Addis Ababa University
College of Natural and Computational Science
Center for Environmental Science
Atmosphere, Energy and Climate Change stream

Spatiotemporal Dynamics of Atmospheric Fine Particulate Matter ($PM_{2.5}$) over Addis Ababa, Ethiopia

Master of Science (MSc.) Thesis
Tofikk Redi Indris

Supervisor: Dr. Eyale Bayable Tegegne

Addis Ababa, Ethiopia,
November, 2024

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A Thesis Submitted to the Center for Environmental Science of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Environmental Science,
Addis Ababa University,
Addis Ababa, Ethiopia,
November, 2024

Addis Ababa University
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Letter of Certification

This is to certify that **Tofikk Redi Indris** has carried out his thesis on the topic "**Spatiotemporal Dynamics of Atmospheric Fine Particulate Matter ($PM_{2.5}$) over Addis Ababa, Ethiopia**". This work is original in nature and is suitable for submission for the award of Degree of Master of Science (MSc.) at Center for Environmental Science (CES).

Signed by the Examining Committee

Name **Signature** **Date**

____________________(Supervisor) ____________ ____________

____________________(External Examiner) ____________ ____________

____________________(Internal Examiner**)** ____________ ____________

_____________________(Chairman of the Center for Environmental Science**)**

____________ ____________

Declaration

I **Tofikk Redi Indris,** Registration Number/I.D. Number GSR/2221/15, do hereby declare that this is my original work and that it has not been submitted, partially or in full by any other person for the award of a degree at any other university/institution.

Name of Researcher: **Tofikk Redi Indris** Signature ____________Date.18/11/2024 GC.

This has been submitted for examination with my approval as the supervisor.

Name of supervisor: **Dr. Eyale Bayable** Signature _____________Date. 18/11/2024 GC

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Abstract

Air pollution affects health, environment, and property globally; however, posing challenges in developing countries due to weak regulations and reusing secondhand factories for investments. Like other cities in the developing countries, Addis Ababa is facing air pollution problem due to rapid industrialization, ineffective transport system, and rapid growth in traffic volumes with increasing population. Hence, the aim of this study was to investigate spatiotemporal dynamics of atmospheric fine particulate matter ($PM_{2.5}$) in Addis Ababa using available PurpleAir (PA) sensors in the city. Measurements from seven PA sensors (Aratkilo, Entoto, Jacros, BLH, ECA, RepiWtE, and Skyline) were processed using R and Python programming. The analysis has shown that the diurnal mean value of $PM_{2.5}$ was peak during morning and early night at each PA monitoring locations. This could be attributed to traffic congestions due to people hurrying to their working place and home for respectively peak and temperature variation with minimum temperature at the early morning and night and maximum at midday. Fluctuations of $PM_{2.5}$ concentrations show clear variability's and daily patterns in the week with increasing from Monday to Friday and decreasing in the weekend. Moreover, about 75% of the daily $PM_{2.5}$ are also above WHO guideline in all PA monitoring locations. Seasonal analyses have shown that the $PM_{2.5}$ data have a maximum value during June to September (Kiremt season) and minimum during October to January (Bega) at each monitoring stations. In the Kiremt season, 87.5 % of the existing daily concentrations of $PM_{2.5}$ were above WHO guideline in all monitoring stations. The concentrations of $PM_{2.5}$ during Belg and Bega seasons were relatively lower than during Kiremt season. However, in these seasons about 75% of $PM_{2.5}$ concentrations above WHO guideline. On average, the 2022 annual mean of $PM_{2.5}$ was 5.5 $\mu g/m^3$ and in 2023 it was 6.5 $\mu g/m^3$, exceeding WHO standards by a value of 0.5 $\mu g/m^3$ and 1.5 $\mu g/m^3$ respectively. There is a significant difference among the daily mean $PM_{2.5}$ concentrations at PA stations with a P-value of 0.01 (alpha=0.05). Relatively, BLH and RepiWtE sites had the highest $PM_{2.5}$ levels, while Entoto recorded the lowest. The number of AQ sensors, more apportionment study, shift to clean energy, use diversify renewables energy, reduce waste, set standards and improve public transportation emissions are advisable in the future to cut pollution.

Keyword: *Addis Ababa, Air pollution, Air Quality, $PM_{2.5}$, PurpleAir.*

Abbreviation and Acronym

AAP	American Academy Pediatrics
AAEPA	Addis Ababa Environmental Protection Authority
AAU	Addis Ababa University
AP	Air Pollution
AQ	Air Quality
AQG	Air Quality Guideline
AQM	Air Quality Monitoring
ANOVA	Analyses of Variance
BAM	Beta Attenuation Mass Monitor
BLH	Black Lion Hospital
CB	Black Carbon
CO	Carbone Monoxide
CO_2	Carbon die Oxide
CSA	Central Statistics Agency
ECA	Economic Commission for Africa
EMI	Ethiopian Meteorology Institute
FDER	Federal Democratic
FEM	Federal Equivalent Method
FRM	Federal Reference Method
GDP	Growth Domestic Product
GHG	Green House Gas
HAP	Hospital Acquired Pneumonia
IEA	International Energy Agency’s
IHME	Institute for Health Metrics and Evaluation
IRENA	International Renewable Energy Agency’s
LOCF	Last Observation Carried Forward
MEFCC	Ministry of Environment, Forest and Climate commission

MoH	Ministry of Health
NASA-MAIA	National Atmospheric Science Administration Multi Angle Imager for Aerosols
NOCB,	Next Observation Carried Backward
NO_2	Nitrogen dioxide
NO_X	Nitrogen Oxide
O_3	Ozone
PAs	PurpleAir
Pb	Lead
$PM_{2.5}$	Particulate Matter air diameter 2.5 micro meter
PM_{10}	Particulate Matter air diameter 10 micro meter
RH	Relative Humidity
SLCPs	short-lived climate pollutants
SO_2	Sulfur dioxide
SO_X	Sulfur Oxide
STL	Seasonal and Trend decomposition using Loess
UNIDO	United Nations Industrial Development Organization
UNDP	United Nation Diplomat Program
UNSD	United Nations Statistics Division
US EPA	United States Environmental Protection Agency
Tair	Air Temperature
TSP	Total Suspended Particle
WHO	World Health Organization
WtE	West to Energy

1. Introduction

1.1. Background

Air pollution significantly alters the atmosphere with chemicals or agents, which adversely harming health, environment, and economy. The World Health Organization (WHO) identifies six basic pollutant that have harmful effects: particulate matter (PM), carbon monoxide (Smiraglia et al.), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2) and lead (Pb). These pollutant contribute to over 1 in 9 deaths globally, with an estimated 8.1 million deaths worldwide (Azene, 2020; State of Global Air, 2024; WHO, 2009). Relatively, ambient $PM_{2.5}$ and household air pollution are major contributor of air pollutants in today's world. The spatial distributions of $PM_{2.5}$ have shown a significant difference across the world. For instance, studies using annual mean satellite $PM_{2.5}$ concentration data have indicated a yearly rising trend of $PM_{2.5}$ in North America, Europe, and India (NASA., 2017). This study has revealed a very noticeable rises of $PM_{2.5}$ from 2005-2013 in India and from 2011-2018 and declining trend in China (Hammer et al., 2020). The economic and technological disparities likely manifest in $PM_{2.5}$ levels, with developed countries showing lower trends compared to India and the Middle East, offering valuable insights for developing nations (Jia et al., 2023).

Air pollution is a newly emerging problem in Africa. The continent is experiencing some of the worst air pollution in the world and air quality has deteriorating rapidly over the past 50 years(Mead et al., 2023). This is attributed to the types of fuel that most people in Africa rely on. About 970 million people in Africa depend on biomass burning, leading to both indoor and outdoor air pollution. Additionally, open waste burning exacerbates pollution continent-wide (Africa Energy Outlook, 2022). Future air pollution is expected to be worse than the current status in Africa. The continent's energy needs are projected to grow by 2050 due to rapid urbanization, industrialization, and motorization, a significant increase compared to since 1970 (Gerland et al., 2022). Nigeria's crude oil exploitation results in black carbon (BC) and particulate pollution (GIWA et al., 2024). Coal mining and power generation in South Africa contribute to high greenhouse gas (GHG) emissions. Furthermore, biomass burning in central Africa leads to elevated CO and CO_2 levels and widespread air pollution (Froese et al., 2016).

Air pollution in East Africa have been witnessed from visibility studies. Visibility studies as a proxy for air pollution in the airports of Nairobi, Kampala, and Addis Ababa during the years 1970s to 2000’s have revealed sharp air pollution increases in the cities (Singh et al., 2021). These studies with similar findings in other unbans in Africa (Williams et al., 2021) have prevailed that , the average $PM_{2.5}$ concentration levels in sub-Saharan African countries ranged from 8.9 to 64.6 $\mu g/m^3$. This may have the problem for people, environment and economies of most Africans. Geological materials from roads, road shoulders, agriculture, and land use sectors contribute to 79% of GHG emissions in rural areas (Dawson and Spannagle, 2015), In Ethiopia, studies indicate a rising health risk due to air pollution, including traffic-related emissions (WHO, 2006). These pollutants are linked to 5% of respiratory infections from indoor and outdoor pollutants (MoH, 2010). The economic costs of both indoor and outdoor air pollutions can reach to $70 million in central Ethiopia alone (World Bank, 2022).

Ethiopia is experiencing a tremendous rise in population, urbanization, and industrialization in several regions. While these developmental processes may benefit society and the economy, they also adversely affect human health and the environment. $PM_{2.5}$ levels in the country averaged 280 $\mu g/m^3$, peaking between 2,417-12,739 $\mu g/m^3$ in 24-hour measurements (Worku et al., 2016). $PM_{2.5}$, identified as a significant health risk by WHO, can enter the bloodstream and lungs, causing systemic damage to organs and tissues. This pollutant is produced by processes that harm human health, the environment, and properties (US EPA, 2016).

Addis Ababa, the capital city of Ethiopia and centered in the highlands of Africa, is experiencing rapid population growth and economic expansion. However, this growth is accompanied by increasing urban air pollution, including PM_{10}, CO, lead, ozone, and SO_2, particularly near roads, indicating potential future increases (Etyemezian et al., 2005). This presents a significant challenge for future air quality in the city. High sulfur fuel contributes to $PM_{2.5}$ levels that exceed WHO guidelines, with the major contributors to this pollution being transportation, urbanization, and road infrastructure (Kumie et al., 2021). These global and local problems could adversely impact society, the environment, and the economy. The problems can also exacerbate a lot in global problems of such increasing prevalence of drought events, global warming and climate change. Understanding the spatiotemporal variability of particulate matter is essential for effective management of air quality, protection of public health, and sustainable development of urban and industrial areas. Therefore, this study focused on the spatiotemporal dynamics of $PM_{2.5}$ in the city of Addis Ababa. The result of the study is expected to provide guidance for managing the environment, transportation, and public health for the wellbeing of the common resource. It can also serve as a baseline resource for planners and researchers.

1.2. Research problem

Human activities has had a major global and local impact on the environment since the industrial revolution, particularly affecting vulnerable populations in emerging nations. Indoor and ambient air pollution has been linked to early deaths in various income countries (World Health Statistics, 2019) . This issue is exacerbated in Africa due to weak regulations and the reuse of factories in the name of foreign investments (WHO, 2023). Additional factors such as rapid population growth, urbanization, and industrialization is aggravating the impacts of air pollution in Ethiopia. Coupled to these factors, Addis Ababa has been experiencing rapid population growth and economic development which may escalate the demand for essential services such as housing, transportation, water, waste management, and energy. Consequently, these factors contribute to notable challenges for the city's environment, like changing air quality. In addition, the city has prominent variations in the physical environment, topography, climatic conditions, polluting emission sources. Thus, these factors contribute to significant variation in the temporal and spatial patterns of pollutant concentrations.

