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Dust and Sandstorm Source Mapping and Monitoring in Mongolia

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ABSTRACT

Dust storms are among the globally observed natural hazards with significant environmental, health, social, and economic impacts. These storms not only degrade air quality but also carry fine particles and heavy metals that pose serious health risks. In Mongolia, a large portion of the land is arid and semi-arid, making dust storms a frequent seasonal phenomenon with considerable negative effects on the environment and society. Identifying the sources of dust storms is a critical step for effective monitoring and control measures at a local level. This review explores methodologies for mapping and monitoring dust and sandstorm (DSS) sources, crucial for addressing the environmental, health, and socioeconomic impacts of these events. DSSs are one of the catastrophic phenomena observed around the world, and the exact sources need to be identified. This article discusses the aspects and possibilities of using remote sensing, weather station or ground-based observations, and numerical modelling, highlighting their advantages and limitations. It is believed that the methodology developed by Ginoux et al (2012) in the research work can be used and monitored at the regional level. The advantages and limitations of each method are discussed, with particular focus on MODIS (Moderate Resolution Imaging Spectroradiometer) data, which allows for rapid data acquisition and temporal analysis crucial for tracking dust sources. This research aims to refine the methodology for accurately identifying dust sources across Mongolia, contributing to more effective monitoring and control systems. It highlights the importance of continuous study and intersectoral collaboration for advancing dust source identification and preventive measures in Mongolia's unique environmental context. Moreover, we applied the methodology developed by Ginoux et al. (2012) on a regional scale to map dust sources across Mongolia from 2001 to 2020, leveraging the accuracy of this approach in pinpointing specific dust source regions. Finally, the conclusion stresses the importance of interdisciplinary collaboration and continued research to advance DSS monitoring efforts effectively.

Keywords: Dust Storm, Sandstorm, Source Mapping, Monitoring

1. INTRODUCTION

Dust and sandstorms (DSS) are significant atmospheric phenomena that impact air quality, climate, and human health. DSS in Mongolia and China pose significant environmental and health challenges, exacerbated by a combination of natural and anthropogenic factors. The regions are characterized by vast arid and semi-arid landscapes, particularly in the Gobi Desert, where strong winds often lift fine particles into the atmosphere. Understanding the sources and dynamics of DSS in these areas is crucial for developing effective management strategies to mitigate their impacts.

The Gobi Desert, spanning northern China and southern Mongolia, is a prominent source of dust due to its extensive sandy and gravelly soils. Natural processes such as wind erosion are exacerbated by the region's sparse vegetation, which is unable to stabilize the soil against erosive forces (Zhang et al., 2018). Both Mongolia and northern China are subject to climatic extremes, including prolonged droughts and high winds, which enhance dust mobilization. The frequency of dust storms has been linked to shifts in climate patterns, leading to increased occurrences in recent decades (Zhang et al., 2007).

Agricultural expansion, overgrazing, and deforestation have substantially altered land surfaces in Mongolia and China, contributing to soil degradation and increased susceptibility to wind erosion. For example, overgrazing by livestock has led to the deterioration of grasslands, reducing vegetation cover that normally protects against dust mobilization (Li et al., 2017). Rapid urban growth and industrial activities in northern China, particularly in regions like Inner Mongolia, contribute to dust emissions. Construction activities disturb large areas of soil, and industrial pollution can exacerbate existing dust problems (Gong et al., 2006). DSS events have significant health implications, as high dust concentrations can lead to respiratory and cardiovascular diseases among affected populations. In urban areas, dust can also reduce air quality, impacting daily life and economic activities (Koch et al., 2009). Environmental impacts include soil degradation, changes in local ecosystems, and altered precipitation patterns, which can affect agricultural productivity and water resources (Zhao et al., 2018).

The review examines the methodologies utilized in this field, focusing on both technological and in-situ approaches. and sandstorms (DSS) pose significant challenges to environmental sustainability, public health, and socio-economic stability, particularly in arid and semi-arid regions of Mongolia. The distribution and pattern of dust sources are complex and have high spatial and temporal variability, which is explained by high variability of topsoil texture, soil structure, land use, socio-economic impacts, and variability of climate and weather conditions. This study discusses various methodologies employed for mapping and monitoring their sources, including remote sensing techniques, field surveys, numerical modeling, and integrated approaches. Each methodology offers unique advantages and contributes to a comprehensive understanding of DSS dynamics.

