

Two distinct spatial and temporal variations of PM2.5 and PM10 concentrations in Mongolia

Erdenebayar Munkhtsetseg

Atsushi Shimizu

2024-03-21

PM2.5 and PM10 data for the 4 distinct sites of Mongolia from 2008 to 2020 is found

Abstract:

Air pollution, particularly particulate matter (PM), poses significant health risks and environmental challenges globally. Mongolia, a country characterized by diverse geographical features and climatic conditions, experiences notable variations in PM2.5 and PM10 concentrations. This manuscript explores the spatial and temporal patterns of PM2.5 and PM10 across Mongolia, identifying/delineating two distinct variations. Utilizing extensive datasets and advanced analytical methods, this study provides comprehensive insights into the dynamics of air quality in Mongolia, which is crucial for formulating effective mitigation strategies and policies.

Keywords: Air pollution, particulate matter, PM2.5, PM10, spatial variation, temporal variation, Mongolia, urban pollution, rural pollution, meteorological factors.

1 Introduction

Mongolia serves as a compelling case study for understanding the complexities of air pollution dynamics. Despite its sparse population, Mongolia faces severe air quality issues, particularly in urban centers like Ulaanbaatar. The capital city experiences extreme winter pollution episodes, earning it the dubious distinction of being one of the most polluted cities globally. This dire situation stems from a unique blend of factors, including rapid urbanization, inefficient heating practices, and unfavorable meteorological conditions.

The impact of air pollution on public health cannot be overstated. Exposure to elevated PM2.5 and PM10 levels is associated with respiratory diseases, cardiovascular disorders, and even premature mortality. Furthermore, air pollution poses a significant threat to Mongolia's fragile ecosystems, exacerbating desertification and contributing to biodiversity loss. Recognizing the

urgency of addressing this issue, this manuscript aims to dissect the spatial and temporal variations of PM_{2.5} and PM₁₀ concentrations in Mongolia, offering insights essential for designing targeted interventions.

This manuscript aims to elucidate the spatial and temporal variations of PM_{2.5} and PM₁₀ concentrations in Mongolia, shedding light on the factors driving these patterns.

Mongolia's unique geography, featuring vast steppes, deserts, and mountain ranges, coupled with its climatic extremes, results in complex patterns of air pollution.

2 Data & Methods

2.1 Study area descriptions

Fine and coarse particulate matter monitoring sites were located at Dalanzadgad (43.57°N, 104.42°E), Sainshand (44.87°N, 110.12°E) and Zamyn-Uud (43.72°N, 111.90°E) in the Gobi Desert, and at Ulaanbaatar (−) in capital city of Mongolia (Figure 1).

The map demonstrates: - (spring wind speed, it ... - elevation with the population number.

The spring is defined as dust season for Mongolia, and Gobi is the one of the 3 major Asian dust sources those are Gobi, Taklamahan and Sahara.

In the last 2 decades, due to poverty and natural disasters there is population immigration has taken place from the rural to urban, especially to capital city of Mongolia. Due to tiny infrastructure to provide the mega city with the dense population, it introduces the urban pollution.

Therefore, Ulaanbaatar air particulate matter mainly reflects the coal burning, and partly, natural dust.

