Authors' response to the review comments #1

Title: OMI NO_2 column densities over North American urban cities: The effect of satellite footprint resolution

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First of all, the authors express their appreciation to the two reviewers and the editor. We believe that their comments are very productive and substantially contributed to improving the manuscript. We offer point-by-point responses to the issues and comments addressed by reviewers. Reviews' comments are shown in italics.

"The manuscript addresses an innovative way of enhancing the spatial resolution of OMI NO2 columns for studies of the urban plumes in the US by adopting the spatial distributions of the NO2 columns from the CMAQ model. Another important point the manuscript emphasizes is careful ways of processing the satellite retrievals and model results for quantitative comparisons that were often neglected. The IDL-based routine developed in this study (Figure 3) will be useful for many users of OMI retrievals. I suggest the authors to share this routine with potential users through the GMD journal."

We thank the reviewer. We will include the IDL routines of "conservative spatial regridding" and "downscaling" of OMI and CMAQ NO_2 VCDs in the supplementary materials with brief descriptions. Users will be able to download and test sample codes, and further modify the codes for their own interest.

"* Page 8457, Figure 4: An interpolation routine should be applied to make plots in Figure 4 from Figure 3. I suggest the authors to explain this part. It would be helpful if the names of cities in the text are given on the map."

Thanks for the comment. We have included city names on the NO_2 VCD spatial plots.

In order to convert irregular-shaped satellite data into model grid, we use a conservative spatial regridding technique based on polygon clipping algorithms instead of traditional interpolation method. We have included descriptions of the method below. More detailed descriptions can be found in Kim et al. (2013).

Regridding of model output or satellite data with different map projection settings is very important for inter-comparisons of modeled results and/or satellite outputs. Spatial regridding is a commonly performed procedure in satellite data processing. It converts a data set between different map projections and resolutions. Among numerous spatial regridding methods, interpolation and pixel aggregation are two of the most common methods. Interpolation is preferred when the target domain resolution is finer than the raw data pixels, on the other hand, pixel aggregation is the preferred way to average all the pixels inside each domain cell when the grid cell size is bigger than the raw data pixel size. Despite their popularity, both methodologies for interpolation and aggregation have numerical limitation especially in dealing with fine resolution data and/or where conservation of measured quantities is required. More mathematically complete methods for spatial regridding is to handle the geospatial data (e.g. satellite data) as "polygon with area" instead of "(dimensionless) pixels". It requires the calculation of fractional areas of overlapping polygons between raw data pixels and modeling grid cells.

The IDL-based Geospatial Data Processor can provide exact fractions using the polygon clipping algorithm, and this information can be used for lossless (zero-loss) spatial regridding in the conservative remapping method. This method reconstructs raw data pixels (e.g. satellite data) into target domain grid cells, by calculating fractional weighting of each overlapping portions between data pixels and domain grid cells. If the raw pixel data is in density units (e.g. concentration) we can calculate the overlapping fractions for each data pixel and grid cell. The grid cell concentration can be calculated as a weighted average of data pixels and fractions. (Fig. R1)

$$f_{i,j} = \frac{Area(P_i \cap C_j)}{Area(C_j)}$$

$$C_j = \frac{\sum P_i \cdot f_{i,j}}{\sum f_{i,j}}$$

where i and j are indices of data pixel, P, and grid cells, C. $f_{i,j}$ is the overlapping fractions, and $\sum f_{i,j}$=1 if no missing pixels are involved in grid cell C_j.

If the satellite pixel data is in mass units, equations for the conservative remapping are slightly different. We need to calculate fractions of overlapped area to raw data pixel size, instead of grid cell size.

$$g_{i,j} = \frac{Area(P_i \cap C_j)}{Area(P_j)}$$

$$C_j = \sum P_i \cdot g_{i,j}$$

where $g_{i,j}$ is the fraction of overlapped area to the data pixel size.

