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Inter-comparison of three AATSR Level 2 (L2) AOD products over China

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Abstract. The Advanced Along-Track Scanning Radiometer (AATSR) aboard on ENVISAT is used to observe the Earth by dual-view. The AATSR data can be used to retrieve aerosol optical depth (AOD) over both land and ocean, which is an important merit in the characterization of aerosol properties. In recent years, aerosol retrieval algorithms both over land and ocean have been developed, taking advantages of the feature of dual-view which can help eliminate contribution of Earth's surface to top of atmosphere (TOA) reflectance. Aerosol_cci project as a part of Climate Change Initiative (CCI) provides users three AOD retrieval algorithms for AATSR data, including the Swansea algorithm (SU), the ATSR-2ATSR dual view aerosol retrieval algorithm (ADV) and the Oxford-RAL Retrieval of Aerosol and Cloud algorithm (ORAC). The Validation team of Aerosol-CCI project has validated AOD (both Level 2 and Level 3 products) and AE (Level 2 product only) against the AERONET data in a round robin evaluation using validation tool of AeroCOM (Aerosol Comparison between Observations and Models) project. For the purpose of evaluating different performances of these three algorithms on calculating AODs over mainland China, we introduce ground-based data from the CARSNET (the China Aerosol Remote Sensing Network) which is designed for aerosol observation in China. Because China is vast in territory and of great differences in surface, the combination of the AEROENT and the CATRNET data can validate L2 AOD products more comprehensively. The validation results show different performances of these products in 2007, 2008 and 2010. The SU algorithm has very good performance over sites with different surface conditions in mainland China from March to October, but it underestimates AOD slightly with varying mean bias error (MBE) from 0.05 to 0.10 over surface of barren or sparsely vegetation in western China. The ADV product has same precision with high correlation coefficient (CC) larger than 0.90 over most of sites and same error distribution as the SU product. The main limits of ADV algorithm are underestimation and applicability, especially it occurs obvious underestimation over sites of Datong, Lanzhou and Urmuchi where the dominated land cover is grassland with MBE larger than 0.2 and the main source of aerosol is coal combustion and dust. The ORAC algorithm has the ability of retrieving

AOD at different ranges including high AOD (larger than 1.0), however, the stability will decease significantly as AOD grows, especially when AOD > 1.0. In addition, ORAC product get matches successfully collocated with CARSNET in winter (December, January and February), whereas other validation results lack matches during winter.

1 Introduction

Aerosol plays a major role on Earth's climate system, including intervening radiation budget and cloud processes, further to affect air quality and human health (Remer et al., 2005; Samet et al., 2000; Kokhanovsky and de Leeuw, 2009). The particles suspended in the troposphere will scatter solar radiation back to cool the atmosphere or absorb solar radiation which warms the atmosphere, causing changes in net effect of aerosols. These particles also could affect formation and microphysical properties of clouds as cloud condensation nuclei (Andreae and Rosenfeld, 2008). The source of aerosol could be anthropogenic or natural. Particles form different sources are mixed into aerosol mass to influence AOD, reduce visibility (Kinne et al., 2003; Remer et al., 2005) and cause spatial and temporal variability of AOD, therefore, the largest uncertainties in estimation of radiative forcing are introduced by aerosol (IPCC, 2013).

Over the past 35 years, different types of satellites have been used to obtain atmospheric information especially on aerosol properties with development of techniques and science (Griggs, 1979; Kokhanovsky and de Leeuw, 2009). Remote sensing provides a means to obtain global and long-term observation of aerosol, especially in the widest ocean and remote regions where ground-based station can't be constructed. Besides, polar-orbiting satellites and geostationary satellites obtain daily globe images, which helps to capture changes of aerosol patterns and properties (Prins et al., 1998; Torres et al., 2002). There are, however, many difficulties in observation of aerosol by satellites, because contribution depending on surface properties to signal received by satellite could be varying strikingly, aerosol components and concentration are varying constantly in situations and the sources can't be determined exactly (Levy et al., 2007).

The Advanced Along-Track Scanning Radiometer (AATSR) aboard on ENVISAT is used to observe the Earth by dual-view. The data from AATSR can be used to retrieve AOD both over land and ocean, which is an important merit in the characterization of aerosol properties (Adhikary et al., 2008). In recent years, it has established some aerosol retrieval algorithms both over land and ocean, taking advantage of feature of dual-view which can help eliminate contribution of surface to top of atmosphere (TOA) reflectance. Aerosol_CCI as part of Climate Change Initiative (CCI) (http://www.esa-aerosol-cci.org/) provides users three algorithms for AATSR data, including the Swansea algorithm (SU) (Bevan et al. 2012), the ATSR-2/AATSR dual view aerosol retrieval algorithm (ADV) (Kolmonen et al. 2015) and the Oxford-RAL Retrieval of Aerosol and Cloud algorithm (ORAC) (Thomas et al. 2009). The aim of this work is to evaluate different performances of these algorithms on calculating AOD over different regions of China in 2007, 2008 and 2010.

Ground-based sun−photometer has been used to take sun and sky measurement directly (Holben et al., 1998). The Aerosol Robotic NETwork (AERONET) has already constructed hundreds of sites all over the world till 2015. These stations found by American National Aeronautics and Space Administration (NASA) are operational worldwide, providing multi-spectral channels validation data for satellite retrieved data to complete synthetical measurements on a global scale.

The China Aerosol Remote Sensing Network (CARSNET) is a ground-based aerosol monitoring system using CE-318 sun-photometers same as AERONET and has constructed 37 sites throughout China (Che et al., 2009). It has been validated that CARSNET AOD measurement has same accuracy as the AERONET/PHOTONS about 0.03, 0.01, 0.01 and 0.01 larger than measurements of AERONET at 1020, 870, 670 and 440nm channels respectively (Che et al., 2009). In this paper, we combine two aerosol observation datasets from AERONET and CARSNET as reference data to validate these three AATSR AOD products over China more comprehensively.

The basic method for assessment is to compare retrieval results with data (AOD mainly) given by AERONET /CARSNET. This direct comparison of retrieval results with AERONET data exists limitation due to different cloud removal processes (de Leeuw et al., 2013), such limitation could influence validation reliability to some extent. To make validation more reliable, comparison of validated retrieval results with high quality data from MODIS or MISR is also one effective method for validation (Kahn et al., 2009). However, AERONET or other ground-based network provides accurate measurements without influence of land surface reflection (Holben et al., 1998), which means comparison of retrieved AOD with ground-based measurements is the basic method. The AATSR L2 products provided by Aerosol_CCI has validated by the validation team via a round robin (RR) test (de Leeuw et al., 2013), on this basis we focused on assessing performances of AATSR aerosol L2 products in mainland China, using the way of comparison of retrieval results with AERONET&CARSNET data.

2 Reference data and validation statistics

AATSR L2 data (see Tab. 1) are daily products with a spatial resolution of $10 \times 10km^2$ and contain a quality flag or a level of confidence for each pixel (de Leeuw et al., 2013). Compared to Level 3 (L3) product with a spatial resolution of $1° \times 1°$, daily L2 data has higher spatial resolution that helps to capture more details of aerosol properties and more related to our follow-up study.

AOD is the most important parameter in characteristic of aerosol properties, different from other retrieved parameters under the project of Aerosol_CCI. It has been proved that the ground-based observation data from the AERONET have ability and precision to be used as reference data when users validate AOD (Holben et al., 1998). There're 12 AEROENT sites in China providing Level 2.0 (L2) data (cloud screened and quality-assured) for 2008, 15 sites for 2008 and 16 sites for 2010, from which the AOD measurement data are available on the website. However, most of these sites are distributed at east China coastal area as shown in Fig. 1, that can't be meet requirements of validating aerosol properties over whole China comprehensively. Hazardous dense aerosol pollutions affect most regions of northern (Li, 2014) and eastern China in winter and heavy dust aerosol from Taklimakan desert in western China could be transported a long distance to eastern China, even to Japan (Takahashi, 2011), showing regional characteristics.

