Accounting for Representativeness in the Verification of Ensemble Forecasts

Zied BEN BOUALLEGUE

ECMWF

2020-IVMW-O

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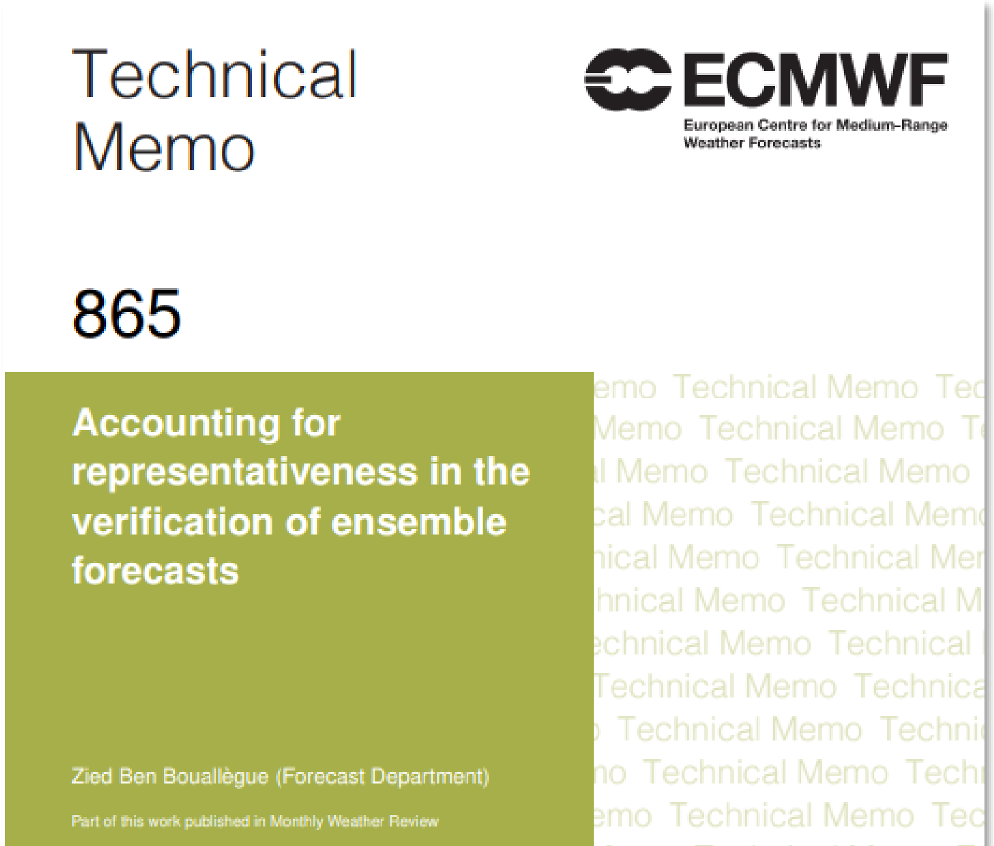
Technical Memo

ECMWF
European Centre for Medium-Range Weather Forecasts

865

Accounting for representativeness in the verification of ensemble forecasts

Zied Ben Bouallègue (Forecast Department)

Part of this work published in Monthly Weather Review

2020-IVMW-O

Motivation

Ensemble forecasts provide information about **forecast uncertainty.**

When verifying ensemble forecasts**, not** accounting for **observation uncertainty** leads to:

- encouraging forecasts of erroneous observations (instead of the truth)
- inaccurate skill estimation
- misleading comparison between forecasting systems

Focus on “**representativeness**”

- **definition**: mismatch between a quantity measured at two different scales
- **assumption**: representativeness is the principal source of observation uncertainty
- **application**: global ensemble forecast verification of surface variables