Limited point studies on air quality in Addis Ababa have shown that air pollution is becoming worse and worse as compared to since 1970s (Embiale et al., 2021). For instance, a study by Etyemezian et al. (2005) on a daily time scale showed that PM_{10} and CO peaked in late afternoon, while O_3 mounted at midday in the city. However, this study did not adequately cover the spatiotemporal distributions of $PM_{2.5}$, which is more dangerous than PM_{10}. Moreover, most reliable studies were done at three localized points using only three Beta attenuation monitoring (BAM) devices (Kumie et al., 2021). Additional previous studies were also conducted using other limited air quality monitoring devices, which restricts understanding of spatial and temporal $PM_{2.5}$ variability in the city. Therefore, this research explored $PM_{2.5}$ levels monitored by seven PurpleAir devices located across the city and it aims to enhance the representativeness of air pollution distribution in the city.

1.3. Research questions

1. What are the temporal and spatial patterns of $PM_{2.5}$ hourly, weekdays, daily, monthly, seasonally, and annually in selected PurpleAir sensor sites in Addis Ababa?
2. Does $PM_{2.5}$ is significantly vary with the spatially and temporally in Addis Ababa?
3. Is the level and limit of $PM_{2\ 5}$ concentration in Addis Ababa the permissible as compared to global standards?

1.4. Objective of the study

The General objective of the study is to analyses the spatiotemporal dynamics of atmospheric ($PM_{2.5}$) in Addis Ababa, Ethiopia and compare its concentration levels to global standards.

1.4.1. Specific objective of the study

To achieve the general objective of the study, the following specific objectives were done:

- Assesse temporal and spatial patterns of $PM_{2.5}$ concentrations in terms of hourly, weekdays, and daily,
- Analyze trend of $PM_{2.5}$ concentrations interims of monthly, seasonally and annually and
- Determine the level of variability in mean of daily $PM_{2.5}$ concentrations among monitoring location with seasons.

1.5. Significant of the study

According to the studies by US EPA, AQ research is a scientific process aimed at reducing the effects of air pollution on human health and environmental properties. Monitoring and evaluating air pollution is one component of air quality research process. Thus, this study has focused focus on the spatiotemporal analysis of atmospheric $PM_{2.5}$. This research is important for the next future as it aims to document any existing gaps and propose recommendations. Furthermore, it is critical to update existing activities and evaluate air pollutants in terms of temporal analysis for the purposes of establishing air quality standards. These standards are used to protect human health, prevent environmental damage, establish priorities for reduction and control, provide a uniform benchmark for assessing air quality guidelines at the national level, and are important for urban management in the environmental, health, transportation, and industrial sectors.

1.6. Limitation of the research

Understanding the sources of air pollution is crucial for assessing its adverse health effects and improving air quality. Research, such as that by (Solomon, et al., 2012), emphasizes the importance of identifying specific pollutant sources and their mixtures to comprehend their biological mechanisms and their impact on health outcomes. Poor air quality varies significantly by source, location, and time, in this research posing challenges in interpreting findings without comprehensive scientific evidence.

This study encountered several challenges related to air pollution research, the limited availability of data from government and non-governmental air quality monitors was a significant hurdle. Existing sensors were sparsely distributed across the city, which compromised the representativeness of the study area.

Furthermore, there is a shortage of scientists and expertise in air quality monitoring within academic institutions and governmental bodies, further complicating efforts to address air pollution Issus effectively.

2. Literature review

2.1. Air quality and Air pollution

Air quality indicates the cleanliness of the air. However, the quality of air can be significantly altered by air pollutants emitted from human activities, which harm living organisms and the environment. Air pollutants are chemicals, compounds, or elements released into the atmosphere as a result of human activities, and they can harm living organisms (Moriarty, 2006). They can be released indoors through the combustion of biomass fuels, and outdoors through vehicles (mobile sources) and industries (stationary sources). Consequently, air pollutants from these sources are among the major causes of global health problems and they can cause nine out of ten people globally to breathe unhealthy air (WHO AQGs, 2021).

Air pollution is rising across Africa, increasing morbidity, mortality, and diminishing economic productivity, due to lake of intervention, it will harm human capital and development(Fisher et al., 2021). It also highly impact African livelihoods and health, varying across countries and regions. In 2019, $PM_{2.5}$ concentrations (i.e. from both ambient and indoor sources) was the leading cause of deaths across the continent(Mlambo C,et al., 2023). A small-scale air pollution study in Ethiopia revealed that air pollution is increasingly becoming a health concern due to high concentrations of indoor pollutants, as well as traffic-related and other ambient air pollutants (FDER, 2002; Sanbata, 2012; Gragam, 2011; WHO, 2006). Around 5% of acute upper respiratory infections cases might be linked to air pollution (MoH, 2010).

2.2. The major source and cause of ambient air pollution

Ambient air refers to atmospheric air in its natural state, typically consisting of 78% nitrogen, 21% oxygen, and a remaining 1% that includes carbon dioxide, helium, methane, argon, and hydrogen. Ambient air pollution is also known as outdoor air pollution and it poses a global health threat stemming from various sources such as combustion devices, vehicles, industries, and fires. The most concerning air pollutants include Particulate Matter (PM), Carbon dioxide (CO), Ozone (O_3), Nitrogen Oxides (NO_X), and Sulfur Dioxide (SO_X). $PM_{2.5}$ is a type of air pollutant that consists of particulate matter with a dimension of 2.5 micrometers or smaller. These particles are so small that they can be easily breathed deeply into the lungs. Hence, $PM_{2.5}$ are thought to be a significant contribution to air pollution and its harmful health consequences.

The combustion of motor cars, power plants, industrial activities, and wildfires can all produce $PM_{2.5}$ emissions. It can also arise from chemical reactions involving other pollutants in the environment, such as Sulphur dioxide and nitrogen oxides. The level of $PM_{2.5}$ in the atmosphere are continually changing and influenced by a range of factors, including weather patterns, industrial activity and traffic emissions. In recent years, there has been an increasing concern about the influence of $PM_{2.5}$ on public health, particularly in densely populated urban areas. $PM_{2.5}$ levels have been shown to vary greatly across the world, with certain locations having high concentrations of the pollutant due to factors such as forest fires and heavy industries. However, developed countries such as the US, Canada, Japan, and the European Union have witnessed significant reductions in $PM_{2.5}$ levels. This improvement is related to the significant steps taken to monitor and reduce $PM_{2.5}$ levels by tightening air quality regulations and encouraging the use of cleaner technologies. Nevertheless, the impacts of $PM_{2.5}$ are not fully mitigated in these countries, and it remains a major environmental and health problem. On the other hand, other countries and regions have various development routes that prioritize economic growth while neglecting environmental pollution control. For instance, there is an increasing trend of $PM_{2.5}$ concentration, mainly occurring in India, the Middle East, Chile, Colombia, and other developing regions. (Xu et al., 2023). These variations could be attributed to differences in advanced science and technology and urban management, leading to diverse distributions of $PM_{2.5}$ with negative impacts. Many African countries have some of the highest estimated annual average PM_{10} and $PM_{2.5}$ concentrations (Malings et al., 2020). This is attributed to the rapid urbanization and poor transport infrastructure on the continent. Studies on the spatio-temporal variations of $PM_{2.5}$ across different geographical regions in Africa have shown that the West African region remains the most affected by high levels of pollution, with a daily average of 40.856 $\mu g/m^3$ in some cities like Lagos, Abuja, and Bamako. In East Africa, Uganda was reporting the highest pollution levels, with a daily average concentration of 56.14 $\mu g/m^3$, and Kigali reports 38.65 $\mu g/m^3$ (Gahungu et al., 2022). Furthermore, studies on three East African countries (Uganda, Ethiopia, Kenya) have found that urban ambient air pollution annual averages exceed WHO limits, with Kampala having the highest values at 55.7 ± 20.3 $\mu g/m^3$, 100% above the WHO limits, (Singh et al., 2021). In another review of eight studies on ambient air pollution in African cities (covering seven countries: Algeria, Egypt, Ethiopia, Mali, Morocco, Nigeria & Zimbabwe), $PM_{2.5}$ concentrations varied between 40 and 260 $\mu g/m^3$ (Naidja et al., 2017) compared to an annual average of 20 μg/m³ in urban Europe (Rys et al., 2022) and 8.20 μg/m³ in the United States (Cheng et al., 2024) in 2020. In a separate systematic review on ambient air pollution, (Katoto et al., 2019) also reported an annual $PM_{2.5}$ concentrations in Cameroon, Kenya, Madagascar, Mauritius, Nigeria, Senegal, South Africa, Uganda, and Tanzania were found to be between 19 μg/m³ and 170 μg/m³.

Most of the population in Africa lives in rural areas, yet current air pollution studies on the continent focus primarily on towns and capital cities, where less than 50% of the population resides. However, air pollution is a significant and growing issue in Africa, driven by population momentum and rapid urbanization in the future. Several African cities are poised to become megacities in the coming decades (Evans, 2016; Liotta and Miskel, 2012; Muggah, 2014), offering opportunities for economic and social development. However, this rapid growth also presents significant challenges, such as the need for effective urban planning, investment in infrastructure, and mitigation of air pollution issues. This is particularly true in East African countries. As East African countries continue to develop, increased industrial activities and urbanization will likely contribute to higher levels of air pollution. Major cities such as Nairobi, Kampala, and Addis Ababa are expected to see significant growth in population and industry, leading to higher emissions from vehicles, factories, and construction. Addis Ababa, the capital city of Ethiopia, differs from other East African cities in several ways regarding air pollution:

1. **High Altitude**: The city is situated at a high altitude, approximately 2,355 meters above sea level. This elevation influences atmospheric conditions, potentially affecting the dispersion and concentration of pollutants differently compared to lower-altitude cities. The mountainous location also affects wind patterns and the natural dispersion of pollutants, leading to localized pollution issues.
2. **Industrial Emissions**: Addis Ababa hosts various manufacturing plants and processing industries, including textiles, food and beverages, and construction materials. These industries emit pollutants such as sulfur dioxide (SO_2), nitrogen oxides (NOx), volatile organic compounds (VOCs), and particulate matter (PM) into the atmosphere. Additionally, the city's recent construction boom contributes to dust and particulate matter in the air. The scale and pace of construction may differ from those in other cities in the region.

3. **Vehicle Emissions**: As Addis Ababa continues to grow, the need for expanded and efficient transportation facilities becomes increasingly critical. The city has a growing number of vehicles, many of which are older and less efficient, leading to higher emissions of pollutants such as NOx and $PM_{2.5}$. The quality and age of the vehicle fleet can differ from other cities, impacting overall pollution levels.
4. **Climate**: Addis Ababa's climate, characterized by a distinct rainy season, influences the dispersion and washout of pollutants. This seasonal variation can differ from the climate patterns in other East African cities, impacting air pollution levels throughout the year.
5. **Environmental Enforcement**: Compared to other East African cities, Ethiopia's environmental enforcement mechanisms and public awareness campaigns are weak in implementation. This contributes to the overall air pollution profile of Addis Ababa. By understanding these factors, it's possible to see how Addis Ababa's unique characteristics contribute to its air pollution profile compared to other East African cities.

Research on air pollution is still in its infancy in Ethiopia. Despite the increasing recognition of air pollution as a significant public health and environmental issue, there has been limited scientific investigation and data collection on the subject. There are only a few air pollution monitoring stations in the country's large cities. Recent air quality monitoring in Ethiopian cities such as Addis Ababa, Hawassa, and Adama has revealed that PM_{10} levels exceed WHO limits, and CO concentrations surpass half of the WHO guidelines for 2005. Total Suspended Particles (TSP) concentrations also exceeded WHO's safe levels, while CO levels in on-road samples are half the WHO air quality guideline (Etyemezian et al., 2005). Gaseous ambient measurements at Black Lion Hospital in Addis Ababa, from 2014 to 2017, showed NO_2, NO, O_3, and CO concentrations ranging between 21-50 $\mu g/m^3$ and 20 mg/m^3 respectively, with NO2 being the highest, possibly due to vehicle emissions (Kumie et al., 2010). High traffic and cooking activities contribute to peak pollutant levels, exacerbated by a projected 285% increase in diesel vehicle consumption from 2015 to 2035 (Keil et al., 2010). In rural areas, air pollution is primarily caused by road and land use, accounting for 79% of greenhouse gas emissions (Dawson and Spannagle, 2015).