Tab. 1 Details of AATSR AOD products.

algorithm	version	sensor	Main parameters	Resolution coverage
ADV/ASV	2.3	AATSR	AOD,ANG	10km,1°global
SU	4.21	AATSR	AOD,ANG	10km,1°global
ORAC	03.04	AATSR	AOD, aerosol type	10km,1°global
algorithm	version	sensor	Main parameters	Resolution coverage

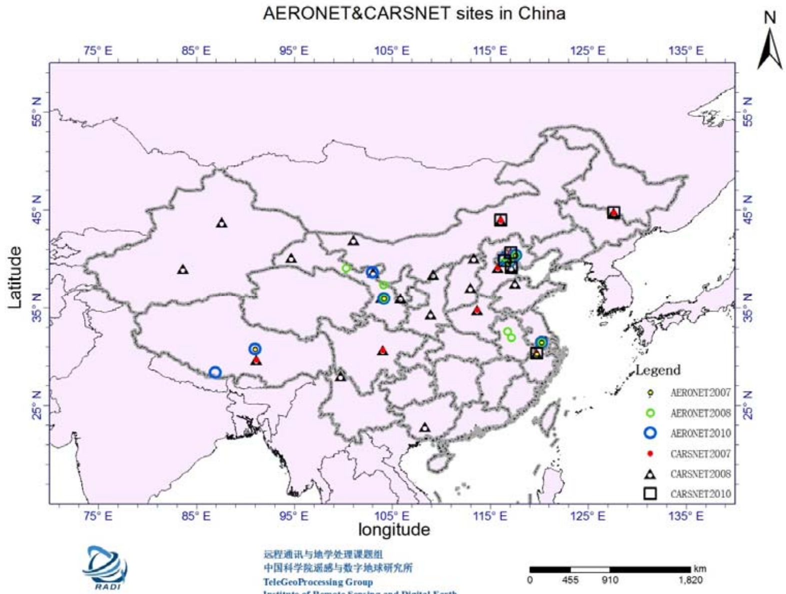

Fig. 1 The distribution of selected AERONET&CARSNET sites in mainland China in 2007, 2008 and 2010.

The measurements from another network, the CARSNET, have same accuracy as AERONET, equipping same calibrated CE-318 instruments. The CARSNET has more sites than the AEROENT's in mainland China and the spatial distribution of the CARSNET sites are more evenly. Therefore, for the purpose of assessing different performances of these three AATSR L2 AOD products, we selected ground-based measurements from both of these two networks as reference data.

The AEROENT provides AOD data at three data quality levels: Level 1.0 (unscreened), Level 1.5 (cloud-screened), and Level 2.0 (L2) (cloud screened and quality-assured) (http://aeronet.gsfc.nasa.gov/new_web/index.html). Here, we selected AERONET L2 data which are screened and quality-assured. Because both of the AEROENT and CARSNET data haven't AATSR products band-effective wavelength, we interpolated the ground-based data to 550nm wavelength. Then AOD of L2 data sets were compared with AEROENT&CARSNET observation data using scatter plots and linear-regression to the data. The comparisons were made for collocating satellite and ground-based observations (Ichoku et al., 2002), i.e. AOD pixels were selected within a spatial extent of +/−50 km with ground-based station in the middle and a time range of +/−30 min of AATSR overpass from ground-based measurements. At least 5 AATSR AOD retrievals and 2 AERONET/CARSNET observations are required in each collocation (Levy et al., 2010).

We made collocations according to years (2007 2008 and 2010) and datasets (ADV ORAC and SU). Totally twenty ground-based observation sites including 12 AERONET sites and 8 CARSNET sites were on the Chinese territory in 2007, of which 6 AERONET and 8 CARSNET inland sites were selected. For 2008, we selected 8 AERONET and 24 CARSNET inland sites, total 32 sites, ignoring island sites and those near shoreline. For 2010, only 6 CARSNET sites are available for us, total 14 inland sites were selected with 8 AERONET inland sites (see Table 2).

Table 2. Selected ground-based sites in China.

	Network	inland	near shoreline	island	Total
2007	AERONET	6	6	0	12
	CARSNET	8	0	0	8
	Total	14	6	0	20
2008	AERONET	8	7	0	15
	CARSNET	24	1	0	25
	Total	32	8	0	40
2010	AERONET	8	7	1	16
	CARSNET	6	0	0	6
	Total	14	7	1	20

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2.1 Statistics

Collocated pairs are analyzed using statistic methods. Then, good matches are determined using expected error (EE). EE envelope was put forward for retrieval of MODIS AOD (Kaufman et al., 1997; Chu et al., 2002) by means of sensitivity studies as Eq. (1) and Eq. (2)

$$\mathrm{EE1} = \pm(0.05 + 0.15\tau) \quad (1)$$

$$\mathrm{EE2} = \pm(0.05 + 0.20\tau) \quad (2)$$

where, τ presents satellite-retrieved AOD. AATSR AOD retrievals are different from MODIS AOD datasets, in this paper, we introduced EE envelope according to feature of AOD underestimation and formation of MODIS EE envelope as Eq. (3) and Eq. (4)

$$\mathrm{EE3} = \pm(0.05 + f2 + (f1 + 0.15)\tau) \quad (3)$$

$$\mathrm{EE4} = \pm(0.05 + f2 + (f1 + 0.20)\tau) \quad (4)$$

where, $f1$ is slope of regression line of scatter points and $f2$ is the correspondent intercept. In the process of retrieving AOD, underestimation tends to be caused by systematic error. Therefore, the EE envelopes suggested by Kaufman et al. or Chu et al. are not fit for validation of AATSR AOD. Such design of EEs as Eq. (3) and Eq. (4) was to take consideration of underestimation, regarding regression line as center, not 1-1 line, for determining accidental error.

After that, to determine how well satellite data match ground-based observation data, exploring what relationship between them. Regression equation and some basic statistics are put on scatter plot, including correlation coefficient (CC), root mean square error (RMSE).

$$\mathrm{CC} = \frac{\sum_{i=1}^{n}(\tau_{aero,i} - \overline{\tau_{aero}})(\tau_{sat,i} - \overline{\tau_{sat}})}{\sqrt{\sum_{i=1}^{n}(\tau_{aero,i} - \overline{\tau_{aero}})^2}\sqrt{\sum_{i=1}^{n}(\tau_{sat,i} - \overline{\tau_{sat}})^2}} \quad (5)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\tau_{sat,i} - \tau_{aero,i})^2} \quad (6)$$

Where, $\tau_{aero,i}$ represents ground-based observation data, τ_{sat} represents satellite retrievals.

Mean satellite-retrieved AOD (MSA) and mean AERONET&CARSNET AOD (MAA) represent central tendency of data.

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Relative mean bias (RMB) is used to determine under- or overestimate of AOD retrievals, it is the ratio of MSA to MAA as Eq. (5)

$$\mathrm{RMB} = \mathrm{MSA}/\mathrm{MAA} \tag{7}$$

Mean bias error (MBE) is mean value of difference between satellite retrievals and AATSR AODs and mean absolute error (MAE) is absolute of mean value of bias error. Together with RMB, MBE and MAE are used to determine the magnitude of difference between two datasets.

2.2 KAPPA Statistics

In scatter plot of collocated pairs, retrieved data and the corresponding collocated ground-based observation data could be considered as two arrays, and the main purpose of KAPPA is to explore how these two arrays match each other. For retrieval of aerosol properties, performances of most algorithms will turn down with increase of AOD, i.e., difficulties in retrieving AOD will be increased as AOD grows. Obviously, when only using $|bias|$ the absolute value of difference between ground-based data and AATSR AOD data in each collocation pair, as assessment standard for different AODs is insufficient and lack of persuasion. Therefore, the combination of $|bias|$ and $|bias|/Ground$, the ratio of $|bias|$ to value of reference data in each collocation pair, used in KAPPA coefficient will make up this shortage and provides a new statistic for assessing agreement between two arrays, taking advantage of KAPPA coefficient.

The KAPPA coefficient was originally proposed as a descriptive statistic indicating degree of beyond-chance agreement between two ratings per subject on a dichotomous form (Bloch and Kraaemer, 1989). KAPPA coefficient with various forms also could be used to measure the accuracy for thematic classification (Rosenfield and Fitzpatrick-Lins, 1986). KAPPA is, in short, a measure of "true" agreement (Cohen, 1960). The pairs collocated by matching ground-based data with AATSR L2 AOD data could be regarded as two different arrays so that we introduced KAPPA coefficient to assess agreement between these two arrays. According to concept about KAPPA coefficient purposed by Cohen (1960), an appropriate modification with two-category nominal scale has been made in Table 3.

Table 3. Design of KAPPA coefficient.

