Evaluation of MODIS columnar aerosol retrievals using AERONET in semi-arid Nevada and California, U.S.A., during the summer of 2012

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HIGHLIGHTS

- MODIS retrievals do not represent column AOD and AEE in California and Nevada.
- Wildfire smoke improved MODIS AOD correlation but not bias compared to AERONET.
- Surface albedo appears to affect AOD retrieval accuracy, especially in desert areas.

ABSTRACT

Satellite characterization of local aerosol pollution is desirable because of the potential for broad spatial coverage, enabling transport studies of pollution from major sources, such as biomass burning events. However, retrieval of quantitative measures of air pollution such as Aerosol Optical Depth (AOD) from satellite measurements is challenging over land because the underlying surface albedo may be heterogeneous in space and time. Ground-based sunphotometer measurements of AOD are unaffected by surface albedo and are crucial in enabling evaluation, testing, and further development of satellite instruments and retrieval algorithms. Columnar aerosol optical properties from ground-based sunphotometers (Cimel CE-318) as part of AERONET and MODIS aerosol retrievals from Aqua and Terra satellites were compared over semi-arid California and Nevada during the summer season of 2012. Sunphotometer measurements were used as a ‘ground truth’ to evaluate the current state of satellite retrievals in this spatiotemporal domain. Satellite retrieved (MODIS Collection 6) AOD showed the presence of wildfires in northern California during August. During the study period, the dark-target (DT) retrieval algorithm appears to overestimate AERONET AOD by an average factor of 3.85 in the entire study domain. AOD from the deep-blue (DB) algorithm overestimates AERONET AOD by an average factor of 1.64.

Low AOD correlation was also found between AERONET, DT, and DB retrievals. Smoke from fires strengthened the aerosol signal, but MODIS versus AERONET correlation hardly increased during fire events ($r^2=0.1–0.2$ during non-fire periods and $r^2=0.0–0.31$ during fire periods). Furthermore, aerosol from fires increased the normalized mean bias (NMB) of MODIS retrievals of AOD (NMB=23%–154% for non-fire periods and NMB=77%–196% for fire periods). Ångström Extinction Exponent (AEE) from DB for both Terra and Aqua did not correlate with AERONET observations. High surface reflectance and incorrect aerosol physical parametrizations may still be affecting the DT and DB MODIS AOD retrievals in the semi-arid western U.S.
1. Introduction

Multiple studies have demonstrated that air quality is negatively impacted by trace gases and near surface PM (Al-Saadi et al., 2005; Stocker et al., 2013). Air pollution varies in space and time (Chu et al., 2003) and the composition of PM depends on emissions, photo-chemical interactions (e.g., secondary aerosol formation), meteorological conditions, deposition, and transport mechanisms (McNair et al., 1996). PM’s direct optical effects cause visibility impairment (Watson, 2002), and impact the radiative budget of the earth (Chylek and Wong, 1995; Kaufman et al., 2002) causing cooling (through light scattering) or warming (through light absorption) (Moosmüller et al., 2009). Meanwhile, PM’s indirect effect on weather is caused by changes in cloud microphysics (Twomey, 1977; Rosenfeld and Lensky, 1998). In addition, air quality awareness has grown rapidly due to the effects of near surface PM inhalation on human health, including cardio-respiratory diseases and premature deaths (Pope and Dockery, 2006; Krewski, 2009; Suja-ritpong et al., 2013).

In general, ground-based PM measurement platforms represent a single point of measurement, and do not provide enough information about the regional and global distributions and transport of aerosol pollution (Gupta et al., 2006). Satellite observations can help address the limitations of surface observations through an improvement in spatial coverage (Hoff and Christopher, 2009; Streets et al., 2013), which has resulted in numerous aerosol and surface studies using satellite retrievals (e.g., Engel-Cox et al., 2004a, 2004b, 2006; Hutchison et al., 2004; Hutchison, 2003; Zhang et al., 2009). In particular, AOD retrieved from MODIS instruments on NASA’s Terra and Aqua satellites has been used to estimate surface PM mass concentration (Liu et al., 2004; van Donkelaar et al., 2010, 2011; Yap and Hashim, 2013).

AOD from satellite retrievals has been used as a spatial predictor in many PM statistical models of exposure estimates for studies of human health (Wang, 2003; Alman et al., 2016). These models are helpful to understand the spatial variability of surface PM concentrations because of the sparse network of surface monitoring stations. However, the models developed for the eastern U.S. (e.g., Liu et al., 2009) are not robust in the western U.S. (Engel-Cox et al., 2004a; Zhang et al., 2009) due to different aerosol formation mechanisms, complicated aerosol transport and dispersion within the atmosphere (Loria-Salazar et al., 2014), the widespread presence of bright surfaces (Gupta et al., 2006; van Donkelaar et al., 2010), secondary organic aerosol formation, smoke from wildfires, transboundary transport of aerosol pollution from Eurasia (Wilkening et al., 2000; Yu et al., 2008), and low background aerosol concentrations. In addition, physical aerosol properties such as the aerosol absorption coefficient and the phase function of non-spherical dust particles are poorly characterized; this leads to additional problems for remote sensing of mineral dust aerosol properties (Hsu et al., 2004).

The research described here uses data from the summer of 2012 to evaluate satellite AOD retrievals as a potential tool for monitoring aerosol pollution in California and Nevada. Accordingly, we present a study comparing retrievals based on ground observations and satellite remote sensing during fire and non-fire conditions. We evaluate whether or not the spatiotemporal variability of the satellite AOD data can be used in future investigations to infer the space-time variability of daily surface PM concentrations in the semi-arid western U.S.

2. Instrumentation

Hourly local aerosol column observations were obtained from Cimel CE-318 sunphotometers located at seven stations in California and three stations in Nevada (Fig. 1). The Cimel CE-318 is a sunphotometer that performs direct-sun, almucantar, and principal plane scans. It provides accurate vertically integrated aerosol optical measurements at a single location (Holben et al., 1998), but does not reveal the global distribution and transport of aerosol pollution (Gupta et al., 2006). NASA’s AERONET uses the Cimel sunphotometer as the standard instrument to quantify aerosol properties at ~400 stations around the globe. The spheroid model for desert dust aerosol types is used in version 2 of AERONET retrieval software (Dubovik et al., 2006), which could improve measurement results in the semi-arid western U.S.

