Particle filter based data assimilation into an air quality model

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What I will talk about

- Experiment for particle filter based data assimilation into the POLYPHEMUS/DLR air quality model
  - Very simple setup, ignoring virtually every problem that should actually be treated
- Assimilation of in-situ stations for O_3 and NO_2.
- Results are promising

Some background

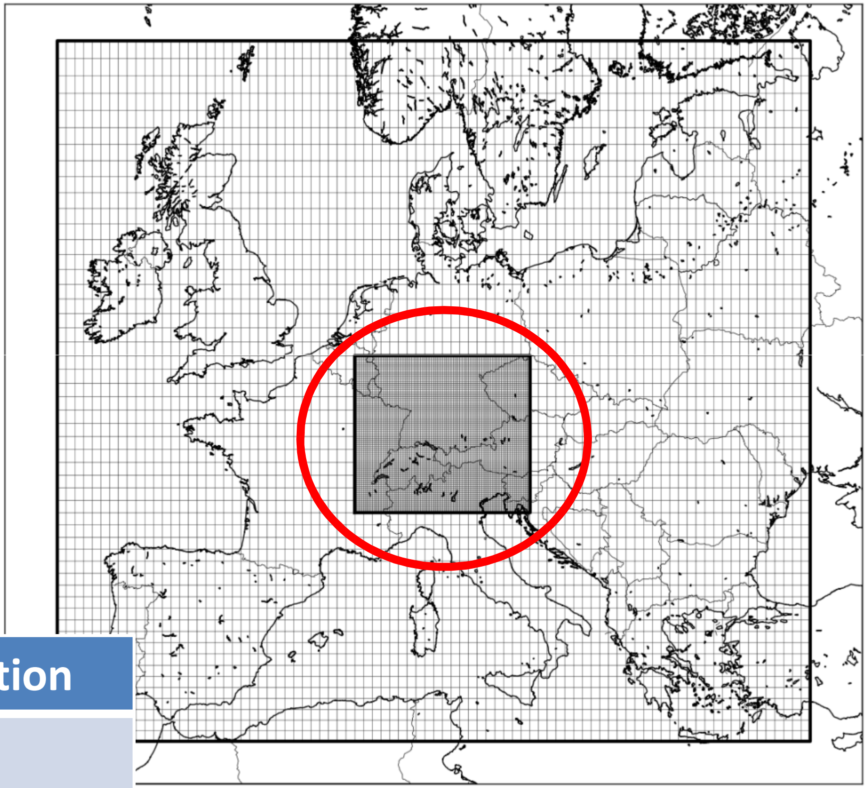
- Air quality models simulate the composition of the lower atmosphere
    - Transport (advection + diffusion)
    - Chemistry
    - Driven by weather parameters and emissions
- Will consider offline models, i.e. no feedback to the weather model
- Assimilation has several issues:
    - Background covariances between different species unknown
        - Schemes with predefined background covariance matrix usually just consider single species
    - 4DVar tricky because of aerosol thermodynamics
        - Some progress has been made there
    - Vertical background covariances are also problematic
- AQ modelling works rather well for ozone but remains tricky for NO_2.

Why should a particle filter work?

- AQ models are highly convergent, i.e. starting with different initial values leads to the same results eventually
- This should prevent ensemble degeneration
- In fact we have to do something to keep the ensemble from collapsing
    - Change model parameters, esp. emissions

The model POLYPHEMUS/DLR

- Provides regional air quality forecasts within PASODOBLE
    - Target area is the Alpine area and the Black Forest
- Eulerian model based on the POLYPHEMUS platform (Mallet et at. 2007).
- Here: Homogeneous chemistry only (72 species)



