COMPARATIVE ASSESSMENT OF CO, NO_2 AND AEROSOLS LEVELS IN BAYELSA STATE AND KANO STATE: A CASE STUDY OF 2019-2024

BY

DAVID ONAOGHENE ONORAKPENE

LSC1906760

DEPARTMENT OF ENVIRONMENTAL MANAGEMENT AND

TOXICOLOGY FACULTY OF LIFE SCIENCES

UNIVERSITY

OF BENIN

BENIN CITY

FEBRUARY, 2025.

COMPARATIVE ASSESSMENT OF CO, NO_2 AND AEROSOLS LEVELS IN BAYELSA STATE AND KANO STATE: A CASE STUDY OF 2019-2024

BY

DAVID ONAOGHENE ONORAKPENE

LSC1906760

AN UNDERGRADUATE DISSERTATION SUBMITTED TO THE DEPARTMENT OF ENVIRONMENTAL MANAGEMENT AND TOXICOLOGY, FACULTY OF LIFE SCIENCES, UNIVERSITY OF BENIN, BENIN CITY, EDO STATE, NIGERIA; IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR AWARD OF BACHELOR OF SCIENCE (B.Sc.) DEGREE IN ENVIRONMENTAL MANAGEMENT AND TOXICOLOGY.

FEBRUARY, 2025.

CERTIFICATION

This is to certify that this study was carried out by **DAVID ONAOGHENE ONORAKPENE** with matriculation number **LSC1906760** of the Department of Environmental Management and Toxicology under the supervision of Dr. C.F. Amaechi, in partial fulfillment of the requirements for the award of Bachelor of Science (BSc) in Environmental Management and Toxicology.

______________________________ ________________________

DR. C.F. AMAECHI **DATE**

(PROJECT SUPERVISOR AND COORDINATOR)

______________________________ ________________________

PROF. A. A. ENUNEKU **DATE**

(HEAD OF DEPARTMENT)

DECLARATION

I, David Onaoghene Onorakpene declare that **Comparative Assessment of CO, NO_2 and Aerosols Levels in Bayelsa State and Kano State: A Case Study of 2019-2024** is my own work and that all sources that I have used or quoted have been acknowledged by means of complete references and that this work has not been submitted before for any other degree at any other University.

______________________________	______________________________
DAVID ONAOGHENE ONORAKPENE	**DATE**

DEDICATION

I dedicate this report to my father Mr. Goodnews Edemevughe who has been a strong support and guide for me, enabling me to carry out my studies, particularly this project.

ACKNOWLEDGMENT

I sincerely want to acknowledge God Almighty who is my strength and sourceand who granted me the wisdom to carry out my studies.

I also want to acknowledge my parents, Mr. Goodnews Edemevughe and Mrs. Voke Edemevughhe, for their love, support, and financial assistance through this journey.

I also want to thank my supervisor, Dr. C.F. Amaechi, for making out the time to guide and encourage me during the course of this project work. My appreciation also goes to Mr. A.K. Okoduwa, for his immense help and assistance throughout the course of this work.

I want to sincerely appreciate Prof. A. A. Enuneku, the head of department of the department of Environmental Management and Toxicology, my genial course adviser, who is always ready to listen and assist, whenever I needed help, and to all my lecturers for all their efforts throughout my academic journey. Finally, I would like to express my sincere gratitude to my friends and colleagues for their support and encouragement throughout the course of this study, God bless you all.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

APPENDICES

ABSTRACT

Air pollution is a growing concern in Nigeria, with significant implications for public health and the environment. This study provides a comparative assessment of air quality in Kano and Bayelsa states from 2019 to 2024 using Sentinel-5P satellite data. The study focuses on key pollutants, including carbon monoxide (CO), nitrogen dioxide (NO_2), and aerosols, to evaluate spatial and temporal variations in air quality between the most populated (Kano) and least populated (Bayelsa) states in Nigeria. The research utilizes remote sensing techniques, Geographic Information System (GIS) tools, and statistical methods to analyze pollutant concentrations and identify trends over the study period. Results indicate that air pollution levels in Kano are primarily influenced by vehicular emissions, industrial activities, and seasonal dust storms, leading to high NO_2 and aerosol concentrations. In contrast, Bayelsa's air quality is significantly impacted by gas flaring and petroleum-related activities, with elevated CO levels being a major concern. Statistical analysis reveals notable differences in pollutant concentrations between the two states, showing that Kano state consistently has higher Aerosol and NO_2 levels than Bayelsa state, and Bayelsa state consistently has higher CO concentrations than Kano state. These results emphasize the role of population density and industrialization in shaping air quality patterns. The study also highlights the influence of population on air pollution, showing that while high population density in Kano contributes to increased emissions, Bayelsa's lower population does not necessarily translate to better air quality due to intensive industrial activities. These findings emphasize the need for targeted air quality management strategies tailored to the unique pollution sources in each state. Policies should focus on enhancing emission regulations for industries in Bayelsa and implementing stricter vehicular emission controls in Kano. Expanding air quality monitoring infrastructure and promoting clean energy alternatives are also recommended to mitigate pollution impacts. The study contributes to a deeper understanding of regional air quality variations in Nigeria, providing valuable insights for policymakers and environmental health practitioners.

CHAPTER ONE

INTRODUCTION

Air quality refers to the condition of the air relative to the presence of pollutants, which may be solids, liquids, or gases. These pollutants, often harmful to both living organisms and the environment, originate from various natural and human activities (Manisalidis *et al*., 2020). Poor air quality is directly linked to significant public health issues, as well as environmental degradation, making it a priority for countries globally to regulate and monitor air pollution (Borge *et al*., 2023). Pollution impacts human health severely. Exposure to pollutants like sulfur dioxide (SO_2), carbon monoxide (CO), and particulate matter (PM) has been correlated with respiratory diseases, cardiovascular conditions, cancer, and premature death (Burnett *et al*., 2018). SO_2, for instance, reacts with water vapor in the atmosphere to produce sulfuric acid (H_2SO_4), leading to acid rain that can cause respiratory irritation and environmental damage (Haq *et al*., 2021). Similarly, fine particulate matter ($PM_{2.5}$) can penetrate deep into the lungs, carrying toxic chemicals associated with cancer risks (Landrigan *et al*., 2017). Beyond health, air pollution damages ecosystems, reduces agricultural yields, and accelerates climate change. Pollutants harm vegetation, acidify soils, and can even alter natural ecosystems (Fowler *et al*., 2020).

West Africa, for example, faces severe air quality challenges. The continent, particularly in urban areas, suffers from high pollution levels due to dense vehicular traffic, unregulated industrial emissions, and widespread use of diesel generators (Gulia *et al*., 2015). In Nigeria, for example, the lack of consistent electricity supply has led to widespread generator use, further increasing CO and PM levels in cities (Amegah and Agyei-Mensah, 2016). In Accra, Ghana, studies reveal that traffic emissions are a primary source of pollution, contributing to hazardous air quality levels and worsening health outcomes for urban residents (Baklanov *et al*., 2014). Efforts to assess pollution levels in West Africa are still ongoing. Projects like the DACCIWA (Dynamics-Aerosol-Chemistry-Cloud Interactions in West Africa) Consortium havestudied air pollution causes and consequences. Findings indicate that pollution levels in West African cities often exceed thresholds considered safe by the World Health Organization (WHO), posing serious health risks to the population (Anenberg *et al*., 2018).

The lack of monitoring infrastructure is a significant barrier to understanding air quality in many African countries. Only half of African countries have accessible data on pollutant levels, and the quality of this data varies (Katoto *et al*., 2019). The DACCIWA project has contributed valuable insights into pollution in specific cities, but regional gaps remain, particularly in rural and underserved areas (Borge *et al*., 2023). West African countries have enacted some air quality standards, but many are outdated. For instance, several countries' PM limits exceed WHO recommendations, emphasizing the need for regulatory updates (Mir Alvarez *et al*., 2020). Modernized policies that account for the latest scientific evidence and include enforceable standards are essential for meaningful progress (Lelieveld *et al*., 2015). In addition, urban planning and transport regulations could mitigate some of the emissions from traffic and industries, which are the main contributors to air quality issues in the region (Apte *et al*., 2015).

Air quality in Nigeria is a significant environmental and public health concern, particularly in urban and industrial centers (Abaje *et al*., 2020). While awareness of air pollution is increasing, Nigeria lacks a comprehensive air quality monitoring network, making it challenging to assess the extent of the problem accurately and develop effective mitigation strategies (Mahmud *et al*., 2023).

Bayelsa state which is the least populated state in the nation (National Bureau of statistics, 2020), for instance, located in the Niger Delta, is heavily affected by pollution due to extensive oil exploration and production activities, with gas flaring identified as a primary source (Ogunsola *et al*., 2023). Studies have recorded high concentrations of methane (CH_4) and carbon dioxide (CO_2) in the atmosphere, stemming from these flaring operations (Ogunsola *et al*., 2023). Beyond gas flaring, other industrial activities such as refining and petrochemical processes also add to Bayelsa's pollution issues (Ogunsola *et al*., 2023). Thispollution has severe implications for human health, increasing the risk of respiratory and other health issues among residents (Ephraim-Emmanuel *et al*., 2023).

Kano state on the other hand, which is the most populated state in the country (National Bureau of Statistics, 2020), is a major urban center in Northern Nigeria, and presents a different set of air quality challenges (Mohammed *et al*., 2021). While industrial emissions contribute to pollution in the area, vehicular traffic from older, poorly maintained vehicles is a primary pollution source, with inadequate emission controls exacerbating the situation (Khadija and Muhammad, 2019). Additionally, Kano's location in the Sahelian region makes it susceptible to seasonal dust storms, increasing levels of particulate matter during the dry season (Abaje *et al*., 2020; Mohammed *et al*., 2021). Studies have also measured high levels of sulfur dioxide (SO_2) and nitrogen dioxide (NO_2), pollutants known to exacerbate respiratory problems and other health issues (Khadija and Muhammad, 2019). The widespread burning of fuelwood for cooking and heating in densely populated areas further contributes to indoor air pollution, a practice driven by limited access to reliable and affordable alternative energy sources (Abulude *et al*., 2022).

Across Nigeria, the combined effects of urbanization, industrialization, and energy needs significantly impact air quality. The contrast between air quality issues in Bayelsa and Kano underscores the complexity of air pollution sources and impacts in Nigeria. For instance, while industrial emissions and gas flaring dominate in Bayelsa, vehicular emissions and dust storms are more problematic in Kano. Furthermore, reliance on biomass for cooking and heating continues to worsen indoor air pollution across Nigeria, particularly in regions with less access to clean energy options (Abulude *et al*., 2022; Asubiojo, 2016). This therefore necessitates air quality monitoring in order to protect public and environmental health.

