OULUN AMMATTIKORKEAKOULU

Ahmed, Ould Boudia

COVID-19 LOCKDOWN EFFECTS ON AIR QUALITY: CASE STUDY OULU AND HELSINKI VS. SARS-COV2 HOTSPOTS

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Ahmed, Ould Boudia
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ABSTRACT

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In response to the global COVID-19 pandemic, nations implemented lockdown measures to contain the virus. This study assessed air pollution levels during and after lockdowns, focusing on heavily affected locations: Oulu and Helsinki in Finland, Paris in France, Madrid in Spain, Milan in Italy, and Wuhan in China. Air Quality Index (AQI) data from these areas over two years were analyzed to understand lockdown effects. COVID-19 lockdowns in six cities were compared with SARS-CoV-2 measures using statistical methods. Pollutant variations were evaluated via tests, showing significant differences. Parametric analyses and regression studied lockdown impacts on pollution and relationships. The study comprehensively analyzed COVID-19 lockdowns' effects on air quality, identifying differences, quantifying changes, and exploring patterns in Oulu and Helsinki. Pollutant correlations varied among cities during lockdowns. Regression analysis highlighted independent variables' impact on pollutants. Decreases in NO_2 were seen in Helsinki, Madrid, Oulu, Paris, and Milan, reflecting reduced traffic and industry. PM2.5 and PM10 reductions occurred in these cities and also Wuhan, except for O_3 levels which increased. Reduced human activities improved air quality, especially for NO_2 and PM10. Regional variations necessitate tailored interventions. The study emphasizes addressing urban PM2.5 and NO_2 pollution influenced by transportation and industry. COVID-19 lockdowns significantly reduced pollution, highlighting environmental measures for better air quality.

Keywords: lockdown, air pollution levels, air quality, pollutants, policy, pandemic-related lockdown measures, COVID-19 pandemic, reduction, environmental interventions.

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Maailmanlaajuisen COVID-19-pandemian vuoksi maat toteuttivat lukitustoimenpiteitä viruksen taltuttamiseksi. Tämä tutkimus arvioi ilmansaasteiden tasoa lukitusten aikana ja niiden jälkeen keskittymällä voimakkaasti vaikuttuneisiin paikkoihin: Oulu ja Helsinki Suomessa, Pariisi Ranskassa, Madrid Espanjassa, Milano Italiassa ja Wuhan Kiinassa. Ilmanlaadun indeksi (AQI) -tiedot näiltä alueilta kahden vuoden ajalta analysoitiin ymmärtääksemme lukitustoimien vaikutuksia. COVID-19-lukitustoimia kuutta kaupunkia verrattiin SARS-CoV-2-toimenpiteisiin tilastollisin menetelmin. Saasteiden vaihteluja arvioitiin testien avulla, mikä osoitti merkittäviä eroja. Parametriset analyysit ja regressio tutkivat lukitusten vaikutuksia saasteisiin ja suhteisiin. Tutkimus analysoi perusteellisesti COVID-19-lukitusten vaikutuksia ilmanlaatuun, tunnistaen eroja, kvantifioiden muutoksia ja tutkien kuvioita Oulussa ja Helsingissä. Saasteiden korrelaatiot vaihtelivat kaupunkien välillä lukitusten aikana. Regressioanalyysi korosti itsenäisten muuttujien vaikutusta saasteisiin. NO_2:n väheneminen nähtiin Helsingissä, Madridissa, Oulussa, Pariisissa ja Milanossa, heijastaen liikenteen ja teollisuuden vähentämistä. PM2.5- ja PM10-vähennykset tapahtuivat näissä kaupungeissa ja myös Wuhania lukuun ottamatta O_3-tasot, jotka kasvoivat. Vähentyneet ihmistoiminnot paransivat ilmanlaatua, erityisesti NO_2:n ja PM10:n osalta. Alueelliset vaihtelut edellyttävät räätälöityjä toimenpiteitä. Tutkimus korostaa kaupunkien PM2.5- ja NO_2-saasteiden käsittelyn tärkeyttä, joita liikenne ja teollisuus vaikuttavat. COVID-19-lukitukset vähensivät merkittävästi saasteita, korostaen ympäristötoimia paremman ilmanlaadun saavuttamiseksi.

Avainsanat: liikkumisrajoitus, ilmansaasteiden tasot, ilmanlaatu, epäpuhtaudet, politiikka, pandemiaan liittyvät liikkumisrajoitustoimet, COVID-19-pandemia, vähentäminen, ympäristötoimenpiteet.

CONTENTS

VOCABULARY

ANOVA Analysis of Variance

AQI Air Quality Index.

AQM Air Quality Monitoring.

BL Before Lockdown

CO carbon monoxide.

CO_2 Carbon Dioxide.

COPD Chronic Obstructive Pulmonary Disease.

COVID-19 Coronavirus-ID 19.

DL During Lockdown

EPA Environmental Protection Agency.

FEF forced expiratory flow.

FEF25-75 Forced Expiratory Flow 25–75%

FEV Forced Expiratory Volume in 1 second

FVC Forced Vital Capacity

FVC vital capacity.

HSD Honestly Significant Difference

LTE: Long-Term Exposure

MSB Mean Square Between groups,

MSW Mean Square Within groups.

NO_2 nitric oxide.

O_3 Ozone.

OLS Ordinary Least Squares regression

PAHs Polycyclic Aromatic Hydrocarbons

PCC Pearson correlation coefficient

PM2.5 and PM10 Particulate Matter.

SO_2 Sulfur Dioxide.

Tukey's HSD Tukey's Honestly Significant Difference test.

UTC Coordinated Universal Time.

VOCs Volatile Organic Compounds

VOC_s Volatile Organic Compounds.

WHO World Health Organization.

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

As a general term, lockdown can mean anything from non-mandatory recommendations to stay at home, to geographical quarantines, to closures of businesses and organizations. Lockdowns have increased in many countries because of earlier restrictions. The success of Wuhan's lock-down scheme led several other countries to adopt similar measures. The possibility of transmission in this case discourages many customers from using public mobility systems. As a result of the decline mentioned above, the public transportation system is usually the most adversely affected [99].

Moreover, the Air Quality Index "AQI" evaluates the present extent of air contamination while also presenting immediate and enduring health consequences. Criteria for air quality are fundamental and a promise for overseeing the quality of surrounding air, aimed at guaranteeing the security of the environment, fostering balanced progress, and protecting the well-being of humanity, society, and the natural world [75].

Due to the outbreak of the Coronavirus pandemic, worldwide public mobility has been severely impacted, improving air quality unexpectedly. The state of the environment, such as the issue of air pollution, wields a significant impact on the general well-being and contentment of individuals worldwide. Multiple detrimental substances play a role in giving rise to unfavourable health effects. These elements encompass carbon monoxide (CO), ozone (O_3), nitric oxide (NO_2), particulate matter (PM2.5 and PM10), as well as volatile organic compounds (VOCs) - chemicals emitted by vehicles and indoor pollutants [66].

Particulate matters, such as PM2.5, emerge from both natural phenomena and human actions. Take the act of burning liquids and solids, for instance – it lets out soot, which adds to the accumulation of PM2.5. Conversely, ozone takes shape via intricate and roundabout chemical interactions involving CO and NOx. Its existence hinges greatly on the prevailing weather conditions [17].

Throughout the pandemic, there was a decrease in human actions and movement, leading to better air quality. This highlighted that our human activities carry an adverse effect on the environment. It remains crucial for us to take steps to lessen air pollution, securing a thriving and lasting environment for the generations to come [75].

Researchers have estimated that there is an increased risk of importation of COVID-19 cases from infected areas in China through air travel to Europe [93]. Moreover, it has been demonstrated that air pollution can act as a carrier of the Coronavirus, allowing it to spread along with the air associated risk factors that contribute to disease development in elderly individuals [15], smokers, hypertension, heart disease, chronic lung disease, and moderate to severe asthmatics [21], as well as people with chronic lung disease.

There have been lockdowns in many countries due to COVID-19, which have positively impacted air quality. AQ has improved due to reduced human activities, transportation, and industries. However, the increased dependence on fossil fuels to keep ourselves warm and cook our meals carries the potential of causing a surge in air pollution levels. This research will specifically concentrate on investigating how lockdown measures impact the Air Quality Index (AQI) and the subsequent repercussions it has on the health and overall welfare of both individuals and the natural surroundings.

The intended research thesis aims to investigate how the restrictions imposed due to the pandemic affected the air quality in Oulu and Helsinki in the spring of 2020. The main emphasis will be on evaluating the concentrations of distinct pollutants, namely PM2.5, PM10, O_3, and NO_2. Additionally, the study will include a comparative examination that incorporates urban areas like Madrid, Paris, Milan, and Wuhan. The goal is to identify possible connections between the virus's transmission and pollution levels.

The methodology employed for this research involves a comprehensive, multi-step approach. It encompasses the collection and subsequent analysis of air quality data. Furthermore, air quality modelling will be utilized to enhance the depth of understanding. The statistical framework will include inferential methods like ANOVA, the Kruskal-Wallis Test, and Tukey's HSD test. Additionally, advanced techniques such as regression analysis and time series analysis will be applied to gauge the influence of lockdown measures on pollution patterns.

The anticipated outcomes of this study are expected to yield valuable insights into the intricate interplay between pandemic-related restrictions and air quality. The knowledge generated could serve as a foundation for informed decision-making in future policy formulation and implementation.

2 TOXICOLOGY OF AIR POLLUTION

Air pollutants refer to any substances present in the atmosphere that can negatively impact human health and the environment. The World Health Organization acknowledges six main air pollutants PM2.5, PM10, O_3, CO, NO_2, and SO_2. These pollutants carry substantial dangers for the health and balance of both humans and the environment. Particulate matter, encompassing elements like dust, fumes, smoke, mists, as well as gaseous contaminants like hydrocarbons, PAHs (polycyclic aromatic hydrocarbons as seen in FIGURE 1), and VOCs (volatile organic compounds), which are substances temporarily suspended or spread within the air, along with halogen derivatives, constitute a range of pollutants present in the atmosphere. When present at high concentrations, these pollutants can lead to various diseases, including different types of cancers. Below, I provide a brief overview of the most important air pollutants and their harmful effects on different organs of the human body, as well as the associated diseases [20],[76].

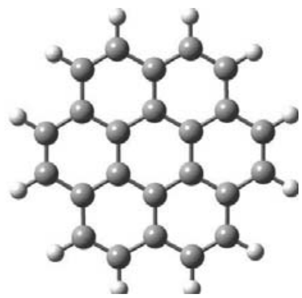


FIGURE 1: PAHs chemical structure [59]

2.1 Pollutant Definition and Sources

2.1.1 Particulate matter (PM2.5, PM10)

Particulate matter PM2.5 and PM10, which are significant air pollutants, are directly emitted and consist of carbonaceous particles combined with reactive metals and adsorbed organic compounds. PM consists mainly of SO_4^{-2} sulfates, NO_3^- nitrates, PAHs, and heavy metals (iron Fe, nickel Ni, copper Cu, zinc Zn, and vanadium V). It is categorized into three groups based on particle size (FIGURE 2): coarse particles (PM10) with a diameter smaller than 10μm, small particles (PM2.5) with a $\emptyset \leq$ 2.5μm, and ultrafine particles (PM10) with a $\emptyset \leq$ 0.1μm. Inhaling PM is particularly worrisome as it can have significant negative effects on the heart and lungs. Indoor levels of PM often exceed outdoor levels due to the migration of outdoor particles indoors and the generation of particles through indoor activities [55],[106].

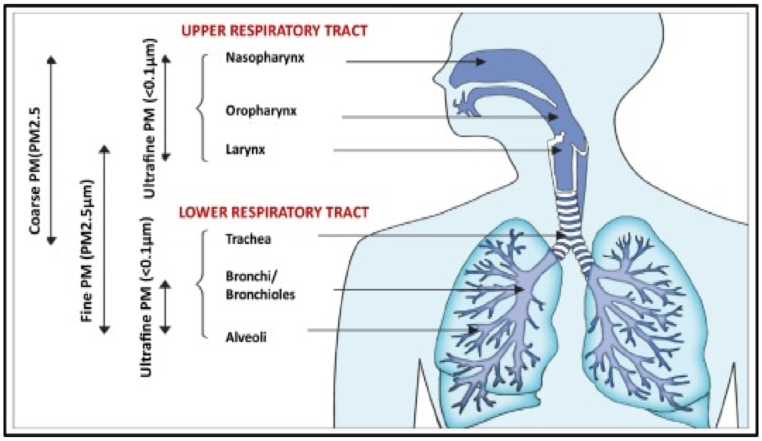


FIGURE 2: Deposition of particulate matter across various size fractions in different compartments of the respiratory tract [126]

Fine particles, particularly PM2.5, present a significant environmental health hazard because of their capacity to infiltrate the innermost regions of the lungs. Conversely, larger particles are unable to access the lower respiratory system, thus they do not induce any health consequences. Airborne particulate matter sized between 0.65 to 1.1µm has the capability to enter and inflict harm within the lung alveolar regions [81],[112].

PM, emitted by various sources such as vehicles, residential areas, energy production, industrial activities, and dust, is a significant pollutant [54]. It has detrimental effects on respiratory health (Figure 02), contributing to respiratory infections, lung diseases, and weakened immune systems [67]. Of particular concern is PM2.5, which has the ability to easily enter the respiratory system and has a higher likelihood of depositing in the lungs [71].

2.1.2 Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Ozone (O_3), Carbon Monoxide (CO), and Carbon Dioxide (CO_2)

Ozone (O_3) is a commonly occurring oxidant gas in urban air, and exposure to it can induce oxidative stress, leading to inflammation of the airways and increased respiratory problems [1]. The concentration of surface ozone is affected by various factors such as the quantity and ratio of precursor gas emissions (NO_x and VOCs), photochemical reactions, atmospheric conditions (weather), and removal processes at the Earth's surface. Therefore, local, regional, and seasonal factors contribute to determining ozone levels. In most regions, reducing NO_x emissions results in a decline in ozone levels. However, in urban zone with heavy traffic and high NO_x emissions, initially, ozone levels may increase in response to declining NOx emissions. Nevertheless, once the urban plume is transported to rural areas, ozone concentrations eventually decrease [29].

Ensuring pure and secure air is vital for the thriving of all life forms. Nonetheless, human actions play a notable role in the pollution of the surrounding air, discharging detrimental substances at elevated levels that jeopardize the well-being of humans [48]. Factors such as economic development, urbanization, energy consumption, transportation, motorization, and the rapid growth of urban populations are the primary causes of air pollution [64]. In our daily lives, the most common air pollutants I encounter include PM, SO_2, NO_2, O_3, CO, and CO_2 [22]. NO2, a notable element of air pollution in urban areas, acts as a precursor to lower-level ozone, particulate matter, and acidic rainfall [12]. The leading source of NO2 in the air arises from the combustion of fossil fuels, encompassing coal, oil, and gas. As outlined by Muhammad et al. [82], NO_2, a pollutant with a high reactivity, is mainly released through the combustion of fossil fuels, with transportation playing a significant role in contributing to NO_2 emissions.