2.3. The major cause and source of indoor air pollution

Indoor air pollution refers to the presence of pollutants in the air within buildings and other enclosed spaces. These pollutants can come from a variety of sources and significantly affect the health and well-being of the occupants. Common sources and types of indoor air pollutants are usually grouped into seven categories: 1) Combustion Sources: These include tobacco smoke, wood-burning stoves, gas stoves, fireplaces, and kerosene heaters. They emit pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), particulate matter (PM), and volatile organic compounds (VOCs). 2) Building Materials and Furnishings: Materials such as asbestos-containing insulation, lead-based paints, certain types of treated wood, and pressed wood products can release pollutants like asbestos fibers, lead dust, and formaldehyde. 3) Household Cleaning and Maintenance Products: Many cleaning agents, disinfectants, and air fresheners release VOCs and other chemicals into the air. 3) Biological Pollutants: These include mold, dust mites, pet dander, bacteria, and viruses. They can be introduced into the indoor environment through various means, including poor ventilation, high humidity, and the presence of pets. 4) Radon: This is a naturally occurring radioactive gas that can seep into buildings from the ground. Radon is odorless and colorless but is a significant cause of lung cancer. 5) Pesticides: The use of pesticides indoors can introduce chemicals into the air that can be harmful if inhaled or ingested. 6) Outdoor Pollutants: Pollutants from the outside can enter indoor spaces through windows, doors, and ventilation systems. These can include outdoor air pollutants like ozone (O_3), particulate matter, and sulfur dioxide (SO_2). 7) Occupant Activities: Activities such as smoking, cooking, and using personal care products can contribute to indoor air pollution. Indoor air pollution can have a range of health effects, from immediate symptoms like headaches, dizziness, fatigue, and irritation of the eyes, nose, and throat, to long-term effects such as respiratory diseases, heart disease, and cancer. The severity of these effects depends on the level and duration of exposure to the pollutants. For instance, indoor air pollution from inefficient combustion and polluting fuels poses health risks to billions of people using solid fuels and kerosene. Women and children who live near inefficient stoves and open fires are primary victims of indoor air pollution. In this regard, studies have shown that about 2.4 billion people worldwide (around a third of the global population) cooked their food using open fires or inefficient stoves fueled by kerosene, biomass (wood, animal dung, and crop waste), and coal in

2020. Most of these people are poor and live in low and middle-income countries. (SDG7, 2021; Wright et al., 2020). This generates harmful household air pollution.

The sub-Saharan Africa region is one of the most energy-impoverished regions in the world, where more than 80% of the people rely on open biomass fuel sources (Vaccari et al., 2012). The situation in Ethiopia is even worse than in most sub-Saharan African countries, as more than 90% of Ethiopian households rely heavily on solid fuels, such as wood as their primary source of energy. Solid biomass is a major source of particulate matter due to its inherent property way of burning such as incomplete combustion, burning conditions, chemical composition, moisture content, other contained contaminants and frequency of use. However, detailed studies on particulate matter at the household and community levels in Ethiopia have not been conducted. Only a few studies have been carried out in Addis Ababa and some smaller towns (Admasie et al., 2019; Endalew et al., 2022; Tamire et al., 2018; Tamire et al., 2021). These studies indicated the levels and peaks of $PM_{2.5}$ in their respective sample sites. For instance, Tefera et al. (2016) had reviewed the few studies conducted in Ethiopia and found indoor $PM_{2.5}$ levels peaked at 280 $\mu g/m^3$ over a 24-hour period (range: 2,417–12,739 $\mu g/m^3$). Similarly, a cross-sectional study conducted by (Sanbata, 2012) in 59 slum neighborhood homes of Addis Ababa found a 24-h indoor $PM_{2.5}$ using the UCB particle monitor. The researchers reported a geometric mean of 818 µg/m3 (SD=3.61), with the highest 24-h geometric mean of $PM_{2.5}$ concentration in homes predominantly using solid fuel, followed by kerosene and clean fuel with means and standard deviations (SD) of 1,134 $\mu g/m^3$ (SD=3.36), 637 µg/m3 (SD=4.44), and 335 $\mu g/m^3$ (SD=2.51), respectively. Moreover, $PM_{2.5}$ levels from kitchens in Addis Ababa exceeded US EPA and the 2006 WHO standards(Wright et al., 2020), reaching 1,580 $\mu g/m^3$, while PM_4 concentrations from roasted coffee beans were also notably high (Keil et al., 2010) in the city.

Cow dung is a type of solid biomass fuel used in various parts of Ethiopia. Due to its low efficiency, burning cow dung typically results in high levels of indoor carbon monoxide (exceeding 4,000 ppm) in addition to particulate matter (Usinger, 2008) as it was evidenced from a pilot study in rural Tigray . This study has exhibited high total suspended particles levels at 20 mg/m^3 (range: 83–175 mg/m^3) due to the use of traditional stoves and biomass fuel, particularly dung, in households. A similar pilot study carried out by (Dyjack et al., 2005) in Gimbie, West Wollega, Oromia Region has shown that the concentrations of respiratory suspended particulate

(RSP) in biomass-fuel-using-homes were 130 times higher than the air quality standards. Similar study by (Desalegn et al., 2011) in Shebedino Wereda, Southern Ethiopia highlighted how the use of biomass fuels, such as dung, poses significant health risks for vulnerable people, such as women and children.

2.4. Impacts of Air pollution

2.4.1. Health impacts

Each year, poor air quality leads to billions of sick days and millions of deaths globally, making it a major environmental threat. In low and middle-income countries, 90% of these deaths occur (Suk et al., 2016), pregnant women, children, and older adults are especially vulnerable. For example, in 2017, air pollution was the third leading risk factor for premature deaths in Ethiopia, accounting for nearly 8% of deaths, or about 41,000 (MOH, 2018). For instance, air pollution was the third leading risk factor for premature deaths, accounting for nearly 8% of deaths almost 41,000 in Ethiopia in 2017 alone (MOH, 2018)

Globally, eight million premature deaths occur annually due to air pollution, making it the foremost environmental threat to public health. However, premature deaths due to air pollution could be prevented by taking stringent actions on policy implementations. For instance, (Ma et al., 2021) found that premature mortality from $PM_{2.5}$ pollution in China decreased by 529,410 between 2014 and 2018. This includes decreases in the number of premature deaths due by ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower respiratory infection (LRI), accordingly(Cohen et al., 2017). Air pollution and climate change are interconnected, sharing sources and impacting health on a global scale (Horne, 2018) This could be attributed to insufficient efforts to address global air pollution, which include monitoring its status, identifying sources, assessing health impacts, and implementing national initiatives. Air pollution has significant health impacts in Africa, contributing to a range of adverse health outcomes. Exposure to air pollutants such as particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) is associated with respiratory and cardiovascular diseases, adverse pregnancy outcomes, and an increased risk of mortality. In Africa, the situation is exacerbated by rapid urbanization, limited regulatory frameworks, and reliance on biomass fuels for cooking and heating. According to the World Health Organization, outdoor air pollution in African cities is responsible for approximately 176,000 premature deaths annually, while household air pollution from biomass cooking fuels causes an estimated 400,000 deaths each year (Fisher et al., 2021). In Ethiopia, air pollution has become one of the leading cause of diseases such as acute lower respiratory infections and chronic obstructive pulmonary diseases (WHO, 2007; IHME, 2014).

Regarding health risks in Ethiopia, the country faces five major challenges: child and maternal malnutrition, air pollution, unsafe water, sanitation, and hand washing, dietary risks, and high systolic blood pressure. Among these, air pollution is a significant concern, contributing to over 76,000 deaths. In 2021 alone, air pollution was responsible for nearly 10% of all deaths in the country. When considered separately, outdoor particulate matter (PM) ranked as the seventh leading risk factor for deaths, while household air pollution (HAP) ranked first. Ozone, however, did not make it into the top 20 risk factors (HEI, 2024).A survey study in Ethiopia reported approximately 1,262,908 cases, constituting 5% of the total, of acute upper respiratory infections, which accounted for 7% of hospital admissions potentially linked to air pollution. In the same year, tuberculosis attributed to 2% of hospital admissions (MoH, 2011). Another study conducted in Addis Ababa from 2006 to 2009 found that 42% of deaths were due to communicable diseases, while 51% were non-communicable. Tuberculosis, respiratory infections, and asthma together accounted for 17% of deaths (Misganaw et al., 2012a; Misganaw et al., 2012b). Diseases such as tuberculosis and respiratory infections were identified as prevalent causes of death in Addis Ababa hospitals during this period, with acute lower respiratory infections particularly associated with high levels of $PM_{2.5}$ in the air, especially among children (CSA, 2012). According to a nationwide report by the Central Statistical Agency (CSA), the national prevalence of acute respiratory infections was 7% (CSA, 2012; Sanbata, 2012; Biruck, 2011).So that, Air pollution is a significant contributor to health problems.

2.4.2. Economic impact

The economic impact of air pollution encompasses various costs and consequences that affect individuals, businesses, governments, and society as a whole. Some of the key economic impacts of air pollution are healthcare costs, lost productivity, decreased labor productivity, agricultural losses**, i**nfrastructure damage among others. .Although impacts of air pollution air pollution is a widespread issue, it disproportionately affects vulnerable populations, resulting in higher hospitalization rates and deaths. This will ultimately reduce the human capital of a certain country. Particulate matter is one of the most important pollutants that can have great economic impacts in developing countries (Anjum et al., 2021; Anwar et al., 2021). Thus, efforts to reduce $PM_{2.5}$ could greatly enhance employment and labor productivity (Cohen et al., 2017; Metrics et al., 2016). However, challenges in policy implementation and enforcement, along with the need for technological advancements, particularly in developing countries, continue to pose significant barriers to attaining these reductions. This is demonstrated by studies that estimated global annual health expenses connected to air pollution reach $8.1 trillion, affecting 6.1% of global GDP (Awe et al., 2022) (World Bank, 2023).

The costs of air pollution are not distributed fairly. Rather, the majority of the costs and deaths from PM2.5 exposure occur in low- and middle-income nations, where air pollution is the primary health concern (Anjum et al., 2021; Anwar et al., 2021; Jion et al., 2023; Naidja et al., 2018; Organization, 2016). Pollution hotspots in South and East Asia, the Middle East, and North Africa have $PM_{2.5}$ levels eight to nine times higher than in North America. China and India account for just over half of all deaths from air pollution(HEI, 2020; Metrics et al., 2016). Air pollution in Africa significantly impacts the economy by affecting both health and productivity. The costs include direct healthcare expenses, loss of labor productivity, and broader economic repercussions due to reduced life expectancy and chronic health issues. In 2019 alone, air pollution killed 1.1 million people in Africa, with 697,000 deaths attributed to household air pollution (HEI, 2020) and 394,300 to ambient air pollution including 383,000 from $PM_{2.5}$ and 11,300 from ozone) . Air pollution has a negative impact on firm performance at lower levels in Africa, although capacity agglomeration increases labor productivity growth more than in other regions (Soppelsa et al., 2021). Air pollution also has considerable economic implications in nations such as Ghana, where expenses were $1.6 billion (0.95% of GDP), and Rwanda, where costs reached $349 million (1.19% of GDP) (Dekker et al., 2024; HEI, 2022). (World Bank, 2022). In Ethiopia, the economic impact of air pollution-related diseases is $3 billion (1.16% of GDP), with premature mortality from PM2.5 exceeding $70 million in Addis Abeba (World Bank, 2022). This demonstrates that air pollution is a major danger to the world economy (Dekker et al., 2024).

2.4.3. Environmental impact

In addition to its impacts on human health and economic growth, air pollution has also numerous environmental impacts. These impacts can be direct or indirect. As air pollutants in the form of particles and gases are emitted into the atmosphere from various sources within the Earth's environment, they can adversely impact the environment in multiple ways, such as causing acid rain and ecosystem damage, being a source of Secondary Pollutants, Ozone depletion, reducing visibility and climate change. Most hazardous gases can be released during the burning of trash, particularly plastics and other dangerous materials, whether at households, landfills, or incinerators, can pollute the air and pose risks to public health. Most air pollutants are derived from improper operation of Waste-to-Energy (WtE) facilities, such as furnaces operating at temperatures below required levels, can result in the release of air pollutants that form toxic dioxins and other hazardous gases. Other air pollutants, such as black carbon (BC) and ozone (O_3), are also considered short-lived climate pollutants (SLCPs). These pollutants can impact climate change and complicate adaptation efforts in physical environment. For instance, O_3 can reduce agricultural productivity for crops like soy, wheat, and maize.

