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ASSESSING SATELLITE-BASED AMBIENT $PM_{2.5}$ IN RELATION TO UNDER-FIVE CHILDREN MORTALITY IN ETHIOPIA

BY

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Abstract

Background: Particulate matter below 2.5 μm diameter ($PM_{2.5}$) is a part of air pollution that has adverse effects on health. Data on exposure to ambient $PM_{2.5}$ is not well monitored in sub-Saharan Africa due to limited resources and skilled manpower. The effect of $PM_{2.5}$ on health is least explored in Ethiopia.

Objectives: The study has assessed the relationship between satellite-based ambient $PM_{2.5}$ pollution and under-five mortality in Ethiopia.

Methods: The study used the data from Ethiopian Demographic Health Surveys conducted in 2016, collected between January 18 and June 27. Under-five children with the child mortality information and coordinates of geographical location were included. Satellite-based ambient $PM_{2.5}$ concentration was extracted from the Atmospheric Composition Analysis Group website at Washington and Dalhousie University, in the United States and Canada, respectively. Datasets were downloaded from their respective websites. Annual pollution level and mortality datasets were matched by children's geographical location, birth, death, and interview dates. The relationship between satellite-based ambient $PM_{2.5}$ and under-five mortality was determined by multilevel multivariable logistic regression. The statistical analyses were two-sided at 95% confidence interval.

Results: The study addressed 10452 children with the proportion of under-five mortality being 5.4% (95% CI 5.0% - 6.8%). The estimated lifetime mean annual exposure of ambient $PM_{2.5}$ was 20.1 ± 3.3 μgm^{-3}. Significant clustering of mean annual $PM_{2.5}$ concentration and under-five mortality proportion were varied by region. A ten-unit increase in lifetime mean annual ambient $PM_{2.5}$ was associated with 2.40 [95% CI 1.51, 3.80] times more odds of under-five mortality after adjusting for other variables. In addition, children with food cooked inside a house but with no separate room, mothers without formal education, very large birth size, twins, born at home, and stunting prevalence were significantly positively.

Conclusions: Clustered spatial distribution of ambient $PM_{2.5}$ concentration and under-five mortality has existed. Satellite-based $PM_{2.5}$ is significantly associated with under-five mortality adjusted for other variables. Validating satellite-based PM data with ground-based measurements is advised. Additional ground-based $PM_{2.5}$ monitoring devices, particularly in Afar where $PM_{2.5}$ and under-five mortality were higher, is suggested.

Abbreviations

ACAG	Atmospheric Composition Analysis Group
AIC	Akaike Information Criterion
ALRI	Acute Lower Respiratory Infection
AOD	Aerosols Optical Depth
AOR	Adjusted Odds Ratio
AQGs	Air Quality Guideline
ARI	Acute Respiratory Infection
BAM	Beta Attenuation Monitor
CI	Confidence Interval
CFU	Colony Forming Unit
CRS	Coordinate Reference System
DHS	Demographic Health Survey
EA	Enumeration Area
EDHS	Ethiopian Demographic Health Survey
eGFR	estimated Glomerular Filtration Rate
EPHC	Ethiopian Population and Health Census
EBK	Empirical Bayesian Kriging
GADM	Database of Global Administrative Areas
GEOS-Chem	Goddard Earth Observatory System Chemical Transport Model
GLM	Generalized Linear Model
GPS	Geographical Positioning System
GWR	Geographically Weighted Regression
HEI	Health Effects Institute
HH	Household
ICC	Interclass Correlation
JMP	Joint Monitoring Program
LMICs	Low and Middle Income Countries
LPG	Liquefied Petroleum Gas
m^{-3}	One per cubic meter
MISR	Multi-angle Imaging SpectroRadiometer
MGWR	Multiscale Geographical Weighted Regression
MODIS	Moderate Resolution Spectroradiometer
OLS	Ordinary Least Square
OR	Odds Ratio
PCV	Percentage Change in Variance
PM	Particulate Matter
SeeWiFS	See-viewing Wide Field-of-view Sensor
SD	Standard Deviation
SNA	Sulfate, Nitrate, Ammonium ions
SNNPR	Southern Nations Nationalities and Peoples Region
ULRT	Upper and Lower Respiratory Tract
URI	Upper Respiratory Tract Infection
US	United States
VIF	Variance Inflation Factor
WASH	Water Sanitation and Hygiene
WHO	World Health Organization
µg	Microgram
µm	Micrometer

Introduction

Background

Ambient air pollution is costing the globe premature deaths, 4.2 million deaths in 2016 alone while contributing to climate change and economic impact. The magnitude of pollution and its impact is higher in low- and middle-income countries (LMICs) (1). Among ambient air pollutants, particulate matter 2.5 μm ($PM_{2.5}$) is one of the most important which is acknowledged globally (2,3). Particulate matter (PM) is suspended particles in the air, ambient and indoor air, that constitute both solid and liquid particles of any kind of chemical composition(4). The size of the mass concentration of particles diameter is measured in micrometer (μm). In various countries, a diameter of below 10 μm (PM_{10}) and below 2.5 μm – fine PM – ($PM_{2.5}$) are monitored as an indicator of ambient air quality (2,4).

Ambient air pollution affects the entire population and all age groups, with children and the elderly being more susceptible (5). Children tend to deposit more pollutants due to their low nasal filtration, high ventilation rate, and higher metabolic rates. Latter, affect the lungs, renal and hepatic functions (6), and the growth of the lungs (7). Every year, 543,000 under-five deaths, globally, are attributed to polluted indoor and outdoor air. The burden is higher in Africa due to the use of polluting fuels, mainly biomass fuel (1).

Short-term $PM_{2.5}$ exposure has been associated with pneumonia (8,9) and upper and lower respiratory tract infection among children (ULRI) (9). Moreover, $PM_{2.5}$ is associated with an increase in viral and bacterial amount (10), cough, wheezing, and lower respiratory infection in children (11). Pneumonia (1,12,13) and acute respiratory illness are the leading causes of under-five mortality in the world (1). In Africa, only a few studies have investigated ambient $PM_{2.5}$ and its negative health effects. A longer time exposure was associated with the rise in under-five mortality, infant mortality rate, and child mortality was recorded in western and central Africa (14), sub-Saharan Africa (15), and Nairobi (16), respectively.

Therefore, this study has investigated the correlation between ambient $PM_{2.5}$ and under-five mortality in Ethiopia. Ground-level air pollution monitoring instruments are staggeringly limited in the country (17). In such situations, using satellite-based $PM_{2.5}$ has been suggested to overcome the shortcomings (15,18–20). Hence, satellite-based $PM_{2.5}$ was employed in this study.

Statement of the problem

Previous studies, showing the strong relationship between ambient $PM_{2.5}$ and its detrimental human health effect, have largely been conducted in developed nations; most are in North America and Europe. In developed nations, there is a relatively low air pollution status (21,22) which might contribute to the small amount of mortality compared to developing countries. Hence, pooled estimates on the magnitude of ambient $PM_{2.5}$ from major studies conducted in the global north might be underestimated (15,18,23). This was apparent in the pooled estimates from a meta-analysis of studies from five WHO regions and systematic reviews in China, (24,25) and at the global level were different (23). Thus, more investigation helps to better understand the degree of the effect of ambient $PM_{2.5}$ in Africa.

In Eastern and Western Africa, under-five mortality has largely reduced between 2000 and 2015 (14). Improved nutrition, sanitation, and vaccination, prevention of communicable diseases, and access to reproductive health services have contributed to huge under-five mortality reduction in Africa (26,27). In Ethiopia, too, under-five mortality has declined substantially (28,29) which could be attributed to various factors. There is a debate that some of the deaths might be attributed to $PM_{2.5}$ and working on it would reduce the deaths (15). Further studies might help to explain the role of $PM_{2.5}$ on under-five mortality.

There are few studies, in Africa, addressing ambient $PM_{2.5}$ and its correlation with infant mortality (15), under-five mortality, and maternal mortality (14). Both studies have used satellite-based "annual bias-corrected average surface $PM_{2.5}$ concentration" (15,30). Neal et.al. (15) studied utero exposure and postnatal exposure to ambient $PM_{2.5}$ and infant mortality. While Owili et al. (14) studied it on under-five and maternal mortality. They either studied at the ecological level – did not control for individual characteristics –(14) or did not study under-five mortality (15). Hence, there is still a clear gap in knowledge of ambient $PM_{2.5}$ and its relation to under-five mortality.

Most developing countries, including Ethiopia, tend to have limited air quality monitoring systems (21). This indicates the country is not keeping track of ambient $PM_{2.5}$ and the consequences associated with it. There is evidence saying the level of pollution is increasing in Ethiopia with increasing urbanization, industrialization, and traffic. Might increase the adverse health effects (22).

Accordingly, this study provided evidence on the risk of under-five mortality incurred from ambient $PM_{2.5}$ exposure. To remedy the absence of air quality monitoring systems, satellite-based $PM_{2.5}$ concentration estimated by the Washington and Dalhousie University, Atmospheric Composition Analysis Group (ACAG), was used. The ACAG at the universities produces estimates of $PM_{2.5}$ across the globe, including Ethiopia, at 0.01^{o} X 0.01^{o} spatial resolution (30). Moreover, individual characteristics and environmental confounders were controlled to contribute knowledge on the magnitude of risk $PM_{2.5}$ exposure might impose in Ethiopia.

The Rationale of the study

Air polluting activities in Ethiopia are increasing, particularly the establishment and expansion of industrial enterprises (31). The use of biomass as the energy source for cooking is still prevalent (29). Across the world, a great number of children are dying as a result of combined household and ambient air pollution (1). Thus, it is important to closely understand the effect of ambient $PM_{2.5}$ on the health of under-five children.

Significance of the study

The results of the study will have a practical influence on various sectors. The government might consider installing air quality monitors and keeping track of pollution with the goal of reducing pollution and enforcing strict policies. The community might take measures to influence the government to engage in activities that reduce $PM_{2.5}$ pollution. Finally, the scientific community will learn more about ambient $PM_{2.5}$ and the impact on under-five mortality and investigate further on other groups of the population. The result has given an idea to work on other related health problems and contribute to the knowledge of improving health.

Literature review

In all regions of the world, people are dying because of outdoor air pollution. It is killing 3 million people every year (32). Particulate Matter is a component of air pollution with serious public health importance. About 87% of the globe's population breathes air that exceeds the 10 µg m−3 $PM_{2.5}$ annual exposure threshold set by WHO air quality guidelines (AQG) in 2013 (22). There is evidence that links infant and under-five mortality to $PM_{2.5}$ exposure (14,15,18). Reporting and monitoring of ambient air pollutants in Africa and Asia are extremely low (21,22,32). In Ethiopia too, there is a huge gap in the documentation and keep track of pollutants trend (33). To understand more about $PM_{2.5}$ health impact in these areas, more epidemiological investigations are required immediately (32).

Chemistry of $PM_{2.5}$

Particulate matter is a composition of chemical compounds and biological agents. It is a collection of solids and liquids hung in the indoor or outdoor air. Through various human activities (i.e. engine combustion in vehicles, burning biomass and other solid-fuels, agricultural and industrial activities, and human-induced dust release) or natural causes (i.e. blown dust from arid areas), PM can be released straight into the air or formed from emitted pollutants i.e. non-methane volatile organic compounds, nitrogen oxides, sulfur dioxide, and ammonia. The biological constituents (bioaerosols) of $PM_{2.5}$ include allergens and microbial compounds (4). A study in South Africa, sampled near an industrial area, determined the bacterial and fungal concentration of $PM_{2.5}$ to be 168-378 colony-forming unit (CFU)/m^3 and 58-155 CFU/m^3 (34).

The use of biomass fuel and fossil burning are the two important sources of organic carbon and elemental carbon (35). The share of compounds that makes PM differs with source type from place to place. A study conducted in the city of Addis Ababa found $PM_{2.5}$ constituted 44.5% of organic matter, 25.4% of elemental carbon, 13.5% of soil dust, and 8.2% of sulfate, nitrate, and ammonium ions (SNA) (36). The share of organic carbon was 28% of $PM_{2.5}$ in rural Bhola, Bangladesh (35). In Yokohama City, Japan organic carbon and elemental carbon made 18.2 % and 9.4% of $PM_{2.5}$ mass concentration respectively (37). This concentration is smaller compared to measurements taken in Addis Ababa.

Unlike other higher diameter size PM, $PM_{2.5}$ can pass the blood gas barrier to circulate in the blood system and reach beyond pulmonary organs such as the liver and kidney. Trace elements constituted in $PM_{2.5}$ will have a chance to accumulate damaging endothelial cells and cause systemic inflammation (38). The organic matter, NO_3^{-2}, and NH_4^+ constituents of

$PM_{2.5}$ are known to be associated with childhood pneumonia (8) while the organic carbon, ozone, and NO_2 constituents of $PM_{2.5}$ are associated with both pneumonia and upper respiratory tract infection among children less than four years old (9). Also, the biological constituents of $PM_{2.5}$ increase the level of viral and bacterial (mycoplasma pneumonia) levels among children (10). Traffic-related $PM_{2.5}$ is related to more cough, wheezing, and lower respiratory infections (11). Both upper and lower respiratory infections during the children's early life can be severe in relation to ozone and organic carbon parts of $PM_{2.5}$, especially the carbon constituent is strongly associated (9).

Seasonal variation of $PM_{2.5}$

Exposure to $PM_{2.5}$ varies across different geographical areas (1,22,24,32,39) and seasons of the year (25,36,37). A study conducted in China cities has explored that the burden of PM varies with seasons and meteorological factors. The study demonstrated there was an apparent trend of increased PM in winter than in the summer half-year (25). Similarly, during the heavy rainy season—the months of June to September—the concentration of $PM_{2.5}$ was higher compared to dry seasons. This was explained by the increased use of fuel for heating during the colder season (36). In Yokohama City, Japan in the spring and winter months elevated concentrations of $PM_{2.5}$ were registered. The authors argued the winter's stable, cold, and dry meteorology promotes a longer life-time for $PM_{2.5}$ in the atmosphere (37).

Geographical distribution of $PM_{2.5}$

The concentration of $PM_{2.5}$ differs from country to country and from one region of the world to another. LMICs are suffering from poor outdoor air quality. In 2017, southeast Asia countries (Nepal, India, Bangladesh, Pakistan, and China) and west sub-Saharan African countries (Niger, Cameroon, Nigeria, Chad, and Mauritania) showed the highest concentrations of $PM_{2.5}$. Almost no population living in China, India, Pakistan, and Bangladesh breathe air below the WHO's set an annual exposure limit of $PM_{2.5}$ – 10 μgm^{-3} (22,39). The situation in Africa is not different from China and India in terms of breathing polluted air. According to WHO, in 2016, all under-five children in Africa and Eastern Mediterranean were exposed to ambient $PM_{2.5}$ >10 μgm^{-3} (1). Across regions, sources of $PM_{2.5}$ pollution vary. Windblown dust from the Sahara Desert in Western Africa, Northern Africa, and the Middle East is one of the major contributors. Dust from construction, burning of coal in industry and power plants, transportation, and burning of solid fuels for households are the major source of PM2.5 in India and China (22,39).

