ABSTRACT

AlSAFARI, IBRAHIM. Quantifying Urban Air Quality Across Global Megacities. (Under the direction of Dr. Viney Aneja).

This study examines trends in air pollutant concentrations across five megacities (Shanghai (China), Delhi (India), Paris (France), Los Angeles (USA), and São Paulo (Brazil)) over the period 2018-2023. Air Quality Data for $PM_{2.5}$, PM_{10}, O_3, NO_2, and SO_2 was obtained from sources such as the World Air Quality Index and the U.S Embassy and Consulates' air quality monitors. These data were analyzed alongside various meteorological elements to assess annual and seasonal trends in air quality. The finding demonstrates distinct patterns in pollutant concentrations, highlighting efforts and challenges associated with air quality management in major global cities.

Shanghai experienced a notable decrease in $PM_{2.5}$ from 106.67 to 81.59 µg/m³ before rising to 88.69 µg/m³ in 2023, with NO_2 levels decline from 18.30 to 12.23 ppm before increasing to 14.96 ppm for the period 2018 to 2022, indicating ongoing efforts to control these pollutants. Also, Delhi revealed marked fluctuations, where $PM_{2.5}$ levels have remained constantly high despite a temporary drop in 2020 (149.84 µg/m³), then rising again to 163.19 µg/m³ in 2023. However, SO_2 levels decreased sharply. The $PM_{2.5}$ and NO_2 concentrations in Paris demonstrated consistent improvements, which indicates that the measures to control pollution are effective. Los Angeles maintained relatively stable air quality with minor fluctuations in $PM_{2.5}$ and steady decreases in NO_2 and SO_2 levels. Furthermore, São Paulo faced challenges with increasing $PM_{2.5}$ levels, although improvements were observed in O_3 concentrations.

The analysis of annual $PM_{2.5}$ exceedance days revealed persistent air quality issues in Shanghai and Delhi, each exceeding 2,100 days. Paris recorded 1,974 exceedance days, while São Paulo had 1,608, indicating ongoing challenges. In contrast, Los Angeles had only 17 exceeding days, reflecting effective air quality management. O_3 exceedance trends were similar, with Paris recording the highest at 2,146 days, followed by Shanghai and Delhi. São Paulo had 1,990 exceedance days, while Los Angeles remained significantly lower at 49 days.

Statistical relationships between temperature and $PM_{2.5}$ varied, with Shanghai (r = -0.28), Paris (r = -0.19), and São Paulo (r = -0.10) showing weak negative correlations, while Delhi had a significant negative correlation (r = -0.59) and Los Angeles a weak positive correlation (r = 0.16). Sea Level Pressure (SLP) showed a strong positive correlation with $PM_{2.5}$ in Delhi (r = 0.62), while

Shanghai, Paris, and São Paulo had weak positive correlations, and Los Angeles showed a negligible correlation (r = -0.02). Wind speed generally reduced $PM_{2.5}$ levels, with Los Angeles showing the strongest negative correlation (r = -0.29), while Delhi (r = -0.21) and Paris (r = -0.19) had weak negative correlations, and Shanghai (r = -0.07) and São Paulo (r = -0.04) showed very weak relationships.

These trends highlight the complexities of urban pollution control and the varying effectiveness of regulatory measures across cities. Delhi and Shanghai remained the most polluted throughout the study period, with persistent air quality challenges. Statistical relationships between meteorological factors and $PM_{2.5}$ levels further emphasize the need for targeted mitigation strategies. Understanding these dynamics can support city-specific air quality management efforts, reinforcing the importance of sustained interventions to reduce pollution

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Quantifying Urban Air Quality Across Global Megacities

by

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DEDICATION

This thesis is dedicated to my parents, family and friends who believed in me throughout my education journey.

BIOGRAPHY

I received my undergraduate degree in meteorology from King Abdulaziz University, Jeddah, Saudi Arabia. I have worked as a lecturer in meteorology at King Abdulaziz University for three years. My work is part of my MS degree in Air Quality and Dynamic Meteorology, Department of Marine, Earth & Atmos Sciences, North Carolina State University.

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1. Introduction

Urban development globally has changed social, economic, and environmental geographies, bringing opportunities and challenges (Chen et al., 2024). While urbanization encourages economic growth and development, it poses serious environmental challenges. For instance, India has exacerbated environmental degradation, manifesting as deteriorating air quality, water contamination, and inadequate waste management systems. Such outcomes highlight the necessity of managing urbanization to minimize its adverse environmental impacts while fostering sustainable urban development (Uttara, Bhuvandas, & Aggarwal, 2012). Similarly, China has been linked to increased air pollution due to industrial emissions and vehicular traffic. This issue is worsened by the limited ability for atmospheric diffusion in densely populated areas, causing pollutants like PM2.5 to accumulate, which poses considerable health risks (Thanvisitthpon et al., 2023) (Zhou et al., 2021).

Urban environments play a unique and critical role in the Earth system. The complex interactions between air pollution, atmospheric chemistry, meteorology, and emissions create intricate feedback. Air pollution has been acknowledged as a critical global issue with far-reaching consequences for public health and environmental justice. According to the United Nations has recently declared clean air a fundamental human right, reflecting the severity of the problem and its implications for millions worldwide. Each year, approximately 6.7 million deaths are attributed to air pollution exposure, which makes it one of the most global health risks (Vilcins et al., 2024). Addressing this challenge requires innovative policies and technologies, such as the transition to electric vehicles, which offer both opportunities for improving air quality. Relevant urban areas continue to face significant challenges related to fine particulate matter $PM_{2.5}$, with most of the world's urban population living in regions exceeding recommended safety thresholds. In this context, during 2024 the U.S. Environmental Protection Agency has modified, its annual $PM_{2.5}$ standard from 9 μg/m³ to 12 μg/m³ in the U.S. to better protect public health, particularly for sensitive populations. Despite these efforts, approximately 86% of the urban population globally is exposed to high levels of $PM_{2.5}$ that exceed even the previous WHO guideline of 10 μg/m³, contributing to an estimated 1.8 million premature deaths annually. These findings highlight the critical need for comprehensive emission reduction strategies and robust public health interventions (Southerland et al., 2022; EPA, 2024). Increased surface concentrations of particulate matter (PM), including $PM_{2.5}$ and PM_{10}, as well as tropospheric ozone (O_3), nitrogen dioxide

(NO_2), and sulfur dioxide (SO_2)—all of which are recognized as criteria pollutants in most countries worldwide—exert significant negative impacts on both human health and the environment (World Health Organization [WHO], 2021; Landrigan et al., 2018; Burnett et al., 2014). Recent research also highlighted their role in exacerbating climate change and posing environmental risks, particularly in high-risk regions (IPCC, 2021; UNEP, 2019).

Approximately 2.5 billion more people are projected to live in the megacities by 2050 (Sicard et al., 2023) . Global trends in urban air pollution reveal a complex and evolving landscape. While $PM_{2.5}$ exposure has shown a slight overall reduction in recent years, many urban areas have experienced increasing levels driven by emissions associated with industrialization and urbanization. NO_2 concentrations have similarly risen in many cities, primarily due to traffic and industrial activities. Meanwhile, O_3 exposure has shown marked growth, with summertime maximum values increased across a majority of urban areas (Sicard et al., 2023). The rapid growth of megacities, defined by dense populations and significant industrial activities, has resulted in considerable environmental challenges. Urban air pollution in these regions originates from a mix of primary sources, including vehicular traffic and industrial emissions, and secondary processes, such as photochemical reactions and the regional transport of pollutants (Molina & Molina, 2004). In addition, the interaction between emissions, urban planning, and meteorological dynamics has complicated efforts to mitigate air quality issues. Sustainable improvements in air quality require integrated strategies that address these complexities while adapting to each megacity's unique conditions (Kumar et al., 2015; Baklanov et al., 2016). Air pollution is among the most crucial issues in these vast metropolitan regions, which poses a serious risk to public health, contributes to climate change, and degrades ecosystems. Megacities such as Delhi, Shanghai, Paris, São Paulo, and Los Angeles are at the forefront of this issue, with complex air quality challenges stemming from both local sources and long-range pollution transport (Figure 1).

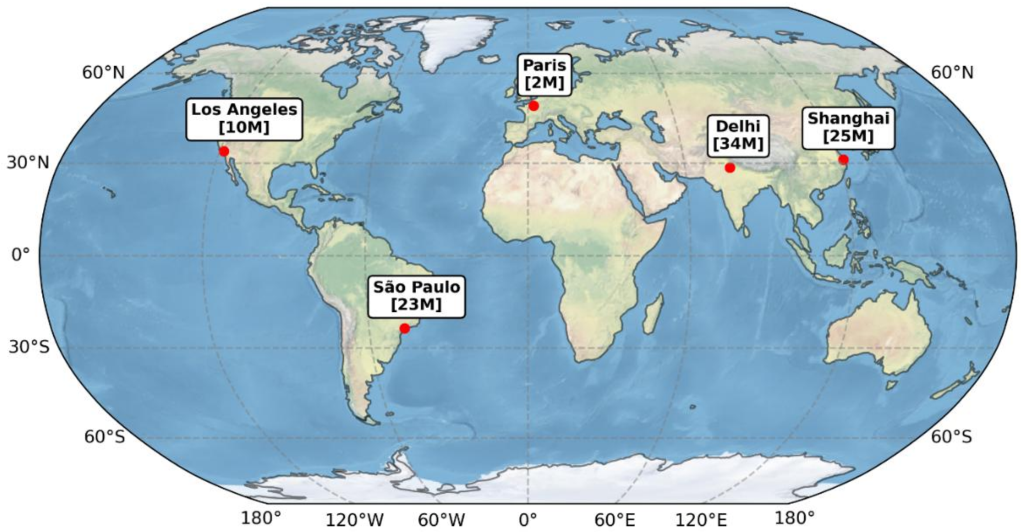

Figure 1: Five megacities around the world with their population (M = 1 million).

Delhi faces severe air pollution driven by emissions and meteorological conditions. The interplay between $PM_{2.5}$ and O_3 is affected by factors such as temperature, relative humidity, and wind direction, with emissions influencing their dynamics during winter and pre-monsoon seasons (Krishnaveni et al., 2024). Seasonal patterns of $PM_{2.5}$ show peaks during winter and post-monsoon periods, with low temperatures exacerbating particulate pollution (Vaishali et al., 2023). Despite technical and judicial interventions over the past decades, Delhi's PM2.5 levels remain 20 times higher than WHO guidelines, underscoring the challenges of effectively addressing urban growth, seasonal pollution sources, and localized emissions (Guttikunda et al., 2023). Furthermore, as a megacity, Paris faces unique challenges related to air quality, influenced by its urban design, transportation networks, and residential emissions. Strategies tailored to enhance urban resilience must address these emission sources while adapting to climate-driven challenges such as extreme heat events and pollution episodes (Baklanov et al., 2016). In addition, Los Angeles faces air quality challenges formed by its distinct topography and meteorological conditions. The combination of thermal inversions and weakened coastal winds, often influenced by high-pressure systems, creates an environment conducive to pollutant accumulation, particularly during winter episodes (Jury, 2020). The efforts have shown promising results in addressing these issues, with the adoption of electric vehicles that reduce $PM_{2.5}$ and ozone levels, which highlights the air quality co-benefits of transitioning from internal combustion engines to cleaner technologies (Skipper et al., 2023). However, the urbanization and transportation emissions in this megacity contribute to localized heat islands and significant pollutant outputs, underscoring the necessity for integrated urban planning to mitigate both environmental and public health impacts (Baklanov et al., 2016). The Metropolitan Area of São Paulo (MASP) exemplifies the complex challenges of air quality management in megacities. Notable progress has been made in reducing primary pollutants through initiatives like PROCONVE. However, São Paulo continues to face high levels of secondary pollutants, such as ozone and fine particulate matter (de Fatima Andrade et al., 2017; Carvalho et al., 2015).

Furthermore, investments in public transportation infrastructure, such as metro expansions, demonstrate potential to alleviate air quality challenges by reducing concentrations of $PM_{2.5}$ and NO_2, ultimately improving public health outcomes (Chiquetto et al., 2024). However, during extreme heat events, ozone levels frequently exceed WHO guidelines, posing significant health risks to vulnerable populations in densely populated areas (Chiquetto et al., 2019). The global COVID-19 lockdowns provided a unique real-world experiment to evaluate the effects of reduced anthropogenic emissions on air quality. Considerable reductions in NO_2, $PM_{2.5}$, and PM_{10} concentrations were observed worldwide due to restricted transportation and industrial activities during this period (Bray et al., 2021). On a broader scale, NO_2 and $PM_{2.5}$ reductions were consistent globally; however, O_3 concentrations increased. This phenomenon reflects the complex atmospheric chemistry, where reduced NOx emissions disrupt ozone titration processes, leading to elevated O_3 levels (Liu et al., 2021). The lockdown period thus highlighted these intricate interactions, underscoring the need for integrated mitigation strategies targeting both primary and secondary pollutants (Gkatzelis et al., 2021). Air pollution in urban regions is primarily driven by anthropogenic sources, with industry and transportation being dominant contributors to $PM_{2.5}$ and O_3 pollution (Li et al., 2021). Sources of $PM_{2.5}$ can vary by region; in developing areas, residential burning and transportation are the main contributors, highlighting differences in pollution sources (Karagulian et al., 2017).

Meteorological conditions play a pivotal role in determining the dispersion, concentration, and removal of air pollutants like $PM_{2.5}$. Stagnant weather patterns, characterized by low wind speeds and a shallow planetary boundary layer height, notably limit the vertical and horizontal dispersion of pollutants, leading to higher concentrations near the surface (Chen et al., 2020). Wind speed and direction are particularly critical factors, as they influence the movement and dilution of particulate matter, explaining a significant portion of $PM_{2.5}$ variability in urban areas (Afrin et al., 2021). Temperature inversions, which are more prevalent in winter, trap pollutants closer to the surface, exacerbating pollution levels (Rowland, 2024). In contrast, favorable meteorological conditions such as higher wind speeds and precipitation promote the dispersion and removal of $PM_{2.5}$. Precipitation effectively reduces particulate concentrations through wet deposition, while elevated temperatures enhance vertical mixing and pollutant dispersion (Zhao et al., 2018; He et al., 2017). Urban expansion further modifies local meteorology, increasing near-surface temperatures and boundary layer height, which can facilitate pollutant dispersion despite higher anthropogenic emissions (Jiang et al., 2023). Collectively, these meteorological parameters—wind speed, temperature, and precipitation—underscore their influence on $PM_{2.5}$ levels and highlight their importance in air quality management.

Seasonal variations are crucial in determining urban air quality, as meteorological conditions impact the dispersion, transformation, and removal of pollutants. Studies have shown that $PM_{2.5}$ concentrations often peak in winter due to stagnant air masses and low boundary layer heights, which limit pollutant dispersion. In contrast, higher boundary layer heights in spring and summer facilitate better mixing and pollutant removal, supported by increased solar radiation and atmospheric dynamics (Singh et al., 2021; Miao et al., 2015). Urban air pollution levels also tend to rise with city size and are more pronounced during spring and summer, as larger urban areas generate more emissions, and monsoonal patterns further exacerbate pollutant accumulation in specific regions (Liu et al., 2018). These seasonal trends are consistent across various urban environments, where pollutant concentrations show distinct seasonal patterns, such as winter peaks due to temperature inversions and summer reductions driven by enhanced atmospheric mixing (Yousefian et al., 2020; Yang et al., 2017). Additionally, the relationship between meteorological parameters and air pollution varies across regions and seasons. For example, low boundary layer heights during winter contribute significantly to severe haze events, while spring and summer conditions allow pollutants to disperse more effectively (Zhang et al., 2015). These findings underscore the importance of considering seasonal variations when developing strategies to mitigate urban air pollution.

Urban air pollution poses a serious challenge to global public health and environmental sustainability, necessitating the development and implementation of effective control strategies (Rasheed et al., 2014, 2015). A systematic review of air pollution control policies highlights the critical role of transitioning to renewable energy sources, adopting clean fuels, and promoting the use of low-emission or no-emission vehicles such as electric vehicles. These measures not only reduce emissions but also foster sustainable urban development, making them essential components of comprehensive air quality management frameworks (Jonidi Jafari, Charkhloo, & Pasalari, 2021). Air pollution in Saudi Arabia has reached critical levels, with the World Health Organization (WHO) categorizing its air quality as unhealthy. The country's annual average concentration of $PM_{2.5}$ is 88 μg/m³—far exceeding the WHO's recommended limit of 15 μg/m³ (IQAir, 2025). This alarming situation has direct health implications, particularly for vulnerable populations.

My motivation for conducting this research is deeply personal. Both my mother and I were diagnosed with asthma due to exposure to poor air quality in Jeddah, Saudi Arabia. This firsthand experience reinforced my commitment to studying urban air pollution and its mitigation. My research aims to contribute to improving air quality in megacities worldwide by identifying pollution sources and assessing their impact on human health and urban environments. This study focuses primarily on $PM_{2.5}$ and O_3, which are recognized as urban air quality issues and serious health challenges (Shu et al., 2024).

This research aims to advance the understanding of urban air pollution dynamics through an integrated approach that combines observational data, analysis, and modeling. It seeks to investigate the intricate relationships between atmospheric chemistry and urban meteorology while evaluating the unique characteristics of various urban environments and their impact on pollution patterns. Specifically, the study will focus on the relationship between weather extremes and air pollution across different urban regions worldwide, identifying regional variations in pollution responses to meteorological conditions. The anticipated outcomes include providing crucial scientific insights to support evidence-based policymaking, enhancing capabilities for air quality management, and delivering targeted policy recommendations. These outcomes aim to promote public health, improve urban air quality, and address environmental justice concerns in urban environments.