MODIS is part of the instrument suite on NASA’s Terra and Aqua satellites. MODIS instruments perform daily, large scale characterization of surface reflectivity, cloud cover, AOD, and land as well as ocean processes. MODIS observations are used to assess air quality on local, regional, and global scales (Levy et al., 2007) and to quantify factors that affect the earth’s surface global radiation budget. MODIS’ wide spectral range uses selected wavelength bands ranging from 0.41 to 15 μm (Remer et al., 2005). The MODIS

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1. PM: Particulate matter.
2. AOD: Aerosol optical depth.
3. MODIS: Moderate Resolution Imaging Spectroradiometer.
4. AERONET: AErosol RObotic NETwork.
sensors are used to retrieve daily aerosol properties over land and ocean (Kauffman et al., 1997; Tanré et al., 1997).

The Terra and Aqua satellites orbit ~705 km above the Earth in sun-synchronous polar orbits. They pass over each location at the same local time every day. Terra is a descending orbit (North to South during daytime) satellite that overpasses at ~10:30 a.m. local standard time (morning satellite). In contrast, Aqua is an ascending orbit (South to North during daytime) satellite and overpasses at ~1:30 p.m. local standard time (afternoon satellite). Studies about bias between Terra and Aqua MODIS AOD retrievals showed that AOD from MODIS-Aqua was usually higher than AOD retrieved from MODIS-Terra. Multiple statistical tests suggested (qualitatively) that there are differences between Terra and Aqua AOD retrievals because of the time dependence between satellite overpasses that induce systematic biases (~1~2%), but these biases are small compared to the random variation in AOD for individual retrievals and may be attributed to instrument calibrations (Hyer et al., 2011). The surface reflectance at 470, 675, and 2130 nm are needed to retrieve AOD from MODIS data (Remer et al., 2005). The DT \(^5\) algorithms for AOD retrievals have been developed for land (15% uncertainty in some studies) and for ocean (5% uncertainty) (Remer et al., 2005, 2013, Levy et al., 2007, 2010, 2013).

Over the eastern U.S., previous studies reported high correlation between the DT land algorithm and AERONET AOD retrievals (\(r^2=0.94\) (Shi et al. 2011) making the DT land algorithm useful for monitoring aerosol pollution in this area. According to Hyer et al. (2011), MODIS land algorithms have lower accuracy than the ocean algorithm for retrieving AOD due to the variability in the underfire surface and the associated effect in the aerosol optical properties (Sorek-Hamer et al., 2015). The MODIS retrieval is based on the ratio of direct sunlight scattered by aerosols to that reflected by the surface. As the surface reflectance is higher and more irregular over land, the ocean retrieval is more accurate than the land retrieval. For the eastern U.S., MODIS correlates well with AERONET because of the fairly uniform mix of sulfates and organic aerosol pollution, the more homogeneous dark surface reflectance, the lower elevation, and the less complicated boundary layer physics.

In the case of very bright surfaces typical of arid landscapes, the DT land algorithm is challenged because it has to recognize the differences between aerosols, such as desert dust, and the underlying surface (e.g., in the Sahara desert and Arabian Peninsula) (Chu et al., 2002; Hsu et al., 2004). Therefore, AOD in desert areas is not retrievable using the standard DT land algorithm. The DB \(^6\) algorithm helps to solve the problem of bright surfaces by using a data base of surface reflectivity, a dynamic surface reflectance, a normalized difference vegetation index, and a radiative transfer model that tracks polarization for select locations (Hsu et al., 2004; 2013).

DB exploits the observation that desert surfaces are dimmer at shorter wavelengths than over dark vegetated areas. AOD retrievals with the DB algorithm were found to be accurate over bright surfaces in Asian and African deserts (e.g. \(r^2=0.74\) with a root mean square error~0.23) (Hsu et al., 2006; Shi et al., 2013). It was also demonstrated that the DB algorithm was able to distinguish dust plumes from fine mode aerosols (Hsu et al., 2006). Previous comparisons between DB MODIS AOD (Aqua) and AERONET AOD retrievals reported that 79% of the MODIS retrievals (collection 6) agreed within ±0.05 + 0.2 (AERONET AOD) over deserts (Hsu et al., 2013).

3. Methods

Here we compare aerosol optical properties derived from ground-based sunphotometers with satellite aerosol products from June 1 to August 31, 2012 for the semi-arid western region of the U.S. MODIS level 2 data (10 km × 10 km resolution) were analyzed from 32° N to 42° N latitudes and from 114° W to 127° W longitudes. The MODIS products used here are corrected land (interpolated 550 nm) AOD from the DT algorithm and land AOD (interpolated 550 nm) from the DB algorithm. AEE \(^7\) were obtained from the DB data for the wavelength pair of 470~660 nm.

We compare MODIS AOD with AERONET stations at Cal Tech, California (34.1° N, 118.1° W); El Segundo, California (33.9° N, 118.4° W); Frenchman Flat, Nevada (36.8° N, 115.9° W); Fresno 2, California (36.8° N, 119.8° W); Goldstone, California (35.2° N, 116.8° W); La Jolla, California (32.9° N, 117.2° W); Railroad Valley, Nevada (38.5° N, 119.5° W); Table Mountain CA, California (34.4° N, 117.7° W); UCSB, California (34.4° N, 119.8° W); and University of Nevada, Reno, Nevada (39.5° N, 119.8° W). Fig. 1 shows the location of the AERONET stations on a MODIS Aqua visible image so differences in land surface and terrain characteristics can be visualized for each location. The relative uncertainty of AOD measured with the Cimel is estimated to be in the range of ±0.01 and ±0.02 (Eck et al., 1999; Eck, 2010).

3.1. Novel fire-filtering algorithm for AERONET AOD and AEE

AOD data during heavy wildfire smoke periods often are removed from the level 2 AERONET data because the smoke plume variability is misinterpreted as cloud variability by the cloud screening algorithm. AERONET level 2 eliminates AOD values based on significant fluctuations of successive AOD measurements without examining AEE values. Because it is possible to have rapid AOD fluctuations during fire events, a filtering algorithm based on AOD fluctuations alone runs the risk of flagging fire plumes as clouds. Large fire events, such as the Chips Almanor fire reported here, have in common with clouds that the fire plumes varied significantly with time. Unfortunately, the statistical analysis in the AERONET level 2 algorithm categorized some of the fire plumes as clouds.

