MAJOR PROJECT-II

CORRELATION BETWEEN PM_{2.5} AND TROPOSPHERIC O₃ IN DELHI: TEMPORAL VARIATIONS AND METEOROLOGICAL IMPACTS

Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

in ENVIRONMENTAL ENGINEERING by SHASHANK S KHARE

(2K18/ENE/09)

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CANDIDATE'S DECLARATION

I SHASHANK S KHARE hereby certify that work which is being presented in the thesis entitled "CORRELATION BETWEEN PM_{2.5} AND TROPOSPHERIC O₃ IN DELHI: TEMPORAL VARIATIONS AND METEOROLOGICAL IMPACTS" in partial fulfillment of the requirements for the award of the Degree of Master of Technology in Environmental Engineering submitted in the Department of Environmental Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from January 2023 to May 2024 under the supervision of Dr. Lovleen Gupta.

The matter presented in the thesis has not been submitted by me for the award of any degree of this or any other Institute.

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This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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Certified that <u>Shashank S Khare</u> (2K18/ENE/09) has carried out their research work presented in this thesis entitled "<u>CORRELATION BETWEEN PM_{2.5}</u> <u>AND TROPOSPHERIC O₃ IN DELHI: TEMPORAL VARIATIONS AND METEOROLOGICAL IMPACTS</u>" for the award of <u>Master of Technology</u> from Department of Environmental Engineering, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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ABSTRACT

Ambient air pollution in India, especially in Delhi, poses severe health risks. The capital experiences alarming levels of pollutants due to vehicular emissions, industrial activities, and crop burning. This pollution leads to cardiovascular issues, respiratory problems and shorter life expectancy.

The pollutant of interest in the present study is ground-level ozone or tropospheric ozone – a secondary air pollutant. Ozone (O_3) is a highly oxidizing triatomic molecule that is desirable in the stratosphere but can be a lethal pollutant in the troposphere. Ecosystems and human health are both harmed by it. Research on tropospheric O_3 is essential to understand its formation, impacts, and to develop effective mitigation strategies, ensuring healthier air quality and environmental protection. While extensive research has taken place on chemistry of O_3 formation, there has been little work done on exploring the relationship between $PM_{2.5}$ and ozone.

This work explores the relationship of O₃ with other gaseous pollutants, particulate matter (PM) and meteorological parameters in Delhi over a six-year period (January 2018-December 2023). Comprehensive statistical analysis for exploring factors influencing ozone formation in Delhi was done on diurnal-basis and seasonal-basis using data from six CAAQMS. Data was taken at hourly intervals throughout the study period.

The maximum concentration of O_3 observed was 53.44 \pm 28.7 μ g/m³ which was experienced in Summer of 2020 (April -June 2020). A negative correlation existed between O_3 and $PM_{2.5}$, except during monsoon season (July-September), with maximum negative correlation observed in Summer of 2020 as -0.55. This may be attributed to: higher concentrations of $PM_{2.5}$ observed throughout Delhi during postmonsoon (maximum of $200.77\pm140.03~\mu$ g/m³ observed in postmonsoon of 2020) and winter (maximum of $210.77\pm125.87~\mu$ g/m³ observed in winter of 2018-19) seasons that reduces solar radiation available for O_3 formation (low scattering albedo) (Concentration during winter was $<30~\mu$ g/m³ for all the years); along with smog, haze, low mixing heights

and temperature inversion which exacerbates the situation. In spring and summer season, though O_3 concentrations increase due to increasing solar radiation and temperature, the relative concentration of $PM_{2.5}$ reduces (maximum concentration: $94.89 \pm 54.77 \,\mu\text{g/m}^3$ observed in summer of 2022). Biogenic VOCs also contribute more to $PM_{2.5}$ concentration proportion, thereby increasing O_3 concentrations. However, during monsoon, a mildly positive, but statistically insignificant, correlation was generally observed. This may be attributed to cleansing effect of rainfall that diminishes $PM_{2.5}$ concentration (maximum concentration of $38.41 \pm 20.02 \,\mu\text{g/m}^3$ observed in monsoon of 2022). Also, wind, that carries relatively less dust, blows in monsoon and overcast weather reduces O_3 formation.

This study will aid policy makers in formulating policies to curb co-pollution of O₃ and PM_{2.5} in Delhi. Also, studies at micro-level are deemed necessary to conclusively establish a theory explaining relationship between O₃ and PM_{2.5} in Delhi; as similar studies in other regions show significant spatial variation in the same.

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LIST OF ABBREVIATIONS

CPCB: Central Pollution Control Board

GLO: Ground level ozone

TPO: Tropospheric Column Ozone

WHO: World Health Organisation

VOC: Volatile Organic Compounds

MAH: Monocyclic Aromatic Hydrocarbons

OECD: Organisation for Economic Cooperation and Development

STE: Stratosphere Troposphere Exchange

NMHC: Non-Methane Hydrocarbons

PBLH: Planetary Boundary Layer Height

Chapter 1: Introduction

Ambient air is the natural state of air in the outdoor environment. The tropospheric ambient air is majorly composed of N₂ (78%), O₂ (20.94%), Ar (0.934%) and CO₂ (0.0315%) (Khare and Nagendra, 2007). In addition to this, its composition varies with the presence of local air pollution sources, meteorological conditions and geographical features. Ambient air quality is influenced by complex interactions between natural and anthropogenic environmental conditions (Mayer, 1999). Its quantification depends upon flow and dispersion of ambient air pollutants – gaseous or particulate.

Ambient air quality has become an area of great concern due to rapid industrialization and urbanization, especially in developing countries. Since the last two decades, air quality is deteriorating alarmingly due to increasing population which leads to unplanned development of industrial and transport sectors. These anthropogenic sources release huge amounts of air pollutants in the ambient air which ultimately affects the public health. Using air quality monitoring texhniques to evaluate the current state of ambient air quality is crucial.

As per the Organisation for Economic Cooperation and Development (OECD), air pollution is the result of contaminant or polluting elements present in the atmosphere that do not adequately disperse, endanger human health or welfare, or have other negative consequences on the environment.

Air pollution can be described as the presence of one or more contaminants or their combinations in the outdoor atmosphere in quantities and for durations that may harm human, plant, or animal life, damage property, or significantly interfere with the enjoyment of life or the environment. Any substance occurring in the atmosphere that

may have adverse effects on humans, animals, plant life, or inanimate materials is an air pollutant(Wark et al., 1998).

Since the industrial revolution, rapid expansion of industries has taken place. This has been accompanied and characterized by and increase in concentrated human activities, which has led to a rise in air pollution levels in most major cities and has become a serious problem for most developing countries. Vehicular (mobile sources), industrial and domestic sources (stationary sources) are the major anthropogenic sources of air pollution. Urbanization is expected to increase further, and hence the emissions from vehicles and industries. This has the potential to negatively impact people's health by exposing a large number of individuals to high levels of ambient air pollution over extended periods of time.

To alleviate the problem of ambient air pollution, it is necessary to study the system being polluted, assess the air quality, and study the transport regime of pollutants. The preceding discussion shows that air pollution, particularly in urban areas, is a serious threat (Hall, 1996; Khare and Nagendra, 2007; Mage et al., 1996).

Air pollution is becoming a major concern globally, especially in developing countries like India, where air quality standards are contravened in 78% of the cities(CPCB, 2020). While there have been significant attempts in India to lower the amount of particulate matter in the atmosphere, emissions of gaseous pollutants, volatile organic compounds (VOCs) and NO_x have been steadily rising. NO_x and VOCs are regarded as the main gaseous precursors of ground level ozone (GLO), a major secondary air pollutant.

Stratospheric ozone shields us from the ultra-violet radiations of the Sun, but O₃

formed at ground level is detrimental to human health and crop productivities and is regarded a pollutant.

The pollutant of interest in the present study is GLO or tropospheric ozone. Ozone is a highly oxidizing triatomic molecule that is desirable in the stratosphere (as it blocks harmful ultraviolet radiation from the sun), but can be a lethal pollutant in the troposphere. The Indian subcontinent exhibits high levels of ozone, which can adversely impact human health, crop productivity, and regional climatic patterns. As a secondary pollutant, ozone forms through reactions involving pollutants such as NOx, CO, and VOCs in the presence of sunlight.

1.1 Effects of tropospheric ozone

Ozone (O₃) causes a wide range of adverse effects on human health, including throat irritation, reduced lung function, respiratory problems like chronic obstructive pulmonary disease (COPD), emphysema, increased mortality, eye irritation, aggravated allergies, and skin damage. Its impact extends to the environment, where it damages the stomata in plants, reducing crop yield and the life expectancy of plants and trees, and causes cracking of rubber, leading to significant material loss. O₃ also contributes to haze and reduced visibility and is recognized as a potent greenhouse gas (GHG). Despite comprising only about one-tenth of the total atmospheric ozone and being primarily located in the troposphere, ground-level ozone (GLO) has a critical role in photochemical reactions, causing the recycling of gases emitted by both anthropogenic and natural sources (Masters, 1998; Rao, 1988). Ozone at this level is significant for two primary reasons: it acts as a secondary pollutant and possesses substantial greenhouse potential, ranking it as the third most potent greenhouse gas following carbon dioxide (CO₂) and methane (CH₄)(Shukla, 2019).

GLO's health impacts are well-documented, with epidemiological studies indicating that exposure to high O₃ concentrations can lead to rise in mortality and morbidity. Clinical studies have provided regional estimates of O₃'s impact on residential populations, with WHO estimating that 21,000 premature deaths occur every year in 25 European Union countries on and post high O₃ levels days(WHO, 2008). Beyond human health, O₃ significantly affects agriculture by damaging plant growth on its stems, roots, leaves, etc. It also adversely affects partitioning of biomass, flowers, seeds, etc. Yields of crops like maize, wheat, etc. are reduced. For example, loss of 36% yield has been observed for wheat in India (Burney and Ramanathan, 2014).

O₃ impacts not just agriculture and health but also materials such as rubber goods and surface coatings, textiles, fabrics, polymeric materials, etc. and causes colour fading (Lee et al., 1996). O₃ is a strong greenhouse gas that contributes to long-term climate change in addition to its local effects. Tropospheric ozone significantly contributes to radiative forcing with estimates of about 0.3 W/m², making it a notable greenhouse gas. The IPCC Fourth Assessment Report highlighted that tropospheric ozone is the third most important greenhouse gas after CO₂ and CH₄ (Chalita et al., 1996; Worden et al., 2008).

Chapter 2: Literature Review

The Indian sub-continent has shown relatively high ozone concentrations, even in regions with low populations and precursor emission intensities, due to atmospheric transport or meteorological processes (Sharma, 2017). O₃ is a secondary pollutant and the primary element of photo-chemical smog, which involves reactions of different precursor species. The principal species known to contribute to the formation of O₃ are NO_x, VOCs, and CO. The relationship between O₃ and its precursors is primarily regulated by complex non-linear photochemical reactions (Sharma, 2017), and it varies significantly with the environmental conditions, including land use, types of weather, emission source intensity, and type of emissions.

2.1 Precursors of Ozone and Formation of ozone

Main cause of occurrence of tropospheric ozone is anthropogenic. However, Stratosphere Troposphere Exchange (STE) and long-range transport also causes occurrence of tropospheric ozone in a region. Ozone is a secondary pollutant that is formed when photochemical reactions take place between Volatile Organic Carbon (VOCs) and NO_x. NO_x includes NO, NO₂, N₂O, N₂O₂, N₂O₃, N₂O₄, N₂O₅. However, only NO and NO₂ are known to cause ground-level ozone formation. These are most prevalent and well-established precursors to ozone formation (Shukla, 2019). Other precursors may include complex hydrocarbons, CO, hydroxyl (OH) ions and NMHC (Non-Methane Hydrocarbons). Besides, photocopy machines are point sources of ozone emissions.

Anthropogenic sources of NO_x include vehicular exhaust emissions, DG sets, power plants, and some industries (such as cement manufacturing, chemical industries that emit NO_x as by-product, etc.). Lightening is a natural source of NO_x. VOCs are compounds characterized with high reactivity and comprising of eight or less carbon

atoms in a molecule (Batterman et al., 2014). Main sources of VOCs include plants/trees (biogenic), evaporative emissions from petrol stations and chemical solvents used in various industrial processes, paints and solvents, evaporating gasolines, vehicular exhausts, consumer products such as sprays and perfumes, etc. Several Monocyclic Aromatic Hydrocarbons (MAH) such as benzene, toluene, xylene, etc. are also VOCs. Incomplete combustion processes, vehicular emissions, biomass burning, agricultural residue burning, etc. are sources of CO.

Apart from the aforementioned precursors, the present study also explores the relationship between ozone and other pollutants such as NH₃, Monocyclic Aromatic Hydrocarbons (MAH) and PM_{2.5} in Delhi. PM_{2.5} represents particulate matter that is less than 2.5 micrometers in diameter; while for the purpose of the present study Monocyclic Aromatic Hydrocarbons (MAH) represents summation of benzene, toluene, xylene, ethyl benzene, ortho xylene, meta para xylene, etc.

The following table summarises the sources and adverse effects of pollutants explored in the present study (Rao, 1988).

Table 2. 1: Pollutants of concern: Sources and Effects

| Pollutant | Sources | Effects | | |
|-----------------|-----------------------------------|----------------------------------------------------|--|--|
| NO ₂ | Lightening, microbial activity | Decrease lung function; Acid rain; | | |
| | in soils, vehicles, power plants, | irritation to eyes, lungs. | | |
| | diesel generator sets | | | |
| NO | Lightening, microbial activity | Forms NO ₂ , O ₃ ; acid rain | | |
| | in soils, vehicles, power plants, | | | |

| | diesel generator sets at higher | |
|-------------------|-----------------------------------|----------------------------------------------|
| | temperatures. | |
| СО | Incomplete combustion of | Asphyxiation; anoxemia |
| | fossil fuels (vehicular | |
| | emissions; biomass or kerosene | |
| | burning for cooking or heating) | |
| VOCs | Combustion sources (biomass | CH ₄ - Grennhouse gas; Monocyclic |
| | burning, automobiles, | Aromatic Hydrocarbons (MAH) – |
| | industries, etc.); painting, | carcinogenic; pulmonary problems; |
| | printing, leather coating, use of | allergies; CNS problems; damages |
| | personal products, exploration | liver, kidney, etc. |
| | and handling of oil products | |
| | etc.; Biogenic sources (Plants) | |
| PM _{2.5} | Vehicles, power plants, | Penetrates deep into the lungs and enter |
| | industrial processes; wildfires; | the bloodstream, causing respiratory |
| | sea spray; chemical reactions in | and cardiovascular diseases; Reduces |
| | atmosphere | visibility (haze) |
| Ozone | Secondary pollutant formed by | Damage crops, forests, and other |
| | chemical/photochemical | vegetation; Throat irritation, coughing, |
| | reactions in the atmosphere | and difficulty breathing; cardiovascular |
| | | and pulmonary diseases; Respiratory |
| | | problems, asthma, bronchitis etc.; |

| | | Assists in formation of Peroxy acetyl nitrate (PAN); cracking of rubber |
|-----------------|----------------------------|-------------------------------------------------------------------------|
| NH ₃ | Fertilizers and animal | Irritation to eyes, lungs. |
| | husbandry operations; | |
| | ammonia synthesis; Emitted | |
| | from soils, wildlife, and | |
| | decomposition of organic | |
| | matter | |

Importance of GLO has been duly recognised by the regulatory authorities in India and Worldwide. WHO prescribes air quality guideline for O_3 as $100~\mu g/m^3$ (8-hour average) as per its latest revision in 2021(WHO, 2021). In India, the Central Pollution Control Board (CPCB) notified the National Ambient Air Quality Standards (NAAQS) which is as follows:

Table 2. 2 National Ambient Air Quality Standards (NAAQS), CPCB (CPCB, 2009)

| | | Standard | Eco-Sensitive |
|---------------------|---------------|---------------|----------------------|
| | Time Weighted | Concentration | Zone Standard |
| Pollutant | Average | (μg/m³) | (μg/m³) |
| Particulate Matter | | | |
| (PM ₁₀) | 24 hours | 100 | 60 |
| | Annual | 60 | 40 |

| Particulate Matter | | | |
|------------------------------------------|----------|------|------|
| (PM _{2.5}) | 24 hours | 60 | 40 |
| | Annual | 40 | 20 |
| Nitrogen Dioxide | | | |
| (NO ₂) | Annual | 40 | 20 |
| | 24 hours | 80 | 40 |
| Sulphur Dioxide | | | |
| (SO ₂) | 24 hours | 80 | 50 |
| | Annual | 50 | 20 |
| Carbon Monoxide | | | |
| (CO) | 8 hours | 2000 | 1000 |
| | 1 hour | 4000 | 2000 |
| Ozone (O ₃) | 8 hours | 100 | 50 |
| | 1 hour | 180 | 90 |
| Lead (Pb) | Annual | 0.5 | 0.2 |
| Ammonia (NH ₃) | Annual | 100 | 50 |
| Benzene (C ₆ H ₆) | Annual | 5 | 2 |

2.2 Chemistry of Ozone Formation

In the 1970s, P.J. Crutzen pioneered research into the photochemistry of tropospheric ozone generation(Crutzen, 1979, 1974). Subsequently, research into its production, chemistry, precursors, destruction, and transport have all improved our

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understanding regarding GLO. An understanding of the non-linear chemistry between

O₃ and its predecessors has become crucial for policy formulation. Numerous studies

have provided explanations of this non-linear connection and the photochemical

behavior of O₃ (Zhang et al., 2008).

At the stratosphere and tropospheric levels, O₃ is created by a variety of

chemical processes. Ozone is created naturally in the stratosphere when sunlight's UV

radiation (λ < 240 nm) is absorbed by oxygen, leading to the formation of nascent

oxygen atoms. Following its reaction with the O₂ molecule, this atom subsequently

produces ozone. This naturally occurring stratospheric ozone descends to the

troposphere in part. Sunlight radiation breaks down ozone in the troposphere into O2

molecules and atoms.

Oxygen converts to O₃ in stratosphere, some of which transports to troposphere and

forms OH radicals.

$$O_3 \rightarrow O_2 + O$$

$$O + H_2O \rightarrow 2OH$$

Primary pollutants like VOCs and CO react with OH and forms RO₂ and OH₂. RO₂ is

an organic chain with an attached O₂ (replacing H).

$$VOC + OH \rightarrow RO_2 + H_2O$$

$$CO + OH \rightarrow OH_2 + CO_2$$

RO2 and OH2 oxidise NO to NO2.

$$RO_2 + NO \rightarrow HO_2 + VOC + NO_2$$

$$OH_2 + NO \rightarrow OH + NO_2$$

NO2 undergoes photolysis to form atomic oxygen, that combines with oxygen to form

O₃ in the troposphere.

The chemical reactions below illustrate the same:

Chemical reactions showing ozone formation are as follows:

 $NO_2 + hv (sunlight) \rightarrow NO + O$

 $O + O_2 + Stable$ Molecule that absorbs excess energy $(O_2/N_2) \rightarrow O_3 + Stable$ Molecule (O_2/N_2)

 O_3 is generated in the presence of sunlight. At night, the primary NO emitted from sources such as vehicles and power plants reacts with O_3 , converting it back to O_2 . This process is known as NO_x titration.

$$O_3 + NO \rightarrow NO_2 + O_2$$

The above reactions are cyclic in nature.

It can be concluded that solar radiation intensity, NO_x concentration and VOC levels, and their ratios significantly influence the formation of ground-level ozone (GLO). These reactions and photochemistry of ozone are further explained in this section in detail.

The formation of ozone depends on local geography, meteorology, and landuse patterns. For example, "trapping regions" and where temperature inversion occurs tend to have higher O₃ concentrations (For example, the infamous Los Angeles smog episode.). Similarly, urban and industrial regions have higher O₃ concentrations due to higher concentrations of precursors present. It is well-established in literature that high temperature and solar radiation favours ozone formation.

There are two primary regimes under which GLO is produced: the NO_x -sensitive regime and the VOC-sensitive regime. In the NO_x -sensitive regime, the NO_x /VOC ratio is low, making ozone concentrations more dependent on NO_x levels. Conversely, in the VOC-sensitive regime, where NO_x /VOC ratios are high, ozone levels decrease with an increase in NO_x and increase with a rise in VOCs.

The reactions involving CO are explained below, wherein O₃ acts as a source of OH (hydroxyl radical) and CO represents VOCs.

$$CO+OH(+O_2) \rightarrow CO_2+HO_2$$

The destruction and generation of O_3 along with limited regimes can be seen in Figures 2.1 and 2.2. O_3 production takes place, both in *VOC-limited* and *NO_x limited* regimes. However, in most cases O_3 generation is in NO_x limited regimes, except during peak summers when O_3 production is mostly governed in VOC-limited regimes (Shukla, 2019).

With presence of VOCs the following reactions occur:

- a. $RH + OH^* \rightarrow R^* + H_2O$
- b. $R^* + O_2 \rightarrow RO_2^*$ (Initiation stage)
- c. $RO_2^* + NO \rightarrow RO^* + NO_2$
- d. $RO^* + O_2 \rightarrow HO_2^* + R'CHO$ (aldehyde)
- e. $HO_2^* + NO \rightarrow NO_2 + OH^*$ (Propagation stage)

Reaction e. shows that removal of NO, formation of NO2 and OH* takes place which all contribute to O₃ formation. These reactions together go through initiation, propagation and termination stages. Reaction terminates when RO₂* and HO₂* react together. Therefore, these complex cyclic reactions are very tough to stop.

An example of VOC reacting to produce ozone is as follows:

$$CH_3CH_3+2O_2+h\vartheta\rightarrow CH_3CHO+H_2O+2O_3$$

The general mechanism of OH-initiated ozone generation can be extended to more complex VOCs i.e., alkanes (Sharma, 2017).

Atkinson (2000) and Kleinman et al. (2002) outlined a fundamental scheme

(general reaction scheme) of reactions based on photochemical equations(Shukla, 2019). These equations are categorized into three groups, representing the initiation, cycling, and termination phases, as described below:

Initiation:

$$O_3+h\upsilon \rightarrow O+O_2$$

$$O + H_2O \rightarrow 2OH$$

HCHO + h
$$\upsilon$$
 → 2HO₂

Alkene + $O_3 \rightarrow Radicals$

Cycling (chain propagation):

$$OH + VOCi \rightarrow aHO_2 + b RO_2 + cRCO_3$$

$$NO + HO_2 \rightarrow OH + NO_2$$

$$NO + RO_2 \rightarrow d (NO \rightarrow NO_2 conversion) + HC oxidation products$$

$$NO + RCO_3 \rightarrow e (NO \rightarrow NO_2 conversion) + HC oxidation products$$

$$NO_2+h\upsilon \rightarrow O+NO$$

$$O_2 + O \rightarrow O_3$$

Termination

 $NO_2+OH\rightarrow HNO_3$

NO+RO₂→Organic nitrate

$$NO_2+CH_3CO_3\rightarrow PAN$$

$$PAN \rightarrow NO_2 + CH_3CO_3$$

Radical + Radical

$$HO_2+HO_2\rightarrow H_2O_2$$

$$RO_2+HO_2 \rightarrow RCOOH$$

$$OH+HO_2 \rightarrow H_2O+O_2$$

$RO_2+R'O_2 \rightarrow Products$

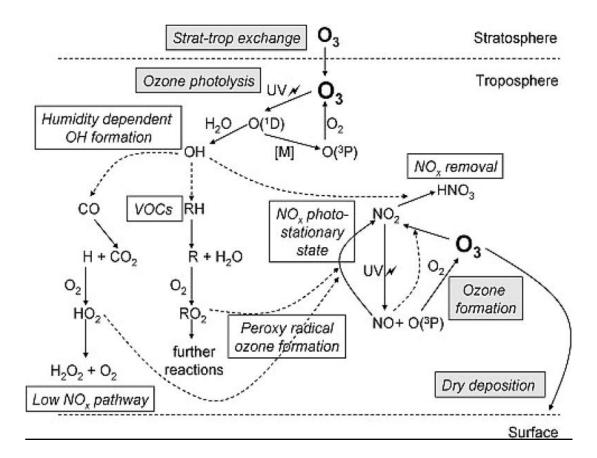


Figure 2.1 Formation of O_3 in Troposphere(Atkinson, 2000)

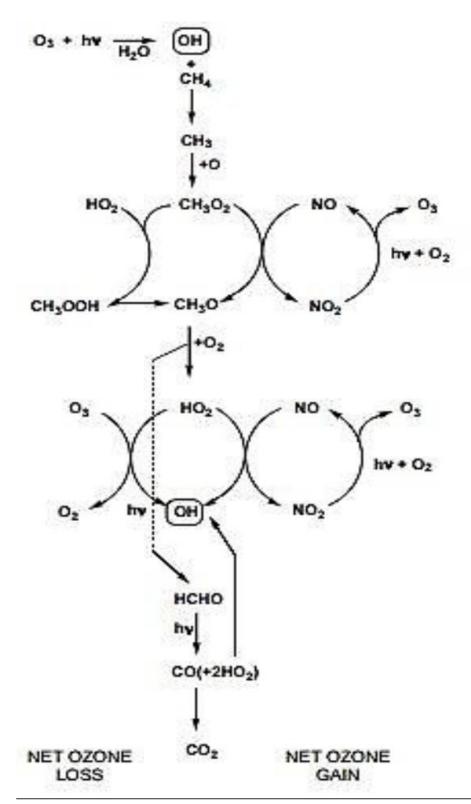


Figure 2. 2 Mechanism for the tropospheric O₃ formation (Lightfoot et al., 1992)

Ground-level ozone (GLO) production can be either limited by nitrogen oxides (NOx)

or volatile organic compounds (VOCs). In NO_x-limited conditions, reactions between RO₂ and NO don't significantly reduce peroxy radicals. In VOC-limited conditions, often found in urban areas, high NO_x levels lead to the production of NO₂ and subsequently ozone (O₃). The concentration of NO_x in the air determines whether the process is NO_x or VOC-limited. Non-methane hydrocarbons (NMHCs) add complexity as they can act as sinks for GLO. Understanding the origins and regional movement of VOCs, HO_x species, OH reactivity, and GLO levels remains inconsistent, emphasizing the need for more targeted research.

