Ensemble Kalman Filter Assimilation of Precipitation with a Simplified AGCM

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Introduction

- In several operational and research centers, much effort has been devoted to the assimilation of precipitation observations.
- However, obtaining benefits from precipitation assimilation has been a great challenge.
  - Methods modifying the model's moisture and sometimes temperature profiles are generally successful in forcing the forecasts precipitation to be close to the observed precipitation during the assimilation [e.g., nudging method in the North American Regional Reanalysis (NARR; Mesinger et al. 2006)], but models tend to "forget" the impact of precipitation assimilation and soon lose their extra forecast skills (Errico et al., 2007; Tsuyuki and Miyoshi, 2007).
- It is expected that assimilation of precipitation using the EnKF method can efficiently change another key dynamical variable, namely, potential vorticity field.
  - The highly non-Gaussian nature of precipitation variables poses severe difficulties.
  - Several transformations on the precipitation variables, such as a simple logarithm, have been used in other studies of precipitation and cloud assimilation (e.g., Bauer et al. 2011; Lopez 2012, ECMWF Technical Memorandum 661).
- ***Objective***: Observation system simulation experiments (OSSE) with a simplified atmospheric GCM.
  - Examine the value and feasibility of precipitation assimilation using a Local Ensemble Transform Kalman Filter (LETKF).
  - A **general transformation algorithm** is introduced to create an intermediate Gaussian variable related to the precipitation data based on the precipitation probability distribution of the model climatology.

Transformation method

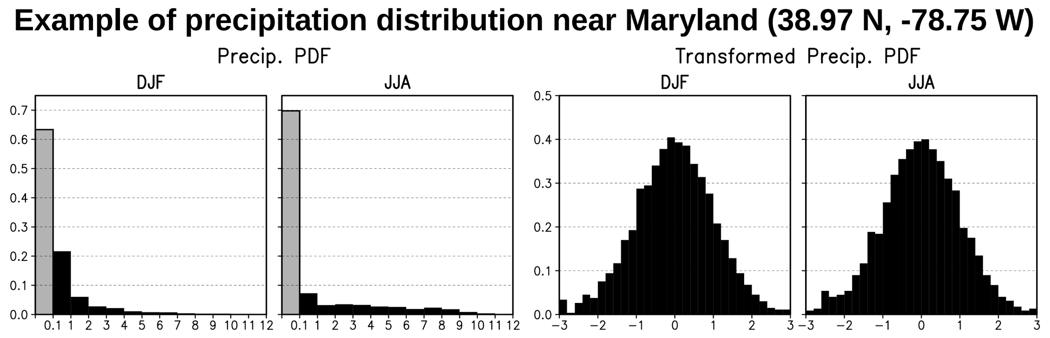
- The "Gaussian anamorphosis" (also used by Schöniger et al. 2012 in hydrology):

$$y_{trans} = G^{-1}[F(y)]$$

y : precipitation variable
F : Cumulative distribution function (CDF) of precipitation variables based on the 10-year model climatology at each grid and each season.
G^{-1} : Inverse CDF of normal distribution.

$$G^{-1}(x) = \sqrt{2}\,\mathrm{erf}^{-1}(2x-1)$$

Example of precipitation distribution near Maryland (38.97 N, -78.75 W)



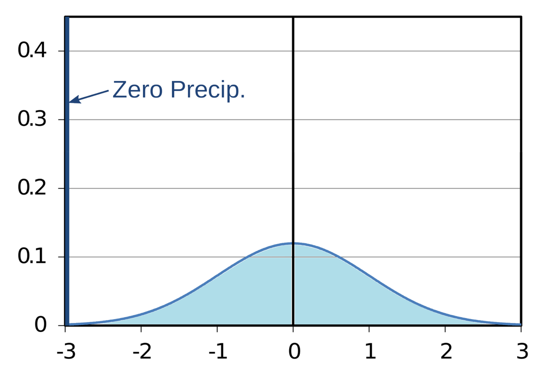
- LETKF is performed on the transformed space.
  - Variables transformed: $\mathbf{y}^{b(i)}_{pp}$, $\bar{\mathbf{y}}^{b}_{pp}$, $\mathbf{y}^{o}_{pp}$.
  - The observation errors associated with each observation also have to be transformed. Conceptually:

$$\sigma^o_{trans} \simeq (y^o+\sigma^o)_{trans} - y^o_{trans} \simeq y^o_{trans} - (y^o-\sigma^o)_{trans}$$

