Spatial non-homogeneous Gaussian regression

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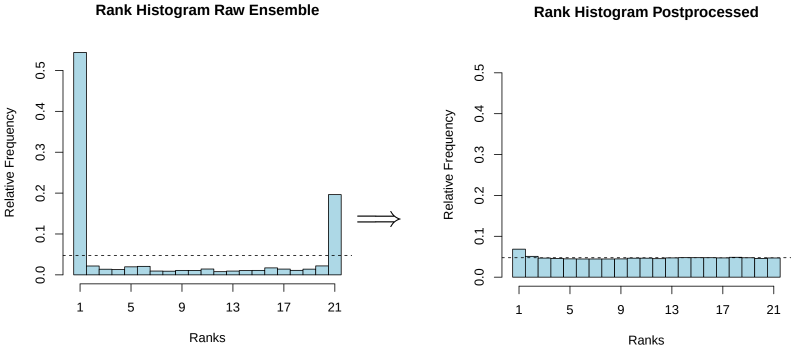
Statistical postprocessing



underdispersive

calibrated

Motivation spatial postprocessing

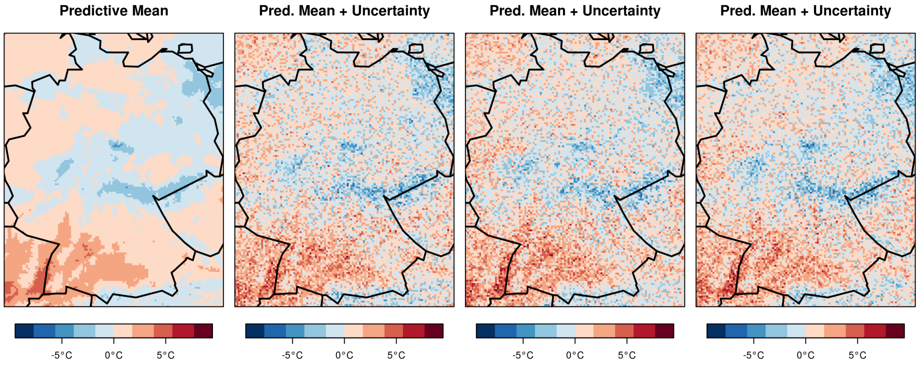
state-of-the-art ensemble postprocessing methods:

- Bayesian model averaging (BMA)
- non-homogeneous Gaussian regression (NGR), also known as ensemble output statistics (EMOS)

BUT: ignore spatial correlation between different observation

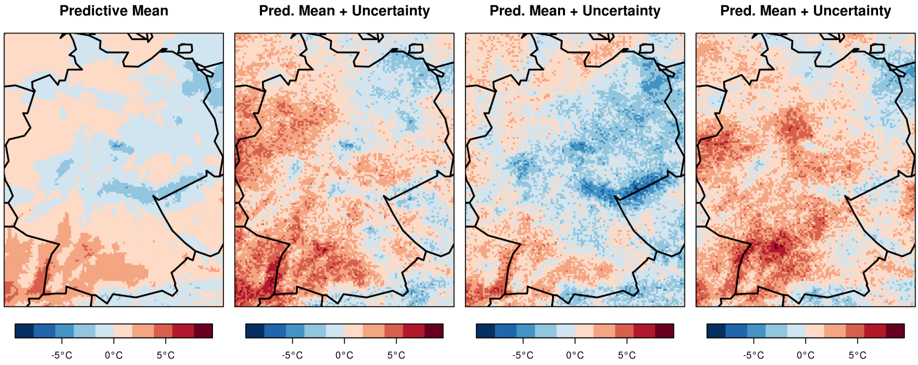
Forecast Fields

Assuming the forecast uncertainties at different sites are independent, then samples of the predictive distribution look like this:



Forecast Fields

We present a statistical postprocessing method which models spatially consistent temperature forecast fields:



Spatial non-homogeneous Gaussian regression - Overview

combination of non-homogeneous Gaussian regression and the geostatistical output perturbation method (GOP)

NGR	GOP
for ensemble	one member
independent sites	weather field

$\Rightarrow$ spatial NGR

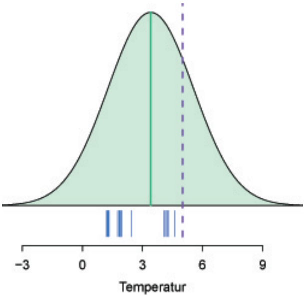
- uses full information of ensemble
- models spatial correlation

Part 1: Non-homogeneous Gaussian regression

- proposed by Gneiting et al., 2007
- applicable to different weather variables, such as temperature, wind speed, precipitation
- yields full predictive distribution
- distribution characteristics are modeled as functions of the ensemble information
- assumption: the forecast error on the verfication day behaves similar to the forecast errors on the *n* previous days

Part 1: NGR for temperature

$$y_s | f_{1s}, ..., f_{Ms} \sim \mathcal{N}(a_1 + b_1 f_{1s} + ... + b_M f_{Ms}, c + dS_s^2),$$



where

- y_s temperature at location s
- $f_{1s}, ..., f_{Ms}$ ensemble forecasts for location s
- S ensemble variance
- $a, b_1, ..., b_M$ bias-correcting parameters
- c, d spread parameters

