We thank the reviewers for their time and insightful comments, which have substantially improved the manuscript. We have revised the manuscript and addressed the comments raised by the reviewers. The reviewers raised important comments on the rationales for our hypothesis, and the effects of our findings on future simulations. The main purpose of the study is to investigate the sensitivity of model predictions to the main inputs into the model. We apply different scenarios to evaluate the importance of major sources during the November 2017 extreme pollution episode over northern India. We feel this evaluation of inputs is needed to understand the extent that the forward model can be configured to capture the events. A contemporary way to try to capture such events in prediction mode is to employ data assimilation. The data assimilation results compensate for deficiencies in the inputs as well as structural problems within the models. But the effectiveness of data assimilation improves as the capabilities of the forward model improves. Therefore, our results are also important for those using data assimilation to improve predictability. Below, please find our responses to the reviewer's comments. The reviewer's comments are shown in black, our responses are shown in red, and the modified section of the manuscript is shown in blue.

We appreciate your time and comments and look forward to your decision.

Best Regards,

Behrooz Roozitalab, on behalf of all co-authors

RC2:

This study investigates the processes causing severe air pollution episodes in New Delhi, India by focusing on one such event observed during November 2017. Specifically, the authors evaluate the impact of biomass burning emissions, long-range transport of dust, and dust emissions on WRF-Chem simulated $PM_{2.5}$. The model captured the day to day variability but missed the peak pollution peak during 7-10 Nov. Secondary Inorganic Aerosols and Secondary Organic Aerosols are estimated to contribute 30% and 27% of total $PM_{2.5}$ concentrations in Delhi. Back trajectories showed influence of agricultural fires in Punjab on $PM_{2.5}$ in Delhi. Long-range transport of dust is not found to affect air quality in Delhi during this time. High biases in model AOD were observed over central India and low biases over the eastern IGP.

While such studies are very important as they provide important information about the sources leading to dangerous air pollution episodes and inform the mitigation strategies, unfortunately this study does not consider all the key sources of uncertainties in the model simulations and may misinform the mitigation strategies. I am particularly concerned about the ignorance of anthropogenic emission uncertainties that were left out irrespective of several evidences pointing to their key role in the analysis presented in the paper itself. The authors should also provide a clear description of the rationale behind selecting biomass burning and dust aerosols as the most important sources of uncertainties in the model simulations. Below I provide my major and minor comments.

Authors Response:

We appreciate the reviewer for pointing to important issues. We addressed the comments and concerns here and below:

We share the view about the critical role of anthropogenic emissions roles in air quality over the IGP. The uncertainty in anthropogenic emissions lead to concentration biases for typical days. Moreover, we acknowledge the importance of anthropogenic emissions since emissions due to heating also increase as the weather gets cold during Oct. and Nov. We added a scenario in which we increased all particles anthropogenic emissions by a factor of 2 based on recent emission work in Delhi (ID: Base_Anth2X). In following comments, we present its results.

However, agricultural fires have a more significant contribution in post-monsoon extreme pollution events in Delhi (Kulkarni et al., 2020). Moreover, (Beig et al., 2019) showed that extreme pollution episodes during November 2017 was mainly due to agricultural fires and long-range transported dust. Lines 46-52 discuss these points although we agree that there are some exceptions, too. For example, extensive use of firecrackers and fireworks in the Diwali festival on October 20th in 2017 led to $PM_{2.5}$ concentrations above 600 (μgm^{-3}) Therefore, we focused only on November to exclude that episode. On the other hand, our simulation results after excluding extreme pollution days show fair statistics (Table S3). We highlighted the importance of anthropogenic emissions in the revised paper and tried to express the reviewers point in the study limitations section in the revised version:

Text:

During this study, we did not primarily focus on improving anthropogenic emissions over the region in order to capture extreme pollution episode. However, anthropogenic emissions are low in global emission inventories and needed to be improved (Jat et al., 2020). Moreover, very low biased concentrations for some days and trajectory results suggest the existence of some other sources, primarily anthropogenic sources, upwind of Delhi that should be studied more.

Main comments:

RC2-1: Figure 3 shows that increasing the fire emissions by a factor of 7 is too high and leads to large overestimation of AOD especially in the western part of the domain. Large underestimation in the IGP is reflecting the underestimation of anthropogenic emissions but no sensitivity experiment was designed to look into that. So, the "base" configuration might be showing good performance in Delhi for wrong reasons.

Authors Response:

We appreciate reviewer's genuine and important concerns. Please find our responses, below. (We split the comments and address each part individually)

Regarding Biases in Fig. 3: As you and reviewer 1 mentioned, we completely agree that model is biased low over the IGP and biased high elsewhere and we have exclusively mentioned this point in the revised version. We acknowledge that uncertainty of anthropogenic emissions is playing an important role in these biases. We did another experiment where we increased anthropogenic emissions for all the particles by a factor of 2 (ID: Base_Anth2X). This modification increased $PM_{2.5}$ concentrations in Delhi up to ~150 µgm^{-3}, which led to overestimation (in contrast to underestimation in base scenario) at most of non-episode days (time-series shown below). Although this scenario did not help capturing concentrations during the episode, it confirms the need for better anthropogenic emissions. On the other hand, it increased the AOD bias over southern IGP while reduced the bias over IGP (bias map shown below). These results suggest anthropogenic emission inventories have higher bias over IGP compared with non-IGP regions. However, we acknowledge the importance of having dynamic (daily) anthropogenic emission inventory.

