IMPROVING CALIPSO LIDAR RETRIEVALS OF SURFACE LEVEL BACKSCATTER AS A PROXY FOR PM2.5 USING MODIS PATH REFLECTANCE CONSTRAINTS

L. Charles, M. M. Oo, B. Herman B. Gross, F. Moshary and S. Ahmed

Optical Remote Sensing Laboratory City College of New York, New York, NY, USA 10031;gross@ccny.cuny.edu

ABSTRACT

In this paper, we explore the potential for improving CALIPSO backscatter profiles through constraints imposed by MODIS derived path reflectances. This is done by processing the 2 channel lidar signals using a wide range of aeronet derived atmosphere models to determine both backscatter and mixing ratio and determining the set of models that satisfy all the MODIS path reflectance constraints.

1. INTRODUCTION

Use of satellite aerosol optical depth (AOD) measurements as a proxy for surface level PM2.5 offers a powerful tool for air pollution monitoring and transport. However, column aerosol loading measurements from passive sensors often show poor correlation with surface level PM2.5. With the much anticipated launch of CALIPSO, range resolved lidar measurements of the aerosol backscatter near the surface, which serves as an excellent proxy for PM2.5, should be feasible

However, the accuracy of the backscatter retrieval depends on a good estimate of the extinction-to-backscatter ratio (S ratio). In the initial operational processing of CALIPSO, the S ratio is assumed constant and is estimated from a set of possible aerosol cluster modes identified using two-channel color ratios as well as ancillary geographical information.[1] This approach results in large uncertainties in the S ratio which can cause large errors in the surface backscatter for high aerosol loading events.

Kaufmann et al [2] devised a method in which the MODIS path radiances were use to constrain the lidar profiles and provide overall retrieval improvement in the backscatter ratio. The main features of this algorithm are:

1. Predetermine set of possible fine and coarse mode aerosol distributions that are based on physical (and observational) constraints This approach, which is in the spirit of calipso lidar processing, is quite different than conventional approaches where the microphysical parameters are left variable. In particular the approach takes into account that physical processes limit the possible development of fine and coarse modes. In particular, by extensive data mining of aeronet aerosol retrievals, a set of possible cluster aerosol modes determined. To develop a given atmosphere, the aerosol modes are determined by a linear mixing of possible fine and coarse modes.

2. Process both calipso lidar channels over all possible atmosphere combinations. In performing this procedure, an iterative scheme equivalent to the Fernauld algorithm for single channel lidar is applied. For a given aerosol mixing mode, both the backscatter of both lidasr channels (532nm, 1064nm and mixing ratio can determined and hence the total path extinction (optical depth)

3. For each lidar retrieval for each mode combination the vertical profiles of aerosol total backscatter and mode ratio properties can be translated into effective phase functions, single scattering albedo and optical depth for each layer.

4. Use Radiative transfer theory to obtain the path reflectance suitable for each mode combination and obtain the atmosphere which best matches the MODIS reflectivity.

2. AEROSOL BACKSCATTER AS PM2.5 ESTIMATOR

To verify the usefulness of the backscatter as a good proxy for PM.5, we first compare the total volume to the optical backscatter for the particle size distributions within the Aeronet database. In particular, given the aeronet PSD retrieval parameters,

$$m_r(\lambda), m_i(\lambda) \quad \left[\frac{dV}{d\log(r)}\right]$$

it is easy to calculate both the total volume and optical backscatter using

$$PM(r_0) = \int_{r_{\min}}^{r_0} \left[\frac{dV}{d\log(r)}\right] d(\log(r))$$

$$\beta(\lambda) = \int_{r_{\min}}^{r_{\max}} \left(\frac{3}{4r}\right) Q_e(q,, m_r(\lambda), m_i(\lambda)) \left[\frac{dV}{d\log(r)}\right] d(\log(r))$$

where $q = 2\pi a/\lambda$ is the mie size parameter. The correlation between volume and backscatter coefficients is presented below and shows very strong linear behavior unless the upper particle diameter is less than 1 micron.

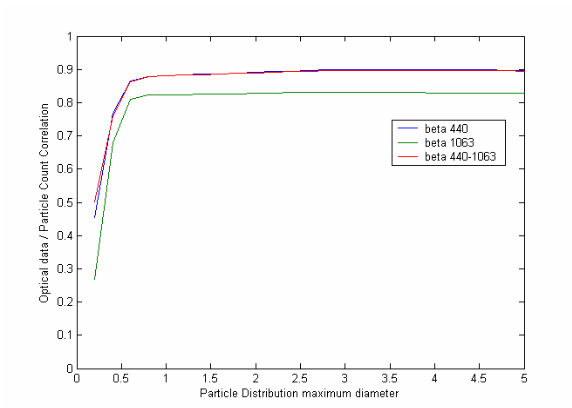


Fig 1 Correlation between partical volume and optical backscatter as function of upper diameter limit.

