Human health risks of exposure to fine particles ($PM_{2.5}$) from the gold mine tailings in the community of eMbalenhle, South Africa

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Executive summary

South Africa is home to some of the world's largest gold mines and contributes significantly to global gold production. However, gold mining activities generate waste in the form of soil, which is stored as Tailing Storage Facilities (TSFs). Gold mine TSFs are a source of ambient $PM_{2.5}$. $PM_{2.5}$ is particulate matter with a diameter of 2.5 micrometers or smaller. Epidemiological studies have found that exposure to fine particulate matter ($PM_{2.5}$) poses potential human health risks. The human health risks posed by exposure to $PM_{2.5}$ include respiratory, cardiovascular and cerebrovascular diseases. $PM_{2.5}$ and heavy metals are transported from their sources to receptors. Mining activities are also a source of heavy metals in nearby soils. The most common heavy metals found in soil are Lead (Pb), Mercury (Hg), Cadmium (Cd), Manganese (Mn), Nickel (Ni), Zinc (Zn) and Arsenic (As). The heavy metals find their way to the ground, thus contaminating the soil.

This study aimed to assess the potential human health risks associated with exposure to $PM_{2.5}$ in the community of eMbalenhle which is near gold mine TSFs. The study was divided into four objectives, 1) to assess the $PM_{2.5}$ spatial and temporal variations at the source (TSFs) and receptor (community), 2) to determine the atmospheric dispersion of $PM_{2.5}$ emissions from gold mine TSFs to nearby communities, 3) to determine the concentrations of heavy metals in the soils collected within the mining area and identifying their sources, 4) to assess the potential human health risks associated with exposure to $PM_{2.5}$ in the community of eMbalenhle.

Ambient $PM_{2.5}$ concentrations were monitored over a year (07 February 2022 to 07 February 2023) using Clarity Node-S Low-Cost Monitors (LCMs). Meteorological data (wind speed, wind direction, solar radiation, atmospheric radiation, rain, relative humidity, and temperature) for the same period were sourced from the South African Air Quality Information System (SAAQIS). Statistical analyses were performed using the Openair packages in R Studio (version 4.0.2) and Stata software (version 18). The American Meteorological Society Environmental Protection Agency Regulatory Model (AERMOD), coupled with meteorological information from the Weather Research Forecasting (WRF) model, was applied to predict the ground-level concentrations of $PM_{2.5}$.

The Inductively Coupled Plasma Mass Spectrometry (ICP-MS) method was used to analyze the heavy metals in the soil samples. The samples were prepared in a 1% Nitric Acid (HNO_3) matrix. About 0.5% Hydrochloric acid (HCl) was routinely added to soil samples to ensure the

stability of the heavy metals. The Absolute Principal Components Score - Multiple Linear Regression (APCS-MLR) Model was used to calculate the contribution rate of the heavy metals at each sampling point. The Enrichment Factor (EF) and Contamination Factor (CF) were calculated to determine whether the heavy metals in the soil samples originated from natural sources or were influenced by anthropogenic activities. The Upper Earth's Crust (UEC) values were used as the soil background values of heavy metals. Mn was chosen as the reference element. The Probabilistic Human Health Risk Assessment (PHHRA) was applied to estimate cancer risks in four population subgroups (toddlers, children, adults and elderly).

The results showed that $PM_{2.5}$ concentrations were higher in Winter and lower in Summer at both the community site and gold mine TSFs. The average daily (24-hour) $PM_{2.5}$ concentrations at the community site and gold mine TSFs were 19.24 and 9.70 µg/m³, respectively. The daily $PM_{2.5}$ concentrations at the community site exceeded the South African National Ambient Air Quality Standard (NAAQS) of 40 µg/m³ twenty-six (26) times and the World Health Organisation (WHO) guidelines of 15 µg/m³ hundred and eighty-one times (181) times. The daily (24-hour) NAAQS was not exceeded at the gold mine TSFs; however, the WHO guideline was exceeded 85 times. Although the higher $PM_{2.5}$ concentrations were recorded in the community compared to the gold mine TSFs, local $PM_{2.5}$ sources could have contributed to the elevated concentrations. The dispersion model indicated a maximum $PM_{2.5}$ 24-hour average concentration of 11ug/m³ and; maximum annual average of 3.4 ug/m³ at the 99th percentile (worst-case scenario). The predicted concentrations were below both the national, Environmental Protection Agency (EPA) NAAQS and World Health Organization (WHO) guidelines.

The mean Cr, As, Pb, U, and Au concentrations were higher in TSFs (89.2±58.8, 22.9±25.7, 10±10, 5.72±4.78, and 0.53±0.54 mg/kg) compared to residential sites (79.7±24.6, 2.6±1,33, 8.98±5.05,1.55±1.42, and 0.08 ±0.07 mg/kg), respectively. There were a significant difference in Mn concentrations (rrb = 0.833, p = 0.038) between the residential sites and TSFs. Results of the APCS-MLR of the heavy metals concentrations at the TSFs sites indicated that Au (92.7%), As (93.3%), U (93.3%) and Cr (88.3%) mainly originated from mining activities. The study findings confirmed that TSFs are basically waste soil and may have affected the surroundings.

The PHHRA results indicated that the Hazard Quotient (HQ) was highest at the 95th percentile for all subgroups. Using the SA NAAQS, the HQ was estimated to be 0.9 for all subgroups,

indicating safe levels. When utilizing the EPA NAAQS, a value of 2.5 was reported, while the WHO guidelines recorded the highest HQ of 3.5, indicating unsafe levels. This demonstrated that the South African NAAQS underestimated exposure to $PM_{2.5}$. For both male and female elders, the Cancer Risk (CR) was approximately 1 in 10, meaning that about 100,000 out of 1,000,000 exposed elders were at an increased risk of developing cancer over their lifetime.

The study had four (4) recommendations based on each objective, 1) revising the current NAAQS to adopt more stringent measures and align them to international benchmarks to safeguard the public from adverse health effects due to $PM_{2.5}$ exposure, 2) future studies should focus on the dispersion and source apportionment of $PM_{2.5}$ to quantify the contribution of various sources in eMbalenhle, 3) integrating other methods alongside bulk sampling and APCS-MLR in future studies to capture heterogeneity within the soil matrix and improve source apportionment resolution 4) carry out an elemental characterization of soil particles and estimate the health risks associated with chronic exposures in these communities.

Keywords: Low-cost Monitors, Fine particles, Monte Carlo simulations, Exposure assessment, Mining activities, Soil contamination, Source apportionment.

Declaration

I, Nomsa Duduzile Lina Thabethe, hereby declare that this thesis, titled " Human health risks of exposure to fine particles ($PM_{2.5}$) from the gold mine tailings in the community of eMbalenhle, South Africa", is my original work and has not been submitted previously for any degree at any other institution. All sources of information, data and references used in this research have been acknowledged.

I confirm that this work has been conducted as per academic integrity and ethical research standards. Any contributions from other researchers have been cited.

Furthermore, I take full responsibility for any errors that may be found in this thesis. Parts of this thesis have been submitted in academic journals, as follows:

- Thabethe, N.D., Makonese, T., Masekameni, DM. and Brouwer, D., 2025. Assessing $PM_{2.5}$ concentrations at a Gold Mine Tailings Facility and Adjacent Community. *Clean Air Journal.*
- Thabethe, N.D., Chidhindi., P., Masekameni, DM., Brouwer, D., Makonese, T. 2025. Integrated Dispersion Modelling and Ambient $PM_{2.5}$ Monitoring in Mining Region: A Comparative Health Risk Assessment of Tailing Storage Facility Emissions and Multi-Source Ambient Concentrations. *The Atmosphere.*
- Thabethe, N.D., Makonese, T., Masekameni, DM. and Brouwer, D., 2025. Bulk Sampling and Source Apportionment of Heavy Metals Within a Gold Mine Area, South Africa. *Journal of Environmental Monitoring and Assessment.*
- Thabethe, N.D., Makonese, T., Masekameni, DM. and Brouwer, D., 2025. Probalistic Human Health Risk Assessment of Exposure to $PM_{2.5}$ at the Community near the Gold Mine Tail Storage Facility. *Frontiers in Public Health. (Published)*

Signature: N. Thabethe

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Date: 29 September 2025

Dedication

I dedicate this study to my Father (the late Zinsimbhi Thabethe and my Mother Matime Sekeku Thabethe), Children (Mogau and Atang Phoku), Husband (Marothi Phoku), Siblings who are well known as “The Big 8” (the late Vusi, Zanele, Nkosinathi, Busisiwe, Nomvula, Bongani and Sibongiseni), Nephews (Sbusiso, Sfiso, Mduduzi, Masego, Hlelo, Nkosinathi, Simangaliso, Atang and Msizi), Nieces (Buhle, Thembi, Thubelihle, Sinothando, Bongiwe, Busisiwe Jr and Bongikuhle), my late Grandmothers (Stephina Mogane, Mantjebane and Lina Thabethe), my late Grandfathers (Moreseng Mogane and Ndlavela Thabethe), Sisters-in-law (Maida and Kabelo Thabethe). I would like to thank you for your unconditional love, sacrifices and belief in my potential. Your guidance and support have been my greatest source of strength.

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To all who have contributed in any way, directly or indirectly to the completion of this study, I extend my sincerest thanks. Your support and assistance will always be remembered with gratitude.

Disclaimer

This thesis may include the repetition of methodologies, references and content that have been presented in various academic platforms. Any similarities are the need for comprehensive discussion, clarity and consistency in presenting research results. Furthermore, while every effort has been made to cite all sources properly, any unintended similarities with other works are purely coincidental.

Table of Contents

List of Figures

List of Tables

CHAPTER 2: LITERATURE REVIEW

CHAPTER 3: METHODS AND MATERIALS

Abbreviations

ACU	African Commission Union
AERMOD	American Meteorological Regulatory Model
Al	Aluminium
APCS-MLR	Absolute Principal Components Score Multiple Linear Regression
As	Arsenic
AT	Average Time
Au	Gold
BSE	Back Scattered Electrons
Ca	Calcium
C_{air}	Concentration of contaminant in air (µg/m^3)
CAMx	Comprehensive Air Quality Model with Extensions
CCB	Continuing Calibration Blank
CCB	Continuing Calibration Blank
CCSEM	Computer-Controlled Scanning Electron Microscopy
CCV	Continuing Calibration Verification
CCV	Continuing Calibration Verification
Cd	Cadmium
CF	Contamination Factor
CF	Contamination Factor
CMAQ	Community Multiscale Air Quality model
CMB	Chemical Mass Balance
COPD	Chronic Obstructive Pulmonary Disease
CR	Cancer Risk
Cr	Chromium
CRM	Certified Reference Material
CRM	Certified Reference Material
CSF	Cancer Slope Factors
DEFF	Department of Environment, Forestry and Fisheries
DHHRA	Deterministic Human Health Risk Assessment
EAC	East African Community
ED	Exposure Duration
EF	Enrichment factor

EF	Enrichment factor
EF	Exposure Frequency
ET	Exposure Time
Fe	Ion
FEM	Federal Equivalent Method
GM	Geometric Mean
GPM	Gaussian Plume Model
GPS	Global Positioning System
GSD	Geometric Standard Deviation
HCl	Hydrochloric Acid
HCl	Hydrochloric Acid
Hg	Mercury
HHRA	Human Health Risk Assessment
HNO_3	Nitric Acid
HPA	Highveld Priority Area
HQ	Hazard Quotient
ICB	Initial Calibration Blank
ICB	Initial Calibration Blank
ICP-MS	Coupled Plasma Mass Spectrometry
ICP-MS	Inductively Coupled Plasma Mass Spectrometry
ICV	Initial Calibration Verification
ICV	Initial Calibration Verification
IUR	Inhalation Unit Rate
LCMs	Low-cost Monitors
LoD	Limit of Detection
LoD	Limit of Detection
MCS	Monte Carlo Simulation
MLR	Multiple Linear Regression
Mn	Manganese
NAAQS	National Ambient Air Quality Standards
NAAQS	National Ambient Air Quality Standards
NEMAQA	National Environmental Management: Air Quality Act
NESREA	National Environmental Standards and Regulations Enforcement Agency
NH^{+4}	Ammonium

NH_3	Ammonia
Ni	Nickel
NO_x	Nitrogen Oxides
PAHs	Polycyclic Aromatic Hydrocarbons
Pb	Lead
PCA	Principal Component Analysis
PCA	Principal Component Analysis
PM	Particulate Matter
PMF	Positive Matrix Factorization
PHHRA	Probabilistic Human Health Risk Assessment
Rfc	Reference Concentration
RfD	Reference Doses
ROS	Regression on Order Statistics
ROS	Regression on Order Statistics
SAAQIS	South African Air Quality Information System
SAAQIS	South African Air Quality Information System
SADC	Southern African Development Community
SANAS	South African National Accreditation System
SANAS	South African National Accreditation System
SAWS	South African Weather Services
SAWS	South African Weather Services
SE	Secondary Electrons
SEM	Scanning Electron Microscopy
Si	Silicon
SO_2	Sulphur Dioxide
TSFs	Tail Storage Facilities
TVOC	Total Volatile Organic Compounds
U	Uranium
UEC	Upper Earth’s Crust
UEC	Upper Earth’s Crust
UNC-PAS	University of California Passive Aerosol Samplers
UNEP	United Nations Environment Programme
USEPA	United States Environmental Protection Agency
VOCs	Volatile Organic Compounds

WHO	World Health Organization
WHO	World Health Organization
WRF-Chem	Weather Research and Forecasting Model with Chemistry
Zn	Zinc

Definition of Terms

Acute Exposure: Short-term exposure to high pollutant concentrations.

Air Dispersion Modelling: The use of mathematical models to predict the transport and spread of pollutants.

Air Quality Monitoring: The process of measuring pollutants in ambient air to assess exposure levels.

Air Quality: The state of the atmosphere in relation to the presence and concentration of pollutants.

Cancer Risk Assessment: Evaluating the probability of developing cancer due to $PM_{2.5}$ exposure.

Chronic Exposure: Long-term exposure to air pollution over months or years.

Data Correction: The process of identifying and rectifying errors, inconsistencies, or biases in collected data to improve accuracy and reliability.

Data Validation: The process of checking data for completeness, accuracy, and consistency to ensure it meets quality standards before analysis.

Deposition: The process by which $PM_{2.5}$ is transferred from the atmosphere to the earth's surface through wet or dry processes.

Deterministic Human Health Risk Assessment: A risk assessment approach that uses fixed values for exposure and toxicity parameters to calculate potential health risks, often yielding conservative results without considering variability.

Diurnal Variations: The fluctuations in pollutant concentrations and meteorological conditions over a 24-hour cycle.

Dose-Response: The correlation between exposure level and health effect severity.

Dry Deposition: The process where $PM_{2.5}$ is deposited onto surfaces from the atmosphere, driven by gravity and wind rather than precipitation.

Exposure Pathways: Routes through which individuals(receptors) come into contact with a stressor, e.g.$PM_{2.5}$.

Factor Analysis: A statistical method for reducing data complexity in source identification.

Federal Reference Method: A regulatory method for $PM_{2.5}$ measurement defined by the United States Environmental Protection Agency

Hazard Quotient: The ratio of exposure to a reference dose.

Heavy Metals: A group of naturally occurring metallic elements, that can be toxic to humans and the environment at elevated concentrations.

Human Health Risk Assessment: The process of evaluating the potential health risks of pollutant exposure.

Inhalation Rate: The volume of air breathed per unit time, important in risk assessment.

Low-Cost Monitor: An affordable air quality sensor used for real-time monitoring of pollutants.

Monte Carlo Simulation: A statistical technique used in probabilistic risk assessment.

Non-Carcinogenic Risk Assessment: Evaluating health effects of $PM_{2.5}$ that do not involve cancer

Particulate Matter: A mixture of solid and liquid particles suspended in the air, categorized by size.

$PM_{2.5}$: Fine particulate matter with an aerodynamic diameter of 2.5 micrometers or less.

Primary $PM_{2.5}$: Particles emitted directly from sources like combustion and industrial processes.

Principal Component Analysis: A statistical technique used to identify pollution sources.

Probabilistic Human Health Risk Assessment: A risk assessment approach that uses statistical methods to estimate the likelihood and variability of health effects from exposure to pollutants, incorporating uncertainty through probability distributions.

Receptor Modelling: The use of models to estimate contributions from various sources at a given location.

Receptor: A specific location or entity that receives and is impacted by air pollutants transported from emission sources.

Reference Concentration: The safe concentration of a pollutant for human exposure.

Reference Data: High-quality, standardized data used as a benchmark for comparison, calibration and validation of other datasets.

Seasonal Variability of $PM_{2.5}$: Differences in $PM_{2.5}$ levels due to meteorology and human activities.

Secondary $PM_{2.5}$: Particles formed in the atmosphere through chemical reactions of precursor gases.

Source Apportionment: The process of identifying and quantifying pollution sources contributing to $PM_{2.5}$.

Source: A location, process or activity that emits pollutants into the environment.

Tailings Storage Facility: A specially designed structure used to store waste materials generated from mining operations.

Uncertainty Analysis: Assessing variability in risk estimates.

Vulnerable populations: Groups more vulnerable to $PM_{2.5}$ health effects, such as children and the elderly.

Wet Deposition: The process where atmospheric pollutants are removed and deposited onto the earth's surface via precipitation.

CHAPTER 1: INTRODUCTION

This chapter provides an overview of $PM_{2.5}$ monitoring, trends over time, sources, dispersion of particles from one point to another, apportionment of $PM_{2.5}$ sources and the assessment of human health risks posed by exposure to $PM_{2.5}$. Attention is given to monitoring approaches used globally, regionally and locally. Furthermore, the research problem statement and knowledge gaps are outlined, followed by the aim and objectives of the study. The significance of the study is provided, along with a discussion on the relevance of $PM_{2.5}$ monitoring in guiding policy and regulatory interventions. This chapter concludes with an outline of the thesis layout.

1.1 Background

Air pollution is one of the most concerning environmental and public health challenges worldwide, with fine particulate matter ($PM_{2.5}$) being a major concern (Mukta et al., 2020). $PM_{2.5}$ refers to airborne particles with an aerodynamic diameter of 2.5 micrometers or less (Jia et al., 2017). It is a significant concern due to its adverse effects on human health (Thangavel et al., 2022). These particles can penetrate deep into the respiratory system affecting the health of exposed individuals (Hu et al., 2024). The health effects resulting from exposure to $PM_{2.5}$ include cardiovascular diseases, respiratory disorders, cancer, increased mortality rate (Pun et al., 2017) and neurological effects (Shi et al., 2020). Given the extensive nature of $PM_{2.5}$ pollution and its severe effects on both the environment and public health, continuous monitoring, dispersion modeling, source apportionment and health risk assessment are needed to develop effective air quality management strategies and policies.

1.2 The Need for $PM_{2.5}$ Monitoring and Trend Analysis

Long-term $PM_{2.5}$ monitoring and trend analysis play a significant role in assessing compliance with National Ambient Air Quality Standards (NAAQS). Monitoring $PM_{2.5}$ at different temporal scales (hourly, daily, monthly, seasonal and yearly) helps identify high peak periods (Brauer et al., 2011). Furthermore, it assists in determining diurnal and seasonal variations and assessing the effectiveness of air pollution control measures (Pui & Zuo, 2014). Temporal $PM_{2.5}$ trends provide information on the impact of meteorological conditions, local sources and dispersion of particles from one point to another (Liu et al., 2020).

The variations in $PM_{2.5}$ concentrations are influenced by multiple factors. These factors include meteorology, local emission sources and transboundary pollutants (Shi et al., 2020). In most urban areas, higher $PM_{2.5}$ levels are observed during winter due to increased emissions from heating activities, temperature inversions and lower atmospheric mixing heights. Lower $PM_{2.5}$ concentrations are observed in summer due to improved dispersion and wet deposition (Siddiqui et al., 2024).

1.2.1 High-resolution $PM_{2.5}$ Monitors Versus Lost-Cost Monitors

High-resolution $PM_{2.5}$ monitors are highly recommended as they provide accurate and regulatory-grade data (Schulte et al., 2020). LCMs have emerged as a complementary technology, offering increased spatial coverage and real-time monitoring. Both technologies serve important roles in air quality assessment, but they differ significantly in terms of accuracy, cost, deployment and data applications (Concas et al., 2021). While high-resolution monitors provide accurate $PM_{2.5}$ measurements, LCMs offer affordable, widespread deployment but with lower precision. High-resolution $PM_{2.5}$ monitors provide regulatory-compliant data that meets global, regional and local air quality standards. They can operate continuously for years with proper calibration and maintenance. Their disadvantages are that they are expensive and require highly skilled personnel for operation. Due to their cost, high resolution monitors are sparingly distributed. This limits spatial resolution and the ability to detect localized $PM_{2.5}$ hotspots (Chen et al., 2017).

LCMs are compact, affordable, easy to deploy and provide real-time air quality data. They mostly use optical sensors to estimate $PM_{2.5}$ concentrations (Badura et al., 2018). The commonly used LCMs for air quality assessment in communities are PurpleAir (Raysoniet al., 2023), AirVisual (Wang et al., 2020) and Clarity NodeS (Thabethe et al., 2025). LCMs are deployed in large numbers to improve the spatial resolution of air quality data. They provide continuous $PM_{2.5}$ readings to quickly detect $PM_{2.5}$ pollution events and may be installed on streetlights and vehicles (Farzaneth et al., 2020). The limitations of LCMs are that they must be co-located with reference $PM_{2.5}$ monitors for correction and recalibration (Zusman et al., 2020).

1.3 Dispersion Modelling and Spatial Analysis

Although monitoring provides the observations of $PM_{2.5}$ concentrations, it should be combined with dispersion modeling for effective mitigation strategies. Dispersion modeling is a powerful tool for predicting $PM_{2.5}$ levels and assessing the impact of different sources (Azhari et al., 2021). Additionally, it estimates $PM_{2.5}$ levels in areas with limited monitoring infrastructure.

Dispersion models simulate the transport, chemical transformation and deposition of $PM_{2.5}$ based on meteorological and emission data (Pan et al., 2021). These models help assess the spatial distribution of $PM_{2.5}$, evaluate the influence of local and regional sources and predict $PM_{2.5}$ levels under different emission scenarios (Farzaneh et al., 2020).

Several models, including Gaussian plume, Lagrangian and Eulerian have been widely used for $PM_{2.5}$ dispersion studies (Kukkonen et al., 2018). These dispersion models require emission inventories, meteorological inputs and topographical data to ensure reliable predictions (Khan et al., 2020). The Gaussian Plume Model (GPM) assumes that $PM_{2.5}$ dispersed in a Gaussian (normal) distribution is transported by wind (Clements et al., 2024). The model incorporates key parameters including emission rates, effective stack heights and turbulence-driven dispersion coefficients (Wilson, 2010). The GPM limitations include the assumption of steady-state meteorological conditions and the inability to account for complex chemical transformations of $PM_{2.5}$ (Turner et al., 2020).

Lagrangian models are advanced atmospheric dispersion models that simulate the transport and diffusion of $PM_{2.5}$ as they move through the atmosphere. Unlike GPM which assumes a continuous steady-state distribution of $PM_{2.5}$, Lagrangian models represent $PM_{2.5}$ as a separate aspect that evolves based on meteorological conditions (Leelőssy et al., 2018). These models effectively capture time-dependent variations in wind speed, turbulence and atmospheric stability. Lagranian models are more suitable for complex environments (terrain and long-range transport of pollutants); (Asadi et al., 2017). One of the most widely used Lagrangian models is CALPUFF, which can simulate $PM_{2.5}$ dispersion over long distances (Johnson, 2022). CALPUFF can account for $PM_{2.5}$ chemical transformations, wet and dry deposition and terrain interactions (Mallia & Kochanski, 2023).

Eulerian models simulate pollutant dispersion by dividing the atmosphere into a fixed three-dimensional grid. These models solve mathematical equations for transport, diffusion, chemical transformation and deposition within each grid cell (Leelőssy et al., 2016). Unlike Lagrangian models, which track individual air pollutants, Eulerian models treat pollutants as concentrations that evolve over time due to advection, diffusion and atmospheric reactions (Tirabassi et al., 2009). Eulerian models include Weather Research and Forecasting model with Chemistry (WRF-Chem), Community Multiscale Air Quality model (CMAQ) and Comprehensive Air Quality Model with Extensions (CAMx); (Kadaverugu et al., 2019).

In this study, AERMOD was used. AERMOD is a steady-state Gaussian dispersion model developed by the United States Environmental Protection Agency (USEPA) for assessing air pollution from industrial and urban emission sources. It is designed to predict local and regional pollutant concentrations (USEPA, 2025). AERMOD is widely used for regulatory applications, environmental impact assessments, and air quality management (Kumar et al., 2017). Unlike traditional Gaussian plume models, AERMOD incorporates complex terrain, meteorological conditions and surface interactions (USEPA, 2025)

The model is composed of two main components, namely, AERMOD Meteorological Processor (AERMET) and Terrain Processor (AERMAP). AERMET processes surface and upper-air meteorological data. AERMAP determines the impact of elevation and land features on $PM_{2.5}$ dispersion (Shukla et al., 2021). Despite its advanced capabilities, AERMOD assumes steady-state meteorological conditions, making it less effective in modeling long-range pollution transport (Yadav et al., 2020).

1.4 $PM_{2.5}$ Source Apportionment

The $PM_{2.5}$ sources are categorized into primary and secondary sources (Hao et al., 2020). Primary sources are emissions that directly release $PM_{2.5}$ into the atmosphere (Dai et al., 2018). These sources are further classified into anthropogenic (human-made) and natural sources (Chang et al., 2019). The anthropogenic sources of $PM_{2.5}$ include industries, construction activities (Dai et al., 2019), residential fuel burning (Sahu et al., 2021) and agricultural activities (Zheng et al., 2019). The natural sources include volcanic eruptions, dust from the soil and wind-blown particles (Hassan et al., 2023). Secondary sources refer to particles that form in the atmosphere through chemical reactions (Zhang et al., 2015). The secondary $PM_{2.5}$ formations include Sulfur Dioxide (SO_2), Nitrogen Oxides (NO_x), Ammonia (NH_3), and Volatile Organic Compounds (VOCs); (Omokpariola et al., 2025).

Source apportionment models are used to identify the contribution of different sources to $PM_{2.5}$ levels. The most used source apportionment models are Positive Matrix Factorization (PMF), Chemical Mass Balance (CMB) and APCS-MLR Model (Traore et al., 2024). PMF is a multivariate factor analysis model that decomposes measured data source contributions and profiles. It incorporates uncertainty estimates for each measured data point (Jain et al., 2018). It helps to identify pollution sources and quantify their contributions without requiring prior information on source compositions (Jandacka & Durcanska, 2021).

The CMB model estimates the contributions of known $PM_{2.5}$ sources to measured ambient concentrations. Unlike PMF, which determines sources statistically, CMB requires prior knowledge of source profiles (Tian et al., 2023). With CMB, the identified sources can be directly attributed to specific $PM_{2.5}$ sources. It operates on the principle of mass conservation, where the measured concentration of each chemical species is assumed to be linear contributions from different sources (Dai et al., 2019). A key advantage of CMB is its ability to provide direct and quantitative source contributions with low computational complexity. However, its accuracy depends on the availability of representative source profiles (Hopke, 2016).

In this study, APCS-MLR was intended to determine the sources of $PM_{2.5}$. Unfortunately, no data could be retrieved for $PM_{2.5}$ composition. Instead, topsoil samples were taken and their composition of heavy metals was used for source apportionment as a proxy for historical dust deposition. The APCS-MLR model integrates Principal Component Analysis (PCA) with Multiple Linear Regression (MLR) to estimate source contributions from a dataset of measured $PM_{2.5}$ concentrations (Li et al., 2021). APCS-MLR involves two main steps. First, PCA is applied to the measured data to extract principal components that represent different pollution sources (Cheng et al.,2020). The PCA produces factor loadings that are unitless and difficult to interpret directly. The APCS is applied to transform these factors into absolute scores that can be used in regression analysis (Yang et al., 2020). The APCS values are calculated by standardizing the principal component scores for each sample (Jain et al., 2017).

In the second step, MLR is used to relate the APCS values to the measured $PM_{2.5}$ concentrations (Jianfei et al., 2020). One of the main strengths of the APCS-MLR model is its ability to handle large datasets with multiple intercorrelated variables (Chen et al., 2023). The accuracy of the results depends on the effectiveness of the initial PCA step and the assumption that the extracted components correspond to real pollution sources (Gibson et al., 2022).

1.5 Human Health Risk Assessment of $PM_{2.5}$ Exposure

Human Health Risk Assessment (HHRA) is a model that can be applied to evaluate the potential negative effects of exposure to $PM_{2.5}$ (Amoatey et al., 2018). The HHRA model consists of four key steps, namely: Hazard identification, Exposure assessment, Dose-response assessment, and Risk characterization (USEPA, 2025). Hazard identification is the first step in HHRA. Its main purpose is to determine whether $PM_{2.5}$ poses a potential health risk (Wang et al., 2021) to the exposed community. This step involves reviewing literature, toxicological and epidemiological data (Chartres et al., 2019).

Exposure assessment quantifies the extent, frequency and duration of human exposure to $PM_{2.5}$ (Gustafsson et al., 2018). This step generally considers various exposure pathways. Exposure pathways include inhalation, ingestion and dermal absorption (Taye et al., 2024). Key factors considered in exposure assessment are the concentration of $PM_{2.5}$ in air, duration and frequency of exposure; and population characteristics (Gerba, 2019).

The dose-response assessment examines the relationship between the level of exposure to $PM_{2.5}$ and the likelihood of health effects (Liu et al., 2017). This step establishes Reference Doses (RfD) for non-carcinogenic substances and Cancer Slope Factors (CSF) for carcinogens (de Almeida et al., 2022). A threshold model is used for non-carcinogens, if low doses may not cause harm. A non-threshold model is applied for carcinogens, assuming that any exposure level carries some risk (Bates et al., 2023).

Risk characterization integrates the findings from hazard identification, dose-response and exposure assessment to estimate the overall risk of exposure to $PM_{2.5}$ (Li et al., 2021). For carcinogenic risks, the CR is calculated (Mohammadi et al., 2019). HHRA can be conducted using deterministic or probabilistic approaches. Deterministic Human Health Risk Assessment (DHHRA) applies fixed values for key exposure parameters (Srinivasan et al., 2021). This approach assumes a single-point estimate for each variable (e.g. $PM_{2.5}$ concentration, exposure duration, body weight, etc) rather than considering a range of possible values (Munshed et al., 2023). One of the limitations of DHHRA is its inability to account for variability in individual susceptibility and exposure patterns (Maertens et al., 2022). As a result, it may overestimate or underestimate actual risks, leading to inadequate protection of public health (Asante-Duah & Asante-Duah, 2017).

Probabilistic Human Health Risk Assessment (PHHRA) is an advanced risk assessment model that accounts for the variability and uncertainty in human exposure to $PM_{2.5}$ (Fadel et al., 2022). Probabilistic HHRA uses probability distributions to model a range of possible exposure and health risk scenarios (Zhang et al., 2022). It uses Monte Carlo simulation, i.e., randomly sampling the assigned probability distributions to generate thousands of potential risk outcomes (Flinders et al., 2025). The results are presented as a probability distribution and show the likelihood of different risk levels occurring within a population (Kaur et al., 2020).

1.6 Problem Statement and Knowledge Gap

$PM_{2.5}$ remains an environmental and public health concern worldwide (Li et al., 2021). Due to its small size, $PM_{2.5}$ can penetrate deep into the respiratory system and bloodstream (Yang et al., 2020), causing lung cancer (Badyda et al., 2017), cardiovascular disorders and premature deaths (Hayes et al., 2020). Despite efforts to regulate air quality at the local, regional and international levels, $PM_{2.5}$ concentrations in many urban areas continue to exceed the NAAQS (Ling et al., 2021; Singh et al., 2021) and guidelines set by the World Health Organization (WHO). The variations of $PM_{2.5}$ levels across different timescales (hourly, daily, seasonal and annual) and its complex dispersion in the atmosphere make it challenging to develop effective mitigation strategies. In addition, accurately identifying $PM_{2.5}$ sources remains a challenge as multiple factors influence its composition and distribution.

Existing studies on $PM_{2.5}$ monitoring have primarily focused on either short-term or long-term trend analysis without integrating multiple factors (Onaiwu & Ayidu, 2024; Wang et al., 2024; Sanguineti et al., 2020). Furthermore, while dispersion modeling is widely used to simulate $PM_{2.5}$ transport, uncertainties related to input parameters and model validation persist. Source apportionment studies often rely on receptor-based models without incorporating real-time monitoring and dispersion simulations (Cheng et al., 2015). This leads to potential gaps in $PM_{2.5}$ mitigation strategies. Moreover, many studies applied the DHHRA to estimate the potential risks associated with exposure to $PM_{2.5}$ (Kim et al., 2019; Matz et al., 2020, Wang et al., 2024) which may underestimate the protection needed for public health.

Therefore, there is a need for this comprehensive study, which integrates real-time $PM_{2.5}$ monitoring, trend analysis, time-scale variations, dispersion modeling, source apportionment and PHHRA. This study aims to bridge these gaps by applying a multi-faceted approach to $PM_{2.5}$ monitoring and protecting public health.

1.7 Relevance of the Study

In South Africa, several mines have reopened after being closed for many years. Unfortunately, many residential areas are established in previously mined land. A legacy of former mining activities is the disposal from excavation and extraction processes collected in so-called gold mine Tail Storage Facilities (TSFs). TSFs are becoming an emerging source of $PM_{2.5}$ due to their composition associated with potential health risks amongst communities nearby (Andraos et al., 2018; Singh et al., 2020). Epidemiological studies have indicated that there is an increase in potential human health risks associated with $PM_{2.5}$ exposure from the gold mine TSFs (Olobatoke & Mathuthu, 2016; Ngole-Jeme & Fantke, 2017; Mensah et al., 2020).

Epidemiological findings often lack appropriate exposure assessment data for different exposure scenarios. High-quality monitors in an air quality monitoring network are widely used globally to quantify $PM_{2.5}$ concentrations from different sources. However, high-quality instruments are often expensive to operate and require a technologically advanced infrastructure to operate. To estimate the concentrations of $PM_{2.5}$ in eMbalenhle, the data from the ambient air monitoring stations in eMbalenhle was interpolated which may result in high uncertainty considering the spatial distributions.

Air quality dispersion models are used for predicting the dispersion of $PM_{2.5}$ in the air. However. there is a high level of uncertainty in the output since dispersion models depend on the quality of the input parameters sourced from different monitoring devices. Literature indicated that the use of LCMs may be useful in improving data quality because of the improved spatial resolution (Manikonda et al., 2016; Zikova et al., 2017; Ahangar, 2019). Very few studies have been conducted to determine the suitability of LCMs in air quality measurements and health risk estimation. Therefore, this study is important to determine the use of LCMs in studying potential health risks from different exposure scenarios.

The community of eMbalenhle lives near gold mine TSFs. Hence, it is very important to determine the human health risks that may emanate because of $PM_{2.5}$ emissions from these gold mine TSFs. The findings of this study will have an impact in informing and influencing policy and decision-making at the local, district, and national levels regarding equipment recommended for ambient air monitoring for compliance with the air quality legislation . This was the first study that utilized data from the LCMs to determine the human health effects of $PM_{2.5}$ from the gold mine TSFs in the community of eMbalenhle

1.8 Study Aim and Objectives

The aim and objectives of this study were as follows:

1.8.1 Aim

To estimate the human health risks which may occur as a result of exposure to $PM_{2.5}$ from the gold mine TSFs in the community of eMbalenhle.

1.8.2 Objectives

- To determine the diurnal and seasonal variations of $PM_{2.5}$ concentrations at the gold mine TSFs fence line (source) and in the community of eMbalenhle (receptor).
- To estimate the transport of $PM_{2.5}$ from the gold mine TSFs to the community of eMbalenhle.
- To determine the potential sources of $PM_{2.5}$ within the mining area and nearby community.
- To estimate the potential human health risks associated with exposure to $PM_{2.5}$ in the community of eMbalenhle

1.8.3 Hypothesis

It is hypothesized that emissions from gold mine TSFs significantly contribute to ambient $PM_{2.5}$ concentrations and potential health risks in the nearby community of eMbalenhle.

1.9 Scope of the Study

This study focused on measuring $PM_{2.5}$ concentrations at TSFs and in the community of eMbalenhle to assess human health risks as described in Figure 1. The estimation of $PM_{2.5}$ dispersion patterns from the TSFs to the community of eMbalenhle was done by applying the AERMOD model. Geographical areas with higher $PM_{2.5}$ concentrations were also identified with this model. Topsoil samples were collected at the TSFs and community sites. The different sources of heavy metals of topsoil samples within the study area were determined by applying APCS-MLR model. The PHHRA model was used to evaluate the potential human health impacts associated with $PM_{2.5}$ exposure in the community of eMbalenhle. The health risks were estimated based on measured $PM_{2.5}$ and modeled exposure factors.

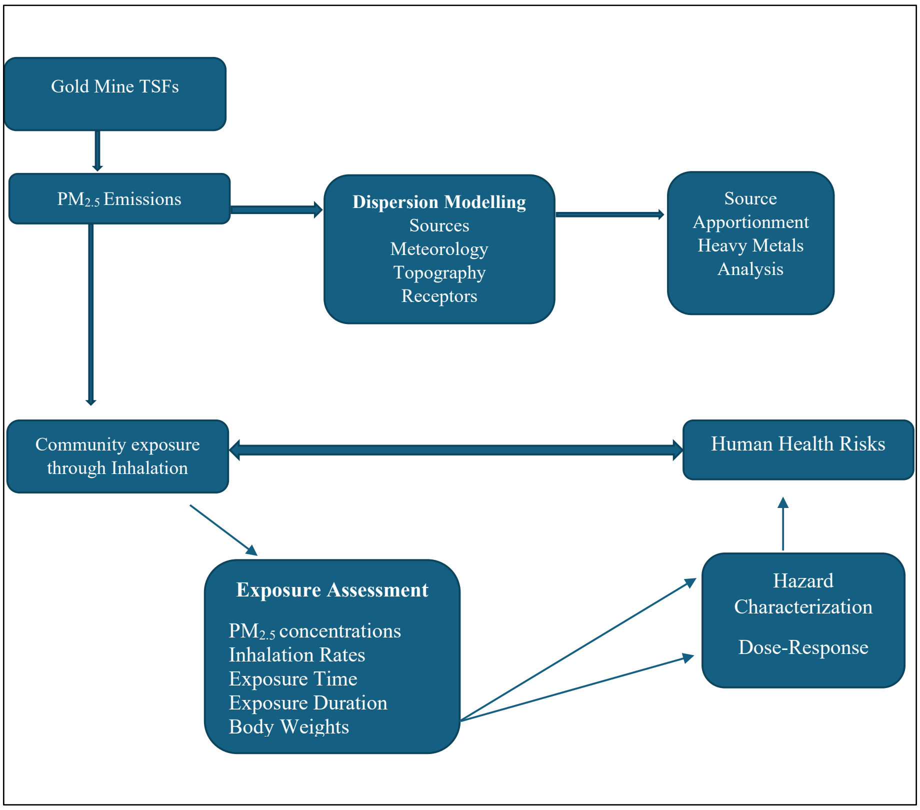


Figure 1.1: Conceptual Framework of the Study

1.10 Overview of the Thesis

Chapter 1: Introduction

This chapter introduces the research topic, problem, gap, aim, objectives and significance of the study. It defines $PM_{2.5}$, its sources, monitoring strategies, dispersion modeling and impact on human health.

Chapter 2: Literature Review

This chapter reviews existing studies on $PM_{2.5}$, temporal and spatial trends, dispersion modeling techniques, source apportionment models and health risks associated with $PM_{2.5}$ exposure. The review includes global, regional and local studies. It identifies gaps in existing knowledge that the thesis aims to address.

Chapter 3: Methodology

This chapter outlines the research design, data collection and analysis methods used in the study. It details the equipment used to collect $PM_{2.5}$ data, the application of the AERMOD dispersion model to estimate the spatial distribution and the use of the APCS-MLR model to identify pollution sources. The methodology for assessing health risks based on exposure data is also be described.

Chapter 4: $PM_{2.5}$ Monitoring at the Source and Receptor

This chapter presents the results of $PM_{2.5}$ concentrations over different time scales (hourly, daily, monthly, seasonal, and yearly) at both the source (TSFs) and receptor (community). It identifies patterns and trends in $PM_{2.5}$ concentrations, indicating peak periods and factors influencing the increase in $PM_{2.5}$ concentrations.

Chapter 5: Spatial Distribution of $PM_{2.5}$ Within the Study Areas

This chapter presents the results of the dispersion modeling used to estimate the spatial distribution of $PM_{2.5}$. It provides maps and spatial data analysis to identify areas with high $PM_{2.5}$ concentrations.

Chapter 6: Source Apportionment of Heavy Metals

This chapter provides the results of the source apportionment analysis. Different sources of heavy metals were identified using the APCS-MLR model.

Chapter 7: Probabilistic Human Health Risk Assessment

This chapter discusses the PHHRA of $PM_{2.5}$ exposure in eMbalenhle. The results are presented according to population sub-groups and the severity of the likelihood of exposure.

Chapter 8: Synthesis, Conclusion and Recommendations

This chapter discusses the findings of the study. It further compares the findings with those of other studies. It also discusses potential limitations of the study and the scope for future research.

Chapter 9: Conclusions and Recommendations

The final chapter summarizes the study's key findings and provides comprehensive conclusions. It offers recommendations for minimizing $PM_{2.5}$ concentrations and improving air quality monitoring for public health protection. The chapter concludes with recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

This chapter describes the key concepts, methodologies and findings from existing research related to $PM_{2.5}$ monitoring, dispersion modeling, source apportionment; and human health risk assessment of exposure to $PM_{2.5}$. The first Section of this chapter focuses on the definition and sizes of Particulate Matter (PM), the composition of $PM_{2.5}$ from TSFs, the composition of $PM_{2.5}$, sources and monitoring of $PM_{2.5}$. The second Section focuses on dispersion modeling, including key factors influencing the transport of $PM_{2.5}$. The third Section delves into source apportionment of $PM_{2.5}$ techniques. The final Section addresses the adverse human health effects of exposure to $PM_{2.5}$. The methods for assessing the human health risk assessment of $PM_{2.5}$ exposure are also discussed.

South Africa is being recognized as one of the world's leading producers of gold, ranking seventh globally and first in Africa (Minerals Council South Africa, 2023). Gold mines play a great economic role by creating jobs and generating income in communities (Wale et al., 2023). However, the mining activities have led to the establishment of TSFs. The TSFs are residues of gold extraction processes and consist of sand and silt particles, which are discharged into a pond to form a dam (Glotov et al., 2018). These TSFs pose environmental and adverse human health risks in surrounding communities (Nkosi et al., 2016). The biggest concern associated with TSFs is their contribution to $PM_{2.5}$ levels in surrounding communities. $PM_{2.5}$ is known for its ability to penetrate deep into the human respiratory system and cause adverse health effects (Hu et al., 2024).

2.1 Definition and Sizes of Particulate Matter

Particulate Matter (PM) is a mixture of solid particles and liquid droplets suspended in the air (Nagar et al., 2014). These particles vary in size, composition and origin. PM is classified based on their aerodynamic diameter which determines how deeply they can penetrate the respiratory system (Thomas, 2013). The classification of PM is divided into three categories, namely: coarse particles (PM_{10}), fine particles ($PM_{2.5}$) and ultrafine particles (PM_{01}); (Saju et al., 2023).

PM_{10} includes particles with an aerodynamic diameter of 10 micrometers or less. These particles are relatively larger and trapped in the upper respiratory tract (Peng et al., 2024). PM_{10} cannot penetrate deeply into the lungs. $PM_{2.5}$ consists of fine particles with an aerodynamic diameter of 2.5 micrometers or less (Chauhan et al, 2024). Due to their small size, $PM_{2.5}$

particles can penetrate deeper into the lungs and even enter the bloodstream. $PM_{2.5}$ is harmful because it can reach the alveoli (Wang et al., 2022). PM_1 are particles with an aerodynamic diameter of 1 micrometers or less. Their extremely small size allows them to travel deep into the lungs and may also pass into the bloodstream (Terzano et al., 2010).

2.1.1 The Composition of $PM_{2.5}$

The composition of $PM_{2.5}$ is complex and varies depending on the source, location and atmospheric conditions (Kfoury, 2013). $PM_{2.5}$ has several components consisting of carbonaceous materials (Ming, 2017), inorganic ions (Jia et al., 2017), heavy metals (Guo et al., 2022), mineral dust and biological materials (Jia et al., 2017). Urban areas experience higher concentrations of carbonaceous materials, whereas rural areas may have a greater presence of dust and soil particles (Yang et al., 2019). Seasonal changes also play a role in the composition of $PM_{2.5}$ (Li, 2020). During winter, more organic carbon may be from residential heating (Yan et al., 2017). The carbonaceous component of $PM_{2.5}$ consists of organic carbon and elemental carbon (Ming, 2017). Elemental carbon is produced through incomplete combustion processes (Long et al., 2013). Organic carbon comes from atmospheric reactions of VOCs; (Mellouki et al., 2015). These organic compounds include Polycyclic Aromatic hydrocarbons (PAHs) and carboxylic acids (Yuan et al., 2023).

Inorganic ions are also a major component of $PM_{2.5}$ (Hassan, 2022). The most common inorganic ions are sulfates, nitrates and ammonium (You et al., 2013). These ions are formed through chemical reactions in the atmosphere (Seinfeld & Pandis, 2016). Sulfates are produced from the oxidation of sulfur dioxide (SO_2), (Tsimpidi et al., 2024) and nitrates are formed from the reaction of nitrogen oxides (NO_x) with atmospheric oxidants (Walters et al., 2024). Ammonium (NH^{+4}) is derived from the release of NH_3 from livestock waste (Sapek et al., 2023). Sulfates contribute to the formation of acid rain and nitrates contribute to the formation of secondary aerosols (Shammas et al., 2020).

Heavy metals found in $PM_{2.5}$ include lead (Pb), cadmium (Cd), arsenic (As), nickel (Ni), and chromium (Cr); (Azahari et al., 2024).

