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Evaluation of the representativeness of ground-based visibility for analysing the spatial and temporal variability of aerosol optical thickness in China

Zhao Yang Zhang [a], Man Sing Wong[*,a], Kwon Ho Lee [b]

[a] Department of Land Surveying and Geo-Informatics,

The Hong Kong Polytechnic University,

Kowloon, Hong Kong

[b] Department of Atmospheric & Environmental Sciences, Gangneung-Wonju National University (GWNU), Korea

*Corresponding author: Man Sing Wong

Email: lswong@polyu.edu.hk

Telephone no.: 852-34008959; Fax: 852-23302994

Highlights

Singular Value Decomposition was applied to evaluate the temporal and spatial variations.

Monthly visibility and AOT variability have large differences.

Variations of inter-annual visibility and AOT agreed well over China.

Aerosol vertical distribution contribute significantly in the relationship between AOT and visibility.

Keywords:

Aerosol optical thickness, Singular value decomposition, Visibility

Abstract

Although visibility is a widely-used indicator to quantify the aerosol loadings, only a few studies have been analyzed the representativeness of visibility in deriving Aerosol Optical Thickness (AOT). In this paper, ground-based visibility, MODerate-resolution Imaging Spectroradiometer (MODIS) and Multi-angle Imaging SpectroRadiometer (MISR) monthly AOT products between July 2002 and December 2014 were analyzed in order to extract the dominant modes of variability using the Singular Value Decomposition (SVD) method. The method has significant merit to reduce data dimension and examine both spatial and temporal variability simultaneously. Results indicated that the satellite retrieved AOTs agreed well with ground-based visibility in terms of inter-annual variability. The correlation coefficients in the first deseasonalized mode are greater than 0.65 between visibility and satellite AOT products. However, large differences were observed in the seasonal variability between ground-based visibility and AOT. In addition, Aerosol vertical distribution from LIdar climatology of Vertical Aerosol Structure for space-based lidar simulation studies (LIVAS) and cloud data from ground-based meteorological station were used to investigate the seasonal variability disagreement. The AOT values derived from LIVAS extinction coefficients between 0 and 500 m above surface have a stronger relationship with visibility, than total column AOT with visibility. It also indicates that seasonal variation of aerosol vertical distribution is the main cause of the disagreement between two parameters, and the uncertainties of satellite products also contribute to the disagreement. Results in this study highlighted that the visibility observation could only be used to depict the inter-annual AOT and more ancillary information could be used for studying seasonal AOT variation.

1. Introduction

Aerosols contain a wide range of particles exhibiting varying kinds of shapes, sizes, compositions, and optical properties in air (Hinds, 1999). Aerosols can heat the atmosphere and cool the earth surface by absorbing and scattering solar radiation (Stocker, 2014). To date, aerosol particles affecting aerosol-cloud interactions remain one of the largest uncertainties in climate change studies (Field et al., 2014). There is a lack of long-term Aerosol Optical Thickness (AOT) data (e.g., more than 40 years), and the observation networks available only include sparse sites, which become a major issue in analyzing the climatic effects from aerosols.

Atmospheric visibility has been used as an indicator of air quality at different ground meteorological stations worldwide (Bäumer et al., 2008; Wang et al., 2009; Li et al., 2015a). In several climatic studies, visibility data were interpreted and correlated with AOT for long-term analyzes (Wang et al., 2009). For example, Elterman (1970) developed relationships between surface particulate matter (PM) and vertical attenuation by deriving an exponential decrease of aerosols with height. Qiu and Lin (2001) derived AOT from visibility by modifying the Elterman method, based on surface water vapor pressure. Lin et al. (2014) investigated AOT over East China using visibility and vertical profiles of aerosol from a chemical transport model. Wu et al. (2014) modified the Elterman method by coupling with new parameters. García et al. (2015) reconstructed daily AOT from visibility and meteorological data using artificial neural network method.