1. Observation uncertainty characterization

2. Ensemble Verification

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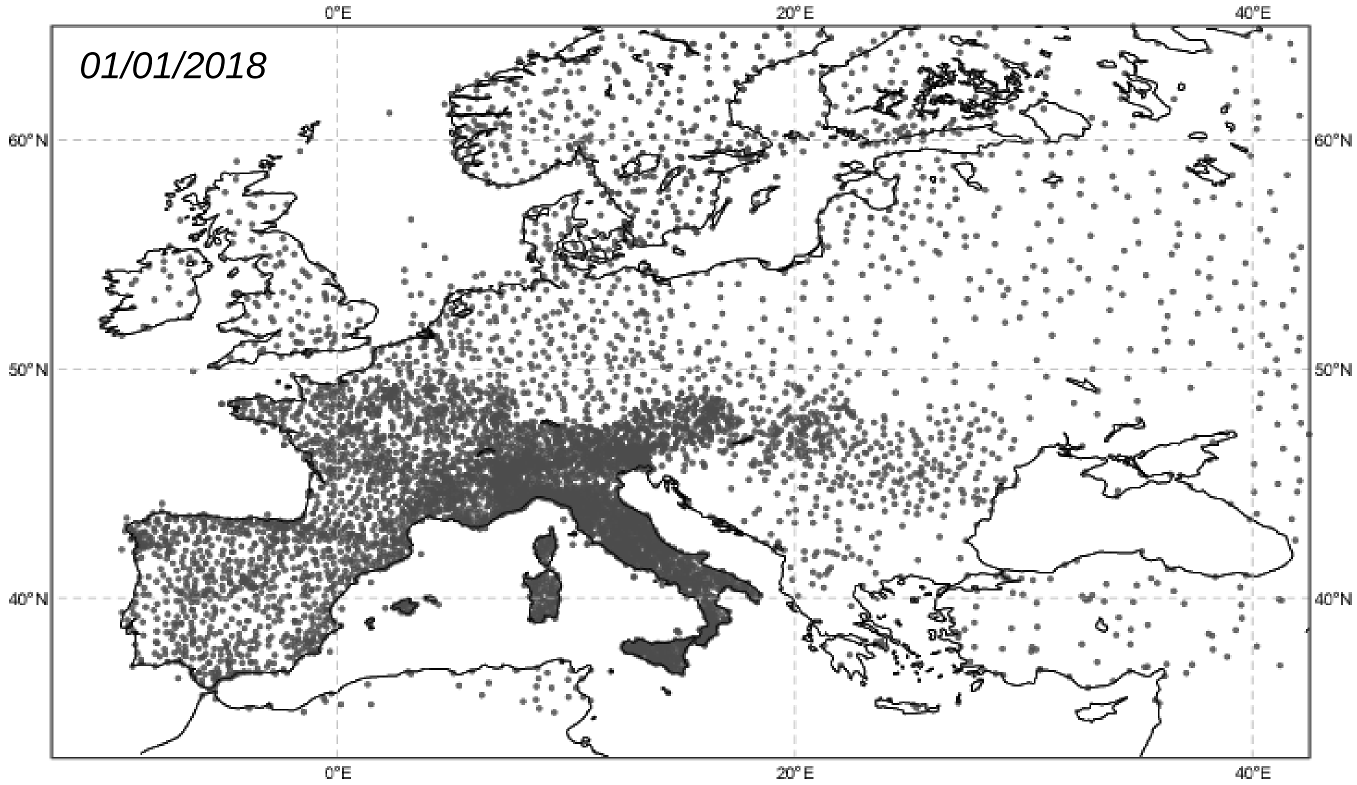
Observation uncertainty characterization

