COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

DEPARTMENT OF STATISTICS

ANALYSIS OF EFFECT OF FINE PARTICULATE MATTER AND METEOROLOGICAL FACTORS ON ACUTE UPPER RESPIRATORY INFECTION HOSPITAL ADMISSION IN ADDIS ABABA, ETHIOPIA

A thesis submitted to the Department of Statistics in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Biostatistics)

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This is to certify that the thesis prepared by Yosef Eyasu, entitled: *Analysis of Effect of Fine Particulate Matter and Meteorological Factors on Acute Upper Respiratory Infection Hospital Admission in Addis Ababa, Ethiopia* and summited in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Biostatistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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DECLARATION

I, the undersigned, declare that this thesis study is my own, that it has not been submitted to this or any other university for consideration, and that all sources of material included in the thesis have been properly acknowledged.

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This thesis research has been submitted for consideration with my approval as a university advisor.

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ACRONOMY

AA	Addis Ababa
ANN	Artificial Neural Networking
ALRI	Acute Lower Respiratory Infection
ARI	Acute Respiratory Infection
AURI	Acute Upper Respiratory Infection
AQ	Air Quality
AQI	Air Quality Index
AQMP	Air Quality Monitoring Program
CO_2	Carbon Dioxide
COPD	Chronic Obstructive Pulmonary Disease
CO	Carbon Monoxide
DALY	Disability Adjusted Life Years
ED	Emergency Department
EDF	Effective Degree of Freedom
GAM	General Additive Model
HAP	Household Air Pollution
HMIS	Health Management Information System
NO_2	Nitrogen Dioxide
NO_x	Nitrogen Oxides
$PM_{2.5}$	Particulate Matter of size less than 2.5 micrometer

PM_{10}	Particulate Matter of size less than 10 micrometer
REML	Restricted Maximum Likelihood
RR	Relative Risk
SO_2	Sulfur Dioxide
UNEP	United Nations Environment Program
US EPA	United States Environmental Protection Agency
VOC	Volatile Organic Compound
WHO	World Health Organization

Abstract

Analysis of Fine Particulate Matter concentration and Respiratory infection Hospital Admission in Addis Ababa, Ethiopia

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Addis Ababa University, 2022

Air pollution has become the greatest health concern in our world, especially in respiratory diseases. The concentration of particulate matter of size less than or equal to 2.5 in micrometer (PM2.5) in Addis Ababa is higher than that of the 2021 WHO guidelines limit of the annual average of 5μg/m^3 and a daily average of 15 μg/m^3 for the last four years of the study period. US EPA controlled single air quality monitor data of PM2.5 concentration for location Addis Ababa-Central is obtained from AirNow.gov and it is used with meteorological data for analysis of health effect. Poisson Generalized Additive Model (GAM) is utilized for the analysis of variables under study from January 1, 2018, to December 31, 2021, in Addis Ababa, Ethiopia. In this study, statistically significant association between fine particulate matter (PM2.5) and acute upper respiratory infection hospital admission in Addis Ababa city and its health effect is observed. Relative risk of acute upper respiratory infection hospital admission associated with 10 μg/m^3 increase in PM2.5 concentration was 1.08 (95% CI: 1.06-1.11). We have also observed a positive effect of relative humidity and precipitation on respiratory infection. Therefore reducing the pollutant concentration in the city needs due attention to help people from difficulty in breathing.

CHAPTER ONE

INTRODUCTION

1.1BACKGROUND OF THE STUDY

Air pollution has become the greatest health concern of our world. Nowadays air quality of our environment is reduced due to the presence of solid, liquid, and gaseous harmful pollutants produced and emitted by our daily activities or by nature itself. The air we breathe, the water we drink, and the soils in which our plants grow are affected by air pollutants. Our climate is changed and individual and public health are affected by solid, liquid, and gaseous pollutants (Stavropoulou *et al.*, 2020). Acidification of fresh waters due to acid rain, corrosion of different construction materials, erosion of historical and cultural treasures, and losses in biodiversity and agricultural products, are some of the most common environmental effects of air pollution. The toxicity nature of some pollutants has direct effect on our health when inhaled (Elvingson and Agren, 2004). According to the World Health Organization (WHO), air pollution has been identified as the single greatest environmental danger to human health due to its significant impact to disease burden (WHO global air quality guidelines, 2021)

In their everyday activity, people are exposed to air pollutants in the air and also a mixture of air pollutants. Particles and mixture particles in the air that are small enough to penetrate respiratory systems are risk factors for many diseases. The global burden of disease caused by air pollution has a huge impact on human health around the world. Air pollution is thought to be responsible for millions of deaths and lost years of healthy life each year (WHO, 2009)

Increased hospitalizations, disability, and early death from respiratory diseases, heart disease, stroke, lung cancer, and diabetes, as well as communicable diseases like pneumonia, have been linked to exposure to outdoor air pollutants like particulate matter (PM2.5) and household air pollution (HAP) (Health Effects Institute and Institute for Health Metrics and Evaluation´s Global Burden of Desease project, 2020). Long and short-term exposure to other different air pollutants affects all populations of different age groups. Even though there is a tolerated level of concentration of pollutants, they can affect different aspects of health

(WHO, 2021). Moreover, the impact of air pollution on health status is greater for respiratory diseases (Nakao *et al.*, 2019)

According to a WHO report, the worldwide burden of disease related with both ambient and home air pollution exposure is substantial, and it is increasing, particularly in emerging countries, due to increased exposure and a lack of long-term environmental information. Pollution levels in many parts of the world continue to exceed WHO standards, despite improvements in air quality in developed countries. Air quality has deteriorated in most low- and middle-income countries as a result of large-scale urbanization and economic development that has primarily relied on the burning of fossil fuels for energy. Globally, inequalities in air pollution exposure are growing (WHO Air quality Gudelines, 2009)

Currently, the level of concentration of ambient air pollutants and particulate matter in Addis Ababa has become a health burden for the population of the city. Data from different sources show that level of concentration is at least 2-3 times the country standard and WHO guidelines. A Global Burden of Diseases study showed in 2017 that air pollution is the second highest risk factor for death and diseases. Since all pollutants are harmful to human, the health burden associated with high concentration significantly affect the health condition of probably the most exposed active and productive subgroup of the city's population, measuring and estimating concentration trend and associated health burden deserves great concern (Addis Ababa City, 2021; Kumie *et al.*, 2021)

Not only increase in the concentration of pollutant in the city, but the prevalence of the respiratory disease is also increasing in Addis Ababa. According to the Addis Ababa City Health Bureau health management information system report acute upper respiratory infections and other respiratory diseases are increasingly recorded in the last five years(Tarekegn and Gulilat, 2018). This increment is assumed to be associated with the rise in air pollutant concentration.

1.2. STATEMENT OF THE PROBLEM

Addis Ababa is showing significant growth in population size, construction, industrialization, and the number of vehicles(Xie *et al.*, 2021). Being the center of the political and economic center, the city has been serving as Head Quarter for many national and International Organizations. These all are causal factors for the rise in the number of vehicles in the city and consequently emission of different kinds of air pollutants and formation of secondary pollutants related to different types of vehicles that are the major source of ambient air pollution in the city(Jida *et al.*, 2020).

Not only vehicles, but our day-to-day activities also contribute a lot to the air pollution in Addis Ababa. Nowadays, the concentration of harmful pollutants like fine particulate matter (PM2.5) in the city is higher than the World Health Organization standard (Kume et al., 2010). The current concentration level of PM2.5 has a significant health impact on the population. A recently published study on air pollution has reported that respiratory and other diseases are highly increased over time (Tarekegn and Gulilat, 2018). Vulnerable population groups are exposed in their day to day activities to the higher levels of pollutants concentration and most of them do not know its health effect (Avis *et al.*, 2020).

The study on the concentration level of pollutants and their health impact is at its infancy level in Addis Ababa. The available ambient air pollutants data and health outcome, for example, acute respiratory infection hospitalizations has not been modeled so far or there is a little study on it and there is an information gap on measurement of the health effect of air pollution in the city and Ethiopia in general(Tefera *et al.*, 2020). In the absence of information on such sensitive environmental risk factors, it is difficult to control the infection and promote the health of the population in the city.

1.3 OBJECTIVE OF THE STUDY

1.3.1 General Objective

The objective of this study was to assess the effect of fine particulate matter (PM2.5) and meteorological factors on acute upper respiratory infection hospital admission in Addis Ababa, Ethiopia.

1.3.2. Specific Objectives

The specific objective is to:

- Describe daily concentration level of PM2.5 with respect to cultural activities in Addis Ababa.
- Assess the association of some meteorological variables and acute respiratory infection

1.4. SIGNIFICANCE OF THE STUDY

Different researches indicate that many pollutants are known to be causal factors for respiratory diseases. Identifying modifiable environmental risk factors like pollutants and measuring the association with respiratory diseases, say acute respiratory infection in terms of hospital admission is useful for the control of disease and promotion of public health.

The result of this thesis research is, therefore, helpful for updating the existing standard and other regulations related to pollutant emission sources like industries and vehicles. Concerned bodies such as Addis Ababa Air Quality Management Program Committee, Ministry of Transport, Addis Ababa transport authority, Ministry of Health, Addis Ababa City administration Health bureau, and Addis Ababa Environmental Protection and Green Commission can use the output of this research to fill the existing knowledge and information gap in the country concerning air pollution and its impact on respiratory diseases. Finally, it will be used as an input for further research in the area.

CHAPTER TWO

LITERATURE REVIEW

Quality of life is more affected due to the continuous rising in air pollution. Globally, Billions of people are breathing polluted air. Almost the entire global population (99%) breathes air that surpasses WHO air quality limits (recommended concentration limit for PM2.5 of annual average 5 µg/m3; 24-hour average of 15 µg/m3 (*WHO air quality guidelines*, 2021)) and threatens their health. A record from over six thousand cities in one hundred seventeen countries shows people are breathing unhealthy levels of PM2.5 and NOx. The report indicates that people in low and middle-income countries are suffering the highest exposures (WHO, 2022).[i] Being the biggest environmental risk to human health, outdoor air pollution alone kills about three million people annually, mainly from non-communicable diseases. Our environment is becoming among the leading risk to health.

Exposure to different levels of concentration of ambient particles and gaseous pollutants has adverse health effects. Living in a higher concentration of air pollutants significantly increases mortality, especially in the most sensitive subgroup of the population. Of many kinds of air contaminants, some harmful pollutants like $PM_{10.}PM_{2.5,}$ SO_2, CO_2, CO, Ozone, and VOC are associated with different diseases. An increase in respiratory diseases, and the consequent respiratory hospital admission, cardiopulmonary and cardiac mortality, lower respiratory symptoms, and an increase in medication use in asthma are attributed as short and long term effects of exposure to these pollutants (Katsouyanni, 2003)

In Ethiopia, especially Addis Ababa, the current level of concentration of ambient air pollutants like particulate matter is a health burden for the population. Data from different sources show that level of concentration is at least 2-3 times the country standard and WHO guidelines (Kumie *et al.*, 2021) A Global Burden of Diseases study showed in 2017 that air pollution is the second highest risk factor for death and morbidity(WHO, 2016).

