



The air we breathe: An In-depth analysis of PM_{2.5} pollution in 1312 cities from 2000 to 2020

Qin Zhou¹ · Mir Muhammad Nizamani² · Hai-Yang Zhang³ · Hai-Li Zhang¹

Received: 31 March 2023 / Accepted: 25 July 2023 / Published online: 31 July 2023

© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2023

Abstract

In recent decades, the phenomenon of rapid urbanization in various parts of the world has led to a significant increase in PM_{2.5} concentration, which has emerged as a growing social concern. In order to achieve the objective of sustainable development, the United Nations Global Sustainable Development Goals (SDGs) have established the goal of creating inclusive, safe, resilient, and sustainable cities and human habitats (SDG 11). Goal 11.6 aims to decrease the negative environmental impact per capita in cities, with an emphasis on urban air quality and waste management. However, the global distribution of PM_{2.5} pollution varies due to disparities in urbanization development in different regions. The purpose of this paper is to explore the global spatial distribution and temporal variation of PM_{2.5} in cities with populations greater than 300,000 from 2000 to 2020, to gain insight into the issue. The findings indicate that PM_{2.5} concentrations are expected to continue increasing as urbanization progresses, but the rate of evolution of PM_{2.5} concentration varies depending on the continent, country, and city. From 2000 to 2020, PM_{2.5} concentration increased significantly in Asia and Africa, with the majority of the increased concentrations located in Asian countries and some African countries. On the other hand, most European and American countries had lower PM_{2.5} concentrations. The results of this study have the potential to inform urbanization policy formulation by providing knowledge about the spatial distribution of PM_{2.5} pollution during global urbanization. Addressing the issue of PM_{2.5} pollution is critical in achieving SDG 11.6 and promoting sustainable and coordinated development in cities worldwide.

Keywords Global spatial distribution · PM_{2.5} concentration · Rapid urbanization · SDG 11.6

Responsible Editor: Gerhard Lammel

Qin Zhou and Mir Muhammad Nizamani are the co-first authors of the article.

Highlight

1. The temporal and spatial distribution of PM_{2.5} concentrations in various continents, countries, and cities varied significantly from 2000 to 2020.
2. Asia and Africa had the highest average annual PM_{2.5} concentrations globally from 2000 to 2020, while Oceania had the lowest.
3. During the first two decades of the 21st century, countries in Asia, Africa, and tropical deserts had the highest annual average PM_{2.5} concentrations, with Bangladesh having the highest and Australia having the lowest.
4. Delhi had the highest average annual PM_{2.5} concentration for 20 consecutive years, while Gold Coast-Tweed Head had the lowest among the 1312 cities surveyed between 2000 and 2020.
5. China's average annual PM_{2.5} concentration has been decreasing slowly since 2015, primarily due to the country's active implementation of Sustainable Development Goals (SDGs).

Extended author information available on the last page of the article

Introduction

In recent decades, the world has undergone rapid urbanization. In the 1960s, only 30% of the world's population lived in cities, but this figure increased to 55% in 2018 and is projected to rise to 68% by 2050. By 2050, it is expected that 4.6 to 7.7 billion people will be living in urban areas, representing 55–78% of the projected total world population of 8.5–9.9 billion (UN 2018; Jiang and O'Neill 2017). Urbanization involves population growth and notable features such as economic and land use transformation (Qin et al. 2018). Although urban areas cover less than 1% of the world's land, they generate 75% of the world's gross domestic product (GDP) and consume approximately 60–80% of the energy. However, they also produce 75% of global waste and carbon emissions (Elmqvist et al. 2019), making the ecological footprint of human activities in urban areas approximately 200 times more environmentally damaging than that of rural areas (Huang et al. 2018). The global spatial distribution and

temporal variation of PM_{2.5} in cities with populations greater than 300,000 is still not well documented in the literature.

Urbanization poses a range of challenges for humans, such as traffic congestion, increased pressure on waste disposal, air pollution, and water pollution. However, urbanization is also the result of economic development. The Environmental Kuznets Curve (EKC) hypothesis, which was originally used to examine the relationship between economic growth and environmental pollution (Grossman and Krueger 1995), has received considerable attention and extensive research on urbanization development. The EKC hypothesis suggests an "inverted U" relationship between economic growth and environmental pollution, meaning that environmental pollution undergoes a process of deterioration and then improvement as economic growth changes, has been widely employed to explore the relationship between urbanization, environmental pollution, and waste emissions (Bekhet and Othman 2017).

Urbanization has emerged as a significant factor influencing climate change. To achieve sustainable and coordinated development between humans, the environment, society, and the economy, the United Nations Global Sustainable

Development Goals (SDGs) (UN 2015) have established the objective of "Building inclusive, safe, resilient, and sustainable cities and human habitats" (SDG 11). The SDG 11.6 aims to reduce the detrimental environmental impacts per capita in cities by 2030, with a particular focus on urban air quality, city waste management, and other areas. The 11.6.2 indicator places emphasis on the annual average urban fine particulate matter (such as PM_{2.5}) values (weighted by population). The outbreak of the COVID-19 pandemic in early 2020 exposed the deficiencies and vulnerabilities of many cities and has prompted countries to hasten the implementation of the 2030 SDGs (UN 2021).

In recent years, the global concentration of PM_{2.5} has received considerable attention from the public, government, and academia (Li et al. 2016). PM_{2.5} refers to particulate matter found in both urban and non-urban environments, with an aerodynamic diameter of 2.5 μm or less. Due to its small size and chemical reactivity, PM_{2.5} can easily penetrate the respiratory system and cause harm to human health (WHO 2021; Chen et al. 2013). The PM_{2.5} concentration index is an essential evaluation project for the SDGs in sustainable city construction, which is critical for the healthy

Table 1 List of PM_{2.5} data sources

Data category	Provider	Website
PM _{2.5} data of 1312 global cities	Aerosol Optical Depth (AOD) Global Rural-Urban	https://sites.wustl.edu/acag/datasets/surface-pm2-5/
Urban extent polygons	Mapping Project, Version 1 (GRUMPv1)	http://sedac.ciesin.columbia.edu/
1312 Global population over Cities with 300,000 or more Residents	UN DESA	https://population.un.org/wup/

Fig. 1 Distribution of 1312 cities with a global population greater than 300,000

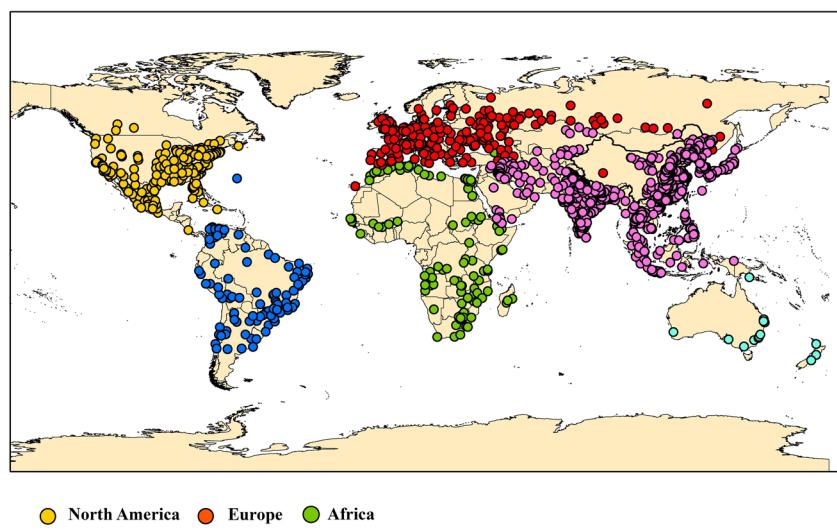


Fig. 2 Global PM_{2.5} average trend in 1312 cities from 2000–2020. (a) 2000 Global PM_{2.5} ($\mu\text{g}/\text{m}^3$) average trend, (b) 2005 Global PM_{2.5} ($\mu\text{g}/\text{m}^3$) average trend, (c) 2010 Global PM_{2.5} ($\mu\text{g}/\text{m}^3$) average trend, (d) 2015 Global PM_{2.5} ($\mu\text{g}/\text{m}^3$) average trend, (e) 2020 Global PM_{2.5} ($\mu\text{g}/\text{m}^3$) average trend