Although some promising results of AOT derivation were obtained using visibility data, some uncertainties still exist. For example, in the case of multiple or elevated aerosol layers, surface observations may not be able to represent the total aerosol loadings in the atmosphere (Li et al., 2015b). Toth et al. (2014) found that surface $PM_{2.5}$ concentrations in the eastern U.S. had the best correlation with the dry mass Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) extinction at 200 to 300 m. Typically, aerosol extinction coefficients at the surface are a common parameter for deriving visibility by a simple inverse formula, named Koschmieder's equation (Koschmieder, 1925). However, Koschmieder's equation is applicable only under specific atmospheric conditions (Horvath, 1971; Yuan et al., 2006; Lee et al., 2014) and the equation may also bring some discrepancies between AOT and visibility. Meyer et al. (1991) illustrated that Koschmieder's equation generally underestimated the visual range using the default value. The range of constant used in the equation is varied from 1.8 to 3.912 in different visibility stations among different applications (Ozkaynak et al., 1985; Yuan et al., 2006; Kessner et al., 2013).

Many studies have investigated the relationship of AOT and visibility on hourly and daily scales at a few ground observation stations, but not for both spatial and temporal variations on significantly large scales. Random observed noise may comprise such limited studies (So et al., 2005; Chan, 2009; Zhao et al., 2015). In this study, MODIS (Terra and Aqua) and Multi-angle Imaging SpectroRadiometer (MISR) AOT datasets were obtained and used to estimate the relationship between satellite-retrieved AOT and ground-based visibility over China. The Singular Value Decomposition (SVD) approach was adopted in order to isolate patterns of different variabilities and reduce the noise level in the relationship. The primary objective of this study is to investigate the representativeness of visibility for estimating columnar AOT in China. This paper is organized as follows. Descriptions of the data used and the methodology are outlined in Section 2. In Section 3, spatial and temporal variability between surface visibility and satellite AOT and the influencing factors were examined. Section 4 summarizes the main conclusions and findings.

2. Data and method

2.1 Satellite retrieved AOT

MODerate-resolution Imaging Spectroradiometer (MODIS) Collection 06 monthly AOT products (MYD08 for Aqua and MOD08 for Terra) were obtained from the NASA Goddard Space Flight Center, archived database (http://ladsweb.nascom.nasa.gov/data/search.html). MODIS AOTs were calculated using three different algorithms for different regions: one algorithm for ocean and two for land — the Deep-Blue (DB) algorithms (Hsu et al., 2004) and Dark-Target (DT) (Levy et al., 2010). The retrieval errors of DT and DB AOT are within $\pm 0.05 \pm 0.15 \times$ AOT (Levy et al., 2013) and $\pm 0.03 \pm 0.2 \times$ AOT (Sayer et al., 2013), respectively. In this paper, MYD08 and MOD08 combined DT and DB products between July 2002 and December 2014 were used. The mean AOTs of both Aqua and Terra in the study period are shown in Figure 1a and 1b, respectively. High AOTs are mainly distributed in the North China Plain (NCP), Yangtze River Delta (YRD), and Sichuan Basin (SB).

MISR onboard of the Terra satellite was launched into earth orbit in December 1999, and was designed to measure aerosol properties with repeat global coverage in between two and nine days (Kaufman et al., 1998; Diner et al., 2002). The MISR instrument consists of nine push-broom cameras. Compared to the MODIS aerosol algorithm, MISR has better capability over bright surfaces due to the multi-angle view (Abdou et al., 2005). The retrieval error of MISR AOT is within $\pm 0.04 \pm 0.18 \times$ AOT (Liu et al., 2004). Monthly 555 nm MISR AOT products with resolution of $0.5^{\circ} \times 0.5^{\circ}$ are illustrated in Figure 1c. The spatial resolution of MODIS and MISR AOT in Figure 3 are $1^{\circ} \times 1^{\circ}$ and $0.5^{\circ} \times 0.5^{\circ}$, respectively. The AOT values from MODIS are higher than those from MISR, especially in the NCP and YRD regions. It may be related to the underestimation in MISR aerosol datasets for high AOT event (Kahn et al., 2005; Kahn et al., 2007; Shi et al., 2011).