Text:

Although different meteorological parameters can be responsible for the biases, accuracy of anthropogenic emissions is important. For example, recent local anthropogenic emission inventories developed for Delhi have higher particle emissions than in the regional inventory used in this study, which impacts modeled $PM_{2.5}$ concentrations for typical days (Kulkarni et al., 2020). We conducted BASE_ANTHRO2X scenario to investigate the effect of uncertainties in the anthropogenic emissions. This scenario increased $PM_{2.5}$ concentrations in Delhi up to ~150 µgm^{-3}, which led to overestimation (in contrast to underestimation in base scenario) at many of non-episode days (Fig. in the supplementary document). Although this scenario did not help in capturing the high concentrations during the episode, it confirms the need for better anthropogenic emissions. On the other hand, it reduced the bias over IGP (Fig. in the supplementary document). These results point out the need for best estimates of emissions of both anthropogenic and biomass.

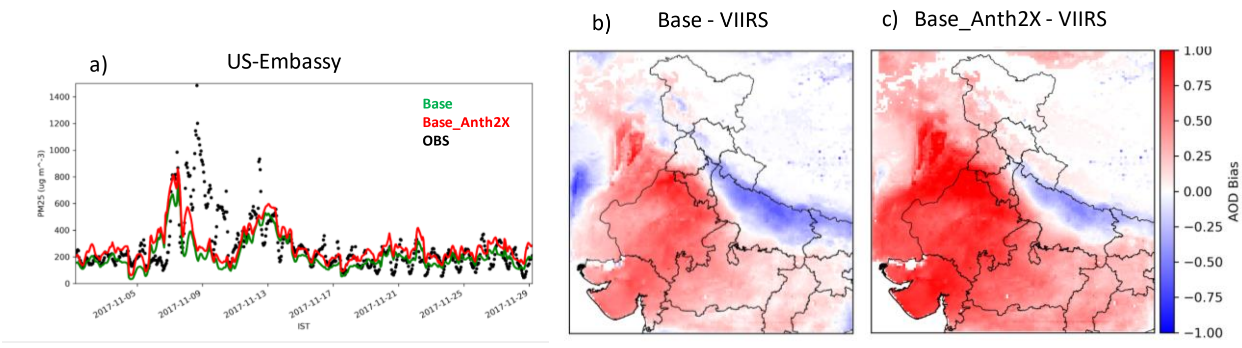

Figure 1 a) Timeseries for $PM_{2.5}$ concentration at the location of US embassy using Base scenario and Base_Anth2X scenario B) Bias of AOD at 550nm averaged over November 2017 base on b) base scenario c) base scenario with 2 times more anthropogenic particle emissions (ID: Base_Anth2X)

In addition, our experiments were primarily focused to capture the extreme pollution episode over Delhi as the reviewer pointed out. On the other hand, we would like to mention an important point regarding the accuracy of the base scenario for other locations:

Below, we show the AOD biases for our base scenario (as in Fig3.c) on left panel, FINN_MERRA2 scenario (a scenario without any enhancement on fire emissions) on middle, and the difference between these two scenarios on the right panel.

The bias pattern of FINN_MERRA2 has also been reported in another study by Jena et al. (2020). They looked at a different time period (Dec. 2017 to Jan. 2018) but they show same pattern with lower values (which is most possibly due to lower concentrations in their period of interest). Their results (specifically Fig.4 in Jena et al., 2020) support the importance of anthropogenic emissions as the reviewer mentioned, and we acknowledge that as discussed above.

On the other hand, looking at base and FINN_MERRA2 reveals that we clearly improved the AOD results for Punjab. It also shows low bias of FINN_MERRA2 shifted to high bias of base scenario for Haryana. The difference between base scenario and FINN_MERRA2 scenario (right panel) shows the impact of increasing FINN emissions by 7 times for a 8-days period; it increased the mean AOD biases over the whole domain by 0.09 (±0.23).

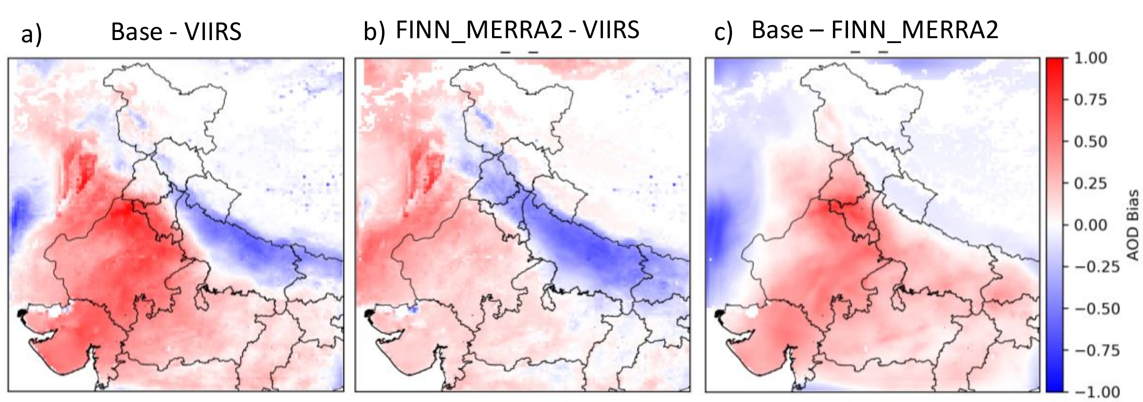

Figure 2 Bias of AOD at 550nm averaged over November 2017 base on a) base scenario b) a scenario without any modifications on biomass burning emissions (ID: FINN_MERRA2), c) difference between Base and FINN_MERRA2

RC2-2: Fig. 4a shows an AOD of 4 which is unrealistic for Jaipur. It looks like the authors paid all the attention to getting $PM_{2.5}$ in Delhi correct simply by upscaling the emissions in the upwind regions but no care was taken to maintain the model performance in the upwind regions. Consequently, the model shows a positive bias in $PM_{2.5}$ in Punjab with a spatial variability (reflected by standard deviation in Table 3) that is nearly 3.5 times higher than the observed variability in Punjab. Nov. 24 case (no fire day) also supports the idea that the anthropogenic emissions are substantially underestimated.

