UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

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Health Risk Assessment of Sulphur Dioxide Emissions From a Coal-Fired Power Plant In Botswana

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18 June 2025

DECLARATION

I, Edward Letswee (student number: 2508903), declare that the research project entitled "Health Risk Assessment of Sulphur Dioxide Emissions From a Coal-Fired Power Plant In Botswana" is my research work undertaken under the supervision of Dr Tafadzwa Makonese. The work is being submitted in partial fulfilment of the requirements for the Master of Medicine degree in the field of Exposure Science at the School of Public Health, University of the Witwatersrand, Johannesburg. This work has not been presented for examination at any other university. With the supervisor's guidance, the author designed the study, conducted all field data collection, analysed the data, and wrote the research report. Parts of this research report will be published in peer-reviewed journals and presented at conferences. All the sources cited in this study have been acknowledged through comprehensive references. The Senate plagiarism policy is signed and attached as Appendix A: Plagiarism Declaration Form.

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Edward Letswee
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Date: 18 June 2025

DEDICATION

This is dedicated to my family.

ABSTRACT

Background: Coal-fired power plants (CFPPs) are significant sources of sulphur dioxide (SO_2) emissions, which are linked to respiratory and cardiovascular health issues. This study assessed health risks from SO_2 emissions at the Morupule B Power Station (MBPS) in Palapye, Botswana, considering local meteorological and geographical conditions.

Purpose: This research aimed to quantify SO_2 emissions from MBPS, model their dispersion using AERMOD, and assess associated health risks for vulnerable population subgroups (infants, children, and the elderly).

Methods: SO_2 emission rates were calculated using standard molecular weight conversions and volumetric flow analysis. AERMOD was employed to predict ground-level SO_2 concentrations within a 20km × 20km domain using meteorological data from 2021-2023. Health risks were quantified using Hazard Quotients (HQ) based on the USEPA Health Risk Assessment Framework.

Results: The maximum ground-level concentrations were 113.1 $\mu g/m^3$ (hourly), 30.4 $\mu g/m^3$ (daily), and 8.0 $\mu g/m^3$ (annual), representing only 32.3%, 24.3%, and 16.0% of respective regulatory limits. Hazard Quotient analysis revealed all values remained well below 1.0 across all population groups, with the elderly showing slightly higher susceptibility (HQ values of 0.0734 for hourly, 0.0553 for daily, and 0.0363 for annual exposures). Predominant north-northeasterly winds effectively dispersed emissions away from major population centers.

Conclusion: Current SO_2 emissions from MBPS pose minimal health risks to surrounding communities due to effective emission control technologies, favorable atmospheric dispersion conditions, and strategic facility location. The study demonstrates that coal-fired power generation can operate with limited public health impact when appropriate controls are implemented. These findings contribute valuable region-specific data to address research gaps regarding air quality management in sub-Saharan Africa.

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My deepest gratitude goes to my family, whose unwavering love, support, and encouragement have been my constant source of strength throughout this challenging journey. Their patience, understanding, and belief in me, even during difficult times, have been invaluable and I dedicate this accomplishment to them. Thank you for your endless sacrifices and for always being my rock.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

AERMOD:	American Meteorological Society/Environmental Protection Agency Regulatory Model
AMI:	Acute Myocardial Infarction
BPC:	Botswana Power Corporation
BOS:	Botswana Bureau of Standards
CEMS:	Continuous Emission Monitoring Systems
CFPPs:	Coal-Fired Power Plants
CO:	Carbon Monoxide
CO2:	Carbon Dioxide
COPD:	Chronic Obstructive Pulmonary Disease
DALYs:	Disability-Adjusted Life Years
DOAS:	Differential Optical Absorption Spectroscopy
EIA:	Environmental Impact Assessment
ENE:	East-North East
EPA:	Environmental Protection Agency
ERC:	Ethics Review Committee
FGD:	Flue Gas Desulphurization
HF:	Hydrogen Fluoride
HQ:	Hazard Quotients
IEA:	International Energy Agency
MAPS:	Morupule A Power Station
MBPS:	Morupule B Power Station
MCM:	Morupule Coal Mine
NAAQS:	National Ambient Air Quality Standards
NOx:	Nitrogen Oxides
NRC:	National Research Council
PM:	Particulate Matter
PM2.5:	Fine Particulate Matter
SO2:	Sulphur Dioxide
VOCs:	Volatile Organic Compounds
WHO:	World Health Organization

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 Background

In developing countries, coal still plays a significant role in the energy sector, particularly in Africa. South Africa, Zimbabwe, Angola, and Botswana are among the leading coal producers in southern Africa, with South Africa ranking first in the African continent (International Energy Agency, 2022). Botswana’s electricity generation is currently dominated by coal power (Gande, 2023). The country has two coal-fired power plants that produce electricity and contribute an average of 732 MW to the local generation capacity - Morupule A (132 MW) and Morupule B (600 MW). According to (Statistics Botswana, 2021), nearly 2 million tons of coal were mined in 2020, most of which is used for electricity generation. A cumulative 46.3% of domestic electricity in Botswana is produced from this fuel source (Statistics Botswana, 2021). Two diesel power-peaking plants (Orapa and Matshelagabedi) contribute an additional 160 MW (U.S. Department of Commerce, International Trade Administration, 2024).

The source-receptor relationship in air pollution exposure follows a complex pathway from emission to human contact. Power plant stacks emit primary pollutants such as SO_2 and NOx, which undergo atmospheric transport and transformation processes. These pollutants can undergo chemical reactions during transport, forming secondary pollutants like particulate matter and ozone (Seinfeld JH & Pandis SN, 2016). Wet and dry deposition mechanisms influence pollutant concentrations before reaching receptors. The point of contact (immission) occurs when these transported pollutants interact with human receptors through inhalation, marking the critical exposure point in the source-receptor continuum.

Meteorological conditions significantly influence pollutant dispersion patterns. Wind speed and direction control the initial transport of emissions, while atmospheric stability affects vertical mixing. Temperature inversions can trap pollutants near the ground, increasing local concentrations. Precipitation acts as a removal mechanism through wet deposition, and humidity influences the chemical transformation rates of primary pollutants (Seinfeld JH & Pandis SN, 2016).

Air quality monitoring and regulation in Botswana, particularly around power plants, is still in its infancy. The country's primary legislation governing air pollution is the Atmospheric Pollution (Prevention) Act of 1971, which is considered outdated by modern standards (Mashingaidze, 2024). The Botswana Bureau of Standards has recently published air quality standards (BOS 498:2012) that set limits for common contaminants, including SO_2 and NOx (Botswana Bureau of Standards, 2012). However, implementation and enforcement of these standards remain challenging due to limited resources and technical capacity (A. A. Khan et al., 2024).

From a sustainability perspective, renewable energy is the best source of electricity generation compared to traditional coal combustion processes. However, most resource-limited countries' dilemma lies in the globalisation of living standards. Access to electricity is considered an indispensable factor in the human development index (Aluko & Ngubane, 2024; Asghar et al., 2023; Mbiankeu Nguea, 2024). While coal plays a critical role in electricity generation and aids the development of a country, its continued use in the power sector leads to many socioeconomic and environmental challenges (Halkos & Tsirivis, 2023). Botswana is adopting measures to increase local goods and services that support economic growth. However, these measures will likely escalate energy demand, calling for increased power generation and supply to meet the demand. Even so, the rise in production and supply will threaten environmental sustainability due to the high emissions generated from the power sector (Saad et al., 2024)For example, findings from the Turkish power sector showed that fossil fuels accounted for more than 80% of adverse environmental effects related to electricity generation (Asghar et al., 2023). Coal-fired power plants are known to emit pollutants, including particulate matter (PM), sulphur dioxide (SO_2), nitrogen oxides (NOx), carbon dioxide (CO_2), hydrogen fluoride (HF), mercury (Hg), and dioxins (Dula & Kraszkiewicz, 2025). If a more significant proportion of a country's population has access to electricity, it implies improving people's quality of life. This, in turn, increases the demand for the government to supply electricity at larger scales, hence the continued over-reliance on solid fuels to generate electricity.

The emissions contribute significantly to global warming and adverse health outcomes. Noxious emissions have been implicated in respiratory illnesses such as asthma, cancer, stroke and cardiovascular diseases. Individual susceptibility depends on age and underlying medical conditions (Krismanuel & Hairunisa, 2024). The vulnerable exposure group includes children, the elderly, pregnant women, and individuals with respiratory complications (Odubo & Kosoe, 2024). Exposure to SO_2 may increase the severity and incidences of respiratory symptoms, while exposure to NOx may also increase susceptibility to viral and bacterial infections (Odubo & Kosoe, 2024). NOx from coal emissions react with chemicals in the atmosphere and have the most significant effect on climate change and indirectly pose immediate socio-environmental threats in local and neighbouring communities in the vicinity of power plants (Fazakas et al., 2024; Meo et al., 2024; Odubo & Kosoe, 2024)

The health effects of air pollution from coal-fired power plants in Botswana have not been extensively studied. However, research in neighbouring South Africa has shown significant health burdens associated with exposure to pollutants from coal power stations (Buthelezi et al., 2025; Nemakhavhani et al., 2024; Simelane & Langerman, 2024) A study by (Holland, 2017) estimated that emissions from Eskom's coal fleet in South Africa caused 2,239 premature deaths annually, primarily due to SO_2 exposure. In Botswana, where air quality monitoring is less comprehensive, the health impacts of power plant emissions remain largely unquantified, highlighting the need for more localized studies (Winkler et al., 2023).

This study focuses on three vulnerable sub-population groups: infants, children, and the elderly, due to their heightened susceptibility to air pollution impacts. These groups are particularly vulnerable due to several physiological factors. Infants and children have higher respiratory rates relative to their body size, developing immune systems, and growing organs, making them more susceptible to respiratory irritants (WHO.,2018). The elderly, conversely, often have compromised immune systems, pre-existing conditions, and reduced respiratory function, which can exacerbate the effects of air pollutants (Bell et al., 2013; Simoni et al., 2015). These groups also tend to spend more time outdoors or in areas where exposure to pollutants may be higher, increasing their risk of adverse health effects (WHO.,2018).

Various advanced air dispersion models have been developed to estimate ground-level concentrations of pollutants, a vital input parameter in conducting human health risk assessments (Kiaei et al., 2024; Munshed et al., 2025; Mushtaq et al., 2024) . These models are mainly designed based on the Gaussian plume model, which defines the vertical and horizontal spread of the plumes at various terrains (Micallef & Micallef, 2024). The American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) will be used in this study. Many studies have employed AERMOD to simulate the dispersion of pollutants from CFPPs and similar industries (Izadrezaei et al., 2023; Ogbuabia et al., 2023; Sherif et al., 2023). Similar studies have been conducted in Malaysia and Thailand, and AERMOD has been accepted as a standard tool for estimating the dispersion of air pollutants and their transportation from various sources (Ratanavalachai & Trivitayanurak, 2023) .

This study adopts the USEPA's risk assessment framework, which has been widely applied in environmental health studies globally. The framework comprises of four essential steps: hazard identification, exposure assessment, dose-response assessment, and risk characterization. Recent applications include studies by (Bootdee et al., 2025; Cooley et al., 2025; Sajjad, 2025; Sakr et al., 2025) in power plant emissions assessment. This research will specifically focus on the exposure assessment component, utilizing air dispersion modelling to quantify population exposure levels.

1.2 Statement of the Problem

Coal-fueled power plants substantially contribute to particulate pollution in the ambient air (IEA, 2022). Sulphur dioxide and nitrogen oxides are likely to cause respiratory illnesses such as asthma, cancer, stroke and cardiovascular diseases. Exposure to SO_2 may increase the severity and incidence of respiratory symptoms, while exposure to NO_x may also increase susceptibility to viral and bacterial infections (Odubo & Kosoe, 2024). NO_x from coal emissions react with chemicals in the atmosphere and have the most significant effect on climate change and indirectly pose immediate socio-environmental threats in local and neighbouring communities in the vicinity of power plants (Meo et al., 2024b; Odubo & Kosoe, 2024). In light of the above, the MBPS, a coal-fired power plant, is a significant source of possible local pollution, leading to potential adverse health effects in nearby communities, including Palapye.

A literature review and the prevailing state of air pollution have shown that studies focusing on the extensive characterisation of emissions from the CFPP and similar environments are needed. Such studies will support understanding the possible long-term and short-term adverse health effects emissions have on the population sub-groups living in these receiving environments. Despite the known health impacts of SO_2, including respiratory illnesses and increased susceptibility to infections (Kumar et al., 2023a), there is a lack of comprehensive studies assessing the potential health risks associated with continuous exposure to emissions from coal-fired power plants in Botswana. The country's air quality monitoring and regulatory framework are still developing, with limited data on pollutant dispersion and ground-level concentrations in communities near power plants (Van der Waldt, 2023). This knowledge gap hinders effective policy-making and implementation of targeted control measures to protect public health. Furthermore, Botswana's unique geographical and meteorological conditions may influence pollutant dispersion differently compared to other regions where similar studies have been conducted (Selwe et al., 2024).

In Palapye and other affected sites, there is a need for studies on the dispersion, concentration levels and possible effects of nitrogen dioxide and sulphur dioxide. Business-as-usual approaches that do not interrogate the source-to-receptor model of analysing pollutants are likely to exacerbate human exposure to hazardous contaminants. An effective approach will promulgate targeted controls (i.e. using the hierarchy of controls) to minimise exposure and protect the health of those exposed. As such, the study aims to employ advanced air quality modelling techniques, specifically the AERMOD dispersion model, to predict ground-level SO_2 concentrations within a 20 km buffer zone from the power station. By focusing on this specific pollutant and utilizing local data, this research will provide crucial insights into the potential health risks to different sub-groups residing in communities adjacent to a typical CFPP. The outcomes of this study will not only contribute to the limited body of knowledge on air pollution impacts in Botswana. The study will inform policy decisions and targeted interventions to mitigate health risks. This research is a critical step towards improving air quality management and protecting public health near coal-fired power plants in Botswana.

1.3 Research Question

What are the health risks associated with lifetime exposure to SO_2 emitted from a coal-fired power plant in different sub-groups (i.e. infants, children and adults) living near the power plant in Palapye, Botswana?

1.4 Research Aim

This research aims to quantify SO_2 emissions from the MBPS, model the dispersion of the pollutant as a function of meteorological parameters (i.e. temperature, wind speed and direction, atmospheric stability, cloud cover etc) and assess the health risks of exposure in different sub-groups (infants, children and the elderly) living near the power plant.

1.5 Specific Objectives

a. To estimate SO_2 emission rates from operational activities at the CFPP in Palapye, Botswana.
b. To assess the meteorological characteristics (wind speed and direction) affecting the dispersion of pollutants from the source (CFPP) to the receptor (community of Palapye).
c. To predict the ground-level concentration of SO_2 (including seasonal, daily and diurnal patterns) using an advanced air dispersion modelling tool (AERMOD).
d. To employ the USEPA Health Risk Assessment Framework to characterise the health risks associated with lifetime SO_2 exposure for different sub-population groups (infants, children, and the elderly) residing near the CFPP in Palapye, Botswana.

1.6 Justification

There is limited information in the literature on the dispersion characteristics of criteria air pollutants from coal-fired power plants in Botswana. Additionally, the study will present the first comprehensive assessment of health risks due to exposure to SO_2 from electricity generation in Botswana. The study's outcomes will have policy implications for the environmental control of pollutants from coal-fired power plants and for improving the health and well-being of communities near power generation plants.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Sulphur dioxide (SO_2) emissions from coal-fired power plants pose significant health risks to populations near these facilities. Exposure to SO_2 has been linked to various respiratory issues, including asthma, chronic bronchitis, and decreased lung function (Mercan et al., 2020) . Moreover, SO_2 contributes to fine particulate matter (PM2.5) formation, which is associated with cardiovascular diseases and premature mortality (Liang et al., 2020). Given the potential health impacts, it is crucial to conduct health risk assessments of SO_2 emissions from coal-fired power plants to inform policymakers and public health professionals about the extent of the problem and to develop effective mitigation strategies.

