Assessment of aerosol plume dispersion products and their usefulness to improve models between satellite aerosol retrieval and surface PM2.5

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1. INTRODUCTION

Fine Particulate Matter less than 2.5 micron in diameter are PM2.5 and studies indicate that they can pose health risk. Therefore, the Environmental Protection Agency (EPA) has set up guidelines to address this issue. To assess this risk, the EPA has deployed a number of PM2.5 monitoring stations around the country. However, surface sampling can be quite expensive and therefore, existing networks are very limited. To provide better coverage, column integrated Aerosol Optical depth information derived by satellite observation can potentially be used to estimate PM2.5.

In recent studies, it has been found that particle mass is often linearly related to the optical scattering coefficient of the particles which implies that the total column integrated aerosol optical depth (AOD) measurements can be connected to surface PM2.5 using a simple linear regression model. However, a wide range of factors such as aerosols variability, meteorology and the vertical structure of aerosols can affect the PM2.5 to AOD relationship.

Studies suggest that the relationship between PM2.5 and AOD does not work well in the presence of aloft plumes. Sources of aloft plumes include forest fires, bio mass burning that can inject smoke aerosols into the atmosphere and these aerosols can be elevated to troposphere and travel long distance.

The ability to identify and quantify aloft plumes is critical for better interpreting the linkage of passive satellite observations of aerosol optical depth (AOD) and surface aerosol concentration ($PM_{2.5}$). A number of numerical models which combine meteorological transport and satellite observations has been developed which attempt to quantify plume vertical height, concentrations and extent including the Navy's NAAPS model and NOAA's GOES ASDTA product.

In this study, we analyze the potential of using these plume forecasts to either filter out or compensate contaminated cases resulting in a better PM2.5 to AOD relationship. We used multi-year MODIS AQUA/TERRA aerosol optical depth and PM2.5 concentration from 20 stations in NY State. Preliminary results show that multi-year GOES-ASDTA smoke product can be used to get a useful smoke indicator that can effectively eliminate smoke contaminated cases and improve the correlation and RMSE between PM2.5 and AOD. In addition to that, LIDAR imagery from CCNY LIDAR were used to filter out aloft plume days and observe the effect of plumes on potential linear behavior between PM2.5 and AOD.

2. METHODOLOGY

First we collected 24 hours of PM2.5 concentration data from NYCDEC website and from the website 15 urban and 5 non-urban station data were available for summer 2010-2012. We used MODIS AQUA/TERRA satellite data to collect AOD data of these PM2.5 stations for the same period of time. Then we analyzed the effect of Smoke Plume events in the relationship between PM2.5 and AOD using aloft plume images from CCNY LIDAR image library. The LIDAR at City College of NY is a ground-based multi-wavelength elastic-Raman scattering LIDAR. It observes 2D vertical distribution of aerosols and clouds at 1064, 532, 355-nm. The LIDAR derives PBL-height and temporal variation of the aerosol loading. In addition, we can identify aloft aerosol layers as smoke/dust. The LIDAR at CCNY is also able to isolates PBL-AOD and aloft plume-AOD.

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We used LIDAR images of summer 2010 to 2012 at CCNY site which can tell us which days have aloft plumes and which days have clear sky. Since the CCNY site is an urban site, we can determine the aloft plume days/clear sky days for all the urban PM2.5 stations in New York and filter out the contaminated days while analyzing the relationship between PM2.5 and AOD for the urban stations of NY.

The CCNY LIDAR image can only tell us if there is any plume incident in the urban area. These images are not suitable for determining plume events outside of the city area. To extend our analysis to bigger domains of interest, we make use of satellite and/or model based aerosol plume products. First we use the NOAA satellite based smoke plume product ASDTA (Kondrugunta et. al) for the summers of 2010-2012 and determined the smoke plume values over the 20 PM2.5 stations in NY State. Using ASDTA smoke plume data as a filter for contamination, we analyzed the PM2.5 to AOD relationship for both urban and non-urban cases in NY State.