NO & NO_2 are two primary nitrogen oxides generated by combustion sources such as stoves and heaters [61]. The concentrations of ambient NO and NO_2 can vary significantly depending on regional sources and sinks. Indoors, their levels are typically half as concentrated as compared to outdoors. However, when gas stoves and heaters are in use, indoor levels often exceed outdoor levels. NO_2 is considered a major pollutant as it is rapidly formed when NO is exposed to ambient conditions. The reaction between NO_2 and water produces nitrous acid (HONO), which is a potent oxidant and commonly found as a contaminant in indoor environments [117]. Studies have demonstrated that the spacing between buildings and traffic lanes has a significant impact on indoor NO_2 levels [13]. Additionally, the airflow between the outside and inside of buildings affects indoor NO_2 levels [100]. Smoking and the use of wood, gas, oil, coal, or kerosene-burning appliances such as stoves, space heaters, ovens, and water heaters are also notable indoor sources of NO_2 [117].

2.2 Air Pollution and its Effects on Health

During 2018, a noteworthy rise of 71% occurred in the mortality rate attributed to chronic diseases among individuals aged 30 to 70 worldwide, as detailed in reference [116]. According to the World

Health Organization's calculations, around 3.23 million lives were expected to be claimed by chronic obstructive pulmonary disease (COPD) around the world in 2019. This ailment has now risen to become the third leading contributor to loss of life [117]. COPD, or chronic obstructive pulmonary disease, is a condition without a cure, marked by restricted airflow within the lungs, affecting individuals' ability to breathe freely.

This projection positioned COPD as the third major cause of death. COPD, which stands for chronic obstructive pulmonary disease, is an irreversible condition marked by constrained airflow in the lungs. Nonetheless, appropriate treatment can mitigate symptoms, decrease mortality risk, and enhance quality of life, as detailed in reference [81]. While smoking stands as the primary risk factor, alternative contributors encompass indoor and outdoor air pollution, along with exposure to chemicals in the workplace, as mentioned in references [31],[87], [63].

In the past few years, there has been an increasing body of research that has been looking into the ways in which pollution in our environment impacts our health. This is particularly relevant when I consider illnesses such as asthma, COPD lung disease, and heart conditions. This research has looked at the links between pollution and these health issues, and some studies are referenced [32],[80],[90]. Environmental Pollution comes from various sources, including things people do (like industry and transportation) and natural processes [38]. The WHO has established GAQ guidelines that classify air pollutants into categories such as particulate matter (PM, O_3, NO_2, andSO_2) [116]. Particulate matter (PM2.5) has been identified as a significant cause of premature death and health issues in Europe, as reported by the European Environment Agency [38]. Numerous studies conducted in Italy in recent years have examined the consort between air pollution levels and hospital admissions for various diseases [44],[93]. These studies have demonstrated that both LTE “long-term” and STE “short-term” Exposure to air pollutants, even at low levels, can increase the risk of hospital admissions for respiratory diseases, with a higher susceptibility observed among older individuals, those with lower incomes, smokers, and individuals working in unhealthy conditions. Peaks in particulate contamination levels have been found to align with spikes in hospitalizations [28],[89],[91], and changes in PM2.5 concentrations directly impact lung function measures such as FEV1, FVC, and FEF25-75. Furthermore, long-term exposure to low-level air pollution, even below the current EU or US limit values, has been linked to the development of COPD. Various analytical methods have also revealed a correlation between peaks in contamination levels and an increase in hospitalization rates over a short time period [21],[55],[93],[101],[106],[121].

2.3 Air Pollution and Its Impact on Human Health

Breathing in safe air is crucial, for the survival of all living beings. Air pollution poses a danger to wellbeing. As per a report by the World Health Organization (WHO) in 2005 7 million individuals lose their lives annually due, to air pollution. In 2016 outdoor air pollution in the form of particulate matter known as PM2.5 caused around 4.2 million deaths worldwide. This issue impacts both rural areas [116]. Furthermore, in that year an alarming 91% of the population resided in regions where air quality exceeded the guidelines set by WHO.

Air pollution has a range of impacts, on wellbeing. These include issues like difficulty in breathing, coughing, worsening of conditions such as asthma and emphysema. Additionally, it is an environmental risk factor that can lead to diseases like lung cancer, ventricular hypertrophy, Alzheimer and Parkinson diseases. It can also contribute to complications, autism, retinopathy, growth problems, in infants and low birth weight [34],[52]. Considerable attention has been directed toward PM, especially PM2.5, in studies related to outdoor air pollution. This heightened focus arises from its ability to penetrate lung tissue, thereby causing both localized and broader physiological impacts [85]. The primary pollutants that significantly impact human health include PM2.5, PM10, SO_2, NO_x, O_3, and CO [50]. These harmful substances have a dual impact. Not do they pose threats, to health but they also have a major impact on global warming by intensifying the greenhouse effect. Consequently, this leads to harm, in ecosystems. As an example, take NO_2, which has a global warming potential 298 times greater than that of CO2 [39]. SO_2 and NO_2 also negatively affect global crop production. Therefore, assessing and monitoring air quality (AQA&M) is crucial for human health, crops, forests, various animals and insects, and climate [5],[53],[71],[73],[97].

Numerous studies have been conducted to explore different aspects of air pollution, including estimation/assessment of pollution parameters, monitoring of pollution parameters, and information dissemination. However, these studies are often scattered across different domains and lack synchronization, making it challenging to gather comprehensive literature on all aspects in one place [123]. Despite the need for such a systematic review, it is currently lacking.

The existing literature on air pollution and its effects is not harmonized to facilitate collaborative research among various stakeholders, including academicians, field researchers, policymakers, space application scientists, geo-informatics professionals, data scientists, and computer technocrats. This collaboration is essential in formulating effective policies for AQA and management, considering that air quality has become a global concern resulting in millions of deaths. Furthermore, collaborations among these stakeholders can aid in the development of an intense network of air quality monitoring (AQM) sensors/systems that integrate space-based inputs, advanced statistics, computer technologies, and internet facilities (IoT devices). The primary role of an AQM network is to collect pollutant concentration data and provide information to the public, scientists, planners, policymakers, and health departments for decision-making and improving air quality/environmental conditions [62]. Integrating technologies such as remote sensing, geographic information systems (GIS), computer technologies, and smart sensor systems with expert opinions can facilitate AQ assessment and management. This coupled framework should encompass pollution measurement (using wet chemistry or digital sensors), modelling and prediction (statistics), and dissemination using technological advancements.

2.4 The Effects of COVID-19 Lockdown on Air Quality

The impact of COVID-19 lockdown measures on air quality has become a recent focus of research studies [51]. Kerimray et al. [65] examined the effects of the lockdown in Almaty, Kazakhstan, from March 19 to April 14, 2020, on air pollutant concentrations. They compared daily levels of PM2.5, NO_2, SO_2, CO, and O_3 before and DL. The study found a 21% reduction in PM2.5 concentration DL. Additionally, there were significant decreases in CO and NO_2 concentrations by 49% and 35%, respectively, but an increase in O_3 levels by 15% compared to the 17 days prior to the lockdown. Otmani et al. [88] assessed the changes in air pollutant levels (PM10, NO_2, and SO_2) in Salé city, Morocco, DL measures. The results showed a difference of 75%, 49%, and 96% in PM10, SO_2, and NO_2 concentrations, respectively, between the pre-lockdown and lockdown periods.

Hashim et al. [58] analyzed the concentrations of four criteria pollutants (NO_2, O_3, PM2.5, and PM10) in Baghdad BL from January 16 to February 29, 2020, and during four periods of partial and total lockdown from March 1 to July 24, 2020. Li et al. [70] aimed to quantify the impact of these measures on outdoor air pollution levels. Donzelli et al. [33] assessed the effect of reduced emissions DL period on air quality in three Italian cities. Fu et al. [43] demonstrated that the reduction in primary pollutants, particularly NO_2, was mainly due to lockdown policies. Huang et al. [60] evaluated the effect of the COVID-19 lockdown on roadside and ambient air quality in Hong Kong, China. Putaud et al. [94] compared observations from Ispra and Milan in northern Italy to determine the specific impact of lockdown measures on air quality. Garg et al. [46] analyzed data on major air pollutants in Punjab before and DL. Munir et al. [83] assessed the performance of air quality monitoring stations in Reading, Berkshire, UK. Faridi et al. [41] conducted a systematic review of studies investigating the impact of COVID-19 on ambient air pollution worldwide. Akan et al. [3], analyzed how air pollution levels changed in countries implementing lockdown measures to combat the COVID-19 pandemic.

3 EXPERIMENTAL METHODS

3.1 Study area and periods

Due to challenges in accessing comprehensive data for all cities in Finland and the difficulties in obtaining data from the authorities, this study focused specifically on Oulu and Helsinki. This study compared ambient concentrations of four criteria air pollutants before, during, and after the implementation of COVID-19 lockdown control measures enforced by the Finnish government.

For the purpose of comparison, the **BL** (Before Lockdown) before pandemic period was defined as June 1st, 2019, to December 31st, 2019. The period associated with the COVID-19 lockdown is **DL (**During Lockdown) spanned from January 1st, 2020, to July 31st, 2020.

A COVID-19 lockdown was implemented in Oulu, Finland, around mid-March 2020. Lockdowns usually end in May or June of 2020, though the exact date may vary. Similar lockdown measures were implemented in Helsinki from mid-March to mid-June.

Paris, France, was under lockdown from March 17, 2020 to May 11, 2020. In Madrid, Spain, the lockdown started on March 14, 2020, and continued until June 21, 2020. Milan, Italy, experienced lockdown measures from March 9, 2020, to May 4, 2020. Wuhan, China, which was the initial epicenter of the COVID-19 outbreak, underwent a strict lockdown from January 23, 2020, until April 8, 2020.

3.2 Collection Data

This study used data from the Global Air Quality Index Project, a non-profit organization established in 2007 to raise public awareness of air pollution and provide comprehensive information on global air quality. bottom. The dataset used in this study contains 5 contaminants. Meteorological data such as PM2.5, PM10, NO_2, O_3, wind speed, temperature, pressure, dew point and humidity. The dataset contains information about the minimum, maximum, median, and standard deviation values for each air pollutant type. According to the AQICN (China Air Quality Index) website, the median and standard deviation calculations for all air pollutant types are based on a specific number of samples transformed according to US EPA standards. increase. gain. The data provided in the dataset are based on UTC and the count column indicates the number of samples used to calculate the median and standard deviation values (http://www.aqicn.org). To ensure data quality, a data cleansing process was performed focusing on the contaminants PM2.5, PM10, NO_2, and O_3. The analysis and results of this study are mainly related to these pollutants in the cities of Oulu, Helsinki, Paris, Madrid, Milan and Wuhan.

3.3 Statistical Analyses

To compare COVID-19 lockdown procedures in Oulu, Helsinki, Paris, Madrid, Milan and Wuhan with those of SARS-CoV-2, I used both “non-parametric” and “parametric” methods.
I used Kruskal-Wallis and Tukey's HSD tests to assess variations in pollutant concentrations. By comparing pollutant levels among different locations, I were able to identify significant differences between them.
In addition, I employed parametric analyses such as two-way ANOVA to investigate the effects of lockdown measures on pollution levels. This analysis helped us evaluate the importance of differences in pollutant concentrations based on cities and time periods.
To further examine the percentage change in pollutant concentrations, I employed regression analysis. This parametric method allowed us to model the relationship between lockdown measures and pollutant concentrations, providing insights into the extent of the impact.
Furthermore, I used time series analysis to study temporal patterns of pollutant concentrations DL period. This analysis enabled us to identify any emerging trends or patterns.
To visualize the spatial distribution of pollutants, I utilized spatial analysis techniques. These methods helped us understand how pollution levels varied across different areas within Oulu and Helsinki, as well as in the areas most affected by SARS-CoV-2.
By employing a combination of non-parametric and parametric methods, our study aimed to comprehensively analyze the impact of COVID-19 lockdown procedures on air quality in Oulu and Helsinki. These analyses permitted us to identify significant differences, quantify the extent of change, and explore spatial and temporal patterns, contributing to a more robust evaluation of the effects of the lockdown measures on air quality in these regions.

3.3.1 Analysis of the Pollutant Concentration Variations:

This section focuses on the analysis of variability in contaminant concentrations. Examine changes and fluctuations in pollutant levels over time with the goal of identifying patterns and trends.

Let $\boldsymbol{Y_{ij}}$ be the contaminant concentration i at the time of measurement. The analysis of concentrates on specific pollutants during a designated time frame. The average of the values is computed as follows in equation ① and ② [131]:

$$\bar{Y}_i = \frac{1}{n}\sum_{j=1}^{n} Y_{ij} \dots\dots\dots\dots\dots ①$$

$$\delta_i = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(Y_{ij} - \bar{Y}_i\right)^2} \dots\dots\dots\dots\dots ②$$

Where:

$\boldsymbol{\bar{Y}_i}$ (mean), $\boldsymbol{Y_{ij}}$ represents the of $\boldsymbol{i}$ pollutant concentration at the $\boldsymbol{j}$ measurement, and $\boldsymbol{\delta_i}$ (median), $\boldsymbol{n}$ is the number of measurements for each pollutant.

3.3.2 Pollutant Concentration

The pollutants concentration is calculated according to $\boldsymbol{\bar{Y}_i}$. It provides information about the levels of pollutants present in the air, indicating the extent of pollution in the studied areas [131]. The calculation is given by equation ③:

$$\bar{Y}_i = \frac{1}{n_{ij}}\sum_{k=1}^{n_{ij}} Y_{ijk} \dots\dots\dots\dots\dots ③$$

Where:

$\boldsymbol{\bar{Y}_{ij}}$ represents the mean of measurement value of pollutant $\boldsymbol{i}$ in city $\boldsymbol{j}$.

$\boldsymbol{n_{ij}}$ is the number of measurements for pollutant $\boldsymbol{i}$ in city $\boldsymbol{j}$.

$\boldsymbol{Y_{ijk}}$ represents the concentration of the $\boldsymbol{k}$ measurement of pollutant $\boldsymbol{i}$ in city $\boldsymbol{j}$.

The method calculates these mean measurement values for each city and pollutant before and DL period.

3.3.3 Reductions in Pollutant Concentration Observed

This subsection highlights the reductions observed in pollutant concentrations. It emphasizes any decreases or changes in pollutant levels, which may indicate the effectiveness of pollution reduction measures or other factors influencing air quality [129]. The reduction is quantified by equation ④:

$$R_{ij} = \overline{Y_{\iota b}} - \overline{Y_{\iota d}} \dots \dots \dots \dots \dots ④$$

Where:

R_{ij} represents the reduction in mean concentration of pollutant i in city j.

