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Comment

Interactive comment on “A multi-model evaluation of aerosols over South Asia: Common problems and possible causes” by X. Pan et al.

X. Pan et al.

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The authors would like to thank the reviewer for constructive comments and guidance on improvement of this paper. Below are <our responses> to the [comments from referee #2]:

[COMMENT FROM REFEREE]: This manuscript compares observations with modeled aerosol properties in South Asia (primarily India), with a focus on the Indo-Gangetic Plain (IGP), from 7 global models. There are a number of strengths of this manuscript. The first is that it addresses a region of clear low bias in the models and seeks to better understand the source of the bias. That this region is home for a large population makes the study even more compelling. The second is that it brings a variety of ob-

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servations (satellite and ground- based remote-sensing, as well as in situ) to compare with model products. A third is the use of a range of global models, which permits comparing different models with different capabilities (e.g. those that include nitrate aerosol versus those that do not), makes the results more robust than if only a single model were used. That said, there are a number of ways that the manuscript could and should be improved. Broadly, two main issues are (1) improving comparisons of model output and observations and (2) quantifying the various explanations for the model low biases.

1. Use of observations (a) The authors accurately state (p. 13, 20-22) “It should be noted that it is difficult for a global model with a coarse spatial resolution to reproduce pollutant concentrations measured in an urban environment...”, which I agree with. However, recognition of this is not, I believe, sufficient. Given this known scale issue, what would constitute "agreement" between model and the point observation? Presumably if the model out- put exactly matched the point observation that would not imply a perfect model. So without some clear idea of what a perfect model would do, how do you know there is a "low bias" in the model? It's possible that the entire mismatch is due to scaling, right? I don't think that this is the case, but it seems that quantifying this issue is required. What if, say, CALIPSO or some other satellite data were used to try to get some sense of the spatial distribution in this particular grid box?

<RESPONSE> The underestimation of BC found in the urban city (e.g. Delhi) could partly attribute to the fact that a global model with coarse spatial resolution is difficult to reproduce pollutant concentrations measured at a station under urban environment. However, the underestimations of BC surface concentration are found in those background stations as well (e.g. over the mountain site of Nainital and the island sites of Minicoy and Port Blair), in Figure 9. In addition, the conclusion that the modeled AODs are too low is based on the comparisons not only with AERONET point observations, but also with the level-3 multiple satellite data from MODIS, SeaWiFS (both 1 degree x 1 degree resolution) and MISR (0.5 degree x 0.5 degree resolution) on regional scales, as shown in Figure 5 and Figure 7. Therefore, the underestimation of modeled BC and

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AOD in the wintertime is more likely due to other factors, as discussed in Section 5, than scaling. We have modified the text to clarify the discussion on model low bias in Section 4.5.

[COMMENT FROM REFEREE]: (b) All observations have their uncertainties and, most importantly for this study, biases. To conclude that the model biases are large, one should probably quantitatively evaluate the observational biases. How much of the model/observation discrepancies might be a result of the observations? For example, my understanding is that AERONET has a very strict cloud-screening requirement. I did not see details on how AERONET data are compared with models. Was it assumed that AERONET is representative of all conditions, regardless of cloud cover? This could lead to substantial biases if there is some correlation between meteorology and aerosol. Or was there a cloud-screening criterion applied to the model output as well? If so, how does one reconcile the model scale with the AERONET scale?

<RESPONSE>: We agree with the reviewer that there is uncertainty to compare cloud-screened AOD with the modeled AOD. AERONET AOD data are only under clear-sky conditions, while the model output are under all-sky conditions, except two models (GISS-modelE and GISS-MATRIX) that also provided clear-sky AOD. As shown in the paper, we used clear sky AOD from these two models in the model-data comparison. Considering the fact that the clear-sky AOD is generally lower than its corresponding all-sky AOD (e.g. by 60% based on GISS-modelE at Kanpur), the low biases in other five models, especially during the winter, would be more pronounced if clear-sky AOD were present in these models. We now have added the discussion on the difference of all-sky and clear-sky AOD in Section 2.1.

[COMMENT FROM REFEREE]: I don't know much about satellite remotely-sensed aerosol products, but I suspect there are a number of potential biases. One obvious one would be the late-morning/early afternoon timing of the overpasses not accurately reflecting a daily average in aerosol.