		Criteria 2		Total
		Relevant (highly)	Relevant (low)	
Criteria 1	Relevant (highly)	a	b	G1
	Relevant (low)	c	d	G2
Total		F1	F2	n

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To estimate KAPPA coefficient, it needs to determine which is “true” or which is “relevant”. However, only given matched collocation pairs, we can’t determine which pair is relevant or which retrieved AOD in the collocation pair is on behalf of high quality. Therefore, the design of criteria1 and criteria 2 needs to be reasonable and fit for the purpose of validation.

For criteria 1, if $|bias|$ is greater than the mean of $|bias|$, then marked “low relevant”, if not, marked “highly relevant”. Here, the bias was from first quartile to third quartile for eliminating possible “outliers”. The $|bias|$only indicates the absolute error of retrieved AOD, and it still needs another statistic for criteria 2, the $|bias|/Ground$ indicates the relative error of retrieval AOD. For criteria 2, if $|bias|/Ground|$ is greater than 0.2 (according to EE4), then marked “low relevant”, if not, marked “highly relevant”. For the conventional formula of calculating KAPPA coefficient:

$$\mathrm{K} = \frac{P_0 - P_c}{1 - P_c} \tag{8}$$

Where P_o is the proportion of observed agreements and P is the proportion of chance agreements.

$$P_0 = \frac{(a + d)}{n} \tag{9}$$

$$P_c = \frac{\left(\frac{F_1 \times G_1}{n}\right) + \left(\frac{F_2 \times G_2}{n}\right)}{n} \tag{10}$$

Algorithms for AATSR AOD retrieval used to underestimate AOD over different region in China including ADV ORAC and SU algorithms, otherwise, on this basis it is good agreement between ground-based observation data and satellite retrievals for ADV and SU algorithms (Che et al., 2015). The main aim of this new KAPPA coefficient is to evaluate comprehensive performance of algorithms, its function is to represent not only degree of underestimation but also level of agreement between different datasets.

3 Validation results and analysis

We have collected different validation reference data of AERONET and CASNET in 2007, 2008 and 2010. Only 14 ground-based observation sites are available for us in 2007, of which some are close to each other. Most of them are located in different provinces, but the numbers of sites are small and the space distribution is not uniform. Therefore, numbers of matches are relative small for all the algorithms. More AERONET/CARSNET data are available in 2008, with totally 32 sites including 8 AERONET sites and 24 CARSNET sites. There’re 14 AERO&CARS sites giving data for validation in 2010.

The focus of this paper is to find differences between ADV, ORAC, and SU L2 AOD products. Therefore, we calculated statistics and analysed validation results separately by year (see Tab. 4).

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Table 4 Main statistics of validation results.

		N	MSA	MAA	MBE	MAE	RMSE	RMB	CC	KAPPA	Within EE3	Within EE4
AATSR ADV	2007	94	0.244	0.347	-0.103	0.115	0.095	0.704	0.885	0.473	74.5%	77.7%
	2008	307	0.211	0.361	-0.151	0.157	0.124	0.583	0.790	0.329	70.0%	77.5%
	2010	136	0.150	0.293	-0.143	0.148	0.089	0.512	0.785	0.180	91.2%	93.4%
AATSR ORAC	2007	137	0.324	0.270	0.054	0.137	0.206	1.200	0.708	0.474	44.5%	50.4%
	2008	612	0.271	0.330	-0.060	0.160	0.209	0.819	0.472	0.439	40.4%	47.4%
	2010	282	0.254	0.274	-0.020	0.141	0.170	0.925	0.665	0.367	42.2%	46.8%
AATSR SU	2007	94	0.330	0.404	-0.074	0.092	0.124	0.816	0.933	0.409	77.7%	87.2%
	2008	435	0.293	0.412	-0.118	0.137	0.140	0.713	0.822	0.484	71.5%	80.2%
	2010	167	0.270	0.375	-0.105	0.119	0.131	0.720	0.888	0.520	77.3%	84.4%

3.1 The ADV algorithm

For 2007, The RMS error is 0.095, minimal of all results, the CC is 0.885 and the distribution of collocated pairs in scatter plot are concentrated near the regression as shown in Fig. 2a, most of collocated pairs within EE3 (about 74.5%), indicating that satellite retrievals agree with AERONET/CARSNET data well. The RMB is 0.704 and the regression line is y = 0.77x – 0.02, which reflect one tendency of underestimation. This kind of underestimation will be more severe as growth of AOD value. Low dispersion and slight underestimation make KAPPA coefficient high (0.473), showing that ADV algorithm has good performance in calculating AOD over China in 2007. ADV algorithm is appropriate for retrieval of low AODs, especially for those less than 1.0, so the MSA for 2007 is 0.244.

For 2008, lower RMB (0.621) means more severe underestimation and lower CC (0.776) and higher RSE (0.130) mean lower accuracy. Similar with 2007, the MSA of ADV is 0.211. Therefore, KAAPA coefficient which is on behalf overall performance is 0.329, lower than result of 2007. For 2010, lowest RMS (0.089) and largest proportion of matched located in EE3 (91.2%) and EE4 (93.4%) in three years mean small accidental error. However, the KAPPA coefficient is 0.180, the lowest in three years.

The most obvious feature of ADV algorithm is underestimation as shown in Fig. 2. The mean $\pm$ 2σ lines in different range are almost within EE4 lines for these three years. The highest MSA is 0.250 in 2007 and the lowest MSA is 0.173 in 2010 in three years. ADV algorithm has ability in retrieving low AOD value well with high accuracy. Actually this “ability” is systematic for either high AODs or low AODs. This also limits range of application of ADV algorithm, especially in calculating AOD in range of high values.

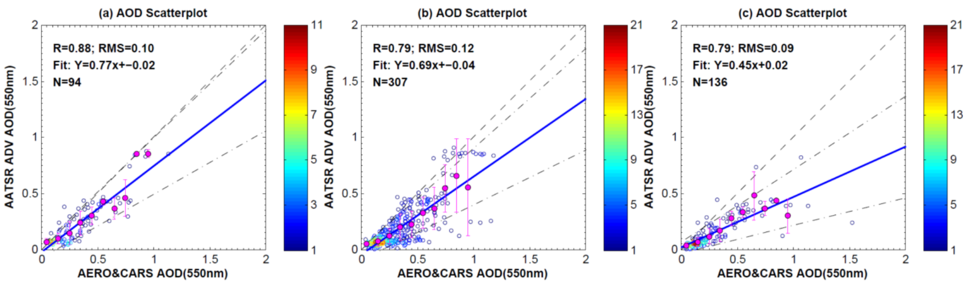

Fig. 2 Scatter plots of AATSR ADV L2 AOD products with ground-based data in China in 2007, 2008 and 2010. The dashed, dotted and blue solid line represents 1-1 line, EE4 line and regression line. The magenta points are means for specific range of AERO&CARS AOD and the magenta lines are mean $\pm$ 2σ for certain range.

3.2 The ORAC algorithm

The ORAC algorithm had good performance in 2007, getting a KAPPA coefficient of 0.474. However, the distribution of those matches is dispersed in Fig. 3b, implying low CC (0.708) and high RMSE (0.206). From the angle of degree of fitness, its performance is not good. There's no obvious trend of underestimation or overestimation, the regression line is close to 1-1 line. Only 50.4% collocated pairs are within EE4 and most of mean $\pm$ 2σ lines are out of EE4 lines, showing that accidental errors influence accuracy of ORAC algorithm. The MSA of ORAC is 0.324.

From the number of matches, ORAC has the most matches (See Fig. 3). Different from 2008, there's obvious underestimation from results of 2007 and 2010 as regression lines shown in Fig. 3b and 3c. For 2008, the RMB is 0.829, showing a trend of slight underestimation. The applicability of ORAC is good with MSA of 0.271. The collocated pairs are relative disperse and almost all mean $\pm$ 2σ lines are out of EE4 lines, influencing RMSE and CC. For 2010, same dispersion of points in scattered plot and low KAPPA coefficient.