Depending on the spatial area affected, air pollution can have local, regional, and global implications that affect environmental health on different scales. Local air pollution mostly affects the environment surrounding pollutant emission sources. These are primarily large urban regions where traffic emissions are most responsible for the degradation of air quality and the ecosystem. There is also a possibility of industrial accidents, in which toxic fog spreads and kills people in the nearby areas. Because the dispersion of local air pollutants can be influenced by a variety of environmental and meteorological variables, such as atmospheric stability and wind (Kelishadi and Poursafa, 2010), pollutants can stay more and polluted local areas where surrounded by mountains via creating micrometeorological process such us mountain valley breezes. Some air pollutants can be vigorous enough to affect areas far from their sources of emissions, resulting in regional impacts. These regional impacts of air pollution can be caused by several factors, including atmospheric transport, the formation of secondary pollutants, mesoscale meteorological processes, and geographical features so on(Seinfeld and Pandis, 2016). Acid rain formation storms are typical examples of air pollution at regional. Air pollution can also affect significant parts of the Earth's atmosphere, as seen in events like the prolonged drought in the 1980s in the Sahelian zone of Africa and the current impacts of climate change. Studies have shown that atmospheric aerosols and pollutants can influence regional climate patterns, contributing to such extreme weather events (IPCC, 2021; Nicholson, 2001). Air pollution research on large-scale environmental system, including climate change, water, aquatic life and soil are extremely scarce in Ethiopia

2.5. Air pollution control effort

Efforts to combat air pollution in Africa are substantial. Ten major African cities have signed the C40 Clean Air Declaration and are using cost-effective sensing technology for better pollution control. These initiatives aim to monitor air quality, reduce emissions, and protect public health through real-time data and informed policy decisions (C40_Cities, 2019; Peltier et al., 2021; WHO, 2020).

However, current efforts are still inadequate in Ethiopia. To address air pollution effectively, improved air quality measurements, expanded data tools, better regulations, and enhanced cooperation are necessary. Tailored solutions and continuous monitoring are crucial for tracking pollution, understanding trends, identifying sources, and evaluating control strategies (Mead et al., 2023). Investment in infrastructure and research is vital to leverage air quality data. By 2040, Africa needs to double its energy demand while transitioning to clean energy sources like solar, hydropower, and wind to improve air quality (Renewable Energy Transition Africa, 2021).

Diversifying renewable sources will help avoid reliance on fossil fuels and improve waste management practices. Incentives for reuse, recycling, and cleaner technologies are essential (Mead et al., 2023). Prioritizing eco-friendly industries, clean technology standards, and tax incentives will support affordability. Key strategies include enhancing public transportation (Mbandi et al., 2023), setting higher emission standards, promoting non-motorized and electric transport options, and implementing region-specific solutions.

3. Data and Methodology

3.1. Study area descriptions

3.1.1. Geographical location

Addis Ababa, the capital city of Ethiopia and situated in the highlands of Africa, is located on the western edge of the Rift Valley escarpment. It spans from 8.833 to 9.01 N degrees latitude and 38.64 to 38.9 E degrees longitude respectively. Figure 1 displays Ethiopia's map highlighting the study area and locations of PA sensors.

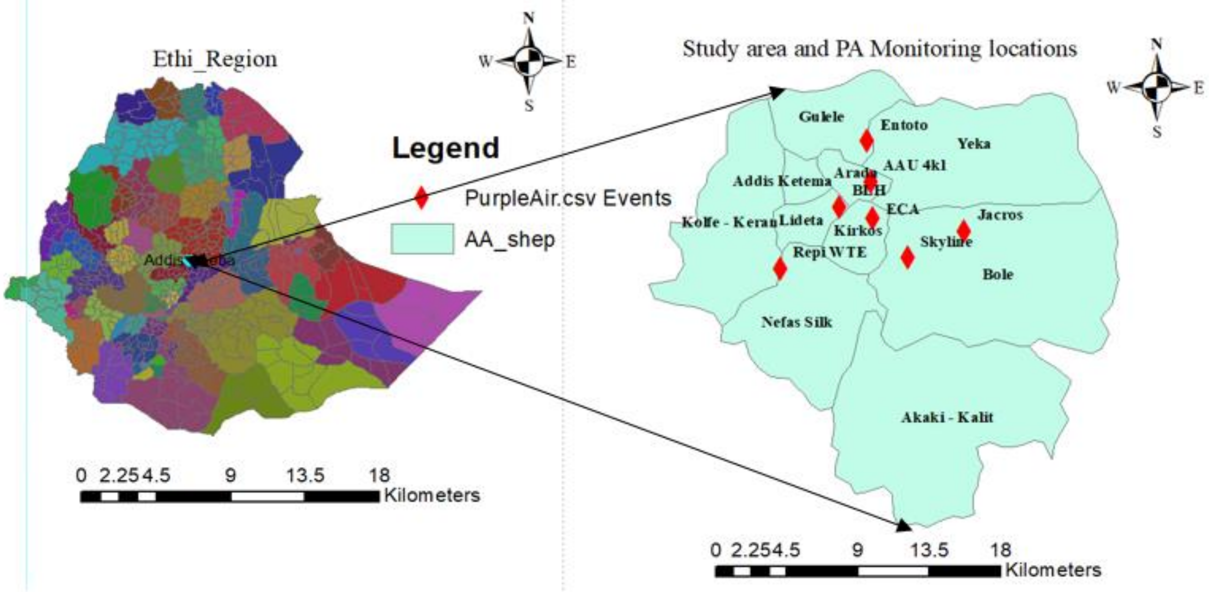

Figure 1. Map of Ethiopia with its zonal boundaries (left), boundary of Addis Ababa with its sub cities and PurpleAir locations with red & slanted squares (right).

The city is surrounded by a mountainous escarpment, locally name the Entoto Mountain from the north. This mountain separates the city from the Sulilta suburb found north of the city and it is stretched in the west to east directions. Most parts of the city is found at the foot of the Entoto range with an altitude of 29,000 meters and scrolling down to 2300 m in the southern periphery towards the Akaki Plains (Wubneh, 2013). This Micro-scale geographical setting can impact the movement of atmospheric pollutants, as the mountains can trap pollutants in the valley, limiting their dispersion by wind(Li et al., 2022; Surmava et al., 2020; Zhang et al., 2022, 2022). Additionally, the city is evolving into an international hub with diverse economic and cultural characteristics. It features major highways, automobiles, buses, minibuses, and trains, serving as a multicultural center with high-rise buildings housing condominiums, offices, shopping centers, hotels, and restaurants. Moreover, other emerging towns such as Bisheftu, Sendafa, Sebeta, Burau, Adama, and Mojo are located in the vicinity of Addis. Most of these towns are expanding rapidly as they are potential sites for industrial growth. Since air pollution knows no borders and is influenced by environmental and meteorological factors, these towns could also become areas of concern for air pollution in the future. All these internal and external factors can collectively influence the city's air quality in the upcoming decades.

3.1.2. Climatology

According to the Ethiopian Meteorology Institute (EMI), Ethiopia experiences three distinct seasons based on temperature and rainfall: Bega (October-January), Belg (February-May), and Kiremt (June-September). Bega is characterized by dry and cold conditions, Belg is a short rainy season in some regions, and Kiremt is the main rainy season for most areas, except the south and southeast (Lemma Gonfa, 1996). This seasonality likely influences air pollution through its impact on pollutant dispersion contributing to variations in atmospheric stability .Addis Ababa is found in central part of the country and it enjoys the three types of seasons. The city has a subtropical climate with an average temperature ranging around 10 °C. From October to January, temperatures are cool (10-15 °C), particularly at night and in the early morning, rising to 20-23 °C during the day. The period from February to May is the warm season, with temperatures often exceeding 23 °C in the afternoon. June to mid-September constitutes the long wet season, characterized by mild temperatures. These variations in atmospheric temperature may lead to fluctuations in atmospheric pollutants both diurnally and seasonally(Jacob & Winner, 2009).

3.1.3. Human Population

Based on the Ethiopian Central Statistical Agency's population census projection report from 2013, the projected female population in Addis Ababa by 2023 is 1,861,000, while the projected male population is 2,084,000 in the same year. With a total projected population of 3,945,000 in 2023, the total population in the city is anticipated to rise to 5,132,000 in 2035. The population growth is expected to lead to increased consumption, which may consequently contribute to changes in atmospheric pollution (Chen & Kan, 2008).

3.1.4. Transportation trend

The current and projected growth of vehicles in Ethiopia's transportation sector have been and will continue to be major contributors to air pollution. It is anticipated that vehicle fuel consumption will increase by approximately 285 percent between 2015 and 2035, with diesel fuel accounting for most of this increase (Danyo et al., 2017). The rising number of vehicles and increased fuel consumption in the transport sector are expected to exacerbate air pollution levels

3.1.5. Industrial trend

According to a 2020 report from the United Nations Industrial Development Organization (UNIDO), Ethiopia currently ranks 114th out of 128 countries in the SDG-9 industry index. Data for Ethiopia show that the share of industry in GDP and total employment is lower than the African average. Despite this, air pollution has become a significant issue in Ethiopia due to ongoing developments in agricultural, industrial, and economic sectors.

3.2. Data types and source

AQ monitoring efforts in Ethiopia are limited. Although some Federal Reference Method (FRM), Federal Equivalent Method (FEM), and low-cost AQ monitoring devices have been installed, they face challenges due to calibration and maintenance issues. FRM and FEM devices are continuous AQ monitoring device that are more accurate in determining basic pollutants, particularly fine particulate matter concentrations. However, they are significantly more expensive to operate and maintaining regularly. Although low-cost sensors like the PA device are less accurate, they can still provide a valuable assessment of fine particulate matter levels.

Thus, for this study, data were collected from seven functional PurpleAir (PA) sensors located at different sites in the city, installed by the NASA-MAIA project: Aratkilo, Entoto, ECA, Blacklion Hospital (BLH), Jacros, Repi, and Skyline. These sensors recorded minute-by-minute data on $PM_{2.5}$ ($\mu g/m^3$), relative humidity (%), and air temperature (°F) from January 2022 to December 2023, using UTC settings. The data were obtained from OpenAQ, an environmental tech nonprofit and the world’s largest free and open-source platform for ground-level ambient air quality data, with all data attributions made to the original data provided by MAIA and PurpleAir. Figure 1 illustrates the locations of the PA sensors in city.

3.3. Handling missing and outlier value

3.3.1. Handling missing value

Handling missing values in any collected data is one of the first issues that must be resolved in order to use that data effectively(Omanovic et al., 2023).Coupled this, PA sensors are electronic gadgets. As a result, like any other electronic device, their usual readings might be thrown off by a variety of reasons such as sensor malfunctions, power and connectivity issues, data transmission and storage issues, weather interferences, and user-related concerns. Missing values in PA time series data can be caused by either of these factors, or by their combination. By considering these factors, the reliability and accuracy of PA sensor readings can be improved through filling the missed data pints. Several methods are available for handling missing values in data, including mean, median, mode, interpolation, last observation carried forward (LOCF), next observation carried backward (NOCB), seasonal/trend adjustment, and regression/machine learning imputation. However, when dealing with data that exhibit seasonal variation, experts recommend using the Seasonal and Trend decomposition using Loess (STL) method for filling missing values (Rudolph et al., 2023). STL splits the data into a seasonal component and a trend component, then performs local-linear loess regression on both to estimate changes over time, this flexible method allows you to choose the polynomial degree for regression and produces convincing results(Harrington, 2020).

Therefore, the STL technique was employed in this study. This method partitions the time series into three components: trend, seasonality, and residuals. It addresses missing values by imputing them to the residuals and subsequently reconstructs the complete time series. Equations 2 illustrates the application of this approach. This explanation succinctly describes how the STL method was utilized to handle missing data in your study, emphasizing its process of decomposition, imputation, and reassembly of the time series components.