2. Data and Methods

2.1 Megacities and Air quality Data

The cities of Shanghai, Delhi, Paris, Los Angeles, and São Paulo are pivotal in studying air quality trends from 2018 to 2023 due to their diverse socio-economic conditions, policy responses, and pollution challenges. Shanghai represents a rapidly industrializing city grappling with balancing economic growth and environmental sustainability, particularly through innovative transportation and regulatory measures (Chen et al., 2020). In contrast, Delhi, with some of the world's highest pollution levels, highlights the intersection of urban pollution, agriculture, and public health, exacerbated by seasonal crop residue burning (Gurjar, 2021). Paris, known for its sustainable urban policies, demonstrates the effectiveness of low-emission zones and electric mobility in reducing pollution (Patil et al., 2023). Los Angeles, a leader in air quality management, offers valuable insights into the role of stringent emission controls in reducing pollutants like ozone and particulate matter (Mousavinezhad et al., 2024). Finally, São Paulo illustrates how urbanization, transportation, and waste management practices influence air quality in rapidly developing cities (Navarro & Consoni, 2019). The 2018-2023 period, including the COVID-19 pandemic, provides a unique opportunity to examine the direct impact of human activity on air quality, offering critical lessons for urban air pollution management worldwide (Alvim et al., 2023).

2.2 Shanghai, China

Shanghai, located at 31.2304°N 121.4737°E on China's eastern coast along the East China Sea, is China's most populous and largest city. As of the most recent census conducted by the National Bureau of Statistics of China in 2021, the city's population stood at 24,870,895. Shanghai covers an area of 6,341 km^2, making it one of the largest urban areas globally.

Shanghai has made important strides in addressing air pollution despite challenges related to rapid industrialization and dense population. The city has implemented the Shanghai Air Pollution Control Action Plan (2013), focusing on reducing particulate matter (PM_{10} and $PM_{2.5}$) levels and transitioning to cleaner energy sources, such as increasing the adoption of electric vehicles (EVs). Real-time air quality monitoring and stricter emissions standards for vehicles and industries have played an essential role in improving air quality. However, challenges remain, particularly during colder months when heating demands rise, leading to pollution spikes.

Balancing economic growth with environmental protection remains crucial for long-term air quality improvements (Chen et al., 2020).

2.3 Delhi, India

Delhi, located at 28°36′36″N 77°13′48″E, had an estimated metropolitan population of 33,807,000 in 2024, making it one of the most densely populated cities globally within a relatively small area of 1,484 km². According to reports from WHO and IQAir, this density exacerbates air pollution, making Delhi the most polluted city in the world. Efforts to mitigate pollution remain challenging as the city grapples with rapid population growth and industrial activity.

Delhi, one of the most polluted cities globally, has taken emergency measures like the Odd-Even Rule to control vehicular emissions and introduced anti-smog guns to reduce dust and particulate matter. The Graded Response Action Plan (GRAP) has been pivotal in implementing emergency measures based on pollution severity, while the expansion of the metro network has contributed to reducing traffic congestion. A serious challenge for Delhi is crop residue burning in neighboring states, which exacerbates seasonal pollution. Cross-border cooperation and incentives for farmers to adopt stubble-burning-free technologies have been introduced, but more efforts are needed to address the root causes of air pollution (Gurjar, 2021; Kajino et al., 2024).

2.4 Paris, France

Paris, France's capital and largest city covers an area of 105.4 km². According to the National Institute of Statistics and Economic Studies (INSEE), the population of Paris was 2,104,154 as of 2023. In recent years, Paris has experienced extreme weather events, including frequent heat waves, exacerbating the challenges urban planners and residents face.

Paris has worked to improve air quality by focusing on transportation reforms and green initiatives. The city introduced low-emission zones (LEZs) to restrict high-polluting vehicles and implemented the Paris Climate Plan (2018) to reduce emissions, particularly from vehicles, and increase green spaces. Furthermore, incentives for adopting electric vehicles (EVs) and investments in expanding public transportation have contributed to reducing NO_2 levels. Public awareness campaigns and the promotion of pedestrian zones and cycling infrastructure have also fostered a cultural shift toward more sustainable mobility. Despite these efforts, challenges related to diesel vehicle emissions persist, necessitating continued policy innovation and public engagement (Patil et al., 2023).

2.5 Los Angeles, USA

Located at 34°03′N 118°15′W, Los Angeles is the most populous city in California, United States, and the second-most populous in the country. According to the United States Census Bureau, the city's population was 10,014,009 as of 2020. As the economic, financial, and cultural hub of Southern California, Los Angeles plays a pivotal role in the region. The city's total area spans 502.7 square miles (1,302 km²), with 468.7 square miles (1,214 km²) consisting of land and 34.0 square miles (88 km²) of water.

Los Angeles, historically known for poor air quality, has made substantial improvements through stringent emission standards and the Clean Air Act (1970). Regulations on vehicle emissions, industry standards, and power plants have reduced ground-level ozone (O_3), NO_2, and PM_{10}. The city has also promoted electric vehicles (EVs) and expanded public transportation networks to reduce traffic-related pollution. However, the region still faces challenges due to its geographic location, high traffic congestion, and persistent ozone pollution. Continued emphasis on sustainable mobility infrastructure and tackling traffic congestion are key to further improving air quality (Y. Li et al., 2024; Mousavinezhad et al., 2024).

2.6 São Paulo, Brazil

Greater São Paulo, situated at 23°53'3 "S 46°61'7 "W, is the largest city in Brazil and one of the largest in the southern hemisphere. According to the United Nations- World Population Prospects, spanning a metropolitan area of 8,000 km², São Paulo is also among the most populated cities in South America, with an estimated metro population of 22,807,000 in 2024.

São Paulo has implemented congestion pricing and low-emission zones to tackle air pollution primarily caused by vehicular emissions. The city has promoted flex-fuel vehicles (which can run on ethanol, gasoline, or both) and expanded its public transportation system. Additionally, the city has made strides in waste management, focusing on reducing open burning of waste, a significant source of particulate pollution. Efforts to improve recycling and composting have shown promise in reducing emissions. However, São Paulo continues to face challenges from seasonal wildfires and urban sprawl, which necessitate continued investment in cleaner technologies and waste management solutions (Chiquetto et al., 2020; Navarro & Consoni, 2019).

The criteria pollutants data for this study were obtained from various specialized agencies and organizations that focus on air quality. The daily mean air quality monitoring data for $PM_{2.5}$ and PM_{10} were collected for five years (2018-2023). Additionally, the 8-hour mean was measured for O_3, and the hourly average was obtained for both NO_2 and SO_2. The air quality data for Shanghai, Delhi, Paris, and Sao Paulo were collected from The World Air Quality Index Project.

Table 1: Sources of pollutant concentration for the Megacities

Megacities	Pollutants	Data Source
Shanghai, China	$PM_{2.5}$, O_3, NO_2, SO_2, and PM_{10}	The World Air Quality Index Project https://waqi.info/#/c/4.102/8.008/2.2z
Delhi, India	$PM_{2.5}$, O_3, NO_2, SO_2, and PM_{10}	The World Air Quality Index Project https://waqi.info/#/c/4.102/8.008/2.2z
Paris, France	$PM_{2.5}$, O_3, NO_2, and PM_{10}	The World Air Quality Index Project https://waqi.info/#/c/4.102/8.008/2.2z
Los Angeles, USA	$PM_{2.5}$, O_3, NO_2, SO_2, and PM_{10}	The U.S. Environmental Protection Agency https://www.epa.gov/outdoor-air-quality-data
São Paulo, Brazil	$PM_{2.5}$, O_3, NO_2, and PM_{10}	The World Air Quality Index Project https://waqi.info/#/c/4.102/8.008/2.2z

Table 2: Sources of Meteorological Elements for Megacities

Megacities	Meteorological Element	Data Source
Shanghai, China **Delhi, India** **Paris, France** **Los Angeles, USA** **São Paulo, Brazil**	Temperature (°C), Precipitation (mm), Sea Level Pressure SLP (hpa), and Wind Speed (m/s)	Visual Crossing Weather Data https://www.visualcrossing.com/

3. Methodology

3.1 Annual Mean Concentration of Air Pollutants, Exceedance days

The annual averages for air pollutants ($PM_{2.5}$, PM_{10}, O_3, NO_2, and SO_2) in the megacities of Shanghai, Delhi, Paris, Los Angeles, and São Paulo were derived from daily observations collected from The World Air Quality Index Project and The U.S. Environmental Protection Agency

(Table 1) for the period 2018 to 2023. Further, the annual and seasonal averages are derived from daily observations to analyze the annual and seasonal concentration of air pollutants. Additionally, we also analyzed the number of exceedance days for daily pollutant levels in each megacity was calculated based on the standards set by the U.S. Environmental Protection Agency (EPA). Specifically, exceedance days for $PM_{2.5}$ and O_3 were determined using the daily standard values of 9 µg/m³ for $PM_{2.5}$ and 0.070 ppm for O_3, considering only instances when the daily concentrations exceeded these thresholds in the period from 2018 to 2023.

3.2 Effect of meteorology on pollutant concentration

The annual meteorological data has been derived from daily observations in megacities to analyze the impact of meteorological variables (temperature, sea level pressure, and wind speed) on annual air pollutants. The scatter plots have been created to examine the relationships between air pollutants and the meteorological variables for each city. Additionally, the correlation coefficients (CC) and slopes were also calculated to assess the relationship between air pollutants and meteorological elements.

3.3. Effect of seasonal variations

To analyze seasonal variations of air pollutants in each megacity, the seasonal mean of $PM_{2.5}$ and O_3 was assessed for each station from 2018 to 2023. The conventional seasons were winter (December–February), Spring (March-May), summer (June- August), and Autumn (September - November). Seasons have been specified for Shanghai as winter (December-January-February), spring (March-April-May), summer (June-July-August), and fall (September-October-November). In contrast, since Sao Paulo is in the Southern Hemisphere, the seasons have been specified as summer (December-January-February), fall (March-April-May), winter (June-July-August), and spring (September-October-November). Similarly, seasons were derived for the meteorological elements, and seasonal scatter analyses were made between $PM_{2.5}$ and O_3 for each megacity.

4. Results

4.1 Annual Mean Concentration of Air Pollutants for Megacities

The annual average concentrations of pollutants in Shanghai showed varying trends. The $PM_{2.5}$ levels decreased over the years, starting at 106.67 µg/m³ in 2018 and dropping to 81.59 µg/m³ by 2022 before slightly rising to 88.69 µg/m³ in 2023. Ozone (O_3) concentrations remained relatively stable, fluctuating between 40.23 ppm and 44.68 ppm during the same period. Also, the PM_{10} levels showed variability, with values ranging from 35.92 µg/m³ to 46.04 µg/m³, which indicates a general downward trend until a slight increase in 2023. In addition, a notable decrease was observed for nitrogen dioxide (NO_2), with concentrations falling from 18.30 ppm in 2018 to 12.23 ppm in 2022, followed by a rise to 14.96 ppm in 2023. Additionally, sulfur dioxide (SO_2) concentration has declined from 3.72 ppm in 2018 to 1.80 ppm in 2021 before increasing to 2.83 ppm by 2023. These trends reflect Shanghai's efforts and challenges in managing air quality amidst urban development and environmental policies. The annual average concentrations of pollutants in Delhi displayed marked fluctuations. The $PM_{2.5}$ levels, a critical indicator of air quality, started at 171.98 µg/m³ in 2018, decreased to 149.84 µg/m³ by 2020, slightly increased to 165.11 µg/m³ in 2021, and then showed a marginal decline to 163.19 µg/m³ in 2023. In addition, the Ozone (O_3) concentration displayed substantial variability that began at 35.39 ppm in 2018 and dropped to 17.88 ppm by 2022, with a slight increase to 18.80 ppm in 2023. Furthermore, the level of PM10 experienced notable changes, which started at 164.99 µg/m³ in 2018, decreased to 106.73 µg/m³ by 2020, and then fluctuated around 130 µg/m³ in subsequent years. Also, the concentration of NO_2 declined, which began at 29.63 ppm in 2018 and fell to 12.36 ppm in 2023, which indicates a reduction in vehicular and industrial emissions. Similarly, the level of SO_2 saw a marked decrease that started at 7.89 ppm in 2018 and dropped to a low of 1.63 ppm in 2023. Paris displayed notable trends in the annual mean concentrations of pollutants. The level of $PM_{2.5}$ began at 64.28 µg/m³ in 2018 and generally showed a decline of 55.6 µg/m³ by 2023, despite slight increases in 2021 and 2022. Also, the concentration of O_3 remained relatively stable, fluctuating slightly with values between 25.46 ppm and 28.51 ppm. In addition, PM_{10} levels decreased from 42.33 µg/m³ in 2018 to 27.34 µg/m³ in 2020 before stabilizing around 31 µg/m³ in the following years. Nitrogen dioxide (NO_2) concentration exhibited a clear downward trend that started at 41.06 ppm in 2018 and steadily decreased to 23.06 ppm in 2023. The steady decline demonstrates that effective measures have been implemented to reduce emissions from vehicles and industrial sources. Los Angeles has revealed trends in the annual average of pollutant concentrations. The $PM_{2.5}$ concentration saw slight fluctuations, starting at 12.19 µg/m³ in 2018, decreasing to 10.09 µg/m³ in 2019, peaking again at 13.06 µg/m³ in 2020, and then gradually declining to 9.89 µg/m³ by 2023. Furthermore, Ozone (O_3) levels remained relatively stable that ranged between 0.04486 ppm and 0.04579 ppm. Also, the concentrations of PM_{10} varied, with initial values at 26.15 µg/m³ in 2018, a decrease to 21.77 µg/m³ in 2019, then rising to 27.45 µg/m³ in 2020, and stabilizing around 23.77 µg/m³ in 2023. Additionally, Nitrogen dioxide (NO_2) levels consistently declined, from 26.82 ppm in 2018 to 23.12 ppm in 2023, revealing improved air quality concerning vehicular and industrial emissions. Similarly, sulfur dioxide (SO_2) concentrations decreased remarkably, starting at 1.62 ppm in 2018 and reducing to 0.80 ppm by 2023. São Paulo exhibited patterns in the mean concentrations of pollutants.

The $PM_{2.5}$ concentrations fluctuated, beginning at 50.24 µg/m³ in 2018, slightly decreasing to 50.09 µg/m³ in 2019, then increasing to 57.27 µg/m³ by 2023. Ozone (O_3) levels showed oscillations, with initial concentrations at 29.17 ppm in 2018, decreasing to 24.72 ppm in 2023 after a series of small rises and falls.

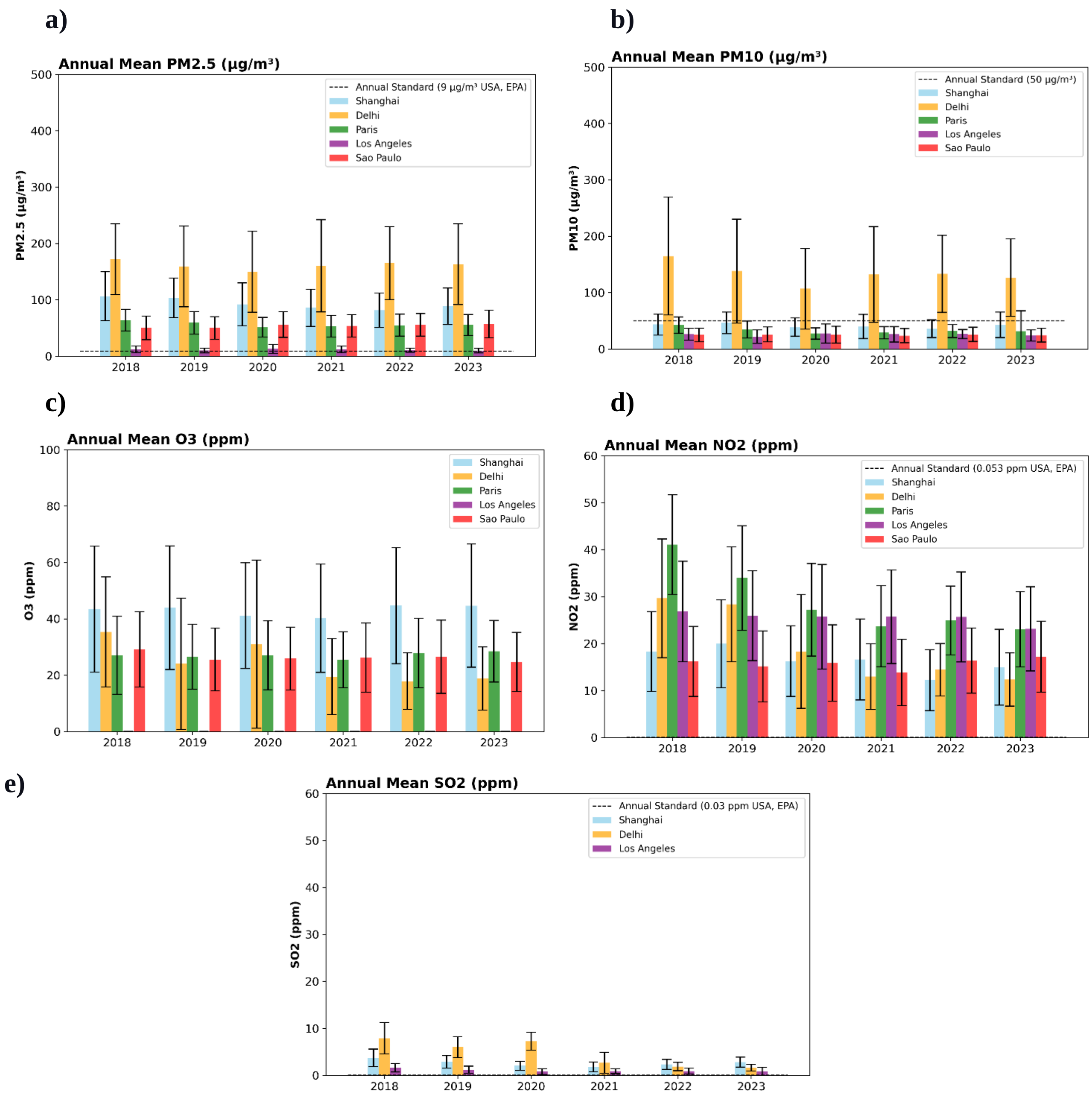

Figure 2: Annual Mean Concentration of Air Pollutants for a) $PM_{2.5}$, b) PM_{10}, c) O_3, d) NO_2, and e) SO_2 for the Megacities (Shanghai, Delhi, Paris, Los Angeles, and Sao Paulo) for the period 2018-2023.