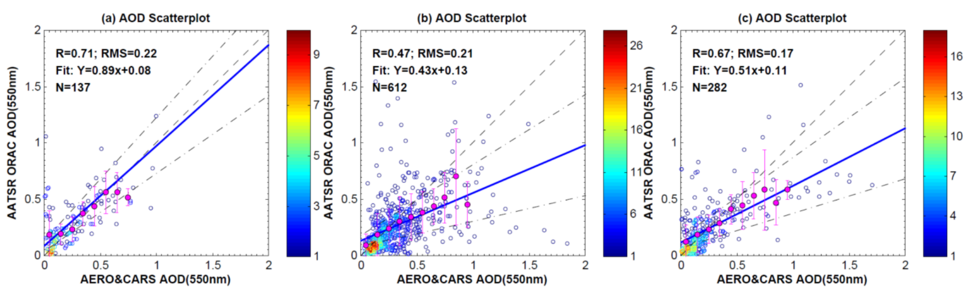

Fig. 3 Scatter plots of AATSR ORAC L2 AOD products with ground-based data in China in 2007, 2008 and 2010.

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Overall, the ORAC algorithm tends to retrieve AODs unstably for either high AODs or low AODs and with a slight underestimation in 2007. The results of 2008 and 2010 have features in common, even though the regression lines are below 1-1 lines, influences of accidental error are larger than systematic error.

3.3 The SU algorithm

The SU algorithm had good performances in three years, getting KAPPA coefficients 0.409, 0.484 and 0.520. Large proportions of EE3 and EE4, almost all the mean $\pm 2\sigma$ lines are within EE4 lines, both showing that the matches concentrate in small regions around regression line. The RMBs are 0.816, 0.713 and 0.720 respectively for 2007, 2008 and 2010, showing underestimation of SU product. The applicability of SU is good with MSA of 0.293 for 2008.

The most obvious feature of SU algorithm is stability in retrieving AOD for different years or different regions (Fig. 4). The MSA are from 0.270 for 2010 to 0.330 for 2007, the KAPPA coefficient is from 0.520 to 0.409, which means that the SU algorithm had better performance in retrieving low AODs. SU algorithm has the best performance in retrieving AOD with highest KAPPA coefficient (0.520).

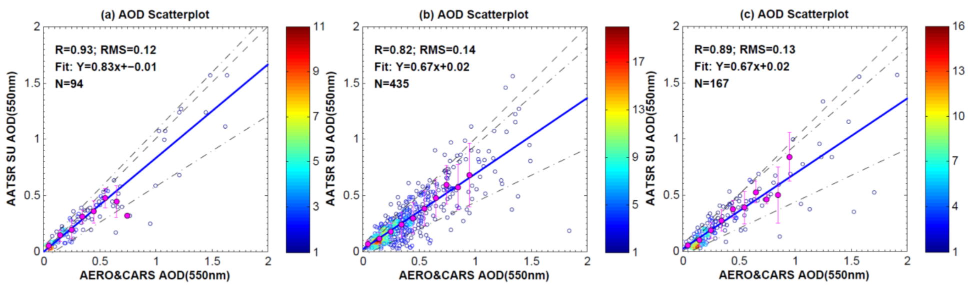

Fig. 4 Scatter plots of AATSR SU L2 AOD products with ground-based data in China in 2007, 2008 and 2010.

Overall, SU algorithm could be applied to retrieve AOD at different range with high precision. Factors in influencing performances of SU algorithm is small systematic error and smaller accidental error.

4 Uncertainty analysis based on aerosol loading

In the previous section, we have validated all three AOD products over mainland China in 2007, 2008 and 2010, discovering that all these three products tend to be existing underestimation at some extent. For the purpose of ascertaining causes of underestimation, in this section, we focus on analysing the AOD uncertainties which are the differences between retrieved AODs and ground-based AODs at special conditions. Collocated pairs are divided into three groups according to aerosol loading, including light loading ($\tau < 0.15$), heavy loading ($\tau > 0{,}4$), and moderate loading (Levy et al., 2010). It's obvious that AOD bias become greater with the growth of AOD for all three products. These products have one feature in common that AOD bias tends to be negative which means that underestimation become more significant with the growth of aerosol loading. The ADV and SU algorithms have good performances on estimating AOD even with little underestimation when aerosol loading is low (light loading) (Fig. 5).

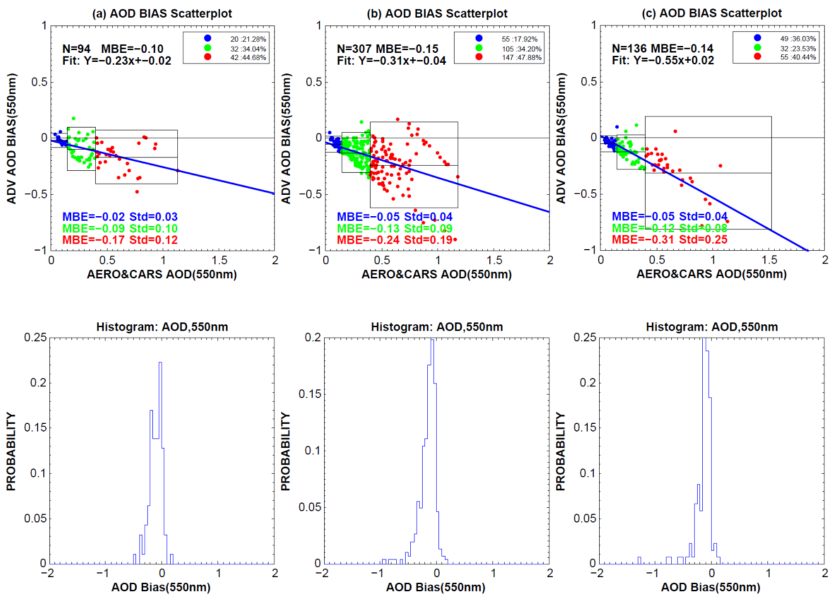

Fig. 5 Scatter plot of AERONET&CARSNET AODs with ADV AOD bias or uncertainties and histrogram of AOD bias. Colors represent different groups, blue for light loading, green for moderate loading and red for heavy loading. Basic statistics are texted on the top left corner, including number of scattered points, MBE and linear regression eqution (Fit). The text on the bottom with different colors are basic statistics of each group. Each group has one box, the borders-bottom and borders-top of which represent $\mathrm{MBE} + 2\sigma$ and $\mathrm{MBE} - 2\sigma$, containing 96% scattered points from each group. The center line of each box represents the MBE of each group. The blue line is the regression line of all scattered points.

Under complex conditions, the ORAC overestimates AOD in regions of light loading and moderate loading compared with the AEROENT as shown in Fig. 6a-6b. Compared to the CARSNET data, it also appears overestimation for light loading, and this overestimation meanly due to two points with large error. In moderate loading region, MBE tends to be positive in Fig. 6a, probably because the distribution of AEROENT sites is uneven that most of sites are located in eastern China.

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The top and bottom borders of the box we draw represent the interval of $[-2\sigma, 2\sigma]$ which contains most of data (about 95%) for a given group. The data outside the box are "possible outliers" due to largest error contained in each group. Those "possible outliers" have one feature in common that the corresponding points in bias scatter plot are far away from other points. Otherwise, the points below or above the box are different. If points are above the box which means satellite-retrieved AOD are larger than ground-based observed AOD, those "outliers" tend to be caused by residual cloud. Because ground-based network measures AOD just from one point, but the satellite retrieved AODs in each collocated pairs are average of 25 pixels. Any one of these 25 pixels with cloud residual will lead to increase of AOD in collocated pair. Therefore, we make a conclusion that the "outliers" above the box are possibly caused by cloud residual. From this view, there's one point above the box of each aerosol loading respectively for ADV product. This kind of "outliers" concentrates up light loading region and moderate loading region for SU product (Fig. 7). The situation of ORAC is relative complex, it exists "outliers" in light loading region which makes box of light loading much larger than box of moderate loading in 2007 and 2010 as shown in Fig. 6a and 6c.