[Please insert Figure 1 here]

2.2 Vertical distribution of aerosols

In this study, vertical aerosol profile products from LIdar climatology of Vertical Aerosol Structure for space-based lidar simulation studies (LIVAS) were acquired (http://lidar.space.noa.gr:8080/livas/index.html). LIVAS products provide profiles of aerosol optical properties solved by combining Cloud-Aerosol Lidar and Infrared

Pathfinder Satellite Observation (CALIPSO) measurements and ground-based measurements. The horizontal spatial resolution of the LIVAS climatology is 1° × 1°, covering all longitudes, and latitudes between 82 °N and 82 °S. Vertical resolution of the data is 60 m from the surface to 20 km, and 180 m from 20 km to 30 km. The algorithms used to constrain extinction coefficients are given in Amiridis et al. (2015). The LIVAS data used in our study cover 4 years from June 2008 to December 2011. Derived extinction coefficients from the surface to 500 m above ground were used for calculating the AOT below 500 m altitude (hereafter AOT_{low}).

2.3 Surface visibility

Surface visibility is measured using visibility meters and human observation in China (Ma and Yang, 2007). Trained observers estimate the visual range using reference objects in different directions. The uncertainty of visibility by human observation varies. The error of visibility measured by visibility meter is within ±10 ~ 20% (WMO, 1996). Hourly visibility datasets were acquired from the Integrated Surface Hourly Data Base (ISD), which is land-based station data available from the America National Centers for Environmental Information (NCEI). Fifty-four quality-assured algorithms of ISD were designed to eliminate obvious errors and ensure with the greatest likelihood that valid values were not removed (Smith et al., 2011). The hourly visibility data for all-sky (including both clear sky and cloudy sky) conditions between 02 and 07 UTC were selected. Figure 2 shows the mean visibility between July 2002 and December 2014 for the selected 387 meteorological stations. Low visibility areas are mainly distributed in parts of the NCP, YRD, and Sichuan Basin. According to the location of the visibility station and corresponding data availability, monthly AOT values were extracted from MODIS datasets between July 2002 and December 2014.

[Please insert Figure 2 here]

2.4 Interpolation of missing data

Missing monthly AOT data were interpolated following the steps proposed by Li et al. (2014b) to assure the completeness of the time-series data. Multi-year monthly average values were removed from the full visibility/AOT dataset. Then, linear interpolation was applied on the remaining time series of data to fill the gaps, and the full dataset was established by adding the multi-year monthly average value back. The interpolation method performs well with relatively small error, which can minimize seasonal variability (Li et al., 2014b; Zhang et al., 2016). One more criterion was proposed and used to further minimize the bias in the paper: each pixel/station must contain at least 70% of available monthly data.

2.5 Singular Value Decomposition (SVD) analysis

Singular Value Decomposition (SVD) technique was performed to separate different modes between two input fields spatially and temporally. The SVD analysis was first applied in meteorological context by Prohaska (1976) to analyze the relationships between monthly surface air temperature in the United States and Northern Hemispheric sea level pressure. The SVD method can decompose two input fields into a set of independent eigenvectors of the cross-covariance matrix (Halldor and Venegas, 1997). Pairs of singular vectors describe spatial patterns for two variables. The two expansion coefficients explain the weighting of the mode in the temporal scale. This approach comprises the following:

Suppose X and Y represent normalized monthly visibility and AOT, respectively, which are centered in time. The cross-correlation matrix can be formulated as in equation 1:

$$M=X^TY. \tag{1}$$

Then, SVD is performed on matrix M. Orthogonal matrices U and V can be found as equation 2, written as

$$M=ULV^T. \quad (2)$$

The time series TX and TY, describing how each mode of variability oscillates in time, are calculated by projecting U back to X and projecting V back to Y (equations 3 and 4).