$\overline{Y_{\iota b}}$ is the mean concentration of pollutant i in city j.

$\overline{Y_{\iota d}}$ is the represents the reduction in mean concentration of pollutant i in city j.

3.3.4 Average of Concentration of Pollutants by City and Period

I examine the average pollutant concentrations across different cities and time periods. It aims to compare and analyze the fluctuations in pollutant levels among various locations and timeframes [128]. The average of concentration is computed using equation ⑤:

$$\mu = \frac{\sum \overline{Y}_{ij}}{n_{ij}} \dots \dots \dots \dots \dots ⑤$$

Where:

μ Average of concentration

$\sum \overline{Y}_{ij}$ represents the mean of measurement value of pollutant i in city j.

n_{ij} is the number of measurements for pollutant i in city j.

The average concentration is determined by dividing the sum of mean concentrations by the number of mean concentrations. This equation is used to calculate the average pollutant concentration for each city and measurement taken during both the pre-lockdown and lockdown periods.

3.3.5 Examination of Changes in Pollutant Concentrations BL and DL

This section examines pollutant concentration variations in BL and DL periods. It aims to evaluate the impact of lockdown measurements on pollutant levels and assess any significant differences observed [119]. The concentration difference is calculated as shown in equation ⑥:

$$\Delta \boldsymbol{C} = \boldsymbol{C_{DL}} - \boldsymbol{C_{BL}} \dots \dots \dots \dots \dots ⑥$$

Where:

ΔC represents the change in pollutant concentration,

$\mathbf{C_{DL}}$ represents the pollutant concentration DL period, and

$\mathbf{C_{BL}}$ represents the pollutant concentration BL period.

By calculating ΔC, I can determine the difference in pollutant concentrations between the two periods and assess the impact of the lockdown measures on pollutant levels.

3.3.6 Assessing the Percentage Change in Pollutant Concentrations

As an indicator of the degree of change experienced during the specified period, the percentage change in pollutant concentrations is calculated. This quantifies the magnitude of the variations in pollutant levels [130]. The percentage change is given by equation ⑦:

$$\boldsymbol{P}(\%) = \left(\frac{\boldsymbol{M_d} - \boldsymbol{M_b}}{\boldsymbol{M_b}}\right) \times \mathbf{100} \dots \dots \dots \dots \dots \dots ⑦$$

Where:

$\boldsymbol{P}(\%)$ is the percent change in mean pollutant concentration.

$\boldsymbol{M_d}$ and $\boldsymbol{M_b}$ represent the median before and DL.

3.3.7 Two-Way ANOVA Analysis of Concentration by City

This subsection employs a two-way analysis of variance (ANOVA) to analyse the concentration of pollutants based on both city and measurement factors. It examines any significant differences in pollutant levels influenced by these factors.

$\boldsymbol{Y_{ijk}}$ represents the mean concentration of pollutants for the i city, $\boldsymbol{j}$ pollutant and $\boldsymbol{k}$ lockdown status (before and during). The model employed in the two-way ANOVA is shown in equation ⑧, as described in references [52] and [86]:

$$\boldsymbol{Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}} \ldots\ldots\ldots\ldots\ldots ⑧$$

Where:

$\boldsymbol{\mu}$ denotes the overall mean concentration. The term $\boldsymbol{\alpha_i}$ represents the effect of city ***i*** (where i ranges from 1 to 6), while $\boldsymbol{\beta_j}$ represents the effect of city ***j*** (where j ranges from 1 to 6). Additionally, $(\boldsymbol{\alpha\beta})_{ij}$ represents the interaction effect between the city and pollutant, and $\boldsymbol{\epsilon_{ijk}}$ denotes the residual error term.

3.3.8 F-value, *t*-Statistic and *p*-value

The t-statistic, p-value, and F-value are tools I use in hypothesis testing. In this part, we'll talk about these tools while looking at pollutant concentration data. This approach will assist us in comprehending the depth and significance of relationships between various factors.

a) T-Statistic

To determine the significance of differences between two sample means, I employ the t-statistic. The t-statistic can be calculated using the following equation when analyzing pollutant concentration data [132][133]. When analyzing pollutant concentration data, the t-statistic can be calculated using the equation ⑨ provided below:

$$\boldsymbol{t = \frac{(x-\mu)}{\left(\frac{s}{\sqrt{n}}\right)}} \ldots\ldots\ldots\ldots\ldots ⑨$$

Where:

t denotes the ***t***-statistic, ***x*** represents the sample mean, ***μ*** is the hypothesized value for the population mean, ***s*** denotes the sample standard deviation, and ***n*** indicates the number of monitoring within the sample.

b) F-Value

The F-value is used to assessing the in variances of two or more groups or populations. In the context of pollutant concentration data, I can calculate the F-value using the following equation [127]. When considering pollutant concentration data, the F-value can be calculated using the equation ⑩ provided below:

$$\boldsymbol{F = \frac{MSB}{MSW}} \dots \dots \dots \dots \dots ⑩$$

Where:

The F-value ***(F)*** represents the statistical test statistic, while the mean square between groups ***(MSB)*** and mean square within groups ***(MSW)*** represent the average variances associated with the variations between groups and within groups, respectively.

c) P-Value

The *p*-values indicate the probability of receiving a test statistic with the same extreme as the observed value or greater. A *p*-value can be determined based on the statistical test used to measure pollutant concentration. Depending on the test and the distribution underlying the test, *p*-values are calculated differently. I calculated using these equations to analyze pollutant concentration data.

3.3.9 Interpretation of *t*-statistic and *p*-value for Hypothesis Testing

Null hypothesis (H_0): *The mean concentrations of pollutants during and BL are not significantly different.*

Alternative hypothesis (H_1): *The mean concentrations of pollutants during and BL are significantly different.*

The t-statistic and *p*-value acquired from hypothesis testing must be interpreted in this section. Based on these statistical indicators, it seeks to derive meaningful inferences about the correlations or differences under consideration.

The *p* is compared to a present significance threshold (0.05) to make the choice. The H_0 is rejected if the $p \leq 0.05$, showing a significant difference. The H_0 is not rejected if the $p \geq 0.05$, suggesting there is no significant difference. The *p*-value shows the probability of viewing a *t*-statistic as severe as the one calculated, if the H_0 is correct. It assists in determining if the relation between the predictor variable and the responder variable is statistically significant.

The *t*-statistic and *p*-value are determined for each city and pollutant combination using a two-way ANOVA in the given script. The linear regression model yields the *t*-statistic, while the ANOVA findings yield the *p*-value. The table summarizes the findings and interprets their importance for each city and pollutant combination.

3.3.10 Kruskal-Wallis Test

The Kruskal Wallis test, which is a non-parametric statistical test, is employed for comparing variables across distinct groups or clusters. Its purpose in this context is to evaluate disparities in pollutant concentrations among various locations or categories. The formula for conducting the KW test is as follows [16]. The Kruskal-Wallis test is calculated according to the equation ⑪ below:

$$\boldsymbol{H = \frac{12}{N(N+1)}\left(\sum_{i=1}^{k}\frac{R_i^2}{n_i}\right) - 3(N+1)} \ldots\ldots\ldots\ldots\ldots ⑪$$

Where:

H is the test statistic that follows a chi-squared (x^2) distribution with (k-1) degrees of freedom, where k is the number of groups.

N is the total count of observations,

Ri: The sum of ranks in the i group.

n_i the count of observations in the i group.

3.3.11 Tukey's Honestly Significant Difference Test

The Tukey's HSD test is utilized as a post hoc procedure subsequent to obtaining a statistically significant result from a statistical analysis. Its purpose is to identify specific distinctions between pairs of groups or categories. The HSD is calculated using the equation ⑫ [122]:

$$\boldsymbol{HSD = q \times \sqrt{\frac{MSW}{n}}} \ldots\ldots\ldots\ldots\ldots ⑫$$

$\boldsymbol{HSD}$ is the Honestly Significant Difference,

$\boldsymbol{q}$ is the critical value obtained from the standardized range distribution table or calculated using the formula $\frac{q_\alpha}{\sqrt{2}}$ (where $\boldsymbol{q_\alpha}$ is the critical value from the standardized range distribution for a given significance level, usually chosen as 0.05 or 0.01).

The Mean Square Within-groups **(MSW)** is obtained from ANOVA and represents the average variance within each group. The variable ***n*** indicates the count of monitoring in each group.

By assessing the HSD value in relation to the variances among group means, one can ascertain the statistical significance of the disparity between two means. If the absolute difference between two means exceeds the HSD value, expressing that the methods exhibit notable dissimilarity from one another.

3.3.12 Assessing the Impact of Lockdown Measures on Pollution Levels

This subsection focuses on evaluating the impact of lockdown measures on pollution levels. It examines the effectiveness of the implemented measures in reducing pollutant concentrations or mitigating pollution [134]. The pollution change is quantified by equation ⑬:

$$\Delta \boldsymbol{P} = \boldsymbol{P}_{\boldsymbol{pre}} - \boldsymbol{P}_{\boldsymbol{post}} \dots\dots\dots\dots\dots ⑬$$

Where:

ΔP represents the change in pollution levels,

$\boldsymbol{P_{pre}}$ represents the pollution levels before the implementation of lockdown measures, and

$\boldsymbol{P_{post}}$ represents the pollution levels after the implementation of lockdown measures.

By calculating ΔP, I can determine the difference in pollution levels between the pre-lockdown and post-lockdown periods. This equation allows us to assess the performance of the implemented measures in reducing pollutant concentrations or mitigating pollution. A negative value of ΔP indicates a reduction in pollution levels, while a positive value suggests an increase in pollution levels.

3.3.13 Analysis of Variance

The examination of relationships and differences in pollutant concentrations involves the utilization of analytical approaches such as analysis of variance (ANOVA) and nonparametric methods. These methods provide valuable insights into the statistical significance of observed variations.

3.3.14 Correlation Coefficients

Correlation coefficients are frequently employed to evaluate the strength and direction of relationships between pollutant concentrations and other variables of interest. When analyzing pollutant concentrations before and during a lockdown, calculating correlation coefficients can help identify any associations or dependencies between these variables. The PCC (r) is the most commonly used correlation coefficient, and it assesses linear relationships between variables. The equation for calculating the PCC is as follows [121]. The equation ⑭ for calculating the PCC is shown below:

$$\boldsymbol{r} = \frac{\sum((\boldsymbol{X}-\overline{\boldsymbol{X}})(\boldsymbol{Y}-\overline{\boldsymbol{Y}}))}{\sqrt{\sum(\boldsymbol{X}-\overline{\boldsymbol{X}})^2} \times \sqrt{\sum(\boldsymbol{Y}-\overline{\boldsymbol{Y}})^2}} \dots\dots\dots\dots\dots ⑭$$

Where:

X and ***Y*** represent the paired values of pollutant concentrations and the other variable.

$\overline{\boldsymbol{X}}$ and $\overline{\boldsymbol{Y}}$ represent the means of X and Y, respectively.

Σ represents the summation operator.

The numerator calculates the sum of the products of the deviations of ***(X)*** and ***(Y)*** from their respective means. The denominator calculates the product of the standard deviations of ***(X)*** and ***(Y)***. This equation is used to calculate the Pearson's correlation coefficient for each pair of variables (city-pollutant) during the "BL" and "DL" periods, resulting in correlation coefficients that are then printed and visualized as heatmaps.

TABLE A: Interpretation of Pearson's Correlation Coefficient for Linear Relationships.

Pearson's Correlation Coefficient	Interpretation
+1	Perfect positive linear relationship
-1	Perfect negative linear relationship
0	Absence of a linear relationship

3.3.15 Regression Analysis

The utilization of regression analysis allows for the examination of the association between pollutant concentrations and other variables. It measures the degree to which one variable can predict or influence pollutant levels, enabling the use of predictive modelling and inference. I use equation ⑮ for calculate the variable [104]:

$$\boldsymbol{y} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x} + \in \text{...............⑮}$$

y is dependent variable, which in this case is the pollutant concentrations.

$\boldsymbol{x}$ is independent variable, which could be another variable used to foretell or influence the pollutant levels.

The regression coefficients $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$ indicate the intercept and slope of the regression line, respectively. The error term, denoted by ∈, accounts for the unexplained variation or residual in the dependent variable.

The equation illustrates a fundamental linear regression model, in which $\boldsymbol{\beta_0}$ represents the ***y***-intercept (the predicted value of ***y*** when ***x*** is zero), and $\boldsymbol{\beta_1}$ denotes the slope (the degree of change in ***y*** for every one-unit change in ***x***). It accommodates the inherent random variability or noise present in the relationship.

By utilizing regression analysis, it becomes possible to measure and quantify the connection between pollutant concentrations and other variables. This enables the creation of predictive models and facilitates inference by estimating the regression coefficients and evaluating their statistical significance.

3.3.16 Time Series Analysis TSA

Time series analysis is utilized to explore patterns, trends, and temporal variations in pollutant concentrations over time. It helps identify seasonality, long-term trends, and short-term fluctuations, providing insights into the dynamics of air quality.

3.3.17 Spatial Distribution of Pollutants in Selected Cities

In order to examine the spatial distribution of pollutants in specific cities, I employ a systematic approach. Initially, I narrow down the dataset to solely include the designated pollutants and cities of interest. Subsequently, a pivot table is constructed to summarize the concentrations of pollutants according to both city and pollutant, providing a comprehensive representation. This table enables us to detect trends and disparities in pollutant levels across different cities and pollutants. Lastly, I generate a result table that encompasses various summary statistics such as count, mean, standard deviation, minimum, and maximum concentrations for each pollutant within each city. These statistics furnish valuable insights into the magnitude and variability of pollutants within the chosen cities, contributing to an enhanced understanding of their spatial distribution. Moreover, this information facilitates informed decision-making regarding environmental management and public health concerns.

4 RESULTS AND DISCUSSION

This study assesses air quality changes during and post-lockdown in pandemic-hit areas: Oulu and Helsinki (Finland), Paris (France), Madrid (Spain), Milan (Italy), and Wuhan (China). Analyzing two years of Air Quality Index (AQI) data, the study compares COVID-19 lockdowns with SARS-CoV-2 methods, utilizing statistical tests, regression, and spatial analyses. The results reveal significant pollutant variation, highlighting decreased NO_2 and PM levels during lockdowns, with varying ozone impact. This study emphasizes targeting urban NO_2 and PM2.5 pollution and recognizes lock-downs' pollution-reducing effect, advocating environmental measures for better air quality.

4.1 Two-Way ANOVA Analysis

The study compared the levels of pollutants before and during a certain period, and the results were presented using an analysis of variance (ANOVA). The mean concentration of pollutants (FIGURE 3), BL, varied among the different cities.