Improvements in air quality were seen in countries where strong policies are implemented to reduce air pollution. United States (US), Brazil, European Union, Japan, Russia, Mexico, and Indonesia have made a relatively large decline in ambient $PM_{2.5}$ concentration between 1990 to 2017 (22,39). China's aggressive specific actions in reducing the use of coal, limiting vehicle numbers, and promoting less-polluting energy sources have brought results—a 1/3 reduction of $PM_{2.5}$ concentration in just four years (between 2013 and 2017) (HEI). However, the problem still persists in most LMICs. Such countries with poor air quality are less likely to provide access to safe drinking water, electricity, and other services for their citizens. The problem does not stop here. In consequence, air quality monitoring systems may not be available adequately as they incur large investments and running costs which usually may not afford by these countries (21).

Methods of measuring ambient $PM_{2.5}$ concentration level

Of its peculiar public health importance, $PM_{2.5}$ is monitored by various air pollutant monitoring stations. In 2005, WHO set average annual exposure of 10 μg m−3 and 24 hours exposure of 25 μgm^{-3} of $PM_{2.5}$ as a threshold (4). Areal PM can be measured at sampling/monitoring stations (40,41). The instrument can be installed at different sites in a municipal city or a state (19,25). They operate with electricity or solar power and are protected from rain and unfavorable weather. Installed on the rooftop (41) or two meters above the ground (36). Measurement devices for $PM_{2.5}$ concentration in the air vary in techniques of measurement, cost, and duration.

Gravimetric method

This technique is the popular and gold standard method. The filter weight before sampling is subtracted from the weight after sampling to measure PM concentration. Care must be in order during the sampling procedure as the gravimetric analysis method is affected by moisture, temperature, and electro statistic effects. The method can easily be reproducible. The disadvantage is that it only takes a few hours of sampling not continuous (42).

Real-time Monitor—Beta-Attenuation Monitor (BAM)

This device has an inlet that allows the entrance of particles into filter tape below the inlet size. Mass particle concentration is measured by taking the before and after difference in the attenuation of the beta radiation that is emitted and passes through the filter tape (41,43). In BAM, continuous or real-time PM measurement is possible (44,45). In Addis Ababa, there are a few Beta-Attenuation Monitor 1022 and 1020 (Met One made instruments). The instrument uses beta radiation degree of intensity (attenuation) that passes through the particles collected by a rolling tape to measure the concentration of PM. The mounting procedure is published elsewhere (45,46). The BAM device is approved by US Environmental Protection Agency (47). Such instruments ensure measurements taken are $PM_{2.5}$ and facilitate the validation and accuracy of models, establishing air quality background, and comparison across different areas for regulatory and health promotion purposes (48).

Low-cost instruments

These devices are photometer – which measures the air transparency which is the light scattered by the "combination of all the particles present in the optical detection volume" (49), optical particle counter which is determining the amount of light scattered (44), or light absorbed by the single suspended particles – (50), or directly measure the mass concentration of $PM_{2.5}$ (44,49). Such Instruments can also take measurements continuously without interruption –real-time measurements. Today, commercial companies like https://www2.purpleair.com/ produce global real-time measurements of PM using PurpleAir sensors. The sensors employ laser particle counters and report their measurements to the cloud through the internet.

Space-borne devices—Remote sensing

Nowadays, remote sensing devices are being used in places where ground-based monitoring is absent. Satellites, human-made machines or natural moon, star, or planet that orbits around a planet. Human-made satellites carried different instruments that can collect data or take imagery for specific purposes i.e. communication, military, or climate change. There are instruments mounted on satellites to collect data on aerosols (51). Satellites that observe the land, atmosphere, and water of earth usually orbit in the lower, exosphere (52). Aerosol data is collected in the form of images which will later be processed to estimate its chemical composition. Based on the chemical transport model the geophysical relationship between Aerosol Optical Depth (AOD) and $PM_{2.5}$ is declared. The bias introduced in the process was adjusted by taking the difference between the declared relationship and ground-based monitor $PM_{2.5}$. The predictors which influence the relationship between AOD and $PM_{2.5}$ include the topographic and aerosol features, the composition of mineral dusts, and coastal effects (30). Even in places where monitoring systems exist, a satellite-based estimate is used in combination with a chemical transport model and ground measurements (30,53,54). The challenge in epidemiological studies is to determine how much a person is exposed to $PM_{2.5}$.

Especially, from ground-level measurements and satellite-based estimates. A land monitor system represents the concentration of $PM_{2.5}$ in the nearby areas. Therefore, finding measurements that match with the residence of the participants – "spatially resolved $PM_{2.5}$ concentration" (19). While determining the concentration of $PM_{2.5}$ from satellite Aerosol Optical Depth (AOD), the key elements are; increasing the resolution or estimating a small grid area and making sure a sound measurement is produced by validating it with ground-level monitoring systems. Dalhousie University and Washington University Atmospheric Composition Analysis Group produce annual mean $PM_{2.5}$ concentration at 0.01^{o} X 0.01^{o} spatial resolution across the globe (30,55).

Air pollution-related policy and regulations

In the past decades, WHO set interim and long-term goals for permissible levels of important air pollutants including $PM_{2.5}$. Countries that implemented strong policies are rewarded with improved air quality or reduced $PM_{2.5}$. In 2021, WHO updated the 2005 air quality guideline and suggested a 15 μgm^{-3} and 5 μgm^{-3} for 24 hours and annual mean ambient $PM_{2.5}$ exposure, respectively. It recommends policymakers to make efforts of air quality and its benefit for health a priority. Moreover, cooperation of sectors and air quality monitoring stations, free access to data, strong regulations, and integrated worldwide air quality standards and management systems (56).

In Ethiopia, the government passed policies (i.e. Environmental pollution control proclamation No.300/2002) that the forbid release of contaminants into the environment including the air. It gives an obligation to the government to regulate, monitor, and oversee compliance. However, the government lacks enough monitoring laboratories and skilled professionals to monitor air quality. As a result, evidence that influences meaningful policy actions and record-keeping regarding air pollution is undersupplied (33).

Determinants of under-five mortality

Globally, during the past two decades, the death of under-five children has reduced considerably (57). In all sub-regions of Africa, a great decline of under-five deaths was recorded between the years 2000 and 2015 (14). The decline is attributed to improved vaccination, prevention of communicable diseases, access to reproductive health services, and improved nutrition and sanitation (26,27). However, still, the world's most deaths occur in sub-Saharan Africa and southern Asia (57). In Ethiopia, the under-five mortality rate declined to 67 deaths/1000 live births in 2016 from 2006's 116 deaths per live births (29).

The aim is to reduce it to 25 deaths per 1000 live births per year (58). The following factors are known to be associated with under-five mortality.

Child health indicators

Infectious diseases such as pneumonia, diarrhea, and malaria are the main causes of under-five mortality (12). Acute lower respiratory infection (ALRI) was the second leading cause of under-five mortality in the world. Almost half of ALRI are attributed to air pollution (outdoor and indoor) (59). $PM_{2.5}$ is a notable air pollutant with the ability to be inhaled, reach the alveoli of the lung, and cause serious health problems (60). Vaccination, maternal health services (antenatal care, skilled delivery, and post-natal), and malnutrition are also significant determinants of under-five mortality. About 45% of deaths in < 5 years old children is attributed to nutrition-related factors (12,26,27). Determinants can be described as child-specific, socio-demography or mother and parent-related factors, and environmental factors.

Child-related factors

Child-specific factors that are known to be associated with under-five mortality include sex of child (61–63), age of a child, plurality of a child, place of delivery (64), preceding birth interval, nutritional status (65), birth weight, and birth order (61,62,64,66).

Socio-demographic factors

Mother and parent-related factors include the mother's educational status (20,62,64), age of the mother (62,64), marital status, sex of household head, residence (61–63), household (HH) wealth index, employment status (62), and family size (64). Poor households are excluded from the economic activity, government health investments in near-poor households are limited, and households spend less on caring for children which are eventually associated with under-five mortality (67).

Environmental related factors

Environmental factors include access to improved drinking water and sanitation facility, and air pollution (indoor and outdoor) (1,4). Epidemiological evidence links outdoor $PM_{2.5}$ exposure with the general population mortality in Massachusetts (19) and under-five mortality across the globe (68), Asia (69), and Africa (70). Also, using a type of cooking fuel as a proxy for indoor air pollution, the use of solid fuel increases the risk of under-five children death from ALRI by 2.35 (95% Confidence Interval (CI) 1.22 – 4.52) among children in Africa (71). Similarly, a study in Nepal (72) and Ethiopia (20) showed the use of polluting fuel for indoor cooking is associated with under-five mortality.

Further, based on the immediacy of the determinants or the whether it “operates directly” and “within the body” (73) to cause the under-five mortality factors can be classified as distal factors (i.e. residence, parent’s educational status, employment status, and wealth index), intermediate factors (i.e. sex of the child, birth order, preceding birth interval, family size, mothers age, WASH, indoor air, and outdoor air), and proximal factors (i.e. diarrhea, vaccination, nutritional status, pneumonia, malaria, and birth weight). Factors that need to be changed at the societal level are distal factors while factors that can be altered by the individual, public health, or medical professional are proximal factors (73). Such classifications improve the scale and depth of the problem under-appreciation. These multiple determinants are interrelated; distal factors influence the intermediate factors which in turn influence the proximal factors (74).

Short- and long-term effects of exposure to $PM_{2.5}$

Evidence depicted mortality can be both the short-term (18,24) and long-term effects of exposure to $PM_{2.5}$ (19). In the short-term exposure, $PM_{2.5}$ was found to be associated with increased levels of viral and bacterial levels among children less than three years old (10). Empirical evidence also supports that $PM_{2.5}$ increases emergency pneumonia (8,9), URI (9), and ALRI (75) in the short term. Long-term exposure to $PM_{2.5}$ has been associated with kidney diseases (38) and problems in the development of different children’s organs (7). Also, long-term exposure is associated with infant mortality (15,76) and under-five mortality (14,77).

Mechanisms of $PM_{2.5}$ on affecting under-five mortality

Unlike adults the body composition of children changes in time, as they grow rapidly, as a result, their response to air pollutants is also different (6). Children’s body grows speedily making their organs more liable to air pollutant-induced inflammation and other damages (1). Furthermore, children have small size and fewer alveoli which requires them to have a higher ventilation rate. This enables pollutants such as $PM_{2.5}$ to move faster and deeper into the alveolar air-blood barrier. They also have lower nasal filtration and breathe through their mouths allowing more pollutants to deposit in the lungs. Experiments on animals’ exposure to air pollutants demonstrated lung function is impacted. It was due to oxidative stress that damages alveoli in neonatal monkeys while hyper-responsive respiratory tracts were recorded in rats (6). Among others, oxidative stress is one of the possible mechanisms that PM poses a risk to children’s health such as allergic disease (78). Post-neonatal respiratory mortality and impaired function and growth of lungs increased with increased exposure to $PM_{2.5}$ (7).

Children have a higher metabolic rate this enables higher cardiac activities for faster exchange of pollutants. Their immature metabolic enzymes are unable to metabolize toxic pollutants into less toxic products. And usually, pollutant metabolism takes a longer time increasing the half-life of pollutants in children and ultimately affecting the renal and hepatic function and hindering the body's distribution of chemicals (6). A panel study in China found a significant reduction in the estimated glomerular filtration rate (eGFR), which informs about renal function, among children aged 4 to 13 years (79).

$PM_{2.5}$ gets its way into the body, various compositions will start acting. NO_3^{-2}, NH_4^+, organic matter (8), NO_2, and ozone (9) bacterial components of $PM_{2.5}$ are known to be associated with pneumonia among children. Although detailed mechanism is still unknown, there is evidence suggesting that air pollution reduces the lungs' antibacterial ability (80). This favors the proliferation of pneumoniae bacteria (10) and exacerbates the existing lung inflammation (80). NO_2 is known to damage the epithelium of alveolar and bronchiolar to further cause bronchiolitis (81). Pneumonia and ALRI are the known causes of under-five mortality (1,12). Also, $PM_{2.5}$ heavy metal components chromium and cadmium affects the function of the kidney (38). Chromium is a known nephrotoxic metal (82).

Methodological approaches relating $PM_{2.5}$ and mortality

In various statistical analyses, the aggregated count continuous (14) or individual binary (15) values have been used in different literature to assign the dependent variable, mortality. Exposure to $PM_{2.5}$ was taken as short-term daily measurements (19), long-term moving average (83), and long-term exposure (76).

A choice of analysis depends on the values of morality which will be considered. Studies considered mortality as aggregated count used Poisson regression while studies considered mortality as a dummy variable equal to one when death occurs used logistic regression. Both models are generalized linear models (GLM) with log-link. Models differ in extended techniques among studies depending on the variability of the values of the outcome variable, method of sampling, or whether the information is collected at different time intervals.

Poisson regression

This model helps to identify factors that determine the difference in counts of mortality among different geographical grid cells or places (14,83). In the short term, helps which days of the week have higher counts of mortality. Also, in the acute association of $PM_{2.5}$ and mortality especially among participants with respiratory-related or other life-threatening problems (84). The disadvantage is all variables in the model needed to be aggregated similar to ecological studies.

Logistic regression

Treating mortality as a binary outcome for each study participant, logistic regression allows to identify the long-term relationship between mortality and $PM_{2.5}$ exposure (19). It allows controlling for variables at an individual level (76,85).

Time series analysis

This method has the advantage to examine the relationships in season and in separate time gaps. It helps to identify which previous day exposure has more effect on mortality in short-term $PM_{2.5}$ exposure. Kloog et al. (19) studied the relationship of "current and previous day exposures" – short-term exposure – to mean $PM_{2.5}$ as primary exposure and mortality among the general population in Massachusetts between 2000-2008 using time-series analysis with an improvement of spatial covariates and random intercepts to the model.

In conclusion, $PM_{2.5}$ has posed a great burden on health across the globe. But the burden is significantly higher among developing countries. The constitutes of $PM_{2.5}$ are various makes it affects different parts of the body which might lead to death. However, there exists limited evidence on the monitoring of $PM_{2.5}$ and the availability of ground-based $PM_{2.5}$ in Ethiopia. Satellite-based geographically weighted $PM_{2.5}$ has now become in use for the investigation of $PM_{2.5}$ and its adverse effects. Since 2000, due to efforts in increasing access to maternal and child services, nutrition, safe drinking water, and child vaccination, under-five mortality has decreased significantly. In Ethiopia, however, a large number of under-five children are still dying every year. Various community-level, socio-demographic, child-related, and environmental-related factors have been known to determine under-five mortality. Satellite-based $PM_{2.5}$ measurements are now freely available and applied in health impact assessments. First, the satellite retrieved AOD and $PM_{2.5}$ relationship is determined using the chemical transport model. Later, based on predictor variables (topographic features, aerosol features, coastal effects, and compositional concentration of mineral dusts) the model is improved by ground-based monitors to estimate a geographically weighted $PM_{2.5}$. Finally, a careful statistical analysis technique selection is important to relate $PM_{2.5}$ exposure and its effect on under-five mortality. In this study, logistic regression was applied making mortality a dummy variable value one being death. There is long-term exposure to $PM_{2.5}$ and its association with under-five children deaths. Due to the nature of sampling, which involved two-stage sampling, the model chosen was a multilevel multivariate logistic regression.

Conceptual Framework

Under-five mortality is determined by various factors which are interacting with one another (Figure 1). Some factors that need to be addressed at a societal level i.e. residence, HH's employment, education, and income status. Others are required to be addressed at HH level (i.e. family size, WASH, Mother's age, $PM_{2.5}$, and indoor air (type of cooking fuel, and place where food is cooked) and individual level (birthweight, birth order, plurality of a child, and place of delivery). On the contrary, some factors might be altered at the community level but their role on under-five mortality might be direct or inside the body i.e. WASH and outdoor air. These determinants are the source of other factor i.e. place of delivery, cooking fuel, contaminated water that could directly affect the body and results in death or other adverse health impacts. Similarly, factors might act directly on the body but alteration might be difficult i.e. sex of the child.

