Use of Multimodel SuperEnsemble Technique for Complex Orography Weather Forecast

Massimo Milelli[1], Daniele Cane[1,2]

[1] *ARPA Piemonte*

[2] *Organizing Committee for the XX Winter Olympic Games Torino 2006*

1 Introduction

The Multimodel SuperEnsemble technique (see Krishnamurti et al, 1999 and 2000 for instance) is a powerful post-processing method able to reduce direct model output errors. Several model outputs are put together with adequate weights to obtain a combined estimation of meteorological parameters. Weights are calculated by square error minimization in a so-called training period. In a previous paper (Cane and Milelli, 2005), we applied the Multimodel technique on the operational 00 UTC runs of Local Area Model Italy (LAMI) by UGM, ARPA-SIM, ARPA Piemonte (`nud00`), Lokal Modell (LME) by Deutscher Wetterdienst (`lkd00`) and aLpine Model (aLMo) by MeteoSwiss (`alm00`). This was one of the first implementations of Multimodel technique on limited-area models (in this case of 0.0625° resolution) and we obtained a strong improvement in temperature forecasts in Piedmont region. In this work we extend the application of temperature and precipitation to larger periods and we introduce the method to the calculation of humidity, wind speed and precipitation.

2 Multimodel Theory

As suggested by the name, the Multimodel SuperEnsemble method requires several model outputs, which are weighted with an adequate set of weights calculated during the so-called training period. The simple ensemble methods with biased (Eq. 1) or bias-corrected (Eq. 2) data respectively, are given by

$$S = \overline{O} + \frac{1}{N}\sum_{i=1}^{N}(F_i - \overline{F_i}) \tag{1}$$

and

$$S = \overline{O} + \frac{1}{N}\sum_{i=1}^{N}(F_i - \overline{O}) \tag{2}$$

The conventional superensemble forecast constructed with bias-corrected data is given by

$$S = \overline{O} + \sum_{i=1}^{N} a_i(F_i - \overline{O}) \tag{3}$$

where N is the number of models, F_i is the i^{th} forecast by the model, $\overline{F_i}$ and $\overline{O}$ are the mean forecasts and the mean observation during the training period T.

The calculation of the parameters a_i is given by the minimization of the mean square deviation

$$G = \sum_{k=1}^{T}(S_k - O_k)^2 \tag{4}$$

by derivation $\left(\frac{\partial G}{\partial a_i} = 0\right)$ we obtain a set of N equations, where N is the number of models involved $(i, j = 1, N)$:

$$\left(\sum_{k=1}^{T} \left(F_{i_k} - \overline{F_i}\right)\left(F_{j_k} - \overline{F_j}\right)\right) \cdot (a_i) = \left(\sum_{k=1}^{T} \left(F_{j_k} - \overline{F_j}\right)\left(O_k - \overline{O}\right)\right) \tag{5}$$

We then solve these equations using the Gauss-Jordan method (see Press et al., 1992).