Moreover, the levels of PM_{10} remained fairly stable, with values spanning from 23.54 µg/m³ to 25.95 µg/m³, indicating minor annual variations. Nitrogen dioxide (NO_2) also demonstrated some variability, which was initiated at 16.21 ppm in 2018, dropping to a low of

13.82 ppm in 2021 and then rising again to 17.20 ppm by 2023, which fluctuation implies changes in emission sources or the effectiveness of air quality control measures over the years.

4.2 Annual Exceedance Days of Air Pollutants for Megacities

Figure 3 demonstrates the $PM_{2.5}$ annual exceedance days of $PM_{2.5}$ for five major cities: Shanghai, Delhi, Paris, Los Angeles, and Sao Paulo, with the levels exceeding the recommended air quality standards (Appendix A).

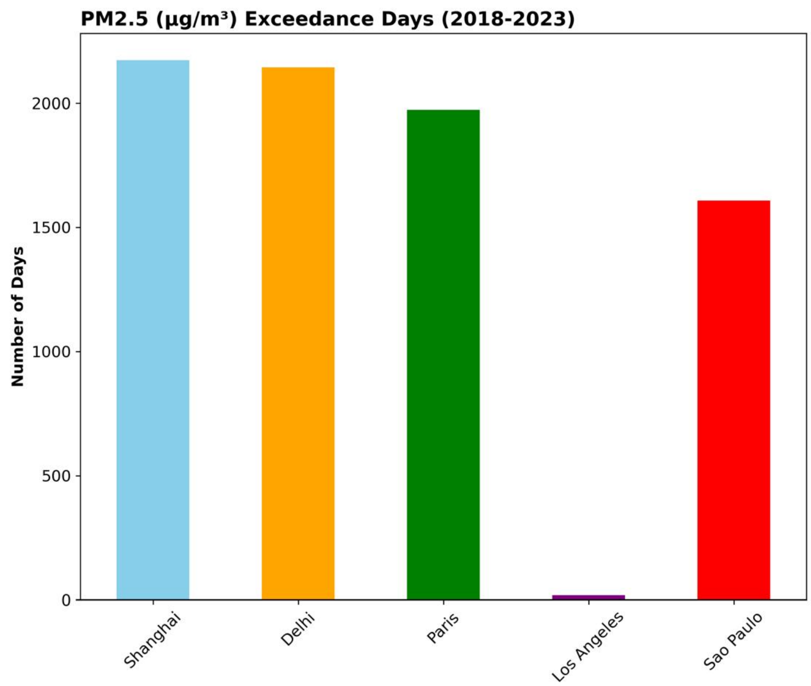

Figure 3: The total number of exceedance days for $PM_{2.5}$ concentrations (μg/m³) from 2018 to 2023 across selected cities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo.

It is observed that Shanghai consistently shows a high number of exceeding days throughout the six years (2018-2023), with a total of 2,173 days (Table 3).

This indicates persistent air quality issues, likely due to industrial activities, traffic emissions, and other sources of pollution. Delhi also experiences a high number of $PM_{2.5}$ exceedance days, which totals 2,144 days over the same period. Delhi's air pollution is primarily attributed to vehicle emissions, construction dust, and seasonal factors like crop burning in surrounding areas. In addition, Paris records a slightly lower, yet still concerning, total of 1,974 exceedance days. While Paris has implemented various measures to combat air pollution, such as restricting vehicle access in certain areas, these numbers suggest that more needs to be done to achieve cleaner air. Los Angeles stands out with a much lower total of 17 exceedance days over the six years, indicating better air quality management compared to the other cities. Sao Paulo shows a total of 1,608 exceedance days, reflecting ongoing air quality challenges.

Table 3: The total number of $PM_{2.5}$ exceeds days from 2018 to 2023 for each city. The table presents the annual exceedance days for Shanghai, Delhi, Paris, Los Angeles, and Sao Paulo, with an accumulative total for the years (2018-2023).

Total Number of $PM_{2.5}$ Exceedance Days (2018-2023) for Each City

Year	Shanghai	Delhi	Paris	Los Angeles	Sao Paulo
2018	364	342	355	3	258
2019	363	358	348	0	258
2020	363	361	314	11	270
2021	357	362	303	3	258
2022	361	364	329	0	292
2023	365	357	325	0	272
Total (2018-2023)	2173	2144	1974	17	1608

Figure 4 illustrates the number of annual exceedance days for O_3 levels in five megacities: Shanghai, Delhi, Paris, Los Angeles, and Sao Paulo, with the levels exceeding the recommended air quality standards (Appendix A). It is observed that Shanghai, Delhi, and Paris consistently show a high number of exceeding days throughout the years (2018-2023), with a total of 2055, 2134, and 2146 days respectively (Table 4).

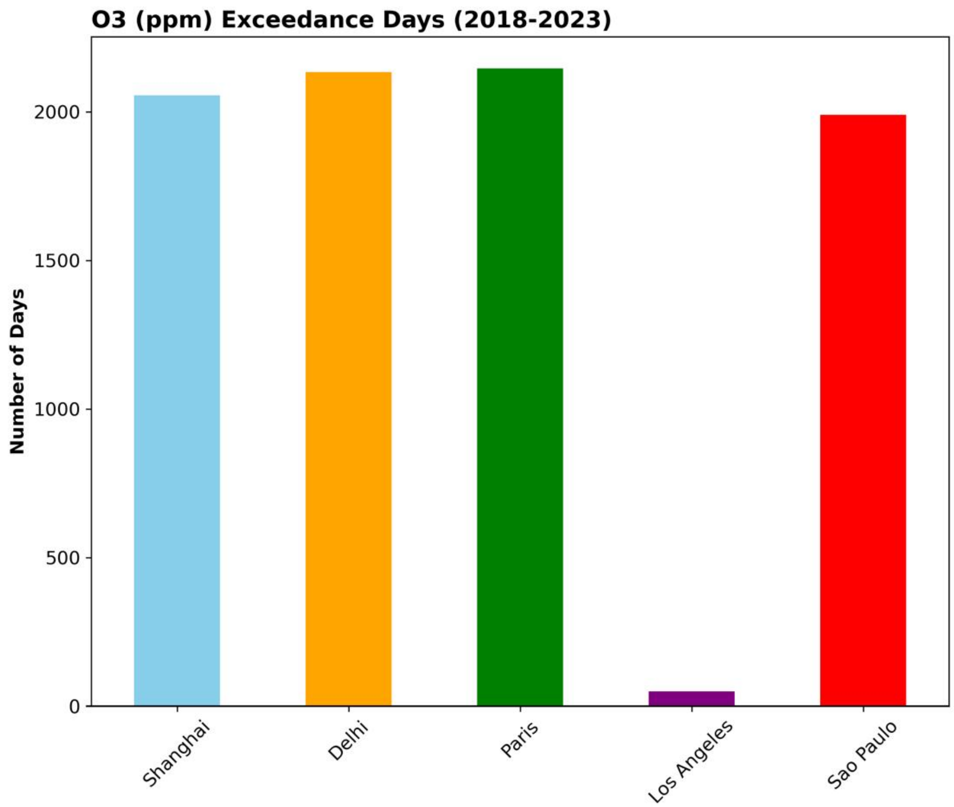

Figure 4: The total number of exceedance days for Ozone (O_3) concentrations (ppm) from 2018 to 2023 across selected cities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo.

Table 4 shows the annual number of exceedance days of O_3 for the period of the five megacities cities. Ground-level ozone is a harmful air pollutant that can cause respiratory and other health issues. Shanghai consistently records a high number of exceedance days for ozone, with a total of 2,055 days over the six years. This highlights ongoing air quality challenges likely due to industrial emissions, vehicular pollution, and meteorological conditions that favor ozone formation. Delhi also shows a significant number of ozone exceedance days, totaling 2,134 days. The city's high levels of ozone pollution are attributed to a combination of vehicular emissions, industrial activities, and climatic factors that promote ozone accumulation. Paris experiences the highest total number of ozone exceedance days among the cities listed, with a cumulative total of 2,146 days.

Table 4: The total number of Ozone (O_3) exceeds days from 2018 to 2023 for each city. The table presents the annual exceedance days for Shanghai, Delhi, Paris, Los Angeles, and Sao Paulo, with an accumulative total for the years (2018-2023).

Total Number of O_3 Exceedance Days (2018-2023) for Each City

Year	Shanghai	Delhi	Paris	Los Angeles	Sao Paulo
2018	311	340	360	5	326
2019	362	358	362	3	345
2020	316	362	362	26	330
2021	365	359	355	1	308
2022	364	359	358	4	345
2023	337	356	349	10	336
Total (2018-2023)	2055	2134	2146	49	1990

The analysis of $PM_{2.5}$ levels for each year from 2018 to 2023 was conducted using standards recommended by the WHO (Appendix A). The results indicate that Delhi and Shanghai consistently rank as the most polluted cities during this period, with Delhi being the most unhealthy among them. From 2018 to 2019, Shanghai's air quality was considered unhealthy for sensitive groups, but it improved to a moderate level after 2020 (Figure 5). In contrast, Paris maintained a steady, moderate air quality throughout the period. Los Angeles, on the other hand, consistently achieved good air quality for the years analyzed. Sao Paulo experienced good air quality from 2018 to 2019 but declined to a moderate level after 2020.

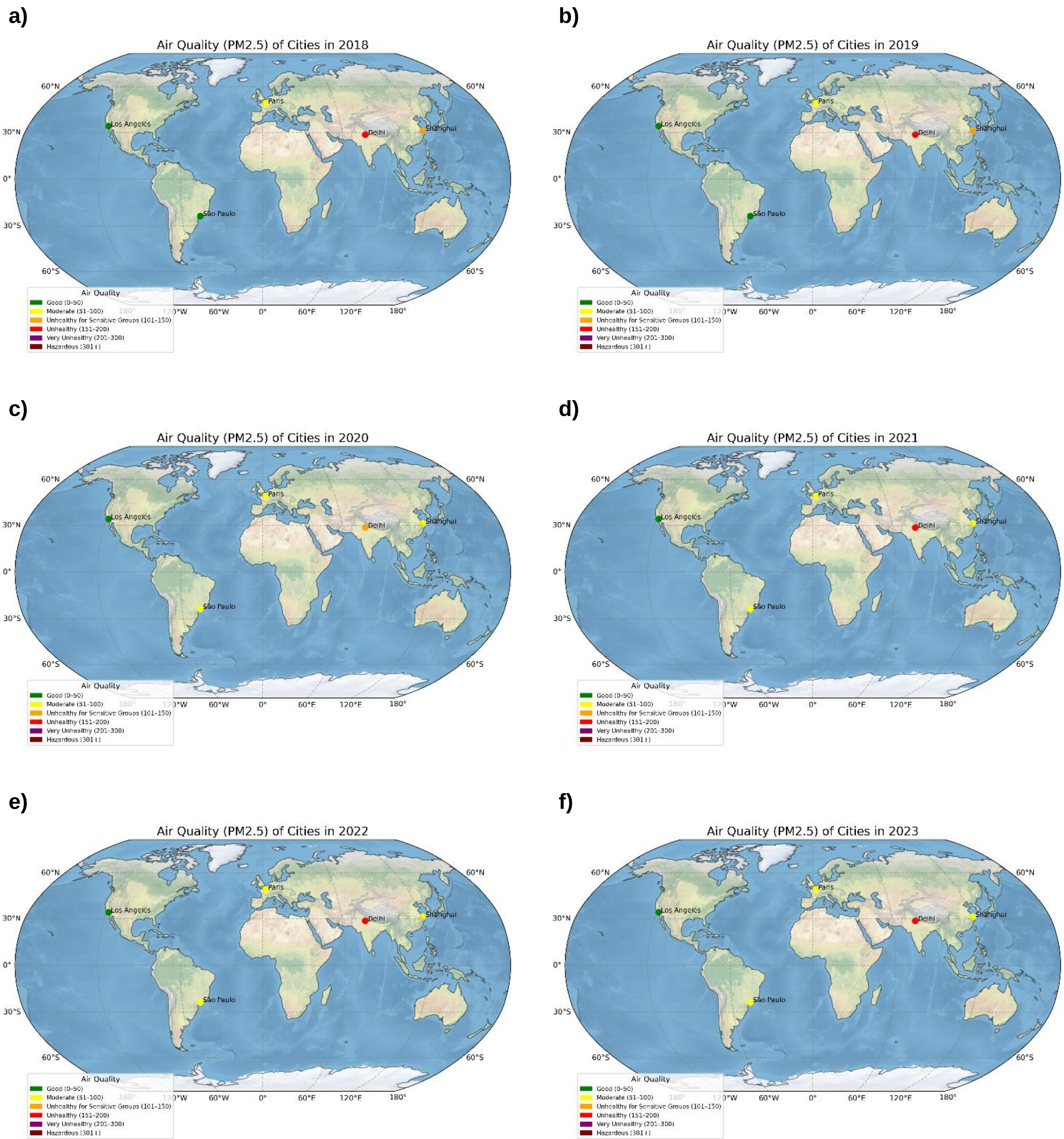

Figure 5: Global distribution of annual mean $PM_{2.5}$ concentrations for selected cities from 2018 to 2023. Each panel represents a different year: (a) 2018, (b) 2019, (c) 2020, (d) 2021, (e) 2022, and (f) 2023. The color scale categorizes air quality based on $PM_{2.5}$ levels, with green indicating good air quality and red indicating hazardous conditions. Notable regions of high $PM_{2.5}$ concentrations appear in Shanghai and Delhi, with varying trends across years.

4.3 Annual Effect of Temperature (°C) on $PM_{2.5}$ (µg/m³)

Figure 6 demonstrates the statistical relationships between temperature (°C) and $PM_{2.5}$ (µg/m³) concentrations in five major cities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo, over the period 2018-2023.

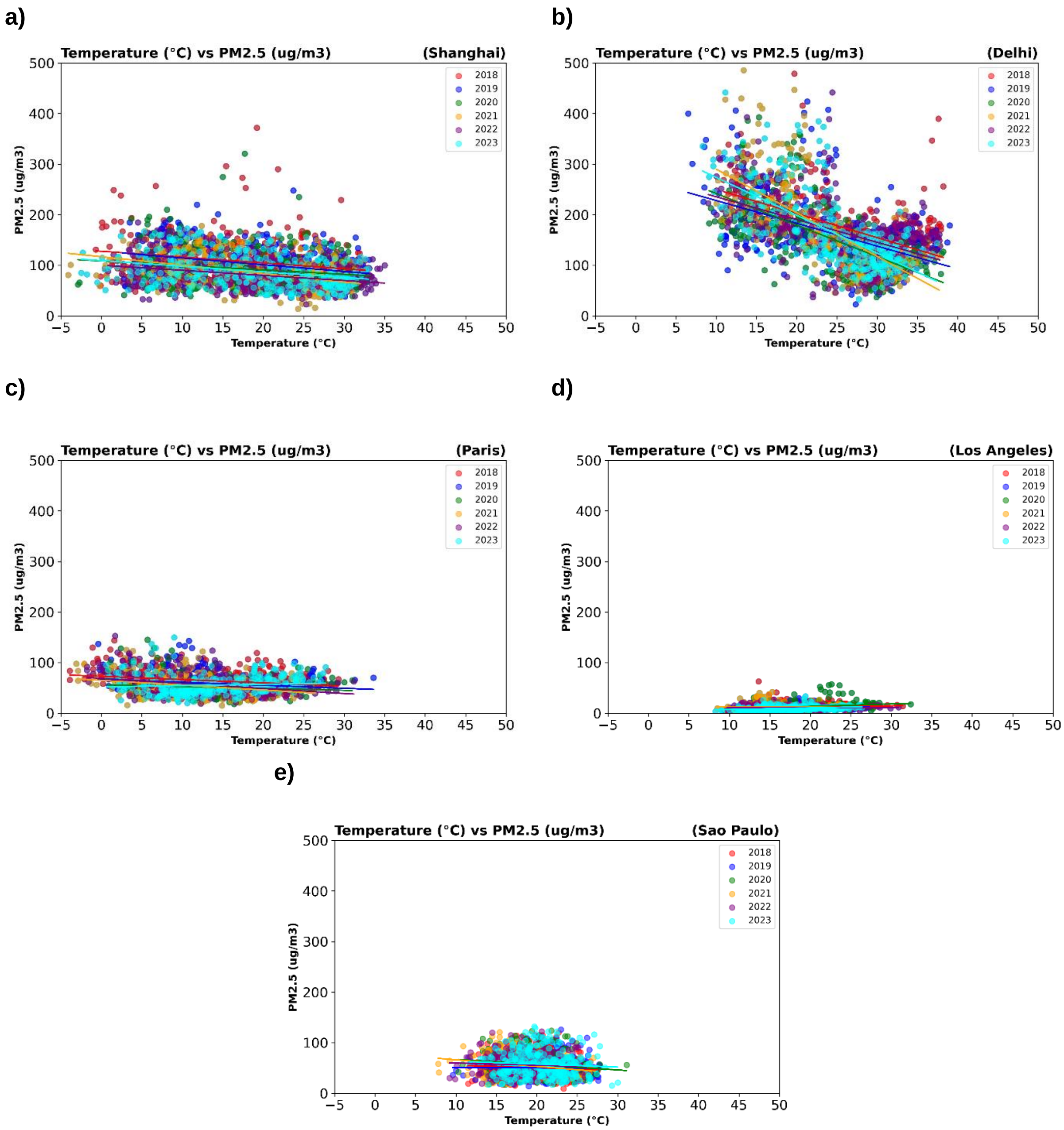

Figure 6: Annual effect of Temperature (°C) on $PM_{2.5}$ (µg/m³) average mass concentration for the Megacities a) Shanghai, b) Delhi, c) Paris, d) Los Angeles, and e) Sao Paulo, for the period 2018-2023.