1.1 Remote Sensing Techniques

Remote sensing is crucial for large-scale monitoring of DSS sources, providing valuable data on land surfaces, dust emissions, and atmospheric conditions.

1.1.1 Satellite Imagery

The study by Liu et al. (2002) focuses on using data from the GMS (Geostationary Meteorological Satellite) S-VISSR (Stretched Visible and Infrared Spin Scan Radiometer) to monitor sandstorms. The research highlights the satellite's ability to capture real-time data and its effectiveness in tracking and analyzing sandstorm occurrences in Asia. Liu and Lin (2004) explore the use of geostationary satellite observations to monitor and study dust storms across Asia. Lin et al. (2011) present a method for categorizing Asian dust weather using a combination of satellite data and ground-based observations. The study integrates remote sensing and surface monitoring techniques to identify and classify dust events more effectively. Their approach enhances the understanding of dust storm patterns, enabling better environmental assessment and management strategies in affected regions. MODIS (Moderate Resolution Imaging Spectroradiometer): MODIS data is frequently utilized to assess aerosol optical depth (AOD), which correlates with dust concentration. Studies have shown that AOD values from MODIS can effectively identify dust source regions in northern China and Mongolia (Levy et al., 2013). Sentinel-2: The high-resolution multispectral imagery from Sentinel-2 allows for detailed analysis of land cover and soil conditions that influence dust emissions. This is particularly useful in identifying areas undergoing land use changes that could increase susceptibility to dust storms (Pettorelli et al., 2014).

1.1.2 LiDAR

LiDAR systems have been applied to measure atmospheric dust particles and assess their vertical distribution. This technique enhances the understanding of dust transport dynamics and provides high-resolution spatial data for source characterization (Baker et al., 2015).

1.1.3 UAV

UAVs equipped with imaging and sensing technologies collect high-resolution spatial data on dust source characteristics. They are particularly useful in remote or difficult-to-access areas, enabling detailed assessments of soil properties and vegetation cover (Anderson & Gaston, 2013).

1.2 Field Surveys

Field surveys complement remote sensing data by providing ground-truth information essential for validating satellite observations.

1.2.1 Ground-Based Measurements

In situ monitoring stations collect data on dust concentration, wind speed, and direction. Instruments such as dust samplers help measure particulate matter in the atmosphere, which is crucial for validating remote sensing models (Boucher et al., 2013).

1.2.2 Soil Sampling

Analyzing soil characteristics—such as texture, moisture content, and composition—helps identify regions susceptible to wind erosion. Field surveys can determine the physical and chemical properties of soils, providing insights into their potential as dust sources (Fitzgerald et al., 2014).

1.3 Numerical Modelling

Numerical models simulate dust emission processes and atmospheric dispersion, allowing for predictions of dust events.

1.3.1 Dust Emission Models

Models such as the Dust Regional Atmospheric Model (DREAM) and the Weather Research and Forecasting model with Chemistry (WRF-Chem) are widely used to simulate the transport and deposition of dust particles based on meteorological data (Zhang et al., 2008). These models can help predict the frequency and intensity of dust storms in response to climatic variations.

1.3.2 Geographic Information Systems (GIS)

GIS technology allows for spatial analysis of dust sources by integrating data from remote sensing, field surveys, and modeling. This facilitates the identification of relationships between land use, vegetation cover, and dust emissions, providing a comprehensive spatial understanding of DSS dynamics (Bai et al., 2018).

1.4 Integrated Approaches

An integrated methodology combines various data sources and stakeholder involvement to enhance understanding and management of DSS sources.

1.4.1 Multi-Source Data Integration

Combining remote sensing data, ground measurements, and numerical modeling outputs provides a holistic view of dust source dynamics. This integration is essential for developing effective management strategies and improving predictive capabilities (Tegen & Lacis, 1996).