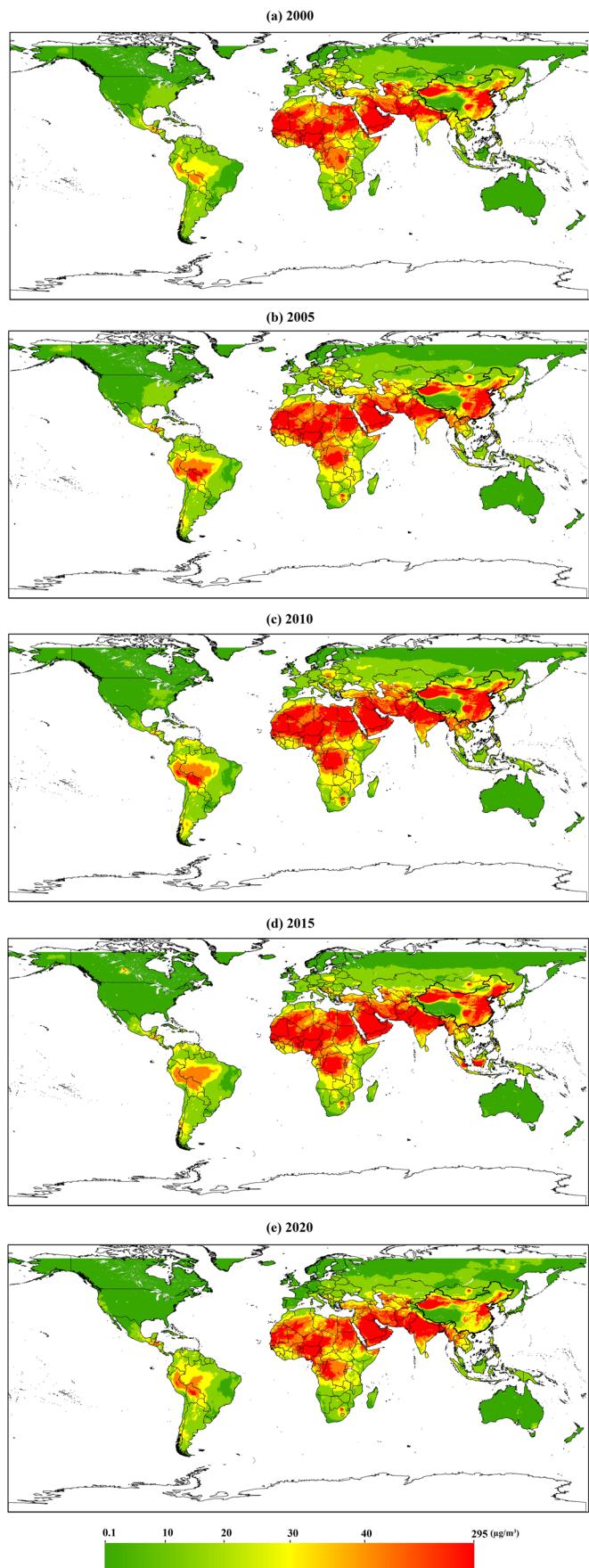
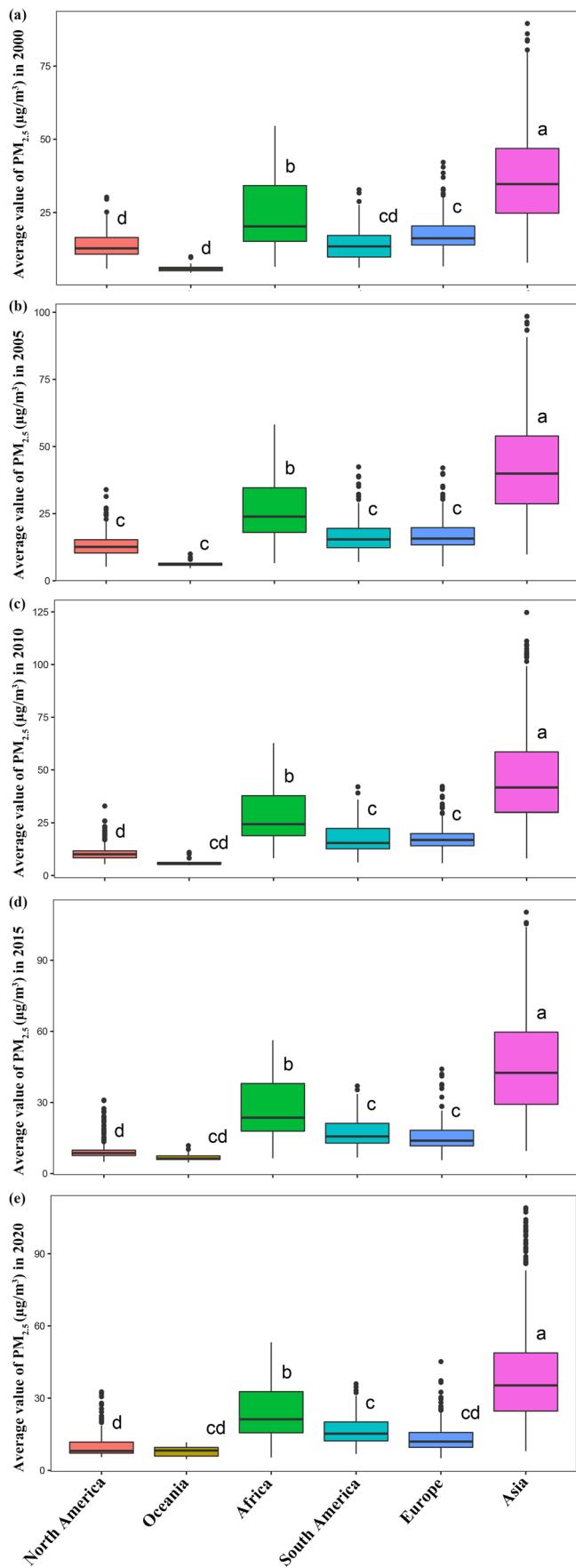


Fig. 3 Box plot of PM_{2.5} mean change by continent from 2000–2020. (a) Average change in PM_{2.5} ($\mu\text{g}/\text{m}^3$) by continent in 2000, (b) Average change in PM_{2.5} ($\mu\text{g}/\text{m}^3$) by continent in 2005, (c) Average change in PM_{2.5} ($\mu\text{g}/\text{m}^3$) by continent in 2010, (d) Average change in PM_{2.5} ($\mu\text{g}/\text{m}^3$) by continent in 2015, (e) Average change in PM_{2.5} ($\mu\text{g}/\text{m}^3$) by continent in 2020



development of the urban environment (Gupta and Vegelin 2016).

The World Health Organization (WHO) issued Air Quality Guidelines (AQG) that included an average annual guideline exposure level for PM_{2.5} of 10 µg/m³ (WHO 2006). This guideline value was intended to inform national policymakers on the level to which air pollution should be reduced to protect people from PM_{2.5} pollution. However, the latest edition of AQG indicates that the risk of non-accidental death did not decrease in environments with PM_{2.5} concentrations lower than 10 µg/m³ (WHO 2021), but rather increased more sharply (Chen and Hoek 2020). As a result, it is recommended that AQG levels in human residential environments should not exceed 5 µg/m³ to safeguard people from PM_{2.5}. Epidemiological studies have confirmed that prolonged exposure to PM_{2.5} can lead to various acute and chronic diseases, such as lung cancer (LC), ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD), lower respiratory tract infection (LRI), asthma, cardiovascular disease, and other health complications (Bartell et al. 2013; Zheng et al. 2015; Wei et al. 2019; Maji et al. 2018; Wang et al. 2023).

The Global Burden of Disease (GBD) report in 2015 estimated that PM_{2.5} caused 409 million (95% UI: 3.7–4.8 million) premature deaths and 103.1 million (95% UI: 90.8–115.1 million) disability-adjusted life years (DALYs), with IHD, COPD, LRI, and LC being the major causes of death. The report also indicated that long-term exposure to PM_{2.5} was responsible for 4.2 million deaths globally in 2015, with eastern and southern Asia having the highest number of deaths. The number of deaths attributable to PM_{2.5} pollution varies between countries, with China and India having the highest deaths among the ten most populous countries (Cohen et al. 2017). In a study by Im et al. (2023), the premature mortality associated with PM_{2.5} in 2050 was projected, showing that demographic factors of exposure to air pollution influence the increase in the mortality rate more than the level of air pollutants themselves. Further studies revealed nine causes of death attributed to PM_{2.5} pollution in 2019, including cardiovascular disease, cerebrovascular disease, chronic kidney disease, chronic obstructive pulmonary disease, dementia, type 2 diabetes, hypertension, lung cancer, and pneumonia (Bowe et al. 2019). Five new causes of death

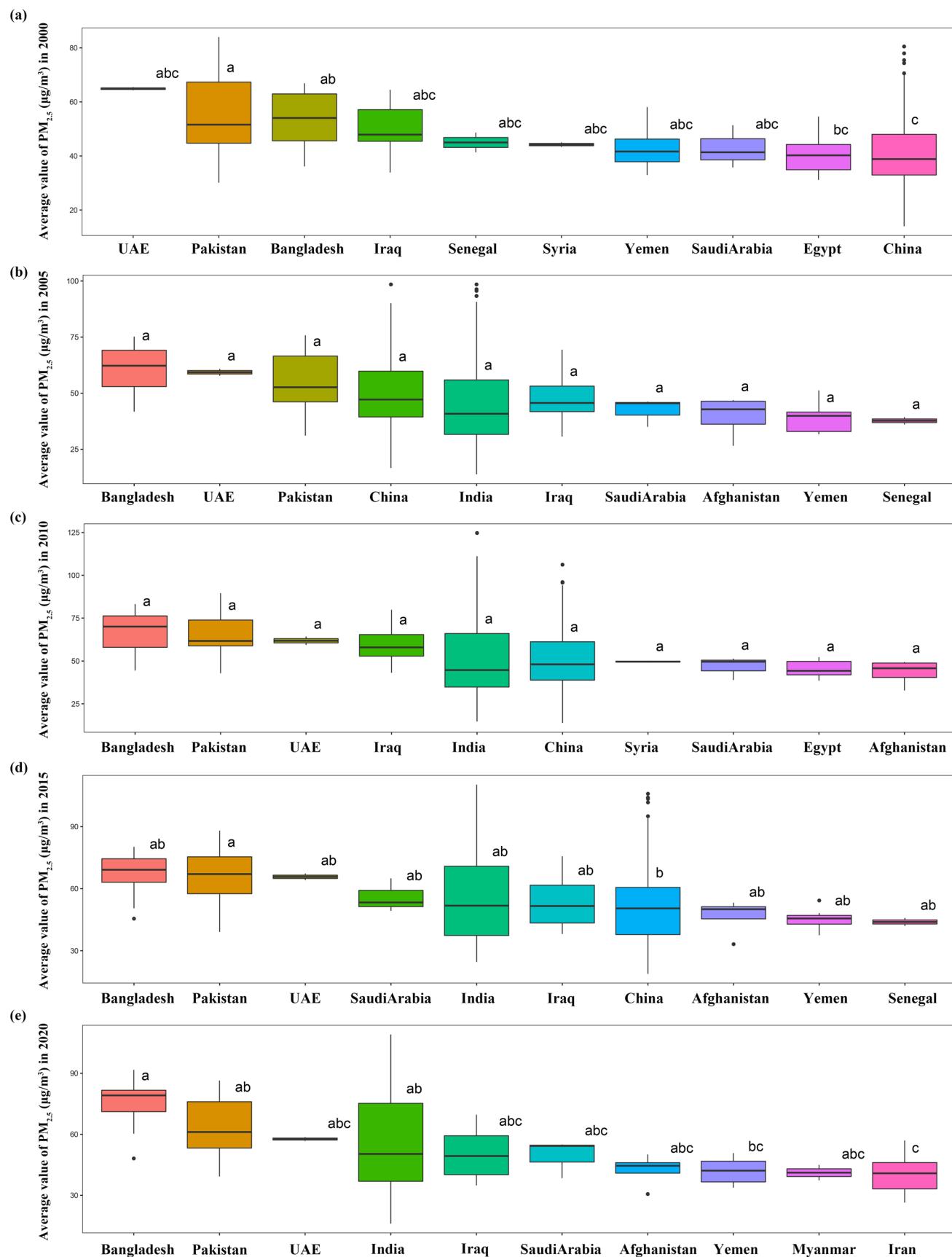
related to PM_{2.5} pollution was added compared to 2016. A growing number of studies have proven that long-term exposure to PM_{2.5} is associated with many unknown causes of death (Pope III et al. 2009; Di et al. 2017; Burnett et al. 2018; Lanigan et al. 2018). Many studies have also focused on deaths attributed to long-term exposure to PM_{2.5} in different countries (Chen and Hoek 2020; Thurston et al. 2016; Pinault et al. 2016; Etchie et al. 2017).

