Generating Calibrated Ensembles of Physically Realistic, High-Resolution Precipitation Forecast Fields Based on GEFS Model Output

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GEFS ensemble forecast (lead time 12h - 24h) and climatology corrected analysis of 12h precipitation accumulations on 20 January 2013.
Postprocessing of ensemble forecasts for precipitation

Quantiles and probabilities of threshold exceedance derived from raw ensemble forecasts directly are often unreliable due to biases, insufficient representation of uncertainty, etc.

Statistical post-processing methods use forecast-observation pairs from the past to identify and correct those shortcomings.
Univariate post-processing of precipitation accumulations

To postprocess ensemble precipitation forecasts, we use the approach proposed by Scheuerer and Hamill (2015), modeling precipitation amounts by censored, shifted gamma distributions.

This method also accounts for an increase of forecast uncertainty with the expected amount of precipitation.

This method yields **reliable, probabilistic forecasts** at each forecast lead time and each location.
Serial dependence of precipitation forecast trajectories

By calculating certain quantiles, the calibrated forecast distributions can be turned back into an ensemble (of any desired size).

Univariate post-processing, however, does not provide any information about *serial dependence*, i.e. we don’t know how to connect the ensemble forecasts at different lead times.
Spatial dependence of precipitation forecast trajectories

Hydrologists need to know not only the intensity of rainfall, but whether or not that intense rainfall is expected at several locations simultaneously.

No problem

a problem when marginal & joint probs. are not well forecast
Standard Schaake Shuffle (StSS)

- select a number of past dates, e.g. same date in the previous 11 years
- determine the rank ordering of this historic ensemble
- order the samples of the predictive distribution in the same way
- this construction preserves the rank correlations as historic ensemble

![Graph showing historical trajectories and predictive marginal distributions over lead times from 0h to 360h with 6-hour precipitation accumulation ranging from 0mm to 40mm.](image)
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Minimum divergence Schaake shuffle (MDSS)

**Idea:** Instead of selecting historic dates ad hoc, choose dates among a set of candidate dates such that the *marginal distributions* of the *historic trajectories* are *similar* to the *calibrated predictive distributions*:

![Graph showing 6-h precip. accumulation over time, illustrating the MDSS method with a subset of 553 trajectories and predictive marginal distributions.](image-url)
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Ensemble copula coupling via quantile reordering (ECC)

Similar idea as Schaake shuffle:

- sample the calibrated, univariate predictive distributions (quantile)
- determine the rank ordering from the raw forecast ensemble
- order the samples of the predictive distribution in the same way
Ensemble copula coupling via quantile reordering (ECC)

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Generating high-resolution precipitation forecast fields

We illustrate the strengths and limitations of these methods in a case study where we generate statistically calibrated, high-resolution precipitation forecast fields over the Russian River basin in California.

- 11 grid points of the 0.5° GEFS grid
- 4 consecutive 6-h accumulation periods starting 1/19/2010, 00 UTC
- forecast lead times: 48 to 54-h, 54 to 60-h, 60 to 66-h, 66 to 72-h
- calibration/downscaling to climatology corrected precipitation analyses (CCPA, resolution 2.5km)
Predicted and observed precipitation fields

GEFS ensemble mean
- Lead time 48 – 54h
- Lead time 54 – 60h
- Lead time 60 – 66h
- Lead time 66 – 72h

CSGD mean
- Lead time 48 – 54h
- Lead time 54 – 60h
- Lead time 60 – 66h
- Lead time 66 – 72h

Analyzed field
- Jan 19, 2010, 0Z – 6Z
- Jan 19, 2010, 6Z – 12Z
- Jan 19, 2010, 12Z – 18Z
- Jan 19, 2010, 18Z – 0Z