Besides the theoretical models, we have alsdo been able to test the relationship using the 910nm channel of the Vaisela Ceilometer. In figure 2, we plot the backscatter profiles obtained over a 36 hour period. The horizontal strips show two altitude ranges for testing the correlation between backscatter and PM2.5. The first strip goes from 20m to 80m while the second strip goes from 220-280 meters.

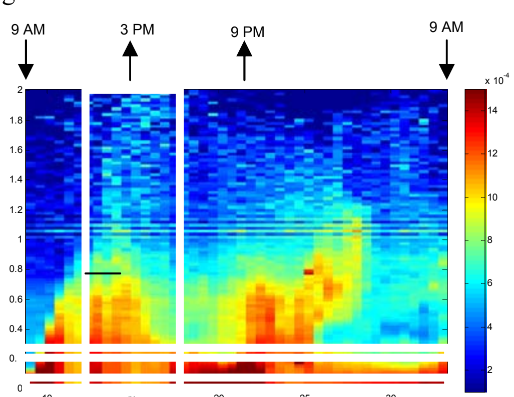


Fig 2 36 Hour Ceilometer measurements of near surface backscatter

The correlations between the backscatter (1 hour average) with the hourly averages of the PM2.5 DEC measurements are given in figure 3 for the 2 vertical layers.

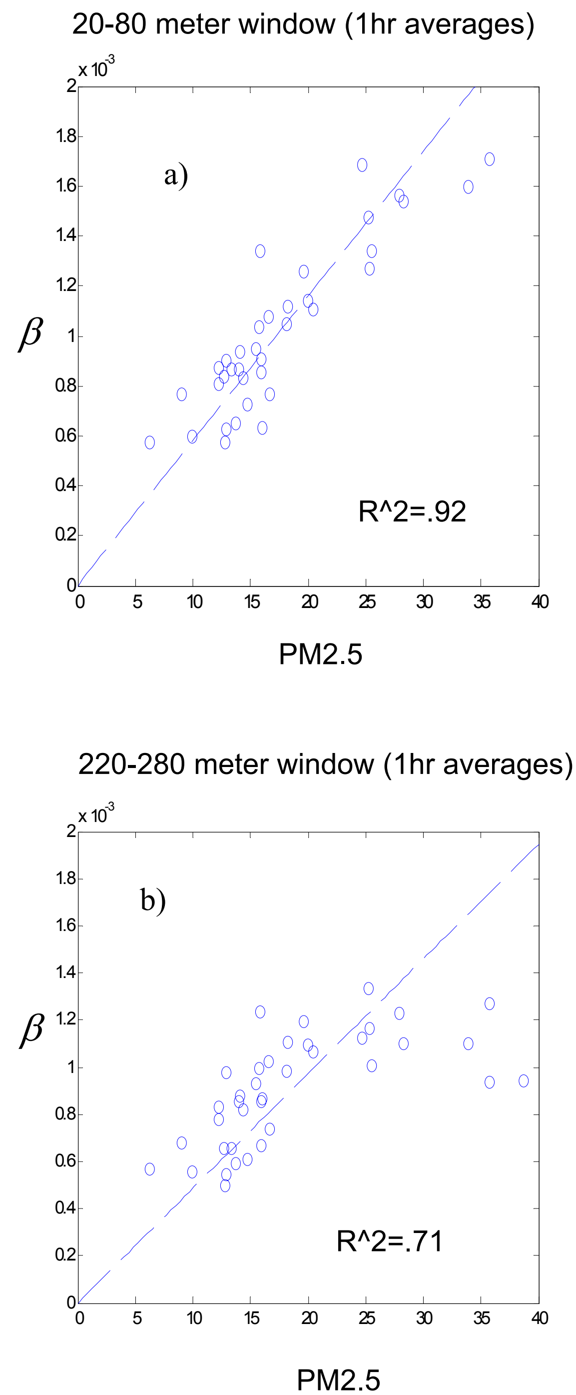


Fig. 3 correlations between the backscatter (1 hour average) with the hourly averages of the PM2.5 DEC measurements a) low layer b) aloft layer

From these correlations, we see clearly the value and pushing lidar measurments of backsdcatter to the ground where the correlation is very high. We also see significant degradation in the correlation for fairly low latitudes showing.

