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Atmospheric Chemistry and Physics Discussions

Interactive comment on "An observation-based approach to identify local natural dust events from routine aerosol ground monitoring" *by* D. Q. Tong et al.

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We thank you for your extensive, constructive suggestions to revise our manuscript. Please find below the changes we made according to your comments.

Responses to comment 1:

a) Per your suggestion, we have changed the title to "Long-term windblown dust climatology in the western United States reconstructed from routine aerosol ground monitoring"; b) We have made a separate Discussion section to enhance the discussion of the major results and the limitations of our approach: c) We have conducted an analysis of the long-term drought condition (using surface wetness as an indicator) to examine

one of the major driving forces underlying the dust 4 year cycle. Results and data are presented in the second section of the Discussion (Section 5.2, Lines 573-598);

"Dust activities display a four-year cycle during the eight-year study period. While more data are needed to verify this four-year cycle observed in this study, we discuss briefly here the possible driving forces behind this interannual variability. Climate models have predicted that a transition to a more arid climate is under way in the southwestern United States, where multiyear drought and the 1930s Dust Bowl will become the new climatology within a time frame of years to decades (Seager et al., 2007). Windblown dust emissions are controlled by a number of important parameters, such as wind speed, soil moisture, surface roughness and erodible dust supply (Marticorena et al., 1995; Gillette et al., 1988; 2004). Among these controlling factors, surface wetness can be used as an indicator to drought condition, which is often associated with dust activities in arid environment. Here we examine the monthly surface wetness over the five dust regions using the Modern Era Retrospective-analysis for Research and Application (MERRA) dataset from the NASA's Goddard Space Flight Center (http://gmao.gsfc.nasa.gov/research/merra/). Figure 8 shows that the lowest surface wetness is found in different months among these regions. The Chihuahuan Desert generally sees an early dry season, while the Sonoran Desert and the Mojave Desert are often associated with a prolonged and drier summer. Although soil moisture controls several factors that influence dust emissions, the monthly surface wetness data here are not in good correlation with the observed dust pattern. The monthly regional mean of surface wetness may not represent the local condition under which dust emissions are initiated. As discussed by many field and model studies, windblown dust emission is a complicated process that has not been fully understood. In addition, these processes are increasingly complicated by human disturbance of the land surface, such as the rapid urbanization in southern Arizona (Sorooshian et al., 2011). Future analysis of the meteorological parameters and surface conditions over these regions is need to further investigate the underlying mechanisms causing the interannual variations. Given the climate model prediction of a drier climate in the Southwest, it is interesting to continue observing how the dust activities will respond to the changes in regional and global climate systems."

Please see the attached Figure 8 for details. Figure 8. Monthly variations of surface wetness over five dust source regions during the study period. The surface wetness is derived from the NASA Modern Era Retrospective-analysis for Research and Application (MERRA) dataset. Five dust regions include the Chihuahuan Desert (CHD), the Sonoran Desert (SOD), the Mojave Desert (MOD), the Great Basin Desert (GBD) and the Colorado Plateau (COP).

d) We have discussed the limitations of this method in the first part of the Discussion (Section 5.1).

Response to Comment 2:

We have substantially revised the introduction part to address the above concerns. Two new paragraphs have been added to provide a review of existing dust identification methods, and we have highlighted the new features of our approach.

"A myriad of observation-based methods have been proposed to identify dust events using satellite observation, computer models and ground and laboratory measurements. These methods vary in complexity and applicability, but in general fall into three categories: laboratory-based approach, and remote sensing-based approach and ground monitor-based approach. In the early years, radioative elements, such as Radon-222, have been used as a tracer of dust transport from Africa (Prospero, 1970). In later studies, the mineral dust component in sampled aerosols was determined by the weight of ash residue from the high-temperature burning of sampling filter after being extracted with deionized water (Prospero, 1999). Another laboratory study differentiated dust particles from other types of transportable particles collected on board the NOAA Research Vessel Ronald H. Brown through individual-particle analysis using an automated scanning electron microscope (SEM) and a field emission scanning electron microscope (FESEM) (Gao et al., 2007).

