Urban dust in the Guanzhong Basin of China, Part I:

A regional distribution of dust sources retrieved using satellite data

Xin Long^{1,2}, Nan Li^{1,3}, Xuexi Tie^{1,4,*}, Junji Cao^{1,5}, Shuyu Zhao¹, Rujin Huang^{1,6,*}, Mudan Zhao⁷, Guohui Li¹, Tian Feng¹

¹ Key Lab of Aerosol Chemistry & Physics, SKLLQG, Institute of Earth Environment, Chinese Academy of Sciences, Xi'an, 710061, China

² University of Chinese Academy of Sciences, Beijing, 100049, China

³ Department of Atmospheric Science, National Taiwan University, Taipei, 10617, Taiwan

⁴ National Center for Atmospheric Research, Boulder, CO, 80303, USA

⁵ Institute of Global Environmental Change, Xi'an Jiaotong University, Xi'an, 710049, China

⁶ Laboratory of Atmospheric Chemistry, Paul Scherrer Institute (PSI), 5232 Villigen, Switzerland.

⁷ College of Urban and Environmental Sciences, Northwest University, Xian, 710127, China

*Corresponding Authors:

(1) Xuexi Tie

xxtie@ucar.edu

(2) Rujin Huang

rujin.huang@psi.ch

Abstract

Urban dust pollution has been becoming an outstanding environmental problem due to rapid urbanization in China. However, it is very difficult to construct an urban dust inventory, owing to its small horizontal scale and strong temporal/spatial variability. With the analysis of visual interpretation, maximum likelihood classification, extrapolation and spatial overlaying, we quantified dust source distributions of urban constructions, barrens and croplands in the Guanzhong Basin using various satellite data, including VHR (0.5 m), Landsat-8 OLI (30 m) and MCD12Q1 (500 m). The croplands were the dominant dust sources, accounting for 40% (17913 km²) of the study area in summer and 36% (17913 km²) in winter, followed by barrens, accounting for 5% in summer and 10% in winter. Moreover, the total constructions were 126 km², including 84% of active and 16% inactive. In addition, 59% of the constructions aggregated on the only megacity of the study area, Xi'an. With high accuracy exceeding 88%, the proposed satellite-data based method is feasible and valuable to quantify distributions of dust sources. This study provides a new perspective to evaluate regional urban dust, which is seldom quantified and reported. In a companion paper (Part-2 of the study), the detailed distribution of the urban dust sources are applied in a dynamical/aerosol model (WRF-Dust) to assess the effect of dust sources on aerosol pollution.

Keywords: Regional construction dust; WRF-Dust model; Urban dust source; Satellite data

1. Introduction

Over the past decades, China has been experiencing rapid urbanization in an unprecedented scale with urban areas increasing exponentially more than 2 times from 1990 to 2010(Wang *et al.*, 2012). The rapid growth in such a short period has resulted in serious environmental problems, in particular the severe particulate air pollution. Meanwhile, dust particle has been recognized as an important source of particulate matter in many Chinese cities (Shen *et al.*, 2007; Su *et al.*, 2014; Wang *et al.*, 2015a), which is particularly an issue for the Guanzhong Basin (Shen *et al.*, 2009; Shen *et al.*, 2011; Huang *et al.*, 2014; Zhang *et al.*, 2014; Wang *et al.*, 2015a), where large construction activities are ongoing due to the ‘China western development’ policy. Numerous works indicate that construction dust emission plays a significant role of the air pollution, especially in urban areas (Ni *et al.*, 2012; Wang *et al.*, 2015a; Wang *et al.*, 2015b).

However, evaluation of emission factors from the construction activities is still a challenging task (Muleski *et al.*, 2005). Relevant studies are still very scarce. For example, the chapter “Heavy Construction Activities” in the U.S. Environmental Protection Agency’s (EPA) emission factor handbook (U.S.EPA, 1995) has remained the same since 1975. Detailed dust emissions from construction activities have not been included in the dust inventory from previous studies, leading to difficulties in estimating the true impact of urban dust particles on air quality and aerosol. Until now, the urban dust sources are not well understood, due to its strongly temporal and spatial variations, especially for the source of constructions, which required the in-situ information of construction activities to assess their emission distribution. Generally, field survey of the construction activities are characterized with low efficiency and high cost, especially in city- or regional-scale. Fortunately, the Very High-Resolution (VHR) optical satellite observations can provide 1 meter or better spatial resolution. In particular, they have been widely used to estimate the ground damage in earthquakes (Saito *et al.*, 2004; Saito *et al.*, 2005; Brunner *et al.*, 2010; Laigen Dong, 2013). The remote sensing technology provides an efficient and cost-effective approach to evaluate

the regional construction activities.

