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COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

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HEALTH AND ECONOMIC IMPACT ESTIMATION OF AMBIENT AIR PARTICULATE MATTER ($PM_{2.5}$) POLLUTION IN ADDIS ABABA USING BenMAP-CE MODEL

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Health and economic impact estimation of ambient air particulate matter ($PM_{2.5}$) pollution in Addis Ababa using BenMAP-CE model

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Declaration

I, Mulugeta Getachew, hereby declare that this thesis entitled "Health and Economic impact estimation of ambient air Particulate matter ($PM_{2.5}$) pollution in Addis Ababa using BenMAP-CE" is my original work and has not been submitted in whole or in part for any other degree. I understand the consequences of plagiarism and any sources used or referred to in this thesis have been properly acknowledged and cited.

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Abstract

Health and economic impact estimation of ambient air particulate matter ($PM_{2.5}$) pollution in Addis Ababa using BenMAP-CE

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Addis Ababa University, 2024

Ambient air particulate matter ($PM_{2.5}$) pollution poses a significant health and economic burden in Addis Ababa, Ethiopia. This thesis used the Environmental benefits mapping and analysis program-community edition (BenMAP-CE) software tool to estimate health and economic impact of ambient air $PM_{2.5}$ pollution. The study evaluated the impact of decreasing the annual average $PM_{2.5}$ concentration in 2019 (32.8µg/m^3) to different international and national air quality standards, including World health Organization`s guidelines and the Ethiopian National Ambient Air Quality standard (NAAQS). Results showed that Addis Ababa exceeded both WHO`s and Ethiopia`s ambient air quality standards in 2019. The study estimated the attributable deaths from cardiovascular, ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD) and lower respiratory infection (LRI) due to $PM_{2.5}$ exposure across three reduction scenarios. Additionally, economic benefits associated with avoided deaths were quantified using the Organization for Economic Cooperation and Development (OECD) Value of Statistical Life (VSL) methodology. The finding demonstrated that reducing $PM_{2.5}$ pollution levels led to a notable decrease in mortality rates from various health conditions in Addis Ababa. Moreover substantial economic benefits, amounting to millions of dollars, were observed across all health endpoints, indicating significant societal savings. This study underscores the importance of implementing interventions to mitigate $PM_{2.5}$ pollution for improved public health and economic well-being in Addis Ababa and similar urban settings.

Keywords: *$PM_{2.5}$, BenMAP-CE, Ambient air pollution, VSL, Health benefits, economic benefits, Addis Ababa*

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List of Abbreviation and Acronyms

PM	Particulate matter
$PM_{2.5}$	Particulate matter 2.5μm or less diameter
BenMAP-CE	Environmental Benefits Mapping and Analysis program-Community Edition
BAM	Beta Attenuation Monitor
BLH	Black lion hospital
GEMM	Global exposure mortality model
VSL	Value of statistical life
US	United States
EPA	The United States Environmental Protection Agency
NAAQS	National ambient air quality standard
RR	Relative risk
HR	Hazard ratio
HIF	Health impact function
CVD	Cardiovascular disease
IHD	Ischemic heart disease
COPD	Chronic obstructive pulmonary disease
LRI	Lower respiratory infection
WHO	World Health Organization
IHME	Institute for Health Metrics and Evaluation
OECD	Organization for economic cooperation and development
GDP	Gross domestic product
COI	Cost of illness
WTP	Willingness to pay
VSL_{OECD}	Value of statistical life in member countries of OECD
USD	United States Dollar
PPP	Purchasing power parity
μm	Micrometer

Chapter One

1. Introduction

1.1. Background of the Study

Air pollution stands as the world's most significant environmental health threat, responsible for millions of deaths and illnesses each year. It imposes an economic burden of over $8 trillion annually on the global economy (The World Bank, 2022). Ambient air pollution is a critical risk factor for cardiovascular diseases worldwide, with particulate air pollution alone accounting for over three million deaths annually (O'Donnell *et al.*, 2010). The 2015 Global Burden of Diseases study attributed 7.6% of global deaths and 4.2% of global disability-adjusted life years (DALYs) to ambient PM air pollution, primarily due to exposure to particulate matter with an aerodynamic diameter of less than 2.5µm ($PM_{2.5}$) (Cohen *et al.*, 2017). In 2019, more than 90% of the global population was exposed to annual average $PM_{2.5}$ levels exceeding the WHO's recommended Air Quality Guideline (AQG) of 10µg/m³, established in 2005 (WHO, 2021). Long-term exposure to $PM_{2.5}$ has been linked to increased mortality risks for several health conditions, including all causes (4-14%), cardiopulmonary diseases (6-13%), cardiovascular diseases (6-26%), ischemic heart disease (10-24%), chronic obstructive pulmonary disease (COPD) (17%), lung cancer (5-37%), among others (Lepeule *et al.*, 2012, Krewski *et al.*, 2009, Cesaroni *et al.*, 2013, Pope III *et al.*, 2002).

Air pollution adversely affects human health, damages ecosystems and infrastructure, and reduces visibility (Bayat *et al.*, 2019). Economically, air pollution increases government expenditures on health insurance, treatment, and rehabilitation (Ansari and Ehrampoush, 2019). Non-communicable diseases like cardiovascular and respiratory illnesses impose significant financial burdens on low- and middle-income countries (Kalantari et al., 2017). Therefore, effective air pollution management can yield substantial health and economic benefits.

The impacts of ambient air pollution on health have been estimated using various methods, including logistic regression, linear models, and concentration-response functions. Software tools such as BenMAP-CE, AirQ, EBD, and SIM-AIR can estimate the health and financial impacts of air quality changes (Anenberg *et al.*, 2016, Bayat *et al.*, 2019). BenMAP-CE (Environmental Benefits Mapping and Analysis Program - Community Edition) is one of the most comprehensive tools, developed by the US Environmental Protection Agency (EPA), for calculating costs and mortality associated with air quality changes (Bayat *et al.*, 2019); Kim *et al.*, 2019).

Measuring the health impacts of air pollution provides clear insights into the public health implications of poor air quality. These studies have several benefits, including raising awareness among individuals and governments about the adverse effects of air pollution, advocating for policies to reduce air pollution, and aiming to decrease morbidity, mortality, and associated economic costs. Ethiopia, undergoing significant industrial expansion, faces numerous environmental challenges, including a large number of outdated vehicles.

This research aims to enhance the understanding of the health and economic costs related to $PM_{2.5}$ pollution in Addis Ababa. A novel aspect of this study is the calculation of financial benefits and the evaluation of avoided deaths from cardiovascular diseases, ischemic heart disease (IHD), stroke, COPD, and lower respiratory infections (LRI) under various regulatory scenarios for $PM_{2.5}$. These aspects have been overlooked in previous studies. Given that the COVID-19 pandemic began in Ethiopia in 2020, this study utilizes the 2019 data to avoid potential confounding effects.

1.2. Statement of the Problem

Air pollution is recognized as the world's largest environmental health threat by the World Health Organization (WHO, 2016a), In 2015, outdoor air pollution was estimated to cause 4.2 million premature deaths globally (Cohen *et al.*, 2017). More recent estimates using the Global Exposure Mortality Model (GEMM) suggest that mortality attributable to outdoor fine particulate matter ($PM_{2.5}$) air pollution is 120% higher than previously thought, accounting for 8.9 million premature deaths (Burnett *et al.*, 2018). Projections based on a business-as-usual emission scenario indicate that the contribution of outdoor air pollution to premature mortality could double by 2050 (Lelieveld *et al.*, 2015).

Exposure to air pollutants is particularly concerning in urban areas due to the dense populations and numerous emission sources (Lelieveld *et al.*, 2015), with traffic emissions being the main contributor (Kumar *et al.*, 2014). Cities, which currently account for 85% of global economic activity and house 55% of the world's population, are expected to grow to 66% by 2050 (UN, 2014). This urbanization drives unprecedented increases in energy consumption, construction, industry, and traffic (Landrigan *et al.*, 2018).

Particulate matter ($PM_{2.5}$) and ozone (O_3), pollutants commonly associated with combustion, lead to higher rates of emergency department visits, hospitalizations, and fatalities due to respiratory and cardiovascular illnesses. Particulate matter with an aerodynamic diameter less than 10μm, particularly $PM_{2.5}$, has been linked to urban health problems (Pope and Dockery, 2006). Epidemiological studies indicate that atmospheric aerosols can have adverse health effects, with coarser particles related to respiratory diseases and finer particles affecting the cardiovascular system (Pope *et al.*, 2004; Dockery and Stone, 2007; Panas *et al.*, 2014).

In Ethiopia, like many developing countries, air quality monitoring systems are limited (Wallner, Hutter and Moshammer, 2014). Consequently, ambient $PM_{2.5}$ levels and their associated health impacts are not adequately monitored. Evidence suggests that pollution levels in Ethiopia are rising due to urbanization, industrialization, and increased traffic, which could lead to more severe health consequences (Donkelaar and Dingenen, 2016).

Air pollution is the third leading risk factor for premature death in Ethiopia, following malnutrition and poor sanitation, contributing to approximately 8% of nearly 41,000 deaths in 2017 alone. Exposure to both outdoor $PM_{2.5}$ and household air pollution is associated with higher risks of hospitalization, disability, and premature mortality from heart disease, stroke, lung cancer, diabetes, respiratory diseases, and communicable diseases such as pneumonia (State of global air, 2019).

In Addis Ababa, the capital of Ethiopia, $PM_{2.5}$ pollution is a major concern due to its health and economic impacts. Daily $PM_{2.5}$ levels are 1.7 times higher than the WHO-recommended 24-hour guideline, and the annual mean $PM_{2.5}$ concentration significantly exceeds the WHO annual standard of 10µg/m^3, resulting in a considerable burden of attributable deaths (Kumie *et al.*, 2021). $PM_{2.5}$ pollution is known to cause respiratory and cardiovascular diseases, leading to increased healthcare costs and reduced productivity.

Despite the known adverse effects of $PM_{2.5}$ pollution, comprehensive data on its health and economic impacts in Addis Ababa is lacking. To address this gap, this study aims to use the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) model to estimate the health and economic impacts of ambient $PM_{2.5}$ pollution in Addis Ababa. This well-established tool provides a systematic approach to estimating health outcomes and economic costs associated with $PM_{2.5}$ exposure.

1.3. General Objective

To estimate the health and economic impacts of ambient air particulate matter ($PM_{2.5}$) pollution in Addis Ababa using the BenMAP-CE model.

1.4. Specific objectives

- To determine the annual average concentration of $PM_{2.5}$ in Addis Ababa for the year 2019.

- To estimate the number of avoided premature deaths and the economic benefits associated with reducing $PM_{2.5}$ pollution in Addis Ababa, focusing on the following health endpoints: cardiovascular disease, stroke, ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD), and lower respiratory infection (LRI).

1.5. Research Questions

This research addresses the following questions:

- What is the health impact of reducing ambient particulate matter ($PM_{2.5}$) pollution in Addis Ababa in 2019?
- What is the economic value of the health impacts associated with ambient particulate matter ($PM_{2.5}$) pollution in Addis Ababa in 2019?

1.6. Significance of the study

The study will provide the first comprehensive assessment of the health and economic impact of $PM_{2.5}$ pollution in Addis Ababa, Ethiopia. The findings of the result will be valuable for policy makers and other stakeholders in developing and implementing effective strategies to reduce air pollution and public health. Additionally, this research will contribute to the growing body of evidence on the impacts of air pollution in Africa, which is essential for informing policy and practice at local, national, and regional levels.

Additional Significance

- The study will provide detailed information on the specific health impacts of $PM_{2.5}$ pollution in Addis Ababa, enabling more targeted interventions and more effective resource allocation.
- It will quantify the economic costs associated with $PM_{2.5}$ pollution, supporting the case for investment in air pollution control measures.

Overall, this study is significant because it will deliver valuable insights into the health and economic impacts of $PM_{2.5}$ pollution in Addis Ababa, Ethiopia, aiding in the creation of evidence-based policies and interventions.

Chapter Two

2. Literature Review

2.1. Ambient Air Pollution

The air we breathe outside, especially in cities, industrial zones, and countryside areas, often contains harmful substances like particles and gases, known as ambient air pollution. Human activities, including transportation, industrial processes, and farming mostly produce these contaminants. The World Health Organization (WHO) recognizes air pollution as a major threat to global health, attributing roughly 7 million annual deaths worldwide to this issue.

The composition of ambient air pollution includes a range of harmful substances, such as particulate matter (PM), nitrogen oxides (NOx), sulfur oxides (SOx), ozone (O_3), and volatile organic compounds (VOCs). Research has associated these pollutants with a variety of negative health outcomes, including disorders affecting the respiratory and cardiovascular systems, cancer, and harm to the nervous system.

Scientific studies have repeatedly shown the negative health effects of being exposed to outdoor air pollution. For example, research in the Lancet reported that ambient air pollution caused 4.2 million early deaths globally in 2016, with most cases happening in countries with low and middle incomes (Cohen *et al.*, 2017). Additionally, a study published in Environmental Health Perspectives revealed that breathing in tiny particles known as $PM_{2.5}$ notably raises the likelihood of developing heart disease (Brook *et al.*, 2010).

Worldwide, authorities and various organizations are taking steps to combat ambient air pollution by reducing emissions and enhancing air quality. Their strategies include supporting the use of clean energy sources, imposing stricter rules on vehicle emissions, and upgrading public transportation systems.

2.2. Urban air quality

Most cities worldwide suffer from serious air quality problems, which have received increasing attention over the past decade. Emissions of air pollutants stem from various anthropogenic sources, including motor traffic, industry, power plants, trade, and domestic fuel use. Among these, motor vehicle traffic is often the most significant source of air pollution in urban areas. As cities expand, the number of vehicles on the road increases, leading to greater distances traveled and longer commutes times (Mayer, 1999).

Urban and industrial air pollution has been recognized as a health hazard for centuries. Currently, over half of the global population resides in urban areas where outdoor air quality frequently fails to meet the health standards set by the World Health Organization (WHO). Each year, air pollution is responsible for the premature deaths of over 3 million people, more than twice the mortality rate from traffic accidents (WHO, 2016a). The primary pollutants contributing to this crisis include nitrogen dioxide (NO_2), carbon dioxide (CO_2), and fine particulate matter with an aerodynamic diameter of less than 2.5 micrometers ($PM_{2.5}$). The most effective way to improve urban air quality is by reducing pollutant emissions. However, authorities worldwide have consistently struggled to achieve significant air quality improvements through emission control measures alone.

2.3. Particulate Matter

Particulate matter (PM), also known as particle pollution, is a complex mixture of extremely small particles and liquid droplets. These particles include acids (such as nitrates and sulfates), organic chemicals, metals, and soil or dust particles. Inhaling particulate matter can have significant health impacts on the heart and lungs. Particulate matter is classified into three categories based on size: $PM_{2.5}$ (particles less than 2.5 microns in aerodynamic diameter), PM_{10} (particles less than 10 microns in aerodynamic diameter), and $PM_{10-2.5}$ (particles between 2.5 and 10 microns in aerodynamic diameter) (USEPA, 2022).

The most serious health impacts caused by air pollution are linked to particulate matter. The respiratory tract is particularly vulnerable to harmful compounds carried by these particles, similar to other air pollution components. The size of the particles, correlated with their aerodynamic diameter (AD), influences their health effects. Most PM10 particles, with an AD range of 2.5 to 10 microns, are deposited in the nasal cavities and upper airways. Smaller particles, such as $PM_{2.5}$ and $PM_{0.1}$ (with ADs of 2.5 and 0.1 microns, respectively), can penetrate the bloodstream, exerting more harmful health effects (Brown, Zeman and Bennett, 2002; Valavanidis, Fiotakis and Vlachogianni, 2008; Franck *et al.*, 2011).

2.4. Sources of $PM_{2.5}$

$PM_{2.5}$ pollution is caused by both natural and man-made factors. According to Kanniah et al. (2013), natural sources include dust and soil particles, sea salt aerosols, and particles produced by volcanic eruptions and forest fires. According to Cohen et al. (2017), anthropogenic sources include emissions from a variety of processes, including combustion (e.g., burning of fossil fuels in vehicles and power plants), industrial emissions, agricultural activities, and domestic sources (such as cooking and heating). The regional factors, atmospheric conditions, and emission sources all affect how $PM_{2.5}$ is made up.