$PM_{2.5}$ may contain significant amounts of mineral dust from soil particles, sand and other minerals (Hu et al., 2024). The composition of mineral dust varies widely depending on the geographical location (Formenti et al., 2014). Mineral dust often contains high levels of silica

(Si), aluminum (Al), calcium (Ca), and iron (Fe); (Engelbrecht et al., 2016). Mineral dust is less toxic than other $PM_{2.5}$ components. Prolonged exposure to mineral dust may cause asthma and chronic bronchitis (Azahari et al., 2024). In addition to inorganic and carbonaceous materials, $PM_{2.5}$ may contain biological components (Chowdhury et al., 2019). The biological components of $PM_{2.5}$ include bacteria, fungi, viruses and pollen.

2.1.2 Studies on the Composition of $PM_{2.5}$

A study conducted in China on seasonal variations and chemical compositions of $PM_{2.5}$ found that predominant chemical compositions were Si, Ca (Calcium), Fe (Ion), Potassium (K), and Aluminium (Al). The major ions identified on $PM_{2.5}$ were SO_4^{2-} (Sulphate ion), NO_3^- (Nitrate ion), and NH_4^+ (Ammonium ion) which accounted for 24.3%, 9.9%, and 8.8% of the total $PM_{2.5}$ mass, respectively (Xu et al., 2012).

Williams et al. (2021) conducted a study in South Africa and presented that the $PM_{2.5}$ samples contained Cl^- (Chloride ion), NO_3^-, SO_4^{2-}, Al, Ca, Fe, Mg (Magnesium), Na (Sodium) and Zn (Zinc). In North America (Dabek-Zlotorzynska et al., 2021) identified organic carbon as the second most significant component, contributing between 21% and 45% of the $PM_{2.5}$ mass. In addition, particle-bound water accounted for 6% to 12%; golden black carbon displayed elevated organic matter levels between 60% and 70%. A study conducted by Murillo et al. (2013) in South America indicated that the primary components of $PM_{2.5}$ were organic matter and elemental carbon, contributing 44.5%–69.9%. The study's findings at two non-urban sites from the polluted region in Europe revealed that the average proportion of primary organic carbon in $PM_{2.5}$ was higher than that of secondary organic carbon at both locations. The total contribution of secondary ions (SO_4^{2-}, NO_3^- and NH_4^+) to $PM_{2.5}$ remained similar across heating and non-heating seasons (Błaszczak et al., 2016).

2.1.3 The Sources of $PM_{2.5}$

The sources of $PM_{2.5}$ are categorized into anthropogenic and natural sources. Anthropogenic sources of $PM_{2.5}$ are human activities that release $PM_{2.5}$ into the atmosphere (Ledoux et al., 2017). Unlike natural sources, anthropogenic $PM_{2.5}$ sources can be controlled or mitigated through regulatory policies, technological improvements and sustainable practices (Sriyanto et al., 2024). The anthropogenic sources are divided into primary and secondary sources (Juda-Rezler, 2020). The anthropogenic sources include combustion of fossil fuels, vehicle emissions, industries, mining and agricultural activities (Fuge, 2012). The natural sources of $PM_{2.5}$ include wildfires, fungi and bacteria (Wei et al., 2019).

2.1.3.1 The Natural Sources of $PM_{2.5}$

Wildfires occurring in forests and savannas release large amounts of $PM_{2.5}$ (Kollanus et al., 2017). $PM_{2.5}$ is generated when strong winds lift particles from the Earth's surface into the atmosphere (Sun et al., 2018). Soil erosion contributes to $PM_{2.5}$ levels (Tian et al., 2021). The ocean releases $PM_{2.5}$ through sea spray aerosols. When ocean waves break, they release fine salt particles into the atmosphere (Feng et al., 2017). Volcanic eruptions release quantities of fine ash, sulfur dioxide (SO_2) and other gases contributing to $PM_{2.5}$ formation (Rais et al., 2022). Active volcanoes continuously emit $PM_{2.5}$ through fumaroles (openings in the earth's surface); (Madonia et al 2022). Natural biological processes release $PM_{2.5}$ through the release of organic aerosols (Cao et al., 2022). Plants and fungi release pollen, fungal spores and bacterial fragments into the air (Després et al., 2012).

2.1.3.2 The Primary Sources of $PM_{2.5}$

Primary sources are those that directly emit $PM_{2.5}$ into the atmosphere (Kleindienst et al., 2010). Industrial and mining activities release fine $PM_{2.5}$ directly into the atmosphere (Ou et al., 2022). Chemical manufacturing industries release $PM_{2.5}$ during production processes (Meng et al., 2015). Additionally, industrial processes that involve burning fossil fuels for heat and power emit $PM_{2.5}$ into the atmosphere (Munsif et al., 2021).

Heavy machinery and construction equipment powered by diesel engines release $PM_{2.5}$ emissions (Montadka, 2017). Mining operations (drilling, blasting and crushing) generate large amounts of $PM_{2.5}$ pollution (Morera de la Vall González, 2018). TSFs are a major source of wind-blown dust, which releases $PM_{2.5}$ (Mpanza, 2019). Residential heating, open waste burning and cooking using coal release $PM_{2.5}$ emissions directly into the atmosphere (Yang et al., 2018). Construction activities including excavation, demolition and cement mixing also generate $PM_{2.5}$ (Mitra and Das, 2022).

Agricultural activities contribute to $PM_{2.5}$ emissions through biomass burning, application of fertilizers and livestock emissions (Pozzer et al., 2017). The open burning of crop residues (Montes et al., 2022). Livestock farming also contributes to $PM_{2.5}$ emissions by releasing ammonia (NH_3) from animal waste and fertilizers. In addition, dust generated from plowing and harvesting releases $PM_{2.5}$ emissions (Ogwu et al., 2024).

2.1.3.3 Secondary Sources of $PM_{2.5}$

Secondary sources involve the atmospheric transformation of gaseous pollutants into $PM_{2.5}$ (Behera and Sharma, 2010). Secondary $PM_{2.5}$ is formed through complex chemical reactions involving SO_2, NO_x, NH_3, and VOCs (Omokpariola et al., 2025). These precursor gases undergo oxidation and other atmospheric processes to form $PM_{2.5}$ (Xu et al., 2022). SO_2 is the major contributor to secondary $PM_{2.5}$ formation. It is released from fossil fuel combustion in power plants, industries and vehicles (Syrek-Gerstenkorn et al., 2024). Once in the atmosphere, SO_2 undergoes oxidation to form SO_4^{2-}. This process is enhanced by the presence of hydroxyl radicals (OH), ozone (O_3) as well as atmospheric moisture (Haagen-Smit and Wayne, 2015).

Nitrogen oxides (NO_x), emitted mainly from industrial activities also contribute to the formation of secondary $PM_{2.5}$ (Zhao et al., 2025). NO_x reacts with atmospheric oxidants to form nitric acid (HNO_3). HNO_3 interacts with NH_3 to produce ammonium nitrate (NH_4NO_3) particles (Liu et al., 2024). VOCs form secondary $PM_{2.5}$ through photochemical reactions. VOCs are emitted from vehicle exhaust, industrial and natural processes (Dai et al., 2018). In the presence of sunlight, VOCs undergo oxidation and react with other atmospheric pollutants to form secondary $PM_{2.5}$ (Song et al., 2022).

2.1.4 The Monitoring of ambient $PM_{2.5}$

Ambient air quality monitoring greatly assesses community exposure to $PM_{2.5}$ (Masri et al., 2022). Generally, $PM_{2.5}$ ambient air quality monitoring is carried out using monitoring stations (Ho et al., 2020). The monitoring stations are equipped with high-precision instruments that measure $PM_{2.5}$ concentrations. These measuring instruments provide reliable and accurate data (Onaiwu et al., 2024). However, the high costs of setting up and maintaining these monitoring stations limit their geographical coverage (Snyder et al., 2013). This limitation is problematic in assessing $PM_{2.5}$ concentrations in communities heavily impacted by air pollution. In addressing these limitations, there has been a growing interest in using LCMs for monitoring $PM_{2.5}$ (Mead et al., 2013; Kumar et al., 2015; Morawska et al., 2018; Thabethe et al., 2025). The LCMs are small, less expensive and easier to deploy in large numbers. They provide a solution for expanding air quality monitoring networks (Fanti et al., 2021). Despite their affordability and ease of deployment, LCMs face challenges related to data accuracy, calibration and long-term stability (Malings et al., 2019).

$PM_{2.5}$ concentrations can vary across different locations due to various factors. These factors include proximity to sources, atmospheric conditions and geographical features (Lin et al., 2014). Areas near major roads and industrial sites often experience higher concentrations of $PM_{2.5}$ than those far from these sources (Tshehla and Wright, 2019). Additionally, atmospheric conditions (wind speed, temperature and humidity) may influence the dispersion and accumulation of $PM_{2.5}$ (Asif et al., 2018). Therefore, a single air quality monitoring station may not provide a comprehensive picture of community exposure given these factors. Studies have shown that the spatial variability of $PM_{2.5}$ concentrations can be different within the same neighborhoods (Eeftens et al., 2015; Kassomenos et al., 2014; Lin et al., 2014). This emphasizes the need for a dense monitoring network to capture these variations and provide more accurate assessments of community exposure. Moreover, $PM_{2.5}$ concentrations fluctuate over time due to changes in seasonal variations and human activities (Zhao et al., 2018). Increased $PM_{2.5}$ concentrations are often observed in colder months when heating activities are more prevalent (Xiao et al., 2018).

LCMs are used for mapping spatial variations in $PM_{2.5}$ concentrations to identify hotspots that might be missed by traditional monitoring networks (Ma et al., 2024). They supplement existing monitoring stations. Since traditional air quality monitoring stations are often limited in number, LCMs help fill those data gaps (Suriano & Prato, 2023). They help a lot in areas with limited access to high-cost monitoring infrastructure. Furthermore, they support citizen science projects by allowing individuals to collect and share air quality data to raise awareness and advocate for cleaner air.

To address the challenges associated with LCMs, there is ongoing research to improve their accuracy and calibration methods (Zimmerman et al., 2018). One of the approaches is using machine learning algorithms and cloud-based correction models to refine sensor readings and reduce measurement errors (Kombo, 2022). Another strategy to increase the reliability of LCMs is deploying them in high-density networks (Choudhary et al., 2020). A greater number of LCMs help account for inaccuracies and provide a more comprehensive assessment of air $PM_{2.5}$ (Bi et al., 2020). Integrating LCMs data with satellite observations and atmospheric models can improve air quality estimates and support decision-making processes (Caquilpán et al., 2019).

2.1.5 Evaluation of $PM_{2.5}$ Low-Cost Monitors Performance

Badura et al., 2018 evaluated the performance of optical $PM_{2.5}$ LCMs by comparing them with four collocated models of low-cost optical sensors with a TEOM 1400a analyzer. The SDS011 (Nova Fitness), ZH03A (Winsen), PMS7003 (Plantower) and OPC-N2 (Alphasense) sensors were used in their study. Badura et al. (2018) concluded that $PM_{2.5}$ LCMs could be effective ambient air quality monitoring tools. A study by (Zikova et al., 2017) assessed the performance of sixty-six new Speck LCMs which were collocated with a Grimm 1.109 particle spectrometer and CO loggers. The evaluation was done to assess the ability of the LCMs to measure $PM_{2.5}$ concentrations under real-use conditions. The study concluded that Speck LCMs may be suitable for monitoring ambient $PM_{2.5}$. However, they have a large bias at low $PM_{2.5}$ concentrations, making them unsuitable for measurements in clean environments (Zikova et al., 2017).

Feenstra et al. (2019) evaluated the performance of twelve (12) $PM_{2.5}$ LCMs. The LCMs were tested under ambient conditions against a Federally Equivalent Method (FEM) instrument at an ambient air monitoring station in Riverside over a 3-year period. The study's results indicated that several of these LCMs can potentially characterize $PM_{2.5}$ levels in ambient environments (Feenstra et al., 2019).

Three LCMs (AirVisual Pro, Speck and AirThinx) were evaluated over one year to assess the built-in calibrations and the need for additional data to achieve high accuracy for long deployments. The study indicated that monthly calibrations yielded highest accuracies. The study concluded that each LCM should be evaluated before the data can be used to confidently evaluate residential exposures (Zamora et al., 2020). A study conducted by Datta et al. (2020) evaluated field calibration of the $PM_{2.5}$ data from a network of LCMs operating in Baltimore. The statistical model offered an improvement in prediction quality over the raw data. Furthermore, the results were robust to the choice of the LCMs used for field calibration and to different seasonal choices of training periods (Datta et al., 2020).

2.2 Dispersion of $PM_{2.5}$ from various sources

$PM_{2.5}$ is carried by wind to areas far from the original emission site (Zhang et al., 2021). $PM_{2.5}$ remains suspended in the atmosphere for extended periods and travels over long distances (Kukkonen et al., 2018). The transport of $PM_{2.5}$ is largely controlled by meteorological conditions (Chao et al., 2019). Strong winds carry $PM_{2.5}$ over long distances, while the wind direction determines where the $PM_{2.5}$ is dispersed (Yan et al., 2024). Changes in wind patterns cause $PM_{2.5}$ to accumulate in certain regions (Sun et al., 2018). Temperature inversions influence the vertical transport and dispersion of $PM_{2.5}$ (Kadir, 2019). A layer of warm air traps cooler air near the ground and prevents $PM_{2.5}$ from dispersing (Zhou et al., 2021).

High humidity causes $PM_{2.5}$ to undergo hygroscopic growth (Leelasakultum, 2013). Hygroscopic growth is when $PM_{2.5}$ absorbs moisture from the air and increases in size (Boreddy et al., 2016). This growth changes the properties of $PM_{2.5}$ and often contributes to haze formation (Kim et al., 2024). Rainfall helps remove $PM_{2.5}$ from the atmosphere through a process called wet deposition (Mukta et al., 2020). As raindrops fall, they capture and dissolve airborne $PM_{2.5}$ and carry it down to the ground. This process reduces $PM_{2.5}$ concentrations in the air (Xie et al., 2019). Wet deposition can occur in two ways: in-cloud scavenging and below-cloud scavenging (Yang et al., 2021). In-cloud scavenging is when $PM_{2.5}$ acts as nuclei for cloud droplets that later fall as precipitation. Below-cloud scavenging is when raindrops collide with and capture $PM_{2.5}$ as they descend (Yang et al., 2019).

The effectiveness of wet deposition depends on rainfall intensity and particle size (Deng et al., 2020). This means that heavy rain removes more $PM_{2.5}$ than light drizzle. $PM_{2.5}$ can be transported both locally and globally depending on the wind and wind direction conditions (Mecca et al., 2024). Short-range transport occurs when $PM_{2.5}$ remains within a specific region, typically within a few kilometers of its source (Liao et al., 2017). Long-range transport happens when atmospheric currents carry $PM_{2.5}$ over hundreds of kilometers (Singh, 2015). This is known as transboundary air pollution, where pollutants cross-national and even continental boundaries (Byrne, 2017).

2.2.1 Temporal and Spatial Variations of $PM_{2.5}$

The daily variations of $PM_{2.5}$ follow a pattern dictated by emission sources and meteorological dynamics (Bamotra et al., 2022). The temporal variations of $PM_{2.5}$ concentrations may show distinct daily patterns influenced by meteorological conditions (Chen et al., 2018). Industrial and mining processes may contribute to short-term fluctuations in $PM_{2.5}$ concentrations (Dergham et al., 2015). During blasting events for instance, there may be a sudden and sharp increase in $PM_{2.5}$ concentrations due to emitted dust. These peak concentrations in $PM_{2.5}$ are observed immediately after blasting and can persist for several hours depending on atmospheric conditions (Morera de la Vall González, 2018).

Transport-related emissions contribute to the diurnal variations of $PM_{2.5}$. Vehicular emissions from road traffic contribute to increased concentrations during peak commuting hours in the morning and late afternoon (Hoffmann, 2019). Temperature inversions, occur during the early morning and late evening. These inversions create atmospheric layers that trap $PM_{2.5}$ near the surface. During an inversion, cooler air remains below a layer of warmer air and prevents the vertical dispersion of $PM_{2.5}$ (Wang et al., 2019). This phenomenon leads to a buildup of $PM_{2.5}$, resulting in higher concentrations in the early hours of the day. When solar radiation increases, the inversion dissipates (Yavuz, 2025).

During dry seasons, $PM_{2.5}$ concentrations are significantly higher due to increased dust emissions from TSFs, unpaved roads and other exposed surfaces (Andraos, 2019). The lack of precipitation during dry seasons allows $PM_{2.5}$ to become easily resuspended by wind. Stronger winds are more common in dry seasons and further increase dust dispersion. The increase in dust dispersion leads to elevated ambient $PM_{2.5}$ concentrations in surrounding communities (Sharma et al., 2024).

Conversely, during wet seasons, precipitation suppresses dust emissions (Aryal and Evans, 2023). On an annual basis, $PM_{2.5}$ concentrations may show long-term trends corresponding to broader climatic variations in mining and industrial activities (Lu et al., 2017).

Annual variations may also be influenced by regulatory changes, improvements in dust suppression techniques and economic factors affecting mining production (Carvalho, 2017). For instance, years with increased mining output often result in higher $PM_{2.5}$ concentrations due to greater blasting, excavation and transportation activities (Jain, 2015). Conversely, years with decreased industrial and mining activities may decrease $PM_{2.5}$ due to economic downturns (Santacatalina et al., 2012).

One of the most significant factors affecting spatial variations in $PM_{2.5}$ is the distance from primary emission sources (Li et al., 2015). Areas closest to active mining sites and TSFs may experience the highest $PM_{2.5}$ concentrations (Petzer, 2020). On the other hand, areas located farther from direct emission sources generally experience lower $PM_{2.5}$ concentrations due to dilution and dispersion (Tshehla and Wright, 2019). The terrain of an area determines how

$PM_{2.5}$ is distributed. Low-lying areas, valleys and basins experience higher concentrations due to the trapping of $PM_{2.5}$ during temperature inversions (Lewis et al., 2010). In contrast, elevated areas and ridges may experience better ventilation and reduced $PM_{2.5}$ concentrations. The presence of hills and mountains can also influence wind flow and create hotspots for $PM_{2.5}$ to accumulate (Danek et al., 2022).

The presence of vegetation and urban infrastructure also influences spatial variations in $PM_{2.5}$. Vegetation helps reduce $PM_{2.5}$ concentrations by acting as a natural barrier (Heshani and Winijkul, 2022). Urbanized areas experience elevated $PM_{2.5}$ concentrations due to the combination of mining-related emissions, traffic-related pollution and industrial activities (Odubo and Kosoe, 2024). Meanwhile, rural or less-developed areas may experience lower background $PM_{2.5}$ concentrations (Rahman et al., 2022).

2.2.2 Studies on Temporal and Spatial Variations of $PM_{2.5}$

A study on spatial and temporal variations of $PM_{2.5}$ in North Carolina observed that $PM_{2.5}$ concentrations were higher in summer and lower in winter (Cheng and Wang-Li, 2019). Jeong et al. (2019) found that traffic-related sources had strong diurnal and spatial variabilities. During morning rush hours, the overall contribution of traffic exhaust and non-exhaust emissions was observed to be up to 35%–48% of total $PM_{2.5}$ mass. The contribution of traffic-related sources at the highway was higher than at the downtown by a factor of 2 to 3. (Jeong et al., 2019).

Zhu and Shi (2018) analyzed the Spatio-temporal variations of $PM_{2.5}$ concentrations in Asia, Africa, and Europe from 2000 to 2018. The study further indicated India (62.6 $\mu g/m^3$), Bangladesh (60.8 $\mu g/m^3$), Nepal (56.4 $\mu g/m^3$), Pakistan (53.3 $\mu g/m^3$), Qatar (52.1 $\mu g/m^3$) and China (51.6 $\mu g/m^3$) were the six countries with the highest average population-weighted $PM_{2.5}$ (Zhu and Shi, 2018). Kalisa et al. (2023) revealed that long-range transport of pollutants to the study area is influenced by distant sources from the eastern, western, southern, and northern parts of Africa. The concentrations of pollutants were found to be influenced by temperature, precipitation and wind patterns (Kalisa et al., 2023).

In Ghana, the diurnal variations of $PM_{2.5}$ were observed with higher concentration at night than daytime; and with the peak in the morning between 6:00 am and 8:00 am. $PM_{2.5}$ concentrations across the city were significantly lower on Saturdays and Sundays and high on the other days of the week (Kagabo, 2018). In South Africa, $PM_{2.5}$ concentrations that exceeded the 24h $PM_{2.5}$ NAAQS of 40 µg/m^3 were observed during the cold period (May and June), while the warm period (March and April) recorded relatively lower concentrations (Moletsane et al., 2021). In Morocco, the highest $PM_{2.5-10}$ concentrations were observed in the summer and the lowest in the winter. However, no significant seasonal variations were distinguished for $PM_{2.5}$.

2.3 $PM_{2.5}$ Source identification and quantification

Temporal variability can further complicate source identification. Winter months may increase $PM_{2.5}$ concentrations due to domestic heating emissions (Huang et al., 2022). On the other hand, summer months might show increased $PM_{2.5}$ concentrations due to agricultural burning (Shi et al., 2014). Reliable source apportionment heavily depends on the quality and availability of $PM_{2.5}$ data (Hopke, 2016). Gaps in monitoring networks and in data collection methods can limit the effectiveness of source identification and quantification. Many regions lack sufficient air quality monitoring infrastructure, which affects accurate source apportionment efforts (Sokhi et al., 2021).

Several methodologies are employed to identify and quantify the sources of $PM_{2.5}$. These methods can be categorized into receptor models (Ka, 2022) and emission-based models (Martenies et al., 2015). Receptor Models rely on the chemical composition of $PM_{2.5}$ measured at monitoring sites to identify and quantify contributing sources (Fadel, 2021). Emission-Based Models Emission-based models estimate $PM_{2.5}$ concentrations based on known sources and their emissions, meteorological conditions and atmospheric processes (Ka, 2020). These models use emission inventories and environmental data to predict the sources of $PM_{2.5}$ (Martenies et al., 2015).

Despite the availability of advanced models and techniques, source identification and quantification for $PM_{2.5}$ face several challenges (Belis et al., 2014). One of the major challenges is the uncertainty surrounding source profiles, which are required for receptor models (Belis et al., 2014). Accurate source profiles are often difficult to obtain for biomass burning and cooking emissions (Reyes-Villegas et al., 2018). $PM_{2.5}$ is a highly complex mixture of both primary and secondary particles. Some sources contribute to both primary and secondary $PM_{2.5}$ (Liu, 2023). $PM_{2.5}$ concentrations vary significantly across both space and time (Guan et al., 2023). $PM_{2.5}$ concentrations tend to be higher near highways and industrial areas but can also be influenced by long-range transport (Chen et al., 2014).

2.3.1 Studies on Source Apportionment Techniques

Yu et al. (2013) applied the PMF method to determine the $PM_{2.5}$ sources in Beijing. Seven (7) sources and their contributions to the total $PM_{2.5}$ mass were identified and quantified. It was observed that secondary sulfur, vehicle exhaust, fossil fuel combustion, road dust, biomass burning, soil dust and metal processing contributed 26.5%, 17.1%, 16%, 12.7%,11.2%, 10.4% and 6.0%, respectively. A study in the Western Mediterranean applied a combination of PMF and Principal Component Analysis (PCA) to determine the source of $PM_{2.5}$.

Four common sources were identified using both models. The identified $PM_{2.5}$ sources were vehicular emissions, fuel-oil combustion, marine aerosols and mineral dust. The study concluded that using both models appeared complementary (Pey et al., 2013).

Choi et al. (2013) identified nine (9) sources of $PM_{2.5}$ in the coastal areas in Korea using PMF. The major sources of $PM_{2.5}$ were secondary nitrate, secondary sulfate, motor vehicles with a lesser contribution from industry, vehicle emissions, biomass burning, soil, combustion and copper production emissions; and sea salt. The PCA confirmed eight (8) of the nine $PM_{2.5}$ sources. The study results concluded that various modeling techniques can effectively identify the potential sources of $PM_{2.5}$ (Choi et al., 2013).

Srimuruganandam and Nagendra (2012) applied the Chemical Mass Balance (CMB) model to identify the source contribution of ambient $PM_{2.5}$ concentrations in India. The results of the study indicated that diesel exhausts (44–65%) and gasoline exhausts (3–8%) were the major source contributors followed by paved road dust (0 –2.3%), brake lining dust (0.2%), brake pad wear dust (0.01%), marine aerosols (0.1%) and cooking (~1.5%).

2.4. Adverse Health Effects of $PM_{2.5}$ Exposure

$PM_{2.5}$ penetrates deeply into the alveoli, impairing normal lung function (Xing et al., 2016). Chronic exposure to $PM_{2.5}$ is linked with Chronic Obstructive Pulmonary Disease (COPD); (Yan et al., 2022). Furthermore, acute exposure to elevated $PM_{2.5}$ levels may lead to shortness of breath and extreme coughing (Sweileh et al., 2018). These adverse human health effects of exposure to $PM_{2.5}$ may even develop in healthy individuals (Feng et al., 2016). In addition to respiratory health risks, $PM_{2.5}$ exposure is also strongly associated with cardiovascular effects (Zhang et al., 2022). $PM_{2.5}$ contributes to cardiovascular disease by inducing inflammation in the blood vessels (Tabua, 2019). This inflammatory response increases the risk of stroke (Rajput et al., 2024) and heart disease (Liu et al., 2022). Long-term exposure to high levels of $PM_{2.5}$ is linked to an increased risk of premature mortality (Dedoussi, 2014). $PM_{2.5}$ may contribute to cognitive decline and neurological diseases (Shi et al., 2020). $PM_{2.5}$ can enter the olfactory nerves and cause inflammation, affecting brain function (Li et al., 2022).

2.4.1.1 Respiratory Diseases

$PM_{2.5}$ can bypass the body's natural defense mechanisms and penetrate deep into the respiratory system because of its small size (Yang et al., 2020). Once $PM_{2.5}$ enters the lungs, it can trigger an inflammatory response (Li et al., 2021). The immune system reacts by activating immune cells which release pro-inflammatory cytokines (Jaffer et al., 2010). This inflammatory response can damage lung tissue over time and; cause structural and functional impairments (Hiemstra et al., 2015). $PM_{2.5}$ exposure generates Reactive Oxygen Species (ROS). ROS increases oxidative stress and causes tissue damage (Qiu et al., 2019). Oxidative stress causes the development of chronic respiratory conditions (Domej et al., 2014). Short-term exposure to $PM_{2.5}$ causes coughing, shortness of breath and asthma (Mainka & Żak, 2022). Long-term exposure is linked to lung fibrosis, pneumonia and bronchitis (Sekine et al., 2014). $PM_{2.5}$ exposure can impair lung function over time, reduce lung capacity and increase the risk of respiratory failure (Bo et al., 2021).

2.4.1.2 Cardiovascular Diseases

Long-term exposure to $PM_{2.5}$ has been linked to hypertension, atherosclerosis, heart attacks, strokes and heart failure (Krittanawong et al., 2023). One of the primary ways $PM_{2.5}$ causes cardiovascular diseases is through systemic inflammation (Dabass et al., 2018). When inhaled, $PM_{2.5}$ can cause inflammation in blood vessels and other organs (Jin et al., 2017). This inflammation causes the thickening and stiffening of blood vessels, thus increasing the risk of hypertension and atherosclerosis (Palombo & Kozakova, 2016).

Exposure to $PM_{2.5}$ may damage the endothelial cells lining the blood vessels (Xie et al., 2021). When damaged, endothelial cells become dysfunctional, producing reduced Nitric Oxide (Tousoulis et al., 2012). Nitric oxide is essential for maintaining normal blood vessel function. It helps to regulate blood pressure and prevent abnormal blood clotting (Bauer & Sotníková, 2010). Endothelial dysfunction is an early step in the development of atherosclerosis (Sitia et al., 2010). Atherosclerosis is a condition in which plaque builds up inside arteries, restricts blood flow and increases the risk of heart attacks and strokes (Gisterå & Hansson, 2017).

$PM_{2.5}$ exposure can also contribute to an imbalance in the autonomic nervous system which regulates heart rate and blood pressure (Liao et al., 2020). This imbalance can lead to increased heart rate, higher blood pressure and a greater likelihood of arrhythmias (Manolis et al., 2021). The inflammation and endothelial dysfunction caused by $PM_{2.5}$ exposure can increase the likelihood of blood clotting (Pope III et al., 2016). When blood clots form within arteries, they block blood flow to the heart and brain and cause heart attacks or strokes (Sarwar et al., 2015).

2.4.1.3 Cerebrovascular Diseases

Prolonged exposure to $PM_{2.5}$ has been linked to neurological disorders (Fu & Yung, 2021). One of the primary ways $PM_{2.5}$ contributes to cerebrovascular diseases is through systemic inflammation (Krittanawong et al., 2023). When blood vessels become inflamed and endothelial function is impaired, the body's normal clotting mechanisms can become overactive (Popescu et al., 2022). If a clot travels to the brain and blocks a cerebral artery, it can cut off oxygen supply. Even small, repeated exposures to $PM_{2.5}$ over time can contribute to a higher risk of Transient Ischemic Attacks (TIAs), (Gaines et al., 2023).

$PM_{2.5}$ exposure has also been linked to hemorrhagic strokes (Wu et al., 2022). Hemorrhagic stroke occurs when weakened blood vessels in the brain rupture and bleed (Boccardi et al., 2017). Beyond strokes, $PM_{2.5}$ exposure has been associated with cognitive decline and an increased risk of neurodegenerative diseases (Cristaldi et al., 2022). This is because $PM_{2.5}$ can cross the blood-brain barrier which prevents harmful substances from entering the brain (Liu et al., 2023). $PM_{2.5}$ may trigger neuroinflammation and damage the neurons. The damage to neurons may cause cognitive impairment over time (Song et al., 2022). Studies have shown that individuals exposed to high levels of $PM_{2.5}$ have a higher risk of developing dementia and other neurological disorders (Qiang et al., 2024; Fu & Yung, 2021).

2.4.2 Vulnerable Groups of Exposure to $PM_{2.5}$

While everyone is at risk of exposure to $PM_{2.5}$, certain groups of people are more vulnerable to its adverse effects (Thabethe et al., 2021). The vulnerable population groups include children, the elderly, pregnant women and individuals with pre-existing medical conditions (Gayer et al., 2020). Children are vulnerable to the harmful effects of $PM_{2.5}$ due to their developing respiratory systems and higher breathing rates relative to their body weight (Castro et al., 2022). Their lungs are still developing; early exposure to air pollution may lead to lasting respiratory problems (Pratiwi et al., 2024). Additionally, because children breathe more air per unit of body weight than adults, they are exposed to higher concentrations of $PM_{2.5}$ in the air (Saadeh & Klaunig et al., 2014) even if the concentrations are the same.

Exposure to $PM_{2.5}$ during childhood may have long-term cognitive and neurological effects, leading to developmental disorders and learning difficulties (Calderón-Garcidueñas et al., 2016). Children born to mothers who were exposed to high levels of $PM_{2.5}$ during pregnancy may have asthma, respiratory infections and cognitive impairments later in life (Chauhan et al., 2025). Older adults are vulnerable to $PM_{2.5}$ exposure due to the natural decline in lung function and the increased prevalence of chronic diseases as they age (Rice et al., 2015). They also have compromised immune systems, making them even more vulnerable (Amnuaylojaroen & Parasin, 2024).

The elderly tend to have less resilience to the effects of $PM_{2.5}$, which can result in more severe health outcomes than younger individuals exposed to similar concentrations (Gao et al., 2022). Pregnant women are also at a higher risk of experiencing adverse effects from $PM_{2.5}$ exposure. $PM_{2.5}$ exposure during pregnancy can seriously affect maternal and foetal health (Xie et al., 2021). $PM_{2.5}$ may affect the placental function, potentially leading to restricted oxygen supply to the foetus (Li et al., 2019).

2.4.4 Communities living near Tail Storage Facilities

Communities living near TSFs are vulnerable to the health effects of $PM_{2.5}$ (Kravchenko & Lyerly, et al., 2018; Simelane & Langerman, 2024). The impact on these communities varies depending on factors such as climate conditions, the composition of the TSFs and the effectiveness of the mitigation measures implemented. Strong winds disperse, $PM_{2.5}$ from TSFs to communities nearby (Mpanza, 2019). Dust storms generated by TSFs emissions can reduce visibility, damage infrastructure and create an unpleasant living environment (Nwaila, 2021). TSFs contain high concentrations of heavy metals which may have a greater impact on the environment and health of nearby communities (Mpanza et al., 2020).

The effectiveness of mitigation measures significantly influences how communities are protected from TSFs emissions (Cacciuttolo & Marinovic, 2022). Well-managed TSFs with proper suppression techniques and vegetation cover can minimize environmental impacts and limit community exposure (Amengual, 2024). Conversely, abandoned and poorly maintained TSFs pose ongoing human health risks as they release dust particles into the atmosphere (Liefferink, 2023).

Soil contamination on agricultural land is also a significant issue for communities near TSFs (Laker, 2023). This may lead to the accumulation of heavy metals in crops (Xiang et al., 2021). Livestock grazing on contaminated soil may also ingest harmful substances, further increasing food safety concerns for these communities. TSFs impact the overall quality of life in nearby communities (Mpanza, 2020).

2.4.5 Health Risk Assessment of $PM_{2.5}$ Exposure

The Human Health Risk Assessment (HHRA) model is a scientific approach used to evaluate the potential health risks associated with exposure to $PM_{2.5}$ (United States Environmental Protection Agency (USEPA), 2025). This model is widely applied in environmental and epidemiological studies to estimate the likelihood and severity of adverse health effects of $PM_{2.5}$ in exposed populations (Sukuman et al., 2023, Bodor et al., 2022, Sakunkoo et al., 2022). The HHRA model consists of four key steps: Hazard identification, Exposure assessment, Dose-response assessment and Risk characterization (USEPA, 2025).

2.4.5.1 Hazard Identification

Hazard identification is the first step in the HHRA model. This step involves determining whether $PM_{2.5}$ poses a potential health risk to exposed populations (Eregno et al., 2016). A review of toxicological and epidemiological studies is needed to identify the potential hazards of $PM_{2.5}$ exposure. Toxicological studies focus on controlled laboratory studies that examine how $PM_{2.5}$ affects biological systems (Garcia et al., 2023). On the other hand, epidemiological studies investigate real-world exposure scenarios by analyzing population health data. These studies help establish associations between $PM_{2.5}$ exposure and adverse health outcomes (Sukuman et al., 2023).

2.4.5.2 Exposure Assessment

The exposure assessment step involves quantifying the extent to which individuals or populations are exposed to $PM_{2.5}$. This process considers the concentration of $PM_{2.5}$ in the environment (Saraswat et al., 2016), the route of exposure, the duration and frequency of exposure (Paustenbach et al., 2024) and the population characteristics (Ouyang et al., 2018). The routes of exposure to $PM_{2.5}$ include inhalation, ingestion and dermal absorption (Feld-Cook and Weisel, 2021). The population characteristics include age, gender, occupation and lifestyle (Alves et al., 2023). In assessing $PM_{2.5}$ exposure in communities near TSFs, $PM_{2.5}$ concentrations in the air need to be measured, determine inhalation rates and assess the time the residents spend outdoors (Sun et al., 2021).

2.4.5.3 Dose-Response Assessment

The dose-response assessment examines the relationship between the level of exposure to $PM_{2.5}$ and the likelihood or severity of health effects. This step determines safe exposure limits and thresholds beyond which adverse health effects occur (Chiu and Slob, 2015). Air quality guidelines and NAAQS are based on dose-response relationships (Strum & Scheffe, 2016). The dose-response assessment distinguishes between non-carcinogenic and carcinogenic effects (Haney Jr, 2015). Non-carcinogenic effects are assessed using RfDs or RfCs. Carcinogenic effects are evaluated using CSFs to estimate excess cancer risk (Farimani-Raad et al., 2021).

2.4.5.4 Risk Characterization

Risk characterization is the final step, where data from the previous steps are integrated to estimate the overall health risk posed by a contaminant (USEPA, 2025). This step provides both quantitative and qualitative descriptions of risk. It considers uncertainty, variability and the combined effects of multiple exposures (European Food Safety Authority, 2019). Health risks are often characterized as Hazard Quotient (HQ) for non-carcinogenic effects and lifetime cancer risk (LCR) for carcinogenic effects. If the HQ is greater than 1, it indicates a potential health risk for non-cancer effects (Yousefi et al., 2022). If the LCR exceeds regulatory thresholds, it indicates an increased probability of developing cancer due to exposure (Ahmad et al., 2021).

2.4.6 Exposure Pathways of $PM_{2.5}$

Exposure to $PM_{2.5}$ occurs through several pathways, including inhalation, ingestion and dermal contact (Feld-Cook and Weisel, 2021). These pathways determine how $PM_{2.5}$ enters the body and cause various health effects. Inhalation is the most direct route of exposure to $PM_{2.5}$ (Alves et al., 2023). Ingestion of $PM_{2.5}$ can also occur through contaminated food, water and hand-to-mouth activity (Tian et al., 2020).

Airborne $PM_{2.5}$ settles on crops, soil and open water sources leading to ingestion. People may consume $PM_{2.5}$ particles when eating unwashed fruits and vegetables, drinking contaminated water or ingesting soil (Brevik, 2010). Hand-to-mouth activity is another way $PM_{2.5}$ is ingested, particularly in children who frequently touch surfaces and put their hands in their mouths (Feld-Cook and Weisel, 2021). Once ingested, $PM_{2.5}$ travels through the digestive system (Kermani et al., 2022) and is absorbed into the bloodstream (Hu et al., 2024). Dermal contact with $PM_{2.5}$ is a less significant pathway than inhalation and ingestion (Balasch et al, 2023). Although the skin acts as a natural barrier against many contaminants, $PM_{2.5}$ may settle on it (Kang et al., 2023) when individuals are outdoors. Frequent exposure to $PM_{2.5}$ may lead to skin irritation and dermatitis (Kim et al., 2016).

2.4.7 Factors Affecting Human Health Effects of Exposure to $PM_{2.5}$

The severity and extent of the human health effects of exposure to $PM_{2.5}$ vary depending on several factors. The impact of $PM_{2.5}$ exposure on human health is influenced by the concentration and composition of $PM_{2.5}$, duration and frequency of exposure, individual susceptibility and route of exposure (Wang et al., 2021).

Higher concentrations of $PM_{2.5}$ increase the likelihood of adverse health outcomes (Lu et al., 2017). The chemical composition of $PM_{2.5}$ also plays a role in its toxicity (Jia et al., 2017). $PM_{2.5}$ is not a single substance but a mixture of different components, including heavy metals, organic pollutants, sulfates, nitrates and black carbon (Anggraini et al., 2024). Some of these components are more harmful than others (Li et al., 2023). $PM_{2.5}$ emitted from TSFs may contain higher concentrations of heavy metals, thus increasing the risk of toxicity (Shi et al., 2023).

The length of time an individual is exposed to $PM_{2.5}$ affects health outcomes (Kloog et al., 2013). Short-term (acute) exposure to high concentrations of $PM_{2.5}$ can cause immediate symptoms and can also trigger existing respiratory conditions (Guaita et al., 2011). Long-term (chronic) exposure is associated with more severe health effects and an increased risk of death (Hajizadeh et al., 2020). Individuals who are continuously exposed to $PM_{2.5}$ may suffer negative health effects (Malecki et al., 2018).

Certain groups of people are more vulnerable to the harmful effects of $PM_{2.5}$ due to individual susceptibility (Huang et al., 2017). Children's lungs are still developing, and they breathe more than adults. This leads to a greater intake of $PM_{2.5}$ per unit of body weight (Amnuaylojaroen and Parasin, 2023). Aging is associated with a weakened immune system. This means that older adults are more susceptible to health risks caused by $PM_{2.5}$ exposure (Chanda et al., 2024). Geographical location also affects $PM_{2.5}$ exposure risks. Communities located near industrial zones (Kermani et al., 2021), mining sites and high-traffic areas experience more exposure to $PM_{2.5}$ (Hernández-Paniagua et al., 2018).

2.4.8 Probabilistic vs Deterministic Human Health Risk Assessment

There are two primary approaches to conducting HHRA, namely, DHHRA and PHHRA. These approaches differ in handling uncertainty, variability and complexity in exposure and toxicity assessment, leading to different interpretations of the outcomes (Herojeet et al., 2023). DHHRA relies on fixed values for exposure parameters and toxicity reference values. This approach involves selecting single values to represent $PM_{2.5}$ concentration, Exposure Duration (ED), Body Weight (BW) and Inhalation Rates (IR), (Khareef et al., 2021). This approach assumes that an individual is exposed to a given contaminant consistently and predictably, simplifying calculations and providing a straightforward risk estimate. An advantage of DHHRA is that it is simple, quick and easy to apply. DHHRA is effective for screening-level assessments, which aim to determine whether further investigation is needed (Munshed et al., 2023).

A limitation of DHHRA is that it does not account for variability within populations and uncertainty in exposure scenarios (Mohan and Sruthy, 2022). It relies on fixed assumptions and the results can either overestimate or underestimate the true risk. For instance, assuming that all individuals in a population are exposed to the maximum detected concentration of $PM_{2.5}$ may lead to an overly conservative risk estimate. This may potentially result in unnecessary regulatory burdens. Conversely, using average exposure values might underestimate risk for highly exposed individuals and vulnerable populations (Rajkumar et al., 2023). Another limitation is that DHHRA does not quantify the probability of different risk outcomes (Chiu and Slob, 2015). It provides a single risk estimate and does not convey how likely or unlikely that estimate is. This makes it difficult to compare multiple risk scenarios effectively.

In contrast to deterministic methods, PHHRA incorporates uncertainty and variability by using statistical techniques to model a range of possible risk outcomes (Kaur et al., 2020). Instead of relying on fixed values, PHHRA assigns probability distributions to exposure levels, BW, ED and IR (Zhang et al., 2022). This approach allows for evaluating multiple exposure scenarios rather than a single and fixed estimate.

PHHRA uses Monte Carlo simulations (MCS). MCS is a computational technique that randomly samples values from probability distributions and repeatedly calculates risk estimates thousands or even millions of times (Poncet and Portait, 2022). This generates a distribution of risk values, rather than a single-point estimate. PHHRA provides risk estimates at various percentiles. It can quantify uncertainty (Cozma et al., 2018). The input parameters are represented as distributions, allowing for the confidence level assessment on risk estimates (Coll et al., 2016). PHHRA can model how risk changes with varying ED, BW, IR and different demographic characteristics (Barrio-Parra et al., 2019).

2.4.9 Studies on Human Health Risk Assessment of $PM_{2.5}$

A study conducted by Omidi-Khaniabadi et al (2019) in Iran observed that 7.3% total mortality (95% CI: 4.2–9.7%), 12.1% cardiovascular mortality (95% CI: 3.5–14.6%) and 3.0% respiratory mortality (95% CI: 0–6.3%) respectively were attributed to $PM_{2.5}$ concentrations exceeding 10 mg/m^3. Bodor et al., 2022 conducted a study in Romania. They observed that there was a positive relative risk in the case of cardiopulmonary and lung cancer morbidity mainly attributed to $PM_{2.5}$ exposure, with the resulting risk for the country average values of 1.26 (± 0.023) and 1.42 (± 0.037), respectively.

A study conducted on the health impacts of weekday traffic of $PM_{2.5}$ emissions during congested periods in Canada showed that the daily mortality had an effect of 206 (boundary test 95%: 116; 297) and 119 (boundary test 95%: 67; 171) deaths per year (all-cause and cardiovascular mortality, respectively), (Requia et al., 2018). In Ghana, Amoatey et al (2018)'s study on the health risk assessment of $PM_{2.5}$ from the oil refinery found that cardiopulmonary disease-related mortalities accounted for 181 deaths in adults and 24 deaths in children. Additionally, lung cancer accounted for 137 deaths in adults and 16 deaths in children (Amoatey et al., 2018).

2.5 Local, Continental and International $PM_{2.5}$ Policies Laws

Governments worldwide have considered the need to set NAAQS for $PM_{2.5}$ levels to protect public health. These NAAQS are aimed at reducing $PM_{2.5}$ levels, compliance with international standards and implementing mitigation strategies (Smith, 2018). The South African government has enacted legislation to monitor and manage $PM_{2.5}$ levels. The National

Environmental Management: Air Quality Act (NEMAQA); (Act 39 of 2004) is the cornerstone of South Africa's air quality management legislation. This Act provides the legal framework for monitoring and regulating $PM_{2.5}$ levels across South Africa (South Africa, 2004). It also mandates the establishment of air quality monitoring stations across the country (South Africa, 2004).

According to the NAAQS set under this NEMAQA (Act 39 of 2004), the maximum permissible 24-hour concentration for $PM_{2.5}$ is 40 µg/m³ and the annual average should not exceed 20 µg/m³ (South Africa, 2012). These NAAQS are aligned with international best practices and are intended to protect public health and the environment (Spickett et al., 2013). In addition, the South African Air Quality Information System (SAAQIS) has been implemented to monitor $PM_{2.5}$ in real-time and ensure that its levels are within the prescribed NAAQS (South Africa, 2025). The Act also authorizes the Department of Environment, Forestry, and Fisheries (DEFF) to take corrective actions against industries that exceed the NAAQS.

In Kenya, the Environmental Management and Coordination Act (EMCA) of 1999 provides the legal foundation for regulating air quality. This act empowers the government to establish the National Environment Management Authority, which shall, in consultation with the relevant lead agencies, advise the Authority on the establishment criteria and procedures for measuring air quality (Republic of Kenya, 1999). In Nigeria, air pollution regulation falls under the National Environmental Standards and Regulations Enforcement Agency (NESREA), which was established to ensure compliance with air quality Regulations. The National Environment (Air Quality Control) Regulations limit maximum air contaminant concentrations (Federal Republic of Nigeria, 2021). Morocco has made significant progress in addressing air quality. The National Charter on Environment and Sustainable Development was developed (Morocco, 2023)

One of the key frameworks is the African Union Commission (AUC)'s Agenda 2063 emphasizes the importance of environmental sustainability and reducing air pollution (AUC, 2015). Under this Agenda, increased efforts have been made to improve air quality monitoring and strengthen environmental Regulations. Another important regional framework is the United Nations Environment Programme (UNEP) Africa Programme. This program has worked to raise awareness about the impacts of air pollution on public health and the environment. UNEP's work in Africa includes efforts to improve air quality monitoring networks, develop policies and support countries in implementing Regulations to address $PM_{2.5}$ levels (UNEP, 2025).