In this study, we proposed a reliable satellite-data based method to quantify the urban dust emission sources including constructions, croplands (cropland with crops) and barrens (croplands without crops, unpaved roads, bare beaches, and other sparsely/none vegetated lands), through which urban dust pollution can be evaluated in regional scale. It is worth noting that we did not clearly clarify road dust source, especially excluded the vehicle-derived road dust source, which currently has a large uncertainty related to emission factors and vehicle kilometers travelled. Three kinds of remote sensing data with different resolution were applied, including the VHR data from commercial supplier, the Landsat-8 Operational Land Imager (OLI) data, and the most widely used product of Moderate Resolution Imaging Spectroradiometer Terra + Aqua Combined Land Cover Type product (MCD12Q1). The objectives of this study were to capture the gridded intensities of dust sources, as well as to offer crucial data support to regional quantification assessment of urban dust by the use of numerical model (WRF-Dust), which will be elaborated in a companion paper (Part-2 of the study).

2. Materials and Methods

2.1. The study area

The study area is in the center of China (**Fig. 1a**), with the Tsinling Mountain located in the south part. Meanwhile, the middle and north distributed the Guanzhong Basin (**Fig. 1b**), which is one of the most important grain production bases of China. As one of the most important cities, Xi'an (the only megacity with a population of 8 million and the area of 988 km²) was highlighted as urban-1 region (**Fig. 1b**). Other urban areas were classified as urban-2 districts, and the rest parts of the research domain were treated as the rural regions.

2.2. Satellite data

2.2.1. The VHR data

The urban-1 dust sources of constructions and barrens were extracted from the cloud free and georectified VHR data of QuickBird, GeoEye-1, Worldview-2, and Pleiades-1, which were bought/obtained from the image supplier (<https://apollomapping.com/imagery/high-resolution-imagery/>) without further rectification. According to their announcement, GEO products are said to have CE90 (Circular Error at 90% probability) positional accuracies of 23 meter for QuickBird, 10 meter for Geo-Eye-1, 3.5 meter for Worldview-2, and 4 meter for Pleiades-1 (**Table 1**). Moreover, 200 meters were overlaid in the co-boundary of each polygon to avoid the gaps of different sensors.

2.2.2. *Landsat-8 OLI data*

Considering the temporal/spatial coverage and data quality, two groups of Landsat-8 OLI images with the least cloud contaminations during or near the seasons were chosen to representing cases of summer and winter (**Fig. 2**). In summer case, we selected the images with the 2rd Worldwide Reference System (WRS-2) path-rows of 126-36 on 2013-08-21, 127-36 on 2013-09-13 and 128-36 on 2013-08-09. While in winter case, we chose images with the WRS-2 path-rows of 126-36 on 2013-12-27, 127-36 on 2014-01-03 and 128-36 on 2013-12-09. The data were open access on the website of U.S. Geological Survey (<http://earthexplorer.usgs.gov/>). Unfortunately, the OLI data cannot completely cover the research domain, with existence of ‘No Data’ regions (< 3%) in south part of study area. Moreover, cloud contaminations existed in the summer images with the path-row of 128-36. Nevertheless, the cloud contaminations and ‘No Data’ areas within the research domain mainly located in Tsinling Mountain, which is a typical forest covered district. Hence, the existing shortages of OLI data would have little impact on the results of dust source distributions in the Guanzhong Basin.

2.2.3. *MCD12Q1 data*

The MCD12Q1 describes the properties of land cover that are derived from observations spanning a year’s input of Terra- and Aqua-MODIS. We obtained the

newest version (2012) of MCD12Q1 product, which can be freely downloaded from the website (https://lpdaac.usgs.gov/data_access/data_pool/). It is treated as the result of 2013 because the cropland is always with few changes in regional scale and for one year time interval.

2.3. Methods

2.3.1. Flow Chart

Figure 3 displays the data processing flow of the satellite-data based method to generate gridded dust source intensities in the Guanzhong Basin, including constructions, croplands and barrens. Overall, the proposed method includes four direct analyses processing of satellite data (stressed by blue dashed box) and three further analysis procedures, involving the extrapolation and two procedures of spatial overlay analysis. The distributions of constructions and barrens in urban-1 region were extracted based on the VHR data. Thereafter, urban-2 dust sources were extrapolated by combining urban-1 results with urban-2 build-up areas distributions. Meanwhile, the rural barren distribution was acquired from the maximum likelihood classification of OLI data. Additionally, the croplands distribution was received from the MCD12Q1 product by excluding the barren part.

