ACP-2013-542

Analyzing time varying trends in stratospheric ozone time series using state space approach by M. Laine et al.

Answers to referee comments, Referee #2

We thank both anonymous Referees for constructive commentary on our manuscript. We hope that we have successfully addressed all the relevant comments and suggestions.

As both Referees were inclined towards a major revision of the manuscript, and many of the concerns were about the presentation, we are writing the answers with the new revision in mind. First, we give a general overview of the changes. Then, we detail answers to the specific questions by the Referee.

First of all, we have simplified the text with respect to computational details on estimating the model parameters. We removed some of the technical details related to statistical computations from Section 2, especially subsections 2.3 and 2.4 for model parameter estimation and Markov chain Monte Carlo methods. A short description of the statistical calculation needed for DLM analysis is given in new Appendix A. Also, we moved the first five paragraphs of Section 3 to Section 2 as suggested by Reviewer #1. For the computational details, and for those interested in using or implementing the method we provide the full Matlab source code. We have expanded the web page that contains the computer code. We have included a dynamic linear model tutorial page that provides more details about the statistical theory and computation. This page or a pdf version of it could be included as supplementary material, also (http://helios.fmi.fi/~lainema/dlm/dlmtut.html).

The work on this paper has been done concurrently with the companion paper [Kyrölä], and some of the modelling decisions made for the companion paper have been reflected on the DLM approach. In particular, we decided to includes autoregressive (AR) residual autocorrelation component in the model, also. Again, we see improvement in the dynamic linear model (DLM) approach over the multiple linear regression (MLR) approach, where an iterative procedure must be used and the uncertainty related to plug-in parameter values is not considered. In DLM, the AR coefficients and the innovation variance can be both estimated and accounted together with all the other model unknowns.

We have included ENSO proxy series by using the MEI index from NOAA, as suggested by Referee #1. We now utilise four proxy variables: Solar 10.7 cm radio flux, QBO 30 mb and 50 mb zonal wind indeces, and MEI. For simplicity and for overall consistency, all the proxies are used in every fit even tough not all of them are known to affect the ozone variability in all geographical regions.

Also, there has been some re-processing of the data compared to that used in the first version of the manuscript. The same data sets that are used in [Kyrölä] are used here.

After some thoughts, we decided to alter the mathematical notation in such a way that we use variable x for model state, instead of θ. This might make the exposition more familiar to people working in geophysics. As a result of the shortening, some of the statistical notations were not needed any more.

The title with a spelling change and an added definite article is now: *Analysing time varying trends in stratospheric ozone time series using the state space approach.*

Referee #2

We thank the Referee for constructive criticism, suggestions, and editorial corrections.

> Overall I feel that the presentation is not clear in important subsections describing the new methodology.

We agree that we did try to include too much technical details on computations. These we important for us when we implemented the method, on the cost on concentrating on the actual subject matter. We have tried to make the presentation more readable by taking account the comments by the Referees and by making some editorial changes already explained in the beginning of this answer. The computer code and technical details on implementation and on statistical analyses are available as supplementary material for those interested.

> The stated year 1997 is actually not consistent with the presented evidence, e.g. in Fig. 4, which usually indicates the change from negative to positive trends around 1999 (1998 to 2002).

We agree, and in the revised version we have changed the text to be more accurate with respect to the actual modelling results.

> There is very little contrasting the new state space approach to the standard multiple linear regression.

The referee is correct, that we did not emphasize the advantages in the first version. We see main advantages of DLM over classical multiple linear regression approach as the following;

- The state space representation allows hierarchical statistical analysis of uncertainties. We can separate observation uncertainty from the process uncertainty.
- Dynamic regression allows non-stationarity in the background distributions, the temporal changes in model states can be estimated from the data and these changes can be restricted by prior specifications, when needed.
- DLM approach allows for both qualitative and quantitative trend analysis and analysis statistical significance of the effects.

In the revision, we have added more comparisons agains the linear regression approach. One of our motivations was to build a simple enough dynamic model that would have the same properties as the piecewise linear model in the companion article. This would then either validate the static linear approach or show that it is not appropriate. The conclusion is somewhere in between. The linear regression model provided quantitatively similar results on the sizes of trend changes, although the probabilistic statements about the significance of the results might not agree so well. Especially, using just one fixed change point for all altitudes and latitudes is now questioned in the revised manuscript.

Further major points

> A major point of the DLM analysis seems to be the arbitrary (?) selection of the model error covariance W.

In any modelling situation, we need both qualitative and quantitative decision. In classical regression, we need to choose wether to include some covariate (e.g. proxy variable) in the model or not, whether to use some transformation before calculations, etc. In DLM, these qualitative decisions include the choice of components of the model and how to formulate the model error matrix W. For example, setting the “level” standard deviation to zero makes it possible to estimate and control the smoothness of the background level by the “trend” standard deviation σ_{trend} as done in the manuscript. We hope that we have explained this more clearly now.

> Do I understand correctly, that the model error covariances related to QBO and solar cycle in W are set to zero?

The Referee is correct. These were set to zero for simplicity. Test runs with positive proxy model errors did not improve the fits. This was one of the many modelling simplifications that we did. However, we are still quite happy with our model.

In the text, we now explicitly note the difference between SAGE II and GOMOS observations in the southmost and northmost zonal bands. However, we do not go into detail in finding explanations to this discrepancy, but refer to a recent article by Toohey et al. One strong point in the DLM approach is that we can allow non-stationary changes, for example in seasonality. Again, this aspect is not fully developed in the manuscript, and is left to a further study.

> Eqs. 8 to 13 should be explained/motivated better.

These equations are not included in the revised version, anymore.

We do use some statistical and computational terminology (e.g. Gibbs sampling) that is probably not familiar to the readers of ACP. We have tried to make the text more accessible, but unfortunately some of the statistical jargon is necessary, still.

> An important contributor to the decadal trends investigated by the authors is the way the solar cycle is handled.

We do use the F10.7 radio flux index to model the solar effect. For these proxies we still refer to companion article, where they are explained in more detail. A new feature in the current manuscript is the use of the MEI ENSO proxy. Also, we now include an extra autoregressive model component that allows autocorrelation in the residuals after the other model components. This had the effect of “explaining” most of the non modelled variabilities left.

References

[Toohey] Toohey, M., et al.: Characterizing sampling biases in the trace gas climatologies of the SPARC Data Initiative, Journal of Geophysical Research: Atmospheres, 118, 1–16, doi:10.1002/jgrd.50874, 2013.