In Shanghai, there is a weak negative correlation (r = -0.28) between temperature and $PM_{2.5}$ concentrations (significant at a 95% confidence level), indicating that as temperature increases, $PM_{2.5}$ levels tend to decrease slightly (Table 5). This inverse relationship may be influenced by factors such as seasonal variations in emissions and atmospheric conditions. Delhi exhibits a significant negative correlation (r = -0.59) between temperature and $PM_{2.5}$ concentrations, significant at a 95% confidence level (Figure 7b and Table 5). This stronger negative relationship suggests that higher temperatures are associated with a more substantial decrease in $PM_{2.5}$ levels. The slope of -5.80 indicates a marked reduction of 5.80 μg/m³ in $PM_{2.5}$ concentrations for each 1°C rise in temperature. This may be attributed to the dispersal of pollutants due to higher temperatures and changes in atmospheric stability.

The correlation between temperature and $PM_{2.5}$ concentrations in Paris is weakly negative (r = -0.19), significant at a 95% confidence level. In addition, the slope of -0.55 indicates a modest decrease in $PM_{2.5}$ levels with rising temperatures. Although this relationship is statistically significant, it is less marked than in other cities. It is possible that factors influencing this trend could include local emission sources and varying meteorological conditions.

Los Angeles is unique among the cities studied, showing a weak positive correlation (r = 0.16) between temperature and $PM_{2.5}$ concentrations. The slope of 0.22 suggests a slight increase in $PM_{2.5}$ levels with higher temperatures. This positive relationship may be influenced by factors such as increased emissions from vehicles and other sources during warmer periods, as well as the formation of secondary pollutants.

In São Paulo, the relationship between temperature and $PM_{2.5}$ concentrations is weakly negative (r = -0.10). The slope of -0.66 indicates a slight reduction in $PM_{2.5}$ levels with increasing temperatures. Similar to other cities with negative correlations, this trend may be influenced by factors like atmospheric dispersion and seasonal variations in emissions. Figure 7 demonstrates the statistical relationships between Sea Level Pressure (SLP) and $PM_{2.5}$ (particulate matter) concentrations for five megacities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo, using annual average mass concentration data collected throughout 2018-2023.

Table 5: Statistical relationships between Temperature (°C) and $PM_{2.5}$ (μg/m³) concentrations average mass concentration for the Megacities **a)** Shanghai, **b)** Delhi, **c)** Paris, **d)** Los Angeles, and **e)** São Paulo, for the period 2018-2023. Significant relationships ($p < 0.05$) are highlighted as *****.

Sr. No	City	Parameter	Correlation (r)	Slope (β)
1	**Shanghai**	**Temperature**	**-0.28***	**-1.20**
2	**Delhi**		**-0.59***	**-5.80**
3	**Paris**		**-0.19***	**-0.55**
4	**Los Angeles**		**0.16***	**0.22**
5	**São Paulo**		**-0.1***	**-0.66**

Figure 7 further demonstrates the statistical relationships between Sea Level Pressure (SLP) and $PM_{2.5}$ (particulate matter) concentrations for five megacities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo, using annual average mass concentration data collected over the period of 2018-2023. For Shanghai, the correlation coefficient (r) between SLP and $PM_{2.5}$ concentrations is 0.22 (significant at a 95% significance level), indicating a weak positive relationship. The slope (β) of 0.87 suggests that as SLP increases, $PM_{2.5}$ concentrations tend to increase slightly (Table 6). This weak positive correlation implies that sea level pressure variations have a minor influence on $PM_{2.5}$ levels in Shanghai, which may be influenced by other atmospheric and urban factors. Delhi exhibits a strong positive correlation between SLP and $PM_{2.5}$ concentrations, with an r-value of 0.62 (significant at a 95% significance level). This indicates that higher sea level pressure is associated with markedly higher $PM_{2.5}$ concentrations. The slope (β) of 6.36 is relatively steep, emphasizing the substantial increase in $PM_{2.5}$ levels with rising SLP (Table 6). This strong relationship highlights the impact of meteorological conditions on air quality in Delhi, where higher pressure conditions might be linked to air stagnation and accumulation of pollutants. The correlation coefficient (r) in Paris is 0.17 (significant at 95% significance level), indicating a weak positive relationship between SLP and $PM_{2.5}$ concentrations. The slope (β) is 0.37, suggesting that $PM_{2.5}$ levels slightly increase with rising sea level pressure (Table 6). This weak correlation signifies that while there is a relationship between SLP and $PM_{2.5}$, other factors are likely to play a more dominant role in influencing particulate matter concentrations in Paris.

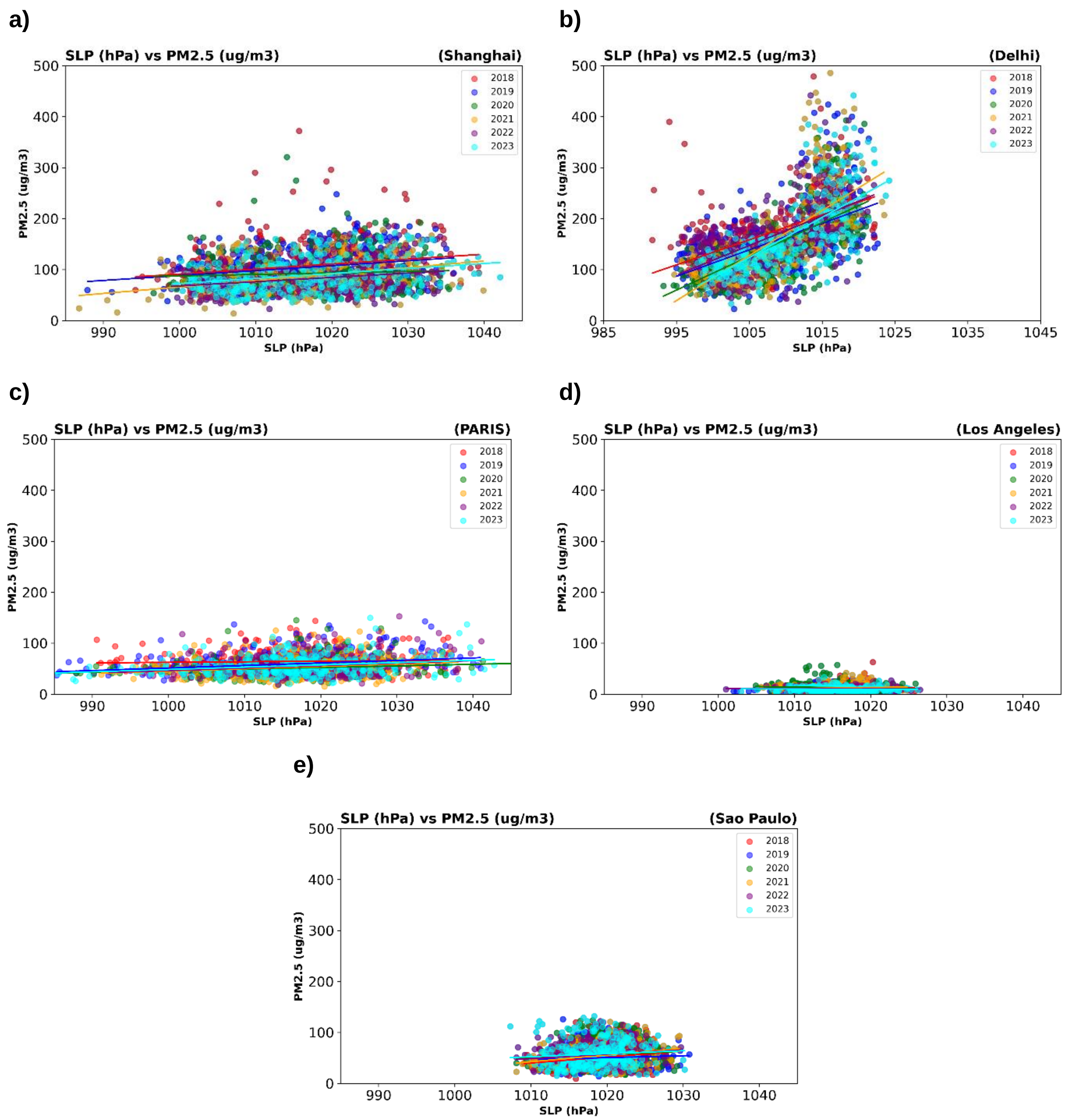

Figure 7: Annual effect of SLP (hpa) on $PM_{2.5}$ (µg/m³) average mass concentration for the Megacities **a)** Shanghai, **b)** Delhi, **c)** Paris, **d)** Los Angeles, and **e)** Sao Paulo, for the period 2018-2023.

Los Angeles presents a unique case where the correlation between SLP and $PM_{2.5}$ concentrations is negligible, with an r-value of -0.02. The negative slope (β) of -0.03 indicates an almost nonexistent relationship (Table 6). This implies that variations in sea level pressure do not have a notable impact on $PM_{2.5}$ levels in Los Angeles, and the air quality is more likely influenced by other local factors such as vehicle emissions, industrial activities, and regional climate patterns.

For São Paulo, the correlation coefficient (r) is 0.14 (significant at a 95% significance level), indicating a weak positive relationship between SLP and $PM_{2.5}$ concentrations. The slope (β) of 0.80 suggests a slight increase in $PM_{2.5}$ levels with rising SLP (Table 6). Like Paris and Shanghai, this weak correlation implies that sea level pressure has a minor influence on $PM_{2.5}$ concentrations in São Paulo, with other factors contributing more significantly to air quality. The analysis of the statistical relationships between SLP and $PM_{2.5}$ concentrations across these megacities reveals varying degrees of correlation. Delhi stands out with a strong positive correlation, highlighting the significant impact of sea level pressure on air quality. In contrast, Los Angeles shows no meaningful relationship, indicating that other factors are more critical in determining $PM_{2.5}$ levels. The weak correlations observed in Shanghai, Paris, and São Paulo suggest that while there is a relationship between SLP and $PM_{2.5}$ concentrations, it is not the primary influencing factor in these cities.

Table 6: Statistical relationships between Sea Level Pressure SLP (hpa) and PM2.5 (µg/m³) concentrations average mass concentration for the Megacities **a)** Shanghai, **b)** Delhi, **c)** Paris, **d)** Los Angeles, and **e)** São Paulo, for the period 2018-2023. Significant relationships ($p < 0.05$) are highlighted as *****.

Sr. No	City	Parameter	Correlation (r)	Slope (β)
1	Shanghai	SLP	0.22*	0.87
2	Delhi		0.62*	6.36
3	Paris		0.17*	0.37
4	Los Angeles		-0.02	-0.03
5	São Paulo		0.14*	0.80

Figure 8 displays the statistical relationships between Wind Speed (m/s) and $PM_{2.5}$ (particulate matter) concentrations for five megacities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo, using annual average mass concentration data collected over the period of 2018-2023.

For Shanghai, the correlation coefficient (r) between Wind Speed and $PM_{2.5}$ concentrations is -0.07 (significant at a 95% significance level), which indicates a very weak negative relationship. The slope (β) of -0.38 suggests that as Wind Speed increases, $PM_{2.5}$ concentrations tend to decrease slightly (Table 7). This weak negative correlation implies that wind speed variations have a minor influence on $PM_{2.5}$ levels in Shanghai, possibly due to other contributing factors. Delhi exhibits a weak negative correlation between Wind Speed and $PM_{2.5}$ concentrations, with an r-value of -0.21

(significant at a 95% significance level). This indicates that higher wind speeds are associated with lower $PM_{2.5}$ concentrations. The slope (β) of -2.05 highlights a more noticeable decrease in PM2.5 levels with increasing Wind Speed. This relationship suggests that increased wind speeds may help disperse pollutants, improving air quality in Delhi. The correlation coefficient (r) in Paris is -0.19 (significant at 95% significance level), indicating a weak negative relationship between Wind Speed and $PM_{2.5}$ concentrations. The slope (β) is -0.64, suggesting that $PM_{2.5}$ levels decrease with rising wind speeds (Table 7). This weak correlation signifies that while wind speed impacts $PM_{2.5}$ concentrations, other factors also play a significant role in influencing air quality in Paris.

Los Angeles shows a slightly stronger negative correlation between Wind Speed and $PM_{2.5}$ concentrations, with an r-value of -0.29 (significant at a 95% significance level). The negative slope (β) of -0.30 indicates that higher wind speeds are associated with lower $PM_{2.5}$ levels. This suggests that wind can help reduce particulate matter concentrations by dispersing pollutants more effectively in Los Angeles.

For São Paulo, the correlation coefficient (r) is -0.04 (significant at a 95% significance level), indicating a weak negative relationship between Wind Speed and $PM_{2.5}$ concentrations. The slope (β) of -0.20 suggests a slight decrease in $PM_{2.5}$ levels with rising wind speeds. Similar to Shanghai, this weak correlation implies that wind speed has a minor influence on $PM_{2.5}$ concentrations in São Paulo, with other factors contributing more significantly to air quality.

The analysis of the statistical relationships between Wind Speed and $PM_{2.5}$ concentrations across these megacities reveals varying degrees of negative correlation. Los Angeles shows a considerable negative correlation, suggesting that wind speed substantially impacts reducing $PM_{2.5}$ levels. In contrast, Shanghai and São Paulo show weak negative correlations, indicating that wind speed minimally affects $PM_{2.5}$ concentrations. The weak negative correlations observed in Delhi and Paris suggest that while wind speed does play a role in influencing $PM_{2.5}$ levels, it is not the primary factor. Understanding these relationships can help inform targeted air quality management strategies and mitigation efforts specific to each city's unique environmental conditions.