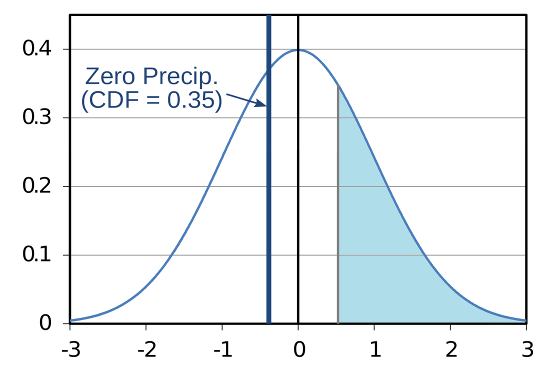
Handling the zero-precipitation data

Example of 70% probability for zero precipitation

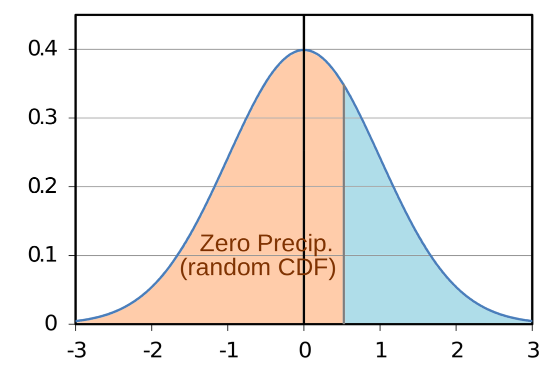
(a) Consider only the non-zero precipitation value in the Gaussian transformation.



(b) Consider all precipitation data in the Gaussian transformation, assign ***middle values*** of no-rain cumulative probability for all zero precipitations.



(c) Consider all precipitation data in the Gaussian transformation, assign ***uniformly distributed random values*** within no-rain cumulative probability for all zero precipitations.



Experimental setup

- Ensemble size = 20 / Horizontal localization scale = 500 km / Adaptive inflation (Miyoshi, 2011)
- Observation errors for precipitation observations = 20% of observed value.
- Selection of precipitation observations:
  (i) Traditional criterion: only assimilating precipitation at locations with observed precipitation (> 0.1 mm/6h).
  (ii) A new criterion: only assimilating precipitation at locations where the number of precipitating members >= a given threshold (10 in this study), even if no precipitation is observed.

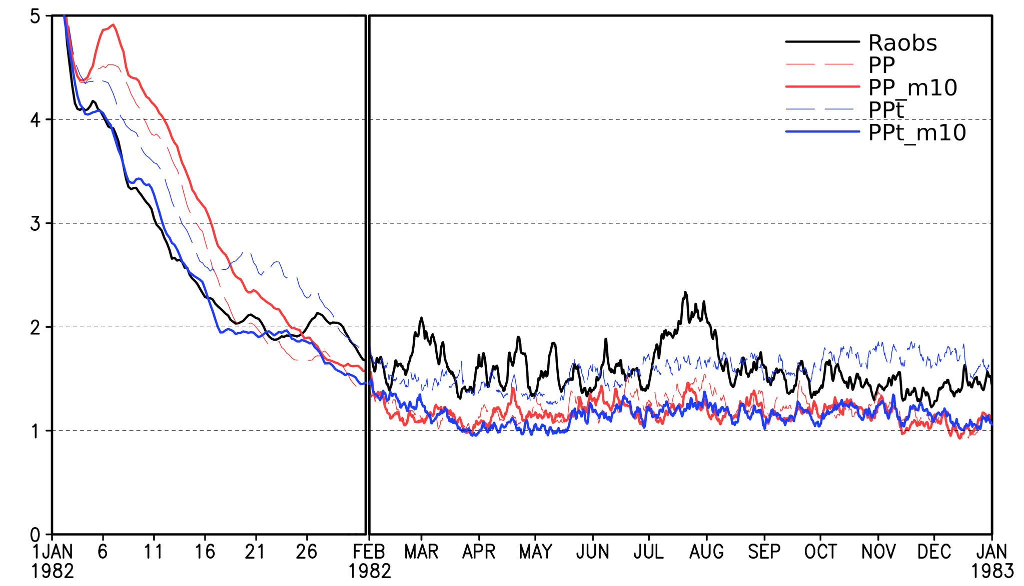
	Assimilated observations		Gaussian transformation	Criteria for precipitation assimilation	
	Conventional radiosondes	Global precipitation	handling zero precipitation with method **(b)** (see above)	**(i)** prcp > 0.1 mm	**(ii)** # of prcp members >= 10
Raobs	X				
PP	X	X		X	
PP_m10	X	X			X
PPt	X	X	X	X	
PPt_m10	X	X	X		X

