Effective Assimilation of Global Precipitation: Simulation Experiments

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Introduction

- Past attempts to assimilate precipitation by nudging or variational methods:
  - Succeeded in forcing the model precipitation to be close to the observed values.
  - However, the model forecasts tend to lose their additional skill after few forecast hours.
  - The change in moisture is not an efficient way to update the potential vorticity field, which is the “master” dynamical variable that primarily determines the evolution of the forecast in NWP models.

- Major difficulties in the current status of precipitation assimilation (Bauer et al. 2011):
  - (1) The linear representation of moist physical processes required for the assimilation stage.
  - (2) The non-Gaussianity of both precipitation observations and model perturbations.
Objectives

- Use an ensemble Kalman filter (EnKF) to avoid the problem (1).
  - The EnKF does not require linearization of the model.

- Propose and test several changes in the precipitation assimilation process to overcome the problem (2):
  - Transform the precipitation variable into a Gaussian distribution based on its climatological distribution.
  - Assimilate both positive precipitation and zero precipitation using a new observation selection criterion.

- Observing system simulation experiments (OSSEs) of precipitation assimilation in SPEEDY, a simplified but realistic atmospheric GCM.
Gaussian transformation

- The “Gaussian anamorphosis” (also used by Schöniger et al. 2012 in hydrology):
  \[ y_{\text{trans}} = G^{-1}[F(y)] \]
- \( y \): Precipitation variable.
- \( F \): Cumulative distribution function (CDF) of precipitation variables based on the 10-year model climatology at each grid and in each season.
- \( G^{-1} \): Inverse CDF of normal distribution. In the case with zero mean and standard deviation one:
  \[ G^{-1}(x) = \sqrt{2} \text{erf}^{-1}(2x - 1) \]
- Precipitation variables contain a large portion of zero values.
  - Zero precipitation values have to be considered in the transformation.
  - A natural choice: assigning the middle value of zero-precipitation cumulative probability to \( F(0) \).
- The observation errors associated with each observation also have to be transformed.
Example of precipitation distribution in DJF near Maryland
Experimental setup

- Ensemble size = 20
- Horizontal localization length scale = 500 km
- Adaptive inflation
- Observation selection criteria for precipitation assimilation:
  - (i) The traditional “ObsR criterion”: only assimilating precipitation at the location with observed positive precipitation (> 0.1 mm/6h).
  - (ii) The “10mR criterion”: only assimilating precipitation at the location where more than 10 (half of ensemble size) background members have positive precipitation.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Observations</th>
<th>Gaussian transf.</th>
<th>Criteria for prcp. assimilation</th>
<th>Obs. error of prcp. obs.</th>
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</thead>
<tbody>
<tr>
<td>Raobs</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PP_GT_10mR</td>
<td>X</td>
<td>X</td>
<td>(ii) 10mR</td>
<td>20%</td>
</tr>
<tr>
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<td>X</td>
<td>X (only updating Q)</td>
<td>(ii) 10mR</td>
<td>20%</td>
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<tr>
<td>PP_noGT_10mR</td>
<td>X</td>
<td>X</td>
<td>(ii) 10mR</td>
<td>20%</td>
</tr>
<tr>
<td>PP_GT_ObsR</td>
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<td>X</td>
<td>(i) ObsR</td>
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<tr>
<td>PP_GT_10mR_50%err</td>
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<td>(ii) 10mR</td>
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<tr>
<td>PP_noGT_10mR_50%err</td>
<td>X</td>
<td>X</td>
<td>(ii) 10mR</td>
<td>50%</td>
</tr>
</tbody>
</table>
Observation distribution
Results

Improvement on analyses and medium range forecasts by precipitation assimilation

(a) Averaged RMS errors: U (m/s) - Analysis

(b) Forecast

(Spin-up) (After the spin-up) (11-month average after the spin-up period)

- Other variables ($V$, $T$, $P_{\text{surface}}$) show similar results.
Impact of Gaussian transformation and observation selection criteria

Averaged RMS analysis errors: U (m/s)
Impact of observation errors

Averaged RMS analysis errors: U (m/s)
Regionally averaged medium range forecast errors

A large portion of improvement by precipitation assimilation comes from southern extratropical regions.
Map of averaged 72-h forecast improvement

RMS errors of 72-hour forecasts: 500 hPa vorticity ($10^{-4}$ s$^{-1}$)

Shaded: (PP_GT_10mR - Raobs)

Contour: Raobs

- Radiosonde observation location
Conclusion

- Precipitation assimilation using an EnKF and with several changes significantly improve the analyses and medium range forecasts in the SPEEDY model.
  - The improvement is much reduced when only modifying the moisture field by precipitation observations with the same approach: Covariances between precipitation variable and mass/wind fields contain important information.
- Applying the Gaussian transformation in precipitation assimilation lead to a faster spin-up and slightly better analyses and forecasts.
  - The benefit is much larger in the case with large observation errors.
- Allowing to assimilate zero precipitation data with the “10mR criterion” also results in better analyses.
- Regional dependency:
  - A large portion of improvement by precipitation assimilation comes from the southern extratropical regions. It prevents the initial errors over the radiosonde-sparse areas from spreading out to the entire southern hemisphere.
  - The northern extratropical region is also improved.
  - The improvement in the tropical region is the smallest.
- Ongoing work:
  - Assimilation of precipitation using the GFS model and with high-resolution TRMM Multi-satellite Precipitation Analysis (TMPA) data.
Thank you for your attention

Questions?
The diagram shows multiple graphs representing different variables over forecast time. Each graph plots data against forecast time and various other parameters.

- **U (m/s)**: Wind speed (meters per second) as a function of surface pressure (hPa) over forecast time.
- **V (m/s)**: Wind speed as a function of water mixing ratio (g/kg) over forecast time.
- **T (K)**: Temperature (kelvins) over forecast time.
- **Surface pressure (hPa)**: Graph showing pressure over forecast time for different regions.
- **Water mixing ratio (g/kg)**: Graph showing mixing ratio over forecast time for different regions.
- **Precipitation rate (mm/6h)**: Graph showing precipitation rate over forecast time for different regions.

The graphs are color-coded to distinguish between different regions:

- **TR (30S ~ 30N)**: Solid blue lines.
- **NH (30N ~ 90N)**: Solid black lines.
- **SH (30S ~ 90S)**: Solid orange lines.

The legend also includes a distinction between observed data (Raobs) and model predictions (PP-Transf-10mRaining-AllVar-20%err) and PP-Transf-10mRaining-qOnly-20%err).
Sensitivity of none-zero precipitation members

Impact of criteria of none-zero precipitation members: $U (\text{m/s})$

$X_m$: number of precipitating members $> X$
Evolution of [Feb 1 ~ Dec 31] mean forecast errors (temporal average)

Raobs  |  PP_GT_10mR  |  PP_GT_10mR_qOnly

Mid-level Vorticity \( (10^{-4} \text{ s}^{-1}) \)

Upper-level Temperature \( (\text{K}) \)

RMS Error: Mid-lvl. Vort. \( (10^{-4} \text{ 1/s}) \) [fcst 000h]

RMS Error: Upper-lvl. T \( (\text{K}) \) [fcst 000h]
TRMM 3B42 Prcp Rate (mm/h) [CDF = 90%, All Seasons]