In India, NO_x-limited conditions are generally more common, but this varies between rural and urban areas. The NO_x/VOC ratio is lower in India compared to developed countries due to high VOC emissions from both natural and human activities, such as the use of biofuels for cooking in rural areas. Urban areas see higher NO_x emissions from vehicles, while rural areas have significant VOC emissions from biomass burning. This suggests that Indian cities are more sensitive to VOCs, whereas rural areas are more sensitive to NO_x in terms of GLO production. VOCs from biomass burning, like alkanes, alkenes, acetylenes, oxygenated compounds, and aromatics, mostly fall within the C2–C4 range and have a high potential to form ozone. Studies in Dehradun and Delhi identified toluene and xylene as having the highest potential to form ozone during winter (Sharma, 2017; Shukla, 2019).

 NO_x is crucial in both forming and breaking down ground-level ozone (GLO). Reducing VOCs affects O_3 generation, but in rural areas where O_3 is NO_x -limited, reducing VOCs is less effective in lowering O_3 levels.

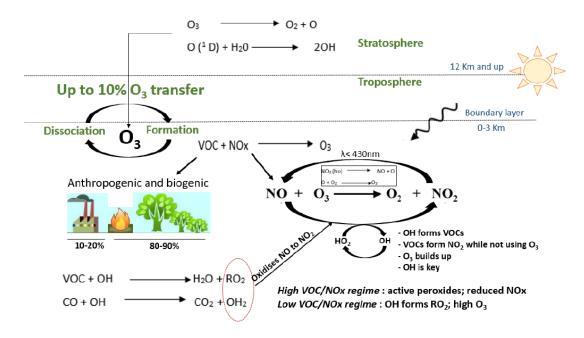


Figure 2. 3 Ozone formation in NO_x limiting and VOC limiting regimes (Shukla, 2019)

Literature on influencing meteorological parameters reveals GLO's relationship with mainly Ambient temperature, relative humidity and solar radiation. Ozone's dependence on other precursors – NO₂, NO, CO, NMHC, etc. have already been discussed.

High ambient temperatures typically enhance ground-level ozone (GLO) formation, as observed in various studies (Dhawan et al., 2023; Lacour et al., 2006). GLO mixing ratios are adversely affected by relative humidity (RH). Excess moisture generates hydroxyl radicals, which are efficient sinks for GLO. Moisture also impacts heterogeneous processes including N₂O₅ hydrolysis and the absorption of NO₃ and NO₂ on wet aerosol surfaces, which in turn consumes HO₂. It also encourages the hygroscopic development of aerosols. GLO concentrations are lowered by these mechanisms, which include HO₂ consumption and N₂O₅ hydrolysis (Shukla, 2019).

Thus, relative humidity is generally negatively correlated with ozone concentrations. On the other hand, GLO concentrations may rise as a result of the irreversible absorption of NO_x molecules, which increases the amounts of OH radicals (Shukla, 2019).

Rainfall is directly related to water vapor dynamics and has a major effect on ground-level ozone (GLO) concentrations. GLO levels frequently alter noticeably in response to rain patterns. Additionally, via affecting the ambient atmosphere's dispersion coefficients, wind speed and the atmospheric boundary layer are critical in controlling GLO dynamics (Shukla, 2019).

Dhawan et al. (2023) observed positive correlation between ozone and windspeed, temperature, solar radiation and a negative one between ozone and relative humidity. They also observed high ozone concentration around green areas, possibly indicating biogenic VOCs contributing to ozone formation (Dhawan et al., 2023).

As previously discussed, ozone is known to vary with its precursors following complex chemical reactions. Zhang et al. (2008) used an observation-based model (OBM) to study the connection between ozone and its precursors. Their research showed that high O₃ concentrations in the upwind direction are mostly caused by onsite photochemical production, which has a non-linear relationship with NO_x (Zhang et al., 2008). Ozone Production Efficiency (OPE) is the number of oxidant molecules (O₃ + NO₂) created photochemically when one molecule of NO_x (NO + NO₂) is oxidized. Seinfeld and Pandis studied OPE(Seinfeld et al., 1998). This indicates a negative correlation between ozone and NO_x. The immediate chemistry of ambient air was studied by Kleinman et al. (2002) using a Constrained Steady State box modeling

approach, with a focus on how NO_x/NO_y rises. Their results imply that regional features, rather than only NO_x levels, determine the effectiveness of O₃ synthesis, mainly because of proportionate variations in the reactivity ratio of VOCs to NO₂. Many factors resulting from emission patterns affect this reactivity ratio (Kleinman et al., 2002). This indicates the unpredictability of O₃ synthesis which varies spatiotemporally. Another example of temporal variance has been studied by Han et al. Their study explored the "weekend effect," where differences in pollutant levels between weekdays and weekends were noted. During weekends, there are typically reductions in NO and NO_x levels compared to weekdays. This reduction is attributed to lower traffic volumes as fewer people commute. Interestingly, despite lower levels of NO_x (which are precursors to ozone), ozone levels do not proportionally decrease during weekends. This counterintuitive result is partly due to the complex chemistry of ozone formation and the reduced titration of ozone by NO (Han et al., 2011). Stratosphere Troposphere Exchange (STE) can also influence O₃ concentrations as shown by Rathore et al. Rathore et al. (2023) have observed that Stratosphere Troposphere Exchange (STE) is maximum during spring season in India and have observed long-range transport of O₃. The study also underscores the substantial contribution of tropospheric ozone to radiative forcing.

Sinha et al. (2021) investigated the levels of surface ozone (O_3) and its interactions with other air pollutants such as nitrogen oxides (NO_x) and carbon monoxide (CO) in various locations throughout Delhi from 2013 to 2019. It found that ozone levels are highest during the summer months. This increase is due to the strong sunlight in summer, which accelerates the chemical reactions that produce ozone from its precursor pollutants like NO_x and CO. However, the study also highlights a complex

relationship between ozone and nitrogen oxides. During daylight hours, as the concentration of nitrogen oxides increases, the level of ozone actually decreases, contrary to what might be expected. This occurs because in urban areas like Delhi, which are sensitive to volatile organic compounds (VOCs), the presence of NO_x can lead to the breakdown of ozone through various chemical reactions. This implies a negative correlation exists between ozone and NO_x (Sinha et al., 2021). During the literature review, studies typically indicated high O₃ concentration during summer and postmonsoon.

2.3 Studies on Interrelationship between ozone and PM_{2.5}

Literature, until very recently, had not explored the interrelationship between GLO and PM_{2.5}; and the influence of other meteorological parameters on this relationship. Findings from some papers that did explore this relationship have been summarized as follows:

Munir et al (2011)

Munir et al.'s (2011) findings include a positive correlation between previous day ozone levels and current ozone levels, indicating that ozone tends to persist over time affecting subsequent concentrations. The study also notes negative correlations between ozone and nitrogen oxides (NO and NO₂) as well as carbon monoxide (CO), which are primarily emitted from traffic sources. This means that higher levels of these pollutants are associated with lower levels of ozone. The relationship with particulate matter (PM_{2.5}) varies; it is negatively correlated with ozone at lower quantiles and turns positive at higher quantiles, suggesting complex dynamics influenced by the

concentration levels of ozone. The quantile regression approach used in the study offers a more detailed understanding of how these pollutants influence ozone compared to traditional regression methods, demonstrating that the impact of air pollutants on ozone varies across different environmental conditions and pollution levels (Munir et al., 2011).

Zhang et al., 2015

Zhang et al. examined the long-term trends and daily variations of $PM_{2.5}$ and ozone (O₃) concentrations and their relationship with meteorological conditions in Beijing over the past decade. It shows that $PM_{2.5}$ levels have decreased whilst ozone concentrations have increased. It also says that light rainfall can reduce ozone concentrations (Zhang et al., 2015).

Coates et al. (2016)

Coates et al. (2016) have discussed in the current section as it focusses on biogenic VOCs – an important precursor to both $PM_{2.5}$ and O_3 . The 2016 study by Coates et al. explores how temperature affects ozone production when nitrogen oxides (NO_x) levels vary, using simulations from a box model incorporating multiple chemical mechanisms. Their research demonstrates that higher temperatures expedite chemical reactions and increase emissions of biogenic volatile organic compounds (BVOCs) like isoprene, both of which elevate ozone concentrations. It was also observed that rate in increase of ozone-mixing ratio was half that of increase in ozone due to rise in temperature. It was recommended that NO_x emissions need to be curbed to control O_3

pollution (Coates et al., 2016).

Jia et al. (2017)

Jia et al. (2017) investigate the seasonal relationships between PM_{2.5} (fine particulate matter) and O₃ (ozone) in Nanjing, China, using environmental data from 2013 to 2015. During the hot seasons (June to August), Jia et al. found a positive correlation between PM_{2.5} and ozone, with a correlation coefficient of 0.40. This positive relationship can be attributed to increased solar radiation and higher temperatures, which enhance photochemical reactions. These reactions are crucial for the formation of ozone. Sunlight drives the photolysis of nitrogen dioxide (NO₂), which leads to the production of ozone. Simultaneously, the increased temperatures and sunlight accelerate the emission of volatile organic compounds (VOCs) from both natural and anthropogenic sources, further fueling the formation of both ozone and secondary particulate matter, which contributes to higher PM_{2.5} levels. Conversely, in the cold seasons (December to February), the correlation between PM_{2.5} and ozone is negative, with a correlation coefficient of -0.16. During this period, the reduced intensity of sunlight and lower temperatures decrease the rate of photochemical reactions necessary for ozone formation. Furthermore, higher concentrations of PM_{2.5} during the cold months can exacerbate this effect by absorbing and scattering solar radiation, which reduces the energy available for these reactions. The study notes that under high PM_{2.5} conditions, surface ozone concentrations can significantly drop, which demonstrates the inhibitory effect of particulate matter on ozone production during colder times (Jia et al., 2017).

Shao et al., 2021

Shao et al. (2021) conducted their study in Beijing and Los Angeles. They state that the importance of $PM_{2.5}$ -induced ozone amplification is contingent upon the optical characteristics of the particles as well as the amounts of $PM_{2.5}$. The author hypothesizes that as $PM_{2.5}$ concentration decreases, the absorption of solar radiation decreases enabling more ozone formation through photochemical reactions. However, this effect becomes less significant once $PM_{2.5}$ concentration falls below 40 $\mu g/m^3$ (Shao et al., 2021).

Liu et al., 2019

The study by Liu et al. provides a detailed analysis of how aerosols, including particulate matter (PM_{2.5}), influence the generation of surface ozone through complex atmospheric interactions, particularly during summer in Shanghai. Aerosol Optical Depth (AOD) is a measure of aerosols' ability to block sunlight. A higher AOD means more particles are present in the atmosphere. The presence of PM_{2.5} can directly reduce the amount of UV light available for ozone formation due to absorption and scattering. Indirectly, the changes in UV radiation affect the photolysis rates of nitrogen dioxide (NO₂), which is a precursor to ozone. This can either suppress or modify the efficiency of ozone production depending on the concentration and type of particulate matter. While high levels of PM_{2.5} generally decrease UV radiation reaching the surface (thus potentially reducing ozone formation), the scattering effect from high SSA can increase diffuse UV radiation, which might still promote ozone formation under certain conditions (Liu et al., 2019).

Chen et al., 2019

Chen et al. (2019) conducted a study using data from 1458 air quality monitoring stations in mainland China from 2013 to 2017 exploring the correlation between PM_{2.5} and ozone on seasonal and diurnal temporal scales. According to the study, precursors to PM_{2.5} include oxides of Sulphur, Nitrogen and VOCs. VOCs are a common precursor to both PM_{2.5} and ozone. The study generally observed a positive correlation between PM_{2.5} and ozone during summer season and a negative correlation during winter and other seasons. It is also to be noted that the study classifies correlation coefficients more than 0.4 in magnitude to be "strong relationships." During summers, high ozone concentrations, low PM_{2.5} concentrations and high Pearson's correlation coefficient (r) were observed. In winter, ozone concentrations were low, PM_{2.5} concentrations were high and Pearson's correlation coefficient was low. It was observed that Pearson's correlation coefficient tended to be positive when O₃ concentration was high, and PM_{2.5} concentration was low; and vice-versa. On a diurnal scale, r tended to be minimum at approx. 10:00 hrs. and maximum at approx. 15:00 hrs. Values of r have been plotted seasonally, which exhibits a trend of having negative Pearson's correlation coefficient at high concentration of PM_{2.5}. However, relationship between Pearson's correlation coefficient and O₃ was not apparent.

The reason for having positive correlation between O₃ and PM_{2.5} in summer season is because of complex chemical reactions occurring. Gaesous pollutants (SO₂, NO_x, NH₃) and VOCs undergo condensation to form secondary organic aerosols (SOA) and particulate matter (PM_{2.5}). These reactions are promoted at higher temperatures, under solar radiation, low windspeed and under ozone that provides an oxidizing environment, thereby causing a positive correlation between ozone and PM_{2.5}. It is to

be noted, however, that in China, summers have been said to be warm, but having high precipitation, as per the study.

During winters, the authors reason that as PM_{2.5} levels increase, the extinction effect and absorption of radiation during intermixing of particulate matter becomes dominant, thereby causing a negative correlation between O₃ and PM_{2.5}. PM_{2.5} also acts as a sink of HO₂ (Hydroperoxy) radicals, thereby bolstering O₃ production. Additionally, during winters vehicular exhausts increase as the vehicles start slowly and may experience knocking problems. Low mixing heights, low wind speeds and temperature inversions exacerbate the situation.

Further, the study has also explored spatial variability in trends observed. Where temperatures and rainfall are low (Inland and Northern China), correlation coefficient is observed to be more negative. In Southern, Eastern and Coastal China, where temperatures and rainfall are higher, correlation coefficient tends to be positive. Authors further explain that monsoons tend to have a cleansing effect that reduce both O₃ and PM_{2.5}, with overcast weather decreasing ozone formation. It is also possible that stable conditions brought by monsoon air mass facilitates PM_{2.5} formation, while ozone is being formed simultaneously due to photochemical reactions (Chen et al., 2019).

Chen et al. (2020)

Chen et al. (2020) discovered that Stratosphere Troposphere Exchange (STE) increases PM_{2.5} concentration. This happens because additional ozone increases atmospheric oxidation capacity forming Secondary Organic Aerosols (SOA). STE's impact is more pronounced during winter and spring when inherent ozone and

oxidation capacity is low. Diurnally, the highest enhancements in $PM_{2.5}$ are observed in the morning due to the accumulation of pollutants overnight and reduced mixing in the atmosphere (Chen et al., 2020).

Dai et al., 2021

Dai et al. (2021) investigated relationship between ozone and PM_{2.5} in the Yangtze River Delta (YRD) from 2013 to 2019. For overall for annual concentrations, the two seem to be negatively correlated. But they exhibited a weak positive correlation during warm months (Dai et al., 2021).

Sharma et al., 2021

Sharma et al. (2021) have measured parameters at only one location at CSIR-National Physical Laboratory in Delhi. Based on this they have observed positive correlation between ozone and NO_x and a negative one with NMHC. The study observed that ozone concentration was more sensitive to NO_x than NMHC (Sharma et al., 2021).

Wang et al., 2023

Wang et al. (2023) conducted a detailed study was conducted from 2015 to 2019, focusing on Eastern China, utilizing data from 883 monitoring locations to analyze the relationship between PM_{2.5} and O₃ across three different regions. Despite stringent air quality measures initiated in 2013, PM_{2.5} levels still exceed standards while O₃ levels are on the rise, indicating a shifting air pollution pattern in China. Both PM_{2.5} and O₃ share common precursors, and their concentrations are influenced by various meteorological conditions; for instance, high temperatures and low wind speeds promote O₃ formation, whereas low temperatures and stagnant conditions favor

PM_{2.5} accumulation.

The study found that at high PM_{2.5} concentrations, typically, a negative correlation exists with O₃, notably with an annual average of about 80 μg/m³ in Nanjing in 2008. However, this correlation turns positive in summer and has recently shown a tendency to be weakly positive or remain negative in winters, due to substantial emissions from heating fuels which boost PM_{2.5} levels and poor meteorological dispersal conditions. Interestingly, the correlation between PM_{2.5} and O₃ becomes more positive as PM_{2.5} levels decrease, influenced strongly by temperature, which not only enhances the generation of secondary particulate matter under high conditions but also reduces the inhibitory effects of PM_{2.5} on ozone production when low.

Spatially, the correlation exhibits notable north-south and seasonal variations; it is generally more positive in southern regions and during summer, turning negative or weakly positive during colder months. This shift suggests a dynamic interplay between air pollution and climatic factors across different parts of Eastern China. Furthermore, the study observed that while PM_{2.5} pollution days decreased annually by 8.6%, O₃ pollution days increased by 19.2%, underscoring the evolving nature of air quality issues in the region. High temperatures and low relative humidity greatly enhance O₃ production, whereas low temperatures, low wind speeds, and low planetary boundary layer heights promote the accumulation of surface PM_{2.5}. Relative humidity was negatively correlated with the O₃ concentration and positively correlated with the PM_{2.5} concentration in the NCP, but was negatively correlated with it in the YRD and PRD.

PBLH was positively correlated with the O_3 concentrations and negatively correlated with the $PM_{2.5}$ concentrations. Intense solar radiation is a key factor in the

formation of O₃, often associated with a high planetary boundary layer height (PBLH). While an increased PBLH aids in the dissipation of O₃, the photochemical reactions driving ozone generation may outweigh the dispersion effects, especially as temperatures rise. RH was positively correlated with PM_{2.5} (till a threshold precipitation) and negatively correlated otherwise, and it was negatively correlated with the O₃ concentration. High humidity enhances the formation of secondary aerosols through aqueous-phase aerosol chemistry. Generally, high wind speeds help disperse PM_{2.5} and O₃. It is noteworthy that the O₃ concentrations exhibited a weak positive correlation in one region. This may be because the high WS reduced the PM_{2.5} and thus reduced the inhibitory effect of the PM_{2.5} on O₃ generation.

This nuanced study highlights the complexities of air pollution control, particularly in a region with diverse meteorological and geographical influences, and underscores the critical need for region-specific strategies in managing air quality (Wang et al., 2023).

Yadav et al., 2023

The study conducted by Yadav et al. delves into the intricate relationships between particulate matter (PM_{2.5}) and ozone (O₃) across different urban settings in India, examining how these relationships change with the seasons—specifically comparing summer and winter scenarios. In cities like Delhi and Bengaluru, the study observed a negative correlation between PM_{2.5} and O₃ during winter. This means that when PM_{2.5} concentrations are high, ozone levels tend to be lower. This phenomenon occurs because particulate matter can block or absorb sunlight, which is essential for the photochemical reactions that produce ozone. Therefore, high levels of particulates can inhibit the formation of ozone, which relies heavily on solar radiation. In contrast,

during the summer months in Bengaluru, there is a positive correlation between these two pollutants. In this case, higher temperatures and more intense sunlight not only increase the rate of ozone formation through enhanced photochemical reactions but also contribute to the secondary formation of particulate matter. This suggests that both pollutants are being driven by similar conditions—mainly temperature and solar radiation. Further, higher humidity can facilitate the formation of secondary organic aerosols, a component of PM_{2.5}. Wind speed affects the dispersion and dilution of pollutants; calmer conditions might lead to higher concentrations of pollutants due to less dispersion, while higher wind speeds can disperse pollutants more widely, potentially lowering local concentrations but spreading pollution over a broader area. During winter, Delhi experiences a negative correlation between PM_{2.5} and O₃. Several factors contribute to this pattern (Yadav et al., 2023):

- Reduced Solar Radiation: Winter months see lower levels of sunlight due to shorter
 days and more frequent foggy and overcast conditions. Since sunlight drives the
 photochemical reactions necessary for ozone formation, less sunlight means less
 ozone production.
 - High Levels of Particulates: Increased particulate matter during winter can absorb
 and scatter solar radiation, further reducing the sunlight available for ozone
 formation. Additionally, particulate matter can also provide surfaces for
 heterogeneous reactions where ozone can be destroyed.
 - Stable Atmospheric Conditions: The colder temperatures bring about more stable atmospheric conditions with less vertical mixing. This stability often results in a shallower boundary layer (the part of the troposphere directly influenced by the

surface and where we experience weather and pollution). With pollutants trapped closer to the ground, higher concentrations of particulates are common, and the dispersal of pollutants is limited.

• Temperature Inversions: Common during winter, temperature inversions occur when a layer of warm air overlays cooler air near the surface, further trapping pollutants like PM_{2.5} and reducing the vertical dispersion that might otherwise disperse ozone.

Conversely, during summer, the study found instances of both non-significant and positive correlations between PM_{2.5} and ozone.

- Increased Solar Radiation: With longer days and more intense sunlight, there's an increase in photochemical activity, leading to higher ozone formation. The sunlight not only drives the formation of ozone from its precursors (NO_x and volatile organic compounds) but also contributes to the secondary formation of particulate matter.
- Higher Temperatures: Elevated temperatures can increase the rate of
 photochemical reactions, boosting ozone production. Higher temperatures also
 lead to a deeper boundary layer, which can dilute pollutants but also allows for the
 vertical accumulation of ozone formed aloft to mix down to the surface.
- Variable Particulate Matter Effects: While particulate matter in summer can still absorb sunlight, the overall higher levels of radiation and heat often offset this effect by enhancing ozone production. Additionally, certain types of particulate matter can act as surfaces for photochemical reactions that generate more secondary organic aerosols, contributing to both PM_{2.5} and ozone levels.

2.4 Research Gap

Understanding the dynamics of ozone (O₃) and its variations in Delhi is crucial for multiple reasons. Ozone, a secondary pollutant, forms through complex chemical reactions involving precursor pollutants such as nitrogen oxides (NO_x) and nonmethane volatile organic compounds (NMVOCs) in the presence of sunlight. Given that Delhi is characterized by high population density, congested roads, and significant industrial activities, the study of ozone variations and its influencing factors is indispensable for effective air quality management and public health protection.

Variations in concentrations of ozone are observed to be dependent on complex chemical reactions and meteorological parameters. As highlighted in the literature review, these variations can change spatially and temporally, exhibiting diurnal as well as seasonal fluctuations. Despite extensive global research on ozone, studies focusing on its interaction with other parameters, particularly in the Indian context, remain limited. Specifically, there is only one notable studies exploring the relationship between PM_{2.5} (particulate matter with a diameter of less than 2.5 micrometers) and ozone in Delhi: Yadav et al. (2023). Yadav et al. (2023) studied the relationship using parameters such as ozone, NO_x, temperature, relative humidity, wind speed, and PM_{2.5}. This gap in research is significant because understanding the interplay between PM_{2.5} and ozone can inform targeted pollution control strategies. A thorough understanding of this relationship is essential for regulatory bodies to formulate policies that prevent the co-pollution of PM_{2.5} and ozone. A theory regarding variations in ozone and PM_{2.5} in context of Delhi may help regulatory bodies formulate policies to prevent co-pollution of PM_{2.5} and ozone. Efforts by regulatory authorities to reduce pollution in

Delhi include measures included in Graded Response Action Plan (GRAP) and National Clean Air Programme (NCAP). Learning from China's experience, where successful pollution-reduction measures managed to reduce particulate matter pollution but inadvertently caused an increase in ozone concentration, it is prudent to further explore the relationship between ozone and PM_{2.5} in Delhi. This knowledge will aid in developing effective strategies to manage both pollutants simultaneously.