- **PPt_m10_qonly**: Same as PPt_m10, but only updating the moisture field for precipitation observations (variable localization).
- **PPtp_m10** / **PPtr_m10**: Same as PPt_m10, but handling zero precipitation with method **(a)** / **(c)**.
- **PPt_m10_l0.5** / **PPt_m10_l0.3**: Same as PPt_m10, but with reduced localization scale (50% / 30%) for precipitation observations.
- **PP_err** / **PPt_m10_err**: Same as PP / PPt_m10, but with greater observation errors (50% of observed values) for precipitation.

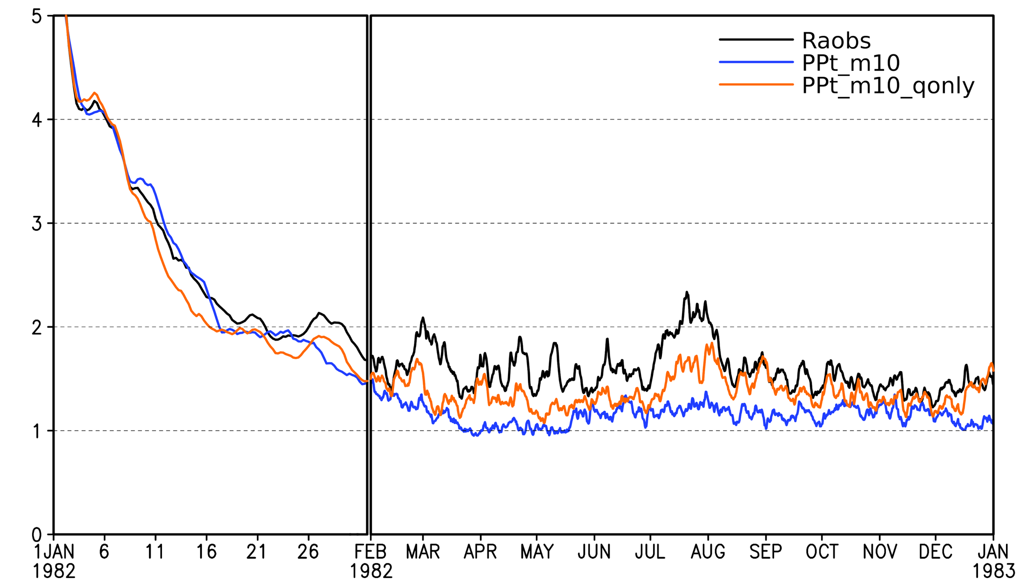
Results

Analysis errors during the spin-up and remaining 1-year period

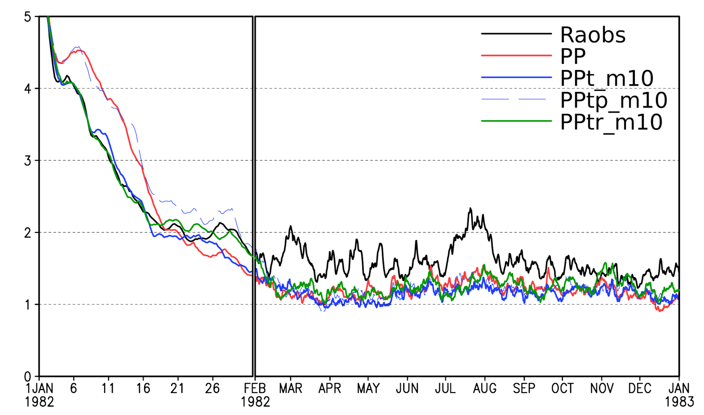
Effect of precipitation assimilation
Globally averaged RMS errors: U (m/s)