3. PROCESSING ALGORITHMS

The lidar processing algorithm as described in [2] is used in this study. In particular, the processing foir each mode pair modes labeled (I,II), we obtain the total aerosol backscatter and mixing ratio profiles and from construction, all relevant extinction and backscatter profiles for each mode. From this information, we can obtain the single scattering optical depth, albedo and phase function for each m ode.

$$\tau_I^j(\lambda_k),\ \omega_{o,I}^j(\lambda_k),\ p_I^j(\theta,\theta',\Delta\Phi,\lambda_k)$$

$$\tau_{II}^j(\lambda_k),\ \omega_{o,II}^j(\lambda_k),\ p_{II}^j(\theta,\theta',\Delta\Phi,\lambda_k)$$

In addition, given the mixing ratio processed from the multichannel lidar algorithm, we can calculate the effective scattering properties as appropriate weights between the molecular and aerosol modes

$$p_{eff,j} = \frac{\omega_{o,m}\tau_m^j p_m^j + \omega_{o,II}^j \tau_{II}^j p_{II}^j + \omega_{o,I}^j \tau_I^j p_I^j}{\omega_{o,m}\tau_m^j + \omega_{o,II}^j \tau_{II}^j + \omega_{o,I}^j \tau_I^j}$$

$$\omega_{o,eff}^j = \frac{\omega_{o,m}\tau_m^j + \omega_{o,II}^j \tau_{II}^j + \omega_{o,I}^j \tau_I^j}{\tau_m^j + \tau_{II}^j + \tau_I^j}$$

Unfortunately, the data fusion method discussed above was limited to ocean scenes. This restriction is based on the fact that ground reflection will dominate any atmospheric signal seen in the MIR.[3] While the passive radiance constraint at other wavelengths, ground contamination is a significant issue Furthermore, it must be emphasized that the data fusion algorithm uses the column radiance (directly observed over oceans) instead of optical depth since the aerosol optical depth depends on the aerosol model class. To extend this method over land, it is necessary to be able to isolate the path radiance from the TOA signal with sufficient accuracy to use as a column constraint. These two cases are as follows

1. If the aerosol loading is sufficiently high over a sufficiently dark surface such as vegetation. This condition is often satisfied in moderate or high pollution events.

2. The path radiance was separated with sufficient accuracy either through spectral correlation

between the MIR and VIS channels, or sufficient spatial diversity to employ EOF analysis

4. AEROSOL MODELS

Assuming that we meet these criterion, we next need to assess the best choice of "modes". Unlike the case aerosols over water, the separation into coarse and fine modes is not very useful since most of the aerosols come from the same global cluster and in addition, the VIS MODIS channels are not very sensitive to isolataing pure coarse modes. Instead, we decided to use a purely statistical approach to choose the set of modes to build up based primarily on the distribution of S ratios observed within the aeronet atmospheres.

In particular, we took as modes, the end-members which are defined as models which take on extreme values of S ratios in $S_{532} - S_{1064}$ plot. Once these end-members were chosen, the S ratios of any linear combination of end-member modes would lie in the convex interior of the S domain thus providing good mixing models which can describe almost any atmosphere as seen in figure 1. In our case, we chose 2 sets of 30 end-members wich are sufficient to cover the S-domain with $\Delta S \approx 2$. To perform simulations, The PBL was taken as 2 km with an aloft layer between 4 and 5 km and the total optical depth at 550 varied was 0.5

5. RESULTS

To begin, we explore the level of uncertainty which is

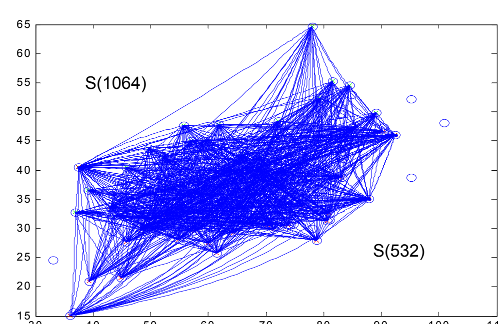


Fig 4 532nm and 1064nm S ratio coverage based on linear combination of end-member reasonable based on no a-priori constraints on path reflectance. In this case, the S ratio uncertainty based on aeronet retrievals shown in figure 5 is about 30%

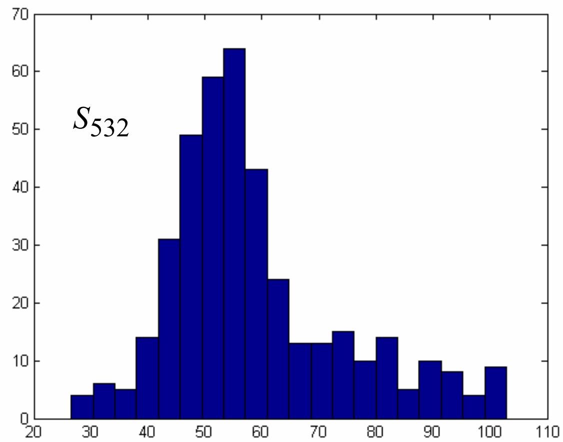


Figure 5. S ratio statistics at 532nm

which is consistent with the standard and fused MODIS-CALIPSO products as well as supporting aerosol transport.