Authors Response:

Regarding Fig4.a, we agree that the model is generally biased high over the Jaipur. Moreover, VIIRS data also show low AOD values for Jaipur during episode days. That is reasonable as MERRA-2 modeling system assimilates satellite AOD. However, it is also important that AERONET is missing data for the pollution episode between Nov. 6th and Nov. 13th as shown in Fig.4a. It suggests, as one possibility, that PM concentrations were too high during this period that the instrument was not able to retrieve data at that specific coordinates. We modified the discussion on Fig.4 in the revised version.

Text:

Figure 4 shows time series of modeled, MERRA-2 product, VIIRS retrievals, and observed AOD at the AERONET stations, located on Fig.1. AOD values at Kanpur, a station in the eastern IGP, were more than 1.0 before the pollution episode and reached up to 2.0 during the episode days, and decreased to values between 0.5 and 1 for the rest of days. The model captured the general trend although missed high AOD's between Nov. 9th and 13th, while MERRA-2 successfully captured the AOD trend through the whole month, including days with enhanced AOD values. This shows that AOD assimilation in MERRA-2 significantly improves AOD predictions. At Jaipur, located in southern IGP, the model overestimated AOD for the first five days of November. During the pollution episode days, the model is biased high compared to MERRA-2 and VIIRS retrievals. AERONET data showed low AOD values before the pollution episode but did not report values during the pollution episode. It suggests, as one possibility, that PM concentrations were too high during this period that the instrument was not able to retrieve data. After the pollution period, AOD values were lower than 0.5, showing relatively low PM concentrations. In general, MERRA-2 showed better performance in terms of NMB (Kanpur: -1.3% and Jaipur:-20.1%) compared with our model (Kanpur:-27.4% and Jaipur: +29.9%). Comparing averaged AOD with VIIRS retrievals for BASE_ANTHRO2X scenario showed lower bias over the IGP (Fig. in the supplementary document). These results show the need for improved estimates of biomass burning as well as anthropogenic emissions.

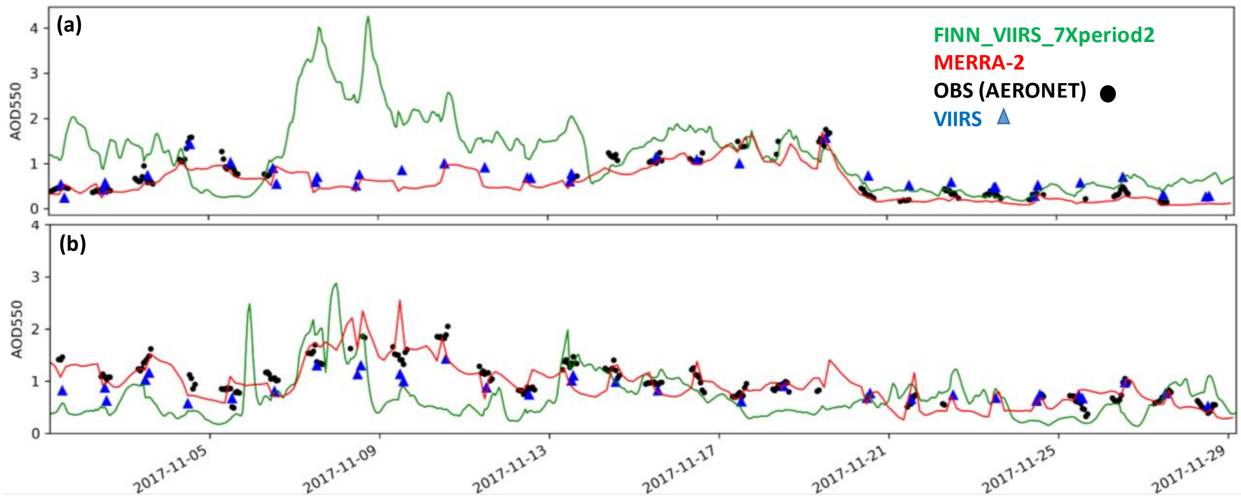

Figure 3 Figure 4 Time series of modeled (green line), VIIRS retrievals (blue triangle), MERRA-2 (red line), and AERONET (black dots) AOD at 550 nm during Nov. 2017 at a) Jaipur, b) Kanpur.

RC2-3: Figure S3 shows that $PM_{2.5}$ concentrations in Punjab were lower than those in Haryana and increasing the fire emissions by a factor of 7 introduced large uncertainties in model simulations as the model $PM_{2.5}$ in Punjab became nearly a factor of 4 higher than the observations. If crop residue burning was the major source of this air pollution episode, one must see the highest observed concentrations in Punjab followed by Haryana and Delhi. Such a pattern exists in the model but not in the observations reflecting that the increasing fire emissions by a factor of 7 is not a reasonable choice. The authors have used back air trajectory to corroborate their assumption that crop residue burning is the major source but backward trajectories only show that the air masses passed over the fire region before arriving at Delhi and are possibly influenced by the fire emissions but they do not tell that agricultural fires are the main source of $PM_{2.5}$ during this episode. Backward trajectory analysis in Figure 7 also shows that $PM_{2.5}$ during the pollution episode was driven by a combination of both the anthropogenic and fire emissions. Thus, this approach presents the danger of attributing missing anthropogenic sources to fire sources and may misinform the mitigation strategies if used for that purpose. Therefore, I recommend the authors to include additional sensitivity simulations exploring the role of anthropogenic emission uncertainties.