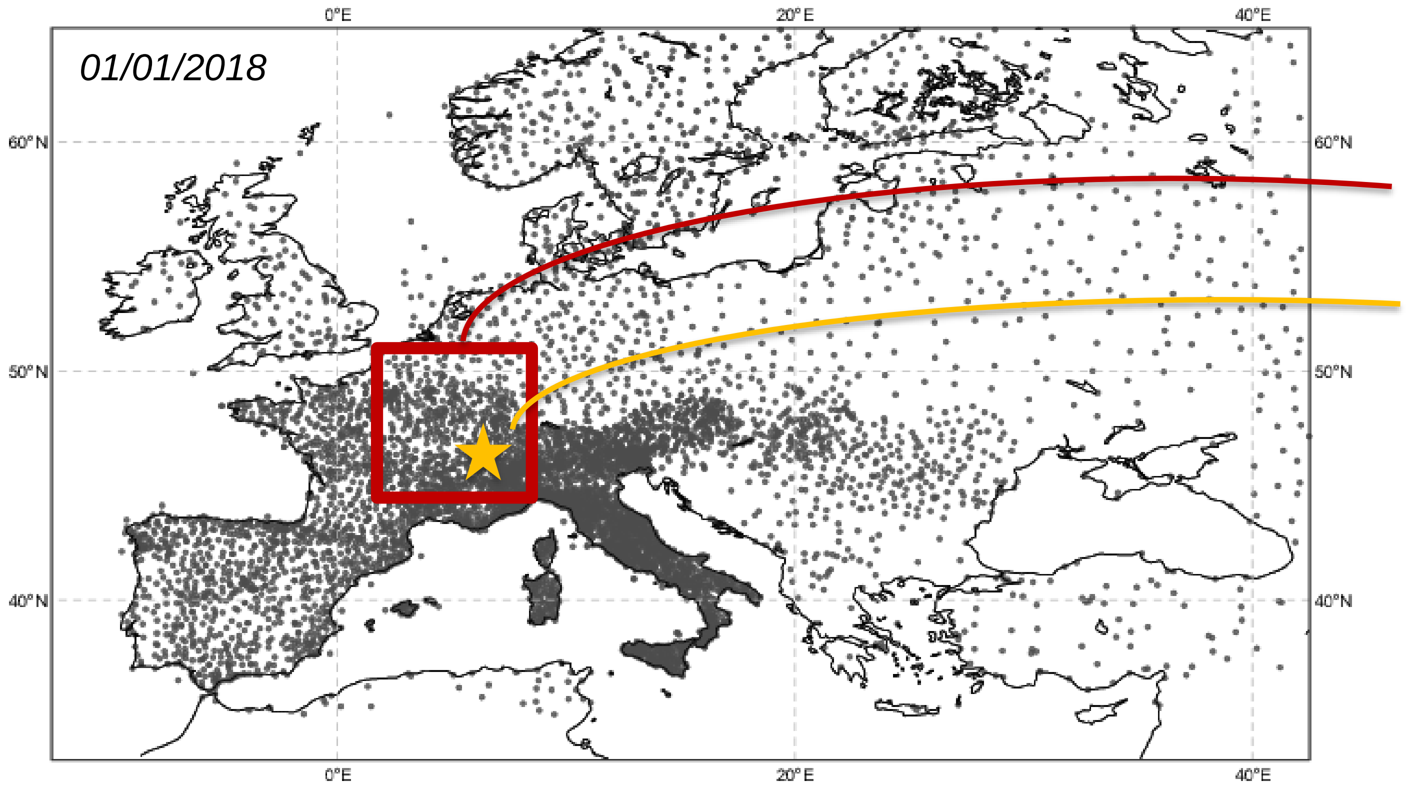
based on **observations only**, a network of **high-density observations** (over Europe)



Observation uncertainty characterization

based on **observations only**, a network of **high-density observations** (over Europe)

- is a single location measurement ★ representative of an average □ over larger areas?



box-average $\mathbf{y_A}$

point-observation $\mathbf{y_B}$

$$\mathbf{P\ (Y_B \,|\, Y_A)\ ?}$$

Parametric models

based on appropriate probability distributions:

- a **normal distribution** for **2 m temperature**
- a **truncated normal** distribution **for 10 m wind speed**
- a **censored and shifted gamma** distribution for **daily precipitation**

