

# On Localised Particle Filters for the Global Weather Prediction Model ICON

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and Andreas Rhodin

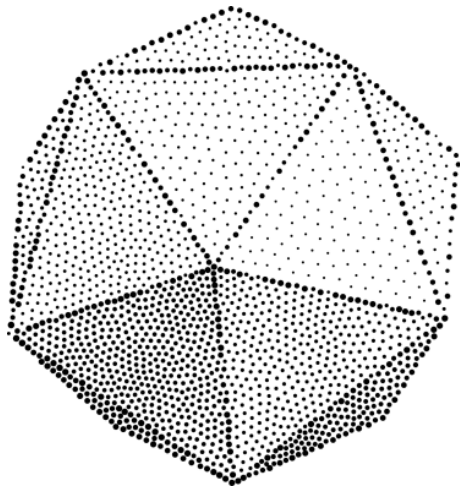
German Meteorological Service (DWD)

Data Assimilation Unit

# Content

1. The ICON-Model and DA-System
2. Bayesian Filtering via Particle Filters
3. The Localised Adaptive Particle Filter (LAPF)
4. The Localised Markov Chain Particle Filter (LMCPF)
5. Numerical Testing
6. Summary

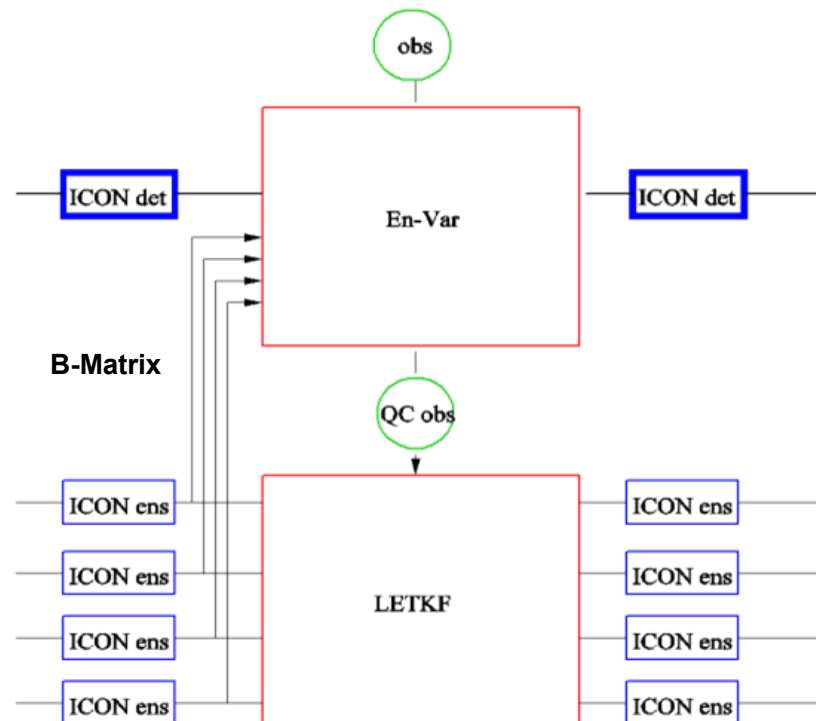
- Operational NWP model of DWD: ICON (ICOsahedral Nonhydrostatic)
- Two-way NEST over Europe (~6.5 km)
- Resolution: 13 km deterministic  
40 km ensemble (40 member)



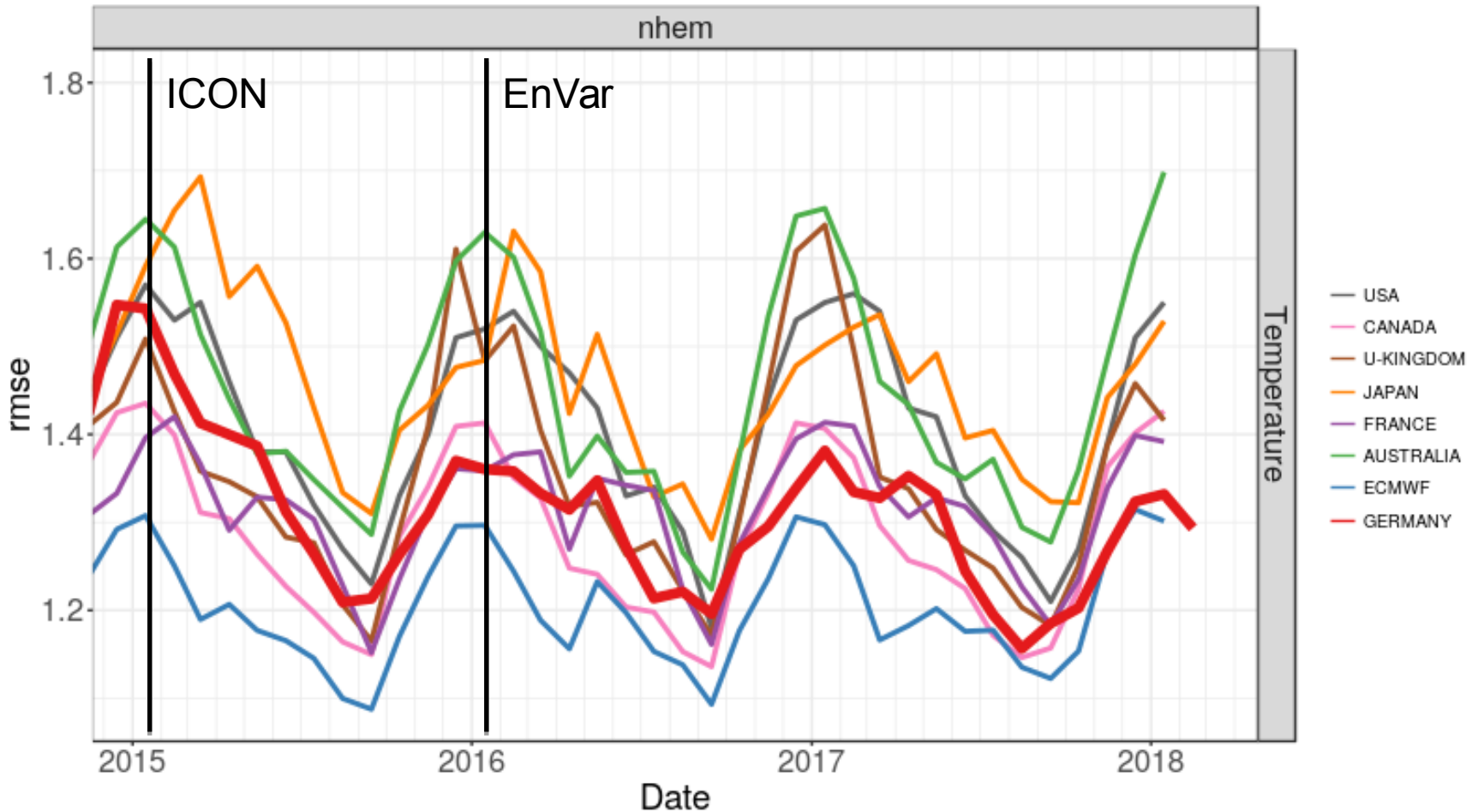
- Hybrid EnVar operational since January 20, 2016

$$X^a = \bar{x}^b + X^b W$$

- Following Hunt et al. (2007), (see also Schraff et al., 2016)
- EnVar B-Matrix: 70% LETKF, 30% Climatology