Authors Response:

Regarding the discussion about low measured concentrations in Punjab, VIIRS satellite images clearly show massive agricultural fires in this state during November (e.g. Fig.10d). However, we do not see any $PM_{2.5}$ enhancement in observation data over Punjab as the reviewer mentioned (Fig. S3). As a result, we believe the observed values during episode days in Punjab have high uncertainty. We have emphasized this point in the revised version. As discussed above and in back trajectory analysis, all the evidences show that extreme pollution episode has been due mainly to agricultural fires but we have pointed out the importance of anthropogenic emissions too. For example, we mentioned in the manuscript that short-term increase in anthropogenic emissions (due to social reasons) may have intensified the pollution but quantifying those sources can be the subject of another whole study.

Text:

In Punjab, measured data did not report $PM_{2.5}$ enhancement during the extreme episode, while the model showed very high concentrations after scaling fire emissions by a factor of 7. However, VIIRS satellite images (e.g. Fig. 10d) clearly show massive agricultural fires in this state during November and its signals were expected in the measured data.

RC2-4: Fig 4 and related discussion: In addition to the AOD, could you please evaluate the Angstrom exponent to examine if there any differences in the abundance of fine and coarse mode particles and if the model was able to capture those variations. Can you also plot VIIRS AOD in Figure 4 to see if the satellite observed an AOD of 4 in Jaipur?

Authors Response:

We thank the reviewer for the comment. VIIRS AOD is added to Fig. 4 in the revised version and show low AOD values over Jaipur. We modified the text as described above.

Regarding Angstrom Exponent, we added the following discussion to the paper and added the figures (shown below) to the supplementary document:

Text:

We also looked at Angstrom Exponent (AE) at Jaipur and Kanpur to understand if the model captured the mode of the particles (Fig. in the supplementary document). Over Jaipur the model is biased high compared to AERONET data (NMB: 30%) and shows more finer aerosols. After Nov. 20th, both AERONET and VIIRS retrievals suggest the dominance of coarser aerosols, while the AE for the model does not follow the same trend. However, $PM_{2.5}/PM_{10}$ ratio shows more coarse aerosols compared to the rest of the month (Fig. in the supplementary document). Over Kanpur, the model AE is biased very high (NMB: 50.8%) and doesn't show any correlation with AERONET data. On the other hand, the model shows closer AE values to VIIRS retrievals. For example, both the model and VIIRS retrieval show similar reduction in AE on Nov. 8th and 9th. (Kumar et al., 2014) also reported slight AE overestimation in WRF-Chem during a pre-monsoon dust storm at Kanpur and Jaipur. Furthermore, model and AERONET have variational trend while MERRA-2 is smooth during the whole month at both Jaipur and Kanpur.

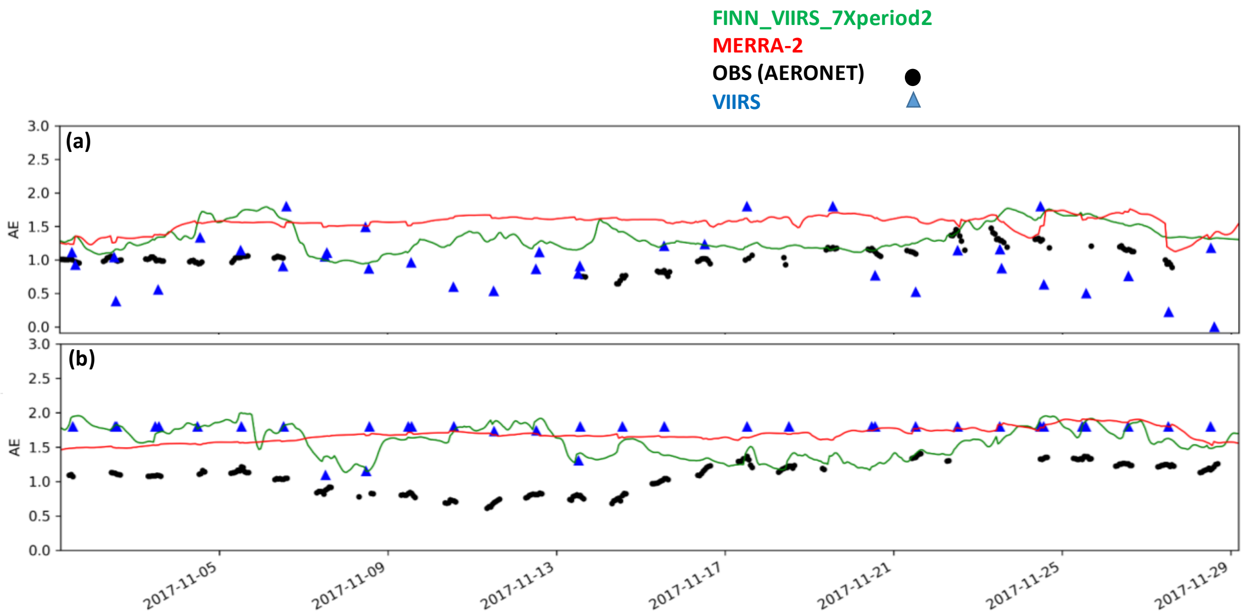

Figure 4 Time series of modeled (green line), VIIRS retrievals (blue triangle), MERRA-2 (red line), and AERONET (black dots) Angstrom Exponent during Nov. 2017 at a) Jaipur, b) Kanpur.