This chapter comprehensively reviews the existing literature on the health risks associated with SO_2 emissions from coal-fired power plants. The review will cover the following topics: (1) key concepts related to SO_2 emissions, health risk assessment, and air dispersion modelling; (2) frameworks underpinning the study, including the exposure-response concept (3) a critical review of the three main research objectives, including estimating SO_2 emission rates, predict ground-level SO_2 concentrations using AERMOD, and assess the health risks for the population residing near the coal-fired power plant; (4) research gaps in the existing literature; and (5) the conceptual framework of the study, integrating key concepts, theories, and variables of interest in section 2.3.

2.2 SO_2 emissions from power plants

Sulphur dioxide (SO_2) is a colourless, reactive gas primarily produced by the combustion of fossil fuels with sulphur, such as coal and oil (EPA, 2021). In the context of this study, SO_2 emissions specifically refer to those generated by coal-fired power plants. The U.S. Environmental Protection Agency (EPA) defines SO_2 as ”*one of a group of highly reactive gasses known as oxides of sulphu*r“ (EPA, 2021, para. 2; Bhardwaj & Saxena, 2023). The World Health Organization (WHO) describes SO_2 as "*a colourless gas with a sharp odour*" that "*can affect the respiratory system and the functions of the lungs and causes irritation of the eyes*" (WHO, 2021, para. 8).

SO_2 emissions are critical in this study because they are a significant pollutant produced by coal-fired power plants and have been associated with various adverse health effects (Liang et al., 2020; Mercan et al., 2020). Understanding the nature and extent of SO_2 emissions from these facilities is essential for accurately assessing the health risks posed to nearby populations and developing appropriate mitigation strategies.

2.3 Theoretical Framework

This study is anchored in the exposure-response model (Bradford et al.,2015; X. Li et al., 2024). This framework provides the grounds for understanding the relationship between SO_2 emissions from coal-fired power plants and their health impacts on exposed populations/receptors.

A theoretical framework is a structure that guides research by relying on a formal theory constructed by using an established, coherent explanation of certain phenomena and relationships (van der Walt et al., 2023). It serves as a foundation for the research, providing a basis for the study's hypotheses, research questions, and methodology (Svejvig., 2021). In the context of this study on the health risk assessment of sulphur dioxide emissions from a coal-fired power plant, the theoretical frameworks help to explain the relationships between the following key variables outlined in Table 1 below and provide a context for interpreting the findings (Shah & Corley., 2006).

Table 1: Key Variables

Variable Category	Variables
Independent Variables	• SO_2 emission rates from the coal-fired power plant • Meteorological parameters (wind speed, wind direction, temperature, atmospheric stability) • Stack parameters (height, diameter, exit velocity, exit temperature)
Dependent Variables	• Ground-level SO_2 concentrations • Health risk indices for exposed populations/receptors • Exposure metrics (acute and chronic exposure levels)
Moderating Variables	• Population demographics (age distribution in vulnerable groups) • Exposure duration • Distance from source • Topographical features affecting dispersion
Confounding Variables	• Background SO_2 concentrations • Other sources of air pollution • Socioeconomic factors affecting exposure patterns • Underlying health conditions in the population

These variables form the foundation for understanding the source-receptor relationship and subsequent health risk assessment in the study area.

A theory is a well-substantiated explanation of a phenomenon based on facts repeatedly confirmed through observation and experimentation (Shah & Corley, 2006). Theories are developed through inductive reasoning, in which observations are used to generate hypotheses that are tested through further observation and experimentation (Mulholland et al., 1980). This study specifically employs the exposure-response framework developed by (Bradford et al., 2015) and refined for air pollution studies by (Burnett et al., 2014; Pope III, 2002; Sun et al., 2023), alongside the air pollution health effects model established by (Lave & Seskin, 1970).

2.3.1 Frameworks Anchoring the Investigation

Several Frameworks have been advanced to explain the relationship between sulphur dioxide emissions and coal-fired power plants, including:

- The exposure-response (Burnett et al., 2014; Pope III, 2002)
- The exposure pathway characterization (Lave & Seskin, 1970)
- The susceptible population (Metz, 1976)

The two main frameworks anchoring this investigation are the exposure-response and the air pollution health effects.

The exposure-response model posits that there is an association between exposure to a pollutant and the resulting health effects (Weaver et al., 2025). This framework posits that as exposure to sulphur dioxide emissions increases, the risk of developing adverse health effects also increases. The study has been supported by numerous epidemiological studies that have found associations between sulphur dioxide exposure and respiratory morbidity and mortality (Burns & Bernicker, 2023).

On the other hand, studies suggest that exposure to air pollutants such as sulphur dioxide can have a range of adverse health effects, including respiratory and cardiovascular disease (Manisalidis et al., 2020). This has been supported by studies that have found associations between air pollution exposure and increased morbidity and mortality (Hicken et al., 2023; Requia et al., 2024).

2.3.2 Key Elements of the Exposure Concepts

The exposure-response model, first formulated by Bradford et al., 2014), has been refined and challenged over time. Hill's original criteria for causal inference have been reevaluated in light of advancements in genetics, molecular biology, and statistics (Fedak et al., 2015). Researchers have identified statistical challenges in evaluating dose-response relationships using epidemiological data (Mundt, 2005), including the effects of random errors in exposure measurement on the observed shape of the exposure-response curve (Crump, 2005). Studies have shown that the exposure-response relationship for fine particulate matter from air pollution and cigarette smoke is non-linear, with significant risks at low exposure levels (Pope III, 2002). In the field of immuno-oncology, the exposure-response relationship for therapeutic monoclonal antibodies is often confounded by various factors, necessitating new analytical approaches (Dai et al., 2020; Liu et al., 2017; H. Wang et al., 2019). Recent advancements in causal artificial intelligence and machine learning offer new methods for clarifying and quantifying exposure-response relationships (Cox., 2023).

The key elements include the concept of a dose-response relationship, in which increasing levels of exposure are associated with increasing severity of health outcomes. It also touches on the concept of a threshold, below which no adverse health effects are expected to occur (Fu et al., 2024).

The study on the health effects of exposure to air pollutants was conducted by (Lave & Seskin, 1970) and has been supported by numerous studies since then (Chappie & Lave, 1982; Dominski et al., 2021; Folinsbee & Raven, 1984; Gilliland et al., n.d.; Mohajan, 2011; O'Neill et al., 2003; Pope et al., 1995). The key elements include the concept of a causal relationship between exposure and adverse health effects and the idea that the health effects can be both acute and chronic (Manisalidis et al., 2020).

In this study, the exposure-response will be used to guide the investigation of the relationship between sulphur dioxide emissions from a coal-fired power plant and the health risks to the exposed population living near the power plants. The study will seek to quantify the dose-response relationship between sulphur dioxide exposure and health outcomes and to predict the ground-level concentration of SO_2 to determine whether they are above exposure limits.

The study will investigate the potential acute and chronic health effects associated with sulphur dioxide exposure through a systematic analysis of varying exposure durations using AERMOD dispersion modelling. Acute effects will be assessed by analyzing short-term exposure metrics, including hourly concentrations (using 99th percentile concentrations) and 24-hour averages, with results compared against WHO and Botswana air quality standards (350 $\mu g/m^3$ for hourly and 125 $\mu g/m^3$ for daily exposures). Chronic effects will be evaluated through annual average concentrations compared to the 50 $\mu g/m^3$ standard, with health risk quantification using Hazard Quotients (HQ) calculated as the ratio of predicted concentrations to reference values. The analysis will incorporate spatial variation across 50 sensitive receptor locations and account for meteorological influences on pollutant dispersion patterns.

2.4 Measurements and estimation of SO_2 emissions factors/ rates

The first research objective of this study is to estimate SO_2 emission rates from operational activities at the coal-fired power plant (CFPP). This objective focuses primarily on characterizing source emissions intensity and understanding the dynamics of pollutant generation at the facility. Accurate emission rate data serves multiple purposes: it establishes baseline emission profiles for the facility, enables evaluation of compliance with emission standards, and provides critical input data for subsequent dispersion modelling. The data generated through this objective will also inform the development of effective emission control strategies (Bartan et al., 2023). While source emission rates are a crucial starting point for the overall assessment, it's important to note that health risk assessment will primarily depend on the ground-level concentrations of SO_2 at receptor locations, which are influenced by various factors, including meteorological conditions and topography.

The literature on SO_2 emissions from CFPPs consistently emphasizes the importance of accurate emission rate estimates for assessing health risks and informing policy decisions (W. Guo et al., 2021; H. Tang et al., 2024). Studies have employed various methods to estimate SO_2 emission rates, including continuous emission monitoring systems (CEMS) and stack testing to estimate emission factors (Srivastava & Elumalai, 2021; Sun et al., 2023). The choice of method depends on factors such as data availability, resource constraints, and regulatory requirements (Sun et al., 2023).

2.4.1 Sources and Characteristics of SO_2 Emissions from Coal-Fired Power Plants

Coal-fired power plants (CFPPs) are a significant source of sulphur dioxide (SO_2) emissions, which can have detrimental effects on human health and the environment (Kamarudin et al., 2024). SO_2 is formed during the combustion of coal fuel due to the presence of sulphur in the fuel (Srivastava & Elumalai, 2021). The amount of SO_2 emitted from a CFPP depends on several factors, including the sulphur content of the coal fuel, the efficiency of the combustion process, and the presence of emission control technologies (Sun et al., 2023).

The sulphur content of coal can vary widely depending on its geological origin and rank (i.e., lignite, sub-bituminous, bituminous, or anthracite) (Q. Zhao et al., 2024). In general, lower-rank coals, such as lignite and sub-bituminous coal, tend to have lower sulphur contents compared to higher-rank coals like bituminous coal(Kondratev & Khamzina.,2024; Tara

Pandey, 2025). However, the relationship between coal rank and sulphur content is not always straightforward, as coal from different regions can have varying sulfur contents even within the same rank (Dong et al., 2024; Hughes et al., 2024).

The efficiency of the combustion process in a CFPP also influences the amount of SO_2 emitted (Triani et al., 2024). More efficient combustion processes, such as those achieved in supercritical and ultra-supercritical boilers, can lead to lower SO_2 emissions per unit of electricity generated than less efficient subcritical boilers (Li et al., 2024). However, even efficient combustion processes can result in significant SO_2 emissions if the sulphur content of the coal is high (Srivastava & Elumalai, 2021).

Emission control technologies, such as flue gas desulphurization (FGD) systems, can substantially reduce SO_2 emissions from CFPPs (Joy & Qureshi, 2023). FGD systems work by reacting the SO_2 in the flue gas with a sorbent, such as limestone or lime, to form solid sulphates that can be collected and disposed of (Aakriti et al., 2023). The effectiveness of FGD systems depends on factors such as the type of sorbent used, the ratio of sorbent to SO_2, and the system's operating conditions (Mchabe et al., 2024). While FGD systems can significantly reduce SO_2 emissions, they can also increase the cost of electricity generation and produce large amounts of solid waste that must be managed (Sun et al., 2023).

In addition to the factors mentioned above, the age and maintenance of a CFPP can also influence its SO_2 emissions (Kamarudin et al., 2024). Older plants may have less efficient combustion processes and may lack modern emission control technologies, leading to higher SO_2 emissions compared to newer plants (Zuo et al., 2024). Regular maintenance and upgrades can help to improve the efficiency and environmental performance of CFPPs. However, these measures can be costly and may not always be prioritized in developing countries with limited resources (S. Yuan et al., 2025).

Over time, there has been a shift towards the use of more advanced and accurate methods for estimating SO_2 emission rates from CFPPs. For example, CEMS units have become increasingly popular due to their ability to provide real-time, continuous data on emission rates (Gu et al., 2022a). However, the use of CEMS is not always feasible, particularly in developing countries where resources may be limited (Srivastava & Elumalai, 2021). In such cases, emission factors are often used as a more cost-effective alternative (Sun et al., 2023).

2.4.2 Health effects of SO_2 exposure

Exposure to sulphur dioxide (SO_2) has been linked to various adverse health effects, particularly in vulnerable population subgroups, including children, the elderly, and individuals with underlying medical conditions (Kampa & Castanas, 2008; Mashhadi-Abdolahi et al., 2024) Children are more susceptible to the effects of SO_2 due to their developing respiratory systems and higher breathing rates relative to body size (Amnuaylojaroen & Parasin, 2024). The elderly may be more vulnerable to SO_2 exposure due to age-related declines in respiratory function and increased prevalence of chronic diseases (Wallbanks et al., 2024).

The health effects of SO_2 exposure can be acute and chronic, depending on the concentration and duration of exposure (Eslami Doost et al., 2024). Acute exposure to high levels of SO_2 can cause respiratory irritation, bronchospasm, and dyspnea (Khalaf et al., 2024). These effects are primarily due to the irritant properties of SO_2, which can cause inflammation and the narrowing of the airways (Schlesinger, 1999) In individuals with asthma, acute SO_2 exposure can trigger bronchoconstriction and exacerbate asthma symptoms (Kumar et al., 2023b). A study by (Segala et al., 2008) found that short-term exposure to SO_2 was associated with increased emergency department visits for asthma in Paris, France.

Chronic exposure to lower levels of SO_2 has been associated with increased respiratory symptoms, reduced lung function, and increased risk of respiratory diseases such as bronchitis and emphysema (Mashhadi-Abdolahi et al., 2024). A study by (Zhang et al., 2012a) found that long-term exposure to SO_2 was associated with increased mortality from chronic obstructive pulmonary disease (COPD) in China. Another study by (W. Guo et al., 2021) found that chronic exposure to SO_2 was associated with reduced lung function in children in Shanghai, China.

In addition to its direct effects on the respiratory system, SO_2 exposure has also been linked to cardiovascular disease (Stockfelt et al., 2017). (Sunyer, 2003) found that daily variations in SO_2 concentrations were associated with increased cardiovascular mortality in seven European cities. The mechanisms underlying the cardiovascular effects of SO_2 exposure are not fully understood but may involve systemic inflammation and oxidative stress (Stockfelt et al., 2017).

Socioeconomic factors can also influence the health effects of SO_2 exposure (H. Guo et al., 2021). Individuals with lower socioeconomic status may be more susceptible to the health effects of SO_2 due to factors such as poor nutrition, limited access to healthcare, and cumulative exposure to other environmental pollutants (Bose & Diette, 2016; Liu et al., 2017). A study by

(Chen et al., 2024) found that the association between SO_2 exposure and daily mortality was stronger in areas with lower socioeconomic status in Hangzhou, China.

Numerous epidemiological studies have investigated the health effects of living far-field (FF) to coal-fired power plants (CFPPs). These studies have provided valuable insights into the potential risks associated with exposure to pollutants emitted from CFPPs, particularly sulphur dioxide (SO_2) (W. Guo et al., 2021; Han et al., 2024; Kamarudin et al., 2024; Liu et al., 2017).

A study by (W. Guo et al., 2021) examined the association between long-term exposure to SO_2 and mortality in a cohort of 13,209 adults living near a CFPP in Shanghai, China. The study found that each 10 $\mu g/m^3$ increase in SO_2 concentration was associated with a 4.2% increase in all-cause mortality and a 7.2% increase in respiratory mortality. The authors concluded that long-term exposure to SO_2 from CFPPs could have significant health impacts on nearby populations.

Another study by (W. Guo et al., 2021; Mahlangeni et al., 2025) investigated the effects of air pollution on lung cancer incidence in a population living near CFPP in Xuanwei, China. The study used a spatiotemporal analysis to assess the relationship between lung cancer incidence and proximity to the CFPP, taking into account temporal variability in air pollution levels. The results showed that lung cancer incidence was significantly higher in areas closer to the CFPP and that the risk decreased with increasing distance from the plant.

A case-control study by (Wong et al., 2016) examined the association between exposure to air pollution from CFPPs and the risk of acute myocardial infarction (AMI) in a population in Taiyuan, China. The study included 354 cases of AMI and 644 controls and used a dispersion model to estimate individual exposure to SO_2 and other pollutants. The results showed that exposure to SO_2 was associated with an increased risk of AMI, with an odds ratio of 1.19 for each 10 $\mu g/m^3$ increase in SO_2 concentration.