To see the kind of errors we can expect for the surface backscatter, we took a synthetic atmosphere with well prescxribed mixing ratio and vertical profile and processed the lidar profiles only using the different S ratios that we can assume a-priori. The results are shown in figure 6 where the spread is shown to be as high as 40% in surface backscastter.

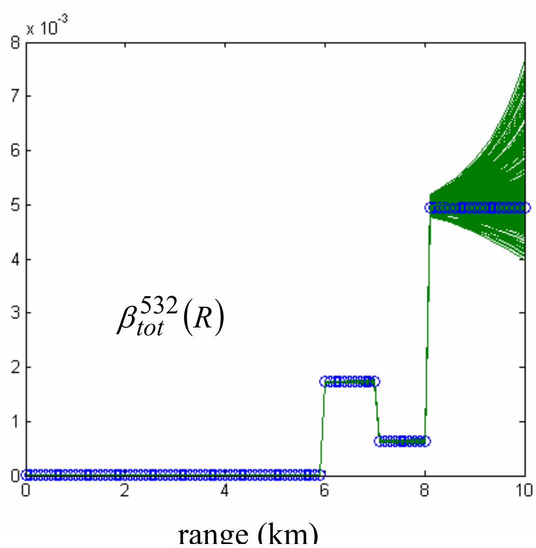


Figure 6. Backscatter retrieval using simple S ratio model showing spreads of 40%.

However the result is much better when we use the 10% reflectivity constraints at both 470 and 660nm. As we see in figure 7, using the constraints significantly improves the retrieval.

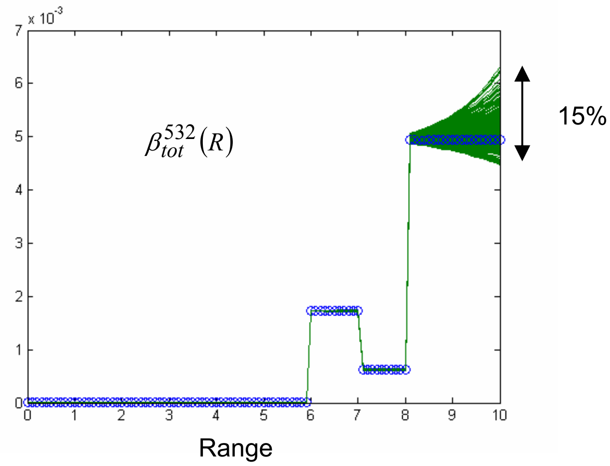


Fig 7 Retreival of Backscater profile assuming 10% constraints from column path reflectances.

Unfortunately, the 670 constraint may be hard to meet so we have also explored the sensitivity of the retrieval improvement as we relax the 670 constraint. The results are given in figure 8.

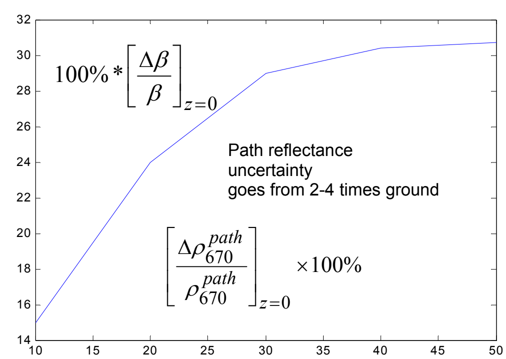


Figure 8. % error of surface backscatter as function of 670nm path reflectance

We see that even if the 670 constrain is not uded at all, the error is somewhat reduced (26%) but with improvements in surface albedo estimation from POLDER, MISR, GOES-R and APS, it might be feasible to pin the 670nm channel sufficiently.

6. CALLIBRATION

All of the previous results assumed that the lidar is perfectly calibrated. However, calibration errors of 10% are expected for the Calipso lidar so it is useful to assess how this problem can be dealt with. For example, if a 10% error in the lidar calibration exists, the resultant retrievals are all biased in a dramatic way as seen in fig.9 for the case of unconstrained retrievals.