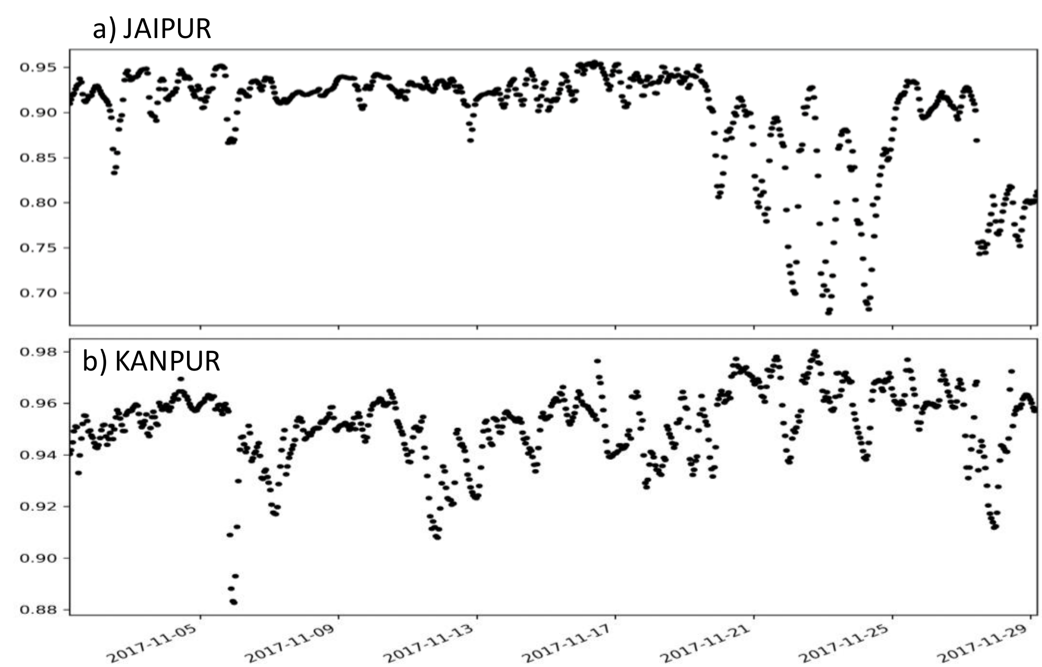

Figure 5 Modeled PM_{25}/PM_{10} ratio (Base scenario) at a) Jaipur and b) Kanpur

RC2-5: Fig 5/Table 3: Could you please add a few panels in Figure 5 showing the evaluation against the CPCB data?

Authors Response:

Fig.6 in the paper shows the box and whisker plots for CPCB stations in Delhi. In general during the whole paper, we show the results only at one station (i.e. US Embassy) when we look at time-series and we show daily box and whisker plots when we look at all CPCB stations. As the model resolution is 15km, we usually see more than one measured CPCB stations are located in one model grid cell. For example, 17 stations in Delhi are located in only 6 grid cells; repetition affects the scatter plot (Fig. 6a below). We also observe lower variability in box and whisker plots of the model compared to observation data due to same reason. In other words, scatter plots will not provide enough insights when considering all individual stations. To show the spatial performance of the model, we plot the scatter plot for averaged concentration of different states. Below, we show the scatter plot for Delhi, Haryana, and Rajasthan, which reveals the good spatial performance of the model (Fig. 6b below). Adding data from Punjab to this plot (Fig. 6c below) significantly degrades the performance. The reason is due to extremely high bias in Punjab data. Punjab observation data doesn't seem to be right as it doesn't show any signal of the pollution episode while satellite data show huge amount of agricultural fires during those days. We added the below scatter plots in the supplementary. However, we think scatter plots were better tools if we had more spatial data (e.g. a gridded dataset).

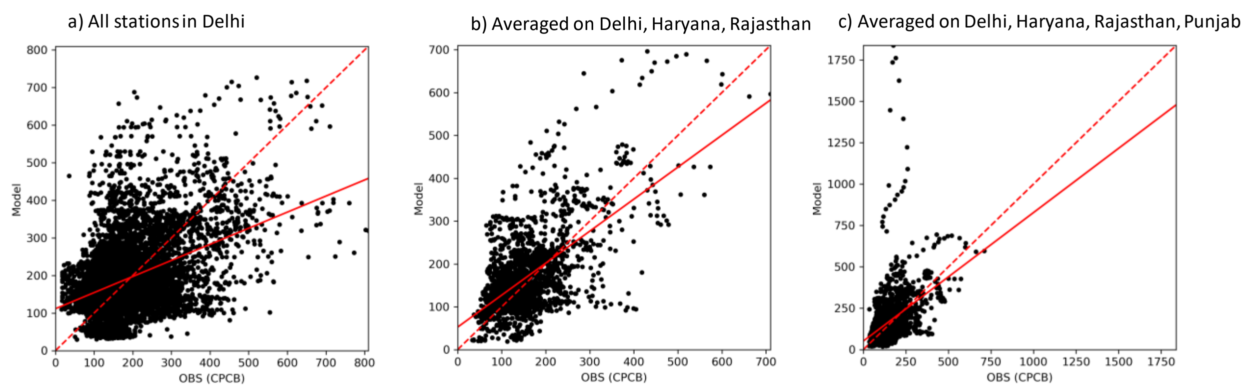

Figure 6 Scatter plots for a) all stations in Delhi combined b) averaged concentrations in Delhi, Haryana, and Rajasthan c) averaged concentrations in Delhi, Haryana, Rajasthan, and Punjab. Filters are applied to CPCB data.