In addition, the Southern African Development Community (SADC) has developed a protocol on environmental management for sustainable development to guide the continent in addressing air pollution (SADC, 2022). The protocol includes calls to the need for clean air and sustainable development. However, the protocol lacks specific targets on the regulations of $PM_{2.5}$ levels. Nonetheless, it provides a platform for member states to collaborate on air quality management (SADC, 2022). The East African Community (EAC) includes air quality management in its environmental policies. The EAC has made efforts to improve the capacity of member states to monitor air pollution and develop national policies and Regulations in line with Continental priorities (EAC, 2015).

2.5.1 International $PM_{2.5}$ Policies and Laws

At the international level, various organizations and governments have developed policies and laws to address the harmful effects of $PM_{2.5}$. One of the organizations that set global $PM_{2.5}$ Guidelines is the World Health Organization (WHO). The WHO Air Quality Guidelines recommend that the annual mean concentration of $PM_{2.5}$ should not exceed 5 µg/m³, and the 24-hour mean should be limited to 15 µg/m³ (WHO, 2021). In the European Union (EU), air quality standards for $PM_{2.5}$ are set within the framework of the Directive (2008/50/EC). This Directive establishes standards for $PM_{2.5}$ and requires that EU member states implement measures to comply with them. The EU's 24-hour standard for $PM_{2.5}$ is set at 50 µg/m³, with an annual standard of 25 µg/m³ (EU, 2010).

2.5.2 Challenges in Implementing and Enforcing $PM_{2.5}$ Regulations in Africa

Despite adopting air quality policies and laws in several African countries, enforcement remains one of the biggest challenges (Amegah & Agyei-Mensah, 2017). Establishing and maintaining air quality monitoring stations requires financial investment (Kumar et al., 2015). Many African Governments face budget constraints and competing priorities which hinder their ability to effectively manage $PM_{2.5}$ levels (Isaifan & Al-Thani, 2024). They also lack real-time air quality monitoring systems (Ngo et al., 2019). This means that the true extent of $PM_{2.5}$ levels may go undetected and compromise the effectiveness of existing policies. Expanding informal settlements and using biomass fuels for cooking in many areas increase $PM_{2.5}$ levels

(Kansiime et al., 2022). In many of those areas, urban planning and control measures are ineffective (Singha & Singha et al., 2024), making it difficult to manage the growing problem of increased $PM_{2.5}$ levels.

In some African countries, there is a lack of political will to enforce $PM_{2.5}$ Regulations. $PM_{2.5}$ Regulations are often seen as a barrier to economic development (Hao et al., 2018). Additionally, there is often limited public awareness of the health effects of $PM_{2.5}$ exposure (Owolabi et al., 2024). This lack of public awareness makes it harder to receive support for stronger Regulations (Xiong et al., 2018). Finally, local, regional and national authorities often lack coordination in implementing $PM_{2.5}$ Regulations (Feng & Liao et al., 2016). In many cases, $PM_{2.5}$ Regulations are not adequately integrated into broader urban planning and development strategies (Guo et al., 2019).

2.6 Mitigation Strategies to Reduce $PM_{2.5}$ Levels

Controlling its sources is one of the most effective strategies for reducing $PM_{2.5}$ pollution. $PM_{2.5}$ emissions can effectively be managed from the sources; industries should adopt cleaner technologies (Venkataraman et al., 2018). The cleaner technologies include the installation of electrostatic precipitators, scrubbers and fabric filters to capture $PM_{2.5}$ before it is released into the atmosphere (Singh & Saumya-Singh, 2019). Furthermore, switching to low-emission fuels and improving production methods reduces the emission of $PM_{2.5}$ (Shen, 2026).

Stricter emission standards for industries can further reduce $PM_{2.5}$ emissions (Zhang et al., 2019). Promoting cleaner vehicle technologies that produce less emissions than traditional combustion engine vehicles can lower $PM_{2.5}$ emissions (Ravi et al., 2023). Public transportation systems should be encouraged to reduce the number of private vehicles on the road and consequently lower $PM_{2.5}$ concentrations (Kresnanto et al., 2025). Adopting sustainable transportation infrastructure including dedicated bike lanes and pedestrian-friendly walkways can further help reduce $PM_{2.5}$ levels (Ogwu et al., 2024).

Reducing open burning of agricultural residues can significantly reduce $PM_{2.5}$ emissions (Zhang et al., 2017). Developing parks and urban forests can also aid in absorbing $PM_{2.5}$ emissions (Shin et al., 2020). Raising awareness about the health risks associated with $PM_{2.5}$ may encourage individuals to adopt behaviors that reduce emissions and exposure thereof

(Singha & Singha, 2024). The use of satellite imagery can assist in identifying $PM_{2.5}$ hotspots and tracking improvements over time (Zheng et al., 2021).

CHAPTER 3: METHODS AND MATERIALS

This chapter describes the methods employed to achieve the objectives of the study. It gives detailed information on (i) the LCMs used to measure the $PM_{2.5}$ concentrations at the TSFs and community fence line, (ii) dispersion modeling of $PM_{2.5}$ using American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD), (iii) APCS-MLR model used to identify the different sources of heavy metals in soil samples and (v) the PHHRA model applied to assess the human health risks associated with exposure to $PM_{2.5}$.

3.1 $PM_{2.5}$ Monitoring at the Source and Receptor

3.1.1 Study Areas

The gold mine TSFs in Evander (-26.483319º S; 29.095546º E) and the community of eMbalenhle (-26º 550613º S; 29.078937º E) were chosen as the source and receptor, respectively. Both areas fall under Govan Mbeki Municipality, situated in the south-eastern part of Mpumalanga Province. Evander and eMbalenhle are part of the Greater Secunda. The Municipality has the most diversified economy, dominated by petrochemical industry, coal and gold mines (Govan Mbeki Municipality, 2021). The climatic conditions in both areas are characterized by a warm and temperate atmosphere. During the winter season, precipitation levels are lower compared to those experienced in summer (Trenberth, 1999).

The population of eMbalenhle is estimated to be 118 889, with an annual growth of 2.5% (Statistics South Africa, 2011). The community of eMbalenhle is situated next to the Evander gold mine TSFs (3.1). eMbalenhle falls within the Highveld Priority Area (HPA). The HPA is an air pollution "hotspot" declared in terms of Section 18 of the National Ambient Air Quality Act (NEMAQA) 2004 (Act 39 of 2004).

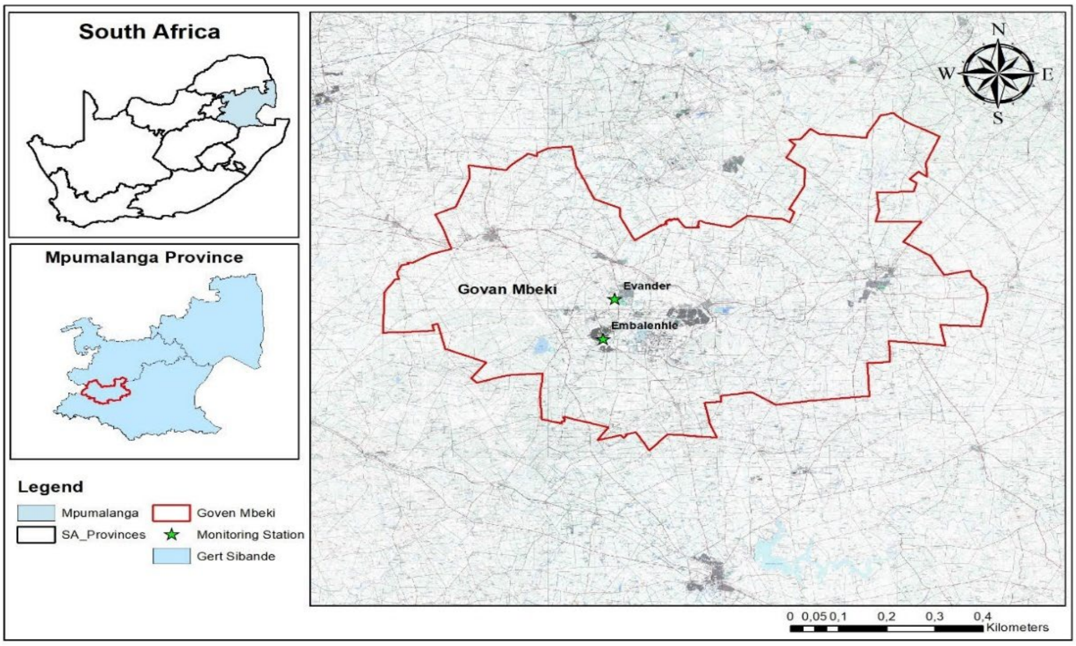


Figure 3.1: Map Indicating the Study Area and Location of Low-Cost Monitors

3.1.2 Data Collection

In this study, $PM_{2.5}$ concentrations were measured at the gold mine TSFs and in the community of eMbalenhle (3.1) for one year (from 07 February 2022 to 07 February 2023) using Clarity Node-S LCMs. The $PM_{2.5}$ concentrations were measured hourly and expressed in micrograms per cubic meter ($\mu g/m^3$). The $PM_{2.5}$ and meteorological data for the same period were obtained from SAAQIS, which is managed by the South African Weather Services (SAWS). The SAAQIS $PM_{2.5}$ data was used as reference data to compare and validate the data collected with the LCMs. The meteorological data included wind speed, wind direction, solar radiation, atmospheric radiation, rain, relative humidity and temperature. The study period was divided into four seasons: Summer (December to February), Autumn (March to May), Winter (June to August) and Spring (September to November).

3.1.3. $PM_{2.5}$ Monitoring Equipment

3.1.3.1 Clarity Node-S Low-Cost Monitors

The Clarity Node-S LCMs were designed to measure $PM_{2.5}$ with high precision (Figure 2.2). They can operate as solar-powered or externally powered devices. External power is required when temperatures drop below 0°C. The Node-S LCMs measure $PM_{2.5}$ using advanced sensor technology. $PM_{2.5}$ concentrations are detected using laser light scattering with remote calibration, providing a detection range of 0–1000 µg/m³ with a 1 µg/m³ resolution. The devices have an accuracy of ±10 µg/m³ for $PM_{2.5}$ concentrations below 100 µg/m³ and within ±10% of the measured value for concentrations exceeding this threshold. The system is well-correlated with USEPA Federal Equivalent Method (FEM) instruments ($R^2 > 0.8$), ensuring high reliability (Clarity Movement, 2025).

The LCMs have a weatherproof rating of IPX3, making them resistant to moderate rain and environmental exposure. The devices function within an operating temperature range of -10°C to 55°C, with an absolute temperature tolerance of -40°C to 70°C. Additionally, it is UV-resistant and capable of functioning in relative humidity levels ranging from 10% to 98%. One of the key features of the LCMs is their cloud-based data retrieval system. With a Subscriber Identity Module (SIM) card, the devices transmit data via global cellular networks (2nd, 3rd and 4th Generations). Users can access real-time air quality data through the Clarity Dashboard (Web Application), RESTful APIs (for programmatic access) and OpenMap (for public data sharing). The LCMs allow users to adjust measurement frequency, with a default setting of once every 15 minutes and a minimum interval of once every 3 minutes (Clarity Movement, 2025).

The devices are designed for energy-efficient operation, with a current consumption of 28 mA during sensing, 30 mA during transmission and <300 µA during sleep mode. It operates at an input voltage of 15V and is powered by a 6400 mAh lithium-ion battery with a nominal voltage of 10.8V. The battery requires approximately five hours to charge fully. The solar panels have a maximum power output of 6 Watts (W), with an open circuit voltage of 21.6 Volts (V) and a short circuit current of 350 mA. Under typical conditions, the devices can operate for 30 days without solar power harvesting and function for over five years with sufficient solar energy exposure. The solar shields further enhance performance by protecting the device from direct heat radiation (Clarity Movement, 2025).

The Node-S LCMs are compact and lightweight. The dimensions of the main units, excluding the shield and solar panel, are 165 mm Width (W) × 84 mm Height (H) × 80 mm Depth (D), with a total weight of 0.91 Kilograms (kg). The solar panel measures 233 mm (W) × 176 mm (H) × 4 mm (D) and weighs 0.47 kg. The optional solar shield has dimensions of 195 mm (W) × 97 mm (H) × 94 mm (D) and weighs 0.27 kg. The total assembled weight of the device is 1.65 kg (3.64 lbs). Beyond $PM_{2.5}$, the LCMs can measure several additional parameters. These include PM_1 and PM_{10} mass and number concentration, internal temperature and relative humidity, wind speed, wind direction (with add-on modules), ambient temperature, relative humidity and atmospheric pressure. Furthermore, FEM-grade ozone concentration and Total Volatile Organic Compounds (TVOCS) concentration (Clarity Movement, 2025) are also included.

Figure 3.2: The Clarity Node-S Low-Cost Monitor (Clarity Movement, 2024)

3.1.4 Data Correction and Validation

The data sets underwent a quality control process as described by Clarity Movement (2024) to ensure that the monitored (both $PM_{2.5}$ data sets monitored with the LCMs at the community and gold mine TSFs) and reference data ($PM_{2.5}$ data monitored by South African Weather Services (SAWS) monitoring station) were not erroneous. Data correction and validation for the LCMs involved using machine learning algorithms to predict $PM_{2.5}$ concentrations accurately. The first step involved using a training dataset to teach the model to identify patterns (Malings et al., 2019). The model learned from the training dataset by adjusting its parameters to make predictions as accurate as possible (Kleine-Deters et al., 2017). Furthermore, cross-validation was applied to assess the performance of the model (Wang et al., 2019). Clarity Movement developed custom calibration algorithms for each network and pollutant (Clarity Movement, 2024). The $PM_{2.5}$ concentrations were normalized by dividing each time series with the mean value (Qu et al., 2020).

3.1.5 Data Management

The South African National Accreditation System (SANAS) criteria for the representativeness of air quality measurements were used to assess the validity of the monitored data (SANAS, 2018). The SANAS data completeness requires 90% data completeness. A completeness threshold of 90% was applied to calculate the hourly average from the $PM_{2.5}$ data monitored with the LCMs and the one obtained from the SAAQIS. The validity percentage of the $PM_{2.5}$ data monitored with the LCMs and the one extracted from the SAAQIS were 80.1 and 63.1% respectively. The data was organized in Microsoft Excel sheets and named according to various variables.

3.1.6 $PM_{2.5}$ Data Analyses

Statistical analyses were performed using the Openair packages in R Studio (version 4.0.2) and Stata software (version 18). A non-parametric Wilcoxon signed-rank test was performed to determine significant differences in $PM_{2.5}$ concentrations between the community and the gold mine TSFs for hourly and 24-hour averages.

3.2 Dispersion Modelling

3.2.1 Emission Rates

TSFs are a significant source of $PM_{2.5}$. The $PM_{2.5}$ shape, height, size, surface area, moisture content and surface compaction of the TSF combined with prevailing meteorological conditions influence the rate of emissions. When estimating windblown dust in the 2.5 µm aerodynamic range, emission factors for wind erosion from other exposed areas and as provided in the National Pollutant Inventory (NPI), Emission Estimation Manual for Mining should be considered (NPI, 2012). The emission factors for Total Suspended Particles (TSP) and $PM_{2.5}$ are given as follows:

$$E_{TSP} = 0.4 \text{ kg/Ha/hr} \qquad \textit{Equation 3.1}$$

$$E_{PM2.5} = 5\% \text{ of TSP} \qquad \textit{Equation 3.2}$$

Where:
E is the emission rate given in units (kg/Hectare/hour)

3.2.2 Meteorological Parameters

Meteorological input data (AERMET (AERMOD Meteorological Preprocessor)) and Weather Research and Forecasting (WRF) files for 2019 to 2021were obtained from Lakes Environment. The base elevation was 1619 m, and the resolution was 12 km. When using the USEPA AERMOD to conduct refined dispersion modeling projects, there is a need to process the meteorological (met) data representative of the general area being modeled. The collected meteorological data was provided in a format unsupported by the AERMOD. Therefore, the meteorological data was preprocessed using the USEPA AERMET program. AERMET prepares meteorological data in two formats – hourly surface data and upper air data (Dewundege, 2020). The preprocessor produced two files that are compatible with AERMOD, namely the Surface File (*.SFC), which provided hourly boundary layer parameter estimates, and the Profile File (*PFL), which included information on temperature, wind speed, wind direction, and standard deviation relating to the fluctuating meteorological parameters.

The following are the minimum requirements when preprocessing meteorological data for use with the AERMOD: For upper air met data, the data was collected twice a day at 0000 GMT and 1200 GMT (Changotra et al., 2020). For surface met data (wind speed, wind direction, dry bulb temperature and cloud cover in tenths) were collected. Most stations in South Africa do not measure cloud cover. This is a prerequisite for AERMOD and must be present in the met data. Due to the lack of such vital information from met stations, researchers worldwide have resorted to the WRF and Mesoscale Model Interface Program (MMIF) files (Ogbuabia et al., 2023, Radford et al., 2021). The WRF is a numerical weather prediction model principally designed for forecasting applications and is now widely used in atmospheric research. AERMOD uses the same equations used in WRF to draw information on observations and historical meteorological data from the region around the modelling site. Therefore, the weather conditions at a specific location within the selected domain are predicted (Christoforou et al., 2023). Table 3.1 provides characteristics of the meteorological data that was used in the model (AERMOD).

Table 3.1: Characteristics of the meteorological data used in AERMET

Met Data Characteristics	Description
Met Data Type	AERMET-Ready WRF (Surface & Upper Air Data)
Start-End Date	Jan 01, 2019 hour 00 - Dec 31, 2021 hour 23
Resolution	12 km
Latitude	26.48331 S
Longitude	29.09556 E
Datum	WGS 84
UTM Zone	-35
Site Time Zone	UTC+0200
Closest City	Johannesburg
Country	South Africa
Station Base Elevation(m)	1614.77
Upper Air Adjustment	-2 hour(s)

3.2.3 $PM_{2.5}$ Modelling

To simulate ground-level $PM_{2.5}$ concentrations and dispersion from the TSF, AERMOD was employed. The AERMOD is built on the theory of planetary boundary layering. The model constitutes building downwash algorithms, pollutant deposition parameters, local terrain and urban heat island effects; and equations for meteorological turbulence calculations (Salami and Popoola, 2023). The model was used to assess ground-level $PM_{2.5}$ concentrations and deposition from a wide variety of sources under varying meteorological conditions, time zones and topography using a receptor grid that extended to a 20 km radius from the centre of the source (Mutlu, 2020; Seangkiatiyuth et al., 2011).

A multi-tier cartesian grid receptor network was used, and it covered an area with a radius of 20,000 m starting from the centre of the deposit and a diameter of 40,000 m. The receptors were set at 150 m from each other (Kerolli-Mustafa et al., 2022) for the fine grid setting, 500m for the medium grid setting, extending to 10 km radius from the TSFs and 1000m for the coarse grid setting, extending to 20 km radius from the TSFs (Figure 3.3). In total, 7104 gridded risk receptors were generated.

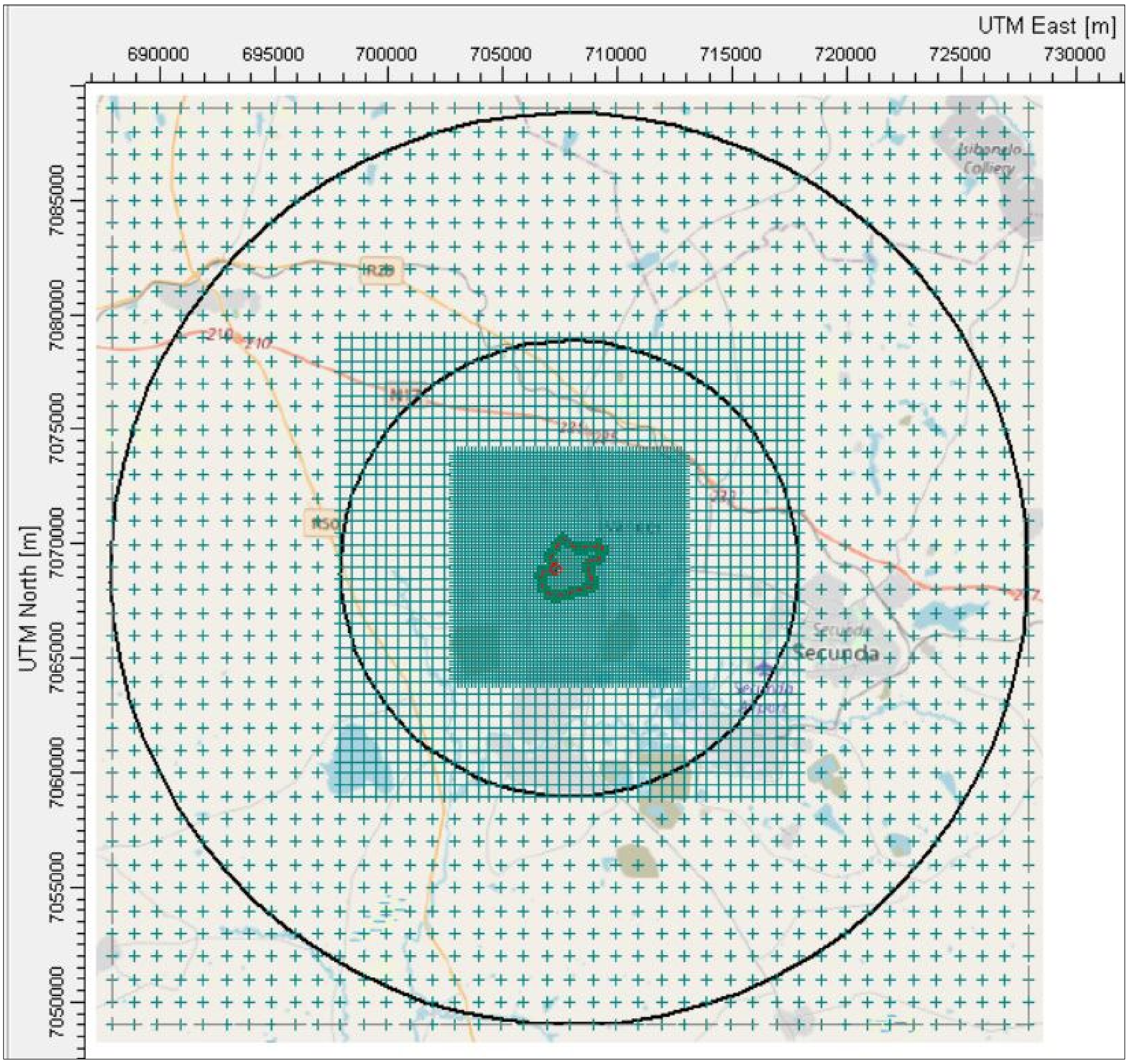


Figure 3.3: A uniform Cartesian network showing risk receptor grids for fine, medium and coarse grids.

In addition to these gridded receptors, sensitive discrete receptors were included in the final modelling domain of 40 km x 40 km. As shown in Figure 3.3. This domain was divided into a grid matrix with a multi-tiered grid resolution. AERMOD Terrain Preprocessor (AERMAP) is a terrain pre-processor developed for use with the model. It is used to estimate the elevation and values of the hill height scale for each receptor, source and building location within a modelling domain. $PM_{2.5}$ dispersion in the atmosphere is mainly influenced by terrain including complex areas (escarpments, valleys and hills). AERMAP employs Digital Elevation Models (DEMs) to measure and predict ground elevations accurately and to determine the features of the terrain likely to influence the vertical dimension of plumes (Irankunda et al., 2024). DEMs determine critical heights AERMOD uses to assess whether a plume will rise or pollutants flow around elevated terrains. The tool computes the height of the source versus the terrain in the modelling domain and allows AERMOD to adjust its dispersion calculations.

3.2.4 Discrete Receptors

Discrete receptors are point locations (Table 3.2) in AERMOD where pollutant concentrations are predicted and assessed because they have vulnerable population groups and sensitive land uses. These receptors were placed at schools, healthcare facilities, daycare centres, old people's homes, etc, where individuals may be regarded to be more susceptible to the health effects of air pollutants. These receptors are different from gridded receptors that cover the entire modelling domain. Sensitive receptors are needed for more targeted evaluations of $PM_{2.5}$ levels at "hotspot" locations. Table 3.2 lists sensitive and discrete receptors with their coordinates in the UTM (Universal Transverse Mercator) coordinate system. The impact of $PM_{2.5}$ emissions from the TSF was predicted at these receptor sites.

Table 3.2: A list of sensitive and discrete receptors with the coordinates presented in Universal Transverse Mercator

Receptor ID	Name	X	Y	Receptor ID	Name	X	Y
DR 1	TP Stratten Primary School.	710222	7070003	DR 27	Teksa Wound Care	719961.4	7064547
DR 2	Tholukwazi Primary School	705857.2	7062455	DR 28	Healing Hands Wound Care Centre	721733.7	7064541
DR 3	Thorisong Primary School	706650	7062817	DR 29	RHI Medi - Care Centre	707041.7	7063692
DR 4	Mbalenhle Primary School	706458.8	7064447	DR 30	Transvalia Clinic	718375.8	7065325
DR 5	Hoërskool Evander	709698.5	7069715	DR 31	Mediclinic Highveld Hospital	722557.7	7067896
DR 6	Shapeve Primary School.	708293.1	7063743	DR 32	Njabulo Xaba Dietetic services	710924.5	7070766
DR 7	Zamokuhle Primary School	706014	7062088	DR 33	Highveld Mediclinic Pediatric Ward	722510.7	7067908
DR 8	Osizweni Secondary School	705806.9	7065461	DR 34	Evander Hospital	711217	7070823
DR 9	Muzimuhle Primary School	712382.1	7066247	DR 35	Trichardt Mediclinic	722523.8	7067909
DR 10	Sizwakele Secondary School	706523	7062974	DR 36	Embalenhle CHC	707193.7	7061899
DR 11	Secunda Homework and Study Centre	720188.9	7067085	DR 37	Sasol mining Hospital	716074.9	7062556

DR 12	Infinity Education Tutorials	717632.3	7066544	DR 38	Sasol Mine Occupational Health Hospital	717289.1	7066701
DR 13	Osizweni Science Centre	706074.6	7066004	DR 39	Medforum	717509.2	7066275
DR 14	Diligent Students	719867	7064244	DR 40	Hoeveld Medi-Clinic-ER	722450.1	7067899
DR 15	NOSA College Secunda | SafetyCloud	717634.8	7066211	DR 41	Naomi Community home based care	708163.6	7061160
DR 16	Supreme Institute of Science and Techno	717462.5	7066597	DR 42	Maria old age home	711508.5	7070387
DR 17	Aleph Learning Academy (Pty) Ltd	717666.2	7066545	DR 43	HOPE Home Based Care	710112.1	7070727
DR 18	Gert Sibande FET College - Evander Cam	710197.4	7070725	DR 44	Ekhaya Mall	708844.5	7064570
DR 19	Educational Therapy	717504.5	7066262	DR 45	Mall@Embalenhle Shopping Centre	707133.1	7062347
DR 20	Pretoria Professional College	717865.8	7066403	DR 46	Sasol Community Recreation Centre eMb	707211.8	7061660
DR 21	Medlife Health Care	717783.5	7066429	DR 47	SharPozi	704482.1	7061649
DR 22	My Gp Health Care	710438.1	7070097	DR 48	Evander Club	710654.8	7069356
DR 23	Evander Primary Healthcare Clinic	711217.5	7070756	DR 49	Walking disabled educational wilderness	710920.4	7071370
DR 24	Embalenhle Clinic	707864.3	7063331	DR 50	Evander Park	709941.6	7071220
DR 25	Buciko Clinic	710412.3	7070238	DR 51	Izizwe Wellness centre	710322.9	7070157
DR 26	Basadi Occupational Health	720943.2	7067070	DR 52	Evander Easy Fitness	710441.5	7070142

**X represents the easting coordinate in the UTM projection.*
**Y represents the northing coordinate in the UTM projection.*
**Coordinates are given in meters, referenced to the relevant UTM Zone.*

3.3 Source Apportionment

3.3.1 Soil Sampling Points

Soil samples were collected at Evander, Winkelhaak, Leslie Remining and eMbalenhle TSFs. Furthermore, samples were also collected within residential sites (Evander High, Evander Station, Muslim School, eMbalenhle Station, eMbalenhle residential site and eMbalenhle Creche as indicated in Figure 3.4)

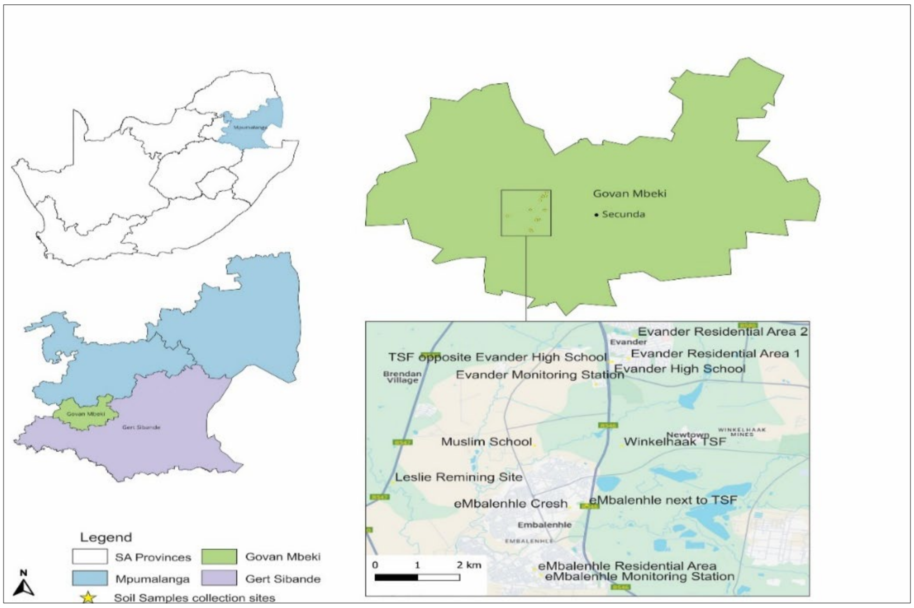


Figure 3.4: Geographical and Soil Sampling Map of the Study Areas

3.3.2 Samples Collection

3.3.2.1 Soil Bulk Sampling

Ten (10) topsoil samples around Evander and eMbalenhle were collected in July 2023. Four (4) samples were collected around the TSFs, and six (6) samples were collected in residential areas. A hand shovel was used to remove the topsoil. The soils were collected at depths between 0-15 cm. The soils were put in 1 kg plastic bags and placed in a container. The samples were labelled according to their site information. The Global Positioning System (GPS) documents the geographical coordinates at sampling points. The soil samples were stored in a cool place to prevent contamination and alterations in soil properties. The soil samples were then taken to the laboratory for analysis.

3.3.3 Sample Preparation and Chemical Analysis

The soil samples were sieved and dried before being analyzed. The Inductively Coupled Plasma Mass Spectrometry (ICP-MS) method, as described by Kubota (2021) and Shaheen et al., (2021) was used to analyze the soil samples. The samples were prepared in a 1% Nitric Acid (HNO_3) acid matrix. About 0.5% Hydrochloric acid (HCl) was routinely added to the soil samples to ensure the stability of elements. For quality control, the Initial Calibration Verification (ICV) and Continuing Calibration Verification (CCV) standards were prepared from the multi-element Environmental Calibration Standard (VHG). The single-element standards were also prepared for Pb, Hg, Cd, Mn, Ni, Zn, As, Au and U. The acid matrix was used as the Initial Calibration Blank (ICB) and Continuing Calibration Blank (CCB); (Kubota et al., 2021). Furthermore, the Certified Reference Material (CRM) was obtained from a reputable supplier (African Mineral Standards). The certificate of analysis for CRM, which indicated detailed information on the materials (including its certified values and uncertainties) was also provided. The Limit of Detection (LoD) for the analyzed heavy metals (Pb, Hg, Cd, Mn, Ni, Zn, As, Au, U) was 0.1 mg/kg.

3.3.4 Statistical Analyses

JASP 0.18.3 (https://jasp-stats.org/) was used to analyze the chemical analysis data. The LoD values were replaced using the NDExpo tool, nested in Expostats (https://expostats.ca/site/app-local/NDExpo/). This method is based on robust Regression on Order Statistics (ROS) which generates estimates based on their rank among the set of detected values. The heavy metal concentrations were grouped according to their origin location, i.e., TSFs or Residential, and the Mann-Whitney U test was used to test the differences between medians. The W-values were used to compute p-values and interpreted as follows.

If the p-value was less than 0.05 ($p< 0.05$), the null hypothesis was rejected, and it was concluded that there was a statistically significant difference between the means medians of the heavy metals concentration at the residential sites and TSFs.

If the p-value was greater than or equal to 0.05 ($p\geq 0.05$), the null hypothesis failed to be rejected and concluded that there was no significant difference.

Pearson's correlation analysis was performed to determine the linear correlation among heavy metals using SPSS v25.0 (https://www.ibm.com/products/spss-statistics). In addition, the rank-biserial correlation (rrb), a non-parametric effect size measure which was used to describe the difference between the concentrations of heavy metals at the residential sites and TSFs in terms of their ranks. It was derived from the Mann-Whitney U statistic as described by Metsämuuronen (2019). The rrb ranged from -1 to 1 and it was interpreted as follows:

rrb=1rrb=1: All observations in one group are higher than all observations in the other.

rrb=−1rrb=−1: All observations in one group are lower than those in the other group.

rrb=0rrb=0: There is no systematic difference between the groups.

∣rrb∣<0.1∣rrb∣<0.1: Very small effect size.

0.1≤∣rrb∣<0.30.1≤∣rrb∣<0.3: Small effect size.

0.3≤∣rrb∣<0.50.3≤∣rrb∣<0.5: Medium effect size.

|rrb|≥0.5|rrb|≥0.5: Large effect size.

3.3.5 The Enrichment and Contamination Factors

The Enrichment factor (EF) was used to assess the presence and intensity of anthropogenic contaminant deposition (Aytop, 2023). EF was calculated using Equation 3.3:

$EF = [Ci/C_{ref}]$ sample/ $[Ci/C_{ref}]$ background *Equation 3.3*

Where: C_i is the heavy metal concentration in the soil sample, C_{ref} is the geological background concentration (Aytop et al., 2023). Mn was chosen as a reference element (Awagu et al., 2014) because it is naturally abundant in the Earth's crust. Furthermore, Mn is mostly unaffected by human activities and remains stable under various environmental conditions. The mean concentrations of each heavy metal over the samples collected at residential sites and TSFs were used as C_i.

In this study, the Upper Earth's Crust (UEC) values were used as the soil background values of heavy metals /reference values for the pre-industrial concentration. The background values of the UEC were applied as 92 mg/kg (Cr), 47 mg/kg (Ni), 67 mg/kg (Zn), 17 mg/kg (Pb); (Rudnick & Rudnick, 2005), 4.8 mg/kg (As); (Rudnick & Gao, 2004), 600 mg/kg (Mn); (Bhattacharya et al., 2014), 2.3 mg/kg (U); (Emsley, 1989), 13.5 mg/kg (Hg); (Tian et al., 2023) and 0.05 mg/kg (Au); (Wyman & Kerrich, 1989). EF values can be categorized into five groups (Barbieri, 2016),

$EF < 2$, minimal enrichment.

$2 \leq EF < 5$, moderate enrichment;

$5 \leq EF < 20$, significant enrichment;

$20 \leq EF < 40$, very high enrichment;

$40 \geq EF$, extremely high enrichment

The Contamination Factor (CF) was used to assess the degree of contamination of heavy metals in the soil samples compared to the background value (UEC) without normalization (Rahmanian & Safari, 2022). The Contamination Factor (CF) was calculated as follows (Ferreira, 2022):

$C^i_f = C^i / C^i_n$ *Equation 3.4*

Where: C^i is the content of element (i) and C^i_n is pre-industrial value (or UEC) of element (i). The CF values are classified as follows:

CF < 1 → Low contamination, 1 < CF < 3 → Moderate contamination, 3 < CF < 6 → Considerable contamination, CF ≤ 6 → Very high contamination (Deliboran et al., 2024).

3.3.6 Determination of the Sources

APCS-MLR model was applied to apportion the different pollution sources at the TSFs and residential areas. The heavy metal concentrations of all samples collected at the TSFs; and all samples collected at the residential sites were used as inputs in the APCS-MLR model. The Stata/MP statistical software was used to conduct APCS-MLR. Generally, environmental datasets don't have normal distributions (Zhang, 2006). This study used the log transform commands in Stata statistical software to normalize the data. The eigenvalues associated with these principal components indicate how much variance each component captures. Larger eigenvalues mean more variance captured by that component. High absolute values means that the variable strongly contributes to that component (Lv et al., 2024). The eigenvectors describe the contribution of each original feature to the new principal components (Kharif & Latypova, 2020).

After analyzing the principal components, a scree plot was used to determine the optimal number of principal components to retain (Dheeraj et al., 2024). The factor scores were used to apportion the contributions of different pollution sources by quantifying how much each factor contributes to the observed pollution levels (Zhang et al., 2023). The factor loading matrix represented the extent to which a variable was associated with different factors. Factor loadings were categorized based on their strength. For instance, values above 0.75 indicated a strong correlation, those between 0.5 and 0.75 signified a moderate correlation and values ranging from 0.3 to 0.5 indicated a weak correlation. These classifications expressed the variables' level of influence on each principal component (Zhang et al., 2022). The steps of APCS-MLR are explained in Figure 3.5.

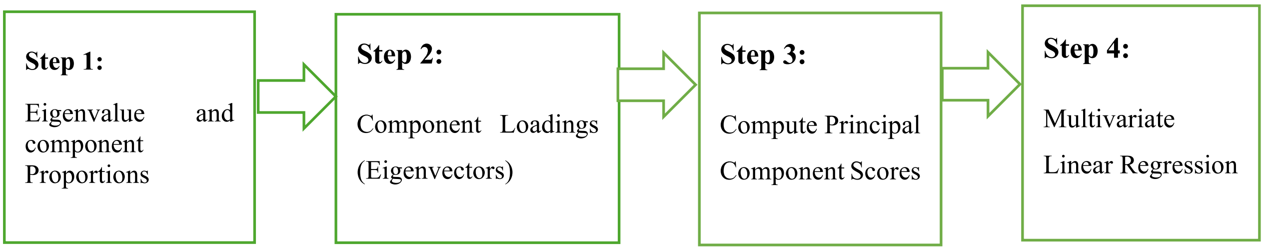


Figure 3.5: Steps Followed in the Application of the APCS-MLR

3.4 Probabilistic Human Health Risk Assessment

The population of eMbalenhle was divided into eight sub-groups because of the differences in exposure duration and development stages. The eight sub-groups included male and female toddlers (1 – 2 years) because their bodies are still developing and they have low IR; male and female children (6 – 11 years) because their bodies have developed and they have increased IR; male and female adults (21 – 60 years) because their bodies are fully developed and they have a much higher IR as compared to the toddlers and children; and male and female elders (61 - 70 years) because their health is weakening (USEPA, 2005).

3.4.1 Monte Carlo Simulation

Monte Carlo Simulation (MCS) was employed to generate samples from probability distributions, using an Oracle Crystal Ball spreadsheet-based application for predictive modeling. parameters, including $PM_{2.5}$ concentrations (C_{air}), EF, Exposure Time (ET), ED, and Average Time (AT), were considered as variables in the model. The ET, EF, ED and AT parameters were allocated triangular, uniform and normal distributions. The C_{air} was allocated a lognormal distribution. The model used Geometric Mean (GM) and Geometric Standard Deviation (GSD) of the annual $PM_{2.5}$ concentrations as C_{air}.

Table 3.3 lists all the variables used in the probabilistic HHRA model. The annual GM and GSD $PM_{2.5}$ concentrations used in the model were measured from February 2022 to February 2023. The ET was assumed to be 16 (minimum), 18 (mode), and 20 (maximum) hours for toddlers and children (16, 22, 24), and 20, 22, 24 for adults and elders. The EF was estimated based on the assumption that all population sub-groups leave the area for a maximum of one month, which translates to 335 days per year and a minimum of two weeks for vacation (i.e. the minimum EF is 350 days per year). The worst-case scenario assumed that all population subgroups are exposed 365 days per year. The AT for CR was based on chronic exposure during the lifetime. Lifetime values were obtained from the life-expectancy data according to the national census and population estimates (South Africa, 2022). Population estimates for life expectancy from 2002 to 2022 were used to compute the life expectancy arithmetic mean and the standard deviation values used in our model.

Once the distributions of the variables were determined as normal, lognormal or triangle, the model randomly selected a value for each variable and calculated the risk. In MCS, each calculation is called an iteration, and a set of iterations is called a simulation (Qin et al., 2021). The probabilistic health risk distribution was obtained by running 10 000 iterations (Zhu et al., 2019 & Mallongi et al., 2023).

The HQ was calculated using Equation 3.5 for each population sub-group to assess the non-carcinogenic health risks associated with exposure to $PM_{2.5}$.

$HQ = C_{air\text{-}adj} / Rfc$ *Equation 3.5*

Where:

HQ is unitless, representing the ratio of the concentration of $PM_{2.5}$ in the air (C_{air}) to the Reference Concentration (Rfc), (USEPA, 2024). Since the Rfc assumes continuous exposure 24 hours/7 days a week and 52 weeks/year, the measured concentration of $PM_{2.5}$ must be adjusted to the actual duration of the exposure. The adjusted $PM_{2.5}$ concentrations ($C_{air\text{-}adj}$) were estimated using Equation 3.6 derived from the USEPA (USEPA, 2024).

$C_{air\text{-}adj} = C_{air} \times (ET \times 1/24 \text{ hours}) \times (EF \times 1/365) \times ED/AT$ *Equation 3.6*

Where:

C_{air} = Concentration of contaminant in air (µg/m^3)

ET = Exposure time (hours/day)

EF = Exposure frequency (days/year)

ED = Exposure duration (years)

AT = Averaging time (years)

For non-carcinogenic health risks/sub-chronic exposure, or when evaluating acute exposures or short-term events where the exposure duration aligns with the exposure averaging time, AT equals ED; therefore, AT and ED can be left out of Equation (3.6). In contrast, for carcinogenic risk/ chronic exposure, the AT is equal to the estimated life expectancy.

The Rfc(s) represent the $PM_{2.5}$ concentration values unlikely to cause adverse human health risks over a specified period. The Rfc(s) were derived from toxicological studies and are expressed in the same units as C_{air} (i.e., $\mu g/m^3$). According to USEPA (USEPA, 2025), if the HQ is less or equal to one ($HQ \leq 1$), the concentration of $PM_{2.5}$ (C_{air}) is equal to or less than the Rfc. If the HQ is greater than one (HQ>1), there is an increased likelihood of developing non-carcinogenic adverse health outcomes.

The CR was calculated using Equation 3.7 for each population sub-group to assess the carcinogenic health risks associated with exposure to $PM_{2.5}$.

$CR = IUR \times C_{air\text{-}adj}$ *Equation 3.7*

Where:

CR is the cancer risk, which represents the estimated probability of developing cancer over a lifetime due to exposure to $PM_{2.5}$ through inhalation.

IUR is the inhalation unit risk, representing the increased risk of cancer per unit exposure to $PM_{2.5}$ through inhalation. The IUR for $PM_{2.5}$ is 0.008 $\mu g/m^3$ (Poppe et al., 2002).

A value greater than 1×10^{-04} (1 in 10 000) indicates a significant CR and may indicate a need for regulatory action or intervention to reduce exposure, as it exceeds the accepted risk threshold. On the other hand, a value less than 1×10^{-06} (1 in 1 000 000) indicates a negligible or “acceptable” risk. It can be ignored as it does not require regulatory action or interventions to reduce exposure (Candeias et al., 2021).

Table 3.3: Variables Used in the Probabilistic Human Health Risk Assessment Model

Parameter	Unit	Distribution	Value	Source
C_{air}	µg/m^3	Lognormal	GM 17 (GSD 1.69)	$PM_{2.5}$ Annual Average Concentrations (Thabethe et al., 2025)
ET (Toddler)	hours/day	Triangle	Min-mode-max 18 -22-24	(Section 3.5.1)
ET (Child)	hours/day	Triangle	16 -22 -24	(Section 3.5.1)
ET (Adult)	hours/day	Triangle	20 -22 – 24	(Section 3.5.1)
ET (Elder)	hours/day	Triangle	20- 22 – 24	(Section 3.5.1)
AT (CR) – All Males	years	Normal	57.26±4.71	(South Africa, 2011)
AT (CR) – All Females	years	Normal	62.19±5.53	(South Africa, 2011)
ED (Toddler)	years	Uniform	Min-max 1 -2	(Section 3.5.1)
ED (Child)	years	Uniform	6 -11	(Section 3.5.1)
ED (Adult)	years	Uniform	21 - 60	(Section 3.5.1)
ED (Elderly)	years	Uniform	61 - 70	(Section 3.5.1)
EF	days/year	Triangle	335 -350 - 365	(Section 3.5.1)
Rfc (Annual $PM_{2.5}$ -SA NAAQS)	µg/m^3	Not Applicable	20	(South Africa, 2004)
Rfc (Annual $PM_{2.5}$ – WHO Guidelines)	µg/m^3	Not Applicable	5	(WHO, 2021)
Rfc (Annual $PM_{2.5}$ US EPA NAAQS)	µg/m^3	Not Applicable	9	(USEPA, 2024)
IUR	µg/m^3	Not Applicable	0.008	(Poppe, 2002)
$C_{air\text{-}adj\ (HQ)}$	µg/m^3	Not Applicable	Calculated	Output
$C_{air\text{-}adj\ (CR)}$	µg/m^3	Not Applicable	Calculated	Output
HQ (SA-NAAQS)	Unitless	Not Applicable	Calculated	Output
HQ (WHO Guidelines)	Unitless	Not Applicable	Calculated	Output
HQ (US EPA NAAQS)	Unitless	Not Applicable	Calculated	Output
Cancer Risk	Unitless	Not Applicable	Calculated	Output

3.5 Ethical Considerations

The study was approved by the University of the Witwatersrand Human Research Ethics Committee (No: HRECNMW21/05/09), see Annexure A. The Researcher obtained permission to conduct research from Gert Sibande District Municipality (see Annexure B). No human subjects were involved in this study.