2.5 Scope and Objectives

The current study is an exploratory analysis of variations in ozone in Delhi on diurnal and seasonal timescales. The study also seeks to explore the factors on which it depends, with particular attention to exploring the correlation between ozone and PM_{2.5}. In the current exploratory analysis, data from six stations in Delhi were used to analyse temporal variations in ozone on diurnal and seasonal timescales. All parameters that could influence ozone formation monitored by CAAQMS (PM_{2.5}, NO₂, NO, CO, NH₃, MAH, windspeed, relative humidity, temperature, solar radiation) were considered. Following this, the key parameters found to be influencing ozone were considered more closely.

The specific objectives of the study were as follows:

- 1. To analyse the trends in O₃ formation in Delhi over a six-year period.
- 2. To determine influencing factors for O₃ formation.
- 3. To explore nature of correlation between O_3 and $PM_{2.5}$.

Chapter 3: Study Area and Site Selection

3.1 Study Area: Delhi

Indian capital, Delhi is bordered by Uttar Pradesh to its east and the state of Haryana borders it from all other directions. It spans an area of about 1483 km². The latitudes binding are 28°24'17" and 28°53' N. The binding longitudes are 76°50'24" and 77°20'37" E. As per the Census, 2011 Delhi has a population of over 1.6 crores. Delhi continues to grow owing to urbanization, rising population and rising living standards in general. In 2022, Delhi received a total rainfall of approx. 811.7 mm, receiving an average annual rainfall of 774.4 mm (Delhi Statistical Handbook, 2023). Due to its geographical location, Delhi experiences a semi-arid climate, with hot summers and cold winters. The temperature can vary from as high as about 45°C during summer season to as low as 4°C during the winter season. Summer is characterised by hot dry winds (loo), winds from Thar desert, dry and hot days. After the southwest monsoon, winds are known to blow from northwest direction in the post-monsoon and winter season (NCERT, 2022). The month-wise seasonal classification for the present study has been done separately and has been described subsequently. The ambient air quality in Delhi shares characteristics with the Indo-Gangetic Plains due to similar climatic conditions (Sharma et al., 2021). In winter, reduced mixing heights limit pollutant dispersion, as the region experiences low wind speeds and high relative humidity. Delhi is infamous for being one of the most polluted cities of the world as anthropogenic pollution combined with unfavourable meteorological conditions adversely affect Delhi's air quality.

3.2 Site Selection

In the present study six Continuous Ambient Air Quality Monitoring Stations (CAAQMS) were selected. UV Photometric / Chemiluminiscence being used to monitor ozone using analysers at CAAQMS according to "Technical Specifications For Continuous Ambient Air Quality Monitoring (CAAQM) Station (Real Time)" by CPCB. The criteria for selecting these stations, in order of importance for the present study, is as follows:

- Availability of hourly-data for important parameters, especially for ozone and PM_{2.5}, during the study period (2018-2023).
- Diversity in types of surroundings of each station.
- Geographical representativeness for Delhi on a macro-scale.

A screenshot showing locations of all stations selected for the study has been placed as Fig. 3.1.

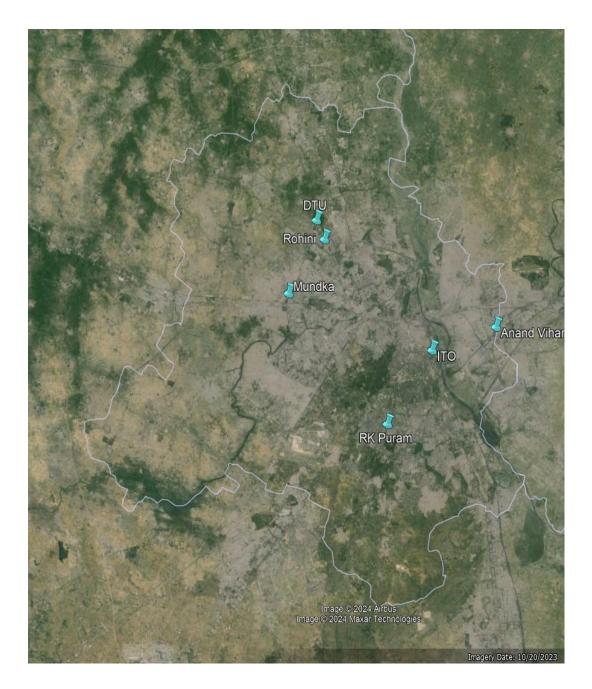


Figure 3. 1 Monitoring site selection in Delhi

Table 3.1 provides approximate geographical coordinates of the CAAQM Stations considered for the study. The type of area has also been mentioned based on past literature (Dhawan et al., 2023) and visual observation.

Table 3. 1 CAAQMS Locations and Area types

| S.No. | CAAQM | Latitude | Longitude | Type of area |
|-------|-------------|----------------|-----------------|----------------------|
| | Station | (degrees East) | (degrees North) | around station |
| 1 | Anand Vihar | 28.65 | 77.32 | Traffic- dominant |
| 2 | DTU | 28.75 | 77.11 | Institutional |
| 3 | ITO | 28.63 | 77.24 | Traffic- dominant |
| 4 | Mundka | 28.68 | 77.08 | Commercial |
| 5 | RK Puram | 28.56 | 77.19 | Residential |
| 6 | Rohini | 28.73 | 77.12 | Residential |

DTU and Rohini represented north Delhi. RK Puram represented South Delhi. Anand Vihar represented East Delhi, while ITO was assumed to represent Central Delhi. Mundka was assumed to represent western part of Delhi. DTU represents an institutional area with relatively high green cover. Rohini and RK Puram represented residential areas. ITO and Anand Vihar represented traffic-dominant areas.

Therefore, the stations selected for the present study was expected to provide a good representation of Delhi's air quality.

Chapter 4: Methodology

An important aspect that needs to be considered while studying air pollution problems is the meteorology of the region. Meteorology literally means science of atmospheric phenomena. It involves the study of dynamics of the atmosphere. Meteorology mainly depends on factors like sunlight, precipitation, humidity, temperature profile, wind direction and wind speed. Therefore, the present study not only considered pollutants, but also meteorological parameters. Data cleaning, validation and appropriate bifurcation was done for all parameters monitored by CPCB's CAAQMS. In this study, the following parameters were considered:

Table 4. 1 Parameters considered - Units and Abbreviations used

| S.No. | Parameter | Unit | Abbreviation used |
|-------|-----------------------------|-------------|----------------------|
| 1 | Particulate Matter < 2.5 μm | $\mu g/m^3$ | PM _{2.5} |
| 2 | Nitrogen Monoxide | $\mu g/m^3$ | NO |
| 3 | Nitrogen Dioxide | μg/m³ | NO ₂ |
| 4 | Ammonia | μg/m³ | NH ₃ |
| 5 | Carbon monoxide | mg/m³ | СО |
| 6 | Ozone | μg/m³ | Ozone/O ₃ |
| 7 | Benzene | μg/m³ | Benzene |
| 8 | Toluene | $\mu g/m^3$ | Toluene |
| 9 | Xylene | μg/m³ | Xylene |

| 10 | Ortho Xylene | $\mu g/m^3$ | O Xylene |
|----|-----------------------------|-------------|-------------|
| 11 | Ethylbenzene | $\mu g/m^3$ | Eth-Benzene |
| 12 | Meta-xylene and Para-xylene | μg/m³ | MP-Xylene |
| 13 | Atmospheric Temperature | °C | AT |
| 14 | Relative Humidity | % | RH |
| 15 | Wind speed | m/s | WS |
| 16 | Wind direction | deg | WD |
| 17 | Solar radiation | W/m² | SR |
| | Monocyclic Aromatic | $\mu g/m^3$ | |
| | Hydrocarbon (MAH) | | |
| | (=Benzene+Toluene+Xylene | | |
| | + O Xylene + Eth-Benzene + | | |
| 18 | MP-Xylene) | | МАН |

Subsequently, the parameters may be referred to by their abbreviations and the units for them would be the same as stated in the aforementioned table.

4.1 Data Validation

In the present study, data at hourly intervals was downloaded from 1st January 2018 to 31st December 2023 from the Central Pollution Control Board (CPCB) website (URL: airquality.cpcb.gov.in). After downloading the data, the data for each station was validated using the following data validation protocol, which is listed step-wise as

follows:

- Negative values, if obtained for parameters that could not have negative values, have been replaced by "NA".
- If value for any parameter repeats consecutively for more than four times consecutively, all such values have been replaced by "NA".
- Values below lower detection limit (LDL) have been replaced by the numeric LDL value for that parameter (thus giving a conservative estimate).
- Absurd values for parameters (such as where PM_{10} is observed to be greater than $PM_{2.5}$) have been replaced by "NA".

4.2 Preparation of Data for Analysis

After validation of data, data for each station was combined together to represent the air quality of Delhi. Averaging out such voluminous amount of data over a period of six years was expected to better represent seasonal trends of air quality in Delhi.

The data was then been bifurcated month-wise and season-wise for analysis of air

quality data on different temporal scales.

A flowchart depicting the methodology has been placed as Fig. 4.1.



Figure 4. 1 Overview of Data Analysis Procedure

Data analysis was conducted using Microsoft Excel and "Jeffreys's Amazing Statistics Program" (JASP). JASP is an open-source statistical software based on R.

4.3 Classification of Seasons

Classification of seasons of Delhi for the purpose of this study was done based on mean temperature of each month. Months having broadly similar characteristics were clubbed together. Such classification is in line with the mean monthly climate data available online for Palam, Ayanangar and Delhi Ridge ("Climate of Delhi," 2024). Such a classification was deemed necessary to better streamline the subsequent statistical analysis, compile the results efficiently and make the same readily-

understandable for regulatory bodies. The classification of seasons is as follows:

Table 4. 2 Classification of Seasons

| S.No. | Season | Months | Remarks in context of the present study |
|-------|--------|-----------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1 | Winter | December, January, February | These months have similar temperature ranges (Mean daily temperature less than 25°C). Solar insolation is low from winter solstice to spring equinox. Temperature inversion is observed in Delhi with elevated pollution levels. Western disturbances may cause some rainfall. |
| 2 | Spring | March | Moderate temperatures (Mean daily temperatures between 25 and 30°C). After western disturbances and NE monsoon have ceded, RH is more than that of summer but less than that of winter in our study. Increased pollination is expected. |
| 3 | Summer | April, May, June | Dry weather (typically RH observed <50% in our study) till mid-June. High temperatures (Mean temperature > 30 ° C). |

| 4 | Monsoon | July, August, | High relative humidity (typically RH |
|---|---------|---------------|-------------------------------------------|
| | | September | observed >50% in our study). |
| 5 | Post- | October, | With withdrawing monsoon, RH is less |
| | monsoon | November | than preceding monsoon and succeeding |
| | | | winter in our study. "October Heat" |
| | | | phenomenon observed during this |
| | | | period. Period of stubble burning, |
| | | | festivities, etc. that may cause elevated |
| | | | pollution levels. |
| | | | |

The above classification seems to be optimally conducive to the objective of the present study and the said classification was observed to ensure that trends observed are not diluted or averaged-out in any way, allowing one to better infer results obtained.

Chapter 5: Results and Discussion

5.1 Diurnal variations

Data for the years 2023 (latest available year) and 2020 (during COVID-19 lockdown) were used for observing diurnal variations in ozone and other related pollutants in every month of the year. This comparison was drawn to see if trends in variations of pollutants depend on their absolute concentrations. In 2020, lockdown was announced across the nation from late-March to June. Following this, the lockdown was relaxed in a phase-wise manner. It is assumed that commercial and vehicular activities throughout 2020 was much lower than in 2023. Therefore, it is presumed (and which was corroborated by data being used) that the year 2020 exhibited lower levels of pollution for all pollutants considered except for ozone.

Values at each hour of the day were averaged for the entire month and the same were plotted on a graph. Sample graphs for month of March 2023 and March 2020 have been placed as Fig. 5.1 and 5.2. All graphs for diurnal variations are annexed as Appendix-II. However, for analysing descriptive statistics for data, months were

classified into seasons to analyse seasonal trends in subsequent sections.

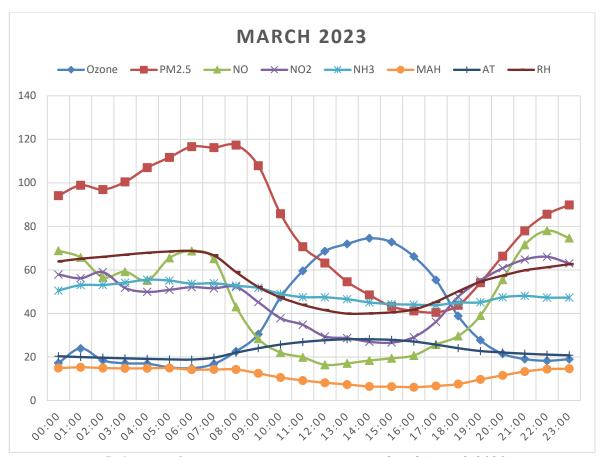


Figure 5. 1 Diurnal variations in parameters considered (March 2023)

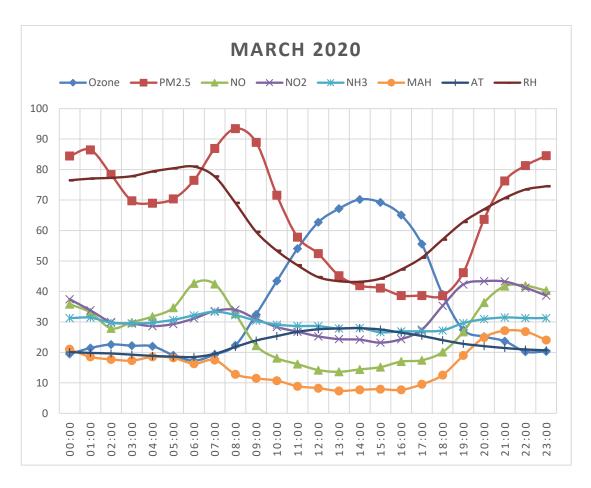


Figure 5. 2 Diurnal variations in parameters considered (March 2020)

Parameters considered were as follows: Ozone, PM_{2.5}, NO, NO₂, NH₃, MAH, AT, RH. SR was also compared, but is not been shown on the graph; while CO was not considered for visual comparison graphically due to large difference in scales of concentration in which they were found to occur. The graphs for diurnal variations suggested that the time-lag between ozone and parameters such as PM_{2.5}, CO, NO, NO₂, RH, WS, SR was not significant on an hourly time-scale throughout the year.

This concurred with literature citing high reactivity with such parameters and short lifespan in troposphere of ozone. In general, concentration of ozone peaked between 13:00 and 15:00 during both – 2020 and 2023. However, during lockdown in Delhi during April-June 2020, the ozone concentration curve was slightly negatively skewed and the peak concentration of ozone occurred at around 16:00. Graphs showing diurnal variations in May, 2020 and June, 2020 (when there was little human activity outdoors due to lockdown) is attached as Figures 5.3 and 5.4.

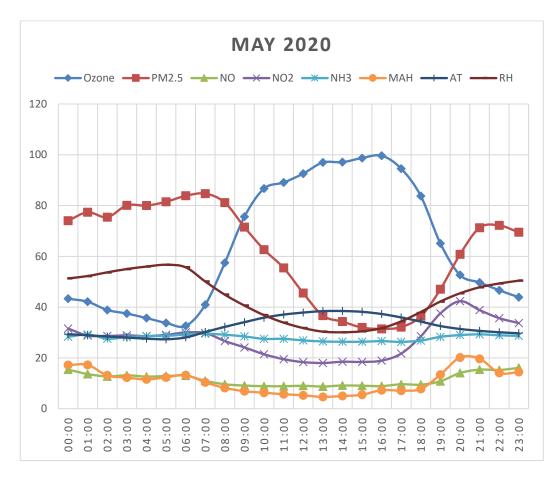


Figure 5. 3 Diurnal variations in parameters considered (May 2020)

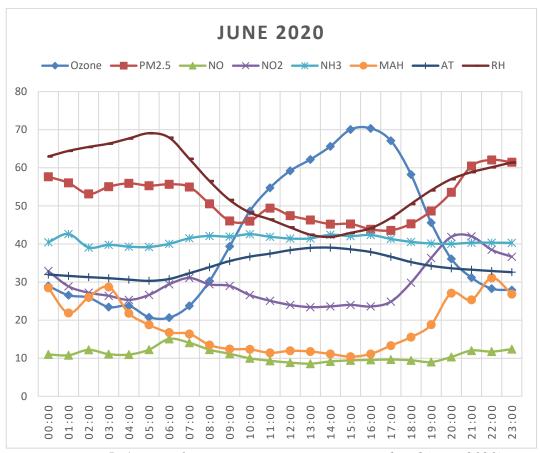


Figure 5. 4 Diurnal variations in parameters considered (June 2020)

Both months- May, 2020 and June, 2020 showed lower concentrations of precursors of O₃, but trends similar to the usual scenario exhibited during the same months of different years. Such diurnal trends indicated that correlations between ozone and other parameters considered followed a similar trend every year on diurnal basis regardless of quantum of concentrations in which they occurred on a daily-average basis. The reason for O₃ concentration being skewed negatively during lockdown period may have been due to unavailability of residual anthropogenic precursors from the previous day and little new emissions of these precursors during the morning hours. Biogenic VOCs were expected to peak during the afternoon hours. Therefore, the peak in O₃ concentration was delayed by about

two hours.

Examining the graphs visually, a negative correlation seemed to exist between ozone and RH, PM_{2.5}, NO, NO₂, MAH and RH. A positive correlation seemed to exist between ozone and AT and SR. However, no clear trend could be inferred from the graphs visually in respect of NH₃. These diurnal trends were broken during months of July and August. This may have been due to the cleansing effect of rain, changes in emission of biogenic VOCs, etc.

Diurnal variations followed trends that did not seem out of the ordinary, which isexplained as follows: Ozone formation begins as the day temperature begins to rise in the morning; and O₃ concentration peaks during afternoons. MAH, NO and NO₂ are precursors to O₃ formation and are consumed in formation of O₃ and thus exhibit a negative correlation. RH impedes ozone formation. The reason for variation for PM_{2.5} may be more complex. If single scattering albedo (SSA) of PM_{2.5} is less and its absorption potential is more, then it can impede ozone formation. For a city like Delhi, black carbon, haze, etc. often occurs and thus this reason may be a likely explanation. Moreover, during day-time, the mixing height typically increases allowing for more dispersion of PM_{2.5} and thus reducing its concentration. The reasons for the exhibited trends have been well-explained in the literature review section.

5.2 Seasonal Analysis

Data from calendar years 2018 to 2023 were considered for the present study. Seasonal variations in tropospheric ozone, and its relationship with other relevant parameters were studied statistically. Table 6.1 shows the seasonal means of all

relevant parameters chronologically. The values are colour coded on red-green scale, with red indicating higher values and green lower.

Table 5. 1 Mean seasonal concentrations of parameters considered

| Period | O ₃ | PM _{2.5} | NO | NO ₂ | СО | NH3 | AT | RH | WS | SR |
|----------------|--------------------|--------------------|--------------------|-------------------|------------------|-------------------|-------------------|--------------------|------------------|----------------------|
| Spring 18 | 45.53 ± 38.451 | 100.58 ± 54.512 | 47.72 ± 42.196 | 61.25 ± 24.857 | 1.38 ± 1.043 | 43.32 ± 11.472 | 24.28 ± 5.442 | 48.22 ± 19.461 | 1.12 ± 0.662 | 149.06 ± 173.249 |
| Summer 18 | 37.61 ± 26.609 | 94.43 ± 55.669 | 40.21 ± 38.673 | 64.62 ± 38.145 | 2.17 ± 1.979 | 52.48 ± 22.395 | 32.09 ± 5.258 | 40.03 ± 15.326 | 1.87 ± 1.614 | 205.08 ± 185.45 |
| Monsoon 18 | 19.57 ± 14.435 | 45.05 ± 21.676 | 19.82 ± 26.044 | 29.44 ± 12.818 | 0.93 ± 0.445 | 38.68 ± 14.656 | 29.47 ± 3.54 | 73.61 ± 15.509 | 1.22 ± 0.584 | 142.85 ± 166.013 |
| Postmonsoon 18 | 35.29 ± 27.91 | 192.54 ± 107.146 | 96.41 ± 83.173 | 79.96 ± 28.524 | 2.15 ± 1.261 | 50.83 ± 14.316 | 23.14 ± 5.686 | 54.95 ± 18.619 | 0.86 ± 0.457 | 117.24 ± 144.413 |
| Winter 18-19 | 28.91 ± 19.742 | 210.77 ± 125.866 | 83.24 ± 82.936 | 66.22 ± 25.428 | 2.12 ± 1.479 | 46.14 ± 15.83 | 14.39 ± 4.737 | 58.7 ± 16.038 | 1.01 ± 0.598 | 101.48 ± 131.105 |
| Spring 19 | 30.18 ± 23.323 | 95.87 ± 50.645 | 38.72 ± 35.991 | 52.25 ± 15.636 | 1.26 ± 0.583 | 31.39 ± 7.916 | 21.52 ± 6.053 | 46.67 ± 16.409 | 1.24 ± 0.671 | 151.95 ± 182.383 |
| Summer 19 | 44.91 ± 33.91 | 87.7 ± 56.404 | 39.37 ± 43.473 | 53.42 ± 21.838 | 1.57 ± 0.749 | 38.12 ± 12.053 | 32.72 ± 5.88 | 34.96 ± 15.21 | 1.38 ± 0.784 | 172.84 ± 191.084 |
| Monsoon 19 | 25.37 ± 14.031 | 44.53 ± 22.26 | 18.92 ± 16.612 | 33.27 ± 10.816 | 1.26 ± 0.425 | 32.75 ± 8.008 | 30.62 ± 3.392 | 65.32 ± 12.762 | 1.2 ± 0.566 | 131.49 ± 150.512 |
| Postmonsoon 19 | 31.28 ± 24.113 | 178.31 ± 137.924 | 50.08 ± 43.729 | 45.19 ± 15.072 | 1.59 ± 0.927 | 34.78 ± 9.641 | 24.67 ± 4.559 | 65.07 ± 14.069 | 0.9 ± 0.416 | 100.91 ± 132.779 |
| Winter 19-20 | 27.75 ± 18.168 | 176.74 ± 98.486 | 53.36 ± 48.134 | 47.51 ± 19.14 | 1.66 ± 1.117 | 43.21 ± 15.456 | 14.59 ± 3.92 | 72.97 ± 15.276 | 1.08 ± 0.591 | 96.11 ± 128.828 |
| Spring 20 | 35.89 ± 22.709 | 65.91 ± 39.883 | 27.76 ± 24.766 | 31.92 ± 15.715 | 0.91 ± 0.572 | 29.78 ± 7.305 | 22.79 ± 4.183 | 64.03 ± 16.048 | 1.29 ± 0.72 | 145.04 ± 177.746 |
| Summer 20 | 53.44 ± 28.7 | 56.21 ± 34.833 | 10.75 ± 5.6 | 25.13 ± 13.256 | 1.06 ± 0.399 | 31.41 ± 9.529 | 31.98 ± 5.142 | 48.2 ± 14.253 | 1.24 ± 0.648 | 152.06 ± 182.499 |
| Monsoon 20 | 28.19 ± 13.033 | 38.41 ± 20.016 | 17.71 ± 13.67 | 29.74 ± 10.587 | 1.05 ± 0.376 | 28.94 ± 6.005 | 32.6 ± 3.057 | 66.94 ± 11.76 | 1.16 ± 0.572 | 136.04 ± 152.761 |
| Postmonsoon 20 | 32.99 ± 30.538 | 200.77 ± 140.025 | 62.89 ± 57.976 | 55.22 ± 21.109 | 2.21 ± 1.283 | 40.83 ± 11.289 | 25.42 ± 5.733 | 56.02 ± 15.469 | 0.83 ± 0.371 | 100.61 ± 127.638 |
| Winter 20-21 | 27.75 ± 18.168 | 176.74 ± 98.486 | 53.36 ± 48.134 | 47.51 ± 19.14 | 1.66 ± 1.117 | 43.21 ± 15.456 | 14.59 ± 3.92 | 72.97 ± 15.276 | 1.08 ± 0.591 | 96.11 ± 128.828 |
| Spring 21 | 33.84 ± 25.287 | 114.92 ± 62.354 | 44.08 ± 46.688 | 45.27 ± 15.778 | 1.44 ± 0.878 | 78.61 ± 24.636 | 24.16 ± 4.764 | 49.2 ± 14.89 | 1.32 ± 0.695 | 125.82 ± 155.532 |
| Summer 21 | 37.74 ± 26.774 | 72.53 ± 55.184 | 19.28 ± 21.846 | 35.01 ± 18.373 | 1.42 ± 0.51 | 59.54 ± 12.328 | 30.67 ± 5.065 | 45.22 ± 15.94 | 1.34 ± 0.746 | 148.45 ± 169.317 |
| Monsoon 21 | 27.44 ± 10.381 | 43.42 ± 19.043 | 15.92 ± 11.504 | 25.19 ± 8.187 | 1.01 ± 0.399 | 38.04 ± 11.343 | 32.08 ± 3.226 | 68.93 ± 13.498 | 1.17 ± 0.521 | 118.82 ± 148.513 |
| Postmonsoon 21 | 30.83 ± 23.827 | 164.93 ± 120.553 | 66.48 ± 60.204 | 54.72 ± 22.838 | 1.96 ± 1.289 | 42.03 ± 10.384 | 24.69 ± 5.59 | 63.71 ± 15.748 | 0.88 ± 0.334 | 109.27 ± 141.04 |
| Winter 21-22 | 28.47 ± 19.292 | 182.65 ± 110.686 | 69.63 ± 72.814 | 44.21 ± 18.512 | 1.78 ± 1.161 | 41.11 ± 11.255 | 14.88 ± 4.3 | 71.9 ± 16.728 | 0.96 ± 0.496 | 97.67 ± 135.77 |
| Spring 22 | 34.29 ± 26.583 | 114.03 ± 54.716 | 42.45 ± 51.91 | 42.3 ± 17.977 | 1.23 ± 0.782 | 36.58 ± 10.183 | 25.44 ± 5.847 | 55.05 ± 17.955 | 0.99 ± 0.456 | 156.62 ± 191.69 |