2.5. Health Effects of Airborne Particulate Matter

Toxicological and physiological evidence suggests that fine particles, particularly $PM_{2.5}$, may have the most significant impact on human health. These particles are often more toxic because they contain sulfates, nitrates, acids, metals, and various chemicals adsorbed onto their surfaces. Compared to larger particles, $PM_{2.5}$ can be inhaled more deeply into the lungs, remain suspended in the air for longer periods, penetrate indoor environments more easily, and be transported over much longer distances (Wilson and Suh, 1997).

One of the most significant studies on the long-term effects of fine particulate air pollution ($PM_{2.5}$) on all-cause, lung cancer, and cardiopulmonary mortality was conducted in the United States by Pope et al. (2004). This study involved 1.2 million adults enrolled in 1982 through the American Cancer Society's Cancer Prevention II study. Participants completed a questionnaire that provided individual risk factor data, including age, weight, smoking habits, diet, and occupational exposure. The risk factor data for 500,000 adults were linked with air pollution data from metropolitan areas across the United States and combined with mortality data up to 1998.

2.6. Health Effects of Long-Term Exposure to $PM_{2.5}$

Long-term exposure to $PM_{2.5}$ involves inhaling small particles over months or years, leading to various adverse health effects, including respiratory issues, cardiovascular disorders, premature death, cancer, and potentially neurological damage. This poses serious public health concerns.

Respiratory Problems: Prolonged exposure to $PM_{2.5}$ is associated with several respiratory issues. Fine particulate matter can irritate the respiratory tract, causing symptoms such as coughing, wheezing, and increased sputum production. Additionally, it has been shown that exposure to $PM_{2.5}$ can cause the onset or worsening of bronchitis, asthma, and chronic obstructive pulmonary disease (COPD) (Dockery et al., 1993). These illnesses not only lower the quality of life for those who are affected but also add to the overall load on healthcare systems.

Cardiovascular Disease: Numerous studies have found a strong link between long-term exposure to $PM_{2.5}$ and an elevated risk of cardiovascular diseases. $PM_{2.5}$ can enter the bloodstream and induce inflammation, leading to atherosclerosis and increasing the risk of heart attacks, strokes, and hypertension (Brook *et al.*, 2010), Given the significant global burden of cardiovascular diseases, this is particularly concerning.

Mortality: The most alarming consequence of long-term $PM_{2.5}$ exposure is its association with premature mortality. Studies consistently show a clear correlation between high $PM_{2.5}$ concentrations and increased mortality rates. It is estimated that millions of deaths annually can be attributed to this form of air pollution, significantly reducing life expectancy (Pope III *et al.*, 2002). This makes long-term $PM_{2.5}$ exposure an urgent public health issue.

Neurological Problems: Recent research suggests a potential link between $PM_{2.5}$ exposure and adverse neurological effects. Fine particulate matter can reach the brain, causing neuroinflammation, cognitive decline, and increasing the risk of neurodegenerative disorders such as Alzheimer's and Parkinson's diseases (Calderón-Garcidueñas *et al.*, 2008). Although more research is needed in this area, the broad impacts of $PM_{2.5}$ on human health are becoming increasingly evident.

2.7. Concentration Response functions, Beta (β)

The symbol beta (β) represents the change in risk or incidence of a specific health endpoint for a one-unit increase in $PM_{2.5}$ concentration. It quantifies the magnitude and direction of the association between $PM_{2.5}$ exposure and the health outcome. If β is positive, it indicates a positive association, meaning higher risk of the health endpoint is related with higher $PM_{2.5}$ concentrations. In contrast, if β is negative, it denotes a negative connection, indicating that lower levels of the health endpoint are linked to higher $PM_{2.5}$ concentrations. The size of tells us how strong the influence is (Pope and Dockery, 2006).

2.8. Economic impact of ambient air pollution

Ambient air pollution is a major concern for both public health and the economy, with particulate matter (PM) of diameter less than 2.5 micrometers ($PM_{2.5}$) recognized as a significant contributor to adverse health effects and economic costs.

A growing body of literature has quantified the economic impact of ambient $PM_{2.5}$ pollution. According to a study by the World Health Organization (WHO), the global economic cost of air pollution, including $PM_{2.5}$, was around 5.11 trillion USD in 2013, equivalent to 7.5% of the world's GDP (WHO, 2016b). The economic costs were attributed to health effects, such as premature mortality, morbidity, and lost productivity due to illness.

The United States' ambient air $PM_{2.5}$ pollution has a significant economic impact, resulting in significant expenses across multiple industries. The Environmental Protection Agency (EPA) estimates that $PM_{2.5}$ pollution has an economic burden on the US economy of up to $89 billion a year, which is a startling figure (US EPA, 2019). According to Fann *et al.*, (2012) these costs total billions of dollars annually and include hospital admissions, ER visits, and medicines associated to $PM_{2.5}$-induced illnesses. Moreover, research indicates that $PM_{2.5}$ pollution costs the economy billions of dollars a year in lost productivity as a result of absenteeism, decreased labor productivity, and early mortality (Fann *et al.*, 2012). The overall financial cost of $PM_{2.5}$ pollution is further increased by the economic impact of environmental deterioration and property damage (Anenberg *et al.*, 2017).

In China, several empirical studies using various techniques and data sources have calculated the economic impact of $PM_{2.5}$ pollution. Xue et al. (2021) found that a 10μg/m³ decrease in $PM_{2.5}$ was linked to an annual savings of 251.6 Yuan per capita in medical expenses. Dong et al. (2021), used a panel data fixed-effects regression model to predict that a 1% rise in $PM_{2.5}$ concentration would result in a 0.05818 percentage point drop in GDP per capita growth rate.

In India, the Indian Council of Medical Research estimated that the economic cost of premature mortality due to $PM_{2.5}$ pollution in 2019 was around 36.8 billion USD, equivalent to 1.4% of India's GDP (Balakrishnan *et al.*, 2019). The research additionally calculated the economic cost of morbidity due to $PM_{2.5}$ pollution was around 11.3 billion USD.

In general, the economic impact of ambient air $PM_{2.5}$ pollution is significant and varies across countries. The economic costs are mainly due to health impacts, such as premature mortality, morbidity, and lost productivity due to illness. Policymakers should consider the economic costs of air pollution when making decisions on pollution control policies and investments.

2.9. Air pollution related policy and regulations in Ethiopia

Air pollution is a significant environmental issue with adverse effects on ecosystems, the economy, and human health. Ethiopia, like many emerging nations, struggles to control air pollution due to its accelerating urbanization and rapid economic growth. The Ethiopian government has established a number of laws and regulations to address air pollution in response to these difficulties.

Countries that implemented strict regulations were rewarded with better air quality or lower $PM_{2.5}$ concentrations. The World Health Organization (WHO) has set short- and long-term objectives for allowable concentrations of key air pollutants, including $PM_{2.5}$. In 2021, WHO updated its recommendations for air quality from 2005 and suggested exposure levels of 15µgm^3 for 24 hours and 5µgm^3 for the exposure to annual mean ambient $PM_{2.5}$, respectively. It recommends policymakers to give priority to action will enhance air quality and its advantages for human health. Collaboration between business and air quality monitoring facilities, open data access, stringent regulations, and integrated worldwide air quality standard and management systems are also important (WHO, 2021).

One of Ethiopia's most significant air pollution policies is the Environmental Pollution Control Proclamation (Negarit, 2002). In order to restrict and control the release of pollutants into the environment, particularly air pollution, this policy was put into place in 2002. The policy defines the regulatory framework for limiting air pollution through the establishment of emission standards and the requirement that industries obtain operating licenses. Penalties for breaching the emission criteria were also introduced.

The Air Quality Management Strategy (AQMS) was put into effect by the Ethiopian government in 2012 in addition to the Environmental Pollution Control Proclamation. The AQMS strives to reduce air pollution while advancing the nation's sustainable development. The plan calls for the construction of air quality monitoring facilities and the creation of a database to monitor air quality trends. It also entails the creation of national standards for air quality.

Ethiopia has ratified several international accords on air pollution, including the United Nations Framework Convention on Climate Change and the Stockholm Convention on Persistent Organic Pollutants (Nations, 1992). These agreements require Ethiopia to take measures to reduce air pollution and its negative impacts on the environment and human health.

To implement these laws and regulations, Ethiopia has established several regulatory organizations, such as the Environmental Protection Authority (EPA) and the Ethiopian National Accreditation Office (ENAO). These organizations oversee and enforce compliance with government-set emission regulations.

Ethiopia's policies and laws to combat air pollution include the Environmental Pollution Control Proclamation, the Air Quality Management Strategy, and international agreements on air pollution. Regulatory bodies have been established to monitor and enforce adherence to these rules. These initiatives demonstrate the Ethiopian government's commitment to mitigating the harmful effects of air pollution on public health, the environment, and the economy.

2.10. Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP-CE)

The Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) is a GIS-based tool developed through a cooperative project to estimate health benefits associated with changes in air quality. BenMAP-CE creates population-level exposure surfaces and analyzes changes in the occurrence of various health outcomes related to ambient air pollution (USEPA, 2022). This sophisticated yet user-friendly software model estimates health benefits from improved air quality due to controls and baseline scenarios at different geographical scales, ranging from national to city levels.

BenMAP-CE serves two main purposes:

1. **Health Impact Calculation:** The software calculates reductions in the incidence rates of health endpoints based on defined improvements in ambient air quality for a specific region and its population. These health endpoints include prevented occurrences of illnesses, premature mortality, poor health, and symptom aggravation. The degree of improvement is based on previously published epidemiological researches that reveal statistical links between pollution exposure and health outcomes (USEPA, 2022).

2. **Economic Valuation:** The second purpose is to assign an economic value to the health issues that were avoided. This valuation is based on previously published economic appraisals of the relevant health endpoints

BenMAP-CE allows users to record the details of a single analysis, enabling replication across multiple environmental quality scenarios. This feature supports systematic comparison of policies, ensuring that the results of each analysis are directly comparable. The flexibility to design a standard framework for diverse research helps maintain consistency in the assumptions driving the analysis over time, making the benefits estimation process more transparent. Additionally, BenMAP-CE tracks each user option at every analysis stage, providing an audit trail for all BenMAP-CE output files (International, 2022;Van Munster, 2018).

Chapter Three

3. Materials and Methods

3.1. Software tool

The Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) version 1.5.8 was used to calculate the health and economic effects of ambient air $PM_{2.5}$ pollution in Addis Ababa. This freely available software program employs concentration-response functions to estimate the costs and mortality burden associated with changes in air quality. Developed by the United States Environmental Protection Agency (EPA), BenMAP-CE serves as a comprehensive tool for risk assessment and analysis (US EPA, 2022).

3.2. Study area

Addis Ababa, the capital city of Ethiopia, is located at an elevation of 2,355 meters (7,726 feet) above sea level and covers an area of approximately 527 square kilometers. As of 2019, the city`s population was estimated to be 3.6 million, according to the Central Statistics Agency (CSA, 2013) making it one of the Africa`s most dense populated urban centers, with a population that continuous to grow steadily. Serving as a capital Addis Ababa holds significant political, cultural, and economic importance with in the country **(**World Population Review, 2023). Notably, approximately 65% of the nation's industries are concentrated in the city (G. Gebre & D Van Rooijen, 2009). However, the fast urbanization created problems such as rising automobile emissions, which brought up difficulties, like air pollutions. The climate is divided in to two seasons based on the amount of precipitation. The months from June to September are rainy; while the months from October to May are dry (Climate-data.org, 2021).

The $PM_{2.5}$ data source was the two monitoring stations within the city. One at US embassy premises located at a latitude 9º 3' 29.1"N and a longitude of 38º 45' 49.1" E. the second was at the black lion hospital with a latitude of 9º 1' 13' N and a longitude of 38º 44' 58" E.

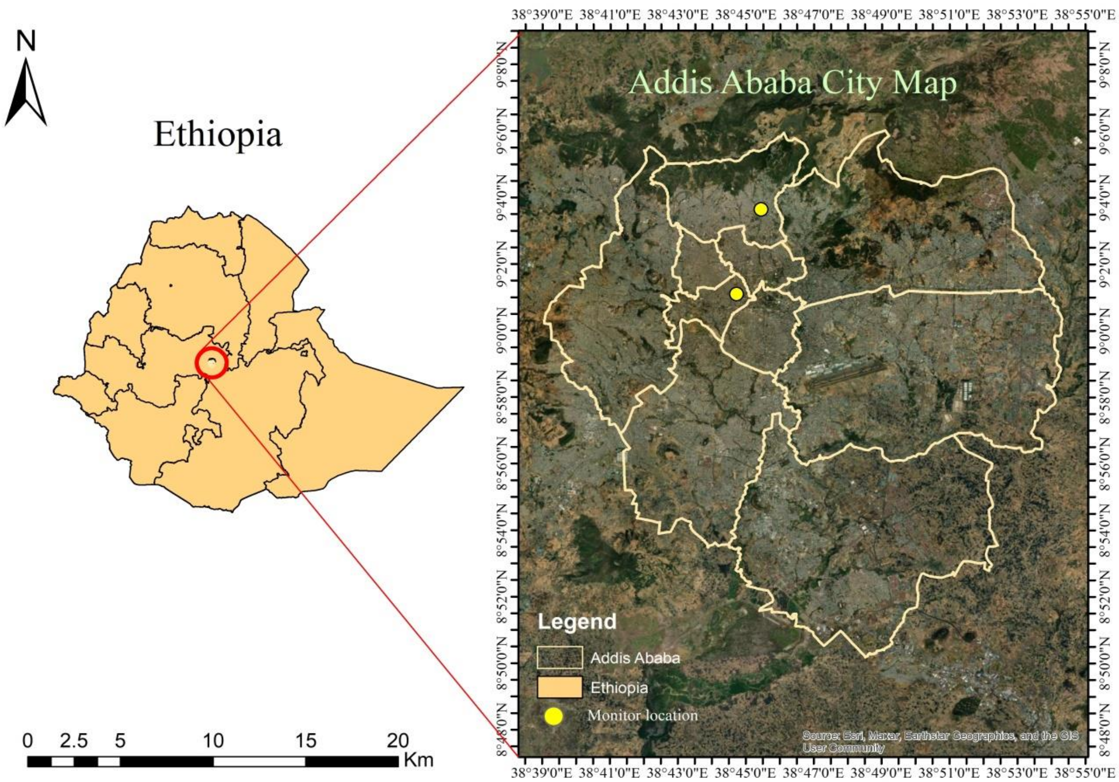

Figure 1. Study area Map

Source, Arc Map 10.8 generated for this study/2023/

3.3. $PM_{2.5}$ Data

To assess air quality in Addis Ababa, three beta attenuation monitors (BAMs) are currently operational. One of these monitors is maintained by Addis Ababa University in collaboration with the East Africa Geo Health hub[1], while the other two are managed by the United States embassy and accessible through the Air-Now international program.[2] The Addis Ababa university $PM_{2.5}$ monitor is located at the college of health sciences, specifically at the black lion hospital (BLH). The US embassy monitoring devices are situated at the US embassy and at international community school in Addis Ababa (AA EP & GDC, 2021).

In this research, data from US embassy and BLH BAMs were used. However, there was a lack of information for the international school BAM for 2019. Hourly $PM_{2.5}$ concentration data were acquired from the Air Now web site and subsequently modified by excluding some negative concentrations. The 24-hour data retrieved from the US Embassy monitoring station was averaged to drive the daily concentration of $PM_{2.5}$. As for the data from BLH BAM, it was validated and consisted of daily average, and thus, was used in its original form. To maximize the data set for analysis, from missing daily average values of BLH BAM (3 days) and from US Embassy BAM (9 days) were recovered using a linear interpolation technique. For this study, a total of 312 days' data from BLH BAM and 300 days data from US Embassy BAM, which corresponded to 85.48% and 82.2% of daily average data used, respectively.

[1] These data are not publicly available and were obtained upon request.
[2] Data are publicly available through the US Air Now-International program at US Air Now - International

To estimate the air quality in unmonitored sites in the city, the Voronoi neighborhood averaging (VNA) approach was applied, it is a spatial interpolation technique utilized in the Environmental Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE). This approach creates a Voronoi diagram of the available monitors and, based on the distance, allocates each population grid cell to the closest monitor or a weighted average of the closest monitors. The VNA approach was used to calculate the population-weighted exposure at the neighborhood level based on the mean yearly and daily PM2.5 concentrations (USEPA, 2022) .

3.4. Health impact assessment

3.4.1. BenMAP-CE

BenMAP (Environmental Benefits Mapping and Analysis Program) was initially developed by the US EPA in 2003 to assess the health and economic impacts of changes in air pollution. In 2015, it was transitioned into an open-source platform known as BenMAP-CE (BenMAP-Community Edition) to enhance accessibility (Sacks *et al.*, 2018). Widely recognized as one of the most comprehensive tools in its field, BenMAP-CE is used for evaluating premature mortality and morbidity associated with air pollution (Anenberg *et al.*, 2016).