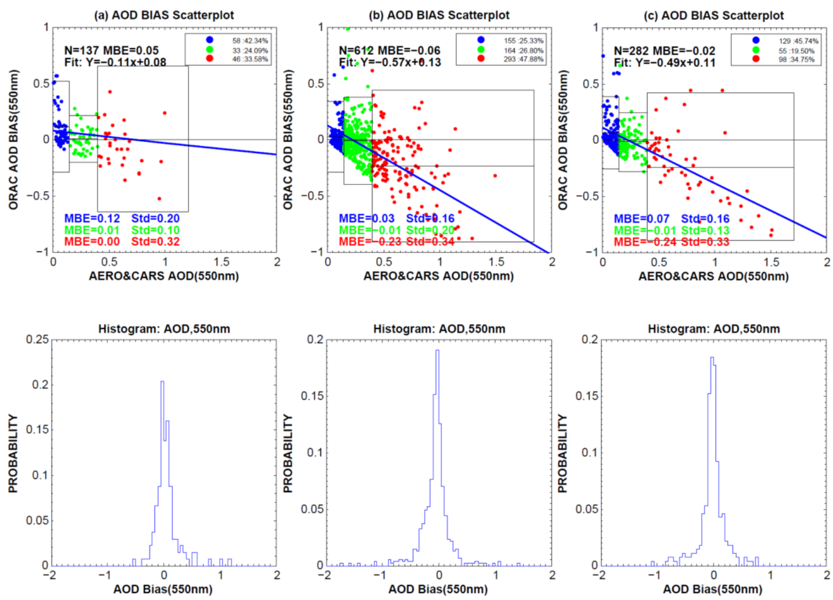

Fig. 6 Scatter plot of AERONET&CARSNET AODs with ORAC AOD bias or uncertainties and histrogram of AOD bias.

The points below box are different from those above the box, most of them are only below the box for hey loading, indicating that the ability of estimating AOD will decrease with the increase of aerosol loading, especially in region of heavy aerosol loading.

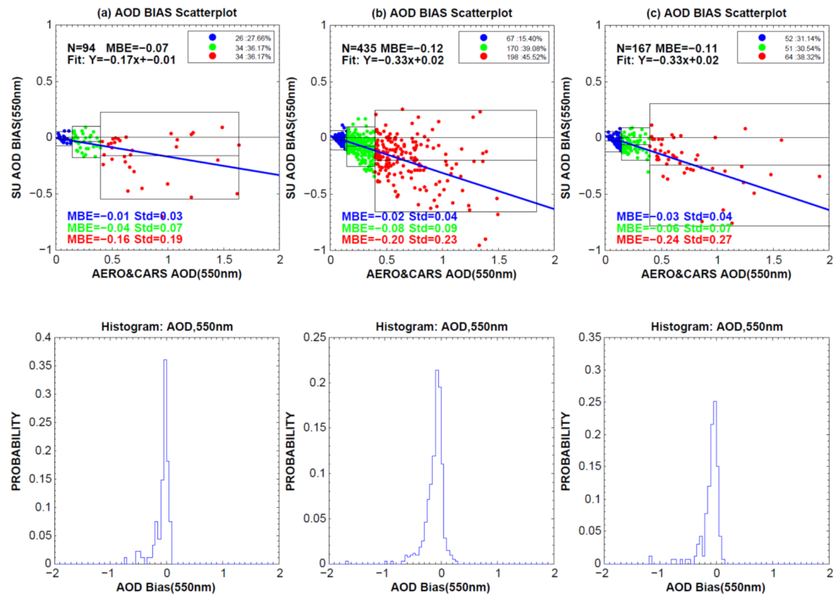

Fig. 7 Scatter plot of AEROENT&CARSNET AODs with SU AOD bias or uncertainties and histrogram of AOD bias.

We make these groups because aerosols have different natures with different loading. In general, the bias or uncertainty of satellite retrieved AOD will increase with the increase of AOD or aerosol loading. As discussed above, all these algorithms underestimate AOD at different level, similarly, it's worth noting that underestimation get more severe with the increase of AOD or aerosol loading.

5 Uncertainty analysis of individual ground measurement site

For the purpose of further evaluating different performances of these three algorithms on estimating AOD over mainland China, we validate these products site by site. It is significant to explore what roles of different factors in estimating AOD. There are several factors maybe have impacts on AOD calculating, including land cover, aerosol type, elevation etc. Therefore, we analyse different validation results of each site to study how these factors work (see Table 5).

5.1 Inter-comparison of algorithms site by site

In this section, we pick five representative AERONET&CARSNET sites in which it collocated more than 30 matches successfully in 2007, 2008 and 2010 to guarantee statistical sample size. These selected sites are located in different regions where the land cover and climatic pattern are different and of representative strongly in mainland China. Two AERONET sites and three CARSNET sites were selected, including SACOL, XiangHe from AERONET and Linan, Shangdianzi and Xilinhot from CARSNET. Most matches of ADV and SU products collocated with ground-based data distributed at March to October, lost data at winter time in 2007, 2008 and 2010 as shown in Fig. 8 to Fig. 12.. The matches of ORAC product distributed at each month over most sites.

Linan is located at 119.73°E,30.3°N, northwest of Zhejiang province. 80% of 50km × 50km surrounding area is green vegetation and the other 20% is covered with urban land. ADV and ORAC algorithm underestimated AOD with MBE = 0.13 and 0.12 in 2010 respectively. The SU has good performance in Linan with slight underestimation. The underestimation of ADV algorithm is more severe than SU and ORAC. Even though ORAC algorithm has most matches in Linan, its performance was unstable which means the levels underestimation were different in different years.

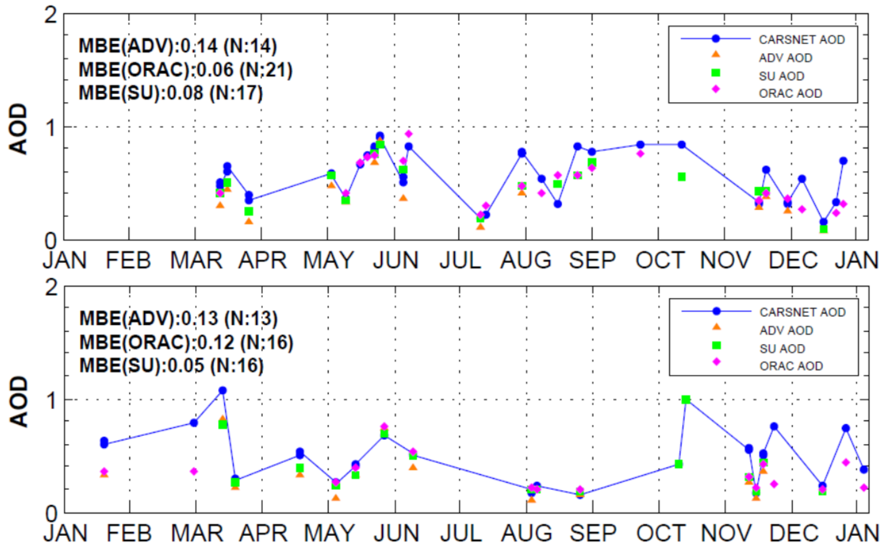

Fig. 8 is the time series comparison of AATSR AOD with CARSNET AOD over the site of Linan in 2008 and 2010.

SACOL is situated at southern bank of Yellow River in Lanzhou city, Gansu province. Lanzhou city is temperate continental climate, having four clearly distinctive seasons. The dominated land cover is grasslands about 95% at a spatial extent of 50km × 50km from the MODIS MCD12C1 land cover data. 30% of surface is acid and semi-acid areas, which can be a source of dust aerosol. SU has good performance on retrieving AOD over SACOL with high CC (0.849) and low RMSE (0.072). Accidental error in the retrievals of ORAC algorithm is obvious, leading to low CC (0.683) and high RMSE (0.170). Most of retrievals (91.3%) of ADV algorithm are within EE4. However, as discussed above, ADV algorithm underestimated AOD

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severely in SACOL. ADV algorithm tended to underestimate AOD of different range severely except small number of matches with high quality. The matches of SU product are of high quality in three years. ORAC collocated matches in January, February, November and December (winter time) when there're no matches of ADV and SU products. However, the accuracies of ORAC in winter time are of great uncertainty, as shown in Fig. 9.

