

LACE/HIRLAM Algorithmic Data Assimilation Developments

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and
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- Introduction
- Handling of background errors
- Including host model information
- Flow-dependent data-assimilation algorithms
- Nowcasting
- Conclusions

Introduction

ACC RD

A Consortium for COnvection-scale modelling
Research and Development



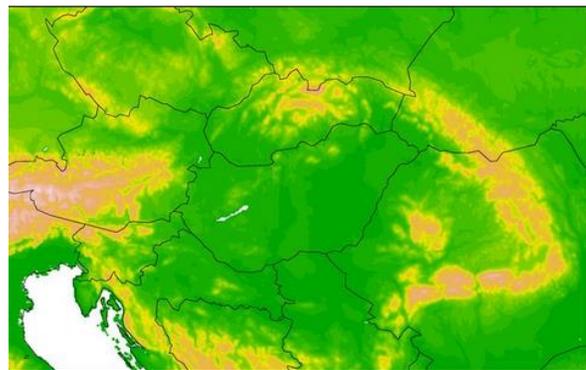
High Resolution
HirLAM
United Area Model



LACE
nwp central europe

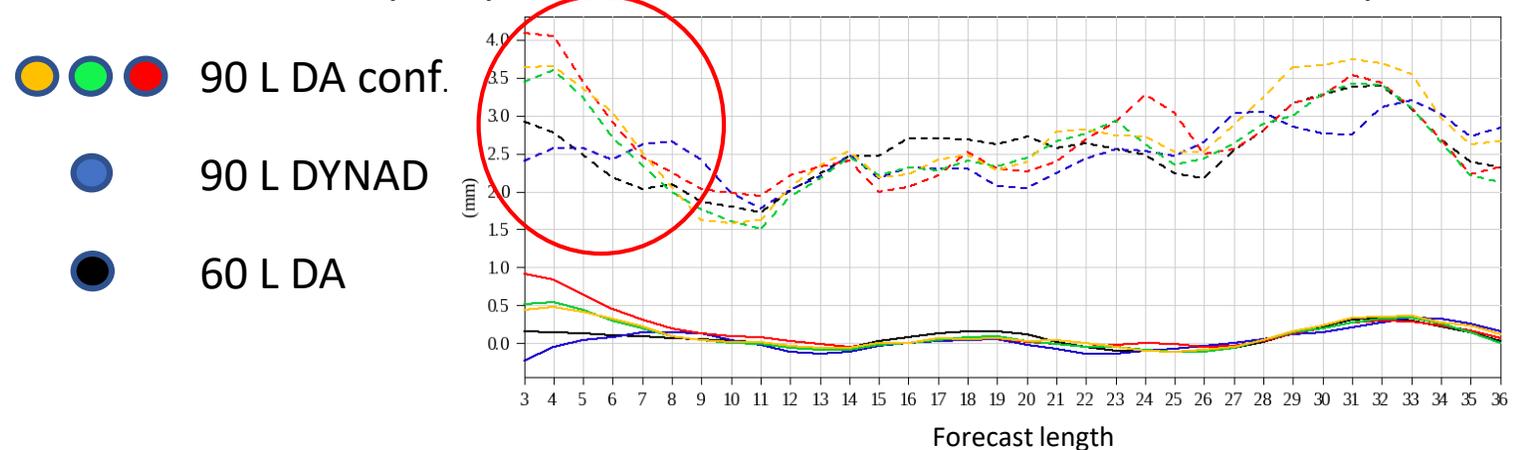


- New vertical geometry for AROME/Hungary (90 instead of 60 levels, but still 2.5 km horizontal resolution).
- Tuning of observation- and background-errors has been carried out by applying the Desroziers' method.
- The sensitivity to the tuning was explored by comparing runs with different error tunings for the 90-level configuration (**orange, green, red**) with each other and comparing also with a 90 level configuration dynamical adaptation run (**blue**) and a run from the operational 60 level configuration (**black**).
- Tuning of the 90-level error characteristics has a clear impact on precipitation spin-up. However, there is still larger **spin-up when data assimilation is applied in the 90-level configuration** as compared with both dynamical adaptation in the 90 level configuration and data assimilation with the old operational 60 level configuration.