Traditional air quality monitoring relies on established networks, which offer comprehensive data but often lack the flexibility needed to capture local pollution variations or address real-time needs (Fowler *et al*., 2020). In response, portable analytical devices have gained importance, allowing measurements to be taken across multiple locations. Portable gas chromatographs, mass spectrometers, and photometric devices can be used on-site to measure pollutants like VOCs and carbon monoxide, though limitations in sensitivity and data resolution remain (Meseke *et al*., 2021). Such devices are especially useful for localized monitoring, supplementing fixed networks, but often require additional calibration to provide accurate results (Shabani, 2023). Biomonitoring offers a biological perspective on air pollution by using organisms like mosses and lichens to capture pollutant data in their tissues. This low-cost method enables sampling in remote or otherwise inaccessible areas and can indicate biological impacts of pollution (Agbo *et al*., 2020). However, biomonitoring lacks standardized procedures, which impacts consistency across different studies and settings (West *et al*., 2016). Another method is passive sampling which provides a low-cost, effective solution for air quality monitoring in areas lacking continuous monitoring infrastructure. The technique, which relies on pollutant diffusion into a sampler and quantification via spectrophotometry, is guided by Fick's Law (Lanzafame *et al*., 2016). Widely adopted in Europe, passive sampling for NO_2 has been validated by the Joint Research Centre, showing high correlation with reference measurements and confirming it as a reliable alternative to continuous monitoring. Environmental factors like wind, temperature, and humidity may affect accuracy, but protective shelters reduce these effects within practical limits.(Lanzafame *et al*., 2016). The development of affordable air quality sensors has also fueled citizen science projects, where individuals and communities can gather air quality data themselves. This crowdsourced approach expands geographic monitoring and increases data coverage, but ensuring data accuracy is a challenge, as variations in device quality can impact readings (Amaechi and Biose, 2016). Interestingly, artificial intelligence (AI) is now frequently employed in air quality monitoring to analyze large datasets, spot patterns, and enhance predictive models. AI can improve forecast accuracy by adjusting for real-time meteorological data, such as wind speed and temperature, and can help with optimal placement of monitoring devices, making it a valuable asset for modern air quality networks (Kök *et al*., 2017). Finally, remote sensing through satellites and aircraft enables extensive air quality monitoring, offering a broad view of pollution levels across regions (Singh *et al*., 2021). The Sentinel-5P satellite, equipped with the Tropospheric Monitoring Instrument (TROPOMI), is particularly useful for this purpose, delivering high- resolution data on pollutants such as nitrogen dioxide (NO_2), carbon monoxide (CO), and aerosols. This capability is essential in areas lacking widespread ground-based monitoring, as in many Nigerian cities, where satellite data fills the gaps and supports spatial analysis of pollution trends. Sentinel-5P's data alsocomplements on-ground networks, correlating well with local measurements and allowing for a comprehensive assessment of air quality trends in both populated and remote areas (Virghileanu *et al*., 2020), which is why it is used in this study.

1.1 STATEMENT OF PROBLEM

Air pollution in Nigeria is a serious issue, often showing in various ways such as vehicular emissions and dust storms in Kano down to gas flaring and oil exploration in Bayelsa, leading to numerous negative health effects, such as respiratory diseases, cancers, abnormal growth and development among others, as well damage to the ecosystem and environment (Manisalidis *et al*., 2020). This necessitates Air quality monitoring and research in a bid to combat these problems. Numerous research has been carried out in such places enabling government and policy makers to make informed decisions when it comes to preserving air quality and reducing pollution (Adamu and Oji. 2021; Barau *et al*., 2023; Ogunsola *et* al., 2023; Ede and edokpa, 2015). However little or no research has been done to analyze the contributions of population to air pollution and air quality. Kano and Bayelsa are significant locations for such comparative analysis as they are the most populated and least populated states in Nigeria respectively. For such large regions, remote sensing using sentinel 5p is a suitable tool for research.

1.2 JUSTIFICATION OF STUDY

There are a number of major gaps/issues this study aims to address. Firstly, there are limited studies which cover the entirety of Kano state and Bayelsa state, as regards air pollution and air quality. Additionally, there has been no use of Sentinel-5P for air quality studies in Bayelsa state, for the period and parameters which this study covers. Finally, there have been no studies which compare the air quality of two states in Nigeria on the basis of population. Kano state and Bayelsa state are the most suitable for such a comparative study, as Kano state is the most populated state in Nigeria (National Bureau of Statistics, 2020) and Bayelsa state the least populated (National Bureau of Statistics, 2020). As such, any influence of population on air quality can be more easily observed. Using data on Carbon monoxide, Nitrogen dioxide and Aerosols from 2019-2024 derived via remote sensing and GIS (Geographic Information System) technologies, this study will compare pollution levels in Kano and Bayelsa states and assess the influence of population on their air qualities.

This study is necessary as it will give government and policy makers a broader view of pollution issues in the study areas, enabling them to make more informed decisions in engineering strategies to reduce pollution levels and improve air quality, such as better/more effective regulation of industrial activities. Knowledge of population impacts will also help foster better urban/town planning methods to better protect public health and the environment.

1.3 AIM OF STUDY

To carry out a comparative assessment of CO, NO_2 and Aerosol levels in Kano and Bayelsa states.

1.4 OBJECTIVES OF STUDY

The objectives of this study are as follows:

1. To assess and compare data for the selected air quality parameters in Kano and Bayelsa states from 2019 to 2024.

2. To determine CO, NO_2 and aerosol concentrations for the years under review.

3. To determine if there is any statistical significant difference for the parameters between the states across the years under review.

CHAPTER TWO

LITERATURE REVIEW

2.1 AIR QUALITY

The loss of millions of healthy years of life has been caused by air pollution, which is one of the world's major causes of death. People in many low- and middle-income nations have been disproportionately affected by the health burden, and the quality of the air is still becoming worse (Goshua *et al*., 2022).

Air quality is a global concern due to its significant impacts on health, ecosystems, and economies. Approximately 90% of the world's population lives in areas where air pollution levels exceed World Health Organization (WHO) guidelines, contributing to reduced life expectancy through respiratory and cardiovascular diseases (Evangelopoulos *et al*., 2020; Fowler *et al*., 2020). Aerosols, carrying toxic chemicals, are linked to cancer and other severe health outcomes, while carbon monoxide (CO) and ozone (O_3) further exacerbate respiratory and cardiovascular risks by disrupting oxygen transport and damaging DNA, respectively (World Health Organization, 2021). Efforts to improve air quality have demonstrated substantial public health benefits. Reductions in PM2.5 levels have been associated with increased life expectancy and reduced hospital admissions for respiratory and cardiovascular conditions (Evangelopoulos *et al*., 2020; Cheng *et al*., 2016). The European Union (EU) offers a model for effective air quality management, with policy-industry collaboration leading to significant improvements over the past four decades (Crippa *et al*., 2016). These policies such as stricter vehicle emission standards and advancements like soot-free diesel engines have contributed to reductions in particulate matter and other pollutants (Fowler *et al*., 2020). Despite these successes, regions such as sub-Saharan Africa and South Asia face persistent challenges due to insufficient policy frameworks and infrastructure (Fowler *et al*., 2020).

2.2 AIR POLLUTION

Air pollution comes from natural processes such as dust storms, wildfires, and sea spray, as well as anthropogenic activities like industrial emissions, vehicular traffic, agricultural practices, and waste burning. These activities release pollutants such as nitrogen dioxide (NO_2), carbon monoxide (CO), and particulate matter (Ede and Edokpa, 2015; Amegah and Agyei-Mensah, 2017). Effective urban air quality management requires stringent emission controls, particularly targeting vehicular emissions in densely populated areas (Meng *et al*., 2021; Huangfu and Atkinson, 2020), as well as identifying these sources to guide interventions that reduce public health risks (Evangelopoulos *et al*., 2020). Globally, population-driven energy demands strain air quality, with industrial and vehicular emissions contributing to Aerosol and NO_2 pollution (Guerreiro *et al*., 2014). Higher pollutant concentrations, particularly in megacities, exacerbate health risks, reduce life expectancy, and increase healthcare costs (Holub *et al*., 2021).

2.2.1 Carbon Monoxide

Carbon monoxide (CO) is a significant air pollutant with severe health implications, originating from the incomplete combustion of fossil fuels and serving as a major contributor to both indoor and ambient air pollution (Vohra *et al*., 2021; WHO, 2014). The dangers of CO exposure have been well documented, particularly in relation to cardiovascular and neurological health risks (Savioli *et al*., 2024; Lee *et al*., 2015). Studies consistently show that short-term exposure to CO is associated with increased risks of myocardial infarction and emergency hospital admissions for cardiovascular diseases (Lee *et al*., 2015; Lee *et al*., 2020; Liu *et al*., 2024). A systematic review and meta-analysis by Lee *et al*. (2020) reinforced this connection, confirming a statistically significant relationship between CO exposure and myocardial infarction. Moreover, experimental research has demonstrated that prolonged exposure to carbon monoxide can promote cardiac remodeling and increase the likelihood of ventricular arrhythmia, as observed in animal models (Chu *et al*., 2021).

A large-scale study across 272 cities in China identified a strong correlation between ambient CO levels and cardiovascular mortality, further underscoring the role of CO as a key environmental risk factor (Liu *et al*., 2018). Additionally, CO exposure has been linked to increased hospital outpatient visits for respiratory diseases, particularly in regions with high pollution levels (Zhao *et al*., 2019). While most research focuses on cardiovascular and respiratory health, some studies have also explored the neurological consequences of CO exposure. Severe CO poisoning has been associated with cognitive and affective impairments, with long-term neuropsychological consequences (Rose *et al*., 2017; Angelova *et al*., 2023).

Interestingly, research has uncovered unexpected associations between CO exposure and certain health outcomes. A study examining hospital records found an inverse relationship between CO levels and outpatient visits for vaginitis, though further research is needed to establish causality and mechanisms behind this correlation (Xu *et al*., 2020).

2.2.2 Nitrogen Dioxide

Nitrogen dioxide (NO_2) is another significant air pollutant with various health implications (Moshammer *et al*., 2020; Zheng *et al*., 2021). Epidemiological studies have consistently demonstrated an association between both spatial and temporal variations in NO_2 and health risks (Dijkema *et al*., 2016; Qian *et al*., 2021; Schwarz *et al*., 2024). Although the experimental evidence regarding NO_2's harmful effects at typical ambient concentrations is not as extensive as that for particulate matter (PM), NO_2 remains a reliable predictor of health risks (Moshammer *et al*., 2020).