While the error is large, it is also expected that most of the retrievals will result in biased path reflectances

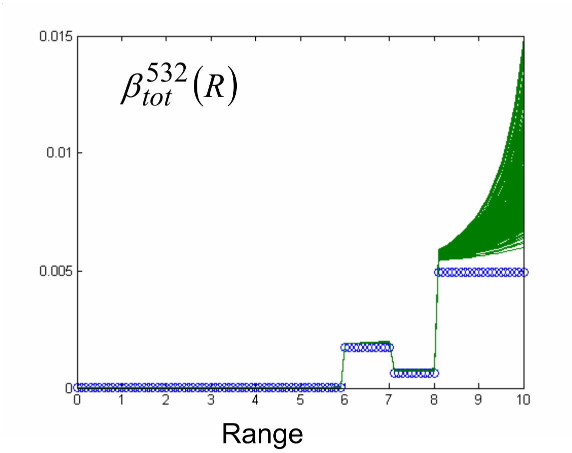


Fig 9 Retreival of Backscater profile assuming 10% error in calibration coefficients

which will reduce the number of atmospheres which meet the constraints as seen in figure10.

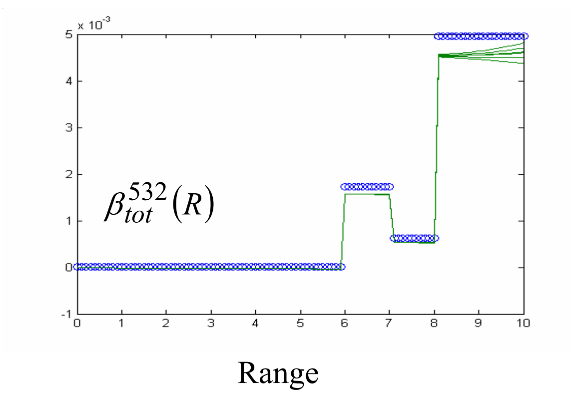
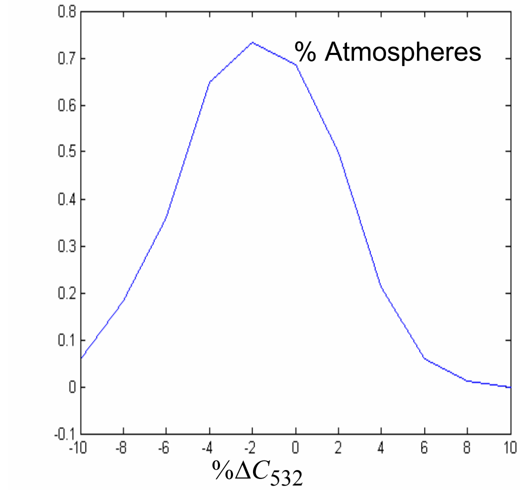


Fig. 10 Constrained Retrieval with calibration error

However, we can overcome this issue by reprocessing over a set of assumed calibration coefficients and examining the % of atmospheres selected with the 10% constraints. The results of this approach are shown in Figure 11 and show that as the calibration constant becomes more inaccurate, the % of atmospheres that fit the path reflectance constraint are reduced. Therefore, we can process the lidart profiles over a sequence of calibration constants and optimize the retrieval by picking the calibrations which maximize the atmospheres.



7. CONCLUSION

The use of path reflectances from MODIS can be used to constrain the calipso profiles allowing more accurate retrieval of near surface backscatter. Furthermore, a more useful approach in selecting the modes using end members is given. Improvements in albedo modeling will allow better utilization of the 670 channel further improving the technique.

ACKNOWLEDGEMENTS

This work was partially supported research grant s NOAA # NA17AE1625 and NASA # NCC-1-03009.

REFERENCES

1. A. H. Omar, D. M. Winker, and J-G. Won, "Aerosol Models for the CALIPSO Lidar Inversion Algorithms", in *Laser Radar Technology for Remote Sensing, Proc. SPIE*, **5240**, Christian Werner, Editor, Deutsches Zentrum fuer Luftund Raumfahrt e.V. (Germany), pp. 104-115, 2004.

2. Kaufman, Y.J.; Tanre, D.; Leon, J.-F.; Pelon,J. " Retrievals of profiles of fine and coarse aerosols using lidar and radiometric space measurements" IEEE Trans. Geosience and Remote Sensing 1743- 1754 (2003)

3. F Waquet, JF Léon, P. Goloub, J. Pelon and D. Tanré, "Maritime and Dust Aerosol Retrieval from Polarized and Multispectral Active and Passive Sensors", J. GEOPHYS. RES., 110 (2005)