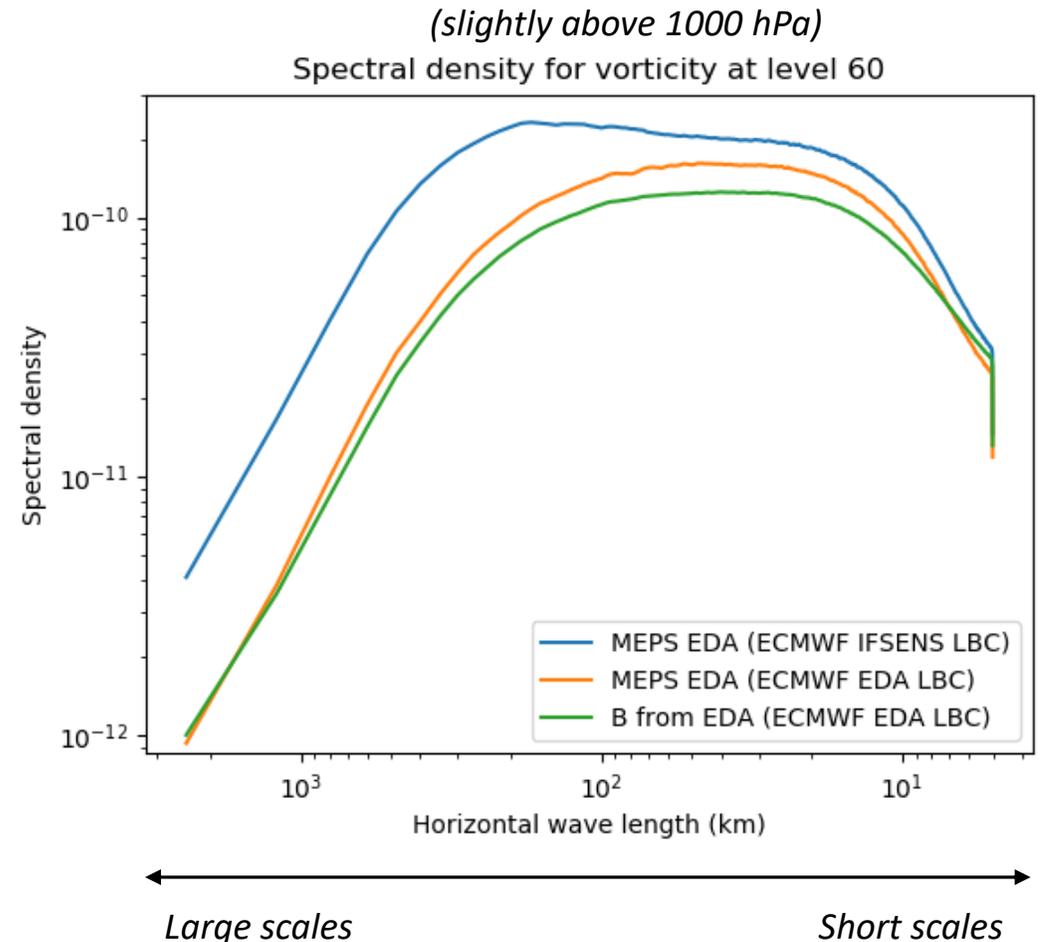


Modelling domain and orography.

3-hour precipitation RMSE and bias for a 3 week summer period



- Operational-like MEPS LAM EDA ensembles have been run for a one-month period to generate background error statistics.
- Operational-like MEPS LAM EDA ensemble uses ECMWF IFS ENS as LBC, which results in too much energy in large horizontal scales in the B-matrix.
- Modifying MEPS LAM EDA to use ECMWF EDA as LBC and modifying the way of using the LBC information in the LAM ensemble has a clear effect. It results in a horizontal background error spectra in better agreement with the operationally used B-matrix.
- The operationally used B-matrix derived applying LAM-EDA, but for a different period than the MEPS LAM EDA.