Legend:
- 0 mm
- 10 mm
- 20 mm
- 30 mm
- 40 mm
- 50 mm
- 60 mm
- 70 mm
- 80 mm
- 90 mm
- 100 mm
- 110 mm
Even the wettest historic field has large areas with zero precipitation. In the absence of reordering information, ranks were assigned at random, which results in unrealistic spatial structures.
The MDSS algorithm selects a set of dates such that the corresponding upscaled analysis fields have marginal distributions similar to the coarse-scale calibrated forecast distributions.
The rank order of these upscaled historic analysis fields is then imposed on the coarse-scale calibrated forecast samples. This yields an ensemble of coarse-scale MDSS forecast fields.
A spatially smooth adjustment factor is then derived that maps the upscaled historic analysis fields to these MDSS forecast fields.
When this adjustment factor is applied to the original historic analysis field, the adjusted field retains the spatial structure of the historic field but has the desired coarse-scale precipitation amounts.
The ECC implementation described above imposes the rank order of the raw, interpolated GEFS ensemble on samples (quantiles) of the fine-scale scale calibrated forecast distributions.
Regularized quantile mapping implementation of ECC

The ECC-Q reordering implies a quantile mapping function at each fine-scale grid point.

At the intersection of interpolated GEFS fields, the rank changes, and this translates into a spatial discontinuity of the mapping function and thus an abrupt change of the values of the ECC-Q ensemble.

If we approximate this discontinuous mapping function by a penalized linear regression spline, the discontinuities can be avoided.
This new ECC-T implementation preserves the good statistical properties of the ECC-Q ensemble but avoids the sharp gradients and produces physically more realistic fine-scale ensemble members.
Verification I: fractions of threshold exceedance

In order to study low, intermediate, and high precipitation amounts separately, it is convenient to convert the precipitation fields into binary threshold exceedance fields:

Analyzed field, Jan 19, 2010, 12Z – 18Z
Exceedance of 25 mm precipitation

This is done for both analyzed and calibrated forecast fields.
For reliable ensemble forecasts the rank of the fraction of threshold exceedance (FTE) of analyzed precipitation should be uniformly distributed among all FTE ranks.
Ensembles with inadequate spatial structure, on the contrary, might result in FTEs that are systematically too small, too large, or too similar to each other.
If we plot the rank of the FTEs of analyzed precipitation amounts in a histogram, we can observe different departures from uniformity.
Verification II: sub-grid scale precipitation maxima

Another way to study the representation of sub-grid scale ensemble properties is to consider the **maximum precipitation** over all 4 lead times and all fine-scale grid points associated with each coarse-scale grid point.

Brier skill scores of the ensemble probabilities of threshold exceedance give an idea about the skill of the respective methods.
Summary

- Modeling **dependence** between lead times, spatial locations, and different weather variables is **crucial in many applications**
- For precipitation amounts, **discrete copula approaches** are common
- The standard implementation of the **Schaake shuffle** needs to randomize whenever the historic trajectories have zeros
- Our **minimum divergence implementation** of it avoids this problem
- The sharp gradients that occur when the **ensemble copula coupling** technique is applied to high-resolution precipitation forecast fields can be avoided by **regularizing the mapping function** implied by ECC-Q

Thanks for listening!
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The Schaake shuffle: A method for reconstructing space-time variability in forecasted precipitation and temperature fields.  

Schefzik, R., Thorarinsdottir, T.L., and Gneiting, T.  
Uncertainty quantification in complex simulation models using ensemble copula coupling.  

Scheuerer, M. and T. M. Hamill  
Statistical post-processing of ensemble precipitation forecasts by fitting censored, shifted Gamma distributions.  

Scheuerer, M., T. M. Hamill, B. Whitin, M. He, and A. Henkel  
A method for preferential selection of dates in the Schaake shuffle approach to constructing spatio-temporal forecast fields of temperature and precipitation.  

Scheuerer, M. and T. M. Hamill  
Generating Calibrated Ensembles of Physically Realistic, High-Resolution Precipitation Forecast Fields Based on GEFS Model Output.  