AERONET data sets in this study were generated using level 1 (raw data) in the presence of smoke from fires and level 2 (with quality assurance) over non-fire periods. Those large fire events have in common that the fire plumes varied significantly with time. AEE was the criteria used to filter the AERONET data sets for fire and non-fire periods. AEE expresses the wavelength dependence of AOD (Angstrom, 1929) and is a qualitative indicator of aerosol size (Schuster et al., 2006; Kaskaoutis et al., 2007). AEE less than one suggests the presence of super-micron particles such as dust or sea salt (Schuster et al., 2006). In addition, Schuster et al. (2006) proposed that AEE tends to be zero as effective particle radius increases (e.g. clouds). Sub-micron particles such as soot from biomass burning have AEE close to or greater than two (Eck et al., 1999). AEE results described in Schuster et al. (2006), Loria-Salazar et al. (2014), and Eck et al. (1999) aimed to make decisions regarding the correct AEE criteria to use as a parameter for filtering the AOD data as fire smoke points (versus clouds) in the data set. Base of the fact that AEE is zero for large effective particle radii. For example, a typical effective radius for cirrus cloud hydrometeors ranges between 10 to a 100 µm for ice clouds. In these size regimes, the AEE tends to be zero.

\(^5\) DT: Dark-target.

\(^6\) DB: Deep-blue.

\(^7\) AEE: Angstrom Extinction Exponent.
The AERONET data set obtained using AEE fire-filtering algorithm is mainly composed of level 2 data (for most cases), and the data points added from level 1 (that were erased from level 2) are those when AEE in level 1 was close to or greater than two. In addition, data points associated with AEE close to 2 (AEE > 1.8) were classified as fire periods. To corroborate the correct treatment of the data, histograms for each station for level 1, level 2, and the combined data sets are shown in the supplementary information. The histograms demonstrate that the merged data set follows the distribution of level 2 data even though some data from the level 1 AOD was added when AEE (level 1) is approximately 2, as those data points are due to submicron combustion particles. Additional information for this method is given in the supplementary information and in Section 4.3 in the Results.

4. Results

4.1. Monthly average of AOD and AEE retrievals

Fig. 2 shows the AOD monthly average of June, July, and August for DT (corrected land; 550 nm) MODIS retrieval for Terra (Fig. 2.a, 2.b, and 2.c) and Aqua (Fig. 2.g, 2.h, and 2.i) satellites over the three
months of the study. Terra-MODIS (Fig. 2.a, 2.b, and 2.c) and Aqua-MODIS (Fig. 2.g, 2.h, and 2.i) AOD monthly averages presented a positive AOD gradient, with AOD increasing from west (California) to east (Nevada). This positive gradient may be due to the influence of brightly reflecting surfaces on aerosol retrievals.

AOD over northern California and the Central Valley varied from ~0.05 to ~0.3 for MODIS Terra and Aqua observations in June (Fig. 2.a and 2.g) and July (Fig. 2.b and 2.h). August AOD from Terra (Fig. 2.c) and Aqua (Fig. 2.i) showed a region with very high AOD (~0.7) due to wildfires in northern California and on the border of California and Oregon. However, Terra-MODIS AOD (Fig. 2.c) monthly averages for August included AODs higher than corresponding Aqua-MODIS averages. Additional differences in AOD retrievals may be due to their different overpass times; Terra overpasses in the morning (~10:30 a.m. local time) when local emissions dominate aerosol production, while Aqua overpasses in the afternoon (~1:30 p.m. local time) when secondary aerosol formation can be significant.

Over Nevada (some regions of the Great Basin) and southern California, MODIS AOD data was sparse, probably due to the high brightness of the surface invalidating data for these locations (van Donkelaar et al., 2010). AOD data from Terra and Aqua MODIS retrievals for the Great Basin showed very high AOD (from ~0.2 to ~0.7). High AOD in the Great Basin could possibly indicate windblown dust, secondary aerosol formation, and/or transport of air pollution from California. However, it is much more likely that the Great Basin AOD is unrealistically high due to the brightness of its surfaces and the nature of the DT aerosol retrieval algorithm because there are not many local sources of aerosol pollution with the exception of windblown dust.

Data point counts are the sum of observations per month for MODIS AOD retrievals. According to Terra and Aqua counts, August (Fig. 2.f and 2.i) was the month with more observation points. June was the month with lowest counts (Fig. 2.d and 2.j) than the later months due to seasonal transition and snow melt that changes surface reflectivity. In general, counts for California were higher than those for Nevada for both satellite sensors in the entire period. This was because AOD over vegetated areas in California more often be retrieved with the DT algorithm (Drury et al., 2008; Shi et al., 2011) than that over bright desert surfaces in Nevada (Levy et al., 2010).

Fig. 3 shows the monthly averages of Terra (Fig. 3.a, 3.b, and 3.c) and Aqua (Fig. 3.g, 3.h, and 3.i) AOD from the DB algorithm. In contrast with DT (Fig. 2) retrieval, AOD from DB did not show an increasing AOD gradient from west to east. AOD from both satellites shows clean conditions from ~0.01 to ~0.1 in northern California (excluding the Sacramento Valley) and Nevada during June (Fig. 3.a and 3.g) and July (Fig. 3.b and 3.h). A ring of high AOD (AOD ~0.3 in average for the entire ring) is found around the Sacramento and the San Joaquin Valleys. This ring of high AOD was particularly strong in July and August. The elevated AOD in this area could be associated with agriculture activities, traffic, and local geological emissions (Chow et al., 1992). Southern California presents sparse centers of high AOD that could be related with industrial emissions and/or fire activities during the entire period. During August (Fig. 3.c and 3.d), AOD retrieved from both Terra and Aqua MODIS instruments increased in northern California due to the presence of multiple fires (EOSDIS Worldview, https://earthdata.nasa.gov/labs/worldview). Both MODIS instruments show AOD values that range from ~0.2 to ~0.7 over the Central Valley in California. In addition, a very high AOD spot around the BRD9, Nevada (40.9’ N and 119.1’W) was found that could be related to windblown dust, but the AOD in this area is probably unrealistically high. No AOD retrievals were found in some areas of the SNMs9. The missing AOD retrievals could not be related to the presence of snow (EOSDIS Worldview, https://earthdata.nasa.gov/labs/worldview), but it may be related with lack of spatial coverage in the area or another physical phenomenon.

