Implementing of lognormal humidity and cloud-related control variables for the NCEP GSI hybrid EnVar assimilation scheme

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Project Summary

- The research project comprises of two components:
- The first is CIRA at CSU where the implementation of a logarithmic transform approach for specific humidity as a control variable, as well introducing this approach for the cloud hydrometers is being undertaken.
- The second is at the University of Maryland which involves assess the current choices of stochastic physics schemes and related parameters.
- These objectives align with the R20 priority area (2) – **improved data assimilation techniques** along with NGGPS priority area (a) on data assimilation: **advancement of techniques for remotely sensed observations.**

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Deliverables

- Changes to static and ensemble contributions in the hybrid EnVar GSI to allow for lognormal approximations for humidity and cloud-related positive definite control variables.
- New non-Gaussian based control variable for the cloud-related control variables which will enable the better assimilation of all sky-radiances.
- Assessment of sensitivity to stochastic physics parameters on cloud variable spread.
- Code modifications to allow for alternate localization strategies for the ensemble contribution to the hybrid EnVar increment for clouds and humidity.
- Utility software to generate initial ensemble members for hydrometeors.
- Utility software to assist in the evaluation of experiments, evaluating and informing parameter tuning.

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Metrics for Success

- The GSI is modified to have more flexibility in terms of choices for humidity and cloud related variables, for both the static and ensemble contributions, as well as for the localization component of the ensemble within the EnVar solver. This will include the capability to initialize individual hydrometeors.
- The assimilation of cloud-impacted radiances is improved as a result of this effort.
- This effort results in a significantly improved cloud analysis as quantitatively measured against both dependent (assimilated) and independent data.
- A larger portion of the cloud analysis is retained in the early part of the model forecast

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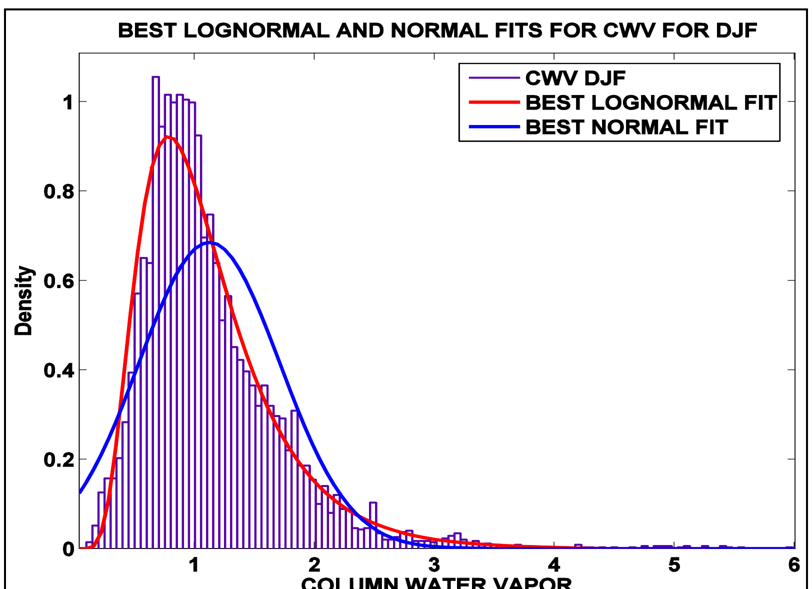
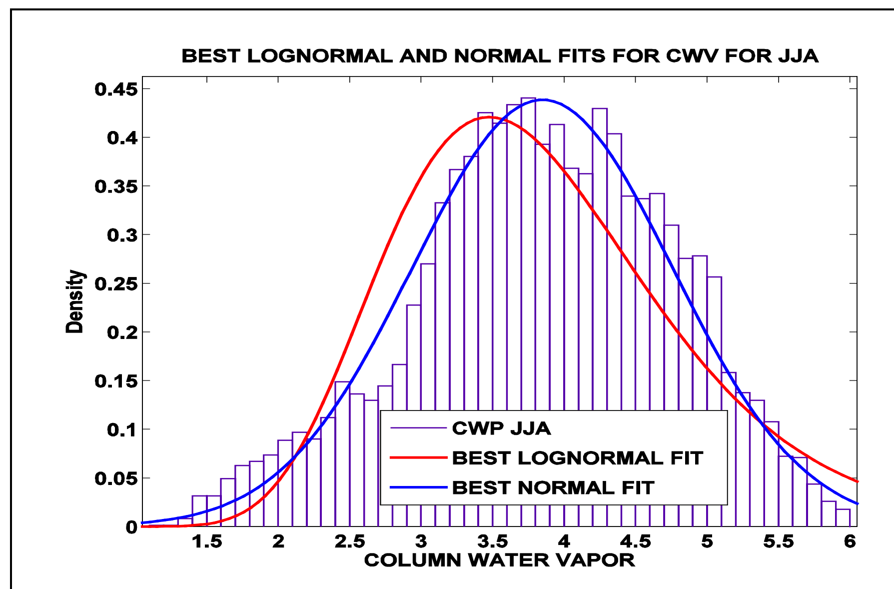
Lognormal based data assimilation