An assessment made on the association between ambient air pollutions and risk of respiratory infection among adults analyzed by using a multiethnic study of atherosclerosis as evidence modeled by a validated spatiotemporal model shows the presence of an association between short term exposure to air pollutants like NO_2, $PM_{2.5}$, and NOx and respiratory diseases. The result of their study shows a statistically greater risk of infection with (PM2.5: RR 1.04 (95% CI: 1.00 to 1.09) (Kirwa *et al.*, 2021)

Modeling pollutant concentrations and examining pollution's short- and long-term effects on public and individual health common nowadays. Environmental and epidemiologic research employs a variety of models depending on the number of pollutants under investigation and the study's goal. The spatiotemporal model was used to estimate ambient PM2.5, NOx, and NO2 concentrations over the course of 2–6 weeks (short-term) and a year (long-term) (Kirwa et al., 2021). When used in conjunction with other models, the generalized Additive Model (GAM) is also employed for its appropriateness for non-normal data such as pollution and other climate data (Ravindra et al., 2019).

Estimation of long-term average exposure to fine particulate matter, the measurement taken from different cities, was made by using a regression model for prediction of annual concentration (Brauer *et al.*, 2003). In a cohort of young children living in Germany, an estimation of individual exposure to traffic-related air pollutants and respiratory diseases was made using a multiple linear regression model that was also used to predict traffic-related air pollutants. Significant association was found between respiratory symptoms and the pollutants(Morgenstern *et al.*, 2007). In the study made in Adama city, Ethiopia, a land-use regression model was used to model a single air pollutant concentration. And significant health effect of PM2.5 is observed in the city(Abera *et al.*, 2020). In their study of health impact assessment of air pollution in Shiraz Iran, they modeled expected hospitalization cases and then used it to evaluate correlation and to calculate the relative risk (Gharehchahi *et al.*, 2013; Belušić, Herceg-Bulić and Klaić, 2015)

Pollutants that are causal factors for certain diseases can't be a significant causal factor for other diseases. Energy generation using solid fuels causes to increase in the level of particulate matter, and the concentration level of harmful gases in the air. Adults with COPD and asthma were studied retrospectively in Spartan hospitals to examine the effect of PM10 and SO2 on asthma and COPD exacerbation. The findings show that PM10 and SO2 have a linear relationship with asthma (Saygın *et al.*, 2017)

2.1 Ambient Air Pollution in Addis Ababa

The concentrations fine particulate matter (PM2.5) and health consequences in Addis Ababa has somewhat greater than other African capitals, such as Cotonou (Benin), Lomé (Togo), and Abidjan (Côte d'Ivoire). The cost of health damage caused by ambient PM2.5 is estimated to be $78 million or 1.3 percent of AA's GDP in 2019. Air pollution causes 1,600 early deaths every year on average. Primary, PM2.5 causes death of stroke, ischemic heart disease, and lower respiratory infections. PM2.5 has the greatest impact on people aged 60 to 84, accounting for around 58 percent of all premature deaths (Xie et al., 2021)

Ethiopia, like many other low- and middle-income countries, suffers from air pollution. The fast expansion and urbanization of these countries have resulted in environmental damage. One of the primary risk factors for acute and chronic diseases in cities is ambient air pollution (WHO, 2016). Air pollution, among other things, is becoming more of a concern in Addis Ababa, posing a threat to public health and local ecosystems. Growing economic activity such as constructions and industrial expansions, as well as increased mobility and transportation in AA, has resulted in increased pollution, traffic congestion, land and environmental degradation, and public health problems (Xie et al., 2021).

Pollutant concentration and distribution are not uniform in the city. Cross-sectional data collected in 65 selected sites from Addis Ababa city to determine vehicle-related roadside concentration levels, spatial and temporal variation of air pollutants like CO, VOC, NO_2, and SO_2 shows temporal variation for CO and VOC, but not for SO_2 and NO_2 show no statistical significance variation (Tsegaye, Leta and Mohammed, 2019)

Since all pollutants are harmful to human, the health burden associated with high concentration significantly affect the health condition of probably the most exposed active and productive subgroup of the city's population, measuring and estimating concentration trend and associated health burden deserves great concern(Addis Ababa City, 2021).

The level of concentration in the city is showing a significant health impact in the city. Assessment made in the city by using real-time monitoring of particulate matter ($PM_{2.5}$) for three year Time Series analysis aimed to see levels and patterns of the ambient pollution concentration and health impact assessment made using AirQ+ by combining different secondary data shows that the estimated annual death attributable to $PM_{2.5}$ is substantially excess. Daily and yearly variation of the pollutant concentration was observed in the city (Kumie *et al.*, 2021).

Pollutant concentration estimation of the roadside concentration of particulate matter made using the ANN model in Addis Ababa in 15 selected sites shows that the city has a greater concentration of $PM_{2.5}$ and PM_{10} as compared with air quality index and WHO standards(Solomon et al 2020). A similar finding was also reported for $PM_{2.5}$ concentration in the city (Kumie *et al.*, 2021). Roadside vehicle emitted pollutants contribute higher percentage to urban environmental pollution. For a city like Addis Ababa and Oromia Special zone surrounding Addis Ababa, Vehicle mileage, age, emission treatment technology, fuel quality, driving style, road construction, and other factors can contribute to exhaust and non-exhaust particles for the ambient air pollution (Solomon et al 2020).

The relationship between meteorological, traffic and vehicle-related particulate matter concentration data collected in 15 sites in Addis Ababa city was accurately measured by the artificial neural network model ANN. The result of their study shows 24-Hr average concentration level of $PM_{2.5}$ exceeds AQI by 13%-144% (Jida *et al.*, 2020).

Literature review on the trend of ambient air pollutants concentration and corresponding respiratory disease in Addis Ababa shows increment over the year. Taking health data from the year 2013-to 2017 respiratory diseases like AURI, COPD and Pneumonia increased with an annual growth rate of 47.18%, 53.44% and 24.89% respectively (Tarekegn and Gulilat, 2018)

A review of the effect of particulate, SO_2, and NO_2 on human health, hazardous effects of the mentioned air pollutant was overviewed. Mortality, morbidity and shortening of life are associated with the level of pollutant concentration(Rahman Khan and Siddiqui, 2014)

Air pollutants suspended in air and their concentration varies by different factors. The features of pollutants and their dynamics (dispersion, deposition, interaction with other pollutants), as well as meteorological conditions, influence the spatial and temporal concentration of pollutants in ambient air. Exposure to different amounts of concentration can be risk factor for different diseases, especially respiratory-related diseases. Again different types of pollutants can be risk factors for specific respiratory infections. For example level of PM2.5 concentration has a significant association with the prevalence of chronic respiratory symptoms(Mekasha *et al.*, 2018)

2.2 Fine Particulate Matter (PM2.5)

Particulate matter consists of solid or liquid found in the air. PM2.5 concentrations in the environment are measured in micrograms of particulate matter per cubic meter of air, or $\mu g/m^3$ (Health Effects Institute and Institute for Health Metrics and Evaluation´s Global Burden of Desease project, 2020). Air pollutants include dust, pollen, and aerosols produced by burning. Particles come from a variety of sources, including mobile, stationary, and natural, and their chemical and physical makeup vary greatly. It can be emitted directly into the air from human day-to-day activities or can be formed in the atmosphere(Mukherjee, 2020). Particles vary in size and diameter, and they enter the respiratory system through inhalation, causing respiratory and cardiovascular disorders, reproductive and central nervous system dysfunctions, and cancer (Stavropoulou *et al.*, 2020).

Ambient PM2.5 concentrations vary greatly within and within regions of the world, according to WHO recommendations. The air quality limits were satisfied by 21% and 46% of all countries with standards for 24-hour averaging times for PM2.5 and PM10, respectively A meta-analytic effect estimate of RR of 1.08 (95% CI: 1.06-1.09) per 10 $\mu g/m^3$ was published in a systematic review of PM2.5 and total non-accidental mortality, assuming a linear connection (*WHO global air quality guidelines*, 2021). Tefera et al studied the chemical Characterization and Seasonality of Ambient Particles (PM2.5) in the City Centre of Addis Ababa and report the following figure representing the PM2.5 composition[1]

[1] Tefera, W. *et al.* (2020) 'Chemical characterization and seasonality of ambient particles (PM2.5) in the city center of Addis Ababa', *International Journal of Environmental Research and Public Health*, 17(19), pp. 1–16. doi: 10.3390/ijerph17196998.

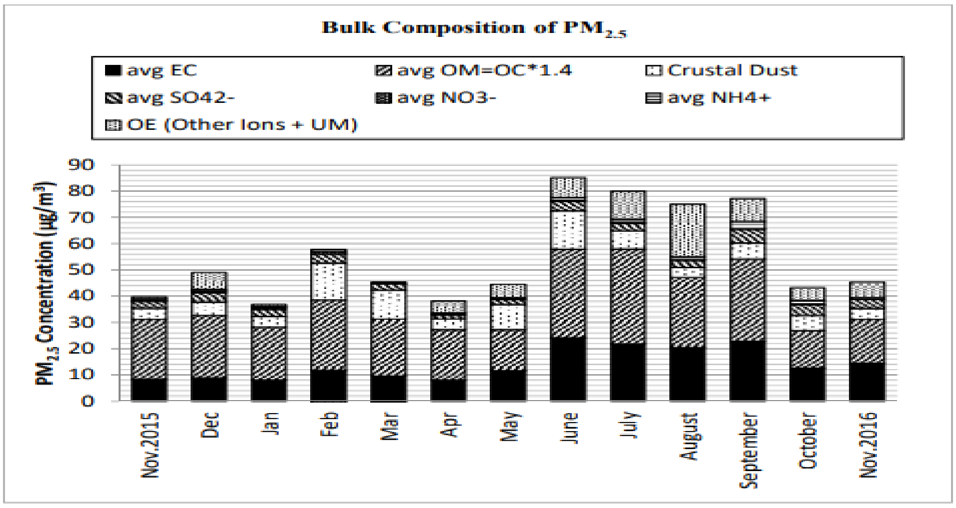

Figure 1. Particulate matter ($PM_{2.5}$) chemical species by concentration ($\mu g/m^3$) of major components in Addis Ababa; EC = Elemental carbon. OM = Organic matter. OE = Other elements. Other Ions = ws Na^+, ws Cl^-, ws K^+, ws Ca^{2+}. Other = Unidentified matter.