Then we collected NAAPS (Navy Aerosol Analysis and Prediction System) aerosol layer data for summer of 2010-2012 and calculated the PBL, aloft and total smoke AOD from the mass concentration profile and total AOD data that were available. Using these three different smoke AOD data as contamination filters, we analyzed the relationship between PM2.5 to AOD for the urban and non-urban PM2.5 stations in NY State. Finally, we compared the results from the ASDTA filter to the NAAPS filter and determined which product can provide us with better result in improving the PM2.5 to AOD relationship.

3. RESULTS

3.1 Hourly PM2.5 vs AOD

After collecting PM2.5 concentration data for available 15 urban and 5 non-urban NY stations from NYDEC for summer 2010-2012 and AOD data at PM2.5 station locations from MODIS AQUA/TERRA for summer 2010-2012, PM2.5 vs AOD was plotted for all 20 PM2.5 station locations at MODIS hours. Low slope and fairly high offset can be observed from the plot in Figure 1.

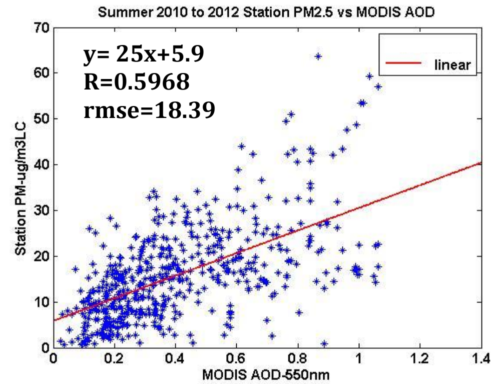

Fig. 1. PM2.5 vs AOD over 15 urban and 5 non-urban PM2.5 stations in NY State.

3.2 LIDAR (Light Detection and Ranging) Imagery for plume detection:

NOAA CREST LIDAR can be used to detect existence of plumes. Direct integration of the extinction coefficient can be used to estimate the plume AOD, as well as the resulting PBL AOD. Plumes can easily be greater than 50% of total AOD. In Figure 2, we note the presence of a significant aloft plume over the PBL layer on June 29th, 2012.

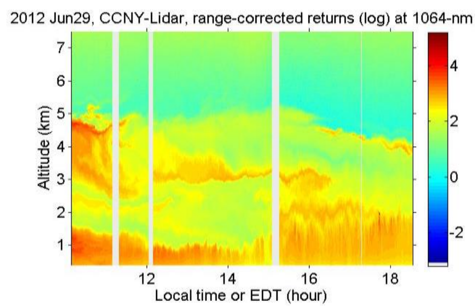

Fig. 2. LIDAR image of plume presence over CCNY site for June 29, 2012 (Collected from NOAA CREST LIDAR imagery website).

The LIDAR imagery can be used to study the effect of plumes on potential linear behavior between satellite AOD and surface PM2.5. We selected the aloft plume days by looking at the LIDAR images as shown in Figure 2 and also determined which days are clear sky days. The images that showed plume presence above the PBL layer were named as plume days and others were determined to be clear sky days. In general, we note a reduction in regression offset as well as an improved slope and correlation in Figure 3(b).

As expected, poor correlation is seen when only the smoke plume cases are studied in Figure 3(c).

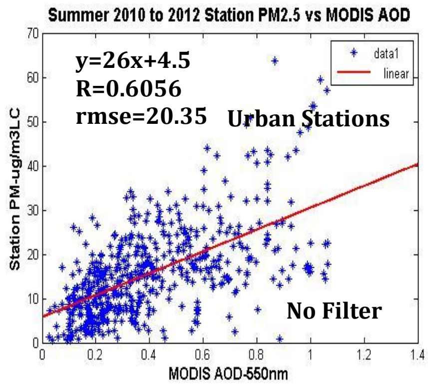

Fig. 3(a). PM2.5 vs AOD over 15 urban PM2.5 stations in NY State without using any filter.