- model **fitting**
- model **validation**

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➢ model **fitting**

➢ model **validation**

2m temperature

Normal distribution

$$\mu = t + 0.0065 D_e$$

$$\sigma = \beta_0 + \beta_1 \sqrt[4]{| D_e |}$$

with D_e the difference between average and point elevation

2m temperature

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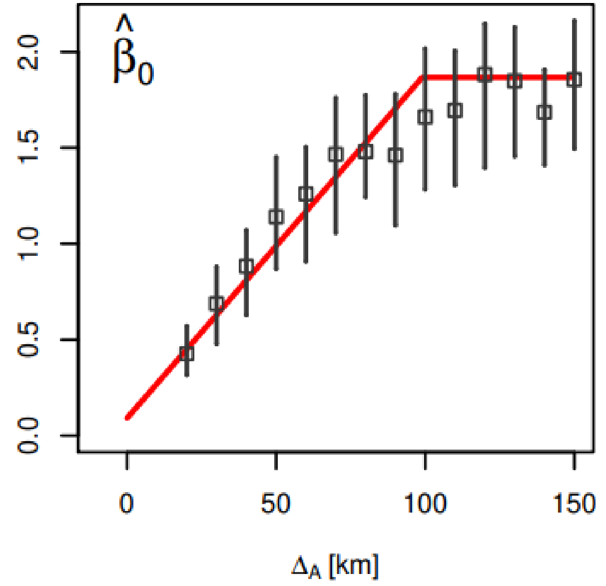
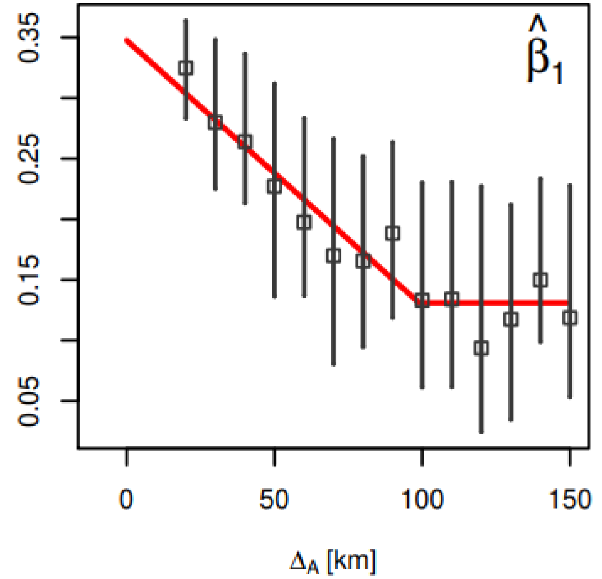


with D_e the difference between average and point elevation

1. Model fitting based on **pairs of (y_A,y_B)**, CRPS optimisation
2. Model fitting **for various averaging scales Δ_A**
3. Simple model of the distribution parameters as a function of $\mathbf{\Delta_A}$ called **generalized uncertainty model**



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1. Observation uncertainty characterization

2. Ensemble Verification

Perturbed ensemble approach

“Raw ensemble + **Observation uncertainty** = **Perturbed ensemble”**

- recommended as a generic method to be applied in the presence of observation errors (**Ferro, 2017**)

```
#Parameters definition
def parameters_2t(deltax) :
    beta0 = min(0.02*deltax,2.)
    beta1 = max(0.35 -0.002*deltax,0.15)
    return [ beta0, beta1 ]

# deltax: model grid resolution
# diff_elevation: model elevation - station elevation
beta  = parameters_2t(deltax)
sigma = beta[0] + beta[1]*abs(diff_elevation)**(1./4.)

#Loop over ensemble members
for im in range(len(ensemble)):
    ens[im] += diff_elevation*0.0065
    ens[im] += np.random.normal(0,sigma)
```

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generalized uncertainty model for 2t

