

# Preservation of physical properties with Ensemble-type Kalman Filter Algorithms

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# Motivation

- ▶ Numerical discretization schemes have a long history of incorporating the most important conservation properties of the continuous system in order to improve the prediction of the nonlinear flow.

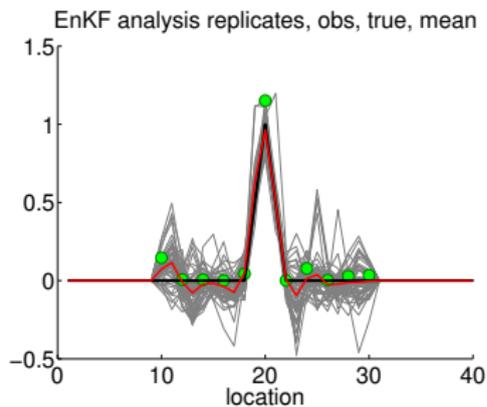
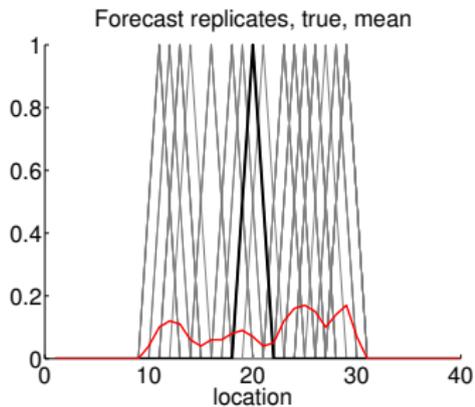
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  - ▶ The question arises, whether data assimilation algorithms should follow a similar approach?
- 1 Explore which conservation properties are well recovered when using an ensemble Kalman filter
  - 2 Include as constraints those that are not in data assimilation
  - 3 Show implication on the prediction

# Preserving physical properties



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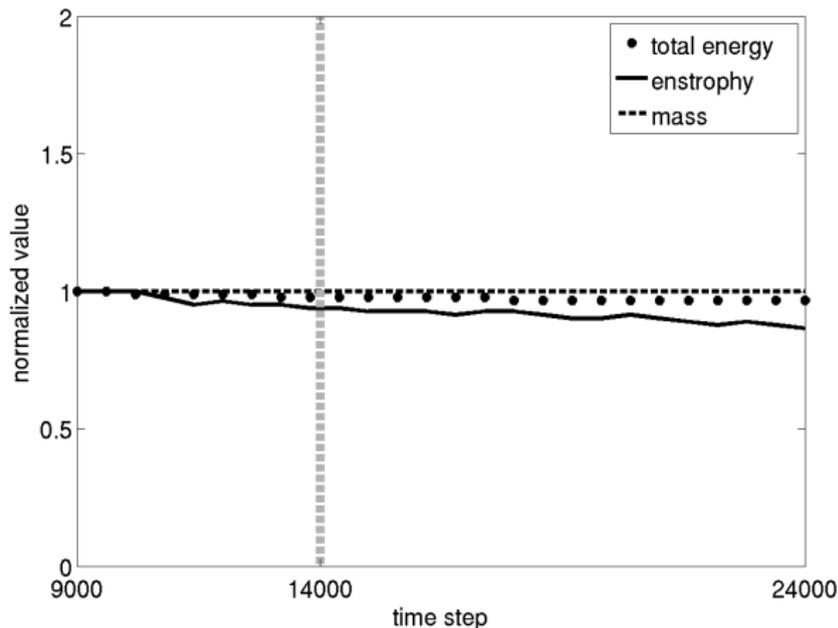
- ▶ Study conservation of mass, energy and enstrophy with LETKF
- ▶ including dependence of the results on the observational type and localization radius
  
- ▶ Non-linear dynamics with 2D nonlinear shallow water model
- ▶ Model settings:
  - 1 Mirror boundaries,
  - 2 constant  $f = 0.0001$ ,
  - 3  $259 \times 259$  grid points with spacing 50km
  - 4 leapfrog scheme with time step 125s
  - 5 Asselin filter with 0.01.

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- ▶ Numerical discretization of the dynamics is such that mass, energy and momentum are conserved and enstrophy for non divergent flow.