During the past few decades, various remote sensing algorithms have been developed to increase the accuracy of dust detection and, subsequently, improve the identification of dust sources based on direct observation of dust particles (Hsu, N.C., .et. al, 2004, Roskovensky & Liou, 2005). Prospero et al. (2002) assumed the frequency of occurrence (FoO) of the total ozone mapping spectrometer (TOMS), aerosol index (AI) > 0.7 for designating dust sources. As a result, topographic depressions were determined as the main sources of dust emission. According to their findings, almost the entire North East Asia is determined as a vast dust source during April. It also concluded that dust sources in the Gobi desert have characteristics similar to those identified in TOMS elsewhere.

Ginoux et al. (2012) proposed a new algorithm for dust source determination in which AI is replaced with the Moderate Resolution Imaging Spectroradiometer (MODIS) deep blue aerosol optical depth (DB AOD). Considering the physical and optical properties of aerosols, they extracted dust optical depth (DOD) from the already retrieved AOD from 2003 to 2009. FoO of DOD > 0.2 was used as a criterion for the determination of dust sources.

This paper aims to introduce a methodology for DSS source mapping at the regional level based on the literature review of recent scientific knowledge, methods, and implications.

2. METHODS

The approach is proposed by Ginoux et al. (2012) in which authors proposed mapping of sources based on Moderate Resolution Imaging Spectroradiometer (MODIS) estimates of DOD in conjunction with other data sets including land use.

The gneral algorithm is as follows (Figure 1):

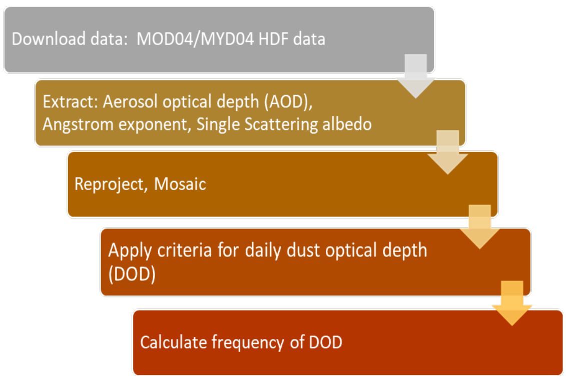


Figure 1: The flowshart of methodology.

The first criterion of the screening method is to restrict the AOD observations to larger aerosol particles (α < 0.5). The deposition of large dust particles is controlled by gravitational settling; therefore, they are more likely to be very close to the source . However, this criterion could also be satisfied in coastal regions where concentrations of sea salt coarse particles are high. To filter out sea salt particles, the second criteria was applied since the SSA of sea salt are higher than mineral dust (~ 1.0). The third criterion is grounded on another specific property of mineral dust, which is a positive difference of SSA between 412 and 650 nm. To summarize, mineral dust is always more absorbent at 412 nm than at 650 nm.

The collection of daily DOD raster datasets, the frequency of occurrence (FO) of DOD greater than a threshold optical depth was calculated, and its seasonal and yearly distributions were investigated. In dust-related studies, AOD values greater than 0.2 are generally considered an indicator of the presence of dust in the atmosphere (Ginoux et al. 2010).

The algorithm for calculating DOD is constantly updating using different modeling approaches and enhancement of Earth Observation (EO) data. One of such alternative is proposed by Gkikas et.al (2021), where DOD calculated as a combination of the quality filtered satellite AOD retrievals from MODIS-Aqua at swath level (Collection 6.1; Level 2), along with DOD-to-AOD ratios provided by the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) reanalysis to derive DOD on the MODIS native grid (Gkikas et.al, 2021).

$$MDF = \frac{AOD_{Dust;Merra2}}{AOD_{Total;Merra2}} \quad (1)$$

$$DOD_{MODIS} = AOD_{MODIS} * MDF \quad (2)$$

EO-based methods (Ginoux et al., 2010; Gkikas et. al, 2021) provide information on active areas both affected and source of sand and dust storms. These sorts of maps are useful for risk assessment and management of risks rather than managing source regions. The advantage of such approaches is that the EOs are freely accessible. The raw datasets, however, are not accessible in open EO processing platforms such as Google Earth engine, so the user must have to download some of the EO datasets, and extensive programming knowledge to follow the algorithms.