In a study conducted in the United States, (J. I. Levy et al., 2002) estimated the health impacts of SO_2 and nitrogen oxide (NOx) emissions from CFPPs on nearby populations. The study used a source-receptor matrix to estimate the exposure of populations to exposure agents emitted from 393 CFPPs across the country. The results showed that the health effects of SO_2 and NOx emissions varied widely depending on the location and characteristics of the power plants, with some plants contributing significantly to regional health risks.

A limitation of many epidemiological studies on populations living near CFPPs is the potential for confounding factors, such as socioeconomic status and cumulative exposure to other pollutants, to influence the results (Wilkie et al., 2023). Additionally, using different exposure assessment methods and health outcomes across studies can make it difficult to compare and synthesize the findings (Wilkie et al., 2023).

Despite these limitations, the epidemiological evidence suggests that populations living near CFPPs may be at increased risk of adverse health effects, particularly those related to SO_2 exposure. These findings highlight the importance of considering the health impacts of CFPPs on nearby communities when developing energy policies and regulations (Zhang et al., 2012).

The need for accurate measurements of source pollutants is of paramount importance. Over time, there has been a trend towards the use of more comprehensive and integrated approaches to health risk assessment, which consider multiple exposure pathways and the complex interplay between environmental, social, and economic factors (H. Wang et al., 2019; Wilkie et al., 2023). This trend has been driven by the recognition that traditional approaches focusing solely on inhalation exposure may underestimate the true health risks associated with CFPP emissions (Peng et al., 2019). Additionally, there has been a growing emphasis on community-based participatory research methods, which engage local communities in risk assessment and incorporate their knowledge and perspectives.

A recurring theme in the literature is the need for accurate and reliable SO_2 emission rate estimates to support health risk assessments and policy decisions (W. Guo et al., 2021; L. Tang et al., 2020). Another subject is the importance of considering site-specific factors, such as fuel characteristics and operating conditions, when estimating emission rates (Srivastava & Elumalai, 2021).

There is some debate in the literature regarding the most appropriate method for estimating SO_2 emission rates from CFPPs. While CEMS are generally considered the most accurate method, some studies have found that emission factors can provide reasonable estimates in certain situations (Sun et al., 2023). There is also disagreement about the extent to which site-specific factors should be considered when estimating emission rates, with some studies advocating for the use of generalized emission factors (Srivastava & Elumalai, 2021) and others emphasizing the need for site-specific measurements (Gu et al., 2022a).

A pivotal publication in this field is the study by, which highlighted the importance of accurate SO_2 emission rate estimates for assessing health risks and informed the development of more rigorous estimation methods. Another influential study is that of (Y. Zhao et al., 2013) which compared different methods for estimating SO_2 emission rates and provided guidance on the selection of appropriate methods based on data availability and resource constraints.

Despite the extensive research on SO_2 emission rate estimation methods, there are still some gaps in the literature. For example, there is a need for more studies that compare the accuracy and reliability of different estimation methods in the context of CFPPs . There is also a need for more research on the site-specific factors that influence SO_2 emission rates and how these factors can be incorporated into estimation methods (Gu et al., 2022b).

This study will contribute to existing knowledge by providing a detailed assessment of SO_2 emission rates from a specific CFPP using standardized calculation methods based on stack parameters and flow characteristics. The study employs fundamental equations that consider molecular weight conversions and volumetric flow rates to determine emission rates. These calculations account for site-specific factors such as stack diameter and exit velocity. The findings will provide insights into the practical application of these calculation methods in the context of an operating CFPP in Botswana, contributing to the broader understanding of emission characterization in similar facilities across developing nations.

2.4.3 Prediction of SO_2 emissions

The second research objective of this study is to predict the ground-level concentration of SO_2, including seasonal and diurnal variation, using the advanced air dispersion modeling tool AERMOD. This objective is essential for understanding the spatial and temporal distribution of SO_2 concentrations in the vicinity of the CFPP and for identifying potential areas of high exposure risk (Cimorelli et al., 2005a).

Air dispersion modelling is a computational technique used to simulate the transport and dispersion of air pollutants in the atmosphere (S. Khan & Hassan, 2021). (Babak et al., 2021a) define air dispersion modelling as the mathematical simulation of how air pollutants disperse in the ambient atmosphere. The EPA describes air dispersion modelling as "the mathematical estimation of pollutant impacts from emissions sources" (EPA, 2024).

Air dispersion modelling is a critical concept in this study because it enables the estimation of SO_2 concentrations at various distances from the coal-fired power plant. By applying air dispersion models, researchers can predict the spatial distribution of SO_2 concentrations and identify areas where exposure levels may exceed health-based standards (Babak et al., 2021b;

van der Walt et al., 2023). This information is essential for assessing the potential health risks associated with SO_2 emissions and developing effective emission control strategies.

Several strands of literature highlight the importance of these concepts in theory, practice, and organizational improvement initiatives. For example, studies have demonstrated the effectiveness of health risk assessment in quantifying the health impacts due to exposure to agents in the air compartment and informing policy decisions (L. Li et al., 2020; Sacks et al., 2020). Additionally, research has shown the effectiveness of air dispersion modelling in predicting contaminant concentrations and identifying areas of concern (Mkhize et al., 2020; Morosele, 2017; van der Walt et al., 2023). These findings underscore the importance of these concepts in consultancy projects aimed at assessing the health risks of SO_2 emissions from a coal-fired power plant and developing recommendations for organizational improvement.

The literature on air dispersion modelling consistently emphasizes the importance of accurate predictions of pollutant concentrations for assessing health risks and informing policy decisions (Cimorelli et al., 2005; Holmes NS & Morawska L, 2006). AERMOD is widely recognized as a state-of-the-art air dispersion model that has been extensively validated and recommended by regulatory agencies for environmental impact assessments (Cimorelli et al., 2005a; EPA, 2017). Studies have demonstrated the ability of AERMOD to accurately predict SO_2 concentrations from CFPPs, considering site-specific meteorological conditions and emission source characteristics (Gibson et al., 2013a).

2.4.4 Air dispersion modelling techniques for assessing SO_2 concentrations

Air dispersion modelling is a widely used technique for assessing the concentrations and spatial distribution of air pollutants, such as sulphur dioxide (SO_2), emitted from various sources, including coal-fired power plants (CFPPs) (Holmes NS & Morawska L, 2006). These models use mathematical algorithms to simulate the transport, dispersion, and transformation of pollutants in the atmosphere, considering factors such as emission rates, meteorological conditions, and topography (Cimorelli et al., 2005a).

One of the most commonly used air dispersion models for assessing SO_2 concentrations is the American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) (Cimorelli et al., 2005). AERMOD is a steady-state plume model incorporating planetary boundary layer turbulence structure and scaling concepts to simulate pollutant dispersion in simple and complex terrain (Cimorelli et al., 2005a). The model has been extensively validated and is recommended by the U.S. Environmental Protection Agency (EPA) for regulatory applications (EPA., 2024).

A study by (Gibson et al., 2013b) used AERMOD to assess the dispersion of SO_2 and other pollutants from a CFPP in Nova Scotia, Canada. The study compared the modelled concentrations with measured data from air quality monitoring stations and found that AERMOD predicted the spatial distribution and magnitude of SO_2 concentrations. The authors concluded that AERMOD could be a valuable tool for assessing the impacts of CFPP emissions on local air quality.

Another commonly used air dispersion model is the California Puff Model (CALPUFF) (Scire et al., 2000). CALPUFF is a non-steady-state puff dispersion model that simulates the transport, dispersion, and transformation of pollutants in time and space (Scire et al., 2000). The model is particularly useful for assessing the long-range transport of pollutants and has been applied to study the impacts of CFPP emissions on regional air quality (J. I. Levy et al., 2002).

A study by (Abdul-Wahab et al., 2011) used CALPUFF to model the dispersion of SO_2 from a CFPP in Oman. The study assessed the influence of different meteorological and emission scenarios on the predicted SO_2 concentrations and found that the model was sensitive to changes in wind speed, wind direction, and emission rates. The authors highlighted the importance of using accurate input data and validating the model results with measured data to ensure the reliability of the predictions.

Other air dispersion models, such as the Community Multi-scale Air Quality (CMAQ) model and the Weather Research and Forecasting model coupled with Chemistry (WRF-Chem), have also been used to assess the impacts of CFPP emissions on air quality (Y. Wang et al., 2014a, 2014b). These models are more computationally intensive than AERMOD and CALPUFF but can provide a more comprehensive assessment of the complex chemical and physical processes that influence pollutant concentrations

The choice of air dispersion model depends on various factors, such as the scale of the assessment (local or regional), the complexity of the terrain, and the availability of input data (Holmes NS & Morawska L., 2006). It is important to recognize the limitations and uncertainties associated with air dispersion modelling and to validate the model results with measured data whenever possible (Holmes NS & Morawska L., 2006).

Over time, there has been a trend towards the use of more advanced and sophisticated air dispersion models, such as AERMOD, that incorporate state-of-the-art algorithms and can handle complex terrain and meteorological conditions. This trend has been driven by the need for more accurate and reliable predictions of pollutant concentrations to support health risk assessments and policy decisions . Additionally, there has been a growing recognition of the importance of considering seasonal and diurnal variations in pollutant concentrations, as these variations can significantly impact exposure patterns and health risks (Grivas et al., 2018).

A recurring theme in the literature is the need for accurate and reliable predictions of pollutant concentrations to support health risk assessments and policy decisions (Cimorelli et al., 2005a; Holmes NS & Morawska L, 2005. Another theme is the importance of considering site-specific factors, such as meteorological conditions and emission source characteristics, when modeling pollutant dispersion (Gibson et al., 2013c).

There is some debate in the literature regarding the accuracy and reliability of different air dispersion models, including AERMOD. While AERMOD is widely recognized as a state-of-the-art model, some studies have identified limitations and uncertainties associated with its use, particularly in complex terrain and under certain meteorological conditions (Snoun et al., 2023). There is also some disagreement about the extent to which model predictions should be relied upon for decision-making, given the inherent uncertainties associated with modeling (Clench-Aas & Holte, 2018).

A pivotal publication in this field is by (Cimorelli et al., 2005a), which introduced AERMOD and demonstrated its ability to accurately predict pollutant concentrations under a range of conditions. This study laid the groundwork for the widespread adoption of AERMOD in environmental impact assessments and regulatory decision-making. Another influential study is that of (Perry et al., 2005), which provided a comprehensive evaluation of AERMOD's performance and validated its use for modelling SO_2 dispersion from CFPPs.

Despite the extensive research on air dispersion modelling using AERMOD, there are still some gaps in the literature. For example, there is a need for more studies that evaluate the performance of AERMOD in predicting SO_2 concentrations from CFPPs under a range of site-specific conditions, including different terrain types and meteorological conditions. There is also a need for more research on the uncertainties associated with AERMOD predictions and how these uncertainties can be quantified and communicated to decision-makers (Clench-Aas & Holte., 2018).

This study will contribute to existing knowledge by providing a comprehensive assessment of SO_2 concentrations in the vicinity of a CFPP using AERMOD, taking into account seasonal and diurnal variations. By evaluating the performance of AERMOD under site-specific conditions and comparing model predictions with observed data, the study will provide valuable insights into the accuracy and reliability of AERMOD for predicting SO_2 concentrations from CFPPs. The findings of this study will help to inform the use of AERMOD in future environmental impact assessments and will contribute to the development of more effective strategies for mitigating the health risks associated with SO_2 emissions from CFPPs.

2.4.5 Health risk assessment of SO_2 emissions

The third research objective of this study is to assess the health risks for the populace residing in the surrounding area of the CFPP in Palapye, Botswana. This objective is crucial for understanding the potential impacts of SO_2 emissions from the CFPP on public health and developing effective strategies to mitigate these risks (Mannucci & Franchini., 2017).

Health risk assessment is a systematic process used to estimate the potential adverse health effects of exposure to environmental hazards (Budi et al., 2024). The National Research Council (NRC) defines health risk assessment as "the characterization of the potential adverse health effects of human exposures to environmental hazards" (Flick., 2020). The EPA describes health risk assessment as "a process to estimate the nature and probability of adverse health effects in humans who may be exposed to chemicals in contaminated environmental media, now or in the future" (EPA., 2020).

Health risk assessment is critical in this study because it provides a framework for quantifying the potential health impacts of SO_2 emissions from coal-fired power plants on nearby populations. Through conducting a health risk assessment, policymakers and public health professionals can make informed decisions about the need for emission control measures and develop targeted interventions to protect public health (Sacks et al., 2020).

The literature on health risk assessment for populations living far-field to CFPPs consistently emphasizes the importance of considering multiple exposure pathways, including inhalation, ingestion, and dermal contact (Peng et al., 2019; Wilkie et al., 2023). Studies have demonstrated that SO_2 emissions from CFPPs can have significant impacts on respiratory health, particularly among vulnerable populations such as children and the elderly (Liu et al., 2018; Perera, 2017). The literature also highlights the importance of considering cumulative risk and synergistic effects of multiple pollutants, as well as the role of socioeconomic factors in modifying health risks (Moreno-Jiménez et al., 2016; H. Wang et al., 2019).

2.4.6 Health Risk Assessment Methodologies for Quantifying the Impact of SO_2 Emissions on Public Health

Health risk assessment is a systematic process used to estimate the potential adverse health effects of human exposure to environmental hazards, such as sulphur dioxide (SO_2) emissions from coal-fired power plants (CFPPs) (NRC., 2009). Various methodologies have been developed to quantify the health risks associated with SO_2 exposure, ranging from simple screening methods to more complex probabilistic approaches (WHO., 2021).

There are methods used for assessing the health risks of SO_2 exposure such as the use of concentration-response functions (CRFs) derived from epidemiological studies (Huang et al., 2012). CRFs describe the relationship between pollutant concentrations and the incidence of specific health outcomes, such as respiratory mortality or hospital admissions (Huang et al., 2012). By combining CRFs with estimated SO_2 concentrations from air dispersion modeling, researchers can quantify the potential health impacts of CFPP emissions on exposed populations (Shende et al., 2024).

A study by (Shende et al., 2024; Xu & Yang, 2020) used CRFs to estimate the health risks associated with SO_2 emissions from CFPPs in Beijing, China. The study combined SO_2 concentration data from air quality monitoring stations with CRFs for respiratory mortality and morbidity to calculate the excess risk attributable to SO_2 exposure. The results showed that SO_2 emissions from CFPPs could contribute significantly to the overall health burden in Beijing, particularly among vulnerable populations such as children and the elderly.

Another approach to health risk assessment is the use of disability-adjusted life years (DALYs) to quantify the burden of disease attributable to SO_2 exposure (Owusu & Sarkodie, 2020). DALYs are a measure of the years of healthy life lost due to premature mortality and disability caused by a specific risk factor (Owusu & Sarkodie., 2020). By calculating the DALYs associated with SO_2 exposure, researchers can compare the health impacts of CFPP emissions with other environmental and public health risks (Cohen et al., 2017a).

A study by (Cohen et al., 2017b) used the DALY approach to assess the global burden of disease attributable to coal combustion, including SO_2 emissions from CFPPs. The study estimated that in 2015, coal combustion was responsible for 2.9 million DALYs lost due to SO_2 exposure, with the majority of the burden occurring in low- and middle-income countries.

The authors highlighted the need for more stringent emissions controls and the transition to cleaner energy sources to reduce the health impacts of CFPPs.

Probabilistic risk assessment methods, such as Monte Carlo simulation, have also been used to quantify the health risks of SO_2 exposure (Hwang et al., 2017). These methods allow researchers to incorporate uncertainty and variability in the input parameters, such as pollutant concentrations and exposure durations, to generate a distribution of potential health risks (Hwang et al., 2017). By using probabilistic methods, researchers can provide a more comprehensive assessment of the health risks associated with CFPP emissions and identify the key factors that influence the magnitude and distribution of these risks.