4.2. MODIS evaluation using AERONET

The inter-comparison between AERONET (single point of measurement) and MODIS (10 km × 10 km resolution) was done as follows:

1. AERONET AOD and AEE hourly averages were determined for each station.
2. One-hour averages, before and after the time of overpass, of AERONET AOD and AEE were chosen according to the times at which Terra and Aqua overpassed each station.
3. MODIS AOD and AEE were averaged over a square consisting of four pixels approximately centered at the point where the AERONET station was located.

Table 1 summarizes the number of data points and the average and standard deviation of minimum, maximum, mean, median, and standard deviation of AOD and AEE for all stations in the study period AERONET (all available hourly data), MODIS DT, and MODIS DB. According to Table 1, AERONET AOD ranged from 0.01 to 0.6, Terra-MODIS DT AOD varied from 0.01 to 0.7, and Aqua-MODIS DT AOD varied from 0.01 to 0.7. In contrast, Terra-MODIS DB AOD varied from 0.02 and Aqua-MODIS DB AOD ranged from 0.01 to 0.67. AERONET AEE for all stations ranges from 0.46 to 2.75. The AEE from the DB algorithm varies from 0 to 1.64 for Terra; and fluctuates from 0.16 to 1.65 for Aqua.

Fig. 4 shows scatter plots between MODIS (DT and DB) and AERONET AOD for June, July, and August of 2012 for all stations. Both DT (Fig. 4.a and 4.c) and DB algorithms (Fig. 4.b and 4.d) show low correlation with respect to AERONET. The DT shows an r2~0.1 with p < 0.01 for Terra (Fig. 4.a) and an r2~0.18 with p < 0.01 for Aqua (Fig. 4.c). Meanwhile, the DB algorithm (Fig. 4.b and 4.d) performs slightly better for Terra (r2~0.14, p < 0.01), but it does worse for Aqua (r2~0.05, p < 0.01). Table 2 presents the average and the standard deviation of the AOD model evaluation using all stations that contains: FB10, GM11, NMSE12, VC13, FAC14 from Chang and Hanna (2004), RMSE15 used by Shi et al. (2013), and the NMB16 (Simon et al., 2012).

In this paper, discussion focuses on two of these evaluation metrics. First, the fractional prediction of two represented as FAC2: FAC2 = 0.5 ≤ AODMODIS AODAERONET ≤ 2.0

where AODMODIS represents the value predicted by the model (MODIS DT or DB retrievals) and AODAERONET is the value observed. FAC2 represents the fraction of the predicted data set which is within a factor of two, or the fraction of data satisfying Equation (1). The second is the bias, NMB defined by:

9 SNMs: Sierra Nevada Mountains.
10 FB: fractional bias.
11 GM: geometric mean bias.
12 NMSE: normalized mean square error.
13 VC: geometric variance.
14 FAC2: fractional prediction of two.
15 RMSE: root mean square error.
16 NMB: normalized mean bias.

9 BRD: Black Rock Desert.
NMB = \frac{\sum_{i=0}^{n} AOD_{MODIS} - AOD_{AERONET}}{\sum_{i=0}^{n} AOD_{AERONET}} \tag{2}

NMB avoids over-inflating the observed range of values, especially at low concentrations. A NMB > 1 indicates over prediction, meanwhile a NMB < 1 represents underestimation from the prediction.

A full description and definition of all evaluation metrics in Tables 2 and 3 is given in the supplementary information.

According to Table 2, the DT algorithm overestimates AOD in the entire region with a mean NMB of 127% (\(\sigma = 127\%\)) (mean FAC2 of 0.28, \(\sigma = 0.27\)) for Terra, and it overestimates AOD for Aqua with a mean 96% (\(\sigma = 103\%\)) NMB (FAC2 of 0.22, \(\sigma = 0.23\)). Meanwhile in the same region, the DB algorithm overestimates AOD with a mean NMB of 36% (\(\sigma = 57\%\)) NMB (FAC2 of 0.61, \(\sigma = 0.19\)) for Terra and a mean NMB of 25% (\(\sigma = 57\%\)) (mean FAC2 of 0.60, \(\sigma = 0.25\)) for Aqua.

An examination of the individual station data in Fig. 4 is shown in Fig. 5 for NMB and Fig. 6 for FAC2. Terra-DT and Aqua-DT (Fig. 5.a and 5.c respectively) algorithm overestimates AOD everywhere but
The Terra-DB and Aqua-DB (Fig. 4.b and 4.d respectively) algorithm overestimates AOD for El Segundo (Terra-DB), Frenchman Flat, Goldstone, La Jolla, Table Mountain CA, UCSB; underestimates AOD for Cal Tech, Fresno 2, Railroad Valley, and meets evaluation metric standards (NMB~0% and FAC2~1) for El Segundo for (Aqua-DB) and for University of Nevada, Reno (for Table 1

Data summary statistics of AOD (top) and AEE (bottom). AOD for AERONET (500 nm), Terra-Aqua MODIS DT (550 nm), and Terra-Aqua MODIS DB (550 nm) and AEE for AERONET (440–675 nm) and Terra-Aqua MODIS DB (470–670 nm) Terra-Aqua during the summer months of 2012 in California and Nevada.