RC2-6: Line 301: I think the model observation comparison for the non-episode periods looks good because of the scale of Figure 5a. A zoom into the figure 5a shows that on several occasions, the model showed a bias of up to 100 ug/m3 even in the non-episode period.

Authors Response:

We appreciate the comment. We agree that for some typical days the error is high, which can be related to the accuracy of anthropogenic emissions and we have mentioned that when presenting the results between lines 320-326. However, statistics for the whole November after excluding days between Nov. 7th and Nov. 10th (4 days), also show fair results as shown below.

Table 1 Statistics for all days in November 2017 after excluding extreme days of Nov. 7th, 8th, 9th, 10th compared with data from CPCB stations in Delhi

Scenario	Hourly Mean	Hourly Standard Deviation	24-hours R	24-hours RMSE	24-hours NMB	24-hours NME	24-hours MB	24-hours ME
CPCB Obs data	215.26	97.58						
FINN_VIIRS_7Xperiod2	209.91	104.94	0.7	55.11	-2.44	18.96	-5	38.94

RC2-7: Line 308: Are you referring to the model biases relative to MERRA-2 here? If yes, is it reasonable to do so given large biases in MERRA-2 simulated PM2.5 itself as shown in Figure 5a?
Authors Response:

We appreciate the reviewer's concern. We agree that MERRA-2 may have large biases, as we saw in Fig. 5a. However, in this paper, we use MERRA-2 as an observation package when we do not have any other data to evaluate our results. Looking at domain wide $PM_{2.5}$ concentrations is one of those cases. We assume that enhancing MERRA-2 modeling system by data assimilation makes it a fair benchmark.

RC2-8: Line 368-369: Why do you attribute this error only to transport and not to uncertainties in anthropogenic emissions or other physical processes in the model.
Authors Response:

We thank the comment. For Nov. 8th, the back trajectory was passing through anthropogenic sources; so, we hypothesized that the model may have missed major fire emission due to transport. But, we agree with the reviewer that other mentioned factors can be important, as well. We have modified that sentence to:

Text:

The model underestimated $PM_{2.5}$ concentrations on Nov. 8th, which can be partly related to errors in transport as the trajectories for Nov. 8th_12 crossed eastern parts of Punjab. However, other physical processes or lower anthropogenic emissions can also be responsible to low bias.

RC2-9: Figure 8: Could you please add PBL height to these panels to help understand whether the smoke was injected in the free troposphere.
Authors Response:

We thank the reviewer for the comment. Below, we added the PBLH line to the cross sections (white line). The line is not obvious on 00 UTC times due to very low extent of the PBL. On Nov. 6th-12, we see very low PBL upwind of Delhi and significant amount of smoke above boundary layer. Therefore, these findings accompanied with Fig. 13b supports the argument that the plume rise in the model released the emissions too high or the model did not mix the smoke down fast enough. We modified the text in the revised version.

Text:

To further understand the regional scale transport of the smoke plumes, we plotted cross section of $PM_{2.5}$ over the path from Punjab through Delhi (Fig. 8, path line shown in Fig. 1). $PM_{2.5}$ concentrations showed typical values on Nov. 5th_00 although they still exceeded the standard limits. On Nov. 5th_12, concentrations significantly increased over Punjab area because of fires and the winds brought them on a path towards Delhi. The Punjab's smoke did not completely cross Delhi yet on Nov. 6th as back trajectories for 00 and 12 UTC hours also showed the effects of anthropogenic emissions and fires in eastern Delhi. On the other hand, a significant amount of smoke was above the boundary layer as shown in Nov. 6th_12 panel. Due to shifting winds on Nov. 7th (as shown in Fig. 7), the smoke upwind of Delhi blew over Delhi and led to extremely high concentrations. Although the model captured the median in Nov. 7th, it missed the maximum extent of observed values. Cross sections on Nov. 8th, 9th, and 10th show the residual Punjab's smoke in the boundary layer, while we saw the model underestimated $PM_{2.5}$ concentrations on these days. Measured $PM_{2.5}$ concentrations over Delhi show a decreasing trend between Nov. 8th and Nov. 10th (Fig. 6). Vertical profiles for the base scenario also show the model captured high biomass burning emission period on Nov. 6th (Fig. 13). However, it also showed high amounts of smoke above the PBL. Vertical cross sections for Nov. 11th to Nov 14th can be found in supporting information (Fig. S4). These results suggest that plume rise in the model release the emissions too high or the model did not mix the smoke down fast enough. Vijayakumar et al. (2016) showed agricultural fires can transport via upper troposphere and subside over Delhi using ECMWF map. Social reasons can be also important as the first reaction of people during hazy days is to drive to work which directly (exhaust emission) and indirectly (road dusts) worsen air pollution.