$$TX=XU, \text{ and} \quad (3)$$

$$TY=YV. \quad (4)$$

The fraction of squared covariance (SCF) explained by the i-th mode can be calculated by letting l_i, denoting the i-th singular value in L (equation 5) as:

$$\text{SCF}_i = {l_i}^2 \Big/ \sum_{i=1}^{N} l_i^2. \quad (5)$$

3. Results

3.1 SVD results for satellite AOT and visibility

SVD was performed on the full dataset by removing the temporal mean value for both the satellite AOT products and visibility. The first two modes explain more than 80% and 90% of the variability for Terra and Aqua MODIS, and MISR, respectively. Thus, only the first two modes in SVD were analyzed and the others were deemed noise. The legend in the spatial pattern indicates the extent of variation. Deep blue and red colours represent large variation, as shown in Figure 3. The correlation coefficient between the time series of satellite AOT and visibility in different modes indicates the relationship of AOT and visibility on the temporal scale. In order to compare spatial modes of visibility and AOT, reverse visibility spatial modes were also illustrated. The first mode is shown in Figure 3, explaining about 50% of the total variance for MODIS and 83% for MISR. The first mode explains a higher percentage of total variance. This may be caused by the underestimation of MISR aerosol datasets for high AOT. Each spatial pattern has a corresponding time series, which is also named Principal Components (PC). PC 1 shows an annual pattern, with the maximum in winter. The correlation between PC 1 of the satellite AOT and visibility are highly correlated, and reach 0.782, 0.779, and 0.803 for Terra, Aqua, and MISR, respectively. Figure 3c shows strong variation in temporal pattern due to the light variations in the spatial pattern. Although some discrepancy exists in the amplitude of variation between visibility and MISR AOT in Figure 3c, similar seasonal and inter-annual variations are demonstrated. Large variation in associated AOT spatial patterns are found in Lop Nur, NCP, and southwest China. However, large variation of visibility in the first mode is found in the eastern and northeastern China. The spatial distribution of AOT and visibility both exhibit significant differences.

[Please insert Figure 3 here]

The second mode of Terra and Aqua accounts for about 32% of the total variance, while the second mode of MISR only explains about 7.7%. The signal is relatively strong for the southeastern and part of western China. The AOT and visibility spatial distribution agrees well. For MISR, strong variation was also observed in central China. Differences in spatial variability between MISR and MODIS from the first two modes may be due to the different temporal resolutions in these satellite data. The associated time series has an annual cycle, and the observed peak occurs in spring season. Correlation between time-series data is greater than 0.8 for all datasets.

[Please insert Figure 4 here]

The representation of visibility in terms of inter-annual AOT, solved by removing the seasonal mean values, was also examined. The first two modes account for about 50% of total variance. The variances explained by deseasonalized MISR and visibility datasets are relatively low and is related to the narrower swath and longer measurement time of MISR (Li et al., 2014a). In the first mode, large variation of visibility and AOT is shown in the highly populated areas of China, which are mainly concentrated in the east. This indicates that AOT and visibility in this region varied significantly during the study period. The second mode is likely associated with the spatial variation of AOT in China. Increasing aerosol trends are shown in Shandong (location 3) and northwest China (location 4), while decreasing trends are shown over parts of southeast coast, Gobi Desert (location 1), and Joint of Shanxi, Sichuan, and Hubei province (location 2). In this study, visibility does not capture the seasonal variation of AOT. However, a promising relationship is shown in inter-annual variation between visibility and AOT for two reasons: first, visibility and AOT both contain some information relating to water vapor. More water vapor can cause lower visibility and higher AOT, and water vapor is one of the factors that can influence the relationship of visibility and AOT. In general, the aerosol loading is the dominant factor. Thus, it implies that the inter-annual change of water vapor may have little impact in the relationship between inter-annual variation of AOT and inter-annual variation of visibility.

[Please insert Figure 5 and Figure 6 here]

3.2 Seasonal variations

The results of SVD indicate that the differences between AOT and visibility are mainly a function of seasonal variability. Figure 7 shows the correlation in each station between different AOT products and all-sky visibility. Some differences in the spatial distribution of correlation are displayed in Figure 7a and Figure 7b. The differences are mainly located in central China, and related to the bias between the DT and DB algorithms (Figure 9). Similar spatial distributions of correlation among DT Terra AOT, DT Aqua AOT and MISR observation are shown in Figure 7. This indicates that uncertainties in DB MODIS AOT also contribute the representativeness of seasonal ground visibility for AOT. The correlation between different types of AOT products and visibility in clear-sky is shown in Figure 8. Comparing between Figure 7 and Figure 8, the influence of cloud contamination on the correlation between AOT and visibility is mainly found in southern China.