It is worth noting that the urban dust sources were assumed to be constant for the whole year, whereas the distributions of barren and cropland contained two scenarios of summer and winter because of the seasonal difference of vegetation coverages.

2.3.2. Urban-1 dust sources interpretation

The most important and fundamental task of visual interpretation is to establish the accurate interpretation keys. Combining the field investigation and constructions' feature, the interpretation signs, i.e. building tower, simple house, sparsely/none vegetated land and unpaved road, are established, which were based on two obvious cases of Pleiades-1 image displayed in **Figure 4**. Each construction site was marked on VHR data by using standard GIS software. In terms of the skills required, the

1 interpreter should have some experience in visual interpretation and GIS data
2 management skills. A field investigation was conducted to estimate the performance.
3
4
5

6 **2.3.3. Urban-2 build-up areas interpretation and dust sources extrapolation**

7
8 Generally, visual interpretation is still an accurate method build-up area, and
9 Landsat data is successfully used to generate build-up areas by Wang et al. (2012). In
10 present study, build-up areas were captured from Landsat-8 OLI data. Thereafter, the
11 results were compared with areas generated from Google Earth, including the typical
12 cities of Xianyang, Weinan and Tongchuan.
13
14
15
16
17

18 Since the VHR data with good quality is not enough to cover the research domain,
19 the extrapolation behavior is a feasible way to quantify urban-2 dust sources.
20 Meanwhile, it is reasonable to assuming that the Factorsource-1 is equal Factorsource-2
21 because the urban-2 and urban-1 areas are all distributed in the Guanzhong Basin and
22 located in the Shanxi Province. What's more, the urban-2 areas are scattered distributed
23 in the research domain, we assumed that the urban-2 dust sources are evenly distributed.
24 With the evenly distributed assumption, urban-2 dust source distributions were
25 calculated by:
26
27
28
29
30
31
32
33
34

$$35 \quad D_{source-2} = D_{urban-2} \times Factor_{source-1} \quad (1)$$

36 where $D_{urban-2}$ stands for the distribution of urban-2 build-up areas; $Factor_{source-1}$
37 were computed by the formula (2), representing the ratios of related dust source in
38 urban-1 region.
39
40
41
42

$$43 \quad Factor_{source-1} = \frac{Area_{source-1}}{Area_{urban-1}} \quad (2)$$

44 where $Area_{source-1}$ stand for the total areas of each urban-1 dust sources, including
45 active construction, total construction and barren. $Area_{urban-1}$ is the total area of the
46 entire urban-1 areas (988 km²).
47
48
49
50
51
52
53
54

55 **2.3.4. Rural barrens using MLC classification**

56 The Maximum likelihood classifier (MLC) has been the most popular parametric
57 classifier used for remote sensing data classification (Foody et al., 1992; Foody, 2013).
58
59
60
61
62
63
64
65

The MLC assumes that a hyper-ellipsoid decision volume can be used to approximate the shape of the data clusters. Moreover, for a given unknown pixel, the probability of membership in each class is calculated using the mean feature vectors of the classes, the covariance matrix and the prior probability (Strahler, 1980). The unknown pixel is considered to belong to the class with the maximum probability of membership. Numerous works have been used Landsat satellite data land cover classification (Gumma *et al.*, 2011; Gong *et al.*, 2013), and the new Landsat-8 OLI data (launched in Feb, 2013) is also reported with a satisfactory performance (Jia *et al.*, 2014). Rural barren was extracted from OLI data using the MLC. Additionally, the confusion matrixes of land cover classification, including overall accuracy and kappa coefficient, were used to assess the results.

2.3.5. *Spatial overlay analyses*

The key idea of spatial overlay is that data fields are assigned from an underlying data layer to an overlay layer. In this study, rural croplands were captured by overlaying the input layer of barrens distribution to the overlay layer of crops from MCD12Q1. Then, pixels specified as crop and not barren was gathered to get the cropland distributions in summer and winter.