To reduce the negative impact of PM_{2.5} pollution on human health, it is crucial to closely and accurately monitor global PM_{2.5} concentrations (Crouse et al. 2012; Guo et al. 2018), particularly in large cities where millions of people live in poor air quality conditions (Baklanov et al. 2016). In Huancayo city, the political capital of the Junín region in the Central utilized the weight method to determine the annual average concentration range of PM_{2.5} (Huamán De La Cruz et al. 2019). However, automatic monitoring of PM_{2.5} requires the use of the β-radiation absorption and micro-oscillation balance methods. In the spring of 2010, the β-radiation absorption method was employed to detect PM_{2.5} in Chongqing, China. The TEOM method, which is based on the micro-oscillation balance principle of conical cells, was also used (Allen et al. 1997; Li et al. 2012; Wang et al. 2023). Nevertheless, PM_{2.5} has a tendency to adhere to the inner wall of the container, which can result in measurement errors and reduced accuracy (Gu et al. 2021).

In recent decades, expertise in using satellite products and computer software to detect PM_{2.5} concentrations has significantly increased. This has led to the emergence of more high-resolution satellite products capable of monitoring changes in PM_{2.5} concentrations more swiftly and efficiently. For instance, Aerosol Optical Depth (AOD) derived from satellite inversion serves as a valuable supplement to ground measurements (Van Donkelaar et al. 2010; Zang et al. 2019; Zhang et al. 2019a). Satellite-inverted AOD provides real-time monitoring of the vertical distribution of PM_{2.5} column concentration from the ground to the atmosphere. As such, it is dependent not only on ground concentration but also on the vertical distribution of PM_{2.5} concentration within the column. Consequently, numerous studies are concentrating on developing regression models to establish a more accurate

Table 2 Global PM_{2.5} averages and standard deviations for 1312 cities from 2000 to 2020

Continent	2000 PM _{2.5} (µg/m ³)	2005 PM _{2.5} (µg/m ³)	2010 PM _{2.5} (µg/m ³)	2015 PM _{2.5} (µg/m ³)	2020 PM _{2.5} (µg/m ³)
North America	13.72 ± 4.26	13.40 ± 4.64	10.94 ± 4.33	10.31 ± 5.02	10.52 ± 5.58
Oceania	6.10 ± 1.64	6.43 ± 1.38	6.36 ± 1.84	7.11 ± 1.95	7.87 ± 2.16
Africa	24.52 ± 11.97	26.49 ± 10.76	28.28 ± 12.04	26.95 ± 12.05	24.04 ± 10.58
South America	14.62 ± 5.79	17.25 ± 7.26	17.75 ± 7.42	17.40 ± 6.54	16.92 ± 6.45
Europe	17.68 ± 5.97	17.28 ± 6.07	17.78 ± 6.00	15.64 ± 6.21	13.54 ± 5.71
Asia	36.68 ± 15.81	42.63 ± 18.91	45.10 ± 21.44	45.93 ± 20.98	39.15 ± 20.36



◀Fig. 4 Boxplot of changes in the top 10 countries with the highest average PM_{2.5} from 2000 to 2020. (a) Top 10 countries with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2000, (b) Top 10 countries with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2005, (c) Top 10 countries with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2010, (d) Top 10 countries with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2015, (e) Top 10 countries with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2020

relationship between AOD and surface PM_{2.5} (Van Donkelaar et al. 2006). Using machine learning (ML) technologies and surface PM_{2.5} data measured by the China National Environmental Monitoring Center, a quantitative relationship between surface PM_{2.5} and AOD was discovered (Dong et al. 2020; Bhatti et al. 2023).

Our study aimed to monitor the changing trends and global distribution of PM_{2.5} across different continents, countries, and cities. To accomplish this, we obtained the annual average value of PM_{2.5} from 2000 to 2020 in 1312 cities with a global population exceeding 300,000. Specifically, we sought to achieve two objectives: (1) track changes in PM_{2.5} levels across various regions and (2) investigate whether the UN's sustainable development policies are being realized.

Methods

City boundary data preparation

The data regarding city boundaries is obtained from the United Nations database (Table 1). This information is utilized to estimate the size of urban populations and agglomerations based on national statistical data. However, it is crucial to note that there is no standardized definition of what constitutes a city, and the definitions can significantly vary within and among countries. The Population Division of the United Nations Department of Economic and Social Affairs attempts to define cities using the urban agglomeration concept whenever possible. Nevertheless, in cases where this information is not consistently available, population data based on administrative boundaries is employed. In this study, we have selected 1312 cities with populations exceeding 30 (Fig. 1), based on the World Urbanization Prospects: The 2018 Revision (DESA 2018). The study necessitates data from 2000 to 2020, with five-year intervals across five phases, which is provided in Table 1. The required data for this research is presented in Table 1.

PM_{2.5} concentration data

The PM_{2.5} emission data utilized in this study are obtained from the global PM_{2.5} data published by Aerosol Optical Depth (AOD) (Aaron et al. 2021). The original spatial data products are available in txt and NetCDF formats, which are

then processed and converted into the GeoTIFF format with a spatial resolution of $0.01^\circ \times 0.01^\circ$. The dataset is a global interannual scale grid product that is based on the chemical transport model GEOS-Chem to establish the correlation between AOD and near-surface PM_{2.5} concentrations. The data from 2000 to 2020 can be downloaded for free, and it has a spatial resolution of $0.01^\circ \times 0.01^\circ$, with a file format of GeoTIFF. This data has removed dust and sea salt ground fine particulate matter and is combined with AOD retrieval from multiple satellite sensors. The accuracy and high fit of this data are verified with 210 global ground monitoring data on PM_{2.5}. To demonstrate the spatial distribution and intensity differences of PM_{2.5} emissions in different regions, we utilized the ArcGIS software.

PM_{2.5} average calculation method

To calculate the average PM_{2.5} concentration for 1312 cities worldwide, we utilized the Zonal Statistics as a Table tool in ArcGIS 10.2. This tool was used to determine the mean value of PM_{2.5} in each city, which was then assigned to all output units within the district. The formula used to calculate the arithmetic mean of PM_{2.5} concentration is as follows.

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$$

where \bar{x} is the mean, x_i is the observed value. N is the number of observations.

To obtain statistical results on the average PM_{2.5} concentration for each city with populations over 300,000, we utilized the Zone Raster tool in ArcGIS 10.2. Firstly, the built-up area boundaries of these cities were inputted into the tool, followed by the values raster that contains the global annual PM_{2.5} grid. Lastly, the output raster was utilized to determine the statistical results of the average PM_{2.5} output for each city.

Analytical method

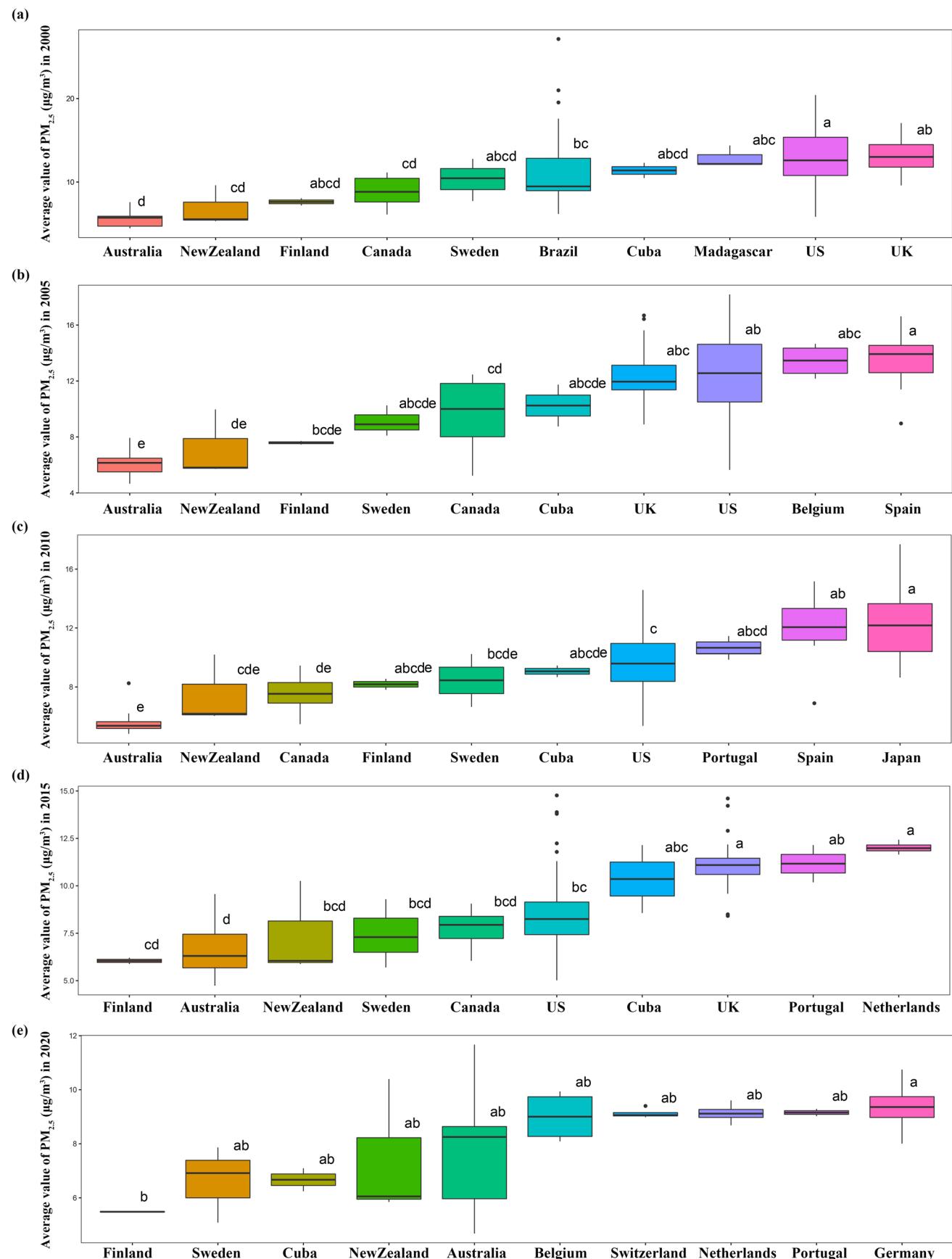
To calculate the mean and standard deviation data of PM_{2.5} concentration for each state and city, we utilized the R language 4.0 software package. Additionally, we also created visualizations using this software package.