The correlation between visibility and satellite AOT is tied to the spatial distribution of correlation between surface reflectance and DB surface reflectance (Figure 10). Negative correlation between surface reflectance and DB surface reflectance can be observed in Sichuan basin, south-central China, and northwest China region. Some significant influences on the aerosol retrievals may be observed in these regions. However, no causal correlation is observed.

[Please insert Figure 7, Figure 8, Figure 9, and Figure 10 here]

In order to analyze seasonal differences, the datasets were divided into four groups according to the correlation of monthly mean AOT and visibility (Figure 11a). Highly negative correlations of AOT and visibility are found in coastal regions and over northwestern China. Highly positive correlations are observed in the Yangtze River Basin. Multi-year average monthly cycles for four groups of data are shown in Figure 11a. For correlation between -1 and -0.5, AOT exhibits high values from March to May, and lower values during the rest of year. Visibility reaches a maximum in October, while the lowest value is found in March. The seasonal variability for visibility and AOT are thus inversely related. Similar variation of visibility is shown in Group 2 and 3. High visibility values occur in July. The peaks of AOT occur in April and June for Group 2 and only one peak occurred in June for Group 3. AOT and visibility show similar variation in Group 4, with high values from April to August. In general, high visibility indicates less aerosol loading. However, our results indicate that high visibility may correspond with high AOT for seasonal average values. This may be caused by variation of aerosol vertical distributions, the influence of clouds, and hygroscopic aerosol growth.

The relationship between AOT and clear-sky visibility were also analyzed. There are some differences between all-sky (Figure 11a) and clear-sky (cloud fraction=0) conditions (Figure 11b). For the first group, there are two peaks for visibility in clear-sky conditions. The visibility peaks occur in May in Group 2. For Group 3, the visibility in clear-sky condition is much higher than that in the all-sky condition. Little differences are observed in Group 4. Thus, it is implied that clouds contribute to the relationship between visibility and AOT. However, due to the lack of aerosol information under clouds, the impact of clouds on the correlation introduces many uncertainties. This will be studied in the future work.

[Please insert Figure 11 here]

3.3 Aerosol vertical distribution

Seasonal spatial distribution of near-surface AOT (e.g. below 500 m,) and columnar AOT from LIVAS were mapped in Figure 12 and Figure 13, respectively. High AOT_{low} were distributed in different regions in different seasons. In spring, high AOT_{low} are concentrated in central China. The NCP region has high AOT in summer. High surface aerosol loadings are observed in the southwestern China in autumn. In winter, high AOT_{low} exists in several regions, such as PRD and YRD. The seasonal spatial distributions of high columnar AOT are similar with AOT_{low}. The fractions of AOT_{low} (e.g. AOT_{low} /total column AOT) are shown in Figure 14, which indicates that AOT_{low} contributes a high proportion in winter and autumn. The variation of fraction of AOT_{low} may thus be well-studied and it would have great impact on the relationship of visibility and columnar AOT.

[Please insert Figure 12, Figure 13, and Figure 14 here]

Figure 15 shows the variation of AOT_{low} and visibility for both clear-sky and all-sky data. However, due to the data availability of LIVAS data, multi-year seasonal data were only used to analyze the variation between AOT_{low} and visibility. These data were divided into four groups using correlation coefficients. Comparing with Figure 11, Figure 15 shows significant negative relationships between visibility and AOT_{low}.