This study utilized BenMAP-CE version 1.5.8, specifically designed by the US EPA to estimate health impacts related to changes in air quality (Kim *et al.*, 2019). The model calculates the number of affected individuals by analyzing concentration changes between control and baseline scenarios, using population and health concentration-response functions. Additionally, it evaluates the cost-effectiveness of these concentration changes (Howard *et al.*, 2019).

BenMAP-CE operates as a Geographic Information System (GIS)-based tool that generates exposure surfaces at the population level, assessing changes in various health outcomes linked to ambient air pollution (USEPA, 2022). It is sophisticated, user-friendly and capable of quantifying the quantity and economic value of health effects resulting from changes in air pollution concentrations (Sacks *et al.*, 2018).

In order to compute health impacts, BenMAP-CE uses a health impact function that takes into account population data, baseline incidence rates, monitoring air quality data, and an effect estimate (Chen, Shi, Gao, *et al.*, 2017; USEPA, 2022).

The mortality reduction from an ambient value to a target or standard can be calculated using $\Delta PM_{2.5}$. Equation (1) is utilized in BenMAP-CE to determine the change in incidence rate as a function of $\Delta PM_{2.5}$:

$$\Delta Y = Yo\left(1 - e^{-\beta * \Delta PM}\right) * Pop \qquad (1)$$

Where:

ΔY = the estimated number of premature death,

β = the risk estimate (or Beta coefficient) from an epidemiologic study,

ΔPM = the defined change in concentration of air pollutant to some target or health standard value

Y_O = the baseline (incident) rate of deaths

Pop = the population affected by air pollution (Sacks et al., 2020).

3.4.2. Exposed Population

The exposed population refers to the number of people impacted by the reduction in air pollution. In this study, the exposed population is defined as the residents of Addis Ababa in 2019. Age-specific population data for Addis Ababa were generated from the 30-year (2007–2037) population prediction by the central statistics authority based on the recently released Inter Central Population Survey (ICPS) 2012 Projection Report (CSA, 2013). In 2019, there were 3.6 million people living in Addis Ababa, of whom 58.7% were above 25 years old.

3.4.3. Baseline Incidence Rate (Y_O)

The baseline incidence rate (Y_O) refers to the annual number of deaths due to all natural causes in each sub-region (Sacks *et al.*, 2018). It is the ratio of death to population size over a given time period (Farzad *et al.*, 2021). Cause-specific mortality data for Addis Ababa, focusing on cardiovascular diseases, stroke, ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD), and lower respiratory infections (LRI), were sourced from the Global Burden of Diseases website (Institute for Health Metrics and Evaluation, 2021). This dataset provides annual age-specific estimates across various 5-year age groups.

3.4.4. Concentration-Response Function (β coefficient)

The β coefficient represents the relationship between $PM_{2.5}$ exposure and specific health outcomes. It is derived from concentration-response functions or health effect models (Burnett *et al.*, 2014), quantifying the risk of adverse health effects associated with a unit change in ambient air pollution. Models such as the Integrated Exposure Response (IER) and the Global Exposure Mortality Model (GEMM) are used to estimate these β coefficients (Burnett *et al.*, 2018).

In epidemiological studies, β coefficients can also be inferred from relative risks (RR), odds ratios (OR), or hazard ratios (HR). The equations for computing β and its standard error (βse) are as follows (USEPA, 2022).

$$\beta = \frac{\ln(RR\ or\ OR\ or\ HR)}{\Delta Pollution} \quad (2)$$

$$\beta se = \frac{\frac{\ln(UCL)-\ln(LCL)}{\Delta pollution}}{2*1.96} \quad (3)$$

$$\text{LCL} = \frac{\beta - \beta 2.5\ percentile}{1.96} \quad (4)$$

$$\text{UCL} = \frac{\beta 97.5\ percentile - \beta}{1.96} \quad (5)$$

Where ln is the natural logarithm, LCL is the lower confidence limit and UCL is the upper confidence limit.

To generate concentration-response function, it is ideal to use local population exposed to $PM_{2.5}$ with similar levels and chemical composition. However, there are no specific studies available for Ethiopia that can be utilized. Consequently, this study utilized international β coefficients (see Table 4).

The study by Krewski et al. (2009), utilized β coefficients derived from the American Cancer Society (ACS) extended follow-up cohort study, involving 552,138 individuals aged 30 years and older across all 50 US states from 1982 to 2000. This study found significant associations between increased $PM_{2.5}$ exposure and mortality from all causes, cardiovascular diseases, ischemic heart disease (IHD), and lung cancer.

Additionally, the Harvard Six Cities (H6C) study, which included 8,096 participants from six eastern US cities aged 25 to 74 between 1974 and 2009, highlighted strong links between $PM_{2.5}$ exposure and lung cancer, cardiovascular diseases, and overall mortality (Lepeule *et al.*, 2012).

Moreover, So et al. (2022) in Denmark reported positive correlations between $PM_{2.5}$, NO_2, black carbon, and mortality from lung cancer, respiratory diseases, and natural causes among 4.4 million participants aged 30-85.

Pope et al. (2015) demonstrated a 12% increased risk of cardiovascular and cardio metabolic mortality per 10μg/m^3 increase in $PM_{2.5}$ exposure in the US, underscoring the significant cardiovascular health risks associated with $PM_{2.5}$.

Lastly, Cesaroni et al. (2013) emphasized significant associations between $PM_{2.5}$, NO_2, and the risk of lung cancer, ischemic heart disease, stroke, and chronic obstructive pulmonary disease in Italy.

3.5. Economic Valuation

Improvements in air quality can significantly reduce adverse health effects in communities, such as mortality and morbidity. In economics, the value of preventing a death is quantified through various methods. BenMAP-CE, for instance, calculates the economic value of health benefits by estimating the number of deaths prevented and multiplying it by the economic value per case (US EPA, 2022).

BenMAP-CE employs three key financial metrics to assess the economic impact of air quality improvements: willingness to pay (WTP), Cost of illness (COI), and value of statistical life (VSL). The COI encompasses expenses related to treatments, hospital stays, and other direct costs, including lost wages. However, it does not account for intangible costs such as pain and suffering (Li, Song and Mao, 2019). WTP extends beyond COI to include costs associated with suffering, dissatisfaction, and the value of leisure time.

The VSL represents the amount individuals collectively agree to pay to marginally reduce the population's risk of premature death due to environmental factors (US EPA, 2022). It is a commonly used metric in BenMAP-CE for estimating economic impacts compared to COI and WTP. Importantly, VSL does not assign a monetary value to individual lives but rather reflects societal preferences regarding risk reductions from environmental hazards.

In the absence of a specific VSL value for a country, references such as the Organization for Economic Cooperation and Development (OECD) or guidelines from the US EPA can be used to derive an appropriate VSL (Ho *et al.*, 2023).

To estimate the economic impact of excess mortality, the avoided mortality rate is multiplied by a locally applicable VSL estimate. Ideally, national or regional studies should determine the economic value of life years lost. In cases where such data are lacking, equation (6) can be used, employing a "benefit-transfer" approach as suggested by Narain and Sall (2016), which adapts unit health costs from external studies to local conditions. This adjustment aims to scale VSL considering income disparities.

For this study, VSL data from OECD countries served as a benchmark to derive VSL estimates for Ethiopia. According to recent estimates (Narain and Sall, 2016), the VSL for OECD nations was USD 3.83 million at 2011 purchasing power parity (PPP). This was adjusted using the following equation:

$$VSL_{ETH\,(2019)} = VSL_{OECD} \times (Y_{ETH\,(2019)} / Y_{OECD\,(2019)})^{b} \qquad (6)$$

Where VSL_{ETH} is the VSL for Ethiopia, Y is the Gross domestic product (GDP) per capita, and b is the income elasticity of the VSL, which captures the typically observed increasing willingness to pay for health with higher incomes. For low- and middle-income nations, b ranges from 1.0 to 1.4, with average estimate of 1.2 (Narain and Sall, 2016).

Table 1. VSL calculation for Ethiopia

Parameter	Value (USD)	Unit (USD)	Reference
VSL_{OECD}	3,832,843	At rates of 2011 market, PPP	World bank website[3]
Y_{ETH}	2,274.2	Current to 2019	Economic research website[4]
Y_{OECD}	39,531.3	Current to 2019	(Narain and Sall, 2016)
VSL_{ETH}	124,567.4	At 2011 market rates	

[3]World Bank website https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
[4]Economic research website https://fred.stlouisfed.org/series/ETHNGDPRPCPPPT

3.6. Counterfactual Scenarios

The difference between the initial air pollution level (baseline) and concentration following an intervention, such as a new regulation (control), is the change in air quality (ΔPM). The annual average $PM_{2.5}$ concentration in this study for 2019 (32.8 μg/m^3) baseline scenario: three control scenarios were considered to be surveyed.

Scenario I: Rollback $PM_{2.5}$ concentration to meet the Ethiopian yearly average standard (NAAQS) of 15μg/m^3 (Federal EPA, 2003).

Scenario II: Rollback $PM_{2.5}$ concentration to meet the WHO's yearly average Air Quality Guideline 10μg/m^3 (introduced in 2005 and updated to Interim Target 4 in 2021) (WHO, 2021).

Scenario III: Rollback $PM_{2.5}$ concentration to the annual average air Quality Guideline value of 5μg/m^3 set by World Health Organization (WHO) (introduced in 2021) (WHO, 2021).

The number of death that would have been prevented as a result of changes in annual average $PM_{2.5}$ concentration between the control scenarios and the baseline was determined using BenMAP-CE.

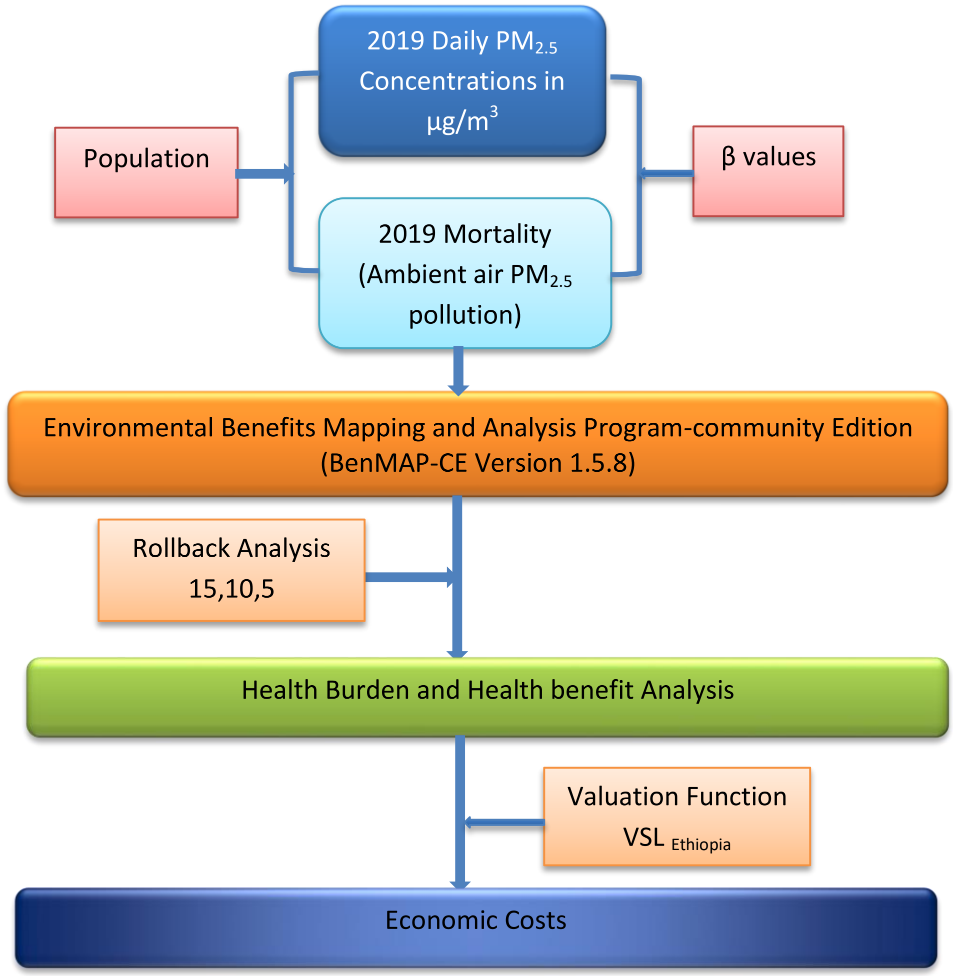

Figure 2. Work flow of the study procedure

3.7. Input Parameters

The following are input parameters to run the BenMAP-CE software

I. $PM_{2.5}$ Data

First, daily average $PM_{2.5}$ data were created in a manner that is compatible with BenMAP-CE. The daily and annual averages as well as the related latitude and longitude of the monitoring stations were then loaded using BenMAP.

II. Population Data

Age specific population data for the city had been derived from the central statistics authority's 30-year (2007–2037) population forecast based on the just-completed Inter Central Population Survey (ICPS) 2012 Projection Report (CSA, 2013). The population data were divided into five-year age groups. The data according to the population projection in the BenMAP-CE format was tabulated as shown in table 2, since it is assumed that there will be no difference in the age group strata between the sub cities of Addis Ababa.

Table 2. Population data of Addis Ababa in the age group

Year	Age	Total
2019	0TO4	394913
2019	5TO9	334459
2019	10TO14	216066
2019	15TO19	243185
2019	20TO24	303375
2019	25TO29	442142
2019	30TO34	440716
2019	35TO39	386436
2019	40TO44	239232
2019	45TO49	189869
2019	50TO54	118391
2019	55TO59	98279
2019	60TO64	74654
2019	65TO69	47706
2019	70TO74	36224
2019	75TO79	21859
2019	80UP	16493

Source: CSA's 2013 population projections.

III. Mortality Rate

The baseline incidence rates related to the five health outcome for Addis Ababa were derived from the website; Global Burden of Disease, Institute for Health Metrics and Evaluation, 2021). The incidence rate of selected health endpoints (cardiovascular (I00-I99), stroke (I60-I69), ischemic heart disease (IHD) (I20-I25), chronic obstructive pulmonary disease (COPD) (J40-J44, J47) and lower respiratory infection (LRI) (J09-J18, J20-J22) per 100000 Population was indicated in the table 3.

Table 3. Baseline incidence used in this study

Health endpoint	Annual Mortality for 2019	Annual Mortality for 2019 by Age		Mortality Incidence rate by Age		Reference
		≥30	25-74	≥30	25-74	
Cardiovascular	659	653	-	0.0004	-	
IHD	307	305	-	0.000183	-	
Stroke	352	349	-	0.00021	-	(GBD, 2021)
COPD	62	-	37	-	1.8E-05	
LRI	142	122	-	7.31E-05	-	

IHD ischemic heart disease, COPD chronic obstructive pulmonary disease, LRI lower respiratory infection

IV. Health Impact Function (HIF)

A health impact function, also known as an exposure-response function, is a mathematical relationship that quantifies the relationship between exposure to a specific environmental factor, such as air pollution, and its health effects on a population. BenMAP-CE uses beta coefficients from epidemiological studies to create health impact functions. These functions estimate the number of deaths and illnesses caused by air pollution. There is a large body of research on the health impacts of air pollution, which is summarized in several reviews (Mccubbin, 2009, Sacks et al., 2018). The number of deaths avoided in this analysis was determined using β coefficients from international studies and shown in Table 4.

Table 4. Beta function for each health endpoint and the studied age group

Health endpoint	RR(95% CI)	β coefficient	β standard error	Studied age group	Reference
Cardiovascular	1.12(1.10-1.15)	0.011333	0.016	$\geq$30	(Pope *et al.*, 2015)
IHD	1.24(1.19-1.29)	0.02151	0.002058	30-99	(Krewski *et al.*, 2009)
Stroke	1.03(0.99-1.08)	0.00296	0.0051	30-99	(Cesaroni *et al.*, 2013)
COPD	1.17(0.85-1.62)	0.01570	0.00206	25-74	(Lepeule *et al.*, 2012)
LRI	1.14(1.09-1.20)	0.0266	0.0052	$\geq$30	(So *et al.*, 2022)

IHD ischemic heart disease, COPD chronic obstructive pulmonary disease, LRI lower respiratory infection

3.8. Basic steps to perform the Analysis Using BenMAP-CE

Step 1: Grid Definition

The initial step in constructing a BenMAP-CE study should be to identify the region of interest and create a Grid Definition. The shape of a grid can be either regular (like the air quality modeling domain, which is frequently divided into squares of uniform proportions) or irregular (like a political boundary) (USEPA, 2022). The irregular "Sub city shape file" of Addis Ababa City administration is used in this research because each data set (air quality, population, and baseline rates of mortality and disease) linked to the shape file can be addressed rather easily. The Addis Ababa city administration's plan and development commission provided the Sub city shape file. The shape file was imported into the BenMAP-CE model was as shown in the Figure 3.