<table>
<thead>
<tr>
<th></th>
<th>AOD Terra DT</th>
<th>Aqua DT</th>
<th>Terra DB</th>
<th>Aqua DB</th>
</tr>
</thead>
<tbody>
<tr>
<td>AOD N</td>
<td>5819</td>
<td>508</td>
<td>485</td>
<td>708</td>
</tr>
<tr>
<td>Min</td>
<td>0.03 ± 0.02</td>
<td>0.10 ± 0.08</td>
<td>0.10 ± 0.09</td>
<td>0.04 ± 0.02</td>
</tr>
<tr>
<td>Max</td>
<td>0.48 ± 0.19</td>
<td>0.72 ± 0.42</td>
<td>0.70 ± 0.37</td>
<td>0.48 ± 0.20</td>
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<tr>
<td>Mean</td>
<td>0.13 ± 0.08</td>
<td>0.35 ± 0.20</td>
<td>0.33 ± 0.18</td>
<td>0.18 ± 0.09</td>
</tr>
<tr>
<td>Median</td>
<td>0.11 ± 0.07</td>
<td>0.34 ± 0.19</td>
<td>0.30 ± 0.17</td>
<td>0.16 ± 0.10</td>
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<tr>
<td>Std</td>
<td>0.07 ± 0.05</td>
<td>0.16 ± 0.10</td>
<td>0.14 ± 0.08</td>
<td>0.10 ± 0.04</td>
</tr>
<tr>
<td>AEE N</td>
<td>5813</td>
<td>N/A</td>
<td>N/A</td>
<td>708</td>
</tr>
<tr>
<td>Min</td>
<td>0.46 ± 0.17</td>
<td>N/A</td>
<td>N/A</td>
<td>0.00 ± 0.00</td>
</tr>
<tr>
<td>Max</td>
<td>2.75 ± 1.15</td>
<td>N/A</td>
<td>N/A</td>
<td>1.64 ± 0.15</td>
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<tr>
<td>Mean</td>
<td>1.39 ± 0.33</td>
<td>N/A</td>
<td>N/A</td>
<td>0.95 ± 0.29</td>
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<tr>
<td>Median</td>
<td>1.43 ± 0.42</td>
<td>N/A</td>
<td>N/A</td>
<td>0.98 ± 0.58</td>
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<tr>
<td>Std</td>
<td>0.38 ± 0.22</td>
<td>N/A</td>
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<td>0.54 ± 0.10</td>
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Fig. 4. AOD scatter plot with linear regression equation between AERONET and Aqua/Terra MODIS DT (left) and DB (right) retrievals in California and Nevada during June, July, and August 2012. Fig. 4.a: Terra-MODIS DT. Fig. 4.b: Terra-MODIS DB. Fig. 4.c: Aqua-MODIS DT. Fig. 4.d: Aqua-MODIS DB. The dotted line represents the 1:1 line.

Table 2

Statistical evaluation metrics for DT and DB Terra-Aqua MODIS AOD (550 nm) with respect to AERONET AOD (500 nm) in June, July, and August 2012.

<table>
<thead>
<tr>
<th></th>
<th>AOD Terra DT</th>
<th>Aqua DT</th>
<th>Terra DB</th>
<th>Aqua DB</th>
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<td>N Pair</td>
<td>335</td>
<td>325</td>
<td>452</td>
<td>441</td>
</tr>
<tr>
<td>FB</td>
<td>−0.84 ± 0.55</td>
<td>−0.82 ± 0.61</td>
<td>−0.23 ± 0.43</td>
<td>−0.14 ± 0.55</td>
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<tr>
<td>MG</td>
<td>0.52 ± 0.52</td>
<td>0.52 ± 0.56</td>
<td>0.90 ± 0.39</td>
<td>1.06 ± 0.64</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.06 ± 1.41</td>
<td>1.92 ± 1.21</td>
<td>0.95 ± 0.67</td>
<td>1.06 ± 0.98</td>
</tr>
<tr>
<td>AMSE</td>
<td>0.15 ± 0.10</td>
<td>0.12 ± 0.08</td>
<td>0.08 ± 0.03</td>
<td>0.08 ± 0.04</td>
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<tr>
<td>VG</td>
<td>10.24 ± 9.09</td>
<td>12.69 ± 21.61</td>
<td>2.42 ± 1.71</td>
<td>2.19 ± 1.03</td>
</tr>
<tr>
<td>Fac2</td>
<td>0.28 ± 0.27</td>
<td>0.22 ± 0.23</td>
<td>0.61 ± 0.19</td>
<td>0.60 ± 0.25</td>
</tr>
<tr>
<td>NMB</td>
<td>126.72 ± 126.76</td>
<td>96.37 ± 103.14</td>
<td>35.62 ± 56.92</td>
<td>25.32 ± 57.12</td>
</tr>
</tbody>
</table>

Table 3

Statistical evaluation metrics for DT and DB Terra-Aqua MODIS AEE (470–660 nm) with respect to AERONET AOD (440–675 nm) in June, July, and August 2012.

<table>
<thead>
<tr>
<th></th>
<th>AEE Terra DT</th>
<th>Aqua DB</th>
</tr>
</thead>
<tbody>
<tr>
<td>N Pair</td>
<td>451</td>
<td>441</td>
</tr>
<tr>
<td>FB</td>
<td>0.16 ± 0.33</td>
<td>0.09 ± 0.35</td>
</tr>
<tr>
<td>MG</td>
<td>1.36 ± 0.47</td>
<td>1.30 ± 0.68</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.41 ± 0.26</td>
<td>0.37 ± 0.30</td>
</tr>
<tr>
<td>AMSE</td>
<td>0.57 ± 0.24</td>
<td>0.51 ± 0.25</td>
</tr>
<tr>
<td>VG</td>
<td>2.31 ± 1.54</td>
<td>3.33 ± 3.72</td>
</tr>
<tr>
<td>Fac2</td>
<td>0.09 ± 0.14</td>
<td>0.71 ± 0.2</td>
</tr>
<tr>
<td>NMB</td>
<td>−21.88 ± 27.78</td>
<td>−12.03 ± 30.65</td>
</tr>
</tbody>
</table>
Terra-DB and Aqua-DB). Additional evaluation statistics for each station can be found in the supplementary information.

Fig. 7 presents scatter plots between Terra and Aqua MODIS DB (470–660 nm) and AERONET (440–675 nm) AEE for June, July, and August 2012 for all stations. No significant trends are found between instruments. AEE from Terra (Fig. 7.a) reveals an $r^2=0.01$ with $p=0.08$ and for Aqua (Fig. 7.b) is $r^2=0$ with $p=0.31$. Table 3 contains the same evaluation parameters for DB AEE as in Table 2 for AOD. According to Fig. 7 and Table 3, the DB AEE algorithm presents a mean NMB of $-22\%$ ($\sigma=28\%$) (average FAC2 0.69, $\sigma=0.14$) for Terra and a mean NMB of $-12\%$ ($\sigma=31\%$) for Aqua (average FAC2 0.71, $\sigma=0.2$). The line patterns obtained in the AEE scatter plot will be further developed in the Discussion section.

