We thank Referee 2 for the time spent in this revision, the suggestions and feedbacks.

In the following our answers are in 'blue' and the referee comments in 'black'

General Comments:

This paper demonstrates an application of the Singular Value Decomposition (SVD) statistical technique to correlate cloud properties observed in satellite data against climate indices.

SVD is commonly-used in the atmospheric sciences as a method to understand the spatio-temporal variability of geophysical data. The authors effectively demonstrate how one can use SVD to compare the modes of variability in a long observational satellite record against climate indices.

Because the authors both a. emphasize the applicability of the technique to any gridded satellite dataset (not just atmospheric fields), and b. position this methodology as primarily novel for climate model validation, this paper may be better suited for a journal focused more generally on climate rather than atmospheric measurements.

While SVD is an established methodology in atmospheric sciences and its novel application here to multiple satellite time-series serves to indicate future potential of this approach for comparison of observations with climate models, the paper does not report new findings on climate per se. We therefore consider AMT to be appropriate rather than climate journals.

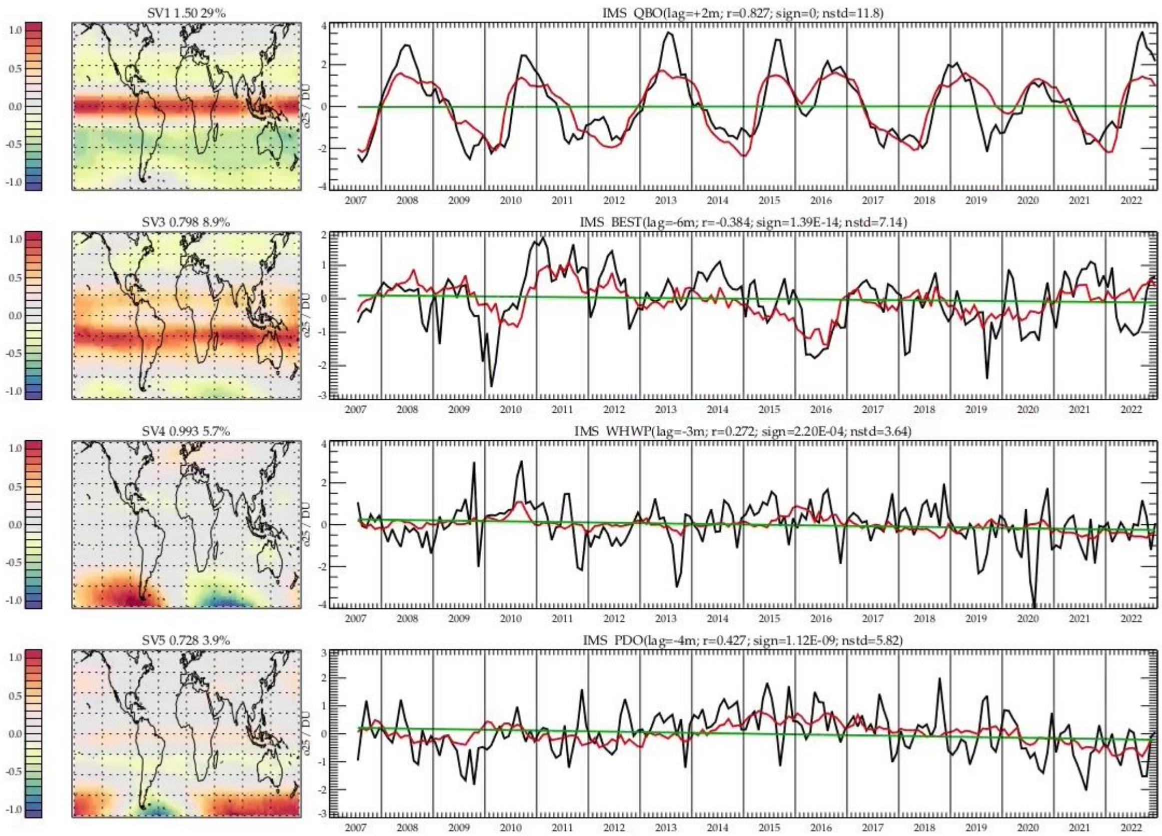
That said, I think it would be appropriate for publication in Atmospheric Measurement Techniques with revisions addressing the specific comments below.