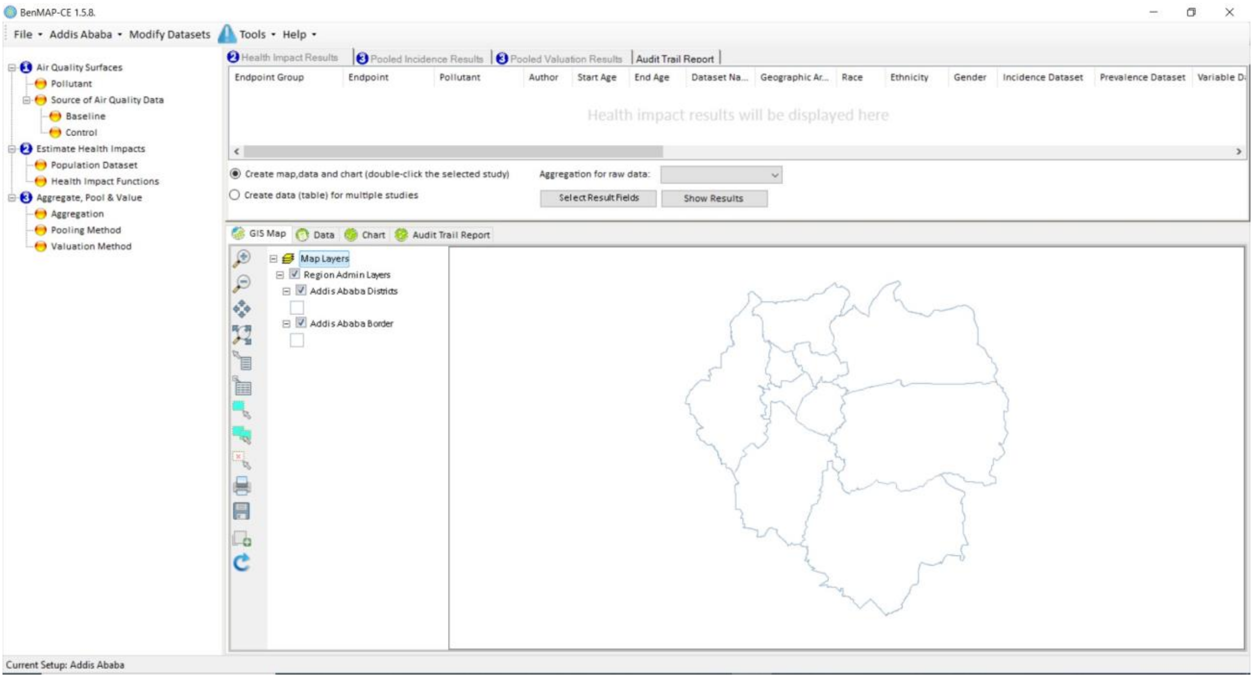

Figure 3. Addis Ababa districts shape file as loaded into BenMAP-CE

(Source: BenMAP-CE generated for this study, 2023)

Step 2: Pollutant Definition

The fundamental features of the pollutant are defined in this step in order to calculate its possible health impacts. For this particular study, the target pollutant $PM_{2.5}$ monitored data for long term periods at an averaging time of 24h used.

Step 3: Population Dataset Preparation

In order to calculate the health impacts linked to a change in air pollution, BenMAP-CE needs population data. It is possible to stratify population data by age, sex, race, and ethnicity. Population settings must be specified before adding population data to BenMAP-CE (USEPA, 2022).

The quantity of adverse health effects linked with changes in air pollution is determined using population statistics to estimate population exposure to those changes. In this case, the population of Addis Ababa city in 2019 was used. The population is defined as all those who are over the age of 24. This age group corresponds to the age range taken in to account in the epidemiologic investigation. Population data for Addis Ababa is used in the analysis to reflect the total number of adults in the city who are at least 25 years old, which was estimated to be 2,112001 in 2019.

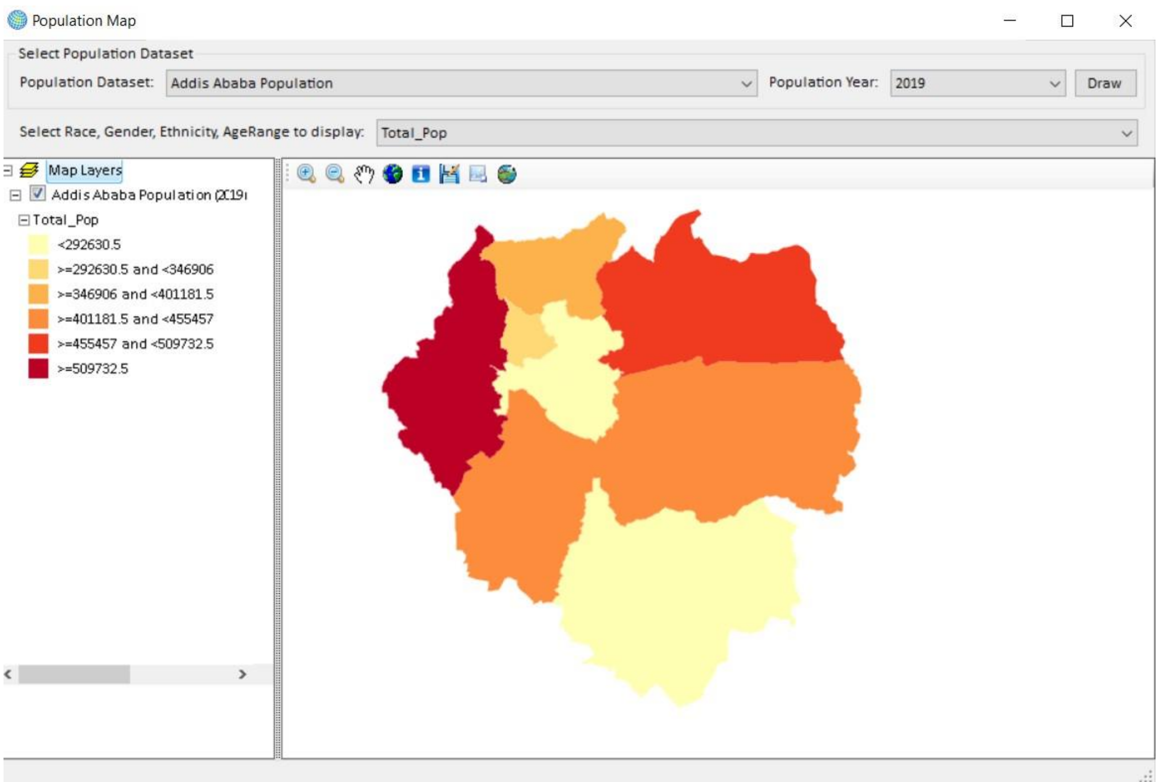

Figure 4. Addis Ababa Population Map of 2019

(Source: BenMAP generated for this study)

Step 4: Incidence Rate Dataset preparation

At this stage a baseline mortality incidence rates for a variety of causes of death were prepared. Using the data obtained from the Global Burden of Disease, Institute for Health Metrics and Evaluation website 2021), the incidence datasets were prepared for the selected health endpoints Cardiovascular, stroke, Ischemic heart disease, chronic obstructive pulmonary disease and lower respiratory infection.

Step 5: Selecting an appropriate Health Impact Function (HIF)

At this stage the appropriate HIF should be selected. There are many HIF available globally, the best one of your application is depend on the specific factors you need to consider. When selecting HIF it is important to consider the target pollutant type, health end point, age group, gender, ethnicity and others. Thus, the health impact functions of the selected health endpoints were selected from prior research at global scale. The target age group in each health impact function is different and the incidence rates are calculated based on the target age group in each health impact function.

Step 6: Load and Run the Model

After accomplishing the preparation of the necessary input parameters in the steps successfully (Step 1-5) the subsequent step is to loading the prepared input parameters according to the procedures of BenMAP-CE and run the model.

Step 7: Analysis of Health Effects

The outcomes of the detrimental health impacts were examined for various health endpoints after the model run.

3.9. Sensitivity Analysis

In this study, the sensitivity analysis aimed to assess the influence of variation in model inputs or parameters on the resulting health benefit outcomes. Specifically, the analysis focused on evaluating how changes in the input parameters of BenMAP-CE impact the concentration response (C-R) coefficients associated with the health benefits. The C-R coefficients characterized by lower and higher bounds, the higher bound of the C-R coefficients were utilized for this analysis to assertion a conservative estimate of the sensitivity. The resulting estimates were then compared with those obtained using the recommended C-R coefficients (Table 3).

3.10. Uncertainty analysis

In this study comprehensive approach that combines data verification and assumption testing was used to address the uncertainty of estimating health and economic impact. The study examines data from reliable sources such as World health organization (WHO) and national statistics services (ESS) to ensure their validity and sustainability for the analysis. These techniques help the thesis to provide more detail and accurate understanding of the uncertainty involved in the estimation process, and to increase trustworthiness the relevance of the study findings.

3.11. Ethical consideration

The study relied on secondary data and did not involve the collection of personal information such as names or contact details. As a result the use of a consent form was not necessary.

Chapter Four

4. Results and Discussion

4.1. $PM_{2.5}$ Concentration

The quality of air in Addis Ababa in 2019 was within acceptable limit based on Ethiopian daily standards for 95 percent (348 days) below 65. However, there were a significant number days in the city where the daily $PM_{2.5}$ level was higher than the WHO recommended daily average air quality guideline (AQG); 91.5 percent (334 days) were higher than 15µg/m^3, and 62.5 percent (228 days) were higher than 25µg/m^3 (Table 5). This indicates that the air pollution in the city caused different health problems in the community.

Table 5. Number of days with daily average $PM_{2.5}$ concentration below and above the national and WHO standard in 2019

Characters	Ethiopian daily average standard (65µg/m^3)		WHO (2005) standard (25µg/m^3)		WHO (2021) AQG (15µg/m^3)	
	$\leq$ 65	>65	$\leq$ 25	>25	$\leq$ 15	>15
Number of days	348	17	137	228	31	334
Percentage	95.34	4.66	37.5	62.5	8.5	91.5

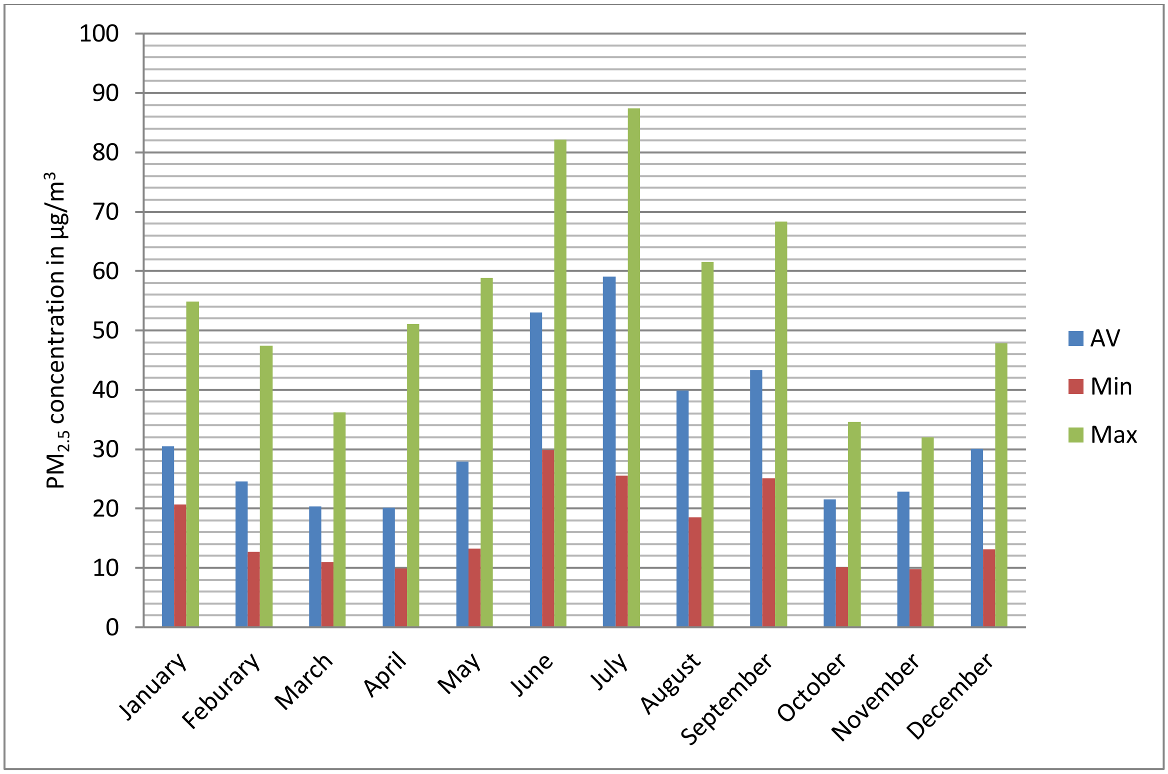

Figure 5. Monthly average, minimum and maximum of PM2.5 concentration in 2019

The Average $PM_{2.5}$ concentrations of the different months in 2019 are shown in Figure 5. As it shown in the figure the average concentration of the $PM_{2.5}$ was in the range 9 to 88µg/m^3 throughout the year. The highest $PM_{2.5}$ concentration was recorded in July (87.42 µg/m^3) and June (82.17µg/m^3) followed by September (68.35µg/m^3) and August (61.58 µg/m^3). On the other hand, the lowest was recorded in November (9.7µg/m^3) and April (9.88 µg/m^3) followed by October (10 µg/m^3) and March (11 µg/m^3). The highest $PM_{2.5}$ concentration in the rainy season (June to September) probably due to the moisture levels in the air, driven by metrological differences accentuated by rainfall in wet season. Day-long natural cloud cover and rain contributed to suspended droplets in the air, raising humidity levels. This elevated humidity likely restricts the upward movement of fine $PM_{2.5}$ particles, causing them to accumulate. Consequently, there is a higher concentration of $PM_{2.5}$ due to ongoing emissions from household and vehicles. The lower $PM_{2.5}$ concentrations in (October to April) compared to other months may be due to the highest daily temperature. The background of ongoing emissions from cars and homes may be influenced by the better air mixing than during the rainy months. This study provides further evidence to support the conclusion drawn from the previous study conducted in 2021 (Kumie *et al.*, 2021). Research conducted in India (Kumar *et al.*, 2018), Mongolia (Wang *et al.*, 2017) and California/US (Cisneros *et al.*, 2014) demonstrated comparably variability in $PM_{2.5}$ levels across these regions. In these studies, it was observed that during the wet months, $PM_{2.5}$ concentrations exceeded those recorded during periods of high rain fall and/or relative humidity.

In 2019, the yearly average $PM_{2.5}$ concentration in Addis Ababa was 32.8µg/m^3. This value was notably higher than the recommended air quality guidelines set by the World Health Organization (WHO), being approximately 6.5 times the WHO annual average guideline, 3.3 times the WHO interim target 4, and 2.2 times the National Ambient Air Quality Standard (NAAQS). These levels were higher than the latest WHO annual average $PM_{2.5}$ guideline established in 2021(5µg/m^3), as well as the previous guideline set in 2005 (10µg/m^3) (WHO, 2021). Furthermore, the $PM_{2.5}$ surpassed the Ethiopian Annual Ambient Air Quality standard (NAAQS) of (15µg/m^3) (Federal EPA, 2003). This indicates that the air pollution in the city caused health hazards to the population exposed to it, such as respiratory issue, cardiovascular problems and other adverse health effects.

4.2. Impacts of $PM_{2.5}$ reduction on Health

According to the defined scenarios using BenMAP-CE, the number of deaths that may have been prevented in 2019 if the three control scenarios for $PM_{2.5}$ concentration had been met is shown in Table 6.