The DOD is a total column measure that does not distinguish between freshly emitted dust plumes and aged dust in the atmosphere. Furthermore, emitted dust particles tend to accumulate and remain trapped in topographic basins (Ginoux et al., 2012; Ginoux et al., 2010; Gkikas et.al, 2021). Consequently, DOD frequency of occurrence is not expected to be consistent with source frequency of occurrence or dust emission model results. The DOD is only partially related to dust emission because atmospheric dust concentration is controlled by dust emission magnitude and frequency, but also by the residence time of dust near the surface which depends on wind speed, and by dust deposition in the dust source region, a size-dependent process. Furthermore, the DOD (deep blue product) is well known in the visible wavebands to be physically restricted to bright land surfaces in the visible wavebands with reduced performance over areas where vegetation is present. The DOD is unable to detect optically thin dust.

3. RESULTS AND DISCUSSIONS

Methodology for DSS source mapping based on surface condition indicators considers the combination of available data that can provide information for the assessment of soil surface potential to emit soil particles under favorable wind conditions. An approach based on implying soil and surface data to gather information that triggers the process of DSS. This approach in DSS source mapping is less used because of its complexity, but can significantly contribute to a better definition of DSS source patterns, including its small-scale features, which is necessary in planning actions related to DSS source mitigation.

Basics of steps for DSS source mapping using surface data in the following steps involved in the process described in the input data criteria:

- Step 1: Determine Input Data Criteria: Define input criteria for each month and land point, including bare land fraction (BLF), soil freezing temperature (TFR), and soil moisture factor (SMF).
- Step 2: Calculate Bare Land Fraction (BLF): BLF is determined based on land cover and Enhanced Vegetation Index (EVI) data. Establish thresholds for EVI values to determine the fraction of bare surface. Adjust BLF values based on land cover type and EVI thresholds.
- Step 3: Calculate Soil Freezing Temperature (TFR): TFR depends on soil moisture content (SMC). Determine TFR based on SMC thresholds, with different values for dry and moist soil conditions.
- Step 4: Calculate Soil Moisture Factor (SMF): SMF is a reducing factor for particle emission when SMC is above 0.15. Calculate SMF based on SMC values using a formula, reducing efficiency for wet soils.
- Step 5: Separate Calculation for Soil Texture Categories: Separate the calculation for three soil texture categories: clay, silt, and sand. Determine the fraction of each texture category in the surface soil layer. Estimate the efficiency of particle emission for each texture category.
- Step 6: Calculate Near Surface Concentration (SC): Calculate SC for each size category (clay, silt, sand) under strong wind conditions. Combine input parameters (BLF, texture fraction, SMF) to calculate SINF for each size category. Calculate SC using the SINF values and friction velocity parameters.
- Step 7: Calculate Total Concentration (CTOT): Sum the SC values obtained for all three particle size categories. Conversion to DSS Source Intensity: Calculate the 99th percentile of CTOT globally. Normalize CTOT values by dividing them by the 99th percentile. Assign a maximum intensity value (1) to sources with intensities above the 99th percentile.

Figure 2 shows the normalize DSS source intensities for all months using the average value of monthly 99th percentiles.

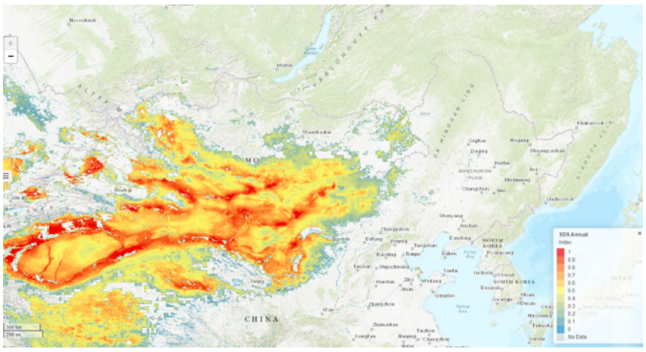


Figure 2: Annual global sand and dust source base map (available at http://maps.unccd.int).