CHAPTER 4: ASSESSING $PM_{2.5}$ CONCENTRATIONS AT A GOLD MINE TAILINGS FACILITY AND ADJACENT COMMUNITY

This chapter presents the manuscript that was submitted to the Clean Air Journal and is awaiting publication. It gives a detailed assessment of $PM_{2.5}$ concentrations at gold mine TSFs and the adjacent community. Furthermore, it provides a comprehensive analysis of monitoring data, the spatial and temporal variations of $PM_{2.5}$ concentrations in the study; and key factors influencing its distribution. The instrumentation used for $PM_{2.5}$ monitoring, data collection procedures, calibration procedures and quality control measures implemented to ensure data reliability are explained. The results of diurnal and seasonal patterns in $PM_{2.5}$ concentrations with comparisons between measurements taken at the TSFs and those recorded in the community are presented.

Abstract

South Africa is home to some of the world's largest gold mines and contributes significantly to global gold production. However, gold mining activities generate waste in the form of soil, which is stored at Tailing Storage Facilities (TSFs). Gold mine TSFs are a source of ambient $PM_{2.5}$. $PM_{2.5}$ is particulate matter with a diameter of 2.5 micrometers or smaller. While many studies have documented the diurnal and seasonal variations of ambient $PM_{2.5}$, limited studies have reported these variations at the source and receptor. This study aimed to assess the $PM_{2.5}$ variations at the source (Evander gold mine TSFs) and receptor (eMbalenhle community). Ambient $PM_{2.5}$ concentrations were monitored over a year (07 February 2022 to 07 February 2023) using Clarity Node-S Low-Cost Monitors (LCMs). Meteorological data (wind speed, wind direction, solar radiation, atmospheric radiation, rain, relative humidity, and temperature) for the same period were sourced from the South African Air Quality Information System (SAAQIS). Statistical analyses were performed using the Openair packages in R Studio (version 4.0.2) and Stata software (version 18). The results showed that $PM_{2.5}$ concentrations were higher in Winter and lower in Summer at the community site and gold mine TSFs. The average daily (24-hour) $PM_{2.5}$ concentrations at the community site and gold mine TSFs were 19.24 and 9.70 µg/m³, respectively. The daily $PM_{2.5}$ concentrations at the community site exceeded the South African National Ambient Air Quality Standard (NAAQS) of 40 µg/m³ twenty-six (26) times and the WHO guidelines of fifteen (15) µg/m³ one hundred and eighty-one (181) times. The daily (24-hour) NAAQS was not exceeded at the gold mine TSFs;

however, the WHO guideline was exceeded eighty five (85) times. Diurnal variations in the community showed a bimodal pattern, with peak concentrations occurring early in the morning (05:00) and late afternoon (16:00 hours). Although the higher $PM_{2.5}$ concentrations were recorded in the community compared to the gold mine TSFs, local $PM_{2.5}$ sources could have contributed to the elevated concentrations. It is recommended that future studies focus on the dispersion and source apportionment of $PM_{2.5}$ to quantify the contribution of various sources in eMbalenhle.

Keywords: Low-cost Monitors, Particulate Matter, Gold Mining, Meteorological data

4.1 Introduction

Gold mining plays an important economic role as it provides sources of employment and income (Wale et al., 2021). Despite their importance, they are a source of $PM_{2.5}$. $PM_{2.5}$ is particulate matter with a diameter of 2.5 micrometers or smaller. They include a mixture of solids and liquid droplets (Ahrens, 2015). Gold mine Tail Storage Facilities (TSFs) include residues of gold extraction processes consisting of sand particles. The residues are discharged into a pond to accumulate and form a dam (Been, 2016). Following dam formation, wind erosion and mechanical processes like drying and crusting can break down the soil and emit $PM_{2.5}$ into the atmosphere (Ojelede, 2012). $PM_{2.5}$ may also originate from industrial processes, vehicular emissions (Tian et al., 2021), power plants (Bai et al., 2020), and natural processes (Kim et al., 2019). The inhalation of $PM_{2.5}$ can lead to asthma, lung disease, and chronic obstructive pulmonary disease (Wang and Liu, 2023). The most influential factor of the particles on human health is their size (Chen et al., 2017). Small particles can penetrate deeper into the respiratory system (Losacco et al., 2018). Studies have indicated that smaller particles are more toxic than larger particles with the same composition. This is due to their high deposition efficiency on the respiratory tract (Sonwani et al., 2021).

Pollution peaks in the early mornings and evenings due to increased human activities (Chen et al., 2020). Furthermore, temperature inversions and reduced dispersion in the morning and evening lead to increased ground-level $PM_{2.5}$ levels (Niedźwiedź et al., 2021). Diurnal concentrations can vary across locations due to local and regional sources (Fu et al., 2020). In most urban areas, $PM_{2.5}$ concentrations are higher during winter, mainly because of increased residential cooking, using traditional fuels for heating, and atmospheric conditions (Xu et al., 2020). On the other hand, summer seasons have lower $PM_{2.5}$ concentrations due to increased rainfall and improved dispersion (Sharma et al., 2022). Once $PM_{2.5}$ is released into the atmosphere, the wind may transport the particles long distances (Kim et al., 2021; Cheng and Hsu, 2019). Wind speed and direction, atmospheric stability and humidity influence the dispersion and transport patterns of $PM_{2.5}$ (Hu et al., 2022; Ma et al., 2021; Sirithian et al., 2022). Most studies have used high-resolution ambient air quality data from monitoring stations to determine diurnal and seasonal trends (Tian et al., 2019; He et al., 2020; Yatkin et al., 2020). The high-resolution data has a high level of precision in terms of spatial, temporal and spectral (Hu et al., 2014).

The concentrations recorded at the ambient air monitoring stations are assumed to indicate what communities are exposed to. However, the spatial resolution of airborne $PM_{2.5}$ can be improved if a network of ambient monitoring stations covers a larger area (Squizzato et al., 2017). This can be achieved by using a network of LCMs (Wendt et al., 2019). LCMs are readily deployed at multiple locations to account for spatial variability (Liu et al., 2019). These monitors are small, lightweight, and have minimal power consumption compared to the high-resolution ones (Johnson et al., 2018). However, the quality of data collected by LCMs may be arguable (Han et al., 2016). Most LCMs do not quantify particle mass concentrations directly but measure the number of particles in the air (Li and Biswas, 2017).

Although the LCMs only provide particle number concentration, the recorded concentrations can be converted to $PM_{2.5}$ mass concentrations using regression algorithms and equations (Han et al., 2016). This study employed LCMs to assess $PM_{2.5}$ concentrations at a gold mine TSFs in Evander and the eMbalenhle community. Simultaneously monitoring concentrations at the source (gold mine TSFs) and the receptor (community) allows for accurate source attribution when determining how much $PM_{2.5}$ emissions are in the affected community. Additionally, this approach will enable the identification of other sources contributing to $PM_{2.5}$ levels in the community.

4.2 Material and Methods

4.2.1 Study Areas

The gold mine TSFs in Evander (-26.483319º S; 29.095546º E) and the community of eMbalenhle (-26º 550613º S; 29.078937º E) were chosen as the source and the receptor, respectively. Both areas fall under Govan Mbeki Municipality which is in the south-eastern part of Mpumalanga Province. Evander and eMbalenhle are part of the Greater Secunda. The

Municipality has the most diversified economy, dominated by the petrochemical industry, coal and gold mines (Govan Mbeki Municipality, 2021). The climatic conditions in both areas are characterized by a warm and temperate atmosphere. During the winter season, precipitation levels are lower compared to those experienced in summer (Trenberth, 1999).

The population of eMbalenhle is estimated to be 118 889, with an annual growth of 2.5% (South Africa, 2016). The community of eMbalenhle is situated next to the Evander gold mine TSFs (Figure 4.1). eMbalenhle falls within the HPA. The HPA is an air pollution hotspot declared in terms of Section 18 of the National Ambient Air Quality Act (NEMAQA) 2004 (Act 39 of 2004).

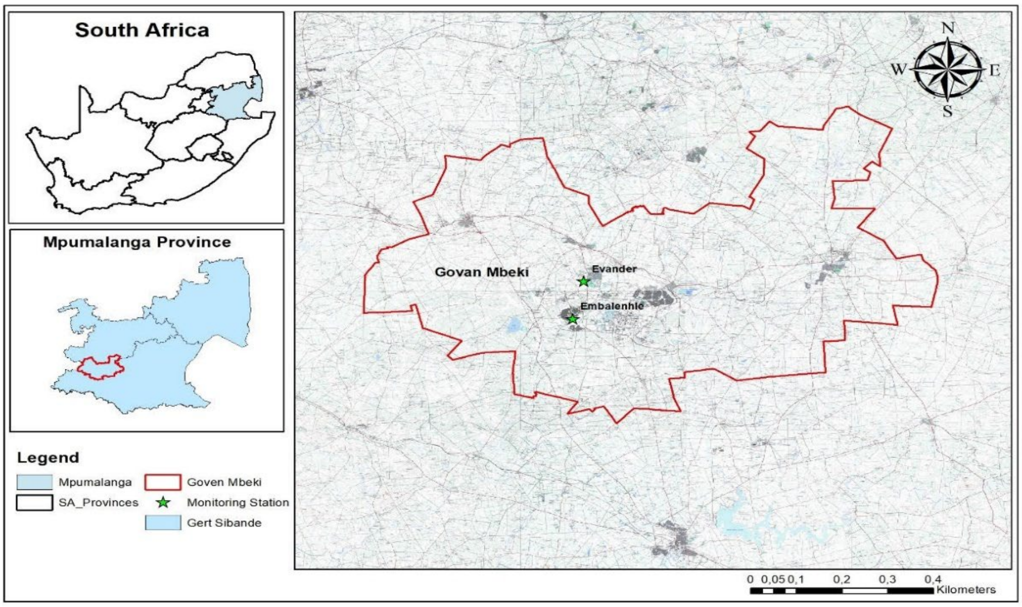


Figure 4.1: Map indicating the study area and location of the low-cost monitors

4.2.2 Data Collection

In this study, $PM_{2.5}$ concentrations were measured at the gold mine TSFs and in the community of eMbalenhle (Figure 4.1) for one year (from 07 February 2022 to 07 February 2023) using the Clarity Node-S monitors LCMs. The $PM_{2.5}$ concentrations were measured every 15 minutes in micrograms per cubic meter (µg/m^3) and averaged hourly. The LCMs use a light scattering method with remote calibration. They have solar panels and batteries that last 15 days in total darkness. The data was available on the website (https://dashboard.clarity.io/overview) and Apple and Android applications (Clarity Movement, 2023).

The $PM_{2.5}$ and meteorological data for the same period were obtained from the South African Air Quality Information System (SAAQIS) managed by the South African Weather Services (SAWS). The SAAQIS $PM_{2.5}$ data was used as reference data to compare and validate the data collected with the LCMs. The meteorological data included wind speed, wind direction, solar radiation, atmospheric radiation, rain, relative humidity, and temperature. The study period was divided into four seasons: Summer (December to February), Autumn (March to May), Winter (June to August), and Spring (September to November).

4.2.3 Data Correction and Validation

The data sets underwent a quality control process as described by Clarity Movement (2024) to ensure that the monitored (both $PM_{2.5}$ data sets monitored with the LCMs at the community and gold mine TSFs) and reference data ($PM_{2.5}$ data monitored by SAWS monitoring station) were not erroneous. Data correction and validation for the LCMs involved using machine learning algorithms to predict $PM_{2.5}$ concentrations accurately. The first step involved using a training dataset to teach the model to identify patterns (Malings et al., 2019). The model learned from the training dataset by adjusting its parameters to make predictions as accurate as possible (Kleine-Deters et al., 2017). Furthermore, cross-validation was applied to assess the performance of the model (Wang et al., 2019). Clarity Movement developed custom calibration algorithms for each network and pollutant (Clarity Movement, 2024). The $PM_{2.5}$ concentrations were normalized by dividing each time series with the mean value (Qu et al., 2020).

4.2.4 Data Management

The South African National Accreditation System (SANAS) criteria for the representativeness of air quality measurements was used to assess the validity of the monitored data (SANAS, 2018). The SANAS data completeness requires 90% data completeness. A completeness threshold of 90% was applied to calculate the hourly average from the $PM_{2.5}$ data monitored with the LCMs and the one obtained from the SAAQIS. The validity percentage of the $PM_{2.5}$ data monitored with the LCMs and the one extracted from the SAAQIS were 80.1% and 63.1%, respectively. The data were organized in Microsoft Excel sheets and named according to various variables. Data cleaning was unnecessary since the instrument did not record negative and zero values.

4.2.5 Data Analyses

Statistical analyses were performed using the Openair packages in R Studio (version 4.0.2) and Stata software (version 18). A non-parametric Wilcoxon signed-rank test was conducted to determine significant differences in $PM_{2.5}$ concentrations between the community and the gold mine TSFs for hourly and 24-hour averages.

4.3 Results

4.3.1 Hourly Concentrations at Community and Gold Mine Tail Storage Facilities

The $PM_{2.5}$ hourly trends at both the community site and gold mine TSFs showed variations in concentrations (Figure 4a). The highest hourly $PM_{2.5}$ concentrations were recorded during the early mornings (between 04:00 (22.23 ±20.51) and 05:00 (24.94±24.45) hours and late afternoons (between 16:00 (36.03±35.74) and 18:00 (31.77±35.57) hours. At the community site, $PM_{2.5}$ concentrations had a distinct pattern with peaks in the morning and evening compared to those observed at the gold mine TSFs (Figure 4b). At the gold mine TSFs, the hourly $PM_{2.5}$ concentrations decreased between 10:00 (10.23±7.64) and 16:00 (10.70±10.10) hours. The $PM_{2.5}$ concentrations increased between 17:00 (11.30±11.93) and 20:00 (08:30±08:75) hours at the gold mine TSFs.

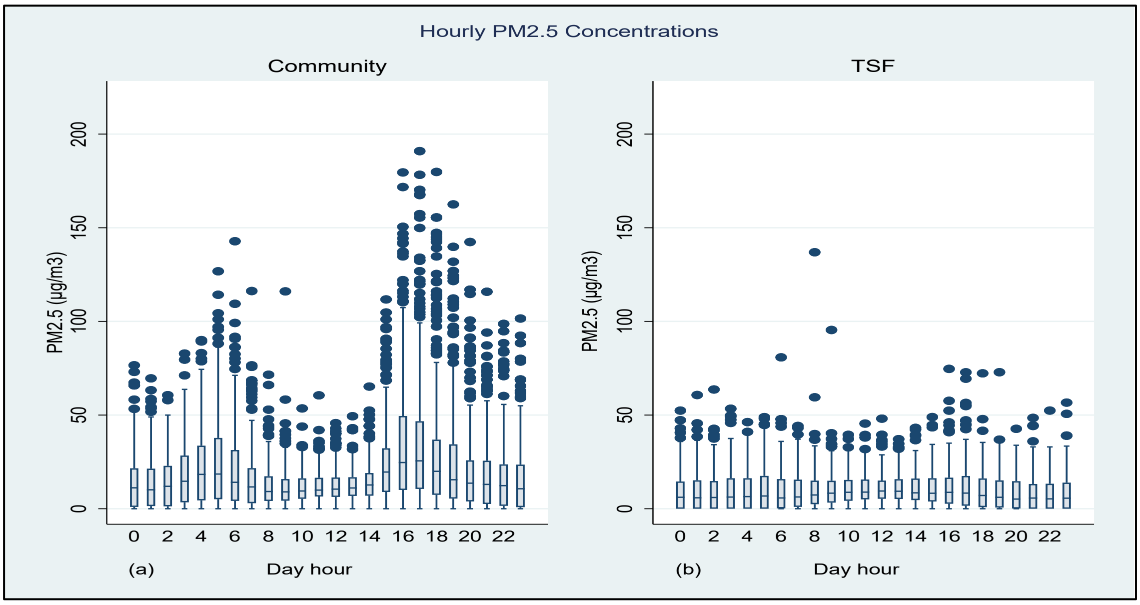


Figure 4.2: Hourly $PM_{2.5}$ concentrations at the (a) community and (b) Gold Mine TSFs

4.3.2 Daily $PM_{2.5}$ Concentrations at the Community and Gold Mine Tail Storage Facilities

The daily (24-hour) $PM_{2.5}$ Concentrations at the Community and gold mine TSFs are shown in Figure 4.3. The average daily (24-hour) $PM_{2.5}$ concentrations at the community site and gold mine TSFs were 19.24 and 9.70 μg/m³, respectively. The daily $PM_{2.5}$ concentrations at the community site exceeded the South African National Ambient Air Quality Standard (NAAQS) of 40 μg/m^3 26 times and the WHO (World Health Organisation) guideline of 15 μg/m^3 181 times (Figure a). A maximum of 4 exceedances per year is permitted for compliance with the NAAQS. The daily (24-hour) NAAQS was not exceeded at the gold mine TSFs. However, the WHO guideline was exceeded 85 times (Figure 3b). At the community site, the 24-hour NAAQS exceedances were more observed in June (seven (7) exceedances) and July (twelve (12) exceedances), with the highest value of 63.23 μg/m^3 recorded on the 7th of July 2022.

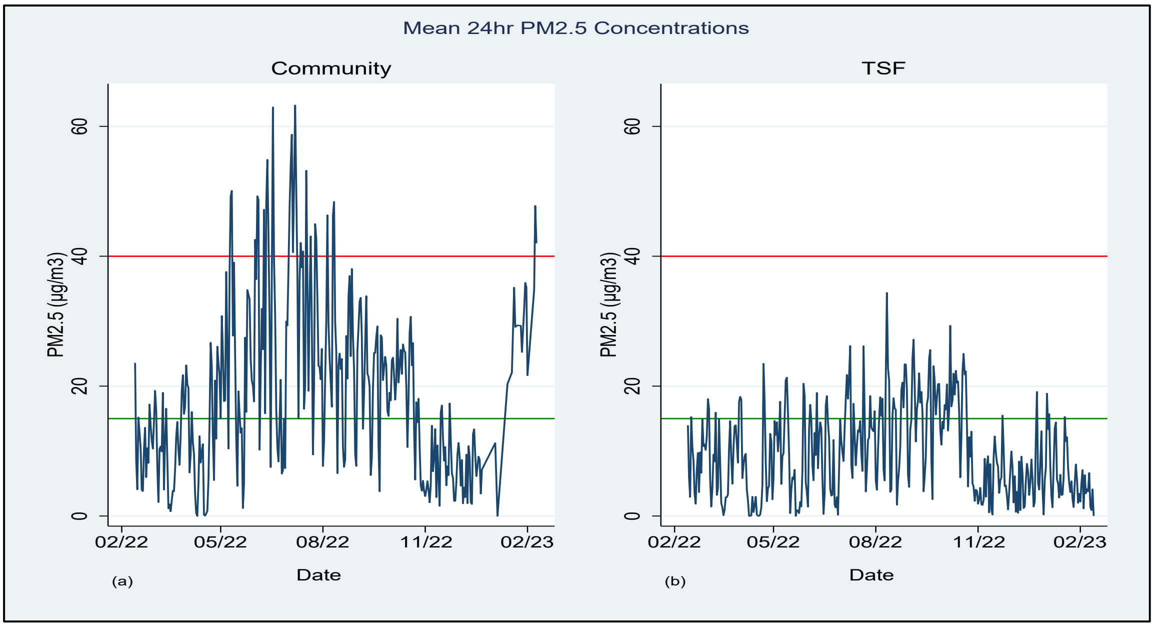


Figure 4.3: 24-Hour $PM_{2.5}$ concentrations at the (a) community and (b) Gold Mine TSFs

**Red line: South African 24-hour NAAQS for $PM_{2.5}$ (40 μg/m^3)*
**Green line: WHO 24-hour guideline for $PM_{2.5}$ (15 μg/m^3)*

Table 4.1 below shows the descriptive statistics of the hourly and the 24-hour $PM_{2.5}$ concentrations over the entire monitoring period at both the community site and the gold mine TSFs. The hourly $PM_{2.5}$ concentrations in the community had a median of 12.87 (IQR: 19.56), much higher than that of the gold mine TSFs (7.5 (IQR: 14.42)). The 24-hour $PM_{2.5}$ concentrations in the community had a median of 32.4 (IQR: 25.98), lower than that of the gold mine TSFs (16(IQR: 18.91).

Table 4.1: Descriptive statistics of the $PM_{2.5}$ concentrations at the community and gold mine Tail Storage Facilities

Duration	Data points	Mean	Std. Dev.	Median	1st Quartile (Q1)	3rd Quartile (Q3)	Min	Max	IQR
	N	$PM_{2.5}$ (µg/m^3)		$PM_{2.5}$ (µg/m^3)	$PM_{2.5}$ (µg/m^3)	$PM_{2.5}$ (µg/m^3)	$PM_{2.5}$ (µg/m^3)	$PM_{2.5}$ (µg/m^3)	
Community hourly	7.511	18.87*	21.74	12.87	4.99	24.55	0.01	190.91	19.56
TSFs hourly	8.735	9.69*	9.68	7.47	1.04	15.46	0.01	136.92	14.42
Community 24-hr	7.887	32.26**	16.52	32.43	18.46	44.44	0.14	99.15	25.98
TSFs 24-hr	8.748	19.26**	13.61	16.94	8.21	27.12	1.69	64.43	18.91

*p<0.001

**p<0.0001

4.3.3 Monthly $PM_{2.5}$ Concentrations at the Community and Gold Mine Tail Storage Facilities

The monthly $PM_{2.5}$ concentrations at the Community and gold mine TSFs are indicated in Figure 10. At the community site (Figure 4.4a), the lowest $PM_{2.5}$ concentrations were observed in December (7.06±3.64 µg/m^3), followed by November (7.71±5.51 µg/m^3). At the gold mine TSFs (Figure 4.4b), the lowest $PM_{2.5}$ concentrations were recorded in November (5.51±3.83 µg/m^3), followed by December (5.59±4.22 µg/m^3). In July, the highest $PM_{2.5}$ concentrations were observed at the community site and gold mine TSFs. The $PM_{2.5}$ concentrations were 35.75±13.69 µg/m^3 and 13.90±5.55 µg/m^3 at the community site and gold mine TSFs, respectively.

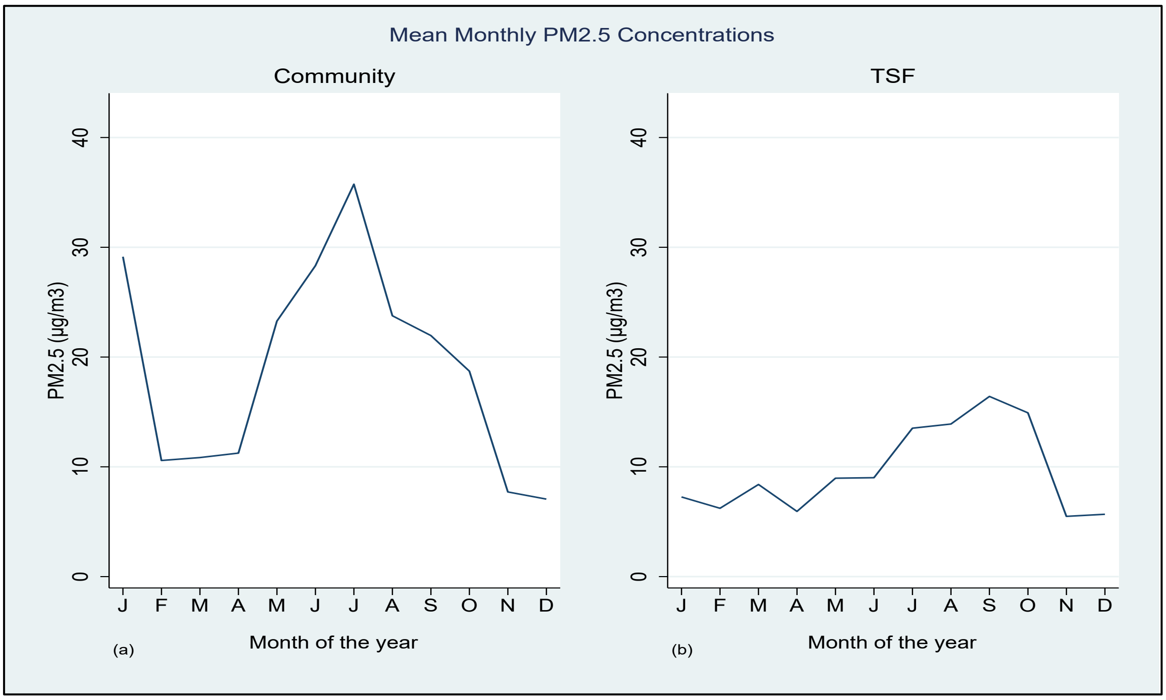


Figure 4.4: Monthly $PM_{2.5}$ concentrations at the (a) community and (b) Gold mine TSFs

4.3.4 Seasonal Variations of $PM_{2.5}$ Concentrations at the Community and Gold Mine TSFs

The seasonal $PM_{2.5}$ concentrations at the community site (Figure 4.5a) and TSFs (Figure 4.5b) are shown below. $PM_{2.5}$ concentrations increased during the Winter (June to August) at both the community site and TSFs compared to the Summer (September to February). The Winter season showed the highest $PM_{2.5}$ concentrations at the community site (29.28 µg/m^3) and TSFs sites (12.38 µg/m^3). Following the Winter season's highest $PM_{2.5}$ concentrations, there was an increase in $PM_{2.5}$ concentrations during Spring at the community site (16.13±12.28) and

12.11±12.28 μg/m^3 at TSFs compared to Autumn. In Autumn, the $PM_{2.5}$ concentrations were 15.12±7.06 and 7.73±1.61 μg/m^3 at the community site and TSFs, respectively.

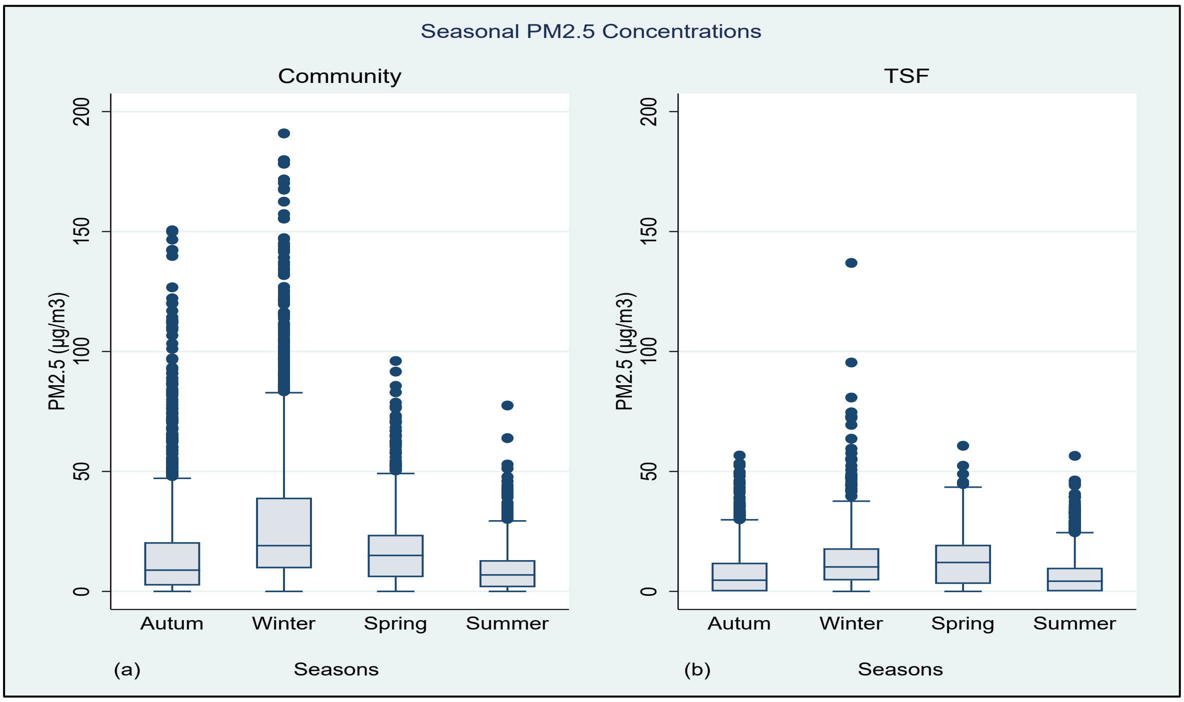


Figure 4.5: Seasonal $PM_{2.5}$ concentrations at the (a) Community and (b) Gold Mine TSFs

4.3.5 Normalised Trend Analysis of $PM_{2.5}$ Concentrations

There were variations in the hourly, diurnal, and monthly $PM_{2.5}$ concentrations at the community site (Figure 4.6a) and TSFs (Figure 4.6b). At the community site, the first peak was observed in the morning, with decreased $PM_{2.5}$ concentrations during the day (between 07:00 and 12:00). The second peak was observed in the afternoon and towards the evening (between 15:00 and 19:00), with $PM_{2.5}$ concentrations decreasing after 20:00. On the other hand, the $PM_{2.5}$ concentrations at the gold mine TSFs increased from 08:00 to 12:00.

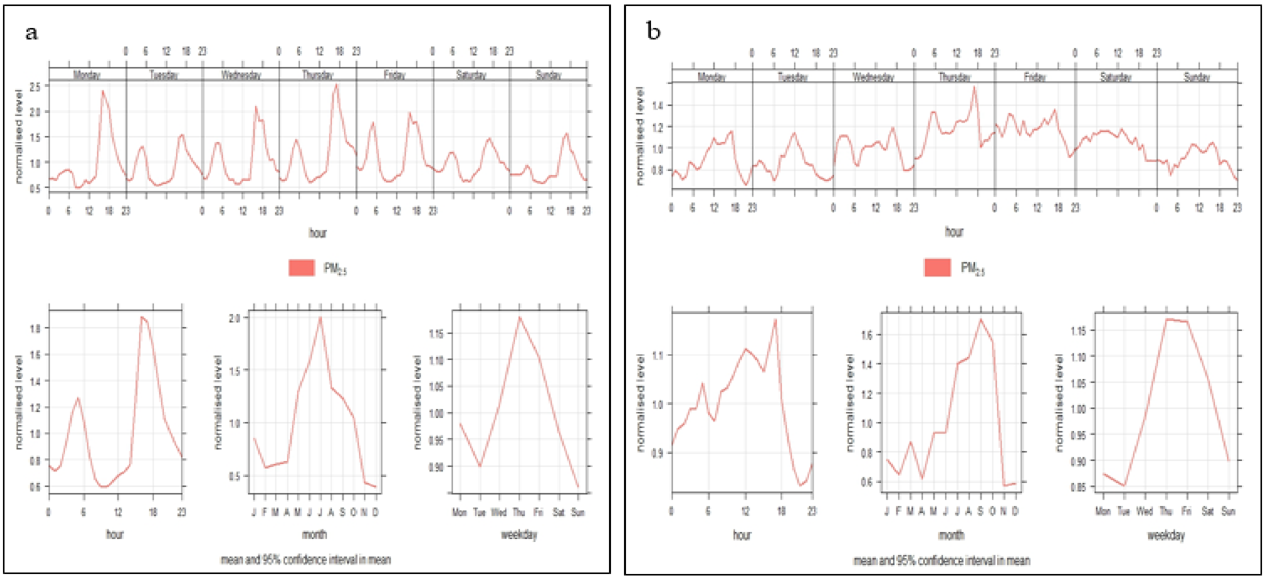
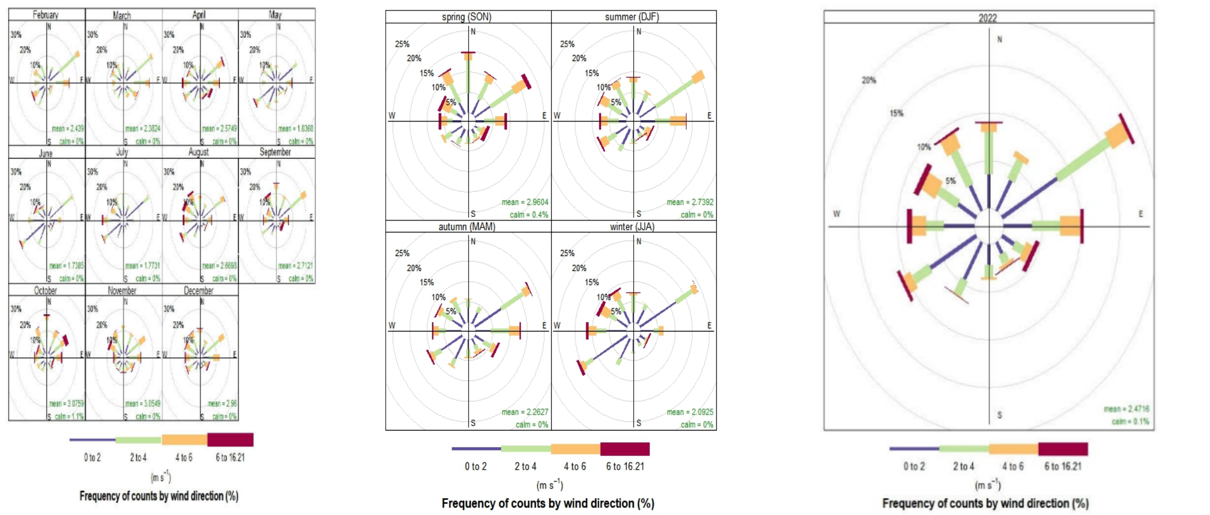


Figure 4.6: Normalised $PM_{2.5}$ concentration trends at the (a) community and (b) Gold Mine TSFs

4.3.6 Influence of Meteorological Conditions on $PM_{2.5}$ Conditions

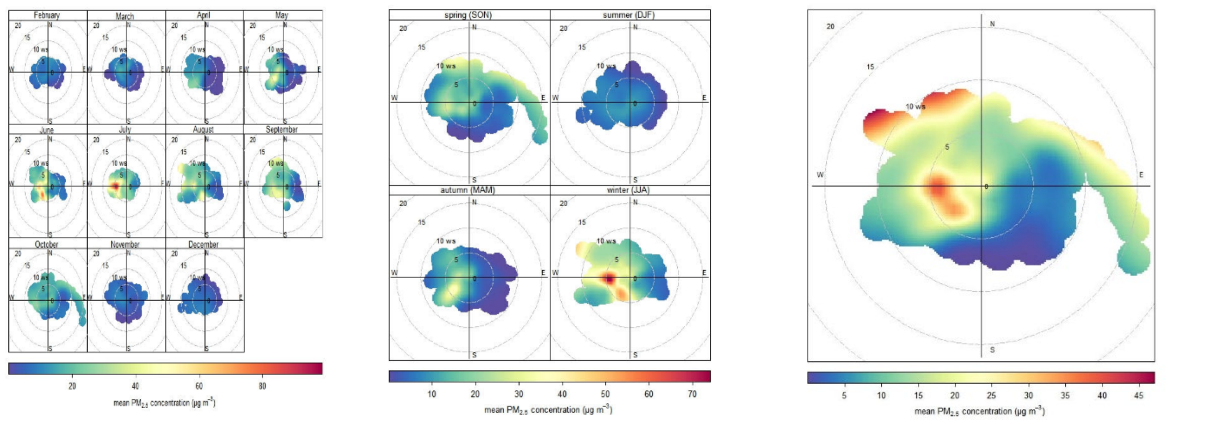
The wind and prevailing wind direction at the community site are presented in Figure 4.7. The North-easterly winds contributed to the increased $PM_{2.5}$ concentrations at the receptor. The gold mine TSFs is situated west of the eMbalenhle community. North-easterly winds prevailed in February, March, April, September, October, November, and December. South-westerly winds were observed in May, June, July, and August (Figure 4.7a). In Spring and Summer, the prevailing winds were mainly North-easterly (Figure 4.7b). South-westerly and North-easterly winds were observed in Winter. The annual wind direction was from the North-easterly and South-westerly (Figure 4.7c).



(a) (b) (c)

Figure 4.7: Monthly (a), seasonal (b) and annual (c) wind and prevailing wind direction at the community site

The $PM_{2.5}$ pollution roses at the community site are indicated in Figure 4.8. $PM_{2.5}$ concentrations between 30 to 50 µg/m^3 were observed in June, July, and August when the wind was predominantly from the South-westerly (Figure 4.8a). $PM_{2.5}$ concentrations decreased in Summer with the wind coming from different directions. In Winter, the increased $PM_{2.5}$ concentrations increased (ranging from 25 to 50 µg/m^3 with wind predominantly from North-westerly and South-westerly (Figure 4.8b). The annual pollution rose (Figure 4.8c) indicates that $PM_{2.5}$ concentrations ranged from 20 – 40 µg/m^3 with wind prevailing from North-westerly.



(a) (b) (c)

Figure 4.8: Pollution plots for $PM_{2.5}$ concentrations at the community site

4.4 Discussion

In this study, two LCMs were deployed for 12 months (07 February 2022 to 07 February 2023) at the source (gold mine TSFs) and receptor (community of eMbalenhle). The validity of the LCMs was evaluated by comparing the $PM_{2.5}$ measurements against the data obtained from a co-located Government ambient air monitoring station managed by SAWS. The variations in daily $PM_{2.5}$ concentrations were observed at both monitoring sites.

The highest hourly $PM_{2.5}$ concentrations were recorded at the community site during the early mornings (between 04:00 and 05:00 hours) and late afternoons (16:00) and evenings (18:00 hours). The $PM_{2.5}$ concentrations decreased from midnight (00:00 hours) to 03:00 hours, followed by a morning peak and an evening peak late in the day (Figure 4.2). The morning peaks are attributed to vehicular traffic emissions (Majewski et al., 2011). The evening peaks appeared more pronounced than the morning ones (Figure 4.2). This finding disagrees with that of Bamola et al. (2024), who found that diurnal $PM_{2.5}$ concentrations were higher during the morning period (at 09:00 hours) and lower in the early evening (between 16:00 and 17:00 hours) in Taj City.

The $PM_{2.5}$ concentrations were higher on weekdays than on weekends, possibly due to increased traffic volumes during the morning rush hour (Figure 4.6). Liu et al. (2015a) contended that morning peaks are due to increased anthropogenic activities. This is evident from Figure 4.6, which shows reduced morning peak levels on Saturdays and Sundays. Tong et al. (2020) found that vehicular $PM_{2.5}$ emission levels were higher on weekdays than on weekends. The evening peaks are attributed to changes in meteorological patterns where the boundary layer height increases during the day. In the late afternoon, there was an increase in rush hour volume and other anthropogenic activities, leading to high evening peaks, as also observed by Liu et al., 2015a.

Given the complexity of factors affecting $PM_{2.5}$ concentrations, it is likely that concentrations would consistently be higher during weekdays and lower on weekends at both measuring sites. The living patterns of the people in the community of eMbalenhle could have influenced this. A study by Feng et al. (2014) observed that the diurnal and seasonal concentrations matched the living styles of the people in the study area.

In contrast, the gold mine TSFs did not show distinct bimodal diurnal patterns. Generally, the gold mine TSFs lacks diurnal human activities, leading to consistent diurnal concentrations. Bimodal patterns are observed when an area experiences different concentrations with varying intensities from local sources during the day. (Liu et al., 2015b). Wind speed increases during the day due to surface heating from the sun, thereby increasing atmospheric turbulence and vertical mixing. This may cause emissions from the gold mine TSFs to be resuspended during the day, increasing the $PM_{2.5}$ concentrations (Figure 4.7). However, wind speeds are often reduced at night, leading to lower $PM_{2.5}$ concentrations (Park et al., 2021).

Meteorological conditions have an overwhelming impact on $PM_{2.5}$ concentrations. In this study, it was expected that the $PM_{2.5}$ concentrations at the source would be higher than that at the receptor (community). However, our findings are contrary to this expectation. In addition to the local sources, regional and long-distance transport of $PM_{2.5}$ due to wind patterns and atmospheric circulation could increase $PM_{2.5}$ concentrations in locations far from the sources (Li et al., 2020). The wind direction was predominantly north-easterly during the twelve (12) months of this study period (07 February 2022 to 07 February 2023). The annual pollution rose showed increased $PM_{2.5}$ concentrations with wind predominantly coming from the North-westerly (Figure 4.8). The community is situated towards the West of the gold mine TSFs. This could suggest that the gold mine TSFs might not have significantly contributed to the high $PM_{2.5}$ concentrations in the community. However, there is a need to undertake source apportionment to determine the gold mine TSFs contribution to the affected community accurately.

In the case study area, summer is mainly characterized by warm and rainy days. It is dry, cold, and sunny in winter with strong winds, especially in August. Autumn is characterized by cold and sunny early mornings, with long and warm days. The diurnal $PM_{2.5}$ concentrations varied based on seasonal changes (Mukta et al., 2020). At both study sites, the seasonal variability was higher during the winter and lower during the summer. This finding agrees with studies carried out elsewhere, which reported seasonal variability of $PM_{2.5}$ observed with the highest in winter and the lowest in summer (Javed et al., 2021; Watson et al., 2021; Indraj and Warpa, 2024). This could result from increased energy consumption and the use of traditional fuels, including biomass and coal, for cooking and space heating (Szatylowicz et al., 2023).

A study by Thabethe et al. (2014) indicated that domestic fuel burning contributed to high concentrations of particulate matter in the eMbalenhle. Other anthropogenic activities, such as vehicular traffic, industrial concentrations, construction, residential heating, and cooking, may release significant amounts of $PM_{2.5}$ into the atmosphere (Dai et al., 2022; Naidja et al., 2022).

Another study found that residential combustion contributed 9 to 13% and 14 to 23% of $PM_{2.5}$ during winter in eMbalenhle (Walton et al., 2021).

Furthermore, as urbanization and industrialization increase, there is the potential for increased $PM_{2.5}$ concentrations in densely populated areas (He et al., 2023). However, these findings contrast with those of Liu et al. (2015a), who found higher $PM_{2.5}$ concentrations in the spring and summer months. This increase was attributed to concentration changes, long-range transport patterns, and meteorology. The decrease in $PM_{2.5}$ in the winter months was attributed to fuel-switching during the heating periods from coal-powered systems to using natural gas (Liu et al., 2015a). In contrast, the summer months at both sites had lower $PM_{2.5}$ levels due to increased temperature and changes in the consumption and use of traditional fuels for heating. Again, meteorological conditions played a role in dispersing, diluting and reducing $PM_{2.5}$ concentrations during summer (Xin and Sun, 2022).

4.5 Conclusion

The results presented in this manuscript are from a 12-month monitoring campaign at a gold mine TSFs and a nearby community. The results revealed that daily $PM_{2.5}$ concentrations at the community site exceeded the 24-hour South African NAAQS of 40 μg/m^3 and the WHO guideline of 15 μg/m^3. However, this study could not confirm if the gold mine TSFs was the main contributor to local air pollution. Therefore, additional studies focusing on source apportionment are needed to ascertain this uncertainty. Due to reported exceedances of the NAAQS and WHO guidelines, a study assessing the risk of exposure to $PM_{2.5}$ amongst residents of eMbalenhle is recommended.

An increase in $PM_{2.5}$ concentrations can indicate continued anthropogenic activities and ineffective strategies for managing air quality in the region. An analysis of one-year $PM_{2.5}$ trends at the gold mine TSFs and the community may not be adequate if the other contributing sources are not considered. It is recommended that the $PM_{2.5}$ measurements should be conducted for at least 72 months (5 years), and multiple monitors should be deployed at each site to increase the spatial resolution of the measurements. This is because the $PM_{2.5}$ concentrations can vary significantly in time and space. This will enable a more comprehensive understanding of the $PM_{2.5}$ variations between the source and the receptor.

It was evident from the results that the measures earmarked for reducing vehicular concentrations, combustion concentrations, and other anthropogenic concentrations would significantly reduce pollution levels in the eMbalenhle community. Moreover, the results indicated that the winter season was the major contributor to $PM_{2.5}$ concentrations in the study areas. Therefore, area dust management controls and systems must be implemented and maintained to reduce $PM_{2.5}$ concentrations.

4.6 Financial Support

We want to thank Gert Sibande District Municipality for granting permission to conduct this study and the University of South Africa for funding the study. TM acknowledges the National Research Fund for financial support through an evaluation and rating grant number 132532.

4.7 Authors' Contributions

This study is part of Ms Nomsa Thabethe's PhD at the University of the Witwatersrand. Ms Nomsa Thabethe drafted the manuscript and analysed the data. Conceptualization: NT, DM, and DB; Data collection and analysis: NT; preparation of the manuscript: NT; editing and proofreading: TM; Review and supervision: TM, DM, and DB.

4.8 Acknowledgments

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4.9 Ethical Considerations

The study was approved by the University of the Witwatersrand Human Research Ethics Committee [HREC] (No: HRECNMW21/05/09).