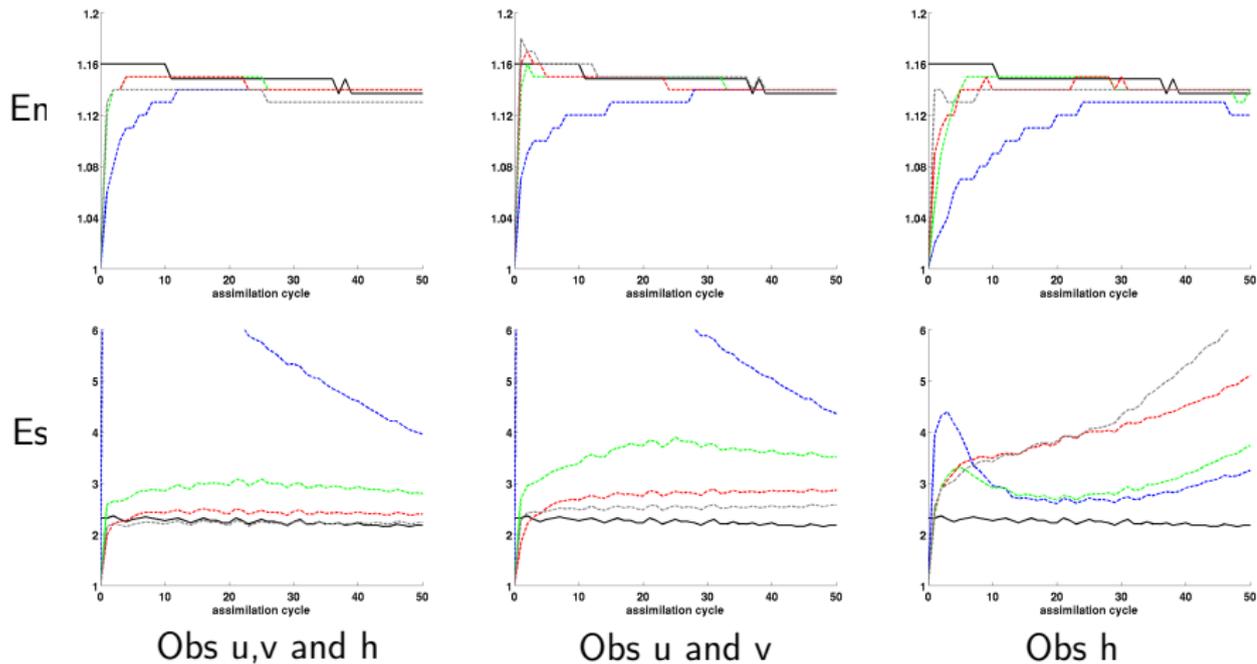
# Nonlinear shallow water model



Time evolution of mass, total energy and enstrophy, normalized with respective initial values, in a nature run.