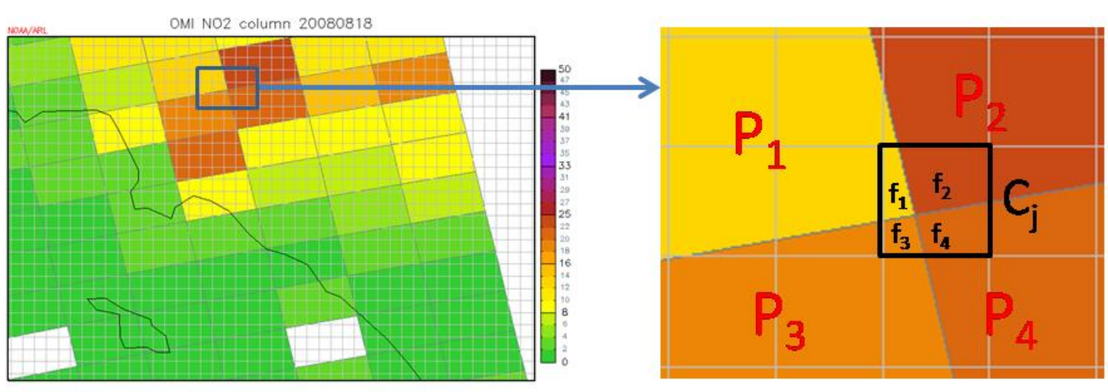

Figure R1. Example of "Conservative spatial regridding" method using variable-pixel linear reconstruction algorithm

"* Page 8459, line 17-19: I think the emission problems are large and that certainly affect the spatial distribution of the plumes. In addition to wind errors, the impact of emission inventory errors from various sectors can be large (see Figures 8 and 10 in the manuscript). Potential problems stemming from this error source need to be written clearly. And which emission inventory was utilized for the model simulations? This may determine the limit of the methodology developed in this study."

Thanks for the comment. We agree that emission information plays a crucial role in the technique described in this study. We have included the descriptions for emission used in the model run. Detailed information on the emission data is also described in (Pan et al., 2014).

We have clarified the limitations of current downscaling technique. Further investigations on the technique using different emission data, different meteorology and/or chemistry model are being conducted, but the results are not included in the current draft yet.

"* Page 8460: I think it is best to show the comparison results for other days (May 7, May 16 etc.) and discuss the causes for agreement or disagreement. Was P3 data averaged for comparison with OMI data (at a model resolution)? Was averaging kernel applied to P3 data?"

Thanks for the comment. Figure 6 already includes measurements from all three days (May 4th ,7th & 16th 2010), and we have clarified it. Spatial plots of the original and adjusted OMI NO_2 VCDs for all days are shown in the Figure R2. Clear enhancements are shown in May 4th & 7th when P3 measurements show strong spatial gradient, and the impact is weaker on May 16th 2010 when its spatial gradient is smoother (Sunday, less traffic due to weekend effect). Current P3 circles are averaged of OMI pixel's coverage since they were initially prepared for the direct comparison between OMI and P3 NO_2 VCDs (Judd et al., in preparation)

Since observations (e.g. OMI and P3) are column-integrated 2 dimensional data and model has 3 dimensional structures, we applied the averaging kernel information to 3 dimensional model structure and converted the model NO_2 concentration into column data (2 dimensional) format (e.g. NO_2 VCD) for the comparison with observations. OMI and P3 are compared directly.

