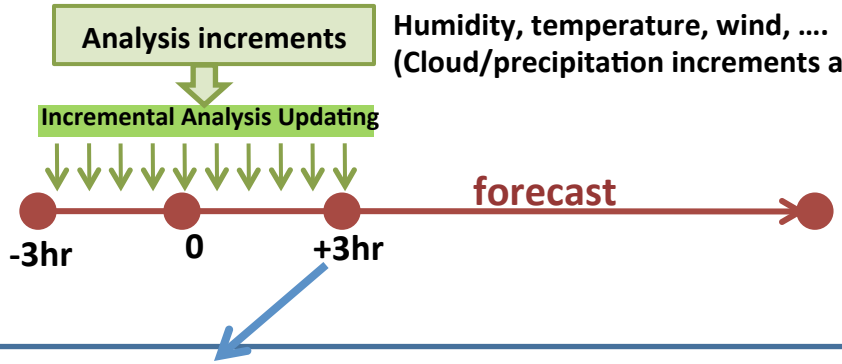
  - Limited number of hydrometeor types
  - non-spherical frozen particle shapes
  - Hydrometeor density + wet snow, dry snow,
  - Particle size distribution → two moment scheme

- **How can we improve moisture balance (q and clouds/precip) ? Do we need to change cloud/precip control variables from ql,qi,qr,qs to other forms? Can correlated errors can help?**

- **Precipitation over land really affects people's life. In general, Improving utilization of MW radiance data over land (e.g. surface contribution in RTM) need to be done to expand all-sky framework to land.**

Backup slide

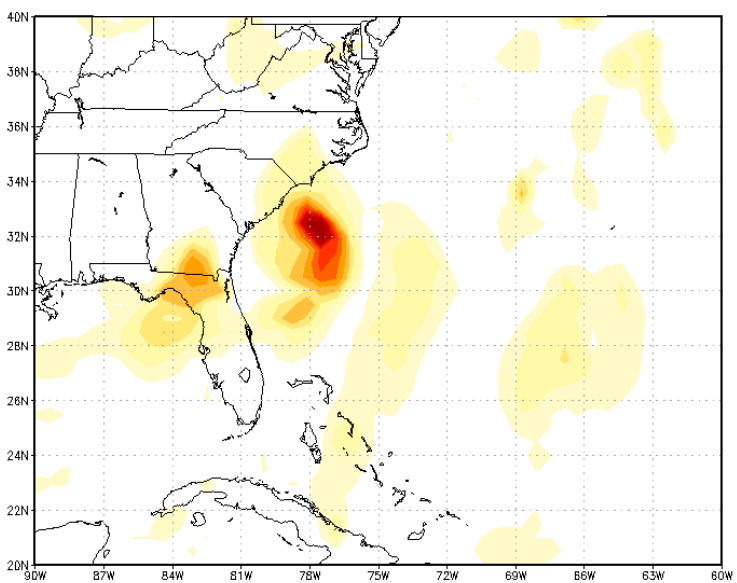
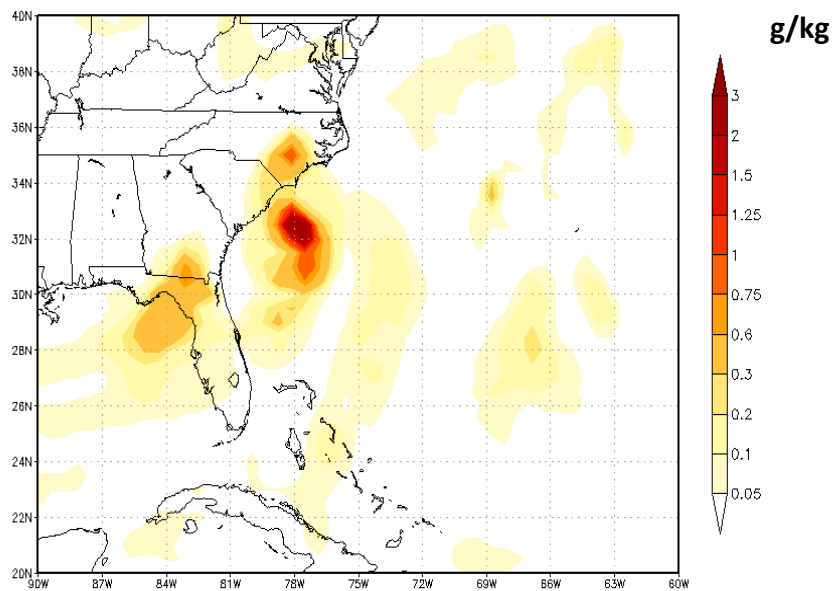
Impacts of GMI Radiance Data on GEOS-5 Precipitation Forecasts



Humidity, temperature, wind, ….
(Cloud/precipitation increments are not applied back to forecast model yet..)

6hr surface precipitation (PRECTOT) forecasts

Conv, other satellite observations +
No GMI data assimilated



Conv, other satellite observations +