$Yt = \hat{Yt} + \hat{St}(1) + \hat{St}(2) + \hat{St}(n) + \hat{Rt}$ ……………………………………………..….equation (2)

Representations,

$\hat{Yt}$ is trend component , $\hat{St}(1) + \hat{St}(2) + \hat{St}(n)$ are seasonal components $\hat{Rt}$ is resigual components

3.3.2. Handling outlier value

Handling outlier values in time series data is crucial because outliers can significantly skew the results of analysis, leading to incorrect conclusions and forecasts Hyndman, R.J., & Athanasopoulos, G. 2018; Aggarwal, C.C. 2013). Effective handling outliers, may ensure that the time series analysis is more accurate and reliable, ultimately leading to better decision-making and insights(Rousseeuw, P.J., & Leroy, A.M. , 2005, Maronna, R.A. et al., 2006). There are different statistical methods to handle outlier values, such as, statistical tests or metrics (z-scores, and Interquartile Range (IQR), square roots, exponential smoothing, Random Forests and algorithms. However, in this study Z score method with threshold level 3 have been applied. Because it is straightforward, mathematically intuitive, and works well in many standard .situations (Moore, D. S., 2012 and Freedman, D., 2007). Accordingly, as presented in figure 2, the red line is the average row $PM_{2.5}$ and green line is outlier handled $PM_{2.5}$ concentrations of at all monitoring site. It successfully identified and cleaned 221 outliers from a dataset of 17,520 and boxplot visual technique was used for replacing the outlier value with mean values.

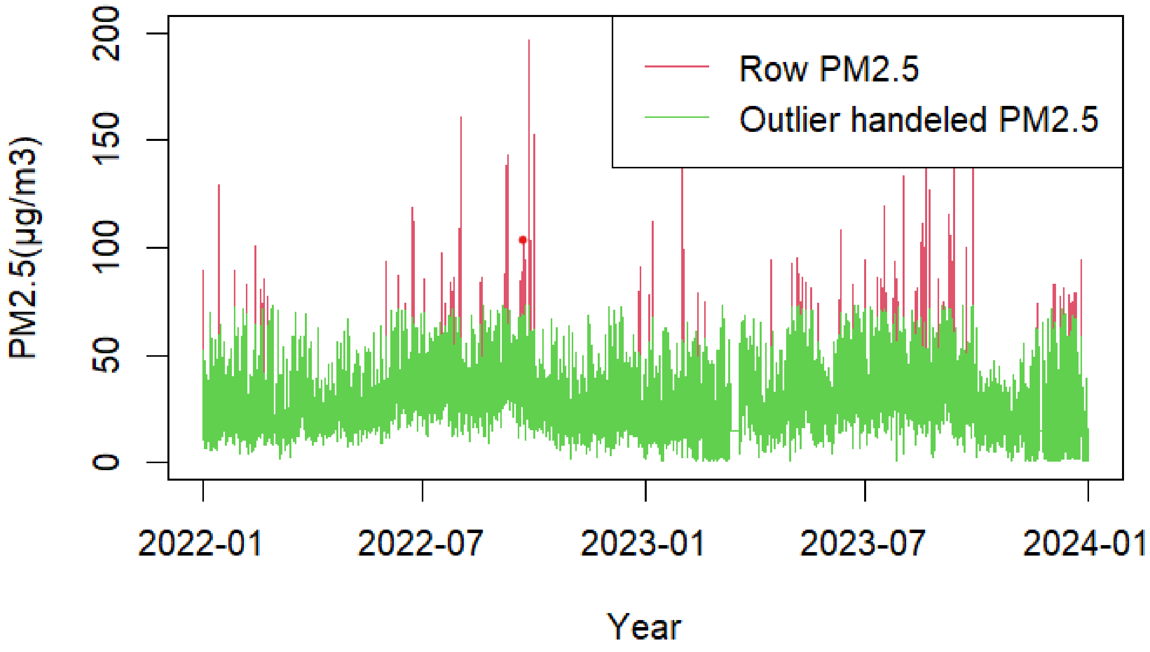

Figure 2. A sample of $PM_{2.5}$ time series graph after (Magenta color) and before (green color) handling the outliers.

3.3.3. Data management and quality assessment

3.3.4. Data quality

The data obtained from these sensors have limitations in reliability and data quality. So that, ensuring data quality is crucial, and the time series data gathered were of sufficient quality to allow for processing and interpretation. To achieve this, several steps were taken to verify completeness, correctness, and consistency of the data from PA sensors. The data initially included alert information, negative values, missing values, and a disorganized timeline. To address these issues, alert information was removed, the timeline was reorganized, and missing data were either filled in or logically removed. Additionally, $PM_{2.5}$ concentrations exceeding 700 µg/m³, which are considered unrealistic, were excluded from the dataset (Tefera et al., 2016).

3.3.2. Calibration

The performance of PA sensors varies by atmospheric conditions (Tryner, J., et al., 2020). Thus, to enhance accuracy and facilitate data interpretation, $PM_{2.5}$ data from PA sensors were adjusted to align with AirNow monitors, as recommended by (Barkjohn et al., 2021). Specifically, a regression model in (equation 1) developed by MAIA using co-located PA and BAM data at US Embassy sites was applied to correct hourly $PM_{2.5}$ concentrations from the beginning of 2022 to the end of 2023.This approach aimed to improve the reliability of $PM_{2.5}$ measurements across all locations monitored by PA sensors in city. The model was created using 75% of the existing data for training, while 25% of the data was used for validation. Accordingly, before the calibration of PurpleAir sensors with AirNow sensors, the root mean square error (RMSE) was 12.46 and the R^2 was 70.2%. After calibration, the RMSE was 7.10 and the R^2 was 75.6%.

$$\mathrm{PM2.5, calibrated} = 17.189 + 0.664 * \mathrm{PM2.5row} + 8 * 10^{-3} * \mathrm{Tair} - 0.153 * \mathrm{RH} \ldots\ldots\ldots\ldots\text{(equation 1)}$$

Representation, $PM_{2.5}$: is $PM_{2.5}$ concentrations after adjustment using the calibration equation. $PM_{2.5row}$: is average value of PA $PM_{2.5}$ (CF_1) from channels A and B in µg/m³. T_{air}: is the air temperature measured by PA in °F and RH: is the relative humidity measured by PA in %. The calibration algorithm is important to increase the accurecy of the PA measurments (Mathieu-Campbell, M. E. et al., 2024), because its recorded afected by local wthers (RH and Tair). We can observe the results in the figures showing the data before and after calibration. Thus, Figure 1 represent the the red line is row $PM_{2.5}$ and the green line is calibrated $PM_{2.5}$ concentrations.

Accordingly, the Mean Absolute Percentage Error (MAPE) is 4.92%, it is less than 10%, thus the model is performing very well, providing correction that are quite close to the actual values on average.

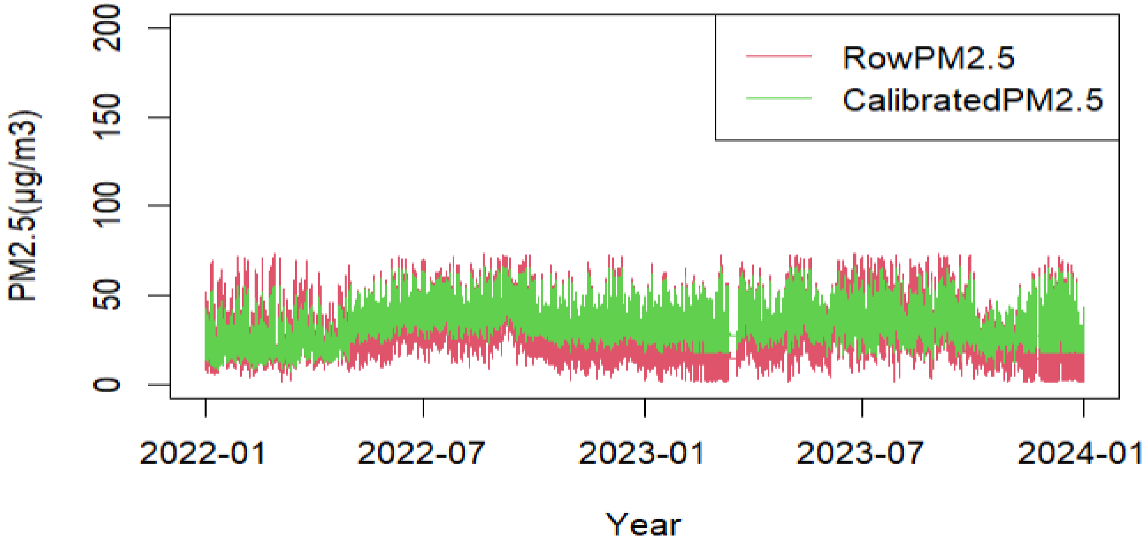

Figure 3. Time series of $PM_{2.5}$ concentrations before (Magenta color) and after (green color) calibration.

3.4. Method

3.4.1. Time series variability analyses

A systematic examination of atmospheric $PM_{2.5}$ concentrations over time. This was designed to understand the $PM_{2.5}$ distribution and variations among monitoring sites. This approach is crucial for determining how temporal variations affect $PM_{2.5}$ levels. Additionally, geographic differences in $PM_{2.5}$ concentrations were investigated at each major monitoring site to better understand their dispersion effects. Furthermore, the study examined trends in $PM_{2.5}$ concentrations to determining a yearly, seasonal, and monthly time scales. This comprehensive technique assists in identifying patterns and trends in $PM_{2.5}$ pollution levels. And also, the study adhered to the World Health Organization's Air Quality Guidelines (AQG), which provide global targets for governments to safeguard public health by reducing air pollution. Clean air is a fundamental human right, yet worldwide air pollution remains a severe threat, contributing to non-communicable diseases such as heart attacks and strokes (WHO, 2021). Therefore, for comparison purposes, the WHO 2021 guidelines for $PM_{2.5}$ levels, (i.e. limits of 15 µg/m³ for 24-hour exposure and 5 µg/m³ for annual exposure) were used in this study.

3.4.2. ANOVA test

Analysis of Variance ANOVA is widely employed by researchers to estimate significant variations among the means different components (Estévez-Pérez & Vilar, 2013). ANOVA is a statistical method used to analyze sample data for specific problems, such as air quality monitoring. In this study, $PM_{2.5}$ concentrations were analyzed using a single-factor ANOVA to determine means, p-values (with a value of 0.05), and variations both between and within groups. Highlighting significant variations in daily $PM_{2.5}$ concentrations across different monitoring locations and seasons is essential. The single-factor ANOVA test was conducted using the following statistical equations: The single-factor ANOVA test was conducted using the following statistical equations:

Sum of Squares between groups means $SSG = \sum_{i=1}^{k} n_i(\overline{x} - \overline{x})^2$ ....equation (3)

Sum of Squares within groups means $SSE = \sum_{i=1}^{k} n_i(n_i - 1){s_i}^2$............................equation (4)

Stands for $Sum\ of\ Squares\ total(SST) = \mathrm{SSG} + \mathrm{SSE}$.................................equation (5)

F statistic $\mathrm{F} = \frac{\mathrm{SSG}}{\mathrm{SSE}}$ ....equation (6)

Representation:

k = the number of values, n_i = the sample size taken from the parameter i, $\bar{x}_i$= the mean of all responses irrespective of parameters, x_i = the i_{th} response sampled from the i_{th} parameters,

s_i = the sample standard deviation from the i_{th} parameters and n = the (total) sample, irrespective of parameters.

3.5. Analysis tool

Python and R have are often used together in data science workflows. Python's versatility makes it a go-to language for a wide range of applications, while R's specialized tools and capabilities make it a powerful choice for statistical analysis and data visualization. The choice between the two often depends on the specific requirements of the task at hand and the user's familiarity with the language. So that, this study utilized both Python version 3 and R version 3.3.6 software to analyze $PM_{2.5}$ data.

Python is renowned for its efficiency in programming tasks and system integration (www.Python.org). It is widely used in various applications, including the analysis of air pollution to understand atmospheric compositions. In this study, Python was specifically employed to manage missing $PM_{2.5}$ data. Its capabilities facilitated the comparison of data before and after handling missing values, helping to select the most accurate method for data imputation.