| Summer 22 | 46.37 ± 35.165 | 94.89 ± 54.767 | 35.83 ± 39.93 | 45.7 ± 19.108 | 1.23 ± 0.679 | 41.03 ± 8.293 | 33.27 ± 4.949 | 43.92 ± 14.679 | 1.1 ± 0.528 | 165.63 ± 187.733 |
|----------------|-------------------|-------------------|--------------------|-------------------|------------------|----------------|-------------------|--------------------|------------------|----------------------|
| Monsoon 22 | 37 ± 14.576 | 39.02 ± 20.146 | 17.61 ± 14.322 | 27 ± 9.094 | 1.01 ± 0.382 | 35.96 ± 5.917 | 29.02 ± 2.924 | 68.03 ± 12.71 | 1.06 ± 0.511 | 138.84 ± 164.315 |
| Postmonsoon 22 | 29.54 ± 23.962 | 146.12 ± 91.917 | 70.75 ± 70.412 | 67.88 ± 34.193 | 1.74 ± 1.227 | 50.24 ± 20.823 | 22.81 ± 4.766 | 56.33 ± 14.51 | 0.82 ± 0.336 | 100.31 ± 134.158 |
| Winter 22-23 | 23.41 ± 20.181 | 171.28 ± 90.87 | 75.57 ± 65.658 | 58.9 ± 28.335 | 1.51 ± 0.882 | 57.85 ± 18.35 | 16.74 ± 4.737 | 63.34 ± 14.444 | 1.05 ± 0.537 | 76.48 ± 103.309 |
| Spring 23 | 35.58 ± 25.22 | 80.5 ± 43.233 | 45.16 ± 40.542 | 47.23 ± 22.784 | 1.24 ± 0.538 | 49.22 ± 9.636 | 22.97 ± 3.8 | 55.46 ± 13.515 | 1.03 ± 0.458 | 109.61 ± 137.16 |
| Summer 23 | 37.19 ± 27.126 | 66.91 ± 44.33 | 38.54 ± 39.869 | 50.57 ± 25.096 | 1.17 ± 0.588 | 38.31 ± 8.999 | 31.51 ± 5.219 | 51.95 ± 16.569 | 1.13 ± 0.498 | 129.8 ± 153.165 |
| Monsoon 23 | 29.57 ± 13.242 | 41.97 ± 16.401 | 19.16 ± 13.452 | 32.76 ± 12.784 | 0.88 ± 0.317 | 43.32 ± 17.999 | 31.63 ± 2.726 | 69.15 ± 12.641 | 1.03 ± 0.442 | 237.97 ± 170.323 |
| Postmonsoon 23 | 27.26 ± 21.575 | 180.62 ± 110.411 | 64.95 ± 63.624 | 68.03 ± 38.844 | 1.92 ± 1.23 | 50.45 ± 21.101 | 24.25 ± 5.419 | 60.17 ± 13.148 | 0.65 ± 0.308 | 298.66 ± 129.909 |

The data in Table 5.1 is shown graphically below:

The following graph illustrates the variations in ozone concentrations and meteorological parameters – AT, RH, WS and SR.

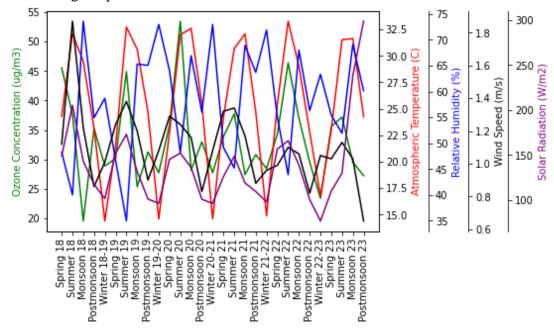


Figure 5. 5 Seasonal variations in concentration of O₃ and meteorological parameters

The following graph shows variations in ozone concentration and other gaseous pollutants: NO, NO₂, CO and NH₃.

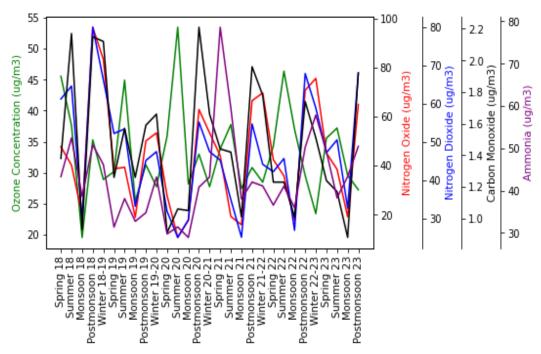


Figure 5. 6 Seasonal variations in concentration of O₃ and gaseous pollutants

However, since the present study was specifically focused on relationship between ozone and $PM_{2.5}$, the following graph illustrates the variation of ozone concentration against $PM_{2.5}$ and meteorological parameters, followed by a graph showing only ozone and $PM_{2.5}$ variations:

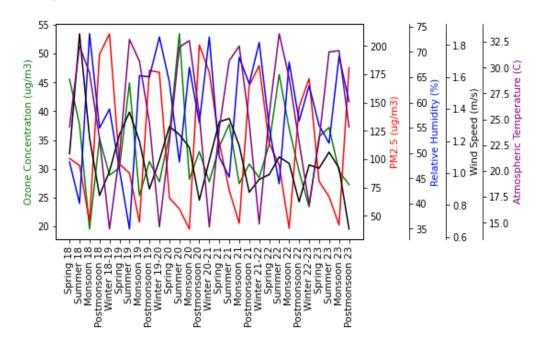


Figure 5. 7 Seasonal variations in concentrations of O₃, PM_{2.5}, RH, WS, AT

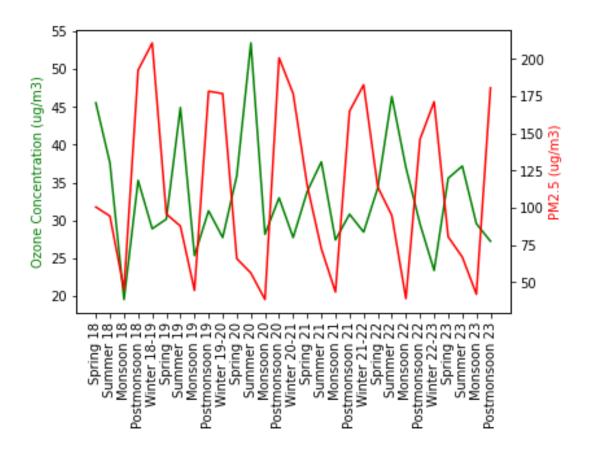


Figure 5. 8 Seasonal variations in concentrations of O_3 and $PM_{2.5}$

The following table shows how the Pearson's Correlation coefficient between ozone and all other parameters considered varied seasonally throughout the years. Colour coding has been done on a red-green scale for each parameter with red indicating lower values and green indicating higher values.

Table 5. 2 Ozone's Correlation Coefficient against other parameters considered

| Period | PM _{2.5} | NO | NO ₂ | СО | NH ₃ | MAH | AT | RH | WS | SR |
|-------------------|-------------------|-------|-----------------|-------|-----------------|--------|------|-------|------|------|
| Spring 18 | -0.46 | -0.51 | -0.51 | -0.48 | -0.52 | -0.34 | 0.80 | -0.77 | 0.67 | 0.70 |
| Summer 18 | -0.17 | -0.35 | -0.22 | -0.14 | -0.18 | -0.22 | 0.53 | -0.49 | 0.17 | 0.55 |
| Monsoon 18 | 0.05* | -0.15 | -0.04* | -0.13 | -0.12 | 0.01* | 0.61 | -0.61 | 0.31 | 0.54 |
| Postmonsoon 18 | -0.31 | -0.50 | -0.36 | -0.44 | -0.34 | -0.35 | 0.65 | -0.71 | 0.39 | 0.67 |
| Winter 18-19 | -0.12 | -0.28 | -0.17 | -0.18 | -0.08* | -0.08* | 0.62 | -0.65 | 0.30 | 0.60 |

| Spring 19 | -0.55 | -0.52 | -0.60 | -0.44 | -0.42 | -0.50 | 0.79 | -0.82 | 0.64 | 0.71 |
|--------------------------------------------------|----------------------------------|-------------------------------------------|-------------------------------------------|-------------------------------------------|--------------------------------------------|-------------------------------------------|--------------------------------------|-------------------------------------------|--------------------------------------|--------------------------------------|
| Summer 19 | -0.29 | -0.44 | -0.38 | -0.41 | -0.01* | -0.38 | 0.71 | -0.64 | 0.39 | 0.70 |
| Monsoon 19 | 0.06* | -0.21 | -0.07 | -0.10 | 0.04* | -0.03* | 0.50 | -0.43 | 0.06* | 0.45 |
| Postmonsoon 19 | -0.27 | -0.47 | -0.26 | -0.39 | -0.13 | -0.40 | 0.74 | -0.81 | 0.34 | 0.67 |
| Winter 19-20 | -0.30 | -0.37 | -0.20 | -0.34 | 0.41 | -0.20* | 0.64 | -0.77 | 0.49 | 0.62 |
| Spring 20 | -0.34 | -0.45 | -0.32 | -0.43 | -0.29 | -0.33 | 0.77 | -0.83 | 0.43 | 0.62 |
| Summer 20 | -0.34 | -0.33 | -0.40 | -0.40 | 0.03* | -0.36 | 0.50 | -0.70 | 0.39 | 0.55 |
| Monsoon 20 | 0.03* | -0.28 | -0.21 | -0.11 | 0.09* | 0.07* | 0.58 | -0.57 | 0.21 | 0.40 |
| Postmonsoon 20 | -0.27 | -0.51 | -0.44 | -0.47 | -0.33 | -0.32 | 0.75 | -0.79 | 0.46 | 0.70 |
| Winter 20-21 | -0.30 | -0.37 | -0.20 | -0.34 | -0.08 | -0.20 | 0.64 | -0.77 | 0.49 | 0.62 |
| Spring 21 | -0.53 | -0.41 | -0.43 | -0.48 | -0.25 | -0.31 | 0.75 | -0.77 | 0.50 | 0.63 |
| Summer 21 | -0.18 | -0.30 | -0.22 | -0.32 | -0.25 | -0.03* | 0.57 | -0.60 | 0.26 | 0.57 |
| Monsoon 21 | 0.15 | -0.14 | -0.03* | -0.03* | 0.06* | -0.01* | 0.29 | -0.22 | 0.10 | 0.23 |
| Postmonsoon 21 | -0.10 | -0.44 | -0.34 | -0.29 | -0.25 | -0.27 | 0.45 | -0.75 | 0.30 | 0.61 |
| Winter 21-22 | -0.36 | -0.41 | -0.31 | -0.39 | -0.17 | -0.26 | 0.69 | -0.79 | 0.44 | 0.65 |
| Spring 22 | -0.48 | -0.40 | -0.40 | | | | | | | |
| G 22 | | 00 | -0.40 | -0.43 | -0.07* | -0.31 | 0.65 | -0.72 | 0.52 | 0.69 |
| Summer 22 | -0.31 | -0.51 | -0.50 | -0.43 | -0.07* -0.06* | -0.31 -0.35 | 0.65 | -0.72 -0.52 | 0.52 | 0.69 |
| Monsoon 22 | -0.31 -0.10 | | | | | | | | | |
| | | -0.51 | -0.50 | -0.50 | -0.06* | -0.35 | 0.76 | -0.52 | 0.36 | 0.67 |
| Monsoon 22 Postmonsoon | -0.10 | -0.51 -0.33 | -0.50 -0.16 | -0.50 -0.29 | -0.06* 0.12 | -0.35 -0.24 | 0.76 | -0.52 -0.60 | 0.36 | 0.67 |
| Monsoon 22 Postmonsoon 22 | -0.10 | -0.51 -0.33 -0.51 | -0.50 -0.16 -0.49 | -0.50 -0.29 -0.47 | -0.06* 0.12 -0.05* | -0.35 -0.24 -0.40 | 0.76 0.67 0.81 | -0.52 -0.60 -0.63 | 0.36 0.27 0.37 | 0.67 0.50 0.69 |
| Monsoon 22 Postmonsoon 22 Winter 22-23 | -0.10 -0.32 -0.34 | -0.51 -0.33 -0.51 -0.44 | -0.50 -0.16 -0.49 -0.31 | -0.50 -0.29 -0.47 -0.40 | -0.06* 0.12 -0.05* -0.17 | -0.35 -0.24 -0.40 -0.32 | 0.76 0.67 0.81 0.71 | -0.52 -0.60 -0.63 -0.78 | 0.36 0.27 0.37 0.36 | 0.67 0.50 0.69 0.63 |
| Monsoon 22 Postmonsoon 22 Winter 22-23 Spring 23 | -0.10 -0.32 -0.34 -0.47 | -0.51 -0.33 -0.51 -0.44 -0.50 | -0.50 -0.16 -0.49 -0.31 -0.54 | -0.50 -0.29 -0.47 -0.40 -0.57 | -0.06* 0.12 -0.05* -0.17 -0.37 | -0.35 -0.24 -0.40 -0.32 -0.47 | 0.76 0.67 0.81 0.71 0.85 | -0.52 -0.60 -0.63 -0.78 -0.73 | 0.36 0.27 0.37 0.36 0.46 | 0.67 0.50 0.69 0.63 0.70 |

^{*:} Statistically insignificant due to higher p values (p>0.01)

The following table shows the count of number of positive and negative correlations observed over the course of six years.

Table 5. 3 Count of positive and negative correlations of parameters with O_3

| | PM _{2.5} | NO | NO ₂ | CO | NH ₃ | MAH | AT | RH | WS | SR |
|-----------------|-------------------|----|-----------------|----|-----------------|-----|----|----|----|----|
| No. of Positive | 5 | 0 | 0 | 0 | 7 | 2 | 29 | 0 | 29 | 29 |
| Correlations | | | | | | | | | | |
| No. of Negative | 24 | 29 | 29 | 29 | 22 | 27 | 0 | 29 | 0 | 0 |
| Correlations | | | | | | | | | | |
| Total | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 29 | 29 |

Average Correlation coefficients with ozone were calculated season-wise and then each parameter was ranked according to the correlation they had with ozone.

Table 5. 4 Seasonwise ranking of each parameter as per correlation with O3

| Season | PM _{2.5} | NO | NO ₂ | СО | NH ₃ | MAH | AT | RH | WS | SR |
|----------------|-------------------|----|-----------------|----|-----------------|-----|----|----|----|----|
| Spring 18 | 9 | 7 | 6 | 8 | 5 | 10 | 1 | 2 | 4 | 3 |
| Summer 18 | 8 | 4 | 6 | 10 | 7 | 5 | 2 | 3 | 9 | 1 |
| Monsoon 18 | 8 | 5 | 9 | 6 | 7 | 10 | 2 | 1 | 4 | 3 |
| Postmonsoon 18 | 10 | 4 | 7 | 5 | 9 | 8 | 3 | 1 | 6 | 2 |
| Winter 18-19 | 8 | 5 | 7 | 6 | 10 | 9 | 2 | 1 | 4 | 3 |
| Spring 19 | 6 | 7 | 5 | 9 | 10 | 8 | 2 | 1 | 4 | 3 |
| Summer 19 | 9 | 4 | 8 | 5 | 10 | 7 | 1 | 3 | 6 | 2 |
| Monsoon 19 | 7 | 4 | 6 | 5 | 9 | 10 | 1 | 3 | 7 | 2 |
| Postmonsoon 19 | 8 | 4 | 9 | 6 | 10 | 5 | 2 | 1 | 7 | 3 |
| Winter 19-20 | 8 | 6 | 9 | 7 | 5 | 10 | 2 | 1 | 4 | 3 |
| Spring 20 | 7 | 4 | 9 | 6 | 10 | 8 | 2 | 1 | 5 | 3 |
| Summer 20 | 8 | 9 | 4 | 5 | 10 | 7 | 3 | 1 | 6 | 2 |
| Monsoon 20 | 10 | 4 | 5 | 7 | 8 | 9 | 1 | 2 | 6 | 3 |
| Postmonsoon 20 | 10 | 4 | 7 | 5 | 8 | 9 | 2 | 1 | 6 | 3 |
| Winter 20-21 | 7 | 5 | 8 | 6 | 10 | 9 | 2 | 1 | 4 | 3 |
| Spring 21 | 4 | 8 | 7 | 6 | 10 | 9 | 2 | 1 | 5 | 3 |
| Summer 21 | 9 | 5 | 8 | 4 | 7 | 10 | 2 | 1 | 6 | 3 |
| Monsoon 21 | 4 | 5 | 8 | 8 | 7 | 10 | 1 | 3 | 6 | 2 |
| Postmonsoon 21 | 10 | 4 | 5 | 7 | 9 | 8 | 3 | 1 | 6 | 2 |
| Winter 21-22 | 7 | 5 | 8 | 6 | 10 | 9 | 2 | 1 | 4 | 3 |
| Spring 22 | 5 | 7 | 8 | 6 | 10 | 9 | 3 | 1 | 4 | 2 |
| Summer 22 | 9 | 4 | 5 | 5 | 10 | 8 | 1 | 3 | 7 | 2 |
| Monsoon 22 | 10 | 4 | 8 | 5 | 9 | 7 | 1 | 2 | 6 | 3 |
| Postmonsoon 22 | 9 | 4 | 5 | 6 | 10 | 7 | 1 | 3 | 8 | 2 |
| Winter 22-23 | 7 | 4 | 9 | 5 | 10 | 8 | 2 | 1 | 6 | 3 |
| Spring 23 | 8 | 6 | 5 | 4 | 10 | 7 | 1 | 2 | 9 | 3 |
| Summer 23 | 9 | 4 | 7 | 6 | 10 | 8 | 3 | 2 | 5 | 1 |
| Monsoon 23 | 8 | 4 | 5 | 7 | 9 | 10 | 1 | 2 | 6 | 3 |
| Postmonsoon 23 | 9 | 5 | 7 | 4 | 10 | 6 | 2 | 1 | 8 | 3 |

The following table shows the order in which each parameter influences O_3 season-wise.

Table 5. 5 Overall ranking of each parameter in each season

| Order of influence | Spring | Summer | Monsoon | Postmonsoon | Winter | Overall |
|----------------------------|--------|--------|---------|-------------|--------|---------|
| on O ₃ /Seasons | | | | | | |
| $PM_{2.5}$ | 5 | 9 | 7 | 10 | 5 | 7 |
| NO | 5 | 3 | 3 | 3 | 4 | 3 |
| NO ₂ | 7 | 6 | 6 | 6 | 7 | 6 |
| CO | 5 | 5 | 5 | 5 | 5 | 5 |
| NH ₃ | 10 | 10 | 8 | 10 | 9 | 10 |
| MAH | 9 | 8 | 10 | 8 | 10 | 9 |
| AT | 3 | 1 | 1 | 4 | 3 | 3 |
| RH | 1 | 2 | 2 | 1 | 1 | 1 |
| WS | 4 | 7 | 4 | 7 | 4 | 4 |
| SR | 2 | 2 | 2 | 2 | 2 | 2 |

It was observed that ozone had the strongest negative relationship with relative humidity; followed by solar radiation and atmospheric temperature. With reference to the parameters considered, PM_{2.5} had a stronger correlation with O₃ than that of MAH and NH₃ only. The strength of correlation of PM_{2.5} with ozone was significantly more during winter and spring season. The non-linear relation with all other parameters considered have been very well-researched in literature for the past four decades. However, research on relation between PM_{2.5} and O₃ is still in its nascent stages. Further, it is to be noted that there was a statistically weak negative linear correlation between ozone and PM_{2.5} that is statistically significant (p<0.001). However, literature cites parameters such as NO, NO₂ and CO having negative correlation with ozone as ozone reacts with these pollutants. However, their Pearson's coefficient was also observed in a similar range as that of PM_{2.5}. It is also observed that Pearson's coefficient for ozone and PM_{2.5} was comparable to that between ozone and NO₂, and ozone and CO in many seasons. Moreover, Chen et al. (2019) have classified correlation more than 0.4 as "strong" (Chen et al.,

2019). This indicates that PM_{2.5} and ozone may have had a relatively strong, albeit not statistically strong, correlation. It is to be noted that ozone's chemical relationships with other gaseous pollutants is non-linear. Therefore, in the present study the terms used to determine strengths of relationships may not be accurate in terms of statistics, but in context of well-established theories in environmental studies, the same may be applicable. Therefore, in context of environmental studies, the relationship may not be assumed to be "weak".

The findings of the study suggested a correlation between ozone and PM_{2.5}. However, a theory for establishing a causal relationship between ozone and PM_{2.5} may be established. An attempt at hypothesizing a theory for explaining the variations in correlation between PM_{2.5} and ozone is made in the present study subsequently.

The cyclicity in the variations in correlation coefficients of Ozone and $PM_{2.5}$ was also observed. The same has been shown graphically below:

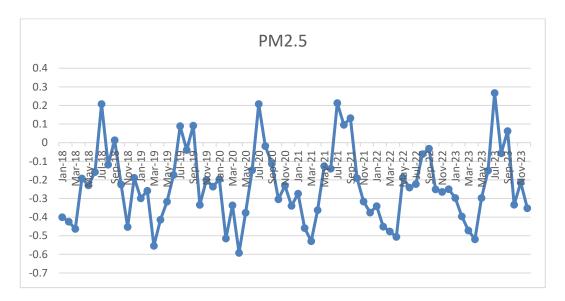


Figure 5. 9 Variations in O_3 -PM_{2.5} correlation coefficient (January, 2018-December, 2023)

As per Wang et al. correlation tends to be positive at low PM_{2.5} concentration; and vice-versa (Wang et al., 2023).

The explanation for the trends observed are as follows: It is hypothesized that during winters, there is haze, smog and higher concentrations of PM_{2.5} observed throughout Delhi. Moreover, the high concentration of black carbon and highly absorbing particulate matter reduces solar radiation available for ozone formation (low scattering albedo). Therefore, there exists a statistically weak negative correlation between PM_{2.5} and ozone. PM_{2.5} can be assumed to have a causal influence on ozone. Moreover, there is relatively more RH compared to summer. This is because of mist in air due to lower temperatures, and due to western disturbance.

During summers, the solar radiation and temperature increases. This causes a substantial increase in O₃ levels. The same is the case during spring season. However, there are two important differences. Firstly, during summers, there is incoming winds from the Thar deserts and dry hot winds (loo), which may cause an increase in particulate matter concentration. However, there is also an increase in mixing heights which causes PM_{2.5} concentrations to reduce. The latter factor should dominate as dry winds usually cause an increase in larger sizes of particulate matter. Therefore, there is a negative correlation between ozone and PM_{2.5}, but a direct causal relationship between the two is not obvious.

In spring season, the correlation is observed to be highly negative. This seems to be the case because around spring the time the rates of change in PM_{2.5} and ozone seem to be the maximum, wherein PM_{2.5} concentrations are falling and ozone concentrations are increasing. Further, biogenic VOCs may be being released into

the atmosphere which increase ozone formation. Rathore et al. and Chen et al. also state that stratosphere-troposphere exchange is maximum during this period (Chen et al., 2020; Rathore et al., 2023). The rates of variation may slow down in summer due to relative increase in $PM_{2.5}$ from dusty winds.