Throughout a series of papers: Fletcher and Zupanski (2006a,b), Fletcher and Zupanski (2007), Fletcher (2010), Fletcher and Jones (2014), Kliewer et al (2016), the lognormal and mixed lognormal-Gaussian distribution based variational data assimilation theory has been developed. A full summary of this theory can be found in Fletcher (2017).

The advantage of lognormal based data assimilation is that it is designed to more consistently model the errors associated with positive definite variables i.e. x>0.





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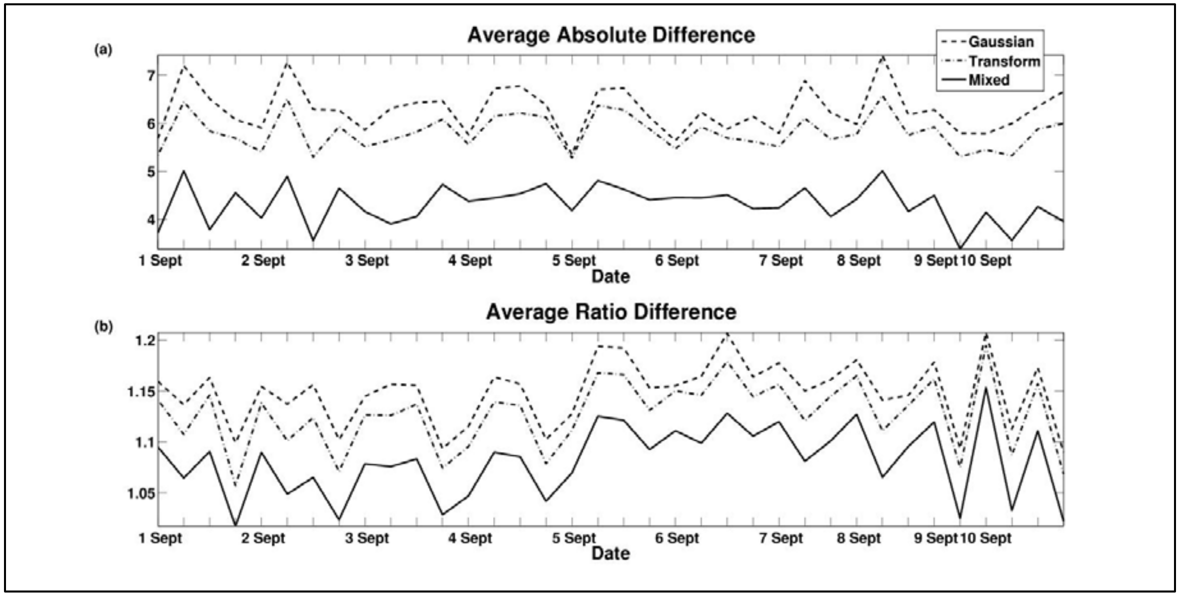
Lognormal based data assimilation

In Kliewer et al (2016) a mixed Lognormal-Gaussian 1D VAR retrieval system was implemented and tested for a median and modal approach against a Gaussian only 1D VAR system.



Comparisons of the three retrieval methods against the Microwave Surface and Precipitation Products Systems (MSPPS) TPW product. Solid is the mixed approach, dot-dashed is the transform and the dashed is the Gaussian.