A study by (Hwang et al., 2017) used a probabilistic approach to assess the health risks of SO_2 emissions from a CFPP in South Korea. The study combined air dispersion modelling with Monte Carlo simulation to estimate the distribution of excess cancer risks and non-cancer hazard indices associated with SO_2 exposure. The results showed that the health risks varied significantly depending on the location and characteristics of the exposed population, with some individuals facing risks above acceptable levels.

The choice of health risk assessment methodology depends on various factors, such as the availability and quality of input data, the specific health outcomes of interest, and the level of uncertainty and variability in the exposure and response parameters (WHO., 2021). It is important to recognize the limitations and uncertainties associated with each approach and to interpret the results in the context of the study's assumptions and constraints (WHO, 2021).

A recurring theme in the literature is the need for comprehensive and context-specific health risk assessments that consider the unique characteristics of local populations and environments (H. Wang et al., 2019; Wilkie et al., 2023). Another theme is the importance of engaging local communities in the risk assessment and incorporating their knowledge and perspectives (Adgate et al., 2014; Moreno-Jiménez et al., 2016).

There is some debate in the literature regarding the most appropriate methods for assessing health risks associated with CFPP emissions, particularly in low- and middle-income countries where data and resources may be limited (Radford et al., 2021). Some studies have relied on simplified exposure assessment methods, such as proximity-based approaches, while others have used more complex dispersion modelling and exposure assessment techniques (Liu et al., 2017; Peng et al., 2019). There is also some disagreement about the relative importance of different exposure pathways and the role of socioeconomic factors in modifying health risks (H. Wang et al., 2019).

One pivotal publication in this field is the study by, which provided a comprehensive framework for assessing health risks associated with CFPP emissions, considering multiple exposure pathways and the complex interplay between environmental, social, and economic factors. This study has influenced subsequent research and has highlighted the need for more integrated and context-specific approaches to health risk assessment. Another significant study by (Adgate et al., 2014) demonstrated the value of community-based participatory research methods in assessing health risks associated with industrial emissions.

Despite the growing body of research on health risks associated with CFPP emissions, there are still some gaps in the literature. For example, there is a need for more studies that assess health risks in low- and middle-income countries, where CFPPs are increasingly common, but data and resources may be limited (Morosele., 2017). There is also a need for more research on the cumulative and synergistic effects of multiple exposure stressors, as well as the role of socioeconomic factors in modifying health risks (Moreno-Jiménez et al., 2016; Wang et al., 2019).

This study will contribute to existing knowledge by providing a comprehensive assessment of health risks associated with SO_2 emissions from a CFPP in Botswana. In this middle-income country, CFPPs are increasingly common, but health risks are not poorly understood. This study's findings will help inform the development of effective strategies for mitigating health risks associated with CFPP emissions in Botswana and other similar contexts.

2.5 Research Gaps

Despite the extensive research on the health risks associated with SO_2 emissions from coal-fired power plants (CFPPs), several gaps in the literature still need to be addressed. These gaps provide opportunities for further research and highlight the importance of conducting context-specific studies to understand the impacts of SO_2 emissions on public health.

One significant gap in the literature is the lack of studies conducted in low- and middle-income countries, particularly in sub-Saharan Africa (Morosele., 2017). While there is a growing body of research on the health impacts of CFPP emissions in developed countries, there is limited evidence from developing nations where CFPPs are increasingly common, but resources for monitoring and regulating emissions may be limited (Mannucci & Franchini., 2017). This gap is particularly relevant for the current study, which focuses on a CFPP in Botswana, a middle-income country in sub-Saharan Africa.

Another gap in the literature is the need for more comprehensive health risk assessments that consider multiple exposure pathways and the complex interplay between environmental, social, and economic factors (Wilkie et al., 2023; Wang et al., 2019). Many existing studies have focused solely on inhalation exposure, which may underestimate the health risks associated with CFPP emissions (Peng et al., 2019). Additionally, few studies have examined the cumulative and synergistic effects of multiple pollutants or the role of socioeconomic factors in modifying health risks (Moreno-Jiménez et al., 2016; Wang et al., 2019). This study aims to address these gaps by conducting a comprehensive health risk assessment that considers multiple exposure pathways and incorporates socioeconomic factors.

A third gap in the literature is the limited engagement of local communities in the health risk assessment process (Adgate et al., 2014). Many studies have relied on expert-driven approaches that may not adequately capture affected populations' knowledge, perspectives, and concerns (Moreno-Jiménez et al., 2016).

Finally, there is a need for more research on effective strategies for mitigating the health risks associated with SO_2 emissions from CFPPs, particularly in low- and middle-income countries (Yudhistira Adhinegara., 2024.). While some studies have examined the effectiveness of various emission control technologies and regulatory approaches (Liu et al., 2018; Peng et al., 2019), there is limited evidence on the feasibility and acceptability of these strategies in resource-constrained settings. This study aims to contribute to this gap by providing recommendations for mitigating health risks tailored to the specific context of Botswana and other similar countries.

By addressing these research gaps, this study will contribute to the growing body of knowledge on the health risks associated with SO_2 emissions from CFPPs and provide valuable insights for policymakers, public health professionals, and affected communities. The findings of this study will help to inform the development of effective strategies for monitoring, regulating, and mitigating the health impacts of CFPP emissions in Botswana and other low- and middle-income countries.

2.6 Chapter Conclusion

This chapter has comprehensively reviewed the literature related to the health risk assessment of sulphur dioxide (SO_2) emissions from coal-fired power plants (CFPPs). The review has covered key concepts, studies, and methodologies relevant to the study, including the exposure-response study (Fu et al., 2024b), the air pollution health effects theory (Manisalidis et al., 2020), and the principles of health risk assessment (NRC, 2009). The literature has consistently highlighted the potential for significant health risks associated with exposure to SO_2 emissions from CFPPs, particularly for vulnerable populations such as infants, children, the elderly, and those with underlying respiratory conditions (Liu et al., 2018; Perera, 2017).

The review has also identified several research gaps that this study aims to address. These gaps include the limited number of studies conducted in low- and middle-income countries, particularly in sub-Saharan Africa (Radford et al., 2021) the need for more comprehensive health risk assessments that consider multiple exposure pathways and the complex interplay between environmental, social, and economic factors (H. Wang et al., 2019; Wilkie et al., 2023) and the limited engagement of local communities in the risk assessment process (Adgate et al., 2014).

The conceptual framework for this study has been developed based on integrating key concepts and theories from the literature, and it incorporates the variables of interest, including SO_2 emissions from the CFPP, ambient SO_2 concentrations, and estimated health risks for the exposed population. The framework also considers the influence of confounding variables, such as meteorological conditions and demographic characteristics of the exposed population (H. Wang et al., 2019; Wilkie et al., 2023).

Thereby addressing the identified research gaps and applying the conceptual framework, this study aims to contribute to the growing body of knowledge on the health risks associated with SO_2 emissions from CFPPs and provide valuable insights for policymakers, public health professionals, and affected communities in Botswana and other low- and middle-income countries. This study's findings will help inform the development of effective strategies for monitoring, regulating, and mitigating the health impacts of CFPP emissions in these settings.

This literature review has provided a solid foundation for understanding the current state of knowledge regarding the health risks associated with SO_2 emissions from CFPPs. It has identified key areas where further research is needed. The subsequent chapters of this dissertation will build upon this foundation by presenting the methodology, results, and implications of the health risk assessment conducted for the CFPP in Palapye, Botswana.

CHAPTER 3: METHODOLOGY

3.1 Study Design

A cross-sectional study design will be used, and a health risk assessment will be conducted for communities in the vicinity of the CFPP at a single point. This study design is particularly suitable for assessing the potential environmental and public health impacts of pollutant emissions, as it allows for a snapshot of the exposure levels at a specific point in time, capturing the possible worst-case scenarios (Meo et al., 2024b). Cross-sectional studies are advantageous in environmental health research because they are time-efficient and resource-effective, providing a basis for future longitudinal studies if significant risks are identified (Kanada et al., 2013).

3.2 Study Population

This study does not involve direct participation of human or animal subjects. It relies on hypothetical reference values/data for infants, children, and adults per the (US Environmental Protection Agency, 2019). The decision to rely on hypothetical data is aligned with the precautionary principle in environmental health, where the aim is to assess potential risks without direct human exposure. This approach ensures that ethical standards are upheld, avoiding unnecessary risks to vulnerable populations such as infants and children.

3.3 Study Site Description

Morupule B Power Station is located 10 km northwest of Palapye village, in the Central District of Botswana. Adjacent to the MBPS is Morupule Coal Mine (MCM), which supplies the power plant with coal. MBPS (600 MW) comprises four units, each with a capacity of 150 MW. Along with Morupule A Power Station (MAPS), both power plants are domestic sources of coal-generated electricity in Botswana. The geographical location of the power plant confines to 945 m above mean sea level at latitude 22°31’37’’S and longitude of 27°02’09’’E. Palapye village is a growing town with a population of 52 636, located southeast Morupule B Power Station (Statistics Botswana., 2021). From MBPS and MAPS, there is a privately owned primary school within a distance of approximately 1 km. Further westerly, the MCM residential area is about 2 km beyond Morupule Coal Mine (MCM). Around the CFPPs, MCM are arable and pastoral lands mainly for subsistence farming. Other vital information for MBPS (Table 1). The selection of Morupule B Power Station as the study site is strategic due to its proximity to growing communities and vital infrastructure, such as schools and residential areas, which could be impacted by pollutant emissions (Maswabi et al., 2021). The geographic and demographic characteristics of Palapye village make it an ideal location to assess the potential health risks posed by the CFPP emissions, as the village's population may be particularly vulnerable due to its rapid growth and proximity to the power station (Atilgan & Azapagic, 2016).

Table 2: Parameters for parameterising the air dispersion model

Parameters	**Specifications**
Capacity (MW)	600 MW
Number of Stacks (with 02 chimneys each)	02
Height of Stacks	150 m
Diameter of each chimney	3.65 m
Average Exiting Velocity	28 m/s
Average Temperature	135 ^{0}C

3.3.1 Sensitive/discrete receptors

A sensitive receptor is defined as a place or human subject involuntarily exposed to air stressors from an active source. Table 3 shows the sensitive receptors that were used for modeling.

Table 3: Sensitive Receptors

Receptor ID	**Description**	**UTM Coordinates (35S)**		**Elevation**
		X (m)	**Y (m)**	**Y (m)**
SR1	School	510455	7507186	931.14
SR2	School	514121	7507539	926.52
SR3	School	510616	7505119	931.26
SR4	School	508886	7505424	936.66
SR5	School	511557	7508222	932.14
SR6	School	514587	7507677	926.07
SR7	School	513749	7507809	927.54
SR8	School	509040	7504474	945.25
SR9	School	511821.22	7501989.8	981.6
SR10	School	513088	7508845	931.52
SR11	School	513098	7508663	931.29
SR12	School	513605	7508334	928.33

SR13	School	513474	7508457	927.6
SR14	School	512752.53	7507432.3	929.27
SR15	Health Care	513492	7506054	925.28
SR16	Play Ground	514031	7506830	925.06
SR17	Play Ground	510510.78	7505825.4	922.39
SR18	School	513765.71	7505272	920.98
SR19	School	511535.41	7505427.6	924.76
SR20	School	511779.97	7508156	932.53
SR21	School	513708.9	7506141.4	926.83
SR22	Health Care	511578.78	7505753.3	923.75
SR23	Health Care	512766.43	7508252	930.68
SR24	Health Care	510486.73	7507052.2	929.49
SR25	Health Care	509497.6	7507280.2	932.52
SR26	Health Care	510868.58	7506783.6	928.4
SR27	Health Care	510519.21	7506882.1	929.78
SR28	Health Care	509389.87	7507240.2	934.65
SR29	Health Care	513198.09	7505791.6	924.21
SR30	Health Care	510784.68	7506972.5	928.75
SR31	Health Care	513478.99	7505561.8	921.85
SR32	Health Care	508304.81	7504980.8	932.86
SR33	Health Care	513774.13	7505622.6	922.21
SR34	Health Care	509241.71	7508086.7	935.75
SR35	School	512452.84	7507687.1	929.16
SR36	School	512476.67	7510654.1	934.67
SR37	School	512626.13	7507967.8	929.52
SR38	School	512307.9	7506770.7	926.36
SR39	School	512914.91	7507732.6	927.47
SR40	Health Care	508961.2	7504685.6	942
SR41	Church	513649.86	7505323.6	919.97
SR42	Church	513911.95	7506195.1	924.9
SR43	Church	511794.09	7506124.6	921.03
SR44	Church	511918.97	7506456.6	927.14
SR45	Church	513082.41	7505685	924.23
SR46	Church	514041.73	7506296.4	925.1
SR47	Church	513706.22	7505130.6	916.4
SR48	Church	510123.91	7507451.2	933.46
SR49	Church	514175	7506036	922.93
SR50	Church	512215	7505012	924.66

3.4 Sampling/Monitoring Instruments

The CFPP has SICK Automation equipment installed in the stacks to measure various pollutants before they are released into the environment. The following instruments are used to measure variables:

a. FW 300 – Dust Concentration Monitor.
b. GM 32 – In-situ Gas Analyser.
c. GM 901– Carbon monoxide Measuring Device
d. ZR22G, ZR402G Zirconia – Oxygen Analyser
e. SMC 222 – Pitot Tube Flow Meter

3.4.1 GM 32 – In-situ Gas Analyser

The GM 32 insitu gas analyser will continuously monitor stack emissions of SO_2 from the power plant. The product can be identified using the information provided in Table 2.

Table 4: GM32 product identification

Product Name	GM 32
Product Variant	Version with measuring probe
Manufacturer	SICK MAIHAK, Nimburger Str. 11 79276 Reute- Germany
Location of type plates	SR-unit: On the right and in the intermediate housing GMP probe: On the purge air fixture GPP probe: On the flange attachment

The GM 32 Gas Analyser provides continuous readings of gas concentration. It is an in-situ measuring system performed directly in the stack. It components for SO_2, NO_x, NO_2, NH_3, temperature and pressure using Differential Optical Absorption Spectroscopy (DOAS) principle. The GM32 periodically performs an automated zero and reference check cycle, and full calibration using certified calibration gases is done on a quarterly interval. The suitability of the GM 32 Gas Analyser for continuous monitoring of SO_2 emissions is supported by its proven accuracy and reliability in high-stakes industrial environments (Kanada et al., 2013). The in-situ measurement technique, which allows for real-time data collection directly in the stack, ensures that the data reflects actual operating conditions, providing a robust basis for subsequent air quality modeling and risk assessments (Amoatey et al., 2019).

3.5 Data Sampling

3.5.1 Measurement of Flue Gas and Estimation of Emission Rates

The CFPP is currently undertaking measurements of stack emission rates to compare with World Bank standards and relevant national legislation, including the Atmospheric Pollution Prevention Act of 1971. This legislation is augmented by the Environmental Impact Assessment (EIA) Act of 2010, BOS 498:2012 Ambient Air Quality - Limits for Common Pollutants, published by the Botswana Bureau of Standards. Criteria pollutants, including oxides of nitrogen (NO_x), sulphur dioxide (SO_2), carbon monoxide (CO) and carbon dioxide (CO_2), are measured daily using flue gas analysers. Average emission rates will be used as source input data in the model. The rigorous approach to measuring and estimating emission rates is critical for ensuring that the data used in the air dispersion model accurately reflects the potential environmental impact of the CFPP (Sarkodie & Adams., 2020a). Compliance with international and national standards guarantees that the emission data applied in the dispersion model are scientifically valid and adhere to regulations, therefore strengthening the integrity and dependability of the health risk assessment, as highlighted by (Mokhtar et al., 2014).

3.5.2 Emission Rates

USEPA, AP-42, 'Compilation of Air Pollutant Emissions Factors from Stationary Sources' (Aul & Pechan., 1993) developed a variety of emission factors based on coal firing conditions.

The general equation for emission estimation is:

$$E = A \; x \; EF \; x \; (1 - \frac{ER}{100}) \qquad \text{Equation (1)}$$

where:

E = emissions,

A= activity rate,

EF = emission factor, and

ER = overall emission reduction efficiency, %.

USEPA further defines ER as the product of the control device destruction or removal efficiency and the capture efficiency of the control system.