This summarizes the dominant components of fine particles for a time period of November 2015 to November 2016, by proportion were Organic matter (43.0%), Elemental Carbon (25.5%), dust (13.0%), sulfate (5.7%), ammonium (1.9%), nitrate (0.6%), and other ions (1.0%), including Na+, Cl−, ws K+, and Ca2+ accounted for an average of 88% of the PM2.5 mass(Tefera *et al.*, 2020).

Fine particulate matter is a very harmful pollutant. Short-term or long-term exposure is harmful to one's health. The health effects of exposure to air pollution concentration levels on public health are significant. In several cities, there has been a rise in hospital admissions and emergency department visits, as well as the risk of premature death and infections. Pollutants have different health effects at different times of the year. The concentration changes depending on the weather. The study objected to estimating PM2.5 concentrations in Xi'an city using a Generalized Additive Model with multi-source monitoring data shows that 0°C represents the suitable weather conditions for PM2.5 accumulation(Song *et al.*, 2015)

Addis Ababa City has been showing a dramatic population increase in recent years (Tarekegn and Gulilat, 2018). These individuals demand personal cars and public transport in their day-to-day activities which leads to raising road traffic to increase in Addis Ababa. Vehicle emissions are now the principal source of air pollutants such carbon monoxide (CO), carbon dioxide (CO2), volatile organic compounds (VOCs), hydrocarbons CHs), nitrogen oxides (NOx), and particle matter (PM) (Jida et al., 2020)

As is true in the most cities of developing countries, there are serious problems of particulate matter emissions from traffic and other activities that contribute to economic growth in Addis Ababa. A shortage of transportation Combined with an increase in the severity and duration of traffic jams, results in a large increase in pollutant emissions and, as a result, a worsening in air quality, especially near main roads(Tsegaye, Leta and Khan, 2019). High-traffic roads are hot spots of air pollution. Therefore time spent near and/or on these high-traffic roads increases exposure to high pollutant concentrations of particles and gaseous and its effects on health increase as well. (Sylla *et al.*, 2017)

2.3 Acute respiratory Infection and PM2.5

Acute respiratory infection is a form of infection that makes breathing difficult. It can impact either our upper respiratory system, which runs from our sinuses to our voice chords, or our lower respiratory system, which runs from our vocal cords to our lungs. Children, the elderly, and persons with immune system disorders are all at risk from this infection[2] (*Respiratory Diseases Ministry of Health and Medical Services, Solomon Islands Healthy Village Facilitator's Guide*, 2021)

According to a report cited in Addis Ababa City Air Quality Policy and Regulatory Situational Analysis, it is the second cause of mortality in Ethiopia (UNEP, 2018). The health effect of PM2.5 on lower respiratory infection in children reported in one study done recently in Adama, Ethiopia shows the significance of the pollution effect. Abera et al report about 20% of mortality due to lower respiratory infection in children are attributed to the pollutant(Abera *et al.*, 2020).

Respiratory illnesses in children are common, and air pollution can exacerbate them. The 18-Year Time-Series Study of Air Pollution and Acute Respiratory Infections in Children 0–4 Years of Age demonstrates an association between ambient air pollutant concentrations, especially particulate matter smaller than 2.5 m in diameter (PM2.5), and ED visits for respiratory infections in young children(Darrow et al., 2014).

Exposure to ambient air pollution is responsible for 7.9% of the disease burden, according to the WHO study report on preventing disease through healthy environments on worldwide evaluation of the burden of disease from environmental risks (in DALYs). The associations

[2] Acute Respiratory Infection: Causes, Symptoms, and Diagnosis (healthline.com), Accessed 5/19/2022

of air pollutants with climate variables cause respiratory infections are likely to be sensitive to climate change, as their incidence varies with different weather patterns such as fluctuations in rainfall and other meteorological variables. (Neira and Prüss-Ustün, 2016). Cause-specific respiratory-related emergency room visit study shows a significant association with PM2.5 in Taiwan(Chang *et al.*, 2017)

In the Setting of Air Quality Policy and Economic Change, researchers used a case-crossover design to investigate the link between respiratory infection and air pollution in New York. They discovered that fine particulate matter air pollution with a diameter of 2.5 mm or less (PM2.5) has been linked to an increased risk of respiratory disease. (Croft et al., 2019)

Study on short-term elevation of PM2.5 air pollution and acute lower respiratory infection conducted in Utah, shows ARIs are a major source of morbidity and mortality, often caused by viruses, such as respiratory syncytial virus and influenza virus. ARI occurs more often in the winter months and may be associated with greater exposure to elevated ambient air pollution, including particulate matter less than or equal to 2.5mm in aerodynamic diameter (PM2.5) and other air pollutants. Evidence linking short-term elevation in PM2.5with ARI is weak and contradictory (Horne et al., 2018)

Among a very large sample of patients from a single health care system, each short-term 10mg/m3 increase in PM2.5 was associated with15–32% higher odds of an ALRI encounter. As a result, short-term exposure to heightened PM2.5 air pollution may be linked to increased healthcare utilization for ALRI diagnosis in both children and adults. PM2.5 levels in the environment in Bhaktapur, Nepal, were linked to daily hospital admissions for ARI among children aged 10 and under (Nishikawa et al., 2021)

CHAPTER THREE

DATA AND METHODOLOGY

3.1.1. Data source

Particulate Matter (PM2.5), also called particle pollution data of size less than 2.5 micrometers in diameter were obtained from the website AirNow.gov, fed by one of the air monitors in the city with a station in with location name Addis Ababa-center controlled by U.S. Department State Ethiopia-Addis Ababa. [3] A single air quality monitor was used for its accessibility and almost completeness of data as compared to other air quality monitors in the city during the study period. The data from this source is freely available and WHO uses the same data for its air quality database. The hourly concentration data obtained from this data source has some missing data which was solved by using multivariate imputation via chained equation method with MICE package in R.

Acute Respiratory Infection Hospital Admission data, as reported in the category of J00-718 of DHIS2 under Respiratory Infection (Acute upper respiratory infection unspecified) from January 2018 to December 31, 2021, in Addis Ababa was obtained from Addis Ababa Health Bureau. The data was complete for the study period monthly. HMIS department of the Bureau provided the requested data after the ethical committee ratified the proposal of this study.

Meteorological variables like Temperature, relative humidity, and precipitation data were obtained from the National Meteorological Agency of Ethiopia.

3.1.2 Study Area

Addis Ababa is Ethiopia's capital and home to the African Union's (AU) and UN Economic Commission for Africa's (ECA) offices. It is located at the center of the country and lies at the foot of mount Entoto with a projected population of 5,006,000 [4]. It is located at 9°01'29.89" North latitude, and 38°44'48.80" East longitude, covering 540 km2 with an elevation of 2334 meters above sea level. The average maximum temperature is about 24.5°C

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[3] https://www.airnow.gov/international/us-embassies-and-consulates/#Ethiopia$Addis_Ababa_Central. Accessed on March 13, 2022.
[4] https://cityaddisababa.gov.et/ Accessed on May 25, 2022

and the extreme maximum temperature is about 31°C. The average minimum temperature is about 12.0°C and the extreme minimum is about 7°C. The total rainfall in a year is about 1255.2mm(Arsiso, 2020). The city is the center of the political, economic, and industrial of Ethiopia(UNEP, 2018; Kumie *et al.*, 2021). The city has 11 sub-cities. There are several health centers and hospitals administered under the Addis Ababa Health Bureau and Federal Hospitals. According to information obtained from the website of the Ministry of Health, Ethiopia, Addis Ababa has 13 Hospitals and 98 health centers[5].

Currently, there are two meteorological sites monitoring by the national meteorological Agency[6]. The air pollution monitoring site in Addis Ababa city is controlled by US Embassy, Addis Ababa Health College, and other private monitoring. As of March 2021, there have been about 20 AQ monitors installed in AA(Xie *et al.*, 2021).

3.1.3. Variable in the study

3.1.3.1 Dependent variable

Monthly acute upper respiratory infection Hospital admission

3.1.3.2 Independent Variables

- Fine Particulate matter (PM2.5) concentration
- Temperature,
- Precipitation and
- Relative humidity were

3.2. Methodology

Monthly Hospital Admission data was complete for the period. The air pollution concentration data for particulate matter of air diameter less than size of 2.5 micrometer which was downloaded from the AirNow.gov website and meteorological data from National Meteorological Agency was not complete for some hours of the day. Missing data and other invalid measurements are imputed by Multiple Imputation Chain Equation MICE using R

[5] Addis Ababa Health Bureau | MINISTRY OF HEALTH - Ethiopia (moh.gov.et) Accessed on 15/6/2022
[6] National Meteorology Agency: Home (ethiomet.gov.et) Accessed on 15/6/2022

package. Microsoft Excel and R statistical software of version 4.1.2 were used to manage and analyze the data.

Then, four years data from January 1, 2018 to December 31, 2021 are used for the analysis. General Additive Model was fitted by using PM2.5 as a linear term and smooth function for other independent variables to measure association between Acute Respiratory Infection Hospital admission in the city and concentration level of particulate matter of size less than or equal 2.5 micrometer in the city.

3.2.1 Generalized Additive Model (GAM)

Generalized additive model is a regression model in which smoothing splines are used instead of linear coefficients for covariates in GLM. The model is suitable to handle non-linear association between covariates including pollutants. We used Poisson regression with logarithmic link in GAM model equation as follows.

Poisson model:

$$log\ [(E(Y)] = B_o + B_1 * PM2.5$$

Generalized Additive Model

$$log\ [(E(Y)] = S_i(X_i) + \dots\dots + S_p(X_p)$$

Poisson regression with logarithmic link in GAM model equation is as follow.

$$log\ [(E(Y)] = B_o + B_1 * PM2.5 + S_i(X_i) + \dots\dots + S_p(X_p)$$

Where Y is the number of monthly hospitalization for Acute Respiratory Infection;

E(Y) denotes the number of expected cases; X_i, i=1,…,p which can be temperature, relative humidity, time, etc.; and S_i, i= 1,…,p denotes smooth functions.

The penalized model was fitted by using REML for parameter and penalized regression splines for smoothing parameters. GAM enables us to model data using flexible and nonlinear functions. And also it is suitable for linear and nonlinear mixed models. It is used in biological and ecological science to understand complex systems (Marra, 2010). GAMs offer a middle ground between simple models, such as those we fit with linear regression, and more complex machine learning models like neural networks (Shiferaw *et al.*, 2019). With a GAM, we can fit data with smooths, or splines, which are functions that can take on a wide variety of shapes. A GAM can capture the nonlinear aspects of different relationship of many nonlinear relationships, because of the flexibility of splines(Hastie and Tibshirani, 1990).

