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Hydrology and Earth System Sciences Discussions

Interactive comment on "Regional climate models downscaling in the Alpine area with Multimodel SuperEnsemble" *by* D. Cane et al.

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We thank Prof. Todini for his very accurate review. We try here to answer to his comments.

TEMPERATURES:

We already knew the Bayesian Model Averaging (BMA) approach by Raftery et al. (2003, 2005) and some of us (Cane et al, 2012) compared the results of the use of our Multimodel SuperEnsemble Dressing precipitation data versus those obtained with the BMA approach to drive an hydrological model. The paper is currently in press on NHESS and we hope it will be visible in a brief time, but of course we can provide it immediately for a deeper knowledge of our work. Unfortunately we did not know the Model Conditional Processor technique, thank you for signalling it.

We did not use the BMA technique or similar because we searched for a simple “deterministic” multi-model correction, being the major source of the error the big biases of the models. We know that temperature fields have an underlying Normal (possibly heteroscedastic) conditional probability density. As you stated, out approach assumed it implicitly (we tested it in the very begin of our work, and the PDF are normal, as expected from temperature data), but we agree that we must explicit and discuss this assumption into details and widen our introduction by introducing a comparison with the techniques you cited. We were already satisfied of the good results in the bias reduction, both on a general average (Fig. 5) and on the monthly means (Fig. 6). In fact, heteroscedasticity does not cause ordinary least squares coefficient estimates to be biased, although it can cause ordinary least squares estimates of the variance of the coefficients to be biased, possibly above or below the true population variance. We already proposed as an answer to the anonymous reviewer n. 1 (www.hydrol-earth-syst-sci-discuss.net/9/C4703/2012/) to evaluate the uncertainty of our temperature estimations. Thanks to your comment we will be very careful to include an estimation of the contribution of the different model distributions to the final error.

We confirm we calculated different weights and bias corrections for each point (and model). From our point of view, this is not a drawback but it is the main advantage of using a Multimodel SuperEnsemble technique: we are able to correct the model scenarios at the higher resolution permitted by our observation datasets. In the Piemonte data case this is a true downscaling of the scenarios, in the EOBS dataset case it is only a bias correction. The contribution of the data to the models via the Multimodel permits to correct the scenarios in a very punctual position, hence allowing for a better representation of local features such the topography of the alpine chain. You have to consider that the Multimodel bias correction and weights apply on a given point, but relate to very long time series (20 years of daily data in the test dataset, 40 years in the future scenario evaluation), then is strongly averaged. The bias reduction accounts for the major part of the error reduction, while the better representation of the monthly cycle is mainly due to the averaging effect of the different models. In both cases, anyway, the correction is spread over a long time. If we wanted to get very accurate daily values, we should apply a very short training period close to the forecast day, with a moving window as we do for weather forecasts (see for example Cane & Milelli 2006), but in this case this technique is not meaningful.

PRECIPITATION:

1) As you proposed we will describe the approach within the frame of alternative used approaches and in particular to BMA, to which the approach is closer.

2) “The second one is to avoid using in their graphs of a log-probability scale, which tends to hide the fact that over 90% of observations and of at least of two models forecasts are zeroes (while it is very strange that two of the used models do not show this characteristics). This is a very important point because one of the major problems for effectively estimating predictive precipitation conditional densities lies in the fact that “misses” and “false alarm” rates can be quite large. Given that the rate of zeroes accounts for over 90% of the cases the effect is enhanced when no precipitation occurs or when the models predict no precipitation.”

We think you are referring to Fig 4: probably we must make more explicit that this is not a general case but an example: we put in the figure four different models for a given day, with different predicted values and dressed them with the PDF related to that given value. Then it is not surprising that the model forecasting 0 mm shows a PDF almost equal to 0, while the model forecasting 16 mm has a flatter PDF. In fact, when in our dataset the first model forecasted 0 mm almost all the observations were quite close to 0, while when the second model was forecasting 16 mm the observed values ranged from 0 to 40 mm with quite significant probability.

3) “The third one is that also in the case of precipitation it is not clear if the averaged

conditional densities are derived for each pixel. This implies the use of a large number of estimated parameters (number of merged models times number of pixels)."

In this case, the PDFs were obtained over all the points of our domain, but for different precipitation values, then we have for each model a set of PDFs ranging from 0 to 300 mm. These PDFs do not depend from the point or from the season, so far we only tested the dependence with altitude in weather forecast models without obtaining significant differences, but of course we should try to differentiate, if it is worthwhile.

REFERENCES

Raftery, A. E., F. Balabdaoui, T. Gneiting, and M. Polakowski, (2003). Using Bayesian averaging to calibrate forecast ensembles, Tech. Rep. 440, Dep. of Stat., Univ. of Wash., Seattle.

Raftery, A. E., T. Gneiting, F. Balabdaoui, and M. Polakowski, (2005). Using Bayesian model averaging to calibrate forecast ensembles, Mon. Weather Rev., 133, 1155-1174.

Cane D., Ghigo S., Rabuffetti D., Milelli M., "Real-time flood forecasting coupling different postprocessing tecniques of precipitation forecast ensembles with a distributed hydrological model. The case study of may 2008 flood in western Piemonte, Italy.", Natural Hazards and Earth System Sciences, 2012, in press

Cane et al., Interactive comment on "Regional climate models downscaling in the Alpine area with Multimodel SuperEnsemble" by D. Cane et al., Hydrol. Earth Syst. Sci. Discuss., 9, C4703–C4711, 2012

Cane D., Milelli M., "Weather forecasts obtained with a Multimodel SuperEnsemble Technique in a complex orography region", Meteorologische Zeitschrift, 2006, Vol. 15, No. 2, 207-214

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 9, 9425, 2012.

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9, C4962–C4965, 2012