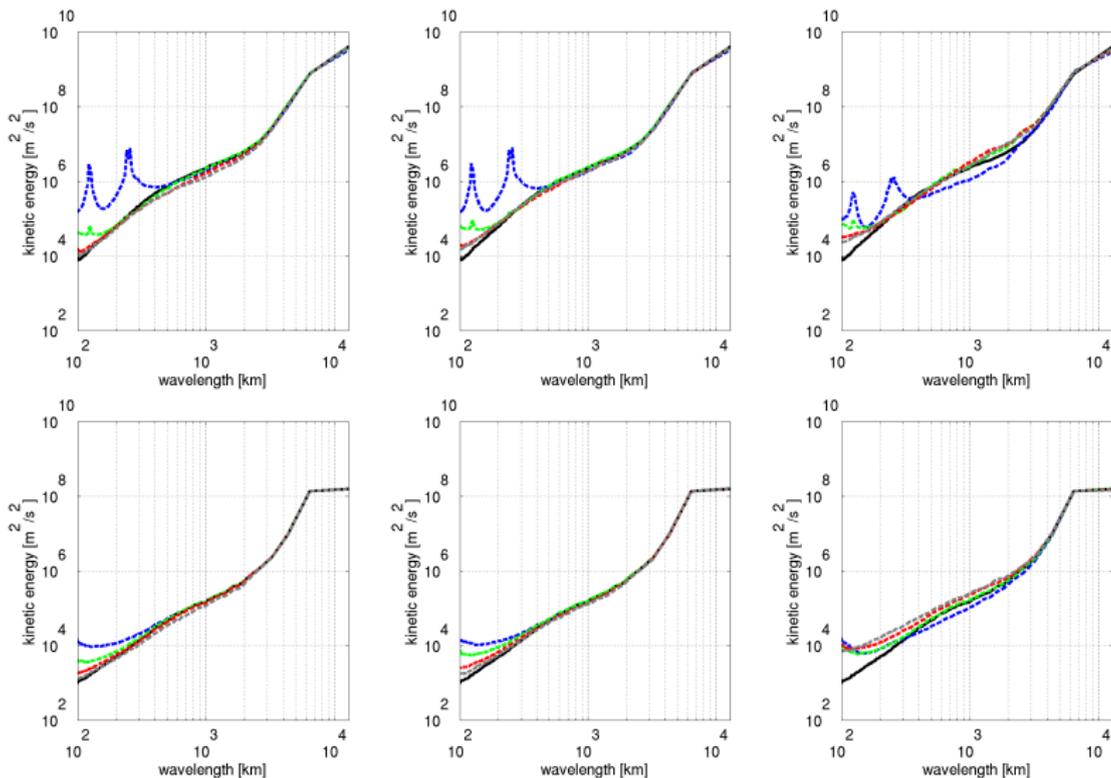
# Energy and Enstrophy

— nature run    - - - E\_L02T05    - · - E\_L04T05    - · - E\_L08T05    - - - E\_L16T05



# Kinetic energy spectra

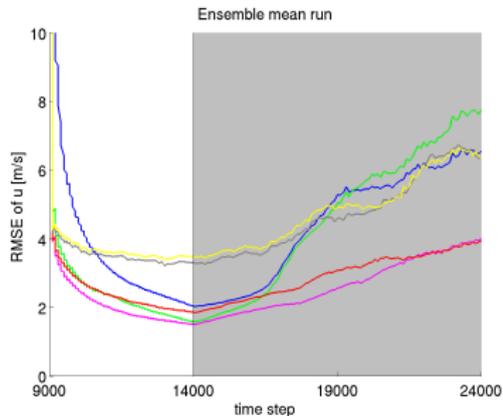
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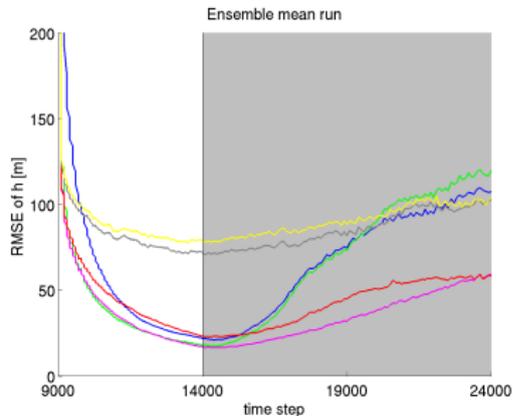
Averaged over the first (upper) and last five assimilation cycles (lower).

# Prediction

— E\_L02T05 — E\_L04T05 — E\_L06T05 — E\_L08T05 — E\_L16T05 — E\_L18T05



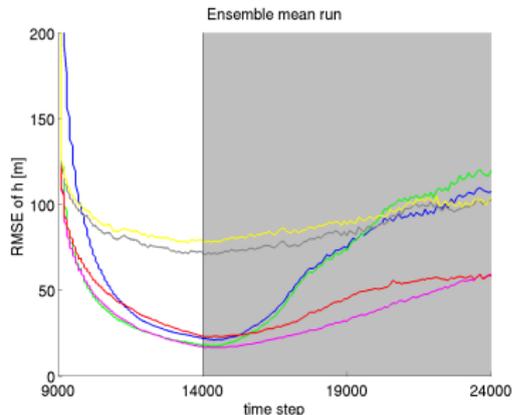
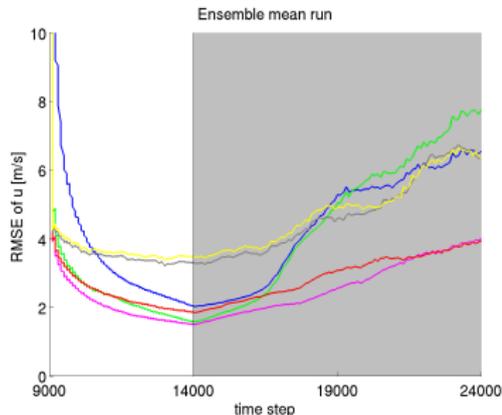
RMSE for u