[Please insert Figure 15 here]

4. Conclusion

Surface visibility data are widely-used as an alternative information for long-term aerosol trend studies (Liepert and Kukla, 1997; Wang et al., 2009; Li et al., 2015a). In this study, the representativeness of surface visibility for analyzing spatial and temporal patterns of Aerosol Optical Thickness (AOT) retrieved from different satellites in China was investigated. The Singular Value Decomposition (SVD) method was applied to separate the dominant and correlated modes of variability from surface visibility, using MODerate resolution Imaging Spectroradiometer (MODIS) and Multi-angle Imaging SpectroRadiometer (MISR) monthly AOT products between July 2002 and December 2014. Both large-scale spatial and temporal variability were examined. Cloud information and aerosol vertical distribution from LIdar climatology of Vertical Aerosol Structure for space-based lidar simulation studies (LIVAS) were also used to investigate the impact on the relationship between visibility and AOT.

Results indicate that large spatial differences occur seasonally between surface visibility and satellite derived AOT, while good agreement exists on all inter-annual scale. However, insignificant correlation between multi-year seasonal visibility and AOT are driven by seasonal variability of the aerosol vertical profile. According to the comparison between multi-year average monthly AOT and visibility in all-sky and in clear-sky, clouds also contribute to the relationship between seasonal visibility and AOT. The results in this paper indicate that the visibility can be used as a good indicator for analyzing the inter-annual variation of AOT values, and more factors such as clouds and near-surface AOT in seasonal scale should be considered. According to the results in the paper, surface visibility will be used as a proxy for retrieving annual AOT in future work, thus allowing to investigate regional AOT over large spatial scales that currently only available from ground instrumentation.

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References

Abdou, W.A., Diner, D.J., Martonchik, J.V., Bruegge, C.J., Kahn, R.A., Gaitley, B.J., Crean, K.A., Remer, L.A., Holben, B., 2005. Comparison of coincident Multiangle Imaging Spectroradiometer and Moderate Resolution Imaging Spectroradiometer aerosol optical depths over land and ocean scenes containing Aerosol Robotic Network sites. Journal of Geophysical Research: Atmospheres 110, D10S07.

Amiridis, V., Marinou, E., Tsekeri, A., Wandinger, U., Schwarz, A., Giannakaki, E., Mamouri, R., Kokkalis, P., Binietoglou, I., Solomos, S., Herekakis, T., Kazadzis, S., Gerasopoulos, E., Proestakis, E., Kottas, M., Balis, D., Papayannis, A., Kontoes, C., Kourtidis, K., Papagiannopoulos, N., Mona, L., Pappalardo, G., Le Rille, O., Ansmann, A., 2015. LIVAS: a 3-D multi-wavelength aerosol/cloud database based on CALIPSO and EARLINET. Atmos. Chem. Phys. 15, 7127-7153.

Bäumer, D., Vogel, B., Versick, S., Rinke, R., Möhler, O., Schnaiter, M., 2008. Relationship of visibility, aerosol optical thickness and aerosol size distribution in an ageing air mass over South-West Germany. Atmos. Environ. 42, 989-998.

Chan, P., 2009. Comparison of Aerosol Optical Depth(AOD) Derived from Ground-Based LIDAR and MODIS. Open Atmospheric Science Journal 3, 131-137.

Diner, D.J., Beckert, J.C., Bothwell, G.W., Rodriguez, J.I., 2002. Performance of the MISR Instrument During Its First 20 Months in Earth Orbit. Ieee T Geosci Remote 40, 1449.

Elterman, L., 1970. Relationships Between Vertical Attenuation and Surface Meteorological Range. Appl. Opt. 9, 1804-1810.

Field, C.B., Barros, V.R., Mach, K., Mastrandrea, M., 2014. Climate change 2014: impacts, adaptation, and vulnerability. Working Group II Contribution to the IPCC 5th Assessment Report-Technical Summary, 1-76.

García, R.D., García, O.E., Cuevas, E., Cachorro, V.E., Barreto, A., Guirado-Fuentes, C., Kouremeti, N., Bustos, J.J., Romero-Campos, P.M., de Frutos, A.M., 2015. Aerosol optical depth retrievals at the Izaña Atmospheric Observatory from 1941 to 2013 by using artificial neural networks. Atmos. Meas. Tech. Discuss. 8, 9075-9103.

Halldor, B., Venegas, S.A., 1997. A manual for EOF and SVD analyses of climate data. McGill University, CCGCR Report, 52.