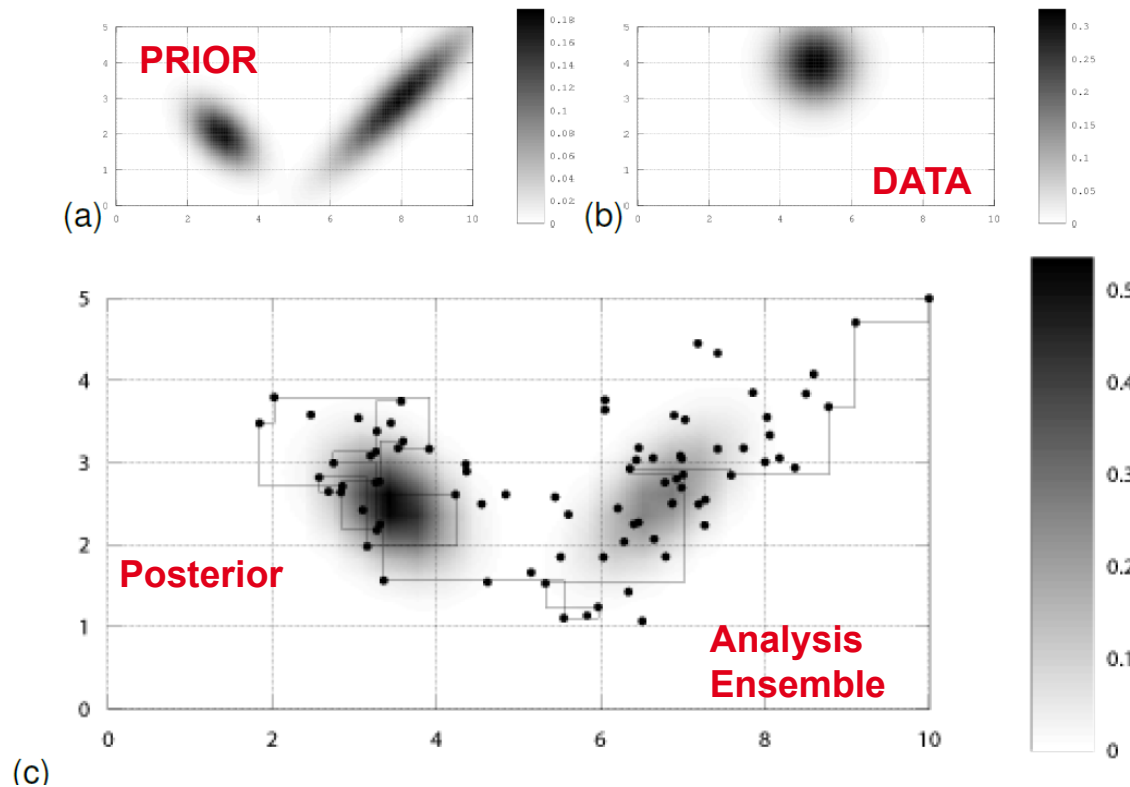


WMO verification against observations  
lead-time: 24h  
valid-time: 12UTC  
level: 850hPa

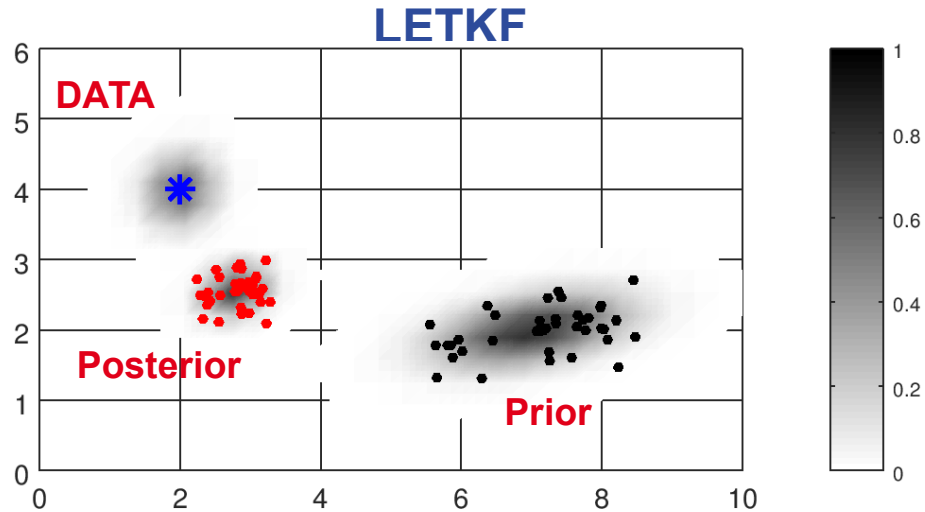


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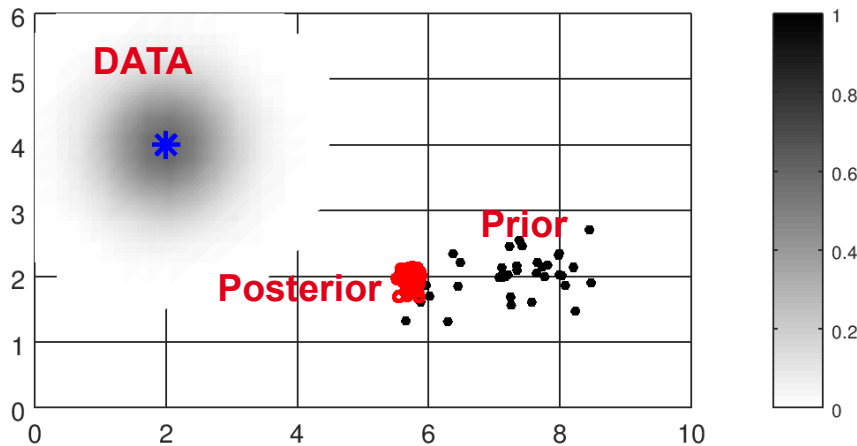
- Our Particle Filters are based on the LETKF philosophy
- Localisation: as LETKF in ensemble space
- Adaptivity: tools for spread control



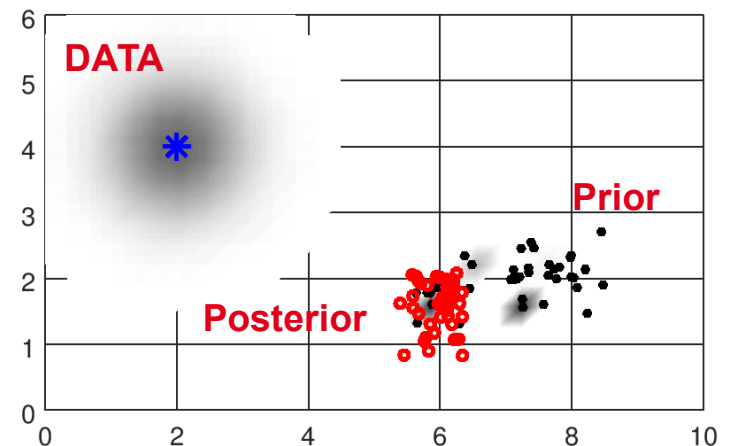
- Able to handle with multi-modal distributions
- Able to handle with Non-Gaussianity



### Classical PF



### LAPF



## First Step: The Classical Particle Filter

- 
- Employ **Bayes formula** to calculate new analysis distribution

$$p_k^{(a)}(x) := p(x|y_k) = c p(y_k|x) p_k^{(b)}(x), \quad x \in \mathbb{R}^n$$

is a normalization factor:

$$c \text{ is a normalization factor: } \int_{\mathcal{X}} p_k^{(a)}(x) dx = 1$$

- To carry out the analysis step at time **a posteriori**
- **weights** are calculated
- **weights**  $p_k^{(a)}$  are calculated

is chosen such that  $p_{k,l} = c e^{-\frac{1}{2}(y-Hx^{(l)})^T R^{-1}(y-Hx^{(l)})}$

$c$  is chosen such that  $\sum_{l=1}^L p_{k,l}^{(a)} = L$



## Second Step: Classical Resampling

- **Accumulated weights** are defined:

$$w_{ac_0} = 0$$

$$w_{ac_i} = w_{ac_{i-1}} + p_i^a, \quad i = 1, \dots, L$$

where  $L$  denotes the ensemble size

- Drawing  $r_j \sim U([0, 1])$ ,  $j = 1, \dots, L$ , set  $R_j = j - 1 + r_j$  and define **transform matrix  $W$**  for the particles by:

$$W_{i,j} = \begin{cases} 1 & \text{if } R_j \in (w_{ac_{i-1}}, w_{ac_i}], \\ 0 & \text{otherwise,} \end{cases}$$

with  $\cdot$  denotes the interval of values  $i = 1, \dots, L$  with  $W \in \mathbb{R}^{L \times L}$ ,  $(s, t]$  denotes the interval of values  $s < \eta \leq t$ .