Here's a mathematical representation of the formula for calculating the standard deviation:

$$\text{Standard Deviation} = \sqrt{\frac{\sum(x - \mu)^2}{N}}$$

Where:

- Σ represents the sum of a series (summing over all values)



◀Fig. 5 Changes in the top 10 countries with the lowest PM_{2.5} average from 2000 to 2020. (a) Top 10 countries with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2000, (b) Top 10 countries with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2005, (c) Top 10 countries with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2010, (d) Top 10 countries with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2015, (e) Top 10 countries with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2020

- x represents an individual value from the table
- μ represents the mean (average) of the values
- N represents the total number of values in the table

Results

Global PM_{2.5} average change by continent

Between 2000 and 2020, the lowest mean PM_{2.5} concentration for the 1312 cities with a population greater than 300,000 worldwide was recorded in 2020 (18.67 ± 10.49) (Fig. 2). In the last 20 years, Oceania had the lowest mean PM_{2.5} concentration among the six continents, as shown in Fig. 2, Fig. 3, and Table 2. Specifically, the mean PM_{2.5} concentrations in Oceania were 6.10 ± 1.64 in 2000, 6.43 ± 1.38 in 2005, 6.36 ± 1.84 in 2010, 7.11 ± 1.95 in 2015, and 7.87 ± 2.16 in 2020. In contrast, the highest PM_{2.5} averages were recorded in Asia over the same 20-year period, which were 36.68 ± 15.81 in 2000, 42.63 ± 18.91 in 2005, 45.10 ± 21.44 in 2010, 45.93 ± 20.98 in 2015, and 39.15 ± 20.36 in 2020. In general, Oceania, North America, and South America were the top three continents with the lowest PM_{2.5} concentrations between 2000 and 2020.

Changes in PM_{2.5} averages in different countries

The statistical results of the top 10 countries with the highest mean PM_{2.5} concentration were analyzed for 2000, 2005, 2010, 2015, and 2020, and the trends during the study period are presented in Fig. 4. Among the 1312 countries assessed, the top 10 countries with the highest mean PM_{2.5} concentrations in 2000 were the United Arab Emirates (64.9 ± 0.57), Pakistan (54.57 ± 13.79), Bangladesh (53.44 ± 10.1), Iraq (49.41 ± 8.6), Senegal (44.99 ± 3.66), Syrian Arab Republic (44.2 ± 0.84), Yemen (42.98 ± 7.63), Saudi Arabia (42.83 ± 6.46), Egypt (40.88 ± 7.11), and China (40.88 ± 11.87). In 2020, the top 10 countries with the highest mean PM_{2.5} concentrations were Bangladesh (75.42 ± 12.36), Pakistan (63.05 ± 14.11), United Arab Emirates (57.68 ± 0.94), India (56.66 ± 23.38), Iraq (49.82 ± 10.59), Saudi Arabia (49.25 ± 7.63), Afghanistan (42.44 ± 7.19), Myanmar (39.43 ± 8.05), Iran (38.92 ± 13.17), and Indonesia (38.05 ± 11.07). Notably, United Arab Emirates, Pakistan, Bangladesh, Iraq, Yemen, and Saudi Arabia were ranked among the top countries with the highest PM_{2.5} averages in both 2000 and 2020. Between 2000 and 2020, the average PM_{2.5} concentrations in the United Arab Emirates

and Yemen decreased by $7.22 \mu\text{g}/\text{m}^3$ and $1.05 \mu\text{g}/\text{m}^3$, respectively, while the average PM_{2.5} concentrations in Pakistan, Bangladesh, Iraq, and Saudi Arabia increased by $1.5 \mu\text{g}/\text{m}^3$, $8.48 \mu\text{g}/\text{m}^3$, $21.98 \mu\text{g}/\text{m}^3$, and $6.42 \mu\text{g}/\text{m}^3$, respectively. The top 10 countries with the highest mean PM_{2.5} concentrations in 2020 did not include Senegal, Syrian Arab Republic, Egypt, and China, but instead added India, Afghanistan, Myanmar, and Iran (Fig. 5).

Change of average PM_{2.5} in different cities

During the study period from 2000 to 2020, Delhi in India, Asia, had the highest annual average PM_{2.5} concentration among the 1312 cities analyzed. Specifically, the annual mean PM_{2.5} concentrations were 89.55 in 2000, 98.49 in 2005, 124.71 in 2010, 110.30 in 2015, and 109.08 in 2020 (Fig. 6). In contrast, Canberra, located in Australasia, had the lowest annual average PM_{2.5} concentration in the recent 20 years, with a mean PM_{2.5} concentration of 4.45 in 2000 (Fig. 7).

Discussion

The causes of PM_{2.5} changes in different continents

This study aimed to investigate the PM_{2.5} concentrations in 1312 cities worldwide with populations greater than 300,000, as defined by the United Nations. Our objective was to analyze the distribution and evolution of PM_{2.5} in urban areas between 2000 and 2020. Our findings revealed that the average global PM_{2.5} concentration in cities with populations greater than 300,000 was $18.67 \mu\text{g}/\text{m}^3$ in 2020, which exceeded the WHO's 2021 annual guideline PM_{2.5} of $5 \mu\text{g}/\text{m}^3$ by more than three times. These results are consistent with previous studies that have identified similar spatial distribution patterns and temporal evolution of PM_{2.5} in global cities (WHO 2016; Southerland et al. 2022; Bhatti et al. 2021, 2022).

The PM_{2.5} concentration in 2020 was $0.22 \mu\text{g}/\text{m}^3$ lower than that in 2000, indicating a positive trend towards achieving the UN global sustainable development goal SDG11.6.2. However, it is essential to note that although the overall trend is positive, several cities and countries continue to experience high PM_{2.5} concentrations, which could have adverse health effects on their populations (Hu et al. 2023). Our study's findings highlight the need for continued efforts to reduce PM_{2.5} concentrations in cities worldwide and achieve the WHO's air quality guidelines to ensure the health and well-being of urban populations.

The spatial distribution of PM_{2.5} pollution in global urban areas over the last 20 years has revealed a trend

Fig. 6 Boxplot of changes in the top 10 cities with the highest average PM_{2.5} from 2000 to 2020. (a) Top 10 cities with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2000, (b) Top 10 cities with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2005, (c) Top 10 cities with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2010, (d) Top 10 cities with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2015, (e) Top 10 cities with the highest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2020

in which developed countries such as Oceania, Europe, and North America exhibit high urbanization rates but low PM_{2.5} concentrations. In contrast, developing countries like Asia and Africa show a low urbanization rate but high PM_{2.5} concentration. Our analysis of the 2000–2020 time period shows that the annual average value of global PM_{2.5} in Oceania, South America, and Asia has shown an upward trend, while Europe, North America, and Africa have shown a downward trend.

Although the average value of PM_{2.5} in Oceania is increasing, it remains below 8 $\mu\text{g}/\text{m}^3$. In contrast, the average value of PM_{2.5} in South America and Asia is consistently higher, at over 14 $\mu\text{g}/\text{m}^3$ and 36 $\mu\text{g}/\text{m}^3$, respectively. Although the average value of PM_{2.5} in Africa decreased from 2000 to 2020, its annual average value remains significantly higher than that in Europe and North America. Therefore, Asia and Africa have consistently shown high growth in PM_{2.5} concentrations, while Europe, North America, and Oceania countries have experienced low growth in PM_{2.5} concentrations.

These findings indicate that, although urbanization plays a critical role in a country's development, it also significantly impacts PM_{2.5} concentrations. Hence, policymakers must adopt effective measures to curb the rise in PM_{2.5} concentrations in developing countries and sustain the progress made in developed countries. The continued use of cleaner fuels, renewable energy sources, and the promotion of public transportation could help in reducing PM_{2.5} concentrations in urban areas worldwide, thus enhancing the quality of life and safeguarding human health.

Reasons for PM_{2.5} changes by country

The spatial and temporal evolution of global PM_{2.5} concentrations are closely related to the high rate of urbanization, and our findings are consistent with previous studies (WCR 2016; WHO 2016). The Environmental Kuznets Curve (EKC) hypothesis can help us better understand the relationship between economic change and environmental pollution (Grossman and Krueger 1995). Our analysis of global PM_{2.5} distribution in the last 20 years confirms the EKC hypothesis that PM_{2.5} concentrations are generally higher in countries with low urbanization rates, while lower PM_{2.5} concentrations are found in most countries with high urbanization rates. This trend is also observed in previous studies by Yang et al. 2018; Li et al. 2016; Wang et al. 2019; Wang et al. 2018; Chen et al. 2018; Wu et al. 2021; Liu et al.