Part 2: Geostatistical output perturbation method

- proposed by Gel et al., 2004
- models forecast errors with a Gaussian random field (GRF)

$$\mathbf{Y}|\mathbf{F} = a\mathbf{1} + b\mathbf{F} + \mathbf{E}_1 + \mathbf{E}_2$$

where

- $\mathbf{Y}$ temperature field
- $\mathbf{F}$ forecast field of one member
- $\mathbf{E}_1$ continuous error field
- $\mathbf{E}_2$ discontinuous error field
- $a_, b$ bias-correcting parameter

Combination of NGR and GOP

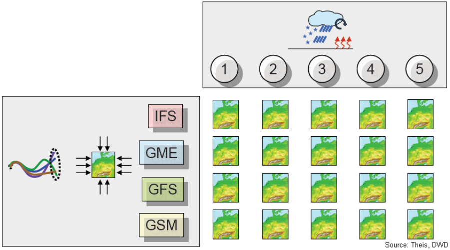
1. fit NGR model as before
2. calculate standardized forecast errors during the training period

$$\frac{y_s - (a + b_1 f_{s1} + \ldots + b_M f_{sM})}{\sqrt{c + dS^2}}, \quad s \in S$$

3. estimate covariance function of GRF based on forecast errors
4. simulate forecast errors according to this GRF and scale them
5. add them to the means of the predictive distributions

COSMO-DE-EPS

- temperature forecasts
- time period: 10 December 2010 to 30 November 2011
- lead time: 21hours
- initialization time: 00:00UTC
- observations at 514 SYNOP stations

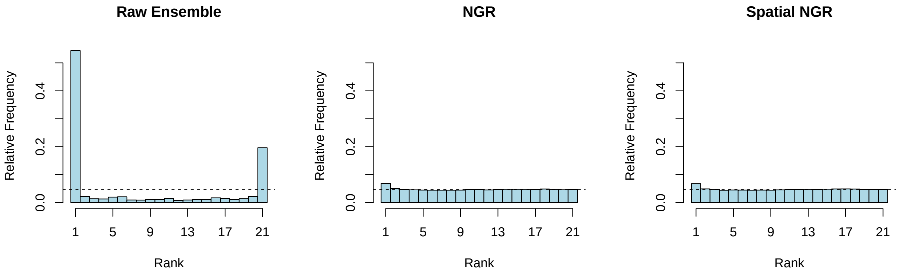


Source: Theis, DWD

Verification Results: overall

If verified individually, the scores for NGR and spatial NGR coincide.

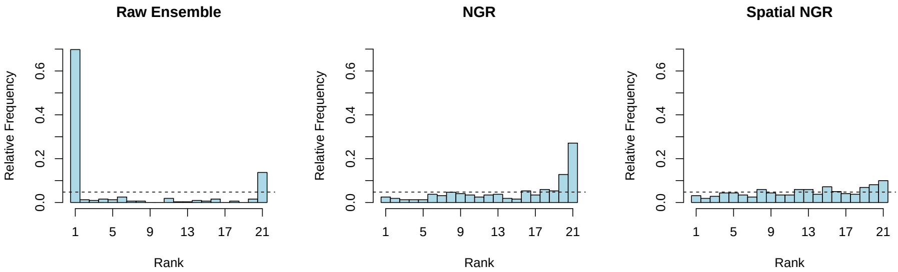
Model	CRPS	MAE
Raw ensemble	1.57	1.77
NGR	1.04	1.46
Spatial NGR	1.04	1.46



Verification results: minimum temperature along A3

17 SYNOP stations at a section of A3 between Frankfurt and Cologne

Model	CRPS	MAE
Raw ensemble	1.72	1.92
NGR	1.05	1.37
Spatial NGR	0.86	1.20



Verification results: minimum temperature along A3

Application: winter road maintenance

- salt the road if temperatures are predicted to drop below zero somewhere on the considered section of the A3
- otherwise don't salt

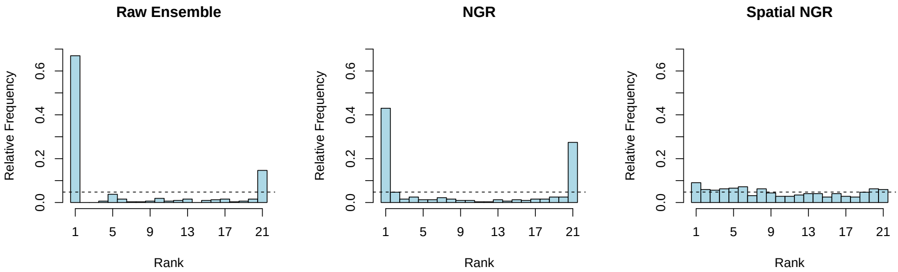
considering winter months of January, February and November 2011

Model	Brier score
Raw ensemble	0.120
NGR	0.114
Spatial NGR	0.083

Verification Results: average temperature

prediction of average temperature in 14 of Germany's states

Model	CRPS	MAE
Raw ensemble	1.26	1.43
NGR	0.85	1.00
spatial NGR	0.71	0.95



Summary

- importance of spatial modeling, especially when considering minima, maxima, totals or averages
- spatial NGR is a method which generates spatially consistent temperature fields
- case study: spatial NGR superior to raw ensemble as well as NGR

Thank you for your attention!

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