We fit a GAM using the gam() function from the mgcv package of R software. When we fit this GAM, we wrap the independent variables in the s(), that is smooth function to specify that we want this relationship to be flexible.

When the assumption of linear models which states effects of covariates are the approximation of true effects does not hold, we can use general additive model. In the case when a single line does not fit data and the rate of change does not remain constant, especially for data that come from time series data, GAM fits well. In the GAM, linear predictors is replaced by additive predictors where replaced(Hastie and Tibshirani, 1990). Smooth functions which will be estimated from the data are used.

In linear models, we model the mean of dependent variable as the sum of linear predicrs.

$$Y_i = B_o + \sum_{j=1}^{p} \mathrm{B}_j X_{ji} + \varepsilon_i$$

For i=1,…,n, and j=,…,p

Here B_j are fixed constant effects of j's covariate.

But in GAM, we use

$$Y_i = B_o + \sum_{j=1}^{p} f_j(X_{ij}) + \varepsilon_i$$

And f_j 's are smooth function of the covariates.

If we model using splines, which are functions composed of simpler function called basis function and each basis function, b_k has coefficient B_k. The flexible smooths in GAMs are actually constructed of many smaller functions. These are called basis functions. Each smooth is the sum of a number of basis functions, and each basis function is multiplied by a coefficient, each of which is a parameter in the model. The resultant spline obtained by the sum of weighted basis functions evaluated at the value of x is

$$s(x) = \sum_{k=1}^{K} \boldsymbol{B_k} b_k(x)$$

To fit the data we have to choose B_k ,the number of basis functions depends upon the number of data we have. The wiggliness of fitted function is measured by

$$\int_R [f'']^2 \, dx = \boldsymbol{\beta' S \beta}$$

Where f'' is second derivative of the smooth function(Hastie and Tibshirani, 1995)

Using penalized log likelihood to avoid over fitting of the data.

$$\mathcal{L}_{\mathrm{p}}(\beta) = \mathcal{L}(\beta) - \frac{1}{2}\lambda \, \beta' \boldsymbol{S} \beta$$

Where $\boldsymbol{\mathcal{L}}_{\mathrm{p}}(\boldsymbol{\beta})$ is penalized log likelihood, $\boldsymbol{\mathcal{L}}(\boldsymbol{\beta})$ log likelihood that measures the closeness of the data, $\boldsymbol{\beta' S \beta}$ is matrix of the covariate and λ measure of wiggliness and is smoothing parameter we used to define trade-off and to measure B_k that maximize penalized log likelihood. And also it balances between likelihood and wiggliness to optimize model fit. β's are the estimates of basis functions, **S** is smoothing matrix. The mcgv of R-package do these all. Because of its stability REML was used for estimation of smoothing parameters. It is recommended fitting models with the REML, or "Restricted Maximum Likelihood" method. While different methods have their advantages, REML is most likely give reliable, stable results

3.2.2 Basis functions and Smoothing

REML model selection criteria was employed. The fitted model is checked with model diagnostic plot like Q-Q plot, Histogram of residuals, linear predictors against residuals and fitted values against response values were used. Stepwise variable and model selection is used and variable with p-value less than 0.05 is used in the model fitting. Since GAM is semi-parametric in nature, the fitted model has two parts. For non-parametric part of the model, the number of basis function used to fit the model was also selected by their p-values. The fitted model was checked for smoothness by *gam.chek* function in *gam* package in R.

Generalized Additive model method is effective and convenient for analyzing health effect of air pollution. It provides for nonparametric adjustments for seasonality, trend, and meteorological variables that can cause confounding. It extends traditional Generalized Linear Model by replacing liner predictor of the form $\eta = \sum_{j=1}^{p} B_j X_j$ with $\eta = \sum_{j=1}^{p} f_j(X_j)$ where $f_j(X_j)$ are unspecified non parametric functions. f_j are estimated by different method based on our variable. One of the methods for GAM estimation is the local scoring algorithm, which is a modification of the Fisher scoring procedure for determining maximum likelihood estimates in GLM. If there are several smoothing parameters in our model, other estimation method called Backfitting algorithm is suitable. Optimal estimate is obtained in GAM by iterative approximation (Wood, 2017)

When we fit GAM model, we can include linear terms in the model. The interpretation of these linear terms are the same as GLM. But, the nonparametric smoothing function which are estimated from basis functions have different parameters. This is because each smooth has several coefficients - one for each basis function.

Then, the summary output from GAM model will be printed. It has parametric and nonparametric part. From the nonparametric part the first column reads edf, which stands for effective degrees of freedom. The smooth's complexity is represented by this value. A straight line or linear is comparable to an edf of one. A quadratic curve has an edf of 2, and so on, with higher edfs describing more wavy curves. The greater the edf, the greater complexity of that smooth is. The edf columns under summary table of *gam* output are test statistics used in an ANOVA test to test overall significance of the smooth. The result of this test is the p-value to the right. It's important to note that these values are approximate, and it's important to visualize the model to check them. A good way to interpret significance for smooth terms in GAMs is this: a significant smooth term is one where you cannot draw a horizontal line through the 95% confidence interval. EDF doesn't mean significance or vice-versa. A smooth may be linear and significant, non-linear and non-significant, or one of each.

One of the most important things to do when interpreting and checking models is to visualize them. This allows us to inspect them and gain intuition for the model relationships. And visualizations the plots are the most powerful way to communicate our results. The plots generated by mgcv's plot() function are partial effect plots. That is, they show the component effect of each of the smooth or linear terms in the model, which add up to the overall prediction.

3.2.3 Poison regression

Since Poisson regression is used to model non negative count values, we started the model fitting by Poisson regression model using gam. The assumption of the model is checked for the fitted data using *dispertiontest()* function built in R statistical software.

ARI hospital admission is count data. Since this data is recorded and reported in monthly basis for, it is assumed to follow time series Poisson distribution. Then Poisson regression with logarithmic link in GAM is fitted.

$$log\ [(E(Y)] = B_o + B_1 * PM2.5\ +\ s(Time) + s(Precipitation +\ s(Relative\ humidity) +\ s(Temperature)$$

gam function by Hastie is used to fit this model in R of version 4.1.2

po<-gam(ARI~ MonthAverage.PM2.5+s(Time,bs="cr",k=15)+s(AverageMonth.Precpt,bs="cr",k=13)+s(MonthAveragerelhum,bs="cr",k=12)+s(AverageTmp,bs="cr",k=10), family =poisson(link = log), data = HA, method = "REML")

The relationship between ARI Hospital admission and predictor variable is non-linear and it is very complicated due to intervention measurement taken during COVID-19. Generalized additive model is suitable for modeling such kind of relationship. Restricted Maximum Likelihood (REML) is used for handling by penalizing the wigglness nature of the function for their non-linear relationship.

The fitted model is diagnosed for over- dispersion assumption and for the distribution of model residual. Finally, it is checked by a function called *gam.check* for the number of basis function used to fit the model for its non-parametric parts and the number of degree of freedom of parameters of smoothing function. If the p-value of the *gam.check* results are large, it indicates that the corresponding basis function is large and adequate for fitting the model.

Time is used in the model as a variable in the number between 1 to 48 to account for long term trends and seasonality. Four-year monthly data of 48 observations are used in this study.

The relative risk (RR) is a measure of the likelihood of an Epidemiology Event occurring given a specific degree of exposure to an exposure factor compared to those who are impacted by the same event but are not exposed to the factor. The RR in this study refers to the increased risk of acute respiratory hospital admission as a result of exposure to PM2.5 concentrations. The RR is calculated using the following equation for the GAM with the standard Poisson distribution:

$$RR(x = k) = e^{(k\beta 1)}$$

Being k the concentration variation of PM2.5, β1 estimated by GAM

3.3 Ethical Clearance

Before beginning the study, Addis Ababa Public Health Research and Emergency Management Directorate has approved it and the ethical clearance is obtained.

3.4 Dissemination

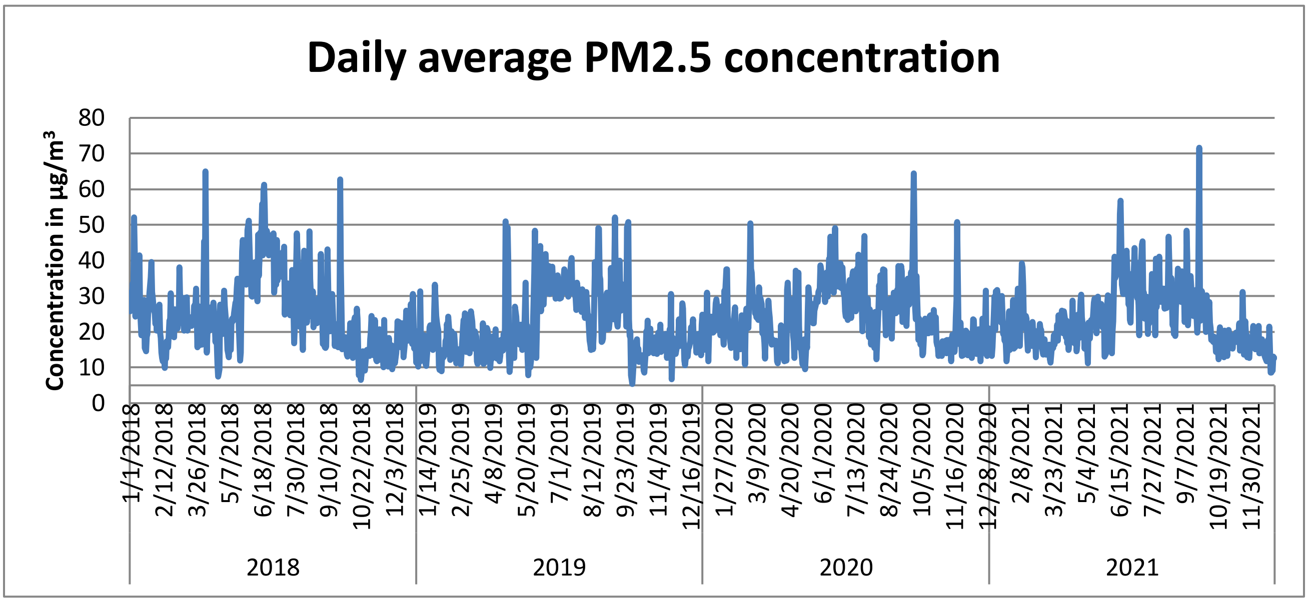
The final result of this study will be submitted to Addis Ababa Health Research and Emergency Management Directorate. It will also published on journals for scientific community and all concerned bodies engaged on reducing air pollution in the city of Addis Ababa.