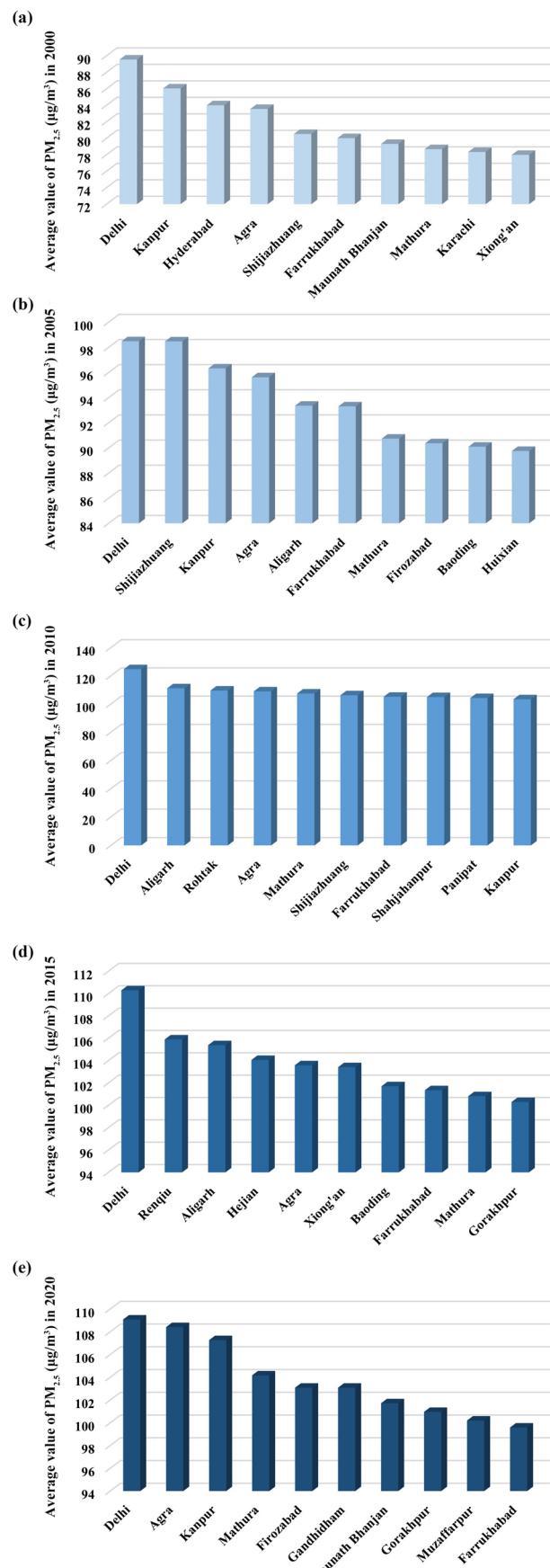


Fig. 7 Boxplot of changes in the top 10 cities with the lowest PM_{2.5} average from 2000 to 2020. (a) Top 10 cities with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2000, (b) Top 10 cities with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2005, (c) Top 10 cities with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2010, (d) Top 10 cities with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2015, (e) Top 10 cities with the lowest average PM_{2.5} ($\mu\text{g}/\text{m}^3$) in 2020

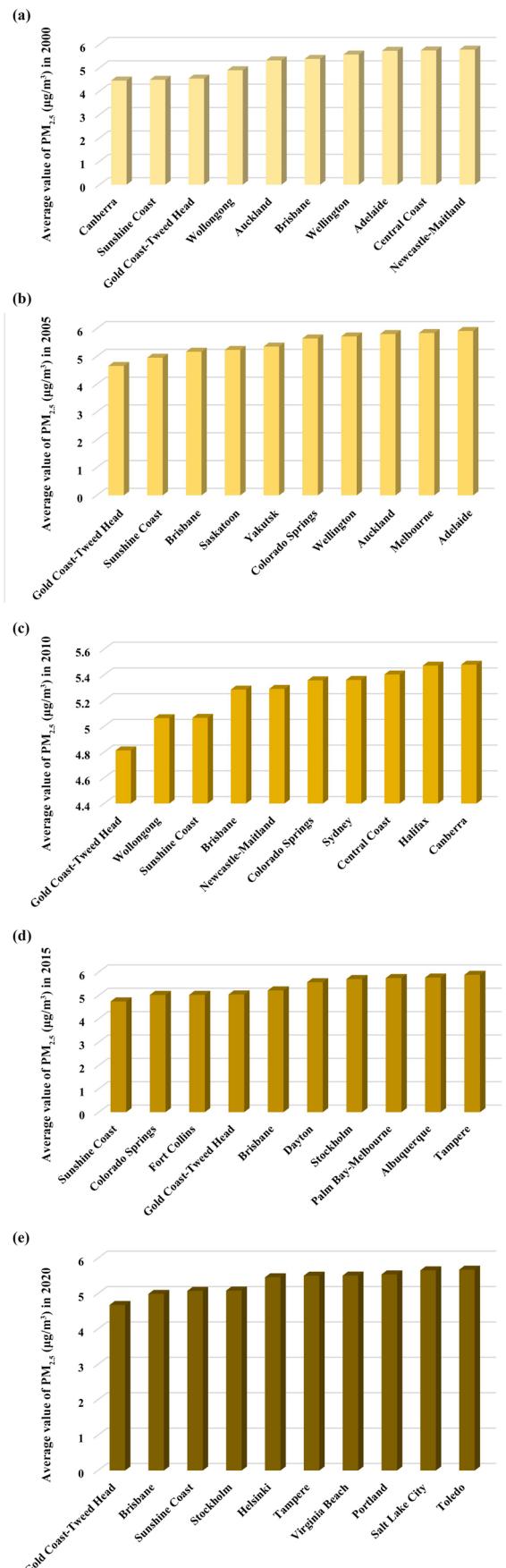
2022, which indicate a negative correlation between PM_{2.5} concentrations and urbanization.

The top 10 countries with the highest global PM_{2.5} averages in the last 20 years include Asian and African countries such as the United Arab Emirates, Pakistan, Bangladesh, Iraq, and Saudi Arabia (Fig. 4), which have high PM_{2.5} concentrations due to their low urbanization rates. It is worth noting that some tropical desert countries with lower urbanization rates, such as the United Arab Emirates, Iraq, and Saudi Arabia, have higher PM_{2.5} concentrations due to desert sources of pollution in the region. In 2020, the average PM_{2.5} concentrations in these countries far exceed the AQG standard for 2021 (5 $\mu\text{g}/\text{m}^3$) by a factor of 11.54, 9.96 and 9.85, respectively.

In contrast, the top 10 countries with the lowest global PM_{2.5} averages are generally countries in Europe and Oceania, which have high urbanization rates and therefore lower PM_{2.5} concentrations. Countries such as Finland, Australia, and New Zealand have PM_{2.5} averages in 2020 that are 1.1, 1.55, and 1.49 times the AQG standard, respectively. These findings indicate that effective measures must be adopted to control PM_{2.5} concentrations in developing countries with low urbanization rates and sustain progress in developed countries with high urbanization rates. The use of cleaner fuels, renewable energy sources, and promoting public transportation could be essential in reducing PM_{2.5} concentrations in urban areas worldwide and enhancing the quality of life while safeguarding human health.

In recent years, there has been a growing effort among countries to achieve the management of PM_{2.5} in response to the United Nations Sustainable Development Goals (SDGs). Our study shows that certain regions like Europe, America, and Oceania have experienced a relatively slow change in annual average PM_{2.5} concentrations over the last 20 years, with countries like Australia, New Zealand, and Finland exhibiting a slow decreasing trend in PM_{2.5} concentrations. Finland, in particular, saw a significant decrease of 39.23% in annual average PM_{2.5} concentration from 2000 to 2020.

The central governmental norms in Europe for preventing pollution and mitigating pollutant emissions are the Air Quality Directive (AQD) and the National Emissions Ceiling Directive (NECD) (UNION 2008). The NECD sets emission caps for pollutants such as sulfur dioxide, nitrogen oxides, non-methane volatile organic compounds, and ammonia emissions (Bourguignon 2015). Studies have shown that the implementation of NECDs and AQDs in



the 28 EU member states has led to a steady decrease in ground-level concentrations of almost all emissions (SO_2 , NO , $\text{PM}_{2.5}$, PM_{10} , NMVOC, NH_3) regarding $\text{PM}_{2.5}$ pollution (Beloconi et al. 2018; Kazemzadeh et al. 2022; Shelestov et al. 2021; Yin et al. 2021). From 2000–2014, both $\text{PM}_{2.5}$ and PM_{10} decreased by about 25% in Europe (Koolen and Rothenberg 2019). The concentrations of $\text{PM}_{2.5}$ and PM_{10} in Germany were reduced by 34% and 20% in 2014 compared to 2000. This decrease is mainly attributed to the increase in clean and renewable energy sources, which has reduced the dependence on fossil fuel energy and, in turn, reduced environmental pollution and $\text{PM}_{2.5}$ emissions.

Similarly, Asian and African countries are also responding positively to the SDGs by optimizing their industrial structure and reducing pollutant emissions. However, these regions still face significant challenges in managing $\text{PM}_{2.5}$ concentrations due to high urbanization rates and increasing energy demands. Implementing regulations and policies to reduce emissions from industrial and transportation sources can help mitigate the $\text{PM}_{2.5}$ pollution problem in these regions. Our study highlights the importance of addressing $\text{PM}_{2.5}$ pollution and achieving the United Nations SDGs. It also emphasizes the need for continuous efforts to reduce emissions and transition towards cleaner and more sustainable energy sources to mitigate the negative impact of urbanization on air quality.

Reasons for different changes in $\text{PM}_{2.5}$ by city

The concentration of $\text{PM}_{2.5}$ varies significantly between cities, and the top ten cities with the highest annual average $\text{PM}_{2.5}$ concentration from 2000–2020 are all located in India, China, and Pakistan, with Indian cities accounting for the largest share. Delhi, India, has been the city with the highest $\text{PM}_{2.5}$ concentration for 20 consecutive years, with $\text{PM}_{2.5}$ levels exceeding ten times that of Washington, D.C., in 2014 (WHO 2014). The primary sources of $\text{PM}_{2.5}$ pollution in Delhi is the residential, transportation, and industrial sectors, with energy consumption being the largest in south Delhi (Sahu and Kota 2017; Cheng et al. 2016; Pant et al. 2015; Mishra et al. 2015; Kumar et al. 2007; Guo et al. 2017; Mandal et al. 2014; Sharma et al. 2016). Chinese cities, on the other hand, are primarily affected by gaseous precursors such as NO_x and SO_2 (Zhang and Cao 2015), which react with oxidants to produce secondary aerosols (Mather et al. 2003). Industries and motor vehicles in cities such as Shijiazhuang emit large amounts of primary pollutants and secondary aerosol precursors, while also transporting pollutants from nearby industrialized areas, contributing to $\text{PM}_{2.5}$ pollution (Xie et al. 2019; Zhang et al. 2020; Chen et al. 2017; Wang et al. 2015, 2017).