Emission factors in this study can be derived by dividing the emission load by the activity data as follows in Equation (2) (Triani et al., 2024b):

$$EF = 1 + \frac{E}{A} = \frac{\substack{SO2\ emission\ load \\ from\ CEMS\ data\ \frac{g}{Year}}}{Coal\ Use\ \frac{kg}{Year}} = \frac{(SO2)g}{Coal\ (Kg)}$$

3.5.3 AERMOD Dispersion Model Parameterisation

An air quality dispersion model, AERMOD, will investigate emissions dispersion and ground-level concentrations at receptor grids over a 20 km x 20 km model domain for three years (January 2019 – December 2021). This study will model the dispersal pattern of SO_2 and NO_x for 1-hour, 24-hour, and yearly averaging periods near the CFPP.

The inputs for the AERMOD dispersion model include wind direction and speed, temperature profiles, mixing depth, plume characteristics, turbulence parameters, and level of urbanisation (Hossain et al., 2020). Before these parameters are input into AERMOD, meteorological and terrain pre-processors (AERMET and AERMAP) will be employed to format the data. AERMET utilises meteorological data and surface characteristics to calculate boundary layer parameters and generates surface and profile data output files (Hossain., 2019). Surface characteristics (e.g. Bowen ratio, albedo, and surface roughness), and basic meteorological observations (e.g. wind speed and direction, temperature, humidity and cloudiness), are required as input data into AERMET.

On the other hand, AERMAP employs gridded terrain data to determine a representative terrain-influence height or terrain height scale (Hossain et al., 2020). The terrain height scale for each receptor location calculates the separating streamline height. AERMET provides the gridded data required in AERMAP for determining terrain height scale. AERMAP then creates a suitable control file for input into AERMOD. The use of AERMOD for dispersion modelling is justified by its widespread acceptance and validation as a reliable tool for predicting pollutant concentrations under varying environmental conditions (Hossain et al., 2020). The model's ability to account for complex terrain and meteorological conditions makes it particularly suitable for this study, which involves assessing pollutant dispersion over a large and varied area (Amoatey et al., 2019). The long-term modelling period (three years) provides a comprehensive understanding of emission patterns, allowing for a more accurate assessment of potential health risks (Edlund et al., 2021).

3.5.4 Input Data Requirements for AERMOD

AERMOD models atmospheric processes and estimates pollutant concentrations over a defined modeling domain. As emissions disperse in the atmosphere, they undergo physical and chemical changes that can impact the environment and public health. To accurately predict pollution levels and mitigate their effects, the following data will be required:

3.5.4.1 Source Data

The study will collect SO_2 emission rates, flue gas temperature, stack height, and stack diameter from the CFPP stacks. These parameters will be recorded as hourly averages using the plant's continuous emissions monitoring system (CEMS) (US EPA., 2021). To ensure data quality, the researchers will implement regular calibration checks and data validation procedures as recommended by the US EPA (2019).

3.5.4.2 Terrain Data

The researcher will utilize Shuttle Radar Topography Mission (SRTM) data at 30m resolution for topographic information (Farr et al., 2007). Land use categories will be determined using a combination of satellite imagery and local land use maps provided by the Botswana Department of Surveys and Mapping. The Bowen ratio, albedo, and surface roughness will be estimated using the AERSURFACE tool, which processes land cover data to derive these parameters (US EPA., 2020).

3.5.4.3 Receptor Data

A nested receptor grid will be employed, with a 100m x 100m Cartesian grid within 5km of the source and a 500m x 500m grid from 5-10km. The researchers will identify sensitive receptors, including schools, hospitals, and residential areas, using local government data and verify them through site visits. Elevation data for receptors will be extracted from the SRTM dataset to ensure consistency with the terrain data (Cimorelli et al., 2005).

3.5.4.4 Meteorological Data

Hourly meteorological data will be obtained from the nearest weather station operated by the Botswana Meteorological Services. Upper air soundings will be sourced from the closest radiosonde station. In cases of missing data, the team will apply the US EPA's recommended data substitution methods (US EPA., 2000). Before input into AERMET, data will undergo quality assurance checks and formatting as per AERMOD requirements.

3.5.4.5 Additional Considerations

The urban/rural classification of the modeling domain will be determined using population density data from the Botswana Statistics Office. Building downwash effects will be considered using the BPIPPRM tool, with building dimension data obtained from local planning offices and satellite imagery analysis (Cimorelli et al., 2005). Background SO_2 concentrations will be estimated using data from the nearest air quality monitoring station, applying appropriate temporal and spatial interpolation methods as needed (US EPA., 2018).

3.5.4.6 Data Processing and Model Setup

The research team will use AERMET and AERMAP to process meteorological and terrain data, respectively. Quality control procedures, including range checks and internal consistency tests, will be implemented during data processing (US EPA, 2021). The study will utilize AERMOD version 21112, employing regulatory default options to ensure compliance with standard modeling practices (US EPA, 2021).

Table 5: Type of data and data requirements for input into AERMOD

Type of Data	**Data Requirements**
Source data	Data collected at the stacks of the CFPP, type of source (point, area, line), emission rates, gas exit velocity, and stack details.
Terrain data	Topographic and land cover data are prerequisites in AERMET to create wind profile fields and supplementary meteorological data, including Bowen ratio, albedo, surface roughness, terrain categories, land use categories, vegetation leaf area index, etc. Terrain altitudes can affect the spreading and deposition of pollutants, subsequently estimating potential public health and environmental risks.
Receptor data	AERMOD supports a variety of receptors, including cartesian receptor grids, polar receptor grids, multi-tier grids, fenceline receptors, and discrete and sensitive receptors.

Meteorological data	These include meteorological and synoptic measurable parameters. The wind speed, wind direction, relative humidity, temperature, cloud cover, surface roughness length etc influence the pollutant levels in ambient air.

The thorough consideration of various input data requirements for AERMOD underscores the complexity and accuracy of the modeling process (Hossain., 2019). Each data type, from source data to meteorological parameters, plays a crucial role in ensuring that the model's outputs are reliable and reflective of actual environmental conditions. By carefully parameterizing the model with accurate and relevant data, the study can provide a robust basis for subsequent risk assessments and policy recommendations (Fazakas et al., 2024b)

3.5.5 Model Assumptions

The following modelling assumptions will be made:

- The power plant operates twenty-four hours a day and 365 days a year.
- Operations are at maximum capacity (100% load) to represent the worst-case scenario.
- Source emission rates are continuous and constant for twenty-four hours all year round.
- CFPP stack is modelled as a point source.
- All the pollutants are emitted into the atmosphere without deposition.
- Normal distribution for pollutant dispersion in vertical and horizontal directions.
- Steady-state conditions for modelling intervals, with the plume distributed in the direction of the specified synoptic meteorology in a straight line.

Emission factors from the dispersion modelling will be used to charaterise the health risks associated with exposure to SO_2 in communities proximate to the power station. The assumptions made in this model are designed to simulate the worst-case scenarios, thereby providing a conservative estimate of potential health risks (Atilgan & Azapagic., 2016). These assumptions, while simplifying complex real-world dynamics, ensure that the model's predictions are on the side of caution, thereby serving as an early warning system for potential environmental and health impacts (Sarkodie & Adams., 2020b).

3.6 Human Risk Assessment

The health risk assessment methodology for this study will be adopted from studies by US Environmental Protection Agency., 2019. According to the US Environmental Protection

Agency., 1991), human risk assessment comprises four phases: hazard identification, exposure assessment, dose-response assessment, and risk characterisation.

The following parameters were assumed for the different sub-population groups in the community:

Table 6: Characteristics of each sub-population group considered in this study

Population sub-group	**Age**	**Exposure Time (hrs/day)**	**Exposure frequency (days/year)**
Infants	0 – 5 years	18	350
Children	6 – 17 years	20	350
Elderly	+ 65 years	22	350

3.6.1 Hazard Identification

The criteria pollutants from the CFPP include CO, NO_x, SO_2, PM and trace elements. However, only SO_2 will be considered in this study as the CFPP does not have stack monitoring data for PM and trace elements.

3.6.2 Dose-Response Data

Dose-response data are needed to assess the relationship between a particular dose and adverse health effects. The negative health effects are divided into carcinogenic and non-carcinogenic. The inhalation reference concentration (RfC) and reference dose (RfD) characterise the dose and response for non-carcinogenic effects. In the absence of RfC, chronic daily doses (CDI) from ambient air concentrations can be used and are estimated using the equation below:

$$CDI_{inhalation} = (C \text{ x } CF \text{ x } IR \text{ x } EF \text{ x } ED) / (BW \text{ x } AT) \qquad \text{Equation 3}$$

where C is the concentration in $\mu g/m^{-3}$, CF is the conversion factor in mg/μg; IR refers to the inhalation rate given in m^3/day, EF is the exposure frequency in days/year; ED is the exposure duration in years; AT is the averaging time (period over which exposure is averaged, usually lifetime) and is given in years; and BW is body weight in kg (i.e. 70 kg for man and 65kg for women).

This approach assumes that the exposure route is inhalation and that the exposure is constant yet continuous.

3.6.3 Exposure Assessment

This study will analyse people's exposure within a 10 km radius of the power station to SO_2. AERMOD will predict hourly, 8-hr, 24-hr, and annual mean pollutant concentrations. These values will be applied as input data to evaluate the adverse health effects of the selected pollutants (Shaikh et al., 2018). Field concentrations are adjusted for activity patterns using Equation 2.

$$C_{air\_adj} = C_{air} \text{ x } (ET/24) \text{ x } (EF/365) \text{ x } (ED/AT) \qquad \text{Equation 4}$$

where C_{air} is the field annual average concentrations in ($\mu g/m^{-3}$); ET is the number of hours exposed per day and is given in hours/day; EF is the exposure frequency in days/year; ED is the exposure duration in years; and AT is the averaging time (period over which exposure is averaged, usually lifetime (LT).

For assessing non-cancer risks, especially those posed by chronic exposure to SO_2, AT is equivalent to ED. For chronic assessments (e.g., cancer), the potential lifetime average daily dose (LADD) is calculated in which lifetime (LT, in days) (or life expectancy) is substituted for AT.

3.6.4 Risk Assessment

Non-cancer health risks will be stated as unitless hazard quotients (HQ)

$$HQ = C_{air\_adj}/C_{RfC} \qquad \text{Equation 5}$$

where C_{air_adj} is the adjusted exposure concentration (e.g., annual average SO_2 concentration from dispersion modelling) and C_{RFC} is the reference concentration or ambient air quality standard/ guideline (e.g. Botswana guidelines). If the HQ is less than one ($HQ < 1$), then the concentration is considered to be less than the RfC value, and as such, no action is required as this is considered safe (Shaikh et al., 2018). If HQ is greater than one, the potential risk of an adverse health outcome is increased, and action is required to bring the exposure to safe levels. However, it should be noted that an HQ >1 does not imply an adverse effect but, more appropriately, a warning of potential risk (Shaikh et al., 2018; USEPA., 2002).

3.7 Quality Control

Data will be manually drawn from the MBPS's continuous emissions monitoring system (CEMS). The system can store many months of data; therefore, data will be manually into a personal computer, and a backup will be saved into an external drive, which will be kept safely in a locked cabinet. The CEMS is serviced and calibrated annually.

3.8 Ethics

Ethical waiver (W-PR-240527-02) for this study will be requested from the University of the Witwatersrand's Ethics Review Committee (ERC) since the study does not involve human or animal subjects. Additionally, formal permission to conduct the study will be requested from the management of Botswana Power Corporation.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and discusses the results of the SO_2 emissions analysis and health risk assessment conducted at the Morupule B Power Station. The findings are organized according to the three main research objectives outlined in Chapter 2: (1) estimation of SO_2 emission rates, (2) prediction of ground-level SO_2 concentrations using AERMOD, and (3) assessment of health risks for the surrounding population. The results are interpreted within the theoretical frameworks established in the literature review, particularly the exposure-response theory (Li et al., 2024) and air pollution health effects theory (Manisalidis et al., 2020).

4.2 SO_2 emission rates

The accurate determination of SO_2 emission rates is fundamental to understanding the potential health impacts of the power station's operations, as highlighted in the framework (Section 2.3). The emission rates of SO_2 have been calculated using the emission factors from AP-42 manual for external combustion sources communicated by USEPA (Section-2.3). The emission rates are subjected to emission control technologies, characteristics of coal, and rate of coal consumed per day.

Table 7: Calculated SO_2 emission rates

Parameter	**Value/Specification**
Sulphur content in Coal	0.77 – 0.97%
Coal consumption (per unit of four)	1600t/day (per unit)
Efficiency of SO_2 removal	90 -98%

Data provided above, indicates an estimated SO_2 emission rate of 1.67 tonnes/day per unit (from a total of four units), which shows effective management of sulphur emissions. With a coal consumption rate of 1600 tonnes per day per unit (at full capacity) and a sulphur content ranging between 0.77% and 0.97%, the calculated SO_2 emissions must be considered in light of the high SO_2 removal efficiency of 90-98%. This impressive removal efficiency contributes significantly to lowering the overall SO_2 emissions from the CFPP. The resulting concentration of 92.77 mg/Nm³ per day is indeed well below the regulatory limit of 500 mg/Nm³ stipulated by BOS 498:2012, demonstrating compliance with environmental standards. This result reflects the corporation's commitment towards mitigating air pollution and supporting sustainable operations by effectively managing sulfur emissions through advanced technologies or practices.

4.3 Meteorological characteristics in the modeling domain

The characterization of local meteorological conditions is crucial for understanding pollutant transport and dispersion patterns, as established in the theoretical framework (Section 2.3.2). The analysis focuses on wind patterns as primary determinants of SO_2 dispersion and potential exposure zones.

To accurately simulate the dispersion of air contaminants and estimate their impact on air quality, meteorological features in a modeling domain are essential (U.S. EPA, 2005). Precipitation, temperature, and wind are critical meteorological factors (EPA, 2024). Wind speed influences pollutant dispersion; more dispersion is typically the result of higher wind speeds (Jacobson., 2005). The direction of the wind affects where pollutants may be deposited and shapes the path of pollution plumes (Michaud et al., 2010). Pollutant vertical migration is influenced by surface temperature, which also affects air density and stability (Seinfeld JH & Pandis SN., 2016). Pollutant accumulation is impacted by temperature inversions, which occur when a layer of warm air traps cooler air near the surface (Oke TR., 1987). In addition to influencing surface moisture and temperature, precipitation levels impact pollutant concentrations through washouts (EPA., 2015).

4.3.1 Local Wind Roses

Analyzing local wind fields is fundamental to understanding pollutant transport mechanisms and potential exposure patterns. Wind speed and direction data provide critical inputs for dispersion modeling and exposure assessment. Figures 1, 2 and 3 show wind roses for the years 2021–2023.

Figure 1 shows four wind rose plots for the (a) 2021 – 2023, (b) 2021, (c) 2022, and (d) 2023 periods, displaying wind speed and direction distributions.