During monsoon, a mildly positive correlation is observed. This trend has been corroborated by similar findings for summer in China. This is because summer season described in China is characteristically similar to monsoon in India (Chen et al., 2019). During monsoon, cleansing effect of rainfall is observed. Wind, that carries relatively less dust, also blows at relatively higher speeds in monsoon. These factors inhibit PM_{2.5}. O₃ concentration is low due to overcast weather and lower availability of precursors. In absence of rain, with higher temperatures at play, both increase together. Therefore, both decrease or increase together. Wang et al. has explained reasons behind this positive correlation. Counter-intuitively, high relative humidity can enhance secondary aerosol formation, increasing PM_{2.5} levels, while also promoting wet deposition, which reduces ozone levels. Low wind speeds can lead to the accumulation of pollutants, including PM_{2.5}, which can inhibit ozone production by similar mechanisms. Further, when PM_{2.5} concentrations are low, there is less scattering of sunlight, which increases the intensity of solar radiation reaching the ground, thereby promoting ozone formation. Under these conditions, PM_{2.5} and ozone concentrations are positively correlated because they share common precursors and favorable meteorological conditions. The positive correlation is evident when PM_{2.5} concentrations are below a certain threshold, as both pollutants are generated from similar sources and conditions conducive to their formation. (Wang et al., 2023).

Post-monsoon season is when monsoon withdraws and the season starts to change, bringing back the negative correlation between O_3 and $PM_{2.5}$.

Chapter 6: Conclusion, Future Scope and Social Impact

In this concluding chapter, key findings of our research, highlighting the significant contributions to the field. Based on limitations encountered during the study, potential directions for future research to address research gaps are proposed. Broader social implications of this study, emphasizing how they can influence policy, practice, and future technological advancements are briefly discussed. This work not only advances academic understanding but also holds the potential to drive meaningful changes in society, promoting sustainability, inclusivity, and improved quality of life.

6.1 Conclusion and Future Scope

The study examined variations in ozone concentration seasonally and diurnally over the city of Delhi and has provided an outcome not previously documented in literature, i.e., in Delhi, there exists a negative correlation between ozone and PM_{2.5} in all periods except during monsoon (July-September), with maximum negative correlation observed in Summer of 2020 as -0.55. In general, the negative correlation seems to be the maximum during spring season (month of March). During monsoon, a mildly positive, but statistically insignificant, correlation was generally observed.

Higher concentrations of PM_{2.5} were observed throughout Delhi during the post-monsoon season (with a peak of 200.77 \pm 140.03 μ g/m³ in 2020) and the winter season (with a peak of 210.77 \pm 125.87 μ g/m³ in 2018-19). These elevated levels reduce the solar radiation available for ozone formation due to low scattering albedo. During winter, though ozone concentrations were below 30 μ g/m³ across

all years, factors like smog, haze, low mixing heights, and temperature inversion worsen the situation. In contrast, during spring and summer, although O_3 concentrations increased with rising solar radiation and temperature, the relative concentration of $PM_{2.5}$ decreased (with a maximum of $94.89 \pm 54.77~\mu g/m^3$ in the summer of 2022). Biogenic VOCs may have also contributed more to the $PM_{2.5}$ proportion, further increasing O_3 concentrations. However, during the monsoon season, there was a mildly positive but statistically insignificant correlation, likely due to the cleansing effect of rainfall reducing $PM_{2.5}$ levels (maximum concentration of $38.41 \pm 20.02~\mu g/m^3$ in the monsoon of 2022). Additionally, monsoon winds, which carry less dust, and overcast weather conditions also reduced O_3 formation.

Future works investigating relationship between ozone and its precursors, especially PM_{2.5}, should be considered for the city of Delhi. Reasons behind having a negative correlation in summer and positive correlation in monsoon season may be explored further. The hypothesis proposed in the present study need to be corroborated by more evidence through experiments or models. Aqueous phase aerosol chemistry involved needs further research. More number of stations should be considered to study the city of Delhi on different temporal scales – monthly, seasonal, etc. Further spatial variations in the correlation should also be investigated. The effect of nearby vegetation and water bodies may play an important role in influencing local concentrations of ozone and its precursors. If monitoring of VOCs such as isoprenes can be undertaken at monitoring sites, then the data may reveal other factors upon which the correlation between ozone and PM_{2.5} depends. Since ozone is a secondary pollutant, it's difficult to comprehend

its formation just by monitoring its concentration. Thus, we need models to simulate its creation under different weather and chemical conditions in the atmosphere. Models may also be used to simulate different scenarios and boundary conditions. The current study has considered only two variables at a time to calculate Pearson's relationship coefficient. A multivariate analysis of ozone and other parameters is required to conclusively derive a theory relating ozone and $PM_{2.5}$. Such analysis may reveal other factors upon which this relationship depends. Moreover, it is imperative to explore the boundary conditions and inflexion points of relevant parameters where observed behaviour between ozone and PM_{2.5} changes drastically. For example, at what percentage RH does the aqueous chemistry become dominant leading to formation of more PM_{2.5}; or at what concentration of PM_{2.5} does the correlation between ozone and PM_{2.5} change its nature (positive to negative) in Delhi. Models that simulate the direct and indirect effect of other parameters on ozone and PM_{2.5} would be vital to conclusively establish the strength of correlation between the two. For example, RH reducing the temperature required for photochemical reactions is an indirect negative impact on ozone. A model can simulate the strength of this effect in isolation. Such perspectives would offer new insights to regulatory policies being formed.

In conclusion, comprehensive research on the variations of ozone and its relationship with PM_{2.5}, precursor pollutants, and meteorological parameters in Delhi is vital. Such studies will not only enhance our understanding of ozone dynamics but also aid in developing effective action plans to mitigate its adverse effects on health and the environment. Addressing this research gap is essential for formulating targeted and efficient pollution control strategies tailored to the unique

characteristics of Delhi and other Indian cities.

6.2 Social Impact

Research gap highlighted in 6.1 is important because targeted pollution reduction efforts can be informed by an understanding of the interaction between PM_{2.5} and ozone. Regulatory agencies must have a complete understanding of this relationship in order to develop regulations that stop PM_{2.5} and ozone from copolluting. Regulatory agencies may find it useful to use a theory about changes in ozone and PM_{2.5} in the Delhi setting when developing measures to avoid copollution of PM_{2.5} and ozone. The National Clean Air Programme (NCAP) and the Graded Response Action Plan (GRAP) are two regulatory bodies' efforts to lessen pollution in Delhi. It is wise to investigate the relationship between ozone and PM_{2.5} in more detail in light of China's experience, where effective pollution-reduction strategies managed to reduce particulate matter pollution but unintentionally generated an increase in ozone concentration.

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APPENDIX-I

```
The code for implementing the validation protocol has been written using R and is
as follows:
# Load the dplyr package for data manipulation
library(dplyr)
# Define a function to clean air pollution data
data_cleaning <- function(file_path) {</pre>
 # Announce the start of the data cleaning process
 cat("Start data cleaning process...\n")
 # Announce the reading of data from a file
 cat("Reading data...\n")
 # Read the CSV file into a dataframe
 data <- read.csv(file_path, header = TRUE, sep = ",")
 # Confirm that the data has been read
 cat("Data read successfully.\n")
 # Start initial data cleaning
 cat("Performing initial data cleaning...\n")
 # Identify all columns except timestamp, date, and time
 numeric_cols <- names(data)[!(names(data) %in% c("Timestamp", "Date",
"Time"))]
 # Replace all negative, zero values, and blanks with NA
```

```
data[numeric\_cols] <- lapply(data[numeric\_cols], function(x) ifelse(x <= 0 | x ==
"", NA, x))
 # Confirm initial cleaning is complete
 cat("Initial data cleaning complete.\n")
 # Ensure PM25 is less than PM10
 cat("Ensuring PM2.5 is less than PM10...\n")
 # Replace PM25 and PM10 values with NA where PM25 >= PM10
 data <- data %>%
  mutate(across(c(PM25, PM10), \sim if_else(PM25 >= PM10, NA_real_, .)))
 # Replace values that repeat more than 4 times consecutively with NA
 cat("Replacing more than 4 consecutive repeats with NA...\n")
 data[numeric_cols] <- lapply(data[numeric_cols], function(column) {</pre>
  # Use run-length encoding to find sequences
  r <- rle(column)
  # Extract the values and their lengths from the encoding
  values <- r$values
  lengths <- r$lengths
  # Replace values where sequences are 4 or longer with NA
  values[lengths >= 4] <- NA
  # Return data with replaced values
  inverse.rle(list(values = values, lengths = lengths))
 })
```

```
# Confirm replacement is complete
 cat("Consecutive repeats replacement complete.\n")
 # Applying additional criteria to set minimum allowable values for pollutants
 cat("Applying additional criteria for specific pollutants...\n")
 data <- data %>%
  mutate(
   PM25 = if_else(PM25 < 4, 4, PM25), # Ensure PM25 is not below 4
   PM10 = if_else(PM10 < 4, 4, PM10), # Ensure PM10 is not below 4
   SO2 = if_else(SO2 < 1.5, 1.5, SO2), # Ensure SO2 is not below 1.5
   NH3 = if_{else}(NH3 < 3, 3, NH3), # Ensure NH3 is not below 3
   NO2 = if_{else}(NO2 < 3, 3, NO2), # Ensure NO2 is not below 3
   CO = if_else(CO < 0.1, 0.1, CO), # Ensure CO is not below 0.1
   Ozone = if_else(Ozone < 3, 3, Ozone), # Ensure Ozone is not below 3
   Benzene = if_else(Benzene < 0.2, 0.2, Benzene) # Ensure Benzene is not below
0.2
  )
 # Validate that NO + NO2 is less than NOx
 #cat("Validating NO + NO2 < NOx...\n")
 #data <- data %>%
 \# mutate(across(c(NO, NO2, NOx), \sim if_else((NO + NO2) > NOx, NA_real_, .)))
 # Confirm the criterion has been applied
 cat("Validation criteria applied.\n")
```

```
# Save the cleaned and modified data to a new CSV file

cat("Saving the final modified data...\n")

write.csv(data, "validated_data.csv", row.names = FALSE)

# Confirm that the data has been saved

cat("Data saved to 'validated_data.csv'.\n")

# Announce the completion of the data cleaning process

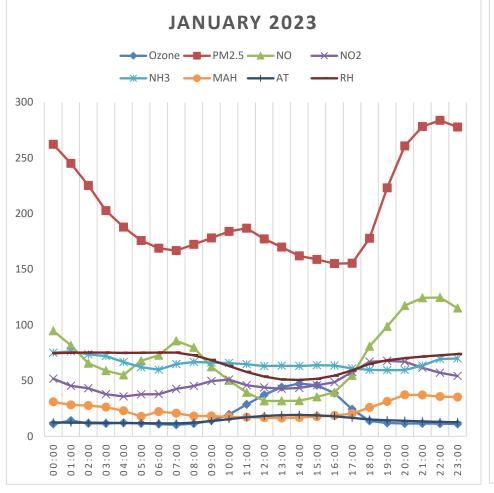
cat("Data cleaning process complete.\n")

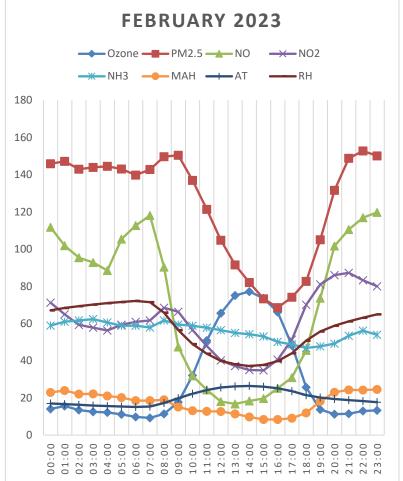
# Return the modified data

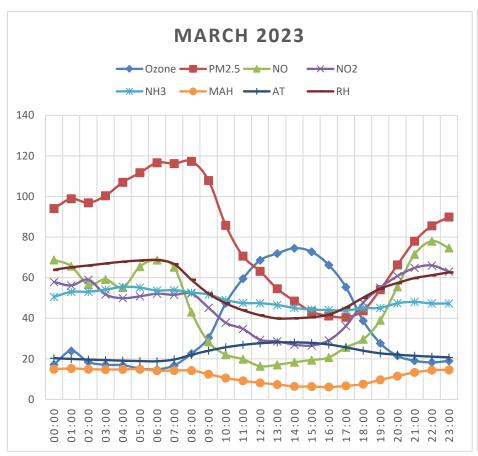
return(data)

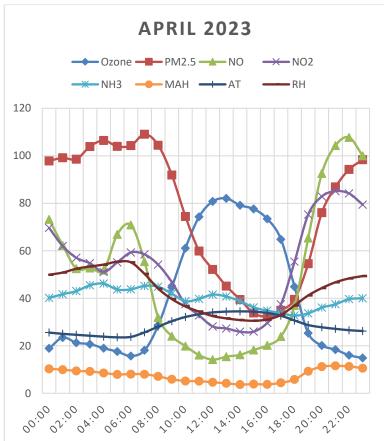
}
```

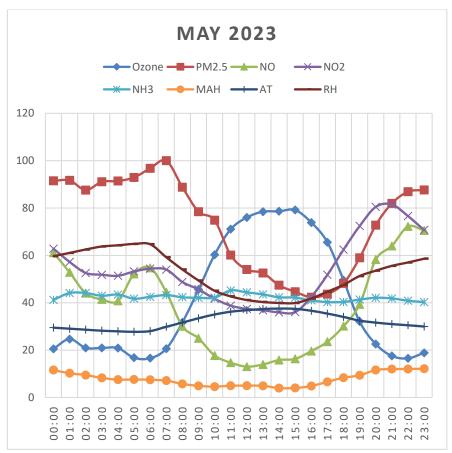
APPENDIX-IIDiurnal variations in ozone and parameters that influence it in the year 2023:

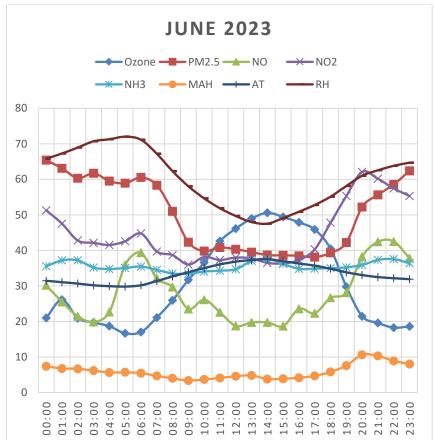


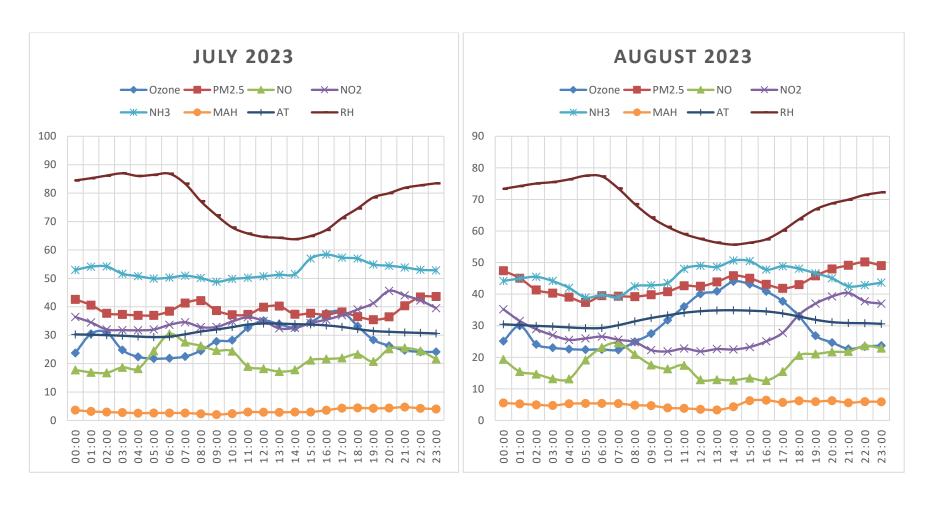


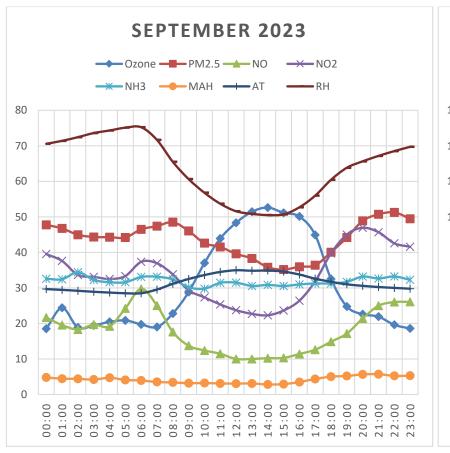


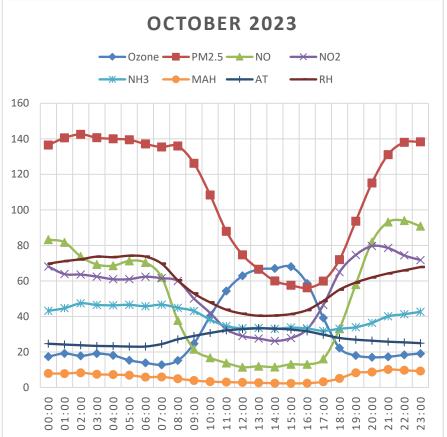


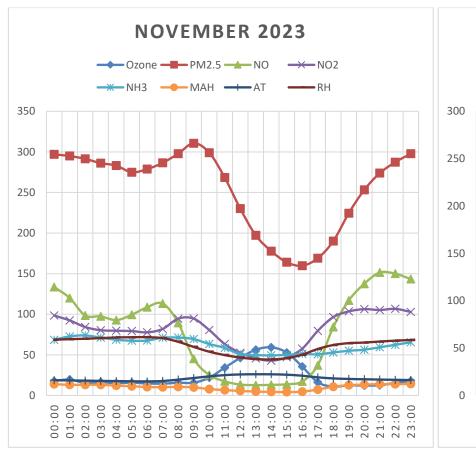


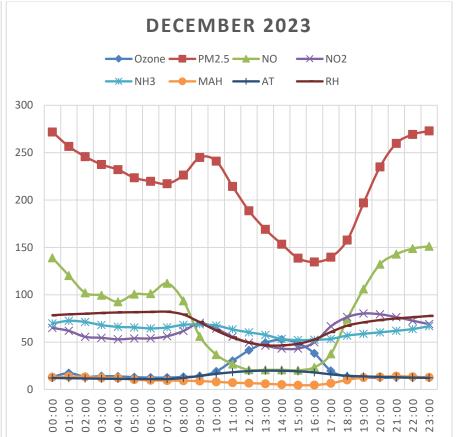




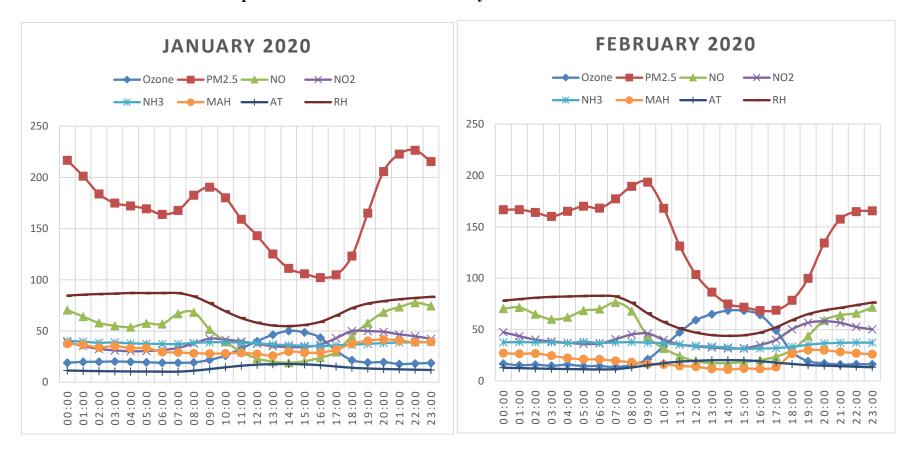


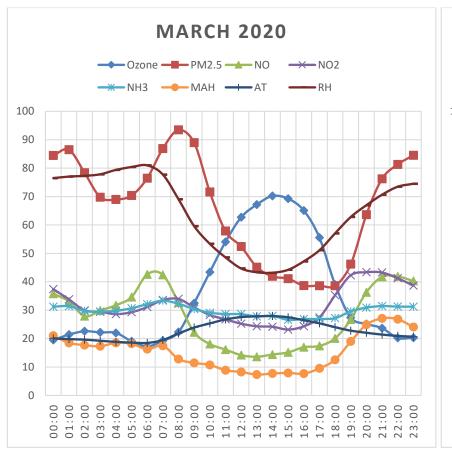


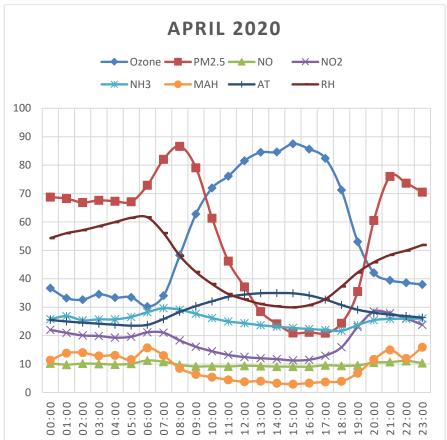


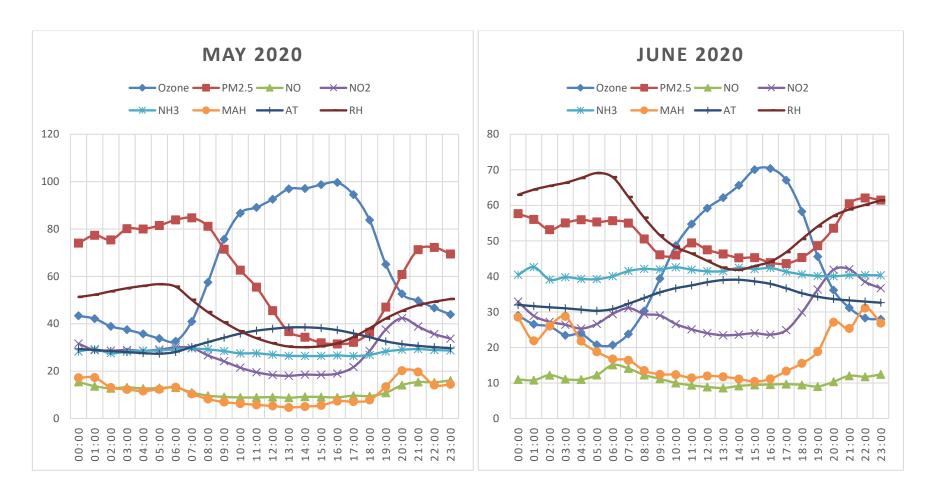


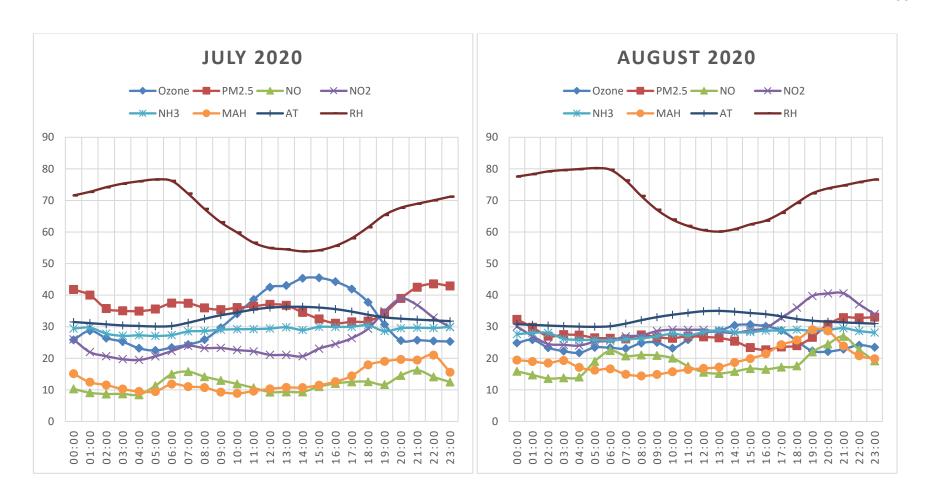
Diurnal variations in ozone and parameters that influence it in the year 2020:

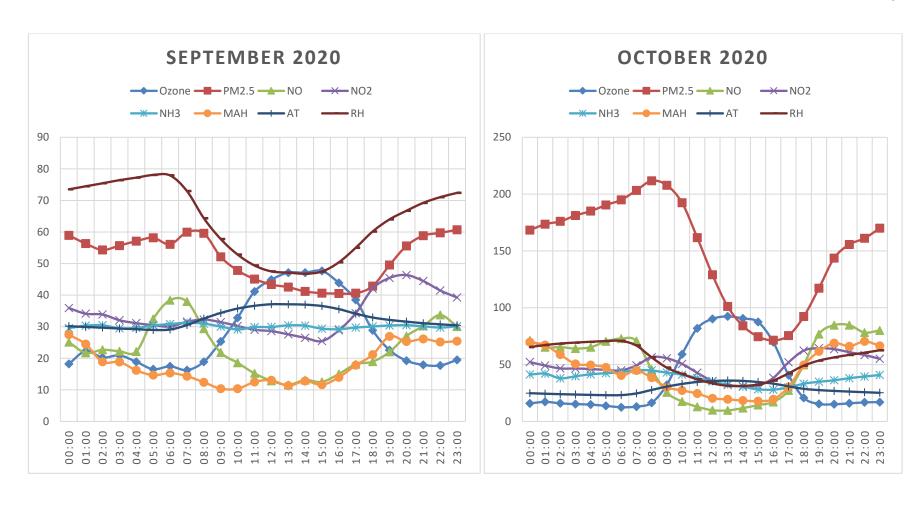


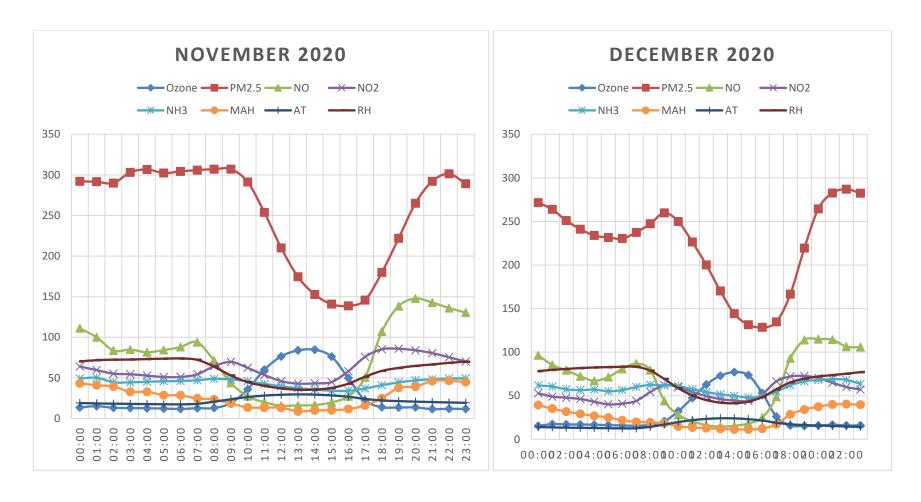












APPENDIX-III

Season-wise: Statistical Descriptive Tables

| Spring 2018 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Median | 32.365 | 87.595 | 30.11 | 56.74 | 1.065 | 41.595 | 23.59 | 48.32 | 0.97 | 21.58 |
| Mean | 45.527 | 100.58 | 47.717 | 61.245 | 1.377 | 43.32 | 24.277 | 48.224 | 1.122 | 149.061 |
| 95% CI Mean Upper | 48.333 | 104.5 | 50.754 | 63.034 | 1.454 | 44.145 | 24.674 | 49.624 | 1.17 | 161.531 |
| 95% CI Mean Lower | 42.722 | 96.657 | 44.68 | 59.456 | 1.301 | 42.494 | 23.88 | 46.823 | 1.075 | 136.592 |
| Std. Deviation | 38.451 | 54.512 | 42.196 | 24.857 | 1.043 | 11.472 | 5.442 | 19.461 | 0.662 | 173.249 |
| Coefficient of variation | 0.845 | 0.542 | 0.884 | 0.406 | 0.757 | 0.265 | 0.224 | 0.404 | 0.59 | 1.162 |
| Skewness | 0.905 | 0.9 | 1.632 | 1.046 | 1.911 | 0.778 | 0.304 | -0.033 | 0.886 | 0.709 |
| Std. Error of Skewness | 0.091 | 0.09 | 0.09 | 0.09 | 0.091 | 0.09 | 0.091 | 0.09 | 0.09 | 0.09 |
| Kurtosis | -0.203 | 0.268 | 2.077 | 1.282 | 4.429 | 0.878 | -0.879 | -1.115 | -0.04 | -1.115 |
| Std. Error of Kurtosis | 0.181 | 0.179 | 0.179 | 0.179 | 0.181 | 0.179 | 0.182 | 0.179 | 0.179 | 0.179 |
| Minimum | 4.38 | 16 | 5.06 | 19.78 | 0.19 | 18.22 | 14.67 | 8.12 | 0.15 | 3.33 |
| Maximum | 171.75 | 291.44 | 237.02 | 169.42 | 7.32 | 99.72 | 38.44 | 86.48 | 3.15 | 541.2 |
| 25th percentile | 12.013 | 57.573 | 20.012 | 43.498 | 0.65 | 34.775 | 19.665 | 31.623 | 0.58 | 6.81 |
| 50th percentile | 32.365 | 87.595 | 30.11 | 56.74 | 1.065 | 41.595 | 23.59 | 48.32 | 0.97 | 21.58 |
| 75th percentile | 75.76 | 135.23 | 60.538 | 73.127 | 1.68 | 50.242 | 28.62 | 65.083 | 1.53 | 309.843 |
| 95th percentile | 117.93 | 207.19 | 142.27 | 107.1 | 3.616 | 63.886 | 33.347 | 77.619 | 2.46 | 459.772 |
| | | | | | | | | | | |
| Summer 2018 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 29.4 | 80.06 | 26.05 | 53.63 | 1.49 | 47.45 | 32.07 | 40.095 | 1.54 | 135.63 |
| Mean | 37.611 | 94.429 | 40.212 | 64.622 | 2.167 | 52.477 | 32.085 | 40.032 | 1.867 | 205.084 |

| 95% CI Mean Upper | 38.727 | 96.768 | 41.835 | 66.223 | 2.25 | 53.416 | 32.307 | 40.676 | 1.935 | 212.866 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95% CI Mean Lower | 36.494 | 92.091 | 38.589 | 63.021 | 2.084 | 51.537 | 31.863 | 39.389 | 1.799 | 197.302 |
| Std. Deviation | 26.609 | 55.669 | 38.673 | 38.145 | 1.979 | 22.395 | 5.258 | 15.326 | 1.614 | 185.45 |
| Coefficient of variation | 0.707 | 0.59 | 0.962 | 0.59 | 0.913 | 0.427 | 0.164 | 0.383 | 0.864 | 0.904 |
| Skewness | 1.295 | 2.532 | 2.155 | 2.203 | 2.456 | 1.262 | 0.025 | 0.126 | 8.648 | 0.583 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.053 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 1.486 | 14.528 | 5.138 | 7.715 | 7.945 | 1.987 | -0.66 | -0.313 | 160.8 | -0.96 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 4.3 | 6.63 | 1.45 | 6.97 | 0.25 | 12.6 | 18.5 | 5.63 | 0.19 | 3.75 |
| Maximum | 165.08 | 658.67 | 262.46 | 369.14 | 14.87 | 166.63 | 44.55 | 88.09 | 37.92 | 781.61 |
| 25th percentile | 17.68 | 57.14 | 16.645 | 40.08 | 0.88 | 36.63 | 28.29 | 29.4 | 0.88 | 56.008 |
| 50th percentile | 29.4 | 80.06 | 26.05 | 53.63 | 1.49 | 47.45 | 32.07 | 40.095 | 1.54 | 135.63 |

| 75th percentile | 50.72 | 116.65 | 46.833 | 77.93 | 2.685 | 63.25 | 35.962 | 50.528 | 2.56 | 373.905 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95th percentile | 90.282 | 199.9 | 125.51 | 141.14 | 6.287 | 97.446 | 40.74 | 65.641 | 3.95 | 520.826 |
| | | | | | | | | | | |
| Monsoon 2018 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 14.36 | 40.26 | 13.03 | 26.885 | 0.82 | 35.195 | 28.96 | 77.42 | 1.08 | 66.695 |
| Mean | 19.57 | 45.05 | 19.817 | 29.441 | 0.926 | 38.682 | 29.466 | 73.613 | 1.219 | 142.848 |
| 95% CI Mean Upper | 20.172 | 45.955 | 20.904 | 29.976 | 0.945 | 39.293 | 29.614 | 74.26 | 1.244 | 149.776 |
| 95% CI Mean Lower | 18.967 | 44.146 | 18.73 | 28.906 | 0.908 | 38.07 | 29.319 | 72.966 | 1.195 | 135.919 |
| Std. Deviation | 14.435 | 21.676 | 26.044 | 12.818 | 0.445 | 14.656 | 3.54 | 15.509 | 0.584 | 166.013 |
| Coefficient of variation | 0.738 | 0.481 | 1.314 | 0.435 | 0.481 | 0.379 | 0.12 | 0.211 | 0.479 | 1.162 |
| Skewness | 2.114 | 1.289 | 4.914 | 1.345 | 2.419 | 1.375 | 0.384 | -0.638 | 0.835 | 1.023 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 5.505 | 2.421 | 30.455 | 2.617 | 9.81 | 2.506 | -0.322 | -0.609 | 0.142 | -0.239 |
| Std. Error of Kurtosis | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 |
| Minimum | 4.33 | 5.5 | 1.63 | 5.38 | 0.3 | 16.48 | 19.87 | 26.72 | 0.27 | 2.04 |
| Maximum | 116.05 | 152.5 | 257.14 | 96.88 | 4.56 | 117.53 | 40.92 | 94.41 | 3.8 | 665.14 |
| 25th percentile | 10.205 | 29.692 | 7.18 | 20.25 | 0.65 | 27.718 | 26.75 | 61.987 | 0.76 | 6.12 |
| 50th percentile | 14.36 | 40.26 | 13.03 | 26.885 | 0.82 | 35.195 | 28.96 | 77.42 | 1.08 | 66.695 |
| 75th percentile | 23.582 | 56 | 22.553 | 35.323 | 1.06 | 45.962 | 32.03 | 87.135 | 1.58 | 255.787 |
| 95th percentile | 51.455 | 85.947 | 53.622 | 54.096 | 1.813 | 67.668 | 35.617 | 92.16 | 2.367 | 482.775 |

| Postmonsoon 2018 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Median | 23.175 | 173.92 | 69.88 | 74.835 | 1.74 | 50.105 | 22.83 | 55.825 | 0.72 | 12.515 |
| Mean | 35.291 | 192.54 | 96.411 | 79.957 | 2.153 | 50.834 | 23.139 | 54.953 | 0.864 | 117.244 |
| 95% CI Mean Upper | 36.722 | 198.03 | 100.68 | 81.42 | 2.217 | 51.568 | 23.43 | 55.908 | 0.888 | 124.648 |
| 95% CI Mean Lower | 33.86 | 187.04 | 92.147 | 78.495 | 2.088 | 50.101 | 22.847 | 53.999 | 0.841 | 109.841 |
| Std. Deviation | 27.91 | 107.15 | 83.173 | 28.524 | 1.261 | 14.316 | 5.686 | 18.619 | 0.457 | 144.413 |
| Coefficient of variation | 0.791 | 0.557 | 0.863 | 0.357 | 0.586 | 0.282 | 0.246 | 0.339 | 0.529 | 1.232 |
| Skewness | 1.331 | 1.091 | 0.88 | 0.689 | 1.105 | 0.339 | 0.266 | -0.105 | 1.696 | 0.895 |
| Std. Error of Skewness | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 |
| Kurtosis | 0.973 | 2.144 | -0.313 | 0.351 | 0.592 | 0.023 | -0.764 | -1.167 | 3.626 | -0.763 |
| Std. Error of Kurtosis | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 |
| Minimum | 6.23 | 32.38 | 4.71 | 18.29 | 0.42 | 17.79 | 12.3 | 15.53 | 0.18 | 3.91 |
| Maximum | 146.08 | 793.25 | 378.68 | 210.9 | 6.93 | 103.57 | 36.32 | 93.27 | 3.38 | 501.55 |
| 25th percentile | 16.008 | 107.98 | 24.367 | 57.773 | 1.22 | 40.905 | 18.63 | 38.925 | 0.55 | 6.13 |
| 50th percentile | 23.175 | 173.92 | 69.88 | 74.835 | 1.74 | 50.105 | 22.83 | 55.825 | 0.72 | 12.515 |
| 75th percentile | 49.413 | 262.78 | 151.21 | 99 | 2.89 | 59.91 | 27.182 | 71.195 | 1.06 | 241.618 |
| 95th percentile | 94.404 | 377.42 | 263.7 | 131.15 | 4.757 | 76.127 | 33.218 | 82.185 | 1.765 | 392.443 |
| | | | | | | | | | | |
| Winter 2018-19 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 23.11 | 182.33 | 47.055 | 60.3 | 1.59 | 42.935 | 13.825 | 60.13 | 0.83 | 6.7 |
| Mean | 28.907 | 210.77 | 83.235 | 66.222 | 2.122 | 46.138 | 14.387 | 58.698 | 1.014 | 101.484 |
| 95% CI Mean Upper | 29.74 | 216.08 | 86.735 | 67.295 | 2.184 | 46.806 | 14.588 | 59.375 | 1.039 | 107.016 |
| 95% CI Mean Lower | 28.074 | 205.46 | 79.736 | 65.149 | 2.06 | 45.47 | 14.187 | 58.022 | 0.989 | 95.952 |

| Std. Deviation | 19.742 | 125.87 | 82.936 | 25.428 | 1.479 | 15.83 | 4.737 | 16.038 | 0.598 | 131.105 |
|----------------------------------------------------------------------------------|----------------------------------------------|-----------------------------------------------|----------------------------------------------|-----------------------------------------------|---------------------------------------------------|--------------------------------------------------------|-------------------------------------------------------|---------------------------------------------------------|---------------------------------------------------|---------------------------------------------------|
| Skewness | 1.218 | 0.857 | 1.316 | 1.293 | 1.355 | 0.813 | 0.334 | -0.312 | 1.69 | 1.045 |
| Std. Error of Skewness | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 |
| Kurtosis | 1.152 | 0.139 | 0.787 | 2.591 | 1.222 | 0.368 | -0.659 | -0.949 | 3.479 | -0.339 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 4.84 | 23.1 | 4.38 | 26.48 | 0.21 | 17.82 | 5.16 | 21.77 | 0.17 | 3.52 |
| Maximum | 120.98 | 706.25 | 378.92 | 231.23 | 8.15 | 107.42 | 27.99 | 87.11 | 4.15 | 503.82 |
| 25th percentile | 14.565 | 111.76 | 21.053 | 48.047 | 1.09 | 34.053 | 10.65 | 46.182 | 0.6 | 6.01 |
| 50th percentile | 23.11 | 182.33 | 47.055 | 60.3 | 1.59 | 42.935 | 13.825 | 60.13 | 0.83 | 6.7 |
| 75th percentile | 39.282 | 285.78 | 119.45 | 78.22 | 2.683 | 55.442 | 17.973 | 72.66 | 1.25 | 197.23 |
| 95th percentile | 68.766 | 466.9 | 262.72 | 117.04 | 5.32 | 76.619 | 22.564 | 81.352 | 2.28 | 356.631 |
| | | | | | | | | | | |
| Spring 2019 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| | | | | | | 11113 | ΛI | 1411 | WS | SK |
| Median | 21.6 | 84.435 | 25.02 | 49.665 | 1.11 | 29.595 | 20.92 | 49.725 | 1.045 | 19.88 |
| Median Mean | 21.6 30.181 | 84.435 95.868 | 25.02 38.717 | 49.665 52.248 | | | | | | 19.88 |
| | | | | | 1.11 | 29.595 | 20.92 | 49.725 | 1.045 | |
| Mean | 30.181 | 95.868 | 38.717 | 52.248 | 1.11 1.257 | 29.595 31.393 | 20.92 21.517 | 49.725 46.668 | 1.045 1.243 | 19.88 151.951 |
| Mean 95% CI Mean Upper | 30.181 31.86 | 95.868 99.513 | 38.717 41.307 | 52.248 53.373 | 1.11 1.257 1.299 | 29.595 31.393 31.963 | 20.92 21.517 21.952 | 49.725 46.668 47.849 | 1.045 1.243 1.291 | 19.88 151.951 165.077 |
| Mean 95% CI Mean Upper 95% CI Mean Lower | 30.181 31.86 28.502 | 95.868 99.513 92.223 | 38.717 41.307 36.126 | 52.248 53.373 51.122 | 1.11 1.257 1.299 1.215 | 29.595 31.393 31.963 30.824 | 20.92 21.517 21.952 21.081 | 49.725 46.668 47.849 45.487 | 1.045 1.243 1.291 1.194 | 19.88 151.951 165.077 138.824 |
| Mean 95% CI Mean Upper 95% CI Mean Lower Std. Deviation Coefficient of | 30.181 31.86 28.502 23.323 | 95.868 99.513 92.223 50.645 | 38.717 41.307 36.126 35.991 | 52.248 53.373 51.122 15.636 | 1.11 1.257 1.299 1.215 0.583 | 29.595 31.393 31.963 30.824 7.916 | 20.92 21.517 21.952 21.081 6.053 | 49.725 46.668 47.849 45.487 16.409 | 1.045 1.243 1.291 1.194 0.671 | 19.88 151.951 165.077 138.824 182.383 |
| Mean 95% CI Mean Upper 95% CI Mean Lower Std. Deviation Coefficient of variation | 30.181 31.86 28.502 23.323 0.773 | 95.868 99.513 92.223 50.645 0.528 | 38.717 41.307 36.126 35.991 0.93 | 52.248 53.373 51.122 15.636 0.299 | 1.11 1.257 1.299 1.215 0.583 0.464 | 29.595 31.393 31.963 30.824 7.916 0.252 | 20.92 21.517 21.952 21.081 6.053 0.281 | 49.725 46.668 47.849 45.487 16.409 0.352 | 1.045 1.243 1.291 1.194 0.671 0.54 | 19.88 151.951 165.077 138.824 182.383 |

| Std. Error of Kurtosis | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Minimum | 4.51 | 18.64 | 3.33 | 18.99 | 0.38 | 18.15 | 8.84 | 9.99 | 0.29 | 5.27 |
| Maximum | 106.31 | 296.36 | 208.96 | 95.93 | 4.28 | 62.76 | 39.78 | 85.71 | 3.65 | 564.97 |
| 25th percentile | 9.938 | 56.093 | 15.19 | 39.642 | 0.827 | 25.435 | 16.785 | 32.24 | 0.73 | 5.89 |
| 50th percentile | 21.6 | 84.435 | 25.02 | 49.665 | 1.11 | 29.595 | 20.92 | 49.725 | 1.045 | 19.88 |
| 75th percentile | 46.998 | 125.86 | 50.153 | 62.715 | 1.59 | 36.115 | 25.69 | 59.523 | 1.59 | 315.667 |
| 95th percentile | 74.494 | 192.5 | 125.64 | 82.561 | 2.33 | 46.83 | 32.118 | 70.994 | 2.59 | 489.368 |
| | | | | | | | | | | |
| Summer 2019 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 34.115 | 72.9 | 22.985 | 49.11 | 1.38 | 35.82 | 32.46 | 33.615 | 1.17 | 74.385 |
| Mean | 44.914 | 87.703 | 39.365 | 53.418 | 1.568 | 38.123 | 32.723 | 34.964 | 1.382 | 172.838 |
| 95% CI Mean Upper | 46.337 | 90.069 | 41.19 | 54.334 | 1.599 | 38.629 | 32.971 | 35.602 | 1.415 | 180.856 |
| 95% CI Mean Lower | 43.491 | 85.336 | 37.541 | 52.501 | 1.536 | 37.617 | 32.475 | 34.326 | 1.35 | 164.82 |
| Std. Deviation | 33.91 | 56.404 | 43.473 | 21.838 | 0.749 | 12.053 | 5.88 | 15.21 | 0.784 | 191.084 |
| Coefficient of variation | 0.755 | 0.643 | 1.104 | 0.409 | 0.478 | 0.316 | 0.18 | 0.435 | 0.567 | 1.106 |
| Skewness | 0.824 | 1.896 | 2.41 | 0.869 | 1.95 | 1.929 | -0.003 | 0.397 | 1.329 | 0.653 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.053 | 0.052 | 0.052 | 0.052 |
| Kurtosis | -0.442 | 4.964 | 6.938 | 0.373 | 5.179 | 7.234 | -0.674 | -0.341 | 2.489 | -1.164 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 5.22 | 9.6 | 1.96 | 15.43 | 0.36 | 15.35 | 17.12 | 5.94 | 0.2 | 3.9 |
| Maximum | 157.24 | 430.57 | 303.45 | 141.23 | 5.74 | 142.34 | 46.44 | 87.17 | 5.9 | 592.24 |
| 25th percentile | 15.957 | 49.492 | 12.145 | 37.288 | 1.09 | 30.123 | 28.39 | 23.235 | 0.78 | 6.04 |
| 50th percentile | 34.115 | 72.9 | 22.985 | 49.11 | 1.38 | 35.82 | 32.46 | 33.615 | 1.17 | 74.385 |

| 75th percentile | 69.302 | 108.73 | 48.805 | 65.403 | 1.8 | 43.12 | 37.3 | 45.33 | 1.82 | 355.153 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95th percentile | 109.93 | 201.23 | 133.03 | 96.576 | 3.05 | 59.368 | 42.298 | 61.533 | 2.808 | 511.43 |
| | | | | | | | | | | |
| Monsoon 2019 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 22.45 | 40.93 | 13.4 | 31.21 | 1.18 | 31.565 | 30.075 | 66.975 | 1.05 | 48.335 |
| Mean | 25.374 | 44.529 | 18.924 | 33.273 | 1.264 | 32.745 | 30.621 | 65.321 | 1.201 | 131.494 |
| 95% CI Mean Upper | 25.96 | 45.459 | 19.617 | 33.724 | 1.282 | 33.079 | 30.762 | 65.854 | 1.225 | 137.775 |
| 95% CI Mean Lower | 24.789 | 43.6 | 18.23 | 32.821 | 1.247 | 32.411 | 30.479 | 64.789 | 1.177 | 125.212 |
| Std. Deviation | 14.031 | 22.26 | 16.612 | 10.816 | 0.425 | 8.008 | 3.392 | 12.762 | 0.566 | 150.512 |
| Coefficient of variation | 0.553 | 0.5 | 0.878 | 0.325 | 0.336 | 0.245 | 0.111 | 0.195 | 0.471 | 1.145 |
| Skewness | 1.753 | 0.773 | 3.005 | 1.43 | 1.839 | 0.912 | 0.553 | -0.431 | 1.189 | 0.822 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 4.839 | 0.358 | 13.864 | 3.517 | 5.72 | 1.225 | -0.207 | -0.633 | 1.445 | -0.741 |
| Std. Error of Kurtosis | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 |
| Minimum | 5.9 | 5.17 | 3.75 | 14.87 | 0.4 | 13.11 | 22.6 | 23.86 | 0.35 | 4 |
| Maximum | 105.95 | 142.69 | 164.5 | 97.56 | 3.81 | 70.61 | 42.11 | 88.46 | 4.06 | 553.18 |
| 25th percentile | 15.178 | 27.65 | 8.58 | 26.057 | 0.99 | 26.807 | 28.098 | 55.51 | 0.76 | 5.87 |
| 50th percentile | 22.45 | 40.93 | 13.4 | 31.21 | 1.18 | 31.565 | 30.075 | 66.975 | 1.05 | 48.335 |
| 75th percentile | 31.488 | 57.965 | 23.46 | 38.132 | 1.44 | 37.392 | 32.912 | 76.245 | 1.52 | 254.382 |
| 95th percentile | 51.316 | 89.009 | 48.329 | 53.4 | 2.037 | 47.809 | 36.83 | 82.452 | 2.31 | 415.801 |
| | | | | | | | | | | |
| Postmonsoon 2019 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 19.455 | 141.63 | 32.78 | 42.505 | 1.32 | 32.965 | 24.165 | 68.2 | 0.79 | 6.935 |
| Mean | 31.278 | 178.31 | 50.078 | 45.194 | 1.59 | 34.783 | 24.674 | 65.065 | 0.898 | 100.907 |