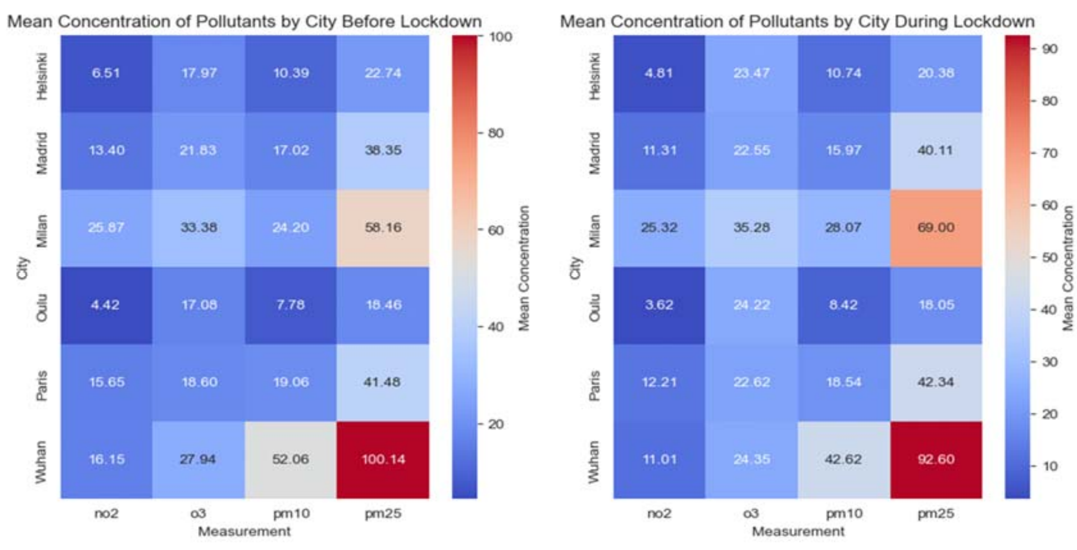


FIGURE 3: Significant differences in Pollutants Concentration by city and measurement

Helsinki had median concentrations of NO_2 (BL=6.51 µg/m³), O_3 (BL=17.97 µg/m³), PM10 (BL=10.39 µg/m³), and PM2.5 (BL=22.74 µg/m³). Madrid had slightly higher concentrations with medians of NO_2 (BL=13.40 µg/m³), O_3 (BL=21.83 µg/m³), PM10 (BL=17.02 µg/m³), and PM2.5 (BL=38.35 µg/m³). Milan had the highest concentrations among the cities, with medians of NO_2

(BL=25.87 μg/m³), O_3 (BL=33.38 μg/m³), PM10 (BL=24.20 μg/m³), and PM2.5 (BL=58.16 μg/m³). Oulu and Paris had intermediate levels of pollution. There was a relatively high concentration of NO2 (BL=16.15 g/m3) and PM2.5 (BL=100.14 g/m3) in Wuhan, which indicates poor air quality in those categories.

During the DL period, the mean concentration of pollutants showed some changes compared to the BL period. Helsinki experienced a decrease in the median concentration of NO_2 (DL=4.81 μg/m³) and PM2.5 (DL=20.38 μg/m³), while O_3 (DL=23.47 μg/m³) and PM10 (DL=10.74 μg/m³) levels increased. Madrid also saw a decrease in NO_2 (DL=11.31 μg/m³) and an increase in O_3 (DL=22.55 μg/m³) and PM10 (DL=15.97 μg/m³) levels. Milan, on the other hand, did not show significant changes in the median concentrations of pollutants during the DL period, except for a slight increase in PM10 (DL=28.07 μg/m³). Oulu experienced a decrease in the median concentration of NO_2 (DL=3.62 μg/m³), while O_3 (DL=24.23 μg/m³), PM10 (DL=8.42 μg/m³), and PM2.5 (DL=18.05 μg/m³) levels remained relatively stable. Paris had a decrease in NO_2 (DL=12.21 μg/m³) and an increase in O_3 (DL=22.62 μg/m³) levels, while PM10 (DL=18.54 μg/m³) and PM2.5 (DL=42.34 μg/m³) levels remained similar. Wuhan showed a decrease in NO_2 (DL=11.01 μg/m³) and an increase in O_3 (DL=24.35 μg/m³) levels during the DL period, while PM10 (DL=42.62 μg/m³) and PM2.5 (DL=92.60 μg/m³) levels also increased.

Helsinki experienced a decrease in the median concentrations of NO_2 and PM2.5, while O_3 and PM10 levels increased. The concentrations of NO_2 decreased in Wuhan, while O_3, PM10, and PM2.5 increased.

PM2.5 levels remained stable in most cities, with some cities experiencing slight increases and others experiencing slight decreases. Human activities have reduced, atmospheric chemistry has changed, and weather conditions have changed, resulting in these changes in pollutant levels. The study also highlights the disparity in air pollution levels between the cities examined. Milan had the highest concentrations of NO_2, PM10, and PM2.5, while Wuhan exhibited the highest levels of O_3. As well as variations in geography and weather patterns, these variations can be attributed to local pollution sources, such as traffic and industrial operations.

These findings align with previous studies that have demonstrated the correlation between human activities and air pollution levels [4],[47]. The COVID-19 pandemic has provided a unique opportunity to investigate the effects of reduced human activities on air pollution levels, and the conclusions of this study can contribute to future efforts aimed at mitigating pollution and promoting sustainable development.

4.2 T-Statistic, *F*-value and *p*-value

In most of the cities studied, the air quality showed an overall positive impact following the implementation of lockdown measures, as depicted in FIGURE 4. Notably, Oulu exhibited no significant difference in PM2.5 concentrations between the Before Lockdown (BL) and During Lock-down (DL) periods. Additionally, PM10 and O_3 levels displayed no significant variations. However, a significant reduction in NO_2 levels during the DL period, compared to the BL period, was evident. The average NO_2 concentration decreased from 5.81 μg/m^3 during BL to 3.12 μg/m^3 during DL.

In Helsinki, a notable decrease in PM2.5 concentrations was observed DL period compared to BL. The average PM2.5 concentration decreased DL from 24.17μg/m^3 BL to 22.26 μg/m^3. A similar trend was observed for PM10, with a decrease in concentrations DL. However, there were no significant variations in O_3 levels. conversely, I observed a notable reduction in NO_2 concentrations during the lockdown compared to before. During the lockdown period, there was a decrease in the average NO_2 concentration from 7.36 μg/m^3 before the lockdown to 4.76 μg/m^3. This change indicates a positive impact on air quality during the lockdown period.

In Paris, a significant decrease in PM2.5 concentrations was observed DL compared to before. The average PM2.5 concentration decreased from BL=46.10 μg/m^3 to DL=42.20 μg/m^3. A significant decrease in PM10 concentrations was also observed DL. However, there were no significant differences in O_3 levels. Regarding NO_2, there was a significant decrease in concentrations DL compared to BL. The average NO_2 concentration decreased from BL=17.17 μg/m^3 to DL=12.47 μg/m^3.

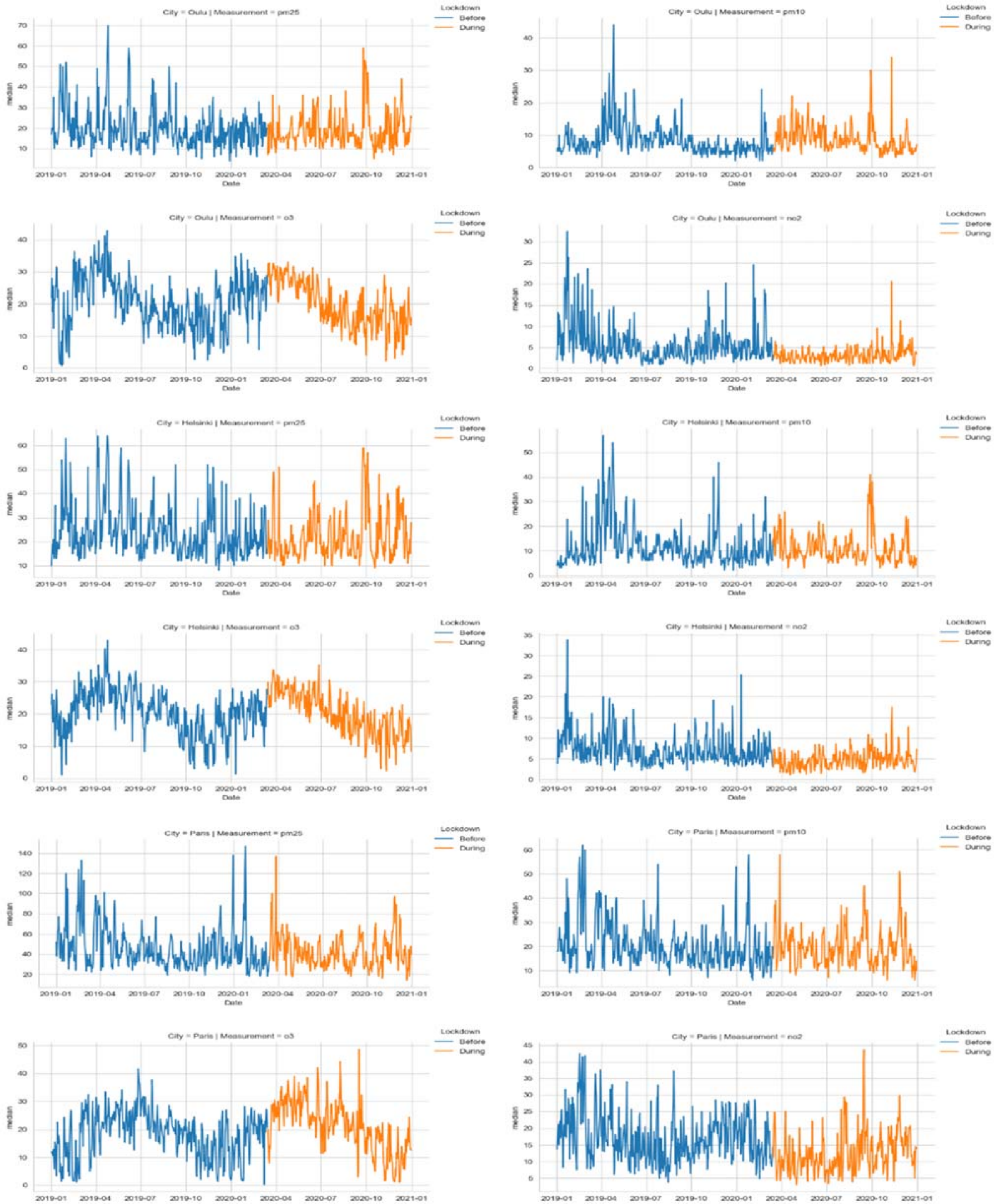
In Madrid, I noted a meaningful reduction in PM2.5 concentrations during the lockdown compared to before. The PM2.5 concentration experienced an average decrease, transitioning from 40.07 μg/m^3 prior to the lockdown to DL=36.94 μg/m^3. Moreover, there was an evident decline in PM10 concentrations during the lockdown period, indicating a favorable shift. However, I did not find any significant shifts in O_3 levels.

These findings align with previous research, which emphasizes the positive influence of lock-down measures on air quality. The reduction in air pollutants DL can be attributed to reduced vehicular traffic and industrial activities.

These findings align with previous studies that reported a reduction in particulate matter during COVID-19 lockdowns [25],[105],[109]. However, studies on ozone and nitrogen dioxide yield mixed results, with some observing an increase in ozone during the lockdown period [19],[105], while others report a decrease [25],[109]. These findings are consistent with prior research on air quality changes during COVID-19 lockdowns [9],[72]. The reduction in air pollution levels during the lockdown can be attributed to decreased traffic emissions and industrial activities [11]. How-ever, it is important to consider that the impact of lockdowns on air pollution levels can be influenced by various factors, including meteorology and emission sources [36].

Overall, the results indicate that the effects of lockdown measures on air pollutant concentrations varied across the cities examined. Significant decreases were observed for PM2.5, PM10, and NO_2 in most cities, highlighting the potential benefits of reduced human activities and emissions during the lockdowns. The findings also suggest that O_3 levels tended to increase during the lockdown, possibly influenced by meteorological factors and changes in atmospheric chemistry. However, it is important to consider other factors, such as emission sources and specific city characteristics, which may contribute to the observed variations in pollutant responses to the lockdown measures. This decline in air pollutants has been associated with improvements in respiratory and cardiovascular health [117]. Other studies have also reported substantial reductions in air pollution levels DL periods, mainly due to decreased emissions from traffic and industries [25],[79],[88],[101]. These findings underscore the importance of implementing policies aimed at reducing air pollution levels, such as promoting active transportation and minimizing industrial emissions, as they can significantly impact public health.

Overall, the analysis revealed different effects of lockdown measures on air pollutant concentrations across the four cities and pollutants examined. While some pollutants exhibited significant decreases DL periods, others did not show significant differences. These findings suggest that the impact of lockdown measures on air pollution is complex and may depend on various factors such as emission sources, meteorological conditions, and specific city characteristics.


