Responses to Anonymous Referee #1

The authors thank the anonymous referee for the detailed review of the manuscript, for the meticulous pointing out of inconsistencies between tables and figures, as well as for all their comments and suggestions allowing a clear improvement of the paper.

<u>Responses to specific comments:</u>

This manuscript is well written and is an important contribution for more comprehensive trend analysis of atmospheric composition data. The work is robust with very good analysis and discussions of the different effects on the trend results using various prewhitening methods in addition to MK without prewhitening. It is very well appreciated the clear guidelines for choosing methods and approaches for assessing long term trends.
I will recommend the paper to be published as it is. I have only some small comments/questions which you may consider:

- Line 125. why is negative autocorrelation rare in atmospheric processes? Maybe explain a bit more the reasons and differences between negative and positive autocorrelation and/or give a reference.

    A negative autocorrelation changes the direction of the influence. In atmospheric processes, persistence is responsible for autocorrelation rather than “reaction” or “rebound” mechanisms. Persistence embodies the fact that atmospheric variables tend to change relatively slowly, and when changes occur, the autocorrelation tends to decrease toward zero rather than reach negative values. The latter would be the sign of some kind of rebound mechanisms where atmospheric parameters having particular values, for instance above average, would result in latter values being more likely below average. We cannot think of such examples in atmospheric processes, except for processes strongly correlated with natural cycles such as the circadian cycle. For instance, the difference of solar irradiance to the daily solar irradiance average would obviously exhibit a negative autocorrelation at 12h time lag, but it is just due to the high correlation of the solar irradiance with the solar zenith angle. Negative autocorrelation is a violation of independence but it is generally less worrisome because it appears less frequently than positive autocorrelation and it produces greater precision in the average than an independent series would.

- Line 272. Why is aerosol number concentration behaving different than the other components regarding the effect of granularity, i.e. the ss remain until the one-year aggregation?

    The number concentration exhibits a less pronounced seasonal cycle than the other parameters, because its seasonal cycle has variable response to the temperature. For example, at JFJ during summer, higher temperatures lead to a larger influence of the planetary boundary layer and higher production/transport of primary aerosol. During winter, the colder temperatures can also lead to increase formation of new particles (secondary particles). The 3-month averaging corresponds approximately to a season, so that the small seasonal cycle is not able to mask the positive autocorrelation.

- Fig. 8 and paragraph 429-436. Here you compare the difference in granularity of monthly and seasonal data. Why use different data (scattering contra absorption)? To illustrate the difference in granularity it would have been more logic to use same dataset?

  The comparison between months and meteorological seasons would have been easiest with the same dataset. The authors however chose two different variables to show that the effect of the time granularities on the variability of the slope and the size of the confidence limits is similar for two different variables. This was an option and we try to give examples from all the time series along the paper to enhance that the results do not only concern a peculiar case of atmospheric parameter. The opposite choice was made for Fig. 10.

- Fig10 and paragraph 493-509. Not sure if I understand how the data selection has been done. Do all the periods contain the whole time series? I.e 10 years contain 3x10years data set if the time series is totally 30 years. I assume you somehow taken into account that the actual trend for the whole period will effect the results. Not homogeneous trend over a 30 year period. But why is it then so few data points for the 4 year trend, I,e N=360 and 120 for monthly and seasonal trends?

  For Fig. 10, only the period ending in 2018 with different lengths (4 years to 30 years) is presented, so that the 10 years correspond to the trend between 2009 and 2018 and contains only one 10 y data. If all potential x years trends were used, the mean of the numerous 4 y trends would potentially mask the increase of the absolute values of the slope and the larger difference between individual time segmentations for shorter period length.
  Since only one period of 4 years is used, the number of data in the time series is N=360 (=4 years*3 months*30 days) for a time segmentation into four meteorological seasons and whereas monthly trends for the same time series are computed with N=120 (=4 years*1 month*30 days) for monthly trends.
  The figure caption was modified in order to clarify the data selection: "*Figure 10: VCTFPW slopes and CL as a function of various period lengths ending in 2018 for the daily aerosol absorption coefficient for the division of the time series into a) 12 months and b) four meteorological seasons. Colors represent time period lengths and bigger symbols represent ss trends.*"

- The new algorithm applied. Is that made available? The scheme sketched in Figure 1 is not very easy to use for others to apply the method. It is recommended that the authors upload the scripts for others to use and adopt if possible.

The new algorithm in Matlab, Python and R will be published in github and the doi will be given in the revised version of the manuscript. We have to finish to documentation of the code before releasing the doi in the next days. . This will happen soon (in conjunction with paper publication). The following section on code availability was added to the manuscript:" *We provide, in dedicated Github repositories hosted within the "mannkendall" organization (https://github.com/mannkendall), a Matlab (DOI: ; https://github.com/mannkendall/Matlab), Python (DOI: ; https://github.com/mannkendall/Python), and R (DOI: ; https://github.com/mannkendall/R) implementation of the algorithm presented in Sec. XX. In particular, these open-source codes, distributed under the BSD 3-Clause License, allow to compute the MK test and the Sen's slope with various prewhitening methods (3PW (default), PW, TFPW-Y, TFPW-WS and VCTFPW). The time granularity, period and temporal segmentation are chosen by the users during the preparation of the datasets. The level of the confidence limits for the MK test, the lag-1 autocorrelation, and the homogeneity between the temporal aggregation can also be defined by the user. The probability for the statistical significance, the statistical significance at the desired confidence level, the Sen's slope and its confidence limits are returned as results. A set a common tests is used to ensure that both the Python and R implementations are consistent with the (original) Matlab implementation of the code."*