RMSE for h

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RMSE for u

RMSE for h

Y. Zeng and T. Janjic, 2016: Study of Conservation Laws with the Local Ensemble Transform Kalman Filter, Q. J. R. Meteorol. Soc., 142:699, 2359–2372.

## — EnKF with constraints —

Janjic, T., D. McLaughlin, S. E. Cohn, M. Verlaan, 2014: Conservation of mass and preservation of positivity with ensemble-type Kalman filter algorithms, *Mon. Wea. Rev.*, 142, No. 2, 755-773.

Zeng, Y., T. Janjić, Y. Ruckstuhl and M. Verlaan, 2017: Ensemble-type Kalman filter algorithm conserving mass, total energy and enstrophy, *Q. J. R. Meteorol. Soc.*, 143:708, 2902–2914, doi:10.1002/qj.3142.

## QPEns algorithm

Inverse of ensemble derived analysis error covariance can be used to minimize the cost function to obtain the analysis

$$\mathbf{w}_k^{a,i} = \mathbf{w}_k^{b,i} + \arg \min_{\delta \mathbf{w}^i} \frac{1}{2} [\delta \mathbf{w}^{i T} (\mathbf{P}^b)^{-1} \delta \mathbf{w}^i + \mathbf{f}^i T \mathbf{R}^{-1} \mathbf{f}^i]$$

subject to

$$\delta \mathbf{w}^i \geq -\mathbf{w}_k^{b,i}.$$

where

$$\delta \mathbf{w}^i = \mathbf{w}_k^{a,i} - \mathbf{w}_k^{b,i}, \mathbf{f}^i = \mathbf{w}_k^{o,i} - \mathbf{H}_k \mathbf{w}_k^{b,i} - \mathbf{H}_k \delta \mathbf{w}^i - \bar{\mathbf{r}}_k^o.$$

## SQPEns algorithm

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subject to

$$\begin{aligned} c_j(\delta \mathbf{w}_j) &\leq 0, \quad j \in \{1, 2, \dots, m_1\} \\ g_k(\delta \mathbf{w}_k) &= 0, \quad k \in \{1, 2, \dots, m_2\} \end{aligned}$$

where

$$\delta \mathbf{w}^i = \mathbf{w}_k^{a,i} - \mathbf{w}_k^{b,i}, \mathbf{f}^i = \mathbf{w}_k^{o,i} - \mathbf{H}_k \mathbf{w}_k^{b,i} - \mathbf{H}_k \delta \mathbf{w}^i - \bar{\mathbf{r}}_k^o.$$

## QPEns algorithm in ensemble space

$\rho = \text{Rank}(\mathbf{P}^b)$ , which is no larger than  $N - 1$

$$\delta \mathbf{w}^i = \mathbf{L} \eta^i$$

$$\mathbf{P}^b = \mathbf{L} \mathbf{L}^T$$

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QPEns Algorithm in ensemble space