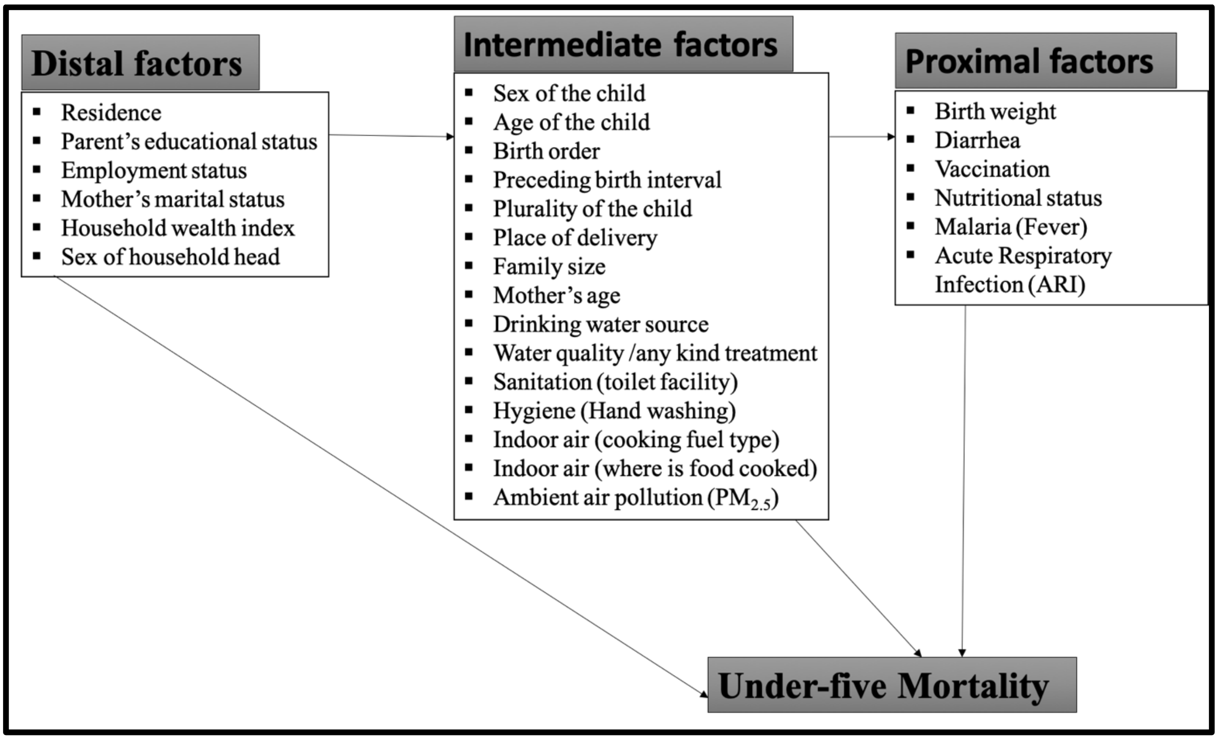

Figure 1 An analytical framework for under-five mortality determinants
Source: Adapted after consulting different literature (1,4,12,20,26,27,59–66,68–74,86,87)

Objectives

General objective:

To assess the relationship between satellite-based ambient $PM_{2.5}$ and under-five mortality in Ethiopia using EDHS 2016 data

Specific objectives:

1. To describe the ambient $PM_{2.5}$ concentration across the geographical areas of Ethiopia
2. To examine the spatial distribution of under-five mortality in Ethiopia
3. To assess the association between satellite-based ambient $PM_{2.5}$ concentration and under-five mortality in Ethiopia

Methods

Study area

Ethiopia is the largest landlocked country, with an estimated population of 110 million, in the horn of Africa, located 3^o to 14^o North and 33^o to 48^o East (Figure 2). It has nine regions and two administrative cities divided for administrative purposes (88).

The Ethiopian Demographic Health Survey (EDHS) followed a two-stage community-based cross-sectional study design. EDHS 2016 was collected in 2016 from January 18 to June 27.

Source and Study population

The source population of the study was all under-five children born five years before the survey period (January 2011 to June 2016) in Ethiopia. While all under-five children born five years before the survey period in the selected Enumeration Areas (EAs) are the study population.

The inclusion criteria: All under-five children born five years before the survey period in the selected HHs whose data and cluster's geographical location coordinates is recorded in the EDHS dataset were included in this study.

The Exclusion criteria: All under-five children born five years before the survey period in the selected HHs whose data or cluster's geographical location coordinates is not recorded in the EDHS dataset were excluded in this study.

Sample size

EDHS 2016 selected 645 EAs (202 urban and 443 rural EAs) (Figure 2). Information was collected for 10,641 (11,022 weighted) under-five children (29). After removing clusters with no location coordinates and data cleaning a total of unweighted 9,856 (10,452 weighted) under-five children were included in this study (Figure 3).

Satellite-based ambient $PM_{2.5}$ concentration data is available across all geographical space in the study area.

Sampling procedures

The EDHS collects samples to be regionally and nationally representative as well as urban and rural areas, data to be comparable across different nations through standardized questionnaires. Households were selected after a list of first-level administrative units and their list of enumeration areas (EAs) is provided. EA is a cluster with an average size of 150-200 households. EA could be either urban EA or rural EA. From all administrative units, relying on the size of the administrative units, EAs in both urban and rural were selected using probability proportional size within each stratum. EAs were divided into smaller EAs if the number of households was found to be more than the average i.e. >300 HHs. Enumeration and registration of households were performed in all selected EAs prior to sampling households. It was from the registered list households were selected, an equal number of HHs (28HHs from each EA), by systematic probability method. Information from all women aged 15-49 years (reproductive-aged women) was collected in all selected households. They did provide information about their under-five children if they have any (29).

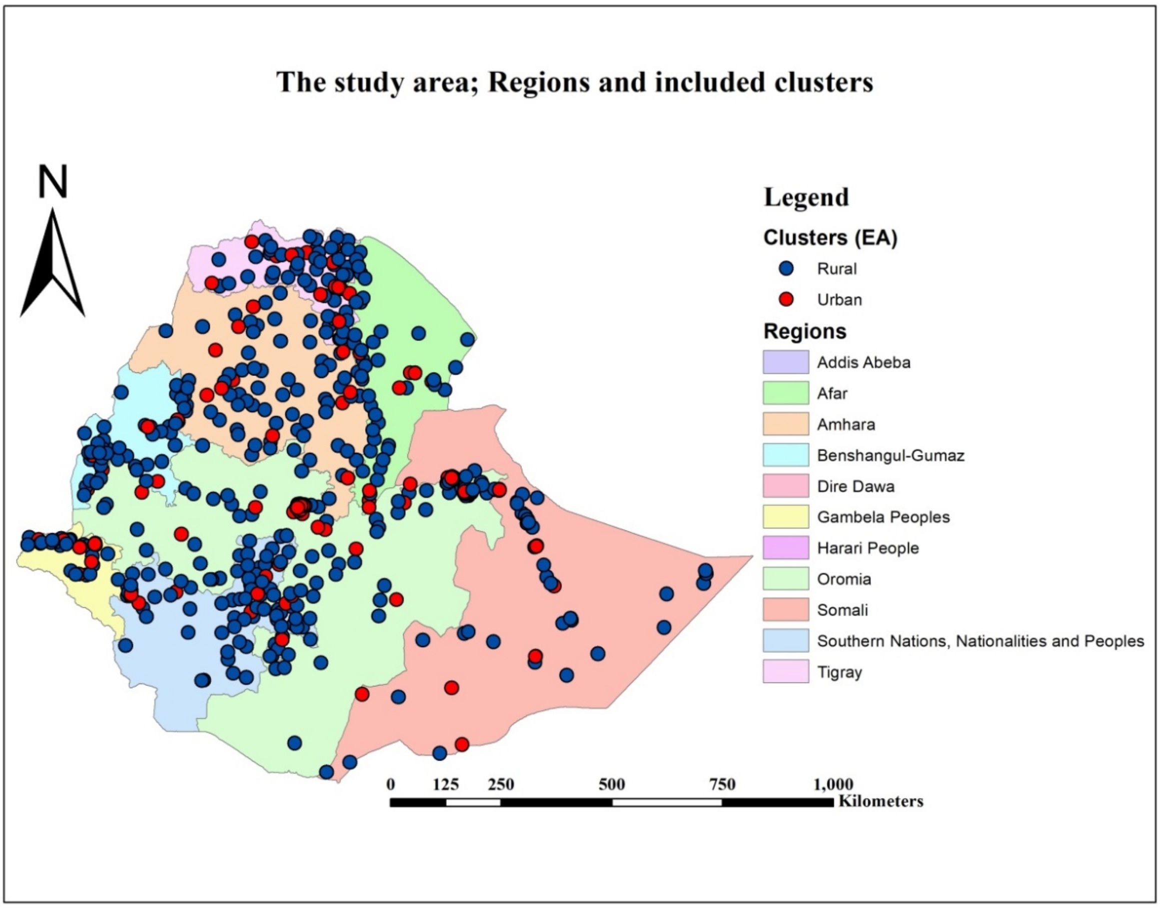

Figure 2 The map of Ethiopia, its administrative regions, and clusters (EAs) (n=622) with GPS coordinate of EDHS 2016; the study area (Source: shapefile from GADM (Database of Global Administrative Areas) 2018: https://gadm.org/)

Data collection procedures

EDHS used paper or personal digital assistants to enter the responses of study participants. EDHS standardized the questionnaire via translating questions into local languages and back to original languages. Interviewers were also calibrated by providing training and frequent supervision before and during data collection, respectively (29).

A DHS account was created at https://dhsprogram.com. A data request form that includes a short concept note was filled. After reviewing the request within twenty-four hours DHS responded and granted access to download the EDHS datasets.

Annual mean $PM_{2.5}$ concentration (in µg m^{-3}) across the geographical areas of Ethiopia was downloaded from ACAG. The group estimates the ground-level $PM_{2.5}$, every year, using satellite remote sensing from multiple instruments (NASA's MODIS, MISR, and SeaWIFS) of AOD retrievals and combining it with chemical transport model (from GEOS-Chem). This study used the $PM_{2.5}$ concentration estimate at a spatial resolution of 0.01^{o} X 0.01^{o}. The model allows to determine the geophysical relationship between AOD and $PM_{2.5}$. They also validate their estimate with land-based $PM_{2.5}$ monitoring systems by employing Geographically Weighted Regression (GWR) (30).

In each grid, collected daily values were used to calculate the monthly mean AOD values. Daily values that are outliers—above the sum of the grid mean and its two standard deviations (SD)—and without 25% or above grid coverage were removed (55). Missing daily values were approximated using the average of available collected values on the missing days and accounting for the month's assigned climatologic ratio (89). The daily local coincidental ratio (a value used to determine the relationship between the daily AOD and $PM_{2.5}$) was derived as a 24-hours ratio to incorporate the temporal differences in AOD retrieval. Grid coverage of less than 50% monthly mean was removed and interpolation was made from the same month of other years. The monthly mean $PM_{2.5}$ was derived from the monthly mean AOD. Then annual mean $PM_{2.5}$ was then computed from the monthly mean concentrations (55).

Data on $PM_{2.5}$ was downloaded from the ACAG group, http://fizz.phys.dal.ca/~atmos/martin/?page_id=140. The satellite $PM_{2.5}$ data was available for the public for free and requires no registration. The annual mean $PM_{2.5}$ concentration for the years from 2011 to 2016 was extracted from the downloaded ASCII — ArcGIS-compatible — gridded dataset. The annual mean was taken because most air pollution-related health impact assessments are based on long-term exposures (39,55,56).

Variables of the study

Dependent Variable

Under-five mortality is the dependent variable. Here, under-five mortality in this study is defined as the death of a child before 60 months (90).

Exposure Variable

Exposure to $PM_{2.5}$ in µg per cubic meter of atmospheric air. Lifetime annual mean $PM_{2.5}$ exposure was calculated for each study participant. In this study, "$PM_{2.5}$ is a mixture of solid and liquid particles suspended in the ambient air" and its "mass concentration of particles diameter is less than 2.5µm"

Controlled variables

All of the controlled variables in this study were extracted from EDHS datasets. They were controlled in the analysis of the possible relationship between $PM_{2.5}$ to avoid confounding bias.

Community-level variables; region, residence ("Urban", "Rural"), and proportion of diarrhea ("in the two weeks preceding the survey"), vaccination (pentavalent coverage), Acute Respiratory Infection (ARI) ("short, rapid breathing which was chest-related and/or difficulty breathing which was chest-related"), fever, and nutritional status ("stunting; height-for-age z-score is below -2*standard deviation (SD) below the mean on the WHO Child Growth Standards (-200)") for each EAs.

The individual factors are; sex of the child ("Male or Female"), birth order (the birth rank "<=3" and ">3"), child age (in years), size of a child at birth, plurality of a child ("Yes" or "No"), and place of birth ("Home" or "Institution").

The socio-economic factors are; Mother's educational status ("no education", "primary education", "secondary education or above"), age of the mother (takes values in years), household (HH) wealth index (computed from presence or absence of permanent assets and respondents housing condition), mother's employment status, mother's marital status, husband's occupational status, husbands' educational level, and family size.

The environmental factors are; Source of drinking water (categorized into "improved" and "unimproved"), type of toilet/latrine facility ("improved" and "unimproved") – categorized according to the updated joint monitoring program (JMP) (https://washdata.org/monitoring/drinking-water), presence of any kind of drinking water treatment in the household ("Yes" or "No"), type of cooking fuel (recorded as 'Clean fuels' if the fuel is liquefied petroleum gas (LPG), natural gas, biogas or electricity other fuel kinds of cooking fuel be in the category of 'solid fuels'), and place where food is cooked ("not inside the house", "inside the house in a separate room", or "inside the house not in a separate room") were included.

Data management procedures

Child, household, and location information were in the dataset whose file names start with ETBR (birth record), ETHR (household record), ETPR (individual record), and ETGE (geographic location), respectively. Datasets were merged using common/identifier variables (ID, cluster, household, line, and birth number) across the datasets. The variables to be included in the statistical analysis were selected from the datasets. Using R v 3.6.3 software dataset was cleaned, recoded, and observations with only under-five children was kept for further analysis. After data were cleaned a total of 9865 (10452 weighted) sample were used in all analyses.