Previous studies have suggested that NO_2 may have acted as a proxy for aggressive particulate matter originating from incineration processes (Evangelopoulos *et al*., 2020); however, more recent research confirms that NO_2 itself remains a valid indicator of adverse health effects (Moshammer *et al*., 2020). Exposure to NO_2 has been strongly associated with increased mortality. Across 398 cities, for example, a 10 μg/m^3 increase in NO_2 concentrations was associated with an increase of 0.46% (95% confidence interval 0.36% to 0.57%) in total mortality (Meng *et al*., 2021). Furthermore, short-term NO_2 exposure has been linked to increased mortality risk in multi-location studies, such as those within the APHEA project (Wang *et al*., 2021; Meng *et al*., 2021).

Long-term exposure to NO_2 is associated with an increased risk of respiratory mortality (Chen *et al*., 2024; Huangfu and Atkinson, 2020). Additionally, NO_2 exposure has been correlated with emergency room visits and hospital admissions for asthma (Zheng *et al*., 2021). Cardiovascular impacts have also been observed, with research demonstrating an association between ambient NO_2 exposure and the severity of coronary atherosclerosis, as well as an increased risk of myocardial infarction (Wang *et al*., 2019; Newby *et al*., 2015).

The health effects of NO_2 exposure can be influenced by the presence of other pollutants. Studies emphasize the importance of evaluating the combined impacts of NO_2 and ozone (O_3) on short-term air pollution health risks, particularly in urban settings (Hossain *et al*., 2021). Additionally, NO_2 plays a critical role in atmospheric chemistry, interacting with organic compounds to influence air quality (Ravina *et al*., 2022*;* Zang *et al*., 2024).

The primary sources of NO_2 pollution are diverse and include road traffic, power generation, industrial combustion processes, and agricultural activities (Waqas *et al*., 2024; World Health Organization, 2021).

2.2.3 Aerosol

Aerosols, which include particulate matter (PM), are a significant concern for public health due to their diverse sources and harmful effects (Kim *et al*., 2015; World Health Organization, 2021; Manisalidis *et al*., 2020). These particles can be suspended in the air and vary in size, composition, and origin, leading to a range of health issues (Bede-Ojimadu and Orisakwe, 2020).

Exposure to aerosols, particularly PM, is associated with numerous adverse health effects (Manisalidis *et al*., 2020; Di *et al*., 2017), with oxidative stress and inflammation playing key roles (Fussell and Kelly, 2021). These effects range from respiratory and cardiovascular problems to more systemic issues (Sangkham *et al*., 2024). Aerosol exposure is a major risk factor for mortality and morbidity (Orellano *et al*., 2020; Burnett *et al*., 2018). PM is known to induce genes involved in inflammation, metabolic syndrome, and atherosclerosis (Brocato *et al*., 2014). Studies have also linked exposure to PM to increased hospital admissions for cardiorespiratory diseases and pneumonia (Requia *et al*., 2023; Liu *et al*., 2021; Kim *et al*., 2020). There is

evidence that PM exposure is associated with long-term survival after stroke (Chen *et al*., 2019; Lu *et al*., 2023). Short-term exposure to PM has been linked with out-of-hospital cardiac arrest and myocardial infarction (Liu *et al*., 2021; Kojima *et al*., 2020; Moderato *et al*., 2023). A study in South Korea found that long-term exposure to PM was associated with increased mortality (Di *et al*., 2017). Studies show that both short-term and long-term exposures to PM are associated with mortality (Yitshak-Sade *et al*., 2018; Seihei *et al*., 2024). It has also been noted that air pollution affects mortality even at very low levels (Weichenthal *et al*., 2022).

The health impacts of aerosols are not limited to adults. Exposure to traffic-related air pollution is associated with the risk of developing childhood asthma (Khreis *et al*., 2017). Children are particularly vulnerable to the effects of aerosols because their respiratory systems are still developing (Dondi *et al*., 2023). Vegetation diversity has been found to offer protection against childhood asthma (Donovan *et al*., 2018). Additionally, ambient pollution has been implicated in reprogramming the human small airway epithelial transcriptome (Rider and Carlsten, 2019).

The composition of aerosols also influences health impacts (Bede-Ojimadu and Orisakwe, 2020). For instance, PM from Saudi Arabia has been shown to induce inflammatory and metabolic changes (Brocato et al., 2014). Desert dust a major aerosol source, significantly impacts air quality and human health (Querol et al., 2019a). Aerosols may also contain toxic substances such as dioxins (Zhang *et al*., 2017) and polycyclic aromatic hydrocarbons (PAHs) (Mukherjee and Agrawal, 2017). Particle size is another important factor; ultrafine particles can penetrate deep into the lungs, exacerbating health risks (de Jesus *et al*., 2019). Black carbon, a component of PM, has significant health effects, particularly regarding cardiovascular disease (Song *et al*., 2022).

In dealing with air pollution as regards particulate matter, studies have evaluated the effectiveness of low- emission zones in reducing particulate exposure (Patel *et al*., 2023; Sarmiento *et al*., 2023; Holman *et al*., 2015). Urban green spaces have also been suggested as a means to mitigate air pollution and improve public health (Ai *et al*., 2023; Diener and Mudu, 2021).

Air pollution, particularly particulate matter and nitrogen oxides, can damage vegetation, reduce crop yields, and disrupt ecosystems (Ede and Edokpa, 2015; Abaje *et al*., 2020). Trees and urban green spaces play a critical role in mitigating air pollution by absorbing pollutants like PM2.5 and carbon dioxide (Abhijith *et al*., 2017). These natural systems not only improve air quality but also provide shaded areas, reduce urban heat islands, and enhance biodiversity (Ulpiani, 2021). Therefore, expanding urban green spaces and integrating green infrastructure into city planning can significantly mitigate air pollution while offering co-benefits for public health and climate resilience (Abhijith *et al*., 2017).

2.2.4 Air Pollution in Nigeria

Nigeria is particularly vulnerable to air pollution due to rapid population growth, urbanization, and industrial activities. Urban centers such as Lagos, Kano, and Abuja experience severe air quality challenges driven by vehicular emissions, overcrowding, and reliance on solid fuels for cooking (Abaje *et al*., 2020; Abulude *et al*., 2022). Additionally, the Niger Delta region suffers from industrial emissions, with activities such as gas flaring and oil exploration contributing to severe ecological damage and air quality degradation (Ede and Edokpa, 2015). Dust storms in northern Nigeria also pose significant challenges, contributing to high aerosol concentrations that adversely affect health and visibility (Ogunjo *et al*., 2022). In Yenagoa, Bayelsa State, satellite-based models reveal that PM2.5 levels often exceed WHO safety thresholds, highlighting the pressing need for targeted air quality management interventions (Abulude *et al*., 2022).

Addressing air pollution in Nigeria is hindered by inadequate monitoring infrastructure mainly ground-based monitoring stations. This limits the ability to collect reliable data for evidence-based policymaking (Shabani, 2023). Expanding monitoring networks and incorporating low-cost sensor technologies could bridge this gap, providing important data for understanding pollution trends (Morawska *et al*., 2018). Effective air quality management in Nigeria requires applying various strategies such as transitioning to renewable energy sources, improving waste management practices, and enforcing stricter industrial and vehicular emission standards. These measures are essential for mitigating air pollution and protecting public health in both urban and rural areas (Abaje *et al*., 2020), as well as making air cleaner.

2.2.5 Benefits of Clean Air

Clean air is fundamental to human health and well-being. Exposure to air pollution contributes to millions of premature deaths annually and the loss of healthy life years, placing it on par with major global health risks such as tobacco smoking and unhealthy diets (Evangelopoulos *et al*., 2020; World Health Organization, 2021). Researchers in the United States have found that when aerosol levels are reduced through air quality improvement measures, there is an increase in average life expectancy (Cheng *et al*., 2016; Fowler *et al*., 2020). Such interventions targeting outdoor air quality improvement have also demonstrated other significant public health benefits, including reduced respiratory and cardiovascular diseases (Evangelopoulos *et al*., 2020). Some of these interventions or strategies to mitigate air pollution include reducing emissions from vehicles and industrial facilities, promoting active transport like cycling and walking, and encouraging the use of cleaner fuels (Amegah and Agyei-Mensah, 2017; Abhijith *et al*., 2017). Low emission zones, for instance, have been effective in reducing personal exposure to ultrafine particles during commutes, leading to improved respiratory health (Javaid *et al*., 2020).

Clean air also provides numerous economic benefits. Improved air quality enhances workforce productivity and reduces healthcare costs associated with pollution-related illnesses (Fowler *et al*., 2020). A notable example is the long-term impact of the Clean Air Act of 1970 in the United States, which resulted in substantial economic gains by lowering healthcare expenditures and boosting productivity across sectors (Crippa *et al*., 2015). Cleaner air has even been shown to enhance performance in unexpected sectors, such as professional soccer, where players' productivity improved in less polluted environments (World Health Organization, 2021). The economic benefits of clean air, therefore extends beyond health to influence broader societal outcomes. Furthermore, clean air is vital for the health of ecosystems. Making air cleaner may be easier said than done in a lot of places given that air quality is affected by population (Borck and Schrauth, 2021).

2.3 POPULATION AND AIR QUALITY GLOBALLY

The relationship between population and air quality is complex and influenced by various factors, including urbanization, resource demand, and transportation needs (Borck and Schrauth, 2021). In densely populated regions, the impacts can vary. Higher population density is often linked to better air quality in specific scenarios due to reduced vehicle emissions, increased public transport use, and enhanced urban planning efficiency (Sterling, 2017; Chen *et al*. 2020).

2.3.1 Population improves Air quality

A study by Sterling (2017) demonstrated that increased population density correlates with shorter driving distances per capita, reducing overall vehicle emissions. In California, Sterling (2017) analyzed the relationship between population density, daily vehicle miles traveled (VMT), and PM2.5 concentrations, finding support for the hypothesis that higher density reduces VMT, a key factor in mitigating transportation emissions.

This is supported by Cheng *et al.* (2016), who highlighted the inefficiency of transit systems in low-density areas. They found that, underutilized buses emit more pollutants per person compared to densely populated regions, and therefore compared to low-occupancy modes of transportation, public transit systems with high occupancy can lower greenhouse gas (GHG) emissions; though, existing transit systems are not built to reduce their environmental effects. They suggested that design and operational changes should be made to transit systems in order to reduce their environmental impacts, such as a transit system with a hierarchical structure (trunk and feeder lines).