With the rapid expansion of remote sensing data, several studies have attempted to detect dust outbreaks using satellite images and other derived products (Kauffman et al., 2000; Prospero et al, 2002; Rivera-Rivera et al., 2010; Lee et al, 2009). The pioneer works by Prospero and colleagues have associated dust sources with barren areas with "depressed" elevations relative to their surroundings (Ginoux et al., 2001) based on satellite-based global observations from the NIMBUS 7 Total Ozone Mapping Spectrometer (TOMS) (Prospero et al., 2002). They found that the major dust sources are invariably associated with topographical lows in arid or semiarid regions with rainfall below 250 mm (Prospero et al., 2002). A recent work by Ginoux et al (2010) combines land use data with the Moderate Resolution Imaging Spectroradiometer (MODIS) Deep Blue algorithm to identify natural and anthropogenic dust sources over the western Africa. This approach is further developed to pin-point active dust sources in the North America by selecting grid cells based on the frequency of high aerosol optical depth (AOD) events (AOD = 0.75) (Draxler et al., 2010). In an effort to quantify the relative impacts of Saharan and local dust in Elche in Southeastern Spain, Nicolas et al. (2008) combined satellite images from the NASA SeaWiFS, two dust prediction models (NAAPS and DREAM), a back-trajectory model (HYSPLIT) and NCEP meteorological reanalysis data to detect the outbreaks of African dust events. Using Positive Matrix Factorization (PMF), they identified six PM10 sources, including local soil and African dust, which are distinguished by the correlation of the source intensity with Ti. In Asia, an operational dust retrieval algorithm has been developed based on the FY-2C/SVISSR through combining visible and water vapor bands observations of the geostationary imager to distinguish dust plumes from surface objects and clouds (Hu et al., 2008). In the United States, data from both polar-orbiting and geostationary satellites have been used to characterize source areas of large dust outbreaks (Lee et al., 2009; Rivera-Rivera et al., 2010). It should be mentioned that all of these dust source identification methods are based on satellite remote sensing that needs to be independently verified using ground observations. For instance, Schepanski et al. (2007, 2012) combined a back-tracking method with high temporal satellite aerosol data (15-min Aerosol Index (AI) from the Ozone Monitoring Instrument (OMI)) to identify dust sources over the Saharan region. They found that the spatial distribution of dust source areas inferred from OMI 15-min AI is distinctly different from that by using the daily MODIS Deep Blue aerosol data (Schepanski et al., 2012).

Beside these laboratory and remote sensing studies, dust identification methods have also been developed based exclusively on aerosol mass concentration and its correlation with meteorological conditions. Kavouras and co-workers (2007) developed a semi-quantitative method to assess local dust contribution in the western United States utilizing multivariate linear regression of dust concentrations against categorized wind parameters. In their study, dust concentrations are assumed equal to the sum of fine soil and coarse particles using an operational definition adopted from Malm et al. (1994, 2000a, 2000b). Escudero et al. (2007) proposed a method to quantify the daily African dust load by subtracting the daily regional background level from the PM10 concentration value. Ganor et al (2009) developed and tested an automated dust identification algorithm for monitoring location in Israel. Their algorithm determined a dust event by three conditions: half-hour PM10 average level exceeds 100 ïĄ■g/m3, this high level maintained for at least three hours, and the peak PM10 ever reaches 180 ïĄ■g/m3. In most aerosol observations, however, the dust emission conditions or visual identification information are not available. Consequently, it is challenging to identify local windblown dust events based on particle concentration or chemical species because of the variability in meteorological conditions, dust strength and the distance from source areas (e.g. Luo et al. 2003)."

In the Discussion section, we have compared the full method to three simple approaches for which chemical data are not required. Please see the new Table 2 and the second paragraph of the new section 5.1.

"Alternatively, we consider here three simplified methods that use only basic aerosol mass concentrations, and compare their capability to pinpoint dust events to that of the full method using all five indicators. The first simplified approach uses two dust

