Atmos. Chem. Phys. Discuss., 12, C1583–C1586, 2012
www.atmos-chem-phys-discuss.net/12/C1583/2012/

Atmospheric Chemistry and Physics Discussions

Interactive comment on "Understanding and forecasting polar stratospheric variability with statistical models" *by* C. Blume and K. Matthes

C. Blume and K. Matthes

christian.blume@met.fu-berlin.de

Received and published: 17 April 2012

We thank this reviewer for very valuable comments that we tried to incorporate in the manuscript. We comment with a point-by-point response below.

1) That is a good point. We have first averaged on the polar cap at 10, 20, 30 hPa to then compute an EOF analysis from these three time series. The first PC is retained as it explains more than 90% variance. We averaged and did not use the full grid for the EOF analysis because 1) it is computationally cheaper and 2) easier to reproduce due to fewer dimensions. The average leads to only three dimensions in the EOF analysis, whereas not averaging leads to more than 5000 dimensions. The leading PCs from both methods are quasi identical (correlation > 0.98). The leading PC from the full grid explains about 2/3 of the variance. Not as much as the 1.PC from the average method

but still representative.

For this analysis, we were looking for a scalar time series (to keep computational costs low) that represents most variability in the polar middle stratosphere. The PC we use is also highly correlated to the regular NAM index in 10/20/30hPa, only reversed in sign. We could have used all three NAMs at these pressure levels. However, they are highly correlated and share so much information (see EOF analysis) that the computational overhead cannot be justified.

It is true that higher order EOFs can carry significant information. The reason we trust the NAM approach to represent most variability in the polar stratosphere is of historical nature. There have been many studies that use the NAM as a scalar index to measure stratospheric change with respect to a climatology (e.g. Baldwin and Dunkerton, 2001; Thompson, 2003; Baldwin and Thompson, 2009). We have also recently shown in Blume et al. (2012) that the first PC, as used here, can be successfully used to classify SSWs. We hope that we made this clearer now and tried to include this information in the data section.

2) Good point. We exchanged 'forecast' with 'hindcast' where appropriate.

We were not sufficiently accurate here and made this more clear. What we mean is that with the current, certainly imperfect methods and the current set of external factors, the sudden warming of 2009 cannot be forecasted. However, we think it will be extremely difficult to forecast (or better hindcast) this event statistically without using too much information from the internal dynamics (such as the NAM in 100hPa). But we would be glad to see a study in the future that contradicts this.

We also tried to make more clear from the beginning on that a priori knowledge about the external factors is required to make a reliable operational forecast.

3) This an excellent point, also raised by the other reviewer. Unfortunately, the model response does change when altering the model setting. We know from our experience

that, for instance, one single neuron more or less can make a difference in the quality of a neural network response. Other methods, such as SVR, are less sensitive with respect to the model setting but also perform less reliable for this application.

Selecting an optimal set of factors from a larger starting set is, in principle, a very interesting task. In this work, however, we wanted to focus on selecting an optimal model architecture (set of tuning parameters) while having a fixed set of external factors. Trying to optimize the set of external factors plus the model architecture is computationally very expensive as it entails computing an optimal architecture for EACH set of external factors. Of course, one could simply hold the model setting constant and then compute information criteria (such as AIC) or cross-validation for each set of factors. The problem is that this would not necessarily tell us something about the importance of the factors in general but only for this specific model setting.

4) We added another section on how the actual winter variability 2011/12 looked like and addressed the skill of our forecast.

References

Baldwin, M. and Dunkerton, T.: Stratospheric harbingers of anomalous Weather Regimes, Science, 294, 581–584, 2001.

Baldwin, M. and Thompson, D. W. J.: A critical comparison of stratosphere-troposphere coupling indices, Q. J. Roy. Meteor. Soc., 135, 1661–1672, 2009.

Blume, C., Matthes, K., and Horenko, I.: Supervised learning approaches to classify sudden stratospheric warming events, J. Atmos. Sci., in press, doi: 10.1175/JAS-D-11-0194.1, 2012.

Deser, C., M. A. Alexander, S.-P. Xie, and A. S. Phillips, 2010: Sea Surface Temperature Variability: Patterns and Mechanisms. Ann. Rev. Mar. Sci., 2, 115–143.

Martius, O., Polvani, L. M., and Davies, H. C.: Blocking precursors to stratospheric sudden warming events, Geophys. Res. Lett., 36, L14806, 2009.

Thompson, D. W. J., 2003: Stratospheric connection to northern hemisphere wintertime weather: Implications for prediction. *J. Climate*, **15**, 1421–1428.

Interactive comment on Atmos. Chem. Phys. Discuss., 12, 5659, 2012.