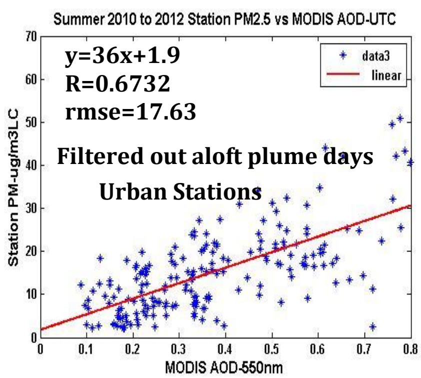

Fig. 3(b). PM2.5 vs AOD over 15 urban PM2.5 stations in NY State after filtering out aloft plume days.

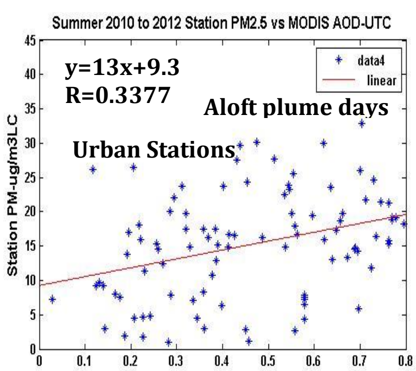

Fig. 3(c). PM2.5 vs AOD over 15 urban PM2.5 stations in NY State when considering only aloft plume days.

3.3 ASDTA Filtering based on average smokiness of entire NY:

To explore a wider domain, we can't use the LIDAR imagery, so we use the different plume products. It should be noted that the ASDTA Smoke Product seems to ignore the smoke AOD values that are closed to zero. 50 % of the collected Smoke AOD tends to be above approximately 0.3 which implies that ASDTA algorithm mainly attempts to construct significant smoke plume cases and is unlikely to accurately estimate smaller plumes. In addition, plume transport algorithms are not expected to have very good spatial accuracy. Therefore, using it to determine the smoke content of a single pixel is not realistic. A more conservative approach is to use an extended domain and estimate the smoke likely hood based on statistics. We quantify the smoke contamination of each event as:

*Smokiness=average smoke AOD in the domain * fraction of smoky pixels in the domain* (1)

Where, Fraction of smoky pixels
= valid number of pixels / total number of pixels (2)

We consider our domain to be the entire NY state and determine the total number of valid pixels in the domain. Valid pixels are those pixels in New York State domain whose smoke AOD values are not NaN values.

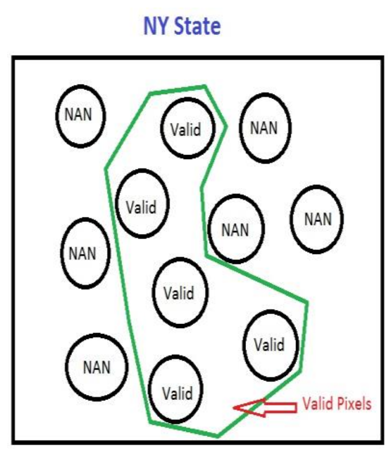

Fig. 4. Quantifying plume contamination as "Smokiness" using ASDTA.

We calculated the average Smokiness of NY state for each hour in summer 2010-2012 for which

PM2.5 and AOD data are available. A CDF distribution allows us to develop a long term climatology of "smokiness" within a given domain. From this, we can study the PM2.5 vs AOD as a function of the degree of "smokiness". Based on the CDF plot in Figure 5, we applied the smokiness filter to the PM2.5 and AOD data and observe that as the smoke indicator decreases, the correlation between PM2.5 and AOD increases in Figure 7(a), the slope increases in Figure 7(b), the RMSE and DC offset keeps decreasing respectively in Figure 7(c) and Figure 7(d). From Figure 1, we filter out the cases whose smokiness values are greater equal to 0.016 (an optimal point chosen from CDF plot) and notice significant improvement in correlation coefficient, slope, RMSE and intercept in Figure 6.

