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Parameter Estimation using the EnKF Approach

Yvonne Ruckstuhl (LMU), Tijana Janjic (Hans Ertel Centre for Weather Research, DWD)

1. Introduction

Motivation

Representation of clouds in convection permitting model is sensitive to NWP parameters that are often only crudely known (for example roughness length).

Goal

Allow for uncertainty in these parameters and estimate them from data using the EnKF Approach.

Challenges

- Distributions associated with parameters are typically non-Gaussian.
- Parameters may be restricted to physical bounds.

2. Modified Shallow Water Model

(Würsch and Craig, 2014)

A simple dynamical model which is designed to represent key features of cumulus convection.

$$\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + \frac{\partial(\varphi + c^2 r)}{\partial x} = \beta_u + D_u \frac{\partial^2}{\partial x^2}$$

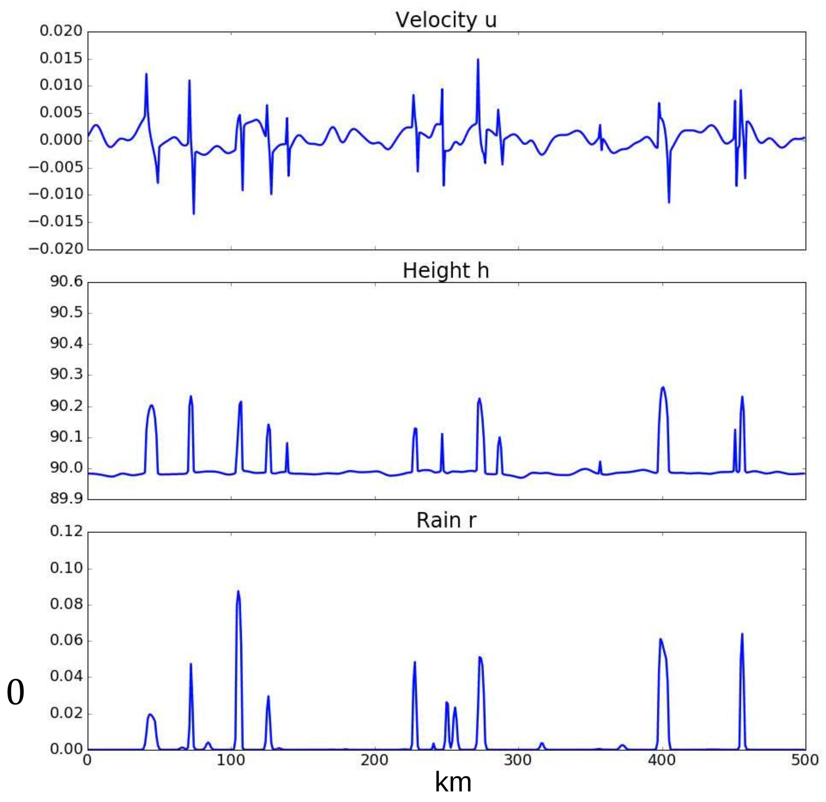
$$\frac{\partial h}{\partial t} + \frac{\partial(uh)}{\partial x} = D_h \frac{\partial^2 h}{\partial x^2}$$

where,

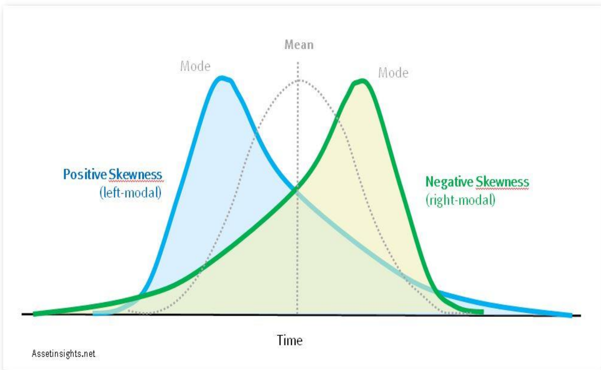
$$\varphi = \begin{cases} \varphi_0, & if \;\; h > H_r \\ gh & otherwise \end{cases}$$

and

$$\frac{\partial r}{\partial t} + u\frac{\partial r}{\partial x} = D_r \frac{\partial^2 r}{\partial x^2} - \alpha r - \begin{cases} \delta \frac{\partial u}{\partial x}, & h > H_r \text{ and } \frac{\partial u}{\partial x} < 0 \\ 0 & otherwise \end{cases}$$



3. Algorithms



EnKF (Evensen, 1994)

Does not deal with non-Gaussianity.