Chen *et al*. (2020) used a panel dataset of 284 cities over the years 2003–2016 and 30 provinces during 2004–2015, and found that increased population density reduces air pollution. The study used PM2.5 and SO2 as air pollution indicators. They found that the concentration of population in cities reduces the average cost of natural monopoly industries, such as electricity, gas, and public transportation, increasing residents' consumption of clean energy and public transportation services. This leads to reduced gas emissions that cause pollution and ultimately improved air quality.

Similarly, Castells-Quintana *et al*. (2021), using a sample of more than 1200 cities globally, found that denser cities show lower emissions per capita. The study combined pollution data with satellite data on built-up areas, population, and light intensity at night at the grid-cell level over the last two decades. They also used a large dataset for more than 190 countries with data from 1960 to 2010, and found that even at the country level, higher density in urban areas is associated with lower emissions per capita, though total higher population density is associated with higher emissions per capita. Their results also suggest that the size and structure of urban areas, as well as income and economic development matters when studying the density- emissions relationship.

In Germany, Fuladlu and Altan (2022) found that while population density correlates with higher concentrations of NO2 and SO2 pollutants, districts with higher densities demonstrated a relative reduction in pollutant levels compared to industrial zones. This suggests that urban planning and localized sources, such as industries, play a crucial role in pollutant distribution.

However, in all these studies, one can observe that population density alone does not enhance air quality (Sterling, 2017), and its benefits hinge on complementary systems, such as alternate forms of public transportation (Sterling, 2017). Boudalia *et al*. (2023) illustrated this in Oran, Algeria, where dense urban areas without sufficient public transit suffered from poor air quality. This highlights the need for mass transit systems to fully realize the environmental benefits of population density.

2.3.2 Population reduces air quality

While some studies highlight how increased population can favour air quality, others report that increased population correlates with higher nitrogen dioxide (NO_2) concentrations, highlighting the complexity of this relationship (Baek and Ban, 2020; Sun *et al*., 2023).

For example, Carozzi and Roth (2023) found that, although denser cities are generally more environmentally friendly because they emit less carbon per person, this does not always imply that residents of denser cities live in better conditions, because air pollution exposure is actually higher in denser cities.

Another study which supports this finds that, rapid population growth, particularly in urban areas, increases the demand for energy, transportation, and industrial activities, leading to higher emissions of air pollutants (Sun *et al*., 2023).

In addition, a study finds that, population growth also increases the demand for transportation, resulting in more vehicles on the road and increased emissions. This extends to shipping activities, both domestic and international, which are significant contributors to air pollution and related health risks (Zhang *et al*., 2021). Yuan *et al*. (2014) conducted a study in Hong Kong and found that, in high-density megacities, air pollution has a higher impact on public health than cities of lower population density. This is due to higher pollution emissions due to human activities as well as air flow stagnation brought on by closely packed tall buildings which reduce dispersion.

Borck and Schrauth (2021) used panel data for German districts to estimate the effect of population density on air pollution and found that, increasing population density by one percent increases NO_2 by 0.25 percent and PM_{10} by 0.07 percent with $PM_{2.5}$ having similar results, though for ozone, denser cities have lower concentrations. They also found that, air quality as measured by the aggregate AQI decreases with population density.

Urban air pollution from vehicular emissions has been linked to cardiovascular and respiratory illnesses, underlining the need for policies promoting clean transportation alternatives (Yu and Stuart, 2017). For this issue, compact urban growth strategies and the adoption of electric vehicles could play a role in reducing urban emissions, although their effectiveness depends on local energy sources and policy implementation (Yu and Stuart, 2017). Low-carbon transportation options and investment in public transit systems can also alleviate traffic-related pollution, improving air quality in urban areas (Javaid *et al*., 2020).

Urbanization and population growth are primary drivers of air pollution in developing countries, particularly in Africa (Abaje *et al*., 2020; Mir Alvarez *et al*., 2020). In Nigeria, cities like Kano, Lagos, Abuja, and Kaduna face severe air pollution challenges due to overcrowding, industrial activities, and vehicular emissions (Abaje *et al*., 2020). Inadequate environmental regulations exacerbate these issues, further degrading air quality and posing significant risks to public health (Mir Alvarez *et al*., 2020). In addition, the Niger Delta region, a major oil-producing area, is proof of the harmful effects of population growth coupled with industrial activities. Gas flaring and oil exploration have caused substantial air quality deterioration, contributing to respiratory diseases and ecological harm (Abaje *et al*., 2020). Sustainable urban planning and stringent regulations are essential to mitigate the negative impacts of urbanization on air quality in rapidly growing African cities (Abera *et al*., 2021).

Strategies to address the impacts of population growth on air quality include implementing emissions controls, promoting renewable energy, and improving urban infrastructure to support sustainable development (Yang *et al*., 2021). Urban green spaces, which reduce particulate matter and improve air quality, are vital components of these strategies (Abhijith *et al*., 2017).

2.3.3 Population and Air Quality in Africa

The relationship between population growth and air quality in Africa, particularly in Nigeria, is a pressing issue. Several studies from recent years have provided valuable insights into this complex interplay, emphasizing the negative environmental impacts of rapid population growth, urbanization, and industrial development.

Agbo *et al*. (2020) reviewed ambient and indoor air pollution across Africa, emphasizing the need for detailed studies to identify pollutant sources, levels, and hotspots in urban and rural areas. They argued that a deeper understanding of these dynamics is crucial for creating effective air quality management strategies in Africa.

Rapid population growth and urbanization in Africa exacerbate air pollution, particularly in cities experiencing inadequate infrastructure and limited regulation (Mir Alvarez *et al*., 2020). Vehicular emissions remain a significant source of air pollution in densely populated cities, with poor fuel standards and aging vehicles contributing to high levels of pollutants such as nitrogen dioxide (NO_2) and fine particulate matter (PM2.5) (Cheng *et al*., 2016).

A scoping review by Mir Alvarez *et al*. (2020) investigated air quality monitoring, policy, and health in West African cities. It highlighted the links between population growth, urbanization, and air quality. They found that increasing urban populations in West Africa make residents more susceptible to health problems like asthma and bronchitis caused by poor air quality. These challenges are compounded by limited air quality monitoring infrastructure and weak enforcement of environmental policies. The situation in West

Africa exemplifies the complexity of urban and rural air quality issues. Air quality monitoring in the region is limited, but available studies show that both rural and urban areas face significant pollution challenges (Mir Alvarez *et al*., 2020). Urban areas experience high pollution levels from vehicular traffic and industrial emissions, while rural areas are predominantly affected by biomass burning for cooking and heating, alongside natural sources such as dust storms from the Sahara Desert (Mir Alvarez *et al*., 2020).

2.3.4 Population and Air Quality in Nigeria

In Nigeria, urban areas like Lagos, Kano, and Abuja face severe air pollution due to a combination of high population density and industrial activities (Abaje *et al*., 2020). In Lagos, studies have shown that illnesses caused by air pollution place a significant financial burden on vulnerable populations, highlighting the public health and economic challenges linked to poor air quality in rapidly growing cities (Croitoru *et al*., 2020). Urban areas are frequently associated with higher levels of air pollution, but rural areas are also significantly affected by various air quality challenges (Mir Alvarez *et al*., 2020). Studies reveal that specific pollutants, such as PM2.5, can sometimes be higher in rural areas compared to urban areas. This is often due to agricultural activities, residential wood burning for heating, and the long-range transport of pollutants from urban and industrial areas (Piracha and Chaudhary, 2022). These findings emphasize that air quality disparities between urban and rural areas depend on pollutant types and geographical contexts.

The Niger Delta region of Nigeria is an example of how industrial activities affect air quality in both rural and urban areas. A study shows that suspended particulate matter (SPM) levels in the atmosphere can reach alarming levels due to oil and gas exploitation, alongside other industrial processes (Echendu *et al*., 2022). The lack of stringent environmental regulations exacerbates these pollution issues, highlighting the need for policy interventions and improved enforcement mechanisms. The Niger Delta region further illustrates the environmental damage caused by industrialization without strong regulatory controls. Activities like gas flaring and oil spills contribute to severe air pollution and harm ecosystems, highlighting the urgent need for better environmental management in the region (Abaje *et al*., 2020).

In the northern parts of the country, air pollution mapping and assessment in Kano metropolis have been the focus of most recent studies in Kano state, highlighting the variability of air quality across different land use zones. A study by Adamu and Oji (2021) investigated air pollution exposure across industrial, residential, commercial, and institutional zones in Kano. Using portable digital air pollution detectors, they monitored ambient air quality parameters, including carbon monoxide (CO), sulfur dioxide (SO_2), hydrogen sulfide (H_2S), nitrogen dioxide (NO_2), and particulate matter (PM_{10}). Spatial distribution maps were created using Geographic Information Systems (GIS) techniques. The research revealed a strong correlation between air pollution levels and land use. High pollution exposure was identified in the industrial and commercial zones of Bompai and Sabon Gari, attributed to industrial activities and vehicular emissions. In contrast, areas like Dorawa and the School of Technology showed relatively lower pollution levels but were noted to be at risk of bioaccumulation over time. These findings highlight the significant role of zones of commercial and industrial activities in shaping spatial pollution patterns and offer critical insights for developing targeted air quality control strategies in Kano.

Benazzi, K. and Muhammad, I. (2019) conducted a four-day assessment in April 2017 to measure SO_2 and NO_2 levels in Kano's ambient air. They recorded high concentrations of these pollutants in urban areas, primarily due to industrial emissions and vehicular traffic.

This short-term analysis highlighted the need for continuous monitoring and stricter enforcement of air quality regulations in the city.

A complementary study by Barau et al. (2023) explored the smellscape clusters and their relationship with air quality in Kano. The research emphasized the rapid expansion of informal settlements and its contribution to worsening air quality. These areas were identified as pollution hotspots due to unregulated waste burning, high population density, and the use of biomass for cooking and heating. The study advocated for inclusive decision-support tools to integrate public perception and scientific data in air quality management.

Bayelsa State, one of the study areas for this research, located in the Niger Delta region of Nigeria, faces significant air quality challenges due to industrial activities, artisanal refining, and domestic energy practices. Several studies have analyzed these issues, providing valuable insights into the sources and impacts of air pollution in the area. Ede and Edokpa (2015) provided a regional perspective on air quality in the Niger Delta, including Bayelsa. They highlighted the combined impacts of industrial emissions, gas flaring, and domestic energy practices on air quality. Their findings indicate that the region's environmental challenges are compounded by weak enforcement of existing air quality regulations and inadequate monitoring infrastructure.