4.3. MODIS evaluation for non-fire and fire periods

The 2012 data were collected during the first year of an ongoing regional drought (2012–2016), which has driven an increasing number of wildfires. The concern about the growing number of wildfires in California has escalated in the past two decades (Stephens and Collins, 2004; Stephens and Fry, 2005; Westerling et al., 2006). Wildfires generate large smoke plumes that can be transported downwind and impact human health due smoke exposure (Alman et al., 2016). Satellite remote sensing can be a useful tool for forecasting near-surface PM$_{2.5}$ (particulate matter with an aerodynamic diameter less than 2.5 μm). However, it is important to evaluate the performance of MODIS during non-fire and fire periods to determine whether MODIS AOD retrievals can be used alone as a spatial predictor in near-surface PM$_{2.5}$ models, or if the AOD retrievals would need additional calibration.

During the fire season of 2012, multiple fires generated aerosol pollution that diminished air quality in the studied domain for nearly 30 days. The evaluation of MODIS during extreme air quality events is highly relevant for policy decision making and radiative transfer studies and therefore, the development of a novel fire-filtering algorithm to obtain more valid AOD data is important. Results of AOD values using the fire-filtering algorithm are shown in Fig. 8. Fig. 8 shows visible images from Terra satellite (Fig. 8.a–f) including cloud free (Fig. 8.a, 8.b, and 8.f), cloud presence (Fig. 8.d and 8.e), and fire plume (Fig. 8.c, 8.d, and 8.e) conditions around the University of Nevada, Reno. Fig. 8.g presents AERONET AOD at 500 nm from level 1 and level 2, the combination of the two levels.
from the novel fire-filtering algorithm, and AOD at 550 nm from Aqua and Terra DB and DT algorithms. Finally, Fig. 8.h presents AEE (440–870 nm) from AERONET level 1, level 2, and combined from the novel fire-filtering algorithm.

Fig. 8.g and 8.h shows how the merged data set directly follows level 2 AERONET data. However, August 3rd is a typical example, where there are no clouds present around the station (Fig. 8.c) and the level 2 AERONET algorithm removed the fire plume from the data set because it was screened as cloud due to the variability of the smoke plume. Fig. 8.h shows for August 3rd that the AEE never reached values for super micron aerosol size (i.e., \( z_0 \) for cloud droplets or ice crystals); instead AEE indicates fine particles (i.e., combustion aerosol). Therefore, level 1 data were added to the merged data to obtain more information about the fire plume. During simultaneous clouds and fire conditions on August 4th and 5th, the merged data set follows level 2 because cloud optical depth dominated the atmospheric optics, as demonstrated by the fact that AEE approaches zero.

Fig. 8.g includes data points from Aqua and Terra AOD retrievals to compare with fire-filtering data set and to ensure that the fire-filtering algorithm is not giving AOD values significantly higher than the MODIS AOD retrievals. From this figure, we inferred that there are moments when the MODIS AOD retrievals over predict or under predict AOD with respect to AERONET level 2 and the combined fire-filtering product. However, during August 3rd the Terra DT AOD met the value from the combined product that otherwise would be removed from the level 2 data sets.

Fig. 9 shows AOD scatter plots comparing MODIS and AERONET data, classified by non-fire periods and fire periods. Table 4 summarizes number of pairs, FAC2, NMB, linear regression equations, \( r^2 \), and significance of regression coefficients, from the scatter plots in Fig. 9 classified by fire and non-fire periods of all MODIS AOD retrievals. During non-fire periods and fire periods, both DT and DB algorithms overestimate AERONET AOD. During fire periods, the sensitivity of MODIS instruments was improved with respect to non-fire periods (with the exception of Aqua-DB) because of enhancement of aerosol pollution. However, the NMB increased during the same period.

5. Discussion

Multiple spatiotemporal studies of aerosol pollution have
obtained surface PM$_{2.5}$ estimates from linear regression relationships between MODIS AOD and surface PM$_{2.5}$ for many locations around the world. Some of those studies (e.g., Strawa et al., 2011) worked directly with MODIS AOD retrievals by averaging a determined number of pixels as a good approximation with respect to AERONET AOD observations (Ichoku et al., 2002; Anderson et al., 2003). AERONET AOD has also been applied to filling the MODIS spatial gaps by using spatial interpolation of AERONET and MODIS observations (Ma et al., 2015). In addition, chemical transport models have been used to correct satellite AOD retrievals (van Donkelaar et al., 2010, 2011) and to account for heterogeneous aerosol vertical profiles. Finally, some efforts to use satellite retrievals over the western U.S. have attempted to improve previous versions of the DT algorithm by employing surface reflectance (Drury et al., 2008).

Previous studies in the western U.S. have demonstrated an improvement in retrieving surface PM from satellite AOD retrievals (Sorek-Hamer et al., 2013, 2015) and an upgrade in satellite retrievals of aerosol optical properties over western North America by using chemical transport and statistical models (Drury et al., 2008; e.g., Sorek-Hamer et al., 2013). An evaluation study using different satellite platforms suggested that AOD and PM$_{2.5}$ agree for the eastern U.S. but do not correlate in the western U.S. mainly due to heterogeneous aerosol vertical distributions (Li et al., 2015) induced by complex terrain and complicated planetary boundary layer physics.

In this study period, MODIS AOD retrievals from both algorithms perform very poorly in comparison with AERONET, making the use of MODIS AOD to estimate surface PM$_{2.5}$ very challenging. A previous investigation over Reno, Nevada in the same temporal domain concluded that aerosol vertical transport was heterogeneous within the atmosphere during non-fire and fire periods (Lória-Salazar et al., 2014). This physical phenomenon may contribute to a poor correlation in future investigations between surface PM$_{2.5}$ and MODIS AOD for both DT and DB algorithms at the University of Nevada, Reno AERONET station. While this physical phenomenon has only been studied in Reno it is expected that similar atmospheric boundary layer physics that induces complicated aerosol transport are impacting the MODIS and AERONET correlation at other places in complex terrain. Therefore, investigations of spatial aerosol vertical profiles, such as the case in Lória-Salazar et al. (2014), are needed to improve the relationship between AOD satellite retrievals and surface PM$_{2.5}$ mass concentration in the western U.S.