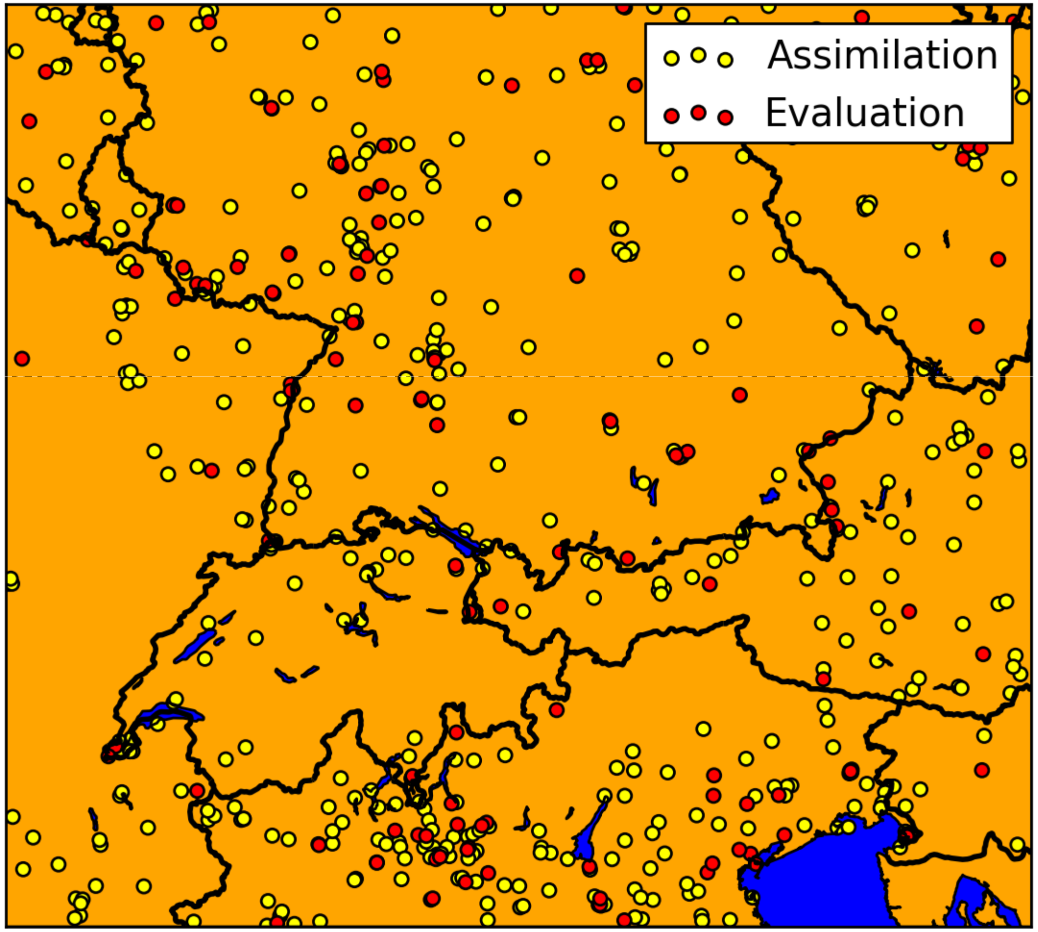
Domain	X-resolution	Y-resolution
Europe	0.5°	0.5°
Bavaria	1°/8	1°/16

Particle filter setup and localisation

- Classical filter: For an individual observation o_i and an ensemble member with corresponding result m_{ij} we obtain a weight $w_{ij} = e^{-\left(\frac{o_i - m_{ij}}{\sigma}\right)^2}$. The total weight is given by $w_j = \prod_i w_{ij}$.
- Localisation approach: Weights are not real numbers but functions $\varphi_{ij}\colon M \to \mathbb{R}$ on the model space. Here we take $\varphi_{ij}(r) = \left(w_{ij}\right)^{\rho(r)}$ where r is the distance to the measurement location. We set $\rho(r) = e^{-\left(\frac{r}{R}\right)^2}$ where R is a falloff length that needs to be specified.

Assimilation setup – observations

- Use operational in-s
- These stations have
  - I will ignore that
  - For all stations
- Split station set in or
  (around 80% for ass
- Use O_3 and NO_2 dat