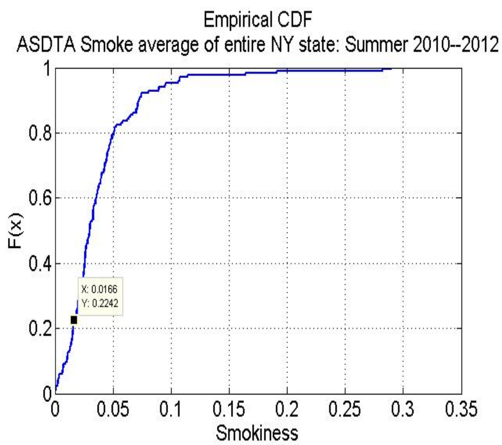

Fig. 5. Cumulative distribution function of Average Smokiness of NY state in summer 2010-2012.

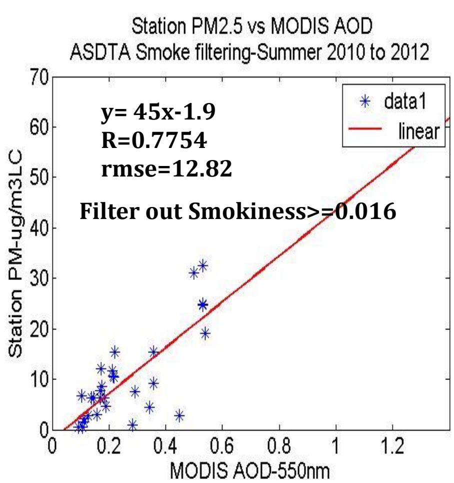

Fig. 6. Filtering based on average smokiness of entire New York State

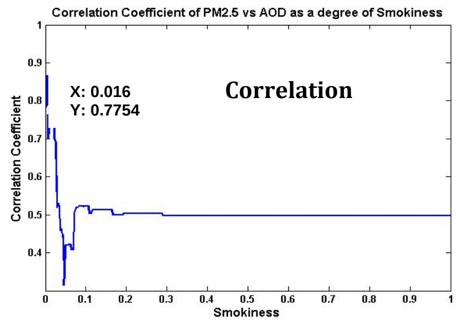

Fig. 7(a). Correlation Coefficient of PM2.5 vs AOD improvement as the Smokiness filter decreases.

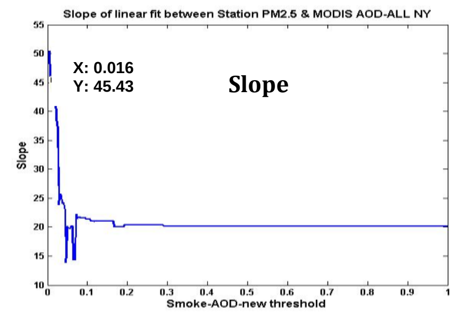

Fig. 7(b). Slope of PM2.5 vs AOD improvement as the Smokiness filter decreases.

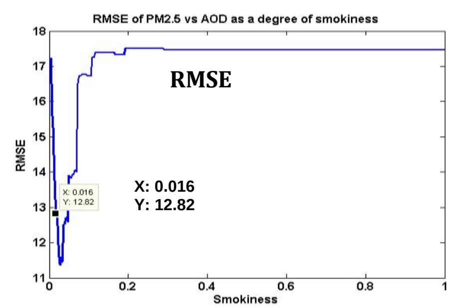

Fig. 7(c). RMSE of PM2.5 vs AOD improvement as the Smokiness filter decreases.