According to the evaluation for the DT algorithm, a relationship has been found between the features of the landscape elevation and the performance of the DT algorithm. The stations closer to the coastline (i.e., Cal Tech, La Jolla, and UCSB) where terrain is less irregular perform better than those more inland (Table Mountain CA, Goldstone, Fresno 2, University of Nevada Reno, Railroad Valley, and Frenchman Flat), with the exception of El Segundo, where the low number of data points can be interfering with the evaluation of this site. Stations closer to the coastline encounter a shallower boundary layer (compared to those inland) associated with the marine atmospheric boundary layer, which causes local sources of aerosol pollution to stay closer to ground level. In addition, Cal Tech, La Jolla, and UCSB have a more vegetated surface that is commensurate with the features of the DT algorithm. The presence of mountainous terrain around the Central Valley and the SNMs produces a more complicated boundary layer, and therefore, more complex aerosol pollution transport where aerosols are not entirely confined within the atmospheric boundary layer. The University of Nevada Reno, Railroad Valley, and Frenchman Flat AERONET stations had the lowest agreement with MODIS AOD, likely due to complicated boundary layer structure that induces complicated aerosol transport and high surface reflectance.
For the DB algorithm, the evaluations for El Segundo and in University of Nevada Reno tend to disagree with Terra and Aqua (Terra overestimates and Aqua meets the estimate or underestimates by small factor). Using the DT algorithm, Cal Tech, and Fresno 2 stations overestimate AOD, meanwhile the DB algorithm underestimates AOD for those two stations. The reverse effect happens in UCSB (DT underestimates AOD, while DB overestimates AOD). The rest of the stations (Frenchman Flat, Goldstone, La Jolla, Railroad Valley, and Table Mountain CA) reduce the factor of overestimation using the DB algorithm with respect to the DT. Our evaluation for the DB algorithm does not reveal patterns related to the type of surface, boundary layer, or landscape elevation;
therefore more investigation is needed to determine the station
specific uncertainty in DB retrieval algorithm.

It has been suggested that surface reflectance models in the DT
MODIS retrievals diminish the correlation between MODIS and
AERONET over bright surfaces. To address this problem, the DB
algorithm was developed, improving the correlation between
AERONET and MODIS especially over the Sahara Desert (Shi et al.,
2013). However, some AOD hot spots in northern Nevada from
the DB algorithm (Fig. 3) caught our attention. Very high monthly
averages of AOD (~0.7) from MODIS DB were found around the BRD
in Nevada during June, July, and August for both Terra and Aqua.
Because the surface reflectance issue appears to be related to the
systematic error in the MODIS DB AOD retrievals, it cannot neces-
sarily be quantified using a propagation of error approach and re-
quires observations to compare with the retrievals (Youden, 1972;
Oreskes, 1998). Moreover, there is a lack of surface albedo moni-
toring stations in the western U.S., especially in Nevada, which
makes it nearly impossible to evaluate the performance of MODIS
retrievals in this area. However, a qualitative analysis of albedo has
been added to this investigation to understand the presence of high
aerosol pollution from the DB algorithm, perhaps unrealistic, in
northern Nevada and other areas in California.

Table 4
Statistical evaluation metrics for DT and DB Terra-Aqua MODIS AOD (550 nm) with respect to AERONET AOD (500 nm) for non-fire and fire periods in June, July, and August 2012.

<table>
<thead>
<tr>
<th></th>
<th>Non-fire</th>
<th>Fire</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Terra DT</td>
<td>Aqua DT</td>
</tr>
<tr>
<td>AOD</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N Pair</td>
<td>279</td>
<td>275</td>
</tr>
<tr>
<td>Fac2</td>
<td>0.19 ± 0.26</td>
<td>0.20 ± 0.21</td>
</tr>
<tr>
<td>NMB</td>
<td>154.12 ± 146.19</td>
<td>109.16 ± 100.64</td>
</tr>
<tr>
<td>m</td>
<td>1.10</td>
<td>1.40</td>
</tr>
<tr>
<td>b</td>
<td>0.20</td>
<td>0.10</td>
</tr>
<tr>
<td>r²</td>
<td>0.10</td>
<td>0.21</td>
</tr>
<tr>
<td>p</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Fig. 10 shows the July 2012 monthly average of Terra AOD at
500 nm from the DB algorithm, a true color image from MODIS-
Terra on July 28, 2012, and July 2012 monthly average of albedo
at 650 nm. The surface albedo is derived from the operational
Bidirectional Reflectance Distribution Function (BRDF) as well as
from MODIS albedo products (MOD43B2) (Schaaf et al., 2002). The
MOD43B2 provides combined Terra and Aqua surface albedo every
16 days at 1 km resolution. In addition, the MOD43B2 provides a
standard suite of black-sky and white-sky albedos in seven spectral bands (MODIS channels 1–7) and three broad bands (0.3–0.7, 0.7–3, and 0.3–5 μm). According to Fig. 10, high MODIS DB AOD in the BRD (Fig. 10.a) matches the area of bright surface reflectance (Fig. 10.c). The spectral dependence of the albedo is shown in the supplementary information. As mentioned before, there is a ring of high MODIS DB AOD in the Sacramento and San Joaquin Valleys, California. The center of the ring is subject of high PM concentrations due to agriculture activity and the perimeter of the ring is more affected by windblown dust (Chow et al., 1992). However, this ring of high MODIS DB AOD (Fig. 10.a) also aligns with a ring of high surface reflectance (Fig. 10.c) in the same area. The visible image presents a mixture of surface between vegetation and more arid regions (Fig. 10.b) in the same zone of the ring. Finally, high MODIS DB AOD in the border of southern California and Arizona (Fig. 10.a) also concurs with high surface reflectance.