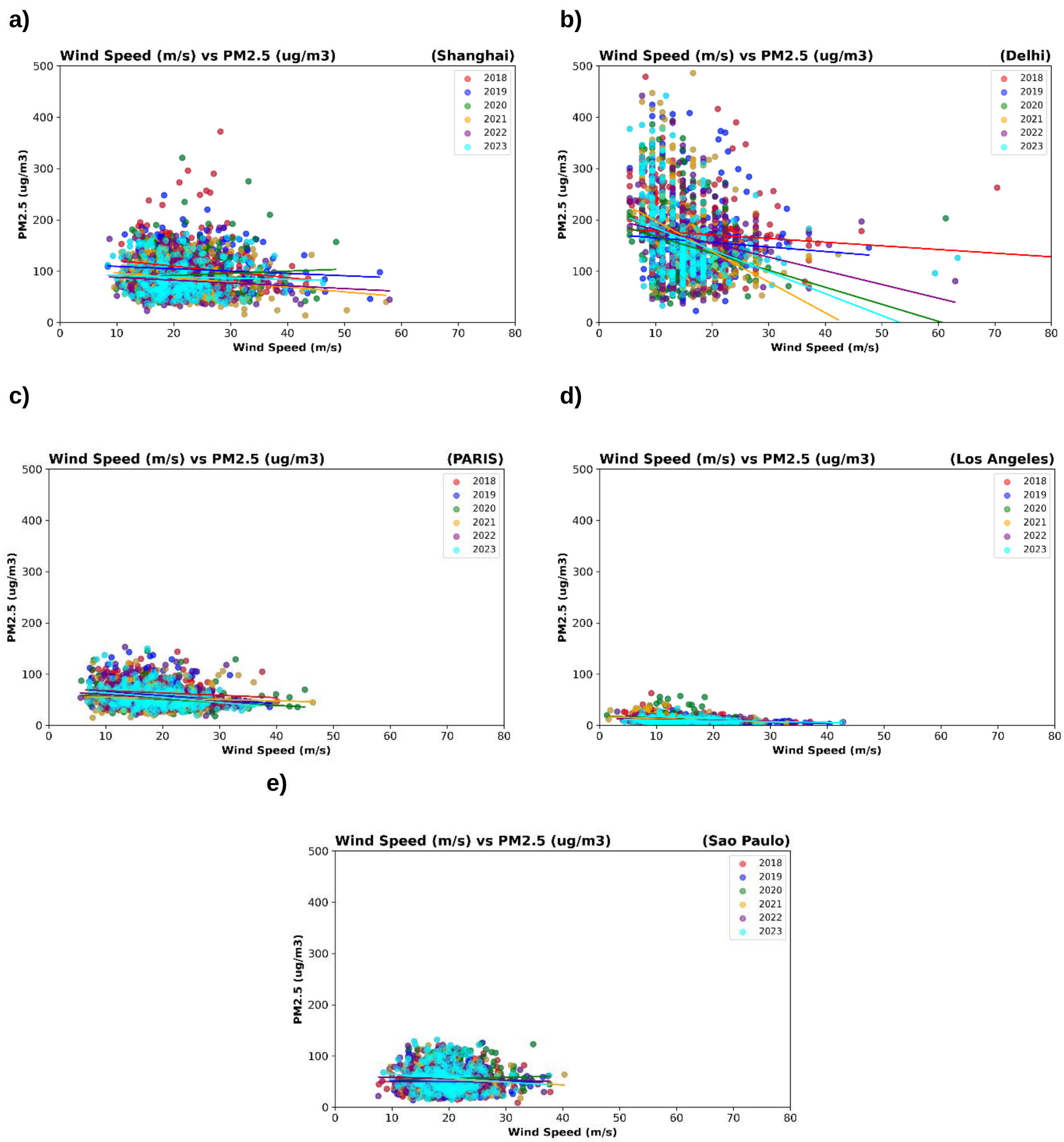

Figure 8: Annual effect of Wind Speed (m/s) on PM2.5 (µg/m³) average mass concentration for the Megacities **a)** Shanghai, **b)** Delhi, **c)** Paris, **d)** Los Angeles, and **e)** Sao Paulo, for the period 2018-2023.

The analysis of the statistical relationships between Wind Speed and $PM_{2.5}$ concentrations across these megacities reveals varying degrees of negative correlation. Los Angeles shows a notable negative correlation, suggesting that wind speed has a more substantial impact on reducing $PM_{2.5}$ levels. In contrast, Shanghai and São Paulo show very weak negative correlations, indicating that wind speed has a minimal effect on $PM_{2.5}$ concentrations. The weak negative correlations observed in Delhi and Paris suggest that while wind speed does play a role in influencing $PM_{2.5}$ levels, it is not the primary factor. Understanding these relationships can help inform targeted air quality management strategies and mitigation efforts specific to each city's unique environmental conditions.

Table 7: Statistical relationships between Wind Speed (m/s) and PM2.5 (μg/m³) concentrations average mass concentration for the Megacities a) Shanghai, b) Delhi, c) Paris, d) Los Angeles, and e) São Paulo, for the period 2018-2023. Significant relationships ($p < 0.05$) are highlighted as *.

Sr. No	City	Parameter	Correlation (r)	Slope (β)
1	Shanghai	Wind Speed	-0.07*	-0.38
2	Delhi		-0.21*	-2.05
3	Paris		-0.19*	-0.64
4	Los Angeles		-0.29*	-0.30
5	São Paulo		-0.04*	-0.20

4.4 Annual Effect of Temperature (°C) on O_3 (ppm)

Figure 9 demonstrates the statistical relationships between temperature (°C) and ozone (O_3) concentrations (ppm) in five major megacities (Shanghai, Delhi, Paris, Los Angeles, and São Paulo) during the period 2018–2023. The findings highlight significant correlations ($p < 0.05$) between these parameters and provide insights into the varying dynamics of O_3 behavior with temperature across different urban environments.

The relationship between temperature and O_3 concentrations in Shanghai exhibited a moderate positive correlation (r = 0.50*), which indicates that temperature increases were associated with higher ozone levels. This could be attributed to enhanced photochemical reactions facilitated by warmer conditions, a trend commonly observed in urban-industrial areas (Table 8). Also, the correlation (r = 0.27*) was relatively weaker in Delhi compared to Shanghai. However, the relationship was still statistically noticeable, implying a consistent yet modest association between temperature and O_3 levels. The slope (β = 0.76) suggests that the increase in ozone concentration with temperature was less pronounced, potentially reflecting the influence of high particulate matter and other atmospheric factors that can suppress ozone formation (Table 8). Paris demonstrated the strongest positive correlation (r = 0.70*), indicating a robust relationship between temperature and ozone concentrations. The slope (β = 1.27) was also the highest among all cities, which shows the sensitivity of O_3 levels to temperature changes. This could be indicative of cleaner atmospheric conditions in Paris compared to cities like Shanghai and Delhi, where such sensitivity may be mitigated by other pollutants (Table 8).

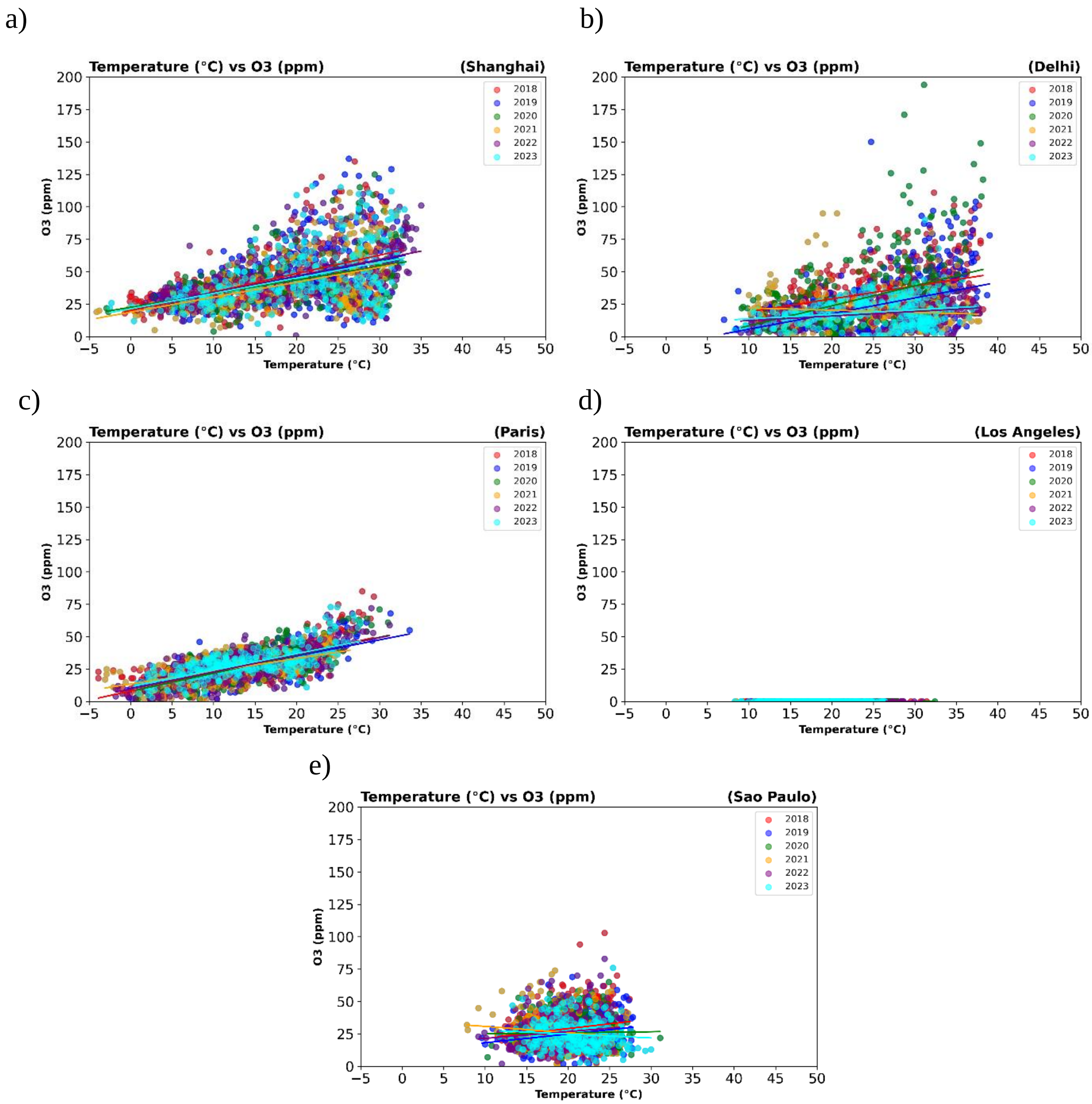

Figure 9: Annual effect of Temperature (°C) on O3 (ppm) average mass concentration for the Megacities a) Shanghai, b) Delhi, c) Paris, d) Los Angeles, and e) Sao Paulo, for the period 2018-2023.

Los Angeles, known for its historical smog issues, showed a strong correlation ($r = 0.65^*$). However, the slope ($\beta = 0.002$) was notably low, indicating that while temperature and ozone are closely linked, the actual increase in O_3 concentrations with temperature is minimal. This suggests that factors such as stringent air quality regulations and the complexity of local atmospheric chemistry play a role in moderating O_3 increases despite warmer temperatures (Table 8). The weakest relationship was observed in São Paulo, with a very low correlation (r = 0.05*) and a slight slope (β = 0.17). While the statistical relationship is marked, the weak correlation suggests that temperature is not a major driver of ozone variations in this region (Table 8). Other factors such as humidity, emissions profiles, and local meteorological conditions likely play a larger role in influencing O_3 levels.

These findings reveal that the relationship between temperature and O_3 concentrations varies considerably among megacities due to differences in climate, pollution sources, atmospheric conditions, and regulatory frameworks.

Table 8: Statistical relationships between Temperature (°C) and O3 (ppm) concentrations average mass concentration for the Megacities **a)** Shanghai, **b)** Delhi, **c)** Paris, **d)** Los Angeles, and **e)** São Paulo, for the period 2018-2023. Significant relationships (p < 0.05) are highlighted as *.

Sr. No	City	Parameter	Correlation (r)	Slope (β)
1	Shanghai	Temperature	0.50*	1.21
2	Delhi		0.27*	0.76
3	Paris		0.70*	1.27
4	Los Angeles		0.65*	0.002
5	São Paulo		0.05*	0.17

4.5 Seasonal Concentration of Air Pollutants for Megacities

Figure 10 demonstrate that $PM_{2.5}$ concentration has reduced in Shanghai across all seasons, which highlights an improvement in air quality. In winter, $PM_{2.5}$ levels decreased consistently, from 125.68 µg/m³ in 2018 to 94.24 µg/m³ by 2023. This reduction indicates the positive impact of strict environmental policies, and there has been a rise in public awareness about air pollution. Similarly, there was a noticeable decrease in $PM_{2.5}$ concentrations, from 121.20 µg/m³ in 2018 to 93.93 µg/m³ in 2023 during the spring, which often characterized by higher pollutant levels due to pollen and dust, benefited from measures to curb emissions and improve air quality. In contrast, summer months showed the lowest $PM_{2.5}$ concentrations compared to other seasons. It started at

84.33 μg/m³ in 2018 and reduced to 74.71 μg/m³ in 2023. The relatively lower levels in summer can be attributed to favorable weather conditions, such as increased rainfall and stronger winds, which help disperse pollutants. Additionally, through summer holiday periods, It often notices reduced industrial activities, contributing to lower $PM_{2.5}$ concentrations. Also, during fall, there was a consistent decrease in $PM_{2.5}$ levels over the years, with concentrations falling from 102.26 μg/m³ in 2018 to 82.91 μg/m³ in 2023. Despite the improvement, fall $PM_{2.5}$ levels remained higher than in summer, likely due to increased agricultural activities such as crop burning that contribute to higher pollution levels. Shanghai has made efforts to improve air quality through comprehensive policies and initiatives to reduce emissions from various sources. However, the higher $PM_{2.5}$ concentrations in winter and spring compared to summer and fall suggest that continued efforts are needed to address seasonal variations and specific sources of pollution during these periods. Over the period from 2018 to 2023, the seasonal average concentrations of $PM_{2.5}$ in Delhi showed distinct seasonal trends. During the winter months, $PM_{2.5}$ concentrations were significantly high, starting at 217.81 μg/m³ in 2018 and fluctuating slightly each year to 222.65 μg/m³ in 2023, with a peak of 232.17 μg/m³ in 2020. Spring months exhibited considerable variability, with $PM_{2.5}$ concentrations dropping from 165.07 μg/m³ in 2018 to 112.47 μg/m³ in 2020, then rising again to 164.80 μg/m³ in 2021 before slightly decreasing to 133.02 μg/m³ in 2023. Summer months showed the lowest $PM_{2.5}$ concentrations, indicating improved air quality during this season. Concentrations started at 128.65 μg/m³ in 2018 and decreased to a low of 90.03 μg/m³ in 2020, with a gradual rise to 107.76 μg/m³ by 2023. During the fall, $PM_{2.5}$ concentrations fluctuated but remained relatively high compared to spring and summer. Concentrations were 179.56 μg/m³ in 2018, reached a low of 167.28 μg/m³ in 2021, and peaked again at 182.93 μg/m³ in 2023. These trends highlight the seasonal variations in air quality in Delhi, influenced by various factors such as weather conditions, industrial activities, and regulatory measures. The overall analysis underscores the critical need for sustained efforts to manage and reduce air pollution in the city.

The $PM_{2.5}$ mass concentrations during winter exhibit variability across the years (Figure 10). The highest levels were recorded in 2018 (66.98 μg/m³) and 2019 (72.75 μg/m³). However, there was a considerable drop in 2020 to 55.09 μg/m³ and a slight increase in 2021 (58.37 μg/m³). Also, spring showed a general decrease in $PM_{2.5}$ levels from 66.11 μg/m³ in 2018 to 52.74 μg/m³ in 2020, with a slight rise to 57.16 μg/m³ in 2021. This indicates improved air quality during the spring season over the years. Throughout summer, Paris experienced a consistent decrease in $PM_{2.5}$

levels, from 57.99 µg/m³ in 2018 to 45.62 µg/m³ in 2020. This trend was consistent with a slight increase in 2021 to 42.50 µg/m³. In the fall, the $PM_{2.5}$ levels showed a reduction from 67.09 µg/m³ in 2018 to 49.38 µg/m³ in 2019, with slight fluctuations, thereafter, peaking at 54.02 µg/m³ in 2020 and falling to 53.56 µg/m³ in 2021. This indicates a positive trend in reducing pollution levels during the fall season.

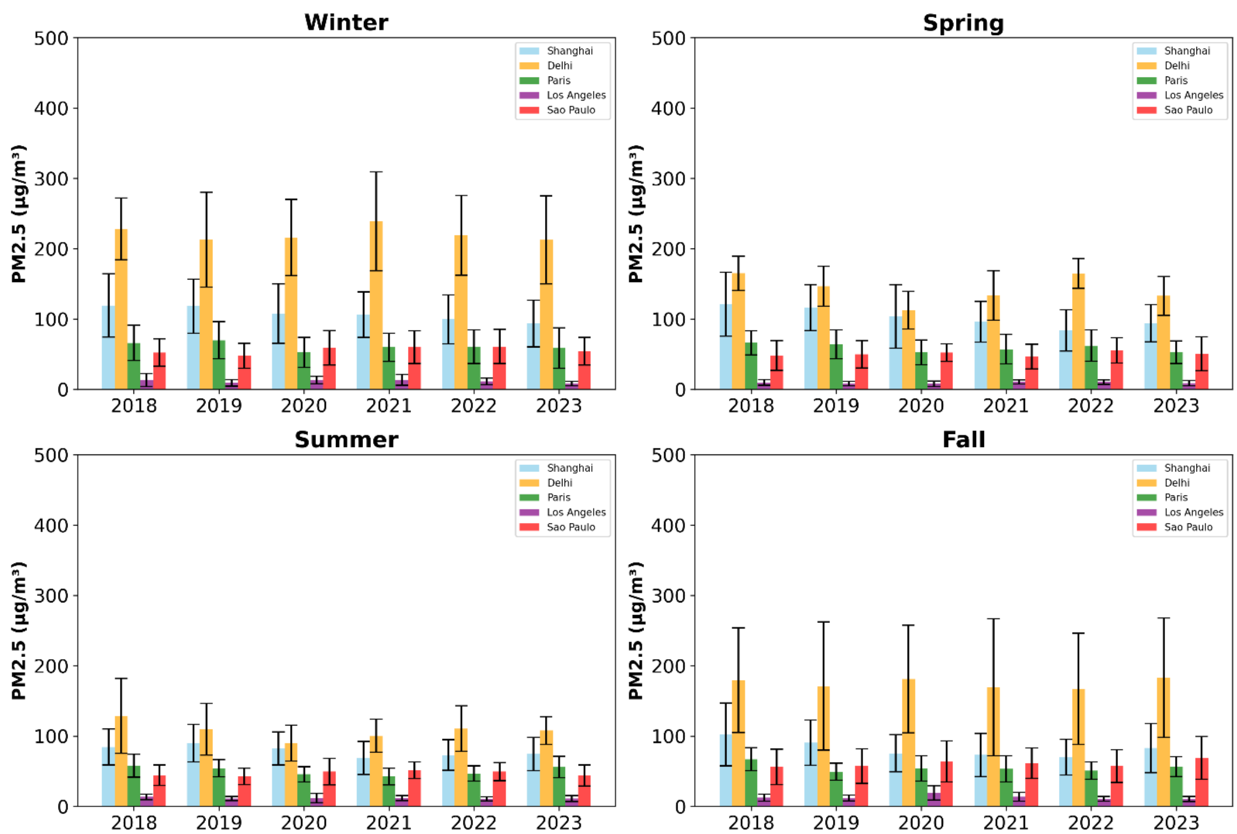

Figure 10: Seasonal variations in $PM_{2.5}$ concentrations from 2018 to 2023 across selected cities. The bar charts represent average $PM_{2.5}$ levels (µg/m³) for each year, categorized by season (Winter, Spring, Summer, and Fall). Error bars indicate yearly variability in measurements.