CHAPTER 5: INTEGRATED DISPERSION MODELLING AND AMBIENT $PM_{2.5}$ MONITORING IN MINING REGION: A COMPARATIVE HEALTH RISK ASSESSMENT OF TAILING STORAGE FACILITY EMISSIONS AND MULTI-SOURCE AMBIENT CONCENTRATIONS

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Abstract

South Africa (SA) is regarded as one of the best gold producers in the world. Although mining brings economic benefits, it is responsible for adverse environmental and human health impacts. Mining produces waste which is left over after gold has been extracted from ore. The waste is stored in a designed structure called Tailing Storage Facility (TSF). Communities near the TSF are at risk of exposure to wind-blown dust during dust storms. This study focused on $PM_{2.5}$ (particulate matter with a diameter of 2.5 micrometers or smaller). $PM_{2.5}$ can penetrate deep into the respiratory tract and cause negative health effects. This study aimed to investigate the atmospheric dispersion of $PM_{2.5}$ emissions from a gold mine TSF (source) to nearby community (receptor). The Low-Cost Monitors (LCMs) were used to measure the $PM_{2.5}$ concentrations at both TSF and in the community. The American Meteorological Society/ Environmental Protection Agency Regulatory Model (AERMOD) was applied to predict the ground-level $PM_{2.5}$ concentrations. This was done to assess the contribution of the TSFs to $PM_{2.5}$ levels in receiving communities. The measured and modeled $PM_{2.5}$ concentrations were used to estimate Cancer Risks (CR) in four population subgroups (toddlers, children, adults and elderly). The measured annual $PM_{2.5}$ concentrations at the TSF and community were 9.68 and 19.27 $\mu g/m^3$ respectively. Dispersion modeling results indicated a maximum 24-hour average $PM_{2.5}$ concentration of 11ug/m^3 and maximum annual average of 3.4 ug/m^3 at the 99th percentile (worst-case scenario). The modeled $PM_{2.5}$ concentrations were below the annual SA National

Ambient Air Quality Standard (NAAQS) of 20 µg/m^3. The calculated Hazard Quotients (HQ) were below 1(0.9) for all population subgroups, indicating minimal health risks in communities proximate to the gold mine TSF. However, the excess lifetime CR values were observed in the Toddlers (4 x 10^{-4}), Children (3 x 10^{-2}) and elders (2 x 10^{-1}). Although the $PM_{2.5}$ concentrations were lower than the NAAQS, there is a potential for adverse health effects due to elements embedded in the dust particles. It is recommended to carry out an elemental characterization of dust particles and estimate the health risks associated with chronic exposures in exposed communities.

Keywords: Dispersion modelling, Ambient air monitoring, Exposure assessment, Waste dumps, Carcinogenic risks, AERMOD

5.1 Introduction

Fine particulate matter ($PM_{2.5}$) is a significant air pollutant with severe implications for environmental quality and human health. Particles with an aerodynamic diameter of 2.5 micrometres or smaller are called $PM_{2.5}$ (Chauhan et al., 2024). Due to its small size, $PM_{2.5}$ can remain suspended in the atmosphere for extended periods and be transported over long distances (Dhaka et al., 2024). Exposure to high concentrations of $PM_{2.5}$ has been associated with a range of adverse health effects. The health effects associated with exposure to $PM_{2.5}$ include respiratory, cerebrovascular and cardiovascular diseases (Wan et al., 2023).

The dispersion patterns of $PM_{2.5}$ play a huge role in analyzing the concentrations and assessing the human health effects of exposure. Dispersion models are useful for predicting the movement and concentrations of $PM_{2.5}$ in the atmosphere (Xiao et al., 2024). These models utilize meteorological data, sources, topography and atmospheric chemistry to simulate how $PM_{2.5}$ disperses and accumulates over time. Gaussian, Lagrangian, and Eulerian dispersion models are widely used in air quality studies (Barbero, 2024, Uliaszy and Pielke, 2024, Zannetti, 2024). Gaussian dispersion models assume that $PM_{2.5}$ disperses in a bell-shaped pattern from a point source. They include AERMOD, Industrial Source Complex Model (ISC3) and Atmospheric Dispersion Modelling System (ADMS); (Jalali and Tourani, 2025).

AERMOD was a chosen as a preferred model in this study because it is used for short-range $PM_{2.5}$ dispersion near industrial facilities. ISC3 is a predecessor to AERMOD used for point, area and volume sources (Amin, 2024). ADMS is an advanced Gaussian model incorporating boundary layer and terrain effects (Snoun et al., 2023). Lagrangian dispersion models track individual particles as they move through the atmosphere. Examples include Hybrid Single-Particle Lagrangian Integrated Trajectory Model (HYSPLIT) and California Puff Model (CALPUFF). HYSPLIT is used for long-range transport and dispersion studies (Deary and Griffiths, 2024). CALPUFF is a non-steady-state model that handles time-varying meteorology and long-range transport (Zeydan and Karademir, 2023). Eulerian dispersion models divide the atmosphere into a 3D grid and solve equations to predict $PM_{2.5}$ concentrations over time. They include CMAQ (Community Multiscale Air Quality Model) and Comprehensive Air Quality Model with Extensions (CAMx); (Emery et al., 2024). CMAQ is used for regional-scale air quality modeling. CAMx is a photochemical model used for $PM_{2.5}$ simulations (Kim et al., 2024).

In South Africa, few studies have quantitatively assessed human health risks from $PM_{2.5}$ emissions specific to TSFs using dispersion techniques. This study used the AERMOD dispersion model as a tool to estimate the spatial distribution of $PM_{2.5}$ concentrations and assess associated health risks. Dispersion modeling was done to strengthen the assessment of the human health effects of exposure to $PM_{2.5}$ in the nearby community. The use of AERMOD dispersion model allowed for the spatial and temporal simulation of ground-level $PM_{2.5}$ concentrations across the study area, under varying meteorological conditions. The model helped estimate $PM_{2.5}$ concentrations from the TSF and link these estimates to the health effects thereof.

Human Health Risk Assessment (HHRA) provides a systematic framework for evaluating the potential adverse effects of $PM_{2.5}$ exposure (Rivai et al., 2024). HHRA involves four key steps: Hazard identification, Exposure assessment, Dose-response assessment and Risk characterization (Chandrasekar et al., 2024). Hazard identification focuses on identifying the toxicological properties of $PM_{2.5}$ and its known health effects. Exposure assessment estimates the extent and duration of human exposure by integrating data from the dispersion models with population demographics and activity patterns (Hoek et al., 2024). The dose-response assessment determines the relationship between exposure levels and health outcomes. Finally, risk characterization synthesizes the findings to estimate the overall likelihood and severity of health risks associated with $PM_{2.5}$ exposure (Castro et al., 2024).

The motivation to conduct this study originated from the lack of localized assessments of $PM_{2.5}$ concentrations from TSFs and their associated health risks. The significance of this study lies in its contribution to understanding CR in mining-affected communities and providing evidence to influence policy and decision-making. While many studies focused either on air dispersion modeling or health risk estimation, this study integrated both the use of AERMOD to simulate the spatial and temporal distribution of $PM_{2.5}$ from TSFs and the application of the United States Environmental Protection Agency (USEPA) risk assessment model to estimate lifetime CR and non-carcinogenic risks in nearby communities. The integration of dispersion modeling with HHRA provided a comprehensive approach to assessing human health risks associated with exposure to $PM_{2.5}$. The objectives of this study were to apply dispersion modeling techniques to assess the transport and distribution of $PM_{2.5}$ from various sources and evaluate the associated health risks in the exposed population. This study contributes to understanding the interactions between sources, atmospheric conditions and health outcomes of $PM_{2.5}$ exposure. The findings will contribute to evidence-based policy and decision-making regarding $PM_{2.5}$ exposure. Furthermore, this study has a great social impact by protecting public health in vulnerable communities, promoting environmental justice and increasing and awareness in $PM_{2.5}$ and health effects associated with exposure.

5.2 Methods and Materials

5. 2.1 Study area

The study area is located on the Highveld Region. This region has been recognized as a region with elevated concentrations of ambient air pollution and was declared an air pollution priority area in 2007 (Walton et al., 2021). The study area included eMbalenhle Secunda and Evander, which are low socio-economic communities (Figure 5.1). Studies have shown that such communities suffer more from the impacts of poor air quality due to their proximity to pollution sources (Frazenburg et al, 2025; Matandirotya et al., 2022). The TSFs assessed in this study are located approximately 2 to 5 kilometers South and North-west of the main residential sections (Mandela Section, Extension 5 and 12).

eMbalenhle is located at 26.5333° S (latitude) and 29.0667° E (longitude) and at an elevation of 1,585 m above sea. eMbalenhle has a population of approximately 119 000 which constitutes 5% of the provincial population. It is characterized largely by informal housing structures commonly known as shacks (City Population, 2016; Wright et al. 2024). Secunda is located at 26.5500° S (latitude) and 29.1667° E (longitude). The town of Secunda has approximately 40 000 residents (Wright et al. 2024). Evander is located at -26.450° S (latitude) and 29.117° E (longitude) The town has approximately 10 166 people (City Population, 2016).

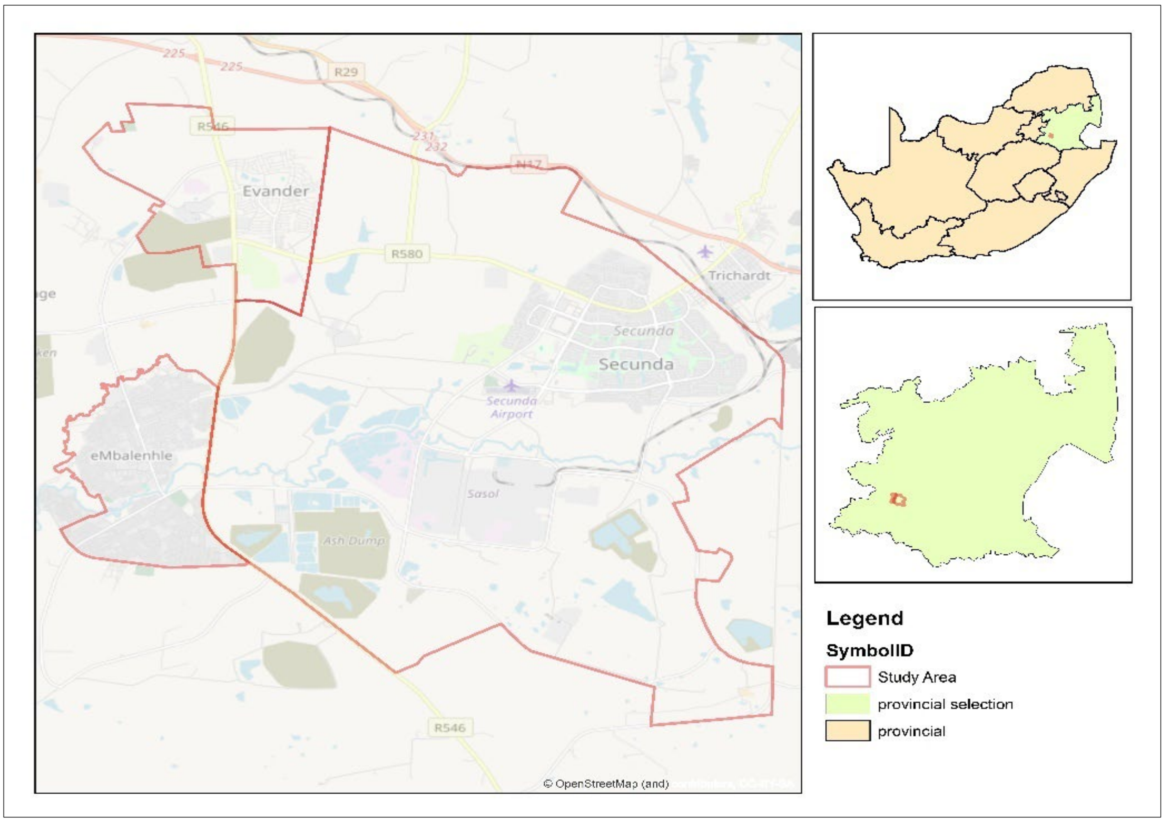

Figure 5.1: Maps Showing the Study Area within the Country, Province and District

5.2.2 $PM_{2.5}$ Monitoring Device

The $PM_{2.5}$ concentrations at TSF and in the community were measured using Clarity-Node-S LCMs. These LCMs can operate either with solar energy or an external power source (in conditions where temperatures fall below 0 °C). Using advanced laser light scattering technology, the LCMs detect $PM_{2.5}$ concentrations (Figure 5.2). Under normal conditions, the LCMs can function for up to 30 days without solar charging. Solar shields are included to protect the LCMs against direct heat radiation (Clarity Movement, 2024).

Figure 5.2: The Clarity Node-S Low-Cost Monitor (Clarity Movement, 2024)

5.2.3 Emission Rates

TSFs are a significant source of $PM_{2.5}$. The $PM_{2.5}$ shape, height, size, surface area, moisture content and surface compaction of the TSF combined with prevailing meteorological conditions influence the rate of emissions. When estimating windblown dust in the 2.5 µm aerodynamic range, emission factors for wind erosion from other exposed areas and as provided in the National Pollutant Inventory (NPI), Emission Estimation Manual for Mining should be considered (Australian Government, 2024). The emission factors for Total Suspended Particles (TSP) and $PM_{2.5}$ are given as follows:

$$E_{TSP} = 0.4 \text{ kg/Ha/hr} \qquad \textit{Equation 5.1}$$

$$E_{PM2.5} = 5\% \text{ of TSP} \qquad \textit{Equation 5.2}$$

Where:

E is the emission rate given in units (kg/Hectare/hour)

5.2.4 Meteorological Parameters

Meteorological input data (AERMET (AERMOD Meteorological Preprocessor)) and Weather Research and Forecasting (WRF) files for 2019 to 2021were obtained from Lakes Environment. The base elevation was 1619 m, and the resolution was 12 km. When using the USEPA AERMOD to conduct refined dispersion modeling projects, there is a need to process the meteorological (met) data representative of the general area being modeled. The collected meteorological data was provided in a format unsupported by the AERMOD. Therefore, the meteorological data was preprocessed using the USEPA AERMET program. AERMET prepares meteorological data in two formats – hourly surface data and upper air data (Dewundege, 2020). The preprocessor produced two files that are compatible with AERMOD, namely the Surface File (*.SFC), which provided hourly boundary layer parameter estimates, and the Profile File (*PFL), which included information on temperature, wind speed, wind direction, and standard deviation relating to the fluctuating meteorological parameters.

The following are the minimum requirements when preprocessing meteorological data for use with the AERMOD: For upper air met data, the data was collected twice a day at 0000 GMT and 1200 GMT (Changotra et al., 2020). For surface met data (wind speed, wind direction, dry bulb temperature and cloud cover in tenths) were collected. Most stations in South Africa do not measure cloud cover. This is a prerequisite for AERMOD and must be present in the met data. Due to the lack of such vital information from met stations, researchers worldwide have resorted to the WRF and Mesoscale Model Interface Program (MMIF) files (Ogbuabia et al., 2023, Radford et al., 2021). The WRF is a numerical weather prediction model principally designed for forecasting applications and is now widely used in atmospheric research. AERMOD uses the same equations used in WRF to draw information on observations and historical meteorological data from the region around the modelling site. Therefore, the weather conditions at a specific location within the selected domain are predicted (Christoforou et al., 2023). Table 5.1 provides characteristics of the meteorological data that was used in the model (AERMOD).

Table 5.1: Characteristics of the meteorological data used in AERMET

Met Data Characteristics	**Description**
Met Data Type	AERMET-Ready WRF (Surface & Upper Air Data)
Start-End Date	Jan 01, 2019 hour 00 - Dec 31, 2021 hour 23
Resolution	12 km
Latitude	26.48331 S
Longitude	29.09556 E
Datum	WGS 84
UTM Zone	-35
Site Time Zone	UTC+0200
Closest City	Johannesburg
Country	South Africa
Station Base Elevation(m)	1614.77
Upper Air Adjustment	-2 hour(s)

5.2.5 Dispersion Modelling

To simulate ground-level $PM_{2.5}$ concentrations and dispersion from the TSF, AERMOD was employed. The AERMOD is built on the theory of planetary boundary layering. The model constitutes building downwash algorithms, pollutant deposition parameters, local terrain and urban heat island effects; and equations for meteorological turbulence calculations (Salami and Popoola, 2023). The model was used to assess ground-level $PM_{2.5}$ concentrations and deposition from a wide variety of sources under varying meteorological conditions, time zones and topography using a receptor grid that extended to a 20 km radius from the centre of the source (Mutlu, 2020; Seangkiatiyuth et al., 2011).

A multi-tier cartesian grid receptor network was used, and it covered an area with a radius of 20,000 m starting from the centre of the deposit and a diameter of 40,000 m. The receptors were set at 150 m from each other (Kerolli-Mustafa et al., 2022) for the fine grid setting, 500m for the medium grid setting, extending to 10 km radius from the TSFs and 1000m for the coarse grid setting, extending to 20 km radius from the TSFs (Figure 5.3). In total, 7104 gridded risk receptors were generated.

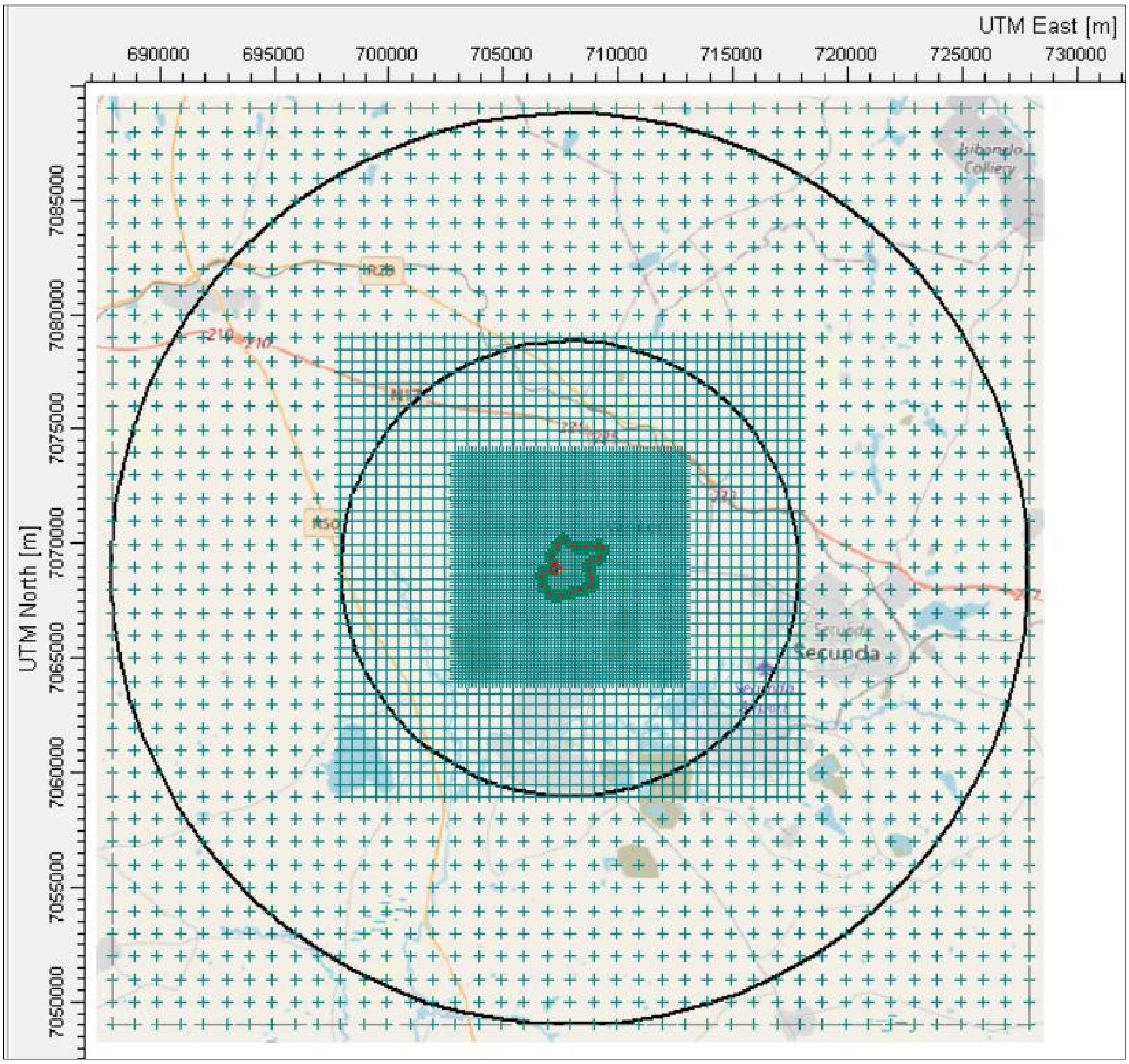

Figure 5.3: A uniform Cartesian network showing risk receptor grids for fine, medium and coarse grids

In addition to these gridded receptors, sensitive discrete receptors were included in the final modelling domain of 40 km x 40 km. As shown in Figure 5.3. This domain was divided into a grid matrix with a multi-tiered grid resolution.

AERMOD Terrain Preprocessor (AERMAP) is a terrain pre-processor developed for use with the model. It is used to estimate the elevation and values of the hill height scale for each receptor, source and building location within a modelling domain. $PM_{2.5}$ dispersion in the atmosphere is mainly influenced by terrain and including complex areas (escarpments, valleys and hills). AERMAP employs Digital Elevation Models (DEMs) to measure and predict ground elevations accurately and to determine the features of the terrain likely to influence the vertical dimension of plumes (Irankunda et al., 2024). DEMs determines critical heights AERMOD uses to assess whether a plume will rise or pollutants flow around elevated terrains. The tool computes the height of the source versus the terrain in the modelling domain and allows AERMOD to adjust its dispersion calculations.

5.2.6 Sensitive Discrete Receptors

Discrete receptors are point locations (Table 5.2) in AERMOD where pollutant concentrations are predicted and assessed because they have vulnerable population groups and sensitive land uses. These receptors were placed at schools, healthcare facilities, daycare centres, old people's homes, etc, where individuals may be regarded to be more susceptible to the health effects of air pollutants. These receptors are different from gridded receptors that cover the entire modelling domain. Sensitive receptors are needed for more targeted evaluations of $PM_{2.5}$ levels at "hotspot" locations. Table 5.2 lists sensitive and discrete receptors with their coordinates in the UTM (Universal Transverse Mercator) coordinate system. The impact of $PM_{2.5}$ emissions from the TSF was predicted at these receptor sites.

Table 5.2: A list of sensitive and discrete receptors with the coordinates presented in Universal Transverse Mercator

Receptor ID	Name	X	Y	Receptor ID	Name	X	Y
DR 1	TP Stratten Primary School.	710222	7070003	DR 27	Teksa Wound Care	719961.4	7064547
DR 2	Tholukwazi Primary School	705857.2	7062455	DR 28	Healing Hands Wound Care Centre	721733.7	7064541
DR 3	Thorisong Primary School	706650	7062817	DR 29	RHI Medi - Care Centre	707041.7	7063692
DR 4	Mbalenhle Primary School	706458.8	7064447	DR 30	Transvalia Clinic	718375.8	7065325
DR 5	Hoërskool Evander	709698.5	7069715	DR 31	Mediclinic Highveld Hospital	722557.7	7067896
DR 6	Shapeve Primary School.	708293.1	7063743	DR 32	Njabulo Xaba Dietetic services	710924.5	7070766
DR 7	Zamokuhle Primary School	706014	7062088	DR 33	Highveld Mediclinic Pediatric Ward	722510.7	7067908
DR 8	Osizweni Secondary School	705806.9	7065461	DR 34	Evander Hospital	711217	7070823
DR 9	Muzimuhle Primary School	712382.1	7066247	DR 35	Trichardt Mediclinic	722523.8	7067909
DR 10	Sizwakele Secondary School	706523	7062974	DR 36	Embalenhle CHC	707193.7	7061899

DR 11	Secunda Homework and Study Centre	720188.9	7067085	DR 37	Sasol mining Hospital	716074.9	7062556
DR 12	Infinity Education Tutorials	717632.3	7066544	DR 38	Sasol Mine Occupational Health Hospital	717289.1	7066701
DR 13	Osizweni Science Centre	706074.6	7066004	DR 39	Medforum	717509.2	7066275
DR 14	Diligent Students	719867	7064244	DR 40	Hoeveld Medi-Clinic-ER	722450.1	7067899
DR 15	NOSA College Secunda | SafetyCloud	717634.8	7066211	DR 41	Naomi Community home based care	708163.6	7061160
DR 16	Supreme Institute of Science and Techno	717462.5	7066597	DR 42	Maria old age home	711508.5	7070387
DR 17	Aleph Learning Academy (Pty) Ltd	717666.2	7066545	DR 43	HOPE Home Based Care	710112.1	7070727
DR 18	Gert Sibande FET College - Evander Cam	710197.4	7070725	DR 44	Ekhaya Mall	708844.5	7064570
DR 19	Educational Therapy	717504.5	7066262	DR 45	Mall@Embalenhle Shopping Centre	707133.1	7062347
DR 20	Pretoria Professional College	717865.8	7066403	DR 46	Sasol Community Recreation Centre eMb	707211.8	7061660
DR 21	Medlife Health Care	717783.5	7066429	DR 47	SharPozi	704482.1	7061649
DR 22	My Gp Health Care	710438.1	7070097	DR 48	Evander Club	710654.8	7069356
DR 23	Evander Primary Healthcare Clinic	711217.5	7070756	DR 49	Walking disabled educational wilderness	710920.4	7071370
DR 24	Embalenhle Clinic	707864.3	7063331	DR 50	Evander Park	709941.6	7071220
DR 25	Buciko Clinic	710412.3	7070238	DR 51	Izizwe Wellness centre	710322.9	7070157
DR 26	Basadi Occupational Health	720943.2	7067070	DR 52	Evander Easy Fitness	710441.5	7070142

5.2.7 Human Health Risk Assessment

A human health risk assessment, focusing on the inhalation route for different population sub-groups was conducted to evaluate the health implications of total and modelled $PM_{2.5}$ concentrations from TSF. The deterministic Human Health Risk Assessment (HHRA) was applied, which was based on Average Daily Dose (ADD). A screening-level approach was adopted to assess the health risks of $PM_{2.5}$ using the hazard quotient (HQ) as the primary metric. Health-protective guidelines (World Health Organization (WHO)) $PM_{2.5}$ guideline of 5 ug/m^3, was used as the primary Reference Concentrations (Rfc), followed by the SA NAAQS of 20 ug/m^3 as the less stringent reference.

Using the US EPA's current methodology for assessing inhalation risk, it was not necessary to estimate an inhaled dose (the intake of a contaminant in air based on inhalation rate and body weight). Inhalation risk assessments require an adjusted air concentration ($C_{air\text{-}adj}$) to represent continuous exposure instead. The Rfc assumes continuous exposure 24 hours a day, 7 days a week, and 52 weeks a year. As such, the measured $PM_{2.5}$ concentration was adjusted to the actual duration of the exposure. For noncarcinogens, the air concentration was adjusted based on the time exposure occurs (i.e. the exposure duration). For carcinogens, the concentration was averaged over the lifetime of the exposed individual (assumed to be 70 years). Table 5.3 presents the variables used in the deterministic HHRA Model for both total and modelled $PM_{2.5}$ concentrations. The adjusted $PM_{2.5}$ concentrations ($C_{air\text{-}adj}$) were estimated using Equation 5.3 (USEPA, 2024).

$$C_{air\text{-}adj} = C_{air} \text{ x } (ET/24 \text{ hours}) \text{ x } (EF/365 \text{ days}) \text{ x } ED/AT \qquad \textit{Equation 5.3}$$

where:

C_{air} = Annual average concentration of $PM_{2.5}$ in the air (µg/m^3)

ET = Exposure time (hours/day)

EF = Exposure frequency (days/year)

ED = Exposure duration (years)

AT = Averaging time (years)

For chronic assessments (CR), potential Lifetime Average Daily Dose (LADD) was calculated in which lifetime (LT) in days was substituted for AT. With that in mind, the HQ was calculated using Equation 5.4

$$HQ = C_{air\text{-}adj} /Rfc \qquad \textit{Equation 5.4}$$

The HQ is unitless, representing the ratio of the concentration of $PM_{2.5}$ in the air (C_{air}) to the Rfc. If the HQ is less or equal to one ($HQ \leq 1$), the concentration of $PM_{2.5}$ (C_{air}) is equal to or less than the Rfc, indicating that no significant non-carcinogenic health risk is expected. If the HQ is greater than one ($HQ>1$), there is an increased likelihood of developing non-carcinogenic adverse health outcomes. The CR was calculated using Equation 5.5 for each population sub-group to assess the carcinogenic health risks associated with exposure to $PM_{2.5}$.

$$CR = IUR \times C_{air\text{-}adj} \qquad \textit{Equation 5.5}$$

Where:
CR is the cancer risk, which represents the estimated probability of developing cancer over a lifetime due to $PM_{2.5}$ exposure through inhalation.
IUR is the inhalation unit risk, representing the increased risk of cancer per unit exposure to $PM_{2.5}$ through inhalation.

This study used an IUR for $PM_{2.5}$ of 0.008 $\mu g/m^3$, derived from the epidemiological paper of Pope III et al. (2002) that identified an association between long-term exposure to $PM_{2.5}$ emissions and increased lung cancer mortality. A value greater than 1×10^{-04} (1 in 10 000) indicates a significant CR and a need for regulatory action or intervention to reduce exposure, as it exceeds an acceptable risk threshold. On the other hand, a value less than 1×10^{-06} (1 in 1 000 000) indicates a negligible or “acceptable” risk. It can be ignored as it does not require regulatory action or interventions to reduce exposure (Candeias et al., 2021).

It should be noted that the LCMs measured total ambient $PM_{2.5}$ concentrations and do not perform source apportionment. This means that the LCMs did not differentiate between contributions from various emission sources. Consequently, the health risk assessment was based on the total $PM_{2.5}$ concentrations measured at the receptor site and compared with risk estimates derived from modelled emission rates attributed to the TSF source (Thabethe et al., 2025).

Table 5.3: Variables Used in the Human Health Risk Assessment Model

Parameter	Unit	Values	Source
C_{air}	µg/m^3	3.35 (Modelled) 19.27 (Measured)	Modelled/ Measured
ET (Toddler)	hours/day	18	Thabethe et al., 2025
ET (Child)	hours/day	20	Thabethe et al., 2025
ET (Adult)	hours/day	20	Thabethe et al., 2025
ET (Elder)	hours/day	22	Thabethe et al., 2025
AT (CR) – All Males	years	64	South Africa, 2011
AT (CR) – All Females	years	69	South Africa, 2011
ED (Toddler)	years	2	Thabethe et al., 2025
ED (Child)	years	6	Thabethe et al., 2025
ED (Adult)	years	40	Thabethe et al., 2025
ED (Elderly)	years	15	Thabethe et al., 2025
EF	days/year	350	Thabethe et al., 2025
Rfc (SA NAAQS)	µg/m^3	20	South Africa, 2004
Rfc (WHO Guidelines)	µg/m^3	5	WHO, 2021
IUR (derived estimate)	µg/m^3	0.008	Pope III, 2016

5.3. Results

5.3.1 Measured $PM_{2.5}$ Concentrations

Table 5.4 presents the hourly, daily and annual $PM_{2.5}$ concentrations measured at both TSF and in the community sites. At the hourly timescale, the community site recorded the mean $PM_{2.5}$ concentration of 18.57 µg/m³ (n = 7511) with a relatively high standard deviation of 21.74 µg/m³. The TSF site reported a lower mean hourly concentration of 9.69 µg/m³ (n = 8735) with a smaller standard deviation of 9.68 µg/m³. For daily averages, the community site had a mean $PM_{2.5}$ concentration of 19.27 µg/m³ (n = 7887) with a standard deviation of 13.61 µg/m³. The TSF recorded a much higher daily mean of 32.26 µg/m³ (n = 8748) and a standard deviation of 16.52 µg/m³. In terms of annual averages, the community site reported a mean concentration of 20.49 µg/m³ (n = 8748) with a standard deviation of 10.41 µg/m³, whereas the TSF site had a lower annual mean of 9.28 µg/m³ (n = 8753) with an equal value for standard deviation (4.10 µg/m³).

Table 5.4: Measured $PM_{2.5}$ Concentrations at the Community and TSF

Period	Site	N	Mean	Std Dev
Hourly	Community	7511	18.57	21.74
	TSF	8735	9.69	9.68
Daily	Community	7887	19.27	13.61
	TSF	8748	32.26	16.52
Annual	Community	8748	20.49	10.41
	TSF	8753	9.28	4.10

Figure 5.4 presents the monthly average $PM_{2.5}$ concentrations measured at the community and TSF over a one-year period. At the community site, $PM_{2.5}$ concentrations fluctuated across the months, ranging from a minimum of 5.70 µg/m³ in March to a maximum of 48.51 µg/m³ in February. The highest values occurred during late summer and winter months (February (48.51 µg/m³), July (35.75 µg/m³) and January (29.14 µg/m³)). The TSF site recorded lower $PM_{2.5}$ concentrations, ranging from 5.51 µg/m³ in November to 16.41 µg/m³ in September. Although the TSF's variation was less compared to the community site, September (16.41 µg/m³), August (13.90 µg/m³) and July (13.52 µg/m³) showed elevated concentrations.

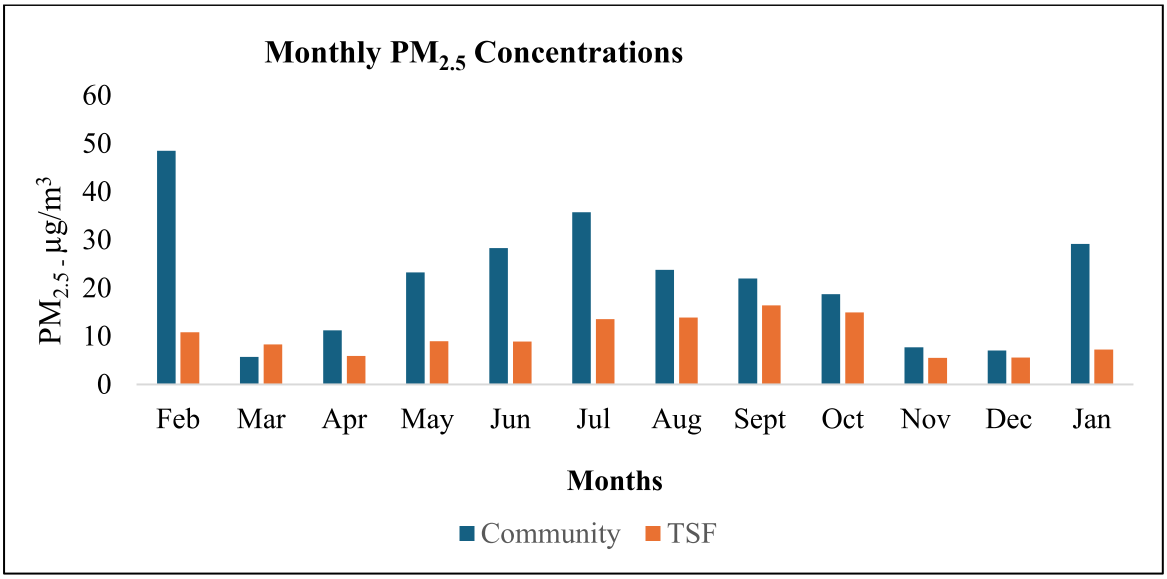

Figure 5.4: Monthly $PM_{2.5}$ Concentrations at the Community and TSF

Figure 5.5 presents the seasonal average $PM_{2.5}$ concentrations measured at the community and TSF sites. The results showed clear seasonal variation, with the community site consistently recording higher $PM_{2.5}$ concentrations than the TSF across all seasons. At the community site, the highest seasonal average $PM_{2.5}$ concentration was recorded in winter (29.28 µg/m³), followed by summer at (21.18 µg/m³). The lowest seasonal concentrations in the community occurred in Autumn (15.12 µg/m³) and Spring (16.13 µg/m³). In contrast, the TSF recorded the highest seasonal $PM_{2.5}$ concentration in Spring (12.28 µg/m³), followed by Winter (12.11 µg/m³). The lowest concentrations were observed in Summer (6.05 µg/m³) and Autumn (7.73 µg/m³).

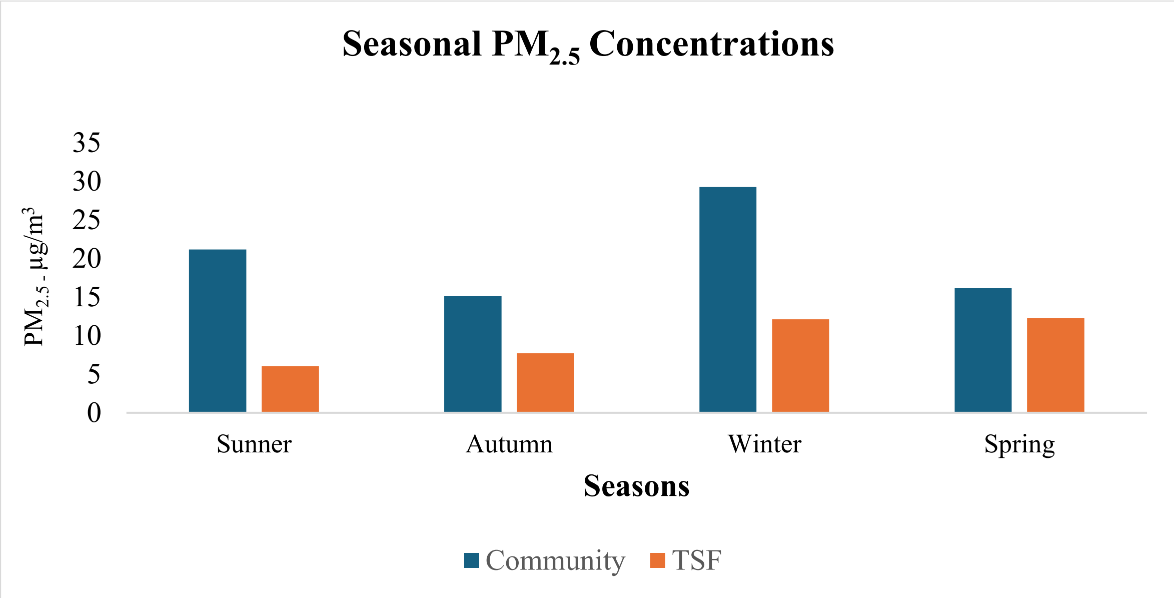

Figure 5.5: Seasonal $PM_{2.5}$ Concentrations at the Community and TSF

5.3.2 Meteorological Parameters

The seasonal wind roses depicting prevailing wind direction and wind speeds for three consecutive years (from 2019 to 2021) are presented in Figure 5.6. In Summer (December – February) and Spring (September – November) months, high-frequency winds blew from the North-eastern quadrant. During the Autumn season, predominant winds were from the North-west, North-east and South-west. Prevailing winds in Winter were like Autumn winds but excluded the occurrence of North-easterly winds. Greater variability in winds was evident during the Autumn season. However, moderate to fast wind speeds prevailed throughout the year, with seasonal calm conditions observed 1.48% of the time (Summer), 2.36% of the time (Autumn), 2.32% of the time (Winter) and 0.76% of the time.

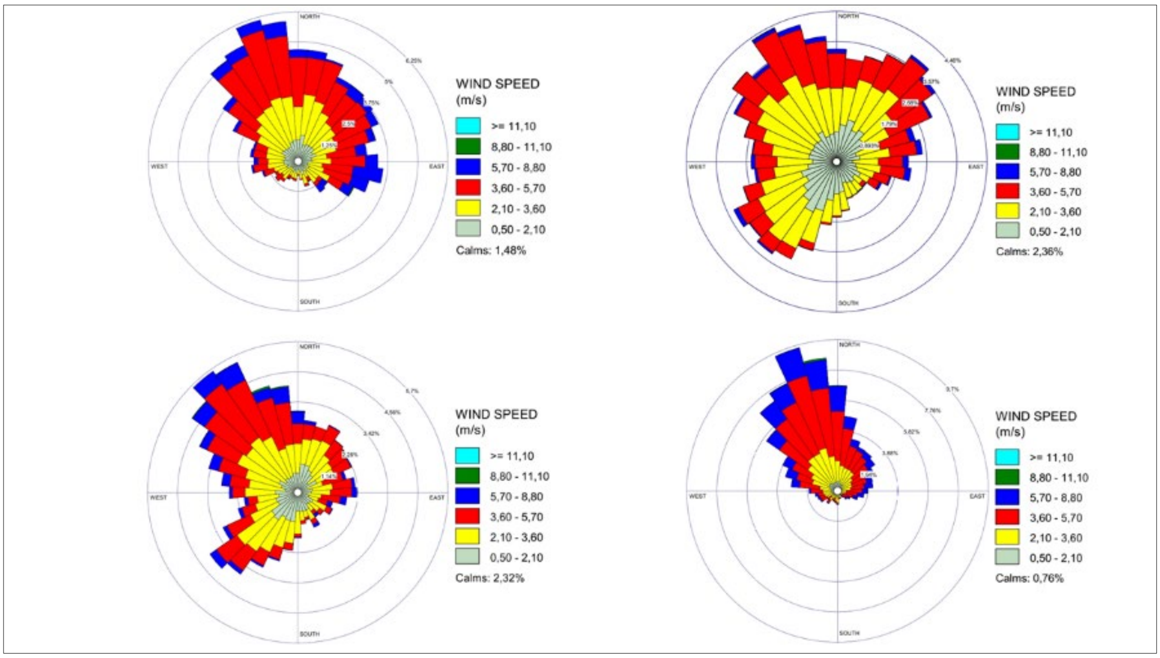

Figure 5.6: Seasonal wind roses depicting prevailing wind direction and wind speeds for three consecutive years (from 2019 to 2021): a = Summer; b= Autumn; c= Winter; d=Spring

5.3.3 Dispersion Modelling Results

Results of the dispersion model simulations associated with activities at TSF are shown in Figures 5.7 (showing source and the discrete receptors) and 5.8 (showing the source and $PM_{2.5}$ dispersion contours). The figures are presented as isopleth plots. Ground-level concentration isopleths showed simulated values using AERMOD for each selected receptor grid point. The image has been zoomed out to show the source, contours and discrete receptors (blue placemarks), (Figure 5.7). For short-term assessment with the SA NAAQS, regulations governing the use of air dispersion modelling for compliance purposes recommended the use of the 99th percentile as the highest concentrations recorded could be regarded as outliers due to variability in meteorological parameters (Department of Environmental Affairs, 2014). This is a conservative approach to protect public health and the environment, given that it could result in extremely high concentrations that the facility may never exceed during normal operations.

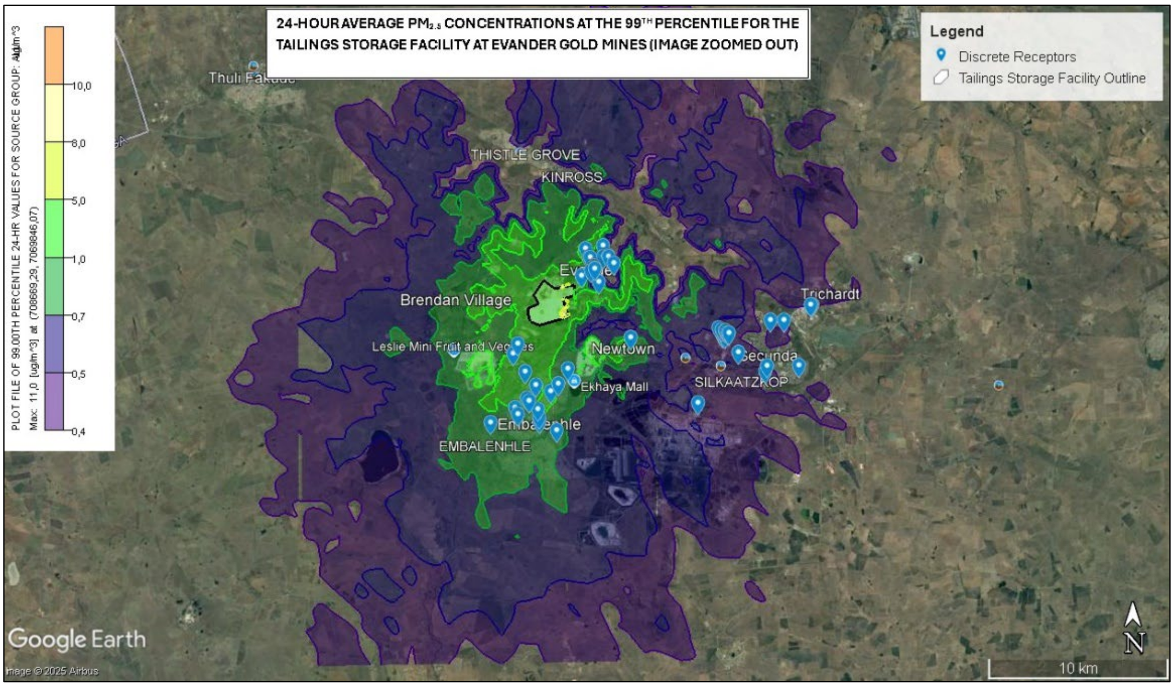

Figure 5.7: 24-hour average $PM_{2.5}$ concentrations at the 99th percentile for the Evander Gold Mine tailings storage facility

**The image has been zoomed out to show the source and the discrete receptors (blue placemarks)*

The modelled results show a maximum daily average $PM_{2.5}$ concentration (99th-percentile) of 11µg/m^3 (Figure 8). This value does not exceed the South African National Ambient Air Quality Standards (SA NAAQS) of 40µg/m^3 and the more stringent WHO guidelines of 15µg/m^3. The pollutants are dispersed towards the south-west quadrants due to dominant north-easterly wind flows. Areas downwind of the TSF are likely to be impacted by emissions from the TSF. The community of eMbalenhle is situated downwind of the TSF in the south-west direction.