equation of the previous slide

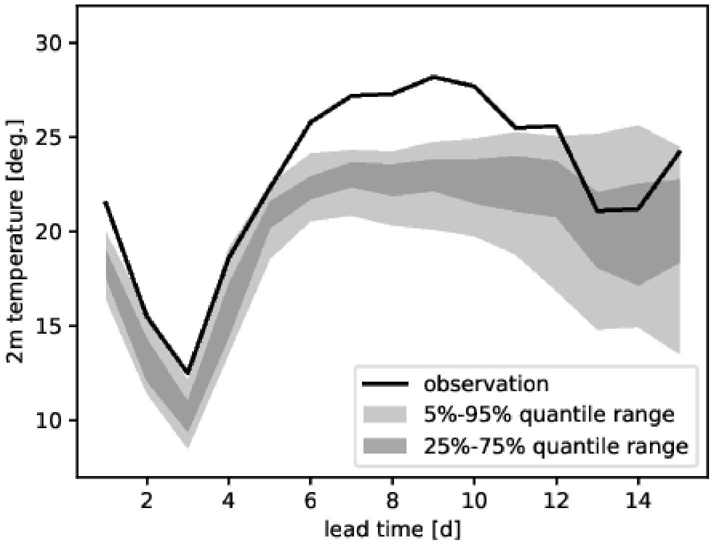
already in your code

random perturbation

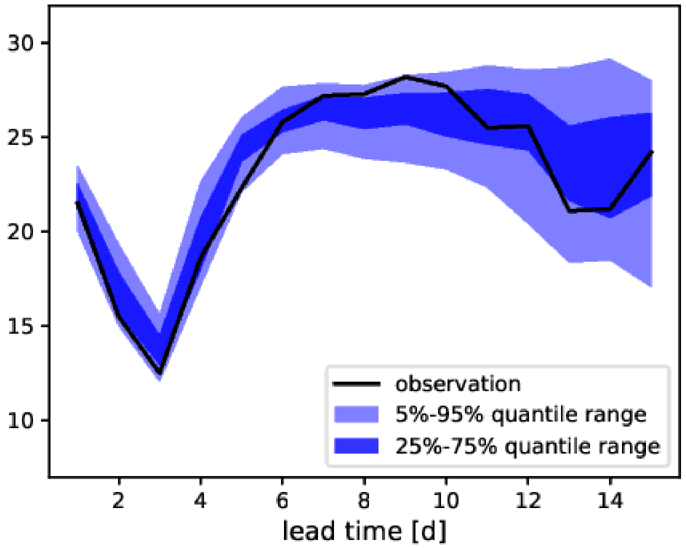
Perturbed ensemble approach

Example: ensemble forecasts of night temperature on 01/08/2020 at Garmisch-Partenkirchen (Germany)

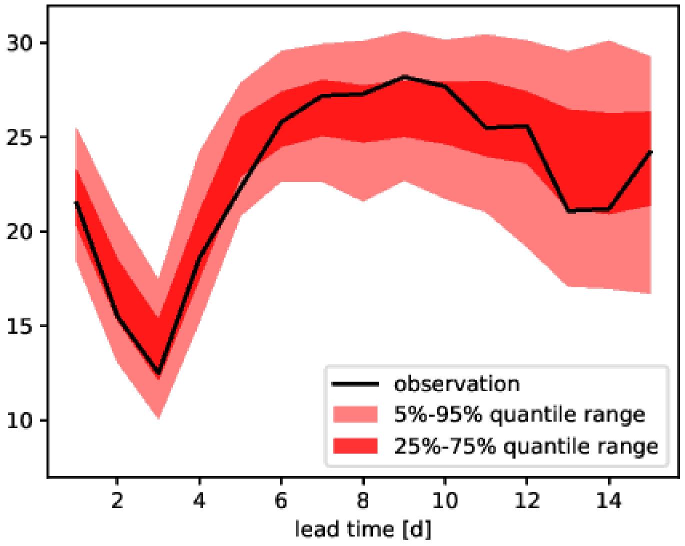
Raw ensemble



+ lapse rate correction



+ (obs. uncertainty) perturbation



➢ **Perturbed ensemble approach** is an **(observation-based) post-processing** method