From 2018 to 2023, the $PM_{2.5}$ concentrations in Los Angeles exhibited seasonal variations, reflecting changes in air quality. During the winter months, the average $PM_{2.5}$ concentrations showed a fluctuating trend, starting at 13.58 µg/m³ in 2018, decreasing to 10.10 µg/m³ in 2019, rising again to 12.00 µg/m³ in 2020, and eventually reaching a low of 9.36 µg/m³ in 2023. The spring season recorded lower $PM_{2.5}$ levels than winter, with concentrations decreasing from 9.77 µg/m³ in 2018 to 8.64 µg/m³ in 2023. This improvement in air quality during spring can be attributed to milder weather conditions and increased rainfall, which help in dispersing pollutants.

In summer, $PM_{2.5}$ concentrations remained relatively stable, with levels starting at 13.48 μg/m³ in 2018 and decreasing to 10.93 μg/m³ in 2023. The lower $PM_{2.5}$ levels in summer can be linked to improved atmospheric conditions, such as increased sunlight and wind, which facilitate the dispersion of pollutants. Fall showed more variability in $PM_{2.5}$ concentrations, with a significant spike in 2020 at 19.28 μg/m³ before stabilizing around 10.46 μg/m³ in 2023. This variability in fall $PM_{2.5}$ levels could be influenced by factors such as wildfires and agricultural activities, which are more prevalent during this season. Overall, the trends suggest an general improvement in air quality in Los Angeles from 2018 to 2023, with seasonal variations influenced by weather conditions and specific pollution sources. These findings underscore the importance of continued efforts to monitor and manage air quality, particularly during the fall and winter months when $PM_{2.5}$ concentrations tend to be higher.

The analysis of $PM_{2.5}$ concentrations in São Paulo and Paris from 2018 to 2023 reveals some interesting seasonal patterns and variations (Figure 10). During winter, it shows significant variability in $PM_{2.5}$ concentrations. 2018 had a moderate level at 51.62 μg/m³, while 2019 saw a slight decrease to 48.68 μg/m³. However, 2020 and 2021 witnessed increases to 59.19 μg/m³ and 61.51 μg/m³, respectively, indicating a trend of rising pollution levels in the winter. The spring season appeared relatively stable, with $PM_{2.5}$ levels ranging from 45.36 μg/m³ in 2021 to 51.93 μg/m³ in 2020. The data suggests slight fluctuations without a clear trend over the years. During summer, Sao Paulo experiences a downward trend in $PM_{2.5}$ levels from 2018 (43.33 μg/m³) to 2020 (42.83 μg/m³), followed by an increase in 2021 (52.35 μg/m³). The year 2019 also shows a moderate concentration at 44.49 μg/m³. Fall presents fluctuating $PM_{2.5}$ levels, began at 56.33 μg/m³ in 2018, increased to 62.06 μg/m³ in 2020, and slightly decreased to 60.94 μg/m³ in 2021. This suggests a general upward trend in fall pollution over these years.

Figure 11 demonstrates the statistical relationships between Temperature (°C) and $PM_{2.5}$ (particulate matter) concentrations for five megacities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo, for seasonal average mass concentration data collected throughout 2018-2023.

The relationship between temperature and $PM_{2.5}$ concentrations in Shanghai varies across seasons. The correlation is almost nonexistent in winter at -0.02 in 2018, indicating that temperature changes have little effect on $PM_{2.5}$ concentration during this season. Over the years, the average correlation in winter is 0.01 with a slope of 0.12, suggesting a slight increase in $PM_{2.5}$ levels with rising temperatures. In spring, a positive correlation of 0.07 suggests a minor increase in $PM_{2.5}$ with rising temperatures, with notable seasonal variability reflected in increased slope values. During summer, the overall correlation is -0.09 (Table 9), indicating a weak negative relationship where higher temperatures slightly reduce $PM_{2.5}$ levels. Fall displays a weak negative correlation of -0.15, suggesting that higher temperatures slightly reduce $PM_{2.5}$ concentrations. These weak correlations imply that temperature has a limited effect on $PM_{2.5}$ levels in Shanghai, with other factors playing a more dominant role.

Delhi exhibits more pronounced relationships between temperature and $PM_{2.5}$ concentrations across all seasons. During winter, a strong negative correlation of -0.27 indicates that lower temperatures are associated with higher $PM_{2.5}$ levels, with a steep slope of -4.96. In spring, a positive correlation of 0.19 suggests that higher temperatures slightly increase $PM_{2.5}$ concentrations. Summer shows a strong positive correlation of 0.54, highlighting a significant increase in $PM_{2.5}$ levels with rising temperatures. A strong negative correlation of -0.64 in fall suggests that higher temperatures are associated with lower $PM_{2.5}$ levels. These pronounced correlations in Delhi indicate that temperature significantly influences $PM_{2.5}$ concentrations, with notable seasonal variability.

Paris shows varying relationships between temperature and $PM_{2.5}$ concentrations. During winter, a strong negative correlation of -0.36 indicates lower temperatures are associated with higher $PM_{2.5}$ levels. In spring, the correlation is almost negligible at -0.02. During summer, a positive correlation of 0.40 suggests higher temperatures are associated with increased $PM_{2.5}$ levels. In the fall, the correlation is almost nonexistent at 0.01. These mixed correlations suggest that while temperature does influence $PM_{2.5}$ levels in Paris, the effect varies significantly across seasons.

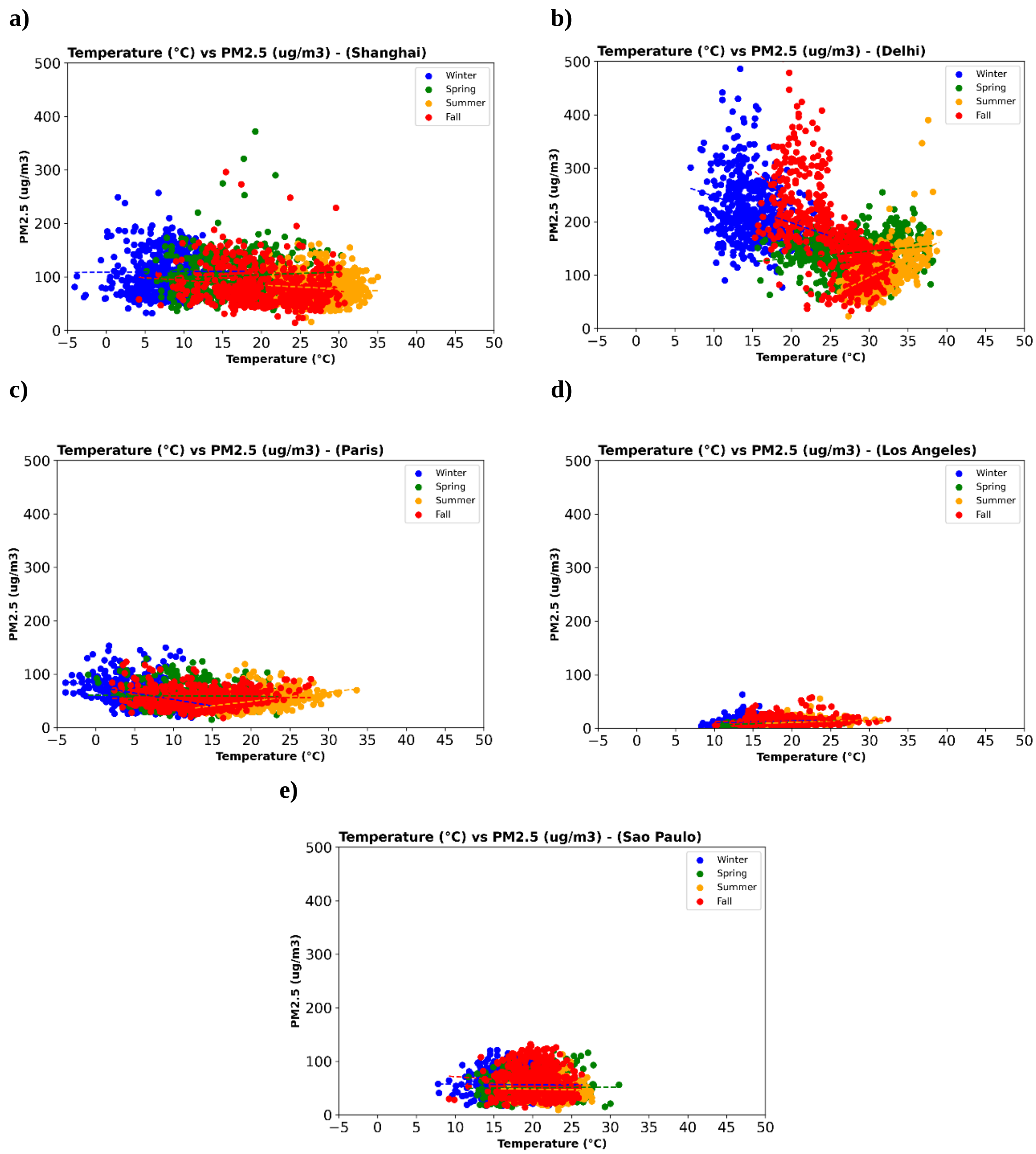

Figure 11: Seasonal effect of temperature (°C) on $PM_{2.5}$ (µg/m³) average mass concentration in megacities: (a) Shanghai, (b) Delhi, (c) Paris, (d) Los Angeles, and (e) São Paulo, for the period 2018–2023. Each scatter plot represents seasonal variations, with winter (blue), spring (green), summer (red), and fall (orange).

Table 9: Statistical relationships between Temperature (°C) and PM2.5 (μg/m³) concentrations average mass concentration for the Megacities **a)** Shanghai, **b)** Delhi, **c)** Paris, **d)** Los Angeles, and **e)** São Paulo, for the period 2018-2023. Significant relationships ($p < 0.05$) are highlighted as *.

Statistical Relationships between Temperature (°C) and PM2.5 (μg/m³) Concentrations									
City	Year	Correlation				Slope			
		Winter	Spring	Summer	Fall	Winter	Spring	Summer	Fall
Shanghai	2018	-0.02	0.22*	-0.16	-0.12	-0.21	1.75	-1.59	-1.08
	2019	0.14	-0.19*	-0.06	-0.02	2.03	-1.23	-0.53	-0.10
	2020	0.00	0.21	-0.03	0.09	0.00	2.80	-0.23	0.50
	2021	-0.01	0.01	0.00	-0.35*	-0.07	0.06	0.02	-1.68
	2022	0.09	0.00	0.12	-0.13	1.21	0.00	0.84	-0.72
	2023	-0.05	0.11	-0.05	-0.34*	-0.58	0.62	-0.42	-2.11
	2018-2023	0.01	0.07	-0.09*	-0.15*	0.12	0.51	-0.71	-1.03
Delhi	2018	-0.48*	0.14	0.68*	-0.65*	-6.18	0.81	13.20	-13.12
	2019	-0.18	0.10	0.61*	-0.50*	-4.13	0.50	7.34	-11.27
	2020	-0.024	0.04	0.52*	-0.63*	-0.44	0.20	5.63	-9.02
	2021	-0.34*	-0.10	0.38*	-0.82*	-7.18	-1.01	3.60	-18.38
	2022	-0.36*	0.30*	0.65*	-0.53*	-7.33	1.41	7.31	-8.49
	2023	-0.46*	0.02	0.27*	-0.73*	-6.77	0.11	2.68	-13.93
	2018-2023	-0.27*	0.19*	0.54*	-0.64*	-4.96	1.30	7.31	-12.03
Paris	2018	-0.58*	0.07	0.14	-0.24*	-3.52	0.23	0.68	-0.76
	2019	-0.01	0.08	0.59*	-0.34*	-0.11	0.50	1.87	-0.93
	2020	-0.32*	-0.04	0.50*	-0.09	-2.25	-0.14	1.44	-0.34
	2021	-0.38*	-0.06	0.46*	-0.04	-1.80	-0.35	2.31	-0.16
	2022	-0.58*	-0.28*	0.32*	0.02	-3.64	-1.38	1.12	0.06
	2023	-0.19	0.15	0.46*	0.63*	-1.60	0.64	2.88	1.56
	2018-2023	-0.36*	-0.02	0.40*	0.01	-2.41	-0.09	1.72	0.03
Los Angeles	2018	0.19*	0.30*	0.16	-0.18*	0.75	0.58	0.22	-0.42
	2019	0.33*	0.35*	0.20*	-0.16	0.73	0.63	0.28	-0.19
	2020	-0.28*	0.67*	0.37*	0.26*	-0.65	0.78	0.96	0.66
	2021	0.00	0.42*	0.17	-0.35*	-0.01	0.48	0.35	-0.79
	2022	-0.10	0.21*	-0.06	0.16	-0.20	0.25	-0.10	0.13
	2023	0.21	0.40*	0.27*	0.15	0.35	0.66	0.45	0.23
	2018-2023	0.12*	0.36*	0.26*	0.04	0.33	0.51	0.47	0.08
São Paulo	2018	0.19*	-0.11	-0.05	-0.12	1.34	-0.88	-0.34	-1.14
	2019	-0.09	0.21*	0.07	-0.12	-0.51	1.18	0.35	-1.49
	2020	0.03	-0.14	0.04	-0.17	0.24	-0.52	0.39	-1.82
	2021	-0.13	-0.02	-0.16	-0.21	-0.92	-0.11	-0.85	-2.54
	2022	-0.13	0.15	0.10	-0.04	-1.18	0.84	0.64	-0.28
	2023	0.20*	0.02	0.14	0.00	1.51	0.13	1.11	-0.01
	2018-2023	-0.01	0.02	-0.02	-0.11*	-0.08	0.12	-0.14	-1.03

Los Angeles displays relatively consistent relationships between temperature and $PM_{2.5}$ concentrations. In winter, a positive correlation of 0.12 indicates that higher temperatures are associated with slight increases in $PM_{2.5}$ levels. During spring, a positive correlation of 0.36 suggests a moderate increase in $PM_{2.5}$ with rising temperatures. Summer exhibits a positive correlation of 0.26, indicating a slight increase in $PM_{2.5}$ levels with higher temperatures. In the fall, the correlation is negligible at 0.04. These positive correlations suggest that higher temperatures are generally associated with increased $PM_{2.5}$ concentrations in Los Angeles, with seasonal variations.

São Paulo exhibits weak and varying relationships between temperature and $PM_{2.5}$ concentrations. During winter, the correlation is almost nonexistent at -0.01. In spring, there is a negligible positive correlation of 0.02. During summer, the correlation is negligible at -0.02. In fall, a weak negative correlation of -0.11 suggests that higher temperatures are slightly associated with lower $PM_{2.5}$ levels. These weak correlations in São Paulo indicate that temperature has a limited effect on $PM_{2.5}$ levels, with other factors likely playing a more significant role.

Shanghai's seasonal ozone (O_3) concentrations exhibited changing patterns across seasons from 2018 to 2023, reflecting the complex interplay between environmental factors and pollution control measures. During the winter months, the average ozone concentrations fluctuated, starting at 30.5 ppm in 2018, dipping to 26.93 ppm in 2019, rising to 29.23 ppm in 2020, and then stabilizing around 26.92 ppm to 29.35 ppm in subsequent years, eventually reaching 26.96 ppm in 2023. In spring, ozone levels were higher compared to winter, starting at 53.75 ppm in 2018 and experiencing slight variations, eventually decreasing to 50.20 ppm in 2023. Also, summer recorded the highest ozone concentrations among all seasons, with levels starting at 57.2 ppm in 2018, fluctuating over the years, and peaking again at 58.46 ppm in 2022 before slightly declining to 51.76 ppm in 2023. In addition, the fall season revealed a relatively stable trend, with ozone concentrations starting at 42.41 ppm in 2018 and hovering around 41 ppm to 44.35 ppm in the following years. These trends highlight the seasonal variations in ozone concentrations, with higher levels during the warmer months, likely due to increased sunlight and temperature, which facilitate ozone formation. The overall analysis underscores the importance of continued efforts to manage and reduce ozone pollution in Shanghai, particularly during the summer and spring months when levels are highest.