| 95% CI Mean Upper | 32.514 | 185.38 | 52.32 | 45.967 | 1.637 | 35.277 | 24.907 | 65.787 | 0.919 | 107.715 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95% CI Mean Lower | 30.042 | 171.24 | 47.836 | 44.422 | 1.542 | 34.288 | 24.44 | 64.344 | 0.877 | 94.1 |
| Std. Deviation | 24.113 | 137.92 | 43.729 | 15.072 | 0.927 | 9.641 | 4.559 | 14.069 | 0.416 | 132.779 |
| Coefficient of variation | 0.771 | 0.773 | 0.873 | 0.333 | 0.583 | 0.277 | 0.185 | 0.216 | 0.463 | 1.316 |
| Skewness | 1.289 | 1.66 | 1.414 | 0.868 | 1.462 | 0.957 | 0.223 | -0.37 | 1.59 | 1.068 |
| Std. Error of Skewness | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 |
| Kurtosis | 0.639 | 3.434 | 1.689 | 0.772 | 2.396 | 0.808 | -0.667 | -1.058 | 3.556 | -0.328 |
| Std. Error of Kurtosis | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 |
| Minimum | 8.94 | 17.27 | 3.03 | 17.03 | 0.21 | 14.65 | 14.26 | 33.73 | 0.17 | 3.14 |
| Maximum | 120.75 | 924 | 247.7 | 110.77 | 5.72 | 68.48 | 35.23 | 91.88 | 2.96 | 499.04 |
| 25th percentile | 13.39 | 76.66 | 17.527 | 34.015 | 0.93 | 28.247 | 21.288 | 52.998 | 0.61 | 5.008 |
| 50th percentile | 19.455 | 141.63 | 32.78 | 42.505 | 1.32 | 32.965 | 24.165 | 68.2 | 0.79 | 6.935 |
| 75th percentile | 43.727 | 234.86 | 71.925 | 54.233 | 2.01 | 39.438 | 27.883 | 76.782 | 1.07 | 188.083 |
| 95th percentile | 81.883 | 462.28 | 140.49 | 74.123 | 3.518 | 55.368 | 32.696 | 83.598 | 1.71 | 368.458 |
| | | | | | | | | | | |
| Winter 2019-20 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 22.375 | 150.87 | 33.975 | 43.065 | 1.29 | 39.27 | 14.09 | 77.455 | 0.94 | 5.88 |
| Mean | 27.749 | 176.74 | 53.358 | 47.508 | 1.66 | 43.213 | 14.585 | 72.968 | 1.082 | 96.108 |
| 95% CI Mean Upper | 28.511 | 180.87 | 55.378 | 48.311 | 1.707 | 43.861 | 14.749 | 73.609 | 1.107 | 101.514 |
| 95% CI Mean Lower | 26.987 | 172.6 | 51.338 | 46.704 | 1.614 | 42.564 | 14.42 | 72.327 | 1.057 | 90.702 |
| Std. Deviation | 18.168 | 98.486 | 48.134 | 19.14 | 1.117 | 15.456 | 3.92 | 15.276 | 0.591 | 128.828 |
| Coefficient of variation | 0.655 | 0.557 | 0.902 | 0.403 | 0.673 | 0.358 | 0.269 | 0.209 | 0.547 | 1.34 |
| Skewness | 1.461 | 1.083 | 1.972 | 1.086 | 1.929 | 2.637 | 0.448 | -0.756 | 1.719 | 1.141 |

| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Kurtosis | 1.724 | 1.267 | 4.075 | 1.119 | 3.915 | 11.423 | -0.111 | -0.626 | 3.989 | -0.126 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 6.65 | 21.15 | 8.8 | 15.47 | 0.38 | 20.64 | 5.69 | 32.43 | 0.27 | 3.48 |
| Maximum | 113.25 | 688.88 | 309.25 | 136.21 | 6.78 | 156.71 | 26.58 | 93.18 | 4.49 | 466.17 |
| 25th percentile | 14.848 | 99.227 | 21.44 | 33.487 | 0.93 | 33.69 | 11.772 | 61.645 | 0.66 | 5.18 |
| 50th percentile | 22.375 | 150.87 | 33.975 | 43.065 | 1.29 | 39.27 | 14.09 | 77.455 | 0.94 | 5.88 |
| 75th percentile | 33.838 | 234.11 | 66.313 | 57.3 | 1.95 | 48.96 | 17.163 | 85.75 | 1.32 | 176.722 |
| 95th percentile | 68.915 | 370.09 | 157.79 | 85.598 | 4.187 | 69.206 | 21.727 | 90.118 | 2.28 | 370.929 |
| | | | | | | | | | | |
| Spring 2020 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 28.02 | 56.025 | 18.325 | 31.14 | 0.71 | 29.11 | 22.41 | 66.565 | 1.09 | 14.855 |
| Mean | 35.888 | 65.913 | 27.756 | 31.921 | 0.905 | 29.782 | 22.785 | 64.033 | 1.29 | 145.04 |
| 95% CI Mean Upper | 37.523 | 68.784 | 29.538 | 33.052 | 0.946 | 30.308 | 23.087 | 65.188 | 1.342 | 157.833 |
| 95% CI Mean Lower | 34.254 | 63.043 | 25.973 | 30.79 | 0.864 | 29.256 | 22.484 | 62.878 | 1.238 | 132.247 |
| Std. Deviation | 22.709 | 39.883 | 24.766 | 15.715 | 0.572 | 7.305 | 4.183 | 16.048 | 0.72 | 177.746 |
| Coefficient of variation | 0.633 | 0.605 | 0.892 | 0.492 | 0.632 | 0.245 | 0.184 | 0.251 | 0.558 | 1.225 |
| Skewness | 0.967 | 1.143 | 2.022 | 0.869 | 2.082 | 0.662 | 0.279 | -0.279 | 1.367 | 0.853 |
| Std. Error of Skewness | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| Kurtosis | 0.04 | 1.779 | 3.739 | 0.749 | 4.892 | 0.863 | -0.655 | -1.067 | 1.887 | -0.833 |
| Std. Error of Kurtosis | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 |
| Minimum | 6.05 | 9.69 | 8.18 | 8.3 | 0.18 | 14.71 | 14.15 | 27.91 | 0.3 | 3.84 |

| Maximum | 109.01 | 263.61 | 133.15 | 98.58 | 3.81 | 55.58 | 32.95 | 98.68 | 4.44 | 579.45 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 25th percentile | 17.925 | 35.737 | 12.005 | 19.01 | 0.55 | 25.085 | 19.75 | 50.098 | 0.78 | 5.33 |
| 50th percentile | 28.02 | 56.025 | 18.325 | 31.14 | 0.71 | 29.11 | 22.41 | 66.565 | 1.09 | 14.855 |
| 75th percentile | 49.575 | 88.15 | 31.005 | 40.892 | 1.022 | 33.593 | 25.87 | 77.412 | 1.63 | 293.39 |
| 95th percentile | 81.514 | 135.78 | 86.924 | 62.207 | 2.089 | 43.578 | 30.257 | 86.365 | 2.75 | 477.112 |
| | | | | | | | | | | |
| Summer 2020 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 48.18 | 47.66 | 9.38 | 22.25 | 0.99 | 30.135 | 31.925 | 48.195 | 1.08 | 34.425 |
| Mean | 53.441 | 56.212 | 10.749 | 25.126 | 1.06 | 31.408 | 31.983 | 48.204 | 1.244 | 152.06 |
| 95% CI Mean Upper | 54.645 | 57.674 | 10.984 | 25.682 | 1.076 | 31.808 | 32.199 | 48.802 | 1.271 | 159.718 |
| 95% CI Mean Lower | 52.237 | 54.75 | 10.514 | 24.57 | 1.043 | 31.008 | 31.767 | 47.606 | 1.216 | 144.402 |
| Std. Deviation | 28.7 | 34.833 | 5.6 | 13.256 | 0.399 | 9.529 | 5.142 | 14.253 | 0.648 | 182.499 |
| Coefficient of variation | 0.537 | 0.62 | 0.521 | 0.528 | 0.377 | 0.303 | 0.161 | 0.296 | 0.521 | 1.2 |
| Skewness | 0.528 | 1.743 | 4.384 | 1.977 | 1.385 | 0.701 | 0.091 | 0.003 | 1.033 | 0.883 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | -0.659 | 4.356 | 25.428 | 6.585 | 4.203 | 0.269 | -0.414 | -0.834 | 0.81 | -0.671 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 11.05 | 4.55 | 1.45 | 8.98 | 0.28 | 13.33 | 18.65 | 16.53 | 0.28 | 3.05 |
| Maximum | 135.58 | 259.43 | 59.43 | 129.29 | 3.84 | 65.05 | 45.96 | 84.88 | 4.29 | 686.38 |
| 25th percentile | 29 | 32.438 | 8.26 | 15.38 | 0.79 | 24.352 | 28.268 | 36.915 | 0.74 | 4.58 |
| 50th percentile | 48.18 | 47.66 | 9.38 | 22.25 | 0.99 | 30.135 | 31.925 | 48.195 | 1.08 | 34.425 |
| 75th percentile | 75.825 | 69.985 | 11.08 | 29.89 | 1.26 | 37.278 | 35.66 | 59.543 | 1.632 | 303.395 |
| 95th percentile | 105.59 | 125.28 | 19.528 | 51.551 | 1.778 | 49.346 | 40.617 | 70.269 | 2.478 | 508.033 |

| Monsoon 2020 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Median | 24.76 | 34.87 | 13.195 | 27.75 | 0.97 | 28.14 | 32.205 | 68.77 | 1.02 | 53.035 |
| Mean | 28.189 | 38.409 | 17.708 | 29.739 | 1.046 | 28.938 | 32.601 | 66.942 | 1.161 | 136.039 |
| 95% CI Mean Upper | 28.733 | 39.245 | 18.279 | 30.181 | 1.062 | 29.189 | 32.729 | 67.433 | 1.185 | 142.414 |
| 95% CI Mean Lower | 27.645 | 37.574 | 17.138 | 29.297 | 1.03 | 28.688 | 32.474 | 66.451 | 1.138 | 129.664 |
| Std. Deviation | 13.033 | 20.016 | 13.67 | 10.587 | 0.376 | 6.005 | 3.057 | 11.76 | 0.572 | 152.761 |
| Coefficient of variation | 0.462 | 0.521 | 0.772 | 0.356 | 0.36 | 0.207 | 0.094 | 0.176 | 0.492 | 1.123 |
| Skewness | 1.12 | 0.848 | 3.012 | 1.288 | 1.539 | 0.598 | 0.309 | -0.341 | 1.571 | 0.768 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 1.06 | 0.51 | 13.326 | 2.621 | 4.148 | 0.41 | -0.552 | -0.767 | 3.514 | -0.871 |
| Std. Error of Kurtosis | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 |
| Minimum | 6 | 4.8 | 3.59 | 9.67 | 0.32 | 14.73 | 24.5 | 36.57 | 0.33 | 4.4 |
| Maximum | 82.37 | 120.34 | 125.22 | 84.24 | 3.64 | 54.84 | 42.23 | 89.51 | 4.33 | 529.22 |
| 25th percentile | 18.42 | 23.328 | 9.395 | 22.523 | 0.8 | 24.65 | 30.288 | 57.855 | 0.75 | 6.14 |
| 50th percentile | 24.76 | 34.87 | 13.195 | 27.75 | 0.97 | 28.14 | 32.205 | 68.77 | 1.02 | 53.035 |
| 75th percentile | 35.192 | 50.16 | 21.1 | 34.87 | 1.22 | 32.612 | 34.88 | 76.303 | 1.412 | 267.05 |
| 95th percentile | 53.293 | 74.841 | 43.246 | 49.395 | 1.73 | 39.677 | 37.9 | 84.01 | 2.22 | 420.766 |
| | T _ | I I | | | | | 1 | | | |
| Postmonsoon 2020 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 17.6 | 161.96 | 40.475 | 50.66 | 1.74 | 38.495 | 25.075 | 58.78 | 0.73 | 7.16 |
| Mean | 32.994 | 200.77 | 62.89 | 55.224 | 2.212 | 40.829 | 25.422 | 56.017 | 0.825 | 100.614 |
| 95% CI Mean Upper | 34.56 | 207.96 | 65.862 | 56.306 | 2.277 | 41.407 | 25.716 | 56.81 | 0.844 | 107.158 |
| 95% CI Mean Lower | 31.429 | 193.58 | 59.918 | 54.142 | 2.146 | 40.25 | 25.128 | 55.224 | 0.806 | 94.07 |
| Std. Deviation | 30.538 | 140.03 | 57.976 | 21.109 | 1.283 | 11.289 | 5.733 | 15.469 | 0.371 | 127.638 |

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|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Coefficient of variation | 0.926 | 0.697 | 0.922 | 0.382 | 0.58 | 0.277 | 0.225 | 0.276 | 0.449 | 1.269 |
| Skewness | 1.161 | 1.707 | 1.364 | 0.993 | 1.212 | 0.733 | 0.271 | -0.258 | 1.505 | 0.989 |
| Std. Error of Skewness | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 |
| Kurtosis | 0.015 | 3.766 | 1.24 | 1.074 | 0.717 | 0.136 | -0.794 | -1.163 | 2.927 | -0.504 |
| Std. Error of Kurtosis | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 |
| Minimum | 5.36 | 29.1 | 2.48 | 17.33 | 0.53 | 18.76 | 14.28 | 21.82 | 0.24 | 5.18 |
| Maximum | 133.71 | 998.62 | 308.98 | 159.62 | 6.4 | 86.81 | 37.88 | 84.9 | 2.74 | 471.5 |
| 25th percentile | 10.94 | 101.21 | 19.117 | 39.953 | 1.27 | 32.06 | 20.683 | 41.58 | 0.56 | 5.97 |
| 50th percentile | 17.6 | 161.96 | 40.475 | 50.66 | 1.74 | 38.495 | 25.075 | 58.78 | 0.73 | 7.10 |
| 75th percentile | 51.213 | 252.7 | 88.418 | 66.793 | 2.82 | 48.872 | 29.45 | 69.15 | 0.99 | 200.813 |
| 95th percentile | 95.412 | 478.24 | 185.8 | 94.549 | 5 | 60.922 | 35.92 | 77.623 | 1.55 | 346.69 |
| Winter 2020-21 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 22.375 | 150.87 | 33.975 | 43.065 | 1.29 | 39.27 | 14.09 | 77.455 | 0.94 | 5.88 |
| Mean | 27.749 | 176.74 | 53.358 | 47.508 | 1.29 | 43.213 | 14.09 | 72.968 | 1.082 | 96.108 |
| 95% CI Mean Upper | 28.511 | 180.87 | 55.378 | 48.311 | 1.707 | 43.213 | 14.749 | 73.609 | 1.107 | 101.514 |
| 95% CI Mean Lower | 26.987 | 172.6 | 51.338 | 46.704 | 1.614 | 42.564 | 14.749 | 73.009 | 1.057 | 90.702 |
| Std. Deviation | 18.168 | 98.486 | 48.134 | 19.14 | 1.117 | 15.456 | 3.92 | 15.276 | 0.591 | 128.828 |
| Coefficient of variation | 0.655 | 0.557 | 0.902 | 0.403 | 0.673 | 0.358 | 0.269 | 0.209 | 0.547 | 1.34 |
| Skewness | 1.461 | 1.083 | 1.972 | 1.086 | 1.929 | 2.637 | 0.448 | -0.756 | 1.719 | 1.14 |
| Std. Error of | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Skewness | 0.032 | 0.002 | 0.002 | 0.002 | | | | | | |

| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Minimum | 6.65 | 21.15 | 8.8 | 15.47 | 0.38 | 20.64 | 5.69 | 32.43 | 0.27 | 3.48 |
| Maximum | 113.25 | 688.88 | 309.25 | 136.21 | 6.78 | 156.71 | 26.58 | 93.18 | 4.49 | 466.17 |
| 25th percentile | 14.848 | 99.227 | 21.44 | 33.487 | 0.93 | 33.69 | 11.772 | 61.645 | 0.66 | 5.18 |
| 50th percentile | 22.375 | 150.87 | 33.975 | 43.065 | 1.29 | 39.27 | 14.09 | 77.455 | 0.94 | 5.88 |
| 75th percentile | 33.838 | 234.11 | 66.313 | 57.3 | 1.95 | 48.96 | 17.163 | 85.75 | 1.32 | 176.722 |
| 95th percentile | 68.915 | 370.09 | 157.79 | 85.598 | 4.187 | 69.206 | 21.727 | 90.118 | 2.28 | 370.929 |
| | | | | | | | | | | |
| Spring 2021 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 25.015 | 104.1 | 27.195 | 42.84 | 1.145 | 75.5 | 23.35 | 49.495 | 1.1 | 13.055 |
| Mean | 33.836 | 114.92 | 44.076 | 45.27 | 1.444 | 78.606 | 24.164 | 49.203 | 1.322 | 125.824 |
| 95% CI Mean Upper | 35.656 | 119.41 | 47.436 | 46.406 | 1.507 | 80.379 | 24.512 | 50.275 | 1.372 | 137.018 |
| 95% CI Mean Lower | 32.016 | 110.43 | 40.716 | 44.135 | 1.381 | 76.833 | 23.817 | 48.132 | 1.272 | 114.629 |
| Std. Deviation | 25.287 | 62.354 | 46.688 | 15.778 | 0.878 | 24.636 | 4.764 | 14.89 | 0.695 | 155.532 |
| Coefficient of variation | 0.747 | 0.543 | 1.059 | 0.349 | 0.608 | 0.313 | 0.197 | 0.303 | 0.526 | 1.236 |
| Skewness | 0.851 | 0.953 | 2.45 | 1.606 | 2.099 | 1.596 | 0.36 | -0.01 | 1.381 | 0.89 |
| Std. Error of Skewness | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.091 | 0.09 | 0.09 | 0.09 |
| Kurtosis | -0.475 | 1.177 | 6.74 | 5.844 | 5.116 | 6.236 | -0.727 | -0.991 | 1.641 | -0.761 |
| Std. Error of Kurtosis | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.181 | 0.179 | 0.179 | 0.179 |
| Minimum | 6.7 | 12 | 5.46 | 12.74 | 0.43 | 38.36 | 14.96 | 16.53 | 0.22 | 4.83 |
| Maximum | 107.38 | 417 | 298.91 | 159.85 | 6.11 | 250.63 | 39.15 | 82.22 | 4.31 | 536.13 |
| 25th percentile | 11.678 | 65.855 | 16.408 | 34.657 | 0.87 | 62.277 | 20.29 | 36.365 | 0.82 | 5.97 |
| 50th percentile | 25.015 | 104.1 | 27.195 | 42.84 | 1.145 | 75.5 | 23.35 | 49.495 | 1.1 | 13.055 |

| 75th percentile | 51.417 | 153.48 | 48.765 | 52.038 | 1.702 | 90.755 | 27.985 | 61.13 | 1.61 | 266.447 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95th percentile | 81.808 | 225.03 | 140.59 | 72.478 | 3.26 | 123.17 | 32.459 | 72.367 | 2.86 | 404.937 |
| | | | | | | | | | | |
| Summer 2021 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 28.725 | 58.55 | 10.85 | 29.005 | 1.28 | 58.105 | 30.49 | 43.375 | 1.11 | 46.45 |
| Mean | 37.738 | 72.527 | 19.279 | 35.014 | 1.419 | 59.542 | 30.673 | 45.218 | 1.343 | 148.453 |
| 95% CI Mean Upper | 38.862 | 74.843 | 20.196 | 35.785 | 1.441 | 60.06 | 30.886 | 45.887 | 1.375 | 155.558 |
| 95% CI Mean Lower | 36.615 | 70.211 | 18.362 | 34.243 | 1.398 | 59.025 | 30.46 | 44.549 | 1.312 | 141.348 |
| Std. Deviation | 26.774 | 55.184 | 21.846 | 18.373 | 0.51 | 12.328 | 5.065 | 15.94 | 0.746 | 169.317 |
| Coefficient of variation | 0.709 | 0.761 | 1.133 | 0.525 | 0.36 | 0.207 | 0.165 | 0.353 | 0.556 | 1.141 |
| Skewness | 1.185 | 2.791 | 3.102 | 1.553 | 1.998 | 1.08 | 0.006 | 0.484 | 1.781 | 0.744 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 0.776 | 11.772 | 11.878 | 2.758 | 5.204 | 2.282 | -0.644 | -0.262 | 4.934 | -0.999 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 6.02 | 4 | 2.83 | 9.2 | 0.53 | 35.95 | 16.05 | 17.45 | 0.38 | 4.66 |
| Maximum | 143.68 | 503.88 | 187.28 | 132.09 | 4.53 | 129.05 | 43.85 | 93.04 | 7.58 | 539.66 |
| 25th percentile | 17.32 | 37.415 | 7.81 | 22.35 | 1.09 | 50.61 | 26.907 | 33.15 | 0.82 | 5.92 |
| 50th percentile | 28.725 | 58.55 | 10.85 | 29.005 | 1.28 | 58.105 | 30.49 | 43.375 | 1.11 | 46.45 |
| 75th percentile | 51.46 | 89.78 | 20.747 | 43.35 | 1.57 | 65.857 | 34.552 | 56.21 | 1.67 | 305.998 |
| 95th percentile | 92.199 | 166.02 | 62.798 | 71.769 | 2.5 | 81.754 | 38.93 | 73.411 | 2.88 | 458.677 |
| | | | | | | | | | | |
| Monsoon 2021 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 25 | 40.155 | 12.37 | 23.45 | 0.94 | 36.215 | 31.58 | 70.44 | 1.015 | 23.465 |
| Mean | 27.443 | 43.423 | 15.919 | 25.189 | 1.013 | 38.044 | 32.08 | 68.934 | 1.168 | 118.817 |

| 95% CI Mean Upper | 27.876 | 44.218 | 16.399 | 25.531 | 1.029 | 38.517 | 32.215 | 69.497 | 1.189 | 125.015 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95% CI Mean Lower | 27.01 | 42.629 | 15.439 | 24.847 | 0.996 | 37.571 | 31.945 | 68.37 | 1.146 | 112.619 |
| Std. Deviation | 10.381 | 19.043 | 11.504 | 8.187 | 0.399 | 11.343 | 3.226 | 13.498 | 0.521 | 148.513 |
| Coefficient of variation | 0.378 | 0.439 | 0.723 | 0.325 | 0.394 | 0.298 | 0.101 | 0.196 | 0.446 | 1.25 |
| Skewness | 1.24 | 0.801 | 2.027 | 1.469 | 1.186 | 0.528 | 0.671 | -0.447 | 1.462 | 1.048 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 1.942 | 0.826 | 5.192 | 3.331 | 1.917 | -0.723 | 0.045 | -0.655 | 2.966 | -0.307 |
| Std. Error of Kurtosis | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 |
| Minimum | 8.3 | 4 | 3.6 | 11.15 | 0.29 | 21.82 | 25.4 | 29.66 | 0.31 | 5.21 |
| Maximum | 82.85 | 142.67 | 87.94 | 73.06 | 3.11 | 77.6 | 43.28 | 89.85 | 4.39 | 531.75 |
| 25th percentile | 19.928 | 29.433 | 8.003 | 19.46 | 0.73 | 27.688 | 29.56 | 59.098 | 0.79 | 6.3 |
| 50th percentile | 25 | 40.155 | 12.37 | 23.45 | 0.94 | 36.215 | 31.58 | 70.44 | 1.015 | 23.465 |
| 75th percentile | 32.83 | 55.345 | 19.86 | 28.91 | 1.21 | 47.355 | 34.185 | 80.37 | 1.42 | 230.075 |
| 95th percentile | 48.537 | 79.053 | 41.037 | 40.77 | 1.77 | 57.496 | 38.017 | 87.537 | 2.177 | 421.197 |
| | | | | | | | | | | |
| Postmonsoon 2021 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 20.38 | 135.78 | 42.35 | 51.365 | 1.62 | 39.77 | 24.48 | 67.24 | 0.8 | 7.405 |
| Mean | 30.829 | 164.93 | 66.475 | 54.721 | 1.963 | 42.03 | 24.686 | 63.706 | 0.879 | 109.271 |
| 95% CI Mean Upper | 32.051 | 171.11 | 69.561 | 55.892 | 2.029 | 42.562 | 24.973 | 64.514 | 0.896 | 116.502 |
| 95% CI Mean Lower | 29.607 | 158.75 | 63.388 | 53.55 | 1.897 | 41.498 | 24.399 | 62.899 | 0.862 | 102.04 |
| Std. Deviation | 23.827 | 120.55 | 60.204 | 22.838 | 1.289 | 10.384 | 5.59 | 15.748 | 0.334 | 141.04 |
| Coefficient of variation | 0.773 | 0.731 | 0.906 | 0.417 | 0.657 | 0.247 | 0.226 | 0.247 | 0.38 | 1.291 |
| Skewness | 1.479 | 1.048 | 1.206 | 0.786 | 1.269 | 1.782 | 0.347 | -0.38 | 1.695 | 1.037 |