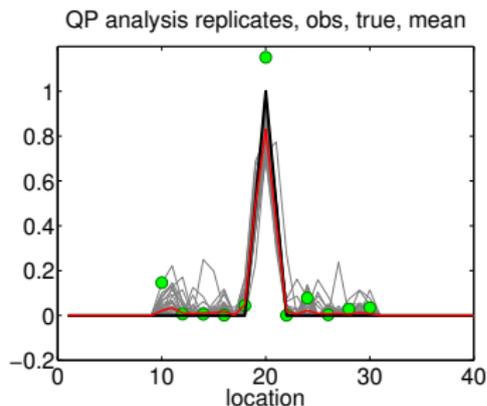
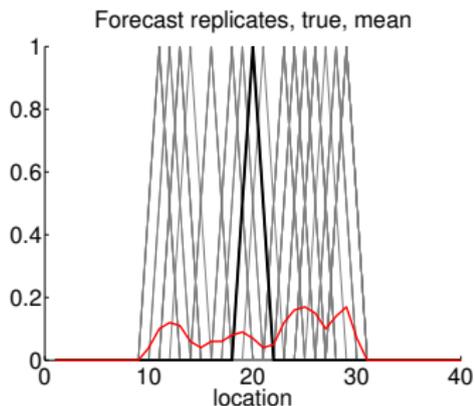
$$\eta^i = \arg \min_{\eta^i} \frac{1}{2} [\eta^{i,T} \eta^i + \mathbf{f}^{i,T} \mathbf{R}^{-1} \mathbf{f}^i]$$

subject to the following non-negativity constraint:

$$-\mathbf{L} \eta^i \leq \mathbf{w}_k^{f,i}.$$

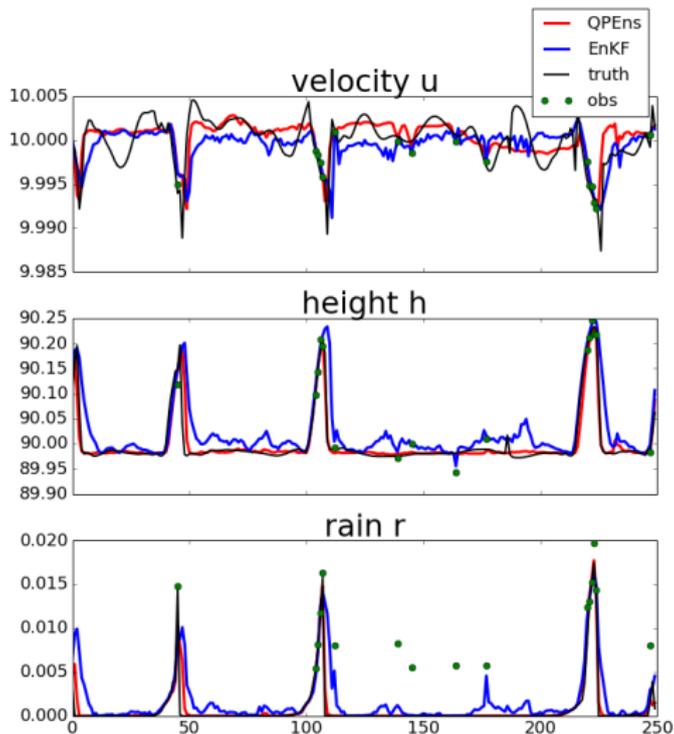
The algorithm reduces to EnKF if there are no constraints present.