Another spatial overlaying was to get the gridded intensities of each dust source, which were extracted by overlaying layers of dust source distributions to grid cells. Then, they were calculated by:

$$I_{X_{i,j}} = \frac{AreaX_{i,j}}{Area_Grid_{i,j}} \quad (3)$$

where i and j are grid line and column number of the domain defined by WRF-Dust model; $AreaX_{i,j}$ stands for the total area of active constructions, total constructions, barren or cropland within the specified grid. $Area_Grid_{i,j}$ is the area of the specified grid.

2.3.6. *Error spread analyses*

It is well known that the error spread rule can be used to evaluate the result error

based on the dependent variable. For the function $z = f(x_1, x_2, \dots, x_m)$, the error of z and error of x_i has the following relationship:

$$\delta_z^2 = \sum_{i=1}^m \left(\frac{\partial z}{\partial x_i} \delta_i \right)^2 \quad (4)$$

where δ_z represents the error of the dependent variable z ; δ_i stands for the error of independent variable x_i and $\frac{\partial z}{\partial x_i}$ is the differential of z to x_i .

In this study, three further analysis procedures were evaluated based on the error spread rule, including the urban-2 dust source extrapolation, spatial overlay analysis of rural cropland and gridded intensities of the research domain.

In view of the formula (1), (2) and (4), the overall accuracies of urban-2 dust source can be calculated by:

$$\delta_{source-2}^2 = Area_{urban-2}^2 \times \frac{\delta_{Area_source-1}^2}{Area_{urban-1}^2} + Factor_{source-1}^2 \times \delta_{Area_urban-2}^2 \quad (5)$$

where $Area_{urban-2}$ represents the entire urban-2 area; $Area_{urban-1}$ stands for the entire urban-1 area; $Factor_{source-1}$ represents the ratios of each urban-1 dust sources. $\delta_{Area_source-1}$ is the error of urban-1 dust sources and $\delta_{Area_urban-2}$ is the error of urban-2 build-up areas.

Moreover, we estimated the rural croplands distributions using an indirect way based on the relationship as follows:

$$Cropland = Crops - Crops_barren \quad (6)$$

where *Cropland* stands for rural croplands distribution of pixels specified as crops and not barren; *Crops* represents the crops distribution resulted from MCD12Q1 and *Crops_barren* is the distribution of pixels specified as crops and barren. It notable that we evaluated the performance of *Crops_barren* by:

$$\delta_{Crops_barren}^2 = \delta_{Crops}^2 + \delta_{Barren}^2 \quad (7)$$

where δ_{Crops}^2 is the error of crops resulted from MCD12Q1 and δ_{Barren}^2 represent the error of rural barren.

Finally, the overall accuracies of gridded intensity were calculated based on formula (3) and formula (4).

3. Results

3.1. Urban-1 dust sources distribution

Figure 5 shows the distributions of constructions and barrens in urban-1 region, also with field investigation verification. The total constructions were 75 km², accounting for 7.5% of the entire urban-1 area. Active constructions were classified at the same time, accounting for 84% of total constructions. The total of barrens were 23 km², accounting for 2.3% of the entire urban-1 region. Furthermore, a 1 km spatial buffer along the route of the field survey was used to estimate the performance. The details of verified constructions and barrens revealed good overall accuracy of 91%. Additionally, the overall accuracies of each dust source were 90% for active construction, 91% for total construction and 92% for barren (**Table 2**).

3.2. Urban-2 dust sources distribution

Depending on the formula (1), the total dust sources were 43 km² for active constructions, 51 km² for total constructions, and 16 km² for barrens. Their distributions were the same with the build-up areas due to the evenly distributed assumption (**Fig. 6**).

The accuracies of urban-2 results were determined by the performance of urban-2 build-up areas and the related dust sources in urban-1 region (**Table 2**) based on error spread rule. Meanwhile, compared with urban-2 typical cities' areas (Tongchuan, Xianyang and Weinan) generated from Google Earth (**Fig. 7**), build-up areas from OLI data were average less 7%, which were consistent with the similar work reported (10%) by [Wang et al. \(2012\)](#). Thereafter, the overall accuracy of urban-2 build-up areas was estimated to be 93%. In summary, the overall accuracies of urban-2 dust sources were 93% for active constructions, 94% for total constructions and barrens, which were calculated by the formula (5).

3.3. Rural dust sources distribution

3.3.1. Barrens

Figure 6 shows the land cover classification results of the OLI data using MLC classifiers, involving rural barren distributions. The total barrens were 2281 km² in summer and 4380 km² in winter. In view of the confusion matrixes for land cover classification, the overall accuracies were 94% for the summer case and 95% for the winter result, with the overall averaged kappa coefficient of 0.92 (**Table 3**). These were consistent with the similar work reported by [Jia et al. \(2014\)](#), which displays with the user's accuracy of 94% for bare land in Beijing.