Quadratic Filter (QF) (Hodyss, 2012)

Takes higher order moments into account, thereby explicitly dealing with non-Gaussianity.

$$\bar{x}^a - \bar{x}^f = \tilde{P}H^T\left(H\tilde{P}H^T + \tilde{R}\right)^{-1}\tilde{v}$$

$$\tilde{P} = \begin{bmatrix} P & P_{skew} \\ P_{skew} & P_{kurt} \end{bmatrix} \quad \tilde{R} = \begin{bmatrix} R & R_{skew} \\ R_{skew} & R_{kurt} \end{bmatrix} \quad \tilde{v} = \begin{bmatrix} v \\ v \cdot v \end{bmatrix}$$

QP-Ensemble (Janjic, 2014)

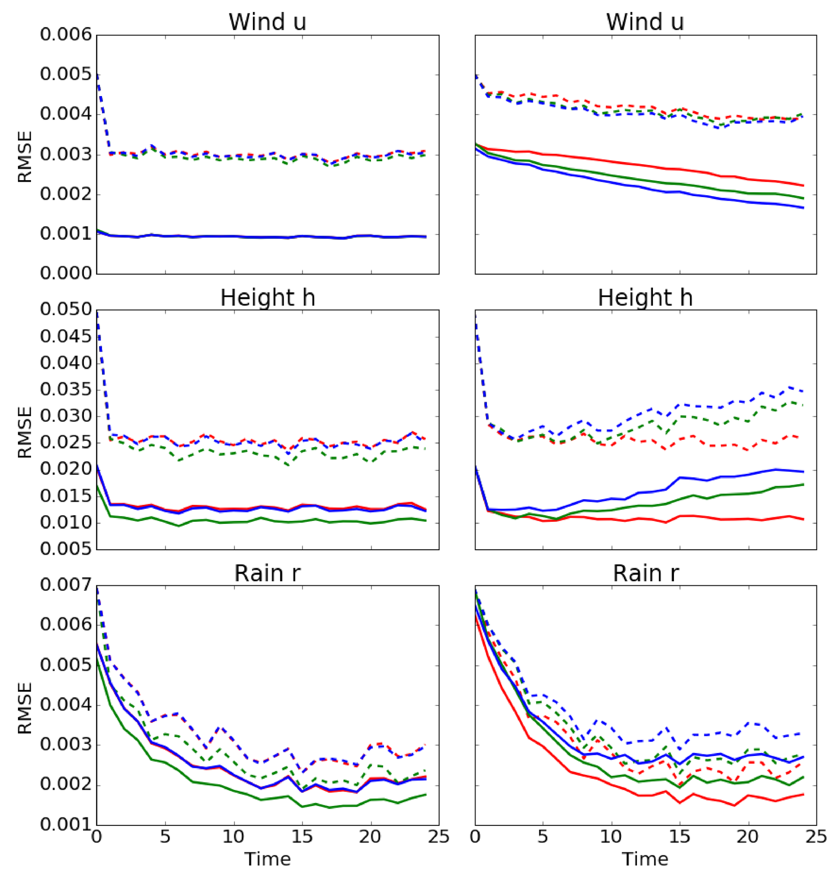
Able to handle linear constraints, i.e. physical bounds are respected and linearly formulated conservation laws are satisfied, thereby implicitly dealing with non-Gaussianity..

$$x_i^a - x_i^f = \min_{\delta x} \; J(\delta x; v_i) \qquad v_i = y + \varepsilon_i^o - H(\bar{x}^f + \varepsilon_i^f)$$

$$\text{subject to} \;\; A\delta x \le a, \quad B\delta x = b$$

4. State Estimation

Covariance Localization with Gaspari Cohn — *No Localization*

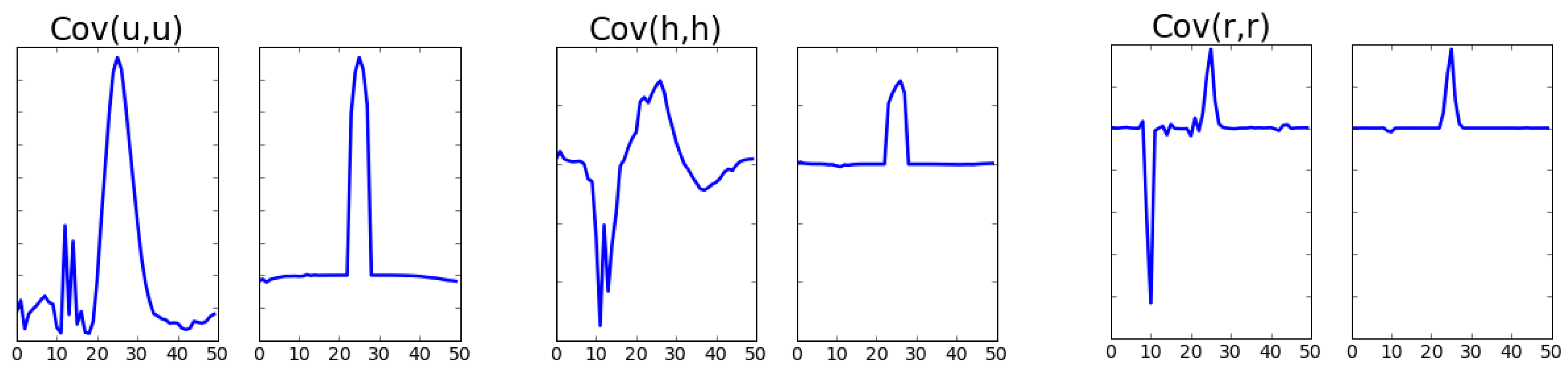


Results

- The QF performs generally better than EnKF, as expected.
- The QF and EnKF perform better in the localized case than in the non-localized case, but for QP-Ens the opposite holds.