3 Results

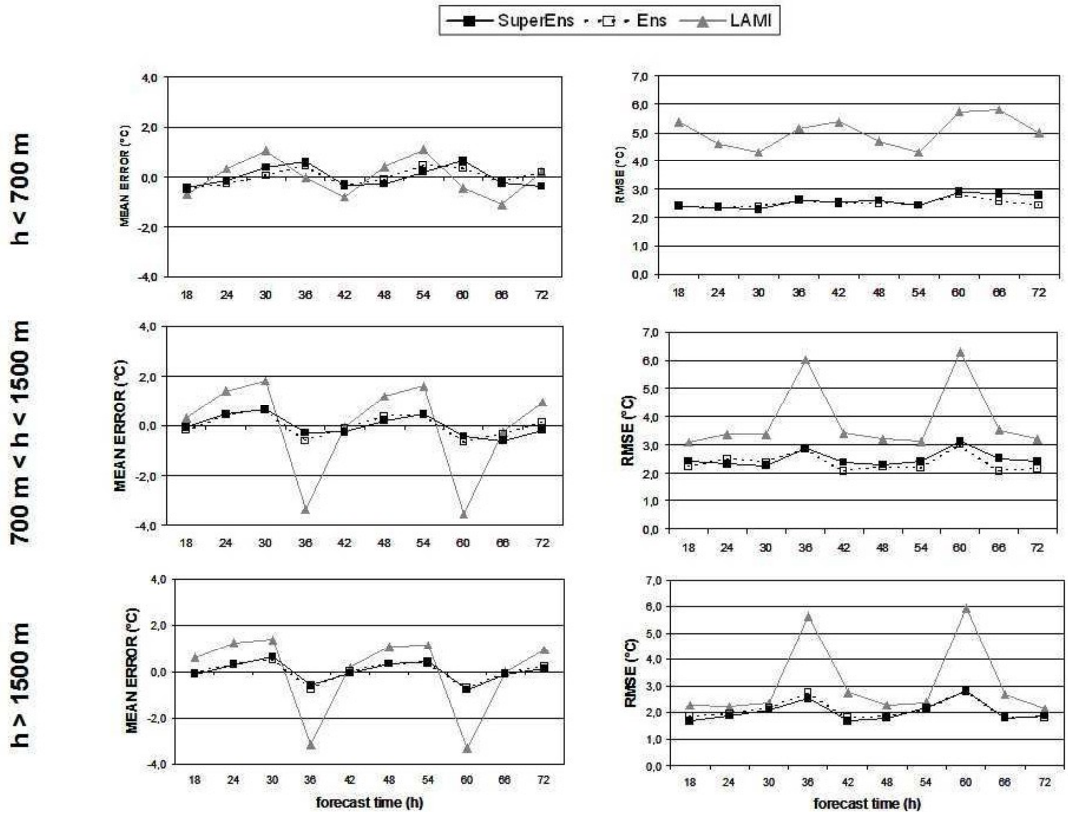

Figure 1: Mean temperature error (left) and RMSE (right) for Superensemble output (black continuous line), Ensemble output (black dotted line) and LAMI output (grey continuous line); low-lying stations (upper panels), middle-mountain stations (middle panels) and high mountain stations (lower panels).

The Piedmont region is monitored by ARPA Piemonte with a very-dense automatic weather station network. We used the data from this non-GTS network for the calculation of the weights in the training period and for validation purposes. In order to obtain more readable graphs, we do not report all the model outputs, but only the operational one (LAMI 00 UTC run). In order to compare with the unbiased values of SuperEnsemble and Ensemble, all the direct model output forecasts here shown are bias-corrected, with the exception of precipitation forecasts since we do not expect to have a systematical error in this case.

Temperature

Stations are grouped by height: 53 low-lying stations (h < 700 m), 34 middle-mountain stations (700 m < h < 1500 m) and 15 high-mountain stations (h > 1500 m). The training period is 90 days (dynamical) and the forecast is on March 2005. We used a bilinear interpolation in the horizontal direction and a linear interpolation (with the geopotential) in the vertical one. In Fig. 1 the BIAS and the RMSE are shown, according to the station elevation. It has to be pointed out the strong systematic error of the direct model outputs, reaching a bias of the order of 4 C, with significant increase around noon (+36 hr and +60 hr forecast time). Multimodel SuperEnsemble substantially eliminates the bias, and the RMSEs also are lower than direct model outputs' ones, with values around 2 C. Moreover we observe a constant performance for all the forecast times.