### Third Step: Spread Control

- 
- Based on the adaptive multiplicative **inflation factor**  $\rho$  determined by the LETKF

$$\rho = \frac{\text{E} [\mathbf{d}_{o-b}^T \mathbf{d}_{o-b}] - \text{Tr}(\mathbf{R})}{\text{Tr}(\mathbf{H}\mathbf{P}^b\mathbf{H}^T)}$$

- **Weighting factor** has been chosen, due to the small ensemble size ( $L = 40$ )
- **Weighting factor**  $\alpha$  has been chosen, due to the small ensemble size ( $L = 40$ )

$$\rho_k = \alpha \tilde{\rho}_k + (1 - \alpha) \rho_{k-1}$$

## Third Step: Spread Control

- 
- **Perturbation factor** is used to add spread to the system

where  $\sigma = \begin{cases} c_0, & \rho < \rho^{(0)} \\ c_0 + (c_1 - c_0) * \frac{\rho - \rho^{(0)}}{\rho^{(1)} - \rho^{(0)}}, & \rho^{(0)} \leq \rho \leq \rho^{(1)} \\ c_1, & \rho > \rho^{(1)} \end{cases}$  and, with

if and if

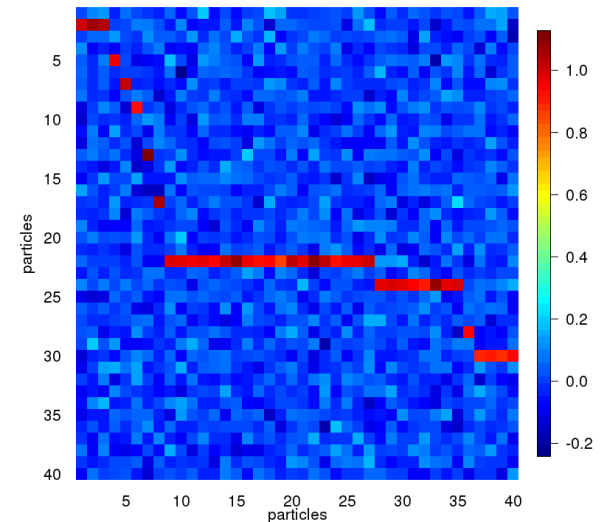
where  $c_0 = 0.02$ ,  $c_1 = 0.2$ ,  $\rho^{(0)} = 1.0$  and  $\rho^{(1)} = 1.4$ , with  $\sigma = c_1$  if  $\rho \geq \rho^{(1)}$  and  $\sigma = c_0$  if  $\rho \leq \rho^{(0)}$

## Fourth Step: Gaussian Resampling

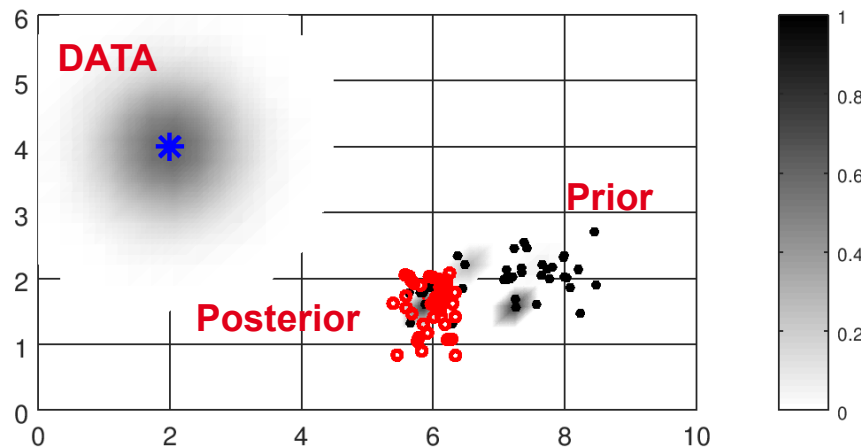
- Weights  $W$  are modified by applying the perturbation factor  $\sigma$

$$W = W + R_{nd} * \sigma$$

with normally distributed random numbers  $R_{nd}$

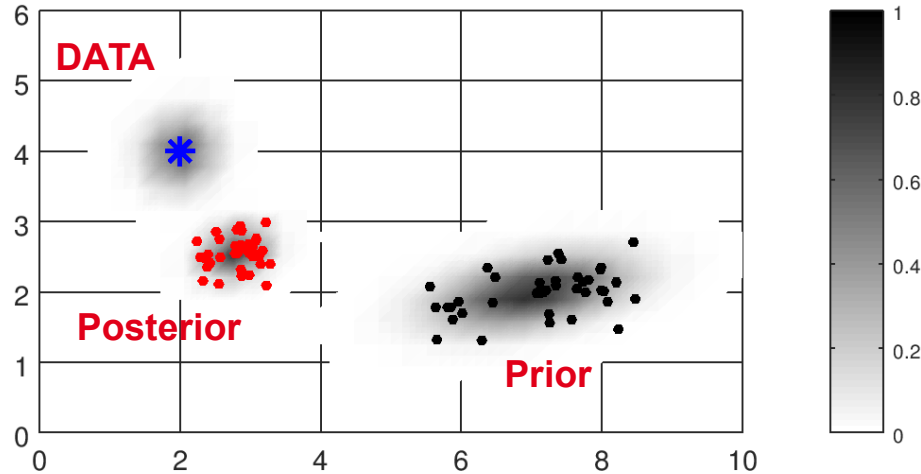


An example for a W-Matrix after applying determined with the LAPF for 60°N/90°E ~500 hPa, 26.05.2016 0 UTC is shown.   
 10 particles are chosen

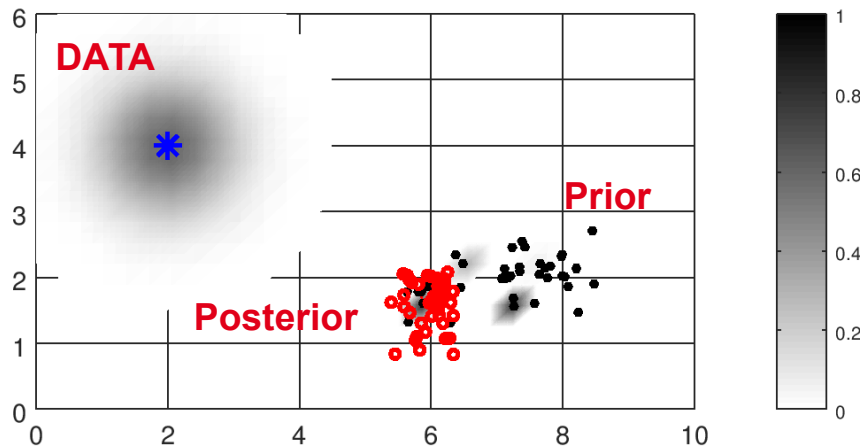


# 4. The LMCPF

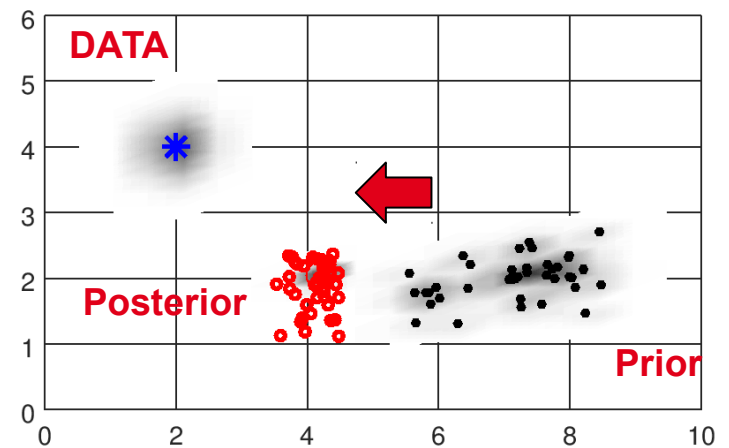
LETKF



LAPF



LMCPF

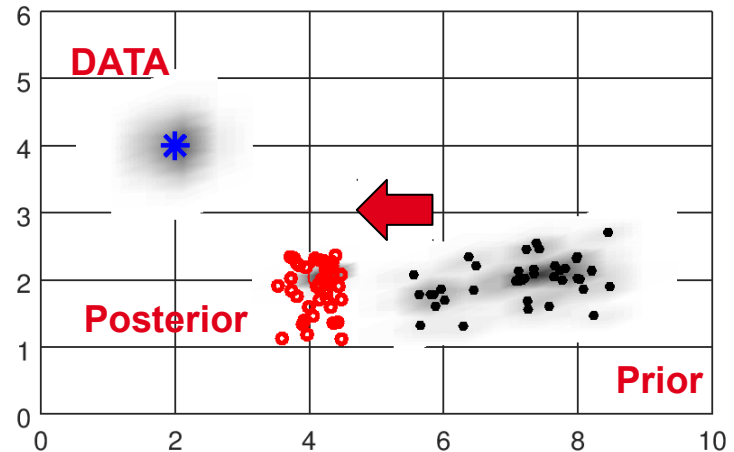


## Fourth Step: Gaussian Resampling

- Weights  $W$  are calculated by drawing from the posterior

$$W = \underbrace{W + A_{shift} * W}_{\text{Centers of posterior RBFs}} + \underbrace{B_{post} * R_{nd} * \sigma}_{\text{Shape of posterior RBFs}}$$

with normally distributed random numbers, and calculated with Gaussian radial basis function (RBF) Approximation for prior density and observation error

