Anonymous Referee #1

The manuscript presents a method to determine trends in NO_x emission over China. The authors apply a methodology, introduced by the same authors in a previous paper, to determine NO_x emission from satellite-based observations. The approach is particularly valuable as it is independent of chemical transport models and their uncertainty/assumptions. The results confirm the observed decline in the Chinese NO_x emissions after year 2011. I recommend the publication after addressing the following comments:

Response: We thank Referee #1 for the encouraging comments. All comments and suggestions have been considered carefully and well addressed below.

Specific comments:

1. Several recent studies have shown decreasing NO_x levels in China from satellite data. Can you evaluate how your trends compare with these existing results? This is mentioned in the introduction but it could be discussed in the conclusion too or where you present your numerical results? The results are derived at different resolutions I guess, but are you able to evaluate how consistent they are? For example, in this manuscript (Recent reduction in NO_x emissions over China: synthesis of satellite observations and emission inventories doi:10.1088/1748-9326/11/11/114002) you analyzed the NO_2 peak year: how do the peak year for the provinces agrees you're your latest city level results? Answering this question you should also be able to stress the added value of this work, compared to existing results.

Response: We thank for the suggestion and add the discussion of the comparison with other existing studies to the conclusion, as follows:

"The average emission trend fitted by this study is consistent with the previous findings, which showed that OMI NO_2 levels peaked in 2011 over China (Krotkov et al., 2016; Duncan et al., 2016) and NO_x emissions from satellite data assimilation peaked in 2011/2012 (Miyazaki et al., 2017; van der A et al., 2017; Souri et al., 2017) respectively. Additionally, the fitted emission peaks for individual cities showed reasonable agreement with the peaks of OMI NO_2 levels at provincial level (Liu et al., 2016b). Half of the investigated cities reached simultaneous emission peaks with the corresponding provinces. For the another half, the majority (over 70%) reached emission peaks prior to the average provincial timeline, which are most likely caused by emission control policies implemented in the city ahead of the provincial schedule, such as the previously discussed new vehicle emission standards in Guangzhou."

2. Section 2.1 and later: You talk about "valid lifetime" or "satisfactory result" for the fitting: could you remind the reader how you define a satisfactory fitting? Especially for the power plants (only 7 good ones) can you explain the reasons for the unsuccessful fits?

Response: We followed the criteria defined in Liu et al. (2016a) to assure a good fit performance (i.e., satisfactory fitting). We add the description for the criteria in Section 2.1, as follows:

“The fitting results with poor performance (i.e., R<0.9, lower bound of confidence interval CI <0, CI width for lifetime >10 h, CI width for the NO_2 mass >0.8×mass) were discarded, in accordance with the criteria in Sect. 2.2 of Liu et al. (2016a).”

We failed to get the satisfactory fitting results for most power plants because their signals are not strong enough to be distinguished from the surroundings, particularly for those located in/near urban areas. More than half of the power plants were discarded from the final analysis because they locate in a radius of 100 km around city centers. Others were dismissed due to the low R or unreasonable CI resulting from the low signal/background ratio. The number of power plants with valid fitting results decreases sharply when NO_2 concentrations over power plants decline because of the installation of denitration devices. The number of power plants with satisfactory results for the period of 2013-2015 is only half of that for the period of 2005-2007.

We have rephrased the sentences in Section 2.3, as follows:

“Among over 200 pre-selected cities, 48 cities (including 14 mountainous sites) were fitted with good performance (see the definition in Sect.2.1). While among over 100 pre-selected power plants, more than half were excluded from the fit procedure, because they are located in a radius of 100 km around prefecture-level city centers, on the basis of a visual inspection of satellite imagery from Google Earth. Only 7 power plants (including 3 mountainous sites) were fitted with good performance.”

3. Fig. 7 and page 8: What do you mean by market share of SCR? Share with respect to what? Could you define that?

Response: We define the market share of SCR as the percentage of unit capacity of power plants installing SCR in the total capacity of all the power plants. We replaced “market share” with “penetration”, which is more commonly used in the emission inventory community, and added the definition in the revised manuscript.