Research by Ogunsola et al. (2023) identified methane (CH_4) as the main contributor to air pollution in Bayelsa State. Using data from the European Space Agency (ESA) and NASA, the study examined CH_4, nitrogen dioxide (NO_2), and ozone (O_3) levels from 2003 to 2012. Bayelsa recorded the highest CH_4 concentrations in the Niger Delta, primarily due to gas flaring and oil extraction. Interestingly, areas without gas flaring exhibited high NO_2 concentrations, highlighting diverse pollution sources beyond industrial emissions. This study highlights the environmental burden imposed by oil and gas activities and calls for stricter controls on industrial emissions.

In Yenagoa, the capital of Bayelsa state, a study by Abulude *et al.* (2022) used satellite-based models to monitor particulate matter (PM2.5), Air Quality Index (AQI), and other meteorological parameters. The findings showed that PM2.5 levels frequently exceeded WHO safety thresholds, categorizing air quality as harmful. This is particularly concerning given the reliance on biomass for cooking and the proximity to industrial activities, which further exacerbate particulate matter concentrations. The study emphasized the urgent need for alternative energy sources and air quality management in Yenagoa.

Artisanal crude oil refineries pose significant public health risks in Bayelsa. A study by Pipa *et al*. (2024) measured suspended particulate matter (SPM) levels at six locations, including a control station. The SPM levels ranged from 69.16 to 117.67 $\mu g/m^3$, exceeding World Health Organization standards of 50$\mu g/m^3$ (Kolawole *et al*., 2023). These emissions were linked to respiratory illnesses, especially among populations near refining sites. The study highlighted the lack of regulation and enforcement in managing emissions from these informal refineries.

Ephraim-Emmanuel *et al*. (2023) investigated the respiratory health effects of pollution caused by artisanal refining activities in Bayelsa. They reported high incidences of respiratory conditions such as chronic bronchitis and asthma among residents. This highlights the significant health burden associated with artisanal refining and the urgent need for community education and stricter controls, as well as the need to apply various air monitoring techniques to obtain more holistic information on air quality in affected regions.

2.4 TECHNIQUES IN AIR QUALITY MONITORING

2.4.1 Portable Analytical Techniques

Portable analytical techniques are essential for air quality monitoring because they provide flexibility and affordability, allowing their use in diverse locations, including resource-limited settings (Seesard *et al*., 2024). These techniques are critical in areas without established monitoring infrastructure, making it possible to assess pollution levels and identify hotspots effectively (Hernández-Gordillo *et al*., 2021). Passive sampling involves collecting air pollutants over an extended period without requiring active air pumping. This makes it particularly suitable for long-term monitoring in areas with limited electricity (Khuriganova *et al*., 2019). Passive samplers work by adsorbing or absorbing pollutants onto a collection medium, such as filters or sorbent materials (Hayes and Gagnon, 2024). These are then analyzed in a laboratory to quantify pollutant levels. Examples of passive sampling devices include diffusion tubes, commonly used to monitor gases like nitrogen dioxide (NO_2), and badges, effective for tracking ozone and volatile organic compounds (VOCs) (Huang *et al*., 2018). Studies have demonstrated the reliability of passive samplers for capturing ambient air quality trends, even in environments with fluctuating pollutant levels (Moshammer *et al*., 2014; Khuriganova *et al*., 2019; Hayes and Gagnon, 2024).

Active sampling on the other hand, employs pumps to draw air through a filter or collection medium, enabling the measurement of pollutant concentrations over shorter durations (Manibusan and Mainelis, 2022). This method is more precise than passive sampling but requires more sophisticated equipment and higher operational costs (Manibusan and Mainelis, 2022). Active sampling is frequently used in urban areas to monitor pollution spikes caused by traffic or industrial emissions (Wong *et al*., 2019). These techniques are also effective in detecting short-term variations in particulate matter (PM) and gaseous pollutants like carbon monoxide (CO) and sulfur dioxide (SO_2) (Marc et al., 2015).

The development of portable sensors has transformed air quality monitoring by offering compact, lightweight devices capable of real-time measurements. These sensors can detect pollutants like PM2.5, NO_2, ozone (O_3), and CO. They are particularly valuable for personal exposure monitoring and community- based air quality assessments (Park *et al*., 2023). Portable sensors can also complement stationary monitoring networks by providing data on pollution in hard-to-reach or underserved areas (Thompson, 2016). Recent advancements in low-cost portable sensors have improved their accuracy and affordability, making them accessible for both scientific studies and public use. These devices employ advanced technologies, such as electrochemical sensing and optical particle counters, to provide high-resolution spatial and temporal data on air pollution (Hernández-Gordillo *et al*., 2021). A 2016 study conducted in Catania, Italy, assessed the use of portable diffusive samplers, specifically the Passam model, to monitor urban air quality in a cost-effective and efficient manner (Lanzafame *et al*., 2016). The study compared concentration values for pollutants such as nitrogen dioxide (NO_2), benzene (C_6H_6), and ozone (O_3), measured by portable samplers with those obtained from continuous samplers at fixed monitoring sites. A strong correlation was observed between the portable samplers and the fixed monitoring stations, demonstrating the reliability of portable diffusive samplers as an alternative to traditional methods (Lanzafame *et al*., 2016).

The quantitative performance and validation of portable air quality monitors are essential for ensuring accurate data collection (Khreis *et al*., 2022). Laboratory conditions offer controlled environments for initial validation. However, field validation remains a crucial step to account for real-world variables, such as fluctuating temperatures, humidity, and pollutant concentrations (Marć *et al*., 2015). Site-specific calibration is necessary for portable monitors to provide accurate readings. A study examining calibration methods highlighted that environmental factors, such as temperature and humidity, significantly impact sensor performance (Nalakurthi *et al*., 2024). Without considering these variables, calibration may result in inaccuracies. For instance, QT-50 measurements were found to overestimate pollutant concentrations, even after calibration, highlighting the importance of proper site-specific adjustments (Languille *et al*., 2020).

Portable air quality monitors have limitations, such as baseline drift and inconsistent correlation coefficients, which makes them less reliable, these issues must be addressed for valid data interpretation (Marć *et al*.,

2015). Studies evaluating low-cost sensors for indoor air quality revealed that these devices provide semi- quantitative responses and suffer from poor detection limits (Khreis *et al*., 2022; Tasic *et al*., 2023). None of the commercially available sensors evaluated met the quantitative standards necessary for precise indoor air quality monitoring. This demonstrates the current technological gap in low-cost indoor air quality sensors (Hernández-Gordillo *et al*., 2021).

2.4.2 Biomonitoring

Another technique Biomonitoring, is invaluable for assessing air quality, offering critical insights into the effects of pollutants on living organisms. This technique relies on bio-indicators, such as lichens, mosses, and certain plant species, to evaluate pollutant levels in the environment. Bioindicators accumulate pollutants over time, making them effective for long-term air quality monitoring and the detection of pollutants not easily measurable through traditional methods (Torretta *et al*., 2015). Lichens are particularly useful as bioindicators because they lack a protective cuticle and depend on atmospheric nutrients, making them sensitive to air pollution. A study conducted in industrial areas shows that lichen species diversity decreases with increasing levels of pollutants such as sulfur dioxide (SO_2) and nitrogen oxides (NO_x) (Torretta *et al.*, 2015). Mosses, similarly, are effective at capturing particulate matter (PM) and heavy metals, providing a clear picture of pollution gradients in both urban and rural areas (Chaudhuri and Roy, 2024)

Two pivotal studies emphasize the potential of biomonitoring techniques in assessing air quality. Van der Wat and Forbes (2015) investigated the application of lichens as biomonitors for organic air pollutants, leveraging their unique physiological characteristics. Lichens lack a protective cuticle and rely entirely on atmospheric deposition for nutrients, making them highly effective accumulators of air pollutants such as polycyclic aromatic hydrocarbons (PAHs), volatile organic compounds (VOCs), and other organic contaminants. This ability enables them to provide insights into the distribution and concentration of pollutants over time and space (Toretta *et al*., 2015). The study emphasized the importance of species selection, as different lichen species exhibit varying sensitivities to pollutants. For instance, foliose and fruticose lichens are more sensitive to air quality changes than crustose lichens. Standardizing sampling protocols and laboratory analysis techniques was also highlighted to ensure consistency and reliability in biomonitoring studies. The authors demonstrated that lichens are particularly valuable in remote or inaccessible areas where traditional monitoring networks are not feasible, offering an alternative for tracking long-term air quality trends (Van der Wat and Forbes, 2015).

Torretta *et al*. (2015) explored the use of bioindicators for assessing air quality in industrially affected regions. Their research focused on identifying the impact of industrial emissions on the environment through bioindicator species capable of capturing pollution gradients. The study incorporated mosses and lichens to evaluate the accumulation of heavy metals and particulate matter in areas with significant industrial activity. The authors highlighted that bioindicators provide spatial data that can identify hotspots of pollution, which is particularly useful for understanding the dispersion of emissions from industrial facilities. They also emphasized that integrating biomonitoring with traditional analytical methods could enhance the accuracy of air quality assessments. The findings illustrated the value of bioindicators in identifying industrial pollution impacts on surrounding ecosystems, aiding regulatory agencies in environmental management and remediation planning (Torretta *et al*., 2015).

Biomonitoring serves as a complementary approach to traditional monitoring networks, particularly in regions with limited access to sophisticated monitoring equipment. Unlike stationary sensors, bioindicators provide spatial and temporal data on pollutant deposition and its ecological impacts (Marć *et al*., 2015). Furthermore, biomonitoring can highlight the biological effects of air pollution, which are not always apparent from chemical analyses alone (Parmar *et al*., 2016).

While biomonitoring offers many advantages, it also has limitations. The sensitivity of bioindicators can vary based on environmental conditions, species selection, and pollutant types (Parmar *et al*., 2016). For example, the response of lichens to air pollutants may differ depending on the humidity and nutrient availability in their environment (Torretta *et al*., 2015). Moreover, integrating biomonitoring data with other air quality monitoring methods, such as portable sensors or remote sensing, remains a challenge due to the differences in measurement scales and data formats (Marć *et al*., 2015).

Advancements in air quality monitoring technologies, such as portable sensors and remote sensing, have opened up possibilities for integrating biomonitoring data into comprehensive air quality assessments.

However, the literature highlights a gap in explicitly linking biomonitoring techniques with big data analytics and modern monitoring networks (Marć et al., 2015). Addressing this gap could enhance the accuracy and applicability of biomonitoring in addressing air quality challenges.