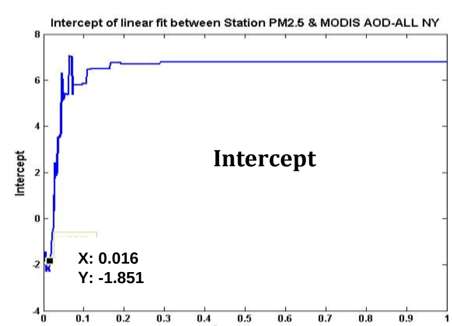

Fig. 7(d). Intercept of PM2.5 vs AOD improvement as the Smokiness filter decreases.

In attempt to improve the resolution, we reduced the domain box from whole NY State to 20km boxes around the PM2.5 stations and calculated smokiness of those boxes for each of the time slots. Then we plotted the CDF function in Figure 8 for smokiness and notice that the CDF is consistent for different regions (urban or nonurban) which is reasonable for transported smoke. After that, we pick an optimal point of smokiness 0.018 and applied the smokiness filter to the PM2.5 vs AOD of urban stations shown in Figure 3(a) and notice significant improvement in the relationship in Figure 9.
In this case, we also notice that continuously decreasing the smokiness filter improves the correlation coefficient, slope, RMSE and intercept of the PM2.5 vs AOD relationship in Figure 10.

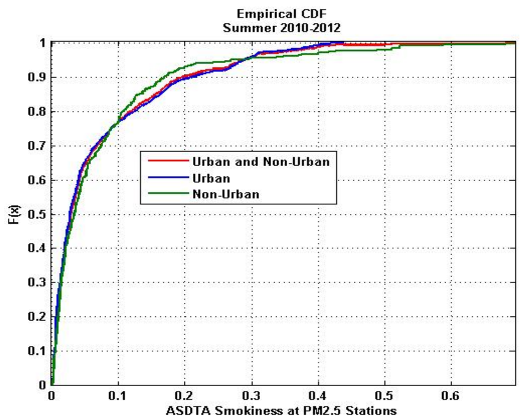

Fig.8. CDF distribution of urban and non-urban smokiness of 20 km boxes around PM2.5 stations.

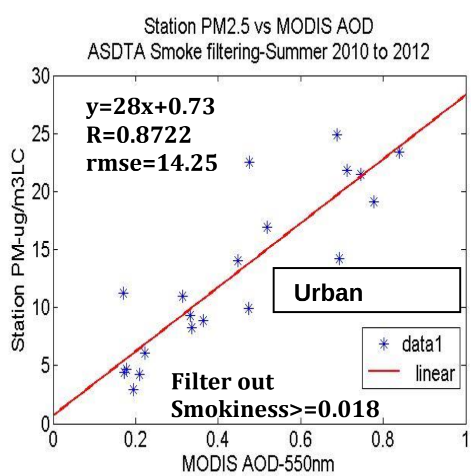

Fig.9. Filtering based on smokiness of 20km boxes around PM2.5 stations.

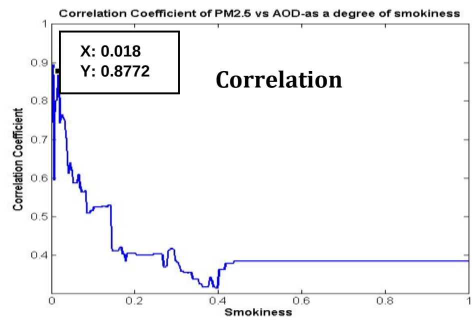

Fig. 10(a). Correlation Coefficient of PM2.5 vs AOD improvement as the Smokiness filter

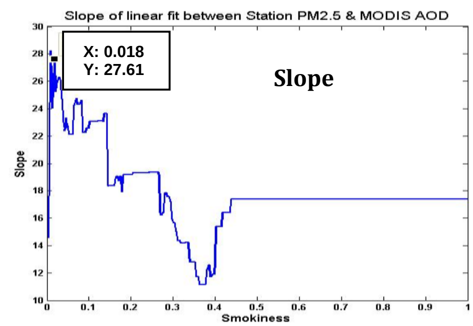

Fig. 10(b). Slope of PM2.5 vs AOD improvement as the Smokiness filter decreases.