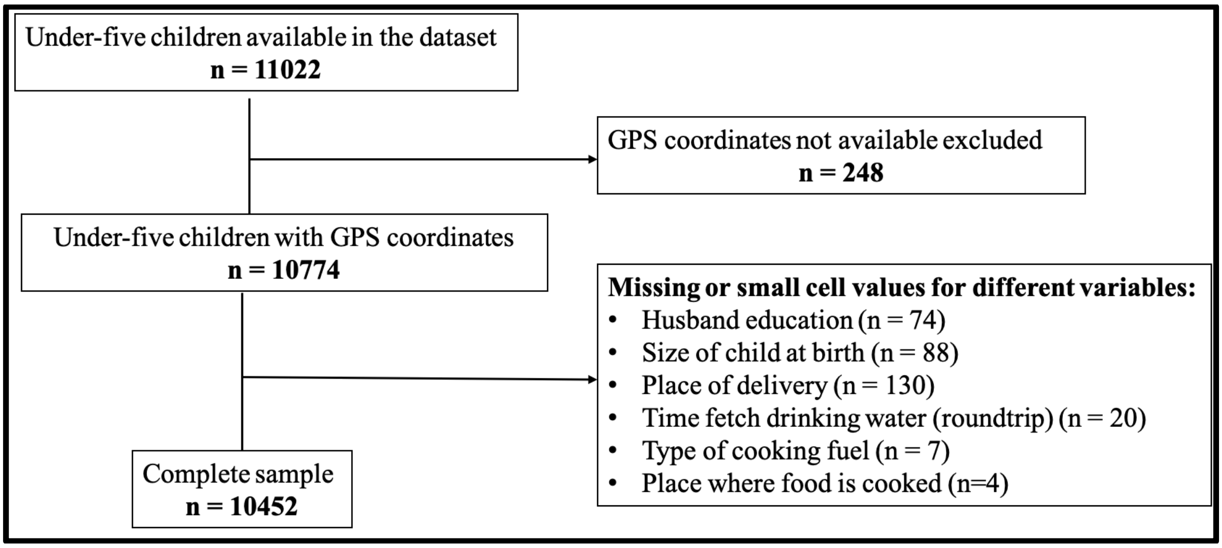

Figure 3 Flow chart of the inclusion of observations in the dataset for each step of this study sample analysis

Arc-GIS v10.7 was employed to manipulate the gridded dataset with $PM_{2.5}$ annual mean concentration. GeoDa v1.20.0.8 and MGWR v2.2.1 software was used for spatial exploration of $PM_{2.5}$ concentration and GWR respectively. Under-five's child exposures to lifetime annual mean $PM_{2.5}$ was determined in five steps;

i) Extracting $PM_{2.5}$ from the gridded datasets of "ArcGIS-compatible ASCII [. asc.zip]".

ii) After limiting the geographical extent to Ethiopia, each cell value was replaced by the average of neighboring cells within the circular radius of 6.6 kilometers for rural areas and 3.3 kilometers for urban areas.

iii) Determine the annual $PM_{2.5}$ concentration for each EAs (cluster) and region after matching the geographical positioning system (GPS) location of the cluster from the datasets.

iv) Count all years backward from the child's time of death or interview date (this time period is considered as an exposure time period) and then match that same year's $PM_{2.5}$ concentration of the child's cluster.

v) If the exposure time period falls in two or more different years a weighted exposure was taken (Table 1). For example, if a 12 months old child died in the seventh month of year *t* then the exposure to $PM_{2.5}$ was computed as *(annual mean $PM_{2.5}$ in year t*7/12) + (annual mean $PM_{2.5}$ in the previous year *5/12)* (15,76). It is assumed that the child exposed *t's* annual mean $PM_{2.5}$ concentration for seven months and *t's previous year's* annual mean $PM_{2.5}$ concentration for five months which equates to twelve months (one year) exposure time.

Table 1 Methods of assigning lifetime annual mean weighted $PM_{2.5}$ exposure of a child in μg m^{-3}

ID	Child age in months	Date of Birth		Date of Death/interview		Lifetime weighted $PM_{2.5}$ exposure of a child in μg m^{-3}
		Year	Month	Year	Month	
00016	12	2015	5	2016	5	$(2016PM_{2.5}*5/age) + (2015PM_{2.5}*7/age)$ ** $= (16.39*5/12) + (17.67*7/12) = 17.14$
00037	16	2014	10	2016	2	$(2016PM_{2.5}*2/age) + (2015PM_{2.5}*12/age) + (2014PM_{2.5}*2/age) = (16.39*2/16) + (17.67*12/16) + (15.94*2/16) = 17.29$
00003	55	2011	10	2016	5	$(2016PM_{2.5}*2/age) + (2015PM_{2.5}*12/age) + (2014PM_{2.5}*12/age) + (2013PM_{2.5}*12/age) + (2012PM_{2.5}*12/age) + (2011PM_{2.5}*2/age) = (16.39*5/55) + (17.67*12/55) + (15.94*12/55) + (17.65*12/55) + (19.13*12/55) + (18.01*2/55) = 17.50$

**The EA's where the child belongs to annual mean $PM_{2.5}$ concentration in μg m^{-3}: for the 2011, 2012, 2013, 2014, 2015, and 2016 was 18.01, 19.13, 17.65, 15.94, 17.67, and 16.39 μg m^{-3} respectively.

Data analysis procedures

Description of dependent and independent variables

Prior to analysis any sample were weighted for the complex survey design. Then variables were described and sensitivity analysis was done. **Sensitivity analysis** is a method to check the influence changes in the values of independent variables i.e. of missing values on the bivariate relationship of the independent and dependent variables (91). Proportions across sub-groups and mean and standard deviations (SD) for continuous variables were summarized variables.

Objective 1: Describe the ambient $PM_{2.5}$ concentration across the geographical areas of Ethiopia

Mean annual $PM_{2.5}$ concentration by urban EAs, rural EAs, and administrative regions were mapped and visualized geographically using ArcGIS 10.7. The trend of mean annual $PM_{2.5}$ concentration across regions, urban EAs, and rural EAs was graphed in Microsoft Excel. Using Global Moran's I statistic measure the distribution of mean annual $PM_{2.5}$ was determined whether the distribution was dispersed, clustered, or random. Global Moran's I is a technique that determines the spatial autocorrelation in the values of a specific variable (ambient $PM_{2.5}$ concentration) between different geographic features using location (neighbor) and the values of the variable in each feature as inputs (92). Statistical significance of clustering and outlier analysis as well, as hots and cold spots clustering of the distribution of $PM_{2.5}$, was tested.

Objective 2: Examine the spatial distribution of under-five mortality in Ethiopia

The spatial dependency of the distribution of under-five mortality was diagnosed using spatial autocorrelation in ArcGIS 10.7. Also, using the Getis-Ord Gi* statistic the statistical significance of the clustered under-five mortality was assessed. The hot spots (higher values) and cold spots (lower values) were determined by Z-scores and p-values. The input for this step of the analysis was the proportion of under-five mortality of each EAs. Finally, under-five mortality was interpolated for areas samples were not taken; using the Geostatistical Empirical Bayesian Kriging (EBK) spatial interpolation technique. Compared to other kriging methods EBK automates the difficult part of building a model and computes errors as a result of a semivariogram— a model that determines how similarity in space decreases with distance—derived from features with collected data (93).

Objective 3: Determining the association between ambient $PM_{2.5}$ concentration and under-five mortality in Ethiopia

First, a bivariate logistic regression model was built to assess the association between under-five mortality and lifetime annual mean $PM_{2.5}$ exposure and other controlled variables separately (ANNEX III). Variables that showed a significance level of 15% were considered for the multilevel multivariate model. Second, the degree of variation of under-five mortality among clusters was determined using two methods; compare the statistically significant difference between a null logistic regression and null multilevel logistic regression model, using EAs as random effect intercept. Also, the heterogeneity of under-five mortality among clusters using interclass correlation (ICC) was described. ICC is *"a measure of the* *proportion of variation in the outcome or under-five mortality that occurs between groups or clusters versus the total variation present"*(94).

In the multilevel multivariate logistic regression model, controlled variables have been added to the model step by step. In the order of socio-demographic, child-related, environmental-related, and community level variables were added to the model, respectively. Model assumptions were checked if they were met. The final model was selected by a backward stepwise selection. At each step variable with a significance level of 15% and variance inflation factor (VIF) > 3 (95) was removed from the model. A model with smallest log likelihood and Akaike Information Criterion (AIC) was selected as the final model. **Model specification:** the final model will appear like this;

$$logit\left[\frac{\pi ij}{1-\pi ij}\right] = \beta 0 + \beta 1 PM_{2.5ij} + \beta 2X2ij + \beta 3X3ij + \cdots + \beta nXnij + \cup 0j,$$

Where, i and j are the factor and the cluster, respectively. π_{ij} = Probability of success of under-five mortality; $1-\pi_{ij}$ = Probability of failure of under-five mortality; β_0 = is log odds of the fixed intercept; $PM_{2.5}$, X_{2ij}, X_{3ij}, …, X_{nij} = are independent variables of the individual- and community-level; β_1, β_1, …, β_n = are slope of individual-level and community-level; The quantities uOj is random effect intercept at the cluster. The distribution of $u0j$ is normal with mean 0 and variance σ2u0. The random effect was explained using ICC, which was calculated using between-cluster variance and within-cluster variance [ICC = σu2/ (σu2+ π2/3)].

In this study, all the analyses were performed at the 95% confidence interval and 5% significance level. All statistical tests were two-sided.

Geographical Weighted Regression (GWR)

The above model will only show if the ambient $PM_{2.5}$ is a determinant of under-five mortality without accounting for spatial variation. Here, we will examine if ambient $PM_{2.5}$ is spatially determinant for under-five mortality. Finally, the spatial association of under-five mortality and ambient $PM_{2.5}$ was determined by employing a binomial geographically weighted regression (GWR) model. GWR is a technique that encourages the different spaces in the study area to have their own specific model or allows independent variables to take different coefficient values for different spaces in the study area (30). The parameters were determined using MGWR v 2.2.1 software while parameter interpolation and mapping were performed on ArcGIS v10.7 software. The model specification appears like this:

$$Ln\left(\frac{pi}{1-pi}\right) = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{k,i} + \varepsilon_i$$

Where, $Ln\left(\frac{pi}{1-pi}\right)$ is log odds of under-five mortality; β_0 is the intercept at (u_i, v_i) while (u_i, v_i) is the coordinate of i^{th} point in space; β_k is the coefficient of independent variable – ambient $PM_{2.5}$ – and of covariate $x_{k,i}$ at (u_i, v_i). $x_{k,i}$ is ambient $PM_{2.5}$ and k^{th} covariate at i^{th} point and e_i is the random error term (96). The Koenker (BP) statistic ($p<0.01$) and multicollinearity among controlled variable using VIF < 3 were used.

Data quality and processing

EDHS carried out the monitoring of the interview and measurement process in three stages to ensure the quality of data collection and processing. Re-interview households, check one to two interviewers' questionnaires per data collector, and review periodical field control tables tools were used. To avoid mistakes during data entry, dual entry of information by two different persons, training of data entry personnel, and cleaning of missed values were performed by the EDHS (29).

In this study, a careful dataset merging using dataset "identifier" or common variables, defensive codding while cleaning the data, and data quality parameters were used (90). Furthermore, care was also taken in the choice of the coordinate reference system (CRS) and statistical packages (97).

The annual mean $PM_{2.5}$ from satellite-based measurement and the three land stationed BAM 1022 in Addis Ababa (46) for similar geographical points were compared. A large concentration difference was noticed at Tikur Anbessa Specialized and International Community School. However, a similar concentration level was observed at US-Embassy in Addis Ababa (Table 2). A difference is expected considering validated satellite-based $PM_{2.5}$ has used a small number of land stations in Africa, including Ethiopia. The use of ACAG data is upheld in this study as only three geographic points were used to compare, the absence of $PM_{2.5}$ data covering this large area in the country, and the data has been used in the recent WHO guideline (56) as well as reputed literature (15,76,98).

Table 2 Comparison of land-based $PM_{2.5}$ and geographically weighted satellite-based $PM_{2.5}$ in μgm^{-3} in Addis Ababa for the year 2017

Geographical points in Addis Ababa	BAM land-station $PM_{2.5}$ (2017-2020)	Geographically weighted ACAG $PM_{2.5}$ (2017-2020)
Tikur-Anbessa Specialized hospital	42.4	27.8
US embassy	24.2	27.2
International Community School	34.7	28.7

Ethical consideration

EDHS has passed through the appropriate ethical clearance and made it available for public use. A waiver of informed consent from the DHS archive was acquired. ACAG has made their global estimate of annual mean $PM_{2.5}$ concentration to be accessed and used for free. Furthermore, this study was submitted to and approved by the College of Health Sciences of Addis Ababa University Ethical Review Committee for official procedures.

Dissemination of results

The results of this will be presented at the dissertation defense where Addis Ababa University professors and students attend. It will also be presented at different conferences and symposiums. Moreover, it will be made accessible to various sectors i.e. Ministry of Health and Environmental Protection Agency. The public will be informed about the results at possible events and gatherings. Finally, it will be published in a peer-reviewed journal to be accessible by the scientific community.

Results

Characteristics of respondents

The size of the sample included in this analysis is 10452. Most (88.7%) of the respondents were residing in rural areas (Table 3). The overall children's mother's age mean (SD) was 29.6± 6.6. Children's mothers with ages between 25-29 years old constitute the majority, 29.9%. Most of the children's mother were married (94.9%), not working (55.5%), with no education status (65.6%), and poorest wealth index (23.2%) (Table 4).

Of the total sample size proportion of under-five mortality was 5.4% (95% CI 5.0% – 5.8%). According to respondents, 52% of under-five children were male, 41.6% had average birth weight, 2.5% were twins, and 26.7% were born in institutions. Children's age mean in months was 27.8 ± 18.7, the category >= 24 months constitutes 54.5% (Table 5).

Description of $PM_{2.5}$ concentration exposure

The mean of lifetime annual satellite-based ambient $PM_{2.5}$ exposure among under-five children was 20.1 ± 3.3μg m^{-3}.

Majority (67.2%) of households collect their drinking water within <=30 minutes roundtrip distance. The proportion of households with improved drinking water source, improved toilet facility, and clean fuel was 56.8%, 5.1%, and 3.4% respectively (Table 6).

Table 3 Community level factors of the study participant n=10452

	Complete Sample n=10452	
	n	**%**
Type of place of residence		
Urban	1179	11.3
Rural	9273	88.7
Region		
Tigray	679	6.5
Afar	112	1.1
Amhara	2009	19.2
Oromia	4628	44.3
Somali	351	3.4
Benishangul	115	1.1
SNNPR	2227	21.3
Gambela	25	0.2
Harari	25	0.2
Addis Ababa	238	2.3
Dire Dawa	43	0.4
Child health indicators		
Diarrhea prevalence	1163	11.8
Vaccination coverage	1003	52.8
Nutritional status (stunting)	3521	36.6
Acute Respiratory Infections (ARI)	646	6.5
Fever	1418	14.3

Table 4 Socio-demographic factors of the study participants n=10452

	Complete Sample n=10452	
	n	**%**
Socio-demographic factors		
Age of the mother		
15-24	2271	21.7
25-29	3192	30.5
30-34	2372	22.7
>=35	2617	25.0
Mothers education		
No education	6858	65.6
Primary	2823	27.0
Secondary and above	771	7.4
Mother's current marital status		
Not in union/ not living with a man	535	5.1
In union/ living with a man	9917	94.9
Mother's employment status		
Not working	5806	55.5
Working	4646	44.5
Wealth Index		
Poorest	2428	23.2
Poorer	2373	22.7
Middle	2173	20.8
Richer	1926	18.4
Richest	1552	14.9
Husband's Education		
No education	4739	47.8
Primary	3945	39.8
Secondary and above	1233	12.4
Husband's employment status		
Not working	737	7.4
Working	9180	92.6
Family size (mean ± SD)		
<= three	5078	48.6
Above three	5374	51.4
Sex of household head		
Female	1434	13.7
Male	9018	86.3

Table 5 Individual/child related factors of the study participants n=10452

	Complete Sample n=10452	
	n	**%**
Individual/child factors		
Sex of the Child		
Female	5018	48.0
Male	5434	52.0
Size of child at birth		
Very large	1891	18.1
Large	1466	14.0
Average	4351	41.6
Small	1059	10.1
Very small	1685	16.1
Child age (in months)		
<=12	2823	27.0
12 to 24	1934	18.5
>24	5695	54.5
Birth order		
<=3	5121	49.0
Above three	5331	51.0
Plurality of a child		
Yes	265	2.5
No	10187	97.5
Place of delivery		
Home	7662	73.3
Institution	2790	26.7

Table 6 Environmental related factors of the study participant n=10452

	Complete Sample n=10452	
	n	**%**
Environmental Factors		
Source of drinking water		
Improved	5940	56.8
Unimproved	4512	43.2
Time to fetch (roundtrip in minutes)		
<=30	7018	67.2
>30	3434	32.8
Any kind of household water treatment		
Yes	881	8.4
No	9571	91.6
Type of toilet facility		
Improved	533	5.1
Unimproved	9919	94.9
Type of cooking fuel		
Clean fuel	352	3.4
Solid fuel	10100	96.6
Place where food is cooked		
Outside the house	5978	57.2
Inside but in a separate room	711	6.8
Inside not in a separate room	3763	36.0

Describing ambient $PM_{2.5}$ concentration across the geographical areas of Ethiopia

The trend in PM2.5 concentration across different regions

Afar, Addis Ababa, Amhara, Tigray, Gambela, and Dire Dawa regions showed a consistently higher $PM_{2.5}$ concentration compared to other regions. Afar and Somali regions had the highest and lowest $PM_{2.5}$ concentration across the years, respectively. In 2014, across all regions lower $PM_{2.5}$ concentration was observed (Figure 4). In the years 2011, 2012, and 2013 rural clusters had higher $PM_{2.5}$ concentration than urban clusters while in the years 2014 and 2016 urban areas had higher $PM_{2.5}$ (Figure 5).