CHAPTER FOUR

RESULTS

4.1 Descriptive analysis

In this chapter, we present the key finding of the study. The line graphs and tables are used to



present the results.

Figure 1 Time series plot of daily PM2.5 concentration in Addis Ababa city from 2018-to 2021

The above figure shows 24-hour average concentration of PM2.5. The concentration is high on the eve of the Ethiopian Meskel celebration called Catara/Damara festival in all four years of study period. The highest concentration is recorded on the Damara day of 2021. Additionally, November 21, 2020 has also high concentration as compared to neighboring days.

Table 1 Daily concentration (μg/m^3) of fine particulate matter of to (PM2.5) Addis Ababa from 2018-2021.

Year	Min PM2.5(μg/m^3)	Mean PM2.5(μg/m^3)	Max PM2.5(μg/m^3)
2018	6.46	25.4	65.0
2019	5.38	21.8	52.1
2020	9.46	24.3	64.4
2021	8.54	23.6	71.6

.

From the above table, we see that the mean daily concentration of PM2.5 is nearly 24. The minimum and maximum mean daily concentration was recorded in the year 2019 and 2021 respectively. The mean concentration is higher for the year 2018 years of study period. Then it decreases from 25.4μg/m^3 to 21.8 μg/m^3 in the year 2019 and rises again to 24.3μg/m^3 in the year 2021. The concentration was low for the year 2019 as compared with the other three years.

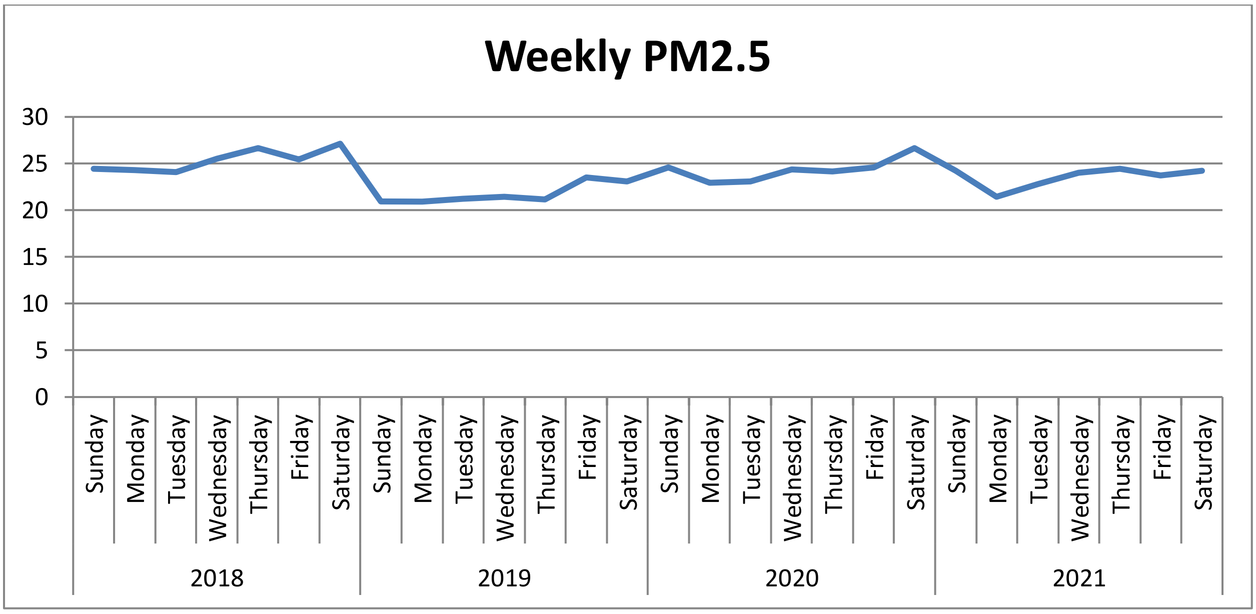


Figure 2 Pollutant concentrations in the Addis Ababa city for the day of the weeks

The average concentration of PM 2.5 does not vary much for the days of the weeks. Sunday has the lowest concentration level and Saturday has the highest concentration. From the above figure, we see that the concentration shows some increment from Monday to Saturday.

Table 2 Monthly average PM2.5 concentration (μg/m3) in Addis Ababa

	Month											
Year	1	2	3	4	5	6	7	8	9	10	11	12
2018	29.8	19.7	24.6	23.1	27.6	42.8	34.5	29.7	23.6	15.6	15.2	18
2019	17.4	15.2	17.8	19.6	18.1	33.5	32	27.6	30.3	14.4	16.9	18
2020	22.8	21	25.4	19.8	23.8	36.2	29.4	25.6	31.8	20.2	18.1	18.1
2021	21.8	22.5	16.8	21.6	21.8	33.1	31.1	30.4	31	19.6	17.9	15.2

From the above table, we see that monthly PM 2.5 concentration is high for all years of study period. The concentration of the month June is the highest for all years of study period. The concentration rises from February to June and fall from this most polluted month to November and December, the months with low concentration as compared to other month. From this study, we see January is the most polluted months of autumn season of Ethiopia. The lowest PM2.5 concentration was observed in October, 2019 and the maximum monthly average concentration is recorded in June, 2018.

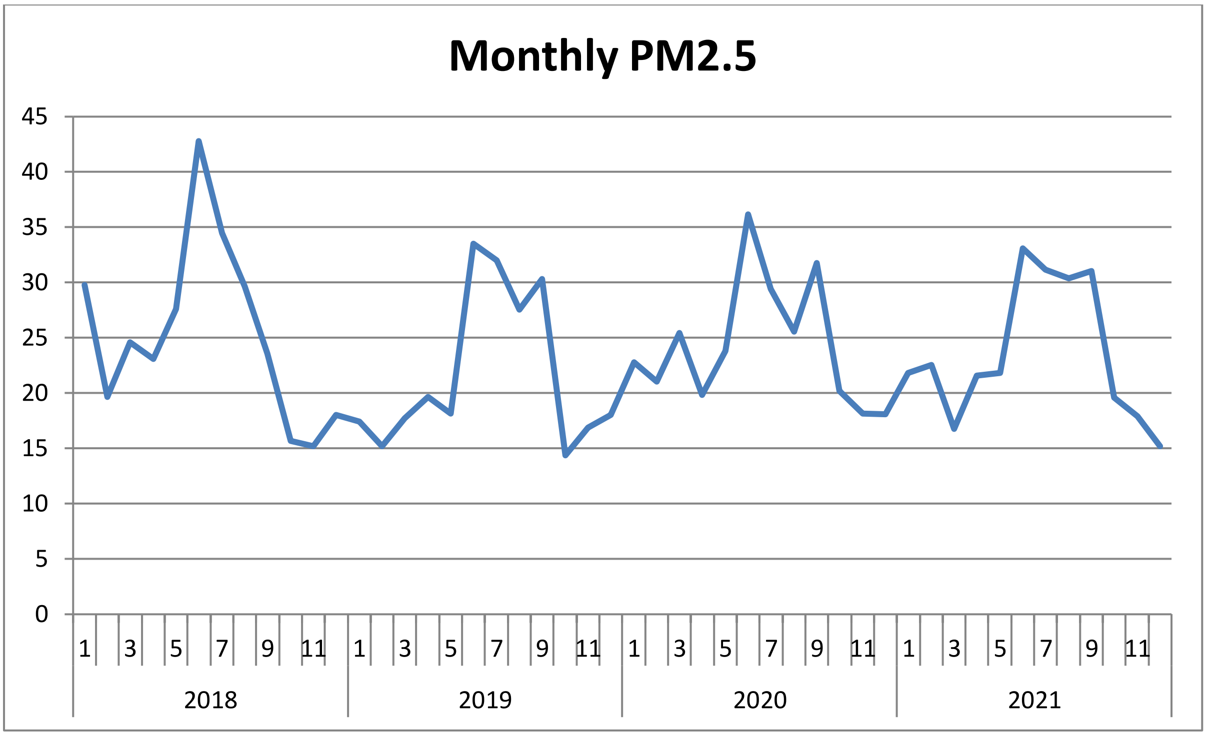


Figure 3 Time series plot of monthly PM2.5 concentration

The pollution concentration of PM2.5 has cyclic nature. It increases and gets its climax in the month of June and then starts to decline seasonally.

Table 3 Annual average concentration (μg/m3) of fine particulate matter (PM2.5) in Addis Ababa

Year	2018	2019	2020	2021
Annual concentration(μg/m^3)	25.379	21.753	24.339	23.557

The annual average PM2.5 concentration of Addis Ababa is 25.379, 21.753, 24.339 and 23.557 in the year 2018, 2019,2020 and 2021, respectively.

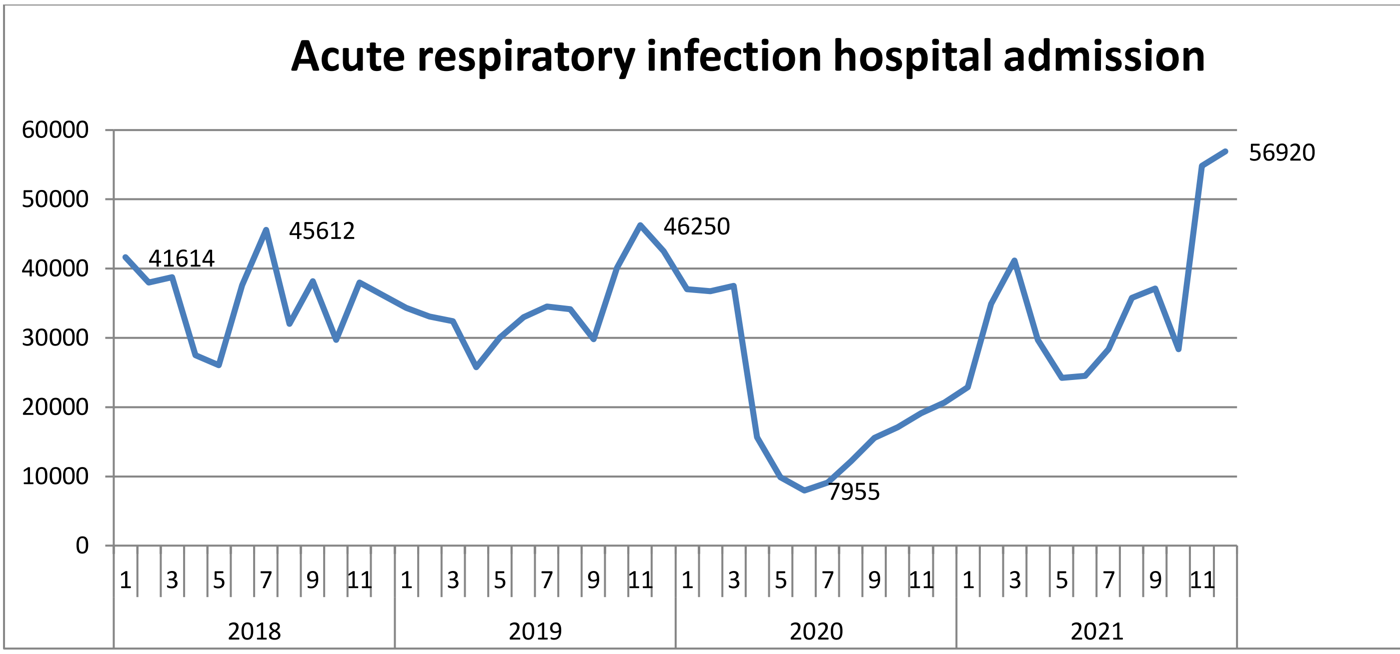


Figure 4 Respiratory hospital admission from 2018 to 2021.