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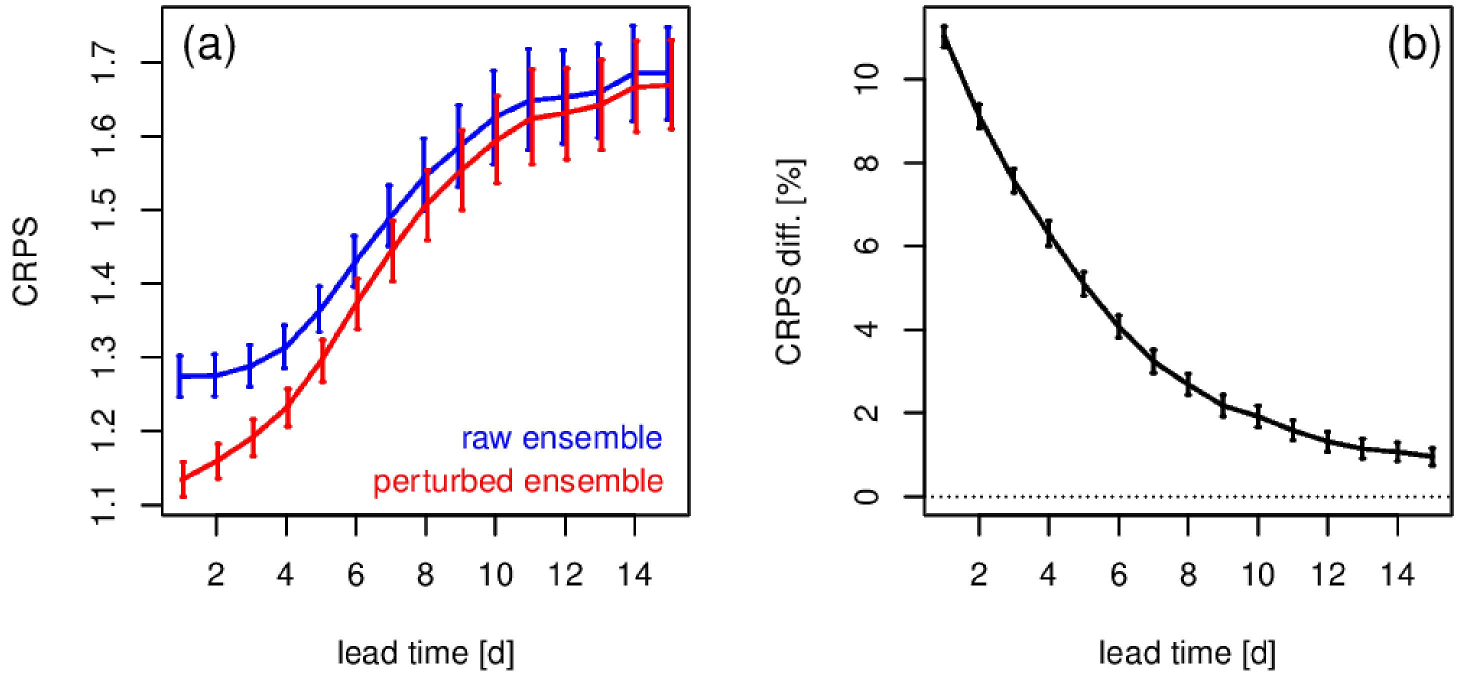
Impact on scores

Comparison of the **raw ensemble** vs the **perturbed ensemble**

- ❑ Summer 2018 - Europe - 00UTC
- ➢ **smaller error** with observation uncertainty