2.4.3 Artificial Intelligence

Artificial Intelligence (AI) is transforming air quality monitoring (AQM), enabling advanced data- driven approaches that improve accuracy, real-time monitoring, and effective pollution management (Olawade *et al*., 2024). Traditional methods, such as ground-based stations, while reliable, have limitations in spatial and temporal coverage, making it difficult to detect localized pollution hotspots (Kaginalkar *et al*., 2021)). AI-driven methodologies address these gaps by leveraging predictive analytics, cost-effective sensor networks, and continuous monitoring capabilities (Kaginalkar *et al*., 2021). Machine learning (ML), a core component of AI, enables systems to predict air quality parameters by learning patterns from historical data without explicit programming. ML has been successfully applied in forecasting pollutant levels such as CO, NO_2, O_3, PM2.5, and PM10 (Bekkar *et al*., 2021). Algorithms like convolutional neural networks (CNNs), random forests, and long short-term memory (LSTM) networks have been used to enhance the accuracy of air quality (Navares and Aznarte, 2020). For instance, ML models have demonstrated their ability to predict NO_2 concentrations in real-time, significantly outperforming traditional statistical models (Goh *et al*., 2021). Deep learning (DL), a subset of ML, leverages artificial neural networks (ANNs) to analyze complex datasets, mimicking human cognitive processes. DL has proven particularly effective in air quality monitoring by forecasting pollutant concentrations such as PM2.5 (Kalantari *et al*., 2024). A study using DL techniques highlighted the potential of LSTM and hybrid models to improve the accuracy of PM2.5 concentration predictions (Zhou *et al*., 2024). Additionally, remote satellite-derived hydro-climatological variables have been integrated into DL models to enhance the forecasting of air quality indices, showcasing the scalability of these techniques (Ahmed *et al*., 2024).

The integration of AI with the Internet of Things (IoT) and big data technologies has revolutionized AQM systems. IoT-enabled devices provide continuous data streams, while AI processes the data to identify trends and predict pollution patterns (Kaginalkar *et al*., 2021). For example, smart in-vehicle air quality monitoring systems using ML algorithms enable real-time pollutant detection and exposure assessments (Goh *et al*., 2021). These integrated systems are particularly effective in urban environments where air pollution levels fluctuate rapidly (Ramadan *et al*., 2024).

Despite its advantages, AI implementation in AQM faces several challenges. One critical issue is the lack of standardization in monitoring systems, which hampers the comparison of data across different regions (Masiol and Harrison, 2015). Furthermore, the accuracy of AI models heavily depends on the quality, diversity, and volume of training datasets. Inconsistent or incomplete data can lead to unreliable predictions, limiting the applicability of these systems in real-world scenarios (Zhou *et al*., 2024).

A study was carried out by Wang *et al*. (2024) which integrated the Parallelized Large-eddy Simulation Model (PALM) with Convolutional Neural Network (CNN) models in Nanjing, China. It aimed to improve the accuracy of urban air pollution predictions by combining physical simulations with machine learning. Urban morphology data further enriched the model, accounting for the influence of buildings and structures on pollutant dispersion.

Another study was carried out by Wu *et al*. (2024) which applied Automated Machine Learning (AutoML) to address data gaps in the Greater Bay Area, China. This study focused on bridging long-term hourly air quality data between neighboring monitoring sites. AutoML optimized model accuracy and scalability without requiring extensive manual intervention, demonstrating its utility in regions with uneven monitoring infrastructure.

Ahmed *et al*. (2024) also carried out a study which developed an advanced deep learning predictive model for forecasting air quality indices (AQI) using satellite-derived hydro-climatological variables. It employed deep learning techniques to analyze and predict pollutant concentrations, demonstrating the effectiveness of integrating AI with satellite data for air quality assessment.

2.4.4 Remote Sensing

Remote sensing techniques, which are used in this study, have revolutionized air quality monitoring (AQM), offering extensive spatial coverage and complementing ground-based methods. Traditional AQM networks, while accurate, often suffer from limited spatial resolution and coverage, especially in remote or underdeveloped regions. This limitation makes it difficult to detect pollution hotspots and assess regional air quality comprehensively (Holloway *et al*., 2021). Remote sensing overcomes these challenges by using satellite data, which enables the estimation of air quality parameters over large areas, filling gaps where ground-based monitoring is insufficient (van Donkelaar *et al*., 2016). A key application of remote sensing in AQM is the assessment of fine particulate matter (PM2.5). Van Donkelaar *et al*. (2016) demonstrated a combined geophysical-statistical method integrating satellite observations, air quality models, and monitoring data to create global PM2.5 estimates. This approach not only enhanced spatial resolution but also improved source attribution, crucial for designing effective mitigation strategies. The integration of geophysical and statistical data highlights remote sensing's role in providing policymakers with actionable insights. Machine Learning (ML) techniques further augment the utility of remote sensing in air quality studies. ML algorithms process satellite-derived data to bridge gaps in monitoring networks, offering real- time and predictive analytics. In the mining sector, Alvarado *et al*.

(2015) utilized airborne sensing systems to monitor dust particles generated by blasting activities. Their study demonstrated the potential of low-cost airborne sensors integrated with remote sensing technologies to assess air quality in industrial zones. This application highlights the adaptability of remote sensing for sector-specific air quality challenges, expanding its relevance beyond urban areas.

Advances in sensor technology and data processing continue to enhance the application of remote sensing in AQM. The development of crowd-sourced and portable sensors, as reviewed by Thompson (2016), complements satellite data by providing localized air quality insights. This integration creates a multidimensional monitoring framework capable of addressing both macro and micro-scale pollution concerns.

Kumar *et al*. (2016) highlighted the potential of real-time indoor air monitoring using remote sensing techniques. Though traditionally focused on outdoor pollution, this study opened pathways for applying satellite-derived data to assess indoor air quality, particularly in urban buildings. The findings underscore the versatility of remote sensing in adapting to various air quality monitoring needs. Remote sensing also plays a critical role in understanding trans-boundary pollution. Fowler *et al*. (2020) noted the importance of satellite data in tracking long-range pollutant transport, such as dust storms or industrial emissions, which affect multiple regions. This capability is particularly significant for global air quality management and international policy development.

Remote sensing has become an indispensable tool for air quality monitoring, offering extensive spatial coverage and complementing traditional ground-based monitoring networks. Its ability to provide data at national and global scales is evident in several key studies that have demonstrated its utility in assessing air pollution patterns and informing public health research.

Expanding on the potential of remote sensing, Larkin *et al*. (2017) created a global land-use regression model for NO_2 pollution. By combining satellite data with global land-use variables, their model enabled the estimation of NO_2 concentrations at fine spatial resolutions worldwide. This was particularly significant for regions with limited monitoring capabilities, as it provided a method to estimate pollutant levels where no ground-based data existed. Their findings highlighted the feasibility and importance of global-scale air quality models for understanding pollution exposure and its impacts on health and the environment.

Jerrett *et al*. (2017) explored the health effects of ambient particulate matter (PM) by comparing exposure estimates derived from ground-based measurements with those obtained using remote sensing data. This study revealed discrepancies between the two methods, emphasizing the need to evaluate the accuracy of remote sensing-derived pollution estimates. Despite these differences, remote sensing was found to be particularly useful for identifying pollution exposure in areas lacking ground-based monitors. The research demonstrated that remote sensing could significantly enhance epidemiological studies by providing comprehensive exposure data over large spatial scales, thus improving the understanding of air pollution's health impacts.

By enabling large-scale and high-resolution pollution assessments, remote sensing addresses gaps in traditional monitoring networks and supports more comprehensive analyses of pollution patterns (Tikader *et al*., 2024). However, the accuracy of remote sensing-derived estimates depends on the integration of satellite data with ground-based observations and advanced modeling techniques (Mzid *et al*., 2020). Discrepancies in exposure estimates, as noted by Jerrett *et al*. (2017), highlight the importance of continued refinement of remote sensing methodologies to improve their reliability for air quality assessments.

2.4.5 Sentinel-5P

Another air monitoring tool, The Sentinel-5 Precursor (Sentinel-5P) is a satellite launched under the European Space Agency's (ESA) Copernicus program, which aims to provide comprehensive environmental data for various applications. It carries the TROPOspheric Monitoring Instrument (TROPOMI), a state-of- the-art sensor designed to measure tropospheric pollutants. TROPOMI data is freely accessible and widely used in air quality research (Compernolle *et al*., 2021). Sentinel-5P can monitor a range of atmospheric pollutants, including nitrogen dioxide (NO_2), carbon monoxide (CO), sulfur dioxide (SO_2), methane (CH_4), ozone (O_3), and aerosol levels. These measurements are crucial for identifying the sources and causes of pollution. For example, the instrument's spatial coverage and high resolution allow researchers to determine whether pollution spikes result from human activities, such as industrial emissions or accidental releases, or natural phenomena like wildfires (Compernolle *et al*., 2021).

The satellite has demonstrated strong correlations between its data and ground-based monitoring stations, enhancing its reliability and enabling its use in regions lacking traditional monitoring networks (Bodah *et al*., 2022). This capability is especially significant for studying areas not frequently monitored, such as the Nile Delta region, where air pollution data is often sparse. Hassaan *et al*. (2023) used Sentinel-5p data to assess vulnerabilities to air pollution in the Nile Delta, examining long-term exposure to nitrogen dioxide (NO_2) and ozone (O_3). Their study highlighted the potential of satellite data to fill critical gaps in air quality monitoring across large and complex geographic areas.

Sentinel-5P has also played a pivotal role in assessing air pollution trends during the COVID-19 pandemic (Amaechi *et al*., 2024). By analyzing reductions in industrial activity and transportation emissions, researchers have gained insights into how anthropogenic activities affect air quality. The satellite's ability to provide consistent and high-resolution data has been instrumental in tracking these changes and evaluating the temporary improvements in air quality during lockdowns (Shindell *et al*., 2020). Sentinel-5P data has also proven valuable for studying long-term air pollution trends. Researchers recommend using its offline and reprocessed data streams to ensure accuracy in historical analyses (Hassaan *et al*., 2023). Such studies are vital for evaluating the effectiveness of air quality regulations and understanding how pollution patterns evolve over time.

The spatial and temporal coverage of Sentinel-5p makes it a powerful tool for air quality research. However, like all remote sensing technologies, it has limitations. While the data correlates well with ground-based measurements, discrepancies can arise due to differences in spatial resolution and the influence of local meteorological conditions (Verhoelst *et al*., 2021). Nonetheless, Sentinel-5p's ability to provide global coverage and real-time monitoring remains a critical asset for researchers and policymakers alike.