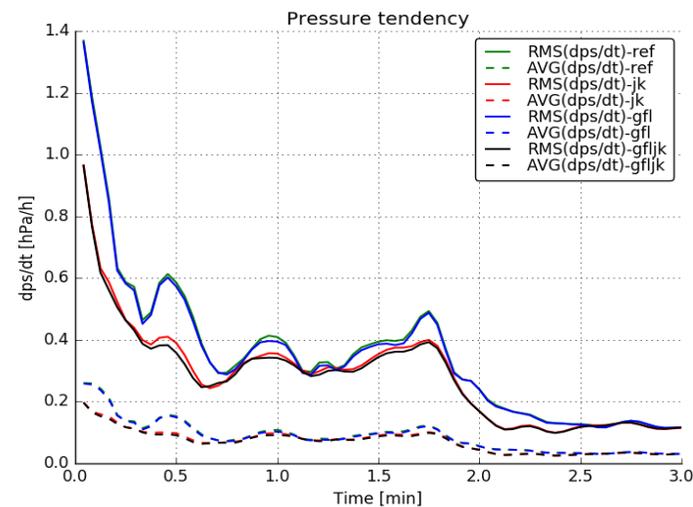
Evaluating the effect of introducing host model information through a J_k – term in cost function and of hydrometeor cycling

- A 17-day winter period parallel experiment with significant weather (precipitation, freezing rain).
- Taking host model information into account by introducing a J_k - term in the cost function has a clear impact on reduced spin-up (Figure to the right).

$$\min_x J(x) = J_b + J_o + J_k$$

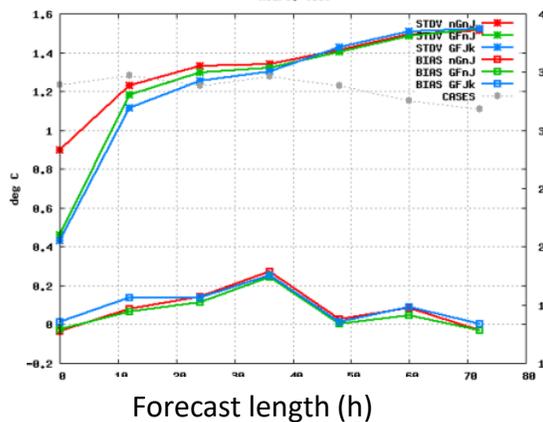
$$= \frac{1}{2}(x - x_b)^T \mathbf{B}^{-1}(x - x_b) + \frac{1}{2}(y - \mathbf{H}x)^T \mathbf{R}^{-1}(y - \mathbf{H}x) + \frac{1}{2}(x - x_c)^T \mathbf{C}^{-1}(x - x_c)$$

- Cycling of hydrometeors has a positive impact on upper-air forecast scores up to 20 h (Figures below).

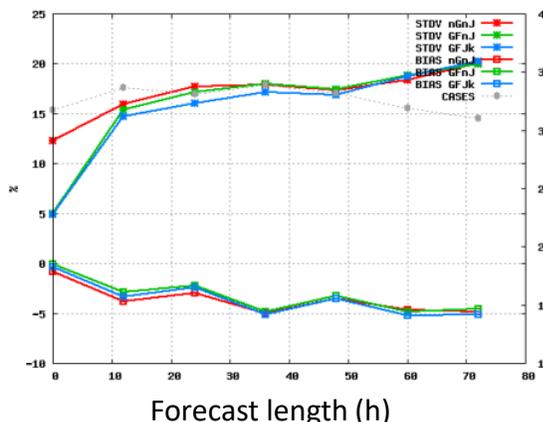


REF
GFL cycling
Jk
Jk + GFL

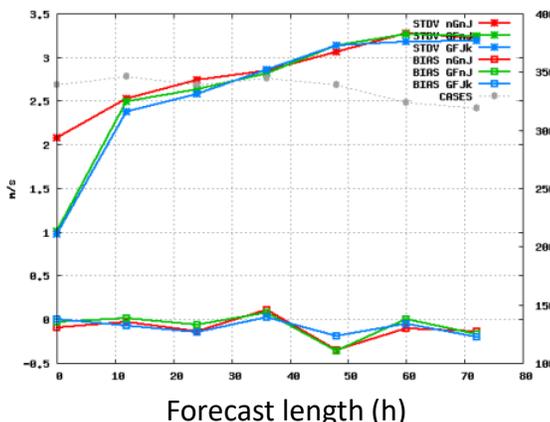
STD and Bias for T at 850 hPa



STD and Bias for RH at 850 hPa



STD and Bias for WSPD at 850 hPa



REF
GFL cycling
Jk and GFL

Traditional J_k – formulation with additional term in cost function:

$$\begin{aligned} \min_x J(x) &= J_b + J_o + J_k \\ &= \frac{1}{2}(x - x_b)^T \mathbf{B}^{-1}(x - x_b) + \frac{1}{2}(y - \mathbf{H}x)^T \mathbf{R}^{-1}(y - \mathbf{H}x) + \frac{1}{2}(x - x_c)^T \mathbf{C}^{-1}(x - x_c) \end{aligned}$$

New approach under development and testing:

Method

we define

$$\tilde{x}_b = \mathbf{C}(\mathbf{B} + \mathbf{C})^{-1}x_b + \mathbf{B}(\mathbf{B} + \mathbf{C})^{-1}x_c$$

and

$$\tilde{\mathbf{B}} = \mathbf{B}(\mathbf{B} + \mathbf{C})^{-1}\mathbf{C} = \mathbf{C}(\mathbf{B} + \mathbf{C})^{-1}\mathbf{B}, \quad \tilde{\mathbf{B}}^{-1} = \mathbf{B}^{-1} + \mathbf{C}^{-1}$$

then

$$J(x) = \frac{1}{2}(x - \tilde{x}_b)^T \tilde{\mathbf{B}}^{-1}(x - \tilde{x}_b) + \frac{1}{2}(y - \mathbf{H}x)^T \mathbf{R}^{-1}(y - \mathbf{H}x)$$

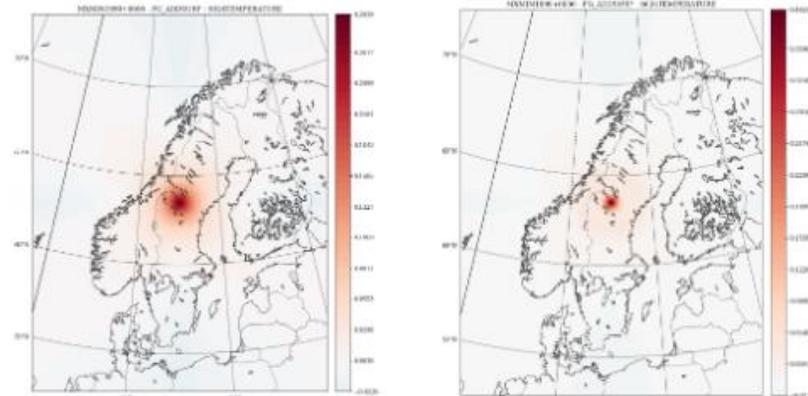
meaning that (at least theoretically) the minimization can be performed without the extra J_k term explicitly present, provided

- we pre-mix x_b and x_c into a new background term \tilde{x}_b
- we use a modified background error covariance matrix $\tilde{\mathbf{B}}$

Not necessarily any simpler for a completely general \mathbf{C} .

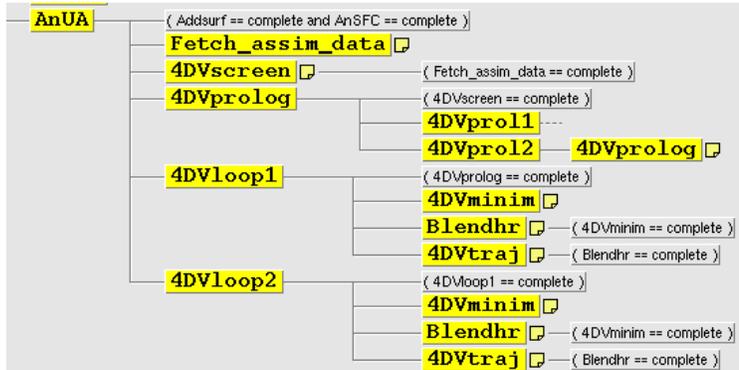
Example of functionality

One single temperature observation +1K at 500 hPa, L24, $\rho(0) = 0.4, \rho(K - 1) = 3$.