Hinds, W.C., 1999. Aerosol Technology: Properties. Behavior, and Measurement of airborne Particles (2nd.

Horvath, H., 1971. On the applicability of the koschmieder visibility formula. Atmospheric Environment (1967) 5, 177-184.

Hsu, N.C., Si-Chee, T., King, M.D., Herman, J.R., 2004. Aerosol properties over bright-reflecting source regions. Geoscience and Remote Sensing, IEEE Transactions on 42, 557-569.

Kahn, R.A., Gaitley, B.J., Martonchik, J.V., Diner, D.J., Crean, K.A., Holben, B., 2005. Multiangle Imaging Spectroradiometer (MISR) global aerosol optical depth validation based on 2 years of coincident Aerosol Robotic Network (AERONET) observations. Journal of Geophysical Research: Atmospheres 110, D10S04.

Kahn, R.A., Garay, M.J., Nelson, D.L., Yau, K.K., Bull, M.A., Gaitley, B.J., Martonchik, J.V., Levy, R.C., 2007. Satellite-derived aerosol optical depth over dark water from MISR and MODIS: Comparisons with AERONET and implications for climatological studies. Journal of Geophysical Research: Atmospheres

112, D18205.

Kaufman, Y.J., Herring, D.D., Ranson, K.J., Collatz, G.J., 1998. Earth Observing System AM1 mission to Earth. Geoscience and Remote Sensing, IEEE Transactions on 36, 1045-1055.

Kessner, A.L., Wang, J., Levy, R.C., Colarco, P.R., 2013. Remote sensing of surface visibility from space: A look at the United States East Coast. Atmos. Environ. 81, 136-147.

Koschmieder, H., 1925. Theorie der horizontalen Sichtweite: Kontrast und Sichtweite. Keim & Nemnich.

Lee, K.H., Wong, M.S., Kim, K., Park, S.S., 2014. Analytical approach to estimating aerosol extinction and visibility from satellite observations. Atmos. Environ. 91, 127-136.

Levy, R.C., Mattoo, S., Munchak, L.A., Remer, L.A., Sayer, A.M., Patadia, F., Hsu, N.C., 2013. The Collection 6 MODIS aerosol products over land and ocean. Atmos. Meas. Tech. 6, 2989-3034.

Levy, R.C., Remer, L.A., Kleidman, R.G., Mattoo, S., Ichoku, C., Kahn, R., Eck, T.F., 2010. Global evaluation of the Collection 5 MODIS dark-target aerosol products over land. Atmos. Chem. Phys. 10, 10399-10420.

Li, C., Martin, R.V., Boys, B.L., van Donkelaar, A., Ruzzante, S., 2015a. Evaluation and application of multi-decadal visibility data for trend analysis of atmospheric haze. Atmos. Chem. Phys. Discuss. 15, 33789-33841.

Li, J., Carlson, B.E., Lacis, A.A., 2014a. Application of spectral analysis techniques in the intercomparison of aerosol data. Part II: Using maximum covariance analysis to effectively compare spatiotemporal variability of satellite and AERONET measured aerosol optical depth. Journal of Geophysical Research: Atmospheres 119, 2013JD020537.

Li, J., Carlson, B.E., Lacis, A.A., 2014b. Application of spectral analysis techniques to the intercomparison of aerosol data – Part 4: Combined maximum covariance analysis to bridge the gap between multi-sensor satellite retrievals and ground-based measurements. Atmos. Meas. Tech. Discuss. 7, 3503-3547.

Li, J., Carlson, B.E., Lacis, A.A., 2015b. How Well Do Satellite AOD Observations Represent the Spatial and Temporal Variability of PM2.5 Concentration for the United States? Atmos. Environ.

Liepert, B.G., Kukla, G.J., 1997. Decline in Global Solar Radiation with Increased Horizontal Visibility in Germany between 1964 and 1990. Journal of Climate 10, 2391-2401.

Lin, J., van Donkelaar, A., Xin, J., Che, H., Wang, Y., 2014. Clear-sky aerosol optical depth over East China estimated from visibility measurements and chemical transport modeling. Atmos. Environ. 95, 258-267.