3.3.2. Croplands

The entire year total crops were 20038 km², which were generated from the MCD12Q1 IGBP (International Geosphere Biosphere Programme) classification and reported with the user's accuracy of 93% ([Mark A. Friedl, 2010](#)). Thereafter, the cropland distributions were extracted from this crops distribution by excluding barrens. The total croplands were 17,913 km² in summer and 16,090 km² in winter. The results revealed the overall accuracies of 88% in summer and 89% in winter, which were estimated using an indirect way based on the formulas of (4), (6) and (7).

3.4. Dust source intensity in the research domain

Gathering up the results of urban-1, urban-2 and rural regions, the overall accuracies and total areas of each dust sources were summarized in **Table 4**. The croplands were the dominant covering, involving 17,913 km² in summer and 16,090 km². It was followed by the barrens, involving 2319 km² in summer and 4418 km² in winter. While the urban constructions were much less, involving active constructions of 106 km² and total constructions of 126 km².

Depending on spatial overlay analysis, the dust source distributions were converted to gridded intensities ($I_{X_{i,j}}$) of construction, barren and cropland by the formula (3) (**Figure 8**). Notably, $I_{X_{i,j}}$ represented the emission potential of the specified dust source in each grid whose value interval was between [0, 1]. The larger

$I_{X_{i,j}}$, the higher dust emission potential. The result shows that the high value of $I_{X_{i,j}}$ occurred in the Guanzhong Basin, whereas very low or even zeros $I_{X_{i,j}}$ distributed in Tsinling Mountain. Moreover, the cropland revealed the highest intensities, with overall average value of 40% in summer and 36% in winter (**Fig. 8c**), followed by the barrens, with the average value of 5% in summer and 10% in winter (**Fig. 8b**). However, the constructions displayed with low value of $I_{X_{i,j}}$ with a small overall average value (<1%), but with a handful of peak value bigger than 80% (**Fig. 8a**).

Simultaneously, considering area of each grid with 1 km^2 , the overall accuracies of $I_{X_{i,j}}$ were numerical equal to that of the distributions based on formula (3) and formula (5). The overall accuracies of each dust source performed well with high accuracy greater than 88% (**Table 4**).

4. Discussion

4.1. Spatial and seasonal variations

We found the gridded intensities ($I_{X_{i,j}}$) of dust sources revealed obvious spatial variations (**Fig. 8**). First, almost all the dust sources distributed in north part, while lower intensities occurred in the south part. These were consistent with the scope of human activities, owing to sparsely populated region of the Tsinling Mountain, where was covered by the evergreen forest. Another interesting spatial variation was the strong opposite correlation of barren (**Fig. 8b**) and cropland (**Fig. 8c**). Namely, both in summer and in winter, the higher/lower $I_{X_{i,j}}$ barren pixel correspond to a lower/higher $I_{X_{i,j}}$ cropland pixel. Here, we suggested that this was due to the farmland fallow or abandon. Moreover, it is worth noting that the constructions aggregated in the Xi'an city (**Fig. 8a**), accounting for 59% of the whole constructions, whereas the urban area only accounts for 2% of the entire domain. Such dense distribution of constructions resulted in the risk of dust pollution in urban district and surrounding areas.

Another major finding was that the croplands and barrens revealed interesting season variations. The croplands in summer was 1824 km^2 larger than that in winter

(Fig. 8c), reflecting that 1824 km² croplands in summer converted into barrens due to slack farming in winter. However, the barrens in summer were 2099 km² lower than that in winter (Fig. 8b). So where did the redundant 275 km² barrens in winter come from? We wish to suggest that this inconsistent may be driven by the wild vegetation-covered area converting to barrens because summer is a more suitable period for growing than winter. Additionally, all the croplands and barrens were distributed all over the Guanzhong basin in summer and in winter.

In view of spatial and seasonal variations, we found that barren and cropland performed considerable dust emission potentials all over the Guanzhong Basin and all the year round. Meanwhile, they were with strong opposite spatial correlation. Furthermore, constructions exhibited high dust emission potential in urban district and surrounding areas, especially in the city of Xi'an, where aggregated most of the constructions (59%). The dust emission potential reveals prominent seasonal variations for barrens, whereas reflecting general seasonal variations for croplands.