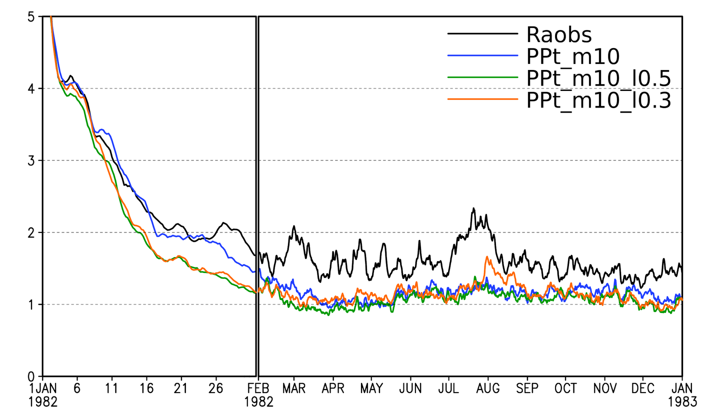
Only updating moisture field (variable localization)
Globally averaged RMS errors: U (m/s)



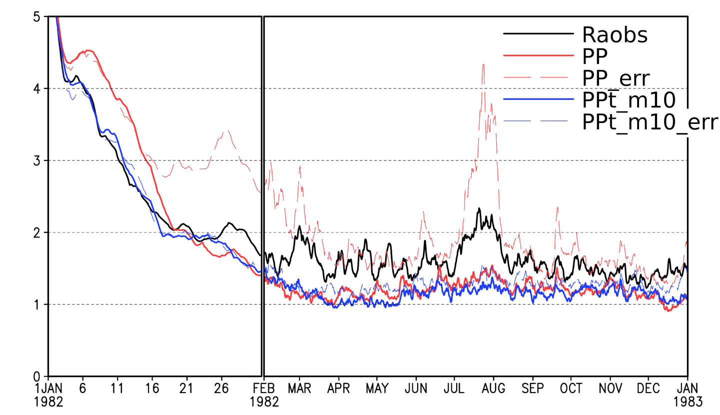
Transformation schemes
Globally averaged RMS errors: U (m/s)



Localization scale
Globally averaged RMS errors: U (m/s)



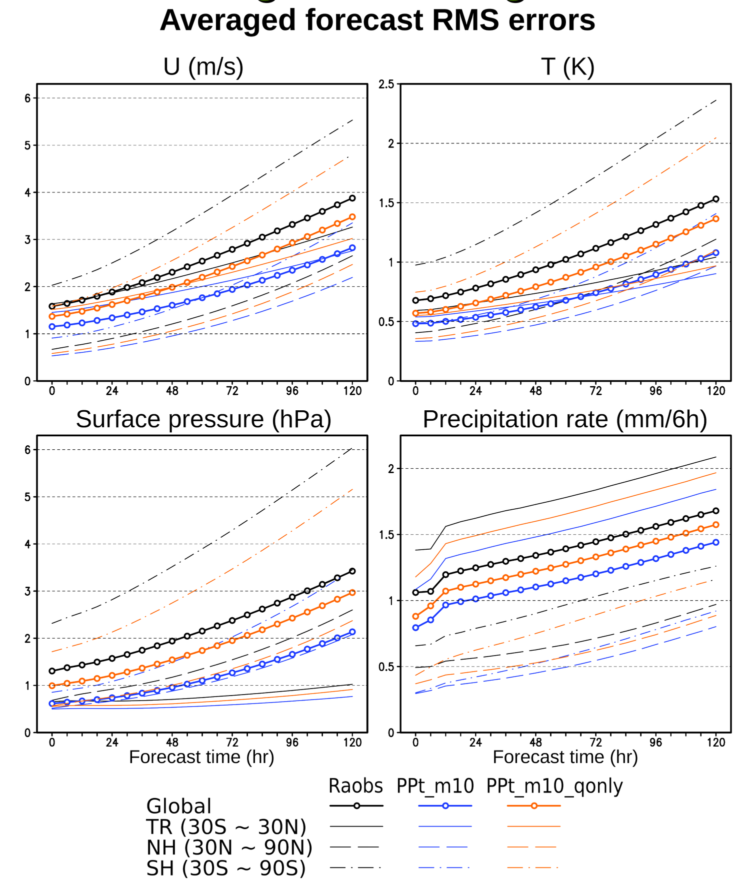
Observation accuracy
Globally averaged RMS errors: U (m/s)



- Other variables show similar results.