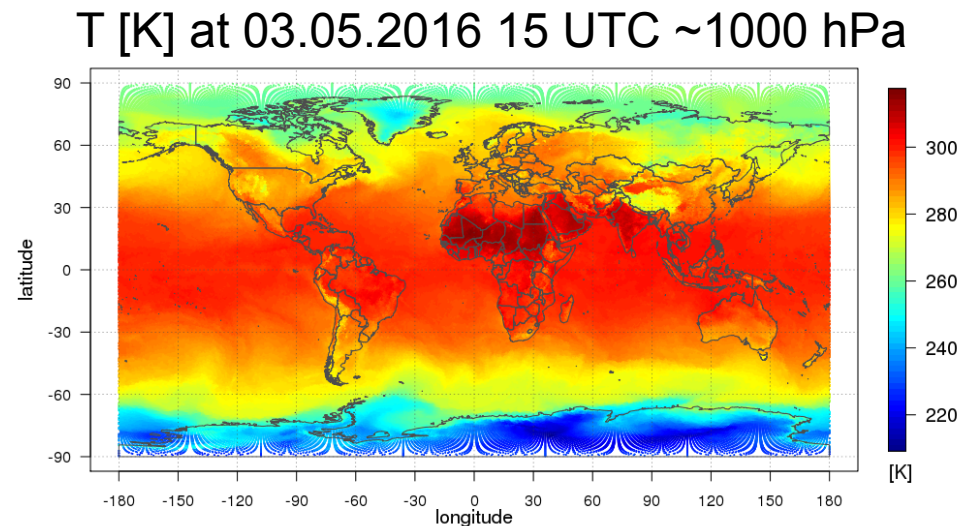


- It is an explicit calculation of the Bayes posterior based on radial basis function approximation of the prior.

# 5. Numerical Testing

## Experimental set-up

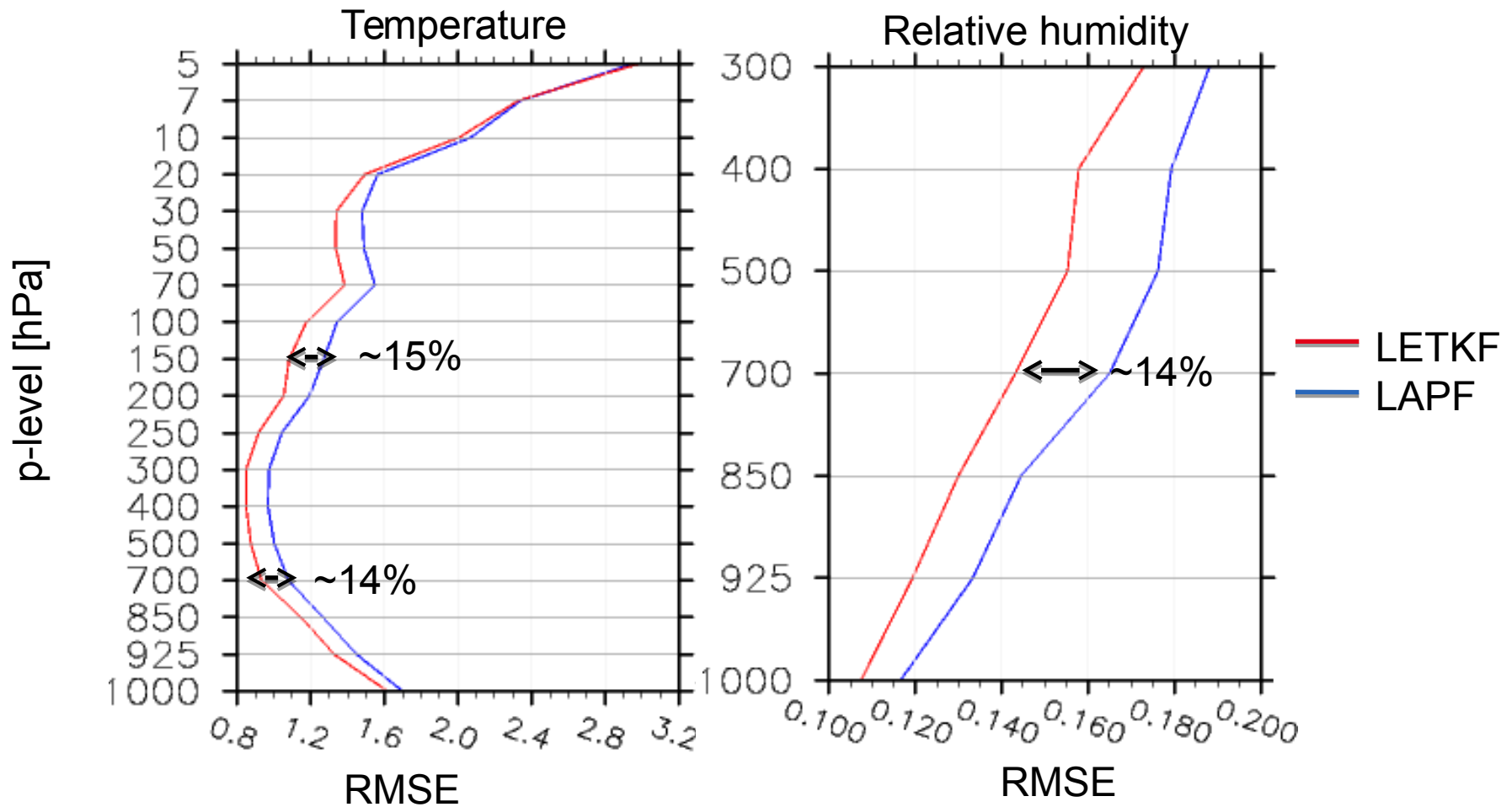
- Full ensemble: 40 members
- Reduced resolution:
  - 26km deterministic
  - 52km ensembles
- Period:  
01.05.2016 – 31.05.2016