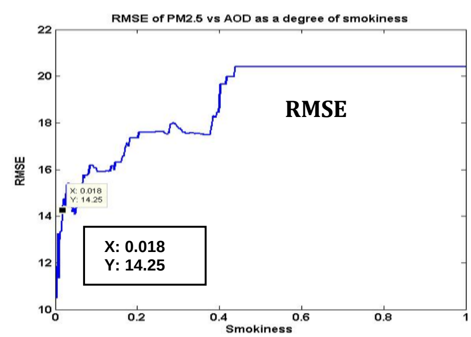

Fig. 10(c). RMSE of PM2.5 vs AOD improvement as the Smokiness filter decreases.

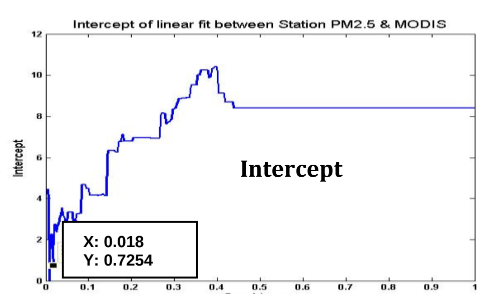

Fig. 10(d). Intercept of PM2.5 vs AOD improvement as the Smokiness filter decreases.

3.4 NAAPS Smoke AOD for filtering contaminated cases:

The CDF function of PBL, aloft and total smoke from NAAPS data in Figure 11 shows us that the PBL smoke and Aloft Smoke is about the same amount present in the atmosphere.

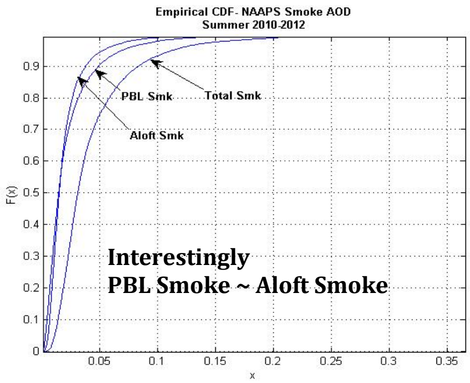

Fig. 11. CDF distribution of NAAPS PBL, aloft and total smoke AOD.

We applied the same technique we used for ASDTA for filtering out the contaminated cases except that for NAAPS, we are directly using the smoke AOD for the filtering. Unlike ASDTA smoke product, NAAPS doesn't give any NaN values of smoke, and that's why we didn't need to calculate the smokiness in this case. We applied three different kind of smoke filter: Aloft Smoke AOD filter, PBL Smoke AOD filter and Total Smoke AOD filter. All three filters produce almost the same improvement in correlation coefficient, slope, RMSE and intercept as the smoke indicator decreases which is shown in Figure 12.

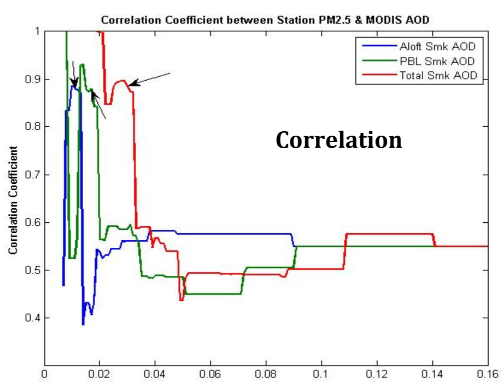

Fig. 12(a) Correlation Coefficient of PM2.5 vs AOD improvement as the NAAPS smoke indicator decreases.