From the figure, the lowest ARI hospital admission is recorded in the month June, 2020. It rises after July each year and falls in the of April and May.

Table 4 monthly acute respiratory infection hospital admission in Addis Ababa

	Month											
Year	1	2	3	4	5	6	7	8	9	10	11	12
2018	41614	37999	38773	27446	26061	37629	45612	32048	38170	29714	38000	36184
2019	34345	33101	32369	25721	29972	32970	34509	34165	29783	40101	46250	42466
2020	36976	36722	37462	15686	9923	7955	9062	12165	15570	17143	19105	20696
2021	22841	34882	41177	29718	24226	24474	28386	35740	37092	28356	54813	56920

The reported monthly unspecified acute respiratory infection hospital admission in Addis Ababa

Table 5 Daily Minimum, mean, maximum and quartiles of the variables of study

Variable	Min	1st Qu	Median	Mean	3rd Qu	Max
AverageMonth.Precpt	0.0000	0.3425	1.8600	3.2750	5.5825	10.9500
MonthAveragerelhum	34.77	45.67	52.66	54.23	62.35	73.81
MonthAverage.PM2.5	14.37	18.05	22.17	23.75	29.68	42.79
AverageTmp	15.04	17.05	17.49	17.82	18.8043	20.72
ARI	7955	25409	33036	[redacted]	37722	56920

During the study period, the daily mean for relative humidity, PM2.5, temperature and precipitation in Addis Ababa is 54.23%, 23.75 µg/m^3, 17.82 C^o and 3.2750 inch respectively.

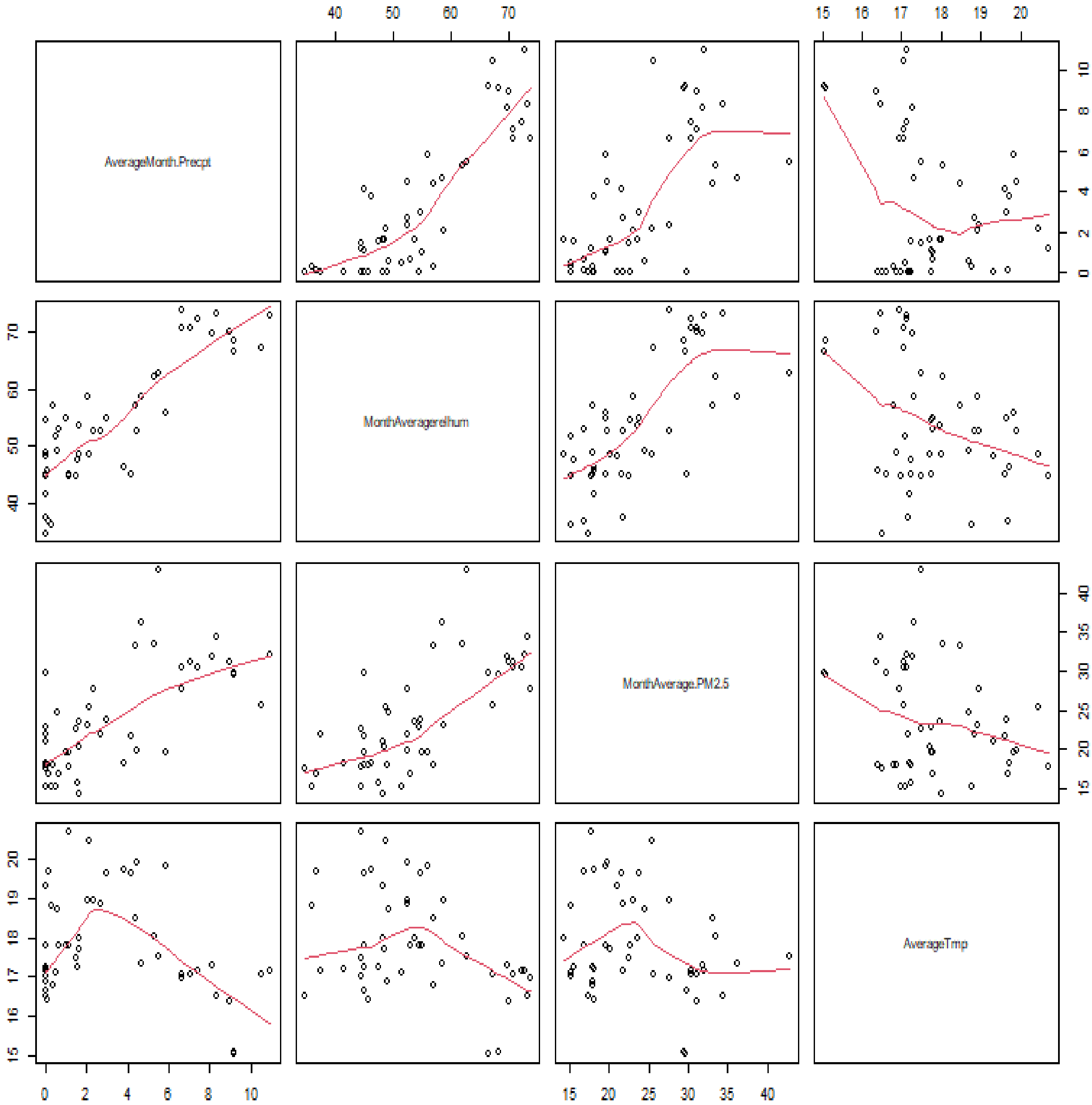


Figure 5 Pair plot of variables under the study

Table 6 correlation matrix with p-value

	ARI	*Precpt*	*relhum*	*PM2.5*	*Tmp*
ARI		-0.341 *(.018)*	-0.174 *(.237)*	-0.213 *(.147)*	-0.047 *(.749)*
Precpt	-0.341 *(.018)*		0.859 *(<.001)*	0.691 *(<.001)*	-0.293 *(.044)*
relhum	-0.174 *(.237)*	0.859 *(<.001)*		0.721 *(<.001)*	-0.381 *(.008)*
PM2.5	-0.213 *(.147)*	0.691 *(<.001)*	0.721 *(<.001)*		-0.274 *(.060)*
Tmp	-0.047 *(.749)*	-0.293 *(.044)*	-0.381 *(.008)*	-0.274 *(.060)*	

Computed correlation used pearson-method with listwise-deletion.

From the above pairs plot and Pearson correlation we see that there is strong positive association between PM2.5 and precipitation (Precpt) and also between pm2.5 and relative humidity (relhum).

4.2 Model fitting

Acute respiratory Infection (ARI) hospital admission is fitted in GAM as dependent variable. Meteorological variables; precipitation, temperature, relative humidity that are assumed to have relationship with respiratory infection are interred the model as smooth function and particulate matter as linear term of predictors. Stepwise variable and model selection method is used.

Then, Poisson regression with logarithmic link in GAM is fitted. We used is a stepwise procedure to select the form of the model and the variables to be included in the model. Then called upon *gam()* function in the *mgcv* package to fit the final model with REML choice of smoothing parameters.

In this model, cubic regression spline were used with meteorological and time variable to fit nonlinear relationship of Acute Respiratory Infection hospital admission with linear term for the PM2.5 and time, precipitation, temperature and relative humidity with smoothing function. Time variable was included in the model to account for long term association and seasonality.

Result of R output from *step.gam* function is:

Start: ARI ~ Time + AverageMonth.Precpt + MonthAverage.PM2.5 + MonthAveragerelhum + AverageTmp; AIC= 1031.073

Step:1 ARI ~ s(Time, 16) + AverageMonth.Precpt + MonthAveragerelhum + MonthAverage.PM2.5 + AverageTmp ; AIC= 970.3132

Step:2 ARI ~ s(Time, 16) + AverageMonth.Precpt + s(MonthAveragerelhum, 16) + MonthAverage.PM2.5 + AverageTmp ; AIC= 961.8118

Step:3 ARI ~ s(Time, 16) + s(AverageMonth.Precpt, 16) + s(MonthAveragerelhum, 16) + MonthAverage.PM2.5 + AverageTmp ; AIC= 954.4945

Step:4 ARI ~ s(Time, 16) + s(AverageMonth.Precpt, 16) + s(MonthAveragerelhum, 16) + MonthAverage.PM2.5 + s(AverageTmp, 16) ; AIC= 911.1718

The result from step 4 is selected for its smallest AIC, and we proceeded to choose the best fit for the smoothing changing its edf.

The data is loaded and the gam() package used:

$$log\ [(E(Y)] = Bo + B1 * PM2.5\ +\ s(Time) + s(Precipitation) \\ +\ s(Relative\ humidity) +\ s(Temperature)$$

gam function by Haiste is used to fit this model in R of version 4.1.2

The final model is then putted in the following format.

po<-gam(ARI~ MonthAverage.PM2.5+s(Time,bs="cr",k=15)+s(AverageMonth.Precpt,bs="cr",k=13)+s(MonthAveragerelhum,bs="cr",k=12)+s(AverageTmp,bs="cr",k=10), family =poisson(link = log), data = HA, method = "REML")

Number of basis function used to fit the smooth is manually chosen based on the p-value and based on k’ and edf, (effective degree of freedom). The model diagnosis for smooth, that is non-parametric part of the model done using gam.chek () repeating this procedure until p-value become insignificant.

4.3 Residuals check

When the gam() function in the *mgcv* package is used to execute a penalized spline fit, the *gam.check()* function applied to *the gam()* fit object yields the residual plots seen in the image in the next page.

A Normal quantile-quantile plot is shown on the top left panel, and a histogram of residuals is shown on the bottom left panel. Both plots indicate a slight deviation from normality, specifically right skewness, but not to the point of being alarming. The residuals against fitted values plot in the top right panel show that the homoscedasticity assumption is reasonable. The response and fitted values are plotted in the bottom right of the graph.