# Preserving physical properties



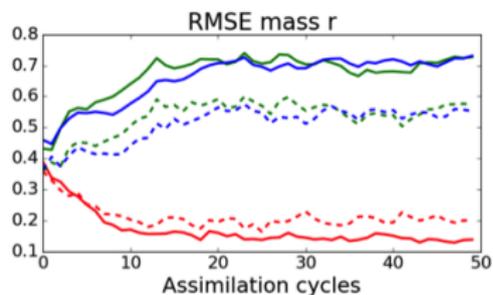
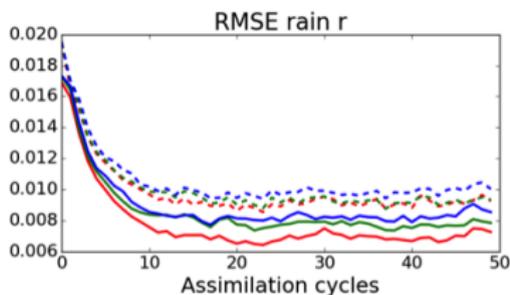
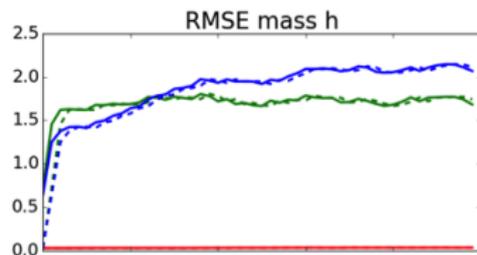
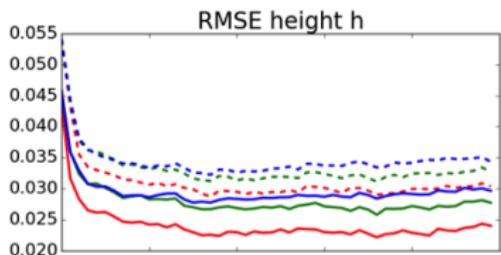
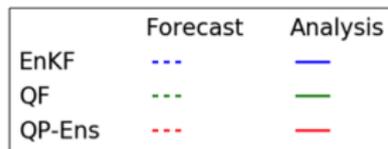
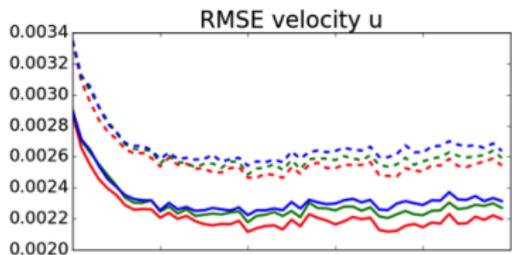
QPEns analysis in ensemble space with positivity constraint. Both mass conservation and positivity constraint improve analysis.

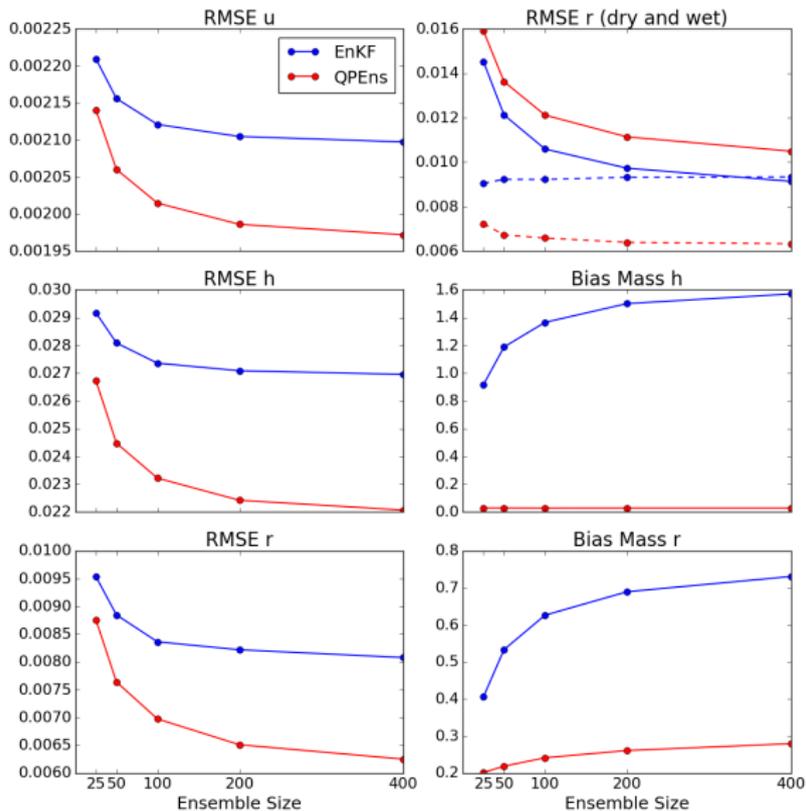
# EnKF vs. QPEns



EnKF vs. QPEns analysis with positivity and mass constraint for modified shallow water model (Wuersch and Craig 2014).