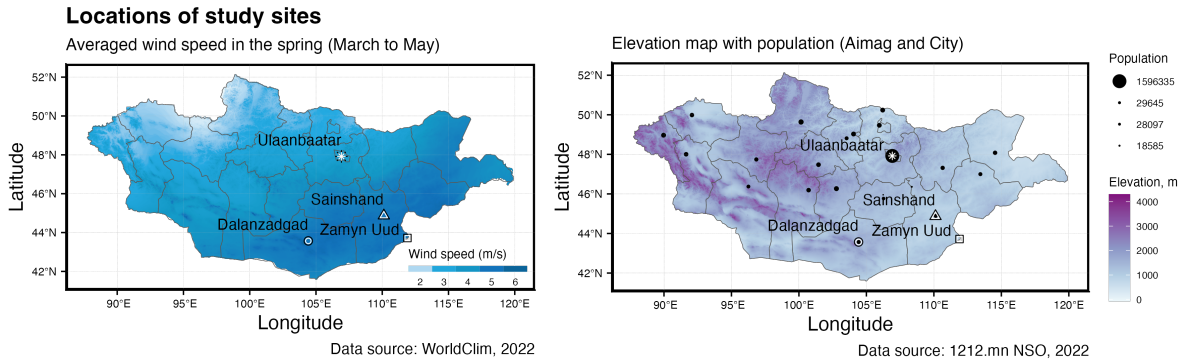


Figure 1: Study sites

Table 1: Data

Table 1. Measured data

SITE	Location		Measured and collected data						Missing data	
	COORDINATE	ELEVATION	TOTAL ¹	WS&WD ²	VIS ³	OPC ⁴	PM2.5 ⁵	PM10 ⁵	PM2.5	PM10
Ulaanbaatar	47.92°N, 106.92°E	1350 m	76656	72603	72886	33241	67940	68777	11.4%	10.3%
Dalanzadgad	43.57°N, 104.42°E	1470 m	60336	46332	33812	-	46066	49172	23.6%	18.5%
Sainshand	44.87°N, 110.12°E	947 m	59040	50513	49720	-	47111	47313	20.2%	19.9%
Zamyn Uud	43.72°N, 111.90°E	967 m	67392	62432	63948	-	57317	58512	14.9%	13.2%

¹ Equipment height: 15 meter at urban site (Ulaanbaatar), 2 meter at Gobi sites (Dalanzadgad, Sainshand and Zamyn Uud); ² Measurement range: 0–60 m/s; 0–365 degrees. Instrument model: Wind speed and direction PGWS-100, Gill, England; ³ Range: 10–20 000 m. Visibility meter PWD10, Vaisala, Finland; ⁴ Optical Particle Counter; ⁵ Range: 0.003–100 mg/m³, Flow rate: 20 L/m, Suction rate: 2 L/ m. Measured by Kosa monitor ES-640, TDK Co. LTD, Japan;

2.2 Study data and data analysis

2.2.1 Data

Particulate matter with aerodynamic diameters less than 2.5 μm (PM2.5) and 10 μm (PM10) were measured at these sites using an instrument that measures light scattering by air-borne particulates. Meteorological parameters, including wind speed, wind direction and visibility were determined by automatic instruments and are detailed in previous articles (Jugder et al., 2011, 2012; Nishikawa, Sugimoto). The instruments for measuring particulate matters were placed 2.0 m above the ground level (AGL) at Dalanzadgad, Sainshand and Zamyn-Uud (Table 1). Wind sensors and visibility (meteorological optical range-MOR) sensors with a maximum measurement range of 20 km were installed at a height of 3 m AGL at the three Gobi sites. At the Ulaanbaatar site, the wind sensor height and a visibility sensor was placed at 15 m AGL.

2.2.2 Datasets

Datasets were obtained from measurements at Dalanzadgad, Sainshand, and Zamyn-Uud from January 2009 to May 2018, and at Ulaanbaatar from the end of April to May 2008. The data used in the study are based on hourly means derived from 1 and 10 min averages.

We examined the PM data quality, and removed spikes those are above 7 μm , and when PM10,. Due to electricity shortage and equipment malfunctions contributed to the bad data, and missing data. In Sainshand station, ... was ... Each stations has some features, we treated each stations separately to remove suspective data.

At last, we filled the missing data with 3-hour maxgaps with `imputeTS` package for univariate time series, and larger gaps using `mtsdi` R package (well-used for time-series data), and improved the missing data percents by... from ... to ... Additionally, meteorological parameters such as wind speed, direction, and visibility are integrated into the analysis to elucidate their impact on PM levels.

The MTSDI method (Junger, Santos, and Ponce de Leon (2003), Junger and Leon (2012)) uses the EM algorithm with the Autoregressive Integrated Moving Average (ARIMA) method, also known as Box–Jenkins model (Box et al. (2015), Meyler, Kenny, and Quinn (1998)). The data provided by ARIMA (p, d, q) depend on the number of autoregressive terms (p), the number of differences (d), and the number of terms in the moving average (q) (Meyler, Kenny, and Quinn (1998)). Default configuration was used. The `mtsdi` method is widely used to impute missing data like in cosmic data Fernandes, Lucio, and Fernandez (2017). Similar multiple imputation methods have been applied for multivariate solar data Zhang et al. (2020), highly univariate seasonal data even with the large amount of missing data Chaudhry et al. (2019), missin data imputation and modeling for leaching processes He et al. (2017). Recently, Motesaddi Zarandi et al. (2022) used the `mtsdi` method to imputing missing data air pollution in Tehran (We used the complete data of temperature (°C), relative humidity (RH) (%), wind speed (m/s), barometric pressure (BP) (mbar), PM10, PM2.5, NO2, CO, and CVD variables to impute SO2 and O3 with the `mtsdi` R package.).