Specific Comments:

1. The study is framed as a technique that can be effectively generalized to any gridded dataset, but only provides examples of cloud observations. An additional example would be helpful to support the generalization.

   We have also applied the SVD technique described in the paper to a number of other atmospheric parameters in the IMS dataset.

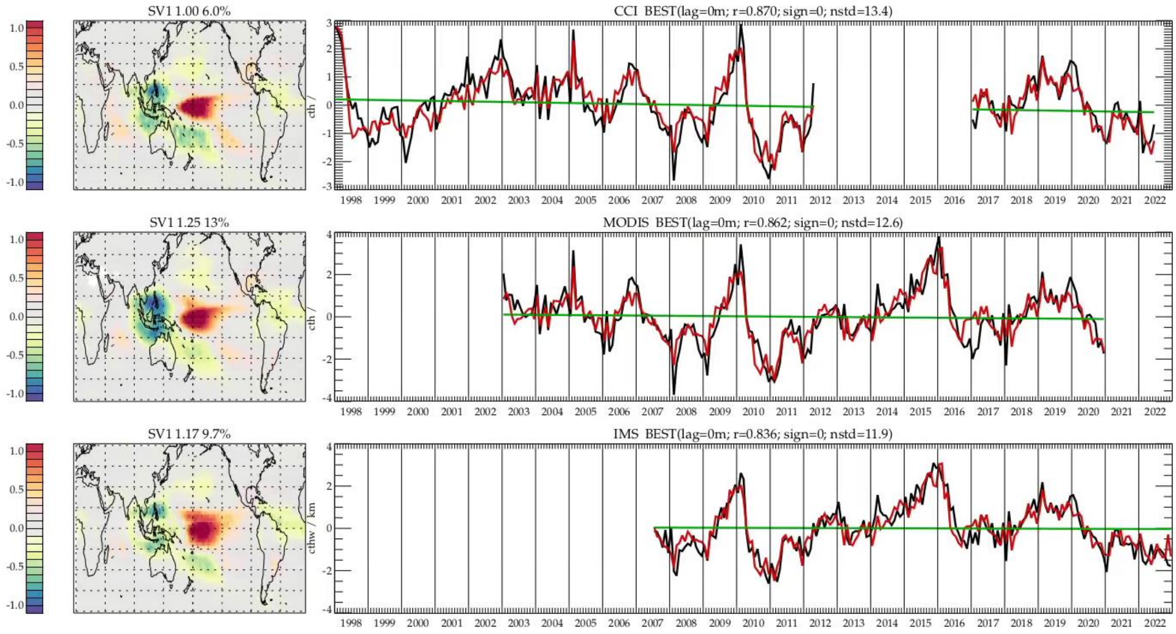
   We illustrate here one such example for stratospheric ozone (between 24-27km) where the temporal weights, associate with the first SV, are fitted with QBO index. Analyses of atmospheric parameters other than cloud are intended in future publications.