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<RESPONSE>: We have used monthly mean AOD from several satellite products (MODIS, MISR, SeaWiFS) to compare with the models. Although the satellite data are averaged over the “snap shot” observations at the local overpassing time (varying between 10:30AM to 1:30PM) and the model results are diurnally averaged, previous studies compared model simulated AOD sampled at MODIS/MISR overpass times with that averaged over diurnal time steps and found the differences were small on monthly mean AOD, only about 10% in south America and southern Africa (i.e. biomass burning regions) and smaller elsewhere (Colarco et al., 2010). Thus, since we are using monthly mean satellite data products in comparison to monthly mean model AOD simulations, the bias caused by time difference is expected to be small. We will note these discussions in the revised manuscript in Section 3.1, per reviewer’s comment.

[COMMENT FROM REFEREE]: Also, my understanding is that some (if not all) of the passive sensors used (MISR, MODIS, SeaWIFS) require a surface albedo in order to make certain retrievals. If so, what albedo product was used? Is there, say, an annual cycle in albedo (perhaps due to vegetation or agricultural cycles) that is not properly represented in this region that causes an observational bias? Is there an issue with retrievals of external aerosol mixtures (e.g. mixed absorbing and scattering aerosol)? As I said, this is not my area but I believe this should be explored much more carefully.

<RESPONSE>: Yes, the satellite-based aerosol retrievals require information about the underlying surface reflectance for different surface types. However, the surface reflectance parameterizations are generally well established in the respective aerosol retrieval algorithms, and have improved significantly in the past decade (e.g. Levy et al. 2007, 2010; Hsu et al. 2006; Kahn et al., 2007, 2010; Sayer et al., 2012, 2013). These aerosol products (from MODIS, MISR and SeaWiFS) are regionally validated retrievals with reference to AERONET sites located worldwide, and include uncertainties (e.g. due to surface reflectance) as part of each product’s accuracy assessment. For example, MODIS dark-target aerosol product has an improved surface reflectance parameterization introduced in collection 5.1 AOD dataset (Levy et al. 2007), which is used in

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our paper, with its overall uncertainty over land reported to be within $\pm(0.05\pm 0.15\%)$ AOD and better for oceanic regions (Levy et al., 2010). Whereas, about 70% of the MODIS Deep Blue (aerosol retrievals over bright reflecting surfaces such as desert/arid regions) and SeaWiFS AOD (over both bright desert/arid regions and vegetated surface) retrievals fall within an expected absolute uncertainty of $0.05 \pm 20\%$ (for the wavelength of 550nm AOD used in our paper) (Sayer et al. 2012, 2013). It should also be noted that only the best-quality aerosol retrievals are aggregated to form the Level-3 gridded monthly mean AOD dataset, which is being used in our paper. Similarly, aerosol retrievals from MISR have comparable or better accuracy assessment as part of their overall uncertainty (Kahn et al. 2010). Therefore, per the extensive validation and improved parameterization of surface reflectance in satellite aerosol retrievals, any large biases or seasonal influences of surface albedo variations on our intercomparison study between satellite/AERONET/model AOD, is unlikely. We have added the aforementioned uncertainties of various AOD products in Section 3.1,

Regarding Reviewer's comment related to issues with retrievals of external aerosol mixtures: satellite-based aerosol retrievals surely take into account external aerosol mixtures (such as varying degrees of mixtures of absorbing and scattering aerosol types). For all three satellite retrievals used in this study, MODIS, MISR and SeaWiFS, they use a lookup table approach including several aerosol optical models consisting of varying degrees of aerosol absorption/scattering and various size bins. Additionally, MODIS aerosol retrievals benefit from a clustering approach based on dominant aerosol types/mixtures assigned to a specific region depending on regional aerosol characteristics compiled from AERONET data.

[COMMENT FROM REFEREE]: (c) Uncertainty/variability Most of the figures showing observations lack any indication of uncertainties or variability (whichever is larger). This should be included to aid in comparing observations with models.

<RESPONSE>: We have added the correlation, relative mean bias and root mean square error of each model in Fig.5, and one standard deviation in Figure 7 and 8

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to show the uncertainty/variability. Please check the improved figures at the end of this file. In addition, variability of AOD from multiple models and satellite (using one standard deviation) was also shown earlier in Figure 4 (in parentheses, alongside mean values).

[COMMENT FROM REFEREE]: 2. Quantifying causes of model biases (a) While the manuscript lists all the potential sources of biases in models, it would be a lot more satisfying if you could actually quantify these bias sources in some way. I understand that it's not easy to do with high precision for a variety of reasons (e.g. model dependence), but even a ranking or sorting the bias sources into tiers (e.g. Tier 1: dominant bias source; Tier 2: major bias source; Tier 3: minor bias source) seems like it would be very useful. Such quantification (or semi-quantification) would be a much more satisfying product of this research than the mostly qualitative statements that are currently provided. In some cases, it seems like it wouldn't take much work to actually provide quantitative estimates, but maybe for others it will require some new analyses. (a) A related issue is that the manuscript addresses the bias sources somewhat superficially. You broadly describe what the problem is, but don't really do a good job of analyzing more carefully what the specific issue is. Here are some examples: * The low bias in relative humidity is described, and there is speculation that the cause is a high bias in temperature. Well, why isn't this checked? It would be quite easy to take the model output, apply a more appropriate T, and see if the humidity bias disappears. Or if it corrects a small fraction of the bias, then one would conclude that it's actually an absolute humidity bias.