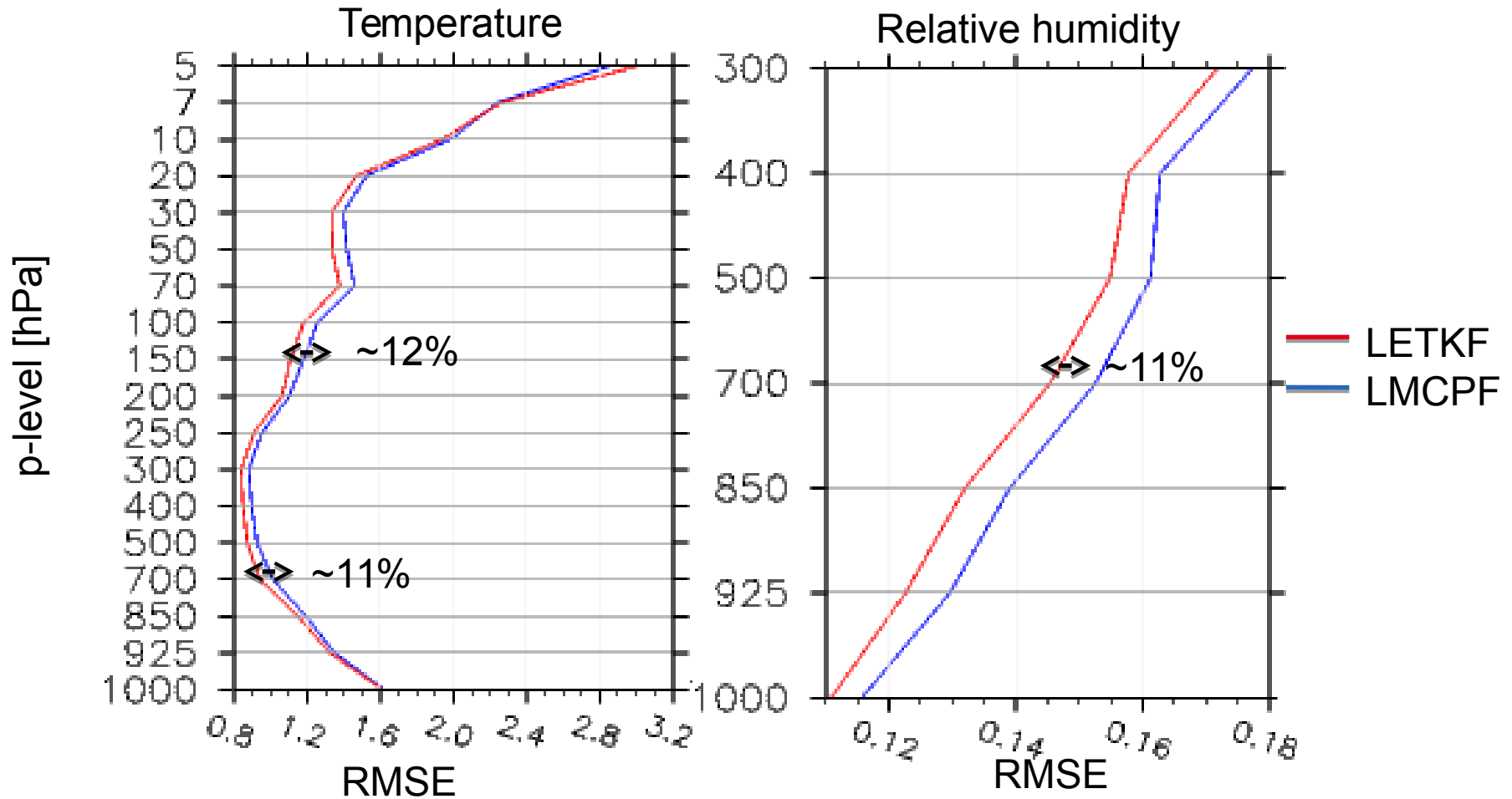


# 5. Numerical Testing Assimilation Cycle

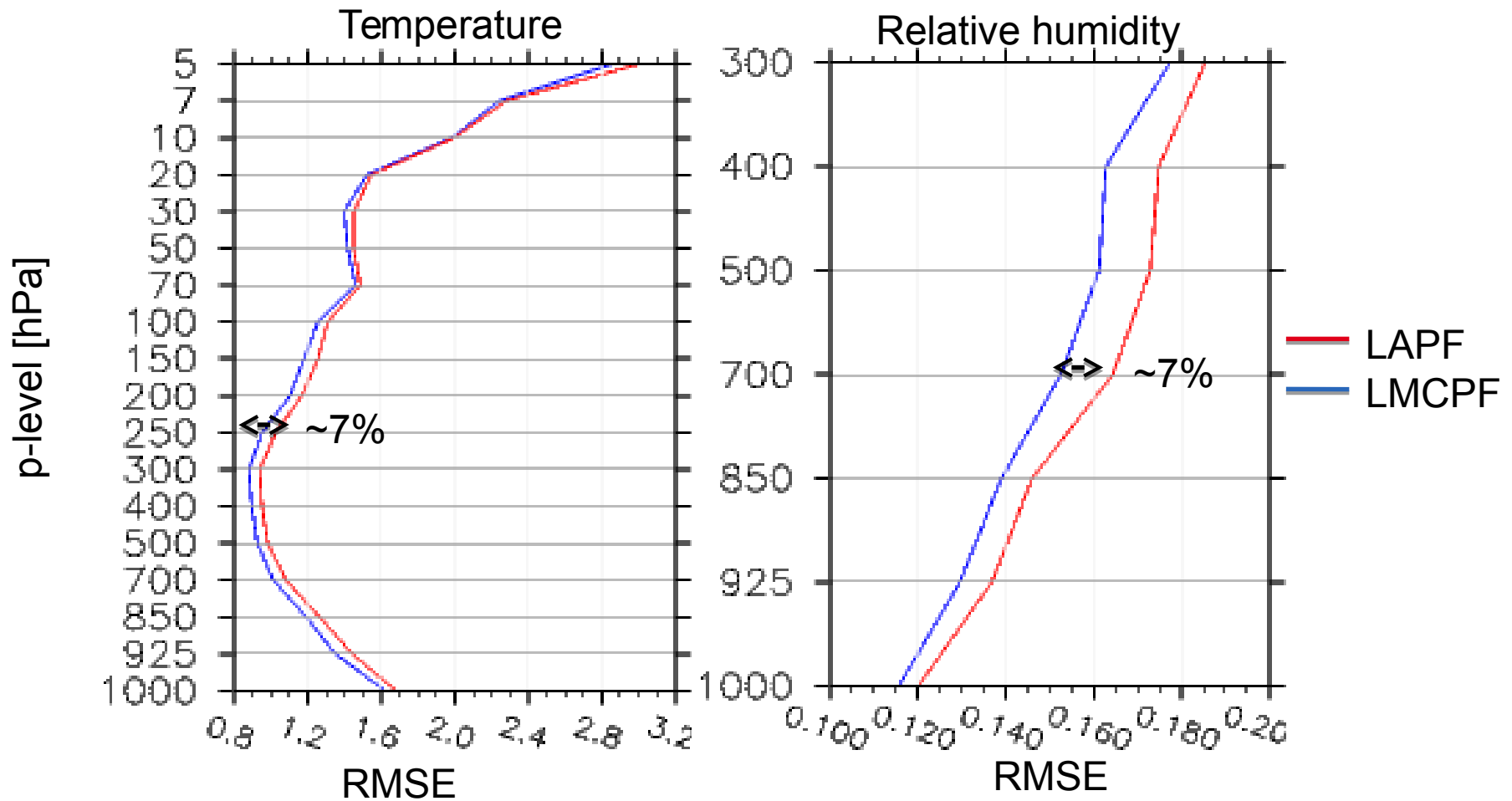
Global **RMSE** for **obs-fg** statistics (Radiosondes vs. Model)  
Period: 08.05.2016 – 31.05.2016