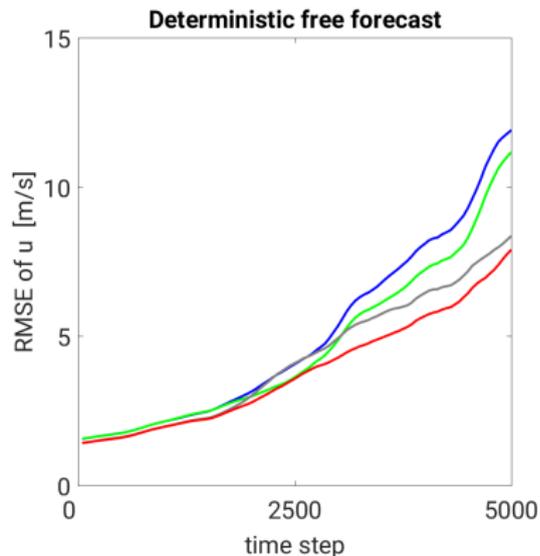
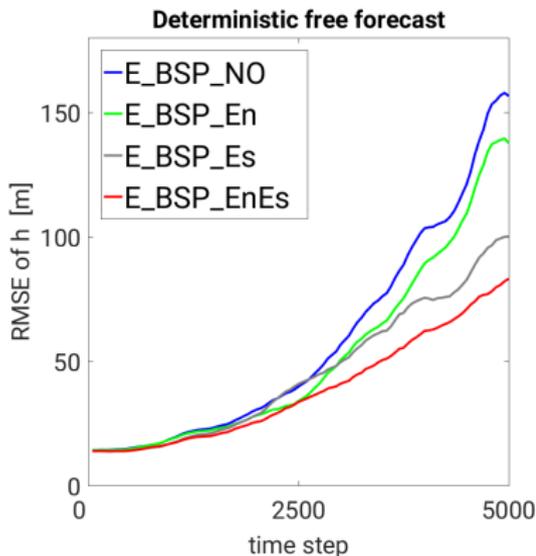
# RMSEs





Figures from Ruckstuhl and Janjic 2018: Parameter and state estimation with EnKF based algorithms for convective scale applications, QJRMS.

# Prediction

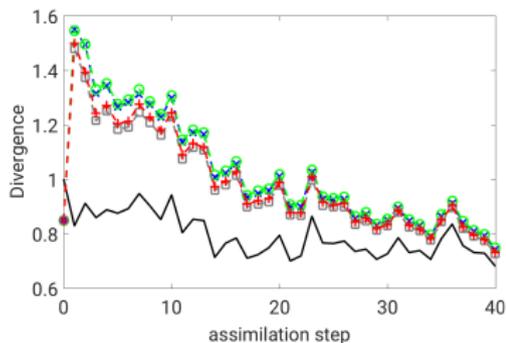


RMSE for h

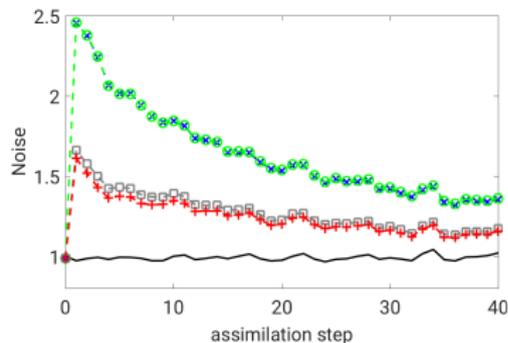
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# Diagnostics