Table 6. The number of avoided death in 2019 attributable to $PM_{2.5}$ among the Addis Ababa population

Health endpoint	Reference for HIF	Baseline Mortality	Scenario I		Scenario II		Scenario III	
			Avoided death	Percentage of reduction	Avoided death	Percentage of reduction	Avoided death	Percentage of reduction
Cardiovascular	(Pope et al., 2015)	653	174	27%	187	28.7%	198	30.3%
IHD	(Krewski et al., 2009)	305	135	44.3%	142	46.6%	151	49.5%
Stroke	(Lepeule et al., 2012)	349	26	7.5%	28	8.0%	31	9%
COPD	(Cesaroni et al., 2013)	37	12	32.4%	13	35.1%	14	37.8%
LRI	(So et al., 2022)	122	61	50%	65	53.3%	69	56.6%

IHD ischemic heart disease, COPD chronic obstructive pulmonary disease, LRI lower respiratory infection

Achieving the National Ambient Air Quality Standards (NAAQS) of 15µg/m^3 (scenario I) could have potentially led to a reduction of 174 (27%), 135 (44.3%), 26 (7.5%), 12 (32.4%), and 61 (50%) premature mortalities for Cardiovascular, Ischemic heart disease (IHD), Stroke, chronic obstructive pulmonary disease (COPD) and lower respiratory infection (LRI) respectively in 2019. Further improvement to the WHO annual average guideline interim target 4 of 10µg/m^3 (scenario II) could potentially have led to a reduction of 187 (28.7%), 142 (46.6%), 28 (8%), 13 (35.1%), and 65 (53.3%) premature mortalities for Cardiovascular, Ischemic heart disease (IHD), Stroke, chronic obstructive pulmonary disease (COPD) and lower respiratory infection (LRI), respectively. Additional Adherence to meet the WHO`s more stringent yearly average air quality guideline of 5μg/m^3 (scenario III) might have resulted even in greater benefits, with estimated reduction 198 (30.3%), 151 (49.5%), 31 (9%), 14 (37.8%) and 69 (56.6%) premature mortalities in the same health categories.

The assessment of health impacts are first computed at district levels, which are then aggregated to the city level. This aggregation can be illustrated in maps that highlight geographic variation in health benefit resulting from reduced $PM_{2.5}$ levels (refer to Figs. 6, 7, and 8).

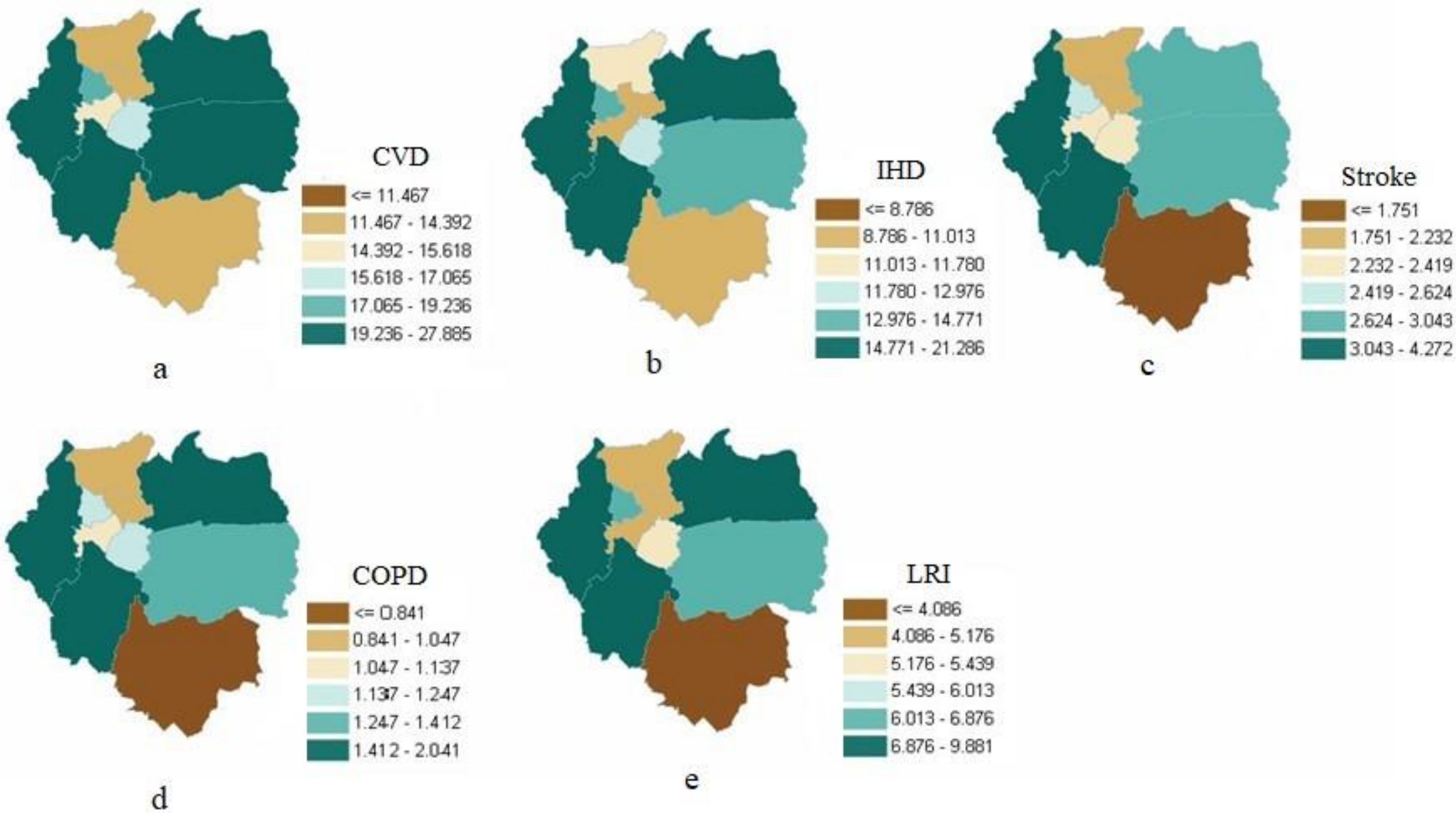

Figure 6. Total avoided death in scenario I (15µg/m3) for (a), CVD, (b), IHD, (c), Stroke, (d), COPD, and (e), LRI

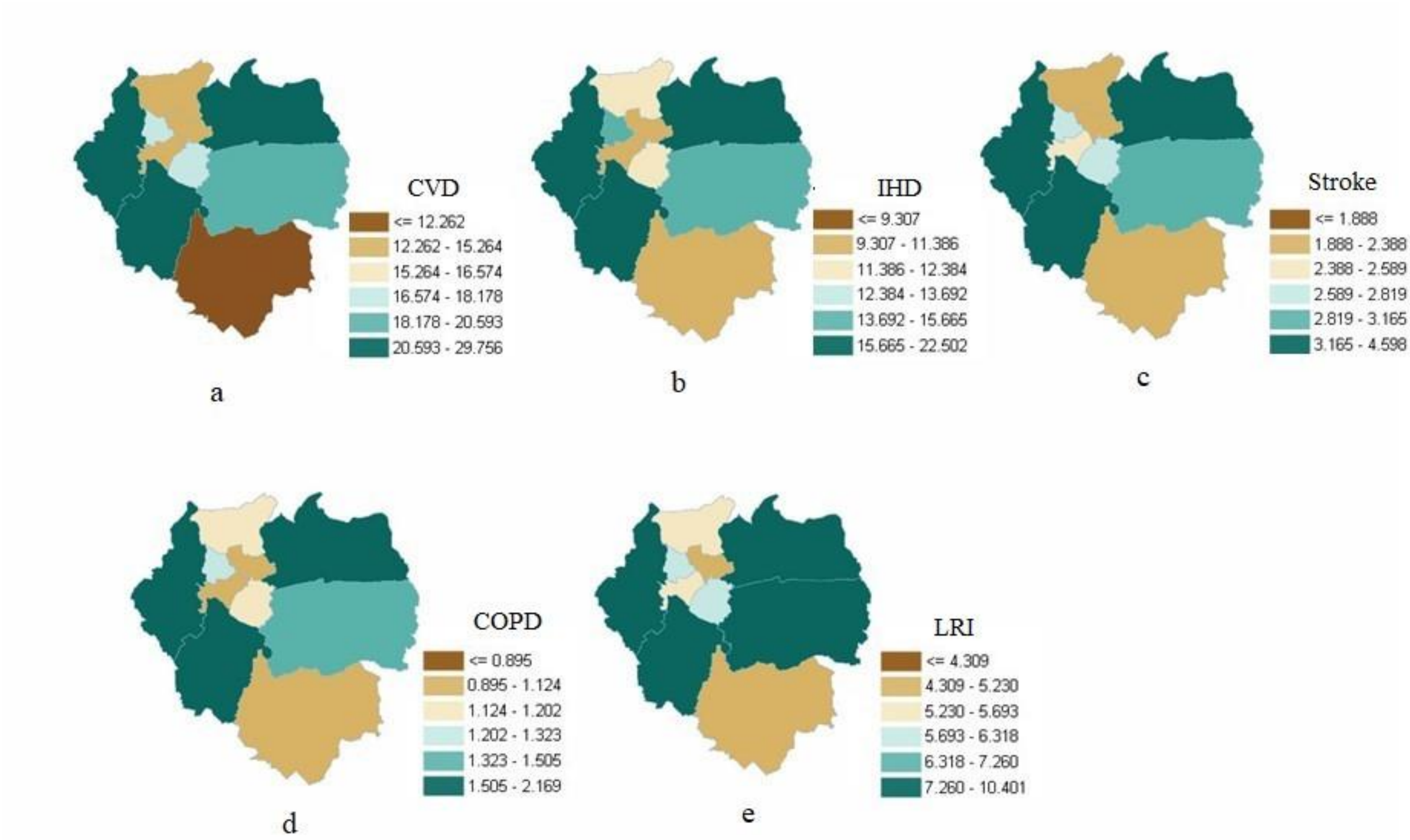

Figure 7. Total avoided death in scenario II (10µg/m3) for (a), CVD, (b), IHD, (c), Stroke, (d), COPD, and (e), LRI

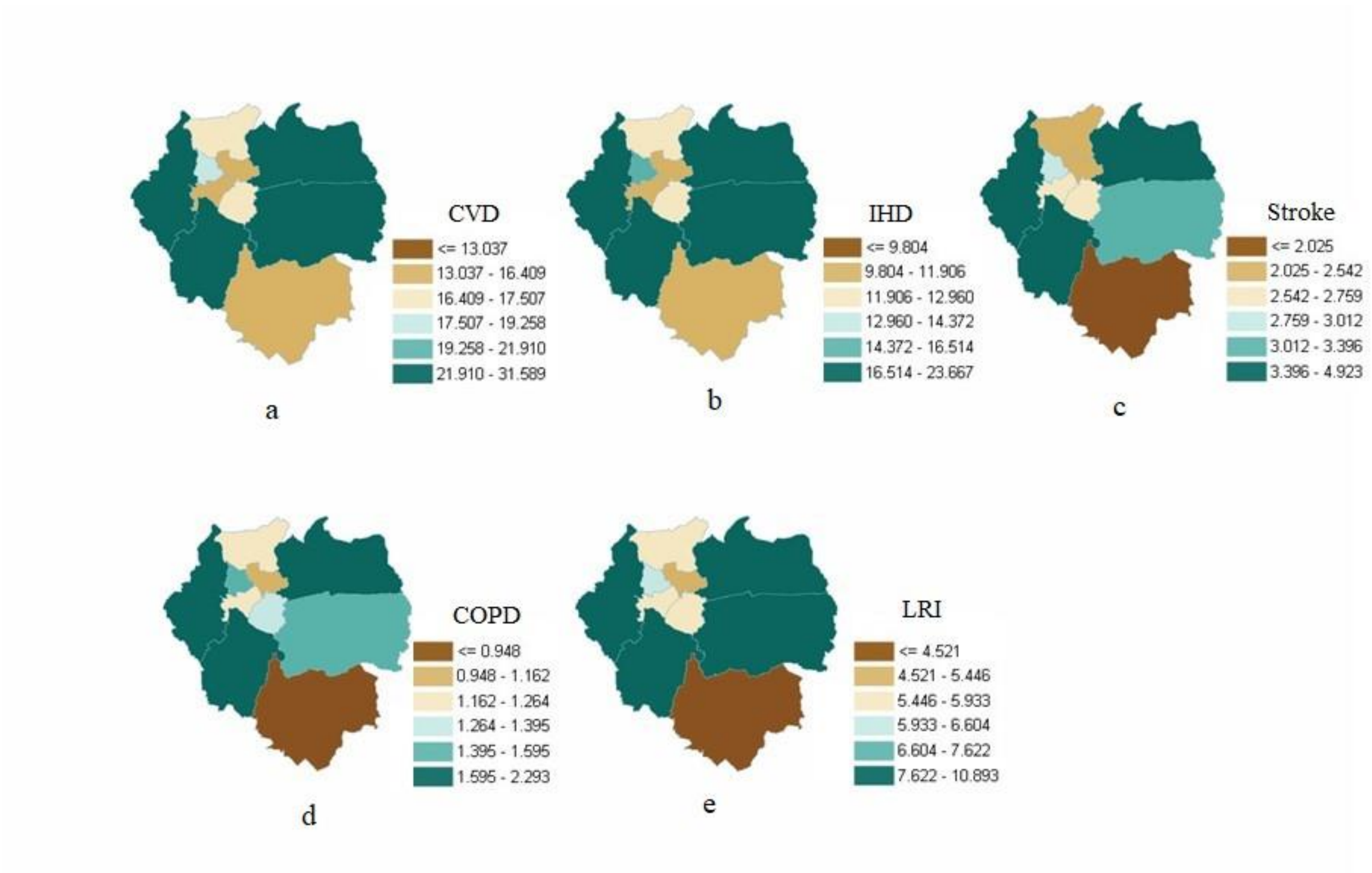

Figure 8. Total avoided death in scenario III (5μg/m3) for (a), CVD, (b), IHD, (c), Stroke, (d), COPD, and (e), LRI

The avoided deaths associated with $PM_{2.5}$ are predominantly higher in areas dense population, designated air quality priority areas, and regions with high pollution levels. Generally, the total number of avoided deaths in any given region is influenced by a mix of factors: the size of population, the reduction in air pollution required to achieve the standard (delta concentration value), the initial mortality rate (Pop, ΔPM, and y_0, respectively in Eqs.1).

The ten districts of Addis Ababa (Akaki kality, Nifas silk Lafto, Kolfe keranyo, Gulele, Lideta, Kirkos, Arada, Addis Ketema, Yeka and Bole) with their associated number of avoided death due to reduction of $PM_{2.5}$ concentration across three scenarios (I, II, and III) are shown in Figs 6, 7, and 8. The largest number of premature mortalities avoided due to cardiovascular, ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and lower respiratory infection (LRI) in all the three scenarios are exhibited in Kolfe Keranio, Nifas silk Lafto, Yeka, and Bole sub-cities. This might be due to higher initial pollution levels or large populations at risk (see Fig 4). On the other hand, Akaki kaliti and Arada sub-cities being in the lowest range might indicate either lower initial pollution level or small number of populations at risk.

In Summary, lowering the $PM_{2.5}$ concentration to meet both the WHO guidelines and NAAQS in 2019 could prevent approximately 408 deaths in scenario I, 435 deaths in scenario II, and 463 deaths in scenario III for cardiovascular diseases, Ischemic heart diseases (IHD), stroke, chronic obstructive pulmonary disease (COPD) and lower respiratory infections (LRI) in total. These findings underscore the health benefits escalates with more aggressive $PM_{2.5}$ reduction scenarios, emphasizing the importance of air quality improvement in Addis Ababa for public health.

Comparing the health benefit across countries using BenMAP-CE might present challenges due to varying input factors. These includes differences in $PM_{2.5}$ level between the baseline and control scenarios, the beta coefficients the mortality rates associated with specific health outcomes. A study conducted in Qom city, Iran using BenMAP-CE model reveled that a reduction in $PM_{2.5}$ levels from 16.39 to 2.4 in 2019 could potentially avert 1498.6 cases of premature mortality from stroke, 711.57 from Chronic obstructive pulmonary disease (COPD), 27.74 from lung cancer (LC), and 2456.59 from ischemic heart disease (IHD). Furthermore, lowering $PM_{2.5}$ levels to 10 could altogether prevent 2475.94 premature deaths associated with these four health outcomes (Safari *et al.*, 2022).