Using Sentinel-5p, Kaplan and Avdan (2020) analyzed NO2 and CO concentrations over North Macedonia from July 2018 to January 2019. They found a strong correlation between NO2 levels and population density, while CO values were inversely correlated with altitude ($R^2 = 0.8$). These findings highlights the utility of Sentinel-5P in identifying pollution hotspots linked to anthropogenic activities like household heating and industrial emissions.

Oxoli *et al*. (2020) examined NO2 trends using Sentinel-5P during the COVID-19 lockdown in Northern Italy. Results showed a 17.5% reduction in NO2 compared to the same period in 2019, with positive correlations ($\rho > 0.75$) between satellite and ground-based data. This highlighted Sentinel-5P's reliability for local air quality monitoring and its potential for detecting pollution reductions due to policy interventions.

Savenets *et al*. (2021) utilized Sentinel-5P to investigate NO2, SO2, and CO distributions from November 2018 to January 2020. They revealed significant contributions of industrial emissions and seasonal variability in pollutant levels, particularly during heating seasons. The data filled gaps in areas without ground-based sensors, notably in uncontrolled eastern territories.

Hassaan *et al*. (2023) assessed air pollution vulnerability in the Nile Delta. They validated CO and NO2 measurements with ground data, confirming Sentinel-5P's applicability for pollution risk assessments in densely populated regions.

Vîrghileanu *et al*. (2020) monitored NO2 over Europe during COVID-19, noting reductions up to 85% in urban areas. The satellite's high resolution allowed for robust validation against ground stations, demonstrating its role in studying lockdown effects on air quality.

Savenets *et al*. (2021) also investigated emissions near the Ukrainian coastline, revealing significant pollution from tourist boats. This highlighted Sentinel-5P's capacity to detect maritime emissions.

2.5 AIR QUALITY MONITORING IN NIGERIA

In Nigeria, Okoduwa and Amaechi (2023) monitored air quality in Benin City, Southern Nigeria, using Sentinel-5P TROPOMI and Google Earth Engine from 2019 to 2022. They mapped atmospheric CO, SO_2, and NO_2 concentrations, highlighting the versatility of satellite data in urban pollution monitoring. Their findings illustrated spatial distribution patterns and temporal trends, providing actionable insights for air quality management.

Omokpariola *et al*. (2024) analyzed short-term trends in Nigeria's air quality from 2018 to 2022 using Sentinel-5P and 3A/B satellite data. They observed stable levels of NO_2, SO_2, O_3, and HCHO, with minimal fluctuations, while CH_4 and CO showed slight variations due to potential atmospheric or emission-related factors.

Hassaan *et al*. (2023) assessed air pollution vulnerability in densely populated Nile Delta areas using Sentinel-5P and ground-based CO measurements. Ground truthing occurred through field trips from October 2020 to June 2021, validating satellite data accuracy. This study reinforced Sentinel-5P's applicability in evaluating pollution risks and informing public health policies.

2.5.1 Air Quality Monitoring in Study Areas

In Kano state, Olusola *et al*. (2020) analyzed Sentinel-5P TROPOMI satellite data to assess the impact of COVID-19 lockdowns on nitrogen dioxide (NO_2) levels across Nigeria, including Kano. They observed a significant reduction in NO_2 concentrations during the lockdown period. The study emphasized the utility of

Sentinel-5P in tracking short-term changes in air quality due to reduced human activity. This demonstrates the satellite's capability in capturing emission patterns tied to anthropogenic activities and regulatory interventions.

Ahmed *et al.* (2024) investigated the relationship between Urban Heat Island (UHI) effects and air quality in Kano Metropolis using Sentinel-5P and other remote sensing data. The study identified a significant correlation between UHI intensity and key air quality indicators, including particulate matter (PM1.0, PM2.5, and PM10), total volatile organic compounds (TVOC), and formaldehyde (HCHO). UHI intensity was found to exacerbate air pollution, particularly in urban centers, due to higher temperatures facilitating chemical reactions that lead to secondary pollutants. This research highlights Sentinel-5P's role in monitoring atmospheric conditions linked to urbanization.

Garba (2016) used Sentinel-5P data to assess gaseous pollutants such as NO_2 and SO_2 in Kano, providing insights into spatial distribution patterns across the metropolis. They linked pollution hotspots to traffic and industrial activities, demonstrating the satellite's effectiveness in identifying localized sources of pollution. The study also recommended integrating Sentinel-5P with ground-based data for a comprehensive understanding of air quality dynamics.

In Bayelsa state, the other study area for this research, there have been several studies done for air quality and air pollution monitoring, however none of them made use of Sentinel 5p for research. For instance, Morakinyo (2015) analyzed flaring and pollution detection in the Niger Delta, including Bayelsa State, using Landsat data spanning 1984–2013. This study evaluated the impacts of gas flaring on vegetation health, highlighting significant environmental degradation associated with flaring activities. The study's data, however, predates the launch of Sentinel-5P and cannot be directly linked to its datasets.

Similarly, Anejionu *et al*. (2015) investigated gas flaring and emissions using MODIS data. Their research focused on detecting gas flares and estimating flaring volumes at individual flow stations. While the findings provide valuable insights into pollution dynamics in the Niger Delta, they do not involve Sentinel-5P datasets. This is also the case for all other studies attributed to air monitoring in Bayelsa state.

Although these studies make use of remote sensing techniques, they do not use Sentinel-5p for the research. There are, however other tools used in accompaniment with remote sensing and Sentinel-5p technologies as well as Geographic Information System (GIS) technologies.

2.5.2 Google Earth Engine and ArcGIS

Google Earth Engine (GEE) is a cloud-based geospatial platform that integrates satellite imagery with computational algorithms to support advanced data analysis for environmental monitoring and management. Among its key applications, GEE is frequently used alongside Sentinel-5 Precursor (S5P), a satellite equipped with the TROPOspheric Monitoring Instrument (TROPOMI), to monitor atmospheric gases, assess air quality, and track climate-related changes globally. TROPOMI's advanced spectrometer capabilities enable daily global data capture, providing detailed information on pollutants such as NO_2, CO, SO_2, and PM concentrations (Okoduwa and Amaechi, 2024; Zhang *et al*., 2022; Mutanga and Kumar, 2019).

In a study focused on Kyiv, researchers employed GEE to analyze NO_2 and CO impacts on urban air quality. They downloaded average CO column density and UV Aerosol Index (UVAI) data to estimate average CO and PM concentrations. These findings highlighted the potential of integrating satellite-derived information for urban pollution management. Similarly, researchers in the Nile Delta region utilized GEE to retrieve Sentinel-5P satellite datasets for mapping pollutant concentrations. Ground-truth data collection complemented the remote sensing analysis, allowing for validation and refinement of air pollution models (Hassaan *et al*., 2023; Zhao *et al*., 2021).

ArcGIS, A Geographic Information System (GIS) software, complements GEE by providing advanced mapping and spatial analysis capabilities. For instance, ArcGIS was used to generate pollution maps and analyze spatial distribution using Sentinel-5P data retrieved through the EO Browser linked to Sentinel Hub. The Spatial Analyst tool in ArcGIS enabled detailed comparisons of retrieved pollution levels with measurement locations, further enhancing the precision of air quality assessments (Okoduwa and Amaechi, 2023; Okoduwa and Amaechi, 2024).

Collectively, these studies illustrate the increasing relevance of remote sensing platforms like GEE and ArcGIS in air quality monitoring. By combining high-resolution satellite imagery with geospatial analysis tools, researchers can derive actionable insights into atmospheric conditions and pollution patterns at both local and regional scales.