Divergence

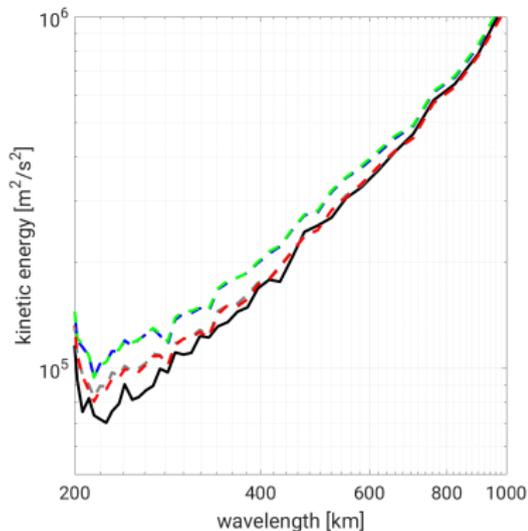


Noise

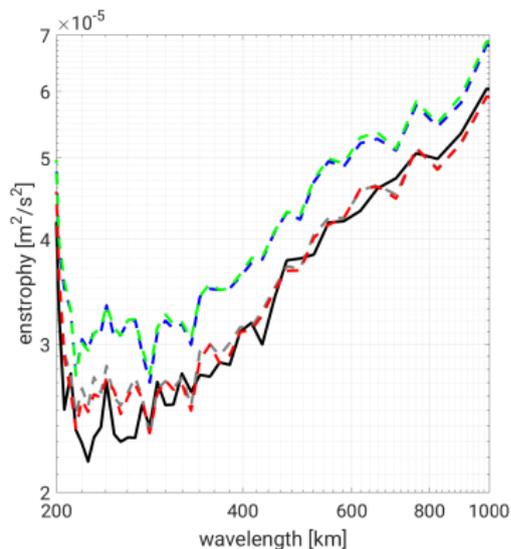
Variations of model diagnostics of divergence and noise within the data assimilation in experiments

$E\_BSP\_NO$   $E\_BSP\_En$   $E\_BSP\_Es$  and  $E\_BSP\_EnEs$ .

# Small scale spectra



Energy spectra



Enstrophy spectra

E\_BSP\_NO E\_BSP\_En E\_BSP\_Es E\_BSP\_EnEs.

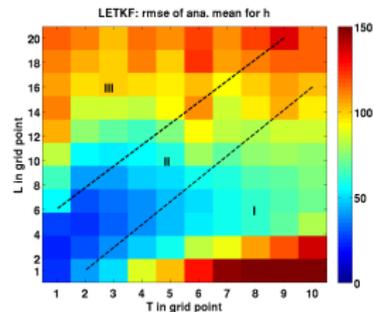
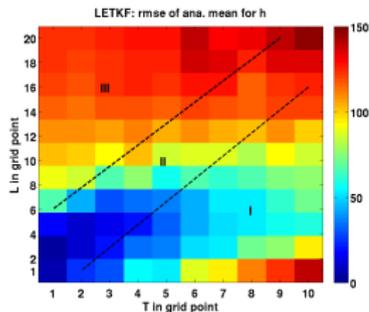
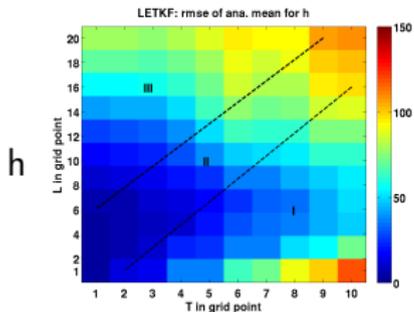
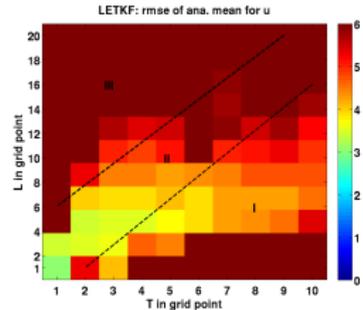
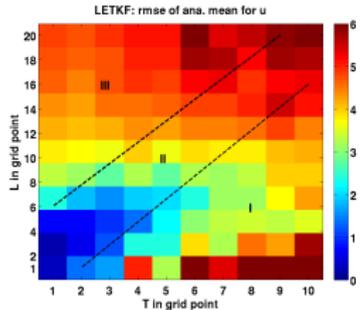
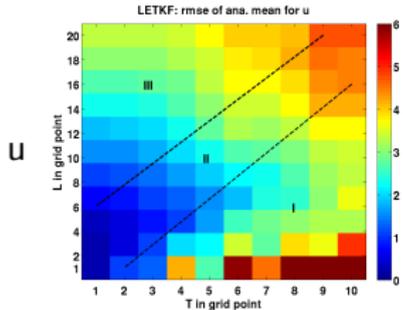
# Conclusion

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  - ▶ Improves accuracy and bias in simple problems
- 
- ▶ Although total energy of the analysis ensemble mean converges towards the nature run value with time, **enstrophy does not**.
  - ▶ Imposing the conservation of enstrophy within the data assimilation effectively avoids the spurious energy cascade of rotational part and this way successfully suppresses the noise.
  - ▶ Conserving mass and positivity reduces the noise in convective scale data assimilation applications.

# RMSE



Obs u,v and h

Obs u and v

Obs h