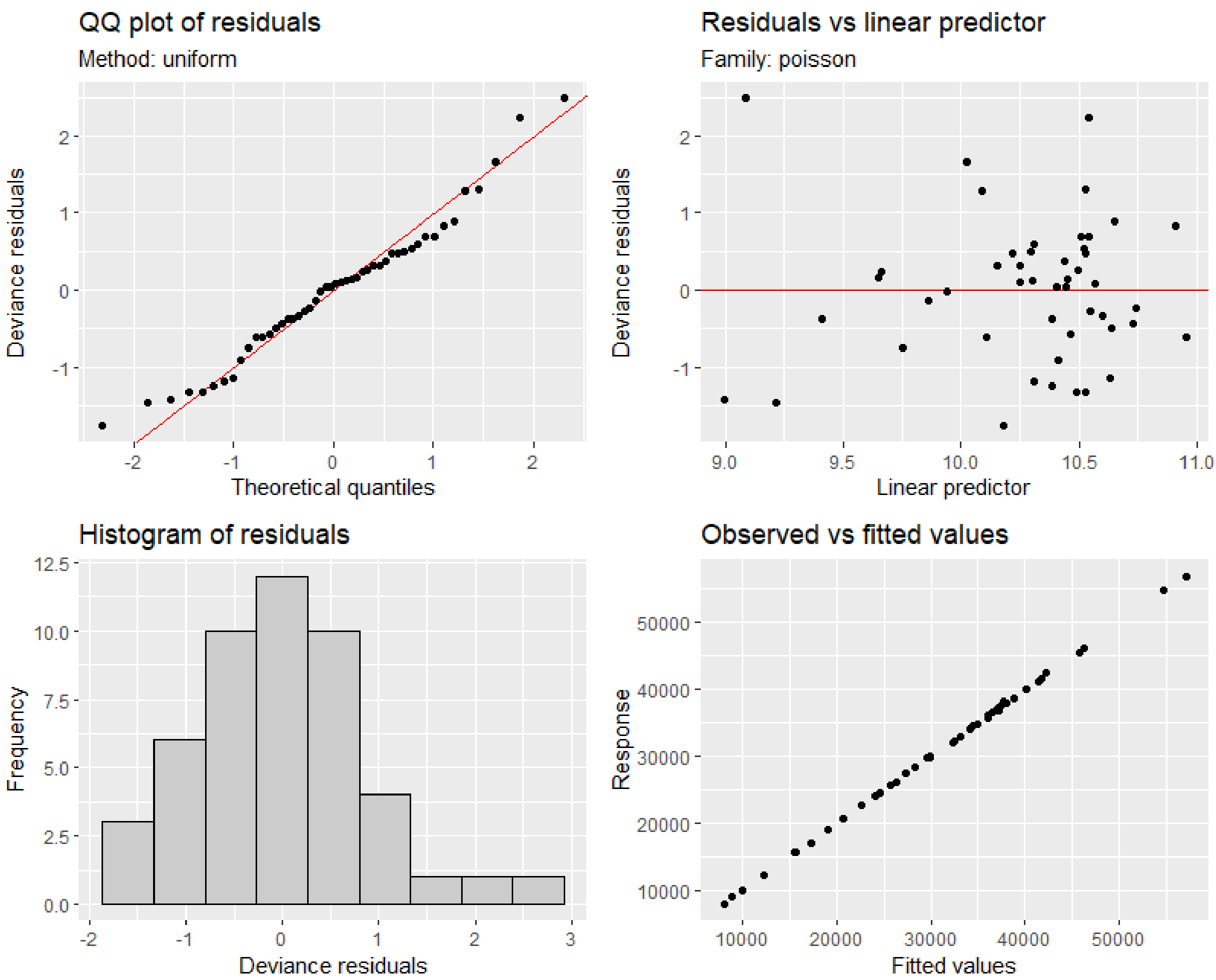


Figure 6 Residual plot of the fitted model

Here Poisson distribution is assumed to measure the effect of PM2.5 Concentration on Monthly ARIHA (Monthly Acute Respiratory Infection Hospital Admission). Thus overdispersion test is done in two different ways. One way is to put scale argument in the model equating it with a negative number checking the value of scale in the model output. If it differs from 1, then there is problem of over dispersion. Thus we used the default argument for scale. The other way of checking for over dispersion is using *overdispersiontest* function in R. in both cases there is no over-dispersion problem.

We used Q-Q plot, histogram, residuals vs fitted value to check the fitted gam model. Gam.check uses residual plot as default. The figure above shows that we have adequate model for our analysis. The family of the distribution we used affects the model residuals that seem that they look like to depart from the normal.

The data we fit has cyclic nature. For such kind of data cyclic splines are recommended. In addition, since we have 4 years monthly data, recommended number of k' that is 3 or 4 per year is used. For time variable k=15 fits the model very well with different k's for the variables in the study.

The fitted model and R summary output of the model and the model diagnosis result is as follows:

```
po<-gam(ARI~ MonthAverage.PM2.5+s(Time,bs="cr",k=15)+
s(AverageMonth.Precpt,bs="cr",k=13)+
s(MonthAveragerelhum,bs="cr",k=12)+
s(AverageTmp,bs="cr",k=10), family =poisson(link = log),
data = HA, method = "REML")
```

```
summary(po)

Family: poisson
Link function: log

Formula:
ARI ~ MonthAverage.PM2.5 + s(Time, bs = "cr", k = 15) +
    s(AverageMonth.Precpt, bs = "cr", k = 13) + s(MonthAveragerelhum,
    bs = "cr", k = 12) + s(AverageTmp, bs = "cr",
    k = 10)

Parametric coefficients:
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)        10.077048   0.031833 316.555  < 2e-16 ***
MonthAverage.PM2.5  0.008224   0.001340   6.139 8.31e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                          edf Ref.df Chi.sq p-value
s(Time)                13.887 13.944  34585  <2e-16 ***
s(AverageMonth.Precpt) 11.461 11.547   4005  <2e-16 ***
s(MonthAveragerelhum)  10.613 10.708  10021  <2e-16 ***
s(AverageTmp)           8.936  8.955   6106  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.992   Deviance explained =  100%
-REML = 552.15  Scale est. = 1        n = 48

> gam.check(po)

Method: REML   Optimizer: outer newton
full convergence after 9 iterations.
Gradient range [-1.407244e-06,3.73067e-05]
(score 552.1509 & scale 1).
Hessian positive definite, eigenvalue range [3.521264,6.200623].
```

```
Model rank =  48 / 48

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                           k'   edf k-index p-value
s(Time)                 14.00 13.89    1.43    1.00
s(AverageMonth.Precpt) 12.00 11.46    1.22    0.89
s(MonthAveragerelhum)  11.00 10.61    1.31    0.98
s(AverageTmp)           9.00  8.94    1.18    0.86
```

From this result, we see that significant positive association between PM2.5 and meteorological variable. The effect of PM2.5 is significant at very small p-value (i.e. 0.008224) with 95% Confidence Interval (0.005598588, 0.01085010). From this we find Relative risk (RR) equals 1.00826 with 95%CI (1.0056, 1.0101) for unit increase in PM2.5. The effect of PM2.5 concentration on ARI is therefore interpreted as follow.

Percentage change in mean monthly response that results for 10 μg/m^3 increase in PM2.5 concentration on acute respiratory infection hospital admission is 8% with 95% confidence interval (5.6%, 10.1%)

Partial residual which is the difference between the partial effect and the data after all partials are accounted for is presented below.

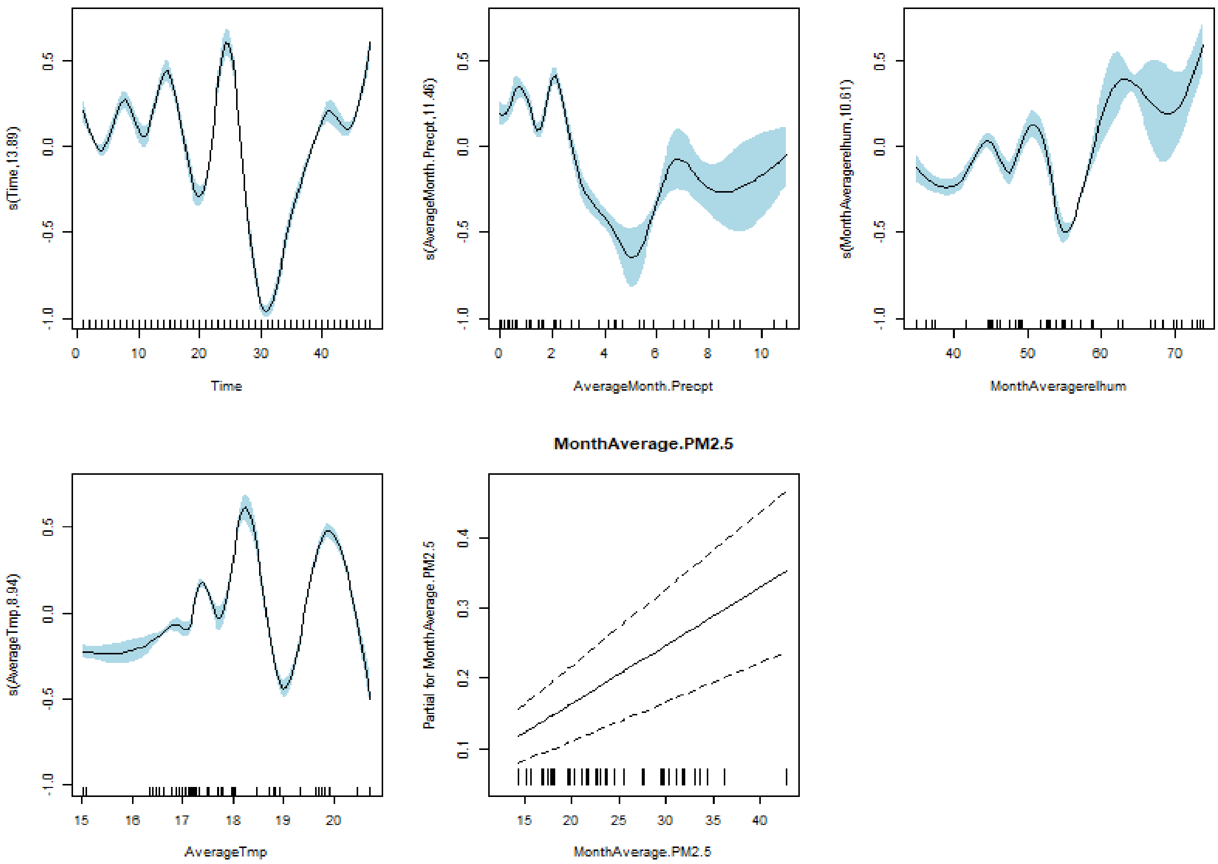


Figure 7 Effects of variable under the study

From this figure we can see that AURI Hospital admission is not linear in times. When we look at the time variable, it AURI remains high for the year 2018 and early 2019 and rise again in near September of the year 2020 and remains higher thereafter. Something uncommon was observed at that time and it needs further analysis related to protection and locks down during COVID-19 breakouts. The number of Acute Respiratory infection decreased dramatically. This may be due to advice given on media to abstain from medical centers. The partial effect of precipitation is also seen from the above figure showing increase effect as precipitation increase. Neglecting the unusual effect of time and other intervention during the COVID-19, the effect of ARI increases with temperature and relative humidity and decrease with precipitation

From the above figure particulate matter of size less than or equals 2.5(PM2.5) has linear effect. The P-value in the model corresponding to this variable is strongly significant. The shaded part of the line of other variables shows the 95% confidence interval of the effect of the each predictor.