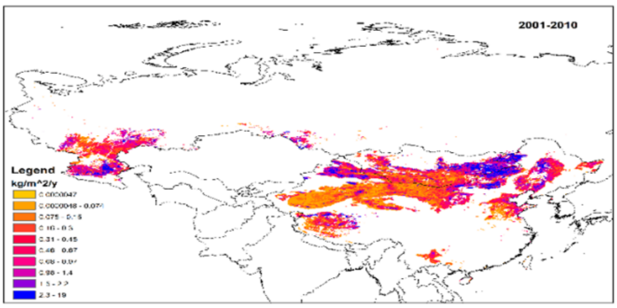
The advantage of this approach is it reveals both potential and active sources. Compared with DOD this method shows the potential of land to be a source of dust emission depending on surface conditions. At the current level, the empirical model used in this methodology does not consider wind as a contributing component for dust emission.

The aforementioned methodology proposed in the dust and sand storm compendium implements an algorithm that is based on filtering indicators depending on a threshold value. The resulting source map is produced by multiplication of binary maps which may reduce or expand source regions depending on selected threshold values.

The above-mentioned methodology can be extended based on the traditional emission model. The model distinguishes several parameters differently.

1. The calculation of friction velocity is considered particle diameters.
2. The use of gravimetric soil moisture for a different condition that supports the attainment of particles by wind.
3. With ERA-land dataset allows us to calculate wind which is one of the major factors that is not considered in recent developments.

The result of the emission model calculated for the spring season of two decades 2001-2010 and 2011-2020 is shown as follows (Figure 3).



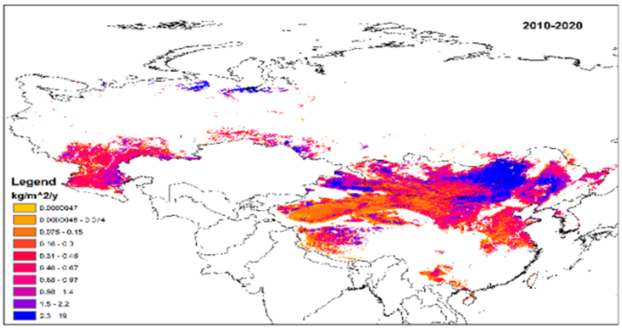


Figure 3. The emission model, 2001-2010 and 2011-2020.

In the figure 3 (s) are preliminary results that have to be validated. At a current level, it can be concluded that some expansion exists in terms of extent, and the emission of dust particles has also intensified. In order to identify drivers of this increase it is important to compare results with land cover, land use changes, and other direct drivers that may affect ground condition.

DSS sources can be defined as regions naturally productive for DSS and as regions that emit DSS. This has been researched with different approaches. If the first approach is more or less linked with natural settings the second has to distinguish different drivers, e.g. wind, available particle size, moisture, and so on. In a modified version of DSS source mapping it is proposed to use an emission model considering different aspects of DSS phenomena. However, in dust emission modelling following issues remain such as:

- collect data that represent the magnitude and frequency of dust emissions associated with different atmospheric conditions.
- monitor, estimate, or calculate an entrainment threshold which varies over space and time.
- Develop a parameterisation for sediment supply/availability changing over space.

It is noteworthy to mention that DSS is a phenomenon that characterized by seasonal shifts. It is therefore important to consider which seasonal shift is important to be addressed under the LDN and/or DLDD.

The modified model requires many empirical expressions which can be easily simplified if the users have threshold values for a certain parameter. The land use/land cover map for masking has to be reconsidered especially for those areas in a temperate zone where cropland intensively abandoned since the 1990s. Those include parts of Buriyaiya, Northern Mongolia, the Altai region of Russia, and so on.

4. CONCLUSION

In conclusion, the effective mapping and monitoring of dust and sandstorm sources demand a multifaceted approach that integrates remote sensing, ground-based observations, and numerical modeling. While each methodology offers distinct advantages, their synergistic integration holds the key to enhancing the accuracy, spatial coverage, and predictive capabilities of dust and sandstorm monitoring systems. Continued research efforts, coupled with interdisciplinary collaborations, are imperative for advancing methodological frameworks and fostering resilience against the adverse impacts of dust and sandstorms on environmental and human health.

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