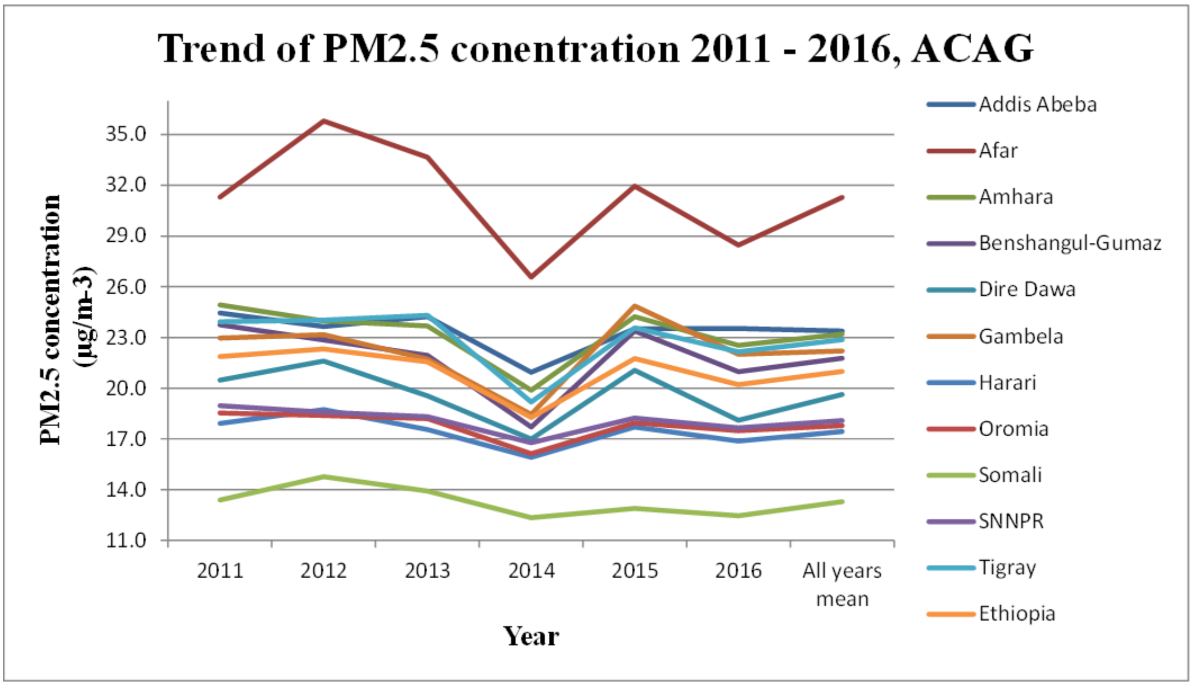

Figure 4: Trends of fine PM concentration in µg m^{-3} across regions in Ethiopia, ACAG

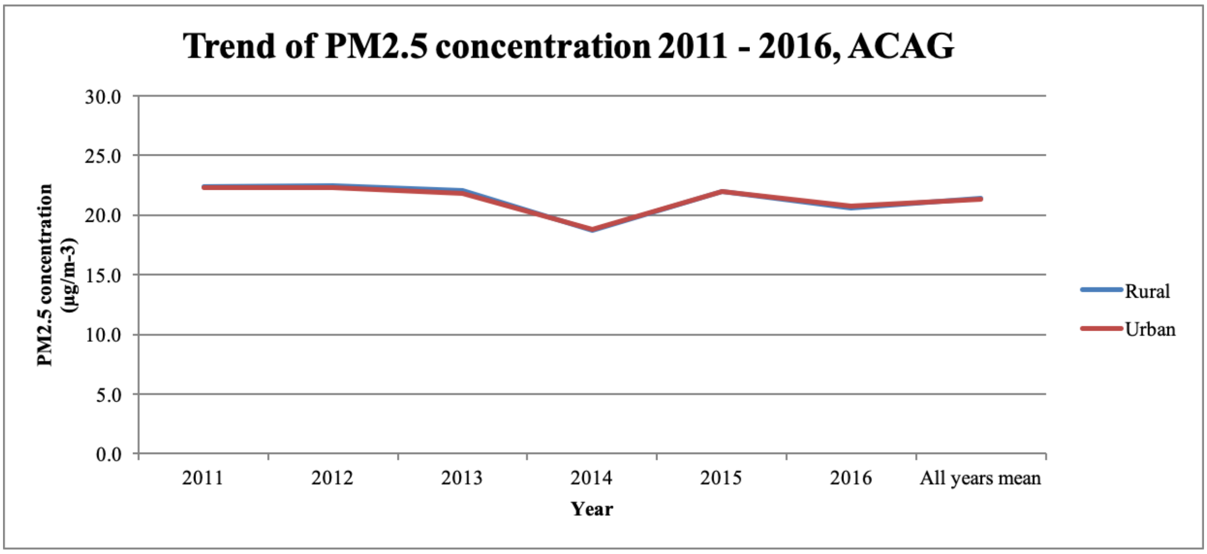

Figure 5: Trends of fine PM concentration in µg m-3 across residence in Ethiopia, ACAG

Spatial distribution of $PM_{2.5}$ concentration

Across the geographical areas of Ethiopia, the annual mean $PM_{2.5}$ concentration is distributed non-random. The six years (2011 - 2016) annual mean $PM_{2.5}$ concentration univariate global Moran's I value was 0.84 (*p*-value = 0.001).

Spatial significance and clustering and outlier analysis of $PM_{2.5}$ concentration

Afar region had the highest annual mean $PM_{2.5}$ concentration (from 2011 - 2016), 31.3 μgm^{-3}, followed by Addis Ababa (23.4 μgm^{-3}), Amhara (23.2 μgm^{-3}), and Tigray (22.9 μgm^{-3}) (Figure 6). Significance spatial dependency in $PM_{2.5}$ concentration was observed in Afar, Eastern Tigray, Eastern and Southeastern Amhara, Somali, Eastern, and Southern Oromia, and Southern SNNPR (Figure 7). Moreover, the higher or clustered $PM_{2.5}$ concentration was in Afar, Eastern Tigray, Eastern and Southeastern Amhara while the lowest or dispersed PM2.5 concentration was in Eastern and Southern Oromia, and Southern SNNPR (Figure 8).

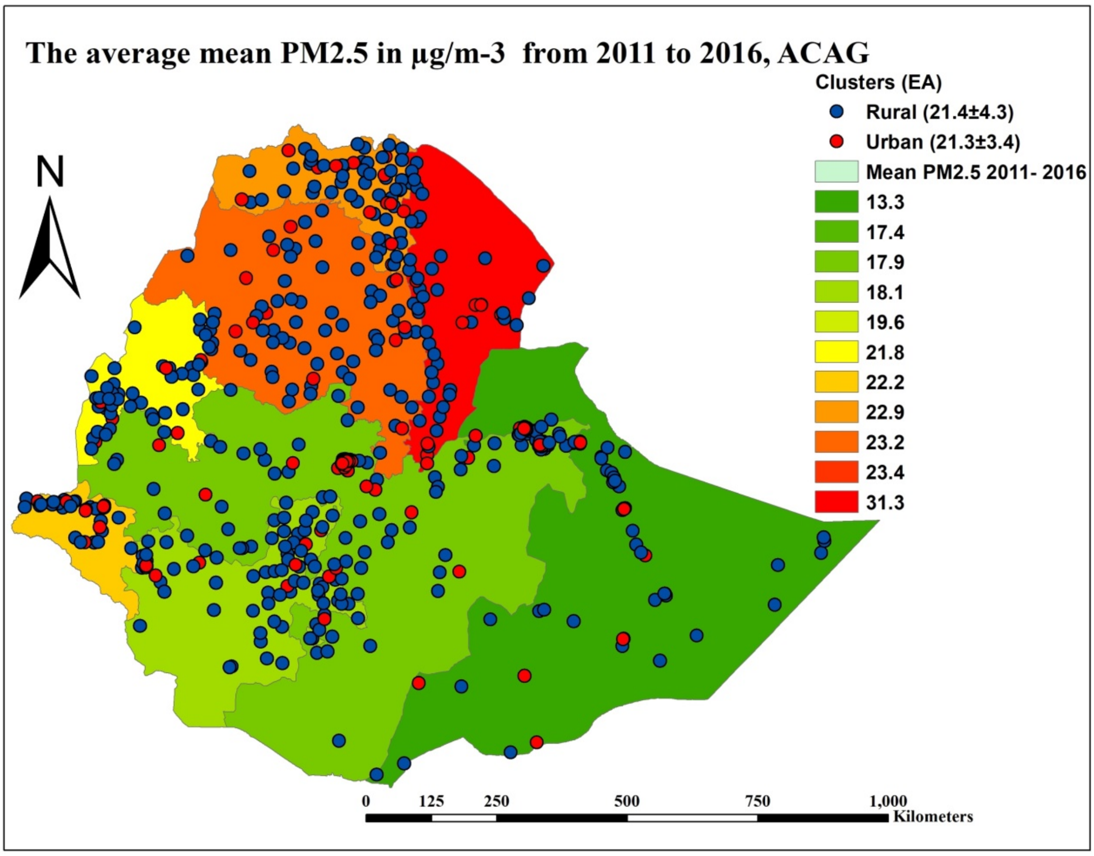

Figure 6: Ethiopia regions and clusters (EAs) average annual mean fine PM concentration in µg m-3 from 2011-2016, ACAG (Source: shapefile from openAFRICA 2013: https://gadm.org/)

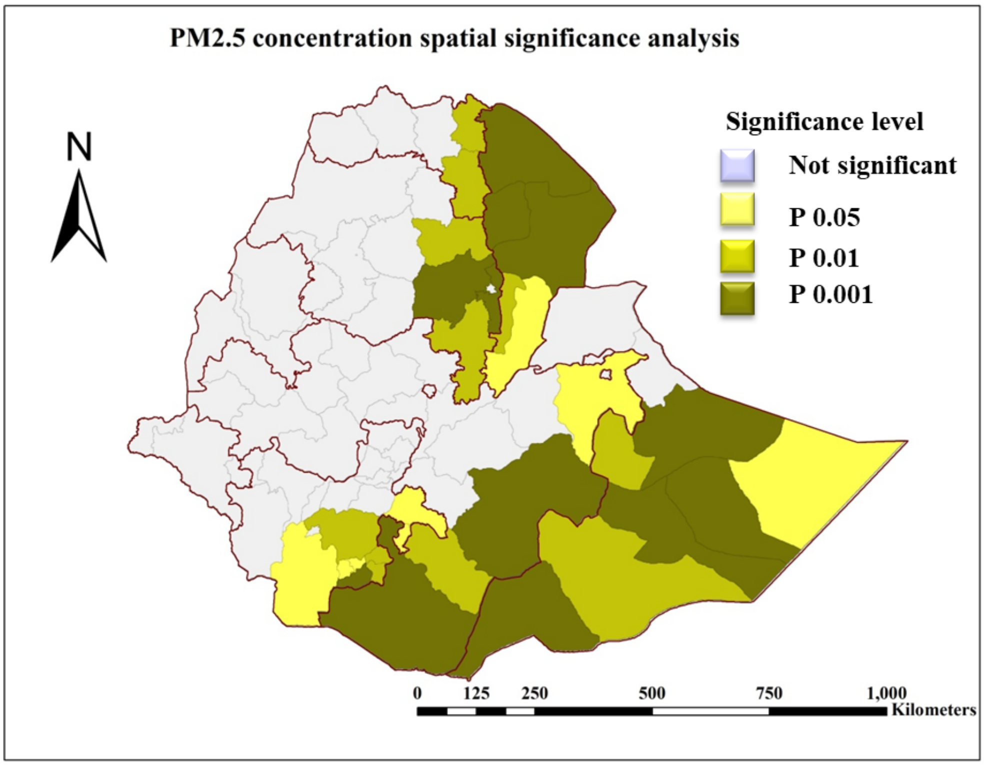

Figure 7: Average annual fine PM concentration spatial dependency significance test, ACAG 2011- 2016 (Source: shapefile from openAFRICA 2013: https://gadm.org/)

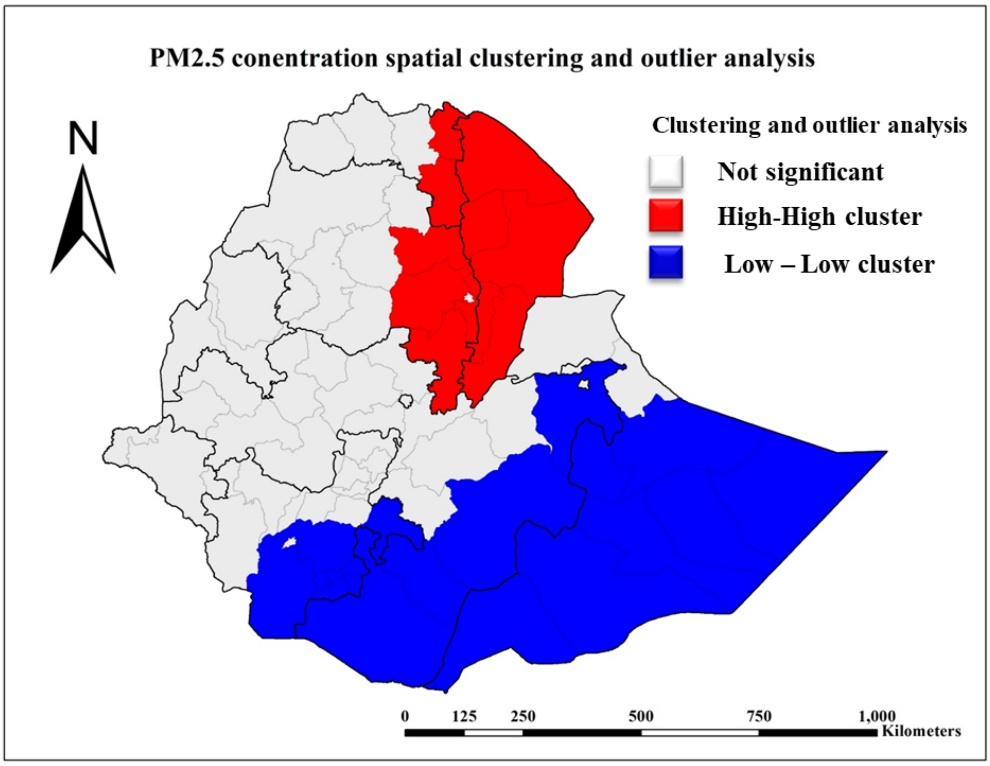

Figure 8: Average annual fine PM concentration spatial clustering and outlier analysis, ACAG 2011- 2016 (Source: shapefile from openAFRICA 2013: https://gadm.org/)

Spatial explorative analysis of under-five mortality in Ethiopia

Spatial distribution of under-five mortality

In Ethiopia, a non-random spatial distribution of under-five mortality was found. In 2016 EDHS, the global Moran's I value was 0.05 with a z-score 4.04 which was significant at a p-value <0.001.

