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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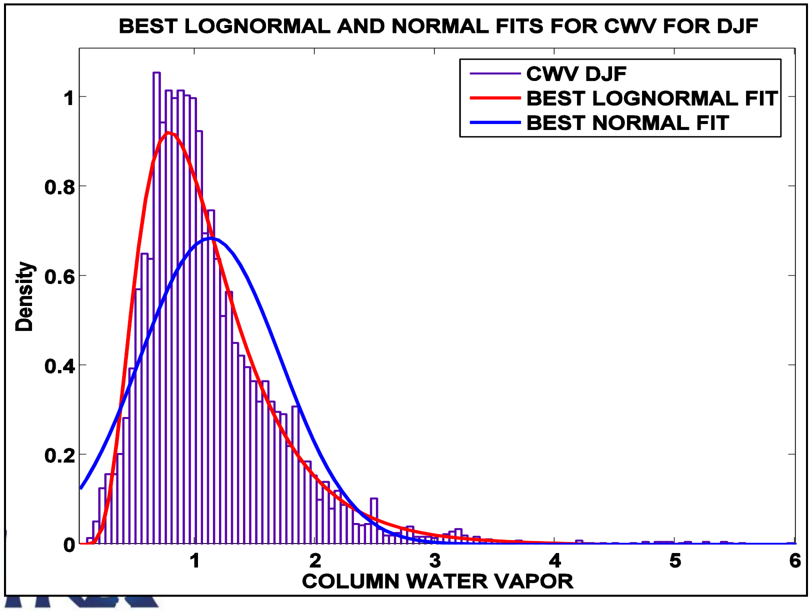
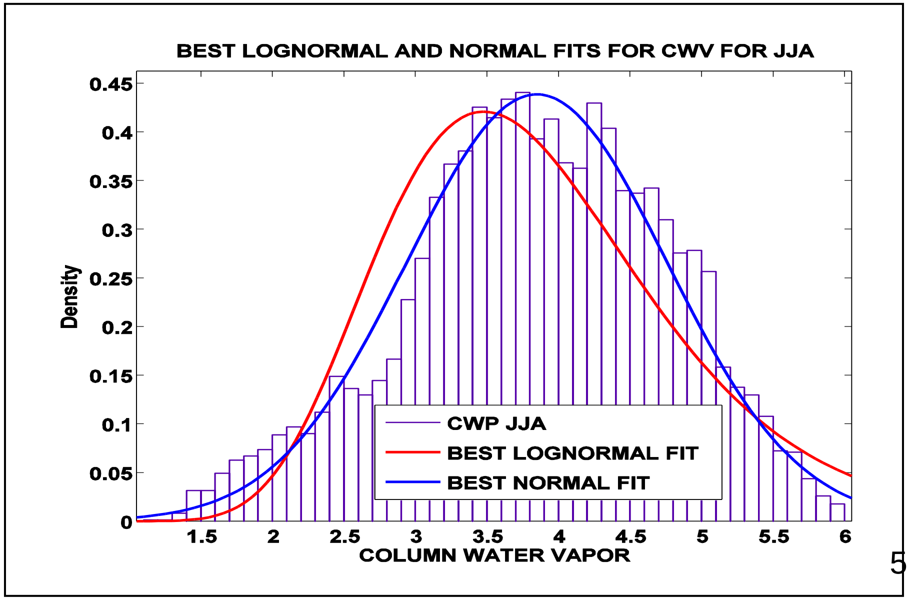
Lognormal based data assimilation

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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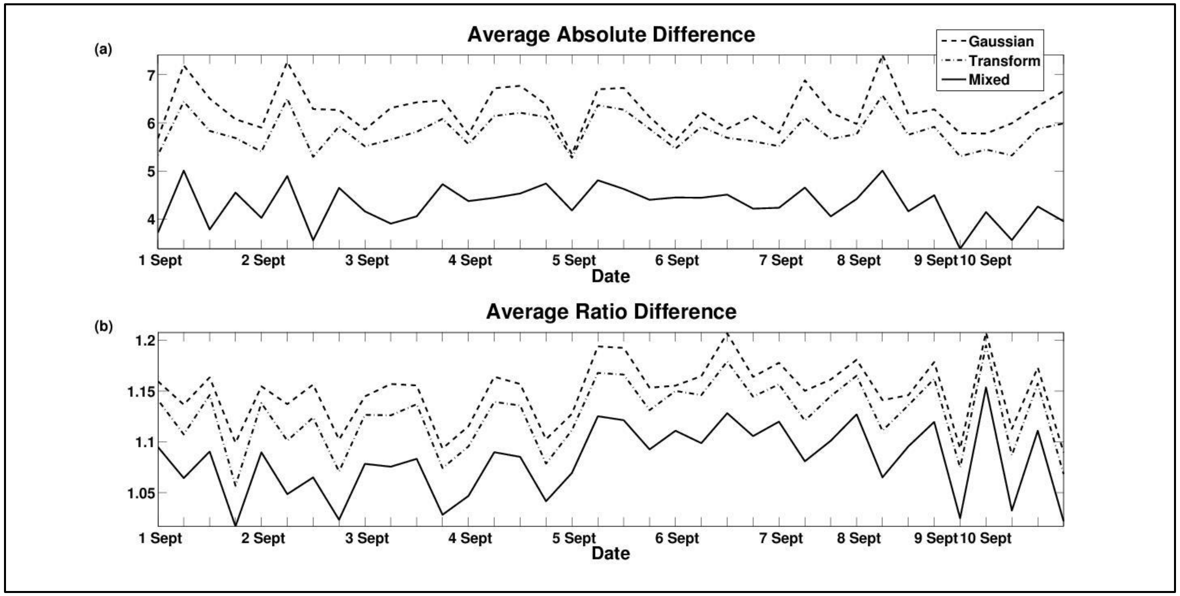
Lognormal based data assimilation

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.

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Lognormal based data assimilation

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

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

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

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

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

The year 1 milestones for the lognormal component was:

- Implement into the GSI hybrid EnVar a capability to utilize lognormal-based control variables for cloud and humidity

This entails changes to IO, processing, Static background error covariance and estimation therefore, cost function, and the control variable transforms.

We are on track to have these changes in place by the end of August for the median based approach, and have initial testing started for specific humidity, and implemented for the cloud hydrometeors.

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