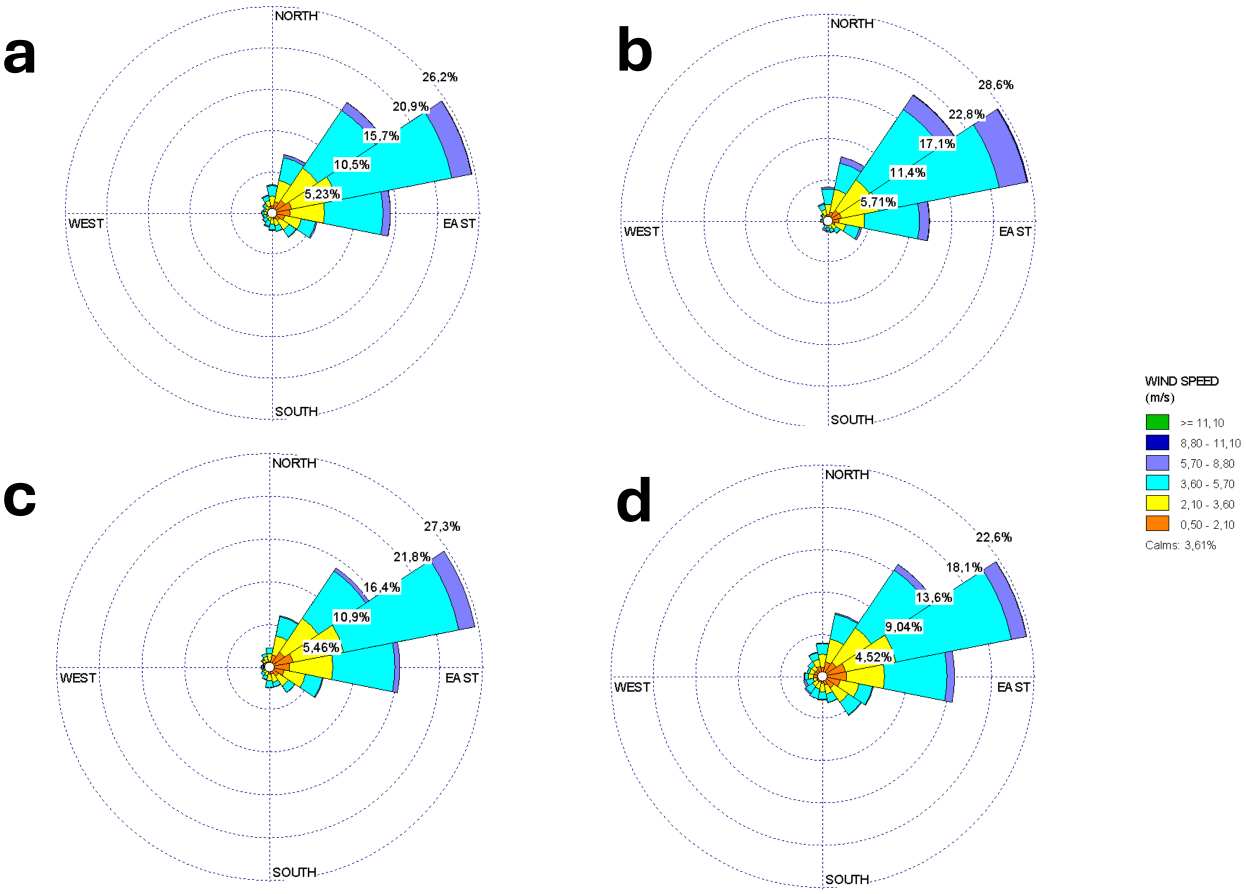
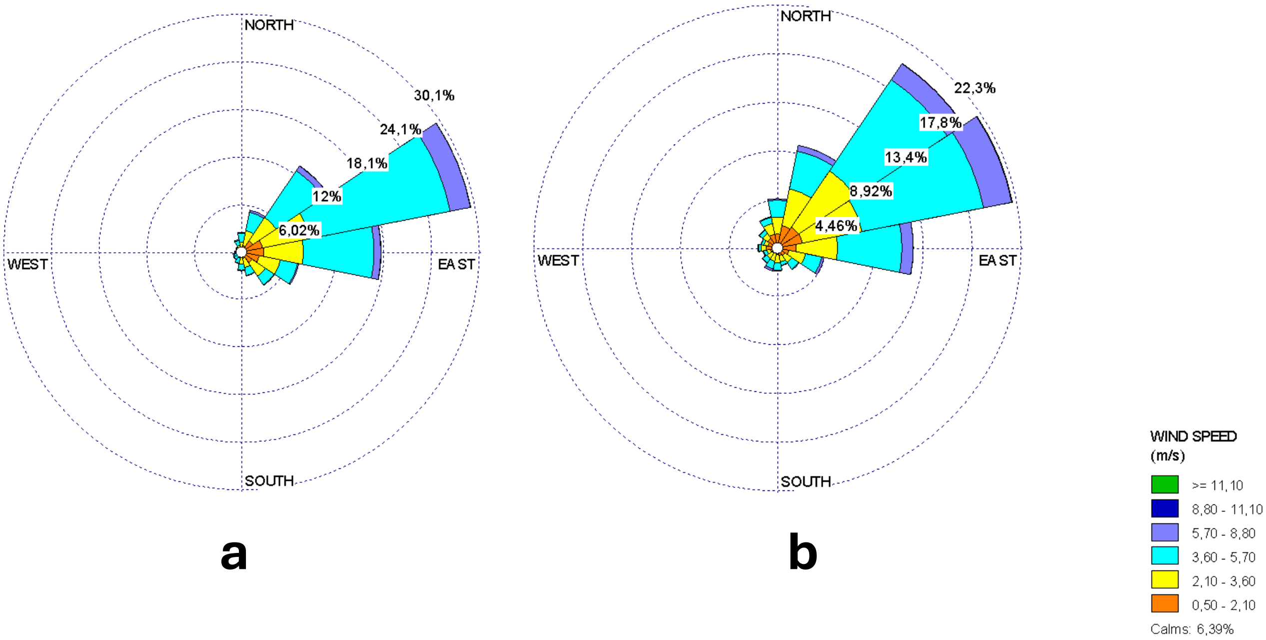


Figure 1: Annual wind rose for (a) 2021 – 2023, (b) 2021, (c) 2022, and (d) 2023.

The predominant wind direction in all four periods are northeasterlies. The highest frequency of wind occurrences is concentrated in these directions throughout the years. The different wind speed classifications ranged from 0.5 m/s to >11.1 m/s, with most wind speeds falling in the 2.1 – 8.8 m/s range. Although they are somewhat less common, higher wind speeds (>8.8 m/s) were observed.

This predominant north-northeasterly wind pattern aligns with regional climatological patterns reported by (Michaud et al., 2010) and reflects the broader atmospheric circulation patterns typical of southern Africa. The observed wind speed distribution, particularly the prevalence of moderate winds (2.1-8.8 m/s), creates conditions conducive to effective pollutant dispersion (Seinfeld & Pandis, 2016). Higher wind speeds (>8.8 m/s) suggest periods of enhanced dispersion potential, which has important implications for exposure assessment. Higher wind speeds would, therefore, generally lead to lower concentrations in the receiving environment due to increased pollutant dilution, thus reducing exposure levels for people and ecosystems

Figure 2: Below Indicates three-year (2021 – 2023) average wind roses for morning and evening periods.



The figure above indicates that wind is stronger and more concentrated in the East-North East (ENE) at 30.1% during evening periods, while the mornings experienced north-easterlies (NE) and east-north-easterlies (ENE) at 17.8 and 22.3%, respectively. Both graphs demonstrate moderate wind speeds of 3.6 - 8.8 m/s. The consistency in wind direction (NNE, NE, and ENE) suggests emissions from MBPS will likely disperse toward the southwest (SW), impacting those regions the most. This area is dominated by ploughing fields and cattle posts activities. Agricultural activities in this area are at a subsistence farming scale.

These diurnal wind patterns align with findings from similar topographical settings discussed in (EPA, 2024) and have significant implications for exposure assessment. The stronger evening winds (30.1% from North-North East) coincide with typical atmospheric stability transitions, potentially creating conditions for enhanced pollutant dispersion, as described by (Oke TR., 1987). The more distributed morning wind patterns (22.3%) suggest an increased potential for localized pollutant accumulation.

The figure below shows wind rose diagrams representing the different seasons from 2021 to 2023. It contains four polar plots that provide a visual presentation of wind direction and wind speed data.

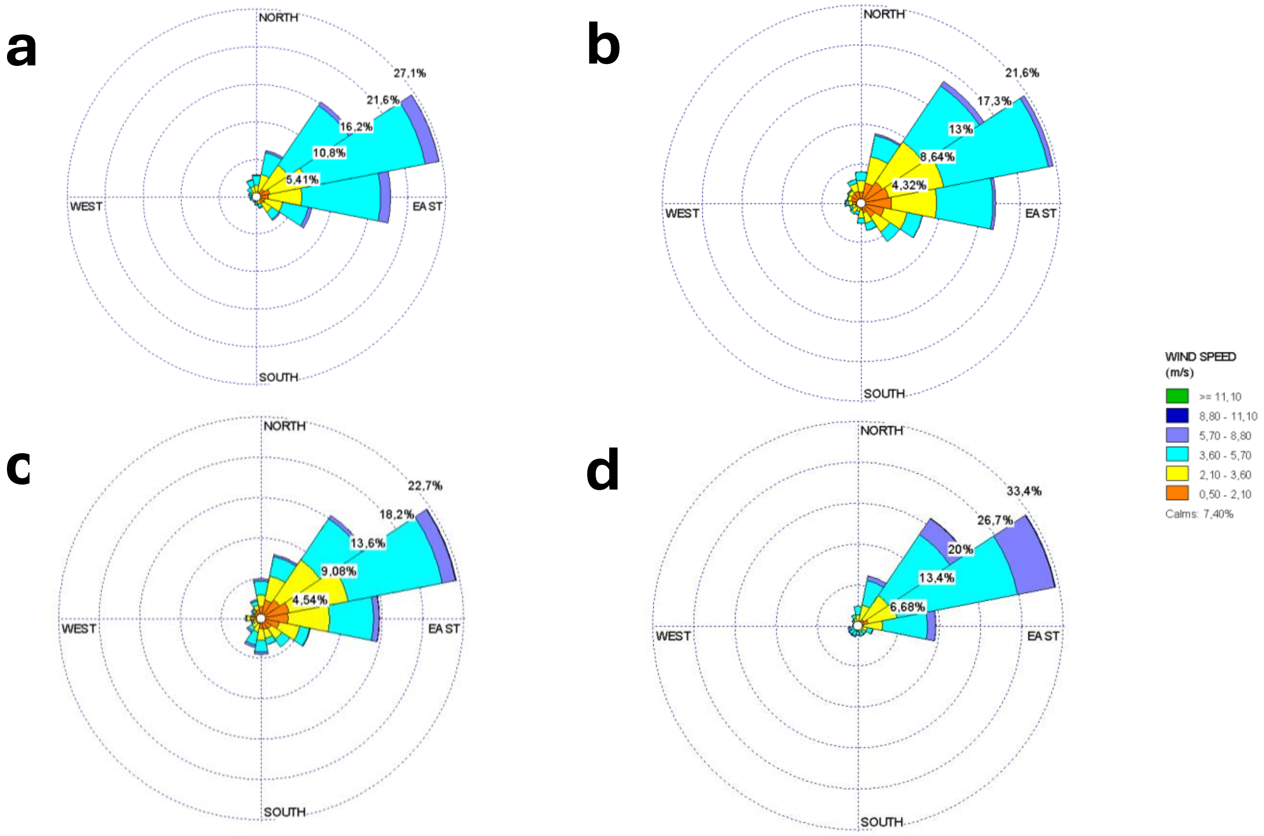


Figure 3: Three-year average (2021 – 2023) (a) summer, (b) autumn, (c) winter, and (d) spring wind roses.

For summer, the prevalence of easterly winds and a higher proportion of higher wind speeds are typical for some summer seasons in many regions due to the influence of weather systems during that time. Spring experiences stronger winds compared to Autumn due to larger temperature differences and changes in atmospheric pressure systems. The region experiences a shift from colder winter temperatures to warmer summer temperatures during the spring (September to November), which intensifies surface heating. As air moves from high-pressure to low-pressure zones, this exacerbates the pressure gradients between the surrounding oceans and the land, leading to greater winds. Autumn (March to May), on the other hand, sees a slow cooling that makes temperature gradients less, atmospheric conditions more stable, and winds generally lighter.

The seasonal wind patterns observed reveal distinct characteristics that are crucial for exposure assessment and risk characterization. In spring, strong easterly winds, as noted by (Grivas et al., 2018) align with enhanced pollutant transport during warmer months. This suggests that higher wind speeds can improve dispersion potential, thereby possibly reducing localized concentration peaks. In contrast, autumn presents a more uniform directional distribution and lower wind speeds, which are conducive to pollutant accumulation. The winter pattern shows similarities to summer conditions but results from different meteorological drivers, indicating complex seasonal exposure patterns. This temporal variability underscores the study from (Manisalidis et al., 2020) on the critical role of seasonal factors in exposure assessment, emphasizing the need for careful consideration in health risk evaluations.

4.4 Dispersion modeling outputs

The dispersion modeling results provide critical insights into the spatial and temporal distribution of SO_2 concentrations. In this case, AERMOD was used to assess the dispersion of SO_2 from the stack of a CFPP in Botswana. The ground-level SO_2 concentrations were estimated in the community of Palapye over time. The outputs provide data on maximum, average, and percentile concentrations for different averaging periods (e.g., 1-hour, 24-hour, annual). Contour plots, concentration maps, and tabulated data were generated showing how SO_2 emissions disperse under various meteorological conditions, considering factors like terrain, emission rates, and stack characteristics. These outputs will be used to assess compliance with air quality standards and evaluate potential health impacts.

4.4.1 Dispersion modeling plots

Figure 4 below presents an analysis of annual average SO_2 Concentrations at the 99th Percentile for Morupule B Power Station – Operational Phase (based on actual stack emission monitoring results)

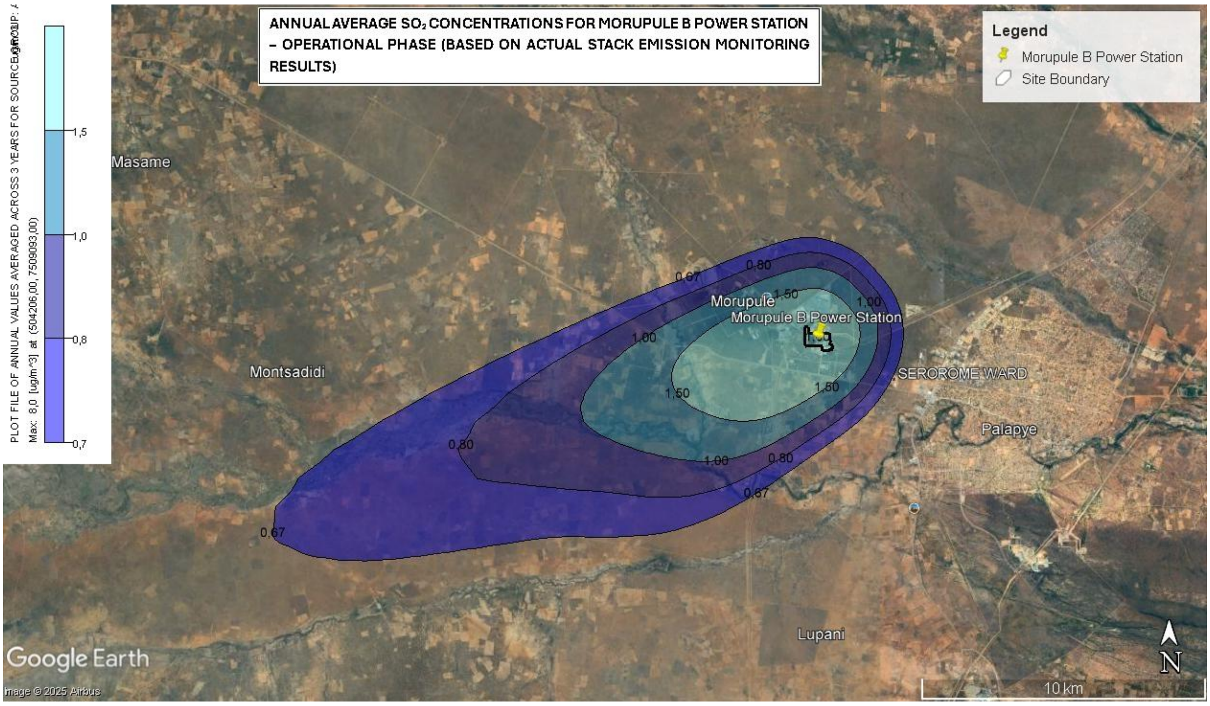


Figure 4: Annual average SO_2 concentrations.

The map features different contour lines representing varying concentrations of SO_2, forming an oval or ellipsoid pattern around the power station. The darker colors indicate lower pollutant concentrations, while lighter colors represent higher concentrations (Figure 5). High-concentration areas are located near the Morupule B Power Station, consistent with expectations, as pollutant concentrations are typically highest close to the emission source before dispersion and dilution reduce concentrations with distance.