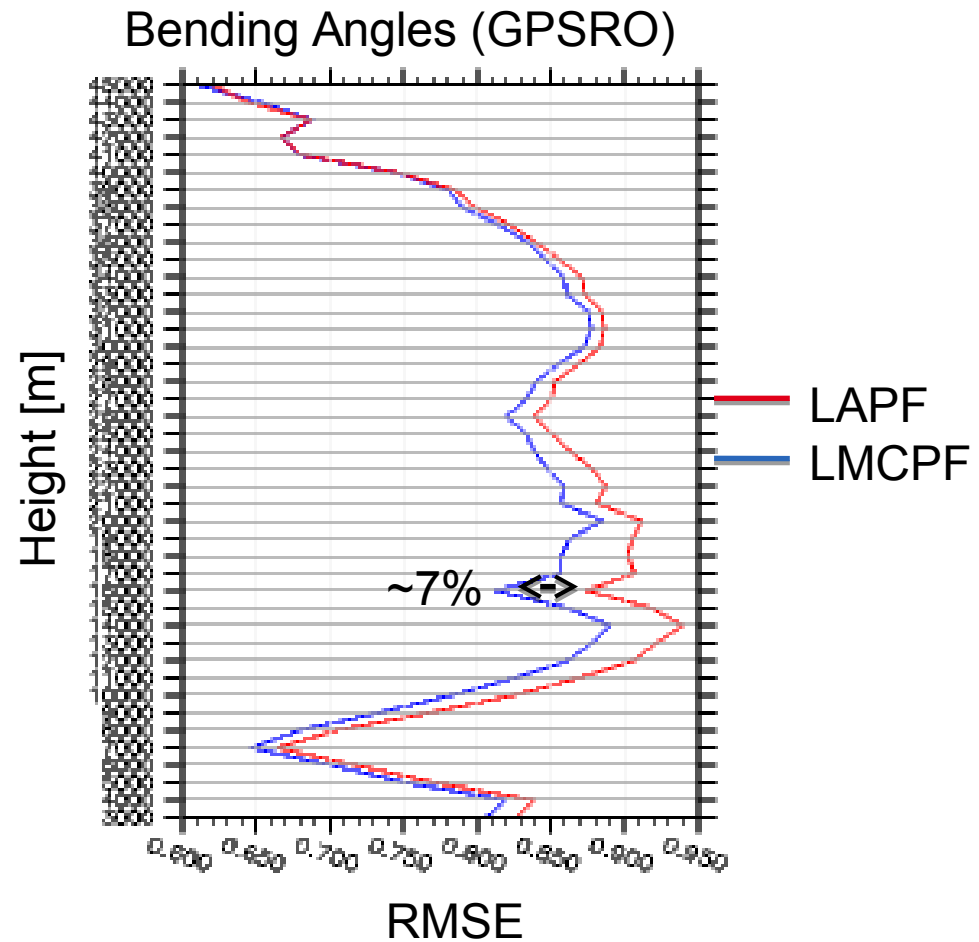
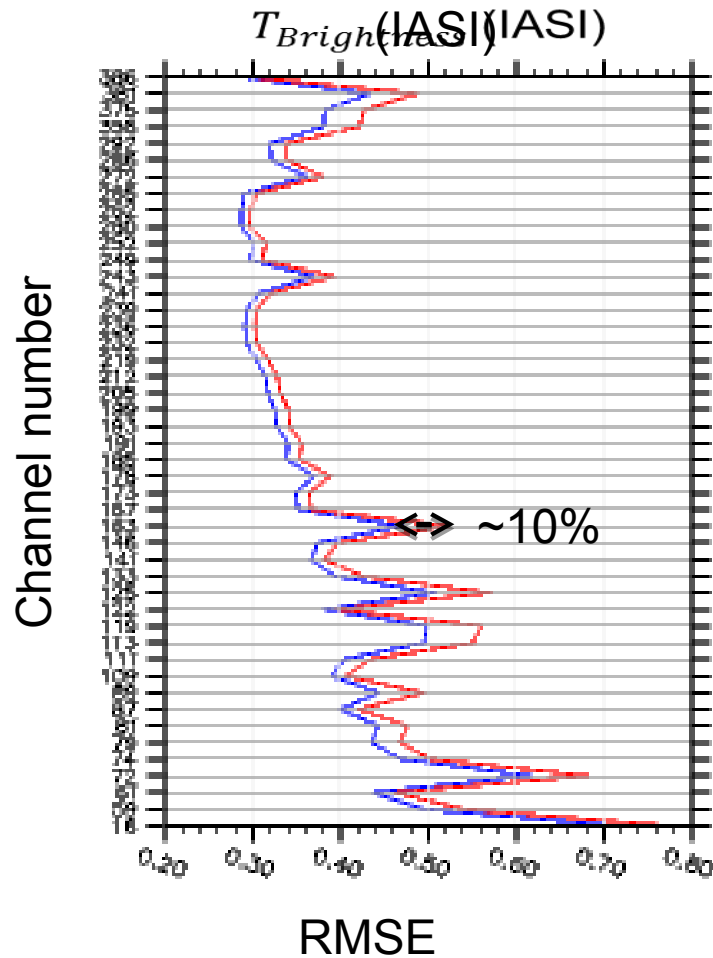
Global **RMSE** for **obs-fg** statistics (Radiosondes vs. Model)  
Period: 08.05.2016 – 22.05.2016



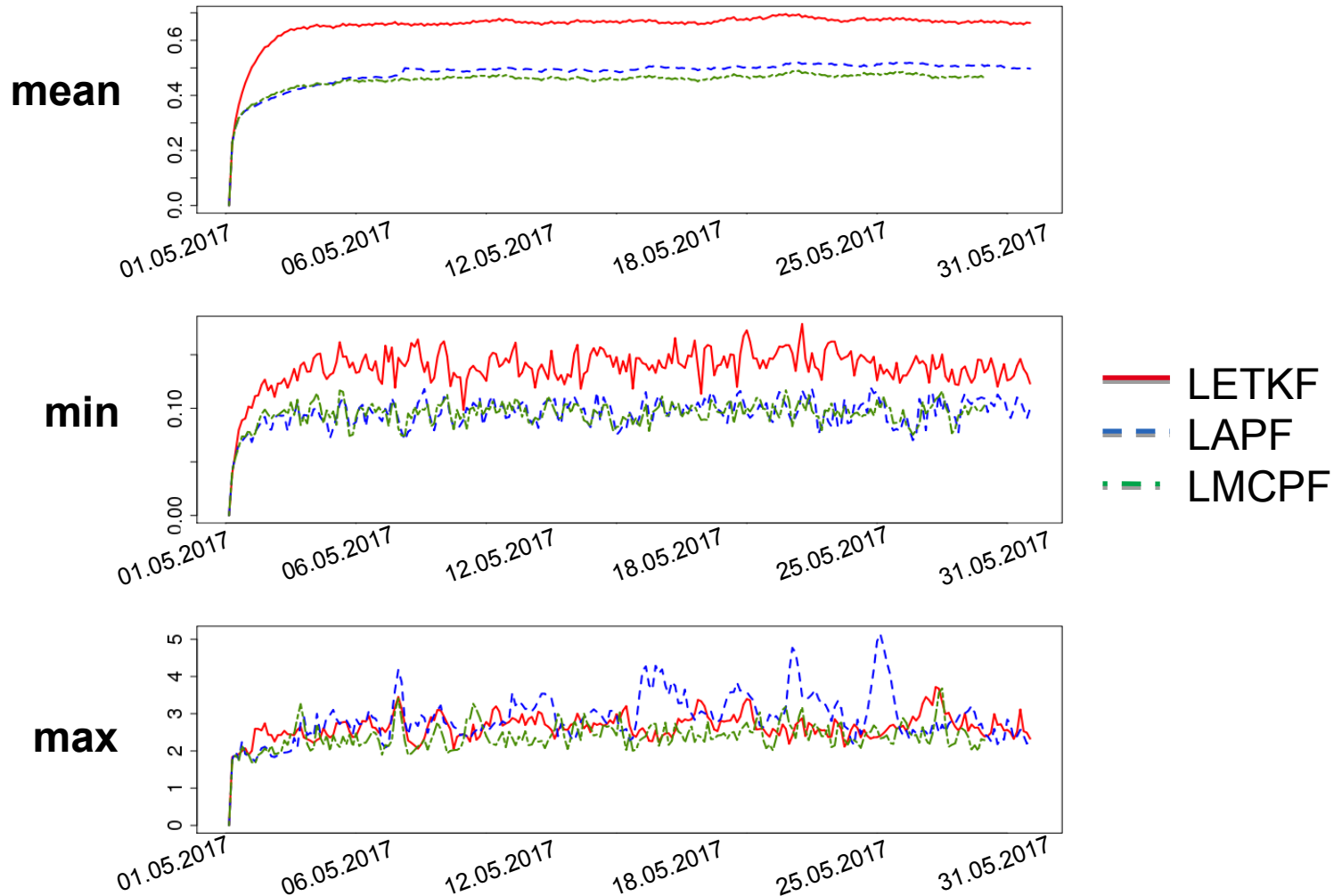
Global **RMSE** for **obs-fg** statistics (Radiosondes vs. Model)  
Period: 08.05.2016 – 22.05.2016