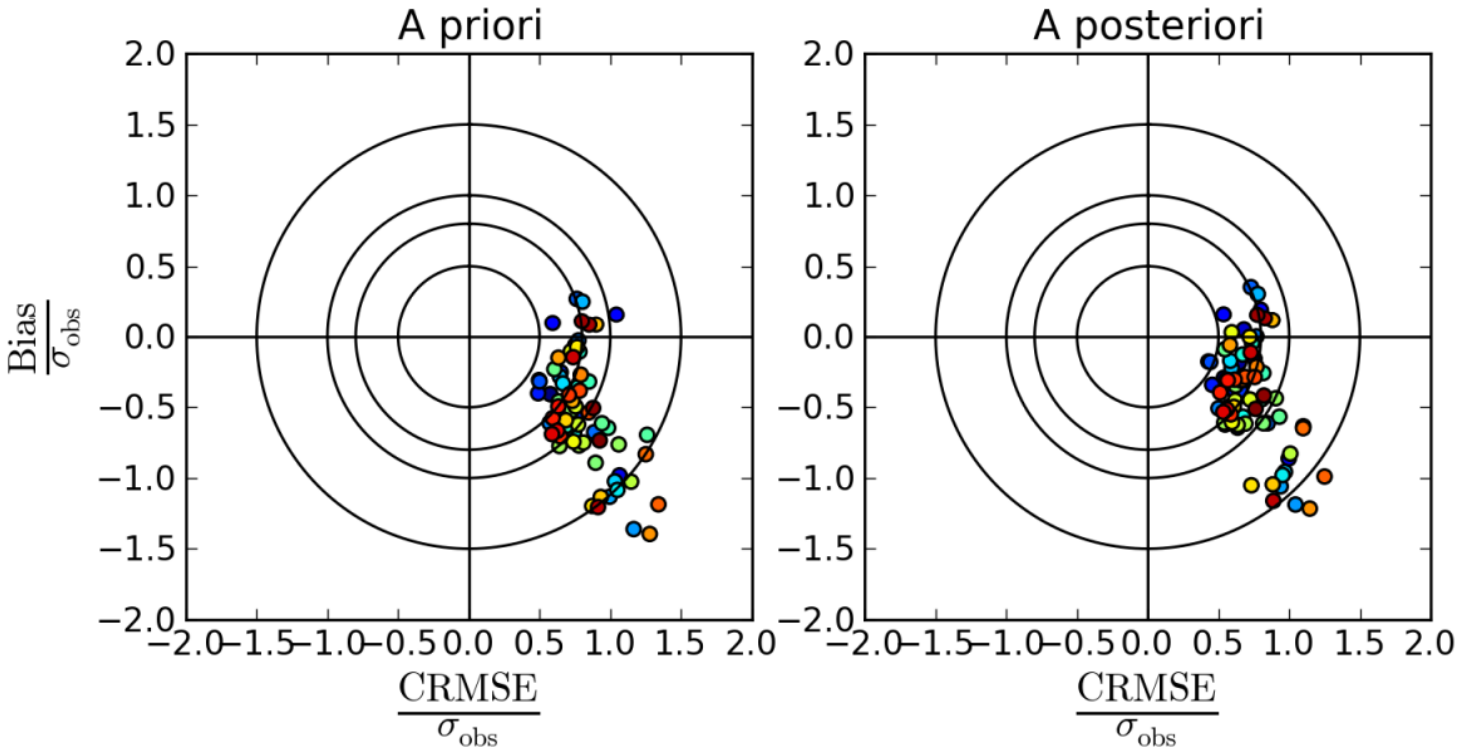


Assimilation setup – ensemble

- Ensemble of 80 members
- Different emissions
    - Basic emission fields provided by TNO via PASODOBLE
    - Main source of uncertainty in the model
    - Little knowledge on the error distribution
    - Try to simulate emission error distribution by applying
        - Spatial noise to the emission field
        - Random processes (green noise) to the temporal disaggregation factors
- Period: May 2011 (a few days in April for spinup)