The seasonal average concentrations of Ozone (O_3) in Delhi displayed variations across different seasons. In winter, the O_3 concentrations started high at 28.79 ppm in 2018, dropped to a low of 9.28 ppm in 2020, peaked at 30.03 ppm in 2021, and finally settled at 14.63 ppm in 2023. This fluctuation indicates the influence of seasonal factors such as temperature inversions and varying pollution sources during colder months. During the spring season, O_3 concentrations remained relatively higher compared to other seasons, starting at 42.95 ppm in 2018 and slightly decreasing to 24.92 ppm by 2023, despite a significant peak of 44.68 ppm in 2019. This pattern reflects the seasonal increase in photochemical reactions that produce O_3 due to longer daylight hours and higher temperatures in spring. In the summer months, O_3 levels showed considerable variability. The concentration began at 32.86 ppm in 2018, surged to 41.83 ppm in 2020, but then sharply decreased to 13.23 ppm in 2021 and 2022, before slightly rising to 14.82 ppm in 2023. This trend underscores the impact of intense sunlight and higher temperatures on O_3 formation, along with changes in meteorological conditions. Fall season O_3 concentrations also demonstrated variability, starting at 36.82 ppm in 2018, dipping to 9.84 ppm in 2019, and then peaking at 39.40 ppm in 2020 before ending at 20.27 ppm in 2023. These variations highlight the seasonal influences on O_3 levels, including changes in weather patterns and emission sources. Overall, these trends reveal the complex dynamics affecting O_3 concentrations in Delhi and emphasize the need for continuous monitoring and targeted pollution control measures to manage air quality effectively.

Paris's winter ozone (O_3)concentrations were relatively stable, ranging from 16.34 ppm in 2019 to 18.90 ppm in 2020. Both 2018 (17.77 ppm) and 2021 (17.67 ppm) recorded similar levels, showing minimal fluctuations over the years. Spring in Paris displayed high O_3 concentrations, peaking at 66.11 ppm 2018. This level slightly decreased in 2019 (63.84 ppm) and continued to decline in 2020 (52.74 ppm). However, there was a slight increase to (57.16 ppm) in 2021. This suggests that spring consistently exhibits high ozone levels with some variability. During summer, Paris consistently decreased in O_3 levels from (57.99 ppm) in 2018 to (42.50 ppm) in 2021, and the concentrations in 2019 (54.24 ppm) and 2020 (45.62 ppm) also reflected this downward trend, indicating an improvement in air quality during the summer months. Fall O_3 concentrations in Paris were notably high, with the highest levels recorded in 2018 (67.09 ppm). The levels decreased significantly to (49.38 ppm) in 2019 and slightly increased to (54.02 ppm) in 2020. In 2021, the level further dropped to 53.56 ppm. This trend shows a general decline in fall ozone levels over the years.

From 2018 to 2023, Los Angeles experienced varying ozone (O_3) concentrations across different seasons, reflecting the dynamic interplay of environmental factors and air quality management efforts. During the winter months, the average ozone concentrations fluctuated slightly, starting at 0.035 ppm in 2018, decreasing to 0.031 ppm in 2019, and then stabilizing around 0.032 ppm to 0.034 ppm in the following years. In spring, ozone levels were consistently higher than in winter, beginning at 0.046 ppm in 2018 and maintaining a range between 0.045 ppm and 0.049 ppm until 2023. The summer season recorded the highest ozone concentrations among all seasons, with levels starting at 0.053 ppm in 2018 and remaining relatively constant, around 0.052 ppm to 0.054 ppm over the years. This trend is consistent with the increased sunlight and warmer temperatures that facilitate ozone formation during the summer months. Fall exhibited some variability in ozone levels, with concentrations starting at 0.046 ppm in 2018, peaking at 0.053 ppm in 2020, and stabilizing around 0.044 ppm to 0.046 ppm in the subsequent years. These trends highlight the seasonal variations in ozone concentrations in Los Angeles, with higher levels observed during the warmer months of spring and summer due to favorable conditions for ozone formation.

The ozone (O_3) concentrations during winter have fluctuated considerably. The highest levels were recorded in 2018 (29.39 ppm) and 2021 (31.11 ppm), while 2019 (22.07 ppm) and 2020 (24.52 ppm) experienced lower levels. This suggests variability in winter ozone levels over the years. During spring, São Paulo showed a moderate range of O_3 concentrations. In 2018, the level was 25.72 ppm, which increased to 27.49 ppm in 2019 but decreased to 24.70 ppm in 2020. The lowest level was recorded in 2021 (20.72 ppm), indicating a general downward trend in spring ozone levels. Summer's ozone (O_3) concentrations were relatively high, with the highest levels observed in 2019 (30.68 ppm) and the lowest in 2020 (25.79 ppm). In addition, both 2018 (29.70 ppm) and 2021 (29.41 ppm) showed similarly high levels, suggesting that summer consistently exhibits elevated ozone concentrations. Fall presented the highest O_3 concentrations among all seasons. In 2018, the level was 31.31 ppm, slightly decreasing to 25.30 ppm in 2019 and 25.33 ppm in 2020. However, 2021 showed a substantial drop to 21.37 ppm. This indicates that fall typically has high ozone levels but with noticeable variability.

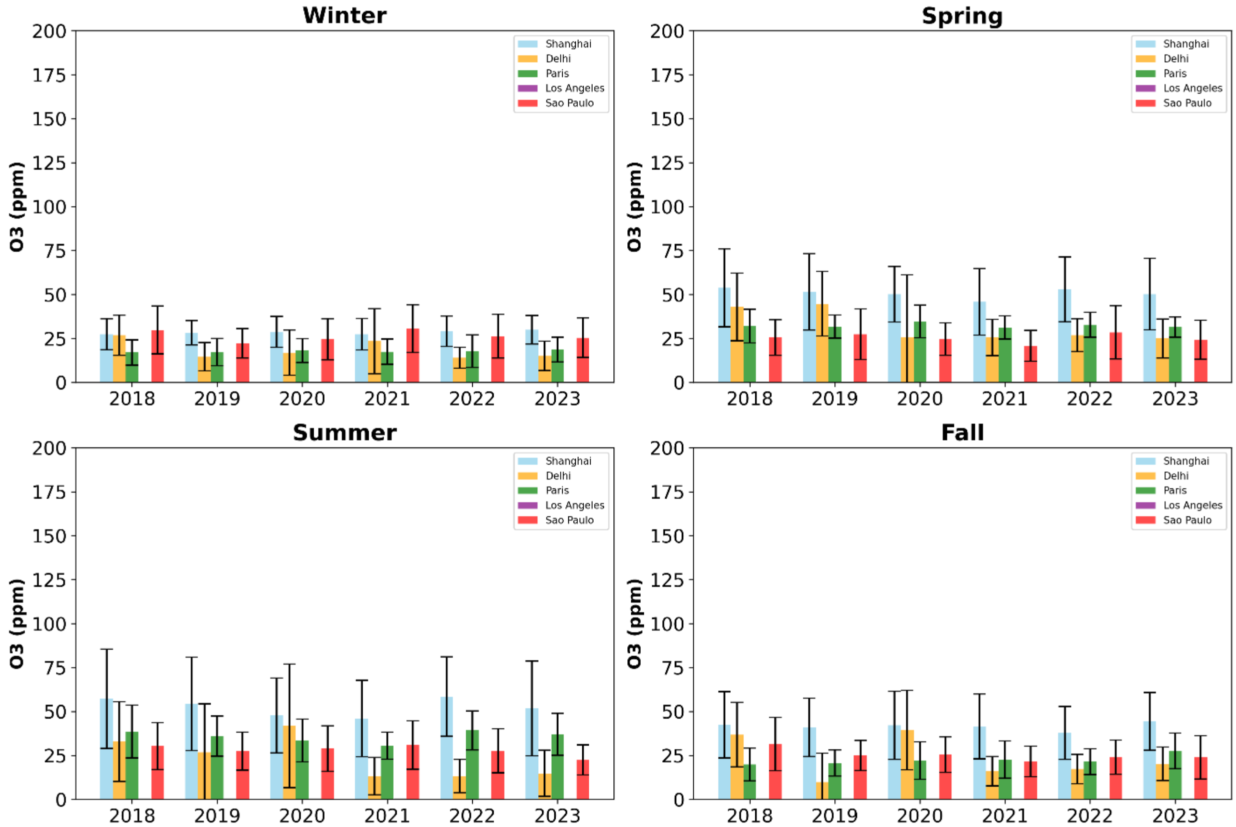

Figure 12: This figure presents the seasonal mean O_3 concentrations (ppm) for Shanghai, Delhi, Paris, Los Angeles, and São Paulo from 2018 to 2023. The data are organized by winter, spring, summer, and fall to highlight seasonal fluctuations. Error bars indicate interannual variability.

Further, the statistical relationships between temperature (°C) and Ozone (O_3) concentrations were analyzed for five megacities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo. Figure 13 reveals diverse statistical relationships between ozone (O_3) concentrations and temperature (°C) across different seasons from 2018 to 2023. Notably, in Shanghai, a positive correlation between ozone levels and temperature was observed consistently in spring (average correlation 0.52) and fall (average correlation 0.46), with the highest slope values reflecting significant seasonal variations (Table 10). Contrastingly, the winter season often showed a negative or weak relationship, suggesting a less direct influence of temperature on ozone concentrations during colder months. In addition, Delhi exhibited a steady positive correlation in most seasons, with spring and summer showing the highest correlations (average 0.44 and 0.36, respectively).

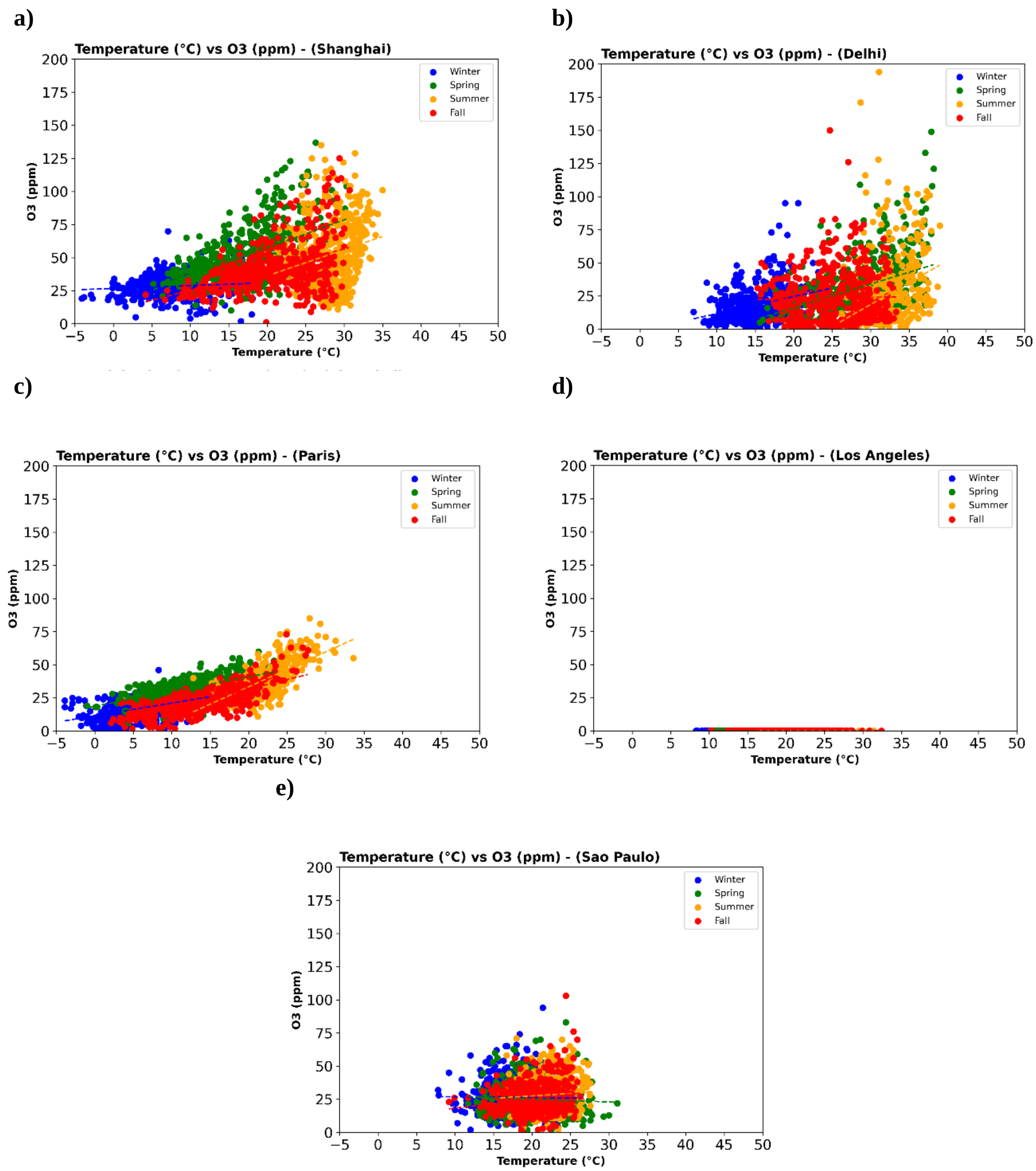

Figure 13: Seasonal effect of Temperature (°C) on O_3 (ppm) average mass concentration in megacities: (a) Shanghai, (b) Delhi, (c) Paris, (d) Los Angeles, and (e) São Paulo, for the period 2018–2023. Each scatter plot represents seasonal variations, with winter (blue), spring (green), summer (red), and fall (orange).

Further, this shows a strong correlation between ozone (O_3) levels and temperature, with the positive slope values in these seasons highlighting this trend. However, the fall season presented a negligible correlation (average 0.03), which suggests other factors might influence ozone levels during this time.

Table 10: Statistical relationships between Temperature (°C) and O_3 (ppm) concentrations average mass concentration for the Megacities a) Shanghai, b) Delhi, c) Paris, d) Los Angeles, and e) São Paulo, for the period 2018-2023. Significant relationships ($p < 0.05$) are highlighted as *.

Statistical relationships between Ozone O3 (ppm) concentrations and Temperature (°C)									
City	Year	Correlation				Slope			
		Winter	Spring	Summer	Fall	Winter	Spring	Summer	Fall
Shanghai	2018	-0.07	0.55*	-0.02	0.45*	-0.14	2.13	-0.17	1.67
	2019	-0.20*	0.42*	0.24*	0.33*	-0.51	1.87	2.04	1.11
	2020	0.05	0.66*	0.33*	0.61*	0.14	2.94	2.35	2.49
	2021	0.44*	0.65*	0.26*	0.51*	0.95	2.46	2.36	1.50
	2022	0.21*	0.51*	0.39*	0.43*	0.70	2.16	2.76	1.42
	2023	-0.29	0.50*	0.17	0.42*	-0.76	2.12	1.64	1.25
	2018-2023	0.09*	0.52*	0.24*	0.46*	0.21	2.12	1.98	1.55
Delhi	2018	0.55*	0.56*	0.48*	0.05	1.84	2.48	3.98	0.27
	2019	0.07	0.56*	0.62*	0.05	0.22	1.78	5.60	0.20
	2020	0.13	0.49*	0.26*	0.36*	0.56	2.70	3.83	1.50
	2021	0.28*	0.38*	0.31*	-0.32*	1.55	1.15	1.33	-0.61
	2022	0.64*	0.25*	0.53*	-0.29*	1.39	0.51	1.73	-0.55
	2023	0.58*	0.42*	0.21*	-0.16	1.13	1.12	1.41	-0.33
	2018-2023	0.33*	0.44*	0.36*	0.03	1.29	1.79	3.31	0.11
Paris	2018	0.36*	0.79*	0.78*	0.76*	0.62	1.37	3.61	1.39
	2019	0.52*	0.47*	0.70*	0.65*	1.24	0.92	2.11	1.10
	2020	0.53*	0.66*	0.73*	0.80*	1.18	1.35	2.35	1.75
	2021	0.35*	0.51*	0.74*	0.80*	0.59	0.93	2.34	1.63
	2022	0.63*	0.48*	0.71*	0.61*	1.54	0.77	2.48	1.09
	2023	0.45*	0.68*	0.60*	0.76*	0.91	1.06	2.76	1.34
	2018-2023	0.47*	0.63*	0.72*	0.74*	0.96	1.11	2.63	1.44
Los Angeles	2018	-0.19*	0.49*	0.18*	0.55*	0.00	0.00	0.00	0.00
	2019	-0.47*	0.57*	0.51*	0.53*	0.00	0.00	0.00	0.00
	2020	0.21*	0.78*	0.58*	0.74*	0.00	0.00	0.00	0.00
	2021	0.28*	0.71*	0.16	0.67*	0.00	0.00	0.00	0.00
	2022	0.21*	0.62*	0.18*	0.66*	0.00	0.00	0.00	0.00
	2023	-0.06	0.47*	0.57*	0.51*	0.00	0.00	0.00	0.00
	2018-2023	0.02	0.59*	0.37*	0.62*	0.00	0.00	0.00	0.00
São Paulo	2018	0.09	-0.03	0.14	0.39*	0.45	-0.11	0.76	2.26
	2019	0.01	0.10	0.49*	0.00	0.02	0.41	2.23	0.01
	2020	-0.05	-0.24*	-0.02	0.07	-0.19	-0.64	-0.10	0.28
	2021	-0.14	-0.27*	-0.20*	0.00	-0.52	-0.87	-1.10	-0.01
	2022	0.13	0.28*	0.05	0.03	0.65	1.25	0.37	0.07
	2023	0.07	-0.33*	0.01	0.12	0.24	-1.07	0.06	0.56
	2018-2023	-0.01	-0.06	0.06	0.17*	-0.06	-0.22	0.36	0.70

Paris consistently demonstrated positive correlations through seasons, particularly in spring and summer (average 0.63 and 0.72, respectively). The slope values in summer highlight the substantial increase in ozone levels with rising temperatures. The consistent pattern across years underscores the impact of temperature on ozone concentrations in Paris.