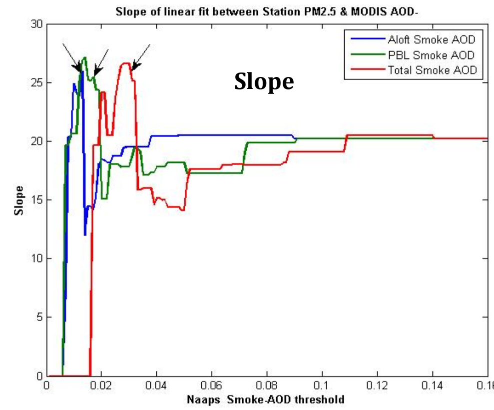

Fig. 12(b) Slope of PM2.5 vs AOD improvement as the NAAPS smoke indicator decreases.

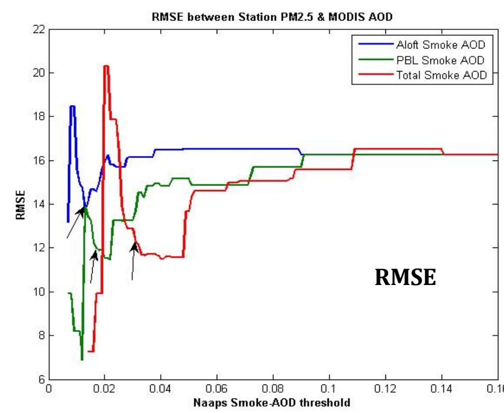

Fig. 12(c). RMSE of PM2.5 vs AOD improvement as the NAAPS smoke indicator decreases.

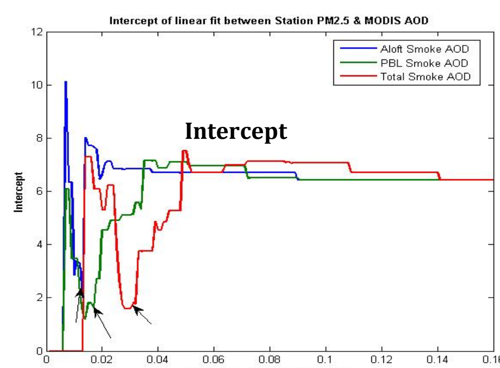

Fig. 12(d). Intercept of PM2.5 vs AOD improvement as the NAAPS smoke indicator decreases.

3.5 NAAPS and ASDTA Smoke Indicator Comparison:

Since using either of the aloft, PBL or total smoke AOD of NAAPS for entire NY state domain provides similar results in improving the relationship between PM2.5 vs AOD, we choose the NAAPS total smoke AOD filter and compare its results with the ASDTA smoke indicator. In this case we are only considering the urban stations. Figure 13 shows the comparison of correlation coefficient, slope, RMSE and intercept changes as the NAAPS and ASDTA smoke indicator changes. The results show that the ASDTA smokiness filter provides us with a smoother and more consistent improvement in the relationship between PM2.5 and AOD.

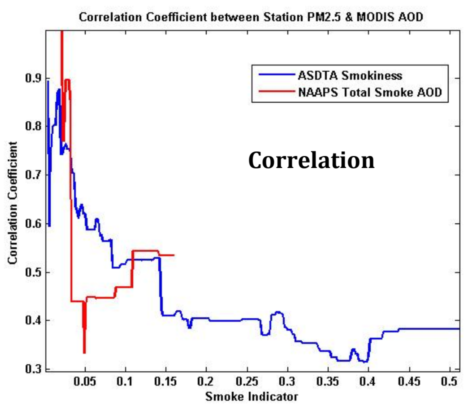

Fig. 13(a) Correlation Coefficient of PM2.5 vs AOD improvement as the NAAPS smoke indicator decreases.

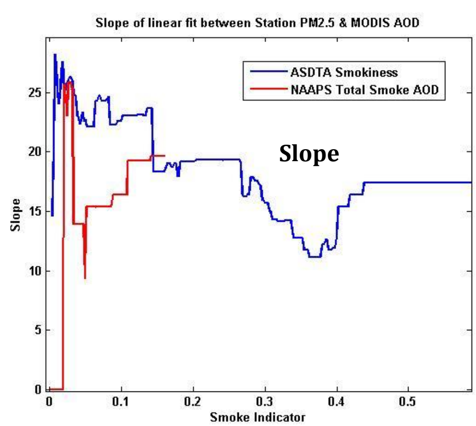

Fig. 13(b). Slope of PM2.5 vs AOD improvement as the NAAPS total smoke AOD and ASDTA smokiness filter decreases.