Global **RMSE** for **obs-fg** statistics  
Period: 08.05.2016 – 22.05.2016

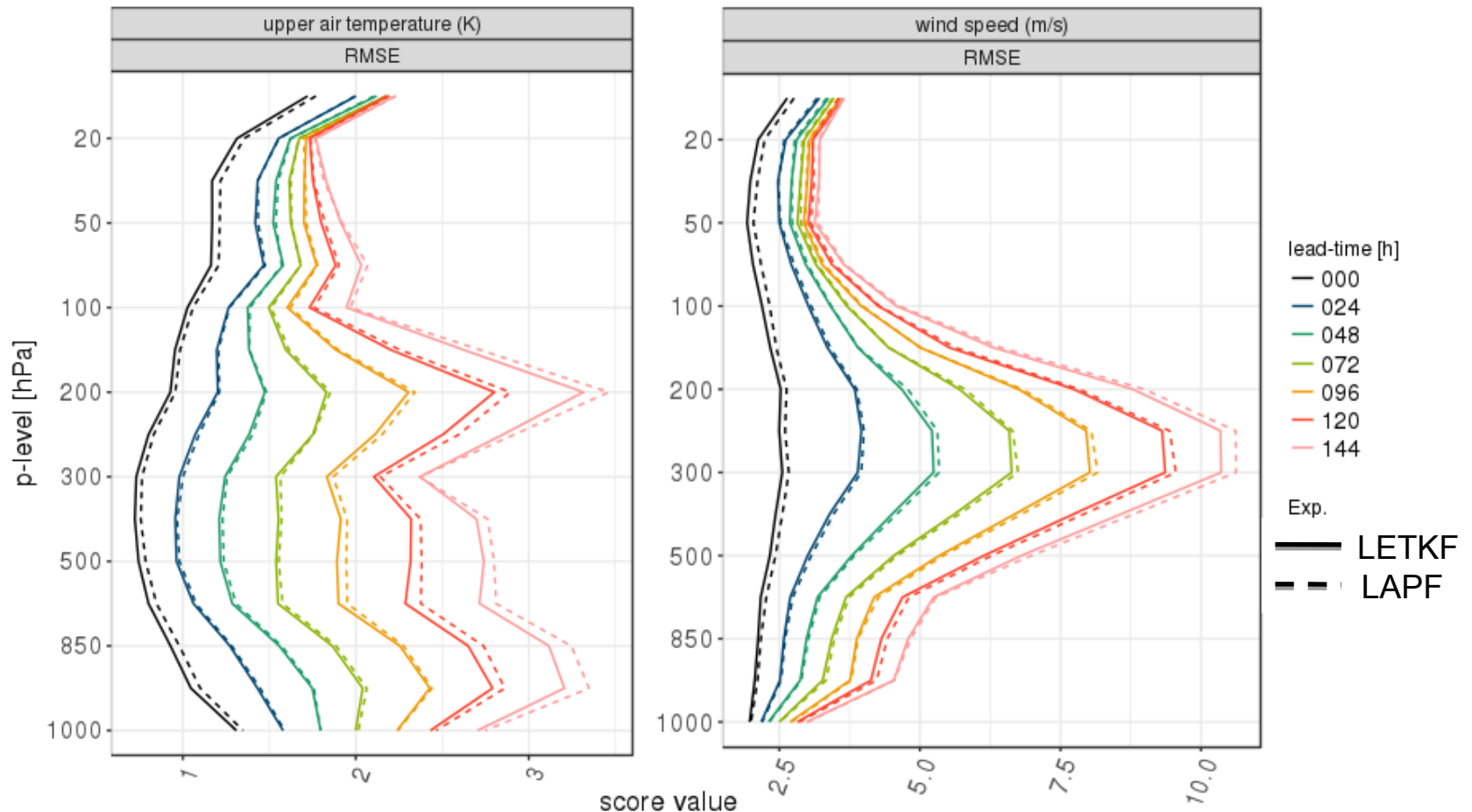


Global spread of T [K] ~ 500 hPa



# 5. Numerical Testing Forecast Cycle

## Global verification of different lead times against Radiosondes Period: 02.05.2016 – 24.05.2016





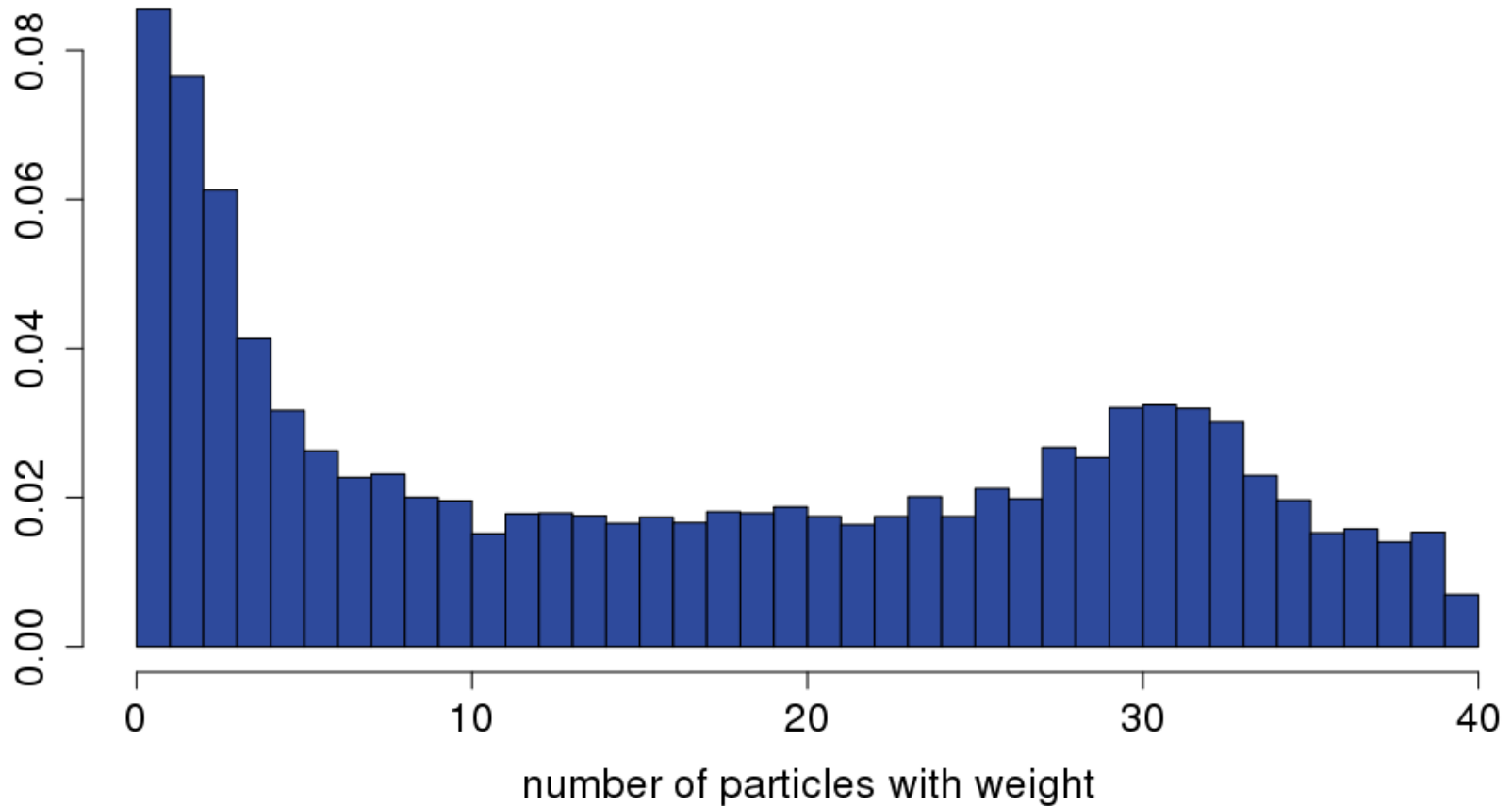
- LAPF and LMCPF implemented in an operational NWP system
- Both Particle Filters are able to provide reasonable atmospheric analysis in a large-scale environment and are running stably over a period of one month
- The LMCPF outperforms the LAPF but not yet the LETKF, but both Particle Filters nearly reach the results of the operational LETKF
- Both Particle Filters are showing promising results; further tuning is in progress.

- Gerald Desroziers and Serguei Ivanov. “*Diagnosis and adaptive tuning of observation-error parameters in a variational assimilation*”. Quarterly Journal of the Royal Meteorological Society, 2001
- Brian Hunt, Eric Kostelich and Istvan Szunyogh. “*Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter*”. Physica D: Nonlinear Phenomena, 2007
- Gen Nakamura and Roland Potthast. “*Inverse Modeling*”. IOP Publishing, 2015
- Roland Potthast, Anne Walter and Andreas Rhodin. “*A Localised Adaptive Particle Filter (LAPF) within an operational NWP Framework*”. submitted to MWR
- Sebastian Reich and Colin Cotter. “*Probabilistic Forecasting and Bayesian Data Assimilation*”. Cambridge University Press, 2015
- Christoph Schraff, Hjendrick Reich, Andreas Rhodin, Annika Schomburh, Klaus Stehphan, Africa Periañez and Roland Potthast. “*Kilometre-scale ensemble data assimilation for the cosmo model (kenda)*”. Quarterly Journal of the Royal Meteorological Society, 2016
- Peter Jan van Leeuwen, Yuan Cheng and Sebastian Reich. “*Nonlinear Data Assimilation*”. Frontiers in Applied Dynamical Systems: Reviews and Tutorials. Springer, 2015