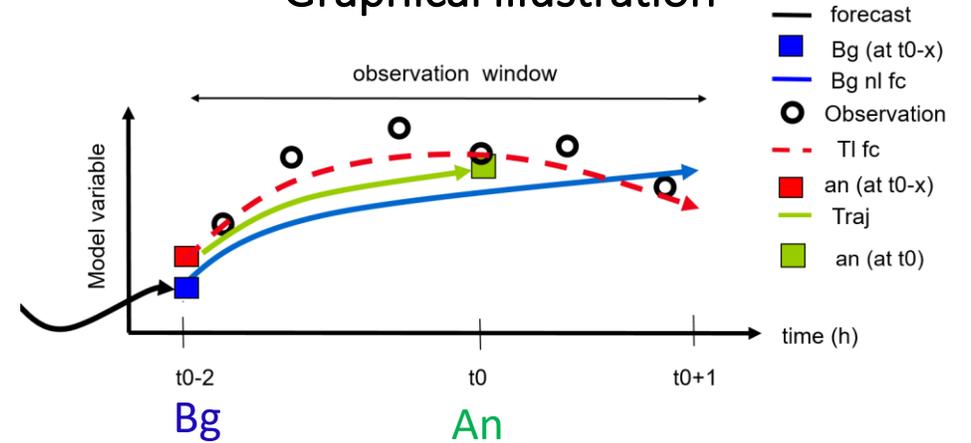


Left with original \mathbf{B} , right with spectrally mixed $\tilde{\mathbf{B}}$.

Multi-incremental formulation



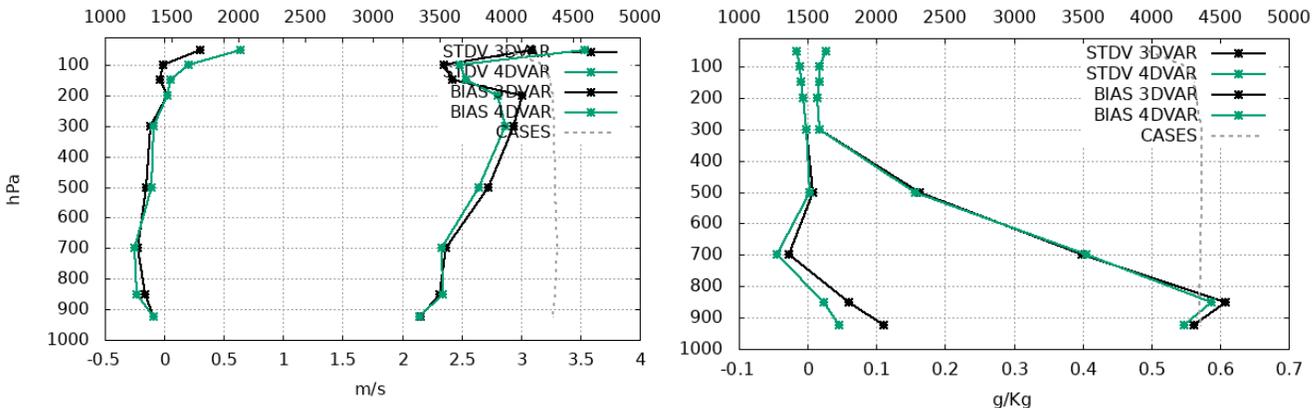
Graphical illustration



Verification scores for a one-month 3D-/4DVar comparison

18 stations Selection: ALL
Wind speed Period: 20200320-20200419
Used 00,06,12,18 + 06 12 18 24 36
No cases

18 stations Selection: ALL
Specific humidity Period: 20200320-20200419
Used 00,06,12,18 + 06 12 18 24 36
No cases



Conclusions and Outlook

- An operationally feasible 4D-Var available (different parts in single precision)
- Daily runs in operational environment
- Explore use in nowcasting
- Further enhancements planned