In contrast, R is a free software environment for statistical computing and graphics, offering a comprehensive suite of tools and packages for data analysis, visualization, data export, web display, and database integration. In this study, R was used for conducting statistical analyses, generating graphs, and managing the extensive monitoring data. This approach highlights the complementary use of Python and R, leveraging their respective strengths to ensure thorough data processing and interpretation in AQ research.

4. Result and Discussion

The study analyzed two years of $PM_{2.5}$ concentration data collected from seven PurpleAir (PA) monitoring located in Addis Ababa. The analysis revealed and deduced that the patterns of variation at hourly, daily, monthly, seasonal, annual levels and the level of variability across the monitoring sites with time. Each of them elaborate din detail below.

4.1. Hourly patterns

Figure 4 and 5 illustrated hourly $PM_{2.5}$ concentrations measured by PurpleAir (PA) sensors across the seven sites: AAU 4kl, Jacros, Entoto, BLH, ECA, RepiWtE, and Skyline. This figures depict consistent variations in $PM_{2.5}$ concentrations, with the first rise starting in the early morning (around 00:00 AM) and peaking between 2:00 and 8:00 AM. The second rise occurs in the early night, between 18:00 and 23:00 PM, with decreasing concentrations in the afternoon, between 6:00 AM and 15:00 PM. However, the first peak in BLH extends from early morning until midday. This pattern may be attributed to the area's commercial activity and the presence of a busy traffic junction with vehicles moving in various directions. Other monitoring locations exhibit similar hourly peak patterns. Similarly, Figure 6 shows the hourly mean variability of PM2.5 concentrations across all PA sensors, with similar patterns of peak concentrations in the early morning and night hours. In addition, Figure 7 and 8 display the hourly variations in $PM_{2.5}$ concentrations on weekdays (Monday to Friday) versus weekends (Saturdays and Sundays). Weekdays shows higher $PM_{2.5}$ levels compared to weekends, which exhibit relatively lower levels. Possibly, this weekly cycle of city air quality is characteristic of most large urban centers, primarily linked to increased mobility during weekdays (Monday to Friday), compared to weekends (Saturday and Sunday) and also more work on weekdays less on weekends. Previous studies have also reported similar patterns, with $PM_{2.5}$ peaking in the mornings, dipping on Sundays, and increasing steadily from Mondays to Fridays (Kumie et al., 2021). This variation can be attributed to high traffic during morning hours and temperature inversions occurring in early morning and night, as noted elsewhere (Abdul-wahab, 2003; Baumbach & Vogt, 2003). The high $PM_{2.5}$ levels on weekdays largely might be result from the increased number of vehicles in Addis Ababa between 2010 and 2019, there was a significant surge in vehicle numbers (Wondifraw et al., 2018), particularly diesel vehicles, which have a substantial impact on air quality in the city. Approximately 55% and 33% of vehicular $PM_{2.5}$ emissions in Addis Ababa originate from heavy-duty diesel vehicles and petrol passenger cars, respectively (Tarekegn & Gulilat, 2018). In east Africa (Addis Ababa, Kampala, and Nairobi) the hourly mean concentrations of $PM_{2.5}$ above WHO guideline and unhealthy(Singh et al., 2021). These emissions could have contribution significantly to higher pollutant concentrations, posing risks to human and environmental health.

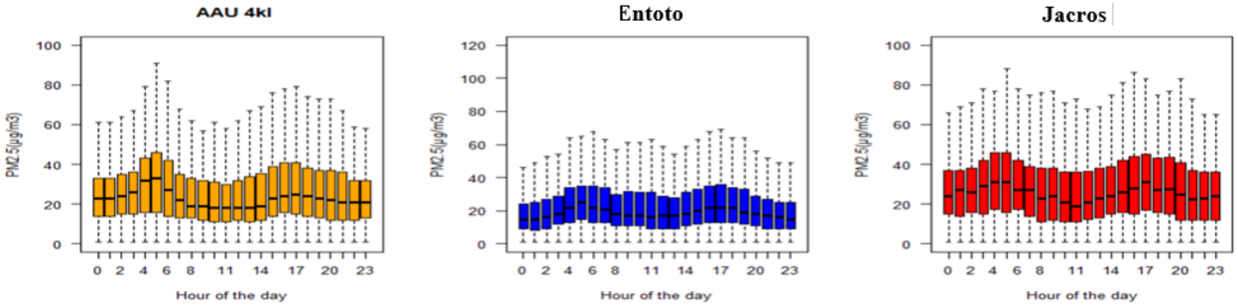

Figure 4.Hourly $PM_{2.5}$ at AAU 4kl, Jacros and Entoto

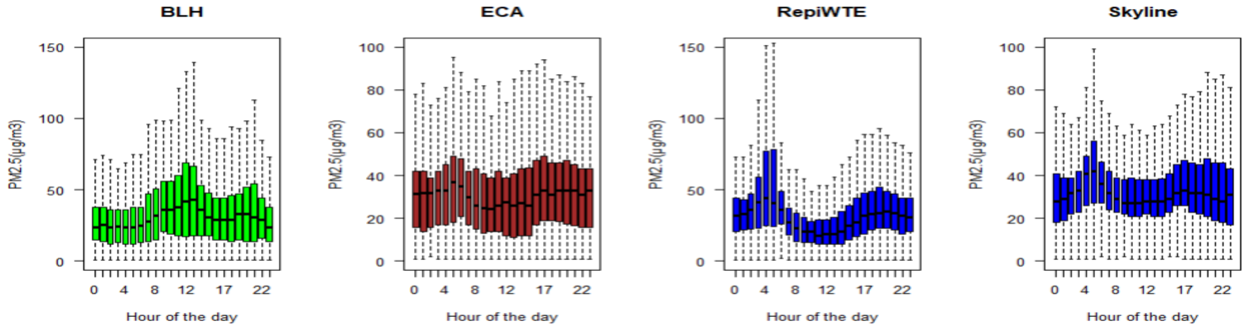

Figure 5.Hourly $PM_{2.5}$ at BLH, ECA, RepiWtE and Skyline

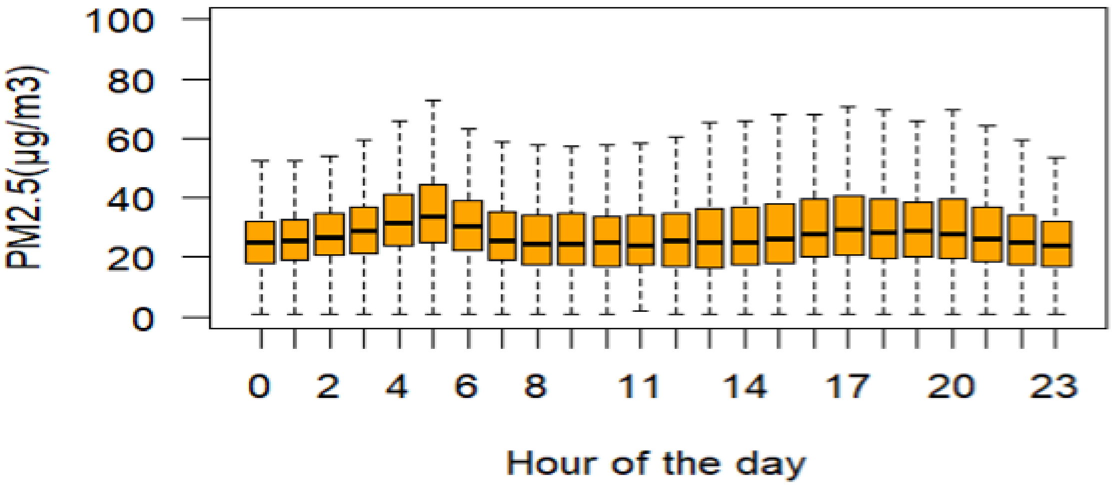

Figure 6.Hourly of $PM_{2.5}$ at all monitoring sits

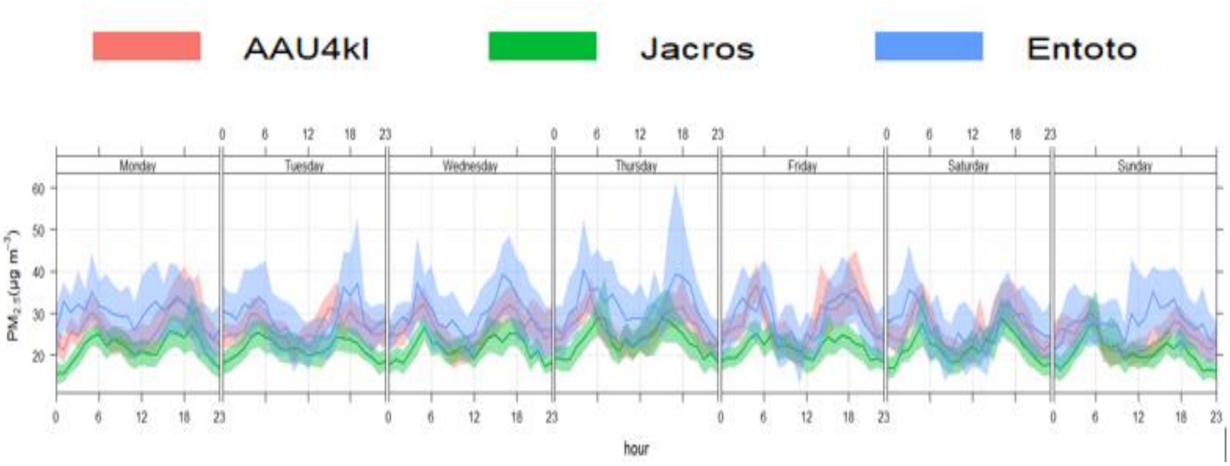

Figure 7.Weekday patterns of $PM_{2.5}$ at AAU4kl, Entoto and Jacros

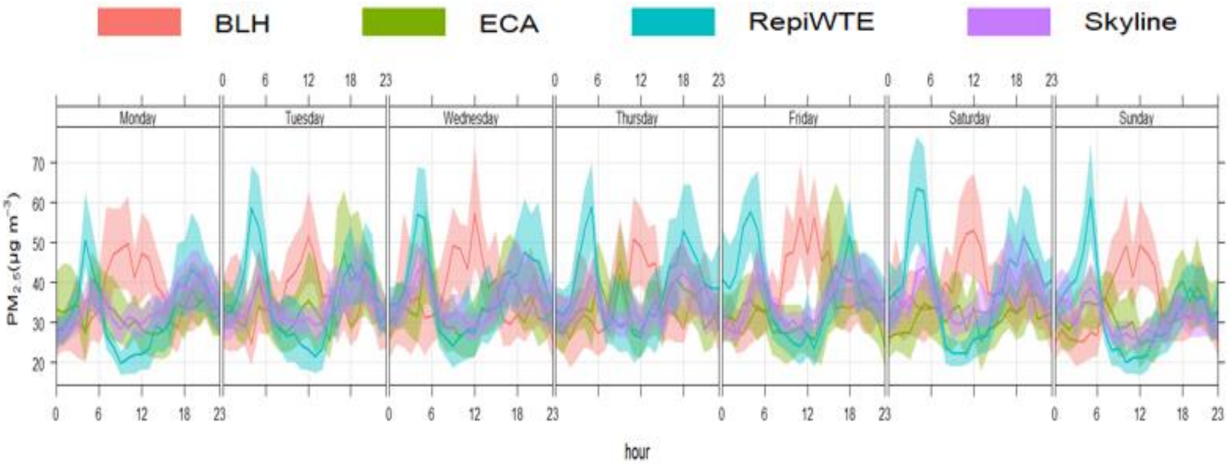

Figure 8.Weekday patterns of $PM_{2.5}$ at Blacklion, ECA, Repi and Skyline

4.1.1. Daily pattern

Figure 9 and 10 demonstrate the daily variability of $PM_{2.5}$ concentrations measured by PurpleAir (PA) sensors at AAU 4kl, Jacros, Entoto, BLH, ECA, RepiWtE, and Skyline. These figures indicate that $PM_{2.5}$ concentrations consistently exceeded the 2021 daily WHO guideline. Likewise, Figure 11 depicts the daily mean variability of $PM_{2.5}$ concentrations across all PA sensors. It shows that 75% of the $PM_{2.5}$ concentrations were above the 2021 daily WHO guideline. In addition, table 1 presented that the daily mean concentrations of $PM_{2.5}$ in the city's is 1.1 times worse than 2021 daily WHO guideline. And also, the highest daily mean concentrations were recorded at RepiWtE. This might be due to the area being a landfill and different work vehicles are there, which may lead to the formation of secondary PM pollutants.