Lognormal based data assimilation

The associated 3D VAR static cost function for a lognormally distributed background errors is given by

$$J(\boldsymbol{x^t}) = \frac{1}{2}(\ln \boldsymbol{x^t} - \ln \boldsymbol{x_b})^T \mathbf{B}^{-\mathbf{1}}(\ln \boldsymbol{x^t} - \ln \boldsymbol{x_b}) + \frac{1}{2}\left(\boldsymbol{y} - \boldsymbol{h}(\boldsymbol{x^t})\right)^{\boldsymbol{T}} \mathbf{R}^{-\mathbf{1}}\left(\boldsymbol{y} - \boldsymbol{h}(\boldsymbol{x^t})\right).$$

However, operational systems deal with incremental var, but here we have two different increments: $\boldsymbol{\delta X} \equiv \ln \boldsymbol{x^t} - \ln \boldsymbol{x_b}$ and $\boldsymbol{\delta x} \equiv \boldsymbol{x^t} - \boldsymbol{x_b}$. Therefore, the equation above becomes

$$J(\delta \boldsymbol{X}) = \frac{1}{2}\boldsymbol{\delta X^T}\mathbf{B}^{-\mathbf{1}}\boldsymbol{\delta X}+\frac{1}{2}(\boldsymbol{y} - \boldsymbol{h}(\boldsymbol{x_b}) - \mathbf{H}\boldsymbol{\delta x})^T \mathbf{R}^{-\mathbf{1}}(\boldsymbol{y} - \boldsymbol{h}(\boldsymbol{x_b}) - \mathbf{H}\boldsymbol{\delta x}).$$

It is possible to link $\boldsymbol{\delta x}$ to $\boldsymbol{\delta X}$ through a Taylor series expansion of the logarithm as

$$\boldsymbol{\delta X} \approx \frac{\boldsymbol{\delta x}}{\boldsymbol{x_b}}.$$

Lognormal based data assimilation

Dr. Kleist of NCEP/EMC has made his NMC code available to the modification to calculate static background error variance and covariance for the natural logarithm of specific humidity.

This code required Dr. Fletcher to have access to the STMP drives on Theia which was requested and eventually granted after a month.

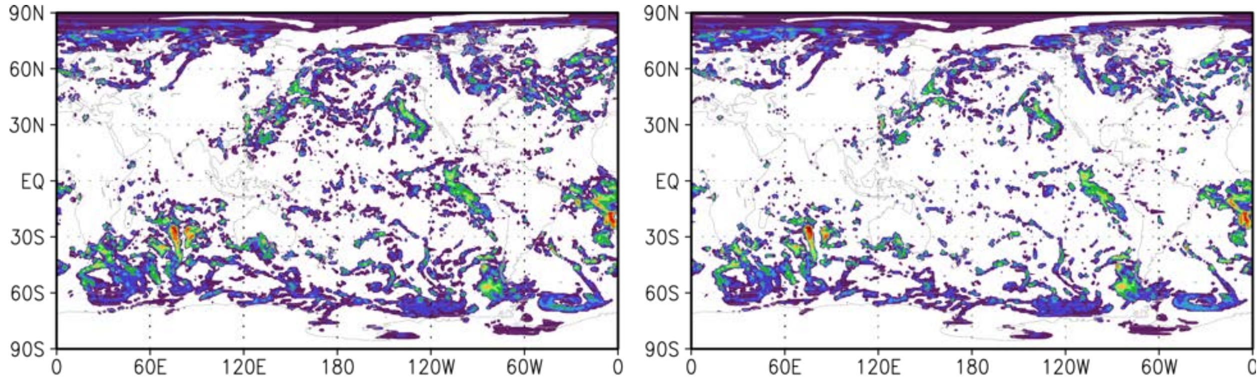
The code has been modified but at the moment there appears to be an MPI issue that Drs. Fletcher and Kleist are working on to resolve.