<RESPONSE>: South Asia is a difficult region for global models to reproduce the aerosol observations, and our focus in this paper mainly includes to evaluate the performance of the multiple global models participating in the AeroCom Phase II model experiments with satellite and ground-based data, to find common problems and model diversity, and to suggest the possible causes of the problems. Because of the limited model output fields in the AeroCom protocol, there are simply no enough information

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to further investigate the source of errors and rank them accordingly across the multiple models. Realizing the importance of understanding the source of the bias, we are currently working on quantifying the problems with ranks of importance via a series of model sensitivity studies using our own model (GEOS5), including change the model spatial resolution, emission strength, additional species, meteorological variables, etc. These sensitivity simulations will allow us to rank the importance of the bias sources, which is not possible to do with the AeroCom models but will definitely provide insights to diagnose the model problems and directions of improvements for all models. We will report the findings in our future publications. The above discussion has been added to the Section 6.

[COMMENT FROM REFEREE]: * Boundary layer depth is mentioned as a source of bias in comparing surface observations. There must be some measure of boundary layer thickness in this region, either in situ or remotely-sensed, that can be used to evaluate this idea quantitatively.

<RESPONSE>: Right, the atmospheric boundary layer (ABL) plays an important role in modulating the surface concentration including BC. In winter, the averaged ABL is 400-500 meters in the GOCART model (similar meteorological data is used by GEOS5, one of the models used in our paper), which is about twice thicker than the observed ABL (Tripathi et al., 2006; Nair et al. 2007), thus a better-constrained ABL in models could be helpful (Moorthy et al. 2013). Unfortunately we don't have ABL information from other models, so it is difficult to address this point in detail. We have added this discussion in Section 5.5.

[COMMENT FROM REFEREE]: * A low-bias in sulfate aerosol is found. Wouldn't it be interesting to try to isolate this problem? Determine whether it is, say, a result of gas-to-particle conversion that is too slow or in the sulfur emission inventory. The former could be diagnosed if *total* sulfur was accurately represented in the model, but the ratio of gas phase to particle phase sulfur was too high. Similarly for organics and nitrate, at least for those models that actually have nitrate.

<RESPONSE>: It is a good suggestion. However, unfortunately there is no observed SO₂ concentration or nitrate precursors available for investigating the gas-to-particle conversion. The sulfur emission inventories used by the models were very similar.

[COMMENT FROM REFEREE]: I've provided a number of other comments in an attached PDF file. Some may overlap with the above and can be ignored. Most identify areas where the wording is awkward, ambiguous or otherwise requiring editing.

<RESPONSE>: We have incorporated your comments in a marked-up manuscript in the supplement.

References: Colarco, P., A. da Silva, M. Chin, and T. Diehl (2010), Online simulations of global aerosol distributions in the NASA GEOS-4 model and comparisons to satellite and ground-based aerosol optical depth, *J. Geophys. Res.*, 115, D14207, doi:10.1029/2009JD012820.

Kahn, R. A., B. J. Gaitley, M. J. Garay, D. J. Diner, T. F. Eck, A. Smirnov, and B. N. Holben (2010), Multiangle Imaging Spectroradiometer global aerosol product assessment by comparison with the Aerosol Robotic Network, *J. Geophys. Res.*, 115, D23209, doi:10.1029/2010JD014601.

Levy, R. C., L. A. Remer, S. Mattoo, E. F. Vermote, and Y. J. Kaufman (2007), Second-generation operational algorithm: Retrieval of aerosol properties over land from inversion of Moderate Resolution Imaging Spectroradiometer spectral reflectance, *J. Geophys. Res.*, 112, D13211, doi:10.1029/2006JD007811.

Sayer, A. M., Hsu, N. C., Bettenhausen, C., Jeong, M.-J., Holben, B. N., and Zhang, J.: Global and regional evaluation of over-land spectral aerosol optical depth retrievals from SeaWiFS, *Atmos. Meas. Tech.*, 5, 1761-1778, doi:10.5194/amt-5-1761-2012, 2012.

