

# Short range ensemble experiments for wind prediction with DMI-HIRLAM

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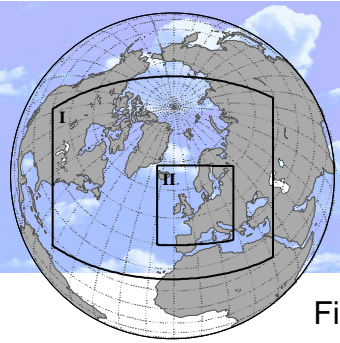


Fig. 1

## Abstract

Two simple ensemble approaches based on downscaling of the ECMWF-EPS over Europe during winter 2002/03 using DMI-HIRLAM have been investigated. The first approach integrated all the individual members of the ECMWF-EPS to address initial as well as boundary state uncertainty. The second ensemble approach utilized multiple parameterization schemes for convection and condensation to address some of the model errors. A verification against observations of 10m wind speed shows no significant enhancement on average by the first DMI-HIRLAM ensemble approach with respect to the host model ensemble. For the second approach a *best member* strategy was tested in order to investigate the possibilities of such a method in the case of this simple ensemble.

## Experiment description

### Model configuration

The model setup is a 1-way nested system of the DMI-HIRLAM version of 2003. There are two HIRLAM domains (Fig. 1). The outer HIRLAM model (I) is nested to the global ECMWF TL255L31 model of the EPS. Depending on the HIRLAM ensemble (see below), this is the control or one of the perturbed members. It has a  $0.6^\circ$  horizontal grid and 31 vertical levels, and it is initialized at 12 UTC by the ECMWF analysis. The lateral boundaries are updated every 6 hours. The outer HIRLAM model runs with a semi-Lagrangian advection scheme, and the time step in dynamics and physics is 600s.

The inner DMI-HIRLAM (II in Fig. 1) model has a  $0.2^\circ$  horizontal grid and also 31 vertical levels. It is initialized and updated hourly at the lateral boundaries by the outer model. The advection is of Eulerian type, and the time step for the dynamics is 90s, and 540s for the physical parameterizations.

### Ensemble members

The first DMI-HIRLAM ensemble of this investigation consisted of 50+1 simulations, each of which was driven by data from one of the ECMWF-EPS members. A comparison between this DMI-HIRLAM ensemble and the ECMWF ensemble is shown below.

The second DMI-HIRLAM ensemble consisted of five simulations with 5 different parameterization schemes for convection and for condensation. The host model data was taken from the ECMWF-EPS control simulations. A *best member/combination* strategy was tested with this DMI-HIRLAM ensemble.

The DMI-HIRLAM model configuration outlined above was used for both HIRLAM ensembles.

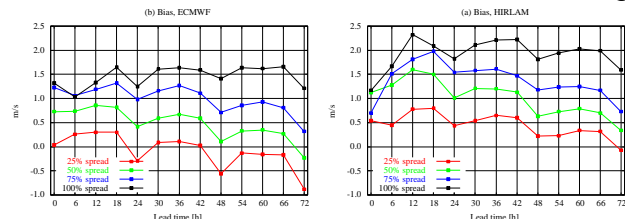
### Model simulations

The DMI-HIRLAM simulations were performed on a daily basis over the period between 2002-12-08 and 2003-03-29. The simulations were started at 12 UTC with a lead time of 72 hours. The ensemble setup (see above) was such that all members could be integrated within one day.

## A comparison of the 50+1 DMI-HIRLAM ensemble and the ECMWF ensemble

The predicted wind speed was verified against SYNOP station observations inside the inner HIRLAM domain (II in Fig. 1; Feddersen and Sattler, 2005). Both the HIRLAM and the ECMWF ensemble predictions were verified for a lead time up to 72 hours.

Fig. 2



Both the DMI-HIRLAM and the ECMWF ensemble exhibit a positive bias in 10m wind speed, which increases with the ensemble spread (Fig. 2). Fig. 2 also indicates that the DMI-HIRLAM ensemble bias is larger than in the ECMWF ensemble.

The ensemble spread (ratio of the difference between 90% and 10% ensemble quantile and the respective quantile range of the observations in the same period) of the DMI-HIRLAM and the ECMWF ensemble are similar. The ECMWF ensemble exhibits a larger spread at the shortest lead times, whereas the DMI-HIRLAM ensemble shows a slightly larger spread after 42 hours (Fig. 3 right panel). The former may be due to the fact that the ECMWF ensemble includes stochastic adaptation of the tendencies from the physical parameterizations.