Ongoing Effort: Stochastic Physics in Ensemble

Motivation:

- Stochastic physics scheme plays a key role in inflating the ensemble spread.
- Yet it may not only lead to overspread of ensemble but also interfere with critical cloud features

Cloud water analysis at 850hPa at 00Z 22 October 2013. → Disappearance of features after one step, due to stochastic physics perturbation

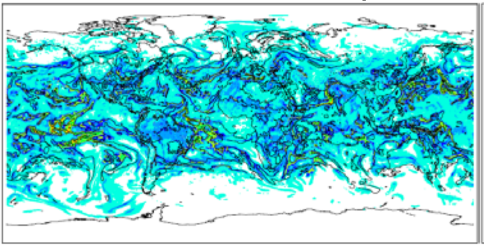


Objectives:

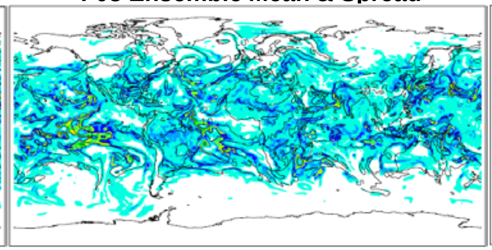
- Aim to address some issues associated with ensemble background error specification
- Assess the stochastic physics schemes: SPPT & SHUM
- Tune the related parameters
- Explore alternate choices for humidity and cloud ensemble perturbation variables within EnVar

Control run (SPPT=1): Specific Humidity

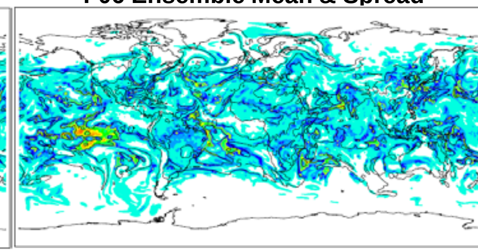
ANL Ensemble Mean & Spread



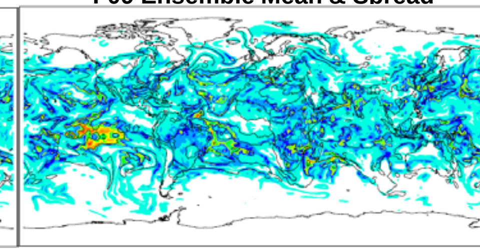
F03 Ensemble Mean & Spread

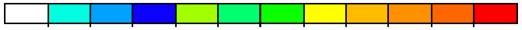


F06 Ensemble Mean & Spread



F09 Ensemble Mean & Spread



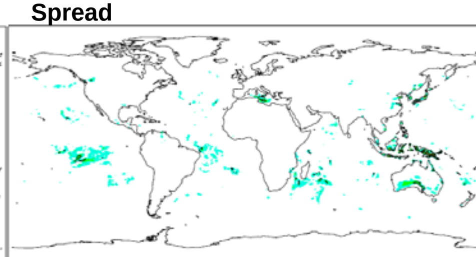


Black contour lines represent specific humidity ensemble mean for the control run at 2015092100Z; filled color represents the specific humidity ensemble spread for the control run at 2015092100Z.

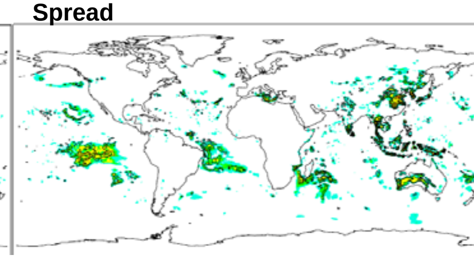
Control (SPPT=1) – Sensitivity (SPPT=0.5): Specific Humidity

ANL Difference in Ensemble Mean & Spread

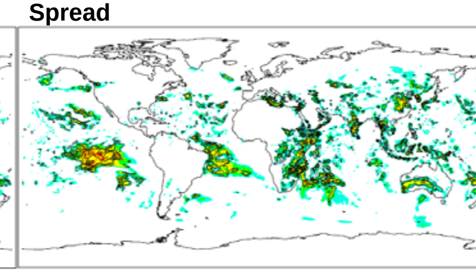
F03 Difference in Ensemble Mean & Spread



F06 Difference in Ensemble Mean & Spread



F09 Difference in Ensemble Mean & Spread



Black contour lines represent specific humidity difference in ensemble mean between the control run (SPPT=1) and the sensitivity run (SPPT=0.5) at 2015092100Z; filled color represents the specific humidity ensemble spread between the control run (SPPT=1) and the sensitivity run (SPPT=0.5) at 2015092100Z.

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