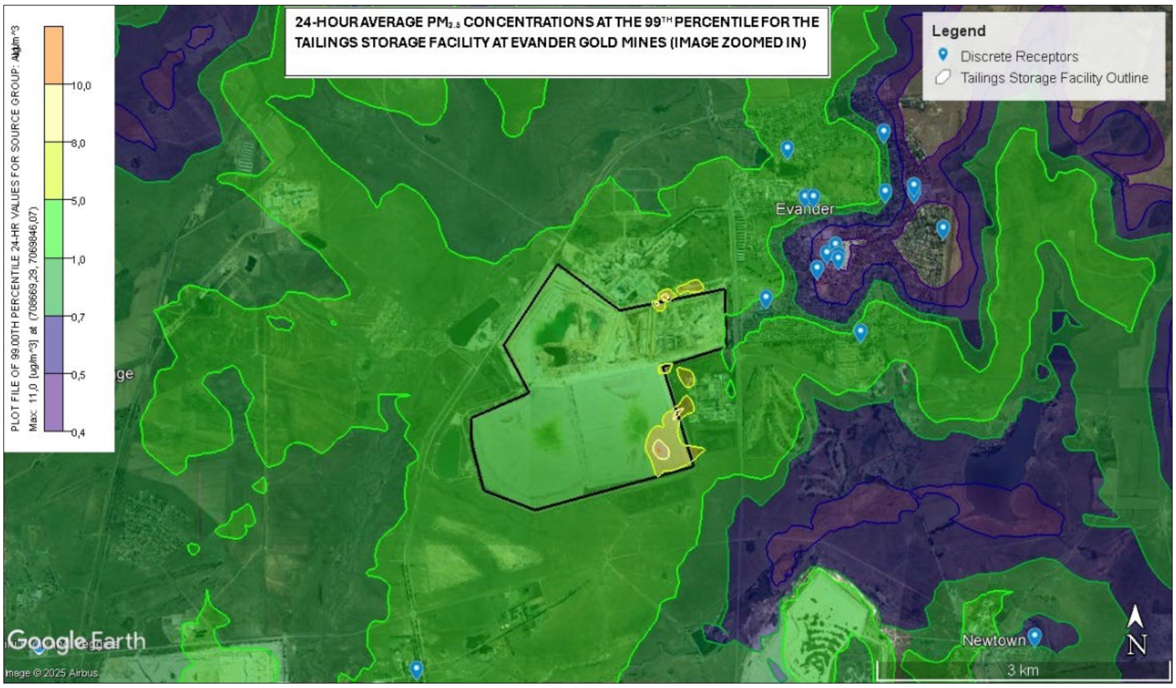

Figure 5.8: 24-hour average $PM_{2.5}$ concentrations at the 99th percentile for the Evander Gold Mine tailings storage facility

**The image has been zoomed in to show the source and $PM_{2.5}$ dispersion contours*

The predicted annual average ground-level $PM_{2.5}$ concentrations were determined and compared to the SA NAAQS and the WHO guidelines. The annual average $PM_{2.5}$ concentration at the 99th percentile for the TSF are shown in Figures 5.9 (source and the discrete receptors) and 10 (the source and $PM_{2.5}$ dispersion contours).

An annual average ground-level $PM_{2.5}$ (99^{th}-percentile) concentration of 3.4 µg/m³ was predicted in the study area. This value is well below the regulatory threshold set by the SA NAAQS for $PM_{2.5}$ at 20 µg/m³, indicating that the TSF complies. However, when compared against the more stringent WHO guidelines of 5 µg/m³, the predicted value is lower yet closer to the recommended limit.

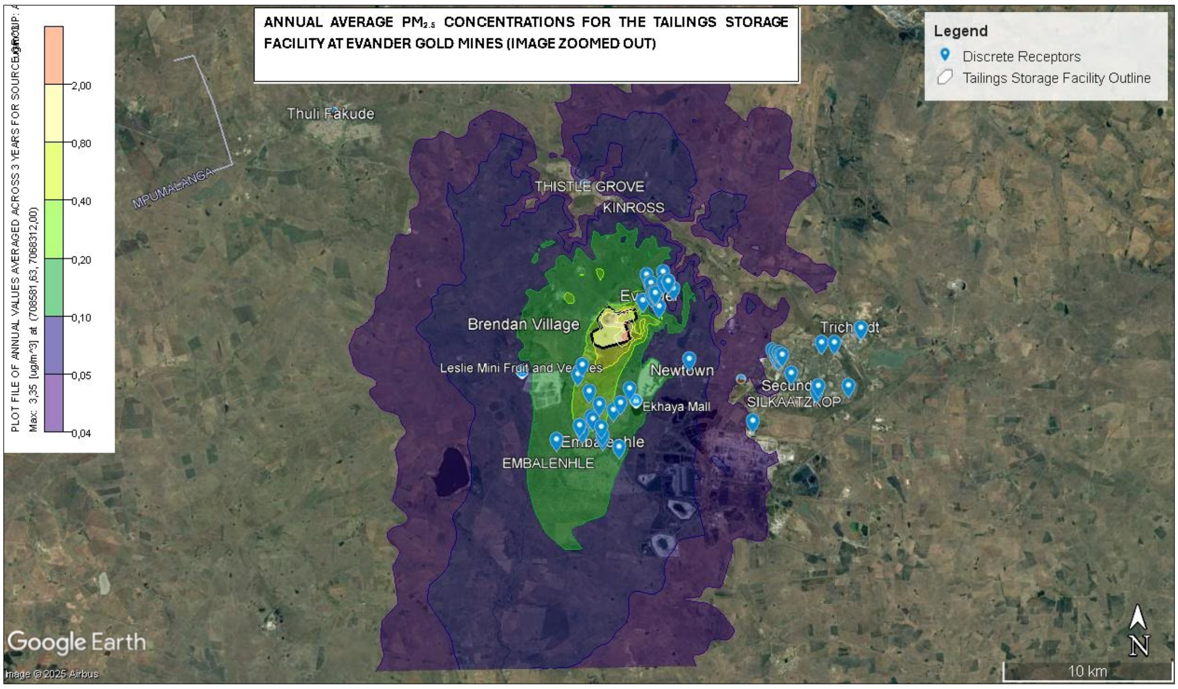

Figure 5.9: Annual average PM2.5 concentrations at the 99th percentile for the Evander Gold Mine tailings storage facility

**The image has been zoomed out to show the source, receptors and PM2.5 dispersion contours.*

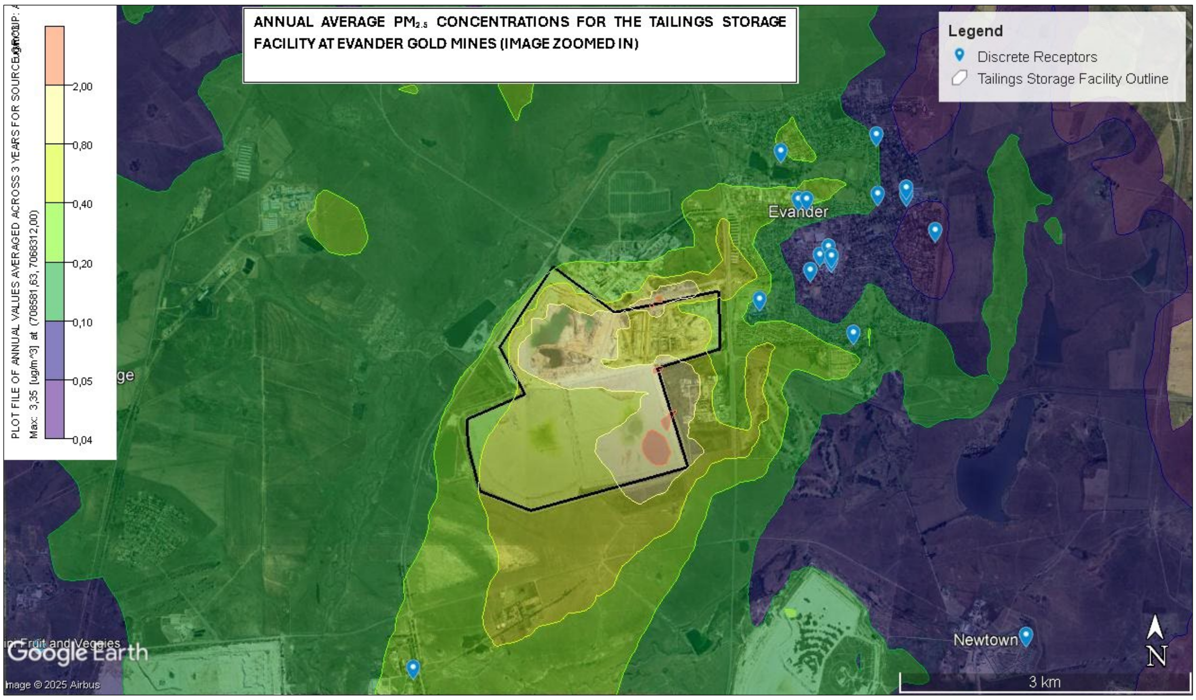

Figure 5.10: Annual average PM2.5 concentrations at the 99th percentile for the Evander Gold Mine tailings storage facility

**The image has been zoomed in to show the source and PM2.5 dispersion contours*

Table 5.5 shows the predicted $PM_{2.5}$ concentrations in several sensitive/ discrete receptor sites in the surrounding communities. Results show that daily average $PM_{2.5}$ concentrations were below 1µg/m³ at many of the receptor sites; except for Mbalenhle Primary School, Osizweni High School, Osizweni Science Centre, eMbalenhle Clinic, Evander Club, etc which recorded concentrations above 1µg/m³ but less than 2µg/m³. The predicted annual average $PM_{2.5}$ concentrations were below 1µg/m³ across all receptor sites. The recorded levels complied with the SA NAAQS and WHO guidelines for daily and annual limits.

Table 5.5: Predicted $PM_{2.5}$ concentrations in several sensitive/ discrete receptor sites

		UTM Coordinates (35S)				
Receptor ID	**Receptor Name**	**X (m)**	**Y (m)**	**Elevation (m)**	**$PM_{2.5}$- Daily (µg/m³)**	**$PM_{2.5}$- Annual (µg/m³)**
SR1	TP Stratten Primary School.	710222.01	7070002.87	1653.51	0.48	0.07
SR2	Tholukwazi Primary School	705857.18	7062454.76	1573.75	0.99	0.19
SR3	Thorisong Primary School	706650	7062817.04	1584.3	0.90	0.20
SR4	Mbalenhle Primary School	706458.84	7064447.22	1577.54	1.09	0.25
SR5	Hoërskool Evander	709698.53	7069715.26	1646.6	0.77	0.15
SR6	Shapeve Primary School.	708293.07	7063743.21	1604.27	0.98	0.17
SR7	Zamokuhle Primary School	706014.04	7062087.85	1575.04	0.90	0.18
SR8	Osizweni Secondary School	705806.94	7065461.27	1588.23	1.16	0.23
SR9	Muzimuhle Primary School	712382.09	7066246.77	1639.64	0.70	0.06
SR10	Sizwakele Secondary School	706522.96	7062974.36	1581.69	0.95	0.20
SR11	Secunda Homework and Study Centre	720188.93	7067085.39	1633.14	0.47	0.02
SR12	Infinity Education Tutorials	717632.35	7066543.84	1631.59	0.49	0.03
SR13	Osizweni Science Centre	706074.64	7066003.69	1600.92	1.39	0.29
SR14	Diligent Students	719867.02	7064243.66	1634.56	0.37	0.03
SR15	NOSA College Secunda | SafetyCloud	717634.78	7066211.23	1617.1	0.43	0.03

SR16	Supreme Institute of Science and Technology	717462.52	7066597.5	1629.69	0.49	0.03
SR17	Aleph Learning Academy (Pty) Ltd	717666.19	7066544.77	1631.2	0.48	0.03
SR18	Gert Sibande FET College - Evander Campus	710197.41	7070725.04	1642.01	0.94	0.14
SR19	Educational Therapy	717504.48	7066262.48	1623.99	0.48	0.03
SR20	Pretoria Professional College	717865.82	7066403.01	1622.6	0.47	0.03
SR21	Medlife Health Care	717783.5	7066428.5	1624.38	0.46	0.03
SR22	My Gp Health Care	710438.1	7070097.03	1658.43	0.41	0.06
SR23	Evander Primary Healthcare Clinic	711217.5	7070755.99	1653.35	0.45	0.05
SR24	Embalenhle Clinic	707864.3	7063330.59	1598.44	1.02	0.18
SR25	Buciko Clinic	710412.28	7070238.11	1658.24	0.38	0.06
SR26	Basadi Occupational Health	720943.17	7067069.66	1637.43	0.44	0.02
SR27	Teksa Wound Care	719961.4	7064547.14	1628.85	0.43	0.03
SR28	Healing Hands Wound Care Centre	721733.74	7064540.63	1645.74	0.27	0.02
SR29	RHI MEDI - CARE CENTRE	707041.72	7063692.45	1588.29	0.96	0.22
SR30	Transvalia Clinic	718375.75	7065324.65	1610.71	0.46	0.03
SR31	Mediclinic Highveld Hospital	722557.69	7067895.53	1625.38	0.33	0.02
SR32	Njabulo Xaba Dietetic services	710924.46	7070766.06	1644.58	0.70	0.09
SR33	Highveld Mediclinic Pediatric Ward	722510.66	7067908.06	1625.2	0.33	0.02
SR34	Evander Hospital	711217.04	7070822.7	1651.28	0.46	0.06
SR35	Trichardt Mediclinic	722523.79	7067909.27	1625.23	0.33	0.02
SR36	Embalenhle CHC	707193.71	7061898.76	1578.03	0.81	0.15
SR37	Sasol mining Hospital	716074.92	7062556.02	1585.21	0.45	0.03
SR38	Sasol Mine Occupational Health Hospital	717289.14	7066701.3	1625.13	0.46	0.03
SR39	Medforum	717509.18	7066274.66	1623.52	0.48	0.03
SR40	Hoeveld Medi-Clinic-ER	722450.06	7067899.07	1625.12	0.33	0.02
SR41	Naomi Community home based care	708163.56	7061160.48	1574.18	0.71	0.10

SR42	Maria old age home	711508.48	7070387.01	1654.26	0.37	0.05
SR43	HOPE Home Based Care	710112.06	7070726.92	1641.13	1.03	0.16
SR44	Ekhaya Mall	708844.5	7064569.97	1602.78	0.91	0.15
SR45	Mall@Embalenhle Shopping Centre	707133.14	7062346.6	1586.05	0.84	0.17
SR46	Sasol Community Recreation Centre eMbale	707211.79	7061660.16	1572.92	0.81	0.14
SR47	SharPozi	704482.09	7061649.37	1560.65	0.87	0.15
SR48	Evander Club	710654.79	7069356.21	1637.43	1.47	0.17
SR49	Walking disabled educational wilderness tou	710920.44	7071370.21	1642.07	0.77	0.11
SR50	Evander Park	709941.59	7071220.44	1620.98	1.18	0.17
SR51	Izizwe Wellness centre	710322.9	7070156.67	1655.48	0.42	0.06
SR52	Evander Easy Fitness	710441.49	7070142.42	1659.3	0.39	0.06

5.4. Risk Assessment of Exposure to $PM_{2.5}$

5.4.1 Carcinogenic and Non-carcinogenic Risks

Table 5.6 compares modelled and measured adjusted $PM_{2.5}$ concentrations along with carcinogenic and non-carcinogenic for four population sub-groups. The modelled $PM_{2.5}$ concentration for Toddlers was 2.4 µg/m³, compared to a measured value of 0.6 µg/m³. Based on the WHO guideline, both modelled and measured HQ values were 0.5. When applying the South African NAAQS, both HQ values were 0.1. The modelled CR for toddlers was 6×10^{-4}, while the measured risk was higher at 4×10^{-3}. For children (6–11 years), the modelled $PM_{2.5}$ concentration was 2.6 µg/m³, while the measured value was 3.2 µg/m³. The HQ values remained constant across modelling and measured $PM_{2.5}$ concentrations for both WHO guidelines (0.5) and SA NAAQS (0.1). The CR increased in the measured $PM_{2.5}$ concentrations (3×10^{-2}) compared to the modelled estimate (2×10^{-3}).

In adults, modelled $PM_{2.5}$ levels were 2.6 µg/m³, whereas measured concentrations were higher at 16.4 µg/m³. HQ values remained constant for WHO guideline (0.5) and SA NAAQS (0.1) in both modelled and measured $PM_{2.5}$ concentrations. For the elderly, the modelled concentration was 2.9 µg/m³, while the measured concentration reached 21.6 µg/m³ and was the highest measured value among all groups. As with other groups, HQ values remained the same for both WHO guideline (0.5) and SA NAAAQS (0.1). The CR in the measured data was 2×10^{-1}, exceeding the modelled estimate of 5×10^{-3}

Table 5.6: Calculated Adjusted Air, Hazard Quotient and Excess Lifetime Cancer Risk

Population (yrs)	Modelled Cair_adj (µg/m³)	Measured Cair_adj (µg/m³)	Modelled HQ (WHO 5 µg/m³)	Measured HQ (WHO 5 µg/m³)	Modelled HQ (SA 20 µg/m³)	Measured HQ (SA 20 µg/m³)	Modelled CR (unitless)	Measured CR (unitless)
Toddlers (1–2)	2.4	0.6	0.5	3.5	0.1	0.9	6×10^{-4}	4×10^{-3}
Children (6–11)	2.6	3.2	0.5	3.5	0.1	0.9	2×10^{-3}	3×10^{-2}
Adults (21–60)	2.6	16.4	0.5	3.5	0.1	0.9	1×10^{-2}	1×10^{-1}
Elderly (65+)	2.9	21.6	0.5	3.5	0.1	0.9	5×10^{-3}	2×10^{-1}

5.5. Discussion

At the hourly scale, the community site recorded almost double the $PM_{2.5}$ concentrations compared to the TSF. This indicated that the community is subject to more frequent short-term spikes in $PM_{2.5}$ concentrations, likely driven by localised sources (domestic fuel burning, traffic and possibly regional transport of $PM_{2.5}$), (Kuppili and Nagendra, 2024). The daily averages showed a different pattern, with the TSF site recording higher concentrations than the community site. This reversal implied that while the community experienced short-lived peaks, the TSF site was subject to sustained emissions over the 24-hour period. This could be due to continuous dust generation from exposed TSF and windy conditions (Mukota and Grobler, 2024).

At the annual scale, the community site showed higher $PM_{2.5}$ concentrations compared to the TSF site. The monthly analysis revealed strong seasonal patterns, with the community site showing peaks in February, July and January. These months correspond to late summer and winter, when temperature inversions trap $PM_{2.5}$, leading to higher concentrations (Roostaei, 2024). An annual modelled average $PM_{2.5}$ concentration of 11 µg/m³ at the 99th percentile, which assumes the worst-case scenario was recorded. This annual concentration was below the South African NAAQS of 20 µg/m³ and WHO Guidelines (5 µg/m³). This indicated that the air quality standards are met, and the exposed population may be safe from the harmful effects of $PM_{2.5}$ exposure from the TSF.

An urgent policy concern is whether these limits provide protection across all population subgroups, including vulnerable groups (children, elderly and those with pre-existing health conditions). Currie et al. (2014) argue that children in developing countries are likely to respond negatively even to low $PM_{2.5}$ concentrations below safe thresholds. Wei et al. (2022) highlighted the limitations of existing regulatory approaches aimed at protecting the public from adverse health effects (intensifications of asthma requiring hospital admissions) due to exposure to various stressors. Marks (2022) is of the opinion that there is no safe amount of air pollution below which adverse effects do not occur. This provides a huge conundrum for policymakers, who must develop effective, evidence-based limits for stressors based on robust epidemiological research. These policies should be tailored to address local conditions and needs as a function of population dynamics.

For instance, countries worldwide use varying ambient $PM_{2.5}$ standards or safe threshold limits. When adopting these standards, they generally consider a balance between environmental, health, social, political and economic imperatives (Purohit et al., 2025). In most cases, developing countries may prioritise economic growth and industrialisation over stricter NAAQS to avoid limiting industrial expansion and economic development (Ali et al., 2020). They may set more lenient NAAQS if they are limited in terms of technological capacity to monitor and regulate air quality (Dudley et al., 2017). In contrast, developed countries may impose more stringent regulations to protect public health and the environment (Huang et al., 2018).

Although the WHO air quality Guidelines are widely adopted and used in many countries, they are not absolute and can be overly simplistic. Firstly, the guidelines fail to account for cumulative risks and variability in individual susceptibility. Secondly, the Guidelines fail to account for risk tolerance, which can vary between populations and regulatory bodies. Given this, there is a greater need to develop more robust and advanced approaches that factor in these issues to reflect real-world exposures accurately. This will avoid underestimating or overestimating risk.

The lifetime CR values exceeded the local and international risk thresholds by substantial orders of magnitude. For instance, the US EPA considers acceptable environmental exposures for lifetime CR in the range of 1×10^{-6} to 1×10^{-4} (Candeias et al., 2021). The South African regulatory risk threshold is more stringent and is set at 5×10^{-6} (Kamunda et al., 2016, Government of South Africa, 2006). The lowest estimated risk for toddlers of 5.59×10^{-4} is an order of magnitude higher than the US EPA limit and nearly two orders above the South African limit. The adult cancer risk of 5.52×10^{-2} is two orders of magnitude above the US EPA limit and nearly four orders of magnitude higher than the South African limit. Our results showed an increase in CR in males than females due to the use of a lower AT in males (64 years) than in females (69 years) (Statistics South Africa, 2024).

Furthermore, males have different hormonal profiles compared to females, and as they age, the risk of developing cancer increases (Konduri et al., 2022). Contrary, Stapelfeld et al. (2020) found that females were more at risk of developing cancer than males. Female toddlers showed the least chance of developing cancer due to continuous exposure to $PM_{2.5}$ compared to the other groups. The present study joins several others worldwide that have failed to demonstrate a concentration below existing local and international standards, below which adverse health effects from exposure to ambient air pollutants do not occur (Wei et al., 2022; Marks, 2022). Marks (2022) argues that reference standards should not be treated as a license or free pass for industries to pollute up to below those concentrations. Urban planning should include consideration of the siting of sensitive receptors (healthcare facilities, schools, old age homes, etc) and the need to minimize exposure to pollutants in these vulnerable populations beyond merely ensuring that threshold limits are met.

This study provided a picture of the health risks of lifelong exposure to $PM_{2.5}$ from mine TSF in a mining-impacted region. This was achieved by integrating predictive ground-level concentrations from AERMOD with receptor-based human health risk estimates, assuming the worst-case scenario to protect public health. It is recommended that future studies focus on epidemiological studies in communities close to the TSF to see if there are elevated rates of adverse health effects in the studied population subgroups relative to a control community without mine TSF.

It is important that one also measures the chemical composition of the $PM_{2.5}$ from the TSF to identify other toxic elements bound to $PM_{2.5}$, including arsenic, lead, or uranium. This approach would allow one to perform a pollutant-specific risk assessment over and above the $PM_{2.5}$ mass-based approach. Another research avenue would be to use advanced modelling methods like computational fluid dynamics (CFD) which account for time-varying emissions. Lastly, satellite remote sensing has gained much traction due to its immense capabilities. Satellite remote sensing can be used to detect dust plumes from TSF and correlate these with model predictions. This will help in understanding the nature and dynamics of pollutants under varying meteorological and topographical conditions.

5.6. Study limitations

The LCMs used in this study did not support source apportionment, thereby limiting the ability to determine the relative contributions of different sources of the $PM_{2.5}$ concentrations. This prevented targeted identification of dominant $PM_{2.5}$ sources and their specific health impacts. The health risk assessment was based on a deterministic approach, which relied on single-point estimates for input variables (exposure time, concentration, frequency). This approach failed to account for the inherent variability and uncertainty in real-world exposure scenarios. This led to either underestimation or overestimation of the health risks of exposure to $PM_{2.5}$. The study simulated results of $PM_{2.5}$ emissions based on the 99th percentile. This assumes the worst-case scenario. However, the 99th percentile is used in regulations to protect public health. The drawback is that this approach may overestimate exposure as communities are less likely to experience such high concentrations over the lifetime of individuals.

The HQ and CR equations were based on estimates, not actual data collected from the affected communities. This study made assumptions for the exposure duration and frequency for all population subgroups. Therefore, the HQ and CR estimates presented in this study can only be considered to flag potential health risks for exposed populations. This can limit the reliability and generalizability of the findings, as these parameters may not accurately reflect the diverse exposure and activity patterns between population subgroups.

AERMOD assumes steady-state conditions and does not account for chemical reactions of $PM_{2.5}$ as it is transported in the air compartment. The model does not consider the time required for transporting the plume and possible interactions. As such, it is unsuitable for near-source dispersion (within 100 m), calm wind conditions and complex urban environments (Contreras, 2015). The model oversimplifies the treatment of turbulence and meteorology, thereby limiting its accuracy when modelling highly variable conditions. Lastly, AERMOD assumes continuous plumes rather than puff-based dispersion, making it less suitable for modelling non-steady or transient emissions compared to CALPUFF

5.7. Conclusions

The study aimed to investigate the health impacts of $PM_{2.5}$ emissions from TSF in a mining-intensive region in South Africa. AERMOD dispersion model was integrated with a receptor health risk assessment to determine the contribution of the TSF to $PM_{2.5}$ emissions and the health risks associated with long-term exposure in exposed communities. These communities are in the vicinity of the TSF. Findings have demonstrated that $PM_{2.5}$ emissions from the TSF do not significantly elevate $PM_{2.5}$ concentrations in communities downwind of the TSF to levels that pose health risks. The modelled maximum ground-level $PM_{2.5}$ concentrations were below the annual SA NAAQS of 20 $\mu g/m^3$ and the WO guidelines of 5 $\mu g/m^3$, leading to HQ values less than 1. However, the CR was high in all age groups, with the adults recording the highest risk due to $PM_{2.5}$ exposure. This highlights that merely meeting the NAAQS may not be adequate, especially when dealing with a pollutant with high carcinogenic potency. Compliance with short-term or non-carcinogenic exposure limits does not guarantee safety in exposed populations. The study demonstrated that those with longer or earlier exposures are more likely to be affected.

Different population subgroups may experience health risks of exposure to $PM_{2.5}$ in different ways. Children and toddlers, face greater susceptibility to both acute and chronic effects of $PM_{2.5}$ exposure. They have higher inhalation rates relative to body mass and their respiratory systems are still developing. Adults, especially those working outdoors or at the TSF, may experience cumulative occupational exposures that increase long-term risk of respiratory and cardiovascular diseases. The elderly, often with pre-existing health conditions, are the most vulnerable to the health risks of $PM_{2.5}$ exposure. To enhance the resolution and relevance of future human health risk assessments of $PM_{2.5}$ exposure, it is recommended that source apportionment techniques be employed. Furthermore, future studies adopt probabilistic human health risk assessment methods, which allow for the incorporation of variability and uncertainty in exposure parameters. The probabilistic human health risk assessment will provide a more realistic and robust characterisation of population health risks of $PM_{2.5}$ exposure.

5.8. Author contributions

Conceptualizing, NT and TM; methodology TM, GM, PC and NT; model simulations NT, GM, PC and TM; writing-original draft preparation, NT; writing, reviewing and editing, NT, TM, DB, and DM. All authors have read and agreed to the final version of the manuscript.

5.9. Conflict of interest

The authors declare no conflict of interest. In addition, the authors have observed all ethical issues as required.

CHAPTER 6: SOIL SAMPLING AND SOURCE APPORTIONMENT OF HEAVY METALS WITHIN A GOLD MINE AREA, SOUTH AFRICA

This chapter presents a manuscript that was submitted to the Journal of Geoscience and Environment Protection for publication. It provides an analysis of bulk sampling and source apportionment of heavy metals within a gold mine area in South Africa. The Chapter outlines the procedures used for collecting soil samples from TSFs and residential sites and the procedures thereof. The source apportionment method used to identify and quantify the contributions of different sources to heavy metal pollution in the study area is explained. The results and discussion on the different sources of heavy metals are presented in this chapter.

Abstract

Studies have indicated that heavy metals originate from both natural and anthropogenic sources. Anthropogenic sources of heavy metals include mining, industries and agricultural activities. The most common heavy metals found in soil are Lead (Pb), Mercury (Hg), Cadmium (Cd), Manganese (Mn), Nickel (Ni), Zinc (Zn) and Arsenic (As). The heavy metals find their way to the ground, thus contaminating the soil. This study was divided into two (2) components: determining the concentrations of heavy metals in the soils collected within the mining area and identifying their sources. A total of ten (10) topsoil samples were collected around Evander and eMbalenhle. The Inductively Coupled Plasma Mass Spectrometry (ICP-MS) method was used to analyze the heavy metals in the soil samples. The samples were prepared in a 1% Nitric Acid (HNO_3) matrix. About 0.5% Hydrochloric acid (HCl) was routinely added to soil samples to ensure the stability of the heavy metals. The Absolute Principal Components Score - Multiple Linear Regression (APCS-MLR) Model was used to calculate the contribution rate of the heavy metals at each sampling point. The Enrichment Factor (EF) and Contamination Factor (CF) were calculated to determine whether the heavy metals in the soil samples originated from natural sources or were influenced by anthropogenic activities. The Upper Earth's Crust (UEC) values were used as the soil background values of heavy metals. Mn was chosen as the reference element. The mean Cr, As, Pb, U, and Au concentrations were higher in Tailings Storage Facilities (TSFs) (89.2±58.8, 22.9±25.7, 10±10, 5.72±4.78, and 0.53±0.54 mg/kg) compared to residential sites (79.7±24.6, 2.6±1,33, 8.98±5.05,1.55±1.42, and 0.08 ±0.07 mg/kg), respectively. There was a significant difference in Mn concentrations (r_{rb} = 0.833, p = 0.038) between the residential sites and TSFs. Results of the APCS-MLR of the heavy metals concentrations at the TSFs sites indicated that Au

(92.7%), As (93.3%), U (93.3%) and Cr (88.3%) mainly originated from mining activities. The study findings confirm that TSFs are basically waste soil and may have affected the surroundings. The study recommends integrating other methods alongside bulk sampling and APCS-MLR in future studies to capture heterogeneity within the soil matrix and improve source apportionment resolution.

Keywords: Soil contamination, Mining, Anthropogenic sources, Absolute Principal Components Score

6.1 Introduction

Soils contaminated with heavy metals and their impact on human health have been widely reported (Zhang et al., 2018; Mondal & Singh, 2021; Nguyen et al., 2022; Guo et al., 2022). Heavy metals threaten agriculture (Qin et al., 2021a) and water bodies. They lead to soil compaction and nutrient loss (Drewry et al., 2021); thus causing a decline in production and quality of agricultural products (Zewide & Sherefu, 2021). Furthermore, when heavy metals are present in the soil, they can be transported by rainwater runoff into streams, rivers and lakes (Kolarova & Napiórkowski, 2021).

Tail Storage Facilities (TSFs) are waste disposal sites for leftover materials after ore excavation and chemical extraction (Schoenberger, 2016). Although TSFs are designed to contain mining waste, they contaminate the surrounding topsoils (Hudson-Edwards et al., 2024). One of the primary contamination pathways is leaching, whereby heavy metals are dissolved and carried to the surrounding soils (Singh & Steinnes, 2020). Besides leaching, dust deposition is another major pathway for soil contamination (Meuser & Meuser, 2010). Wind erosion disperses soil particles containing heavy metals over large areas (Huang, 2020). These contaminated soil particles settle in nearby areas and reduce soil fertility (Wuana & Okieimen, 2011).

Heavy metals are released from both natural and anthropogenic sources (Hanfi et al., 2020). The natural sources include the weathering of rocks, volcanic activities and forest fires (Bello, 2023). The anthropogenic sources include agricultural activities, mining operations and industrial processes (Kapoor et al., 2021). The most common heavy metals are Lead (Pb), Mercury (Hg), Cadmium (Cd), Manganese (Mn), Nickel (Ni), Zinc (Zn), Arsenic (As). Heavy metals released from industrial activities include Cd and Zn (Jia et al., 2023a). Naturally occurring heavy metals are Pb and Hg (Pratush et al., 2018). Mining operations and metal smelting release Ni, Cr, Au and U into the environment (Dai et al., 2022).

Various chemical extraction methods are used to recover Au from ores. These methods include cyanidation, aqua regia, thiourea leaching and chlorination (Gökelma et al., 2016). Cyanidation involves dissolving Au with a sodium or potassium cyanide solution in the presence of oxygen (Anning et al., 2019). Au is then recovered by the precipitation with zinc dust and adsorption onto activated carbon, followed by elution (Ottan, 2024). Aqua regia is a concentrated hydrochloric and nitric acid mixture (Mousavi et al., 2019). Au recovery is achieved by precipitation with reducing agents (Manyuchi et al., 2022). In the thiourea leaching process, Au is dissolved in an acidic thiourea solution with an oxidant to form a gold-thiourea complex (Guo et al., 2017). Chlorination involves reacting gold with chlorine gas in the presence of water to form a soluble Au chloride (Kumar, 2024). Although chlorination is effective, it has been replaced by cyanidation due to technological advancements (Liu et al., 2022). The common heavy metals from the cyanidation process include Cu, Pb, Zn, Mn and Cd (Zhang et al., 2021).

Source apportionment methods are widely used to trace heavy metals to their respective sources (Liu et al., 2020). These methods include Chemical Mass Balance (CMB), Positive Matrix Factorisation (PMF) and APCS-MLR Model (Xu et al., 2020). CMB estimates source contributions based on the chemical composition of pollutants (Hong et al., 2020). PMF is a multivariate statistical technique that identifies and quantifies pollution sources from complex data sets (Hong et al., 2020). It further analyses the variability in heavy metal concentrations across multiple sampling sites and identifies their sources (Su et al., 2022; Liu et al., 2023). It reveals sources based on the correlation structure of pollutant data (Yang et al., 2020). This study preferred APCS-MLR because of the small number of soil samples collected. Although APCS-MLR helps with the source apportionment, it does not directly identify specific sources. The components are categorized by identifying the heavy metals with high concentrations in that factor (Shi et al., 2022).

Several methods are used to identify and quantify heavy metals in soil samples. The methods are Computer-Controlled Scanning Electron Microscopy (CCSEM); (Li et al; 2023), Atomic Absorption Spectroscopy (AAS); (Abraham et al., 2021), Inductively Coupled Plasma Mass Spectrometry (ICP-MS); (Shaheen et al., 2021), X-ray Fluorescence (XRF) Spectroscopy (Zamanova, 2022), Electrochemical methods (Xu et al., 2021), Colorimetric and Spectrophotometric Methods (Hyder et al., 2022); and Neutron Activation Analysis (NAA); (Das et al., 2024). The ICP-MS method was the most preferred in this study due to its high sensitivity, accuracy and multi-element detection capabilities (Michalke, 2022). This study distinguished anthropogenic and natural heavy metals in soil samples collected from TSFs and residential areas. This was done to determine the relationship between mining activities and heavy metals in the soils around Evander and eMbalenhle.

6.2 Methods and Materials

6.2.1 Study areas

The selected study areas were Evander (26.4683º S; 29.1076º E) and eMbalenhle (26º 5524º S; 29.0751º E) situated within the mining area of the Govan Mbeki Municipality (GMM) as indicated in Figure 6.1. GMM forms part of the Gert Sibande District Municipality, South Africa (Local, 2014). The GMM is an economic hub due to its mines and industries (GMM, 2009). The population of eMbalenhle is estimated to be 118889 people with an annual growth of 2.5%. Most of the population are black Africans (99%), with 52.4% males and 48.6% females. The population of Evander is 10,166 (5,278 males and 4,887 females); (Statistics South Africa, 2011). Evander and eMbalenhle fall within the Highveld Priority Area (HPA). The HPA is a declared area regarding air pollution levels exceeding the National Ambient Air Quality Standards (South Africa, 2004). TSFs are in the west direction at 1 km and 6 km from Evander and eMbalenhle, respectively.

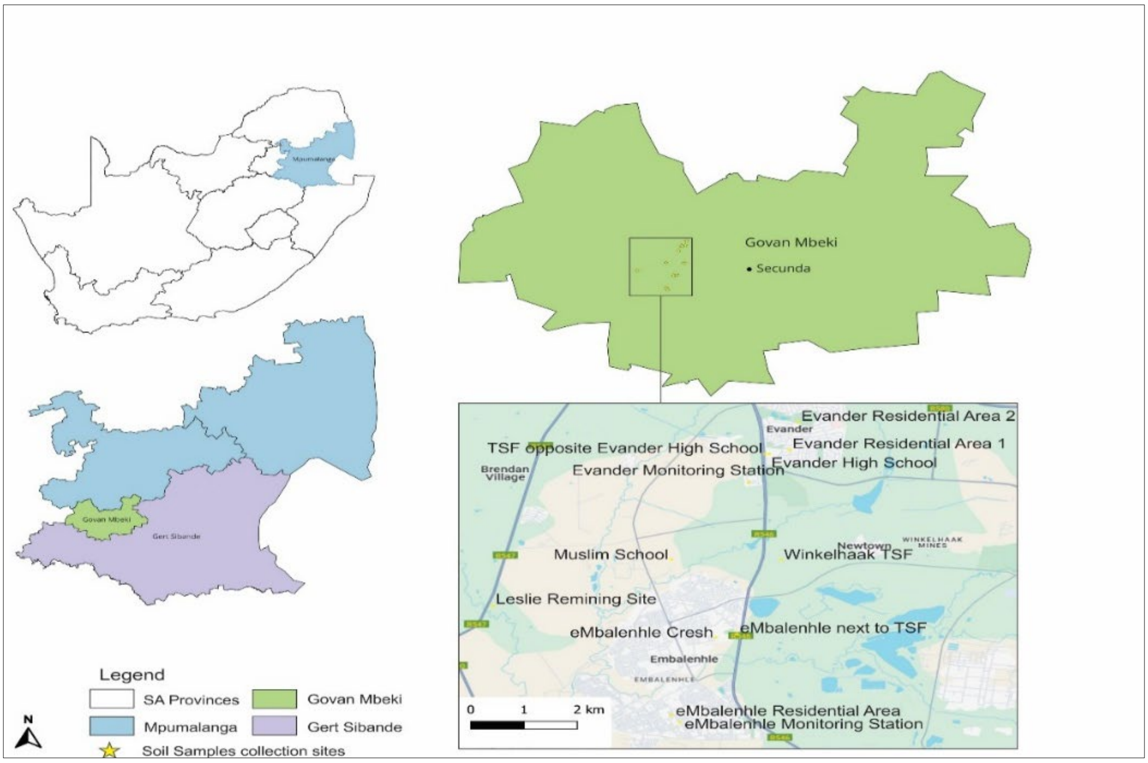

Figure 6.1: Geographical and Sampling Map of the Study Areas

6.2.2 Samples Collection

6.2.2.1 Soil Bulk Sampling

Ten (10) topsoil samples around Evander and eMbalenhle were collected in July 2023. Four (4) samples were collected around the TSFs, and six (6) samples were collected in residential areas. A hand shovel was used to remove the topsoil. The soils were collected at depths between 0-15 cm. The soils were put in 1 kg plastic bags and placed in a container. The samples were labelled according to their site information. The Global Positioning System (GPS) documents the geographical coordinates at sampling points. The soil samples were stored in a cool place to prevent contamination and alterations in soil properties. The soil samples were then taken to the laboratory for analysis.

6.2.2.2 Sample Preparation and Chemical Analysis

The soil samples were sieved and dried before being analyzed. The Inductively Coupled Plasma Mass Spectrometry (ICP-MS) method, as described by Kubota (2021) and Shaheen et al., (2021) was used to analyze the soil samples. The samples were prepared in a 1% Nitric Acid (HNO_3) acid matrix. About 0.5% Hydrochloric acid (HCl) was routinely added to the soil samples to ensure the stability of elements. For quality control, the Initial Calibration Verification (ICV) and Continuing Calibration Verification (CCV) standards were prepared from the multi-element Environmental Calibration Standard (VHG). The single-element standards were also prepared for Pb, Hg, Cd, Mn, Ni, Zn, As, Au and U. The acid matrix was used as the Initial Calibration Blank (ICB) and Continuing Calibration Blank (CCB); (Kubota et al., 2021). Furthermore, the Certified Reference Material (CRM) was obtained from a reputable supplier (African Mineral Standards). The certificate of analysis for CRM, which indicated detailed information on the materials (including its certified values and uncertainties) was also provided. The Limit of Detection (LoD) for the analyzed heavy metals (Pb, Hg, Cd, Mn, Ni, Zn, As, Au, U) was 0.1 mg/kg.

6.2.2.3 Statistical Analyses

JASP 0.18.3 (https://jasp-stats.org/) was used to analyze the chemical analysis data. The LoD values were replaced using the NDExpo tool, nested in Expostats (https://expostats.ca/site/app-local/NDExpo/). This method is based on robust Regression on Order Statistics (ROS) which generates estimates based on their rank among the set of detected values. The heavy metal concentrations were grouped according to their origin location, i.e., TSFs or Residential, and the Mann-Whitney U test was used to test the differences between medians. The W-values were used to compute p-values and interpreted as follows (Lew, 2006). If the p-value was less than 0.05 ($p < 0.05$), the null hypothesis was rejected, and it was concluded that there was a statistically significant difference between the means medians of the heavy metals concentration at the residential sites and TSFs. If the p-value was greater than or equal to 0.05 ($p \geq 0.05$), the null hypothesis failed to be rejected and concluded that there was no significant difference. Pearson's correlation analysis was performed to determine the linear correlation among heavy metals using SPSS v25.0 (https://www.ibm.com/products/spss-statistics).

In addition, the rank-biserial correlation (rrb), a non-parametric effect size measure was used to describe the difference between the concentrations of heavy metals at the residential sites and TSFs in terms of their ranks (Nikitina and Chernukha, 2023). It was derived from the Mann-Whitney U statistic (Metsämuuronen, 2019). The rrb ranges from -1 to 1 and it is interpreted as follows:

rrb=1rrb=1: All observations in one group are higher than all observations in the other.
rrb=−1rrb=−1: All observations in one group are lower than those in the other group.
rrb=0rrb=0: There is no systematic difference between the groups.
∣rrb∣<0.1∣rrb∣<0.1: Very small effect size.
0.1≤∣rrb∣<0.30.1≤∣rrb∣<0.3: Small effect size.
0.3≤∣rrb∣<0.50.3≤∣rrb∣<0.5: Medium effect size.
∣rrb∣≥0.5∣rrb∣≥0.5: Large effect size.

6.2.3 The Enrichment and Contamination Factors

The Enrichment factor (EF) was used to assess the presence and intensity of anthropogenic contaminant deposition (Aytop, 2023). EF was calculated using Equation 6.1:

$$EF = [Ci/C_{ref}]\ sample / [Ci/C_{ref}]\ background \qquad \textit{Equation 6.1}$$

Where: C_i is the heavy metal concentration in the soil sample, C_{ref} is the geological background concentration (Aytop et al., 2023). Mn was chosen as a reference element (Awagu et al., 2014) because it is naturally abundant in the Earth's crust. Furthermore, Mn is mostly unaffected by human activities and remains stable under various environmental conditions. The mean concentrations of each heavy metal over the samples collected at residential sites and TSFs were used as C_i.

In this study, the Upper Earth's Crust (UEC) values indicated in Table 4 were used as the soil background values of heavy metals /reference values for the pre-industrial concentration. The background values of the UEC were applied as 92 mg/kg (Cr), 47 mg/kg (Ni), 67 mg/kg (Zn), 17 mg/kg (Pb); (Rudnick & Rudnick, 2005), 4.8 mg/kg (As); (Rudnick & Gao, 2004), 600 mg/kg (Mn); (Bhattacharya et al., 2014), 2.3 mg/kg (U); (Emsley, 1989), 13.5 mg/kg (Hg); (Tian et al., 2023) and 0.05 mg/kg (Au); (Wyman & Kerrich, 1989). EF values can be categorized into five groups:

$EF < 2$, minimal enrichment.
$2 \leq EF < 5$, moderate enrichment;
$5 \leq EF < 20$, significant enrichment;
$20 \leq EF < 40$, very high enrichment;
$40 \geq EF$, extremely high enrichment (Barbieri, 2016)

The Contamination Factor (CF) was used to assess the degree of contamination of heavy metals in the soil samples compared to the background value (UEC) without normalization (Rahmanian & Safari, 2022). The Contamination Factor (CF) was calculated as follows (Ferreira, 2022):

$$C^i_f = C^i / C^i_n \qquad \textit{Equation 6.2}$$

Where: C^i is the content of element (i) and C^i_n is pre-industrial value (or UEC) of element (i). The CF values are classified as follows:

$CF < 1 \rightarrow$ Low contamination, $1 < CF < 3 \rightarrow$ Moderate contamination, $3 < CF < 6 \rightarrow$ Considerable contamination, $CF \leq 6 \rightarrow$ Very high contamination (Deliboran et al., 2024).

6.2.4 Source Apportionment

APCS-MLR model was applied to apportion the different pollution sources at the TSFs and residential areas. The heavy metal concentrations of all samples collected at the TSFs; and all samples collected at the residential sites were used as inputs in the APCS-MLR model. The Stata/MP statistical software was used to conduct APCS-MLR. Generally, environmental datasets don't have normal distributions (Zhang, 2006). This study used the log transform commands in Stata statistical software to normalize the data. The eigenvalues associated with these principal components indicate how much variance each component captures. Larger eigenvalues mean more variance captured by that component. High absolute values means that the variable strongly contributes to that component (Lv et al., 2024). The eigenvectors describe the contribution of each original feature to the new principal components (Kharif & Latypova, 2020).

After analyzing the principal components, a scree plot was used to determine the optimal number of principal components to retain (Dheeraj et al., 2024). The factor scores were used to apportion the contributions of different pollution sources by quantifying how much each factor contributes to the observed pollution levels (Zhang et al., 2023). The factor loading matrix represented the extent to which a variable was associated with different factors. Factor loadings were categorized based on their strength. For instance, values above 0.75 indicated a strong correlation, those between 0.5 and 0.75 signified a moderate correlation and values ranging from 0.3 to 0.5 indicated a weak correlation. These classifications expressed the variables' level of influence on each principal component (Zhang et al., 2022). The steps of APCS-MLR are explained in Figure 6.2.