Sayer, A. M., N. C. Hsu, C. Bettenhausen, and M.-J. Jeong (2013), Validation and uncertainty estimates for MODIS Collection 6 “Deep Blue” aerosol data, *J. Geophys.*

Res. Atmos., 118,7864–7872, doi:10.1002/jgrd.50600.

Please also note the supplement to this comment:

<http://www.atmos-chem-phys-discuss.net/14/C11480/2015/acpd-14-C11480-2015-supplement.pdf>

Interactive comment on Atmos. Chem. Phys. Discuss., 14, 19095, 2014.

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14, C11480–C11494,
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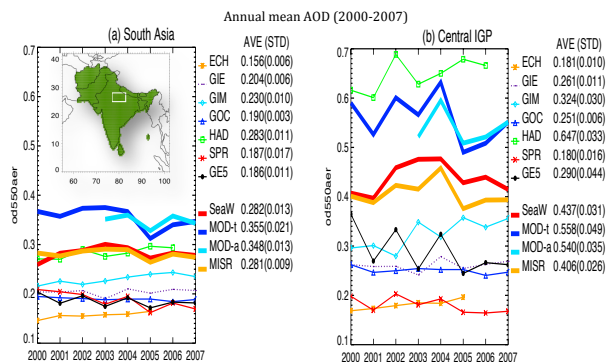


Figure 4. The annual averaged mean AOD for 2000-2007 over (a) South Asia (the green area in the map); (b) Central IGP (77°-83°E; 25°-28°N, the white box in that map). The thin curves with symbols represent seven models, and the thick curves represent four NASA remote sensors, with corresponding multi-year averaged annual mean AOD and the standard deviation followed.

Fig. 1.

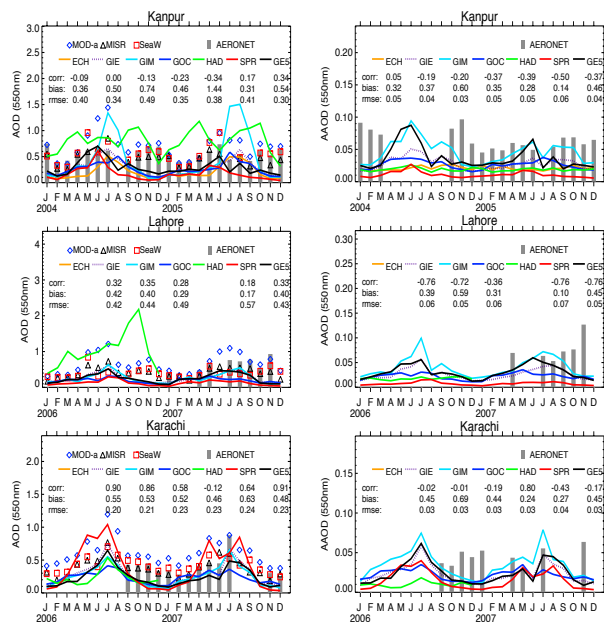


Figure 5. Monthly mean AOD (left column) and AAOD (right column) in a two-year period over 3 AERONET stations in South Asia. The gray bar represents measurement from AERONET. The thin curves represent seven models, and symbols represent three NASA remote sensors. On each panel, corr=correlation coefficient of a model with AERONET, bias=relative mean bias, i.e. $\Sigma(\text{MODEL})/\Sigma(\text{AERONET})$, rmse=root-mean-square error relative to AERONET.

Fig. 2.

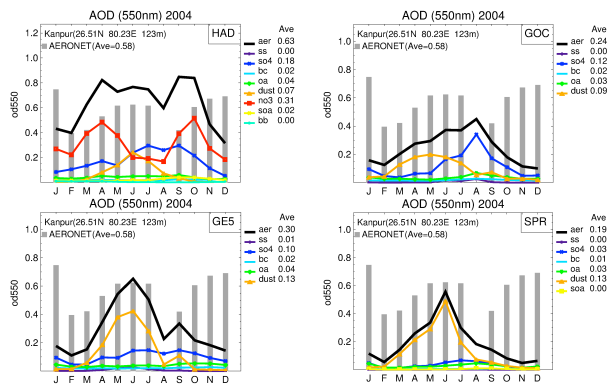


Figure 6. AOD of total aerosol (aer) and components (ss, so4, bc, oa, dust, no3, soa and bb) at Kanpur for 2004 in 4 models, HAD (upper left), GOC (upper right), GES (lower left) and SPR (lower right). The gray bar represents measurement from AERONET. The annual mean AOD value is followed after the name of each symbol. NOTE: bc and oa represent emission from fossil fuel only and bb represents emission from biomass burning only).