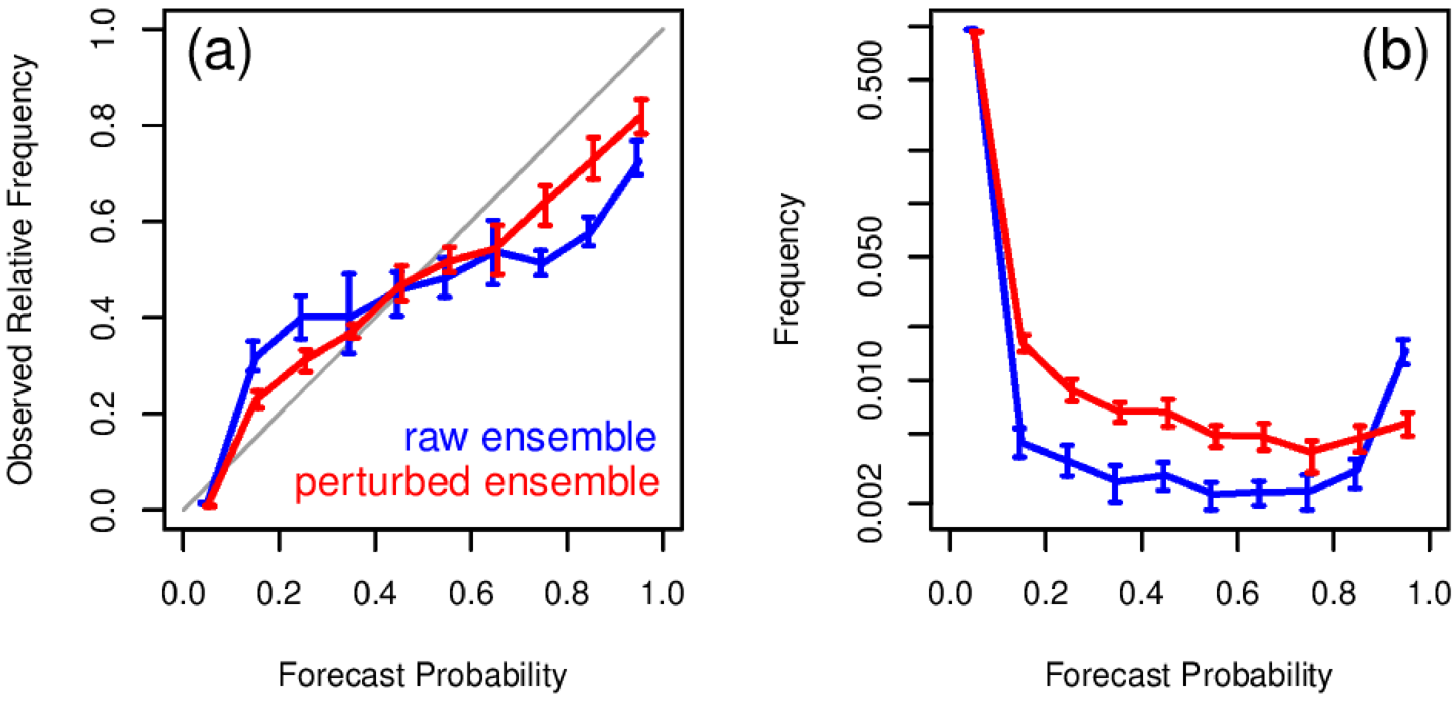
Impact on scores

Large impact on **reliability/sharpness** attributes

- ❑ Summer 2018 - Europe - 00UTC - day 5 - threshold: 25 deg.
- ➢ **more reliable** probabilistic forecasts with observation uncertainty