In contrast, the top ten cities with the lowest annual global $\text{PM}_{2.5}$ averages in the last 20 years are located in Oceania,

Europe, and North America, with Oceania cities accounting for the largest share. Sunshine Coast, Gold Coast-Tweed Head, and Brisbane in Queensland, Australia, have been in the ranking, but their overall fluctuation is no more than one $\mu\text{g}/\text{m}^3$. EU member states have actively practiced SDGs and implemented governmental norms, such as the Air Quality Directive and the National Emissions Ceiling Directive, leading to a year-on-year decrease in ground-level concentrations of almost all emissions, including $\text{PM}_{2.5}$. Australia has also invested heavily in biomass energy research to achieve the government-mandated SDGs (Hua et al. 2016). Siting of the plant can effectively reduce long-distance transportation and increase the rational allocation of resources within reach, ensuring the sustainability of economic development, environmental protection, and human development (Jayarathna et al. 2022).

Overall, our study shows that countries worldwide are actively responding to SDGs by optimizing their industrial structure and reducing pollutant emissions, resulting in a slow decrease in annual average $\text{PM}_{2.5}$ concentrations in some regions. However, differences in $\text{PM}_{2.5}$ concentrations between cities and countries persist, and further action is needed to reduce pollution levels to meet WHO's annual guideline $\text{PM}_{2.5}$ of 5 $\mu\text{g}/\text{m}^3$.

Necessary policy changes

Follow necessary policy change should be take to reduce air pollutions.

Strengthen emission standards Governments should enforce stricter emission standards for industries, power plants, and vehicles, which are some of the primary contributors to $\text{PM}_{2.5}$ pollution (Zhang et al. 2019b; Xiao et al. 2020; Chemel et al. 2014). This includes requiring the installation of modern pollution control technologies and promoting the use of cleaner fuels (Sofiev et al. 2018; Zhao et al. 2018; Pope et al. 2017; Shen 2016). **Promote Renewable Energy:** Policies should encourage the shift from fossil fuels to renewable sources of energy like wind, solar, and hydroelectric power. This can be done through incentives like subsidies for renewable energy projects and tariffs for fossil fuel usage.

Improve public transportation By improving public transportation systems, cities can reduce the number of private vehicles on the road, thus reducing emissions. This could involve expanding public transit networks, making them more efficient, and providing incentives for their use (Shi et al. 2017; Ham et al. 2017).

Urban planning Urban planning should prioritize green spaces and pedestrian-friendly areas to help absorb pollutants and promote clean air. The layout of cities should also be designed to minimize pollution exposure to residential areas.

Raise public awareness Governments should invest in education and awareness campaigns about the risks of PM_{2.5} pollution and the steps that individuals can take to reduce their emissions, such as reducing energy consumption and car use(Yue et al. 2020; Huang et al. 2017).

Conclusion

The analysis of global PM_{2.5} concentration and its spatial and temporal distribution over the past two decades has provided valuable insights into the inverse relationship between PM_{2.5} concentration and urbanization, confirming the Environmental Kuznets Curve hypothesis. Our study has demonstrated that countries with low urbanization rates typically have higher PM_{2.5} concentrations, whereas those with high urbanization rates have lower concentrations. The top 10 countries with the highest global PM_{2.5} concentrations are mainly located in Asia and Africa, with a few countries in the Middle East, where low urbanization rates and desert pollution sources are the primary contributors to high PM_{2.5} concentrations. Conversely, the countries with the lowest global PM_{2.5} concentrations are generally found in Europe and Oceania, with high urbanization rates being the primary factor contributing to lower PM_{2.5} concentrations. These findings provide crucial insights into the relationship between economic development, urbanization, and environmental pollution, particularly for PM_{2.5}. Identifying the factors contributing to high levels of PM_{2.5} pollution can inform policy decisions and interventions to mitigate its effects on public health and the environment. Therefore, it is essential to continue monitoring the spatial and temporal patterns of PM_{2.5} pollution and to work towards achieving sustainable urban development that balances economic growth and environmental protection.

Acknowledgements The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author contributions Conceptualization, H.L.Z., Q.Z., H.Y.Z., and M.M.N.; methodology, H.L.Z., Q.Z., H.Y.Z and M.M.N.; software, H.L.Z., Q.Z., and M.M.N.; validation, H.L.Z., Q.Z., and M.M.N.; formal analysis, H.L.Z., Q.Z., and M.M.N.; investigation, H.L.Z., Q.Z., and M.M.N.; resources, H.L.Z., Q.Z., and M.M.N.; data curation, H.L.Z., Q.Z., and M.M.N.; writing—original draft preparation, M.M.N., H.L.Z., and H.Y.Z.; writing—review and editing, H.L.Z., Q.Z., and M.M.N.; visualization, H.L.Z., Q.Z., and M.M.N.; supervision, M.M.N., H.L.Z., H.Y.Z., and Q.Z.; project administration, M.M.N., H.L.Z., and Q.Z.; funding acquisition, Q.Z., M.M.N., and H.L.Z. All authors have read and agreed to the published version of the manuscript.

Data availability Data usage can be obtained by asking the author.

Declarations

Ethical approval and consent to participate No studies involving human participants or human tissue in the paper.

Consent to publish Not applicable.

Competing interests The authors declare that they have no competing interests.

References

- Allen G, Sioutas C, Kourakis P, Reiss R, Lurmann FW, Roberts PT (1997) Evaluation of the TEOM® method for measurement of ambient particulate mass in urban areas. *J Air Waste Manag Assoc* 47(6):682–689. <https://doi.org/10.1080/10473289.1997.10463923>
- Baklanov A, Molina LT, Gauss M (2016) Megacities, air quality and climate. *Atmos Environ* 126:235–249. <https://doi.org/10.1016/j.atmosev.2015.11.059>
- Bartell SM, Longhurst J, Tjoa T, Sioutas C, Delfino RJ (2013) Particulate air pollution, ambulatory heart rate variability, and cardiac arrhythmia in retirement community residents with coronary artery disease. *Environ Health Perspect* 121(10):1135–1141. <https://doi.org/10.1289/ehp.1205914>
- Bekhet HA, Othman NS (2017) Impact of urbanization growth on Malaysia CO₂ emissions: evidence from the dynamic relationship. *J Clean Prod* 154:374–388. <https://doi.org/10.1016/j.jclepro.2017.03.174>
- Beloconi A, Chrysoulakis N, Lyapustin A, Utzinger J, Vounatsou P (2018) Bayesian geostatistical modelling of PM10 and PM2.5 surface level concentrations in Europe using high-resolution satellite-derived products. *Environ Int* 121:57–70. <https://doi.org/10.1016/j.envint.2018.08.041>
- Bhatti UA, Zeeshan Z, Nizamani MM, Bazai S, Yu Z, Yuan L (2022) Assessing the change of ambient air quality patterns in Jiangsu Province of China pre-to post-COVID-19. *Chemosphere* 288:132569. <https://doi.org/10.1016/j.chemosphere.2021.132569>
- Bhatti UA, Tang H, Wu G, Marjan S, Hussain A (2023) Deep learning with graph convolutional networks: An overview and latest applications in computational intelligence. *Int J Intell Syst* 2023:1–28. <https://doi.org/10.1155/2023/8342104>
- Bhatti UA, Yu Z, Chanussot J, Zeeshan Z, Yuan L, Luo W, ... Mehmood A (2021) Local similarity-based spatial-spectral fusion hyperspectral image classification with deep CNN and Gabor filtering. *IEEE Trans Geosci Remote Sens* 60:1–15. <https://doi.org/10.1109/TGRS.2021.3090410>
- Bourguignon D (2015) Reducing air pollution-National emission ceilings for air pollutants. <https://policycommons.net/artifacts/1336465/reducing-air-pollution/1943608/> on 04 Feb 2023. CID: 20.500.12592/5xn6bj
- Bowe B, Xie Y, Yan Y, Al-Aly Z (2019) Burden of cause-specific mortality associated with PM_{2.5} air pollution in the United States. *JAMA Netw Open* 2(11):e1915834–e1915834. <https://doi.org/10.1001/jamanetworkopen.2019.15834>
- Burnett R, Chen H, Szyszkowicz M, Fann N, Hubbell B, Pope CA III, Spadaro JV (2018) Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proc Natl Acad Sci* 115(38):9592–9597. <https://doi.org/10.1073/pnas.1803222115>
- Chemel C, Fisher BEA, Kong X, Francis XV, Sokhi RS, Good N, Folberth GA (2014) Application of chemical transport model CMAQ