indicators, the PM10 mass concentration (> 40 ug/m3) and the PM2.5/PM10 ratio (< 0.35) as the filtering criteria. The PM10 cutoff and the PM2.5/PM10 ratio cutoff are taken from the lower and upper 95% values of the corresponding parameters in the local dust group identified by the full method as proposed in this study, respectively. The second method is similar to the first one, except using a PM2.5/PM10 cutoff of 0.20, the median value of the dust group. This ratio is also used by the US EPA to split fugitive dust PM10 into PM2.5 (MRI, 2005). Compared to the first one, the second method is considerably more exclusive. The third method simply uses PM10 > 100 ug/m3 as the identifying indictor, following Ganor et al. (2009). Due to the IMPROVE sampling protocols, 24-hour mean PM10 concentrations are used here, instead of hourly PM10 data as in Ganor et al. (2009). Table 2 compares the performance of the three simplified methods to identify dust events to that of the full method. Here we define the performance using two categorical evaluation metrics as introduced by Kang et al. (2009): Hit Rate and False Alarm Rate. Hit Rate is the percentage of "true" dust events identified by the simple method to all events by the full method, while the False Alarm Rate is the percentage of "false" events (i.e., not considered local dust events by the full method) to all events selected by the simple methods. The first simplified method has the highest hit rates, catching 27% of the dust events identified by the full method. Meanwhile, it is also associated with the highest false alarm rate, with 68% of the dust events it selected deemed false by the full method. When the PM2.5/PM10 ratio is further constrained to 0.20, the false alarms rate has been reduced significantly (to 16%), but at the cost of hit rate, which shows that the second method can catch only 13% of the all dust events. The revised Ganor method demonstrates dust identifying capability between the two simplified methods. Although these simplified methods show varying effectiveness to identify local dust events, it should be pointed out that chemical fingerprint is still needed to assure the origin of measured aerosols. For example, the measurement data over the three urban sites can satisfy all selection criteria for local dust events, except the high levels of anthropogenic components. Such information reveals either human contamination of the dust aerosols, or human motivated dust sources (such as road dust from unpaved road). Regardless of its complexity, our proposed approach is likely to work most efficiently when all five identification criteria are concurrently applied."

Please see Table 2 in the revised manuscript for more details.

Response to Comment 3:

We have now explained how the 0.35 value is chosen in the manuscript. Following the comments above, we have conducted a simple sensitivity analysis to see the effect of the choice of PM2.5/PM10 ratio on the results (section 5.1) using two statistical metrics. We found that using a smaller ratio (0.2 instead of 0.35) leads to a lower hit rate, but also considerably reduce the false alarm rate (see the Responses to Comment 2).

Response to Comment 4:

We have now added more information on the cluster analysis, with a highlight in the introduction, and more details in the methodology. While it is definitely possible to apply the cluster analysis for other sources, we feel it goes beyond the scope of the current study.

Please also note the supplement to this comment:
http://www.atmos-chem-phys-discuss.net/12/C2628/2012/acpd-12-C2628-2012-supplement.pdf

Interactive comment on Atmos. Chem. Phys. Discuss., 12, 4279, 2012.

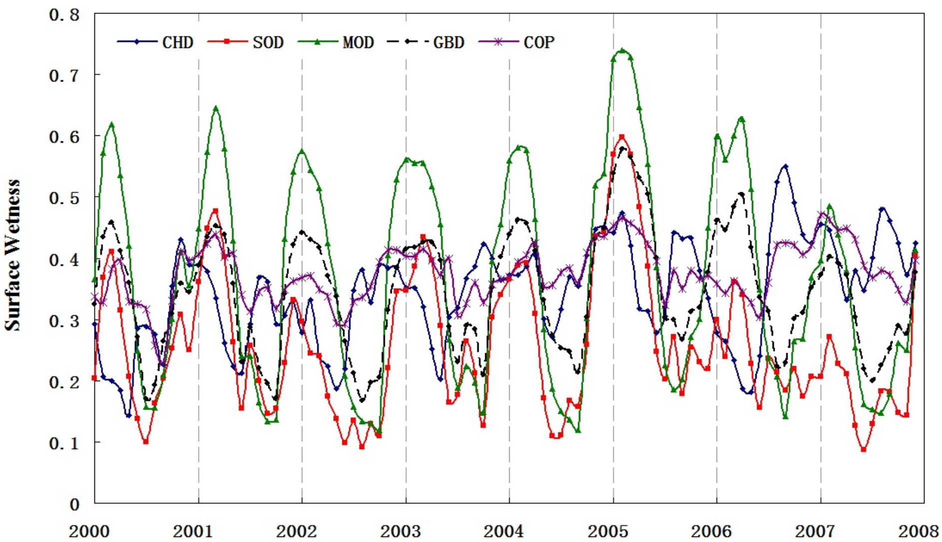

Fig. 1. Long-term change in surface wetness over five dust regions