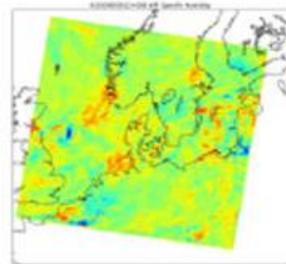
Introducing ensemble information into the variational data assimilation through an α control variable

$$J(\delta \mathbf{x}_{\text{var}}, \boldsymbol{\alpha}) = \beta_{\text{var}} J_{\text{var}}(\delta \mathbf{x}_{\text{var}}) + \beta_{\text{ens}} J_{\text{ens}}(\boldsymbol{\alpha}) + J_0$$

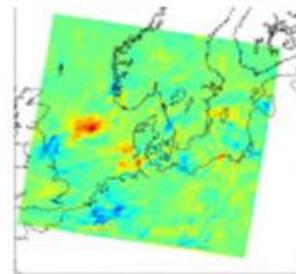
- 20+1 ensemble members
- Compare HYBRID EN-(3D)VAR using ensembles generated with different techniques on EDA, BRAND, BREND
- Different localisation scales
- Visualisation of structures

Humidity-increments at 700 hPa

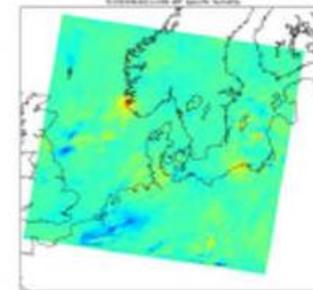
BREND (500 km)



BREND (100 km)

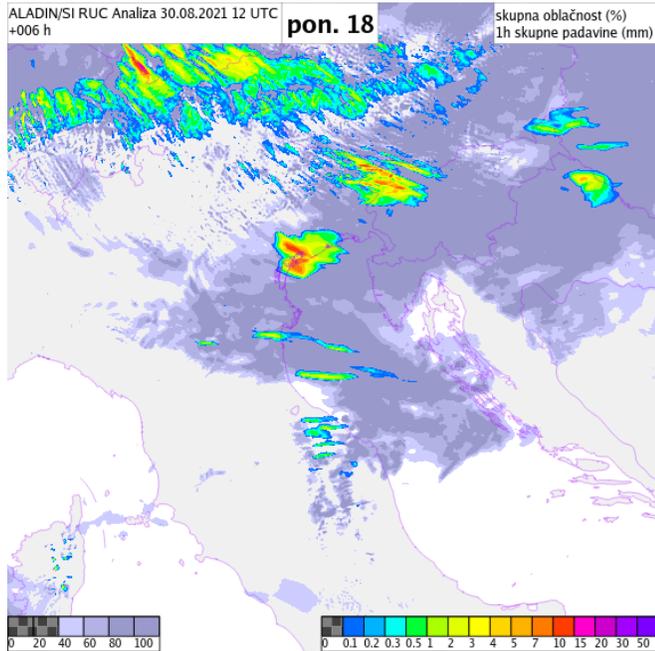


EDA (100 km)



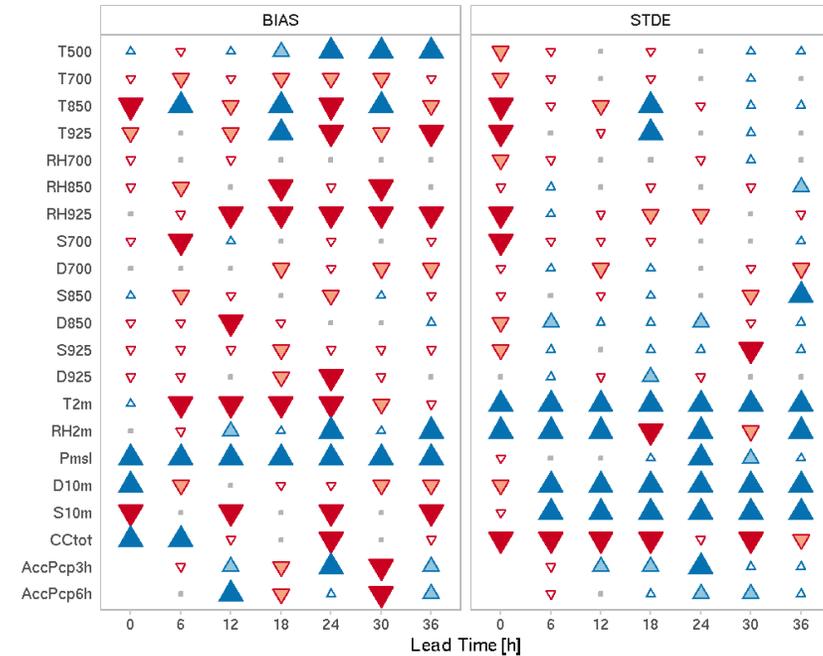
Results from a one-month winter-period parallel run