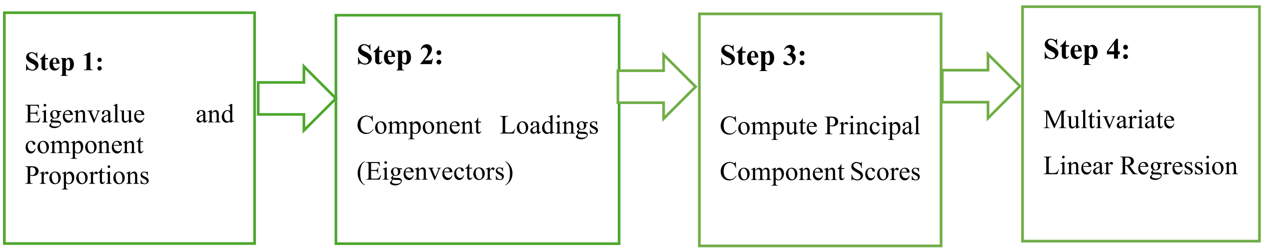

Figure 6.2: Steps Followed in the Application of the APCS-MLR

6.3 Results

The concentrations of heavy metals (Cr, Mn, Ni, Zn, As, Au, Hg, Pb, and U) at residential sites and TSFs are presented in Table 6.1. Of all the samples collected at the TSFs, Leslie Remining showed the highest concentrations of heavy metals. Evander High School had the highest concentration of Mn (952 mg/kg) and Ni (55.3 mg/kg). GMM Crech had lower concentrations of Pb and U (1.8 and 0.3 mg/kg) respectively. At all sites, Hg concentrations were below the LoD (<0.1 mg/kg). Au concentrations were low across all sites, ranging from <0.1 to 0.7 mg/kg.

6.3.1 Bulk Soil Sampling Results

Table 6.1: Concentrations of the heavy metals in samples collected at the TSFs and Residential Sites in units (mg/kg)

Sources	Cr	Mn	Ni	Zn	As	Au	Hg	Pb	U
TSFs									
Evander	54.1	69.7	31.5	26.2	20.2	0.7	<0.1	12.1	7
Winkelhaak	28.6	40.8	11.6	11.1	8.5	0.2	<0.1	3.5	3.3
Leslie Remining	158	76.5	75.8	31.7	59.9	1.2	<0.1	17.4	11.8
eMba	116	503	68.8	78.9	3	<0.1	<0.1	27.4	0.8
Residential Sites									
Evander High	104	952	55.3	89	2.3	0.1	<0.1	13.6	0.8
Evander Station	73.9	750	43.3	51.7	4.8	0.2	<0.1	9.6	4.1
Muslim School	113	276	41.9	80.9	2.6	0.1	<0.1	15.4	1.1
eMba Station	76.7	965	67.3	95.4	2	<0.1	<0.1	8	0.7
eMba Res	48.1	225	28	53.2	3.1	<0.1	<0.1	5.5	2.3
eMba Creche	62.5	560	206	49.9	0.8	<0.1	<0.1	1.8	0.3

**Concentrations measured in mg/kg*

Descriptive statistics of heavy metal concentrations at residential sites and TSFs are displayed in Table 6.2. The mean Cr, As, Pb and U concentrations were higher in TSFs (89.2±58.8, 22.9±25.7, 10±10 and 5.72±4.78 mg/kg) compared to residential sites (79.7±24.6, 2.6±1,33, 8.98±5.05 and 1.55±1.42 mg/kg), respectively. The As concentrations at the TSFs were almost nine times higher than at the residential sites, while the U concentrations were four times higher. The mean Mn, Ni and Zn concentrations at the TSFs (172±221, 46.9±30.5, 37±29.3 mg/kg) were lower than residential sites (621, 73.6 and 70 mg/kg) respectively. Although residential sites and TSFs had low Au concentrations, TSFs indicated slightly higher mean (≤0.55±≤0.50) and median (≤0.45) values. The concentrations of Hg were ≤0.1±0 mg/kg at both TSFs and residential sites.

Table 6.2: Descriptive Statistics of Heavy Metal Concentrations at the Residential Sites and TSFs

Heavy Metals	Sites	Mean	Median	Standard Deviation
Cr	Residential sites	79.7	75.3	24.6
	TSFs	89.2	85	58.8
Mn	Residential sites	621	655	324
	TSFs	172	73.1	221
Ni	Residential sites	73.6	49.3	66.2
	TSFs	46.9	50.2	30.5
Zn	Residential sites	70	67.1	20.7
	TSFs	37	29	29.3
As	Residential sites	2.6	2.45	1.33

	TSFs	22.9	14.4	25.7
Au	Residential sites	0.08	0.07	0.07
	TSFs	0.53	0.45	0.54
Hg	Residential sites	0.1	0.1	n.a
	TSFs	0.1	0.1	n.a
Pb	Residential sites	8.98	8.8	5.05
	TSFs	10	14.8	10
U	Residential sites	1.55	0.95	1.42
	TSFs	5.72	5.15	4.78

**Heavy metals concentrations in mg/kg*

Table 6.3 presents the results of the Mann-Whitney test to compare the distributions the heavy metals concentrations at the residential sites and TSFs. The rank-based comparison, significance level (p-value), and the magnitude of the difference (effect size or Rank-Biserial Correlation (rrb) between the residential sites and TSFs heavy metals concentrations. Mn showed a large positive effect size (rrb = 0.833, p = 0.038), showing a significant difference in Mn levels between the residential sites and TSFs. On the other hand, As indicated a large negative effect size (rrb = -0.833, p = 0.038), meaning that almost all As concentrations of the residential samples are lower than those from the TSFs. Zn presented a large effect size (rrb = 0.750, p = 0.067) showing a strong difference between the heavy metal concentrations at residential sites and TSFs. Pb had a moderate negative effect size (rrb = -0.417, p = 0.352). However, the p-value is not statistically significant. Cr and Nickel Ni had very small effect sizes (rrb = -0.083 and 0.083, respectively), with high p-values (p = 0.914), and no difference in the heavy metals concentrations between both sites.

Table 6.3: Description of the difference between heavy metals concentrations at the residential sites and TSFs

Heavy Metals	W-Statistics*	P**	Effect Size***
Cr	11.000	0.914	-0.083
Mn	22.000	0.038	0.833
Ni	13.000	0.914	0.083
Zn	21.000	0.067	0.750
As	2.000	0.038	-0.833
Pb	7.000	0.352	-0.417
U	4.500	0.134	-0.625
Au	6.500	0.283	-0.458

** Mann Witney U test, significance level p<0.05*
***Effect size is given by the rank biserial correlation.*

6.3.2 Enrichment and Contamination Factors Indices

The pollution risk indices of heavy metals (EF and CF) are presented in Table 6.5. There was no significant contamination by the reference element (Mn) compared to the background (CF = 1.03 at the residential sites and 0.28 at TSFs). In addition, there was minimal enrichment (EF 1.21 at the residential sites and 0.34 at TSFs). At the residential sites, the CF for Cr (0.86), Zn (0.12), As (0.54) and Pb (0.52) showed low contamination. The CF for Ni (1.56) and Au (1.6) at the residential sites showed moderate contamination. In contrast, As (EF = 5.584) and Au at the TSFs (EF = 12.39) were significantly enriched relative to Mn. U had a slight depletion at the residential sites (CF = 0.68 and EF = 0.79), while at the TSFs, U was moderately enriched (CF = 2.51 and EF = 2.93). Hg concentrations at residential sites and TSFs were below detection.

6.3.3 Source Apportionment Based on Soil Material

The eigenvalues of each component and their proportions of variance at TSFs and residential sites are indicated in Table 6.4. Component 1 at the residential sites and TSFs showed the highest eigenvalues (4.81428 and 6.24455), indicating 60.18% and 78.06% of the total variance, respectively. Components 3 (three) to 8 (eight) at both the residential sites and TSFs indicated values less than 1 (one). Components 4 (four) to 8 (eight) at both residential sites and TSFs contributed only small amounts to the total variance (less than 10% combined).

Table 6.4: The Eigenvalues of Each Component and Their Cumulative Proportions

Components	Sites	Eigenvalues	Proportion	Percentage (%)	Cumulative Proportion
Component 1	Residential	4.81428	0.6018	60.18%	0.6018
	TSFs	6.24455	0.7806	78.06%	0.7806
Component 2	Residential	1.7409	0.2176	21.76%	0.8194
	TSFs	1.75545	0.2194	21.94%	1.0000
Component 3	Residential	0.815264	0.1019	10.10%	0.9213
	TSFs	0	0.0000	0.00%	1.0000
Component 4	Residential	0.462082	0.0578	5.78%	0.9791
	TSFs	0	0.0000	0.00%	1.0000
Component 5	Residential	0.143822	0.0180	1.80%	0.9970
	TSFs	0	0.0000	0.00%	1.0000
Component 6	Residential	0.020091	0.0025	0.25%	0.9996
	TSFs	0	0.0000	0.00%	1.0000
Component 7	Residential	0.003559	0.0004	0.04%	1.0000
	TSFs	0	0.0000	0.00%	1.0000
Component 8	Residential	3.7934×10^{-07}	0.0000	0.00%	1.0000
	TSFs	0	0.0000	0.00%	1.0000

Table 6.5: Heavy Metals within the Study Areas According to Pollution Risk Index Classes

Heavy Metals	UEC (mg/kg)	CF-Residential	Interpretation	CF-TSFs	Interpretation	EF-Residential	Interpretation	EF-TSFs	Interpretation
Cr	92	0.866	Low contamination	0.969	Low contamination	1.013	Minimal enrichment	1.134	Minimal enrichment
Mn	600	1.036	Moderate contamination	0.288	Low contamination	1.211	Moderate enrichment	0.336	Minimal enrichment
Ni	47	1.567	Moderate contamination	0.999	Low contamination	1.832	Moderate enrichment	1.168	Minimal enrichment
Zn	67	0.126	Low contamination	0.219	Low contamination	0.148	Minimal enrichment	0.256	Minimal enrichment
As	4.8	0.542	Low contamination	4.771	Considerable contamination	0.634	Minimal enrichment	5.58	Significant enrichment
Au	0.05	1.6	Moderate contamination	10.6	Very high contamination	1.871	Moderate enrichment	12.398	Significant enrichment
Hg	13.5	-	Not applicable	-	Not applicable	-	Not applicable	-	Not applicable
Pb	17	0.528	Low contamination	0.888	Low contamination	0.618	Minimal enrichment	1.039	Minimal enrichment
U	2.3	0.68	Low contamination	2.513	Moderate contamination	0.795	Minimal enrichment	2.939	Moderate enrichment

Figure 6.3 (a and b) presents the scree plots of eigenvalues after analyzing principal components at the residential sites and TSFs respectively. Component 1 (one) captured the large eigenvalues at both residential sites (4.8) and TSFs (6.2). Component 1 was the most significant principal component, followed by components 2 (1.7 at residential sites) and (1.6 at TSFs). Components 3 and beyond had eigenvalues below 1 at both residential sites and TSFs. These scree plots confirmed that the first three principal components at the residential sites; and the first two at TSFs be retained for further analysis as they effectively capture the variance in the data.

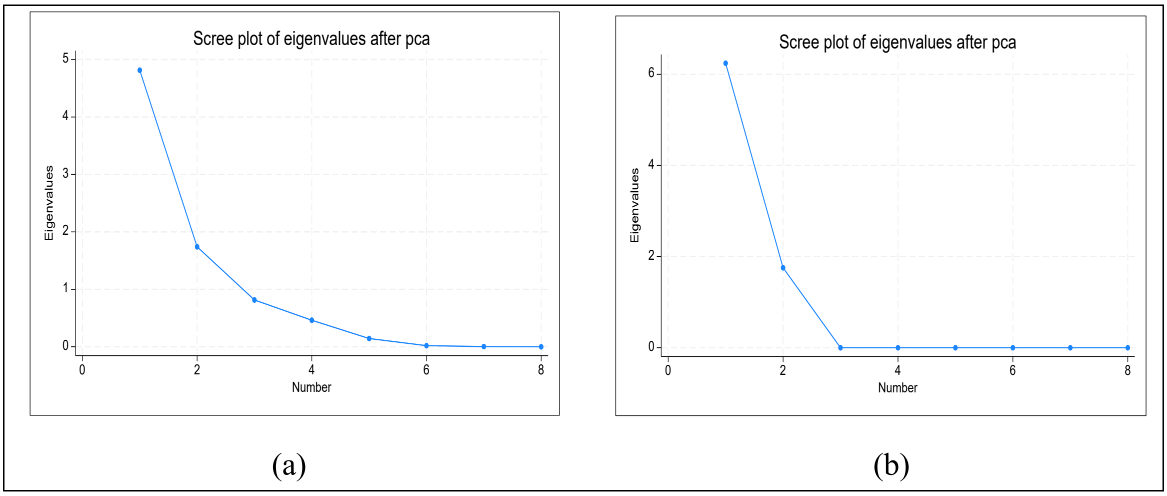

Figure 6.3: The Scree Plot of Eigenvalues after the Analysis of Principal Components at Residential Sites (a) and TSFs (b)

The factor loadings of the principal component analysis for each heavy metal are illustrated in Figure 6.4 (residential sites) and Figure 6.5 (TSFs). These loadings indicated how strongly each heavy metal is associated with each component. At the residential sites, Factor 1 was dominated by Mn (98.64%), Zn (92.63%), Pb (83.05%), Cr (88.32%) and Ni (84.04%) which could have originated from various sources (industrial, vehicle emissions, domestic fuel burning). On the contrary, Au (54.43%), As (38.32%) and U (29.45%) showed more significant contributions in Factor 2. These heavy metals also emanated from mining activities. Mn and Zn were very low in Factor 2, with contributions of 1.56% and 7.37% respectively.

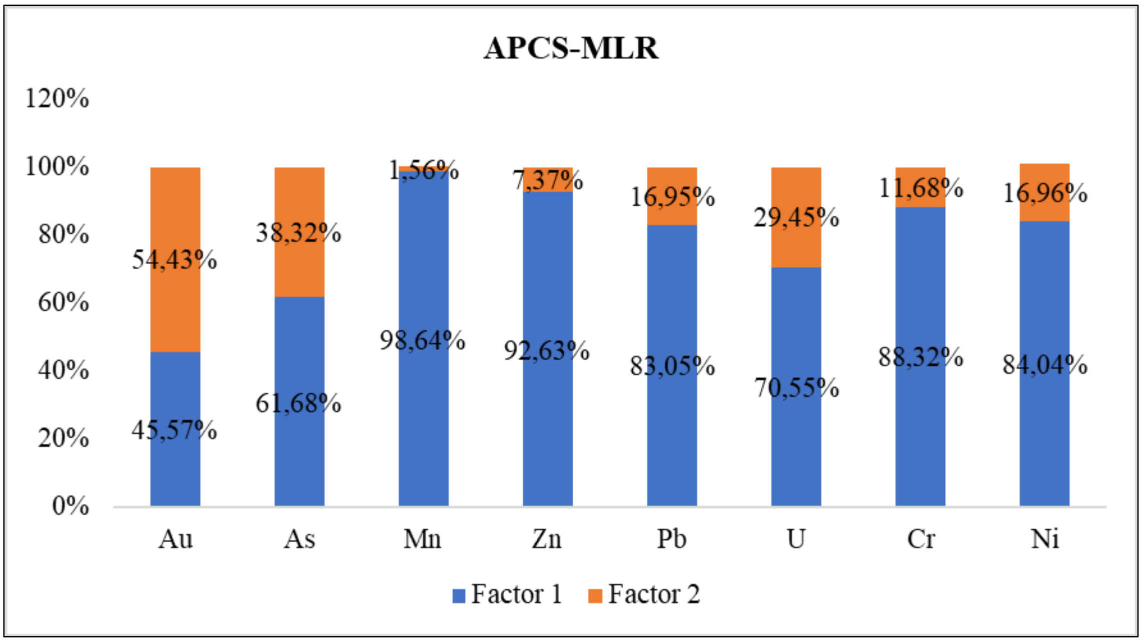

Figure 6.4: Source contributions of each factor generated by the APCS-MLR Model at residential sites

At the TSFs, Factor 1, Au (92.7%), As (93.3%), U (93.3%) and Cr (63.1%) represented a grouping of heavy metals that had a common pattern in their concentrations. Furthermore, Au, As, U and Cr in Factor 1 may have originated from the same source, thus representing mining activities. Factor 2 was strongly associated with Ni (54.4%) and Pb (44.0%), indicating a different pattern of variation from Factor 1. Ni and Pb mainly originate from industrial processes, hence this factor was considered to represent industrial activities. Factor 3 had a higher loading of Ni (44.2%) indicating a unique source distinguishing it from other heavy metals.

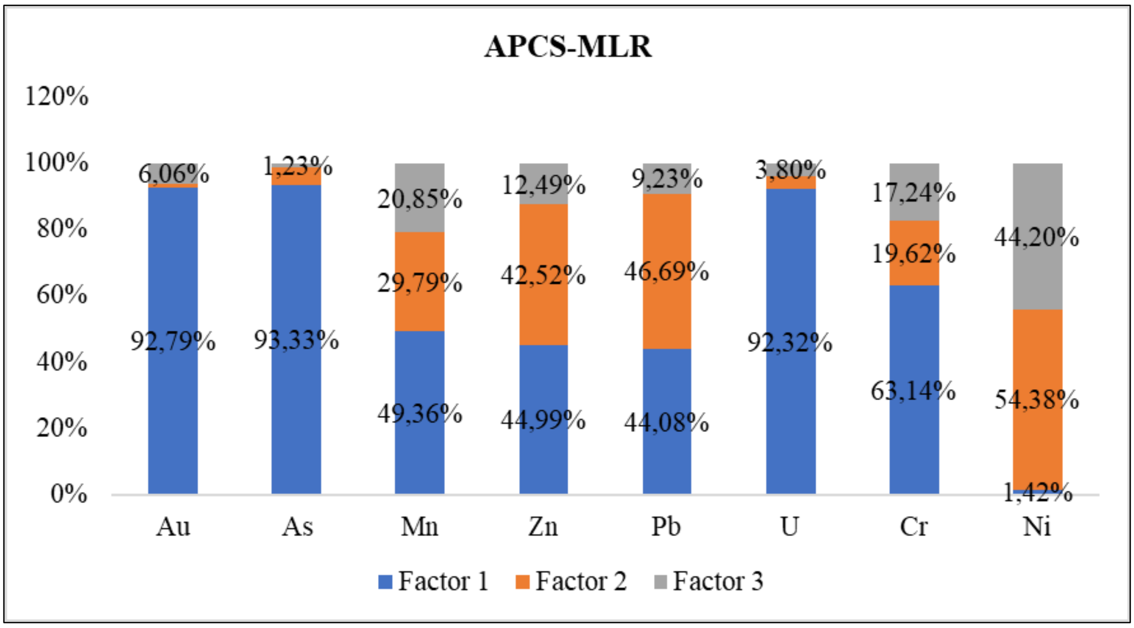

Figure 6.5: Source contributions of each factor generated by the APCS-MLR Model at TSFs

Table 6.6 and Table 6.7 present the correlation matrix of heavy metals at the residential sites and TSFs respectively. The correlation coefficients ranged from -1 to 1. The positive values indicated a direct relationship, while negative values showed an inverse relationship with the residential sites; Cr had a positive correlation with As (0.7551, Au) (0.7436) and Pb (0.8837). A negative correlation existed between Cr and Mn (-0.3438). Furthermore, Mn showed negative correlations with As (-0.5863), Au (-0.5863) and U (-0.6125). Ni showed weak correlations with most heavy metals. Zn indicated a negative correlation with As (-0.6362), Au (-0.6549), and U(-0.7299). Pb moderately correlated with As (0.5395) and Au (0.5239).

Table 6.6: The Correlation Between the Concentrations of Heavy metals at the Residential Sites

	Cr	Mn	Ni	Zn	As	Au	Hg	Pb	U
Cr	1.0000								
Mn	-0.3438	1.0000							
Ni	-0.1576	0.0451	1.0000						
Zn	-0.1607	0.7120*	-0.2571	1.0000					
As	0.7551*	-0.5863	-0.0186	-0.6362	1.0000				
Au	0.7436*	-0.5863	-0.0021	-0.6549	0.9984*	1.0000			
Hg	.	.	.	.	.	.	.		
Pb	0.8837*	-0.3285	-0.4902	-0.0214	0.5395	0.5239	.	1.0000	
U	0.6557	-0.6125	-0.1342	-0.7299*	0.9619*	0.9683*	.	0.2003	1.0000

Significant at 0.05 and 0.01 levels.

At the TFS, the correlation results indicated a positive correlation among Cr and Ni (0.9981), Cr and Zn (0.9973); and Ni and Pb (0.9999). In contrast to the positive associations among heavy metals, As and U showed negative correlations with most heavy metals. As (-0.7077) had negative correlations with Mn (-0.7077), Cr (-0.5264), Ni (-0.4726) and Zn (-0.5878). Similarly, U (-0.6038) was negatively correlated with Zn (-0.6614), Cr (-0.6038), Mn (-0.7795) and As (-0.9956). A strong positive correlation existed between Au and As (0.9869).

Table 6.7: The Correlation Between the Concentrations of Heavy metals at the TSFs

	Cr	Mn	Ni	Zn	As	Au	Hg	Pb	U
Cr	1.0000								
Mn	0.9733	1.0000							
Ni	0.9981*	0.9571*	1.0000						
Zn	0.9973	0.9876 *	0.9908*	1.0000					
As	-0.5264	-0.7077	-0.4726	-0.5878	1.0000				
Au	-0.3822	-0.5842	-0.3241	-0.4494	0.9869*	1.0000			
Hg	.	.	.	.	.	.	.		
Pb	0.9972*	0.9532*	0.9999*	0.9889*	-0.4608	-0.3114	.	1.0000	
U	-0.6038	-0.7795	-0.5565	-0.6614	-0.9956	-0.9674	.	-0.54203	1.0000

**Significant at 0.05 and 0.01 level.*

6.4 Discussion

This study assessed the contamination of soils by heavy metals in the mining area, identifying their concentrations and potential sources. Soil samples collected from the re-mining areas (TSFs) showed higher concentrations for five out of nine heavy metals than residential areas, consistent with previous research (Demková et al., 2017). Among the detected metals, Au showed the highest contamination and enrichment at the TSFs, followed by As and uranium U. This trend aligns with the findings by Abraham et al. (2018), who reported elevated As and U levels in legacy mine sites due to their strong association with historical mining waste. Au is highly enriched at the TSF (EF = 12.398), indicating its accumulation in gold mining waste..

The economic feasibility of Au recovery from TSFs using modern recovery techniques is driven by volume. Low residual Au concentrations accumulate over large-scale deposits, reinforcing the significance and uses of modern and effective secondary extraction methods. On the other hand, Mn was moderately enriched in the residential areas and depleted in the TSFs, probably due to dilution and leaching. Ni indicated moderate contamination risk in the residential areas but remained low in the TSFs. These heavy metals often accumulate and persist in the soil even after mining operations cease, as they can be distributed through wind erosion and surface run-off to nearby communities. As such, there is a great need for continued monitoring and remediation strategies to minimize risk (Agboola et al., 2020).

Pb and U concentrations were low at the creche in eMbalenhle, which is located about 6.5 km from the TSFs. The Pb and U concentrations were among the lowest across all sampling sites, suggesting that they could have been diluted or dispersed in minimal quantities over longer distances. However, Pb concentrations were higher at Muslim School and Evander High School. However, legacy lead-based paint residues, historical vehicular emissions, older plumbing infrastructure and contaminated fill material in schoolyards cannot be ruled out as potential additional sources (Elom et al., 2013).

Evander High School is situated close to the busy R546 freeway pointing to the influence of past traffic-related Pb deposition where leaded fuel emissions could persist in surface soils. Results showed that Pb contamination was low in residential sites and insignificant at TSFs, with only minor enrichment in TSFs. This is consistent with the high U concentrations recorded in Leslie Remining and Evander TSFs, compared to much lower levels at the creche in eMbalenhle. Although wind transports soil particles from one point to another, results have shown that heavy metals settle close to the source (TSFs) with minimal amounts migrating further into residential areas in reduced concentration, as observed by Akoto et al., 2023. Hg concentrations were below the LoD at all sampled sites. Historical Au extraction processes involved Hg amalgamation, where it was used to bind with Au particles (Esdaile and Chalker, et al). However, the transition to modern Au recovery techniques, including cyanidation, gravity separation and thiosulphate leaching has led to elimination of Hg use in large-scale mining operations, resulting in the absence of Hg in gold mine waste (Manzila, 2022). The moderate and significant enrichment factor for Au, in the residential area and the TSFs, respectively, give evidence of Au mining activities. However, the absolute concentrations of Au in the residential and re-mining areas are relatively low. Since, modern Au extraction methods are highly efficient, there is minimal residual Au in mine waste (Kee and Shoparwe, 2024). This contrasts with historical mining practices, where inefficient extraction left significant Au residues in TSFs.

In this study, the reference element Mn showed a large positive effect size, indicating a statistically significant difference in levels between residential sites and TSFs. Findings showed that this is due to the strong depletion of Mn at the TSFs indicating that the TSFs soil strongly deviates from natural soil. Conversely, As showed a large negative effect size which was also statistically significant, indicating that As concentrations were substantially higher in TSFs than at residential sites. Apparently, no findings in the literature align with the previous observation, where TSFs had nearly nine times higher As concentrations than residential sites. However, it is noted that As is associated with historical gold extraction processes. These findings strongly implicated TSFs as the primary sources of As contamination in the soils, as described by Moreno-Jiménez et al. (2010), who noted that TSFs act as long-term reservoirs for As, with potential dispersion into surrounding environments driven by wind and water transport mechanisms.

In the current study, Cr, Zn and Pb had low CF values at both residential and TSFs, indicating only slight contamination above baseline levels, a trend consistent with the study by Gogoi et al., (2024). Based on the averages of all locations in Morigaon (Assam), it was found that CF values for Cr (0.56 to 0.84), Mn (0.38 to 0.78), and Zn (0.35 to 0.65) were low, showing minimal anthropogenic influence on metal accumulation in soils (Gogoi et al., 2024). Comparing these results with findings from other geographical regions, it can be argued that Cr, Zn and Pb demonstrated low contamination levels, indicating that natural geochemical variations may dominate their distribution.

This assertion contrasts with findings from Uduma and Awagu (2013) who used Mn as a reference element in Nigerian farming soils and found very high enrichment factors (EF = 59.41) for Zn. The differences in Zn enrichment factors between Uduma and Awagu (2013) and this study highlight the importance of site-specific factors in determining heavy metal accumulation patterns. Awagu and Uduma (2013) suggested that elevated Pb levels in their study were due to anthropogenic activities. This suggestion strengthens arguments presented in this study that while Pb contamination appears low, localized sources may have influenced its contamination. These findings demonstrate the need to integrate CF and EF together, with geochemical fingerprinting to distinguish between naturally occurring elements and anthropogenically generated heavy metals to accurately assess risks in areas affected by mining activities.

The apportionment of sources was separated into residential sites and TSFs and the factor loadings were named differently depending on the dominant heavy metals. Factor 1 was strongly associated with Mn, Zn, Pb, Cr and Ni at residential sites. These heavy metals are commonly emitted from industries, vehicle emissions and domestic fuel burning. These metals may also originate from various sources, including metal smelting, fossil fuel combustion and the wear and tear of vehicle components, indicating a mixed-source contribution. Given these diverse origins, Factor 1 was identified as anthropogenic source encompassing multiple pollution pathways. In contrast, Factor 2 showed stronger associations with Au, As and U, elements that are characteristically linked to mining activities. Windborne dust or water runoff from mining-related activities may have contributed to the presence of elevated As, Au, and U levels in residential areas (albeit lower than in TSFs). Consequently, Factor 2 was identified as the mining-related source in residential areas.

At the TSFs, the source contributions followed a different pattern. Factor 1 was characterized by high Au, As, U and Cr loadings. These loadings indicated a common pattern in their concentration variations. Given that Au, As, and U are directly associated with mining activities, Factor 1 represented mining-related contamination. Factor 2 was dominated by Ni Pb and Zn, which are mainly common in industrial activities rather than direct mining processes. This supports the notion that heavy metals from external industrial emissions may also affect mining sites. These findings highlight the complex interactions between mining activities, industrial pollution and environmental transport mechanisms. At residential sites, chromium (Cr) positively correlated with As, Au and Pb indicating that these heavy metals tend to increase together due to common sources. Heavy metals are commonly associated with mining residues, so their correlation with Cr indicate that historical and ongoing mining activities may have contributed to their presence in residential soils (Abdul-Wahab and Marikar, 2012).

In contrast, Mn showed a negative correlation with Cr, As, Au and U. This suggests that Mn originates from a different source other than mining activities. The negative correlation could be attributed to dilution effects, where Mn is mostly prevalent in naturally occurring soils, while As, Au, U and Cr accumulate due to mining-related deposition (Jarsjö et al., 2017). Alternatively, the depletion of Mn in TSFs compared to its enrichment in some residential areas could suggest that its mobility, leaching potential and geochemical behaviour is likely different from that of other heavy metals associated with the TSFs and mining activities.

Although the EF has been widely used to assess soil contamination, it has inherent limitations that must be considered. This study confirms that Mn was an appropriate reference element for normalizing other heavy metal concentrations, yet some researchers have raised concerns about the accuracy and reliability of EF results (Halgren et al., 2004; Agyeman et al., 2023; Aytop et al., 2023). One key limitation is that selecting a reference element and baseline composition is subjective, making EF calculations dependent on the researcher's expertise and site-specific conditions, affecting comparison across studies (Dominech et al., 2022). An example from this study highlighting the relative nature of EF calculations is the case of Au which showed a high EF (EF = 12.398) despite its marginal maximum concentration of 1.2 mg/kg in TSFs. This discrepancy arises because EF compares the presence of a metal in a sample relative to a reference metal rather than reflecting absolute abundance. Even small residual concentrations in TSFs can appear highly enriched if the natural background is low. As such, one has to be cautious when interpreting EF values, as high enrichment does not necessarily indicate significant contamination or the widespread presence of a given metal in the soil.

6.5 Limitations

Although this study assesses heavy metals in the soils and their sources thereof, it had limitations. Only ten (10) topsoil samples were collected in the study areas; the true extent of pollution and its spatial distribution areas may not accurately represent the study. Some heavy metals in the collected soil samples presented very low concentrations (below the LoD) which could lead to an underestimation of heavy metal contamination of the soil in the area. The minimum number of samples could have affected the reliability of the APCS-MLR model. Categorization of the principal components in the APCS-MLR was based on assumptions depending on the heavy metal concentrations. The mean value for the reference element was below the UEC. The accuracy of EF depends on the choice of a reference element that is assumed to have a predominantly natural origin. In this study, Mn was chosen as a reference element. If Mn was also affected by anthropogenic activities, the EF calculations may be biased.

6.6 Conclusion

The study's main aim was to determine whether (historical) gold mining activities contribute to heavy metal contamination in the surrounding environment. The findings confirmed that TSFs are not natural soil but mine waste. Mine waste has distinct chemical and physical characteristics compared to natural soil, e.g. high concentrations of residual heavy metals. The Au enrichment at residential sites indicates that mining activities contributed to soil contamination in surrounding areas, e.g. .by soil erosion of TSFs, dispersion by wind, and deposition in nearby communities. This study indicated the importance of distinguishing the different sources when assessing soil contamination by heavy metals. This assists in understanding the extent of contamination and its sources to develop effective environmental management strategies. Furthermore, the study recommends integrating other methods alongside bulk sampling and APCS-MLR in future studies to capture heterogeneity within the soil matrix and improve source apportionment resolution.

6.7 Author Contributions

Conceptualisation (NT, DB), methods (NT, DB), data analysis (NT), manuscript preparation (NT). Review, editing and supervision (DB, DM, TM). All authors have read and approved the final version of the manuscript.

6.8 Conflict of Interest

The authors declare that they have no conflict of interest that could influence the work presented in this paper.

6.9 Acknowledgments

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CHAPTER 7: PROBABILISTIC HUMAN HEALTH RISK ASSESSMENT OF $PM_{2.5}$ EXPOSURE IN COMMUNITIES AFFECTED BY LOCAL SOURCES AND GOLD MINE TAILINGS

This chapter presents a manuscript that was submitted to Frontiers in Public Health Journal. The primary objective of this manuscript was to estimate the potential health risks associated with $PM_{2.5}$ *using a probabilistic approach that accounts for variability and uncertainty in exposure levels. Differences in risk exposure levels between various population subgroups were considered to identify the most vulnerable groups. The findings from the PHHRA are presented in this chapter. The probability distributions of health risk estimates, including HQ(s) for non-cancer effects and CR for carcinogenic effects were assessed to determine the likelihood of adverse health outcomes.*

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Probabilistic human health risk assessment of $PM_{2.5}$ exposure in communities affected by local sources and gold mine tailings

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Epidemiological studies have found that exposure to fine particulate matter ($PM_{2.5}$) poses potential human health risks, including respiratory, cardiovascular and cerebrovascular diseases. This study aimed to assess the potential human health risks associated with exposure to $PM_{2.5}$ in the eMbalenhle community which is near gold mine Tailings Storage Facilities (TSFs). Ambient $PM_{2.5}$ concentrations were measured for 1 year (from February 2022 to February 2023) using the Clarity Node-S low-cost monitor (LCM). The United States Environmental Protection Agency (USEPA) equations were used to estimate the carcinogenic and non-carcinogenic health risks associated with exposure to $PM_{2.5}$ in toddlers, children, adults and the older adult. Lastly, a probabilistic Human Health Risk Assessment (HHRA) model, which employs Monte Carlo simulations (MCS), was applied to assess the sensitivity and uncertainty risks. The annual $PM_{2.5}$ Geometric Mean (GM) concentration were 17, with a Standard Deviation of (SD) of 10.4 and a Geometric Standard Deviation (GSD) of 1.69 µg/m³. This was below the South African annual National Ambient Air Quality Standards (NAAQS) of 20 µg/m³. However, this concentration exceeded the World Health Organization (WHO) guidelines and the USEPA annual limit values of 5 and 9 µg/m³, respectively. For the WHO guidelines, South African and USEPA NAAQS, the HQ was highest at the 95th percentile for all subgroups. For the South African NAAQS, the HQ was estimated to be 0.9 for all subgroups, indicating safe levels. When utilizing the USEPA NAAQS, a value of 2.5 was reported, while the WHO guidelines recorded the highest HQ of 3.5, indicating unsafe levels. This demonstrated that the SA NAAQS underestimated exposure to $PM_{2.5}$ concentrations. Probabilistic HHRA assessed potential cancer risk (CR) due to continuous exposure to $PM_{2.5}$ concentrations. For both male and female elders, the CR was approximately 1 in 10, meaning that about 100,000 out of 1,000,000 exposed elders were at an increased risk of developing cancer over their lifetime. The study recommends revising the current South African $PM_{2.5}$ NAAQS to adopt more stringent measures and align them to international benchmarks to safeguard the public from adverse health effects due to $PM_{2.5}$ exposure.

KEYWORDS
fine particulate matter, exposure assessment, Monte Carlo simulations, sensitivity analysis, mining activities

Open Rubric

1 Introduction

Ambient air pollution is regarded as a significant threat to human health. According to the World Health Organization (1), the combined effects of ambient air pollution and household air pollution account for 6.7 million premature deaths globally. Fine particulate matter, with an aerodynamic diameter of 2.5 µm ($PM_{2.5}$), has been associated with many adverse health outcomes (2–5) because it can penetrate deeper into the alveolar regions of the lungs (6, 7). Human health risks of exposure to $PM_{2.5}$ extend beyond respiratory diseases to include cerebrovascular and cardiovascular diseases (8, 9), lung cancer, cardiopulmonary mortality, stroke, asthma, arrhythmia (10, 11). Exposure to $PM_{2.5}$ affects individuals differently based on their health status, age (12), gender and duration of exposure (13).

Vulnerable population sub-groups are likely to develop diseases due to lifetime $PM_{2.5}$ exposure to $PM_{2.5}$ (14). These groups include pregnant women, infants and children. Children breathe faster than adults because smaller lungs require more frequent breaths to meet oxygen demands (15, 16). Exposure to high $PM_{2.5}$ in these groups can affect how their lungs develop over time, increasing their chances of developing lung diseases (17). Exposure to $PM_{2.5}$ during pregnancy can impact fetal development and may have long-term health consequences (18, 19). The physiological development, high Inhalation Rate (IR), Body Weight (BW), Exposure Duration (ED) and Exposure Frequency (EF) are some factors that make individuals vulnerable to the adverse health risks of $PM_{2.5}$ exposure (20). Organs such as the lungs and heart undergo significant maturation over time (21). Exposure to $PM_{2.5}$ during these stages of organ development can lead to long-term health risks (22). The older adult are more at risk of developing adverse health risks due to weakened respiratory and cardiovascular systems (23). Furthermore, pre-existing medical conditions, including asthma, heart disease and chronic obstructive pulmonary disease (24), increase their vulnerability to the harmful effects of pollution (25).

Fine particulate matter ($PM_{2.5}$) is emitted from natural and anthropogenic sources (26). Natural sources of $PM_{2.5}$ include forest fires and volcanic eruptions. Forest fires emit huge amounts of $PM_{2.5}$ from the combustion of vegetation and biomass (27). Volcanic eruptions release ash and $PM_{2.5}$ into the atmosphere. Anthropogenic sources of $PM_{2.5}$ include industrial processes, domestic fuel burning, mining operations and agricultural activities. Burning of wood, coal and other solid fuels for residential heating and cooking also emits $PM_{2.5}$ (28). Gold mine tailings storage facilities (TSFs) are also a potential source of $PM_{2.5}$ emissions. The TSFs are designed to store waste generated during mineral extraction and processing. These tailings consist of crushed rocks, particles and residuals of chemicals left over from the gold extraction process (29).

$PM_{2.5}$ comprises a complex mixture of biological and chemical components (30). The chemical and biological components of $PM_{2.5}$ may originate from various sources (31). The biological components of $PM_{2.5}$ include bacteria, fungi, viruses and pollen (32). The chemical components of $PM_{2.5}$ include organic compounds (33), inorganic compounds (34) and trace elements (35). The physicochemical properties of fine particulate matter influence their toxicity and health impacts. Particles with larger surface areas and reactive chemical elements, can induce oxidative stress and inflammation, resulting in adverse respiratory and cardiovascular outcomes (36).

The assessment of exposure to $PM_{2.5}$ is a complex process. It requires information about the sources, site selection and data quality assurance (37). $PM_{2.5}$ concentrations vary spatially due to differences in emission sources, meteorological conditions, and topographical features. Furthermore, $PM_{2.5}$ concentrations can fluctuate over time due to diurnal patterns and seasonal variations (38). Human health risks can be assessed by applying the HHRA model (39), which estimates the likelihood of adverse human health risks associated with $PM_{2.5}$ exposure (40). Most studies have used deterministic HHRA models to assess potential human health risks (41–43). A deterministic HHRA model uses single-point estimates for input parameters to calculate specific risk values. One of the advantages of deterministic risk assessment is its simplicity. The disadvantage is its inability to account for the variability among individuals and the uncertainties in environmental data (44).

This study used a probabilistic HHRA model to estimate the potential human health risks of continuous exposure to $PM_{2.5}$ concentrations. The probabilistic HHRA model was chosen because it uses statistical techniques to account for variability and uncertainty in risk estimates (45). Furthermore, the model employs Monte Carlo simulations to generate a distribution of risk estimates based on random sampling from the probability distributions of input parameters (46). The advantage of probabilistic HHRA provides a more complete picture of potential health risks by estimating the range and likelihood of different outcomes. The disadvantage is that it requires detailed data on the distribution of input parameters (47).

This study introduces a novel approach by applying a probabilistic Human Health Risk Assessment (HHRA) to evaluate the health risks associated with $PM_{2.5}$ exposure in eMbalenhle, a community near gold mine tailings storage facilities (TSFs). While most existing studies rely on deterministic risk assessments that often fail to capture the inherent uncertainties and variability in $PM_{2.5}$ exposure (39, 41, 43), this study addresses these limitations by adopting a probabilistic framework. Furthermore, the application of this method to communities affected by gold mine TSFs remains limited in the current literature. Importantly, this is the first study to assess human health risks in eMbalenhle using $PM_{2.5}$ data collected from low-cost monitors (LCMs), offering a cost-effective and practical strategy for air quality and risk assessment in resource-constrained settings. The findings of this study will contribute to Sustainable Development Goal 3 (SDG 3). SDG 3 aims at ensuring good health and well-being for all. Monitoring the ambient $PM_{2.5}$ contributes to achieving Target 3.9 of SDG 3, which addresses environmental pollution and its health consequences (48).

2 Methods and materials

2.1 Study design

The study followed a cross-sectional design following quantitative data collection and analysis methods.

2.2 Study area

eMbalenhle (−26°550613°S; 29.078937°E) is in the Govan Mbeki Municipality, Mpumalanga, South Africa. eMbalenhle has a population of 118,889 people with an annual growth of 2.5% (49).

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eMbalenhle is known for its gold and coal mining operations, which are potential sources of $PM_{2.5}$. The area falls within the Highveld Priority Area (HPA). This area was declared an air pollution "hotspot" in terms of Section 18 (5) of the National Ambient Air Quality Act, Act 39 of 2004 (50). The town is close to industries, open-cast mines, and coal-fired power stations. As of the 16th of July 2024, the real-time Air Quality Index (AQI) displayed a $PM_{2.5}$ concentration in eMbalenhle of 155 µg/m^3, about 31 times above the WHO annual air quality Guideline value (51). This further indicated an unhealthy situation for vulnerable groups living in the area (52).

2.3 Data collection and analysis

The $PM_{2.5}$ emissions were measured at the Sasol Recreation Centre (−26°550613°S; 29.078937°E) in eMbalenhle for 1 year (February 2022 to February 2023) using Clarity Node-S low-cost monitors (LCM) (53). These LCM measured $PM_{2.5}$ concentrations every 15 min in micrograms per cubic meter (µg/m^3). The ambient $PM_{2.5}$ data monitored by the government ambient air monitoring station (also collocated at the Sasol Community Recreation Centre) for the same period was used as reference data. The reference data was used to compare and validate the data collected with the LCM. Both data sets (LCM and reference data) underwent quality control to ensure that the monitored and reference data were not erroneous (54). The meteorological data for the same period (February 2022 to February 2023) was obtained from the South African Air Quality Information System website (55). The average annual $PM_{2.5}$ concentrations were calculated in a Microsoft Excel sheet and compared with the SA NAAQS, USEPA NAAQS and the WHO Guidelines. The $PM_{2.5}$ annual Reference Concentrations (Rfc) values used in this study are given in Table 1.

2.4 Probabilistic human health risk assessment

The population of eMbalenhle was divided into eight sub-groups because of the differences in exposure duration and development stages. The eight sub-groups included male and female toddlers (1–2 years) because their bodies are still developing and they have low IR; male and female children (6–11 years) because their bodies have developed and they have increased IR; male and female adults (21–60 years) because their bodies are fully developed and they have a much higher IR as compared to the toddlers and children; and male and female elders (61–70 years) because their health is weakening (56).

TABLE 1 Local and international ambient $PM_{2.5}$ annual reference concentration values.

Standard	Reference value (µg/m^3)	Description
NAAQS (SA)	20	National Standard
US EPA (USA)	9	National Standard
WHO	5	Guidelines

2.4.1 Monte Carlo simulation

Monte Carlo Simulation (MCS) was employed to generate samples from probability distributions, using an Oracle Crystal Ball spreadsheet-based application for predictive modeling. parameters, including $PM_{2.5}$ concentrations (C_{air}), EF, Exposure Time (ET), ED, and Average Time (AT), were considered as variables in the model. The ET, EF, ED and AT parameters were allocated triangular, uniform and normal distributions. The C_{air} was allocated a lognormal distribution. The model used Geometric Mean (GM) and Geometric Standard Deviation (GSD) of the annual $PM_{2.5}$ concentrations as C_{air}.

Table 2 lists all the variables used in the probabilistic HHRA model. The annual GM and GSD $PM_{2.5}$ concentrations used in the model were measured from February 2022 to February 2023. The ET was assumed to be 16 (minimum), 18 (mode), and 20 (maximum) hours for toddlers and children (16, 22, 24), and 20, 22, 24 for adults and elders. The EF was estimated based on the assumption that all population sub-groups leave the area for a maximum of 1 month, which translates to 335 days per year and a minimum of 2 weeks for vacation (i.e., the minimum EF is 350 days per year). The worst-case scenario assumed that all population subgroups are exposed 365 days per year. The AT for CR was based on chronic exposure during the lifetime. Lifetime values were obtained from the life-expectancy data according to the national census and population estimates (57). Population estimates for life expectancy from 2002 to 2022 were used to compute the life expectancy arithmetic mean and the standard deviation values used in our model.

Once the distributions of the variables were determined as normal, lognormal or triangle, the model randomly selected a value for each variable and calculated the risk. In MCS, each calculation is called an iteration, and a set of iterations is called a simulation (58). The probabilistic health risk distribution was obtained by running 10,000 iterations (59, 60).

The HQ was calculated using Equation 1 for each population sub-group to assess the non-carcinogenic health risks associated with exposure to $PM_{2.5}$.

$$HQ = C_{air-adj} / Rfc \quad (1)$$

Where:

HQ is unitless, representing the ratio of the concentration of $PM_{2.5}$ in the air (C_{air}) to the Reference Concentration (Rfc), (61). Since the Rfc assumes continuous exposure 24 h/7 days a week and 52 weeks/year, the measured concentration of $PM_{2.5}$ must be adjusted to the actual duration of the exposure. The adjusted $PM_{2.5}$ concentrations ($C_{air-adj}$) were estimated using Equation 2 derived from the USEPA (61).

$$C_{air-adj} = C_{air} \times (ET \times 1/24 \text{ hours}) \times (EF \times 1/365) \times ED / AT \quad (2)$$

Where:

- C_{air} = Concentration of contaminant in air (µg/m^3)
- ET = Exposure time (hours/day)
- EF = Exposure frequency (days/year)
- ED = Exposure duration (years)
- AT = Averaging time (years)

TABLE 2 Variables used in the probabilistic human health risk assessment model.