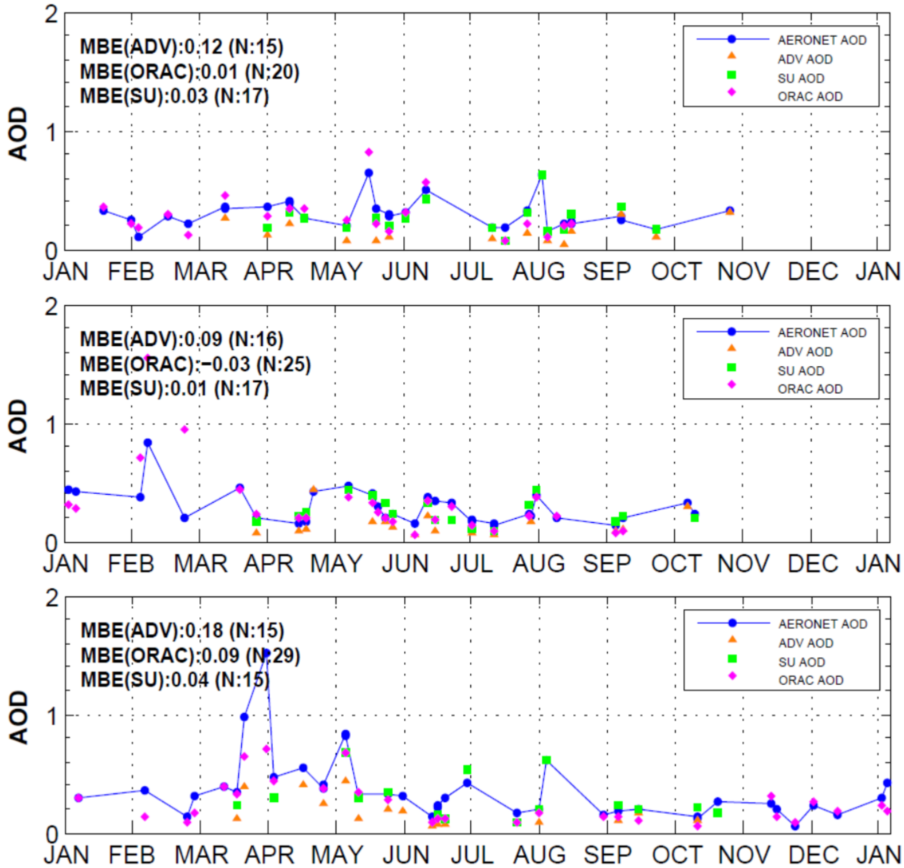

Fig. 9 is the time series comparison of AATSR AOD with AERONET AOD over the site of SACOL in 2007, 2008 and 2010.

Shangdianzi is situated at 94.68°E,40.15°N with complex land cover about 45% of croplands, 30% of mixed forest, 18% of closed shrublands, 5% of grasslands, 1% of water and 1% of evergreen needleleaf forest. The SU algorithm has high precision of AOD calculating over this site from March to October, when most of land cover is green. The ADV algorithm has good

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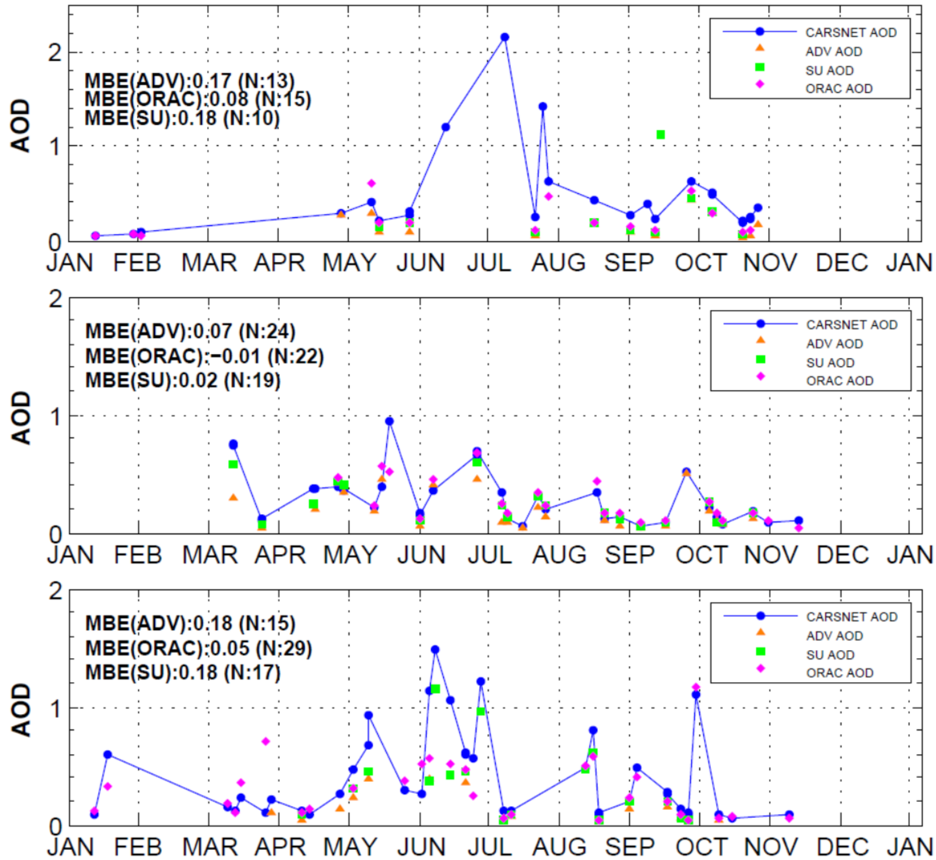
performances on calculating AOD over these three sites with slight underestimation. The performance of ORAC algorithm in Shangdianzi is unstable, good agreement with ground-based data from March to October and severe underestimation in winter time as shown in Fig. 10.



5 **Fig. 10 is the time series comparison of AATSR AOD with CARSNET AOD over the site of Shangdianzi in 2007, 2008 and 2010.**

Xianghe is located at southeast of Beijing, having same climatic pattern as Beijing. About 98% of surface is covered with urban land from MCD12C1 data at extent of 50km × 50km. The performances of these three algorithms are at same level with high quality. ADV algorithm still underestimated AOD at level of MBE = 0.12 in 2007 and 0.10 in 2008.

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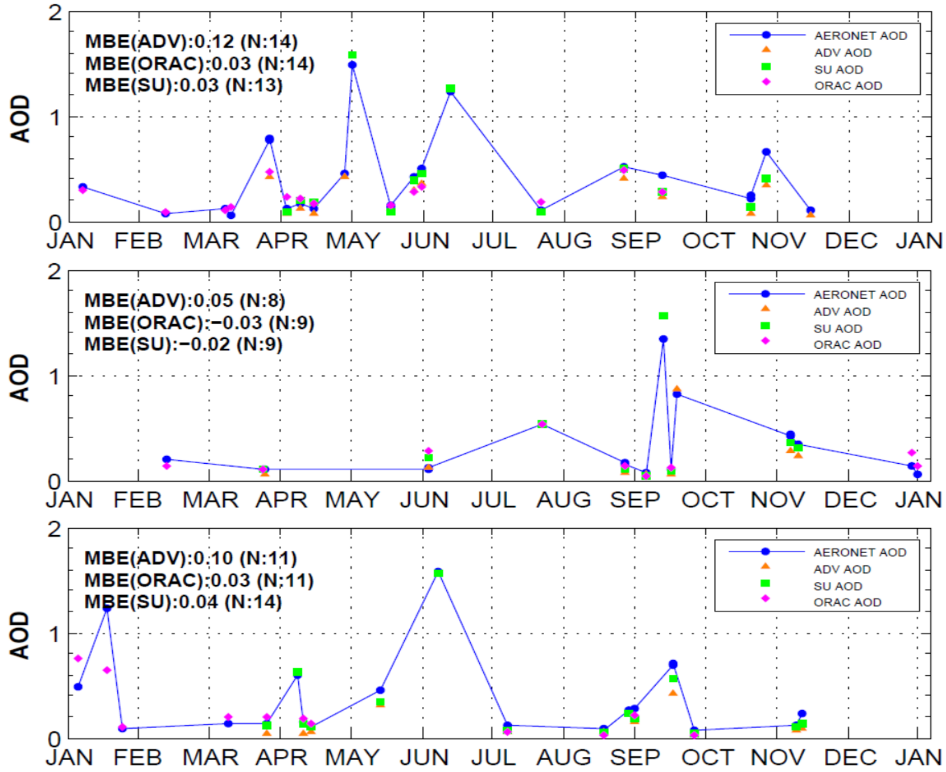

Fig. 11 is the time series comparison of AATSR AOD with AERONET AOD over the site of XiangHe in 2007, 2008 and 2010.

Xilinhot is situated at 116.07°E,43.95°N at the centre of Xilinguole grassland. The main land cover is grassland (100%) from MODIS MCD12C1 data at spatial extent of 50km × 50km. The surface circumstance and climate features of Xilinhot are much like SACOL's, and the performances of the SU algorithm on these two sites are same with high R and low RMSE both. ADV algorithm underestimated AOD slightly with MBE of 0.10~0.13. The ORAC AOD had not good agreement with Xilinhot data, mainly because it exits possible "outliers" in March to June 2008 and March 2010.