Relative Humidity

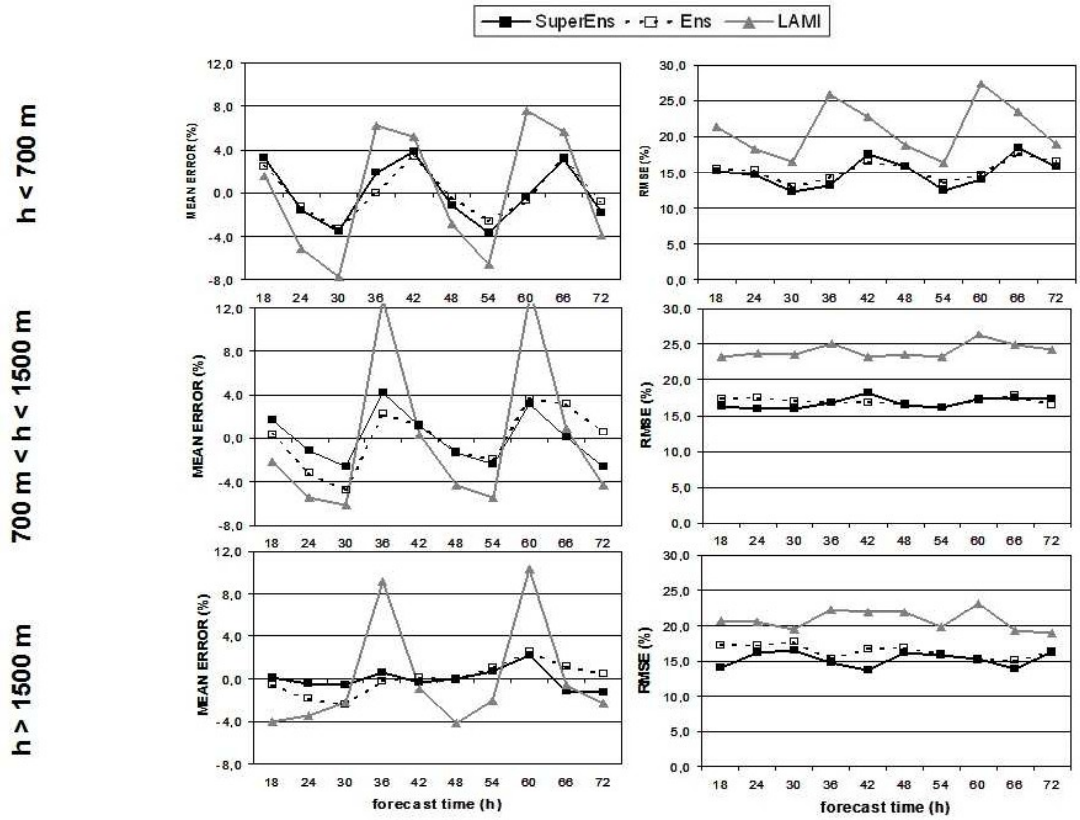

Figure 2: Mean relative humidity error (left) and RMSE (right) for Superensemble output (black continuous line), Ensemble output (black dotted line) and LAMI output (grey continuous line); low-lying stations (upper panels), middle-mountain stations (middle panels) and high mountain stations (lower panels).

The stations are grouped as before and the training period, the forecast time and the interpolation methods are the same used for the temperature forecast. Relative humidity (Fig. 2) shows strong systematic error of the direct model outputs, as temperature does, with high biases and RMSEs. Also in this case the errors are strongly dependent from the forecast time. SuperEnsemble practically eliminates bias, especially for higher elevation stations, with slightly better performances by SuperEnsemble. We also obtained a good RMSE reduction. Both biases and RMSEs are very stable with respect to the forecast time. It has to be highlighted that relative humidity, due to its non-gaussian error distribution, does not satisfy Kalman filter hypothesis. In fact Kalman filter post-processing does not improve significantly relative humidity forecasts. Multimodel SuperEnsemble, on the other hand, does not assume any hypothesis and is suitable to be applied to every meteorological parameter.