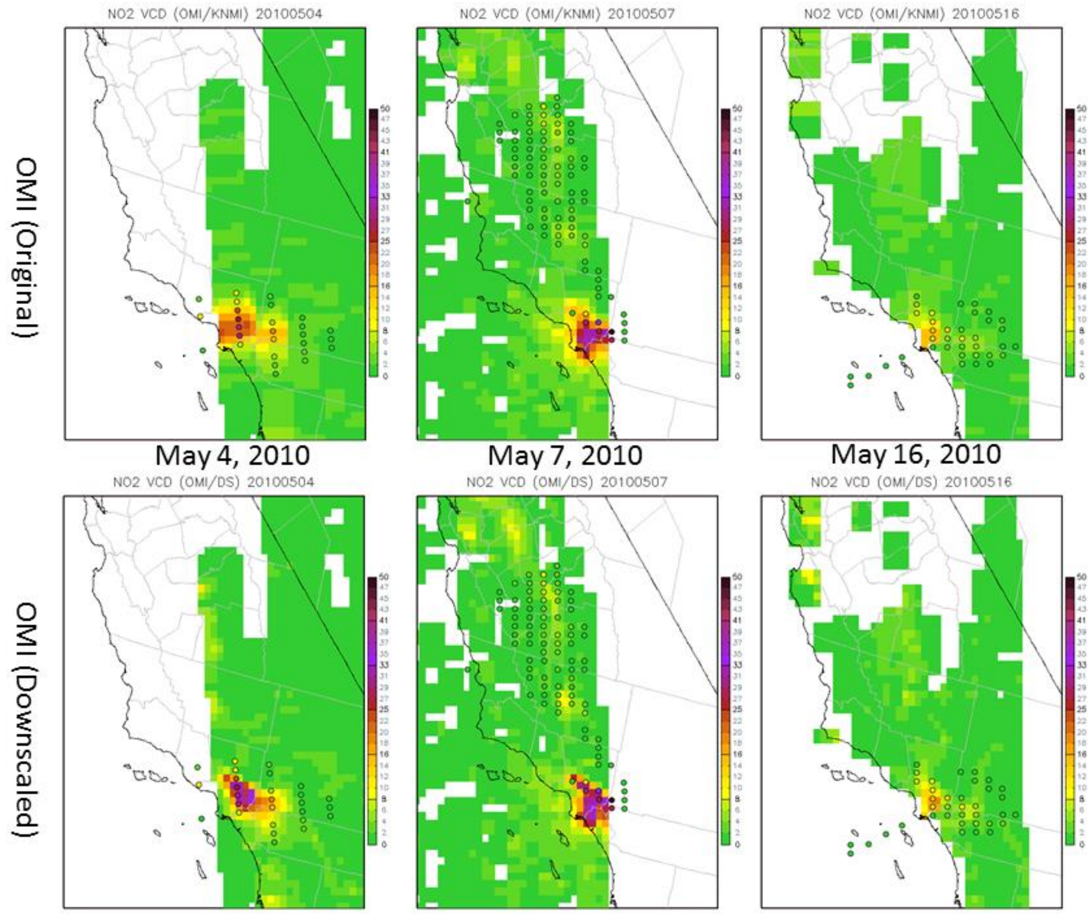

Figure R2. Comparisons of spatial distributions of OMI and P3 NO2 VCDs for May 4th, 7th, & 15th, 2010.

"* Page 8462: For Figure 9, the period of analysis needs to be given in the main text. The results in this manuscript are based on a short-term analysis. Please mention this clearly in the many plots and analyses in the manuscript. Explain the differences in Figure 9d. Which points show large discrepancies between the OMI data and the model results in Figure 9d?"

Thanks for the comment. We have included that Figure 9 is for a one month period of September 2013. In addition, we like to note that we have tested all months in 2013 & 2014 and results are mostly consistent.

Since this study mainly focuses on the uncertainty of satellite to model comparison due to spatial resolution differences between satellite footprint pixels and model grid cells, we did not emphasize on the implication of the comparison. However, we notice that the comparison in this draft shows general agreement with previously research. For urban locations (e.g. higher NO_2 VCD values), the trend of continuous NO_x emissions reduction, especially from the mobile sources, might be the main reason of the overestimated CMAQ NO_2 VCDs. On the other hand, the underestimation of CMAQ NO_2 VCDs in the rural areas (e.g. lower NO_2 VCD points) might be attributed to the lack of natural NO_x emission sources in the current modeling system, especially the soil NO_x emissions. It also should be noted the rural NO_2

VCD level is usually near the lower boundary of detection limit from space-borne instrument, so it has relatively high uncertainty in the rural area.

"* Page 8463, line 5-6: it is not clear that the recent shale-gas development is a significant source of NOx. One even assumes zero emission from this source. I could not find a reference (Chang et al., 2015) in the reference section."

Thanks for the comment. Although the emission from recent shale-gas development is a very important topic, we agree that there is no clear consensus on detailed information on those emissions yet, and they are beyond the scope of this study. We have clarified it in the main context.

"* Figure 10: Discuss causes for the differences between the OMI data and the model results."

Thanks for the comment. We have included additional discussions on the causes of discrepancies between OMI and modeled NO2 VCDs. As already mentioned for the comment on Figure 9, the reduction trend of urban NOx emission (e.g. mobile sources) might be the main reason of overestimated CMAQ NO2 VCDs, and missing natural NOx emission sources in rural area could be the reason for the underestimation of CMAQ NO_2 VCDs.

"* Acknowledgements: The P3 data from the CalNex campaign and related scientists should be acknowledged."

Thanks for the comment. We have included acknowledge for the P3 campaign and scientists.

Thanks again for very productive comments.

References

Judd, L., Lefer, B., & Kim, H. C. (n.d.). Influences of environmental heterogeneity on OMI NO2 measurements and improvements using downscaling. *in preparation*

Kim, H., Ngan, F., Lee, P., & Tong, D. (2013). *Development of IDL-based geospatial data processing framework for meteorology and air quality modeling*. Retrieved from http://aqrp.ceer.utexas.edu/projectinfoFY12_13%5C12-TN2%5C12-TN2 Final Report.pdf

Pan, L., Tong, D., Lee, P., Kim, H.-C., & Chai, T. (2014). Assessment of NOx and O3 forecasting performances in the U.S. National Air Quality Forecasting Capability before and after the 2012 major emissions updates. *Atmospheric Environment*, *95*(x), 610–619. doi:10.1016/j.atmosenv.2014.06.020