Hypothesis

Localization destroys useful information from which QP-Ens is able to take advantage, in contrast to QF and EnKF.



Covariance as a function of location for a fixed grid point in the middle of the domain. Left plots are without localization and right plots are with localization. 5000 ensemble members were used to reduce the sampling error as much as possible.

5. Parameter Estimation

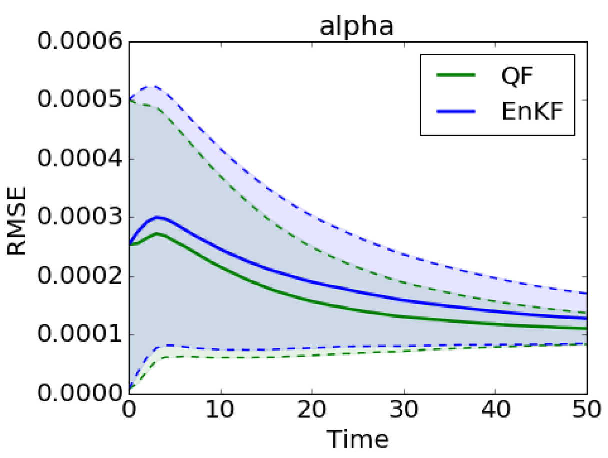
The classical approach of simple state augmentation introduces problems when applied to *global* parameters, because:

- There is no natural way to localize global parameters to deal with sampling errors.
- The error covariance matrix of the model forecast needs to remain positive definite.

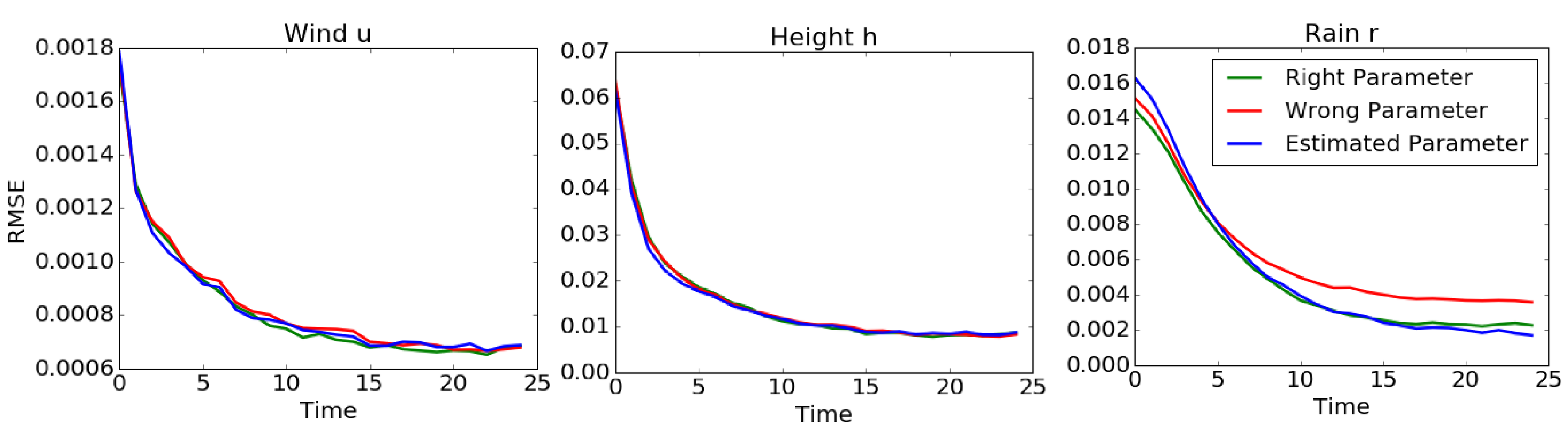
A way to circumvent these issues is to treat global parameters as location dependent during the analysis step, i.e. $\alpha \in \mathbb{R} \rightarrow \alpha \in \mathbb{R}^n$ (Aksoy, 2006).

Results

We applied parameter estimation to α, which effects the rate at which the rain variable r decays.



- RMSE of parameter is reduced from 50% to 23%.
- The true value does not lie within one standard deviation as calculated from the ensemble spread.
- Difference between performance of QF and EnKF is small, perhaps due to averaging.



Effect of parameter estimation on the state. The rain field r is clearly positively influenced by parameter estimation. The wind u and height h field is not effected.

6. Conclusions

- Covariance plots above show non-isotropy. By applying covariance localization with Gaspari Cohn the correlation peaks are suppressed.
- Though EnKF and the Quadratic Filter still benefit from localization, the QP-Ens does not. This serves as a motivation to investigate different localization techniques.
- Parameter estimation with EnKF and QF positively effects the RMSE of the state.
- Further research is needed for validation of treating global parameters as local parameters.
- By treating parameters as constant during the model run, the spread does not grow during the forecast period. This causes the parameter spread to collapse. Therefore, further research in resampling of the parameters is needed.

7. Literature

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