Parameter	Unit	Distribution	Value	Source
C_{air}	µg/m³	Lognormal	GM 17 (GSD 1.69)	$PM_{2.5}$ Annual Average Concentrations (53)
ET (Toddler)	hours/day	Triangle	Min-mode-max 18–22–24	(Section 2.3.1)
ET (Child)	hours/day	Triangle	16–22–24	(Section 2.3.1)
ET (Adult)	hours/day	Triangle	20–22–24	(Section 2.3.1)
ET (Elder)	hours/day	Triangle	20–22–24	(Section 2.3.1)
AT (CR) – All Males	years	Normal	57.26 ± 4.71	(49)
AT (CR) – All Females	years	Normal	62.19 ± 5.53	(49)
ED (Toddler)	years	Uniform	Min-max 1–2	(Section 2.3.1)
ED (Child)	years	Uniform	6–11	(Section 2.3.1)
ED (Adult)	years	Uniform	21–60	(Section 2.3.1)
ED (older adult)	years	Uniform	61–70	(Section 2.3.1)
EF	days/year	Triangle	335–350–365	(Section 2.3.1)
Rfc (Annual $PM_{2.5}$ -SA NAAQS)	µg/m³	Not Applicable	20	(50)
Rfc (Annual $PM_{2.5}$ – WHO Guidelines)	µg/m³	Not Applicable	5	(51)
Rfc (Annual $PM_{2.5}$ US EPA NAAQS)	µg/m³	Not Applicable	9	(53)
IUR	µg/m³	Not Applicable	0.008	(63)
$C_{air-adj\,(HQ)}$	µg/m³	Not Applicable	Calculated	Output
$C_{air-adj\,(CR)}$	µg/m³	Not Applicable	Calculated	Output
HQ (SA-NAAQS)	Unitless	Not Applicable	Calculated	Output
HQ (WHO Guidelines)	Unitless	Not Applicable	Calculated	Output
HQ (US EPA NAAQS)	Unitless	Not Applicable	Calculated	Output
Cancer Risk	Unitless	Not Applicable	Calculated	Output

For non-carcinogenic health risks/sub-chronic exposure, or when evaluating acute exposures or short-term events where the exposure duration aligns with the exposure averaging time, AT equals ED; therefore, AT and ED can be left out of Equation 2. In contrast, for carcinogenic risk/chronic exposure, the AT is equal to the estimated life expectancy.

The Rfc(s) represent the $PM_{2.5}$ concentration values unlikely to cause adverse human health risks over a specified period. The Rfc(s) were derived from toxicological studies and are expressed in the same units as C_{air} (i.e., µg/m³). According to USEPA (62), if the HQ is less or equal to one ($HQ \le 1$), the concentration of $PM_{2.5}$ (C_{air}) is equal to or less than the Rfc. If the HQ is greater than one ($HQ > 1$), there is an increased likelihood of developing non-carcinogenic adverse health outcomes.

The CR was calculated using Equation 3 for each population sub-group to assess the carcinogenic health risks associated with exposure to $PM_{2.5}$.

$$CR = IUR \times C_{air-adj} \tag{3}$$

Where:

CR is the cancer risk, which represents the estimated probability of developing cancer over a lifetime due to exposure to $PM_{2.5}$ through inhalation.

IUR is the inhalation unit risk, representing the increased risk of cancer per unit exposure to $PM_{2.5}$ through inhalation. The IUR for $PM_{2.5}$ is 0.008 µg/m³ (63).

A value greater than 1×10^{-04} (1 in 10,000) indicates a significant CR and may indicate a need for regulatory action or intervention to reduce exposure, as it exceeds the accepted risk threshold. On the other hand, a value less than 1×10^{-06} (1 in 1,000,000) indicates a negligible or "acceptable" risk. It can be ignored as it does not require regulatory action or interventions to reduce exposure (64).

3 Ethical considerations

The study was approved by the University of the Witwatersrand Human Research Ethics Committee [HREC] (No: HRECNMW21/05/09).

4 Results

4.1 Probabilistic human health risk assessment

4.1.1 Adjusted $PM_{2.5}$ concentrations for non-carcinogenic and carcinogenic health risks

The adjusted $PM_{2.5}$ concentrations for non and carcinogenic health risks of the different population sub-groups in eMbalenhle are presented in Table 3. The 50th, 75th, and 95th percentile for adjusted $PM_{2.5}$ concentrations for non-cancer risks was slightly higher in male and female adults compared to other subgroups due to the higher

TABLE 3 The adjusted $PM_{2.5}$ concentrations (μg/m³) for non and carcinogenic health risks.

Sub-groups	50th percentile		75th percentile		95th percentile	
	*NCR	**CR	*NCR	**CR	*NCR	**CR
Male toddlers	14.4	0.4	15.6	0.5	17.4	0.6
Female toddlers	14.5	0.4	15.6	0.4	17.4	0.5
Male children	14.0	2.2	15.3	2.6	17.2	3.2
Female children	14.1	1.9	15.3	2.2	17.2	2.7
Male adults	14.9	10.5	16.0	13.1	17.8	16.4
Female adults	14.9	9.6	16.0	12.0	17.7	15.1
Male elders	14.9	17.0	16.0	18.7	17.7	21.6
Female elders	14.9	15.7	16.0	17.3	17.7	20.0

*NCR: Non-Carcinogenic Health Risks.
**CR: Carcinogenic Health Risks.

TABLE 4 Non-carcinogenic risk assessment of $PM_{2.5}$ among population sub-groups in eMbalenhle.

Population	Standard/guideline	Percentile	HQ
*All Population Sub-groups (Male and Female Toddlers, Children, Adults, and Elders)	SA NAAQS	50th	0.7
		75th	0.8
		95th	0.9
	USEPA	50th	1.7
		75th	1.8
		95th	2.0
	WHO	50th	3.0
		75th	3.2
		95th	3.5

*The computed HQ values for each subpopulation group are the same based on the NCR values presented in Table 3.

estimated ET. The 50[th] percentile (median) adjusted $PM_{2.5}$ concentrations for CR ranged from 0.4 μg/m³ (male and female toddlers and children) and 10.9 μg/m³ (male elders) due to the different estimates of the AT.

Non-carcinogenic health risks based on $PM_{2.5}$ annual reference standards are presented in Table 4. Based on the annual $PM_{2.5}$ SA NAAQS, all population sub-groups in eMbalenhle showed 95th percentile HQ values below 1. Using the USEPA NAAQS, all population subgroups showed HQ values greater than 1, using the 50th, 75th and 95th percentiles of $C_{air\text{-}adj}$. Throughout all the reference standards (WHO Guidelines, SA and US EPA NAAQS), the 50th, 75th and 95th HQ percentiles indicated varying health risks of exposure to $PM_{2.5}$ eMbalenhle. The WHO Guidelines showed the highest potential to curb non-carcinogenic risks, followed by USEPA and the SA NAAQS. When estimating the hazard quotient (HQ) for the 95th percentile of the SA NAAQS, the risk of developing non-carcinogenic health effects was four times lower than WHO's HQ. This difference indicates that using NAAQS to evaluate health risks could underestimate the risk for individuals exposed to $PM_{2.5}$ in eMbalenhle.

4.1.2 Carcinogenic risk assessment of exposure to $PM_{2.5}$ in eMbalenhle

The results in Table 5 and Figure 1 report the CR for male and female age groups in eMbalenhle based on exposure to adjusted $PM_{2.5}$ related to their characteristics. For both male and female elders, the CR was approximately 1 in 10, meaning that about 100,000 out of 1,000,000 exposed elders were at an increased risk of developing cancer over their lifetime due to $PM_{2.5}$ exposure at the reported levels. Even for toddlers born and raised in eMbalenhle, the probability of developing cancer during their lifetime exceeds the critical 1×10^{-04} level.

4.1.3 Sensitivity analysis of model inputs based on non-cancer and cancer risks

The contribution of input parameters to the variance in non-cancer risks is shown in Figures 2, 3. The variation of C_{air} showed the highest contribution to the variance in the non-cancer risk (72.4%, range of 57–87%), whereas on average, ET and EF contributed 25.5% (range of 11–41%) and 4% (range of 1–7%), respectively to the variance in non-cancer risks.

Figure 3 shows that the parameter sensitivity for the variance in CR for the older adult subgroups deviates from the other age groups. The highest contributions to the CR variance for the older adult were the C_{air} and the AT, whereas the ED showed the highest sensitivity for the other subgroups.

5 Discussion

This study reported an annual GM $PM_{2.5}$ concentration of 17 μg/m³. Various $PM_{2.5}$ sources, including traffic emissions, industrial

TABLE 5 Carcinogenic human health risks of exposure to $PM_{2.5}$.

Population sub-groups	50th-percentile	75th-percentile	95th-percentile
Male toddlers	3×10^{-3}	4×10^{-3}	4×10^{-3}
Female toddlers	3×10^{-3}	3×10^{-3}	4×10^{-3}
Male children	2×10^{-2}	2×10^{-2}	3×10^{-2}
Female children	2×10^{-2}	2×10^{-2}	2×10^{-2}
Male adults	8×10^{-2}	10×10^{-2}	1×10^{-1}
Female adults	7×10^{-2}	10×10^{-2}	1×10^{-1}
Male elders	1×10^{-1}	2×10^{-1}	2×10^{-1}
Female elders	1×10^{-1}	1×10^{-1}	2×10^{-1}

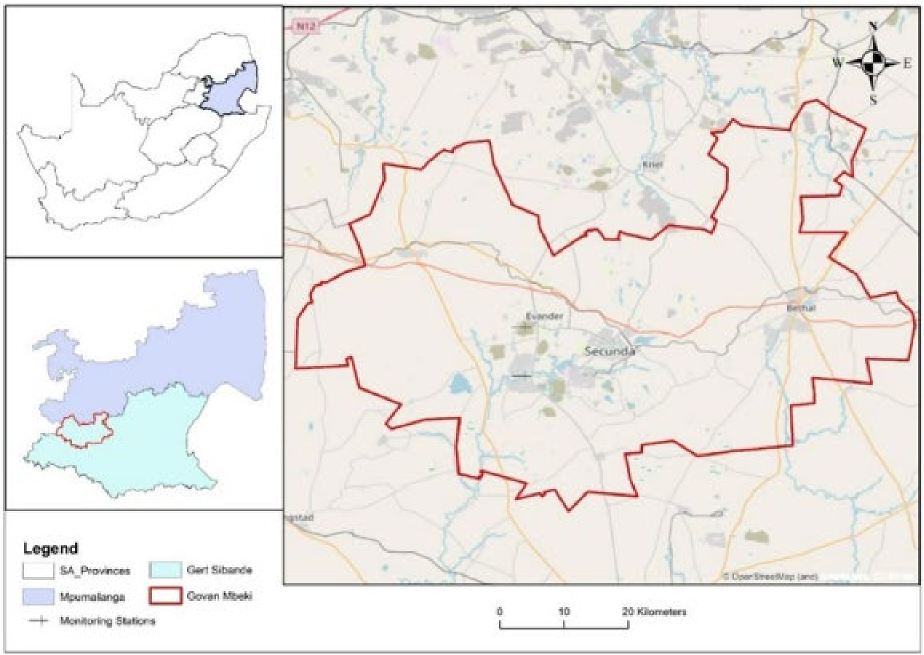

FIGURE 1
Maps showing the study area within the Country, Province, and District.

activities, domestic cooking, space heating, waste-burning and dust from gold mine TSFs, could have contributed to the increased levels of $PM_{2.5}$ in eMbalenhle. This annual concentration level was below the South African NAAQS of 20 µg/m³. However, it exceeded the WHO air quality guidelines and the USEPA NAAQS of 5 µg/m³ and 9 µg/m³, respectively. This indicated that although the local air quality standards are met, the exposed population may still experience significant health risks when the reported $PM_{2.5}$ concentrations are compared with international reference standards. The exceedances of international standards from February 2022 to February 2023 indicated a potential public health concern, especially for vulnerable population sub-groups living close to sources of $PM_{2.5}$ and gold mine TSFs. Although annual $PM_{2.5}$ emissions reported in this study are slightly below the SA NAAQS, Millar et al. (65) that, for the past 10 years (2009–2019), the annual $PM_{2.5}$ concentrations in eMbalenhle exceeded the SA NAAQS each year. The study used high-resolution data from the South African Weather Service (SAWS) air quality monitoring station.

Different countries have varying ambient $PM_{2.5}$ NAAQSs. This is due to environmental, health, social, political and economic factors (66) affecting these countries. The WHO (51) provides guidelines for air quality, but countries adopt these recommendations differently based on their national circumstances. In most cases,

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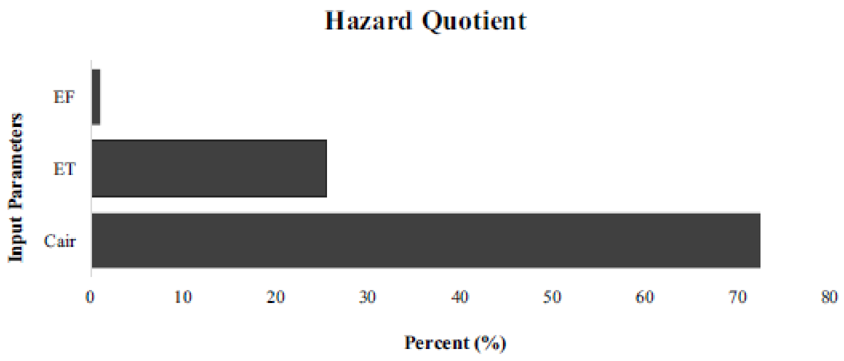

FIGURE 2
Sensitivity analysis of the parameters based on non-cancer risks.

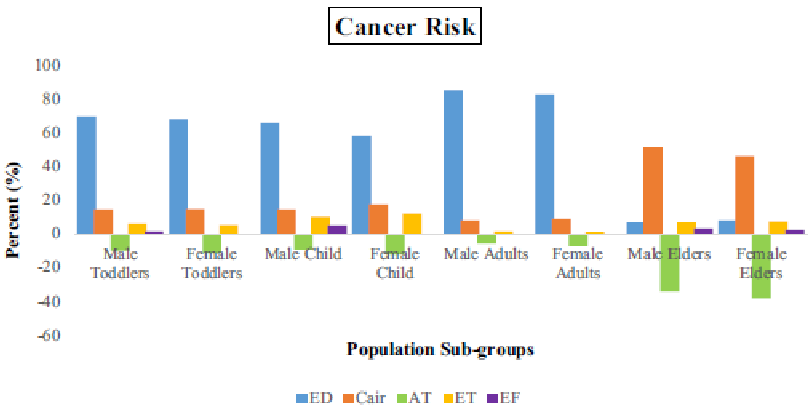

FIGURE 3
Sensitivity analysis of the input parameters based on cancer risks.

developing countries may prioritize economic growth and industrialization over strict air quality standards to avoid limiting industrial expansion (67). In contrast, developed countries may impose more stringent regulations to protect public health and the environment. Moreover, countries with advanced air quality management and monitoring technologies may set and enforce stricter NAAQS (68). Countries with less technological capacity may set more lenient standards due to challenges in air quality monitoring (69).

For the probalistic HHRA, the $PM_{2.5}$ concentrations were adjusted to reflect an accurate estimation of an equivalent full-day exposure over 1 year in the eMbalenhle population. The results showed that the median (50th percentile) for non-carcinogenic risk was low (below 1) across all population subgroups based on SA NAAQS. However, compared to the more restrictive USEPA and WHO air quality guidelines, even the median HQ values demonstrated a substantially increased risk with HQ values of 1.5 and 2.8, respectively. Amnuaylojaroen and Parasin (70) computed higher HQ values than this study. This is partly because they used RfC of 35 μg/m^3 to calculate the HQ and worst-case assumptions regarding the risk parameters. The mean HQs were 2.93, 2.59, 2.28, 1.88, and 1.26 for newborns, toddlers, young children, school-age children, and adolescents, respectively.

Although the WHO air quality guidelines are widely adopted and used in many countries, they are not absolute and can be overly simplistic. First, the guidelines fail to account for cumulative risks and variability in individual susceptibility. Second, the guidelines fail to account for risk tolerance, which can vary between populations and regulatory bodies. Given this, there is a greater need to develop more robust and advanced approaches that factor in these issues to reflect real-world exposures accurately and avoid underestimating or overestimating risk.

For the cancer risk (CR), results showed values greater than 1.0×10^{-4} (1 in 10,000) for all population subgroups, which is generally considered significant, calling for stricter regulatory action and interventions to prevent further exposure. For example, the 50th, 75th and 95th percentile values indicated significant CRs (all greater than 1.0×10^{-4}) across all population sub-groups. The CR became more significant in male and female elders. This result is similar to Wu et al. (71), who found the CR more significant in male elders. In contrast, Stapelfeld et al. (72) found that females were more at risk of developing cancer than males. In our study, the slightly higher CR for men was due to the lower life expectancy than women, but this difference is not statistically significant. Furthermore, males have different hormonal profiles compared to females (73) and as they age, the risk of developing cancer increases (74).

The female children showed the least chance of developing CR because of $PM_{2.5}$ exposure compared to the other groups. Our estimations were determined by the ED/AT ratio, which was the lowest for toddlers and the highest for elders. Since toddlers and children are young, their risk for developing cancer is reduced because they have less accumulated genetic mutations (75). Contrary to this, Siegel et al. (76) observed that pediatric cancers were more pronounced in male children than in females.

The sensitivity analysis indicated that C_{air} and ET had the most significant impact on non-cancer risks. Since C_{air} is measured, the estimates for ET are key for estimating the extent of non-cancer risk. These findings call for regulatory action and policies to reduce exposures, especially to vulnerable groups. Strategies could include promulgating stringent emission standards for petrochemical industries, power plants, coal mines and gold mines. Inside the community, there should be an advocation for the transition to cleaner fuels, energy-efficient cookstoves and renewable energy sources to mitigate combustion-related $PM_{2.5}$ emissions (77). Other strategies could include the spatial resolution of air quality monitoring in the area by adopting low-cost sensors (78), issuing early warnings for high pollution days (79), and raising public awareness to empower communities to take protective measures. On the other hand, the ED was the most sensitive parameter for the CR due to the assumed uniform distribution in the adult subgroup. For the older adult, where the ED/AT ratio is close to one, the variation in C_{air} becomes more significant for the estimates of the CR. In a similar study, Amoatey et al. (80) observed that long durations of exposure to ambient $PM_{2.5}$ increased adverse health outcomes amongst the Roman population.

Applying the probabilistic HHRA model may be more complex than the deterministic approach (81). The determinist HHRA approach uses fixed point estimates for input variables (ED, ET, EF, AT) (82). Often, the maximum values are used, resulting in worst-case assessments. In contrast, the probabilistic HHRA uses probability distributions for input variables to account for variability and uncertainty (83). Amnuaylojaroen and Parasin (70) applied a deterministic risk assessment model to assess the health impacts of exposure to $PM_{2.5}$ in different age groups of children in Northern Thailand. Compared to the probabilistic HHRA model that was applied in this study, their model considered the body weight and inhalation rate as variables, as also in Morakinyo et al. (84). The study also postulated that $PM_{2.5}$ exposure might affect children differently depending on gender, with males at a higher risk than females in adolescence (70).

6 Conclusion

The findings of the study demonstrated that the SA NAAQS may not adequately protect public health as it may underestimate the risks associated with $PM_{2.5}$. To protect public health, there is a need for the government to adopt more stringent standards and align them closely with international standards, including the WHO guidelines.

Using a probabilistic human health risk assessment (HHRA) approach, the study revealed that non-carcinogenic risks were low when benchmarked against the SA NAAQS, but substantially elevated when compared with international guidelines. Vulnerable groups, particularly newborns and toddlers, exhibited higher hazard quotients (HQs), underscoring their increased susceptibility. For cancer risks (CR), results exceeded the generally acceptable threshold of 1 in 10,000 across all population groups, particularly affecting the older adult.

$PM_{2.5}$ concentrations were the most significant factor in increased non-cancer health problems in all sub-population groups. This emphasizes the need for control measures to reduce $PM_{2.5}$ concentrations, including the maintenance of TSFs and increasing monitoring in hot spot areas. The ED was the most critical factor for the cancer risks, followed by the air concentration for all population sub-groups except for the older adult. Strategies to reduce the ED and EF, such as limiting outdoor activities during high pollution events could further minimize health risks associated with exposure to $PM_{2.5}$. The sensitivity analysis indicated that ambient $PM_{2.5}$ concentration (C_{air}) and exposure time (ET) had the most influence on non-cancer risk estimates, while exposure duration (ED) was key for cancer risks. These observations indicate the urgent need for targeted interventions to minimize exposure, especially among vulnerable populations. Policy actions could include tighter emissions controls, community-level interventions to promote dust control alternatives, TSF management strategies, and expanded air quality monitoring networks using low-cost sensors.

Considering the above, this study calls for an urgent review of the current South African NAAQS. However, policymakers should strike a good and functional balance between economic imperatives and public health outcomes. Even though the WHO provides global benchmarks, countries can adopt these to meet their socio-economic context, technological feasibility and regulatory frameworks.

7 Study limitations

The LCM measurement results over the year represent the temporal variations; however, spatial variations were not covered, limiting the representativeness of the $PM_{2.5}$ concentration data for the general population of eMbalenhle. In addition to this measured parameter (C_{air}), the HQ and CR risk equations, distribution and values for all other parameters, except life expectancy, were only estimates and not based on actual data or information from the community. In-depth population studies are needed to collect more relevant information, especially for the highest sensitivity risk parameters. Therefore, this study's HQ and CR probability distributions can only be considered to flag potential health risks for the eMbalenhle residents. Lastly, this study made assumptions for the ED and EF for all population subgroups. This can limit the reliability and generalizability of the findings, as these parameters may not accurately reflect the diverse exposure patterns across the population subgroups. Uniform distribution patterns and assumptions of uniform exposure may overlook important activity data, including age-specific behaviours and varying susceptibility. This could lead to potential underestimation or overestimation of risks.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Author contributions

NT: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. TM: Supervision, Writing – review & editing. DM: Supervision, Writing – review & editing. DB: Formal analysis, Supervision, Methodology, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that Gen AI was used in the creation of this manuscript. AI was used to improve the language and grammar.

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Appendix A: sensitivity analysis for population sub-groups in eMbalenhle

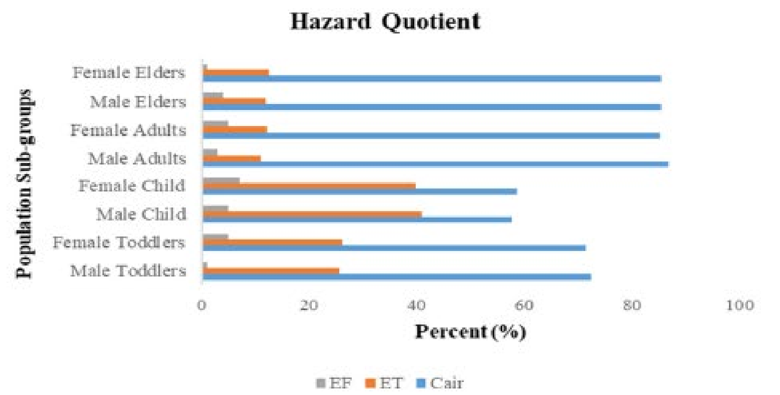

FIGURE A1
Sensitivity analysis of the parameters based on non-cancer risks in eMbalenhle.

CHAPTER 8: SYNTHESIS, CONCLUSIONS AND RECOMMENDATIONS

This chapter provides a comprehensive synthesis of the findings presented throughout this thesis and offers recommendations. The synthesis section begins by summarizing the study's key findings, starting with the measurement of $PM_{2.5}$ concentrations in the community and TSFs. The results from the dispersion modelling and source apportionment studies are integrated to demonstrate the complex interactions between various sources of $PM_{2.5}$. The key conclusions on the PHHRA evaluate whether there is an impact of gold mine TSFs on the health of the community in eMbalenhle.

8.1 Key Findings of the Study

8.1.1 $PM_{2.5}$ Measurements at the source and receptor (Objective 1)

The variations in daily $PM_{2.5}$ concentrations were observed at the TSFs (source) and community (receptor) monitoring sites. The highest hourly $PM_{2.5}$ concentrations were recorded at the community site during the early mornings (between 04:00 and 05:00 hours), late afternoons (16:00) and evenings (18:00 hours). The $PM_{2.5}$ concentrations decreased from midnight (00:00 hours) to 03:00 hours, followed by a morning peak and an evening peak late in the day, possibly due to increased traffic volumes during rush hours. The $PM_{2.5}$ concentrations were higher on weekdays than on weekends. The $PM_{2.5}$ concentrations were generally higher at the community fence line compared to the TSFs.

The gold mine TSFs did not show distinct diurnal patterns. Generally, the gold mine TSFs lack diurnal human activities, leading to consistent diurnal concentrations. Meteorological conditions impacted $PM_{2.5}$ concentrations at the TSFs and in the community. In this study, it was expected that the $PM_{2.5}$ concentrations at the TSFs would be higher than that at the receptor. However, our findings were contrary to this expectation.

The annual pollution rose showed increased $PM_{2.5}$ concentrations with wind predominantly coming from the North-westerly. The community of eMbalenhle is situated towards the West of the gold mine TSFs. This could indicate that the gold mine TSFs might not have significantly contributed to the high $PM_{2.5}$ concentrations in the community. However, there is a need to undertake comprehensive source apportionment to determine gold mine TSFs contribution to $PM_{2.5}$ levels in eMbalenhle. The diurnal $PM_{2.5}$ concentrations varied based on seasonal changes. The seasonal variability was higher during winter and lower during summer at both study sites. The overall findings concluded that there was no evidence of substantial contribution of TSFs to $PM_{2.5}$ concentrations in community

8.1.2 $PM_{2.5}$ Dispersion Modelling (Objective 2)

For the summer (December – February) and spring (September – November) months, high-frequency winds blew from the north-eastern quadrant. During the autumn season, predominant winds are from the northwest, northeast and southwest. The community of eMbalenhle is situated towards the West of the gold mine TSFs. The modelled results show a maximum daily average $PM_{2.5}$ concentration (99th-percentile) of 11µg/m3 at the TSF site, not exceeding the NAAQS. An annual average ground-level $PM_{2.5}$ (99th-percentile) concentration of 3.4 µg/m^3 at the community site was predicted in the study area which was way below yearly NAAQS.

8.1.3 Source Apportionment (Objective 3)

Gold (Au) showed the highest contamination and enrichment at the TSFs, followed by As and U. Au was highly enriched at the TSF and moderately in the residential areas. Mn was moderately enriched in the residential areas and depleted in the TSFs. Ni indicated moderate contamination risk in the residential areas but remained low in the TSFs. The Pb and U concentrations were among the lowest across all sampling sites.

Hg concentrations were below the LoD at all sampled sites. The reference element (Mn) showed a large positive effect size, indicating a statistically significant level difference between residential sites and TSFs. Conversely, As showed a large negative effect size which was also statistically significant, indicating that As concentrations were higher at TSFs than residential sites. These findings implicated TSFs as the primary sources of As contamination in the soils. Cr, Zn and Pb had low CF values at both residential and TSFs indicating only slight contamination above baseline levels.

The apportionment of sources was separated into residential sites and TSFs. The factor loadings were named differently depending on the dominant heavy metals. Factor 1(the strongest factor) was strongly associated with Mn, Zn, Pb, Cr and Ni at residential sites. In contrast, Factor 2 showed stronger associations with Au, As and U, elements that are characteristically linked to mining activities. At the TSFs, the source contributions followed a different pattern. Factor 1 was characterized by high Au, As, U and Cr loadings, elements that are directly associated with mining activities. Factor 2 was dominated by Ni, Pb and Zn which are mainly common in industrial activities rather than direct mining processes. At residential sites, Cr positively correlated with As, Au and Pb indicating that these heavy metals tend to increase together due to common sources. The findings of objective 3 concluded that the TSF soil is strongly affected by mining activities. It was assumed that the heavy metals in soil are proxy for historical dust deposition, there is some evidence of a contribution from historical mining activities to the heavy metal profile in the residential areas.

8.1.4 Probabilistic Human Health Risk Assessment (Objective 4)

Based on South African NAAQS as reference concentration, the median (50th percentile) for non-carcinogenic risk (HQ) was below 1 across all population subgroups. However, compared to the more restrictive USEPA NAAQS and WHO air quality guidelines, the median values demonstrated an increased risk with HQ values of 1.5 and 2.8, respectively.

The CR results showed median values greater than 1.0 x 10^{-4} (1 in 10 000) for all population subgroups, which is generally considered significant. The female children showed the least chance of developing cancer due to $PM_{2.5}$ exposure compared to the other population subgroups. The sensitivity analysis indicated that $PM_{2.5}$ concentration (C_{air}) and the exposure time (hours/day, ET) had the most significant impact on non-cancer risks. On the other hand, the exposure duration was the most sensitive parameter for the CR in the adult subgroup. The findings for objective four (4) concluded that $PM_{2.5}$ concentrations from various sources (not only from TSFs) may pose health risks in the exposed community.

8.2 Synthesis of the Findings and Hypothesis Analysis

It was hypothesised that emissions from gold mine TSFs significantly contribute to ambient $PM_{2.5}$ concentrations and potential health risks in the nearby community of eMbalenhle. The findings showed distinct bimodal peaks in $PM_{2.5}$ concentrations, with higher concentrations in the community in the early mornings and late afternoons to early evenings. These peaks aligned with anthropogenic activities, including increased vehicular emissions during rush hours and domestic fuel burning. The concentrations were also higher on weekdays than on weekends, further strengthening the influence of human activity on $PM_{2.5}$ patterns.

In contrast, the $PM_{2.5}$ concentrations at the gold mine TSFs remained relatively stable throughout the day, likely due to the absence of diurnal human activities. However, meteorological factors (particularly wind speed and direction) appeared to play a significant role in $PM_{2.5}$ dispersion. Wind speed increased during the day, enhancing atmospheric turbulence and vertical mixing. At night, reduced wind speed led to lower $PM_{2.5}$ concentrations.

These findings indicated that even though the TSFs did not show distinct diurnal patterns, they may still be a significant source of $PM_{2.5}$, especially when considering meteorological conditions. The findings from the $PM_{2.5}$ monitoring using LCMs indicated that multiple sources contributed to $PM_{2.5}$ concentrations in eMbalenhle, including the gold mine TSFs.

The modelled dispersion of $PM_{2.5}$ in the study area is largely influenced by seasonal wind patterns with winds predominantly originating from the northeastern quadrant in summer. These variations in wind direction influenced the transport and spatial distribution of $PM_{2.5}$, affecting different regions within eMbalenhle at different times of the year. The modelled maximum concentration (99th -percentile) of $PM_{2.5}$ at the TSF (11µg/m^3) matched quite well with measured concentrations (objective 1). The predicted 99th-percentile daily average $PM_{2.5}$ concentration in the community emanating from wind-blown dust erosion at the TSFs was relatively low (3.4 µg/m^3) compared to the measured (yearly averaged) concentration (19µg/m^3) The maximum daily and annual concentrations predicted by the model indicated that the $PM_{2.5}$ concentrations generally remain within regulatory limits over both short- and long-term exposure periods.

The contamination and enrichment of soils by As, U and Au at the TSFs, strongly implicates mining activities as a major contributor. It also indicated the potential for airborne transport of these toxic elements to the community. The moderate enrichment of Au in the residential soils, together with the As, Au, U and Cr contributing factor, provided some evidence that (historical) dust deposition from TSF or mining activities-related sources may have occurred.

The health risk assessment based on measured (multi-source) $PM_{2.5}$ concentrations demonstrated significant non-carcinogenic and carcinogenic risks, whereas (TSF-related) $PM_{2.5}$ concentrations showed increased carcinogenic risk.In conclusion, the study provided no evidence that $PM_{2.5}$ concentrations emanating from gold mine TSFs would significantly contribute to health risks in the community of eMbalenhle. The research questions were tackled from various angles, i.e. $PM_{2.5}$ monitoring comparisons between TSF-Community, 2) Modelling of the dispersion of $PM_{2.5}$ emission at TSF onto the community, and 3) source apportionment. Unfortunately, the source apportionment could not be done for $PM_{2.5}$ but soil was used as proxy for historical dust deposition. The results of the separate parts all indicated that no strong association between $PM_{2.5}$ concentration at TSFs and at community exists. $PM_{2.5}$ exposure in the community was demonstrated to pose health risks, however, the contribution of $PM_{2.5}$ from TSF emissions cannot be demonstrated.

Table 8.1 Summary of the key findings

Objective	Paper #	Key Findings	Conclusion
1	1	$PM_{2.5}$ concentrations in community (receptor) were higher than at TSFs (source) fence line. $PM_{2.5}$ concentrations were associated with other anthropogenic sources other than the TSFs. $PM_{2.5}$ concentrations were higher in winter due to domestic fuel burning for heating and cooking. The prevailing wind direction was not from TSFs towards the community.	There was no evidence of substantial contribution of TSFs to $PM_{2.5}$ concentrations in community.
2	2	Modelled daily and annual $PM_{2.5}$ concentrations were lower than the NAAQS	$PM_{2.5}$ concentrations from the TSFs do not significantly affect the community of eMbalenhle
3	3	Source apportionment of heavy metals in soil samples showed enrichment of the TSF soil with Au mining-related HMs as a primary profile. This profile formed the secondary profile at the community site and resulted in a slight enrichment (particularly Au).	If soil is considered a proxy for historical dust deposition, there is some evidence of a contribution from historical mining activities.

4	4	Various subpopulations in the community showed increased (non-)cancer risk associated with exposure to $PM_{2.5}$.	$PM_{2.5}$ concentration in the community may pose health risk
Hypothesis		It is hypothesized that emissions from gold mine TSFs significantly contribute to ambient $PM_{2.5}$ concentrations and potential health risks in the nearby community of eMbalenhle."	The study found no evidence to support the hypothesis; thus, the hypothesis is rejected.
Aim		To estimate the human health risks resulting from exposure to $PM_{2.5}$ from the gold mine TSFs in the community of eMbalenhle.	The study found evidence of health risks associated with exposure to $PM_{2.5}$ among subpopulations. However, the study found no evidence of a significant/ substantial contribution of TSFs-emitted $PM_{2.5}$ to the population's exposure and, thus, their health risks.

8.3 Strengths of the study

This study used LCMs to measure the $PM_{2.5}$ concentrations at both the source (TSFs) and the receptor (community). The use of LCMs to measure $PM_{2.5}$ concentrations at both sites provided high temporal and spatial accuracy to reduce uncertainty in measurements (Chapter 4). A further strength lies in the consideration of $PM_{2.5}$ dispersion from TSFs and other sources. Both approaches confirmed that wind-driven dust from TSFs only marginal contributes to airborne $PM_{2.5}$ concentrations in nearby residential areas (Chapter 5). Another strength was applying a PHHRA model rather than a deterministic approach. The PHHRA incorporated variability and uncertainty in key exposure parameters, providing a more realistic assessment of health risks. This approach identified population subgroups at higher risk thereby informing targeted public health interventions (Chapter 7). The study strengthened its findings by comparing $PM_{2.5}$ concentrations with South African, USEPA NAAQS and stricter WHO guidelines. This comparative analysis indicated the potential health risks even when local air quality standards were met, strengthening the argument that current regulations may not be protective enough. The study provided compelling evidence for policymakers to consider stricter regulatory measures in line with global best practices.

8.4 Limitations of the study

The $PM_{2.5}$ monitoring in this study was conducted for only one year, from February 2022 to February 2023. This limited monitoring period may not have fully capture long-term seasonal and inter-annual variations in $PM_{2.5}$ concentrations. $PM_{2.5}$ levels can fluctuate significantly due to changes in meteorological conditions, industrial activities and local emissions patterns. A longer monitoring period (for multiple years) would provide a more comprehensive representation of $PM_{2.5}$ trends over time. The study relied on only two LCMs, one placed at the TSFs and another in the community. This limited spatial coverage may not have fully capture the variability in $PM_{2.5}$ concentrations across different areas in eMbalenhle. More LCMs distributed across the study area would give a better representation of the $PM_{2.5}$ concentrations in eMbalenhle.

Machine learning models were used to correct and validate $PM_{2.5}$ data obtained from LCMs. While these models improve data accuracy, their performance is influenced by the environmental conditions under which they were trained. This limitation could introduce uncertainties in the $PM_{2.5}$ measurements, potentially affecting the reliability of the exposure assessment.

A significant limitation of the study was the inability to determine the chemical composition of $PM_{2.5}$. Chemical characterization is important for identifying specific sources of $PM_{2.5}$ and assessing its potential toxicity. Without this data, distinguishing between $PM_{2.5}$ concentrations from gold mine TSFs, industrial activities, domestic combustion and traffic-related pollution was challenging.

The heavy metals source apportionment analysis relied on soil samples as a proxy for historical dust deposition rather than real-time airborne $PM_{2.5}$ compositions. The identified sources may not accurately reflect the primary contributors to $PM_{2.5}$ concentrations in the air. Additionally, only 10 soil samples were collected and analyzed, which limit the representativeness of the findings. A larger number of soil samples would strengthen source apportionment results for heavy metal concentrations.

The accuracy of the APCS-MLR model used for source apportionment depends on the quality and representativeness of the input data. The source profiles used in the model may not have fully give all possible sources, potentially leading to misclassification and misinterpretation of heavy metals origins.

The PHHRA model depended on $PM_{2.5}$ concentrations measured with LCMs, which may not fully represent personal exposure levels. Individual exposure can vary based on time spent outdoors, occupational activities and proximity to pollution sources. Since personal exposure data was not collected, the model assumed that ambient concentrations reflected individual exposures, which may be inaccurate.

Additionally, the study used exposure factors, e.g exposure duration, and frequency from the USEPA Exposure Factors Handbook (2011) and previous studies. While these values provide useful benchmarks, they may not fully reflect the specific lifestyles and exposure behaviours of the eMbalenhle population. The lack of individual exposure data means that the health risk estimates could be underestimated or overestimated. The health risk parameters and reference values used in the study assumed that all individuals in eMbalenhle were generally healthy, without pre-existing medical conditions and for variations in individual susceptibility to $PM_{2.5}$

exposures. This could impact the accuracy of health risk estimates, as individuals with pre-existing health conditions may face greater risks than those assumed in the model.

8.5 Scholarly contribution of the study

This is the first study that used LCMs to measure $PM_{2.5}$ concentrations at the source (TSFs) and receptor (community) in South Africa. Furthermore, it is the first study to use LCMs generated data to assess the human health impacts of exposure to $PM_{2.5}$ in South Africa. While deterministic risk assessment approaches are commonly used in air pollution studies, this study advances the field by incorporating probabilistic methods, which account for variability and uncertainty of the risk assessment parameters. Furthermore, by applying this model in a South African mining community, the study contributes to the broader body of literature on environmental health in developing countries. It indicated the need for context-specific risk assessments that consider regional air quality standards, exposure patterns and population vulnerabilities instead of relying solely on risk thresholds derived from developed countries.

The study contributes to policy-relevant scholarly discussions by comparing South African NAAQS with those of international bodies. It demonstrates that while local $PM_{2.5}$ concentrations comply with NAAQS, they significantly exceed international guidelines, implying potential underestimation of health risks under current regulatory frameworks. This finding stresses the need for more stringent air quality regulations. It provides evidence to support policy revisions in developing countries where standards may not yet align with global health recommendations.

Beyond its scientific contributions, the study is an important bridge between academic research and policy implementation. The discussion of policy implications based on the study's findings indicates how research can inform evidence-based decision-making. The study also contributes methodologically by demonstrating the effectiveness of integrating multiple approaches (air quality monitoring, dispersion modelling, source identification PHHRA and policy analysis) within a single framework. This multidisciplinary approach provides a more holistic understanding of the air pollution-health nexus and can be used as a model for future studies investigating complex environmental exposure scenarios.

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Annexure A: Sensitivity Analysis for Population Sub-groups in eMbalenhle (Chapter 4)

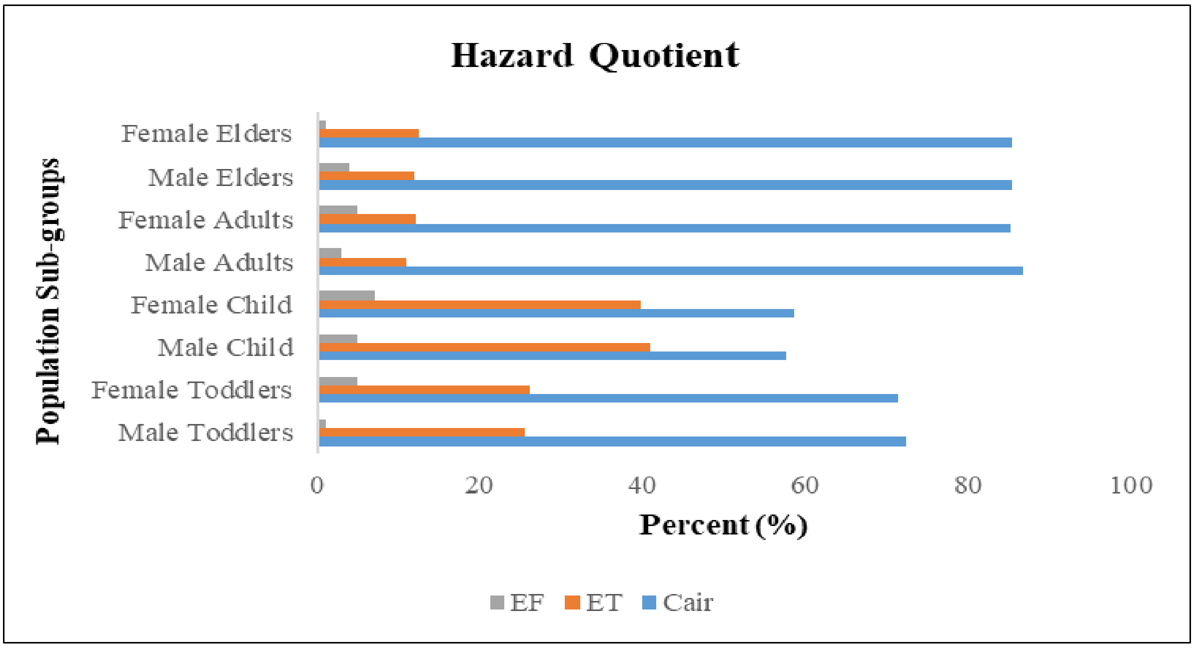

Figure A1: Sensitivity Analysis of the Parameters Based on Non-cancer Risks in eMbalenhle

Annexure B: Ethics Approval

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)

Registration number: REC-101114-044

13 May 2021

Re: Ms. Nomsa Thabethe (511272)

Waiver letter number: HRECNMW21/05/09

To whom it may concern,

Ms. Thabethe is currently a registered PhD student at the School of Public Health at the University of the Witwatersrand, Johannesburg. This letter is to confirm that, at the time of writing, Ms. Thabethe does not need ethical clearance for her PhD study entitled *'Human health risks of exposure to fine particles (PM2.5) from the gold mine tailings in the community of eMbalenhle, South Africa'*. This decision has been reached based upon a description of the project supplied by Ms. Thabethe to the University Human Research Ethics Committee (Non-Medical), which has been evaluated by the Chairs and Deputy Chairs. If, however, Ms. Thabethe changes the methods of data collection and analysis for this study, this decision may no longer be valid. If such changes take place, this should be communicated to the University Human Research Ethics Committee (Non-Medical) as soon as possible. This waiver letter is valid until 12 May 2024.

Please feel free to contact me should you require any further information.

Thank you.

Yours sincerely,
S Schoeman

Annexure C: Letter Requesting Permission to Conduct the Study

UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

University of the Witwatersrand,
School of Public Health

Gert Sibande District Municipality
P O Box 1748
ERMELO
2350

24 February 2021

Dear Sir/Madam,

Re: Permission to conduct research at eMbalenhle (Gert Sibande District Municipality).

My name is Nomsa Duduzile Lina Thabethe.

I am studying for a PhD in the Public Health at the University of the Witwatersrand. I am seeking permission to do research at eMbalenhle (Gert Sibande District Municipality).
I am conducting research on Human health risks of exposure to fine particles ($PM_{2.5}$) from the gold mine tailings in the community of eMbalenhle, South Africa. This project is aimed at assessing the potential health effects associated with exposure to $PM_{2.5}$ from the gold mine tailings.

The research will entail collecting data using the low-cost monitors which will be installed at eMbalenhle from July 2021 to July 2022. No human participants will be involved in this study. The results will be communicated in the dissertation and they will also be published in the scientific journals. There are no foreseeable risks in conducting this study.

I therefore request permission in writing to conduct my research at your Municipality. The permission letter should be on your organisation's headed paper, signed and dated, and specifically referring to myself by name and the title of my study.

Please let me know if you require any further information. I look forward to your response as soon as is convenient.

Yours sincerely,

Nomsa Duduzile Lina Thabethe
076 641 2834

Prof Derk Brouwer
011 717 2387
derk.brouwer@wits.ac.za

Annexure D: Permission Granted to Conduct the study

Gert Sibande District Municipality

Please address all correspondence to:

The Municipal Manager
P O Box 1748
ERMELO
2350

Corner Joubert & Oosthuise Street
ERMELO
2350

Office hours:
Mondays to Thursdays
07:30 – 13:00 / 13:30 – 16:00
Fridays: 07:30 – 14:00
Tel.: (017) 801 7000
Fax: (017) 811 1207

Website: www.gsibande.gov.za
e-mail: records@gsibande.gov.za

OFFICE OF THE MUNICIPAL MANAGER

ENQUIRIES: Daniel Hlanyane (017 801 7112) Our ref: 9/1/2/1/Research/02/2021

02 April 2021

Attention : Ms Nomsa Thabethe
Email : 511272@students.ac.za

Dear Madam,

CONSENT LETTER TO CONDUCT RESEARCH IN GERT SIBANDE DISTRICT MUNICIPALITY

Gert Sibande District Municipality hereby grants permission to conduct research in eMbalenhle titled: **"Human health risks of exposure to fine particles ($PM_{2.5}$) from the gold mine tailings in the community of eMbalenhle, South Africa"**.

The permission is granted under the following conditions:

1) Upon completion of this study, a bound copy of the final research report must be provided to Gert Sibande District Municipality and
2) Any article to be published on this study shall be approved by our Communication Department to ensure that the Rights and integrity of the Community of eMbalenhle will not be violated.

Yours truly,

……………………………

TD HLANYANE
SENIOR MANAGER:
MUNICIPAL HEALTH & ENVIRONNMENTAL SERVICES

02/04/2021
DATE

Annexure E: Turnitin Report

Prof MD Masekameni

01 April 2025 - Thesis - Thabethe - Final Version.docx

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Dr T Makonese

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