- to policy decisions regarding PM2.5 in the UK. *Atmos Environ* 82:410–417. <https://doi.org/10.1016/j.atmosenv.2013.10.001>
- Chen J, Hoek G (2020) Long-term exposure to PM and all-cause and cause-specific mortality: a systematic review and meta-analysis. *Environ Int* 143:105974. <https://doi.org/10.1016/j.envint.2020.105974>
- Chen Y, Ebenstein A, Greenstone M, Li H (2013) Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proc Natl Acad Sci* 110(32):12936–12941. <https://doi.org/10.1073/pnas.1300018110>
- Chen F, Zhang X, Zhu X, Zhang H, Gao J, Hopke PK (2017) Chemical characteristics of PM2.5 during a 2016 winter haze episode in Shijiazhuang, China. *Aerosol Air Qual Res* 17(2):368–380. <https://doi.org/10.4209/aaqr.2016.06.0274>
- Chen J, Zhou C, Wang S, Li S (2018) Impacts of energy consumption structure, energy intensity, economic growth, urbanization on PM2.5 concentrations in countries globally. *Appl Energy* 230:94–105. <https://doi.org/10.1016/j.apenergy.2018.08.089>
- Cheng Z, Luo L, Wang S, Wang Y, Sharma S, Shimadera H, Hao J (2016) Status and characteristics of ambient PM2.5 pollution in global megacities. *Environ Int* 89:212–221. <https://doi.org/10.1016/j.envint.2016.02.003>
- Cohen AJ, Brauer M, Burnett R, Anderson HR, Frostad J, Estep K, Forouzanfar MH (2017) Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *Lancet* 389(10082):1907–1918. [https://doi.org/10.1016/S0140-6736\(17\)30505-6](https://doi.org/10.1016/S0140-6736(17)30505-6)
- Crouse DL, Peters PA, van Donkelaar A, Goldberg MS, Villeneuve PJ, Brion O, Burnett RT (2012) Risk of nonaccidental and cardiovascular mortality in relation to long-term exposure to low concentrations of fine particulate matter: a Canadian national-level cohort study. *Environ Health Perspect* 120(5):708–714. <https://doi.org/10.1289/ehp.1104049>
- Di Q, Wang Y, Zanobetti A, Wang Y, Koutrakis P, Choirat C, Schwartz JD (2017) Air pollution and mortality in the Medicare population. *N Engl J Med* 376(26):2513–2522. <https://doi.org/10.1056/NEJMoa1702747>
- Dong L, Li S, Yang J, Shi W, Zhang L (2020) Investigating the performance of satellite-based models in estimating the surface PM2.5 over China. *Chemosphere* 256:127051. <https://doi.org/10.1016/j.chemosphere.2020.127051>
- Van Donkelaar A, Martin RV, Park RJ (2006) Estimating ground-level PM2.5 using aerosol optical depth determined from satellite remote sensing. *J Geophys Res: Atmospheres* 111(D21)
- Elmqvist T, Andersson E, Frantzeskaki N, McPhearson T, Olsson P, Gaffney O, Folke C (2019) Sustainability and resilience for transformation in the urban century. *Nat Sustain* 2(4):267–273. <https://doi.org/10.1038/s41893-019-0250-1>
- Etchie TO, Sivanesan S, Adewuyi GO, Krishnamurthi K, Rao PS, Etchie AT, Smith KR (2017) The health burden and economic costs averted by ambient PM2.5 pollution reductions in Nagpur, India. *Environ Int* 102:145–156. <https://doi.org/10.1016/j.envint.2017.02.010>
- Grossman GM, Krueger AB (1995) Economic growth and the environment. *Q J Econ* 110:353–377. <https://doi.org/10.2307/2118443>
- Gu K, Liu H, Xia Z, Qiao J, Lin W, Thalmann D (2021) PM_{2.5} Monitoring: Use Information Abundance Measurement and Wide and Deep Learning. *IEEE Trans Neural Netw Learn Syst* 32(10):4278–4290. <https://doi.org/10.1109/TNNLS.2021.3105394>
- Guo H, Kota SH, Sahu SK, Hu J, Ying Q, Gao A, Zhang H (2017) Source apportionment of PM2.5 in North India using source-oriented air quality models. *Environ Pollut* 231:426–436. <https://doi.org/10.1016/j.envpol.2017.08.016>
- Guo C, Zhang Z, Lau AK, Lin CQ, Chuang YC, Chan J, Lao XQ (2018) Effect of long-term exposure to fine particulate matter on lung function decline and risk of chronic obstructive pulmonary disease in Taiwan: a longitudinal, cohort study. *Lancet Planet Health* 2(3):e114–e125. [https://doi.org/10.1016/S2542-5196\(18\)30028-7](https://doi.org/10.1016/S2542-5196(18)30028-7)
- Gupta J, Vegelin C (2016) Sustainable development goals and inclusive development. *Int Environ Agreem: Politics Law Econ* 16(3):433–448. <https://doi.org/10.1007/s10784-016-9323-z>
- Ham W, Vijayan A, Schulte N, Herner JD (2017) Commuter exposure to PM2.5, BC, and UFP in six common transport microenvironments in Sacramento, California. *Atmos Environ* 167:335–345. <https://doi.org/10.1016/j.atmosenv.2017.08.024>
- Hu F, Qiu L, Xiang Y, Wei S, Sun H, Hu H, ... Zeng M (2023) Spatial network and driving factors of low-carbon patent applications in China from a public health perspective. *Front Public Health* 11:1121860. <https://doi.org/10.3389/fpubh.2023.1121860>
- Hua Y, Oliphant M, Hu EJ (2016) Development of renewable energy in Australia and China: A comparison of policies and status. *Renew Energy* 85:1044–1051. <https://doi.org/10.1016/j.renene.2015.07.060>
- Huamán De La Cruz A, Bendezu Roca Y, Suárez-Salas L, Pomalaya J, Alvarez Tolentino D, Gioda A (2019) Chemical characterization of PM2.5 at rural and urban sites around the metropolitan area of Huancayo (Central Andes of Peru). *Atmosphere* 10(1):21. <https://doi.org/10.3390/atmos10010021>
- Huang L, Rao C, van der Kuijp TJ, Bi J, Liu Y (2017) A comparison of individual exposure, perception, and acceptable levels of PM2.5 with air pollution policy objectives in China. *Environ Res* 157:78–86. <https://doi.org/10.1016/j.envres.2017.05.012>
- Huang DD, Zhou M, Yu CG, Zhu SH, Wang YC, Qiao LP, Li L (2018) Physiochemical properties of the aerosol particles and their impacts on secondary aerosol formation at the background site of the Yangtze River Delta. *Environ Sci* 39(12):5308–5314. <https://doi.org/10.13227/j.hjkx.201802107>
- Im U, Bauer SE, Frohn LM, Geels C, Tsigaridis K, Brandt J (2023) Present-day and future PM2.5 and O3-related global and regional premature mortality in the EVAv6.0 health impact assessment model. *Environ Res* 216:114702. <https://doi.org/10.1016/j.envres.2022.114702>
- Jayaratna L, Kent G, O'Hara I, Hobson P (2022) Geographical information system based fuzzy multi criteria analysis for sustainability assessment of biomass energy plant siting: A case study in Queensland, Australia. *Land Use Policy* 114:105986. <https://doi.org/10.1016/j.landusepol.2022.105986>
- Jiang L, O'Neill BC (2017) Global urbanization projections for the Shared Socioeconomic Pathways. *Glob Environ Chang* 42:193–199. <https://doi.org/10.1016/j.gloenvcha.2015.03.008>
- Kazemzadeh E, Koengkan M, Fuinhas JA (2022) Effect of Battery-Electric and Plug-In Hybrid Electric Vehicles on PM2.5 Emissions in 29 European Countries. *Sustainability* 14:2188. <https://doi.org/10.3390/su14042188>
- Koolen CD, Rothenberg G (2019) Air pollution in Europe. *Chemsuschem* 12(1):164–172. <https://doi.org/10.1002/cssc.201802292>
- Kumar N, Chu A, Foster A (2007) An empirical relationship between PM2.5 and aerosol optical depth in Delhi Metropolitan. *Atmos Environ* 41(21):4492–4503. <https://doi.org/10.1016/j.atmosenv.2007.01.046>
- Landrigan PJ, Fuller R, Acosta NJ, Adeyi O, Arnold R, Baldé AB, Zhong M (2018) The Lancet Commission on pollution and health. *Lancet* 391(10119):462–512. [https://doi.org/10.1016/S0140-6736\(17\)32345-0](https://doi.org/10.1016/S0140-6736(17)32345-0)
- Li G, Fang C, Wang S, Sun S (2016) The effect of economic growth, urbanization, and industrialization on fine particulate matter (PM2.5) concentrations in China. *Environ Sci Technol* 50(21):11452–11459. <https://doi.org/10.1021/acs.est.6b02562>
- Li L, Jiayan Y, Lei B, Chongzhi Z (2012) Concentration analysis of atmospheric particulate matter under typical spring weather condition in Chongqing. *Chinese J Environ Eng* 6(6). <http://hjhx.rcees.ac.cn/en/article/id/20120647?viewType=HTML>