Ground-based monitoring data from urban and rural Gobi sites are compared to capture distinct variability. Temporal variations are examined through comprehensive time-series analysis, considering seasonal trends, diurnal patterns, and long-term trends.

3 Results

3.1 PM intercomparisons of sites between anthropogenic and natural PM sources

The analysis reveals two distinct spatial and temporal variations in PM2.5 and PM10 concentrations across Mongolia. In the first pattern, urban areas, especially the capital city Ulaanbaatar, exhibit significantly higher PM levels compared to rural regions (Batmunkh et al., 2020). This disparity is attributed to anthropogenic activities, including residential heating, industrial emissions, and vehicular traffic. Temporally, winter months coincide with peak pollution levels in urban centers due to increased heating demand and temperature inversions exacerbating pollutant accumulation (Dashdondog et al., 2019).

Conversely, rural and remote areas display lower PM concentrations, with seasonal variations influenced by factors such as dust storms, wildfires, and agricultural practices (Battsengel et al., 2021). Spring and summer elevated PM levels in these regions, primarily driven by dust storms originating from arid landscapes and biomass burning activities. Moreover, meteorological conditions, including wind patterns and precipitation, play a crucial role in dispersing pollutants and shaping temporal trends (Enkhbat et al., 2020).

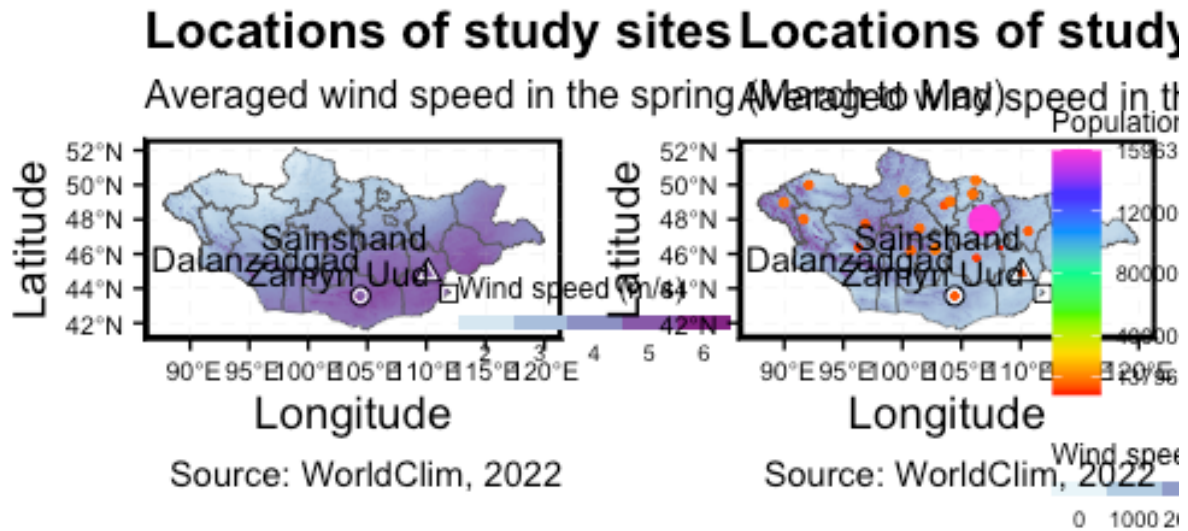


Figure 2: Extended PM datasets (red color presents the data filled by mtdsi)

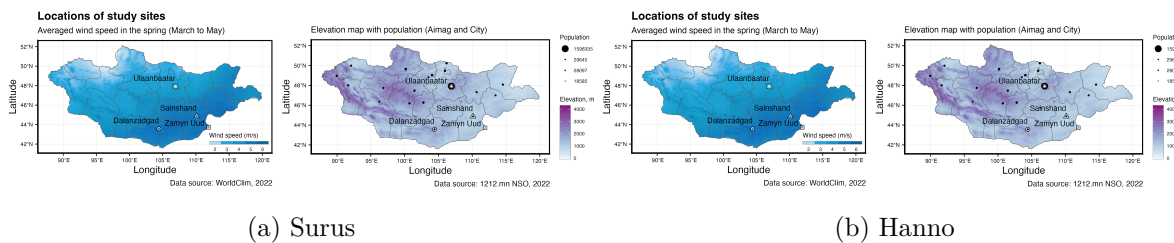


Figure 3: Famous Elephants

3.2 Temporal variations

To demonstrate the temporal variations of PM10/PM2.5: by illustrating annual and seasonal changes from 2008 to 2020. a) Discuss the changes in the seasonal maximums (peaks)