In contrast, the lowest concentrations were recorded at Entoto. This might be because the area is located in the background of the city, resulting in low development activities taking place. Previous studies in Addis Ababa, Nairobi and Kampala, such as (Kumie et al., 2021, Singh et al., 2021) the daily mean $PM_{2.5}$ was exceed WHO guidelines and unhealthy AQI. This infer that the cities atmosphere exist unhealthy AQI. These findings convey that $PM_{2.5}$ could have adverse impacts on human health, property, and environmental well-being.

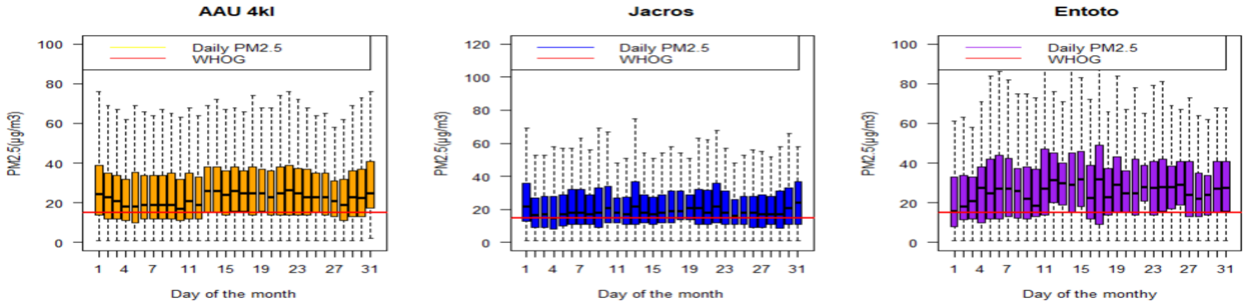

Figure 9. Daily $PM_{2.5}$ variation at AAU 4kl, Jacros and Entoto

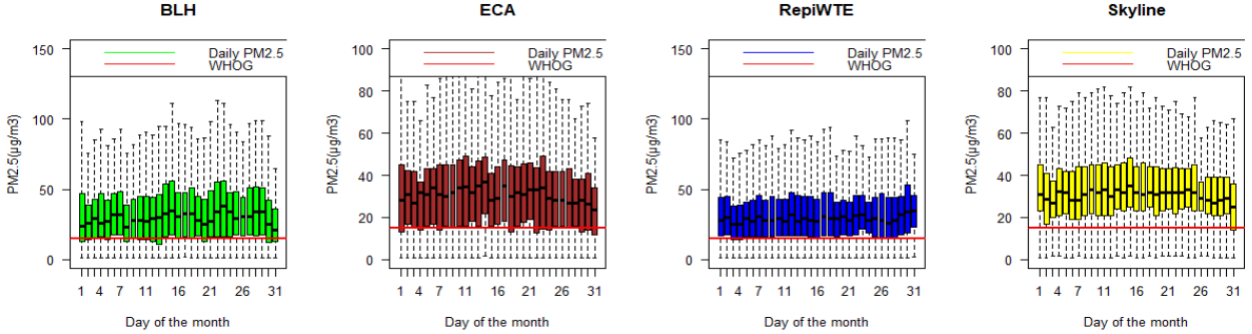

Figure 10.Daily $PM_{2.5}$ variation at BLH, ECA, RepiWtE and Skyline

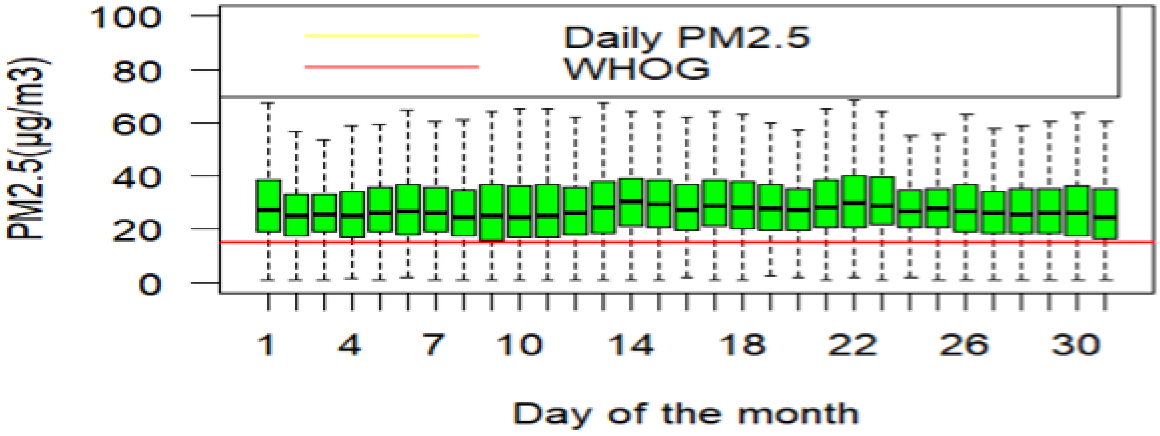

Figure 11.Daily Mean of $PM_{2.5}$ at all PA sites

4.2. Monthly patters and seasonal trend

Figures 12, 13 and 14 illustrate the monthly mean and median variability of $PM_{2.5}$ across PA monitoring sites, accordingly figure 12 highlighting peak concentrations from June to September. Median $PM_{2.5}$ concentrations typically range between 15 µg/m^3 and 25 µg/m^3 at all sites. Also, Figure 13 displays the trend of hourly mean concentrations of $PM_{2.5}$ in each monthly across all PA monitoring sites, ranging from 15 µg/m^3 to 50 µg/m^3. Notably, $PM_{2.5}$ concentrations show a significant increase from June to September, but decreases in other months. In other studies have demonstrated significant variations in $PM_{2.5}$ concentrations on a monthly basis (Thangavel et al., 2022). For instance, in November 2017, air quality in Hidar Sitaten was deemed unhealthy for sensitive groups, with an air quality index of 112 and $PM_{2.5}$ levels at 44.2 µg/m^3 (Bulto, 2020). Lower $PM_{2.5}$ levels in April and May have been attributed to higher daily temperatures (Etyemezian et al., 2005). These variations may be influenced by atmospheric phenomena and seasonal changes, such as local climate variability. For instance, temperature inversions, which are more pronounced from June to September than other months, could contribute to these patterns.

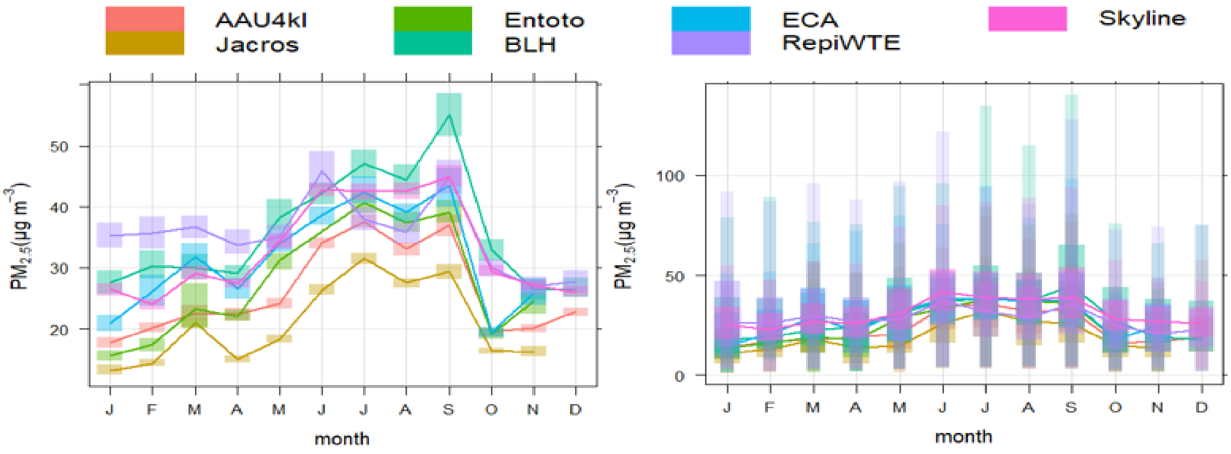

Figure 12.Monthly mean (left) and median (right) variations of $PM_{2.5}$ at all PA sites

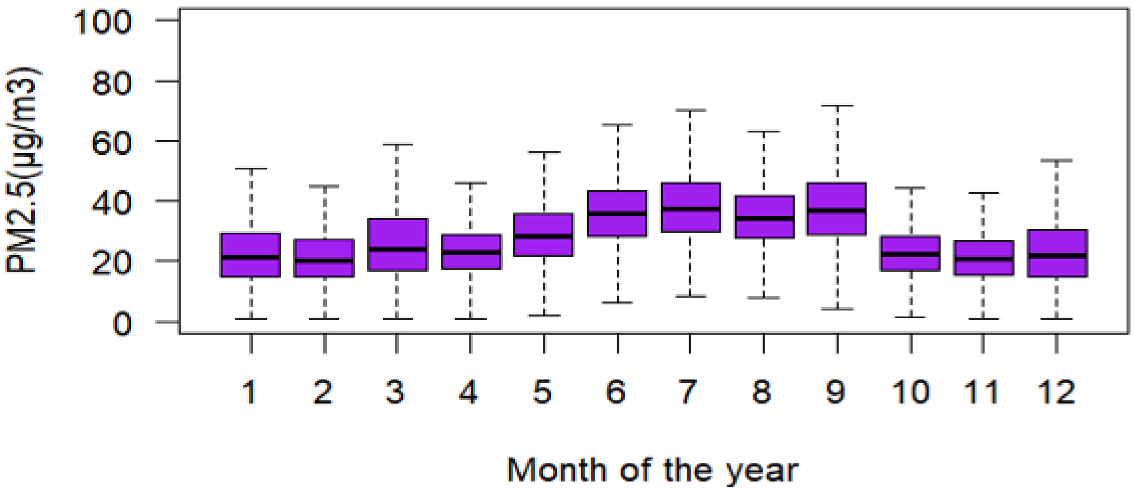

Figure 13. Monthly mean of $PM_{2.5}$ at all PA sites

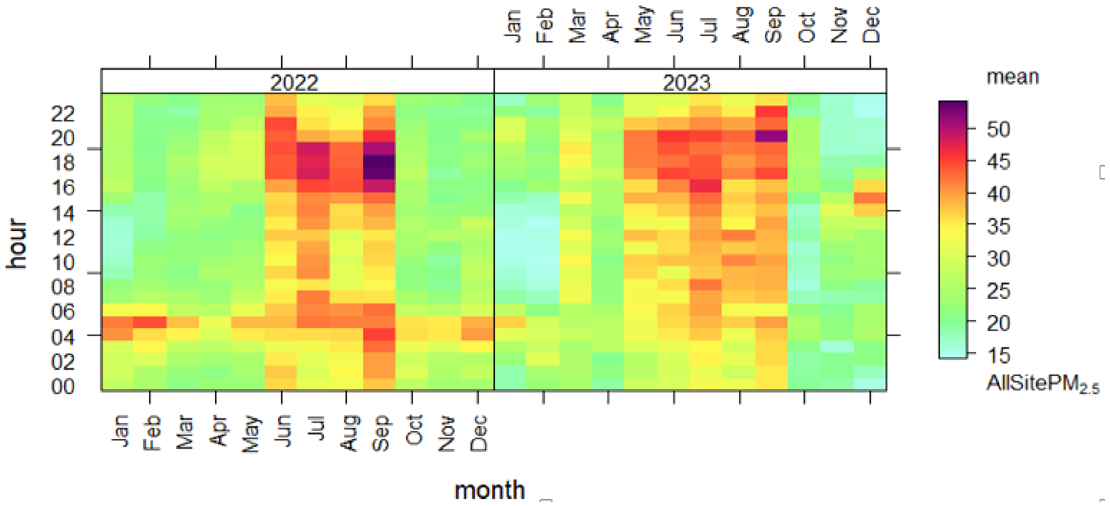

Figure 14.Monthly patterns of $PM_{2.5}$ at all PA sites

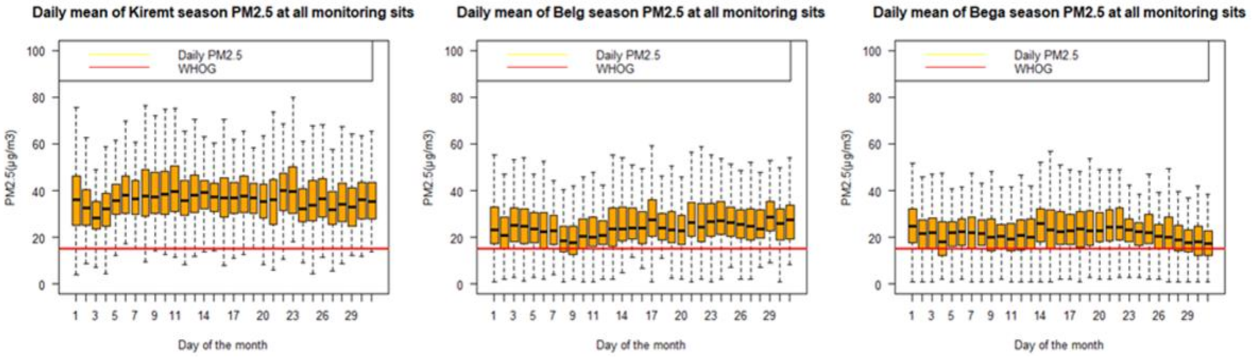

Figure 15.Daily mean of Kiremt (left), Belg (middle) and Bega (right) seasons of $PM_{2.5}$ at all PA sites