Hot spot analysis

The proportion of under-five mortality was higher in rural clusters, 5.6%, compared with 4.3% in urban clusters. Under-five mortality proportion was also highest in Afar (8.7%), Benishangul (7.4%), Harari (6.9%), Somali (6.4%), and Gambela (6.1%) regions. Furthermore, higher under-five mortality clustering was observed in Eastern Afar, Southwestern Afar - near borders of Amhara, central to southeastern Amhara, West, Central and Southern Benishangul, and Southwestern SNNPR (Figure 9).

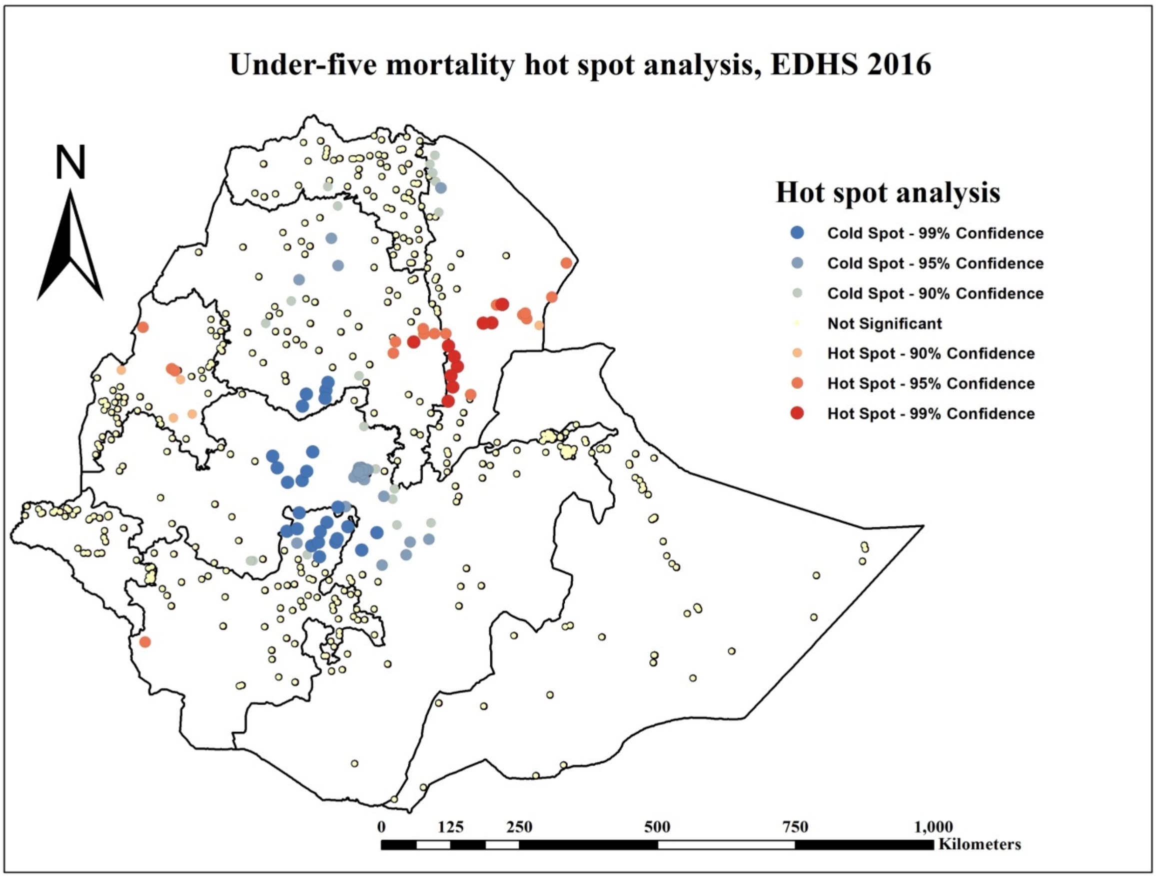

Figure 9: Under-five mortality hot spot analysis in Ethiopia, EDHS 2016 (Source: shapefile from GADM (Database of Global Administrative Areas) 2018: https://gadm.org/)

Clustering and outlier analysis

Clustering with higher under-five mortality surrounded by other clusters with higher under-five mortality was observed in Northern Gambela, Western and Southern Benishangul, Southwestern Oromia, Southwestern Amhara, and Eastern, Central, and Southwestern Afar - near borders of Amhara region. However, clusters with higher under-five mortality surrounded by other clusters with lower under-five mortality were observed in Addis Ababa, Northeastern SNNPR, Central Oromia, Central Amhara, and Eastern Tigray regions (Figure 10).

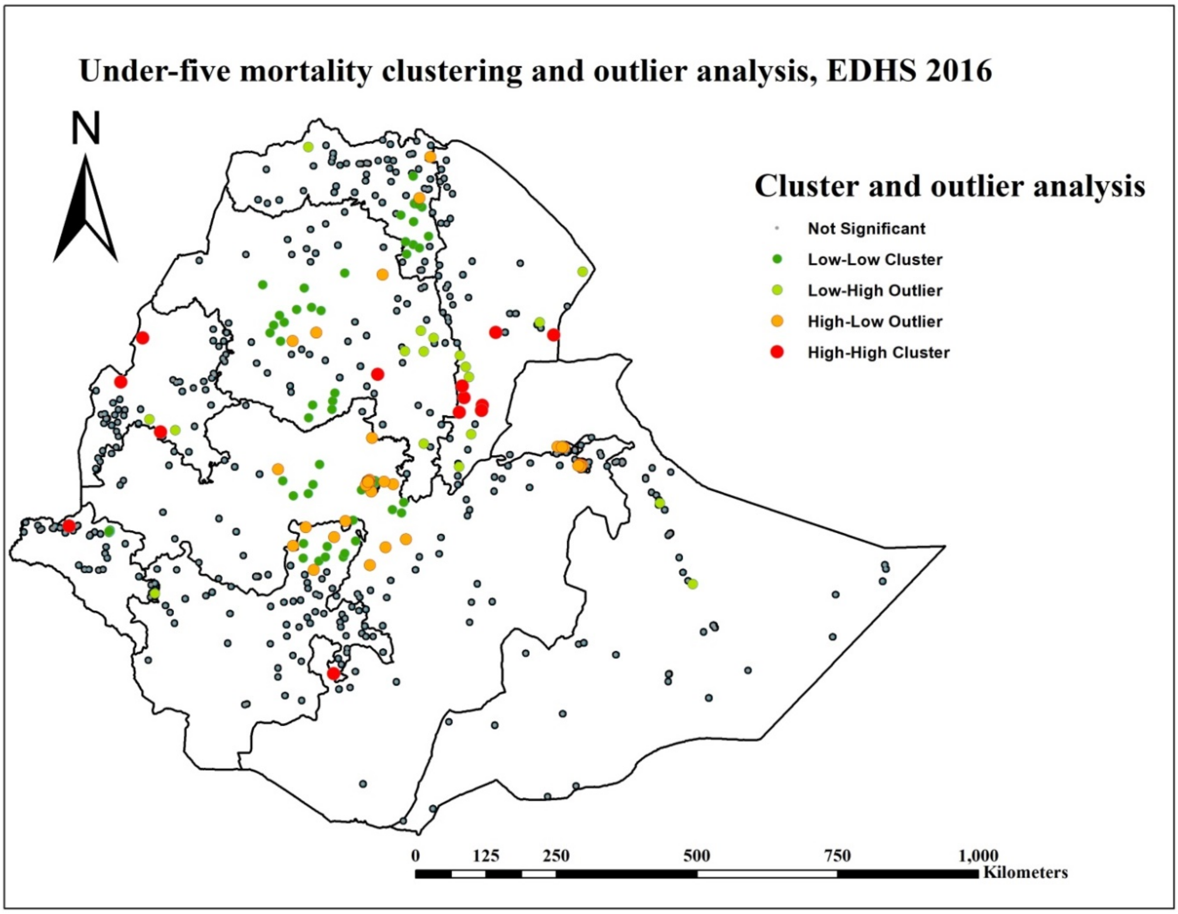

Figure 10: Under-five mortality clustering and outlier analysis in Ethiopia, EDHS 2016 (Source: shapefile from GADM (Database of Global Administrative Areas) 2018: https://gadm.org/)

The interpolated proportion of under-five mortality

EDHS 2016 clusters proportion of under-five mortality was interpolated spatially using the Empirical Bayesian Kriging method. The interpolated proportion of under-five mortality was lower, less than 8.6% in Oromia, Harari, Dire Dawa, and Addis Ababa than in other regions. The interpolated proportion of under-five mortality of higher than 8.6% was detected in

Southern Benishangul, Eastern and Central Afar, Northern and Eastern Somali, Southeastern Amhara, Southwestern SNNPR, Southern Gambela, Central Oromia – Southeastern to Addis Ababa, and Central to Southern Tigray. On the other hand, an under-five mortality proportion of 1.7% or less was observed in Northeastern and Southeastern Tigray, Southern and Central Amhara - around lake Tana, western Gambela, and western and Central Oromia – Eastern to Addis Ababa (Figure 11).

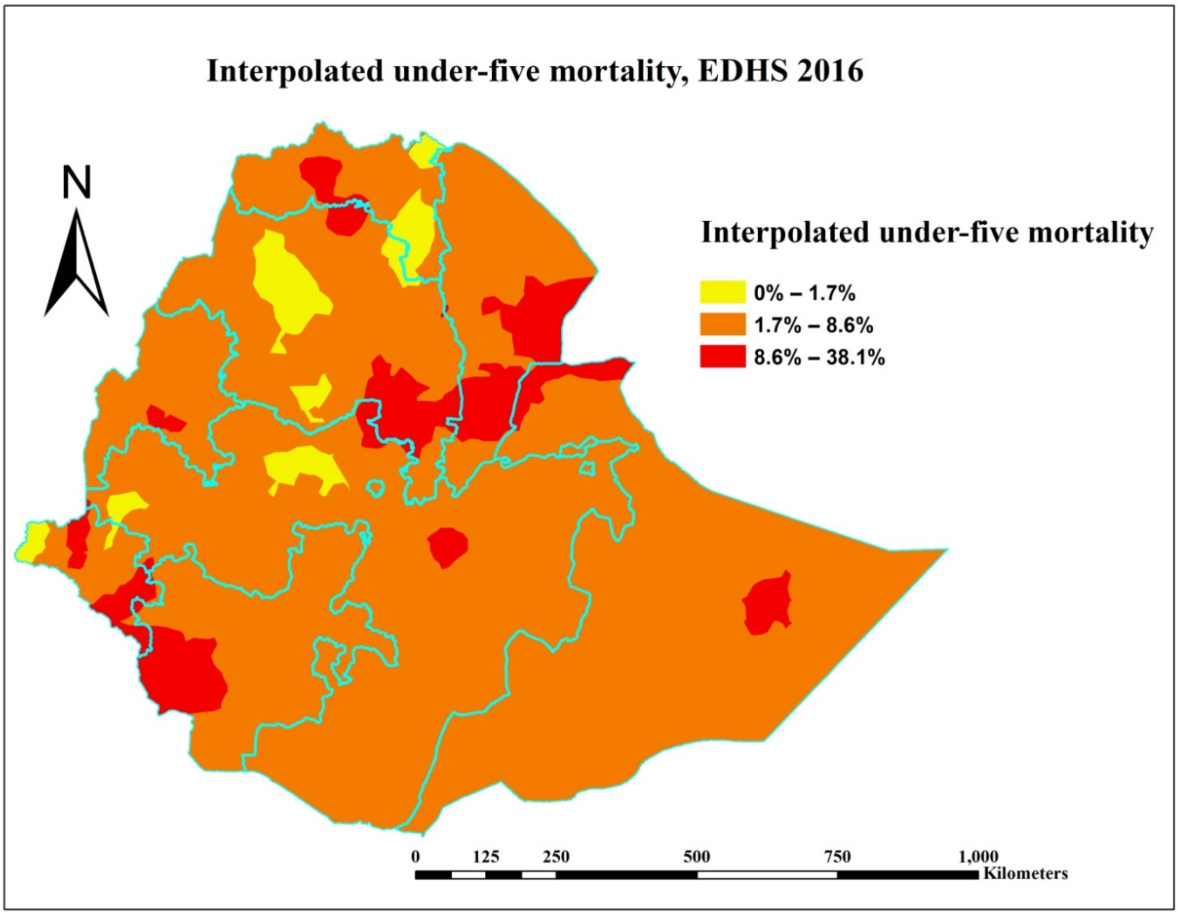

Figure 11: Empirical Bayesian Kriging interpolation of under-five mortality in Ethiopia, EDHS 2016 (Source: shapefile from GADM (Database of Global Administrative Areas) 2018: https://gadm.org/)

Determining the association between ambient $PM_{2.5}$ concentration and under-five mortality in Ethiopia

Bivariate association of independent variables and under-five mortality

The sensitivity analysis, before and after missing values were removed, showed similar results of bivariate analysis between controlled variables and under-five mortality in the presence of $PM_{2.5}$ (Table 7 - 9). A life-time annual mean $PM_{2.5}$ showed a significant association with under-five mortality ($p = 0.001$). Variables that were significant and $p < 0.15$ in the bivariate analysis were included in the multilevel binary logistic regression model.