b) Discuss the changes in duration of the dusty or polluted periods

c) Discuss the inter-annual variations

4 Discussion

The observed spatial and temporal variations in PM2.5 and PM10 concentrations underscore the intricate interplay between anthropogenic and natural factors shaping air quality in Mongolia. While urban areas grapple with pollution stemming from industrialization and urbanization, rural regions contend with the impacts of climatic events such as dust storms and wildfires. This stark dichotomy necessitates tailored interventions that address the specific challenges faced by different regions. Effective air quality management strategies must account for these disparities, emphasizing targeted interventions tailored to specific regions and seasons.

To combat air pollution effectively, holistic strategies integrating regulatory measures, technological innovations, and public awareness campaigns are imperative. In urban areas, transitioning to cleaner heating technologies, improving public transportation infrastructure, and enforcing emissions standards can significantly mitigate pollution levels. In rural regions, initiatives focusing on sustainable land management practices and early warning systems for dust storms and wildfires are essential.

Furthermore, international collaboration and knowledge sharing can play a pivotal role in addressing Mongolia's air quality challenges. Leveraging expertise and resources from global partners can enhance monitoring capabilities, foster innovation, and support capacity-building efforts in air quality management.

5 Conclusions

This manuscript highlights the complexity of air pollution dynamics in Mongolia, characterized by two distinct spatial and temporal variations in PM2.5 and PM10 concentrations.

Future work requires to : By elucidating the contributing factors and underlying mechanisms driving these patterns, this study provides valuable insights for policymakers, urban planners, and environmental stakeholders. Addressing air quality challenges in Mongolia necessitates multifaceted approaches that integrate regulatory measures, technological innovations, and public awareness campaigns to safeguard human health and ecological well-being.

(marrero2019?) # References {.unnumbered}

{#refs}

- Box, George EP, Gwilym M Jenkins, Gregory C Reinsel, and Greta M Ljung. 2015. *Time Series Analysis: Forecasting and Control*. John Wiley & Sons.
- Chaudhry, Aizaz, Wei Li, Amir Basri, François Patenaude, et al. 2019. “A Method for Improving Imputation and Prediction Accuracy of Highly Seasonal Univariate Data with Large Periods of Missingness.” *Wireless Communications and Mobile Computing* 2019.
- Fernandes, Ronabson Cardoso, Paulo Sérgio Lucio, and José Henrique Fernandez. 2017. “Data Imputation Analysis for Cosmic Rays Time Series.” *Advances in Space Research* 59 (9): 2442–57.
- He, Dakuo, Zhengsong Wang, Le Yang, and Wanwan Dai. 2017. “Study on Missing Data Imputation and Modeling for the Leaching Process.” *Chemical Engineering Research and Design* 124: 1–19.
- Junger, W, and APde Leon. 2012. “Mtsdi: Multivariate Time Series Data Imputation.” *R Package 0.3* 3.
- Junger, W, N Santos, and A Ponce de Leon. 2003. “Missing Data Imputation in Multivariate Time Series via EM Algorithm.” *Cadernos Do IME* 15 (8): 21.
- Meyler, Aidan, Geoff Kenny, and Terry Quinn. 1998. “Forecasting Irish Inflation Using ARIMA Models.”
- Motesaddi Zarandi, Saeed, Mostafa Hadei, Seyed Saeed Hashemi, Elahe Shahhosseini, Philip K Hopke, Zahra Namvar, and Abbas Shahsavani. 2022. “Effects of Ambient Air Pollutants on Hospital Admissions and Deaths for Cardiovascular Diseases: A Time Series Analysis in Tehran.” *Environmental Science and Pollution Research*, 1–13.
- Zhang, Wenjie, Yonghong Luo, Ying Zhang, and Dipti Srinivasan. 2020. “SolarGAN: Multivariate Solar Data Imputation Using Generative Adversarial Network.” *IEEE Transactions on Sustainable Energy* 12 (1): 743–46.