In other Chinese study, the reduction in $PM_{2.5}$ concentration to 35μg/m^3 (NAAQS) in 2014 would have prevented 47,000, 89,000, and 32,000 deaths from heart disease, respiratory conditions, and lung cancer, respectively (Chen, Shi, Gao, *et al.*, 2017). Furthermore, a Wuhan, China study's findings revealed that a 43.6% decrease in $PM_{2.5}$ concentration prevented 21,384 premature deaths (Qu *et al.*, 2020). Reducing the yearly $PM_{2.5}$ concentrations from 23 to 10μg/m^3 in 2017 would prevent 64, 715 and 357 premature deaths from LC, IHD and COPD, respectively, according to the other study conducted in Ho Chi Minh City (HCMC), Vietnam (Ho *et al.*, 2023).

4.3. Economic impacts of $PM_{2.5}$ reduction

Improving the yearly average $PM_{2.5}$ concentration produce a considerable financial benefit for Addis Ababa, as indicated in Table 7. Using the Ethiopian VSL, which was estimated to be 124,567.4 USD (Table 1), according to the OECD VSL reference associated with each cause of death in scenario I (15µg/m^3) for Cardiovascular, IHD, stroke, COPD and LRI were 21,674,727.6, 16,816,599, 3,238,752.4, 1,494,808.8 and 7,598,611.4 USD, respectively. In scenario II (10µg/m^3), the economic benefit amounted to 23,294,103.8, 17,688,570.8, 3,487,887.2, 1,619,376.2, and 8,096,881 USD for Cardiovascular, IHD, Stroke, COPD and LRI, respectively. In scenario III (5µg/m^3), estimated to be 24,664,345.2, 18,809,677.4, 3,861,589.4, 1,743,943.6 and 8,595,150.6 USD in the same health categories.

Table 7. Estimated economic benefits in three $PM_{2.5}$ reduction scenarios using OECD VSL in Addis Ababa in 2019

Health endpoint	Reference for HIF	Baseline Mortality	Scenario I (USD)	Scenario II (USD)	Scenario III (USD)
Cardiovascular	(Pope et al., 2015)	653	21674727.6	23294103.8	24664345.2
IHD	(Krewski et al., 2009)	305	16816599	17688570.8	18809677.4
Stroke	(Lepeule et al., 2012)	349	3238752.4	3487887.2	3861589.4
COPD	(Cesaroni et al., 2013)	37	1494808.8	1619376.2	1743943.6
LRI	(So et al., 2022)	122	7598611.4	8096881	8595150.6
Summation		**1466**	**50,823499.2**	**54,186,819**	**57,674,706.2**

IHD ischemic heart disease, COPD chronic obstructive pulmonary disease, LRI lower respiratory infection

The economic benefits in total for these health categories was estimated to be 50.8 million USD in scenario I (15μg/m^3), 54.2 million USD in scenario II (10μg/m^3), and 57.6 million USD in Scenario III (5μg/m^3). The result of this analysis showed that reducing $PM_{2.5}$ concentration in Addis Ababa has a significant positive economic impact. As the scenarios demonstrate progressively lower $PM_{2.5}$ concentration targets from 15μg/m^3 to 5μg/m^3 the estimated economic benefits also increase correspondingly. This suggests that more stringent air quality improvement could lead to greater economic savings, likely due to the health-related costs and the enhancement of public health.

Numerous researches have highlighted the substantial economic impacts linked to $PM_{2.5}$, and this analysis confirms those estimates. The economic advantages of the 2015 $PM_{2.5}$ reduction in Tianjin, China, were estimated by Chen et al. (2017) to be between 18 and 4800 million Yuan of China. Additionally, Bayat et al. (2019) used the VSL approach to evaluate the economic expenses associated with $PM_{2.5}$ for the city of Tehran. According to this study, the annual economic cost of $PM_{2.5}$ pollution is projected to be 2.7 billion dollars, or 4.3% of GDP of Tehran's.

4.4. Sensitivity of Results

The sensitivity of the health benefit results in the three scenarios using the higher bound of C-R coefficient was given in table 8.

Table 8. Sensitivity analysis result using higher bound of C-R coefficient

Health endpoints	Reference health impact functions	β coefficient (95% CI)	Main Analysis result			Sensitivity Analysis result		
			Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III
Cardiovascular	(Pope et al., 2015)	0.011333 (0.00953, 0.014)	174	187	198	208	222	235
IHD	(Krewski et al., 2009)	0.02151 (0.0174, 0.0255)	135	142	151	151	159	167
Stroke	(Lepeule et al., 2012)	0.00296 (-0,001, 0.0077)	26	28	31	65	70	75
COPD	(Cesaroni et al., 2013)	0.0157 (-0.0163, 0.04824)	12	13	14	27	28	29
LRI	(So et al., 2022)	0.0266 (0.01724, 0.0365)	61	65	69	76	79	83

IHD ischemic heart disease, COPD chronic obstructive pulmonary disease, LRI lower respiratory infection

As shown in the Table 8, in the main analysis the number of death attributed to cardiovascular, IHD, stroke, COPD and LRI in three scenarios (I, II, and III) ranges from 174 to 198, 135 to 142, 26 to 31, 12 to 14 and 61 to 69, respectively. However, in the sensitivity analysis, using the higher bound of the C-R coefficient, the number of deaths increased from 208 to 235, 151 to 167, 65 to 75, 27 to 29 and 76 to 83 in three scenarios for the same health categories. The finding indicates that higher-bound C-R coefficients were showed potentially greater health impact compared to recommended coefficients. The analysis underscores the significance of input parameters, specifically the C-R coefficients in BenMAP-CE, influencing health impact estimates. These results emphasize the importance of the selection of appropriate C-R coefficients in health impact analysis.

4.5. Uncertainty analysis

The health benefits analysis in this study incorporated diverse input data, including air quality metrics, population exposure levels, health impact functions (HIFs), and mortality rates. Each of these variables carrying varying degree of influence on the final out comes. The interpretation of result accuracy approached with caution in subsequent discussions. Reliable data sources were used to derive the population and death incidence rates such as Ethiopian statistical service (ESS) and Global burden of disease (GBD) websites. The reliability of health impact assessments primarily hinges on the selection of health impact functions (HIFs). Notably quantitative investigations in to the relationship of air pollution, particularly $PM_{2.5}$ and health impacts in Addis Ababa are lacking, constituting a significant source of uncertainty. To mitigate potential errors, HIFs were chosen based on associations between health endpoints and factors like age group and population type. Despite employing various strategies to minimize uncertainty, it remains unavoidable.

To establish the non-anthropogenic background concentration of $PM_{2.5}$, we adopted a methodology that relied on data from US Embassy $PM_{2.5}$ monitoring stations. These stations, particularly one situated in a relatively "clean site" in Addis Ababa, recorded the lowest $PM_{2.5}$ concentration of 1.0μg/m^3 over the period 2016 to 2023. Due to the absence of a formally established background concentration of $PM_{2.5}$ in Addis Ababa, we employed this approach as a means to determine a baseline value.

The concentration of $PM_{2.5}$ derived from the two city-based stations for monitoring could be considered the representative estimate of population exposure, since transportation being identified as the primary contributor of total emission in Addis Ababa (Tefera *et al.*, 2021). Pervious researches suggests that pollutant concentration measured at fixed monitoring stations can serve as acceptable proxy for estimating individual exposure among residents residing within approximately 40 km of the monitoring station (Dockery *et al.*, 2005; Wing *et al.*, 2015; Xie *et al.*, 2015; Tian *et al.*, 2017). All 10 districts of Addis Ababa were located within 40 km radius of the monitoring stations, insuring the reliability of our result.

4.6. Strengths and Limitations

The primary strength of this study lies in its novelty. To our knowledge, no prior research has been carried out to examine the effects of ambient $PM_{2.5}$ pollution on health and economy in Addis Ababa. Furthermore, the study incorporated rigorously validated data obtained from EPA-approved air quality monitors and mortality statistics sourced from the website of Global Burden of Disease, Institute for Health Metrics and Evaluation, 2021. This approach not only enhances the reliability of our findings but also underscores the significance of the relationship between air quality levels and their impact on economy and public health outcomes.

A limitation of this research is the application of beta coefficients derived from other countries. Since there are no Ethiopian cohorts that link $PM_{2.5}$ to different health outcomes, we therefore utilized concentration-response coefficient values that were obtained from international cohorts. These coefficients may not be adequately representative of Addis Ababa Population. Furthermore, our estimations of the health benefits do not take composition into account; they only depend on $PM_{2.5}$ mass. The age-specific baseline incidence rate available for the entire city, but district level age-specific data is not available. Therefore, in the future, our estimate could be improved by using district level baseline incidence rates and concentration-response coefficients derived from Ethiopian cohorts. Another limitation was that this research relied on data from two stationary monitoring stations to estimate pollution levels for the entire city. In regions without monitoring stations, the VNA method is used to extrapolate air quality data from nearby stations situated in neighboring districts. The accuracy of these estimations could be enhanced through the installation of monitoring stations in currently unmonitored areas.

Chapter Five

5. Conclusion and Recommendation

5.1. Conclusion

In this study, the impact of $PM_{2.5}$ on health and economy in Addis Ababa was estimated using BenMAP-CE software. In examining the air quality situation in Addis Ababa, it was found that, the yearly average $PM_{2.5}$ concentration in 2019 was 32.8μg/m³. The data clearly indicates that Addis Ababa faced significant challenges regarding air quality, with the yearly average $PM_{2.5}$ concentration exceeding international standards set by the world health organization (WHO) and the Ethiopian ambient air quality standard. The high level of $PM_{2.5}$ pollution poses considerable health risks to the city`s residents. As evidenced by the majority of days surpassing the WHO standards for both yearly and daily averages.

The finding underscores that, $PM_{2.5}$ concentration reduction to meet the international standards set by the world health organization (WHO) and the national ambient air quality standard (NAAQS) across three scenarios (I, II, III), leads to the notable decrease in mortality attributed to Cardiovascular disease, ischemic heart disease (IHD), Stroke, Chronic obstructive pulmonary disease (COPD), and Lower respiratory infections (LRI) in Addis Ababa. The economic benefits based on the avoided deaths as a result of reduction in $PM_{2.5}$ levels are considerable. Using OECD VSL methodology, the economic valuation of these benefits in terms of millions of dollars indicates significant societal savings across all health end points. These benefits are particularly prominent in scenarios with more aggressive $PM_{2.5}$ reduction targets. This supports the argument for prioritizing and implementing measures to mitigate air pollution in the city, not only for the improvement of public health, but also for significant economic gains that can result from a healthier population. For future health impact analysis, it is essential to investigate the particular concentration-response function and determine the value of statistical life (VSL) specific to the Ethiopian population.

5.2. Recommendation

- Policymakers should prioritize implementing strategies to reduce ambient $PM_{2.5}$ levels in Addis Ababa.
- Increase public awareness on the health risk associated with $PM_{2.5}$ pollution and the potential benefit of pollution reduction measures.
- Allocate the resources for the establishment of robust air quality monitoring systems and research initiatives to better understand the sources of dynamics of $PM_{2.5}$ pollution in Addis Ababa.
- Enforce stringent vehicle emission standards to ensure that vehicles, particularly the older ones, meet the acceptable pollution levels. Implement regular emission testing programs for vehicles and enforce penalties for non-compliance.
- Invest in the expansion and improvement of public transportation systems to reduce reliance on personal vehicles. Encourage the use of buses and trains by improving their reliability, frequency, affordability and courage.
- Develop infrastructure for to support walking and cycling as a viable mode of transportation. Create bike lanes, safe crossings and walk ways that are conductive to

pedestrians, encourage active transportation and reduce the number of vehicle trips for short distance.

- Incentivize the adoption of cleaner vehicle technologies such as electric, hybrid vehicles and vehicles powered by compressed natural gas.
- Foster collaboration and partnership between academic institutions, government agencies, international stakeholders and non-governmental organizations to leverage expertise, resources and best practices in addressing air pollution challenges comprehensibly.

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Appendices

I. Percentage of $PM_{2.5}$ data used for this study

Data source	Available days	Missed Days	Recovered days	% of recovered data out of missed	% of available data out of recovered days	% of available data with recovered days
BLH	309	56	3	0.054	84.66	85.48
US Embassy	291	74	9	0.122	79.73	82.2

II. (a). Monthly Max, Min and average values of $PM_{2.5}$ conc. from the two BAM`s data

Monthly	January	February	March	April	May	June	July	August	September	October	November	December
Max	54.85	47.39	36.24	51.04	58.79	82.17	87.42	61.58	68.35	34.57	31.96	47.88
Min	20.71	12.69	11	9.88	13.25	29.89	25.58	18.52	25.06	10.08	9.78	13.12
AV	30.54	24.52	20.37	20.16	27.92	53.07	59.01	39.88	43.27	21.55	22.84	30.02

(b). Available, missed and recovered days from the two BAM`s data

Data source	Available days	Missed Days	Recovered days	% of recovered data out of missed	% of available data out of recovered days	% of available data with recovered days
BLH	309	56	3	0.054	84.66	85.48
US Embassy	291	74	9	0.122	79.73	82.2

III. The age distribution of the Population in Addis Ababa in 2019

Row	Column	Year	Population	Race	Ethnicity	Gender	Age Range
1	1	2019	26118	ALL	ALL	ALL	0TO4
1	1	2019	22120	ALL	ALL	ALL	5TO9
1	1	2019	14290	ALL	ALL	ALL	10TO14
1	1	2019	16083	ALL	ALL	ALL	15TO19
1	1	2019	20064	ALL	ALL	ALL	20TO24
1	1	2019	29242	ALL	ALL	ALL	25TO29
1	1	2019	29147	ALL	ALL	ALL	30TO34
1	1	2019	25557	ALL	ALL	ALL	35TO39
1	1	2019	15822	ALL	ALL	ALL	40TO44
1	1	2019	12557	ALL	ALL	ALL	45TO49
1	1	2019	7830	ALL	ALL	ALL	50TO54
1	1	2019	6500	ALL	ALL	ALL	55TO59
1	1	2019	4937	ALL	ALL	ALL	60TO64
1	1	2019	3155	ALL	ALL	ALL	65TO69
1	1	2019	2396	ALL	ALL	ALL	70TO74
1	1	2019	1446	ALL	ALL	ALL	75TO79
1	1	2019	1091	ALL	ALL	ALL	80UP
2	1	2019	45584	ALL	ALL	ALL	0TO4
2	1	2019	38605	ALL	ALL	ALL	5TO9
2	1	2019	24940	ALL	ALL	ALL	10TO14
2	1	2019	28070	ALL	ALL	ALL	15TO19
2	1	2019	35018	ALL	ALL	ALL	20TO24
2	1	2019	51036	ALL	ALL	ALL	25TO29
2	1	2019	50872	ALL	ALL	ALL	30TO34
2	1	2019	44606	ALL	ALL	ALL	35TO39
2	1	2019	27614	ALL	ALL	ALL	40TO44
2	1	2019	21916	ALL	ALL	ALL	45TO49
2	1	2019	13666	ALL	ALL	ALL	50TO54
2	1	2019	11344	ALL	ALL	ALL	55TO59
2	1	2019	8617	ALL	ALL	ALL	60TO64
2	1	2019	5507	ALL	ALL	ALL	65TO69
2	1	2019	4182	ALL	ALL	ALL	70TO74
2	1	2019	2523	ALL	ALL	ALL	75TO79
2	1	2019	1904	ALL	ALL	ALL	80UP
3	1	2019	61802	ALL	ALL	ALL	0TO4
3	1	2019	52341	ALL	ALL	ALL	5TO9
3	1	2019	33813	ALL	ALL	ALL	10TO14
3	1	2019	38057	ALL	ALL	ALL	15TO19
3	1	2019	47477	ALL	ALL	ALL	20TO24
3	1	2019	69193	ALL	ALL	ALL	25TO29
3	1	2019	68970	ALL	ALL	ALL	30TO34
3	1	2019	60475	ALL	ALL	ALL	35TO39
3	1	2019	37438	ALL	ALL	ALL	40TO44
3	1	2019	29714	ALL	ALL	ALL	45TO49
3	1	2019	18528	ALL	ALL	ALL	50TO54