**Thanks for the attention!**

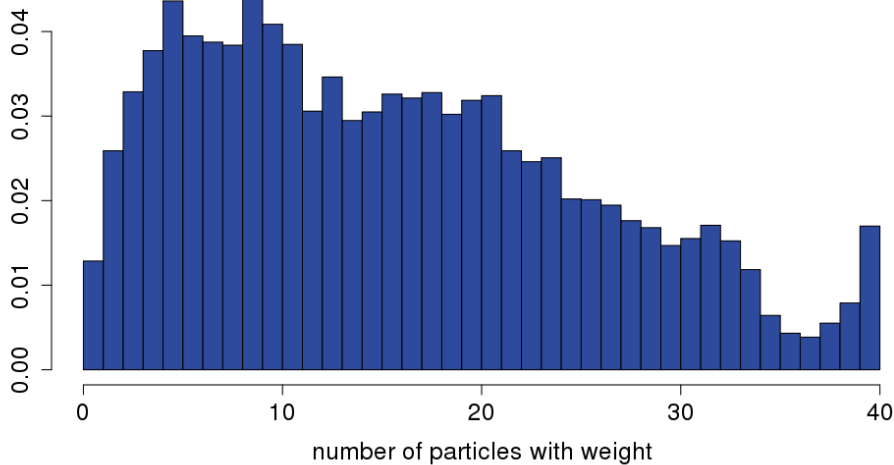
# Appendix

Global histogram of number of particles with weight  
31.05.2016 21 UTC ~1000 hPa

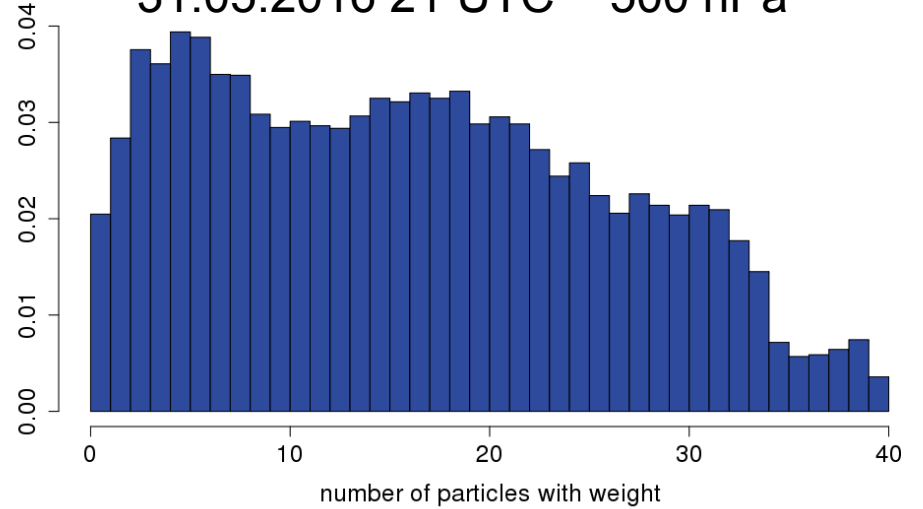


## Global histograms of number of particles with weight

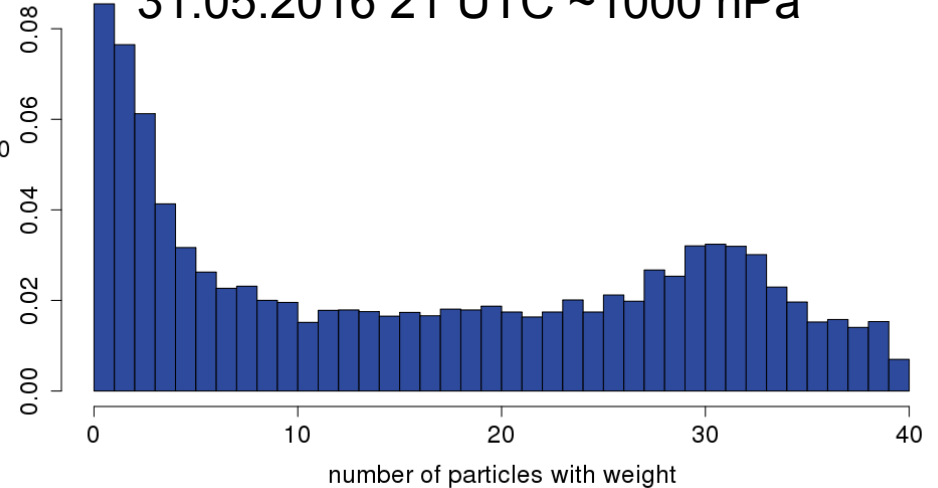
31.05.2016 21 UTC ~ 100 hPa



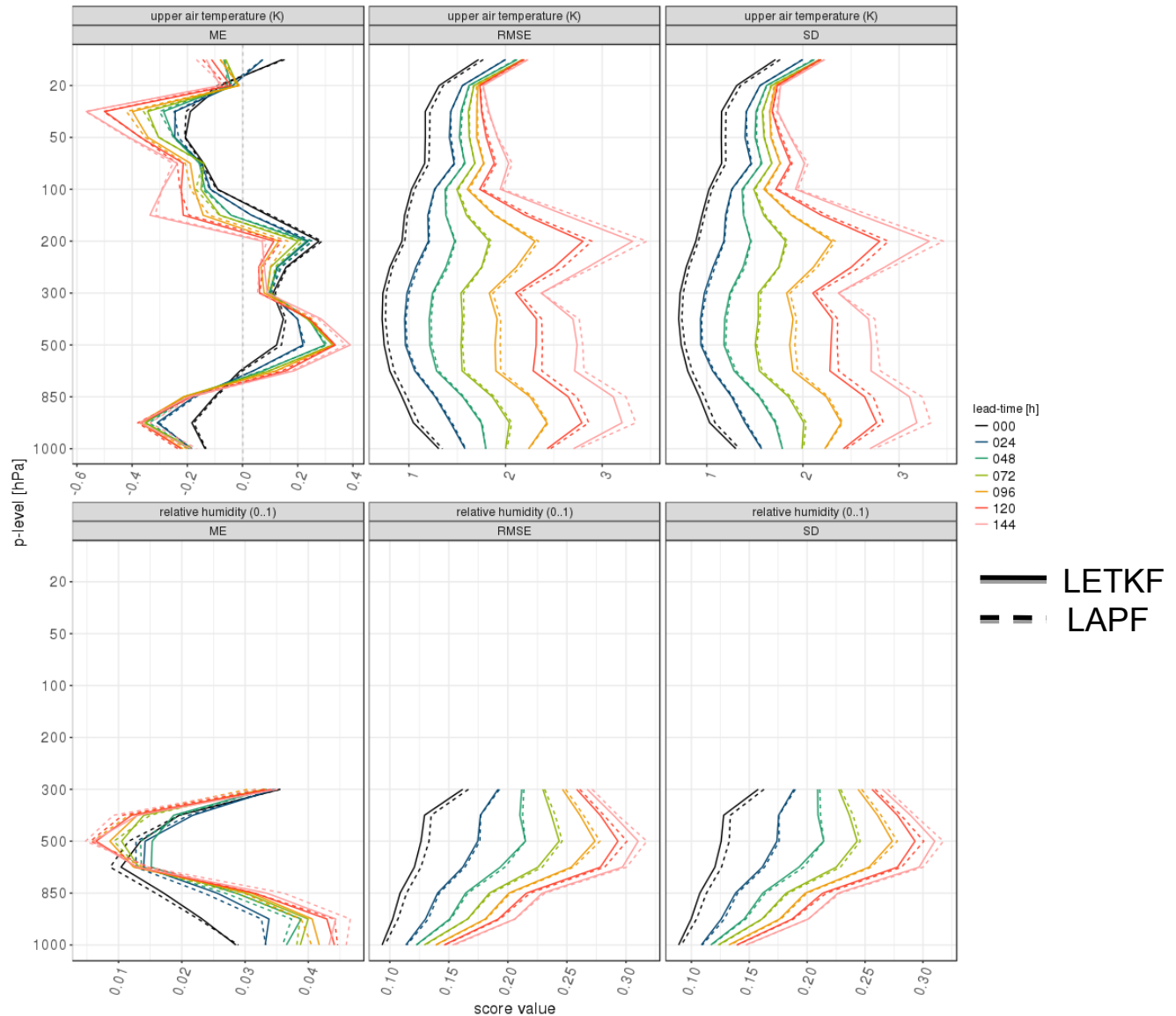
31.05.2016 21 UTC ~ 500 hPa



31.05.2016 21 UTC ~ 1000 hPa



Global verification of  
different lead times  
against  
Radiosondes  
Period: 02.05.2016 –  
24.05.2016



Global verification of  
different lead times  
against  
Radiosondes  
Period: 02.05.2016 –  
24.05.2016