Reliability

Sharpness

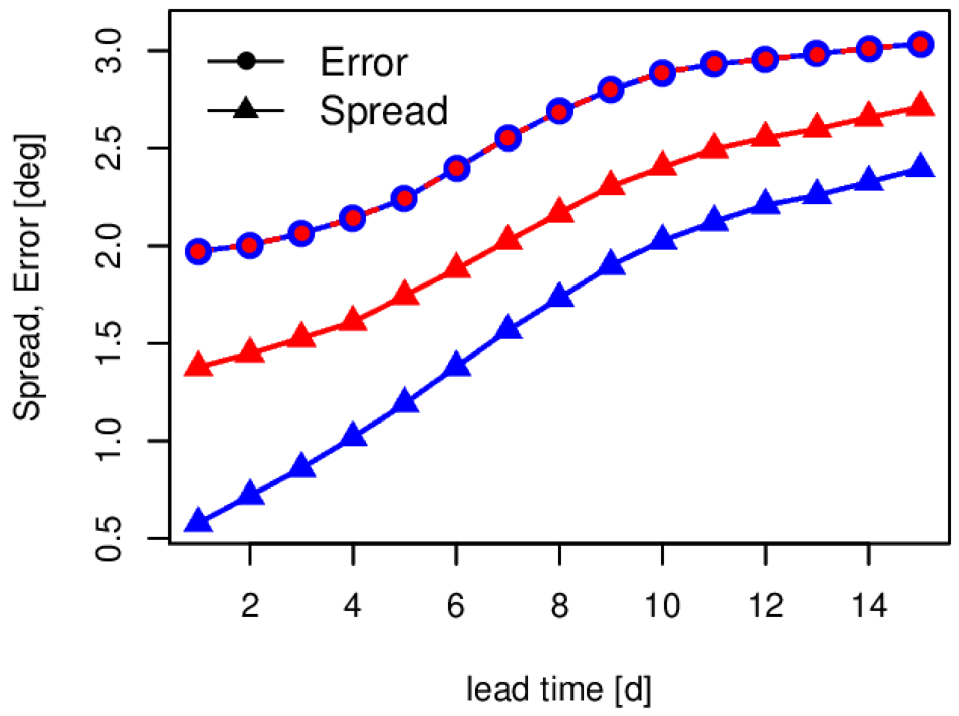


Spread/skill relationship - Forecast deficiencies

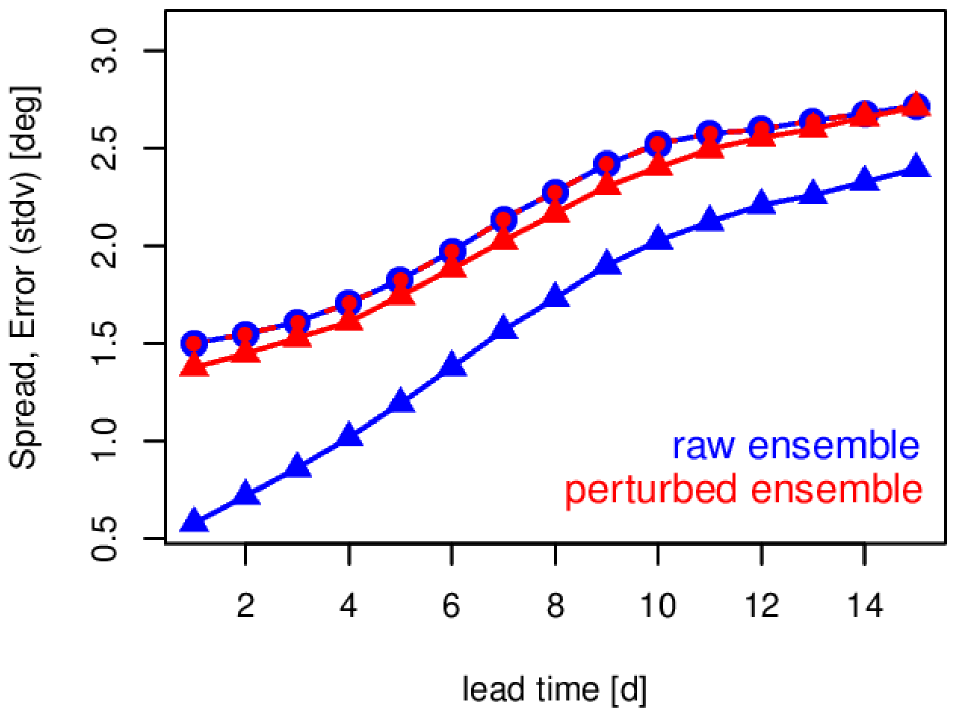
Good spread-skill relationship when comparing stdv of the error and spread of the perturbed ensemble

- perturbed ensemble accounts for representativeness error in the observation, **not in the forecast**

No bias correction



With “bias correction”



Summary

Observation uncertainty characterization:

- ❑ **representativeness** is the main source of observation uncertainty for surface variables
- ❑ simple models are proposed for **t2m, 10 m wind speed, and 24h precipitation**
- ❑ **applicable to any NWP ensemble** (function of the model grid-resolution only)

In ensemble verification:

- ➢ the **perturbed ensemble approach** is easy to implement
- ➢ observation-based **post-processing** before verification
- ➢ accounting for representativeness leads to **more accurate skill estimation**

Links

Ben Bouallegue, Z. (2020).

Accounting for representativeness in the verification of ensemble forecasts.

Tech Memo 865.

Ben Bouallegue, Z., Haiden, T., Weber, N. J., Hamill, T. M. and Richardson, D. S. (2020).

Accounting for representativeness in the verification of ensemble precipitation forecasts.

Monthly Weather Review, 148(5), 2049–2062.