Liu, Y., Sarnat, J.A., Coull, B.A., Koutrakis, P., Jacob, D.J., 2004. Validation of Multiangle Imaging Spectroradiometer (MISR) aerosol optical thickness measurements using Aerosol Robotic Network (AERONET) observations over the contiguous United States. Journal of Geophysical Research: Atmospheres 109, D06205.

Ma, S., Yang, Z., 2007. Specifications for surface meteorological observation. China Meteorological Administration, Beijing, 96-98.

Meyer, F.G., Curry, J.A., Brock, C.A., Radke, L.F., 1991. Springtime Visibility in the Arctic. Journal of Applied Meteorology 30, 342-357.

Ozkaynak, H., Schatz, A.D., Thurston, G.D., Isaacs, R.G., Husar, R.B., 1985. Relationships between Aerosol Extinction Coefficients Derived from Airport Visual Range Observations and Alternative Measures of Airborne Particle Mass. J. Air Pollut. Control Assoc. 35, 1176-1185.

Prohaska, J.T., 1976. A Technique for Analyzing the Linear Relationships between Two Meteorological Fields. Monthly Weather Review 104, 1345-1353.

Qiu, J., Lin, Y., 2001. A parameterization model of aerosol optical depths in China. Acta Meteorol. Sin. 59, 368-372.

Sayer, A.M., Hsu, N.C., Bettenhausen, C., Jeong, M.J., 2013. Validation and uncertainty estimates for MODIS Collection 6 “Deep Blue” aerosol data. Journal of Geophysical Research: Atmospheres 118, 7864-7872.

Shi, Y., Zhang, J., Reid, J.S., Hyer, E.J., Eck, T.F., Holben, B.N., Kahn, R.A., 2011. A critical examination of spatial biases between MODIS and MISR aerosol products - application for potential AERONET deployment. Atmos. Meas. Tech. 4, 2823-2836.

Smith, A., Lott, N., Vose, R., 2011. The Integrated Surface Database: Recent Developments and Partnerships. Bulletin of the American Meteorological Society 92, 704-708.

So, C., Cheng, C., Tsui, K., 2005. Weather and environmental monitoring using MODIS AOD data in Hong Kong, China, Proceedings of the First International Symposium on Cloud-prone and Rainy Areas Remote Sensing, The Chinese University of Hong Kong, p. 57.

Stocker, T., 2014. Climate change 2013: The physical science basis.

Toth, T.D., Zhang, J., Campbell, J.R., Hyer, E.J., Reid, J.S., Shi, Y., Westphal, D.L., 2014. Impact of data quality and surface-to-column representativeness on the PM2.5 / satellite AOD relationship for the contiguous United States. Atmos. Chem. Phys. 14, 6049-6062.

Wang, K., Dickinson, R.E., Liang, S., 2009. Clear Sky Visibility Has Decreased over Land Globally from 1973 to 2007. Science 323, 1468-1470.

WMO, 1996. WMO guide to meteorological instruments and methods of observation.

Wu, J., Luo, J., Zhang, L., Xia, L., Zhao, D., Tang, J., 2014. Improvement of aerosol optical depth retrieval using visibility data in China during the past 50 years. Journal of Geophysical Research: Atmospheres, 2014JD021550.

Yuan, C.-S., Lee, C.-G., Liu, S.-H., Chang, J.-c., Yuan, C., Yang, H.-Y., 2006. Correlation of atmospheric visibility with chemical composition of Kaohsiung aerosols. Atmospheric Research 82, 663-679.

Zhang, Z.Y., Wong, M.S., Nichol, J., 2016. Global trends of aerosol optical thickness using the ensemble empirical mode decomposition method. International Journal of Climatology, n/a-n/a.

Zhao, H., Che, H., Ma, Y., Xia, X., Wang, Y., Wang, P., Wu, X., 2015. Temporal variability of the visibility, particulate matter mass concentration and aerosol optical properties over an urban site in Northeast China. Atmospheric Research 166, 204-212.