4.2. Emission potential

It is notable that big differences of dust emission potential existed in various types of dust sources with an equivalent $I_{X_{i,j}}$, which was reported as erosion factor by Grini et al. (2005). Indeed, the erosion factor is set to 0.5 for barren and 0.12 for cropland in the regional chemical model WRF-Chem (version 3.2) (Grell et al., 2005). Moreover, we wish to suggest that construction dust emission potential was much higher than that of barren, especially for active construction areas. The dust emission potential of constructions resulted from not only wind erosions (higher than that in barren areas), but also human operations (U.S.EPA, 1995; Muleski et al., 2005; Pianalto and Yool, 2013). Besides, the highly aggregated distribution highlighted the construction dust pollution potential. Therefore, we concluded that all the dust sources of constructions, barrens and croplands were crucial sources, though constructions were only with small proportion of the study area.

5. Conclusion

The constructions, barrens and croplands were crucial sources for urban dust in the Guanzhong Basin. Constructions exhibited high dust emission potential in urban district and surrounding areas, especially in the Xi'an city. Barrens and croplands performed considerable dust emission potentials with strong opposite spatial correlation in the Guanzhong Basin. Moreover, higher dust emission potentials revealed in summer for barrens, but appeared in winter for croplands.

All the data processing procedures performed well, involving direct analysis processing accuracy greater 90% and further analytical procedures accuracy exceeding 88%. Meanwhile, the satellite data had reasonable costs, widespread coverage and high spatial and temporal resolution, expanding the feasible and valuable of proposed method. This study has proposed a satellite-data based method to quantify distributions of dust sources, especially for construction distribution, which is seldom quantified and reported in regional scale. Moreover, it proposes a new perspective to quantify regional assessment of urban dust on aerosol pollution using a dynamical/aerosol model (WRF-Dust).

Acknowledgment

This work was supported by the National Natural Science Foundation of China (NSFC) under Grant Nos. 41275186, 41430424, and the Open Fund of the State Key Laboratory of Loess and Quaternary Geology (SKLLQG1413). The National Center for Atmospheric Research is sponsored by the National Science Foundation.

References

- APOLLO MAPPING. Available at: <https://apollomapping.com/imagery/high-resolution-imagery/>. (Accessed: 26th May 2015).
- Brunner, D., Lemoine, G., Bruzzone, L., 2010. Earthquake damage assessment of buildings using VHR optical and SAR imagery. *IEEE T. Geosci. Remote* 48, 2403-2420.
- Foody, G.M., 2013. Ground reference data error and the mis-estimation of the area of land cover change as a function of its abundance. *Remote Sens. Lett.* 4, 783-792.
- Foody, G.M., Campbell, N., Trodd, N., Wood, T., 1992. Derivation and applications of probabilistic