Table 7 A bivariate associations of socio-demographic and under-five mortality n= 10452

	Complete Sample *n= 10452*		
	Under-five mortality		
	n	**%**	***p***
Socio-demographic factors			
Age of the mother			*0.31*
15-24	2271	5.9	
25-29	3192	5.8	
30-34	2372	5.1	
>=35	2617	6.4	
Mother's education			<0.001*
No education	6858	6.5	
Primary	2823	5.0	
Secondary and above	771	3.8	
Mother's current marital			*0.88*
Not in union/not living with a partner	535	6.0	
In union/living with a partner	9917	5.8	
Mother's employment status			*0.36*
Not working	5806	6.0	
Working	4646	5.6	
Wealth Index			<0.001*
Poorest	2428	7.2	
Poorer	2373	6.1	
Middle	2173	5.3	
Richer	1926	6.1	
Richest	1552	3.3	
Husband's Education			*0.003**
No education	4739	6.6	
Primary	3945	5.5	
Secondary and above	1233	4.4	
Husband's employment status			*0.15*
Not working	737	6.9	
Working	9180	5.7	
Family size (mean)			*<0.001**
<= three	5078	6.9	
Above three	5374	4.7	
Sex of household head			*0.47*
Female	1434	5.5	
Male	9018	5.9	

*used in the multilevel multivariate analysis

Table 8 A bivariate associations of child (individual) and under-five mortality n= 10452

	Complete Sample *n= 10452*		
	Under-five mortality		
	n	%	*p*
Child/individual factors			
Sex of the Child			<0.001*
Female	5018	4.9	
Male	5434	6.7	
Size of child at birth			<0.001*
Very large	1891	6.8	
Large	1466	4.8	
Average	4351	5.0	
Small	1059	5.9	
Very small	1685	7.8	
Child age (in months)			<0.001*
<=12	2823	18.3	
12 to 24	1934	3.6	
>24	5695	0.5	
Birth order			*0.06**
Third and below	5121	5.4	
Fourth and above	5331	6.3	
Plurality of a child			<0.001*
Yes	265	20.4	
No	10187	5.4	
Place of delivery			<0.001*
Home	7662	6.7	
Institution	2790	4.0	

*Used in the multilevel multivariate analysis

Table 9 A bivariate associations of environmental-related and community-level variables and under-five mortality n= 10452

	Complete Sample *n= 10452*		
	Under-five mortality		
	n	%	*p*
Environmental Factors			
Source of drinking water			*0.009**
Improved	5940	5.3	
Unimproved	4512	6.6	
Time to fetch (roundtrip in minutes)			0.02*
<= 30	7018	5.4	
>30	3434	6.6	
Any kind of household water treatment			*0.31*
Yes	881	5.1	
No	9571	5.9	
Type of toilet facility			*<0.01*
Improved	533	3.1	
Unimproved	9919	6.1	
Type of cooking fuel			*<0.001**
Clean fuel	352	2.3	
Solid fuel	10100	6.0	
Place where food is cooked			<0.001*
Outside the house	5978	5.1	
Inside but in a separate room	711	5.0	
Inside not in a separate room	3763	7.6	
Type of place of residence			
Urban	1179	3.1	<0.001*
Rural	9273	6.5	
Region			<0.001*
Tigray	679	3.8	
Afar	112	8.7	
Amhara	2009	4.8	
Oromia	4628	5.5	
Somali	351	6.4	
Benishangul	115	7.4	
SNNPR	2227	5.4	
Gambela	25	6.1	
Harari	25	6.9	
Addis Ababa	238	2.7	
Dire Dawa	43	5.5	
Child health indicators			
Diarrhea prevalence	1163	11.9	0.03*
Vaccination coverage	1003	45.2	<0.001*
Nutritional status (stunting)	3521	36.1	<0.001*
Acute Respiratory Infections (ARI)	646	4.7	0.68
Malaria (Fever)	1418	14.5	0.19

*Used in the multilevel multivariate analysis

Fitting multilevel multivariate logistic regression model

There was a significant difference between the null multilevel model, EAs being the random effect intercept, and the empty generalized linear model (p-value <0.001). The ICC and the random effect intercept variance of the null model were 9.4% and 0.34, respectively.

In the final model, a ten-unit increase in lifetime mean annual exposure to ambient $PM_{2.5}$ was associated with 2.40 [95%CI 1.51 – 3.80] times more odds of being dead, adjusted for all other variables (Table 10).

Moreover, in the final model, a unit increase in the prevalence of malnutrition status (stunting) in the community was associated with higher odds of under-five mortality. Furthermore, under-five children with mothers without formal education, very large birth size, and those that were twins, born at home, with food cooked inside a house without a separate room, and residing in the Somali, Harari, and Dire Dawa regions were more likely to die compared with secondary and above education, large birth size, singletons, institutional delivery, with food cooked outside of the house, and residency of Tigray region, respectively, the results were statistically significant at p-value < 0.05. In contrast, under-five children with family size above three, age between 12 and 24 months, age >= 24 months, and female sex were less likely to die compared with family size <=3, age <=12, and being male under-five children, respectively, the results were statistically significant at p-value < 0.05 (Table 10).

Table 10 Multivariable multilevel logistic regression analysis of $PM_{2.5}$ and other factors association with under-five mortality, EDHS 2016. n=10452

		AOR** 95% CI	AOR*** 95% CI	AOR**** 95% CI
	Under-five mortality (%)	**Mode 2**	**Model 3**	**Model 4**
$PM_{2.5}$ ($\mu g\ m^{-3}$) (mean ± SD)	21.7 ± 5.2	1.34 (1.07, 1.66) *	1.34 (1.08, 1.66) *	2.40 (1.51, 3.80) *
Mother's education				
No education	6.5	1.58 (1.08, 2.31) *	1.85 (1.24, 2.74) *	1.53 (1.00, 2.35) *
Primary	5.0	1.15 (0.78, 1.69)	1.20 (0.80, 1.79)	1.06 (0.69, 1.61)
Secondary and above	3.8	(reference)	(reference)	(reference)
Wealth Index				
Poorest	7.2	2.08 (1.49, 2.89) *		
Poorer	6.1	1.84 (1.29, 2.63) *		
Middle	5.3	1.59 (1.09, 2.32) *		
Richer	6.1	1.95 (1.35, 2.82) *		
Richest	3.3	(reference)	(reference)	(reference)
Family size				
<= three	6.9	(reference)	(reference)	(reference)
Above three	4.7	0.55 (0.46, 0.66) *	0.57 (0.47, 0.71) *	0.58 (0.47, 0.71) *
Sex of the Child				
Female	4.9		0.67 (0.55, 0.81) *	0.66 (0.55, 0.80) *
Male	6.7		(reference)	(reference)
Size of child at birth				
Very large	6.8		1.44 (1.01, 2.05) *	1.46 (1.02, 2.08) *
Large	4.8		(reference)	(reference)
Average	5.0		0.89 (0.65, 1.21)	0.91 (0.66, 1.25)
Small	5.9		0.96 (0.63, 1.44)	0.99 (0.66, 1.51)
Very small	7.8		0.95 (0.67, 1.34)	0.98 (0.69, 1.40)
Child age (in months)				
<=12	18.3		(reference)	(reference)
12 to 24	3.6		0.16 (0.12, 0.21) *	0.16 (0.12, 0.21) *
>24	0.5		0.02 (0.01, 0.03) *	0.02 (0.01, 0.03) *

* Statistically significant at $p < 0.05$
Adjusted for socio-demographic variables * Adjusted for socio-demographic and child-related variables
****Adjusted for socio-demographic, child-related, environmental related, and community level variable
Model 1 was built previously separately for each controlled variable in the presence of $PM_{2.5}$

Table 10 Multivariable multilevel logistic regression analysis of both individual and community level factors associated with under-five mortality, EDHS 2016. n=10452 (continued)

		AOR** 95% CI	AOR*** 95% CI	AOR*** *95% CI
	Under-five mortality (%)	**Mode 2**	**Model 3**	**Model 4**
Plurality of a child				
Yes	20.4		5.71 (3.81, 8.57) *	5.35 (3.55, 8.06) *
No	5.4	(reference)	(reference)	(reference)
Place of Delivery				
Home	6.7		2.48 (1.96, 3.17) *	2.09 (1.61, 2.73) *
Institution	4.0	(reference)	(reference)	(reference)
Place where food is cooked				
Outside the house	5.1	(reference)	(reference)	(reference)
Inside but in a separate room	5.0			1.09 (0.68, 1.75)
Inside not in a separate room	7.6			1.36 (1.09, 1.72) *
Type of residence				
Urban	3.1	(reference)	(reference)	(reference)
Rural	6.5			1.41 (0.95, 2.11)
Region				
Tigray	3.8	(reference)	(reference)	(reference)
Afar	8.7			0.80 (0.47, 1.37)
Amhara	4.8			0.79 (0.49, 1.30)
Oromia	5.5			1.19 (0.75, 1.87)
Somali	6.4			2.94 (1.58, 5.44) *
Benishangul	7.4			1.51 (0.95, 2.43)
SNNPR	5.4			1.34 (0.83, 2.15)
Gambela	6.1			1.47 (0.87, 2.47)
Harari	6.9			2.22 (1.27, 3.9) *
Addis Ababa	2.7			1.15 (0.54, 2.48)
Dire Dawa	5.5			2.10 (1.19, 3.74) *
Child health indicators				
Nutritional status (Stunting)				2.21 (1.08, 4.54) *
Random effects				
ICC in %		**7.6**	**5.9**	**5.1**
Model Comparison				
Log likelihood		**-2130.6**	**-1582.8**	**-1565.5**

* Statistically significant at $p < 0.05$
Adjusted for socio-demographic variables * Adjusted for socio-demographic and child-related variables
**** Adjusted for socio-demographic, child-related, environmental related, and community level variable
Model 1 as built previously separately for each controlled variable in the presence of $PM_{2.5}$

Geographically weighted regression

A binomial GWR model was fitted to determine factors that are spatially associated with under-five mortality. Compared to the previous multilevel model, the GWR model had a lower AIC value, 1342.3. In the analysis, mean annual lifetime ambient $PM_{2.5}$ (figure 13), very large birth size, twins, and born at home were positively while family size >=3, female sex, age between 12 and 24 months, and age >=24 months were negatively spatially associated with under-five mortality. The analysis was statistically significant.

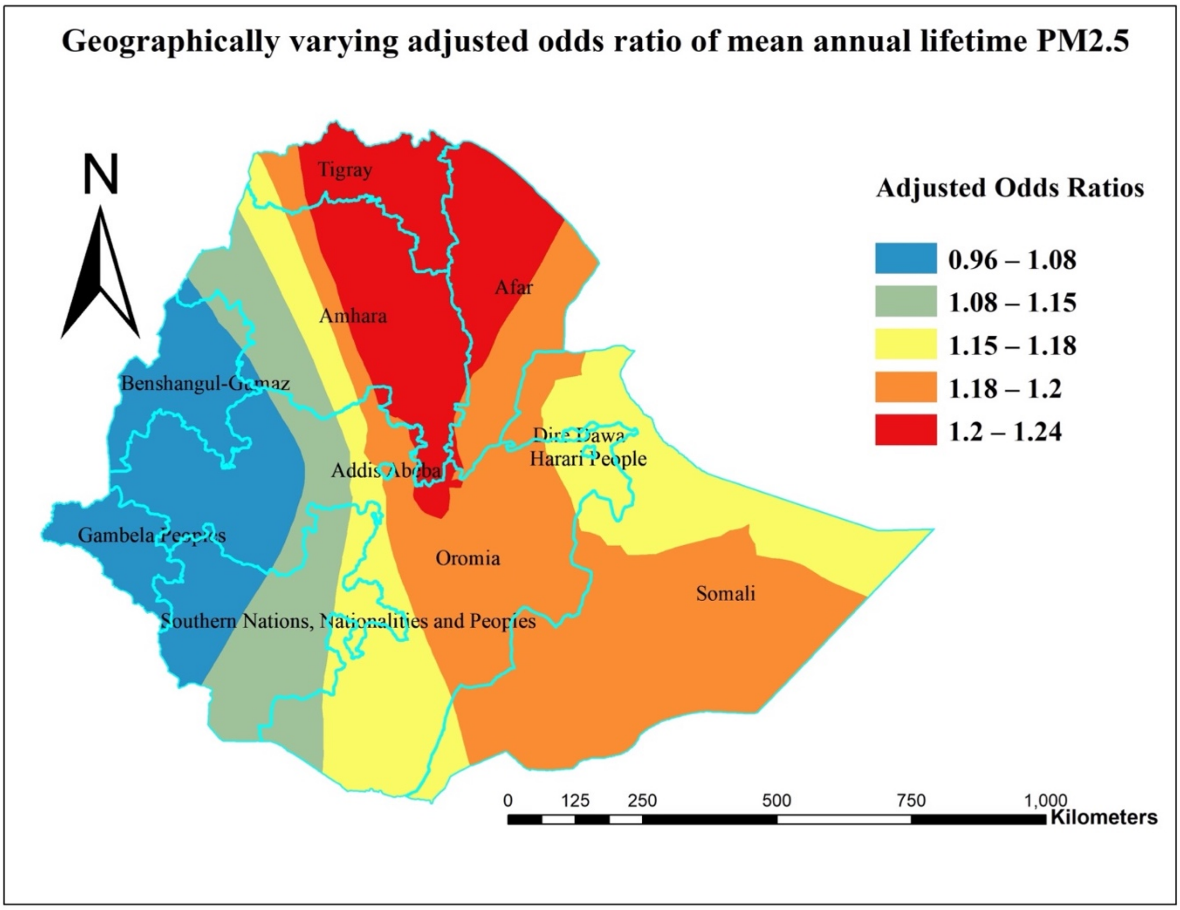

Figure 12 The geographically varying AOR of mean annual lifetime fine PM on under-five mortality in Ethiopia 2016 (Source: shapefile from GADM (Database of Global Administrative Areas) 2018: https://gadm.org/)

Discussion

In this study, 10452 under-five children were included in the final analyses. In the 2016 EDHS, 5.4% of under-five children died during the period among those born between 2011 and 2016. The mean annual satellite-based ambient $PM_{2.5}$ exposure of children in their lifetime was 20.1 ± 3.3 μgm^{-3}. The spatial distribution of satellite-based ambient $PM_{2.5}$ concentration and under-five mortality were non-random. Overall, all regions, in all years, had an annual mean $PM_{2.5}$ concentration higher than the WHO recommendation, 10 $\mu g\ m^{-3}$. In the Eastern and Southeastern Amhara, Eastern Tigray, and Afar areas there was a significant spatial dependency in higher $PM_{2.5}$ concentration was observed. Under-five mortality proportion, on the other hand, hotspots were identified in Eastern Afar, Southwestern Afar – near the borders of Amhara, central to southeastern Amhara, West, Central, and Southern Benishangul, and Southwestern SNNPR. Furthermore, adjusted for other variables, a 10 μgm^{-3} increase in ambient $PM_{2.5}$ was significantly correlated with 2.34 times more odds of being dead. In addition, children with with food cooked outside of the house, mothers without formal education, very large birth size, twins, and born at home were found to be significantly and positively associated with under-five mortality. On the contrary, family size above three, age between 12 and 24 months, age >= 24 months, and female sex were significantly and negatively associated with under-five mortality.

This study's result, a consistent above 10μgm^{-3}—the WHO recommendation for mean annual ambient $PM_{2.5}$ concentration—across all regions, was coherent with previous studies in developing countries like China (24) and Africa (1,32). Higher levels of ambient $PM_{2.5}$ is expected with fast population growth (39,99), the use of solid fuel for cooking (39), and limited air quality monitoring and control measures (21). The almost similar annual mean $PM_{2.5}$ between urban and rural clusters might be because areas that are not much different, in terms of the $PM_{2.5}$ polluting sources, from rural areas are included the urban category. According to the Ethiopian Central Statistics Agency 1984, areas above with a population of 2000 and above are considered urban areas (100).