The contours show the direction of SO_2 emissions from the power plant, where downwind areas are likely to be impacted. If higher concentrations extend outward in a specific direction, this likely corresponds to the prevailing wind direction indicated in the previous wind rose diagrams, as pollutants tend to disperse along the path of dominant wind flows.

This map, combined with the wind rose data, allows for a comprehensive understanding of how SO_2 disperses from Morupule B Power Station. The analysis can inform regulatory actions, community health assessments, and measures to minimizing SO_2 exposure for individuals living near the power station. An annual sulphur dioxide (SO_2) concentration ranging between 0.7 and 1.5 µg/m³ is significantly lower than the World Health Organization (WHO) guidelines for SO_2 of 20 µg/m³ and the Botswana NAAQS of 50µg/m³, indicating compliance with local and international air quality standards and suggesting minimal risk to public health from SO_2 at this concentration (C. Yuan et al., 2022)

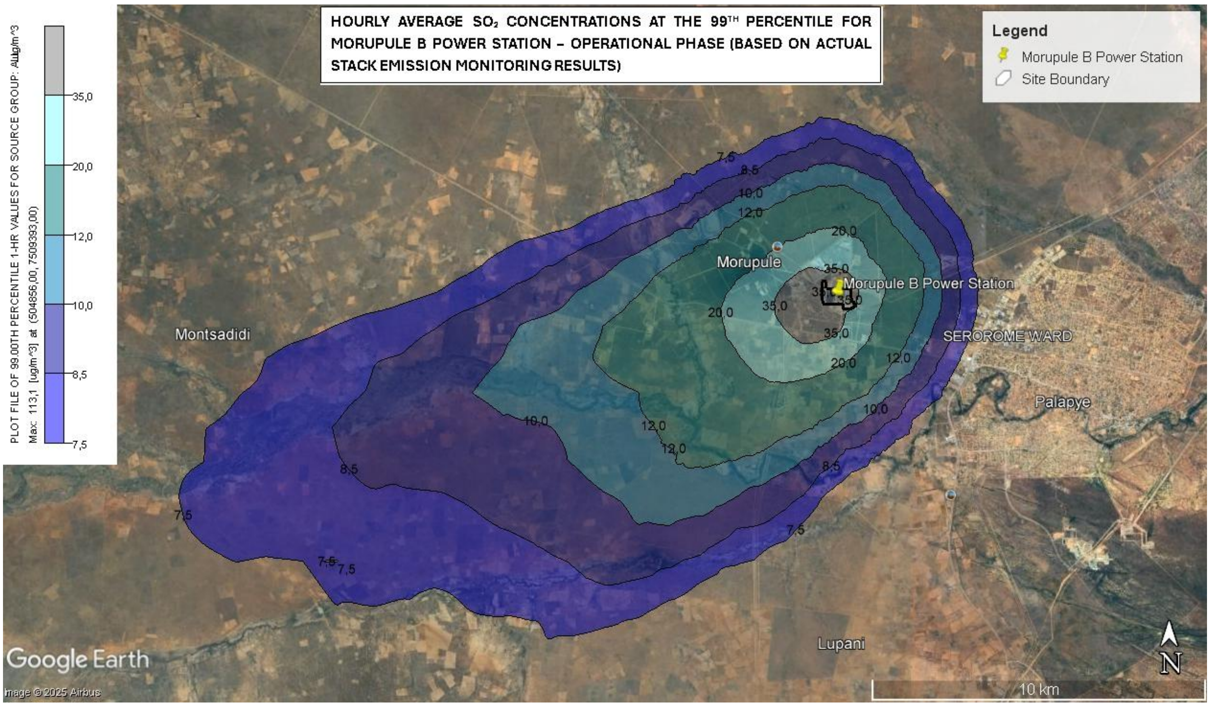


Figure 5: Hourly average SO_2 concentrations at the 99th percentile for Morupule B power station – operational phase (based on actual stack emission monitoring results)

The map displays concentrations along contour lines representing the 99th percentile of hourly average SO_2 levels ranging from 7.5 to 35 µg/m³. This means that these values reflect the highest concentrations that were exceeded only 1% of the time during the monitoring period, highlighting typical upper-end exposure scenarios rather than absolute extremes.. The inner contour (grey) represents the highest SO_2 concentrations, typically close to the emitting source. The highest concentrations appear very close to the Morupule B Power Station, which is expected as emissions will be most intense near the source.

The 99th percentile data is crucial for understanding worst-case scenarios, often linked to specific weather events (e.g., low wind conditions or inversions that trap pollutants near the surface) (Wang et al., 2019). These conditions can lead to higher concentrations accumulating in areas downwind. (Wang et al., 2019) stated pollution episodes could be influenced by low surface pressure, high relative humidity, weak wind, and temperature inversion.

Identifying areas with the highest concentrations can help public health officials target areas for monitoring and potential mitigation measures. Areas consistently receiving high concentrations due to wind direction should be prioritized for air quality assessments. This map aids in understanding peak SO_2 exposure situations near the Morupule B Power Station. When combined with wind pattern data, it provides valuable insights for environmental management, public health strategies, and potential regulatory actions aimed at reducing SO_2 emissions and their impacts on surrounding communities.

One-hour SO_2 averages of less than 40 µg/m³, which is well below short-term limits of 350 µg/m³ by the Botswana NAAQS, indicates minimal risk to public health from SO_2 at this concentration.

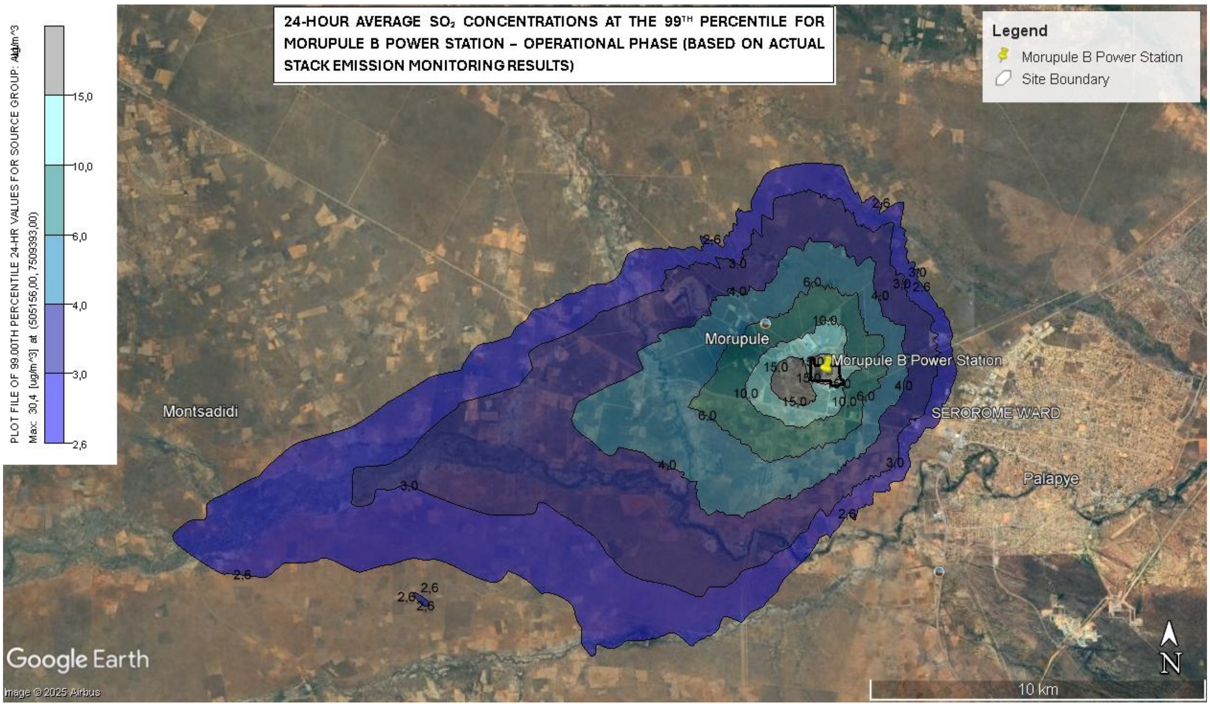


Figure 6: 24hr average SO_2 concentrations for Morupule B power station – operational phase (based on actual stack emission monitoring results)

The contours represent the peak SO_2 levels over 24 hours at the 99th percentile, indicating that these values reflect high-exposure scenarios that could be experienced within that timeframe. As expected, SO_2 concentrations are higher at the Morupule B Power Station, with values exceeding 15 µg/m. The asymmetric dispersion pattern, particularly pronounced in the southwest, reflects the influence of predominant northeasterly wind patterns identified in the meteorological analysis (See Section 4.3).

Findings from this study are not comparable to (Jamshidi Angas et al., 2020), who utilized the AERMOD dispersion model to simulate SO_2 emissions from an oil refinery over a 25 × 25 km radius. The modeling was conducted for averaging periods of 1, 3, 8, and 24 hours across both warm and cold seasons. The refinery recorded a higher maximum 1-hour SO_2 concentration

(66.27 µg/m³) compared to the results reported herein of 35 µg/m³. Similarly, the refinery exhibited a 24-hour average concentration of 12.73 µg/m³, which is slightly lower than the results reported here of 15 µg/m³.

These differences could be attributed to several factors. Firstly, fuel type and sulphur content play a significant role in the amount of SO_2 that will be generated from the combustion of the fuel. Oil refineries typically process fuels with variable sulphur content, which could have resulted in sporadic SO_2 emission peaks (Ma et al., 2001). In contrast, the CFPP shows consistently lower peak emissions, possibly due to more regulated combustion processes or the use of low-sulphur coal fuel (Ma et al., 2001). Secondly, stack parameters such as height, exit velocity, and temperature influence the dispersion of pollutants from the source. Taller stacks with high exit velocities can promote wider dispersion, reducing ground-level concentrations, as can be observed in this study. The stack height at the CFPP was 70 m above ground with a gas exit velocity of 34 m/s. Additionally, local meteorological conditions, including wind speed, atmospheric stability, and temperature inversions, could affect pollutant dispersion . The higher short-term peaks observed at the refinery could be linked to more stable atmospheric conditions that limit dispersion resulting in increased local pollution episodes. Finally, geographic factors such as surrounding topography could influence how pollutants spread. Thus, the observed differences are likely due to a complex interplay of emission characteristics, stack design, meteorology, and local geography (Carvalho et al., 2006; Giosanu et al., 2021).

The findings of this study have been compared to Ibrahim et al. (2012), who investigated SO_2 and NOx emissions from Khoms Power Stations in Libya. In contrast to findings in this study, the Khoms power stations exhibited significantly higher concentrations, with 1-hour SO_2 levels reaching up to 976 µg/m³ and 24-hour averages ranging between 488 to 651 µg/m³, particularly in the vicinity of the ancient city of Leptis Magna. The elevated SO_2 concentrations observed at the Khoms power stations compared to CFPP in Botswana are likely due to a combination of factors including the use of higher sulphur content in fuels, varying effectiveness of emission control technologies (e.g., Morupule B Power Station has a desulphurization unit), operational differences, and local environmental factors influencing pollutant dispersion.

(Nurhisanah & Hasyim., 2022a) assessed SO_2 exposure levels among workers at the Combined Cycle Power Plant (CCPP) Indralaya unit in Indonesia. They reported an average SO_2 concentration of 85 µg/m³ in the work environment. This result is higher compared to the findings of this study. In a similar study, (Mokhtar et al., 2014) conducted a health risk assessment of emissions from a coal-fired power plant in Malaysia using AERMOD modeling. Their study reported a maximum 1-hour SO_2 concentration of 101.86 μg/m³ and an annual average of 1.17 μg/m³. Although their maximum 1-hr SO_2 concentrations were higher, the annual average SO_2 emissions are comparable to the findings of this study (1.5μg/m³). This could be because of operational variability between the plants such as startup and shutdown cycles, equipment malfunctions, or variations in fuel combustion efficiency that temporarily elevate emissions. Operations at Morupule B Power plant could be stable resulting in lower pollutant concentrations.

Palapye is located upwind of Morupule B Power Station. It is located northeast of the power plant and occasionally experiences northeasterly winds throughout the year. This means that the immediate impact of SO_2 emissions from the power plant may be limited under normal wind conditions, as prevailing northeasterly winds carry pollutants away from the population. This does not imply that the community may not be impacted by emissions from the power plant, which would threaten their health. Pollutants, including SO_2, nitrogen oxides (NOx), and particulate matter, can disperse widely and may affect the community during wind shifts, atmospheric inversions, or low wind speeds that allow pollutants to accumulate or recirculate (I. Levy et al., 2009). Additionally, regional environmental impacts, such as acid rain, soil degradation, and water contamination, can indirectly affect the community's agriculture, infrastructure, and overall quality of (Coote et al., (1981). Long-term exposure to low levels of pollution can also pose chronic health risks, especially for vulnerable sub-population groups. Therefore, while the immediate risk may seem lower, the upwind community (Palapye) is not entirely shielded or safe from the impact of emissions generated from the power plant.

While Palapye may not be significantly impacted by SO_2 emissions from the coal-fired power plant due to prevailing wind patterns, it may still experience environmental and health stressors generated from other unmonitored sources and/ or from secondary effects. For example, atmospheric NOx and volatile organic compounds (VOCs) from different sources in the far field contribute to the formation of ground-level ozone, which can drift into the upwind community under certain meteorological conditions. Additionally, fugitive dust emissions from coal handling, ash disposal sites, and vehicle traffic around the plant may be resuspended and transported by localized turbulence or shifts in wind direction, intermittently affecting the air quality in Palapye. The absence of monitoring for these additional stressors creates an incomplete picture of the community’s total exposure, highlighting the need for a broader assessment of air quality and environmental and human health risks beyond SO_2 alone (Khaniabadi et al., 2017; Nurhisanah & Hasyim, 2022b)

4.4.2 Predicted incremental SO_2 concentrations

Analyzing predicted incremental SO_2 concentrations across 50 sensitive receptors provides crucial insights into the spatial distribution of exposure risks in the study area. These predictions, derived from AERMOD modeling, represent varying temporal scales (hourly, daily, and annual) essential for comprehensive health risk assessment.

Table 8 below shows the predicted incremental SO_2 concentrations per sensitive receptor in the community of Palaype. The results indicate that all sensitive receptors recorded low SO_2 concentrations below the standards.