The trend in Los Angeles was more complex, showing a notable positive correlation in spring (average 0.59) and fall (average 0.62). Despite a general increase in ozone levels with temperature, the winter season occasionally showed a negative correlation, reflecting varying environmental factors. The absence of slope values suggests a unique interaction between temperature and ozone (O_3) concentration in this city.

São Paulo presented the most variable relationships, with no consistent trends across seasons. While some years showed positive correlations, others exhibited negative or negligible relationships. The fluctuating slope values indicate that temperature alone was not a reliable predictor of ozone levels in this region, which implies the influence of multiple interacting factors.

The comprehensive analysis highlights the complex and city-specific nature of the relationship between ozone concentrations and temperature, which is influenced by regional climate, urbanization, and local environmental policies.

Discussion:

The study examines the annual and seasonal mean concentrations of air pollutants, the number of exceedance days, and their relationship with meteorological parameters across five megacities: Shanghai, Delhi, Paris, Los Angeles, and São Paulo. Key trends and observations provide insights into megacities' challenges and efforts in air quality management. This analysis covers 2018 to 2023, including the pre-, during, and post-COVID-19 phases.

The decreasing levels of $PM_{2.5}$ from 2018 to 2022 indicate that mitigation efforts have successfully reduced particulate matter pollution. However, the slight increase observed in 2023 underscores the need for sustained attention and adaptive strategies. The stability of ozone (O_3) levels, alongside a slight rise in PM_{10} and NO_2 in 2023, highlights the intricate challenges of urban air quality management. While efforts to curb sulfur dioxide (SO_2) emissions have been largely successful, the recent increase indicates a need for reinforced control measures (Figure 2).

The noticeable fluctuations in $PM_{2.5}$ levels in Delhi reflect persistent challenges in achieving long-term air quality improvements (Figure 2). The city's success in reducing NO_2 and SO_2 concentrations demonstrates the positive impact of mitigation policies. (Figure 2). The city's success in reducing NO_2 and SO_2 concentrations demonstrates the positive effects of mitigation policies. However, the variability in O_3 levels and the rising PM_{10} concentrations suggest that pollution sources remain multifaceted. A comprehensive approach integrating emission controls, transportation policies, and meteorological considerations is essential for sustainable improvements. In Paris, the overall decline in $PM_{2.5}$, PM_{10}, and NO_2 levels points to the effectiveness of air quality interventions, particularly in reducing vehicle and industrial emissions (Figure 2). Nevertheless, the relatively stable O_3 levels highlight the ongoing difficulty of managing secondary pollutants. Despite these advancements, the persistence of exceedance days for $PM_{2.5}$ and O_3 indicates the need for stricter policies to achieve cleaner air (Figure 3).

Los Angeles has demonstrated commendable progress in reducing $PM_{2.5}$ and PM_{10} levels, with a substantial downward trend over the years (Figure 2). The stability in O_3 levels and the relatively low number of exceedance days suggest that air quality management strategies have been effective (Figure 4). However, fluctuations in PM_{10} concentrations signal the need for continued efforts to control particulate matter pollution comprehensively, particularly in the context of local meteorological influences and emission dynamics.

São Paulo's trends in $PM_{2.5}$, O_3, and NO_2 concentrations reflect the complexities of urban air quality management (Figure 2). Variability in these pollutants suggests changes in emission sources, meteorological conditions, or the effectiveness of control measures over time.

The seasonal concentration of air pollutants reveals varied patterns across Shanghai, Delhi, and Los Angeles. In Shanghai, there was a decline in $PM_{2.5}$ concentrations across all seasons, highlighting an overall improvement in air quality. Winter levels decreased from 125.68 µg/m³ in 2018 to 94.24 µg/m³ in 2023, reflecting the impact of strict environmental policies and increased public awareness. Spring, summer, and fall also exhibited consistent decreases in $PM_{2.5}$ levels, underscoring the effectiveness of Shanghai's air quality initiatives (Figure 10).

In Delhi, seasonal $PM_{2.5}$ concentrations showed distinct trends. Winter levels remained extremely high, with fluctuations peaking at 232.17 µg/m³ in 2020 before slightly decreasing. Spring and summer exhibited notable variations, influenced by meteorological conditions and regulatory measures. Fall concentrations remained relatively high, emphasizing the persistent challenge of managing air quality in the city (Figure 10). Los Angeles exhibited seasonal variations in $PM_{2.5}$ concentrations, reflecting changes in air quality due to local meteorological conditions and pollution sources. Winter levels fluctuated, while spring and summer showed moderate decreases over time. Fall recorded more variability, influenced by factors such as wildfires and agricultural activities. These trends suggest a general improvement in air quality from 2018 to 2023, with seasonal variations shaped by environmental factors (Figure 10). The statistical relationships between temperature and $PM_{2.5}$ concentrations across the five megacities reveal city-specific trends. In Shanghai, temperature had a limited effect on $PM_{2.5}$ levels, with weak correlations across all seasons. Delhi exhibited a strong negative correlation in winter and a significant positive correlation in summer, indicating the role of temperature in shaping pollution levels. Paris showed mixed correlations, with strong negative relationships in winter and positive correlations in summer. Los Angeles presented consistent positive correlations in winter, spring, and summer, while São Paulo exhibited weak and inconsistent relationships (Figure 11). The study also examined seasonal O_3 concentrations from 2018 to 2023, revealing varied trends across the megacities. In Shanghai, spring and summer recorded higher ozone levels, reflecting the influence of increased sunlight and temperature on ozone formation. Delhi exhibited significant seasonal variations, with peak ozone levels occurring in summer due to intense photochemical reactions.

Los Angeles experienced consistent seasonal variations, with the highest ozone levels in summer, reinforcing the impact of temperature and photochemical activity on ozone formation (Figure 11).

The statistical relationships between temperature and O_3 concentrations further highlight city-specific trends. Shanghai displayed a positive correlation between ozone levels and temperature in spring and fall, while winter showed a weaker relationship. Delhi exhibited a steady positive correlation in spring and summer, emphasizing the temperature dependence of ozone levels. Paris showed consistently high positive correlations across all seasons, underscoring the pronounced influence of temperature on ozone concentrations. Los Angeles displayed complex seasonal trends, with notable positive correlations in spring and fall. São Paulo presented the most variable relationships, with inconsistent seasonal trends (Figure 12). A major limitation of this study is the reliance on annual and seasonal concentration data, which may not fully capture short-term pollution spikes. Additionally, the study's observational nature limits the ability to establish causality between pollution control measures and air quality improvements.

Future research should focus on evaluating the effectiveness of specific pollution control measures and exploring the impact of occurring pollutants. Longitudinal studies with higher temporal resolution and larger datasets could provide a more comprehensive understanding of air quality trends. Further, while considerable strides have been made in improving air quality in Shanghai, Delhi, and Los Angeles, urban air pollution remains a persistent challenge. Effective air quality management requires continuous monitoring, adaptive strategies, and robust regulatory measures to address diverse pollution sources and achieve sustainable improvements.

Conclusion:

The study examines the annual and seasonal mean concentrations of air pollutants, the number of exceedance days, and their relationship with meteorological parameters across five megacities such as Shanghai, Delhi, Paris, Los Angeles, and São Paulo.

The findings highlights varying trends in annual average concentrations of air pollutants across megacities: Shanghai's $PM_{2.5}$ levels decreased from 106.67 µg/m³ in 2018 to 81.59 µg/m³ by 2022 before slightly rising to 88.69 µg/m³ in 2023, with relatively stable O_3 concentrations and notable fluctuations in PM_{10} and NO_2 levels; Delhi's $PM_{2.5}$ levels decreased from 171.98 µg/m³ in 2018 to 149.84 µg/m³ by 2020, with significant variability in O_3 and PM_{10} concentrations and an apparent reduction in NO_2 and SO_2 levels by 2023; Paris showed a decline in $PM_{2.5}$ from 64.28 µg/m³ in 2018 to 55.6 µg/m³ by 2023, stable O_3 levels, and a consistent decrease in NO_2 concentrations; Los Angeles saw slight fluctuations in $PM_{2.5}$, decreasing from 12.19 µg/m³ in 2018 to 9.89 µg/m³ by 2023, with stable O_3 levels and a decline in both NO_2 and SO_2 concentrations; São Paulo exhibited variability in $PM_{2.5}$ levels, ranging from 50.24 µg/m³ in 2018 to 57.27 µg/m³ by 2023, with fluctuations in O_3 and NO_2 levels, reflecting ongoing challenges in urban pollution control.

The annual exceedance days of $PM_{2.5}$ and ozone levels for five major cities from 2018 to 2023 reveal significant air quality challenges: Shanghai consistently shows high exceedance days for both $PM_{2.5}$ (2,173 days) and ozone (2,055 days), reflecting persistent air quality issues; Delhi experiences similarly high exceedance days for $PM_{2.5}$ (2,144 days) and ozone (2,134 days), mainly due to vehicle emissions and seasonal factors; Paris records 1,974 $PM_{2.5}$ exceedance days and the highest ozone exceedance days (2,146 days) among the cities, indicating ongoing pollution challenges despite measures to combat air pollution; Los Angeles stands out with much lower exceedance days for both $PM_{2.5}$ (17 days) and ozone (49 days), suggesting effective air quality management; and São Paulo shows significant exceedance days for $PM_{2.5}$ (1,608 days) and ozone (1,990 days), reflecting ongoing urban pollution control challenges.

Delhi and Shanghai remain the most polluted cities based on WHO-recommended air quality standards throughout the analysis period.

The annual statistical relationships between temperature and $PM_{2.5}$ concentrations reveals varying trends: Shanghai shows a weak negative correlation ($r = -0.28$), indicating a slight decrease in $PM_{2.5}$ levels with increasing temperatures, likely influenced by seasonal variations; Delhi exhibits a significant negative correlation (r = -0.59), with $PM_{2.5}$ levels decreasing by 5.80 μg/m³ for each 1°C rise in temperature, attributed to pollutant dispersal and atmospheric stability changes; Paris has a weakly negative correlation (r = -0.19), showing a modest decrease in $PM_{2.5}$ levels with rising temperatures, influenced by local emissions and meteorological conditions; Los Angeles is unique with a weak positive correlation (r = 0.16), indicating a slight increase in $PM_{2.5}$ levels with higher temperatures, potentially due to increased emissions and secondary pollutant formation; and São Paulo displays a weakly negative correlation (r = -0.10), with a slight reduction in $PM_{2.5}$ levels as temperatures rise, influenced by atmospheric dispersion and seasonal emission variations.

Similarly, the statistical relationships between Sea Level Pressure (SLP) and $PM_{2.5}$ concentrations reveal varying trends: Shanghai shows a weak positive correlation (r = 0.22) indicating a minor influence of SLP on $PM_{2.5}$ levels; Delhi exhibits a strong positive correlation (r = 0.62) with $PM_{2.5}$ levels significantly increasing as SLP rises, highlighting the impact of meteorological conditions on air quality; Paris has a weak positive correlation (r = 0.17) suggesting a slight increase in $PM_{2.5}$ levels with rising SLP, influenced by other dominant factors; Los Angeles presents an almost nonexistent relationship (r = -0.02) between SLP and $PM_{2.5}$, implying air quality is influenced by local factors; and São Paulo displays a weak positive correlation (r = 0.14) indicating a minor influence of SLP on $PM_{2.5}$ concentrations. Overall, Delhi stands out as having a strong positive correlation. At the same time, Los Angeles shows no meaningful relationship and other cities exhibit weak correlations, suggesting that SLP is not the primary influencing factor in $PM_{2.5}$ levels for most of these cities.

The analysis of statistical relationships between Wind Speed and $PM_{2.5}$ concentrations demonstrate varying degrees of negative correlation: Shanghai shows a very weak negative correlation (r = -0.07), indicating a minimal influence of wind speed on $PM_{2.5}$ levels; Delhi exhibits a weak negative correlation (r = -0.21) with noticeable decreases in $PM_{2.5}$ levels as wind speed increases, suggesting improved air quality; Paris has a weak negative correlation (r = -0.19), showing a modest decrease in $PM_{2.5}$ levels with rising wind speeds; Los Angeles presents a slightly stronger negative correlation (r = -0.29), indicating that higher wind speeds help reduce $PM_{2.5}$ levels more effectively; and São Paulo displays a very weak negative correlation (r = -0.04), suggesting that wind speed has a minor influence on $PM_{2.5}$ concentrations. While wind speed does play a role in influencing $PM_{2.5}$ levels, it is not the primary factor in most cities, except for Los Angeles, where it has a more substantial impact.

The analysis of $PM_{2.5}$ concentrations highlights notable seasonal trends and air quality improvements across megacities. Shanghai experienced a consistent decline in $PM_{2.5}$ levels across all seasons, with winter levels dropping from 125.68 μg/m³ in 2018 to 94.24 μg/m³ by 2023, reflecting the positive impact of strict environmental policies and increased public awareness. Delhi showed distinct seasonal trends, with winter $PM_{2.5}$ concentrations significantly high at 217.81 μg/m³ in 2018 and slightly rising to 222.65 μg/m³ in 2023, while summer months had the lowest levels, starting at 128.65 μg/m³ in 2018 and decreasing to 107.76 μg/m³ by 2023, highlighting the critical need for sustained efforts to manage air pollution. Los Angeles exhibited seasonal variations, with winter $PM_{2.5}$ concentrations fluctuating from 13.58 μg/m³ in 2018 to a low of 9.36 μg/m³ in 2023 and more variability in fall due to factors like wildfires, suggesting an overall improvement in air quality influenced by weather conditions and specific pollution sources. These trends emphasize the importance of continued efforts to monitor and manage air quality, particularly during the fall and winter months when $PM_{2.5}$ concentrations tend to be higher.

The analysis of statistical relationships between temperature and $PM_{2.5}$ concentrations from 2018 to 2023 for five megacities reveals seasonal variations: Shanghai shows weak correlations with a slight increase in $PM_{2.5}$ levels in winter and spring and a minor decrease in summer and fall, indicating limited temperature influence. Delhi exhibits more pronounced relationships, with strong negative and positive correlations in winter and fall in spring and summer, highlighting significant temperature influence. Paris has mixed correlations, with a strong negative correlation in winter and a positive correlation in summer, suggesting varying temperature effects across seasons. Los Angeles shows consistent positive correlations, indicating higher temperatures generally increase $PM_{2.5}$ levels with seasonal variations. São Paulo displays weak correlations, indicating limited temperature influence on $PM_{2.5}$ levels.

For seasonal ozone (O_3) concentrations, Shanghai experienced fluctuating winter ozone levels, starting at 30.5 ppm in 2018 and stabilizing around 26.96 ppm by 2023, with higher spring (53.75 ppm to 50.20 ppm) and summer levels (57.2 ppm to 51.76 ppm), indicating increased ozone formation during warmer months. Delhi showed significant seasonal variations, with winter ozone levels starting high at 28.79 ppm in 2018 and settling at 14.63 ppm by 2023, spring levels fluctuating from 42.95 ppm to 24.92 ppm, and summer levels peaking at 41.83 ppm in 2020 before decreasing to 14.82 ppm by 2023, reflecting the impact of sunlight and temperature on ozone formation. Los Angeles exhibited more stable trends, with winter ozone levels starting at 0.035 ppm in 2018 and stabilizing around 0.032 ppm to 0.034 ppm, higher spring levels ranging from 0.045 ppm to 0.049 ppm, and consistent summer levels around 0.052 ppm to 0.054 ppm, influenced by favorable conditions for ozone formation during warmer months.

The statistical relationships between temperature and ozone (O_3) concentrations in megacities reveal diverse seasonal trends. Shanghai consistently exhibited positive correlations in spring (average 0.52) and fall (average 0.46), while winter showed negative or weak correlations, indicating less temperature influence on ozone during colder months. Delhi showed steady positive correlations in most seasons, with the highest in spring (average 0.44) and summer (average 0.36), reflecting strong temperature dependence on ozone levels. Paris demonstrated consistently high positive correlations across all seasons, particularly in spring (average 0.63) and summer (average 0.72), underscoring the significant impact of temperature on ozone concentrations. Los Angeles displayed a complex trend with notable positive correlations in spring (average 0.59) and fall (average 0.62) and occasional negative correlations in winter, suggesting varied environmental factors. São Paulo showed the most variable relationships, with no consistent trends, indicating multiple interacting factors influence ozone levels.

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Appendix A

Table 11: Air Quality Index (AQI) Categories and Associated Health Impacts

Category	AQI Category	$PM_{2.5}$ ($\mu g/m^3$) (24 hr)	O_3 (ppb) (8 hr)	Health Impact
1	Good	0–9.0	0–50	Clean air quality
2	Moderate	9.1–35.4	51–100	Individuals who are highly sensitive to air pollution may experience slight respiratory discomfort
3	Unhealthy for Sensitive Groups	35.5–55.4	101-150	People with pre-existing lung or heart conditions may feel mild to moderate discomfort
4	Unhealthy	55.5–125.4	151-200	Harmful for individuals with health conditions and increased sensitivity. Limited outdoor activities
5	Very Unhealthy	125.5–225.4	201-300	Hazardous to vulnerable groups and may pose risks to the general population; outdoor exposure should be minimized
6	Hazardous	225.5+	>301	Extremely hazardous, requiring everyone to avoid outdoor activities entirely to protect their health