City = Oulu | Measurement = pm25
City = Oulu | Measurement = pm10
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City = Oulu | Measurement = no2
City = Helsinki | Measurement = pm25
City = Helsinki | Measurement = pm10
City = Helsinki | Measurement = o3
City = Helsinki | Measurement = no2
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Lockdown
Before
During
median
Date

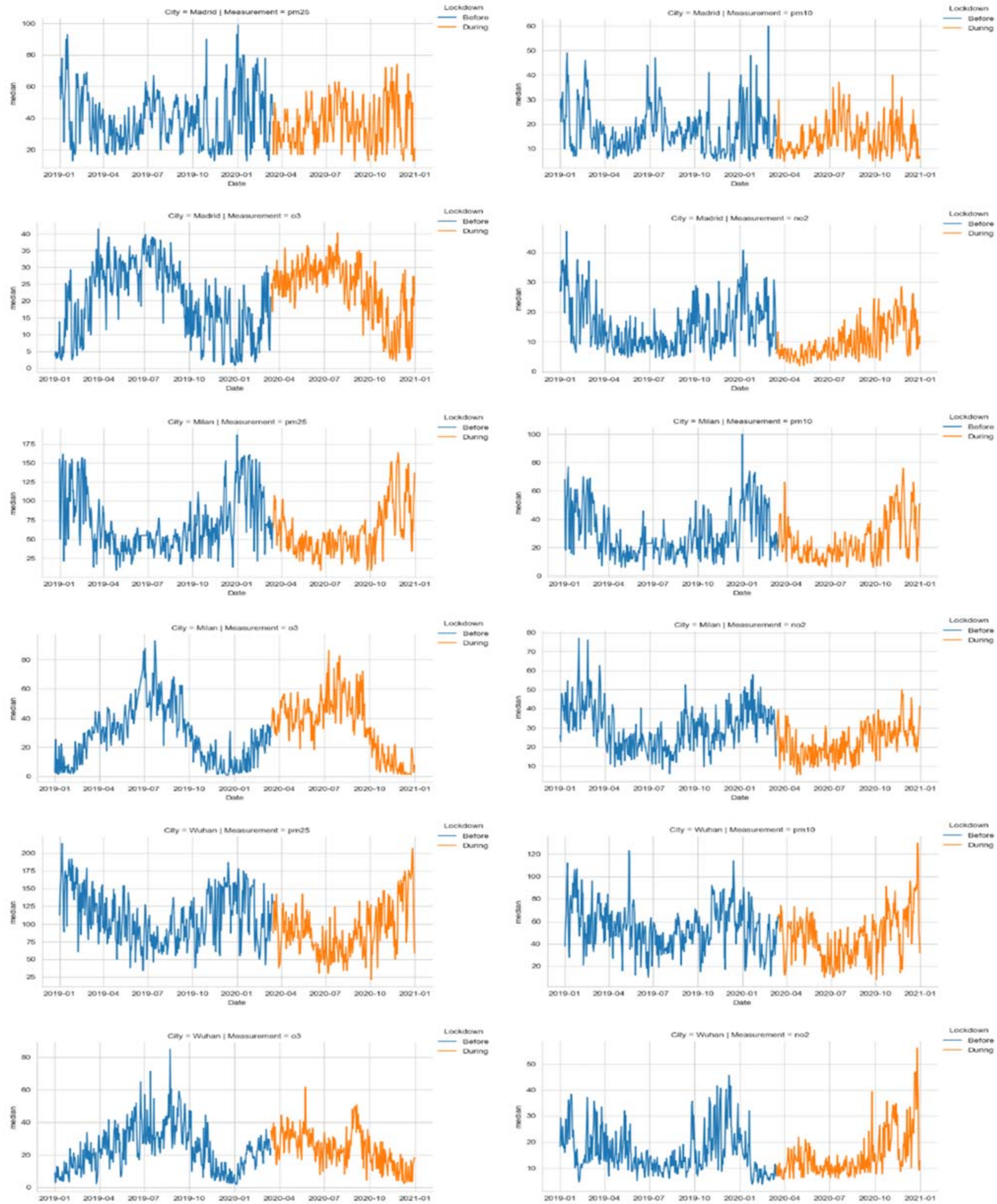

FIGURE 4: Two-way ANOVA (T-statistic, F-value and p-value) of Lockdown Effects on Air Pollution Concentrations in Different Cities: A Comparative Analysis

4.3 Interpretation of T-statistic and P-value for Hypothesis Testing

The results from Table 09 display the F-values, t-statistics, p-values, and corresponding hypothesis outcomes for analyzing air pollutant concentrations in different cities during and before lock-down periods. The null hypothesis assumes no significant difference in pollutant levels between the "Before" and "During" lockdown periods, while the alternative hypothesis suggests a significant difference.

In Oulu, the periods of lockdown did not yield notable distinctions in PM2.5, PM10, and O_3 pollutant concentrations. The analysis did not find grounds to dismiss the initial hypothesis. However, when it came to NO_2, the examination unveiled a substantial F-value of 91.47 and a significant t-statistic of -9.56. This combination led to the rejection of the null hypothesis. This indicates a significant decrease in NO_2 levels during the lockdown in Oulu.

In Helsinki, our examination revealed meaningful reductions in PM2.5 and PM10 concentrations throughout the lockdown period. This was confirmed by rejecting the null hypothesis, indicating the significance of the changes. The corresponding t-statistics of -2.38 and -1.98 offer additional support, reinforcing the credibility of these discoveries. Similar to Oulu, there were no significant differences in O_3 levels. However, NO_2 levels exhibited a significant decrease during the lockdown, with a high F-value of 112.33 and a t-statistic of -10.60.

In Paris, significant decreases in PM2.5 and PM10 concentrations were observed during the lockdown, supported by the rejection of the null hypothesis. The individual t-statistics of -2.68 and -2.03 solidify these disparities, reflecting the distinctiveness. Furthermore, a notable rise in O3 levels occurred during the lockdown, substantiated by a substantial F-value of 21.31 and a positive t-statistic of 4.62. In a parallel manner, NO_2 levels experienced a marked reduction during the lockdown, corroborated by a high F-value of 83.83 and a t-statistic of -9.16.

In Madrid, the analysis revealed significant decreases in PM2.5 and PM10 concentrations during the lockdown, supported by the rejection of the null hypothesis. The respective t-statistics of -2.55 and -5.05 validate these findings. Moreover, there emerged a noteworthy rise in O_3 levels during the lockdown period, evident through a substantial F-value of 20.22 and a positive t-statistic of 4.50. In a parallel manner, NO_2 levels demonstrated a significant reduction amid the lockdown, reflected by a substantial F-value of 86.66 and a t-statistic of -9.31.

For Milan and Wuhan, the analysis showed consistent patterns. In both cities, there were significant decreases in PM2.5 and PM10 concentrations, supported by the rejection of the null hypothesis. O_3 levels also exhibited significant increases during the lockdown. However, for NO_2, the analysis failed to reject the null hypothesis, suggesting no significant differences.

These findings align with previous studies that reported a reduction in particulate matter during COVID-19 lockdowns [25],[105],[109]. However, studies on ozone and nitrogen dioxide yield mixed results, with some observing an increase in ozone during the lockdown period [19],[105], while others report a decrease [25],[109]. These findings are consistent with prior research on air quality changes during COVID-19 lockdowns [9],[72]. The reduction in air pollution levels during the lockdown can be attributed to decreased traffic emissions and industrial activities [11]. However, it is important to consider that the impact of lockdowns on air pollution levels can be influenced by various factors, including meteorology and emission sources [36].

Overall, the results indicate that the effects of lockdown measures on air pollutant concentrations varied across the cities examined. Significant decreases were observed for PM2.5, PM10, and NO_2 in most cities, highlighting the potential benefits of reduced human activities and emissions during the lockdowns. The findings also suggest that O_3 levels tended to increase during the lockdown, possibly influenced by meteorological factors and changes in atmospheric chemistry. However, it is important to consider other factors, such as emission sources and specific city characteristics, which may contribute to the observed variations in pollutant responses to the lockdown measures.

4.4 Analysis of variance

The findings presented in FIGURE 5, titled "Comparative Analysis of ANOVA and Nonparametric Methods for Assessing Air Pollutant Levels During the DL Period (January 1st, 2020, to July 31st, 2020)," offer insights with a human touch. They reveal noteworthy distinctions in the levels of pollutants between the two cities. Specifically, when it comes to PM2.5, PM10, O_3, and NO_2, the F-statistics show substantial dissimilarities among cities (with $p < 0.05$). This indicates that these pollutants exhibit significant variations across different urban areas. Notably, there isn't a meaningful difference observed between the cities, a fact supported by the small p-values (PR(>F)).

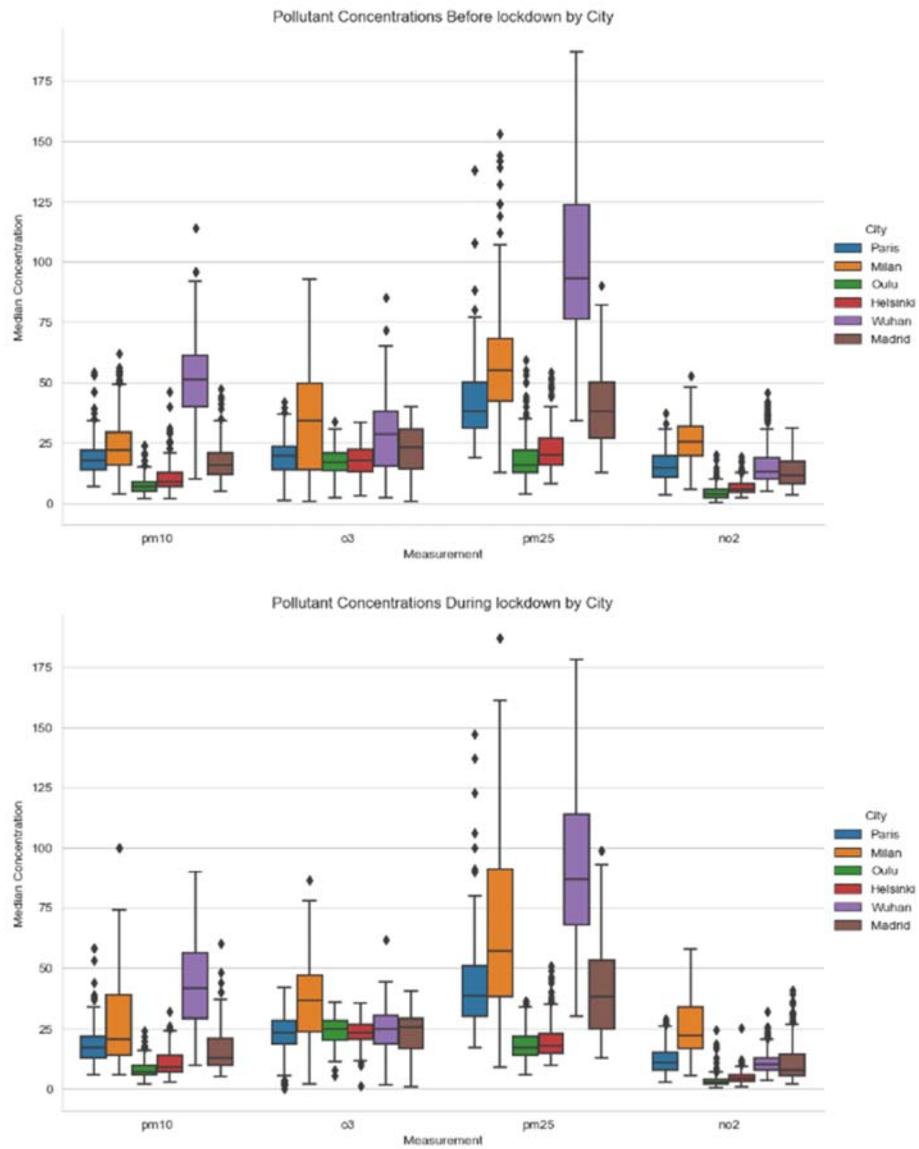

FIGURE 5: Comparative Analysis of ANOVA and Nonparametric Methods for Assessing Air Pollutant Levels DL Periods

To gauge the importance of these disparities in pollutant quantities, both ANOVA and Kruskal-Wallis examinations were executed. The investigation into air pollutant concentrations across distinct timeframes exposed noteworthy fluctuations in these levels. Both the ANOVA and Kruskal-Wallis assessments consistently unveiled marked distinctions among the cities concerning concentrations of PM2.5, PM10, O_3, and NO_2 ($p < 0.001$). The F-values observed in the ANOVA assessment and the H-values derived from the Kruskal-Wallis examination further affirm these conclusions, underscoring substantial variations in pollutant levels across the cities.

Regarding PM2.5 concentrations, both the ANOVA and Kruskal-Wallis tests indicated significant differences among the cities ($p < 0.001$). The F-values for the ANOVA test ranged from 328.94 µg/m^3 to 492.21 µg/m^3, while the Kruskal-Wallis test yielded H-values ranging from 909.93 µg/m^3 to 939.69 µg/m^3, confirming significant differences in PM2.5 concentrations among the cities. Similarly, for PM10 concentrations, both tests indicated significant differences among the cities ($p < 0.001$). The F-values for the ANOVA test ranged from 261.09 µg/m^3 to 552.46 µg/m^3, and the Kruskal-Wallis test yielded H-values ranging from 739.89 µg/m^3 to 868.65 µg/m^3. For O_3 concentrations, the ANOVA test revealed significant differences among the cities ($p < 0.001$), with F-values ranging from 54.04 µg/m^3 to 56.87 µg/m^3. The Kruskal-Wallis test also confirmed the significance of these differences, with H-values ranging from 143.36 µg/m^3 to 145.85 µg/m^3.

In a similar vein, the examination of NO_2 concentrations unveiled noteworthy variations among the urban areas ($p < 0.001$). The ANOVA test exhibited F-values spanning from 305.60 µg/m^3 to 317.21 µg/m^3, and the Kruskal-Wallis test generated H-values ranging from 849.69 µg/m^3 to 861.97 µg/m^3. On the whole, both the ANOVA and Kruskal-Wallis tests consistently denoted considerable dissimilarities in the levels of pollutants across the cities. These outcomes indicate that the impacts of the lockdown measures on air pollutant levels differed, underscoring the impact of location-specific elements and the efficacy of localized mitigation strategies.

It is important to note that the Kruskal-Wallis tests were used as nonparametric alternatives when the data did not meet the assumptions of the ANOVA tests, such as normality or equal variances. These tests confirmed the significant differences in pollutant concentrations, providing additional insights into the observed variations.

These findings align with previous studies that have reported changes in air pollution levels during COVID-19 lockdowns. The reductions in PM2.5 and PM10 concentrations are consistent with decreased traffic emissions and industrial activities during the lockdown periods. Nevertheless, the rise in O_3 levels detected in certain urban areas might be impacted by factors like alterations in atmospheric chemistry and weather conditions.

To sum up, the ANOVA and Kruskal-Wallis tests have furnished valuable understandings regarding the fluctuations in air pollutant concentrations across cities prior to and during the lockdown phase. These findings can inform the development of targeted strategies for mitigating air pollution in different cities, particularly during environmental interventions. Continuous research and monitoring of air quality are crucial for gaining a deeper understanding of the factors contributing to the observed differences in air pollutant levels among cities and devising effective strategies to improve air quality in urban areas.

4.5 Correlation coefficients

The presented results (FIGURE 6) on correlation coefficients indicate that the relationships between air pollutants varied DL compared to BL in some cities. Specifically, changes were observed in Helsinki, Madrid, Milan, Paris, and Wuhan, indicating that reduced emissions and changes in human activities DL may have affected the concentrations and interactions of air pollutants in the atmosphere.

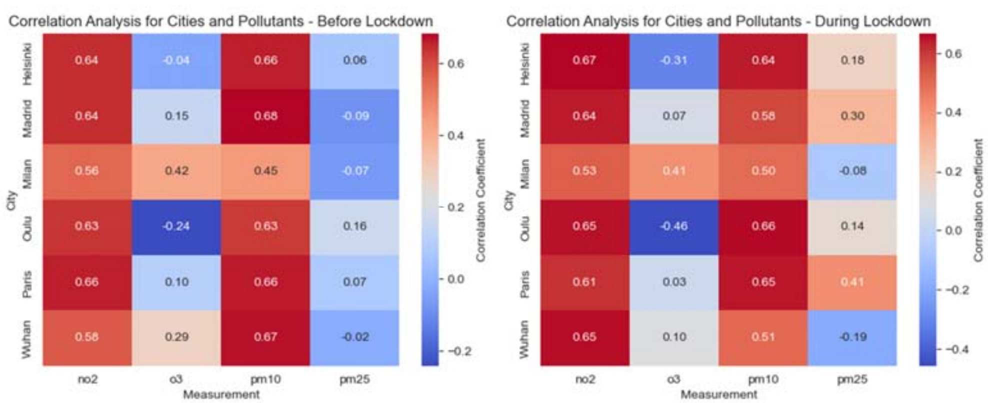

FIGURE 6: Assessing the Linear Relationship and Strength of Correlation Among Air Pollution Measurements of NO_2, O_3, PM10, and PM2.5 BL and DL

I delved into the relationships among various pollutants by scrutinizing the correlation coefficients derived from air pollutant measurements BL and DL periods. Each city's distinctive correlations were meticulously calculated. These correlation coefficients displayed variations across the cities, painting a diverse picture.