4. Fig. 8 Can you comment on why for power plants there is a sort of bias, with bottom-up emissions generally higher than your emissions? (All points are below the 1:1 line)

Response: We agree that there are certain uncertainties of the fitted emissions, which are explained in detail in Section 3.4. Emissions for mountainous sites are expected to be biased due to the bias in wind fields (Liu et al., 2016a). But we do not expect a systematic bias associated with those uncertainties for non-mountainous sites. This is confirmed by the comparison for power plants with valid fitting results for the period of 2010-2012 in the figure S1. There are differences between the fitted and bottom-up estimates, but no significant bias. It is thus probably coincidence that the fitted emissions for the four power plants (blue points in Fig. 8a & S1) that have valid fitting results for each three consecutive years from 2005 to 2015 are lower than the bottom-up estimates.

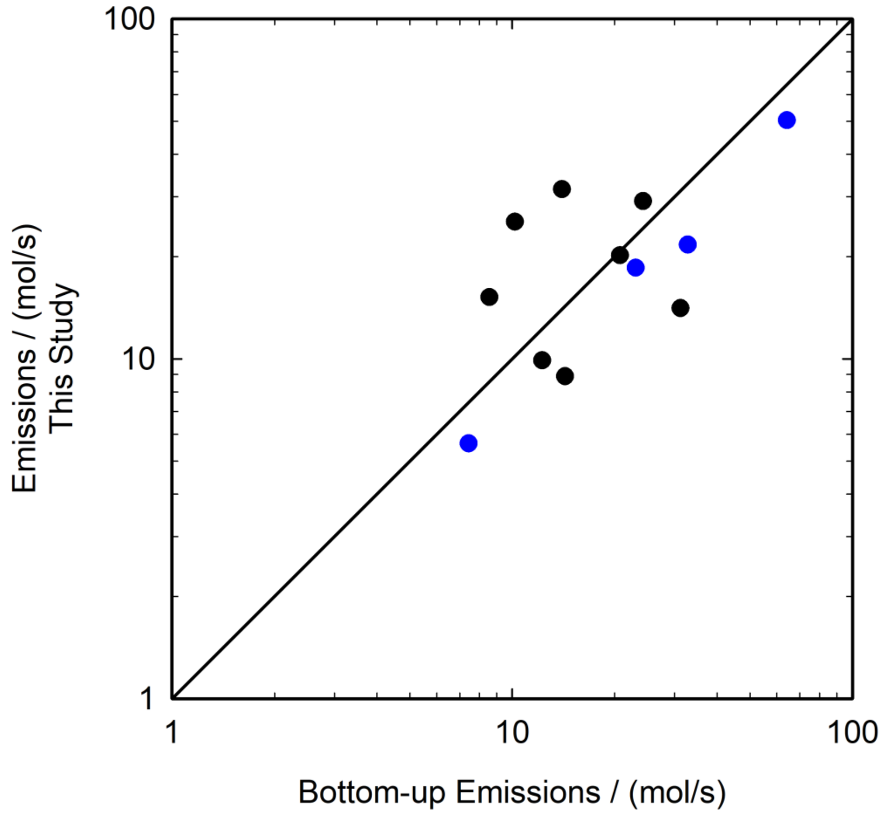

Figure S1: Scatterplots of the fitted NO_x emissions for the investigated non-mountainous power plants versus the bottom-up emission inventories (MEIC) during 2010 to 2012. The sites displayed in Fig.8a are color coded by blue.

5. Section 3.4 What kind a error/bias is due to the fact that you use summer days and clear sky data? How do you see this might affect your comparison with bottom-up inventories?

Response: Concerning the usage of summer data, we generally agree that there are monthly variations in NO_x emissions for cities and power plants in China. Emissions typically peak in December of each year because of high year-end industrial activities (Li et al., 2017). Thus, the fitted emission rates based on non-winter satellite data maybe biased compared to the annual mean rates. However, it will not affect the comparison with bottom-up inventories, because only bottom-up emissions for non-winter seasons were used for comparison (see Section 2.2).