The wavelength dependence of the albedo depicted at 650 nm in Fig. 10 is given in the supplementary material, and shows the lack of spectral variability in the BRD. There is more spectral variability in areas around the Central Valley and southern California, but those areas present high surface reflectance for all wavelengths. The mineral composition of deserts in Nevada is often referred to as “alkali deserts” with dominant elements associated with alumino-silicate minerals (e.g., Si, Al, K, and Ti) (Gillies et al., 1999). Studies have shown that the Saharan dust composition presents elements such as quartz (SiO2), dolomite (CaMg(CO3)2), and calcite (CaCO3) as more abundant (Díaz-Hernández et al., 2011). In addition, it has been demonstrated that the physical composition of dust, such as refractive index, also varies between desert regions (Sokolik and Toon, 1999). As mentioned before, the DB algorithm was found to be accurate in desert areas in Asia and Africa (Shi et al., 2013). However, the difference in chemical composition between regions, surface reflectance, and physical parametrizations in the DB algorithm may be affecting the accuracy of MODIS DB algorithm to retrieve AOD in the semi-arid western U.S. A surface albedo investigation made at the NOAA Table Mountain site located in semi-arid Colorado during spring (April–May, 2010) (Kassianov et al., 2014) found very similar albedos between tower measurements, MODIS albedos, and albedos derived from atmospheric transmission data. Additionally, these albedos are close to those found in Nevada in the summer of 2012. These results imply that MODIS, while retrieving surface albedo reasonably well in many places in the semi-arid west, may have similar problems in retrieving AOD and AEE in the semi-arid regions of Colorado and in other regions of the semi-arid western U.S.

The AEE in the DB algorithm is retrieved by calculating the natural log of the negative gradient of AOD with respect to the natural log of wavelengths pair:

$$AEE = -\frac{\ln(AOD(\lambda_1)/AOD(\lambda_2))}{\ln(\lambda_1/\lambda_2)}$$

In low AOD conditions, AEE is set to a fill value (AEE = 1 over desert areas and AEE = 1.5 elsewhere) (Sayer et al., 2014). In the case of the disagreement of AEE between MODIS DB and AERONET (Table 3), it has been found that AEE is indeed predefined by the DB algorithm in the presence of the low aerosol signal, and therefore, it is expected that AEE from MODIS DB does not necessarily agree with AERONET. In addition, considering these results during fire and non-fire conditions, AEE from MODIS should not be used to diagnose fire plumes or dust storms in forecasting and/or forensic studies of aerosol pollution in the western U.S. The AEE in the DB algorithm can be improved with measurements from AERONET stations in this area.

The results obtained in this investigation are similar with those to Sayer et al. (2014). According to Sayer et al. (2014), in a global scale evaluation, the DT algorithm often correlates better with AERONET than the DB, but DT also has higher errors in comparison to AERONET in the presence of low aerosol signal. During non-fire periods, the regional evaluation in this investigation found that Terra DB correlates better and has lower error than the Terra DT. In the case of Aqua, the correlation of DB and DT with AERONET is about the same; however DB has a smaller error.

Both MODIS algorithms failed to retrieve AOD well during fire and non-fire conditions. Fire conditions resulted in an improvement of the correlation of AOD between MODIS DB and AERONET (except for Aqua DB) because of the increasing strength of the aerosol signal (Table 4). However, the NMB of MODIS also increased, making MODIS AOD a very uncertain tool to retrieve surface PM2.5 in the western U.S. for fire periods.

6. Summary

The goal of this paper is to compare satellite observations of aerosol optical depth (AOD) with ground-based observations of the same. We evaluated satellite AOD with an eye towards using them to estimate surface-level aerosol pollution. We used observations that took place during the summer of 2012 in California and Nevada, part of the semi-arid region of the western U.S.
We found:

(1) The novel algorithm proposed here is able to incorporate 5% of AOD data during fire time periods that originally was removed from AERONET level 2.

(2) MODIS dark-target (DT) retrievals showed a positive gradient of aerosol optical depth (AOD) from northern California and the Central Valley to the Great Basin. One might try to explain this positive gradient with the transport of air pollution from California and aerosol modification over the Sierra Nevada Mountains (SNMs) providing secondary organic aerosol precursor emissions. However, this concept is not likely to be correct if there are continuous sources of emissions in California, therefore the increase of surface brightness and its impact on retrieval accuracy is a much more likely cause.

(3) MODIS retrievals overestimated AOD in comparison to AERONET measurements. According to the fractional prediction “within a factor of two” statistics (FA2C), just 25% of AOD can be predicted using the DT and 60% of AOD for deep-blue (DB) during the entire studied period. A slight improvement in the correlation between MODIS and AERONET AOD was found during fire periods because of higher aerosol signal, but the normalized mean bias (NMB) (NMB ~ 132% for DT and NMB ~ 34% for DB for non-fire periods) did not improve (NMB ~ 211% for DT and NMB ~ 81% for DB for fire periods).

(4) AEE from DB did not present any relationship with AERONET observations (r2 < 0).

(5) Surface reflectance still affects AOD retrievals in both algorithms especially at low aerosol signal. In addition, physical and chemical aerosol parametrizations in the MODIS retrievals are influencing the performance of both these algorithms in the semi-arid western U.S at higher aerosol loading.

With the above points in mind, we conclude that MODIS retrievals in collection 6 would not be useful in estimating the column-integrated aerosol pollution levels and particle size over Nevada and California in the summer months of 2012. Therefore, the satellite retrievals are not yet useable to make policy assessments or to estimate health effects without considerable additional analysis and AOD calibration. This reinforces the notion that satellite monitoring of aerosol pollution over the western region of the U.S. continues to be a challenge due to factors such as complex terrain and the semi-arid environment that enhances surface reflectance. These considerations should be taken into account for improving DT (Levy et al., 2015) and DB retrievals for new instruments and missions such as the VIIRS75 instrument aboard the Suomi NPP polar orbiting satellite.

Acknowledgements

This material is based upon work supported by NASA EPSCoR under Cooperative Agreement No. NNX10AR89A. The AERONET and MODIS data used in this study are freely available from NASA.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.atmosenv.2016.08.070.

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http://dx.doi.org/10.1016/S1352-2310(03)00128-6.