Wind Intensity

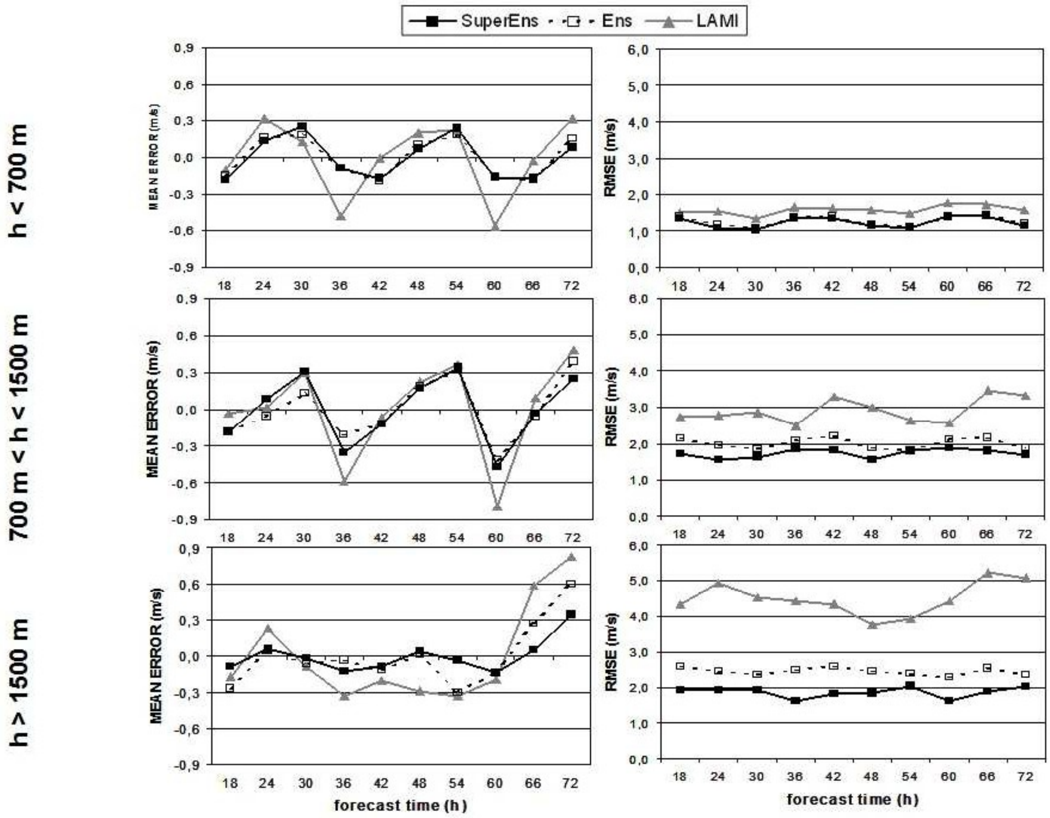

Figure 3: Mean wind intensity error (left) and RMSE (right) for Superensemble output (black continuous line), Ensemble output (black dotted line) and LAMI output (grey continuous line); low-lying stations (upper panels), middle-mountain stations (middle panels) and high mountain stations (lower panels).

Due to model data availability, for this parameter only the ECMWF IFS and the Italian LAMI (00 UTC and 12 UTC operational runs) were used. Stations are grouped in the same groups as for temperature and the training period and the forecast time are the same used for the temperature forecast but here we used the model grid point nearest to the observation. Direct model outputs (Fig. 3) show again strong, forecast time dependent errors. Multimodel permits a strong improvement both in biases and RMSEs, very stable with respect to the forecast time. In this case there is room for improvements: in fact in this work we used model outputs on pressure level, due to data availability, but it would be interesting to check the performance with the model level fields.

Precipitation

Precipitation cannot be easily interpolated to station location without introducing huge errors. For this reason we grouped the same stations we used before in 11 warning areas defined for the regional Civil Protection warning system (see Cane and Milelli, 2005). For each warning area we calculated the 6-hour average and maximum precipitation values. We extracted the same precipitation from the models, calculating the average and maximum values of the grid points covering each warning area. The same method is used operationally for standard precipitation verification at ARPA Piedmont. For further details see Milelli et al., 2003. The training period is 180 days (dynamical). We applied Multimodel Ensemble and SuperEnsemble technique on the average and maximum values, considering as forecast the period July 2004 - March 2005, in order to achieve a good statistics with at least 40