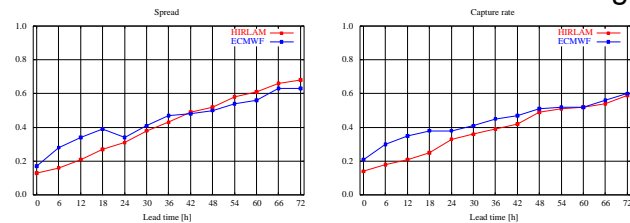


Fig. 3

Because of the larger bias of the DMI-HIRLAM ensemble, the capture rate (here: percentage of observations falling within the 10% and 90% quantile) of the DMI-HIRLAM ensemble remains below the rate from the ECMWF ensemble even at the 72 hour range (Fig. 3 right panel).

The increase of the bias with the ensemble spread (Fig. 2) may be a first indicator for a spread-skill relationship. This becomes, however, less obvious when looking at the average correlation in time between the ensemble mean and the verifying observations (Fig. 4).

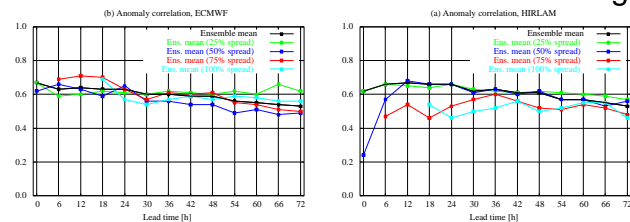


Fig. 4

The significant drop in correlation in the 50% category in the HIRLAM predictions at 0 lead time is a result of lack of data, as the spread almost always falls in the low spread category for 0 lead time. The fact that DMI-HIRLAM was initialized by the host model only without incorporation of the HIRLAM data assimilation may play an important role here.

## A best member/combination strategy tested for the 5 member DMI-HIRLAM multiple scheme ensemble

The second DMI-HIRLAM ensemble consists of  $N=5$  simulations using different schemes for convection/condensation. It was used for testing a *best member* (BM) strategy adopted from Roulston and Smith (2003), which is based on the normalized distance between an ensemble member and the verification in the parameter space of  $d$  variables:

$$R_{i,d}^2 = \sum_{k=1}^d \frac{(x_{i,k} - y_k)^2}{\Omega_k^2}, \quad (1)$$

where  $x_{i,k}$  is the forecast of ensemble member  $i$ ,  $y_k$  is the verifying observation, and  $\Omega_k$  is the standard deviation of the simulation ensemble for the  $k^{\text{th}}$  variable. A BM is then identified by the minimum of  $R_{i,d}^2$ . The variables of the parameter space may consist of different forecasts, forecast quantities, locations or lead times. The choice of the dimension  $d$  of the underlying parameter space should ideally have no impact on the identification of the BM. The condition

$$\min(R_{i,d}^2) = R_{j,d}^2 \wedge \min(R_{i,d+1}^2) = R_{j,d+1}^2 \quad (2)$$

should ideally hold for the BM for all  $d$ . If it is not fulfilled, then a *false best member* has been identified. The fraction of how often (2) is fulfilled gives an indication on the usefulness of the BM identification.

The BM strategy of Roulston and Smith (2003) was extended such that in addition to the single members all possible combinations of the ensemble members were taken into account, too. For the current ensemble there are 26 combinations. This results in 31 possibilities for the forecast, from which the *best member/combination* (BMC) was determined.

### Multivariate parameter space

This investigation made use of parameter spaces consisting of different variables, locations and lead times. Variables were 10m wind speed ( $v_{10}$ ) and direction ( $d_{10}$ ), mean sea level pressure (mslp), 2m temperature ( $t_{2m}$ ) and 2m relative humidity ( $rh_{2m}$ ). The locations were SYNOP stations in Denmark with no or very few missing observations within the simulation period (Fig. 5).