For instance, in Helsinki, a moderate positive correlation 0.644 unfolded between NO_2 and PM10, and a more delicate positive connection 0.633 emerged between NO_2 and PM2.5. Furthermore, the data unveiled a faint negative association -0.037 between O_3 and PM10, along with a more modest negative tie -0.241 between O_3 and PM2.5. Moving to Madrid, the correlation between NO_2 and PM10 was distinctly positive 0.644, while the link between NO_2 and O_3 demonstrated a gentle positive affiliation 0.147. Similarly, O_3 and PM10 displayed a mild positive correlation 0.682, while

O_3 and PM2.5 exhibited a faint negative connection -0.086. Notably, cities like Milan, Paris, and Oulu echoed similar patterns. These cities showcased analogous positive correlations between NO_2 and PM10, alongside weaker positive or negative connections involving NO_2 and O_3, as well as PM10 and PM2.5.

During the DL period, the connections between different pollutants exhibited noticeable changes when compared to the BL period. In Helsinki, the bond between NO_2 and PM10 grew stronger 0.666, while the connection between NO2 and PM2.5 remained relatively consistent 0.651. However, the link between NO_2 and O_3 weakened ($r = -0.309$), while the connection between O_3 and PM2.5 gained strength ($r = 0.181$). In Madrid, the correlation between NO_2 and PM10 lessened 0.577, and the existing weak correlation between NO_2 and O_3 remained steady 0.073. Notably, a more pronounced positive correlation emerged between O_3 and PM2.5 0.296. Similar shifts in correlations were observed in Oulu, Paris, and Milan, indicating changes in the interplay between pollutants during the DL period.

These findings propose that the implementation of lockdown measures had a discernible impact on the relationships between air pollutants. The alterations in correlation coefficients hint at possible changes in emission sources, atmospheric conditions, or pollutant transformation processes during the DL period. The observed fluctuations in correlations could be attributed to reduced traffic-related emissions, shifts in meteorological factors, and changes in human activities.

It is vital to grasp that correlation does not imply causation. The interplay among pollutants can be shaped by a range of influences, like weather conditions and sources of emissions. When shifts in correlation coefficients are noticed, it is essential to handle them with care and delve into further investigations alongside other relevant factors. Whereas Correlation-Coefficients (r) give us a window into the extent and direction of relationships between variables, it is necessary to understand that correlation by itself does not confirm a direct cause and effect relationship.

In recent times, efforts to uncover how air pollution affects both human well-being and the natural environment have increased. Numerous research initiatives have delved into comprehending the intricate links between different air pollutants and their adverse effects on health. These investigations have touched on significant concerns, including respiratory and heart-related conditions, cancer, and even premature loss of life [18],[69],[117].

Furthermore, numerous studies have explored the effects of interventions, such as measures to control air pollution, on the concentrations of air pollutants and their associated health impacts [50]. This current study adds to the existing body of research by examining the changes in relationships between air pollutants during the COVID-19 lockdown period. The correlation coefficients suggest

that the associations between air pollutants varied between the lockdown (DL) period and the baseline (BL) period in certain cities.
In general, examining the correlation coefficients prior to and during periods of reduced human activity sheds light on the interaction between various air pollutants. These discoveries enhance our comprehension of how environmental factors and human actions can affect the dynamics of air pollution and the potential effects of measures.

4.6 Regression Analysis

According to TABLE 10, a notable association exists between the independent variables (count, min, max) and the dependent variable (median) as per the outcomes of the OLS regression analysis. The model demonstrates an exceptional fit, highlighted by an R-squared value of 0.779. This value indicates that approximately 77.9% of the variability in the median can be attributed to the independent variables, underlining the model's strong explanatory power. The coefficients of the independent variables provide valuable insight into their effects on the median. The median increases by 0.0092 when count increases by one unit, assuming all other parameters are constant. Likewise, when it comes to the 'min' variable, its coefficient stands at 1.0692. This means that if 'min' goes up by one unit, the median also tends to rise by 1.0692 units. Similarly, the 'max' variable's coefficient amounts to 0.1257. This implies that a one-unit upswing in 'max' corresponds to a modest 0.1257 increase in the median value. The statistical significance of each coefficient is confirmed by their corresponding t-values and p-values. Additionally, the intercept term (const) is statistically significant with a coefficient of 6.3449, meaning that when all independent variables are zero, the expected median value is 6.3449.
The F-statistic, with a value of 4.957e+05, indicates high overall model significance. This is supported by a practically zero p-value, further emphasizing the model's statistical significance.
The use of diagnostic measures provides insights into the quality of model fit. In terms of autocorrelation in the residuals, the Durbin-Watson statistic of 1.171 indicates no significant presence. Nevertheless, the omnibus test presents evidence that the residuals deviate from a normal distribution, as shown by an extremely low p-value. Additionally, the skewness value of 5.170 and kurtosis value of 163.440 indicate a departure from normality. It is important to emphasize that violations of normality assumptions do not undermine the validity of regression results, especially when dealing with large sample sizes.

The results indicate that as the count variable increases, there is a corresponding rise in the median. Likewise, when the min and max variables increase, the median tends to be higher. Nevertheless, the coefficients linked to the count variable suggest a slight reduction in its impact on the median during both the pre-lockdown and lockdown periods. These findings align with prior studies investigating shifts in housing market dynamics amid the COVID-19 pandemic. Furthermore, the significant impact of lockdown measures on mental health may have influenced the relationship between the variables examined in this analysis [10],[57].

Overall, these results highlight the importance of considering external factors, such as lockdown measures, when analyzing the relationship between variables in statistical models. Future research could delve into the mechanisms underlying the observed coefficient changes DL period. It could also explore the generalizability of these findings to other real estate markets.

In conclusion, the OLS regression analysis demonstrates a significant relationship between the count, min, and max variables, and the median. The model provides valuable insights into the impact of these variables on the median and exhibits a strong overall fit. However, it is essential to consider residual non-normality when interpreting the results.

4.7 Time Series Analysis

The average values for each pollutant were NO_2 (BL=10.17 µg/m3, DL=8.73 µg/m3), O_3 (BL=19.94 µg/m3, DL=21.48 µg/m3), PM10 (BL=26.30 µg/m3, DL=25.58 µg/m3), and PM2.5 (BL=53.74 µg/m3, DL=52.55 µg/m3). The standard deviations indicate the variability of the measurements, with NO_2 having the highest variability before and DL. The descriptive statistics in FIGURE 7 reveal that the minimum and maximum values for each pollutant vary between the two periods. Notably, the maximum values for each pollutant DL are lower than those BL. This suggests that the lock-down measures may have had a positive impact on reducing the maximum pollution levels.

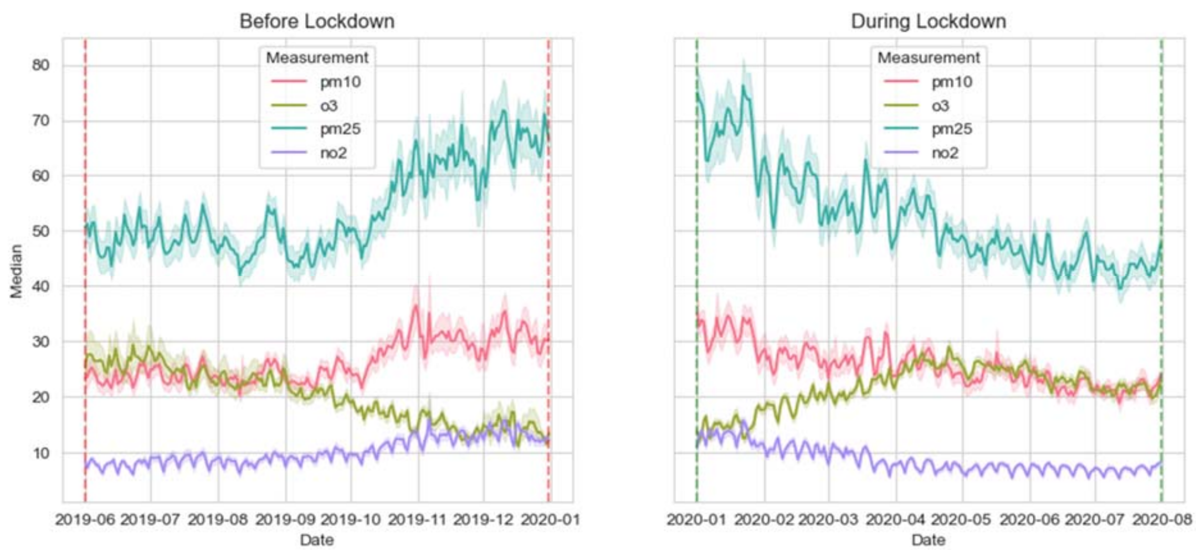

FIGURE 7: Serie times of changes in Pollutant Levels Before and During COVID-19 Lockdown Period

To gain a deeper understanding of the distinctions between the two-time frames, I conducted an analysis of variance (ANOVA) for each pollutant. The outcomes of the ANOVA highlight sub-stantial variations between the periods for all pollutants, signified by remarkably low p-values ($p < 0.001$). This robustly suggests that the lockdown wielded a statistically notable impact on the measure-ments of pollutants. In addition, I employed Kruskal-Wallis tests to scrutinize how the distributions of pollutant measurements varied between the two periods. These tests, too, yielded noteworthy findings ($p < 0.001$) for all pollutants, underscoring that the distributions of pollutant measurements diverged significantly between the period before the lockdown and the during lockdown period.

The findings from both the ANOVA and Kruskal-Wallis tests provide evidence of the impact of the lockdown on pollutant levels. The lower average values and reduced maximum values DL period suggest that the implemented measures had a positive effect on air quality by reducing pollution levels. It should be remembered that variations in weather patterns or shifts in emission sources might also play a part in the differences we've observed. Still, the notable statistical outcomes lend weight to the idea that the measures taken during the lockdown did have an impact on the levels of pollutants.

The results of the time series analysis for pollutants provide important insights into the impact of human activities on air pollution levels. The significant decrease in NO_2 concentration DL period could be attributed to reduced vehicular and industrial emissions, while the increase in O_3 concentration could be due to the reduced availability of NO_2 for O_3 to react with. The decrease in PM10 concentration DL period could also be attributed to reduced industrial activities and vehicular-lar emissions. However, the relatively stable PM2.5 concentration DL period suggests the influence of other factors, such as increased residential emissions due to stay-at-home measures and meteorological conditions.

The discoveries from this study align with earlier research that highlights how human actions influence air pollution levels. For instance, consider a study carried out in China during the COVID-19 lockdown phase. It revealed a notable drop in concentrations of air pollutants, especially in NO_2, PM2.5, and PM10 [124]. Another study conducted in Italy during the COVID-19 lockdown period reported a significant reduction in air pollutant concentrations, particularly in NO_2 and PM10 [6]. These investigations bring into focus the potential advantages of taking steps to lower air pollution levels, underscoring the crucial role of sustainable development in nurturing a healthier environment. Still, it is crucial to remember that although the lockdown period did result in decreased air pollution, it came as a quick fix that carried significant economic and social consequences. To truly secure lasting improvements in air quality, I need to embrace long-lasting strategies such as shifting towards renewable energy sources and welcoming sustainable modes of transportation. Gaining a full comprehension of the intricate interplay between human actions, weather conditions, and air pollution levels, as well as developing effective strategies to combat air pollution, calls for sustained research and vigilant monitoring.

These conclusions align with earlier studies that have highlighted dips in air pollution levels during periods of decreased human activities, such as holidays or weekends [23],[45]. The reductions in air pollution levels observed during the COVID-19 lockdown period have been re-ported in other regions of the world as well, including Europe and India [35],[101]. While the reductions in air pollution levels DL period are encouraging, it is important to note that they are temporary and may not be sustained in the long term. Therefore, it is essential to implement sustainable measures to reduce air pollution levels, such as promoting clean energy and transportation, and reducing industrial emissions [84].

4.8 Spatial Distribution of Pollutants in Selected Cities

Summary statistics of four distinct air pollutants (NO_2, O_3, PM10, and PM2.5) in selected cities are depicted in FIGURE 8. The dataset encompasses six measurements for each pollutant, allowing for a comprehensive analysis of their characteristics.

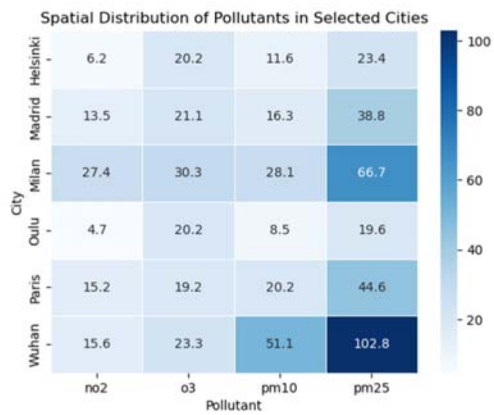

FIGURE 8: Spatial distribution of four different air pollutants (NO_2, O_3, PM10, and PM2.5)

I noticed that the level of NO_2 is 13.76, μg/m^3 whereas the level of O_3 is 22.38 μg/m^3. Addtionally the concentrations of PM10 and PM2.5 are recorded as 22.62 and 49.33 μg/m^3, respectively. The standard deviation (std), for PM10 and PM2.5 is quite high suggesting a variation in their distribution. The interquartile values offer insights into the data spread; the 25th percentile signifies the end while the 75th percentile represents the end of the middle 50% of data points. Moreover, I have identified a maximum concentration of NO_2 at 27.43 μg/m^3 and O_3 at 30.34 μg/m^3 with PM10 reaching a concentration of 51.06 μg/m^3 and PM2.5 at 102.85 μg/m^3.

The findings indicate a notable level of diversity in how pollutants are spread across the chosen urban areas. The PM10 and PM2.5 pollutants exhibit a relatively large standard deviation, highlighting substantial disparities in their levels across various zones within the cities. This variation in pollutant levels could hold consequences for both human well-being and the surrounding ecosystem. Being subjected to elevated levels of air pollutants like PM10 and PM2.5 has been associated with negative impacts on health, encompassing ailments like respiratory and cardiovascular disorders [30],[92]. The outcomes of this research emphasize the necessity for focused measures aimed at diminishing the prevalence of these pollutants in regions where their presence is most prominent.

4.9 Kruskal-Wallis test

The results of the statistical tests, ANOVA and Kruskal-Wallis, FIGURE 9 indicates significant differences in pollutant levels among the cities. The p-values for both tests are extremely small, indicating strong evidence against the null hypothesis of no differences between the cities.