Figure 14 explains the seasonal patterns of hourly mean $PM_{2.5}$ concentrations across all PA monitoring sites, ranging from 30 µg/m³ to 50 µg/m³ during the Kiremt season and 15 µg/m³ to 40 µg/m³ during both the Belg and Bega seasons. These figures indicate that $PM_{2.5}$ concentrations were highest during the Kiremt season compared to Belg and Bega seasons. Alike, Figure 15 presents the daily mean $PM_{2.5}$ concentrations across the three seasons. It shows that during the Kiremt season, 87.5% of $PM_{2.5}$ concentrations exceeded the 2021 daily WHO guideline, while during both Belg and Bega seasons, 75% of $PM_{2.5}$ concentrations exceeded the 2021 daily WHO guideline. Previous studies have noted that $PM_{2.5}$ levels are elevated during heavy rains, with crustal dust ranging from 2.9% to 37.6%, peaking in dry months (Tefera et al., 2020; Fikeraddis & Endeshaw, 2020). These variations may be attributed to seasonal changes in meteorological factors, dust levels, and construction activities. Anthropogenic emissions related to heating demand may increase during Kiremt and Belg seasons, exacerbated by temperature inversions and a shallow mixed boundary layer hindering pollutant dispersion in the atmosphere. Conversely, during Bega seasons, more favorable atmospheric conditions for air pollution dispersion, prevailing winds, and atmospheric mixing contribute to lower particle concentrations.

4.2.1. Annual trend

Table 1 presents the annual mean $PM_{2.5}$ trend across all PA monitoring sites in 2022 and 2023 exhibited an increasing trend, averaging 5.5 µg/m^3 and 6.5 µg/m^3 respectively, which exceeded the 2021 WHO annual guideline at each site by 0.5 to 1.5 times. Notably, Blacklion and Repi consistently recorded the highest concentrations during these years. In other similar studies, in Ethiopia the annual mean satellite estimation of $PM_{2.5}$ concentration was 17 µg/m^3 (Shiferaw et al., 2023), in Addis Ababa, surpassed WHO guideline (Kumie et al., 2021), many African cities exceed the WHO annual guideline, PM increased Approximately by 4.1% per year in Nairobi(Singh et al., 2021), in Nairobi were 30% higher in 2019 when compared to 2017 measured in the some months Feb-Mar (Pope et al., 2018). This increase in pollution could be due to the growing demands of the population for transportation and industries.

Table 1. Daily and Annual $PM_{2.5}$ trend and spatial distribution of PA measurements.

PA measurements	2022 Annual mean	Annual WHO AQG	2023 Annual mean	Annual WHO AQG
AAU4kl	26	4.2> times	29	4.8 >times
Entoto	22	3.4 >times	24	3.8 >times
Jacros	29	4.8> times	28	4.6>times
ECA	28	4.6 >times	34	5.8>times
BLH	40	7> times	41	7.2>times
RepiWtE	40	7>times	40	7>times
Skyline	36	6.2 >times	38	6.6>times

4.3. Analysis of variance (ANOVA)

4.3.1. Spatial analyses of variance

Table 2 displays the one-way Analysis of Variance (ANOVA) test conducted for different PA monitoring sites (AAU4kl, Entoto, Jacros, BLH, ECA, RepiWtE, and Skyline) yielded significant results, with F values computed as 1723.493 at a significance level of $P < 0.01$. This indicates substantial variation in $PM_{2.5}$ concentrations among these monitoring locations. Specifically, the highest $PM_{2.5}$ concentration of 40.5 µg/m³ was observed at BLH and RepiWtE, attributed to high traffic congestion and commercial activity, while the lowest concentration of 23 µg/m³ was recorded at Entoto, reflecting its more rural background. A similar study in Ethiopia found that the annual mean $PM_{2.5}$ concentration varies significantly across different regions (Shiferaw et al., 2023). In East African cities, such as Addis Ababa, Kampala, and Nairobi, the $PM_{2.5}$ and PM_{10} concentrations at both roadside and urban background sites were significantly above WHO limits (Singh et al., 2021). This variation is might be due to increasing demands from various developmental activities, including transportation, industry, agriculture, and construction. These findings underscore the spatial variability of atmospheric $PM_{2.5}$ levels, which are influenced by developmental activities across different locations and times.

Table 2.Spatial anova single factor analyses of $PM_{2.5}$ concentrations

Summary

Groups	Count	Sum	Average	Variance
AAU4kl	14639	383567	26.20172	409.7617
Entoto	13000	282749	21.74992	273.0718
Jacros	5145	149043	28.96851	461.0181
BLH	8819	318836	36.15331	1042.877
ECA	6153	202832	32.96473	653.627
RepiWtE	10957	394658	36.0188	1164.536
Skyline	12242	417051	34.06723	511.6284

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	7483829	9	831536.5	1723.493	0	1.879968
Within Groups	55160025	114328	482.4717			
Total	62643854	114337				

4.3.1. Seasonal analyses of variance

Table 3 presents the seasonal mean concentrations of $PM_{2.5}$ were analyzed using one-way Analysis of Variance (ANOVA) across different monitoring stations based on seasons (Kiremt, Belg, and Bega). The ANOVA results revealed significant variation among seasons, with computed F values of 104.1062 for Kiremt, 316.0415 for Belg, and 287.7407 for Bega (all with $P < 0.01$). Maximum concentrations were observed during the Kiremt season, whereas the Bega season recorded the lowest concentrations. However, the Belg season exhibited higher $PM_{2.5}$ concentrations compared to Bega. In a similar study, NO_x concentrations during the wet season were nearly twice as high as those during the dry season, whereas no such difference was observed for CO (Fikeraddis & Endeshaw, 2020). Emitted pollutants are often trapped beneath temperature inversions (Baumbach & Vogt, 2003). Therefore, these variations might be attributable to each seasonal differences in meteorological factors such as temperature, wind, pressure, and relative humidity, which influence pollution levels.

Table 3.Seasonal anova single factor analyses of $PM_{2.5}$ concentrations

SUMMARY

Groups	Count	Sum	Average	Variance
Kiremt AAU4kl	5122	181504	35.43616	631.5531
Belg AAU4kl	4625	103298	22.3347	262.1488
Bega AAU4kl	4892	98956	20.22813	207.2115
Kiremt Entoto	4592	80184	17.46167	151.6866

Belg Entoto	4592	80184	17.46167	151.6866
Bega Entoto	5436	155975	28.69297	371.1942
Kiremt Jacros	2038	79668	39.09127	604.2322
Belg Jacros	1684	43422	25.78504	325.8314
Bega Jacros	1423	25953	18.23823	142.432
Kiremt BLH	3084	145167	47.07101	1453.901
Belg BLH	2672	85364	31.9476	828.9445
Bega BLH	3052	88178	28.89187	643.8795
Kiremt ECA	2865	117133	40.88412	825.6604
Belg ECA	1815	55121	30.3697	503.4437
Bega ECA	1473	30578	20.759	225.4222
Kiremt RepiWtE	4208	184185	43.7702	6734.024
Belg RepiWtE	3260	114728	35.19264	977.8806
Bega RepiWtE	3489	107574	30.83233	810.561
Kiremt RepiWtE	4654	201138	43.21831	771.8178
Belg Skyline	4067	119055	29.27342	317.6271
Bega Skyline	3510	96741	27.56154	211.4478

5. Conclusion and Recommendation

5.1. Conclusion

Nowadays, air pollution remains a critical global issue impacting societies and environments worldwide, particularly affecting vulnerable populations in developing countries with significant premature deaths linked to poor air quality, inadequate air quality guidelines (AQG) and implementing policy. This research focused on assessing the spatial and temporal variability of ambient $PM_{2.5}$ pollution in Addis Ababa.

The study revealed distinct patterns in $PM_{2.5}$ levels, with peaks observed in the early morning and early night hours, higher concentrations on weekdays compared to weekends across all monitoring stations, consistently exceeding daily WHO guidelines. Monthly mean $PM_{2.5}$ concentrations ranged from 15 µg/m^3 to 50 µg/m^3, with peaks occurring from June to September and lower levels in other months. Median concentrations typically varied between 15 µg/m^3 and 25 µg/m^3 across all sites, with seasonal peaks observed during the Kiremt season (30 µg/m^3 to 50 µg/m^3) and lower concentrations in the Belg and Bega seasons (15 µg/m^3 to 40 µg/m^3).

Daily mean $PM_{2.5}$ levels surpassed WHO guidelines in all three seasons, with rates exceeding 87.5% during Kiremt and 75% during Belg and Bega seasons. Annual mean $PM_{2.5}$ concentrations increased from 5.5 µg/m^3 in 2022 to 6.6 µg/m^3 in 2023, indicating levels above WHO standards by approximately 0.5 and 1.6 times in respective years.

The ANOVA test highlighted significant spatial variations in $PM_{2.5}$ concentrations (F=1723.493, P<0.01) among PurpleAir monitoring locations that is ranging from 23 µg/m3 at Entoto to 40.5 µg/m^3 at BLH and RepiWtE. Seasonal analysis further confirmed significant variations (F=104.1062, 316.0415, 287.7407, P<0.01), with higher $PM_{2.5}$ concentrations observed during the Kiremt season compared to Belg and Bega seasons.

Therefore, this study infers that the urgent need for targeted interventions to mitigate air pollution in Addis Ababa, informed by comprehensive data-driven approaches to address varying spatial and temporal patterns of $PM_{2.5}$ concentrations across the city.

5.2. Recommendation

Based on the findings of this research, the following suggestions are made: 1) there is a need to investigate the specific sources contributing to $PM_{2.5}$ pollution using advanced source apportionment techniques. Future research should focus on identifying contributions from vehicular emissions, industrial activities, biomass burning, and dust. Understanding the chemical composition and toxicity of these sources will aid in health impact assessments and help develop targeted mitigation strategies. 2) It is essential to examine how $PM_{2.5}$ and other pollutants affect environmental systems. 3) It is important to reduce waste generation and enhance waste management practices to minimize open burning. 4) Improve public transportation systems, reduce vehicle emissions, and enforce stricter emission standards and encourage the adoption of electric vehicles and cleaner fuels. 5) Must be collaborate with neighboring regions to develop regional air quality management strategies, share data, coordinate emission reduction efforts, and implement joint monitoring programs. 6) Expand educational programs and training initiatives to increase the number of air quality scientists and experts. Foster interdisciplinary research collaborations to build local capacity for air quality monitoring, analysis, and policy development. 7) Continuous monitoring is recommended for providing valuable data to assess intervention effectiveness and track progress towards air quality improvement goals.

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