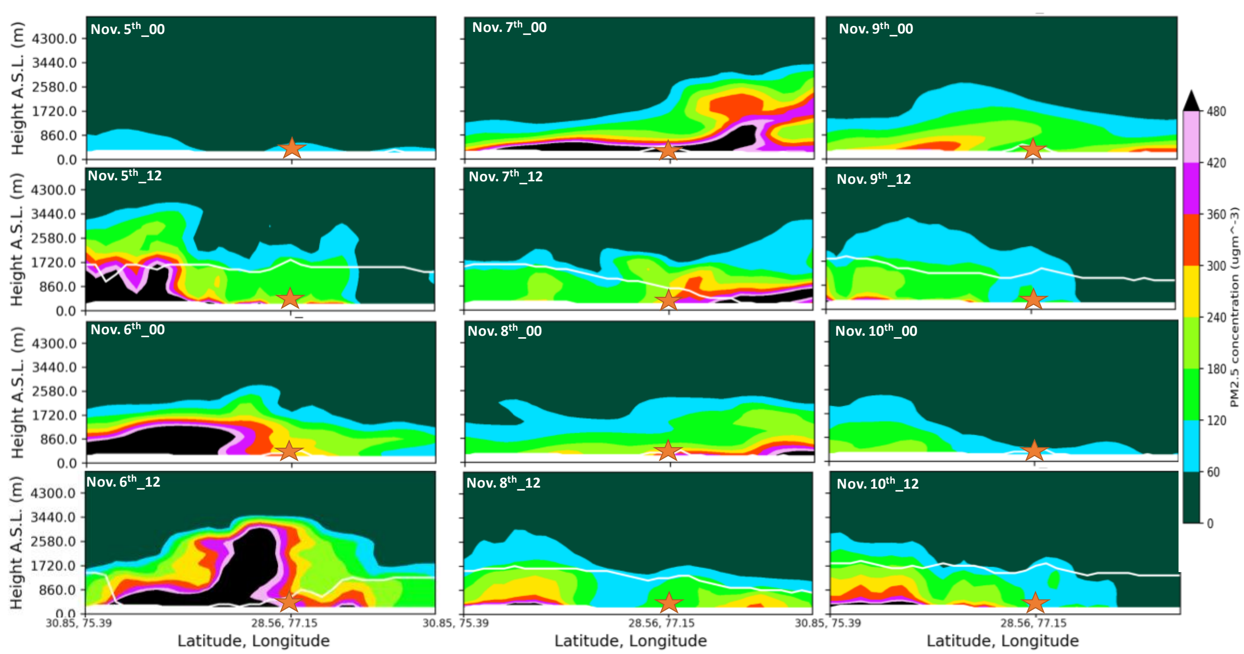

Figure 7 Figure 8 Vertical cross section of $PM_{2.5}$ concentration through the path shown in Fig. 1 for the days between Nov. 5th and Nov. 10th. For each day, two snapshots are shown at 00UTC (5:30AM local time) and 12UTC (5:30PM local time). The orange star shows the location of Delhi through the path. White line shows the PBL height across the path

Minor comments:

RC2-10: Line 100: Replace '*' with the 'x' and also elsewhere in the paper where you describe the resolution.

Authors Response:

We replaced all of them.

RC2-11: Line 194-195: Have you applied any filtering criteria to the CPCB data?

Authors Response:

We didn't apply any filter to this data as we relied on quality control done by CPCB (https://cpcb.nic.in/quality-assurance-quality-control/). However, we studied how applying the following filters, done by Jena et al. (2020) and Kumar et al. (2020), change the dataset consisting of total 12768 hourly data points:

> **Filter 1: Remove less than 10 μgm^{-3} instances: removes 31 data-points**
>
> **Filter 2: Remove the hourly difference between 100 (or 150 or 200) μgm^{-3}: removes 186 (or 71 or 31) hourly-data**
>
> **Filter 3: Remove values more than 200 (400) μgm^{-3} right after NAN value: 33 (19). It basically removes data for Nov. 9th as it was applied after filter #2.**

We found that the order of applying these filters is important. Below, statistics and timeseries for different orders of filters are presented. Order of filters (1,2,3) removes data for Nov. 9th and significantly improves the model performance over Delhi. We added these findings in the supplementary document and described in the revised version.

Text:

No additional quality control filters, other than the ones by CPCB (https://cpcb.nic.in/quality-assurance-quality-control/), were applied. We evaluated the results after applying the filters proposed by other studies (e.g. Kumar et al. (2020)); they had slight impacts on statistics (shown in the supplementary document).

Table 2 Effect of applying filters to CPCB data on $PM_{2.5}$ statistics in Delhi

Province	Hourly Obs. Mean (±std) (μgm^{-3})	Hourly Model Mean (±std) (μgm^{-3})	24-hours NMB (%)	24-hours NME (%)	24-hours R (%)
CPCB-Delhi	255.5 (±146.6)	213.9 (±113.9)	-16.6	27.6	0.48
Only filter 3	248.4 (±140.3)	214.5 (±114.5)	-13.9	26.4	0.49
Filter123	215.5 (±95.5)	214.8 (±115.2)	-1.9	23.6	0.64
Filter132	248.6 (±140.8)	214.6 (±114.5)	-13.9	26.4	0.49