- measures of class membership from the maximum-likelihood classification. *Photogramm. Eng. Rem. S.* 58, 1335-1341.
- Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S., 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. *Int. J. Remote Sens.* 34, 2607-2654.
- Grell, G.A., Peckham, S.E., Schmitz, R., McKeen, S.A., Frost, G., Skamarock, W.C., Eder, B., 2005. Fully coupled "online" chemistry within the WRF model. *Atmos. Environ.* 39, 6957-6975.
- Grini, A., Myhre, G., Zender, C.S., Isaksen, I.S.A., 2005. Model simulations of dust sources and transport in the global atmosphere: Effects of soil erodibility and wind speed variability. *J. Geophys. Res.* 110, D02205.
- Gumma, M.K., Thenkabail, P.S., Hideto, F., Nelson, A., Dheeravath, V., Busia, D., Rala, A., 2011. Mapping irrigated areas of Ghana using fusion of 30 m and 250 m resolution remote-sensing data. *Remote Sens.* 3, 816-835.
- Huang, R.-J., Zhang, Y., Bozzetti, C., Ho, K.-F., Cao, J.-J., Han, Y., Daellenbach, K.R., Slowik, J.G., Platt, S.M., Canonaco, F., 2014. High secondary aerosol contribution to particulate pollution during haze events in China. *Nature* 514, 218-222.
- Jia, K., Wei, X., Gu, X., Yao, Y., Xie, X., Li, B., 2014. Land cover classification using Landsat 8 Operational Land Imager data in Beijing, China. *Geocarto Int.* 29, 941-951.
- Laigen Dong, J.S., 2013. A comprehensive review of earthquake-induced building damage detection with remote sensing techniques. *ISPRS J Photogramm.* 84, 85-99.
- Mark A. Friedl, D.S.-M., Bin Tan, Annemarie Schneider, Navin Ramankutty, Adam Sibley, Xiaoman Huang, 2010. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sens. Environ.* 114, 168-182.
- Muleski, G.E., Cowherd Jr, C., Kinsey, J.S., 2005. Particulate emissions from construction activities. *J. Air Waste Manage.* 55, 772-783.
- Ni, T., Han, B., Bai, Z., 2012. Source Apportionment of PM₁₀ in Four Cities of Northeastern China. *Aero. Air Quality Res.* 12, 571-582.
- Pianalto, F.S., Yool, S.R., 2013. Monitoring fugitive dust emission sources arising from construction: a remote-sensing approach. *Gisci. Remote. Sens.* 50, 251-270.
- Saito, K., Spence, R., de C Foley, T.A., 2005. Visual damage assessment using high-resolution satellite images following the 2003 Bam, Iran, earthquake. *Earthq. Spectra* 21, 309-318.
- Saito, K., Spence, R.J., Going, C., Markus, M., 2004. Using high-resolution satellite images for post-earthquake building damage assessment: a study following the 26 January 2001 Gujarat earthquake. *Earthq. Spectra* 20, 145-169.
- Shen, Z., Cao, J., Arimoto, R., Han, Z., Zhang, R., Han, Y., Liu, S., Okuda, T., Nakao, S., Tanaka, S., 2009. Ionic composition of TSP and PM_{2.5} during dust storms and air pollution episodes at Xi'an, China. *Atmos. Environ.* 43, 2911-2918.
- Shen, Z., Cao, J., Arimoto, R., Zhang, R., Jie, D., Liu, S., Zhu, C., 2007. Chemical composition and source characterization of spring aerosol over Horqin sand land in northeastern China. *J Geophys Res.* 112.
- Shen, Z., Cao, J., Liu, S., Zhu, C., Wang, X., Zhang, T., Xu, H., Hu, T., 2011. Chemical composition of PM₁₀ and PM_{2.5} collected at ground level and 100 meters during a strong winter-time pollution episode in Xi'an, China. *J. Air Waste Manage.* 61, 1150-1159.
- Strahler, A.H., 1980. The use of prior probabilities in maximum likelihood classification of

remotely sensed data. *Remote Sens. Environ.* 10, 135-163.

1 Su, X., Cao, J., Li, Z., Lin, M., Wang, G., 2014. Column-Integrated Aerosol Optical Properties
2 during Summer and Autumn of 2012 in Xi'an, China. *Aero. Air Quality Res.* 14, 850-861.

3 U.S.EPA, 1995. Compilation of Air Pollutant Emission Factors, AP-42, fifth edition. I, 13
4 Available at: <http://www.epa.gov/ttn/chief/ap42/ch13/index.html>.

5
6 Wang, L., Li, C., Ying, Q., Cheng, X., Wang, X., Li, X., Hu, L., Liang, L., Yu, L., Huang, H., 2012.
7 China's urban expansion from 1990 to 2010 determined with satellite remote sensing. *Chinese*
8 *Sci. Bull.* 57, 2802-2812.

9
10 Wang, P., Cao, J.-j., Shen, Z.-x., Han, Y.-m., Lee, S.-c., Huang, Y., Zhu, C.-s., Wang, Q.-y., Xu,
11 H.-m., Huang, R.-j., 2015a. Spatial and seasonal variations of PM 2.5 mass and species during
12 2010 in Xi'an, China. *Sci. Total Environ.* 508, 477-487.

13
14 Wang, R., Zou, X., Cheng, H., Wu, X., Zhang, C., Kang, L., 2015b. Spatial distribution and source
15 apportionment of atmospheric dust fall at Beijing during spring of 2008–2009. *Environ. Sci.*
16 *Pollut.* 22, 3547-3557.

17
18 Zhang, Q., Shen, Z., Cao, J., Ho, K., Zhang, R., Bie, Z., Chang, H., Liu, S., 2014. Chemical profiles
19 of urban fugitive dust over Xi'an in the south margin of the Loess Plateau, China. *Atmos. Pollut.*
20 *Res.* 5.

21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Tables

Table 1

Selected VHR data using for urban-1 dust source extraction. Pan means panchromatic. CE90 stands for circular error at 90% probability, representing positional accuracy, exclusive of terrain effects, which means that location of objects in the image are 90% of the time within this accuracy provided that the study area does not contain much terrain relief.