Modelling domain and 1h accumulated precipitation for one particular case



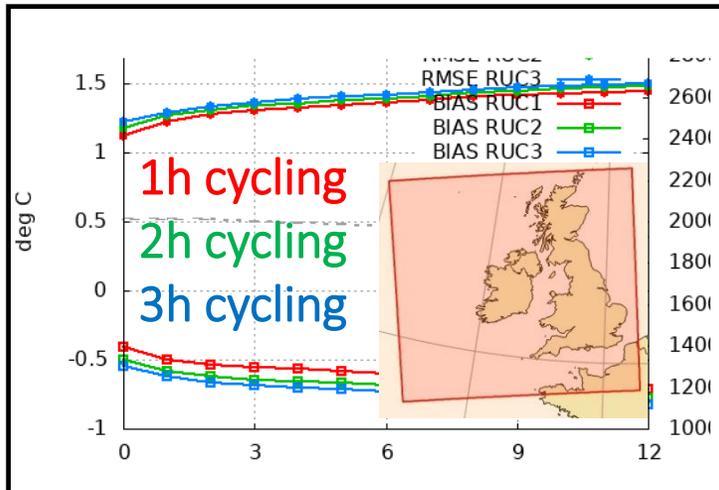
Scorecard

blue – improvement of hourly vs. 3h cycle - winter



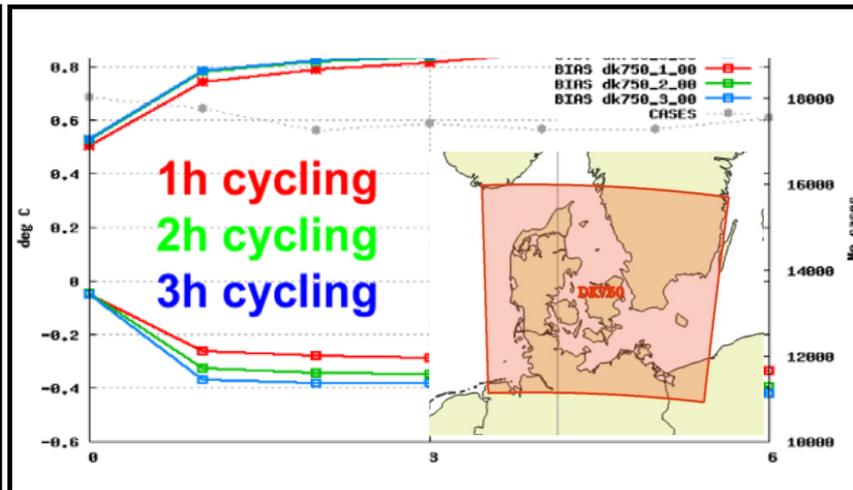
- ▽ nwc1 worse than ref4 with significance > 99.7%
- △ nwc1 better than ref4 with significance > 68%
- ▽ nwc1 worse than ref4 with significance > 95%
- △ nwc1 better than ref4 with significance > 95%
- ▽ nwc1 worse than ref4 with significance > 68%
- △ nwc1 better than ref4 with significance > 99.7%
- No significant difference between nwc1 and ref4