Improvement in ozone results

Target diagram for verification stations with O_3 observations

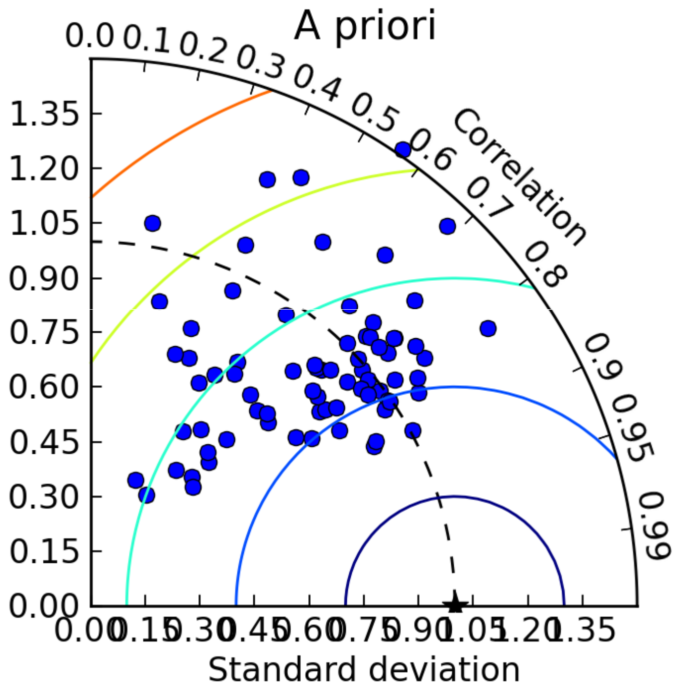


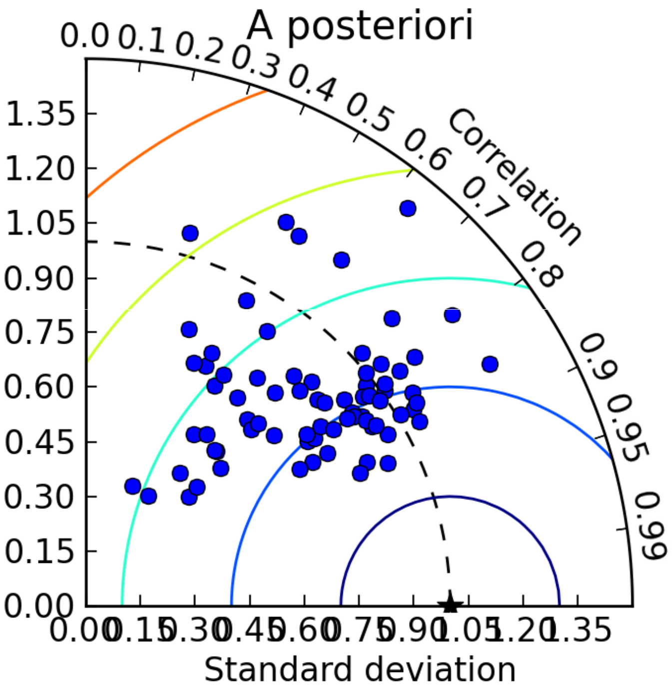
Mean CRMSE: $0.80\sigma_{obs}$
Mean bias: $-0.53\sigma_{obs}$
Mean correlation: 0.65

Mean CRMSE: $0.72\sigma_{obs}$
Mean Bias: $-0.41\sigma_{obs}$
Mean correlation: 0.71

Improvement in ozone results

Taylor diagram for verification stations with O_3 observations





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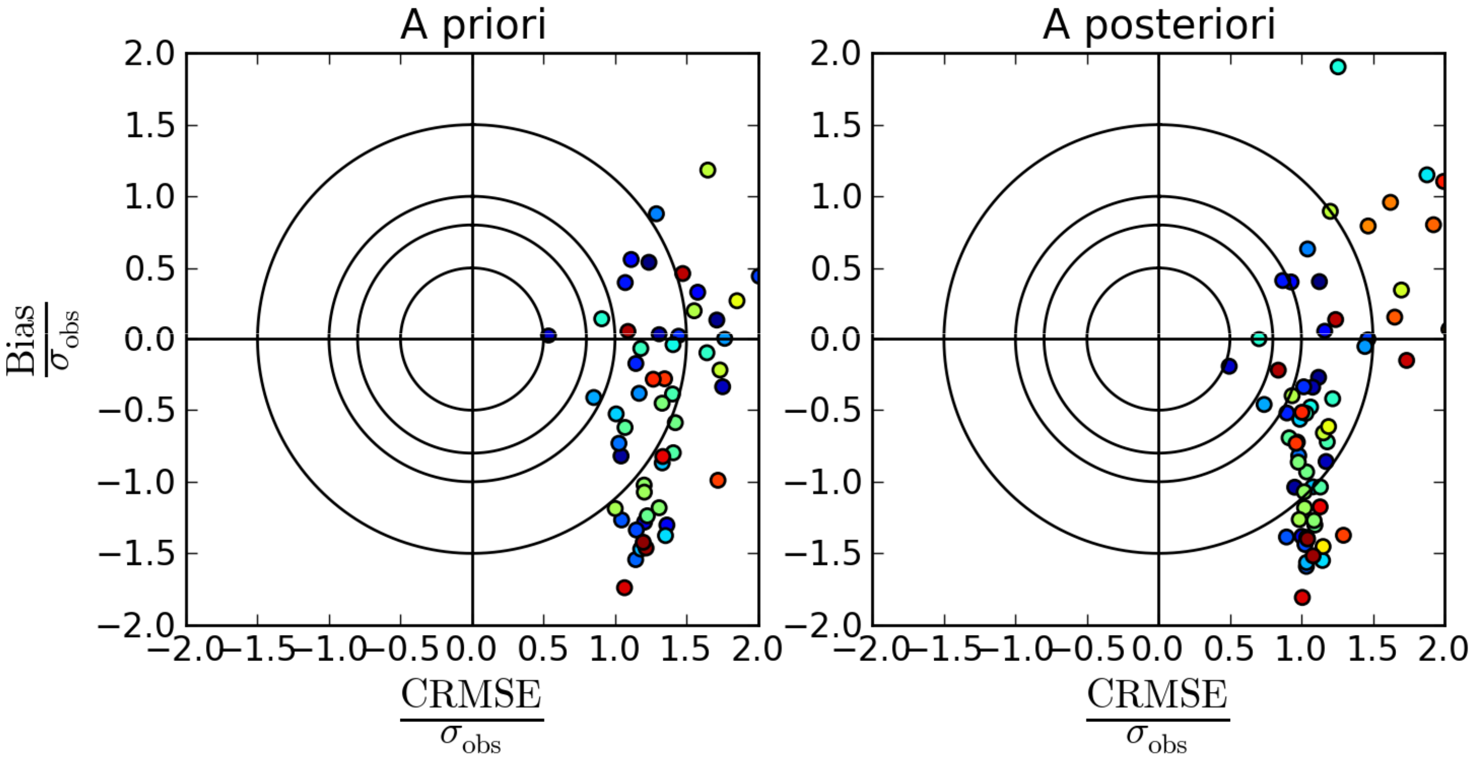
Improvement in NO_2 results