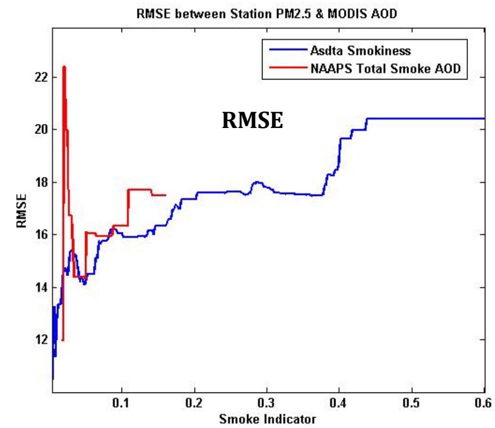

Fig. 13(c). RMSE of PM2.5 vs AOD improvement as the NAAPS total smoke AOD and ASDTA smokiness filter decreases.

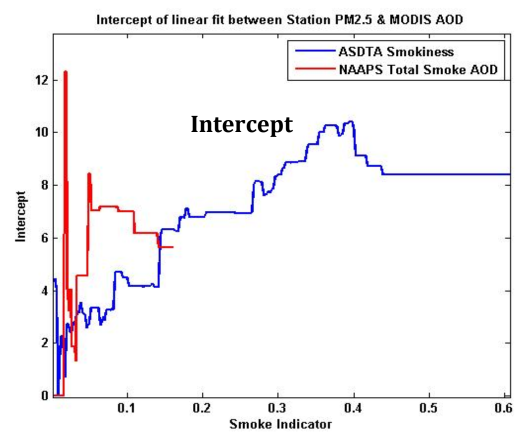

Fig. 13(d). Intercept of PM2.5 vs AOD improvement as the NAAPS total smoke AOD and ASDTA smokiness filter decreases.

4. CONCLUSION

In general, we have demonstrated that by applying either ASDTA or NAAPS smoke indices as a filter of smoke plumes, there is a general improvement in the resultant relationship between satellite AOD and station PM25 as the Smoke Index decreases. In particular, the correlation and slope increases as the smoke index becomes lower and the RMSE and y-intercept decreases which is consistent with removal of smoke from inorganic aerosol condition. This implies that the SI indices can be used in a pre-processing mode to filter smoke cases. The use of the ASDTA smoke index over the entire New York State domain seems to provide a useful indicator of smoke contaminated cases. We see that as SI decreases, the PM2.5 / AOD ratio increases, the correlation improves and the DC offset decreases. The increase in the slope is consistent with observations that smoke contamination (both PBL and aloft) will decrease the ratio. If we try to make the SI too low, the statistics becomes too sparse and the positive trends break down. The results are even more dramatic over the NYC area. When the domain size shrinks, the CDF is skewed to higher value which is reasonable since it is easier to fill a smaller cell with smoke. In addition, we see that the CDF is consistent for different regions (urban or nonurban) which is reasonable for transported smoke. NAAPS smoke index over the entire New York State domain also seems to provide a useful indicator of smoke contaminated cases. All three smoke indicators: Aloft Smoke AOD, PBL Smoke AOD and Total Smoke AOD seems to perform almost similarly in increasing the Correlation Coefficient, Slope and decreasing the RMSE and DC Offset. However, the Total Smoke AOD tends to have smoother increase in Correlation Coefficient. Finally the ASDTA smoke indicator seems to perform the best in improving the PM2.5 to AOD relationship. In the future, we plan to add the Smoke Index as an additional factor to more complex processing approaches such as NN's to improve PM25 estimations.

4. REFERENCES

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