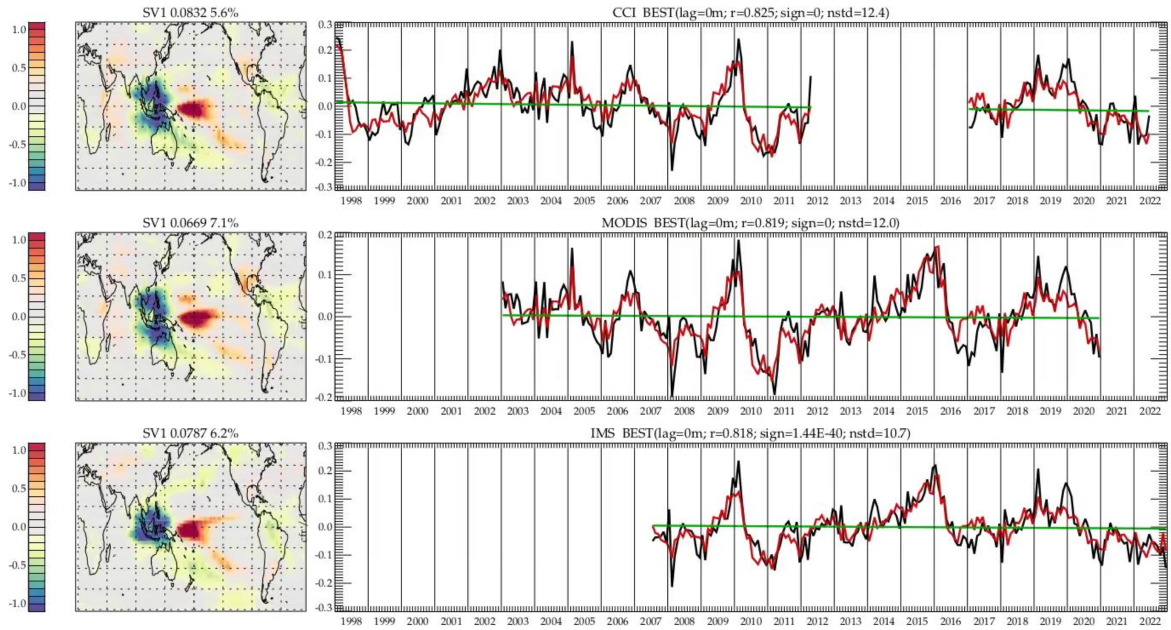


Maps on the left side are the first four spatial SVs for ozone between 24-27km from IMS the dataset; the legend above each map present: the number of singular vector (SV1), the standard deviation of the temporal weights, the percent of variance associate with the singular vector. Plots on the right show the associated time series of the temporal weights (black line) and the fits with climate indices in red, while the green lines represents the offset and the slope obtained in the fitting. The legend above each plot shows the best fitting climate index together with lag, correlation coefficient (r), the significance and number of standard deviations by which the distribution deviates from the from the null-hypothesis.

2. The authors report strong correlations in the results but omit statistical significance.

Statistical significances 'sign' are now added in the time series plots titles, together with 'nstd' the number of standard deviations from the expected value from the null-hypothesis . Both values are obtained with the IDL r_correlate routine (*Numerical Recipes, The Art of Scientific Computing (Second Edition)*, Cambridge University Press (ISBN 0-521-43108-5).





These plots are the new versions of figs 4 and 5 of the paper, with the addition of significances (sign) and numbers of standard deviations (nstd) from the expected value from the null-hypothesis in the labels together with lag and correlation.

For CFC and CTH the significance is less than 1.5x 10^{-40} and 'nstd' is greater than 10 for all the 3 datasets.

3. Spend time exploring what the authors themselves state as one of the novel aspects of using this technique: understanding the underlying causes of the variability.

The intention of the paper is to describe the methodology and point towards its potential for such future analyses. Although we agree with the Referee that inclusion would strengthen the paper, extensive further work would be entailed to incorporate climate modelling which we view to be out of scope and not strictly necessary for the paper to serve its intended purpose.

4. Did the authors try any other decomposition methods? How does using SVD compare to other methods such as using EOFs or other approaches? A clear statement for why this technique was chosen and what its limitations are should be included.

SVD is the procedure used to derive temporal weights for spatial EOFs through the decomposition of a matrix. There is a lot of different notation used in the literature to describe what, in the end, provide very similar ways for decomposing a matrix into orthonormal basis vectors. Please see also the introduction to our answer Referee 1.

We decompose our matrices in space and time patterns that represent the most variance of the dataset. We can add a paragraph explaining this in the paper.

One additional step in this analysis which we may investigate in the future is the rotation of singular vectors in order to minimise the correlation between the different principle basis vectors, but this has not been attempted in the presented analysis and is beyond the scope of this paper.

Technical Corrections:

- Paragraph 45: typo: de-seansonalised
- Paragraph 145: typo: de-sesonalized
- Paragraph 185: type: series off time-lags
- Figs 3, 4, 5: consider centering the maps on the Pacific Ocean instead of the Atlantic to better show the ENSO correlation

Maps are now centred in the Pacific. Our thanks to Ref 2 for these suggestions!