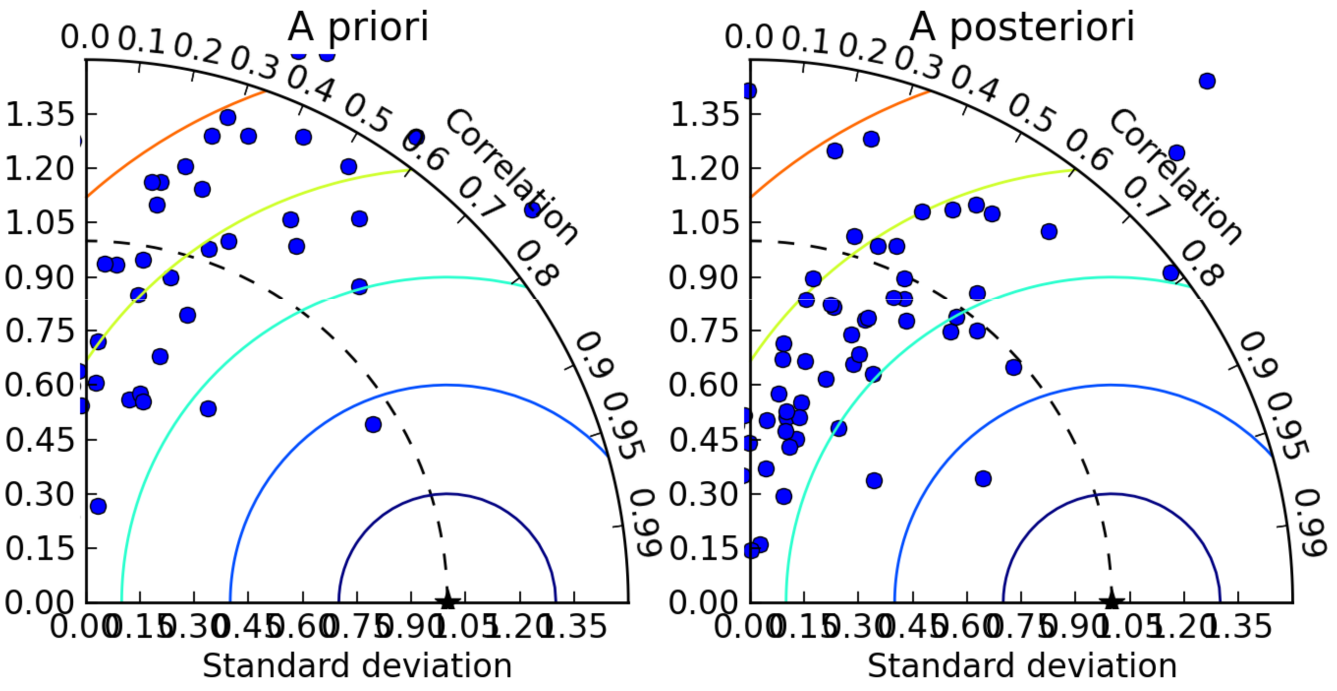
Target diagram for verification stations with NO_2 observations



Mean CRMSE: $2.1\sigma_{obs}$	Mean CRMSE: $1.4\sigma_{obs}$
Mean Bias: $0.44\sigma_{obs}$	Mean Bias: $-0.20\sigma_{obs}$
Mean correlation: 0.25	Mean correlation: 0.35

Improvement in NO_2 results

Taylor diagram for verification stations with NO_2 observations



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Summary

- Constructed a localised particle filter
- First experiments encouraging
- Following this approach, it remains possible to perform one ensemble run and afterwards do fast assimilation experiments
    - Speeds up research: More fun

Thank you for your attention!

DLR