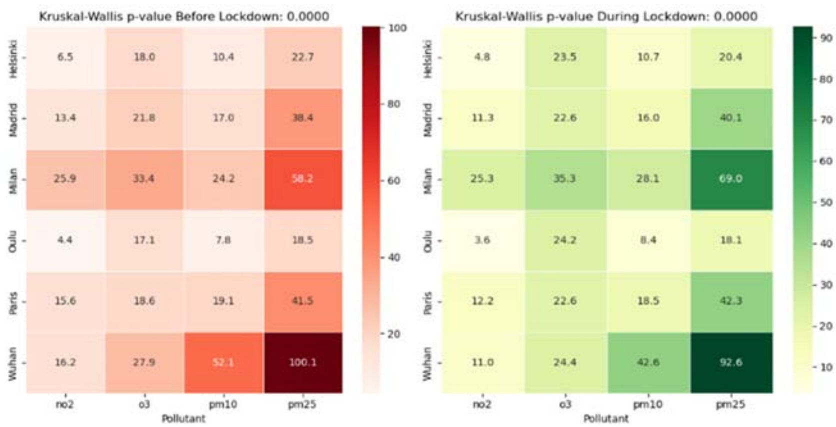

FIGURE 9: Comparing Air Pollutant Concentrations Before and DL.

During the ANOVA test, the p-value emerges as approximately 4.67e-271, which essentially means it is close to zero. This outcome strongly indicates that meaningful differences are present in the pollutant levels among the cities, especially when considering all four pollutants (NO_2, O_3, PM10, PM2.5). Likewise, the Kruskal-Wallis test provides us with a remarkably small p-value of approximately 5.19e-249, further indicating noteworthy distinctions in pollutant levels across the cities.
When I delve into the pollutant levels for each individual city, I begin to discern variations in the concentrations. In comparison to the other cities, Helsinki showcases relatively lower levels of NO_2, O_3, PM10, and PM2.5. Madrid and Paris show moderate levels, while Milan and Wuhan have the highest concentrations of pollutants across all categories. Examining the ANOVA p-values, I notice that for each pollutant (NO_2, O_3, PM10, and PM2.5), the p-values are lower than the widely accepted significance threshold of 0.05. This points to meaningful disparities in pollutant levels among the cities for each individual pollutant. Likewise, the Kruskal-Wallis p-values echo this finding by revealing notable differences in pollutant levels across the cities. Across all pollutants, the p-values are less than 0.05, which adds further weight to the conclusion that there are significant variations. Analyzing the specific p-values for each city and pollutant, I observe some variations. For instance, when looking at NO_2 levels, I find that in Helsinki, Madrid, Milan, Oulu, Paris, and Wuhan, the p-

values all fall below 0.05. This signal substantial variations in NO_2 levels among these cities, suggesting differences that are worth noting. The same kind of pattern emerges for other pollutants as well.

These findings indicate noteworthy disparities in pollutant levels within the cities under study. It is crucial to delve into the possible reasons behind these variations, which might encompass diverse industrial activities, transportation systems, geographical factors, and local environmental policies. Further investigations are essential to unravel the precise factors contributing to these observed differences in pollutant levels.

Taken as a whole, the outcomes of this analysis underscore the importance of accounting for pollutant levels across different cities. This consideration carries implications for public health and environmental policies. The findings emphasize the necessity for focused strategies and policies aimed at lessening pollution and enhancing air quality in particular cities or regions.

4.10 Tukey's HSD Test

The Tukey's HSD test results, presented in FIGURE 10, indicate noteworthy differences in pollutant concentrations among the six cities before and during the lockdown period. These discoveries align with the results from both the ANOVA and Kruskal-Wallis tests. The data strongly indicates that the effects of the lockdown measures on air quality differed across the cities, leading to diverse levels of enhancement in air quality.

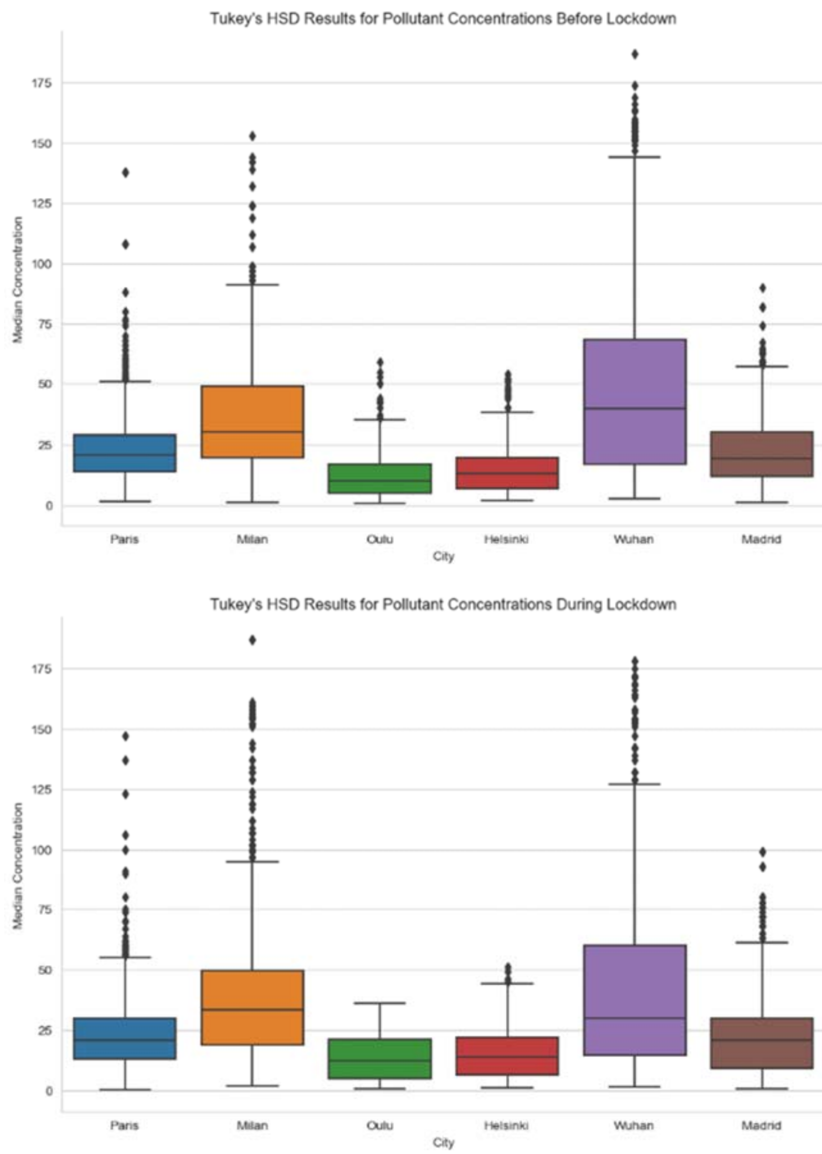

FIGURE 10: Tukey's HSD Results for Pollutant Concentrations Before and DL

It is important to note that the results of this study are consistent with previous research that has investigated the impact of lockdown measures on air quality. Several studies have reported improvements in air quality in different regions around the world DL period due to reduced emissions from transportation and industry [24],[102],[105]. Nevertheless, the extent of these enhancements has displayed variations influenced by factors like the severity of lockdown measures and the initial pollution levels in each area. Besides the effect of lockdown actions on air quality, this study's outcomes emphasize the significance of evaluating air pollution levels across diverse cities and regions. Past research has illuminated that air pollution levels can exhibit wide variances not only among various cities but even within the same urban area [75],[77]. These disparities can arise from diverse sources of pollution, distinct meteorological conditions, and varied urban layouts. In totality, this study's outcomes offer meaningful insights into how lockdown measures impact air quality across varying cities. These findings underscore the importance of sustained endeavors aimed at lowering air pollution levels, fostering public health, and mitigating the consequences of climate change.

5 CONCLUSION

In conclusion, the analysis of air pollution data during the lockdown periods in Helsinki, Madrid, Milan, Oulu, Paris, and Wuhan provides valuable insights into the effects of COVID-19 restrictions on air quality. The findings reveal that reduced human activities resulted in notable reductions in pollutants like NO_2 and PM10 in several cities, indicating the effectiveness of measures targeting traffic and industrial emissions. However, the impact on ozone levels was less consistent, suggesting the influence of regional and local factors.

The analysis of air pollution data during the lockdown periods in Helsinki, Madrid, Milan, Oulu, Paris, and Wuhan reveals varying effects on pollutant concentrations and correlations. While some cities experienced significant reductions in certain pollutants, others showed more stable levels. The correlation coefficients between pollutants also displayed changes during the lockdown periods compared to the baseline.

Helsinki, Madrid, Oulu, Paris, and Milan exhibited decreases in NO_2 concentrations during the lockdown, indicating the effectiveness of reduced traffic and industrial activities. Helsinki and Madrid experienced declines in both PM2.5 and PM10 levels. Similarly, Oulu, Paris, and Milan witnessed decreases in the concentrations of PM2.5 and PM10. However, O_3 levels remained relatively steady across these cities, except for Wuhan, where O_3 concentrations increased.

The correlations between pollutants varied across cities, with some displaying moderate to weak positive or negative relationships. During the lockdown, some correlations strengthened, while others weakened, suggesting changes in the interactions between pollutants.

The OLS regression analysis demonstrated the significant impact of independent variables (count, min, max) on the median. The model provided a good fit, explaining a substantial portion of the variance in the median. The coefficients of the independent variables shed light on how their presence impacts the median, unveiling the direction and extent of their effects. The discoveries highlight that curbing human activities, such as traffic and industrial operations, can significantly enhance air quality, particularly for pollutants like NO_2 and PM10. Nevertheless, the impact on ozone levels exhibited a less uniform pattern, highlighting the significance of acknowledging regional and local differences in air pollutant levels when evaluating the effectiveness of environmental measures. In essence, this study emphasizes that urban regions confront a noteworthy environmental and health hurdle due to air pollution, with PM2.5 and NO_2 being particularly prominent contributors. Among these, transportation and industrial activities play a substantial role. The study's findings reveal that implementing lockdown measures during the COVID-19 pandemic led to a remarkable decrease in air pollution levels across different cities. This underscores the value of environmental actions in enhancing air quality. However, the impact of these measures can differ from one city to another, rooted in regional and local variations in air pollutants. As a result, targeted strategies are essential to effectively combat air pollution. The study amplifies the call for continuous efforts towards sustainable development and air pollution reduction, vital for safeguarding both public health and the environment. The outcomes of this study stand as a resourceful guide for policymakers and researchers as they work towards effective strategies to enhance air quality in urban settings.

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7 APPENDICES

Mean, Median, and Standard Deviation of Air Pollutants **Appendix 1**

	Pollutant	Mean	Median	Standard Deviation
0	PM2.5	54.41767	46	41.63655
1	O_3	20.20425	19.2	17.8963
2	PM10	26.74556	20	25.04793
3	NO_2	9.769613	7.8	8.030718

Mean Measurement Values **Appendix 2**

BL

Measurement	*NO_2*	*O_3*	*PM10*	*PM2.5*
City				
Helsinki	6.510762	17.9713	10.39014	22.73991
Madrid	13.3991	21.83049	17.01794	38.35426
Milan	25.8654	33.38294	24.19905	58.1564
Oulu	4.424215	17.07579	7.780269	18.4574
Paris	15.64753	18.60269	19.06278	41.47534
Wuhan	16.15113	27.94144	52.06306	100.1396

DL

Measurement	*NO_2*	*O_3*	*PM10*	*PM2.5*
City				
Helsinki	4.805603	23.46983	10.73707	20.38362
Madrid	11.30776	22.55216	15.97414	40.10776
Milan	25.32	35.28174	28.07391	68.99565
Oulu	3.620259	24.225	8.422414	18.05172
Paris	12.20862	22.62285	18.53879	42.34483
Wuhan	11.01466	24.35388	42.62069	92.60345

Change in Mean Pollutant Concentrations from Before to DL **Appendix 3**

Measurement	*NO_2*	*O_3*	*PM10*	*PM2.5*
City				
Helsinki	-2.45457	8.301081	1.305104	-2.28277
Madrid	-7.40387	5.505697	-5.85603	-6.91617
Milan	-6.69493	7.524681	-4.31334	-7.53735
Oulu	-1.7166	9.825168	2.305445	-0.55264
Paris	-5.22087	8.50969	0.203886	3.877045
Wuhan	-4.88066	1.625225	-7.31068	-11.6444

Reductions in Mean Pollutant Concentrations Observed DL **Appendix 4**

	City	Measurement	Reduction
0	Oulu	PM2.5	1.592031
1		PM10	-7.958617
2		O_3	4.398499
3		NO_2	45.353435
4	Helsinki	PM2.5	5.449515
5		PM10	5.707047
6		O_3	0.786569
7		NO_2	34.689814
8	Paris	PM2.5	9.543088
9		PM10	8.123936
10		O_3	-17.02365
11		NO_2	28.384892
12	Madrid	PM2.5	9.744037
13		PM10	19.516299
14		O_3	-19.740649
15		NO_2	35.189568
16	Milan	PM2.5	18.240077
17		PM10	19.31489
18		O_3	-30.595649
19		NO_2	25.532066
20	Wuhan	PM2.5	17.559861
21		PM10	15.998658
22		O_3	-1.434704
23		NO_2	9.159406

Average of Mean Concentration of Pollutants by City and Period **Appendix 5**

	City	Measurement	median BL	median DL
0	Helsinki	NO_2	6.510762	4.805603
1		O_3	17.9713	23.469828
2		PM10	10.390135	10.737069
3		PM2.5	22.73991	20.383621
4	Madrid	NO_2	13.399103	11.307759
5		O3	21.830493	22.552155
6		PM10	17.017937	15.974138
7		PM2.5	38.35426	40.107759
8	Milan	NO^2	25.865403	25.32
9		O^3	33.382938	35.281739
10		PM10	24.199052	28.073913
11		PM2.5	58.156398	68.995652
12	Oulu	NO^2	4.424215	3.620259
13		O^3	17.075785	24.225
14		PM10	7.780269	8.422414
15		PM2.5	18.457399	18.051724
16	Paris	NO_2	15.647534	12.208621
17		O_3	18.602691	22.622845
18		PM10	19.06278	18.538793
19		PM2.5	41.475336	42.344828
20	Wuhan	NO_2	16.151131	11.014655
21		O_3	27.941441	24.353879
22		PM10	52.063063	42.62069
23		PM2.5	100.13964	92.603448