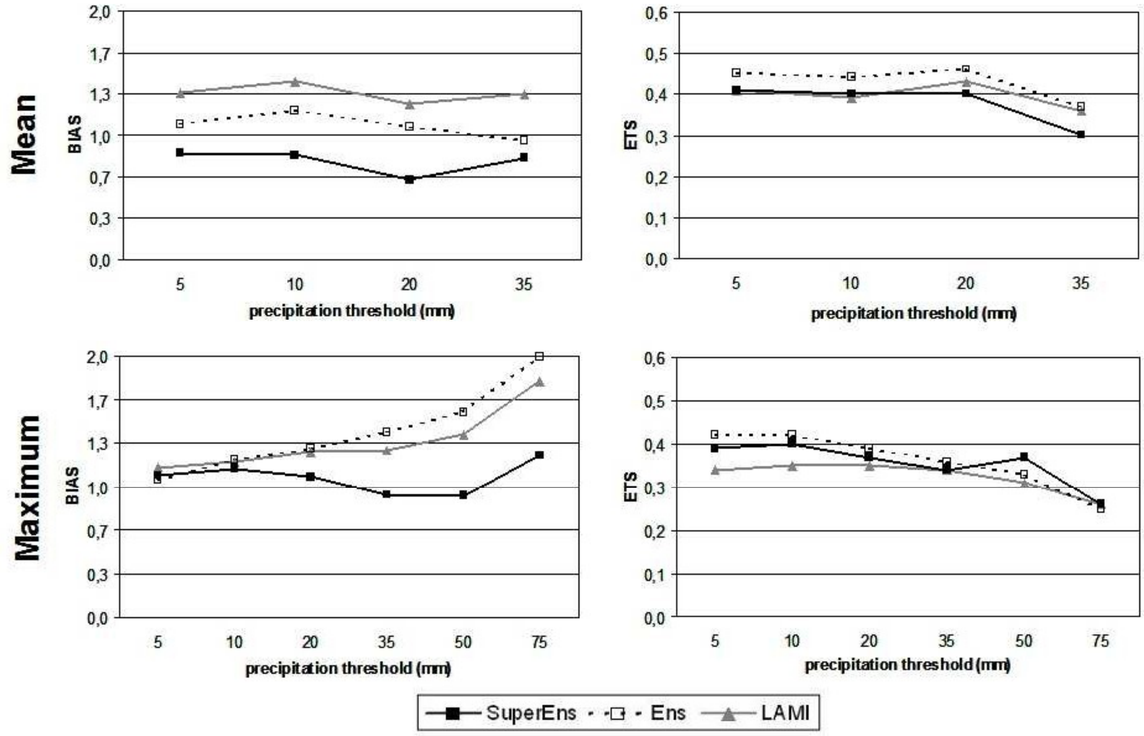

Figure 4: Mean values (upper panels) and maximum values (lower panels) of precipitation in 24h (from +12 to +36) for Superensemble output (black continuous line), Ensemble output (black dotted line)and LAMI output (grey continuous line); BIAS (left panels) and ETS (right panels).

events for each precipitation threshold. We compared the models and Multimodel results by Normalized Bias and Equitable Threat Score (ETS) (see for instance Wilks, 1995). In Piedmont the models usually overestimate average precipitation, as we can see by the BIAS values higher than 1 (Fig. 4 and Fig. 5). Multimodel SuperEnsemble gives a good BIAS reduction. The best improvement is obtained in the spatio-temporal localization of the precipitation events, as described by ETS, for which it shows the highest values. Moreover Multimodel performances are very stable with respect to forecast time, with almost the same BIAS and ETS values for 12-36 UTC and 36-60 UTC forecasts.

4 Conclusions and future perspectives

The Multimodel SuperEnsemble technique has been applied on limited-area and global model in a complex orography alpine region and verified against a large number of weather stations for several weather parameters. For each of them the Multimodel results show good error improvements with respect to the direct model outputs, providing a new powerful post-processing tool. In particular, SuperEnsemble is always superior to Ensemble, except for mean precipitation over warning areas and for ETS in general. The possible future implementations of this technique can be here summarized:

- Extension to other areas and/or variables (observation ⇒ ECMWF analysis):
  - Geopotential
  - MSLP
  - Tracking of cyclones (original purpose, see Krishnamurti et al, 1999 and 2000).