| Std. Error of Skewness | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Kurtosis | 1.306 | 1.273 | 0.783 | 0.387 | 1.507 | 5.086 | -0.714 | -1.035 | 5.076 | -0.421 |
| Std. Error of Kurtosis | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 |
| Minimum | 7.92 | 4 | 5.56 | 14.85 | 0.28 | 23.78 | 14.72 | 29.02 | 0.29 | 4.77 |
| Maximum | 133.73 | 832 | 318.1 | 141.34 | 7.39 | 102.99 | 38.5 | 90.05 | 3.42 | 462.06 |
| 25th percentile | 13.94 | 66.14 | 18.805 | 37.035 | 0.98 | 35.08 | 19.907 | 50.195 | 0.65 | 6.17 |
| 50th percentile | 20.38 | 135.78 | 42.35 | 51.365 | 1.62 | 39.77 | 24.48 | 67.24 | 0.8 | 7.405 |
| 75th percentile | 39.177 | 245.19 | 101.26 | 68.247 | 2.57 | 46.343 | 28.71 | 76.627 | 1.04 | 215.02 |
| 95th percentile | 85.31 | 369.62 | 187.31 | 97.198 | 4.637 | 61.057 | 35.319 | 85.306 | 1.51 | 395.554 |
| | | | | | | | | | | |
| Winter 2021-22 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 21.015 | 163.65 | 37.565 | 40.885 | 1.44 | 39.685 | 14.22 | 77.5 | 0.81 | 6.73 |
| Mean | 28.469 | 182.65 | 69.63 | 44.214 | 1.775 | 41.106 | 14.881 | 71.898 | 0.958 | 97.673 |
| 95% CI Mean Upper | 29.283 | 187.32 | 72.703 | 44.995 | 1.824 | 41.581 | 15.063 | 72.605 | 0.979 | 103.408 |
| 95% CI Mean Lower | 27.655 | 177.98 | 66.558 | 43.433 | 1.726 | 40.631 | 14.699 | 71.192 | 0.937 | 91.937 |
| Std. Deviation | 19.292 | 110.69 | 72.814 | 18.512 | 1.161 | 11.255 | 4.3 | 16.728 | 0.496 | 135.77 |
| Coefficient of variation | 0.678 | 0.606 | 1.046 | 0.419 | 0.654 | 0.274 | 0.289 | 0.233 | 0.518 | 1.39 |
| Skewness | 1.295 | 1.107 | 1.472 | 0.966 | 1.732 | 0.862 | 0.548 | -0.813 | 2.324 | 1.376 |
| Std. Error of Skewness | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 |
| Kurtosis | 0.704 | 1.338 | 1.562 | 0.902 | 3.636 | 1.197 | -0.432 | -0.512 | 7.154 | 0.772 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 7.69 | 11.25 | 3.62 | 12.24 | 0.28 | 14.19 | 7.23 | 26.4 | 0.29 | 4.52 |

| Maximum | 95.06 | 634.74 | 426.13 | 128.44 | 7.96 | 88.5 | 27.8 | 92.87 | 3.77 | 560.52 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 25th percentile | 14.768 | 98.33 | 16.285 | 30.025 | 0.97 | 33.487 | 11.51 | 60.74 | 0.64 | 6 |
| 50th percentile | 21.015 | 163.65 | 37.565 | 40.885 | 1.44 | 39.685 | 14.22 | 77.5 | 0.81 | 6.73 |
| 75th percentile | 36.21 | 239.78 | 105.23 | 53.995 | 2.18 | 46.76 | 17.65 | 85.68 | 1.11 | 172.365 |
| 95th percentile | 71.564 | 393.38 | 233.53 | 81.001 | 4.16 | 61.932 | 23.249 | 90.71 | 1.93 | 404.048 |
| | | | | | | | | | | |
| Spring 2022 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 22.81 | 106.15 | 19.93 | 39.465 | 1.01 | 34.735 | 24.885 | 54.815 | 0.89 | 16.4 |
| Mean | 34.289 | 114.03 | 42.452 | 42.304 | 1.232 | 36.583 | 25.444 | 55.05 | 0.994 | 156.623 |
| 95% CI Mean Upper | 36.202 | 117.97 | 46.188 | 43.598 | 1.288 | 37.316 | 25.865 | 56.342 | 1.027 | 170.42 |
| 95% CI Mean Lower | 32.376 | 110.1 | 38.716 | 41.01 | 1.175 | 35.85 | 25.023 | 53.758 | 0.961 | 142.827 |
| Std. Deviation | 26.583 | 54.716 | 51.91 | 17.977 | 0.782 | 10.183 | 5.847 | 17.955 | 0.456 | 191.69 |
| Coefficient of variation | 0.775 | 0.48 | 1.223 | 0.425 | 0.635 | 0.278 | 0.23 | 0.326 | 0.458 | 1.224 |
| Skewness | 1.099 | 0.714 | 2.15 | 1.206 | 2.462 | 1.97 | 0.256 | -0.037 | 1.097 | 0.841 |
| Std. Error of Skewness | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| Kurtosis | 0.468 | -0.018 | 4.588 | 2.125 | 9.336 | 7.858 | -0.34 | -1.105 | 0.984 | -0.911 |
| Std. Error of Kurtosis | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 |
| Minimum | 5.5 | 25.87 | 3.79 | 14.07 | 0.28 | 17.93 | 11.66 | 19.52 | 0.18 | 4.82 |
| Maximum | 129.29 | 282.22 | 292.72 | 131.81 | 6.62 | 110 | 40.56 | 88.18 | 2.8 | 648.18 |
| 25th percentile | 13.22 | 71.263 | 10.315 | 29.15 | 0.72 | 30.158 | 21.26 | 40.042 | 0.64 | 6.01 |
| 50th percentile | 22.81 | 106.15 | 19.93 | 39.465 | 1.01 | 34.735 | 24.885 | 54.815 | 0.89 | 16.4 |
| 75th percentile | 55.083 | 146.88 | 48.383 | 50.93 | 1.48 | 41.167 | 29.35 | 70.48 | 1.24 | 296.663 |
| 95th percentile | 82.937 | 222.73 | 158.05 | 75.791 | 2.804 | 52.097 | 35.607 | 82.944 | 1.87 | 507.707 |

| Summer 2022 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Median | 35.35 | 80.105 | 18.09 | 40.325 | 1.03 | 40.7 | 32.825 | 41.935 | 0.96 | 65.875 |
| Mean | 46.37 | 94.892 | 35.832 | 45.7 | 1.234 | 41.026 | 33.267 | 43.919 | 1.101 | 165.633 |
| 95% CI Mean Upper | 47.846 | 97.19 | 37.507 | 46.502 | 1.262 | 41.374 | 33.474 | 44.535 | 1.124 | 173.51 |
| 95% CI Mean Lower | 44.894 | 92.594 | 34.156 | 44.898 | 1.205 | 40.678 | 33.059 | 43.303 | 1.079 | 157.755 |
| Std. Deviation | 35.165 | 54.767 | 39.93 | 19.108 | 0.679 | 8.293 | 4.949 | 14.679 | 0.528 | 187.733 |
| Coefficient of variation | 0.758 | 0.577 | 1.114 | 0.418 | 0.55 | 0.202 | 0.149 | 0.334 | 0.48 | 1.133 |
| Skewness | 0.931 | 1.569 | 1.942 | 0.986 | 1.79 | 0.986 | 0.182 | 0.771 | 1.231 | 0.742 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | -0.074 | 3.389 | 3.724 | 0.637 | 3.742 | 4.543 | -0.767 | 0.298 | 2.477 | -1.001 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 4.66 | 9.5 | 3.61 | 12.85 | 0.33 | 20.1 | 22.21 | 18.89 | 0.3 | 3.7 |
| Maximum | 159.08 | 420.66 | 266.17 | 122.65 | 5.16 | 102.71 | 46.46 | 92.52 | 4.7 | 610.61 |
| 25th percentile | 16.78 | 57.345 | 9.79 | 30.74 | 0.79 | 35.88 | 29.55 | 32.73 | 0.7 | 5.98 |
| 50th percentile | 35.35 | 80.105 | 18.09 | 40.325 | 1.03 | 40.7 | 32.825 | 41.935 | 0.96 | 65.875 |
| 75th percentile | 67.095 | 119.37 | 43.462 | 57.765 | 1.45 | 45.34 | 37.103 | 52.555 | 1.42 | 319.993 |
| 95th percentile | 117.91 | 197.58 | 127.29 | 82.254 | 2.718 | 54.538 | 41.48 | 71.9 | 2.068 | 505.381 |
| | | | | | | | | | | |
| Monsoon 2022 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 33.89 | 34.495 | 12.375 | 24.82 | 0.92 | 35.245 | 28.635 | 69.12 | 0.92 | 44.65 |
| Mean | 37.001 | 39.02 | 17.612 | 26.996 | 1.005 | 35.963 | 29.016 | 68.033 | 1.06 | 138.844 |
| 95% CI Mean Upper | 37.609 | 39.861 | 18.21 | 27.376 | 1.021 | 36.21 | 29.138 | 68.564 | 1.082 | 145.702 |
| 95% CI Mean Lower | 36.393 | 38.179 | 17.015 | 26.617 | 0.989 | 35.716 | 28.894 | 67.503 | 1.039 | 131.987 |
| Std. Deviation | 14.576 | 20.146 | 14.322 | 9.094 | 0.382 | 5.917 | 2.924 | 12.71 | 0.511 | 164.315 |

| Coefficient of variation | 0.394 | 0.516 | 0.813 | 0.337 | 0.38 | 0.165 | 0.101 | 0.187 | 0.482 | 1.183 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Skewness | 1.218 | 0.978 | 2.571 | 1.195 | 1.827 | 0.833 | 0.335 | -0.184 | 1.322 | 0.919 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 2.183 | 0.69 | 9.073 | 1.659 | 4.808 | 1.932 | -0.595 | -0.957 | 1.939 | -0.556 |
| Std. Error of Kurtosis | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 |
| Minimum | 5.67 | 5.63 | 2.93 | 10.13 | 0.39 | 20.3 | 23.07 | 39.62 | 0.28 | 3.82 |
| Maximum | 108.73 | 115.85 | 118.63 | 73.34 | 3.28 | 72.1 | 37.08 | 92.53 | 3.48 | 585.78 |
| 25th percentile | 27.87 | 24.215 | 8.428 | 20.53 | 0.75 | 32.04 | 26.86 | 57.752 | 0.68 | 6.08 |
| 50th percentile | 33.89 | 34.495 | 12.375 | 24.82 | 0.92 | 35.245 | 28.635 | 69.12 | 0.92 | 44.65 |
| 75th percentile | 43.98 | 50.922 | 22.108 | 31.57 | 1.14 | 39.34 | 31.152 | 78.615 | 1.32 | 255.132 |
| 95th percentile | 65.876 | 80.826 | 45.332 | 45.087 | 1.77 | 46.392 | 34.3 | 87.177 | 2.06 | 462.435 |
| | | | | | | | | | | |
| Postmonsoon 2022 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 18.565 | 132.02 | 39.445 | 63.265 | 1.3 | 44.26 | 22.495 | 57.17 | 0.73 | 6.75 |
| Mean | 29.538 | 146.12 | 70.747 | 67.883 | 1.735 | 50.237 | 22.811 | 56.325 | 0.823 | 100.312 |
| 95% CI Mean Upper | 30.766 | 150.83 | 74.357 | 69.636 | 1.798 | 51.304 | 23.055 | 57.069 | 0.84 | 107.189 |
| 95% CI Mean Lower | 28.31 | 141.41 | 67.137 | 66.13 | 1.673 | 49.169 | 22.567 | 55.581 | 0.806 | 93.434 |
| Std. Deviation | 23.962 | 91.917 | 70.412 | 34.193 | 1.227 | 20.823 | 4.766 | 14.51 | 0.336 | 134.158 |
| Coefficient of variation | 0.811 | 0.629 | 0.995 | 0.504 | 0.707 | 0.414 | 0.209 | 0.258 | 0.409 | 1.337 |
| Skewness | 1.332 | 0.87 | 1.292 | 0.611 | 1.56 | 0.836 | 0.124 | 0.218 | 1.371 | 1.234 |
| Std. Error of Skewness | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 |
| Kurtosis | 0.762 | 1.155 | 0.877 | -0.083 | 2.453 | 0.11 | -0.509 | -0.4 | 2.037 | 0.29 |

| Std. Error of Kurtosis | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Minimum | 3.85 | 4.5 | 1.96 | 8.81 | 0.18 | 17.65 | 12.59 | 28.53 | 0.29 | 4.65 |
| Maximum | 110.39 | 588.43 | 343.09 | 208.46 | 7.54 | 132.59 | 34.24 | 93.56 | 2.56 | 516.33 |
| 25th percentile | 13.32 | 74.645 | 17.495 | 40.18 | 0.86 | 33.107 | 19.46 | 44.628 | 0.59 | 5.9 |
| 50th percentile | 18.565 | 132.02 | 39.445 | 63.265 | 1.3 | 44.26 | 22.495 | 57.17 | 0.73 | 6.75 |
| 75th percentile | 40.385 | 203.38 | 107.24 | 90.25 | 2.262 | 64.745 | 26.072 | 65.985 | 0.98 | 184.435 |
| 95th percentile | 83.146 | 309.98 | 213.86 | 132 | 4.27 | 89.542 | 31.118 | 83.217 | 1.528 | 393.454 |
| | | | | | | | | | | |
| Winter 2022-23 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 14.58 | 154.73 | 49.355 | 52.385 | 1.26 | 56.58 | 16.035 | 65.74 | 0.92 | 11.8 |
| Mean | 23.414 | 171.28 | 75.574 | 58.9 | 1.508 | 57.851 | 16.744 | 63.344 | 1.047 | 76.484 |
| 95% CI Mean Upper | 24.266 | 175.12 | 78.345 | 60.096 | 1.545 | 58.625 | 16.944 | 63.954 | 1.07 | 80.843 |
| 95% CI Mean Lower | 22.563 | 167.45 | 72.804 | 57.705 | 1.471 | 57.076 | 16.544 | 62.735 | 1.024 | 72.124 |
| Std. Deviation | 20.181 | 90.87 | 65.658 | 28.335 | 0.882 | 18.35 | 4.737 | 14.444 | 0.537 | 103.309 |
| Coefficient of variation | 0.862 | 0.531 | 0.869 | 0.481 | 0.585 | 0.317 | 0.283 | 0.228 | 0.512 | 1.351 |
| Skewness | 1.55 | 0.934 | 1.511 | 1.055 | 1.613 | 0.71 | 0.541 | -0.35 | 2.392 | 1.554 |
| Std. Error of Skewness | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 | 0.053 |
| Kurtosis | 1.767 | 1.103 | 1.642 | 0.989 | 2.652 | 1.59 | -0.307 | -0.833 | 9.462 | 1.62 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 4.08 | 21 | 4.39 | 11.82 | 0.36 | 18.26 | 7.81 | 30.97 | 0.32 | 4.25 |
| Maximum | 120.93 | 592.7 | 335.84 | 181.78 | 5.8 | 171.16 | 30.83 | 95.56 | 4.76 | 464.88 |
| 25th percentile | 9.52 | 101.94 | 29.88 | 38.43 | 0.9 | 45.825 | 13.24 | 52.23 | 0.69 | 5.39 |
| 50th percentile | 14.58 | 154.73 | 49.355 | 52.385 | 1.26 | 56.58 | 16.035 | 65.74 | 0.92 | 11.8 |

| 75th percentile | 30.72 | 227.78 | 100.43 | 73.593 | 1.81 | 67.535 | 19.86 | 75.037 | 1.23 | 126.49 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95th percentile | 67.577 | 333.68 | 225.8 | 115.64 | 3.48 | 90.337 | 25.88 | 81.411 | 1.94 | 319.61 |
| | | | | | | | | | | |
| Spring 2023 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 26.335 | 71.455 | 28.46 | 42.09 | 1.135 | 47.99 | 22.085 | 56.025 | 0.94 | 13.05 |
| Mean | 35.584 | 80.503 | 45.162 | 47.225 | 1.237 | 49.215 | 22.965 | 55.458 | 1.025 | 109.611 |
| 95% CI Mean Upper | 37.399 | 83.614 | 48.079 | 48.865 | 1.275 | 49.909 | 23.239 | 56.431 | 1.058 | 119.483 |
| 95% CI Mean Lower | 33.769 | 77.391 | 42.244 | 45.586 | 1.198 | 48.522 | 22.692 | 54.485 | 0.992 | 99.739 |
| Std. Deviation | 25.22 | 43.233 | 40.542 | 22.784 | 0.538 | 9.636 | 3.8 | 13.515 | 0.458 | 137.16 |
| Coefficient of variation | 0.709 | 0.537 | 0.898 | 0.482 | 0.435 | 0.196 | 0.165 | 0.244 | 0.447 | 1.251 |
| Skewness | 0.978 | 0.968 | 1.951 | 1.058 | 0.917 | 0.783 | 0.509 | 0.129 | 1.417 | 1.061 |
| Std. Error of Skewness | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| Kurtosis | -0.031 | 0.965 | 3.666 | 0.827 | 0.442 | 1.091 | -0.885 | -0.663 | 3.137 | -0.329 |
| Std. Error of Kurtosis | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 | 0.179 |
| Minimum | 7.83 | 12.06 | 4.05 | 11.78 | 0.4 | 28.03 | 17.1 | 30.14 | 0.36 | 4.58 |
| Maximum | 118.65 | 277.08 | 220.67 | 127.92 | 3.25 | 90.55 | 31.73 | 91.67 | 3.48 | 473.1 |
| 25th percentile | 14.998 | 46.155 | 18.902 | 29.822 | 0.83 | 42.435 | 19.775 | 43.595 | 0.68 | 8.098 |
| 50th percentile | 26.335 | 71.455 | 28.46 | 42.09 | 1.135 | 47.99 | 22.085 | 56.025 | 0.94 | 13.05 |
| 75th percentile | 52.235 | 109.38 | 55.83 | 58.947 | 1.52 | 54.457 | 26.072 | 65.68 | 1.26 | 207.718 |
| 95th percentile | 81.212 | 159.75 | 133.9 | 94.095 | 2.34 | 67.458 | 29.887 | 77.099 | 1.87 | 382.245 |
| | | | | | | | | | | |
| Summer 2023 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 28.465 | 51.92 | 23.285 | 44.55 | 1.04 | 38.095 | 31.55 | 49.09 | 1.03 | 39.63 |
| Mean | 37.186 | 66.906 | 38.542 | 50.574 | 1.169 | 39.309 | 31.506 | 51.951 | 1.13 | 129.804 |

| 95% CI Mean Upper | 38.324 | 68.768 | 40.215 | 51.627 | 1.194 | 39.687 | 31.725 | 52.646 | 1.151 | 136.233 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| 95% CI Mean Lower | 36.048 | 65.045 | 36.869 | 49.521 | 1.145 | 38.932 | 31.287 | 51.255 | 1.109 | 123.376 |
| Std. Deviation | 27.126 | 44.33 | 39.869 | 25.096 | 0.588 | 8.999 | 5.219 | 16.569 | 0.498 | 153.165 |
| Coefficient of variation | 0.729 | 0.663 | 1.034 | 0.496 | 0.503 | 0.229 | 0.166 | 0.319 | 0.441 | 1.18 |
| Skewness | 1.051 | 1.867 | 2.232 | 1.43 | 2.088 | 0.698 | -0.145 | 0.52 | 1.026 | 0.955 |
| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 |
| Kurtosis | 0.34 | 4.989 | 5.284 | 2.586 | 7.093 | 0.574 | -0.254 | -0.562 | 1.032 | -0.532 |
| Std. Error of Kurtosis | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 | 0.105 |
| Minimum | 5.07 | 8.75 | 2.32 | 9.09 | 0.34 | 17.41 | 17.51 | 23.1 | 0.31 | 4.54 |
| Maximum | 143.57 | 431.5 | 250.72 | 181.65 | 5.56 | 76.55 | 44.21 | 95.71 | 3.23 | 534.78 |
| 25th percentile | 15.607 | 37.632 | 14.027 | 32.608 | 0.77 | 32.95 | 28.15 | 39.38 | 0.75 | 8.14 |
| 50th percentile | 28.465 | 51.92 | 23.285 | 44.55 | 1.04 | 38.095 | 31.55 | 49.09 | 1.03 | 39.63 |
| 75th percentile | 54.078 | 82.645 | 45.16 | 61.455 | 1.363 | 44.412 | 35.105 | 63.775 | 1.41 | 239.16 |
| 95th percentile | 91.992 | 157.36 | 130.64 | 101.22 | 2.308 | 56.562 | 40.039 | 83.166 | 2.09 | 440.291 |
| | | | | | | | | | | |
| Monsoon 2023 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 26.69 | 40.455 | 15.02 | 30.6 | 0.83 | 37.92 | 31.34 | 69.15 | 0.96 | 249.355 |
| Mean | 29.573 | 41.97 | 19.156 | 32.763 | 0.884 | 43.318 | 31.633 | 69.149 | 1.034 | 237.967 |
| 95% CI Mean Upper | 30.126 | 42.655 | 19.717 | 33.297 | 0.897 | 44.069 | 31.751 | 69.681 | 1.052 | 245.355 |
| 95% CI Mean Lower | 29.021 | 41.286 | 18.594 | 32.23 | 0.871 | 42.566 | 31.514 | 68.618 | 1.015 | 230.579 |
| Std. Deviation | 13.242 | 16.401 | 13.452 | 12.784 | 0.317 | 17.999 | 2.726 | 12.641 | 0.442 | 170.323 |
| Coefficient of variation | 0.448 | 0.391 | 0.702 | 0.39 | 0.358 | 0.416 | 0.086 | 0.183 | 0.427 | 0.716 |
| Skewness | 1.502 | 0.512 | 2.229 | 1.134 | 1.196 | 1.957 | 0.257 | -0.035 | 0.738 | 0.367 |

| Std. Error of Skewness | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.052 | 0.054 | 0.052 | 0.052 | 0.054 |
|---------------------------|--------|--------|--------|--------|-------|--------|--------|--------|-------|---------|
| Kurtosis | 3.172 | 0.376 | 7.297 | 2.009 | 2.738 | 4.857 | -0.59 | -0.511 | -0 | -0.462 |
| Std. Error of Kurtosis | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 | 0.108 | 0.105 | 0.104 | 0.108 |
| Minimum | 5.69 | 6.75 | 3.34 | 9.48 | 0.2 | 16.88 | 22.11 | 32.41 | 0.06 | 5.35 |
| Maximum | 101.38 | 111.88 | 124.82 | 100.34 | 2.93 | 149.99 | 38.7 | 99.72 | 2.74 | 703.86 |
| 25th percentile | 20.265 | 30.53 | 9.988 | 23.205 | 0.66 | 31.852 | 29.56 | 60.245 | 0.68 | 72.788 |
| 50th percentile | 26.69 | 40.455 | 15.02 | 30.6 | 0.83 | 37.92 | 31.34 | 69.15 | 0.96 | 249.355 |
| 75th percentile | 35.282 | 52.468 | 23.76 | 39.625 | 1.042 | 49.16 | 33.593 | 78.002 | 1.3 | 330.61 |
| 95th percentile | 55.099 | 71.491 | 44.779 | 56.967 | 1.447 | 82.406 | 36.47 | 90.076 | 1.917 | 560.706 |
| | | | | | | | | | | |
| Postmonsoon 2023 | Ozone | PM25 | NO | NO2 | CO | NH3 | AT | RH | WS | SR |
| Median | 18.585 | 163.44 | 36.515 | 56.475 | 1.54 | 46.75 | 23.765 | 60.465 | 0.58 | 257.11 |
| Mean | 27.263 | 180.62 | 64.948 | 68.03 | 1.922 | 50.45 | 24.254 | 60.171 | 0.653 | 298.655 |
| 95% CI Mean Upper | 28.369 | 186.29 | 68.21 | 70.021 | 1.985 | 51.532 | 24.532 | 60.845 | 0.669 | 305.315 |
| 95% CI Mean Lower | 26.157 | 174.96 | 61.686 | 66.038 | 1.859 | 49.368 | 23.977 | 59.497 | 0.637 | 291.995 |
| Std. Deviation | 21.575 | 110.41 | 63.624 | 38.844 | 1.23 | 21.101 | 5.419 | 13.148 | 0.308 | 129.909 |
| Coefficient of variation | 0.791 | 0.611 | 0.98 | 0.571 | 0.64 | 0.418 | 0.223 | 0.219 | 0.471 | 0.435 |
| Skewness | 1.315 | 0.646 | 1.214 | 0.877 | 1.173 | 0.988 | 0.067 | -0.098 | 2.103 | 0.058 |
| Std. Error of Skewness | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 | 0.064 |
| Kurtosis | 1.133 | -0.279 | 0.484 | 0.172 | 0.757 | 1.023 | -0.68 | -1.032 | 9.394 | 0.751 |
| Std. Error of Kurtosis | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 | 0.128 |
| Minimum | 4.74 | 16.4 | 4.85 | 10.9 | 0.46 | 16.84 | 13.06 | 34.33 | 0.19 | 7.97 |

| Maximum | 127.15 | 591.63 | 281.09 | 216.38 | 6.39 | 136.91 | 36.3 | 86.35 | 3.28 | 639.88 |
|-----------------|--------|--------|--------|--------|-------|--------|--------|--------|------|---------|
| 25th percentile | 10.995 | 84.795 | 15.638 | 37.258 | 0.987 | 35.43 | 20.76 | 49.318 | 0.45 | 253.207 |
| 50th percentile | 18.585 | 163.44 | 36.515 | 56.475 | 1.54 | 46.75 | 23.765 | 60.465 | 0.58 | 257.11 |
| 75th percentile | 38.365 | 256.59 | 100.87 | 94.16 | 2.56 | 61.72 | 28.262 | 70.747 | 0.79 | 348.027 |
| 95th percentile | 72.139 | 381.98 | 201.8 | 141.42 | 4.46 | 93.535 | 33.627 | 80.716 | 1.19 | 560.282 |