Satellite	QuickBird	GeoEye-1	Worldview-2	Pleiades-1
Launch date	2001-10	2008-09	2009-10	2011-10
Orbit (km)	482	681	770	695
Pan Nadir Resolution (m)	0.65	0.41	0.46	0.7
Natural Color Resolution (m)	0.6	0.5	0.5	0.5
Area proportion	10.41%	3.44%	14.82%	71.33%
CE90 (m)	23	<10	<3.5	<4
Data acquisition time	Aug. 2013	Aug. 2013	Sep. 2012	Aug. 2013
Revisit (days)	2.5 (<45°)	2.1 (<35°)	1.1 (<45°)	4 (<30°)
	5.6 (<20°)	2.8 (<28°)	3.7 (<20°)	5 (<20°)
Spectral Resolution (nm)	R	590-710	624-694	590-710
	G	466-620	506-586	500-620
	B	430-545	442-515	430-550

Table 2

The field verification of urban-1 dust sources, including constructions and barrens.

Dust source	Verified area (km ²)	Misclassified area (km ²)	Accuracy
Active construction	36.1	3.6	90%
Total construction	42.4	3.8	91%
Barren	7.6	0.6	92%
Overall	50.1	4.5	91%

Table 3

Overall accuracy and kappa coefficient of barrens extracted from Landsat-8 OLI data.

Accuracy Group	Path-row	Overall accuracy	Kappa coefficient	Average	
				Overall accuracy	Kappa coefficient
Summer	128-36	99.7%	0.99	94%	0.92
	127-36	95.2%	0.93		
	126-36	87.8%	0.83		
Winter	128-36	96.1%	0.92	95%	0.92
	127-36	93.7%	0.90		
	126-36	95.6%	0.93		

Table 4

The overall accuracy and total areas (km²) of each dust source, including in urban-1, urban-2, rural regions and the research domain.

Region	Constructions		Croplands		Barrens	
	active	inactive	summer	winter	summer	winter
Urban-1	90.0% (63)	90.9% (12)	--	--	91.7% (23)	91.7% (23)
Urban-2	93.1% (43)	93.8% (8)	--	--	94.3% (15)	94.3% (15)
Rural	--	--	88.3% (17913)	88.7% (16090)	88.4% (2281)	88.9% (4380)
Domain	88% (106)	89% (126)	88% (17913)	89% (16090)	88% (2319)	89% (4418)

FIGURES

Figure 1

Figure 1. Locations and surrounding geographical environment of the research domain in the Guanzhong Basin, China. (a) The location in China. (b) Surrounding geographical environment, which with the background of MODIS true color map on 2015-04-13. The edges of Xi'an city was highlighted with green lines.

Figure 2

Figure 2. The capture time, spatial coverage and related true color maps of selected Landsat-8 OLI data: (a) in summer and (b) in winter. The black areas represented 'No Data' regions of the research domain.

Figure 3

Figure 3. The flow diagram of data processing procedures from initial satellite data to the final dust sources of gridded intensities, including constructions, croplands and barrens. The four direct analysis procedures were stressed by blue dashed box. Meanwhile, the other three further analysis procedures of *Extrapolation* and *Spatial overlay analysis* were noted on the top of the related box.

Figure 4

Figure 4. Interpretation signs on obvious constructions cases of Pleiades-1 image (a) case-1 near the location of 34.1941°N, 108.8391°E and (b) case-2 near the location of 34.1491°N, 108.9621°E.

Figure 5

Figure 5. The distributions and field verification of constructions and barrens in urban Xi'an.

Figure 6

Figure 6. Urban-2 build-up areas and land cover classification results of the OLI data using MLC classifiers (a) in summer and (b) in winter.

Figure 7

Figure 7. The agreement between the interpretation results from OLI data and with the corresponding high-resolution images in Google Earth. The OLI data over of (a₁) Tongchuan city, (b₁) Xianyang city, and (c₁) Weinan city was acquired on 2013-09-13, whereas the related hi-resolution Google Earth images were acquired on 2013-08-29 of (a₂) Tongchuan and (b₂) Xianyang, and on 2013-08-19 of (c₂) Weinan. The boundary of urban-2 regions are shown in dark in OLI data, and displayed in yellow in Google Earth images.

Figure 8

Figure 8. Gridded intensities of (a) constructions, (b) barrens and (c) croplands of the year 2013 over the study area. The colors indicate the fractions of the gridded cells covered by constructions, croplands, and barrens. The area of bold green line indicates the urban area of the Xi'an city.