3	1	2019	15380	ALL	ALL	ALL	55TO59
3	1	2019	11683	ALL	ALL	ALL	60TO64
3	1	2019	7466	ALL	ALL	ALL	65TO69
3	1	2019	5669	ALL	ALL	ALL	70TO74
3	1	2019	3421	ALL	ALL	ALL	75TO79
3	1	2019	2581	ALL	ALL	ALL	80UP
4	1	2019	38564	ALL	ALL	ALL	0TO4
4	1	2019	32660	ALL	ALL	ALL	5TO9
4	1	2019	21099	ALL	ALL	ALL	10TO14
4	1	2019	23747	ALL	ALL	ALL	15TO19
4	1	2019	29625	ALL	ALL	ALL	20TO24
4	1	2019	43176	ALL	ALL	ALL	25TO29
4	1	2019	43037	ALL	ALL	ALL	30TO34
4	1	2019	37736	ALL	ALL	ALL	35TO39
4	1	2019	23361	ALL	ALL	ALL	40TO44
4	1	2019	18541	ALL	ALL	ALL	45TO49
4	1	2019	11561	ALL	ALL	ALL	50TO54
4	1	2019	9597	ALL	ALL	ALL	55TO59
4	1	2019	7290	ALL	ALL	ALL	60TO64
4	1	2019	4659	ALL	ALL	ALL	65TO69
4	1	2019	3537	ALL	ALL	ALL	70TO74
4	1	2019	2135	ALL	ALL	ALL	75TO79
4	1	2019	1611	ALL	ALL	ALL	80UP
5	1	2019	29069	ALL	ALL	ALL	0TO4
5	1	2019	24619	ALL	ALL	ALL	5TO9
5	1	2019	15904	ALL	ALL	ALL	10TO14
5	1	2019	17901	ALL	ALL	ALL	15TO19
5	1	2019	22331	ALL	ALL	ALL	20TO24
5	1	2019	32545	ALL	ALL	ALL	25TO29
5	1	2019	32441	ALL	ALL	ALL	30TO34
5	1	2019	28445	ALL	ALL	ALL	35TO39
5	1	2019	17610	ALL	ALL	ALL	40TO44
5	1	2019	13976	ALL	ALL	ALL	45TO49
5	1	2019	8715	ALL	ALL	ALL	50TO54
5	1	2019	7234	ALL	ALL	ALL	55TO59
5	1	2019	5495	ALL	ALL	ALL	60TO64
5	1	2019	3512	ALL	ALL	ALL	65TO69
5	1	2019	2666	ALL	ALL	ALL	70TO74
5	1	2019	1609	ALL	ALL	ALL	75TO79
5	1	2019	1214	ALL	ALL	ALL	80UP
6	1	2019	31886	ALL	ALL	ALL	0TO4
6	1	2019	27006	ALL	ALL	ALL	5TO9
6	1	2019	17446	ALL	ALL	ALL	10TO14
6	1	2019	19636	ALL	ALL	ALL	15TO19
6	1	2019	24496	ALL	ALL	ALL	20TO24
6	1	2019	35700	ALL	ALL	ALL	25TO29
6	1	2019	35585	ALL	ALL	ALL	30TO34
6	1	2019	31202	ALL	ALL	ALL	35TO39

6	1	2019	19317	ALL	ALL	ALL	40TO44
6	1	2019	15331	ALL	ALL	ALL	45TO49
6	1	2019	9559	ALL	ALL	ALL	50TO54
6	1	2019	7935	ALL	ALL	ALL	55TO59
6	1	2019	6028	ALL	ALL	ALL	60TO64
6	1	2019	3852	ALL	ALL	ALL	65TO69
6	1	2019	2925	ALL	ALL	ALL	70TO74
6	1	2019	1765	ALL	ALL	ALL	75TO79
6	1	2019	1332	ALL	ALL	ALL	80UP
7	1	2019	30484	ALL	ALL	ALL	0TO4
7	1	2019	25817	ALL	ALL	ALL	5TO9
7	1	2019	16678	ALL	ALL	ALL	10TO14
7	1	2019	18772	ALL	ALL	ALL	15TO19
7	1	2019	23418	ALL	ALL	ALL	20TO24
7	1	2019	34129	ALL	ALL	ALL	25TO29
7	1	2019	34019	ALL	ALL	ALL	30TO34
7	1	2019	29829	ALL	ALL	ALL	35TO39
7	1	2019	18466	ALL	ALL	ALL	40TO44
7	1	2019	14656	ALL	ALL	ALL	45TO49
7	1	2019	9139	ALL	ALL	ALL	50TO54
7	1	2019	7586	ALL	ALL	ALL	55TO59
7	1	2019	5763	ALL	ALL	ALL	60TO64
7	1	2019	3682	ALL	ALL	ALL	65TO69
7	1	2019	2796	ALL	ALL	ALL	70TO74
7	1	2019	1687	ALL	ALL	ALL	75TO79
7	1	2019	1273	ALL	ALL	ALL	80UP
8	1	2019	36795	ALL	ALL	ALL	0TO4
8	1	2019	31162	ALL	ALL	ALL	5TO9
8	1	2019	20132	ALL	ALL	ALL	10TO14
8	1	2019	22657	ALL	ALL	ALL	15TO19
8	1	2019	28266	ALL	ALL	ALL	20TO24
8	1	2019	41196	ALL	ALL	ALL	25TO29
8	1	2019	41063	ALL	ALL	ALL	30TO34
8	1	2019	36005	ALL	ALL	ALL	35TO39
8	1	2019	22290	ALL	ALL	ALL	40TO44
8	1	2019	17691	ALL	ALL	ALL	45TO49
8	1	2019	11031	ALL	ALL	ALL	50TO54
8	1	2019	9157	ALL	ALL	ALL	55TO59
8	1	2019	6956	ALL	ALL	ALL	60TO64
8	1	2019	4445	ALL	ALL	ALL	65TO69
8	1	2019	3375	ALL	ALL	ALL	70TO74
8	1	2019	2037	ALL	ALL	ALL	75TO79
8	1	2019	1537	ALL	ALL	ALL	80UP
9	1	2019	49967	ALL	ALL	ALL	0TO4
9	1	2019	42318	ALL	ALL	ALL	5TO9
9	1	2019	27338	ALL	ALL	ALL	10TO14
9	1	2019	30769	ALL	ALL	ALL	15TO19
9	1	2019	38385	ALL	ALL	ALL	20TO24

9	1	2019	55942	ALL	ALL	ALL	25TO29
9	1	2019	55762	ALL	ALL	ALL	30TO34
9	1	2019	48894	ALL	ALL	ALL	35TO39
9	1	2019	30268	ALL	ALL	ALL	40TO44
9	1	2019	24023	ALL	ALL	ALL	45TO49
9	1	2019	14979	ALL	ALL	ALL	50TO54
9	1	2019	12435	ALL	ALL	ALL	55TO59
9	1	2019	9446	ALL	ALL	ALL	60TO64
9	1	2019	6036	ALL	ALL	ALL	65TO69
9	1	2019	4583	ALL	ALL	ALL	70TO74
9	1	2019	2766	ALL	ALL	ALL	75TO79
9	1	2019	2087	ALL	ALL	ALL	80UP
10	1	2019	44535	ALL	ALL	ALL	0TO4
10	1	2019	37717	ALL	ALL	ALL	5TO9
10	1	2019	24365	ALL	ALL	ALL	10TO14
10	1	2019	27424	ALL	ALL	ALL	15TO19
10	1	2019	34212	ALL	ALL	ALL	20TO24
10	1	2019	49860	ALL	ALL	ALL	25TO29
10	1	2019	49700	ALL	ALL	ALL	30TO34
10	1	2019	43578	ALL	ALL	ALL	35TO39
10	1	2019	26978	ALL	ALL	ALL	40TO44
10	1	2019	21412	ALL	ALL	ALL	45TO49
10	1	2019	13351	ALL	ALL	ALL	50TO54
10	1	2019	11083	ALL	ALL	ALL	55TO59
10	1	2019	8419	ALL	ALL	ALL	60TO64
10	1	2019	5380	ALL	ALL	ALL	65TO69
10	1	2019	4085	ALL	ALL	ALL	70TO74
10	1	2019	2465	ALL	ALL	ALL	75TO79
10	1	2019	1860	ALL	ALL	ALL	80UP

IV. Incidence rate of each health endpoints per 100000 population

Endpoint G	Endpoint	Type	Race	Gender	Ethnicity	Start Age	End Age	Column	Row	Value
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	1	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	1	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	1	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	1	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	1	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	2	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	2	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	2	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	2	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	2	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	3	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	3	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	3	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	3	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	3	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	4	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	4	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	4	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	4	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	4	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	5	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	5	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	5	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	5	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	5	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	6	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	6	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	6	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	6	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	6	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	7	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	7	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	7	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	7	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	7	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	8	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	8	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	8	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	8	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	8	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	9	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	9	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	9	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	9	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	9	0.0000731
Mortality	Mortality, Cardiovascula	Incidence	All	All	All	0	99	1	10	0.0004
Mortality	Mortality, Ischemic Hear	Incidence	All	All	All	0	99	1	10	0.000183
Mortality	Mortality, Cerebrovascul	Incidence	All	All	All	0	99	1	10	0.00021
Mortality	Mortality, COPD	Incidence	All	All	All	0	99	1	10	0.000018
Mortality	Mortality, Lower Respira	Incidence	All	All	All	0	99	1	10	0.0000731

V. VSL of Ethiopia calculation from VSL of OECD

$$\mathbf{VSL_{ETHIOPIA\,(2019)} = VSL_{OECD} x\ (Y_{ETHIOPIA\,(2019)} / Y_{OECD\,(2019)})^{b}}$$

Where $VSL_{ETHIOPIA}$ is the VSL for Ethiopia,

VSL_{OECD} = VSL of Organization for economic cooperation and development countries

Y = the Gross domestic product (GDP) per capita

b = the income elasticity of the VSL ranges from 1.0 to 1.4, with average estimate of 1.2 for low and middle income countries

VSL_{OECD}	3832843$	At 2011 market rates, PPP
$Y_{ETHIOPIA}$	2274.2$	Current to 2019
Y_{OECD}	39531.3$	Current to 2019

$VSL_{ETHIOPIA}$ (2019) = VSL_{OECD} x ($Y_{ETHIOPIA}$ (2019) / Y_{OECD} (2019)) b

3832843 x (2274.2/39531.3)

3832843 x (0.05753)1.2

3832843 x 0.0325

124567.4$

VI. Economic Impact of PM2.5 in US dollar and Ethiopian birr in 2019.

Endpoint Name	Health impact func	Baseline Mortality	Senario I (Rollback to 15µg/m3)	Economic Impact,US $	Economic Impact In Ethiopia Birr	Senario II (Rollback to 10µg/m3)	Economic Impact, US$	Economic Impact In Ethiopia Birr	Senario III (Rollback to 5µg/m3)	Economic Impact, US $	Economic Impact In Ethiopia Birr
Cardiovascular	(Pope et al., 2015)	653	174	21,674,727.60	633,168,645.07	187	23,294,103.80	680,474,348.44	198	24,664,345.20	720,502,251.29
IHD	(Krewski et al., 2009	305	135	16,816,599	491,251,534.97	142	17,688,570.80	516,723,836.78	151	18,809,677.40	549,473,939.11
Stroke	(So et al., 2022)	349	26	3,238,752.40	94,611,406.73	28	3,487,887.20	101,889,207.25	31	3,861,589.40	112,805,908.03
COPD	(Cesaroni et al., 201	37	12	1,494,808.80	43,666,803.11	13	1,619,376.20	47,305,703.37	14	1,743,943.60	50,944,603.63
LRI	(Lepeule et al., 2012	122	61	7,598,611.40	221,972,915.80	65	8,096,881	236,528,516.84	69	8,595,150.60	251,084,117.87
Summation		**1466**	**408**	**50,823,499.20**	**1,484,671,305.68**	**435**	**54,186,819**	**1,582,921,612.67**	**463**	**57,674,706.20**	**1,684,810,819.93**

1 dollar exchange rate in Ethiopian birr in 2019 is 29.2123

https://www.exchangerates.org.uk/

VII. *E*stimated health benefit of lowering $PM_{2.5}$ concentration to 15, 10, and 5 in each subcity.

Rolback to 15													
Col	Row	Endpoint	Author	Start Age	End Age	Point Estin	Populatior	Delta	Mean	Baseline	Percent of	Standard D	Variance
Akaki													
1	1	Mortality	Pope et al.	30	99	11.46733	110438	26.52	8.405224	44.1752	19.027	15.13232	228.9872
1	1	Mortality	Krewski et	30	99	8.786188	110438	26.52	8.76326	20.21016	43.3607	0.607929	0.369577
1	1	Mortality	Cesaroni e	30	99	1.75093	110438	26.52	1.532694	23.19198	6.6087	2.859267	8.17541
1	1	Mortality	Lepeule et	25	74	0.840713	137143	26.52	0.837441	2.468574	33.9241	0.086712	0.007519
1	1	Mortality	So et al.	30	99	4.085793	110438	26.52	4.043713	8.073017	50.0892	0.54241	0.294208
N. Silk													
1	2	Mortality	Pope et al.	30	99	20.73419	192750	27.64	14.99457	77.09999	19.4482	27.43142	752.4828
1	2	Mortality	Krewski et	30	99	15.80936	192750	27.64	15.76744	35.27325	44.7008	1.079749	1.165859
1	2	Mortality	Cesaroni e	30	99	3.179792	192750	27.64	2.769695	40.4775	6.8426	5.189463	26.93053
1	2	Mortality	Lepeule et	25	74	1.51684	239359	27.64	1.510817	4.308462	35.0663	0.155015	0.02403
1	2	Mortality	So et al.	30	99	7.335294	192750	27.64	7.258277	14.09002	51.5136	0.958768	0.919236
Kolfe													
1	3	Mortality	Pope et al.	30	99	27.88532	261325	27.38	20.22942	104.53	19.3527	36.8693	1359.345
1	3	Mortality	Krewski et	30	99	21.28589	261325	27.38	21.22964	47.82248	44.3926	1.458183	2.126298
1	3	Mortality	Cesaroni e	30	99	4.272141	261325	27.38	3.725454	54.87825	6.7886	6.973147	48.62478
1	3	Mortality	Lepeule et	25	74	2.041007	324516	27.38	2.032939	5.841289	34.8029	0.209029	0.043693
1	3	Mortality	So et al.	30	99	9.88143	261325	27.38	9.778131	19.10286	51.1867	1.296239	1.680235
Gulele													
1	4	Mortality	Pope et al.	30	99	14.05252	163065	21.41	10.93523	65.226	16.7651	18.40391	338.704
1	4	Mortality	Krewski et	30	99	11.01319	163065	21.41	10.98682	29.84089	36.818	0.808138	0.653087
1	4	Mortality	Cesaroni e	30	99	2.102808	163065	21.41	1.882521	34.24365	5.4974	3.44497	11.86782
1	4	Mortality	Lepeule et	25	74	1.040551	202495	21.41	1.036897	3.644911	28.4478	0.111895	0.012521
1	4	Mortality	So et al.	30	99	5.175628	163065	21.41	5.127728	11.92005	43.0177	0.737312	0.543629
Lideta													
1	5	Mortality	Pope et al.	30	99	14.39224	122917	30.56	10.04291	49.1668	20.4262	19.19817	368.5696
1	5	Mortality	Krewski et	30	99	10.83731	122917	30.56	10.80746	22.49381	48.0464	0.715373	0.511758
1	5	Mortality	Cesaroni e	30	99	2.23245	122917	30.56	1.919428	25.81257	7.436	3.638279	13.23708
1	5	Mortality	Lepeule et	25	74	1.047059	152639	30.56	1.042697	2.747502	37.9507	0.10446	0.010912
1	5	Mortality	So et al.	30	99	4.999639	122917	30.56	4.944758	8.985231	55.0321	0.627416	0.393651
Kirkos													
1	6	Mortality	Pope et al.	30	99	15.61827	134831	30.17	10.95121	53.9324	20.3054	20.80814	432.9785
1	6	Mortality	Krewski et	30	99	11.78002	134831	30.17	11.74773	24.67407	47.6116	0.78116	0.610211
1	6	Mortality	Cesaroni e	30	99	2.418959	134831	30.17	2.08341	28.31451	7.3581	3.942919	15.54661
1	6	Mortality	Lepeule et	25	74	1.137092	167434	30.17	1.132384	3.013812	37.5731	0.113808	0.012952
1	6	Mortality	So et al.	30	99	5.438649	134831	30.17	5.379277	9.856146	54.5779	0.686238	0.470923
Arada													
1	7	Mortality	Pope et al.	30	99	13.91661	128896	27.76	10.04966	51.5584	19.4918	18.41718	339.1924
1	7	Mortality	Krewski et	30	99	10.60561	128896	27.76	10.57744	23.58797	44.8425	0.723333	0.523211
1	7	Mortality	Cesaroni e	30	99	2.135252	128896	27.76	1.85888	27.06816	6.8674	3.484542	12.14203
1	7	Mortality	Lepeule et	25	74	1.017861	160065	27.76	1.013811	2.88117	35.1875	0.103919	0.010799
1	7	Mortality	So et al.	30	99	4.919661	128896	27.76	4.867905	9.422297	51.6637	0.641958	0.41211
Addis Ketema													
1	8	Mortality	Pope et al.	30	99	17.06536	155587	28.28	12.24612	62.23479	19.6773	22.61405	511.3954
1	8	Mortality	Krewski et	30	99	12.97607	155587	28.28	12.94135	28.47242	45.4522	0.879667	0.773814
1	8	Mortality	Cesaroni e	30	99	2.623695	155587	28.28	2.278837	32.67327	6.9746	4.280498	18.32266
1	8	Mortality	Lepeule et	25	74	1.246913	193209	28.28	1.241907	3.477762	35.7099	0.12676	0.016068
1	8	Mortality	So et al.	30	99	6.013054	155587	28.28	5.949258	11.37341	52.3085	0.778977	0.606805
Yeka													
1	9	Mortality	Pope et al.	30	99	20.12536	211279	24	15.1975	84.5116	17.9827	26.43572	698.8473
1	9	Mortality	Krewski et	30	99	15.59144	211279	24	15.55234	38.66405	40.2243	1.110633	1.233505
1	9	Mortality	Cesaroni e	30	99	3.042592	211279	24	2.693115	44.36859	6.0699	4.97598	24.76038
1	9	Mortality	Lepeule et	25	74	1.482682	262368	24	1.477181	4.722624	31.2788	0.156111	0.024371
1	9	Mortality	So et al.	30	99	7.287689	211279	24	7.216187	15.44449	46.7234	1.001815	1.003633
Bole													
1	10	Mortality	Pope et al.	30	99	19.23635	188311	26.02	14.184	75.3244	18.8306	25.35786	643.0213
1	10	Mortality	Krewski et	30	99	14.77094	188311	26.02	14.73268	34.46091	42.7519	1.027955	1.056691
1	10	Mortality	Cesaroni e	30	99	2.931412	188311	26.02	2.571716	39.54531	6.5032	4.788343	22.92823
1	10	Mortality	Lepeule et	25	74	1.411646	233846	26.02	1.406201	4.209229	33.4076	0.146196	0.021373
1	10	Mortality	So et al.	30	99	6.875777	188311	26.02	6.805599	13.76553	49.4394	0.919145	0.844827