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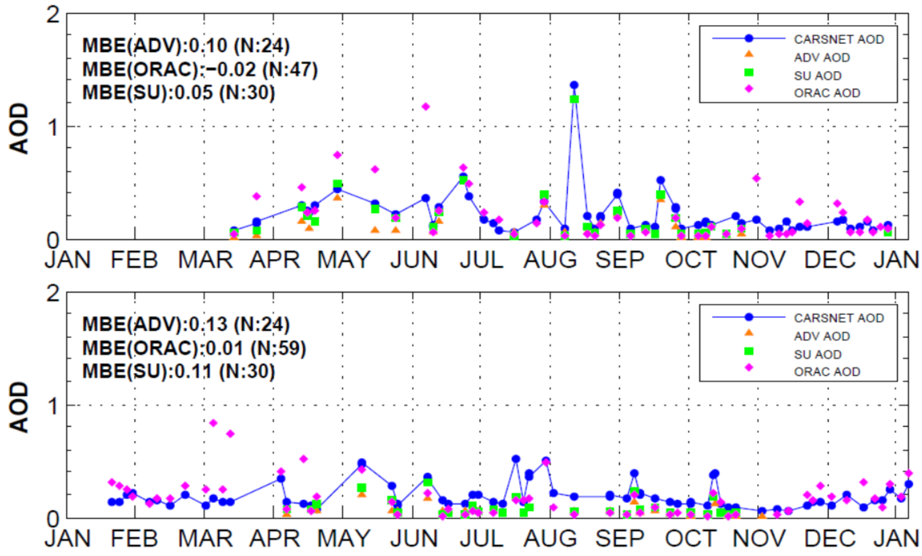

Fig. 12 is the comparison of SU AOD with CARSNET AOD over the site of Xilinhot in 2008 and 2010.

Table 5 Statistics of validation results of different products over different sites.

Site	Algorithm	N	MSA	MAA	MBE	MAE	RMSE	RMB	CC	KAPPA	Within EE3	Within EE4
	ADV	33	0.346	0.462	-0.116	0.122	0.088	0.748	0.916	0.341	84.9%	90.9%
Linan	ORAC	48	0.426	0.470	-0.044	0.131	0.144	0.906	0.647	0.668	58.3%	70.8%
	SU	40	0.430	0.484	-0.054	0.082	0.093	0.889	0.917	0.650	85.0%	90.0%
	ADV	46	0.156	0.285	-0.129	0.132	0.068	0.547	0.763	0.283	89.1%	91.3%
SACOL	ORAC	74	0.286	0.314	-0.028	0.102	0.170	0.910	0.683	0.595	67.6%	73.0%
	SU	49	0.265	0.291	-0.027	0.062	0.072	0.908	0.849	0.878	77.6%	83.7%
	ADV	52	0.172	0.297	-0.125	0.131	0.087	0.578	0.780	0.339	78.9%	90.4%
Shangdianzi	ORAC	66	0.267	0.304	-0.037	0.107	0.134	0.879	0.781	0.407	54.6%	65.2%
	SU	46	0.285	0.402	-0.117	0.128	0.101	0.710	0.924	0.457	82.6%	87.0%
	ADV	33	0.184	0.284	-0.100	0.102	0.070	0.649	0.921	0.169	97.0%	97.0%
XiangHe	ORAC	34	0.227	0.240	-0.013	0.091	0.096	0.946	0.825	0.577	73.5%	76.5%
	SU	36	0.368	0.392	-0.024	0.058	0.077	0.939	0.984	0.444	88.9%	91.7%
	ADV	49	0.082	0.198	-0.116	0.117	0.046	0.414	0.814	0.148	95.9%	95.9%
Xilinhot	ORAC	110	0.190	0.182	0.008	0.109	0.166	1.043	0.517	0.389	42.7%	48.2%
	SU	61	0.140	0.220	-0.081	0.085	0.063	0.634	0.937	0.444	88.9%	91.7%

For guarantee of statistical reliability, there must be more than 30 collocated pairs in one site. The determination of surface on each site is according to the proportion (> 80% for one land type) of each land cover type from MCD12C1 data at a spatial extent of 50km × 50km. If there's no one land cover's proportion larger than 80% in a site, it will be identified mixed, then we select two or more (sum > 80%) land types with the largest proportions as main land cover.

5.2 Analysis of algorithm performances in west China

Because it lacks enough ground-based data in west China from AERONET measurements, only data from CARSNET sites are used in 2008. We picked six CARSNET sites which are located in west China and in which there're more than 25 matches.

Urumchi is situated at 87.62°E,43.78°N, provincial capital of Xinjiang Uyghur Autonomous Region, the most remote city in China from any sea in the world. The dominated land cover at the spatial extent of 50km × 50km is grasslands about 85%. ADV, ORAC and SU algorithms all underestimated AOD severely, MBE = 0.22, 0.12 and 0.17 respectively. The MBE is lowest mainly because of the "outlier" in April which decreases its MBE.

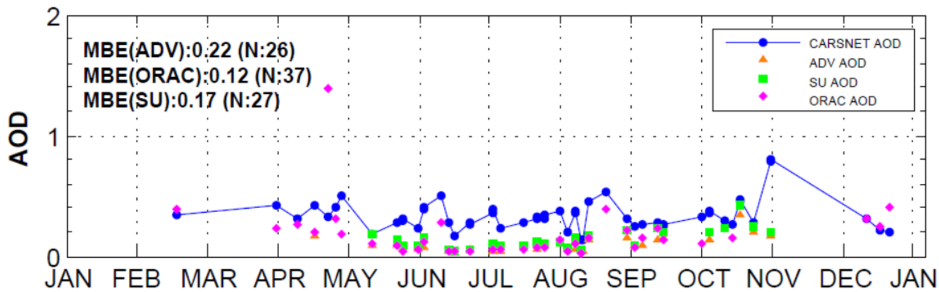

Fig. 13 is the time series comparison of AATSR AOD with CARSENT AOD over the site of Urmchi in 2008.

Ejina is situated at 101.07°E,41.95°N, its main land cover of barren (84%) ground. The performances of ORAC and SU are at same level with high quality, the MBEs are 0.02 and 0.09 respectively. Another reason why we chose this site is that there're no matches of ADV product collocated successfully with ground-based data. As result from Fig. 15., the ORAC algorithm has strong applicability in Ejina and high accuracy in retrieving AOD. The SU algorithm had good performance too. This explains another limit of ADV algorithm is applicability in calculating AOD in China. Dunhuang is situated at 94.68°E,40.15°N, surrounded by barren ground (85%). The same situation is like Ejina that it arises a little bit underestimation on each point but high R and low RMSE for ORAC algorithm. The performance of SU algorithm was not good as ORAC because of its underestimation with MBE = 0.10. The limits of underestimation and applicability of ADV were more obvious in this site,

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only 6 matches on demand and severe underestimation with MBE = 0.17. Tazhong is situated at 83.67°E,39°N surrounded by barren or sparsely vegetation surface. Almost all land cover is barren ground from MODIS MCD12C1 data. Similar with the former two sites, ADV product didn't collocated any matches in this site. Both of ORAC and SU algorithm had severe underestimation of retrievals with MBE = 0.17 and 0.20 respectively. The outliers of ORAC product in February are much higher than observation data which makes MBE lower.

The dominated climate pattern in west China is temperate continental climate with clearly four seasons and less precipitation in winter and spring. In conclusion, compared to east China, the applicability of ADV algorithm is not strong and the underestimation is more severe. In the four selected sites in west China, the performance of ORAC algorithm is best, even though it exists severe underestimation in some sites. The accuracy of SU algorithm is not good as ORAC product with more severe underestimation and the applicability is not strong as ORAC.

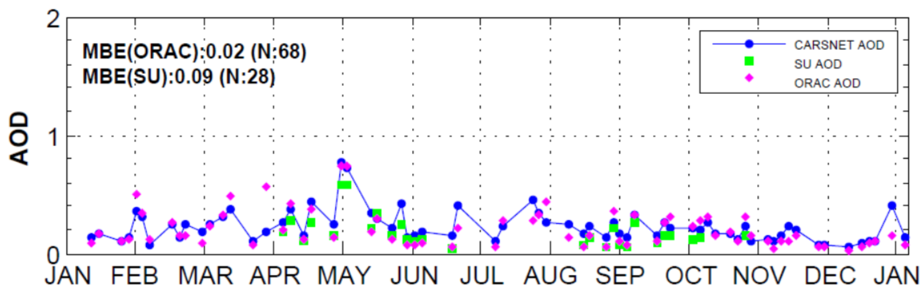

Fig. 14 is the time series comparison of AATSR AOD with CARSENT AOD over the site of Ejina in 2008.