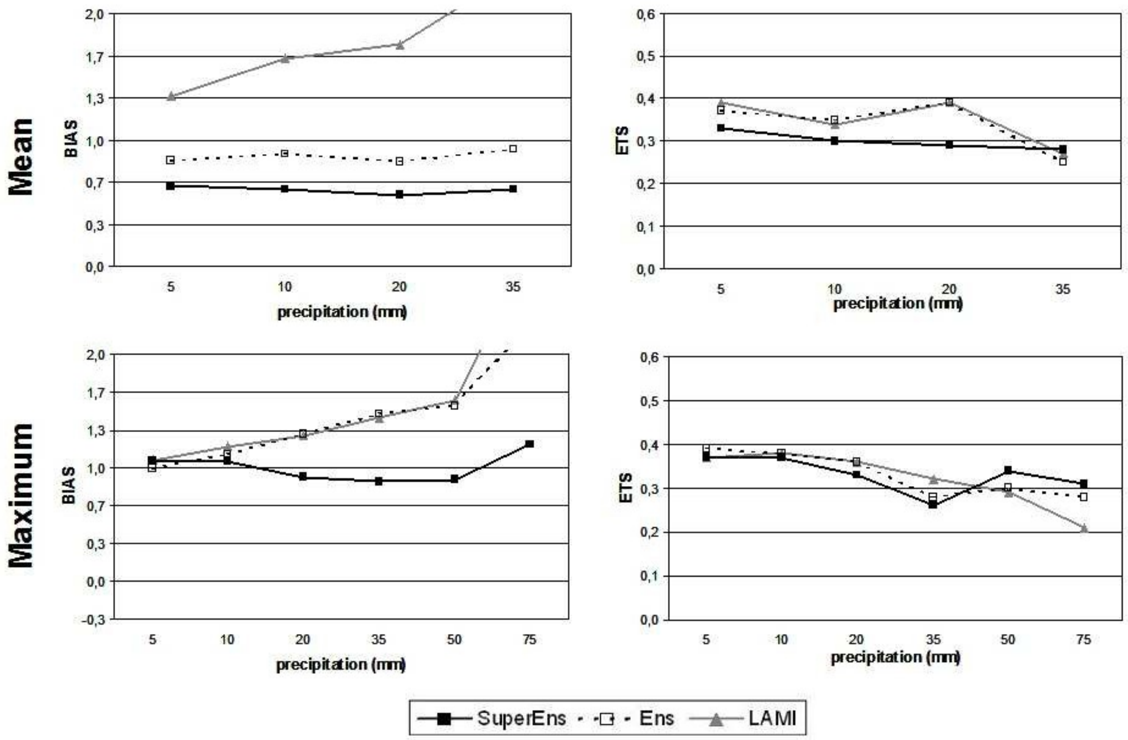

Figure 5: Mean values (upper panels) and maximum values (lower panels) of precipitation in 24h (from +36 to +60) for Superensemble output (black continuous line), Ensemble output (black dotted line)and LAMI output (grey continuous line); BIAS (left panels) and ETS (right panels).

- Study of a spread interval in the forecast of any variable by the introduction of the MultiModel for maximum, mean and minimum values over predefined areas (analogous to precipitation)
- Application to vertical profiles

Moreover, in the framework of the Interreg IIIB-Medocc project Amphore the Multimodel technique will be applied on the Italian LM, Aladin (from MeteoFrance), MM5 (from the University of Balearic Islands), Bolam (from ARPA Liguria) and ECMWF global model for the prediction of 2m temperature and total precipitation.

Acknowledgements

We wish to thank the Deutscher Wetterdienst and MeteoSwiss for providing the model outputs for this research work.

References

Krishnamurti, T. N. et al., *Science*, 285, 1548-1550, 1999

Krishnamurti, T. N. et al., *J. Climate*, 13, 4196-4216, 2000

Cane, D. and Milelli, M., *COSMO Newsletter*, No. 5, 2005

Press, et al., Numerical Recipes in Fortran, Cambridge University Press, 1992

Milelli, M., Oberto, E., Bertolotto, P., Pelosini, R., Proc. of the ECAM/EMS Annual Meeting, Rome, Italy, September, 2003

Wilks, D., Academic Press, 1995