Spring
std and bias



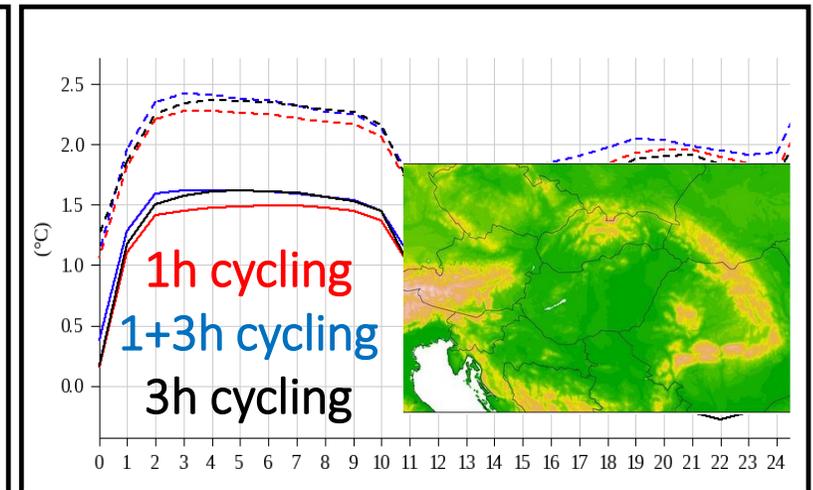
Forecast length (h)

Autumn
std and bias



Forecast length (h)

Summer
rmse and bias



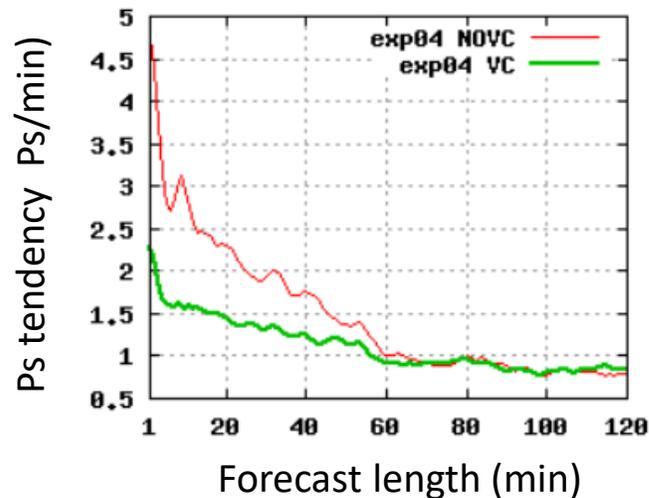
Forecast length (h)

Short range two-meter temperature scores in general better with 1h cycling
(not the same for short range forecasts of moisture variables)

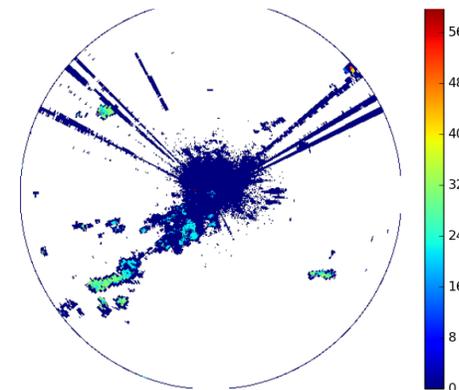
No benefit for this summer period of 1 upper-air DA and 3h surface DA cycle

On-going work and plans

- Exploiting and optimizing time-filtering through initialisation approaches.
- Assimilation procedures adopted to nowcasting.
- Improved use of cloud products (machine learning, optical thickness).
- Methods for handling/initialisation of hydrometeors.
- Various studies of spin-up and sensitivity to observation usage etc.
- A framework for sub-hourly data assimilation cycles is being set-up.



 Without filtering
 Application of VC
 Variational Constraint (VC)
 work by C Ceigo, AEMET



*3D hydrometeor
classification
in a radar scan
work by ZAMG*

C. Ceigo, F. Meier., K. Szanyi et al. (ZAMG), S. v. Veen, E. Gregow, T. Landelius, C. Pederssen, A. Stanešić, O. Vignes, M. Dahlbom, J. Bojarova, J. Barkmeijer, B. Stranjar, X. Yang, U. Andrae et al.

- An operationally feasible 4D-Var has been developed.
- There is on-going work towards bringing data-assimilation and operational ensemble system closer together.
- Taking host model information into account in data assimilation procedure can lead to more balanced initial states and shorter scale analysis increments.
- Encouraging results were obtained with 1h-RUC, although there are remaining challenges.
- LACE and HIRLAM are working increasingly closer together with upper air data assimilation developments within the newly formed ACCORD consortium.