Evolution of averaged forecast errors after the spin-up stage (11-month temporal average from Feb. 1 to Dec. 31)

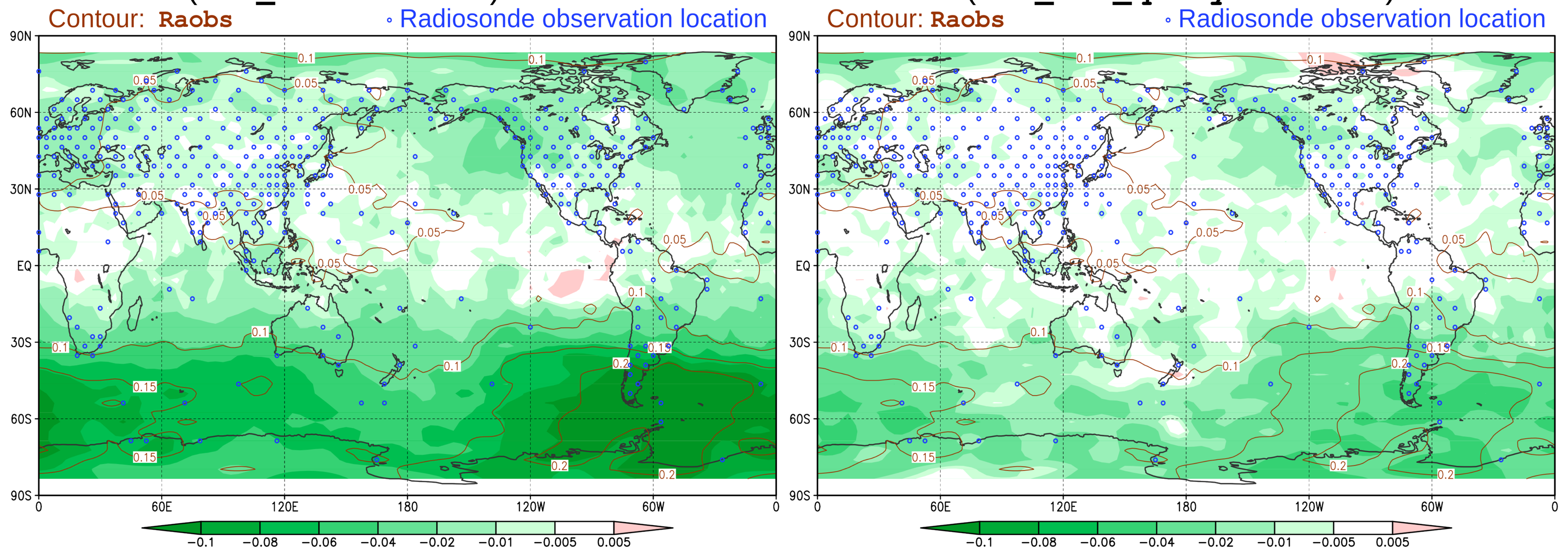
Regional average
Averaged forecast RMS errors



Maps of 3-day forecast improvement
72h Forecast RMS errors: 500hPa Vorticity (10^-4 1/s)

Shaded: (PPt_m10 – Raobs) Contour: Raobs • Radiosonde observation location

Shaded: (PPt_m10_qonly – Raobs) Contour: Raobs • Radiosonde observation location



- A large portion of improvement by precipitation assimilation comes from southern extratropical regions.

Conclusion

- Precipitation assimilation with optimal settings substantially reduces the mean analysis errors in the SPEEDY model.
- The improvement from precipitation assimilation remains large throughout the 5-day forecast period.
- Applying the Gaussian transformation in precipitation assimilation lead to a faster spin-up and slightly better analyses and forecasts. The benefit is larger in the case with large observation errors.
- Criterion **(ii)** of precipitation observation selection (only assimilate values where precipitating members >= 10 in the model first guess) is particularly good for experiments with Gaussian transformation.
- Covariances between precipitation variable and mass/wind fields contain important information. **Only updating the moisture field in precipitation assimilation (PPt_m10_q) results in worse analyses and forecasts.**
- Applying smaller localization scale for precipitation assimilation is also beneficial to the spin-up.
- A large portion of improvement by precipitation assimilation comes from southern extratropical regions. It prevents the initial errors over the radiosonde-sparse areas from spreading out to the entire southern hemisphere.
  - Northern extratropical regions are also improved, but the improvement in tropical regions is very small.
- Future work:
  - Study the structure of forecast error covariance.
  - Application of 4D-LETKF / ensemble smoother / running in place (RIP; Yang et al. 2012).