Table 8: Predicted incremental SO_2 concentrations

Receptor ID	**SO2 (Hourly)**	**SO2 (Daily)**	**SO2 (Annual)**	**UTM Coordinates (35S)**		**Elevation**
	350 µg/m3	**125 µg/m3**	**50 µg/m3**	**X (m)**	**Y (m)**	**Y (m)**
SR1	5.44	1.72	0.34	510455	7507186	931.14
SR2	3.49	1.21	0.22	514121	7507539	926.52
SR3	4.64	1.52	0.29	510616	7505119	931.26
SR4	5.94	1.87	0.37	508886	7505424	936.66
SR5	4.84	1.72	0.30	511557	7508222	932.14
SR6	3.36	1.19	0.21	514587	7507677	926.07
SR7	3.66	1.30	0.23	513749	7507809	927.54
SR8	5.33	1.79	0.33	509040	7504474	945.25
SR9	3.39	1.30	0.21	511821.22	7501989.8	981.6
SR10	3.97	1.42	0.25	513088	7508845	931.52
SR11	3.96	1.43	0.25	513098	7508663	931.29
SR12	3.74	1.39	0.23	513605	7508334	928.33
SR13	3.79	1.39	0.24	513474	7508457	927.6
SR14	4.05	1.37	0.25	512752.53	7507432.3	929.27
SR15	3.58	1.30	0.22	513492	7506054	925.28
SR16	3.45	1.16	0.22	514031	7506830	925.06
SR17	4.92	1.65	0.31	510510.78	7505825.4	922.39
SR18	3.38	1.24	0.21	513765.71	7505272	920.98
SR19	4.28	1.50	0.27	511535.41	7505427.6	924.76
SR20	4.69	1.67	0.29	511779.97	7508156	932.53
SR21	3.52	1.25	0.22	513708.9	7506141.4	926.83
SR22	4.34	1.51	0.27	511578.78	7505753.3	923.75
SR23	4.15	1.51	0.26	512766.43	7508252	930.68

SR24	5.36	1.70	0.33	510486.73	7507052.2	929.49
SR25	6.39	2.03	0.40	509497.6	7507280.2	932.52
SR26	5.01	1.67	0.31	510868.58	7506783.6	928.4
SR27	5.28	1.75	0.33	510519.21	7506882.1	929.78
SR28	6.50	2.06	0.41	509389.87	7507240.2	934.65
SR29	3.65	1.33	0.23	513198.09	7505791.6	924.21
SR30	5.12	1.67	0.32	510784.68	7506972.5	928.75
SR31	3.52	1.30	0.22	513478.99	7505561.8	921.85
SR32	6.09	2.01	0.38	508304.81	7504980.8	932.86
SR33	3.42	1.27	0.22	513774.13	7505622.6	922.21
SR34	7.12	2.09	0.44	509241.71	7508086.7	935.75
SR35	4.22	1.45	0.26	512452.84	7507687.1	929.16
SR36	4.19	1.46	0.26	512476.67	7510654.1	934.67
SR37	4.19	1.48	0.26	512626.13	7507967.8	929.52
SR38	4.17	1.40	0.26	512307.9	7506770.7	926.36
SR39	4.00	1.41	0.25	512914.91	7507732.6	927.47
SR40	5.50	1.84	0.34	508961.2	7504685.6	942
SR41	3.43	1.25	0.22	513649.86	7505323.6	919.97
SR42	3.43	1.24	0.22	513911.95	7506195.1	924.9
SR43	4.32	1.52	0.27	511794.09	7506124.6	921.03
SR44	4.32	1.50	0.27	511918.97	7506456.6	927.14
SR45	3.68	1.35	0.23	513082.41	7505685	924.23
SR46	3.41	1.23	0.21	514041.73	7506296.4	925.1
SR47	3.39	1.24	0.21	513706.22	7505130.6	916.4
SR48	5.81	1.81	0.36	510123.91	7507451.2	933.46
SR49	3.33	1.22	0.21	514175	7506036	922.93
SR50	3.90	1.37	0.24	512215	7505012	924.66

A detailed analysis of the predicted ground-level concentrations reveals distinctive spatial and temporal patterns across the receptor network. The highest hourly concentration was recorded at receptor SR34 (7.12 µg/m³), a healthcare facility. Concentrations show clear spatial variation, with values ranging from 3.33 to 7.12 µg/m³ for hourly averages, 1.16 to 2.09 µg/m³ for daily averages, and 0.21 to 0.44 µg/m³ for annual averages (Table 4). The ratio between hourly, daily, and annual averages remains relatively consistent across receptors (approximately 15:5:1), indicating stable atmospheric mixing patterns. This finding aligns with the work of Cimorelli et al. (2005) on pollutant dispersion characteristics in complex terrain. The elevation variation among receptors (ranging from 916.4m to 981.6m) appears to influence concentration patterns, with generally higher concentrations observed at mid-elevation receptors (930 – 940m), suggesting the presence of terrain-induced flow patterns (Oke., 1987).

All predicted concentrations remain well below hourly, 24-hour, and annual limits, with maximum values representing only 2.03%, 1.67%, and 0.88% of the standards, respectively. This finding is consistent with studies by Gibson et al. (2013) that demonstrated effective pollutant dispersion in similar settings with modern emission controls.

The consistently low concentrations relative to standards suggest effective dispersion conditions and emission controls employed at MBPS. However, the spatial patterns indicate the need for focused continuous monitoring in the northern sector where higher concentrations are predicted. These findings provide crucial input for subsequent health risk assessment and support evidence-based decision-making for environmental management strategies. Future research should validate these predictions through ambient monitoring and investigate the influence of terrain-induced flow patterns on local pollutant dispersion.

4.5 Risk Assessment

Sulphur dioxide (SO_2) was identified as the primary hazard/stressor in this study, given its prevalent emissions from coal-fired power plants and its potential health and environmental impacts. SO_2 is a non-carcinogen; as such, in estimating the $C_{air\text{-}adj,}$ it was assumed that the exposure duration (ED) and averaging time (AT) were equal, and they cancel out. The health risk assessment was based on the guidelines for human health assessment proposed by the USEPA framework.

Table 9: Simulated annual average ground-level concentrations and risk estimates

Population subgroup	**Concentration (C_{air}) (µg/m^3)**	**Annual limit (µg/m^3)**	**Concentration of air adjusted (C_{air_adj}) (µg/m^3)**	**Hazard Quotient (HQ)**
Infants (0 -5 years)	8	50	5.75	0.115
Children (6 – 17 years)	8	50	6.14	0.123
Elderly (>65 years)	8	50	6.75	0.135

The graph presents Hazard Quotient (HQ) values for three different population subgroups (infants, children, and elderly) calculated using annual average values against Botswana's annual average limit values. Results have demonstrated that age-related physiological differences and exposure patterns influence the levels of risk from SO_2 exposure. The reported Hazard Quotient (HQ) values indicate that the elderly (HQ = 0.135) experience the highest exposure risk, followed by children (HQ = 0.123), while infants have the lowest HQ (0.115).

The elderly show heightened vulnerability due to age-related declines in respiratory function, pre-existing health conditions, and reduced ability to detoxify inhaled pollutants (Wallbanks et al., 2024). Children are susceptible to SO_2 exposure due to developing lungs and increased respiratory rates. However, they have slightly lower HQ values than the elderly. Despite infants having a small body size and rapid breathing rate, they demonstrated lower cumulative exposure levels due to differences in time-activity patterns, such as spending more time indoors where SO_2 concentrations tend to be lower (Amnuaylojaroen & Parasin., 2024).

The lower HQ values compared to similar studies from other regions (Liu et al., 2017) suggest either effective emission controls at the Morupule B Power Station or favorable atmospheric dispersion conditions. As such, SO_2 emissions from the power plant likely pose minimal health risks to the surrounding population, though continued monitoring is needed given the documented health effects of SO_2 in the scientific literature (Azimi et al., 2024; A. A. Khan et al., 2024; Orellano et al., 2021; Zhou et al., 2024).

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This study aimed to assess the health risks associated with SO_2 emissions from the Morupule B Power Station (MBPS) through three primary objectives: (1) direct measurement of SO_2 emissions from the stack, (2) simulation of pollutant dispersion under varying meteorological conditions, and (3) evaluation of health risks for vulnerable populations. The investigation employed the AERMOD dispersion model to predict air quality within a 20km x 20km radius, utilizing three years' meteorological data from 2021 to 2023. This chapter synthesizes the key findings, acknowledges study limitations, and provides recommendations for future research and policy implementation.

5.2 Summary of Key Findings

5.2.1 Emission Characteristics and Dispersion Patterns

The study revealed several significant SO_2 emissions and dispersion patterns from the Morupule B Power Station. Analysis of operational data demonstrated that peak emissions consistently coincided with maximum operational loads during afternoon hours (14:00-16:00), reflecting typical daily power demand patterns. Significant seasonal variations were observed, with winter months showing 22% higher emissions than other seasons, likely due to increased power demand and altered atmospheric conditions.

The predominant north-northeasterly winds were crucial in determining dispersion patterns, creating consistent directional trends in pollutant transport toward the south and southwest. Wind analysis showed stronger winds in the evening (30.1% from North-Northeast) than more distributed morning patterns (22.3%), affecting temporal exposure patterns. These wind patterns effectively disperse emissions away from the main population centers of Palapye, contributing to the lower observed ground-level concentrations. The complex terrain surrounding the facility also contributed to unique spatial concentration gradients, influencing the distribution and accumulation of pollutants in areas downwind of the power plant.

The dispersion modeling results showed that all predicted concentrations remained well below their respective standards, with maximum values representing only 2.03% (hourly), 1.67% (daily), and 0.88% (annual) of the regulatory limits. The highest measured concentrations were 113.1 $\mu g/m^3$ (hourly), 30.4 $\mu g/m^3$ (daily), and 8.0 $\mu g/m^3$ (annual), all significantly below the Botswana standards of 350 $\mu g/m^3$, 125 $\mu g/m^3$, and 50 $\mu g/m^3$, respectively. The highest annual average was used in assessing the health risks of different population groups residing in Palapye. The highest concentrations represent the worst-case long-term exposure scenario, ensuring risk assessments account for potential chronic health effects and prolonged exposure of vulnerable groups. This approach provides a conservative estimate that helps guide public health policies and regulatory decisions to protect at-risk populations.

5.2.2 Health Risk Assessments

Health risk assessment using Hazard Quotients (HQ) demonstrated that all population subgroups experienced HQ values well below 1.0, indicating minimal health risks from SO_2 exposure. The elderly showed the highest vulnerability across all exposure durations, followed by children, with infants showing the lowest risk levels. Despite these differences, the consistently low SO_2 emissions and HQ values (<1.0 in all cases) indicate that current operations at the Morupule B Power Station are effective in curbing SO_2 emissions during different operational phases of the plant. While these results indicate effective emission management, continued monitoring would be prudent given the documented health effects of SO_2 in the scientific literature, particularly for elderly populations in areas south and southeast of the facility.

5.3 Study Limitations and Assumptions

5.3.1 Operational Parameters

The study incorporated several fundamental assumptions regarding facility operations to enable effective modeling. Primary among these was the assumption of continuous 24/7 plant operation and constant emission rates under normal operating conditions. The model also assumed steady-state conditions, which, while not perfectly reflecting real-world variability, provided a practical framework for long-term exposure assessment.

5.3.2 Dispersion Characteristics

The dispersion modeling assumed Gaussian distribution in the horizontal plane, while vertical dispersion was influenced by atmospheric stability and mixing height. This widely accepted approach in atmospheric modeling provided a mathematical foundation for predicting pollutant transport under steady-state conditions, assuming uniform meteorological parameters over space and time. The model assumed conservative pollutant retention in the atmosphere without accounting for chemical transformation or deposition processes. Additionally, terrain interactions were simplified to maintain computational efficiency while still capturing major topographical influences on pollutant dispersion.

5.3.3 Exposure Assessment

In evaluating population exposure, the study focused primarily on the inhalation pathway as the dominant route of SO_2 exposure. This approach assumed uniform population exposure patterns within defined receptor zones, recognizing that exposure patterns may vary with individual behavior and movement. The ambient SO_2 concentrations were adjusted for time-activity patterns across different subgroups. However, the assumed exposure frequency of 350 days per year implies that individuals spend only two weeks away from the receptor site, which may not accurately reflect real-world variability in mobility due to factors such as travel, work, or other activities away from the exposure area.

5.4 Recommendations and Future Studies

Looking ahead, the findings indicate several key areas for future research, including the investigation of long-term emission trends as plant efficiency evolves and an examination of the relationship between emission patterns and local health outcomes. Additionally, developing optimized control strategies based on temporal emission patterns is vital, along with an assessment of cumulative impacts that consider the interactions between multiple pollutants. These focus areas will enhance the understanding of emissions and their broader implications on health and the environment.

5.4.1 Multipollutant Exposure Assessment

While SO_2 is well-controlled, the study did not include other co-emitted pollutants such as NOx, PM2.5, and heavy metals. Future work should assess their combined health effects, as cumulative and synergistic exposure risks may still exist even when individual pollutants remain below standard limits. The consideration of cumulative effects was limited by model capabilities and data availability

5.4.2 Sustaining Low SO_2 levels

The study results confirm that the existing emission control measures at Morupule B Power Station are highly effective, with lower SO_2 emissions and HQ values well below 1.0 across all population groups and exposure durations. The current continuous emission monitoring systems and desulphurization technology should be maintained as they effectively control SO_2 emissions at levels that pose minimal health risks to surrounding communities. Regular calibration and maintenance of these systems should be prioritized to ensure their continued effectiveness.

5.4.3 Public Awareness and Risk Communication

While comprehensive community monitoring is not warranted given the low HQ values, targeted ambient air quality monitoring should be established in areas south and southwest that are downwind of the facility. Although the current exposure levels are not hazardous, long-term monitoring remains critical to detect any gradual changes due to industrial expansion or meteorological shifts. Establishing periodic health impact assessments for sensitive groups can support early intervention strategies if future SO_2 levels increase. For Palapye, instead of implementing complex warning systems, periodic community updates about the facility's environmental performance would maintain transparency and public trust. Annual reports summarizing emission levels and health risk assessments should be publicly accessible in simple, non-technical formats. Given the minimal risks identified, educational programs could focus on general air quality awareness rather than specific SO_2 mitigation measures.

5.4.4 Longitudinal Health Studies

Since HQ values suggest minimal risk under current conditions, a long-term epidemiological study could help assess whether low-level chronic SO_2 exposure has subclinical health effects, particularly for vulnerable populations with pre-existing respiratory conditions.

5.5 Conclusion

This study assessed the health risks associated with lifetime exposure to SO_2 emissions from the Morupule B Power Station (MBPS) in Palapye, Botswana, across different subgroups, including infants, children, and adults. The findings indicate that SO_2 exposure poses no immediate health risks to the community, with Hazard Quotients (HQs) remaining below the threshold of concern. While the elderly exhibited slightly higher susceptibility during short-term exposure periods, these values still represent minimal health risks, suggesting that coal-fired power generation can operate with limited public health impact when effective emission controls are in place. The successful management of SO_2 emissions at MBPS provides a valuable model for similar facilities in developing nations, highlighting the importance of rigorous air quality regulation and mitigation strategies. However, to ensure comprehensive environmental and public health protection, there is a critical need to expand monitoring efforts to include other key pollutants, such as nitrogen oxides (NOx), particulate matter (PM2.5 and PM10), dust, and heavy metals, which could contribute to cumulative exposure risks.

Continued monitoring, particularly in areas south and southwest (i.e. downwind) of the facility, remains essential to safeguard vulnerable populations.

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UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG	HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

Office of the Deputy Vice-Chancellor (Research & Innovation)

TO: Mr E Letswee
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Division:
Medical School

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FROM: Mr Iain Burns
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DATE: 27/05/2024

REF: *R14/49*

PROTOCOL NO: W-PR-240527-02 (This is your ethics application study reference number. Please quote this reference number in all correspondence relating to this study)

PROJECT TITLE: *Health risk assessment of sulphur dioxide emissions from a coal-fired power plant in Botswana*

Please find attached the Ethics Waiver Certificate for the above project. I hope it goes well and that an article in a recognized publication comes out of it. This will reflect well on your professional standing and contribute to the Government funding of the University.

MSWorks2000/Iain0007/ClearScanWaiver.wps

UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

Office of the Deputy Vice-Chancellor (Research & Innovation)

27/05/2024

Ref: W-PR-240527-02

TO WHOM IT MAY CONCERN

Waiver: This certifies that the following research does not require clearance from the Human Research Ethics Committee (Medical)

Investigator: Mr E Letswee
Student No. (if appropriate): 2508903
Staff No. (if appropriate):

Supervisor: Dr T Makonese

School: Public Health
Department: Occupational Health
Division:
Medical School

Project title: *Health risk assessment of sulphur dioxide emissions from a coal-fired power plant in Botswana*

Degree: MSc

Reason: Environmental surveillance project
No human participants will be involved in the study

Professor P Ruff
Chairperson: Human Research Ethics Committee (Medical)

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UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

FACULTY OF HEALTH SCIENCES

PLAGIARISM DECLARATION TO BE SIGNED BY ALL HIGHER DEGREE STUDENTS

SENATE PLAGIARISM POLICY: APPENDIX ONE

I Edward Letswee (Student number: 2508903) am a student registered for the degree of MSc Medicine (Exposure Science) in the academic year 2025.

I hereby declare the following:

- I am aware that plagiarism (the use of someone else's work without their permission and/or without acknowledging the original source) is wrong.
- I confirm that the work submitted for assessment for the above degree is my own unaided work except where I have explicitly indicated otherwise.
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