Rollback 10													
Col		Row	Endpoint	Author	Start Age	End Age	Point Estin	Populatior	Delta	Mean	Baseline	Percent of	Standard D	Variance
1	Akaki	1	Mortality	Pope et al.	30	99	12.26188	110438	28.69	8.75537	44.1752	19.8197	16.26648	264.5983
1		1	Mortality	Krewski et	30	99	9.307192	110438	28.69	9.282154	20.21016	45.9282	0.627943	0.394312
1		1	Mortality	Cesaroni e	30	99	1.888208	110438	28.69	1.637038	23.19198	7.0586	3.079938	9.486021
1		1	Mortality	Lepeule et	25	74	0.89524	137143	28.69	0.891621	2.468574	36.1189	0.090703	0.008227
1		1	Mortality	So et al.	30	99	4.309427	110438	28.69	4.263409	8.073017	52.8106	0.555098	0.308133
1	N. Silk	2	Mortality	Pope et al.	30	99	22.11591	192750	29.83	15.57243	77.09999	20.1977	29.43443	866.3857
1		2	Mortality	Krewski et	30	99	16.70502	192750	29.83	16.65942	35.27325	47.2296	1.112164	1.236909
1		2	Mortality	Cesaroni e	30	99	3.420789	192750	29.83	2.950741	40.4775	7.2898	5.576771	31.10037
1		2	Mortality	Lepeule et	25	74	1.611196	239359	29.83	1.60456	4.308462	37.2421	0.161714	0.026151
1		2	Mortality	So et al.	30	99	7.717543	192750	29.83	7.633703	14.09002	54.1781	0.978419	0.957303
1	Kolfe	3	Mortality	Pope et al.	30	99	29.75568	261325	29.56	21.02153	104.53	20.1105	39.57061	1565.833
1		3	Mortality	Krewski et	30	99	22.50156	261325	29.56	22.44035	47.82248	46.9243	1.502813	2.258448
1		3	Mortality	Cesaroni e	30	99	4.597642	261325	29.56	3.970658	54.87825	7.2354	7.496282	56.19425
1		3	Mortality	Lepeule et	25	74	2.168878	324516	29.56	2.159984	5.841289	36.9779	0.218173	0.047599
1		3	Mortality	So et al.	30	99	10.40095	261325	29.56	10.28841	19.10286	53.858	1.323596	1.751906
1	Gulele	4	Mortality	Pope et al.	30	99	15.24469	163065	23.49	11.58071	65.226	17.7547	20.01016	400.4064
1		4	Mortality	Krewski et	30	99	11.83703	163065	23.49	11.8076	29.84089	39.5685	0.84815	0.719358
1		4	Mortality	Cesaroni e	30	99	2.300085	163065	23.49	2.040459	34.24365	5.9587	3.762876	14.15923
1		4	Mortality	Lepeule et	25	74	1.124227	202495	23.49	1.1201	3.644911	30.7305	0.118864	0.014129
1		4	Mortality	So et al.	30	99	5.538648	163065	23.49	5.484888	11.92005	46.014	0.766757	0.587916
1	Lideta	5	Mortality	Pope et al.	30	99	15.2639	122917	32.8	10.35567	49.1668	21.0623	20.51953	421.051
1		5	Mortality	Krewski et	30	99	11.38566	122917	32.8	11.35348	22.49381	50.4738	0.732039	0.535881
1		5	Mortality	Cesaroni e	30	99	2.388279	122917	32.8	2.032907	25.81257	7.8756	3.888705	15.12203
1		5	Mortality	Lepeule et	25	74	1.105822	152639	32.8	1.101059	2.747502	40.0749	0.108294	0.011728
1		5	Mortality	So et al.	30	99	5.23018	122917	32.8	5.171078	8.985231	57.5509	0.636072	0.404588
1	Kirkos	6	Mortality	Pope et al.	30	99	16.57442	134831	32.4	11.30198	53.9324	20.9558	22.2484	494.9911
1		6	Mortality	Krewski et	30	99	12.38394	134831	32.4	12.3491	24.67407	50.0489	0.799986	0.639978
1		6	Mortality	Cesaroni e	30	99	2.589327	134831	32.4	2.208002	28.31451	7.7981	4.2167	17.78056
1		6	Mortality	Lepeule et	25	74	1.201663	167434	32.4	1.196517	3.013812	39.7011	0.118071	0.013941
1		6	Mortality	So et al.	30	99	5.693066	134831	32.4	5.629047	9.856146	57.112	0.696263	0.484783
1	Arada	7	Mortality	Pope et al.	30	99	14.83519	128896	29.94	10.43172	51.5584	20.2328	19.75094	390.0998
1		7	Mortality	Krewski et	30	99	11.20035	128896	29.94	11.16973	23.58797	47.3535	0.744723	0.554612
1		7	Mortality	Cesaroni e	30	99	2.295621	128896	29.94	1.979211	27.06816	7.312	3.742268	14.00457
1		7	Mortality	Lepeule et	25	74	1.080557	160065	29.94	1.076099	2.88117	37.3494	0.108356	0.011741
1		7	Mortality	So et al.	30	99	5.173335	128896	29.94	5.117045	9.422297	54.3078	0.654861	0.428844
1	Addis Ketema	8	Mortality	Pope et al.	30	99	18.17761	155587	30.48	12.69694	62.23479	20.4017	24.24142	587.6462
1		8	Mortality	Krewski et	30	99	13.69234	155587	30.48	13.65466	28.47242	47.9575	0.904681	0.818447
1		8	Mortality	Cesaroni e	30	99	2.818742	155587	30.48	2.42438	32.67327	7.4201	4.593936	21.10425
1		8	Mortality	Lepeule et	25	74	1.322653	193209	30.48	1.317149	3.477762	37.8735	0.132042	0.017435
1		8	Mortality	So et al.	30	99	6.317741	155587	30.48	6.24847	11.37341	54.9393	0.793715	0.629983
1	Yeka	9	Mortality	Pope et al.	30	99	21.66097	211279	26.13	15.95091	84.5116	18.8742	28.56047	815.7005
1		9	Mortality	Krewski et	30	99	16.62474	211279	26.13	16.58161	38.66405	42.8864	1.155495	1.335168
1		9	Mortality	Cesaroni e	30	99	3.302325	211279	26.13	2.89571	44.36859	6.5265	5.393877	29.09391
1		9	Mortality	Lepeule et	25	74	1.589239	262368	26.13	1.583097	4.722624	33.5216	0.16444	0.027041
1		9	Mortality	So et al.	30	99	7.73699	211279	26.13	7.657863	15.44449	49.5831	1.032694	1.066458
1	Bole	10	Mortality	Pope et al.	30	99	20.59265	188311	28.18	14.79525	75.3244	19.642	27.28115	744.2612
1		10	Mortality	Krewski et	30	99	15.66488	188311	28.18	15.62303	34.46091	45.3355	1.063184	1.130359
1		10	Mortality	Cesaroni e	30	99	3.16476	188311	28.18	2.750005	39.54531	6.9541	5.163493	26.66166
1		10	Mortality	Lepeule et	25	74	1.504929	233846	28.18	1.498898	4.209229	35.6098	0.153116	0.023445
1		10	Mortality	So et al.	30	99	7.260477	188311	28.18	7.183568	13.76553	52.1852	0.941887	0.887152

Rollback 5													
Col	Row	Endpoir	Author	Start Ag	End Age	Point Es	Populat	Delta	Mean	Baselin	Percent	Standar	Varianc
	Akaki												
1	1	Mortality	Pope et al.	30	99	13.03713	110438	30.86	9.063449	44.1752	20.5171	17.40738	303.0167
1	1	Mortality	Krewski et	30	99	9.804433	110438	30.86	9.777329	20.21016	48.3783	0.64492	0.415922
1	1	Mortality	Cesaroni e	30	99	2.024608	110438	30.86	1.738397	23.19198	7.4957	3.299125	10.88423
1	1	Mortality	Lepeule et	25	74	0.94794	137143	30.86	0.943973	2.468574	38.2396	0.094337	0.0089
1	1	Mortality	So et al.	30	99	4.520518	110438	30.86	4.470693	8.073017	55.3782	0.564915	0.31913
	N. Silk												
1	2	Mortality	Pope et al.	30	99	23.45768	192750	32.01	16.07462	77.09999	20.8491	31.44391	988.7194
1	2	Mortality	Krewski et	30	99	17.55566	192750	32.01	17.50648	35.27325	49.631	1.13929	1.297982
1	2	Mortality	Cesaroni e	30	99	3.659139	192750	32.01	3.125728	40.4775	7.7221	5.959786	35.51905
1	2	Mortality	Lepeule et	25	74	1.701952	239359	32.01	1.694705	4.308462	39.3343	0.16777	0.028147
1	2	Mortality	So et al.	30	99	8.076559	192750	32.01	7.986181	14.09002	56.6797	0.993182	0.98641
	Kolfe												
1	3	Mortality	Pope et al.	30	99	31.58866	261325	31.75	21.7174	104.53	20.7762	42.30442	1789.664
1	3	Mortality	Krewski et	30	99	23.66675	261325	31.75	23.60064	47.82248	49.3505	1.540578	2.373381
1	3	Mortality	Cesaroni e	30	99	4.922526	261325	31.75	4.209847	54.87825	7.6712	8.01835	64.29393
1	3	Mortality	Lepeule et	25	74	2.293003	324516	31.75	2.283276	5.841289	39.0886	0.22652	0.051311
1	3	Mortality	So et al.	30	99	10.89339	261325	31.75	10.7719	19.10286	56.3889	1.344459	1.80757
	Gulele												
1	4	Mortality	Pope et al.	30	99	16.40909	163065	25.57	12.16415	65.226	18.6492	21.61179	467.0696
1	4	Mortality	Krewski et	30	99	12.62482	163065	25.57	12.59234	29.84089	42.1983	0.883182	0.78001
1	4	Mortality	Cesaroni e	30	99	2.496151	163065	25.57	2.194217	34.24365	6.4077	4.078421	16.63352
1	4	Mortality	Lepeule et	25	74	1.205215	202495	25.57	1.200605	3.644911	32.9392	0.125278	0.015695
1	4	Mortality	So et al.	30	99	5.882129	163065	25.57	5.822594	11.92005	48.8471	0.791232	0.626049
	Lideta												
1	5	Mortality	Pope et al.	30	99	16.10997	122917	35.03	10.62023	49.1668	21.6004	21.85167	477.4955
1	5	Mortality	Krewski et	30	99	11.90593	122917	35.03	11.87152	22.49381	52.7768	0.745565	0.555868
1	5	Mortality	Cesaroni e	30	99	2.542388	122917	35.03	2.142447	25.81257	8.3	4.136494	17.11058
1	5	Mortality	Lepeule et	25	74	1.162306	152639	35.03	1.157145	2.747502	42.1162	0.111734	0.012484
1	5	Mortality	So et al.	30	99	5.446444	122917	35.03	5.383335	8.985231	59.9131	0.64192	0.412061
	Kirkos												
1	6	Mortality	Pope et al.	30	99	17.50671	134831	34.63	11.60127	53.9324	21.5108	23.70601	561.9751
1	6	Mortality	Krewski et	30	99	12.95958	134831	34.63	12.92226	24.67407	52.3718	0.815404	0.664884
1	6	Mortality	Cesaroni e	30	99	2.758575	134831	34.63	2.32883	28.31451	8.2249	4.488794	20.14927
1	6	Mortality	Lepeule et	25	74	1.264012	167434	34.63	1.258428	3.013812	41.7554	0.121917	0.014864
1	6	Mortality	So et al.	30	99	5.932829	134831	34.63	5.864376	9.856146	59.4997	0.703197	0.494486
	Arada												
1	7	Mortality	Pope et al.	30	99	15.7354	128896	32.13	10.76654	51.5584	20.8822	21.10157	445.2764
1	7	Mortality	Krewski et	30	99	11.77039	128896	32.13	11.73737	23.58797	49.76	0.762772	0.58182
1	7	Mortality	Cesaroni e	30	99	2.455688	128896	32.13	2.096581	27.06816	7.7456	3.999488	15.9959
1	7	Mortality	Lepeule et	25	74	1.141417	160065	32.13	1.136548	2.88117	39.4474	0.112403	0.012634
1	7	Mortality	So et al.	30	99	5.413782	128896	32.13	5.353109	9.422297	56.8132	0.664619	0.441718
	Addis Ketema												
1	8	Mortality	Pope et al.	30	99	19.25761	155587	32.67	13.08676	62.23479	21.028	25.8758	669.5571
1	8	Mortality	Krewski et	30	99	14.37247	155587	32.67	14.33191	28.47242	50.3361	0.925493	0.856537
1	8	Mortality	Cesaroni e	30	99	3.011645	155587	32.67	2.565015	32.67327	7.8505	4.903938	24.04861
1	8	Mortality	Lepeule et	25	74	1.395494	193209	32.67	1.389494	3.477762	39.9537	0.13681	0.018717
1	8	Mortality	So et al.	30	99	6.603839	155587	32.67	6.529333	11.37341	57.4088	0.804598	0.647377
	Yeka												
1	9	Mortality	Pope et al.	30	99	23.15301	211279	28.25	16.62067	84.5116	19.6667	30.67867	941.1805
1	9	Mortality	Krewski et	30	99	17.60723	211279	28.25	17.56015	38.66405	45.4172	1.194039	1.425728
1	9	Mortality	Cesaroni e	30	99	3.559217	211279	28.25	3.091805	44.36859	6.9685	5.806868	33.71971
1	9	Mortality	Lepeule et	25	74	1.691817	262368	28.25	1.685028	4.722624	35.6799	0.172032	0.029595
1	9	Mortality	So et al.	30	99	8.159603	211279	28.25	8.073073	15.44449	52.2715	1.057498	1.118303
	Bole												
1	10	Mortality	Pope et al.	30	99	21.91012	188311	30.33	15.33254	75.3244	20.3553	29.20525	852.9464
1	10	Mortality	Krewski et	30	99	16.51438	188311	30.33	16.46902	34.46091	47.7904	1.093057	1.194773
1	10	Mortality	Cesaroni e	30	99	3.395551	188311	30.33	2.922445	39.54531	7.3901	5.534375	30.6293
1	10	Mortality	Lepeule et	25	74	1.594692	233846	30.33	1.588072	4.209229	37.7283	0.159397	0.025408
1	10	Mortality	So et al.	30	99	7.622063	188311	30.33	7.538666	13.76553	54.7648	0.959589	0.920812