- Liu Y, Tian J, Zheng W, Yin L (2022) Spatial and temporal distribution characteristics of haze and pollution particles in China based on spatial statistics. *Urban Clim* 41:101031. <https://doi.org/10.1016/j.ulclim.2021.101031>
- Maji KJ, Ye WF, Arora M, Nagendra SS (2018) PM_{2.5}-related health and economic loss assessment for 338 Chinese cities. *Environ Int* 121:392–403. <https://doi.org/10.1016/j.envint.2018.09.024>
- Mandal P, Sarkar R, Mandal A, Saud T (2014) Seasonal variation and sources of aerosol pollution in Delhi, India. *Environ Chem Lett* 12:529–534. <https://doi.org/10.1007/s10311-014-0479-x>
- Mather TA, Allen AG, Oppenheimer C, Pyle DM, McGonigle AJS (2003) Size-resolved characterisation of soluble ions in the particles in the tropospheric plume of Masaya volcano, Nicaragua: Origins and plume processing. *J Atmos Chem* 46:207–237. <https://doi.org/10.1023/A:1026327502060>
- Mishra D, Goyal P, Upadhyay A (2015) Artificial intelligence based approach to forecast PM_{2.5} during haze episodes: A case study of Delhi, India. *Atmos Environ* 102:239–248. <https://doi.org/10.1016/j.atmosenv.2014.11.050>
- Pant P, Shukla A, Kohl SD, Chow JC, Watson JG, Harrison RM (2015) Characterization of ambient PM_{2.5} at a pollution hotspot in New Delhi, India and inference of sources. *Atmos Environ* 109:178–189. <https://doi.org/10.1016/j.atmosenv.2015.02.074>
- Pinault L, Tjepkema M, Crouse DL, Weichenthal S, van Donkelaar A, Martin RV, Burnett RT (2016) Risk estimates of mortality attributed to low concentrations of ambient fine particulate matter in the Canadian community health survey cohort. *Environ Health* 15(1):1–15. <https://doi.org/10.1186/s12940-016-0111-6>
- Pope CA III, Ezzati M, Dockery DW (2009) Fine-particulate air pollution and life expectancy in the United States. *N Engl J Med* 360(4):376–386. <https://doi.org/10.1056/NEJMsa0805646>
- Pope D, Bruce N, Dherani M, Jagoe K, Rehfuss E (2017) Real-life effectiveness of ‘improved’ stoves and clean fuels in reducing PM_{2.5} and CO: Systematic review and meta-analysis. *Environ Int* 101:7–18. <https://doi.org/10.1016/j.envint.2017.01.012>
- Qin Y, Zhang Q, Li X, Zhao HY, Tong D, Zheng YX, He KB (2018) Patterns of Mortality from Air Pollutant Emissions in China’s Coal-fired Power Plants. *Environ Sci* 39(12):5289–5295. <https://doi.org/10.13227/j.hjkx.201804157>
- Sahu SK, Kota SH (2017) Significance of PM_{2.5} air quality at the Indian capital. *Aerosol Air Qual Res* 17(2):588–597. <https://doi.org/10.4209/aaqr.2016.06.0262>
- Sharma SK, Mandal TK, Jain S, Sharma A, Saxena M (2016) Source apportionment of PM_{2.5} in Delhi, India using PMF model. *Bull Environ Contam Toxicol* 97:286–293. <https://doi.org/10.1007/s00128-016-1836-1>
- Shelestov A, Yailymova H, Yailymov B, Kussul N (2021) Air quality estimation in Ukraine using SDG 11.6.2 indicator assessment. *Remote Sens* 13(23):4769. <https://doi.org/10.20944/preprints202110.0299.v1>
- Shen G (2016) Changes from traditional solid fuels to clean household energies—opportunities in emission reduction of primary PM_{2.5} from residential cookstoves in China. *Biomass Bioenerg* 86:28–35. <https://doi.org/10.1016/j.biombioe.2016.01.004>
- Shi H, Wang S, Zhao D (2017) Exploring urban resident’s vehicular PM_{2.5} reduction behavior intention: An application of the extended theory of planned behavior. *J Clean Prod* 147:603–613. <https://doi.org/10.1016/j.jclepro.2017.01.108>
- Sofiev M, Winebrake JJ, Johansson L, Carr EW, Prank M, Soares J, Corbett JJ (2018) Cleaner fuels for ships provide public health benefits with climate tradeoffs. *Nat Commun* 9(1):406. <https://doi.org/10.1038/s41467-017-02774-9>
- Southerland VA, Brauer M, Mohegh A, Hammer MS, Van Donkelaar A, Martin RV, ... Anenberg SC (2022) Global urban temporal trends in fine particulate matter (PM_{2.5}) and attributable health burdens: estimates from global datasets. *Lancet Planet Health* 6(2):e139–e146. <https://doi.org/10.2139/ssrn.3871717>
- Thurston GD, Burnett RT, Turner MC, Shi Y, Krewski D, Lall R, Pope CA III (2016) Ischemic heart disease mortality and long-term exposure to source-related components of US fine particle air pollution. *Environ Health Perspect* 124(6):785–794. <https://doi.org/10.1289/ehp.1509777>
- UN (2015) Transforming our world: The 2030 Agenda For Sustainable Development
- Union P (2008) Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe. Official Journal of the European Union. <http://news.cleartheair.org.hk/wp-content/uploads/2013/02/LexUriServ.pdf>
- United Nations. Department of Economic and Social Affairs (DESA) (2018) World youth report: Youth and the 2030 agenda for sustainable development. United Nations Publications, New York
- United Nations (2018) Department of Economic and Social Affairs, Population Division, World Urbanization Prospects, 2018–05–16, 2021–10–15. <https://esa.un.org/unpd/wup/>
- United Nations. The Sustainable Development Goals Report (2021) New York: United Nations. <https://www.un.org/en/desa/sustainable-development-goals-sdgs>
- Van Donkelaar A, Martin RV, Brauer M, Kahn R, Levy R, Verduzco C, Villeneuve PJ (2010) Global estimates of ambient fine particulate matter concentrations from satellite-based aerosol optical depth: development and application. *Environ Health Perspect* 118(6):847–855. <https://doi.org/10.1289/ehp.0901623>
- Wang L, Wei Z, Wei W, Fu JS, Meng C, Ma S (2015) Source apportionment of PM_{2.5} in top polluted cities in Hebei, China using the CMAQ model. *Atmos Environ* 122:723–736. <https://doi.org/10.1016/j.atmosenv.2015.10.041>
- Wang G, Cheng S, Lang J, Yang X, Wang X, Chen G, Zhang H (2017) Characteristics of PM_{2.5} and assessing effects of emission-reduction measures in the heavily polluted city of Shijiazhuang, before, during, and after the ceremonial parade 2015. *Aerosol Air Qual Res* 17(2):499–512. <https://doi.org/10.4209/aaqr.2016.05.0181>
- Wang N, Zhu H, Guo Y, Peng C (2018) The heterogeneous effect of democracy, political globalization, and urbanization on PM_{2.5} concentrations in G20 countries: Evidence from panel quantile regression. *J Clean Prod* 194:54–68. <https://doi.org/10.1016/j.jclepro.2018.05.092>
- Wang Q, Kwan MP, Zhou K, Fan J, Wang Y, Zhan D (2019) The impacts of urbanization on fine particulate matter (PM_{2.5}) concentrations: Empirical evidence from 135 countries worldwide. *Environ Pollut* 247:989–998. <https://doi.org/10.1016/j.envpol.2019.01.086>
- Wang Y, Lu C, Niu S, Lv J, Jia X, Xu X, ... Yan S (2023) Diverse dispersion effects and parameterization of relative dispersion in urban fog in eastern China. *J Geophys Res: Atmos* 128(6), e2022JD037514. <https://doi.org/10.1029/2022JD037514>
- Wei J, Huang W, Li Z, Xue W, Peng Y, Sun L, Cribb M (2019) Estimating 1-km-resolution PM_{2.5} concentrations across China using the space-time random forest approach. *Remote Sens Environ* 231:111221. <https://doi.org/10.1016/j.rse.2019.111221>
- WHO (2014) World Health Statistics 2014. <https://www.who.int/news-item/15-05-2014-world-health-statistics-2014#:~:text=Some%20other%20key%20facts%20from%20%22World%20Health%20Statistics,were%20overweight%20or%20obese%20in%202012.%20...%20E6%9B%84%E5%A4%9A%E9%A1%B9%E7%9B%AE>
- World City Report (2016) Urbanization and Development: Emerging futures, UN Habitat. Available from. <http://wcr.unhabitat.org/wp-content/uploads/2017/02/WCR-2016-Full-Report.pdf>
- World Health Organization (2006) The world health report 2006: working together for health. World Health Organization. <https://www.who.int/publications/i/item/the-world-health-report--2006---working-together-for-health>

- World Health Organization (2016) Air pollution levels rising in many of the world's poorest cities. Available from. <http://www.who.int/mediacentre/news/releases/2016/air-pollution-rising/en/>
- World Health Organization (2021) WHO global air quality guidelines: particulate matter (PM_{2.5} and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide: executive summary. World Health Organization. <https://www.who.int/publications/item/9789240034433>
- Wu X, Liu Z, Yin L, Zheng W, Song L, Tian J, ... Liu S (2021) A haze prediction model in chengdu based on LSTM. *Atmosphere* 12(11):1479. <https://doi.org/10.3390/atmos12111479>
- Xiao Q, Geng G, Liang F, Wang X, Lv Z, Lei Y, He K (2020) Changes in spatial patterns of PM2.5 pollution in China 2000–2018: Impact of clean air policies. *Environ Int* 141:105776. <https://doi.org/10.1016/j.envint.2020.105776>
- Xie Y, Liu Z, Wen T, Huang X, Liu J, Tang G, Wang Y (2019) Characteristics of chemical composition and seasonal variations of PM2.5 in Shijiazhuang, China: Impact of primary emissions and secondary formation. *Sci Total Environ* 677:215–229. <https://doi.org/10.1016/j.scitotenv.2019.04.300>
- Yang D, Ye C, Wang X, Lu D, Xu J, Yang H (2018) Global distribution and evolution of urbanization and PM2.5 (1998–2015). *Atmos Environ* 182:171–178. <https://doi.org/10.1016/j.atmosenv.2018.03.053>
- Yin L, Wang L, Huang W, Liu S, Yang B, Zheng W (2021) Spatiotemporal analysis of haze in Beijing based on the multi-convolution model. *Atmosphere* 12(11):1408. <https://doi.org/10.3390/atmos12111408>
- Yue H, He C, Huang Q, Yin D, Bryan BA (2020) Stronger policy required to substantially reduce deaths from PM2.5 pollution in China. *Nat Commun* 11(1):1462. <https://doi.org/10.1038/s41467-020-15319-4>
- Zang L, Mao F, Guo J, Wang W, Pan Z, Shen H, Wang Z (2019) Estimation of spatiotemporal PM1.0 distributions in China by combining PM2.5 observations with satellite aerosol optical depth. *Sci Total Environ* 658:1256–1264. <https://doi.org/10.1016/j.scitotenv.2018.12.297>
- Zhang YL, Cao F (2015) Fine particulate matter (PM2.5) in China at a city level. *Sci Rep* 5(1):1–12. <https://doi.org/10.1038/srep14884>
- Zhang Q, Zheng Y, Tong D, Shao M, Wang S, Zhang Y, Hao J (2019a) Drivers of improved PM2.5 air quality in China from 2013 to 2017. *Proc Natl Acad Sci* 116(49):24463–24469. <https://doi.org/10.1073/pnas.1907956116>
- Zhang T, Zang L, Wan Y, Wang W, Zhang Y (2019b) Ground-level PM2.5 estimation over urban agglomerations in China with high spatiotemporal resolution based on Himawari-8. *Sci Total Environ* 676:535–544. <https://doi.org/10.1016/j.scitotenv.2019.04.299>
- Zhang W, Liu B, Zhang Y, Li Y, Sun X, Gu Y, Feng Y (2020) A refined source apportionment study of atmospheric PM2.5 during winter heating period in Shijiazhuang, China, using a receptor model coupled with a source-oriented model. *Atmos Environ* 222:117157. <https://doi.org/10.1016/j.atmosenv.2019.117157>
- Zhao B, Zheng H, Wang S, Smith KR, Lu X, Aunan K, Hao J (2018) Change in household fuels dominates the decrease in PM2.5 exposure and premature mortality in China in 2005–2015. *Proc Natl Acad Sci* 115(49):12401–12406. <https://doi.org/10.1073/pnas.1812955115>
- Zheng S, Pozzer A, Cao CX, Lelieveld J (2015) Long-term (2001–2012) concentrations of fine particulate matter (PM 2.5) and the impact on human health in Beijing, China. *Atmos Chem Phys* 15(10):5715–5725. <https://doi.org/10.5194/acp-15-5715-2015>
- Zhongming Z, Linong L, Xiaona Y, Wei L (2011) NEC Directive status report 2010: Reporting by the Member States under Directive 2001/81/EC of the European Parliament and of the Council of 23 October 2001 on national emission ceilings for certain atmospheric pollutants. <http://119.78.100.173/C666/handle/2XK7JSWQ/10154>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

Authors and Affiliations

Qin Zhou¹ · Mir Muhammad Nizamani² · Hai-Yang Zhang³ · Hai-Li Zhang¹ 

 Hai-Li Zhang
hailizhang@hainanu.edu.cn

¹ Hainan Key Laboratory for Sustainable Utilization of Tropical Bioresources, School of Life Sciences, Hainan University, Haikou 570228, China

² Department of Plant Pathology, Agricultural College, Guizhou University, Guiyang 550001, China

³ College of International Studies, Sichuan University, Chengdu 610065, China