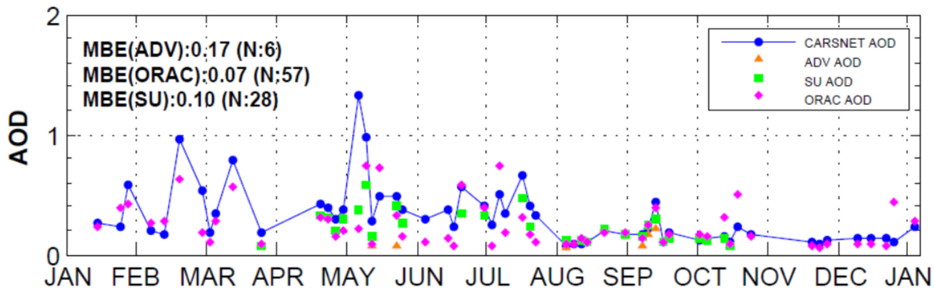

Fig. 15 is the time series comparison of AATSR AOD with CARSENT AOD over the site of Dunhuang in 2008.

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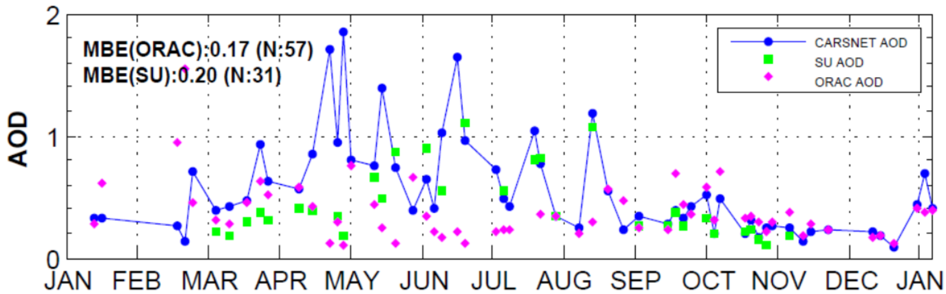

Fig. 16 is the time series comparison of AATSR AOD with CARSENT AOD over the site of Tazhong in 2008.

5.3 Inter-comparison

In conclusion, the SU algorithm has good performances on calculating AOD over different land cover from March to October. Slight underestimation occurs over barren or sparsely vegetation at different time, and there are no obvious features of precision on time series over grasslands. For complex land surface where dominated land cover is vegetation, the SU algorithm has extremely good performance on estimating AOD. In the last section, we draw a conclusion that the SU algorithm underestimates AOD over mainland of China in 2008, probably because the dominated land cover in the western China is barren or sparsely vegetation, over which the SU algorithm underestimates AOD more severely.

The ADV algorithm underestimates AOD in most sites we selected. We categorize these sites into four classes according to MBEs of different sites: Class1 (MBE<0.1), Class2 (0.2>MBE>0.1), Class3 (0.3>MBE>0.2), Class4 (MBE>0.3). The ADV algorithm underestimates AOD over all selected sites, leading to all MBEs we select larger than 0. We make such categories for the purpose of assessing contribution of different surfaces to AOD estimation. Only XiangHe of 2008 belongs to Class1, Linan, Shangdianzi, SACOL were classified into Class2. Only Urumchi is in Class3. Note that, even though Lanzhou and Datong were not selected due their location, they should be classified into Class4.

Overall, the ADV algorithm underestimates AODs at all sites but at different level as the categories we make above. Serious underestimation occurs over the sites in Class3 and Class4 in the western China where the dominated land cover is mixing of a small portion of urban area and a large portion of grasslands. For the sites in Class2, there're differences between Beijing and SACOL. SACOL is much like the sites in Class3 and Class4, the main land cover of which is grasslands. Over the sites in Class1 the algorithm has good performance with high R and low MBE, but there're no features in common on the surface circumstance.

The ORAC product collocate most pairs of all these products. Most pairs the SU product and ADV product collocate are distributed at March to October, but the collocated pairs of the ORAC product distribute at each month over some sites in 2008.

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Otherwise, more matches mean more errors, for the target of determination of the contribution of "outlier" to overall performance of the ORAC algorithm, we introduce ratio of individual difference to average differences for each site,

$$\mathrm{DR} = \frac{\left|\tau_{AERO,i} - \tau_{sate,i}\right|}{\left(\sum_{i=1}^{n}\left|\tau_{AERO,i} - \tau_{Sate,i}\right|\right)}/n \quad (11)$$

where DR<1, indicating a "relatively good" match. Where 3 >DR >1, it's a "relatively poor" match. Where DR >3, it's probably an "outlier" (see Table 6).

There are no obvious "possible outliers" in Ejina shown in Fig. 15 Most of DRs are in a range from 0 to 3, only two DRs are larger than 3, and the maximal (overestimation) is 5.112. The retrieved AOD in March is possible "outlier", because it is overestimated but most are underestimated. Another two sites with dominated land cover of barren or sparsely vegetation are Dunhang (about 85%) and Tazhong (100%). The circumstance in Tazhong is complex and there are no obvious laws between the CARSNET data and the ORAC AODs. Most of DRs are less than 3, total 8 DRs are larger than 3. It's basically identified that the one in February is "outlier", because the varying tendencies are different between the ORAC product and the ground-based data and only this points was overestimation.

Table 6 Distribution of DRs of specific sites.

Site	DR<1	1<DR<3	3<DR<5	5<DR	Total
Urumchi	47	40	2	1	90
Ejina	51	43	1	1	96
Tazhong	63	17	5	3	88
Dunhuang	57	31	1	2	91

The ORAC product has the largest coverage at the cost of losing accuracy especially exist of "outlier", and only the ORAC product collocate validation pairs over some sites at each month in three years. The ORAC algorithm underestimates AODs over Ejina, Tazhong and Dunhuang, but the "possible outliers" reduce the differences between the CARSNET data and the ORAC product. Xilinhot, Urumchi and SACOL have same main land cover of grasslands. The problem is that the underestimations over these sites are not at one level.

It is worth noting that the ORAC algorithm has ability in calculating high AOD, however, most of AOD of which DRs are larger than 3, indicating the estimation of high AOD is unstable with large error, even to reduce the whole precision.

6 Conclusions

These three algorithms (the SU algorithm, the ADV algorithm and the ORAC algorithm) have different performances on estimating AOD over mainland China in 2007, 2008 and 2010. However, there's no one having better performance than the other two algorithms. The SU and the ADV product have higher accuracy over most of sites we select but less coverage, the ORAC product has more coverage at the cost of accuracy.

All these algorithms tend to underestimate AOD to some degree. Underestimation gets more severe with increase of AOD or aerosol loading. The method of grouping helps to find more, especially "possible outliers" in different regions of aerosol loading.

The precision of SU algorithm and ADV algorithm is at same level over different surface. However, the difference is that SU product has more strict quality control than ADV product and it eliminates AODs to make MBE less than 0.10 over different sites (de Leeuw et al. 2013). Over grasslands and barren vegetation, the SU has good performance with slight underestimation (MBE < 0.10), the limits of underestimation and applicability of ADV are more obvious over such sites. For complex surface mixed of two or more land cover, the performances of these three algorithms are at same level. Note that, Lanzhou and Datong are different from other sites, even though the main land cover of them is grasslands. All these algorithms have underestimated AOD at a high level, perhaps because these algorithms are un-sensitive to absorptive aerosol.

Only the ORAC product exists "possible outliers" identified by equation (7) which decrease accuracy a lot. Almost, the most obvious feature of "possible outliers" is that the retrieved AODs are higher than the ground-based measurement.

As reference data, AERONET L2 data have some limitations, including the distribution and number of sites in mainland China. Most of sites of AERONET distribute in eastern China and coastal region of China for special experimental use, leading to we can't get enough reference data to validate AOD product. The CARSNET data made up for this shortage, because there're more CARSNET sites in China, especially in west China where hardly any AERONET sites had built. Limited both by reference data and satellite retrievals, most co-allocated pairs are distributing in March to November and few are distributing in winter (December January and February).

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