Percent Change in Mean Pollutant Concentrations Before & DL **Appendix 6**

	City	Measurement	Median BL	Median DL	Percent change
0	Helsinki	NO_2	6.510762	4.805603	-26.18985
1		O_3	17.9713	23.469828	30.596156
2		PM10	10.390135	10.737069	3.339075
3		PM2.5	22.73991	20.383621	-10.361913
4	Madrid	NO_2	13.399103	11.307759	-15.608093
5		O_3	21.830493	22.552155	3.305752
6		PM10	17.017937	15.974138	-6.133524
7		PM2.5	38.35426	40.107759	4.571848
8	Milan	NO_2	25.865403	25.32	-2.108619
9		O_3	33.382938	35.281739	5.687938
10		PM10	24.199052	28.073913	16.012449
11		PM2.5	58.156398	68.995652	18.638111
12	Oulu	NO_2	4.424215	3.620259	-18.171734
13		O_3	17.075785	24.225	41.867565
14		PM10	7.780269	8.422414	8.253503
15		PM2.5	18.457399	18.051724	-2.197899
16	Paris	NO_2	15.647534	12.208621	-21.977348
17		O_3	18.602691	22.622845	21.610606
18		PM10	19.06278	18.538793	-2.748745
19		PM2.5	41.475336	42.344828	2.096406
20	Wuhan	NO_2	16.151131	11.014655	-31.802578
21		O_3	27.941441	24.353879	-12.839574
22		PM10	52.063063	42.62069	-18.136415
23		PM2.5	100.13964	92.603448	-7.525683

Mean Concentration of Pollutants by City **Appendix 7**

BL

	City	Measurement	median
0	Helsinki	NO_2	6.510762
1		O_3	17.9713
2		PM10	10.390135
3		PM2.5	22.73991
4	Madrid	NO_2	13.399103
5		O_3	21.830493
6		PM10	17.017937
7		PM2.5	38.35426
8	Milan	NO_2	25.865403
9		O_3	33.382938
10		PM10	24.199052
11		PM2.5	58.156398
12	Oulu	NO_2	4.424215
13		O_3	17.075785
14		PM10	7.780269
15		PM2.5	18.457399
16	Paris	NO_2	15.647534
17		O_3	18.602691
18		PM10	19.06278
19		PM2.5	41.475336
20	Wuhan	NO_2	16.151131
21		O_3	27.941441
22		PM10	52.063063
23		PM2.5	100.13964

DL

	City	Measurement	median
0	Helsinki	NO_2	4.805603
1		O_3	23.469828
2		PM10	10.737069
3		PM2.5	20.383621
4	Madrid	NO_2	11.307759
5		O_3	22.552155
6		PM10	15.974138
7		PM2.5	40.107759
8	Milan	NO_2	25.32
9		O_3	35.281739
10		PM10	28.073913
11		PM2.5	68.995652
12	Oulu	NO_2	3.620259
13		O_3	24.225
14		PM10	8.422414
15		PM2.5	18.051724
16	Paris	NO_2	12.208621
17		O_3	22.622845
18		PM10	18.538793
19		PM2.5	42.344828
20	Wuhan	NO_2	11.014655
21		O_3	24.353879
22		PM10	42.62069
23		PM2.5	92.603448

Effect of COVID-19 Lockdown on Air Pollutant Concentrations in Different Cities. **Appendix 8**

City	*Pollutant*	*F-value*	*T-statistic*	*P-value*	*Hypothesis*
Oulu	PM2.5	1.47	-1.21	0.22574	Fail to reject null hypothesis
	PM10	1.19	1.09	0.27547	Fail to reject null hypothesis
	O_3	2.16	-1.47	0.14211	Fail to reject null hypothesis
	NO_2	92.67	-9.63	0	Reject null hypothesis
Helsinki	PM2.5	5.45	-2.33	0.01986	Reject null hypothesis
	PM10	4.15	-2.04	0.04193	Reject null hypothesis
	O_3	0.45	-0.67	0.50481	Fail to reject null hypothesis
	NO_2	113.12	-10.64	0	Reject null hypothesis
Paris	PM2.5	5.25	-2.29	0.02226	Reject null hypothesis
	PM10	3.11	-1.76	0.07808	Fail to reject null hypothesis
	O_3	18.79	4.33	0.00002	Reject null hypothesis
	NO_2	82.34	-9.07	0	Reject null hypothesis
Madrid	PM2.5	7.52	-2.74	0.00626	Reject null hypothesis
	PM10	27.28	-5.22	0	Reject null hypothesis
	O_3	20.69	4.55	0.00001	Reject null hypothesis
	NO_2	88.71	-9.42	0	Reject null hypothesis
Milan	PM2.5	19.56	-4.42	0.00001	Reject null hypothesis
	PM10	18.38	-4.29	0.00002	Reject null hypothesis
	O_3	26.04	5.1	0	Reject null hypothesis
	NO_2	97.84	-9.89	0	Reject null hypothesis
Wuhan	PM2.5	42.88	-6.55	0	Reject null hypothesis
	PM10	24.23	-4.92	0	Reject null hypothesis
	O_3	0	0	0.99694	Fail to reject null hypothesis
	NO_2	2.66	-1.63	0.10337	Fail to reject null hypothesis

Regression Analysis Findings Prior to Lockdown **Appendix 9**

OLS REGRESSION RESULTS BL

DEP. VARIABLE	Median		**R-squared**		0.985	
MODEL	OLS		**Adj. R-squared**		0.985	
METHOD	Least Squares		**F-statistic**		2.804e+07	
DATE	Wed, 19 Apr 2023		**Prob (F-statistic)**		0.00	
TIME	18:50:16		**Log-Likelihood**		-6.5815e+06	
NO. OBSERVATIONS	1314271		**AIC**		1.316e+07	
DF RESIDUALS	1314267		**BIC**		1.316e+07	
DF MODEL	3					
COVARIANCE TYPE	nonrobust					
	Coef	**Std err**	**t**	**P > | t |**	**[0.025**	**0.975]**
CONST	-4.1601	0.041	-101.046	0.000	-4.241	-4.079
COUNT	-0.0088	0.000	-51.577	0.000	-0.009	-0.008
MIN	0.4125	0.000	1604.292	0.000	0.412	0.413
MAX	0.5869	0.000	2282.605	0.000	0.586	0.587
OMNIBUS	1316775.708		**Durbin-watson**		1.304	
PROB (OMNIBUS)	0.000		**Jarque-Bear (JB)**		10436313501.679	
SKEW	-3.463				0.00	
KURTOSIS	439.498				584.	
NOTES	Standard Errors assume that the covariance matrix of the errors is correctly specified					

OLS REGRESSION RESULTS BL

DEP. VARIABLE	Median		**R-squared**		0.985	
MODEL	OLS		**Adj. R-squared**		0.985	
METHOD	Least Squares		**F-statistic**		2.804e+07	
DATE	Wed, 19 Apr 2023		**Prob (F-statistic)**		0.00	
TIME	18:50:16		**Log-Likelihood**		-6.5815e+06	
NO. OBSERVATIONS	1314271		**AIC**		1.316e+07	
DF RESIDUALS	1314267		**BIC**		1.316e+07	
DF MODEL	3					
COVARIANCE TYPE	nonrobust					
	Coef	**Std err**	**t**	**P > | t |**	**[0.025**	**0.975]**
CONST	-4.1601	0.041	-101.046	0.000	-4.241	-4.079
COUNT	-0.0088	0.000	-51.577	0.000	-0.009	-0.008
MIN	0.4125	0.000	1604.292	0.000	0.412	0.413
MAX	0.5869	0.000	2282.605	0.000	0.586	0.587
OMNIBUS	1316775.708		**Durbin-watson**		1.304	
PROB (OMNIBUS)	0.000		**Jarque-Bear (JB)**		10436313501.679	
SKEW	-3.463				0.00	
KURTOSIS	439.498				584.	
NOTES	Standard Errors assume that the covariance matrix of the errors is correctly specified					

Kruskal-Wallis test

Appendix 10

	ANOVA P-VALUE				KRUSKAL-WALLIS P-VALUE			
POLLUTANT	**NO_2**	**O_3**	**PM10**	**PM2.5**	**NO_2**	**O_3**	**PM10**	**PM2.5**
CITY								
HELSINKI	4.805603	23.46983	10.73707	20.38362	4.805603	23.46983	10.73707	20.38362
MADRID	11.30776	22.55216	15.97414	40.10776	11.30776	22.55216	15.97414	40.10776
MILAN	25.32	35.28174	28.07391	68.99565	25.32	35.28174	28.07391	68.99565
OULU	3.620259	24.225	8.422414	18.05172	3.620259	24.225	8.422414	18.05172
PARIS	12.20862	22.62285	18.53879	42.34483	12.20862	22.62285	18.53879	42.34483
WUHAN	11.01466	24.35388	42.62069	92.60345	11.01466	24.35388	42.62069	92.60345

Tukey's HSD Results for Pollutant Concentrations BL **Appendix 11/1**

Multiple Comparison of Means - Tukey HSD, FWER=0.05

GROUP1	GROUP2	MEANDIFF	P-ADJ	LOWER	UPPER	REJECT
HELSINKI	Madrid	8.2474	0	5.4626	11.0323	TRUE
HELSINKI	Milan	20.9979	0	18.1737	23.8221	TRUE
HELSINKI	Oulu	-2.4686	0.1164	-5.2535	0.3163	FALSE
HELSINKI	Paris	9.2941	0	6.5092	12.0789	TRUE
HELSINKI	Wuhan	34.7079	0	31.9191	37.4967	TRUE
MADRID	Milan	12.7505	0	9.9263	15.5747	TRUE
MADRID	Oulu	-10.716	0	-13.5009	-7.9312	TRUE
MADRID	Paris	1.0466	0.8928	-1.7382	3.8315	FALSE
MADRID	Wuhan	26.4605	0	23.6717	29.2493	TRUE
MILAN	Oulu	-23.4665	0	-26.2907	-20.6423	TRUE
MILAN	Paris	-11.7039	0	-14.5281	-8.8797	TRUE
MILAN	Wuhan	13.71	0	10.8819	16.538	TRUE
OULU	Paris	11.7627	0	8.9778	14.5475	TRUE
OULU	Wuhan	37.1765	0	34.3877	39.9653	TRUE
PARIS	Wuhan	25.4139	0	22.6251	28.2026	TRUE

Tukey's HSD Results for Pollutant Concentrations BL **Appendix 11/2**

Multiple Comparison of Means - Tukey HSD, FWER=0.05

GROUP1	GROUP2	MEANDIFF	P-ADJ	LOWER	UPPER	REJECT
HEL-SINKI	Madrid	7.6364	0	4.7035	10.5693	TRUE
HEL-SINKI	Milan	24.5688	0	21.6295	27.5081	TRUE
HEL-SINKI	Oulu	-1.2692	0.8204	-4.2021	1.6637	FALSE
HEL-SINKI	Paris	9.0797	0	6.1469	12.0126	TRUE
HEL-SINKI	Wuhan	27.7991	0	24.8662	30.732	TRUE
MADRID	Milan	16.9324	0	13.9931	19.8716	TRUE
MADRID	Oulu	-8.9056	0	-11.8385	-5.9727	TRUE
MADRID	Paris	1.4433	0.7254	-1.4896	4.3762	FALSE
MADRID	Wuhan	20.1627	0	17.2298	23.0956	TRUE
MILAN	Oulu	-25.838	0	-28.7772	-22.8987	TRUE
MILAN	Paris	-15.4891	0	-18.4283	-12.5498	TRUE
MILAN	Wuhan	3.2303	0.0215	0.2911	6.1696	TRUE
OULU	Paris	10.3489	0	7.416	13.2818	TRUE
OULU	Wuhan	29.0683	0	26.1354	32.0012	TRUE
PARIS	Wuhan	18.7194	0	15.7865	21.6523	TRUE

Mean Measurement Values **Appendix 12**

BL

MEASUREMENT	NO_2	O_3	PM10	PM2.5
CITY				
HELSINKI	6.510762	17.9713	10.390135	22.73991
MADRID	13.399103	21.830493	17.017937	38.35426
MILAN	25.865403	33.382938	24.199052	58.156398
OULU	4.424215	17.075785	7.780269	18.457399
PARIS	15.647534	18.602691	19.06278	41.475336
WUHAN	16.151131	27.941441	52.063063	100.13964

DL

MEASUREMENT	NO_2	O_3	PM10	PM2.5
CITY				
HELSINKI	4.805603	23.469828	10.737069	20.383621
MADRID	11.307759	22.552155	15.974138	40.107759
MILAN	25.32	35.281739	28.073913	68.995652
OULU	3.620259	24.225	8.422414	18.051724
PARIS	12.208621	22.622845	18.538793	42.344828
WUHAN	11.014655	24.353879	42.62069	92.603448

Correlation Coefficients **Appendix 13**

BL

MEASUREMENT	NO_2	O_3	PM10	PM2.5
CITY				
HELSINKI	0.644469	-0.036707	0.656893	0.061625
MADRID	0.643154	0.146624	0.681964	-0.085576
MILAN	0.555554	0.416956	0.450797	-0.066808
OULU	0.633302	-0.24107	0.626202	0.159402
PARIS	0.658332	0.099357	0.663735	0.073693
WUHAN	0.576887	0.287643	0.668198	-0.019971

DL:

MEASUREMENT	NO_2	O_3	PM10	PM2.5
CITY				
HELSINKI	0.666104	-0.30875	0.641529	0.18092
MADRID	0.644023	0.073343	0.577279	0.295788
MILAN	0.528838	0.410022	0.49586	-0.078065
OULU	0.651101	-0.456979	0.660364	0.137373
PARIS	0.612662	0.030648	0.64559	0.414647
WUHAN	0.654347	0.099887	0.50535	-0.193529

Descriptive Statistics for Pollutants **Appendix 14**

BL

	COUNT	MEAN	STD	MIN	25%	50%	75%	MAX
MEASUREMENT								
NO_2	106676	10.173495	9.209041	0	4.7	8.2	12.8	500
O_3	100302	19.944402	20.815201	0	10.8	18.4	25.9	500
PM10	105855	26.301032	23.422114	0	12	20	33	999
PM2.5	108451	53.739112	40.28884	0	25	45	68	999

DL

	COUNT	MEAN	STD	MIN	25%	50%	75%	MAX
MEASUREMENT								
NO_2	113853	8.725331	6.9534	0	4.2	6.9	11.2	183.8
O_3	106173	21.481502	10.998334	0	13.5	21.6	28.5	274
PM10	114529	25.577783	22.549483	1	11	19	33	882
PM2.5	117935	52.550127	39.825652	1	25	42	68	834

Summary Statistics of Pollutant Concentrations in Selected Cities **Appendix 15**

MEASUREMENT	NO_2	O_3	PM10	PM2.5
COUNT	6	6	6	6
MEAN	13.748625	22.436689	22.616491	49.2765
STD	8.136903	4.158567	15.510619	31.105365
MIN	4.656919	19.2547	8.511749	19.644909
25%	8.059786	20.212631	12.814075	27.24277
50%	14.322704	20.683485	18.21627	41.648072
75%	15.425981	22.802827	26.079621	61.084014
MAX	27.423537	30.433511	51.040576	102.714286