With respect to clear sky data, we agree that the selection of cloud-free OMI NO_2 TVCDs used for fitting emissions does not represent the average level for all days, due to the accelerated photochemistry and different meteorological conditions (e.g. boundary layer height, atmospheric transport) under clear sky conditions. But still the emission estimates are appropriate, as both the NO_x lifetime and total mass derived from the NO_2 TVCDs are derived consistently, both of which reflect the values under clear sky conditions. Thus, this effect is of minor importance for this study and is not expected to bias the estimated NO_x emissions.

Technical comments

6. Figure 6 Please specify in the caption that you mean anthropogenic as bottom-up inventory, the emission you calculate by fitting are also anthropogenic, they might get confused. Also the color coding in confusing, could you use something else than redblue in b-panel, because one might thing they relate to the red-blue of panel a, while they are not.

Response: Thanks. We have specified it in the caption and changed the color to green/grey in Figure 6 in the revised manuscript.

References

Duncan, B. N., Lamsal, L. N., Thompson, A. M., Yoshida, Y., Lu, Z., Streets, D. G., Hurwitz, M. M., and Pickering, K. E.: A space-based, high-resolution view of notable changes in urban NO_x pollution around the world (2005–2014), J. Geophys. Res., 121, 976–996, doi: 10.1002/2015jd024121, 2016.

Krotkov, N. A., McLinden, C. A., Li, C., Lamsal, L. N., Celarier, E. A., Marchenko, S. V., Swartz, W. H., Bucsela, E. J., Joiner, J., Duncan, B. N., Boersma, K. F., Veefkind, J. P., Levelt, P. F., Fioletov, V. E., Dickerson, R. R., He, H., Lu, Z., and Streets, D. G.: Aura OMI observations of regional SO_2 and NO_2 pollution changes from 2005 to 2015, Atmos. Chem. Phys., 16, 4605–4629, doi: 10.5194/acp-16-4605-2016, 2016.

Li, M., Zhang, Q., Kurokawa, J. I., Woo, J. H., He, K., Lu, Z., Ohara, T., Song, Y., Streets, D. G., Carmichael, G. R., Cheng, Y., Hong, C., Huo, H., Jiang, X., Kang, S., Liu, F., Su, H., and Zheng, B.: MIX: a mosaic Asian anthropogenic emission inventory under the international collaboration framework of the MICS-Asia and HTAP, Atmos. Chem. Phys., 17, 935–963, doi: 10.5194/acp-17-935-2017, 2017.

Liu, F., Beirle, S., Zhang, Q., Dörner, S., He, K., and Wagner, T.: NO_x lifetimes and emissions of cities and power plants in polluted background estimated by satellite observations, Atmos. Chem. Phys., 16, 5283–5298, doi: 10.5194/acp-16-5283-2016, 2016a.

Liu, F., Zhang, Q., Ronald, J. van der A., Zheng, B., Tong, D., Yan, L., Zheng, Y., and He, K.: Recent reduction in NO_x emissions over China: synthesis of satellite observations and emission inventories, Environmental Research Letters, 11, 114002, 2016b.

Miyazaki, K., Eskes, H., Sudo, K., Boersma, K. F., Bowman, K., and Kanaya, Y.: Decadal changes in global surface NO_x emissions from multi-constituent satellite data assimilation, Atmos. Chem. Phys., 17, 807–837, doi: 10.5194/acp-17-807-2017, 2017.

Souri, A. H., Choi, Y., Jeon, W., Woo, J.-H., Zhang, Q., and Kurokawa, J.-i.: Remote sensing evidence of decadal changes in major tropospheric ozone precursors over East Asia, J. Geophys. Res., 122, 2474–2492, doi: 10.1002/2016JD025663, 2017.

van der A, R. J., Mijling, B., Ding, J., Koukouli, M. E., Liu, F., Li, Q., Mao, H., and Theys, N.: Cleaning up the air: effectiveness of air quality policy for SO_2 and NO_x emissions in China, Atmos. Chem. Phys., 17, 1775–1789, doi: 10.5194/acp-17-1775-2017, 2017.