CHAPTER FIVE

DISCUSIOON, RECOMMENDATION AND CONCLUSON

5.1 Discussion

Daily mean pollutant concentration in the city is about four to five times greater than World Health Organization guidelines. The 24-hour daily pollutant concentration has seasonality nature. The daily PM2.5 concentration in (µg/m^3) is 23.76. Three years data obtained and analyzed recently by Kumie et al shows the average result of 24.2(Kumie *et al.*, 2021). The difference may be due to data management and imputation technique employed in addition to unobserved data for 2021 year by the researchers.

The mean concentration of PM2.5 in the city shows daily and seasonal variation. From the figure 2, we see that some differences in the average concentration for days of week. The increment through working days gives us a clue that air pollution has some relationship with our day to day activities. Vehicle exhaust and residential were identified as the two major annual pollutant sources for the year 2018(Xie *et al.*, 2021). In addition to Vehicle exhaustive, most people spent weekend at home. The next highest source of PM2.5, the residential area may also contribute to the rise in the concentration on Saturday.

A close look at the days of highest concentration indicates cultural activities have a significant contribution to air the quality of the city. Public ceremonies and cultural religious practices that involve fire ceremonies produce high PM2.5 concentration. From figure 1, high PM2.5 concentration measurements are occurred on the eve of Ethiopian Meskel, called Katara or Damara fire ceremony for all year of study period. The celebration on Ethiopia new year, called saint John day, which involves fire ceremony for celebration in Orthodox religion, has also slightly high concentration. The highest concentration is recorded at the the celebration on Damara day of 2021and this is also observed in study done by (Tefera *et al.*, 2020). In addition, November 21, 2020 has also high concentration as compared to neighboring days. And this is also addressed in recent study in the city by (Bulto, 2020). The health effect of these peak pollutant days was not observed due to the lack of daily hospital admission which can be observed in the form of lag days.

Summer appears to be the most polluted season in Ethiopia, while spring appears to be the cleanest. According to this study, there is a link between pollution concentration and climatic variables. Relative humidity is highly related with PM2.5, as shown in Figure 5. The rise in relative humidity throughout the summer caused the pollutant's concentration to rise. The concentration of PM2.5 can be increased by both relative humidity and precipitation in the air. This result is similar with Abera et al that reports wet season has higher PM2.5 concentration than the dry season(Abera *et al.*, 2020)

The maximum on Damara celebration date, September 26, 2021) and minimum concentration in the city in this study during study period is 71.6μg/m^3 and 5.38μg/m^3, respectively. This figure is far below than the maximum concentrations observed in other study(Jida *et al.*, 2020). This variation may be due to the imputation method employed in this study for both missing values and invalid observation in hourly pollutant concentration.

The concentration of PM2.5 is not reduced during locked down due to COVID-19 as observed in many countries of the world (Health Effects Institute. 2020. State of Global Air 2020. Special Report. Boston, 2020). The same result was reported from a study on implication of fine particulate matter on COVID-19 (Bulto *et al.*, 2020). As stated above, this indicates that the source of this pollutant is not only related to vehicle and other fuel combustion. Residential area can account for that increment (Xie *et al.*, 2021).

Air Monitoring station from which we obtained real time PM2.5 concentration data is presented as the cleanest place as compared to other monitors in the city(Kumie *et al.*, 2021). If the cleanest place in the city has such significant association to acute respiratory infection hospital admission, it is simple to assume that the more strong association will be observed from multi monitor multi pollutant data.

Acute respiratory infection Hospital admission varies with pollutant concentration seasonally in Addis Ababa. Summer is identified with season when hospital admission due to infection is high. However, a lower record was observed between May 2020 and September 2020. This time was identified as during COVID-19. The data obtained form COVID-19 center, which cannot be obtained from Addis Ababa Health Bureau, indicates that higher COVID 19 cases were observed (Bulto *et al.*, 2020).

When we see smoothed effect of seasonal variation in terms of months on the acute respiratory disease hospital admission, we see increment in summer and decreasing in winter months. In other words, respiratory infection hospital admission rises in wet seasons when relative humidity and precipitation are high.

To see the effect of PM2.5 on acute respiratory hospital admission the pollutant interred the model as linear term and other meteorological variables are considered as confounders. These confounders were controlled during analysis by smoothing parameters. Then relative risk (RR) of the pollutant is calculated by exponentiation the coefficient of the PM2.5(Álvaro-Meca *et al.*, 2022).

Air pollution has statistically significant risk of increasing acute respiratory infection. Particularly, risk of fine particulate matter on this infection is reported to be (PM2.5: RR 1.04 (95% CI: 1.00 to 1.09(Kirwa *et al.*, 2021)). As cited in WHO report of 2021, the systematic review on PM2.5 and all non-accidental mortality reported a meta-analytic by Chen and Hoek published in 2020 that effect estimate of RR of 1.08 (95% CI: 1.06-1.09) per 10 µg/m^3 PM2.5, assuming a linear relationship (*WHO global air quality guidelines*, 2021)

In this study, we observed significant association between acute respiratory hospital admission and fine particulate matter. Relative risk (RR) equals 1.00826 with 95%CI (1.0056, 1.0101) for one µg/m3 increase in PM2.5. In order to make this figure comparable, we can also report the finding as follow. That means, each 10 µg/m^3 increase in PM2.5 concentration was associated with a relative risk (RR) of 1.08 (95% CI: 1.06-1.11). Thus, hospital admission due to respiratory infection increases by 8% for each 10µg/m^3 in fine particulate matter. The effect of PM2.5 concentration on Acute Respiratory Infection Hospital Admission is therefore statistically significant in the city. Cause- specific respiratory related emergency room visit study shows significant association with PM2.5 in Taiwan(Chang *et al.*, 2017)

Percentage change in mean monthly response that results for each 10 µg/m^3 increase in PM2.5 concentration on acute respiratory infection Hospital Admission is 8.57% with 95% confidence interval (5.6%, 10.1%).

Hospital admission for respiratory infection varies from moth to month. Variation of different pollutant concentration including PM2.5 may contribute to this difference. The risk in developing countries also varies according to the concentration level of the pollutant of the city. If the relative risk is analyzed for specific group of peoples in the same city, there is also significant variation. A study done in Nepal shows children are more affected by air pollution than other population groups. Their report indicates that 10 µg/m3 increase in PM2.5 was associated with a relative risk (RR) of 1.16 (95% confidence interval [CI]: 1.02–1.31) (Nishikawa et al., 2021). The difference in the RR can be due to the population group selected for the study.

The other one-year study on children for slightly cleaner than Addis Ababa shows increase relative risk of hospitalization by 5.6% for increase in PM2.5 by 4.2 µg/m³. We observed greater risk for this city analyzed by GAM. Their data was, however, categorized and lag distributed model is employed (Nascimento *et al.*, 2017).

5.2 Recommendations

There are many recommendations on these matters and the progress in the city on maintaining air monitoring and importing fuels with lower Sulfur does not got due recognition yet. Even though achieving a pollution-free environment is difficult, according to the World Health Organization, it is possible to be reduced to make the cities suitable places by controlling primary sources of the pollutant. Reducing the concentration of PM2.5 in the city needs to focus on these identified places and cultural activities where most people are exposed

Currently used energy source during summer in residential areas needs to be identified to reduce higher concentration in this season.

Collection, managing and dissemination of air quality data in the city is not at its encouraging status in the city. In the absence of air quality related data maintained by Addis Ababa Environmental protection and green development commission and national meteorological agency planning and promoting health will be difficult. Maintaining and publicizing air quality from different monitors is necessary for all air quality monitors to promote researches on this area is highly recommended.

Public awareness on exposure to and emission of fine particulate matter is needed to reduce difficulty in breathing due to infection. The right to live in clean environment can only attained through public awareness to maintain air quality in this city by reducing emission. The measurement taken so far in the city in the developing city five year plan and informing public need to start with national celebration that involves fire ceremony. The recent damara celebration which is identified as the highest concentration indicates public awareness need implementation of the plan.

According to report of World Bank the fuel imported and used in Ethiopia is not recommended for the desired air quality. The old vehicles in the city are also challenging the city's air quality. Awareness of population and religious leaders on health effect of air pollution is not at its deserve level.

5.3 Conclusion

The concentration of fine particulate matter in Addis Ababa increases the likelihood of acute respiratory hospital admission by a statistically significant amount. In other words, we can say that the more PM2.5 concentration in ambient air, the more our respiratory systems affected. The chemicals in the fine particulate matters of size less than or equals to 2.5 in micrometer, damage respiratory organs causing difficulties in breathing that leads to increase hospital admission due to the infection.

In this study, we have seen some days are more polluted than other days. Days identified as cultural and religious days that involve celebration with fire ceremony more polluted than ordinary days. In addition, working days including Saturday have higher concentration levels than Sunday. This indicates that pollution is related to our day to day activities. The trend observed in the weeks may indicate cumulative emission effect that may be attributed to road-traffic.

PM2.5 seems to be associated with relative humidity and precipitation. In addition, months of summer are usually identified as wet season, in the city is identified with higher concentration. Increase in energy consumption in these seasons may contribute for this as reported in Kumie et al(2021). Humidity and precipitation favor formation of the particle in wet seasons in air in addition to primary sources we saw above and this may cause increase in summer.

A data from single air quality monitor station and single pollutant (PM2.5) is used in this study. Absence of relatively complete and reliable data for the study period measurement of other pollutants is at its infancy period(Xie *et al.*, 2021). Multi-pollutant health effect from multi-monitor was not observed in this research. Again, Addis Ababa Health Bureau has no daily hospital admission data. Short term health effect less than one month is also not analyzed in this study.

In order to better understand sort term health impact of the pollutant and to make comparison with other mega cities, daily reported health data is needed. Further study on this area is therefore recommended for different health outcome on multi-pollutant from multi-monitor data.

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