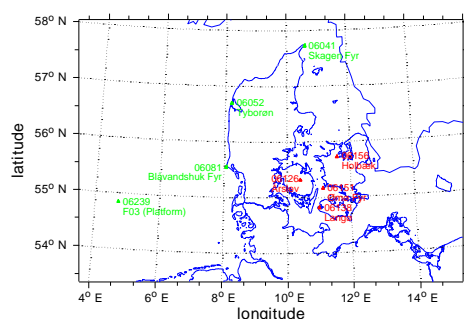


Fig. 5

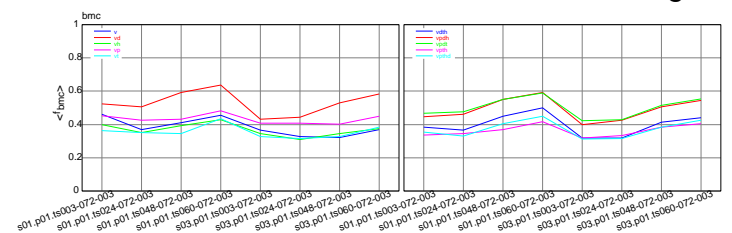
Different sets of variables, locations and lead times were regarded in order to try to optimize the BMC identification. For this purpose the fraction of the identified BMC was determined by

$$\langle f_{\text{BMC}} \rangle = \frac{1}{n_{\text{days}} \sum_{\text{days}} \frac{n_{\text{BMC}}}{n_d}}, \quad (3)$$

where  $n_{\text{BMC}}$  denotes the frequency of how often the identified BMC was the *best* one when performing  $n_d$  tests according to (2), and  $n_{\text{days}}$  is the number of days in the simulation period. This is a complementary formulation to the fraction of *false best members* used by Roulston and Smith (2003).

Fig. 6 shows the mean fraction of the BMC for different variable combinations (in colors) as a function of the choice of two sets of SYNOP locations (red (s01) and red+green (s03) in Fig. 5) and different ranges of lead time (3-72h, 24-72h, 48-72h, 60-72h). Only the parameter space "vd" (Fig. 6 left panel) with 4 sites included (S01) and regarding the lead time beyond 60h (ts060-072) reaches values over 0.6, which indicates the difficulties connected to the identification of a best member/combination. However, deficiencies in the underlying ensemble simulations may also play a role.

Fig. 6



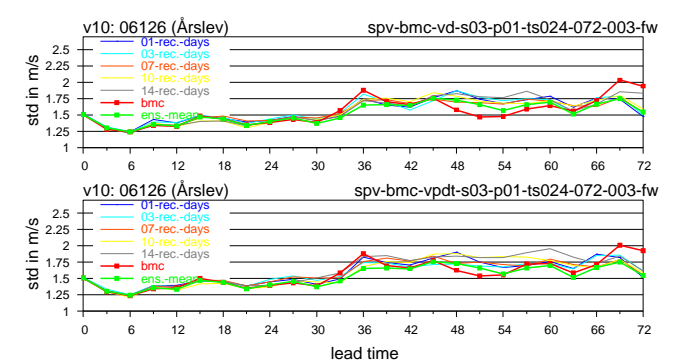
### A quasi-operational trial

In an operational environment the *best member/combination* is not known in advance when forecasts are to be issued. In order to simulate such a situation, the BMCs identified for the recent days  $z-m$ , with  $m=1, \dots, 14$  were used to select a member/combination for the forecast to be issued for day  $z$  and beyond. This selected member/combination (SMC) was identified on basis of  $\langle f_{\text{BMC}} \rangle$  as follows:

$$f_{\text{SMC}} = \max \left( \sum_{l=1}^m f_{\text{BMC},l} \right). \quad (4)$$

The forecasts created by this selection strategy were verified for v10 against the SYNOP stations shown in red in Fig. 5. Fig. 7 shows results for station Årlev for two choices of variable combination as an example.

Fig. 7



## Conclusions

The use of a simple dynamical downscaling of all members from the global ECMWF-EPS using the higher resolution HIRLAM model does not improve the 10m wind predictions over Denmark on average. Possibly, the benefit of a simple dynamical downscaling is only seen in complex terrain and in extreme weather.

The application of a *best member/combination* strategy on a 5-member HIRLAM multiple-scheme ensemble was tried in a second experiment of this work. Apart from the difficulties connected with a robust identification of the *best member/combination*, the 5-member HIRLAM ensemble has the deficiency that all members were driven by the same initial and boundary conditions, which kept the spread between the members small. A trial to exploit the strategy for short-range forecasting has not yet shown the desired result.

## References

- Feddersen and Sattler, 2005: Verification of wind forecasts for a set of experimental DMI-HIRLAM ensemble experiments. *HIRLAM Newsletter*, 47, in press.
- Roulston M.S. and Smith L., 2003: Combining dynamical and statistical ensembles. *Tellus*, 55A, 16-30.

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