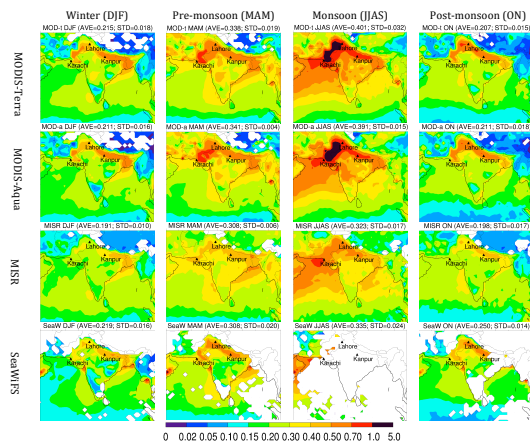


Figure 7a. Spatial distribution of AOD over South Asia in 4 seasons averaged for 2000–2007 in three satellite observations (two from MODIS, MISR and SeaWiFS). The corresponding area averaged annual mean AOD value is listed in each panel (domain: 0–36°N; 55°E–100°E). Three AERONET stations used in this study are labeled in the maps. Regions in white indicate insufficient sampling sizes of aerosol retrievals due to the presence of bright surface or frequent cloud cover in satellite data.

Fig. 4.

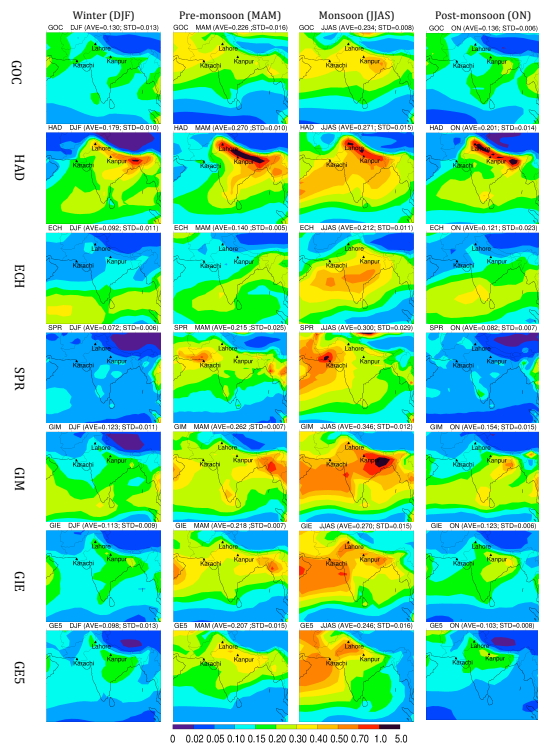


Figure 7b. Spatial distribution of AOD over South Asia in 4 seasons averaged for 2000–2007 in seven models (the first three models with the anthropogenic emissions from A2-MAP and the rest with A2-ACCMP). The corresponding area averaged annual mean AOD value is listed in each panel (domain: 0–36°N; 55°E–100°E). Three AERONET stations used in this study are labeled in the maps.

Fig. 5.

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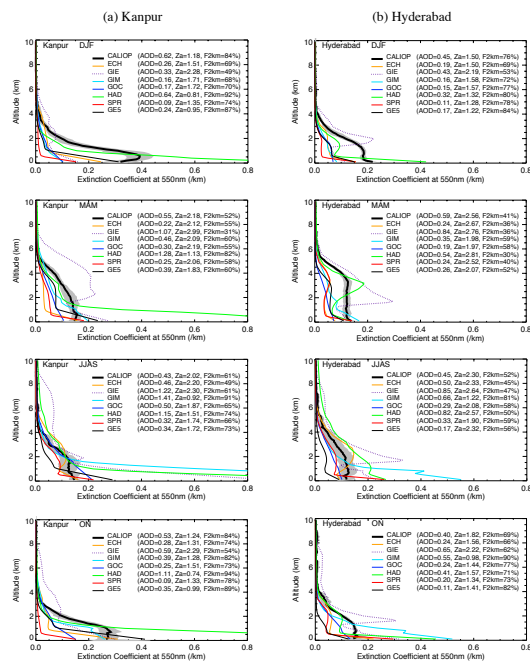


Figure 8. The seasonal mean of vertical profile of extinction coefficient (units: 1/km) at (a) Kanpur, and (b) Hyderabad from CALIOP and seven models. Units of Z_a is km. The corresponding averaged AOD, Z_a and F_{2km} are listed after each symbol name. The gray shaded area in CALIOP shows one standard deviation relative to 2006–2011 averages.

Fig. 6.