The high clustering of satellite-based ambient $PM_{2.5}$ in Eastern and Southeastern Amhara, Eastern Tigray, and Afar areas might be attributed to the country's major import-export highway route passing through these areas (101). A one-year study with weekly $PM_{2.5}$ sampling (n=62) in Addis Ababa indicated traffic flows contributed to 28% of the mass of PM, which perhaps might be aligned with the sources of import-export highway vehicles (102). Also, due to the $PM_{2.5}$ nature of regional pollutant, it is transported to other nearby areas (39). The transport sector is one of the major contributors to the increasing ambient $PM_{2.5}$ (98). In Afar and Eastern Tigray, in particular, the consumption of agricultural residues (animal dung and crop stalks and stubbles) as cooking fuel is higher due to the scarcity of woody biomass (103). Biomass sources (18.3%) are the second biggest contributors to $PM_{2.5}$ in Addis Ababa (102). Afar region is a relatively arid area with less tree coverage and is home for the Danakil desert. Desert areas like Danakil desert, semi-arid, and arid areas are known to be hit by sand and dust storms with a potential to reach neighboring regions or even countries (104). Dust and sands are the major sources as well as constituents of $PM_{2.5}$ (22,39,102). However, the authors still believe further investigation into the country-specific sources and drivers of $PM_{2.5}$ is needed.

Most of the identified hotspots in under-five mortality proportion were around the district, regional, or international border areas (Eastern Afar, Southwestern Afar - near the borders of Amhara, central to southeastern Amhara, West, Central, and Southern Benishangul, and Southwestern SNNPR). Similarly, previous studies demonstrated the spatial disparity of under-five mortality in India (105) and Lesotho (106). Promotion of health and ease of access to health care facilities around borders, especially cross-border access— an important determinant of under-five mortality— is highly limited (107). Strong policy improvement and health service access mapping are important (108). Authors are convinced additional investigations in the hotspot and cold-spot areas would clarify the inherent spatial disparities in the proportion of under-five mortality.

A significant association of a $10\mu gm^{-3}$ increase in ambient $PM_{2.5}$ and under-five mortality, in this study, is consistent with previous studies in India (109), Asia (69,110), and sub-Saharan Africa (76). However, there is a difference between this study's estimated effect sizes—2.40 (95% CI 1.51 – 3.80) increase in odds of under-five mortality with a ten unit increase in lifetime annual mean $PM_{2.5}$ concentration adjusted for other variables—and other studies (14,70). This might be attributed to the use of different definitions—death per 1000 live births—, separate estimations for the different types of $PM_{2.5}$, and differences in adjusted variables. It may also be because the estimate by Karimi and Shokrinezhad (70) is a pooled estimate and the majority of studies included were from the developed nations. The magnitude of the effect of $PM_{2.5}$ on under-five mortality is higher among developing and least developed countries compared to developed countries (111). Fine particulate matter, as a result of its smaller diameter size, can penetrate the blood-gas barrier. This allows the different chemical constituents of $PM_{2.5}$ to circulate in the blood system and reach different organs of humans (38). Especially, $PM_{2.5}$ deposition in children is higher due to their fast breathing, lower nasal filtration, higher metabolic rate, and limited ability to metabolize toxic pollutants (6). Different substances, i.e. organic matter, elemental carbon, soil dust, sulfate, nitrate, and ammonium ions form $PM_{2.5}$ although it varies from place to place (36). Nephrotoxic heavy metals—chromium and cadmium—components of $PM_{2.5}$ reach the kidney to affect its function (82), which might lead to death. $PM_{2.5}$ is also associated with notable under-five mortality killer diseases pneumonia (1,8,12) and ARI (12,112,113).

Environmental-related variables—the type of drinking water source, toilet facility, and cooking fuel— were not significant in the final model. The following reasons could be the important factors that come into play. First, not all sources labeled as improved drinking water are free of fecal or disease-causing organisms (114). Second, reintroduction of microbes into the drinking water during collection by contaminated hands, containers, utensils, and/or insects (115,116). Finally, households with improved drinking water may not necessarily have improved toilet facility or vice versa (117). Even after access to improved facilities the quality is influenced by human behavior, i.e. hand washing, personal hygiene, and consistent use of improved facilities (115,116). Similarly, the use of clean fuel does not mean households are well ventilated and indoor air relatively acceptable (118). This study supports the statement. Cooking food inside a house with no separate room, a proxy to ventilation, was associated with the higher odds of under-five mortality.

Adjusted for other variables, under-five children residing in Dire Dawa, Harari, and Somali regions were significantly more likely to die than under-five children residing in the Tigray region. In Dire Dawa and Harari, in particular, a relatively lower mortality was expected as the majority of the regions were urban settings. This might be because of the existing highest, pastoral residents in these regions and development projects were challenging, existing cultural beliefs requiring the hiding of children for the first 40 days, and poor health service promotion (119).

Strengths and limitations

The study provides insights into the relationship between ambient $PM_{2.5}$ concentration level and under-five mortality at the individual level for the first time, to the best of our knowledge, in Ethiopia. The study overcame the absence of ground-level ambient $PM_{2.5}$ concentration data by using a freely available satellite-based estimate of ACAG. The study explored and determined the areas with significant spatial dependency in the distribution of ambient $PM_{2.5}$ concentration and under-five mortality. Also, interpolation and identification of areas with clustering under-five mortality across the geographical areas of Ethiopia were performed. Furthermore, the study employed GWR analysis which enabled us to determine factors that were significant for specific geographical areas. The study is limited in accounting for indoor stay ($PM_{2.5}$ exposure from indoor air was not quantified) and movement of children from place to place in determining exposure to ambient $PM_{2.5}$. In other words, the exposure to ambient $PM_{2.5}$ was computed with the assumption that study participants had never left their place of residence. Another limitation is the information on the hours covered in a day and days covered in a month to estimate the annual satellite-based $PM_{2.5}$ was not provided with dataset. It is also limited in not using ground-based $PM_{2.5}$ nor making adjustments to the retrieved satellite-based $PM_{2.5}$. Currently, ground-based data is assumed to be a gold standard relative to satellite-based data.

Conclusions

This study determined the five-year (2011 to 2016) proportion of under-five mortality 5.4% and the mean annual satellite-based ambient $PM_{2.5}$ exposure of children in their lifetime was 20.1 ± 3.3 µgm-3. All regions showed mean annual $PM_{2.5}$ concentration >10µgm^{-3} from the years 2011 to 2016. Significant spatial disparity and clustering of the distribution of ambient $PM_{2.5}$ concentration and the proportion of under-five mortality were observed. Significant spatially clustered mean annual $PM_{2.5}$ concentration was observed in the Eastern and Southeastern Amhara, Eastern Tigray, and Afar areas. Under-five mortality proportion was found to be spatially clustered in the Eastern Afar, Southwestern Afar - near borders of Amhara, central to Southeastern Amhara, West, Central, and Southern Benishangul, and Southwestern SNNPR, it was statistically significant. A ten-unit increase in ambient $PM_{2.5}$ was significantly correlated with higher odds of under-five mortality, adjusted for other variables. Children with food cooked inside a house but not in a separate room, mothers without formal education, very large birth size, twins, and born at home were significantly related with more odds of under-five mortality. However, family size above three, age between 12 and 24 months, age >= 24 months, and female sex were significantly related with smaller odds of under-five mortality.

The authors recommend improvement in the rigorous satellite-based $PM_{2.5}$ estimation using the existing ground-based measurements in Ethiopia. It is also important to examine sources of ambient $PM_{2.5}$ and the magnitude of their contribution in areas where $PM_{2.5}$ concentration is clustered. Investigations on the reasons behind regions where $PM_{2.5}$ is highly associated with mortality and clustering of under-five mortality exists would be invaluable. It is also recommended to study which constituents of ambient $PM_{2.5}$ are greatly influencing under-five mortality. Moreover, the installation of more ground-level $PM_{2.5}$ monitoring devices is recommended.

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Annex

I. A tool used to download EDHS 2016 data from DHS program

- **EDHS 2016 data was downloaded from the DHS program official website. https://dhsprogram.com/**

S.N.	Activity	Website	Time of completion
1	**Create DHS account**	https://dhsprogram.com/data/new-user-registration.cfm	Already done
2.	**Register for dataset access**	https://dhsprogram.com/data/dataset_admin/index.cfm?action=createproject	June/2021

The data registration form to be completed online		
***Project title:**	Assessment of satellite-based ambient pm2.5 in relation to under-five children mortality in Ethiopia	
***Co-researchers:**		
name	**Email address**	
Abera Kumie (PhD)	aberakumie2@yahoo.com	
Worku Tefera (MPH, PhD. candidate)	workutefera2000@yahoo.com	

***Description of Study**:	Please provide a 1 paragraph abstract text describing how you plan to use the DHS data. Include the analysis you propose to perform with the data. This is required to obtain authorization. Applications without sufficient detail in the abstract text will be rejected. **The description must be at least 300 characters but no more than 2500.**

Particulate matter below 2.5 µm diameter ($PM_{2.5}$) has importance as an integrant of air pollution and its adverse effect on health. Data on exposure to ambient $PM_{2.5}$ is not well monitored in Africa in consequence of resource and skilled manpower. And, the effect of $PM_{2.5}$ on health is least explored in Africa including Ethiopia. The study will assess the relationship between satellite-based ambient $PM_{2.5}$ and under-five mortality in Ethiopia. The study will use the data from Ethiopian Demographic Health Surveys (EDHS) conducted in 2016. All under-five children with the child mortality information – the dependent variable – and covariates i.e. child specific characteristics, mother's socio-economic factors, source of drinking water, type of toilet facilities and cooking fuel, and information whether the toilet is shared or not will be included. Satellite-based ambient $PM_{2.5}$ will be extracted from the Atmospheric Composition Analysis Group (ACAG) dataset. Description of variables will be done using mean and proportions for continuous categorical variables, respectively. The relationship between satellite-based ambient $PM_{2.5}$ and under-five mortality will be determined by multilevel multivariate logistic regression. The random effects will be Enumeration Areas (EAs). To investigate if $PM_{2.5}$ is spatially associated with under-five mortality geographical weighted regression (GWR) will be used. The statistical analysis will be run at a 95% confidence interval (CI), two-sided p-values, and odds ratio (OR) on R v3.6.3 and Q-GIS v3.8 software.

***Choose Region:**	**Sub-Saharan Africa**
Select Country dataset	**Ethiopia**

A tool used to download EDHS 2016 data from DHS program

S.N.	Activity		Time of completion
The data registration form to be completed online			
If you want to see GPS datasets click a "Show" hyperlink below.		Show GPS datasets	
☑ **You have accepted the conditions of use for The DHS Program datasets**			
Justifications for using the DHS program geographic datasets (minimum 100 characters)		The $PM_{2.5}$ concentration level is provided by locations. Using the DHS program GPS datasets will allow determining the under-five children's ambient $PM_{2.5}$ exposure level.	

II. A tool used to download ACAG $PM_{2.5}$ data from the ACAG group website

The group does not request any registration or request for dataset access. Thus, the satellite-based $PM_{2.5}$ data was downloaded just by visiting the http://fizz.phys.dal.ca/~atmos/martin/?page_id=140 website and looking for the appropriate year annual $PM_{2.5}$ concentration data. The site generally provides free PM data for the global locations downloaded in a raster file format.

III. Models built in the order of analysis

Model 1: bivariate logistic regression model

a) Determining the bivariate association between under-five mortality and lifetime mean annual $PM_{2.5}$

$$logit\left[\frac{\boldsymbol{\pi}}{1-\boldsymbol{\pi}}\right] = \beta 0 + \beta 1 PM_{2.5}$$

b) Add each controlled variable separately to the above model "a"

$$logit\left[\frac{\boldsymbol{\pi}}{1-\boldsymbol{\pi}}\right] = \beta 0 + \beta 1 PM_{2.5} + \beta 2 mage$$

$$logit\left[\frac{\boldsymbol{\pi}}{1-\boldsymbol{\pi}}\right] = \beta 0 + \beta 1 PM_{2.5} + \beta 2 meducation$$

$$logit\left[\frac{\boldsymbol{\pi}}{1-\boldsymbol{\pi}}\right] = \beta 0 + \beta 1 PM_{2.5} + \beta 2 moccupation$$

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$$logit\left[\frac{\boldsymbol{\pi}}{1-\boldsymbol{\pi}}\right] = \beta 0 + \beta 1 PM_{2.5} + \beta 2 X_i$$

Where, $\boldsymbol{\pi}$ = Probability of success of under-five mortality;

$1 - \boldsymbol{\pi}$ = Probability of failure of under-five mortality;

$PM_{2.5}$ = lifetime mean annual exposure in microgram per cubic meter;

$X_i =$ a controlled variable (individual or community level)

β_0 = is log odds of the intercept:

$\beta 1$ = the slope (coefficient) of $PM_{2.5}$;

$\beta 2 =$ the slope coefficient of the controlled variable

Null model:

$$logit\left[\frac{\boldsymbol{\pi}_{ij}}{1-\boldsymbol{\pi}_{ij}}\right] = \beta 0 + \cup 0j$$

Where, $\boldsymbol{\pi}_{ij}$ = Probability of success of under-five mortality;

$1 - \boldsymbol{\pi}_{ij}$= Probability of failure of under-five mortality;

$\beta 0$ = is log odds of the fixed intercept;

$\cup 0j$ = random effect intercept at the cluster

Model 2: Multilevel multivariate logistic regression

$$logit \left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta 0 + \beta 1 PM_{2.5ij} + \beta 2 X2_{ij} + \beta 3 X3_{ij} + \cdots + \beta nXnij + \cup 0j$$

Where, i and j are the factor and the cluster, respectively.

π_{ij} = Probability of success of under-five mortality;

1-π_{ij} = Probability of failure of under-five mortality;

β_0 = is log odds of the fixed intercept;

$PM_{2.5}$,

X_{2ij}, X_{3ij}, …, X_{nij} = are controlled variables of the socio-demographic variables; β_1, β_1, …, β_n = are slope of socio-demographic variables;

The quantities uOj is random effect intercept at the cluster.

Model 3: Multilevel multivariate logistic regression

$$logit \left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta 0 + \beta 1 PM_{2.5ij} + \beta 2 X2_{ij} + \beta 3 X3_{ij} + \cdots + \beta nXnij + \cup 0j$$

X_{2ij}, X_{3ij}, …, X_{nij} = are controlled variables of the socio-demographic and child-related variables; β_1, β_1, …, β_n = are slope of controlled variables of the socio-demographic and child-related variables;

Model 4: Multilevel multivariate logistic regression

$$logit \left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta 0 + \beta 1 PM_{2.5ij} + \beta 2 X2_{ij} + \beta 3 X3_{ij} + \cdots + \beta nXnij + \cup 0j$$

X_{2ij}, X_{3ij}, …, X_{nij} = are controlled variables of the socio-demographic, child-related, environmental-related, and community-level variables;

β_1, β_1, …, β_n = are slope of controlled variables of the socio-demographic, child-related, environmental-related, and community-level variables;

The distribution of *u0j* is normal with mean 0 and variance σ2u0. The random effects was explained using ICC, which was calculated using between-cluster variance and within-cluster variance [ICC = σu2/ (σu2+ π2/3)].

In this study, all the analyses were performed at the 95% confidence interval and 5% significance level. All statistical tests were two-sided.

Declaration

I, the undersigned declare that this thesis is my original work in partial fulfilment of the requirement for the degree of Master of Public Health. I also declare that it has never been presented in this or any other university and that all resources and materials used in the thesis have been duly acknowledged.

Name of the student: Ashenafie Bereded Shiferaw

Signature: 

Place of Submission: Addis Ababa University School of Public Health

Date: May, 2022

This thesis has been submitted with my approval as a university advisor

Advisor name: ____

Signature: ____

Date of Submission: ____