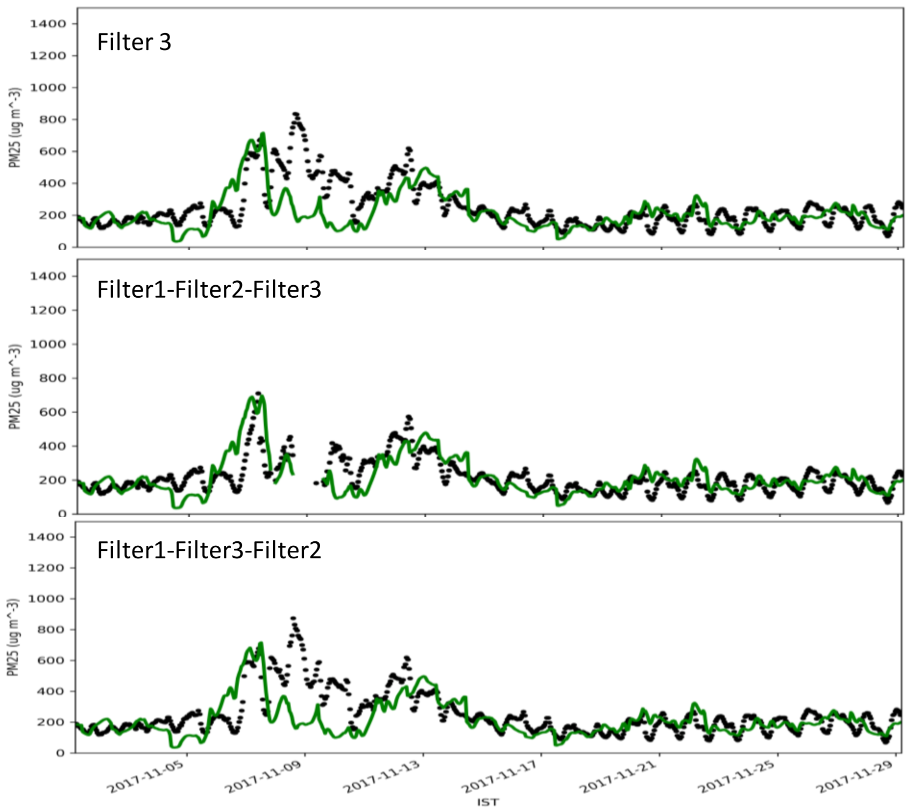

Figure 8 Effect of applying additional filters to CPCB data on averaged $PM_{2.5}$ timeseries in Delhi

RC2-12: Equation (1): I assume this equation is used to calculate MERRA-2 $PM_{2.5}$ and not WRF-Chem.
Authors Response:

Yes, it is to calculate $PM_{2.5}$ for MERRA-2 and we used WRF-Chem diagnosed $PM_{2.5}$ variable directly.

RC2-13: Line 288-289: But the underestimation could also be because of the underestimation of emissions from Delhi.
Authors Response:

Yes, we modified the sentence:

Text:

This suggests either low anthropogenic emissions in Delhi or some missing pollution sources upwind of Delhi that were not included in the emission estimates.

RC2-14: Line 322-333: This is not true as EDGAR-HTAP provides monthly varying emissions with higher emissions in winter.

Authors Response:

We appreciate the reviewer and apologize for this mistake. All the experiment have been done using monthly EDGAR-HTAP data and it was just a drafting mistake. It has been removed in the revised version.

RC2-15: Figure 6: It would be useful to mark period 1 and period 2 in the figure.

Authors Response:

Thanks for the comment. We added period1 and period2 that have been used for emission modifications to Fig. 6.

RC2-16: Line 365: Change "lower" to "smaller".

Authors Response:

We changed that.

RC2-17: Line 567: change "intensify" to "accuracy".

Authors Response:

We changed the "intensify the accuracy" to "improve the accuracy"

References

Beig, G., Srinivas, R., Parkhi, N. S., Carmichael, G., Singh, S., Sahu, S. K., Rathod, A., and Maji, S.: Anatomy of the winter 2017 air quality emergency in Delhi, Science of The Total Environment, 681, 305-311, 2019.
Jat, R., Gurjar, B. R., and Lowe, D.: Regional pollution loading in winter months over India using high resolution WRF-Chem simulation, Atmospheric Research, 105326, 2020.

Jena, C., Ghude, S. D., Kulkarni, R., Debnath, S., Kumar, R., Soni, V. K., Acharja, P., Kulkarni, S. H., Khare, M., and Kaginalkar, A. J.: Evaluating the sensitivity of fine particulate matter (PM 2.5) simulations to chemical mechanism in Delhi, Atmospheric Chemistry and Physics Discussions, 1-28, 2020.

Kulkarni, S. H., Ghude, S. D., Jena, C., Karumuri, R. K., Sinha, B., Sinha, V., Kumar, R., Soni, V., and Khare, M.: How Much Does Large-Scale Crop Residue Burning Affect the Air Quality in Delhi?, Environmental Science & Technology, 54, 4790-4799, 2020.

Kumar, R., Barth, M., Madronich, S., Naja, M., Carmichael, G., Pfister, G., Knote, C., Brasseur, G., Ojha, N., and Sarangi, T.: Effects of dust aerosols on tropospheric chemistry during a typical pre-monsoon season dust storm in northern India, Atmospheric Chemistry & Physics, 14, 2014.

Kumar, R., Ghude, S. D., Biswas, M., Jena, C., Alessandrini, S., Debnath, S., Kulkarni, S., Sperati, S., Soni, V. K., and Nanjundiah, R. S.: Enhancing Accuracy of Air Quality and Temperature Forecasts During Paddy

Crop Residue Burning Season in Delhi Via Chemical Data Assimilation, Journal of Geophysical Research: Atmospheres, 125, e2020JD033019, 2020.

Vijayakumar, K., Safai, P., Devara, P., Rao, S. V. B., and Jayasankar, C.: Effects of agriculture crop residue burning on aerosol properties and long-range transport over northern India: a study using satellite data and model simulations, Atmospheric research, 178, 155-163, 2016.