CHAPTER THREE

METHODOLOGY

3.1 STUDY AREAS

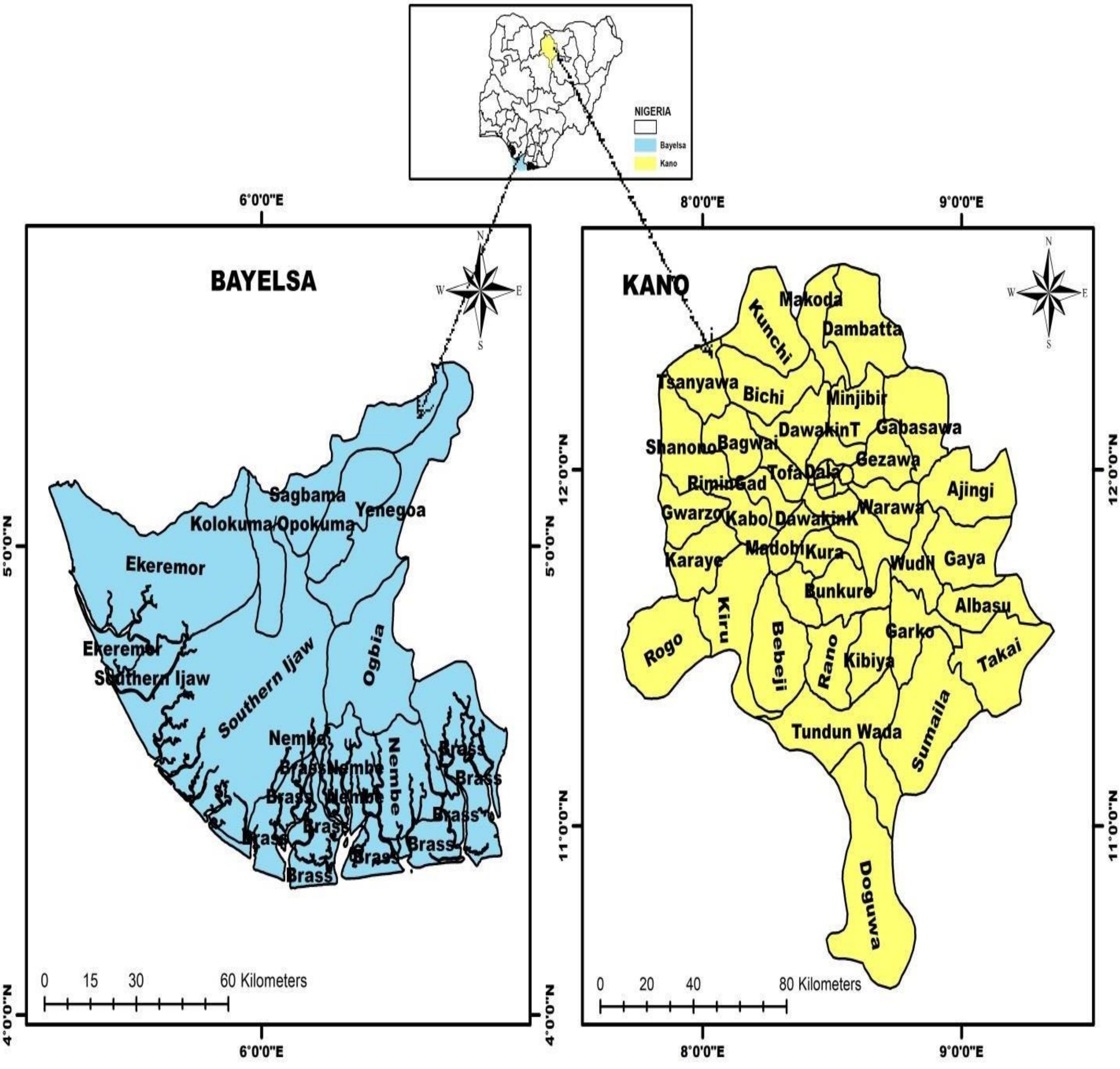


Figure 3.1: Map of study areas

3.1.1 Bayelsa State

Bayelsa state (Figure 3.1) is situated between latitudes 4°20'N to 5°20'N and longitude 5°20'E to 6°40'E (Berezi and Nwankoala, 2023). Its borders are shared by Rivers State to the east, Delta State to the north, and the Atlantic Ocean to the west and south. Bayelsa State with a land area of 9372.72 km^2, is shaped like a triangle, with the apex located northeast of the Sagbama Local Government Area, where the River Niger splits into the Forcados and Nun River systems. The state's vegetation is characterized by brackish water swamp forests, freshwater swamp forests, and riparian woods (Jack and Tokpo, 2021; Izah and Seiyaboh, 2018).

It is located in the Niger Delta region of Nigeria, and is notable for its rich biodiversity, including diverse aquatic habitats and waterways, as well as a shallow aquifer that supports agricultural activities (Abaje et al., 2020). The state's weather is influenced by both the dry, dust-filled tropical continental air mass and the humid tropical marine air mass. While the latter originates from the Sahara Desert's high-pressure belt and passes over the state during the dry season, the former is more common during the rainy season and comes from the Atlantic (Jack and Tokpo, 2021). These climatic patterns significantly influence agricultural and industrial activities in the region.

Bayelsa State which has a population of 2,394,725 (National Bureau of statistics, 2020), has a rich sociocultural life which stems from its collective traditions and practices. This is mostly depicted in ceremonies and rites of passage including marriages, funerals, traditional wrestling matches, festivals, dance, and the arts, among others (Jack and Tokpo 2021), and takes place in its 8 local government areas, namely; Brass, Yenagoa, Sagbama, Ekeremor, Kolokuma, Opokuma, Nembe, Ogbia, and Southern Ijaw. Interestingly, the name Bayelsa is a combination of the acronyms of the first three LGAs: Brass LGA (BALGA), Yenagoa LGA

(YELGA), and Sagbama LGA (SALGA) (Official website of Bayelsa state government, 2024).

The primary drivers of Bayelsa State's local economy are petty trading and subsistence farming. Farmers make up the majority of the population, which is primarily concentrated in rural areas. Crops like cassava, several yam species, cocoyam, sugarcane, potatoes, groundnuts, and vegetables like okra, pepper, pumpkin, and garden eggs are grown for subsistence and occasionally in commercial amounts (Jack and Tokpo, 2021). In addition, the people engage in fishing for subsistence, as the state has many lakes, ponds and swamps. Common jobs include canoe carving, logging, fish farming, palm wine tapping, small-scale animal farming, and the manufacturing of palm oil and fiber (Jack and Tokpo, 2021). Finally, multinational corporations such as Shell Petroleum Development Company (SPDC), the Nigeria Agip Oil Company (NAOC), Chevron Nigeria Ltd., Aiteo, Connoil, First E&P, etc., conduct exploration activities in the state, as it has enormous crude oil and gas resources (Jack and Tokpo, 2021).

Bayelsa and the wider Niger Delta region have suffered extensive environmental degradation due to the expansion of Nigeria's oil industry. The combination of rapid population growth and insufficient environmental regulation has exacerbated pollution levels. Pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), and particulate matter often exceed recommended limits in many parts of the region, impacting air quality and public health (Ogunsola *et al*., 2023).

Artisanal refining is a prevalent yet environmentally detrimental activity in Bayelsa State. This industry contributes to the release of toxic fumes and suspended particulate matter, posing considerable public health risks, particularly respiratory issues among residents (Suku *et al*., 2024). Studies have highlighted the adverse health outcomes associated with exposure to pollutants from artisanal refining, including elevated risks of respiratory diseases (Ephraim-Emmanuel *et al*., 2023).

3.1.2 Kano State

Kano state (Figure 3.1) is positioned in the Sudano-Sahelian region of Nigeria as it lies between longitudes 8° 45 E and 12° 05 E and latitudes 10° 30 N and 13° 02 N, it is about 840 kilometers south of the Sahara Desert, and occupies a land area of 20,760sq kilometers. The average elevation of Kano is around 472.45 meters above sea level, with the highest point at about 1000m above sea levels at Rishi hills (Isah *et al*., 2020; Aliyu *et al*., 2021).

Even if it occasionally hits 10 degrees Celsius during the harmattan season, the average temperature in Kano is always between 33 and 15.8 degrees Celsius (Muhammad *et al*., 2021). Kano experiences two distinct seasons: a prolonged dry season that typically lasts from October to April, and four to five months of rain, with an annual rainfall average of approximately 690 mm (Isah *et al*., 2020; Bello *et al*., 2014; Tanko *et al*., 2017; Aliyu *et al*., 2021). The Sudan Savannah, which has a sparse distribution of trees, grasses, and shrubs across the majority of the state, and the Northern Guinea Savannah, which has abundant biodiversity at its southern tip, are the two main vegetation types in Kano State, and are significant for the region's biodiversity and agricultural practices (Wakawa *et al*., 2016; Aliyu *et al*., 2021).

Kano state is composed of 44 local governments, and is the largest industrial and economic hub in Northern Nigeria, a status historically tied to its prosperous marketing activities and strategic positioning as a center for trade and industry (Bello *et al*., 2014). It boasts more than 400 privately held industrial sectors and 43 active marketplaces, and features a diverse range of industries, including textiles, tanning, footwear, cosmetics, plastics, enamelware, pharmaceuticals, ceramics, and furniture (Garba and Yunusa, 2016).

With a population of 14,253,549 (National Bureau of statistics, 2020), it is the most populated state in the country, and its urbanization has been driven by migration from rural areas, spurred by employment opportunities, commercial growth, and its role as a seat of government, industry, commerce, and education (Salisu, 2023). Rapid urban growth has contributed to significant environmental challenges, including air pollution, the urban heat island effect, and congestion, which have become pressing issues for sustainable development (Tanko *et al*., 2017; Garba and Yunusa, 2016).

3.2 DATA TYPE AND DATA SOURCE

The data used in this research is obtained from Sentinel 5p through Google Earth Engine (GEE). Sentinel 5p provides data on the levels of carbon monoxide (CO), Nitrogen dioxide (NO_2) and Aerosols, which are the pollutants focused on, in the study areas.

3.2.1 Sentinel- 5P

The Sentinel-5 Precursor (Sentinel-5P) is a satellite launched under the European Space Agency's (ESA) Copernicus program, which aims to provide comprehensive environmental data for various applications. It carries the TROPOspheric Monitoring Instrument (TROPOMI), a state-of-the-art sensor designed to measure tropospheric pollutants, and it measures ultraviolet earth-shine radiances at high spectral resolution. TROPOMI maps the global atmosphere daily with a resolution of 7 km × 3.5 km for all the spectral bands. TROPOMI data is freely accessible and widely used in air quality research (Compernolle *et* *al*., 2021; Virghileanu *et al*., 2020; Reshi *et al*., 2024). Sentinel-5P provides near real-time level 2 images, including data on a range of atmospheric pollutants, such as nitrogen dioxide (NO_2), carbon monoxide (CO), formaldehyde (CH_2O), sulfur dioxide (SO_2), methane (CH_4), ozone (O_3), and aerosol, and gives results for their concentration in mol/m^2 except for aerosols which have no SI unit. The data collected by Sentinel-5P can be accessed through platforms such as EO Browser and processed using software like ArcGIS. These measurements are crucial for identifying the sources and causes of pollution, assess air quality trends, study the relationship between pollutants and demographic data, and investigate the impact of wildfires on atmospheric composition (Reshi *et al*., 2024; Shikwambana *et* al., 2020; Okoduwa and Amaechi, 2023).. For example, the instrument's spatial coverage and high resolution allow researchers to determine whether pollution spikes result from human activities, such as industrial emissions or accidental releases, or natural phenomena like wildfires (Compernolle *et al*., 2021). The satellite has demonstrated strong correlations between its data and ground-based monitoring stations, enhancing its reliability and enabling its use in regions lacking traditional monitoring networks (Bodah *et al*., 2022). The spatial and temporal coverage of Sentinel-5P makes it a powerful tool for air quality research. However, like all remote sensing technologies, it has limitations. While the data correlates well with ground-based measurements, discrepancies can arise due to differences in spatial resolution and the influence of local meteorological conditions (Verhoelst *et al*., 2021). Nonetheless, Sentinel-5P’s ability to provide global coverage and real-time monitoring remains a critical asset for researchers and policymakers alike.

3.3 METHOD OF DATA COLLECTION

The information of the study areas (shapefiles), Kano state and Bayelsa state were exported from ArcMap after being clipped out of the shapefile of Nigeria. These shapefiles were imported into Google Earth Engine (GEE) which accesses the Sentinel-5P TROPOMI sensor, and the results were gotten by querying GEE using a script of codes run on the editor. These codes give information to GEE on the time period to be studied (2019-2024) and the pollutants in question (CO NO_2 Aerosol), which it can use to generate the required results.

3.3.1 Google Earth Engine

Google Earth Engine (GEE) is a cloud-based geospatial platform that integrates satellite imagery with computational algorithms to support advanced data analysis for environmental monitoring and management (Tamiminia *et al*., 2020; Okoduwa and Amaechi 2024). It provides a database of satellite imagery taken in near real time, which covers everywhere on earth, and therefore can be used to obtain captured images of areas of interest which show or describe information of interest such as land cover and vegetation cover data, flooding data, weather and climate, as well as Air quality data. It is therefore a suitable remote sensing tool for this study. Among its key applications, GEE is frequently used alongside Sentinel-5 Precursor (S5P), a satellite equipped with the TROPOspheric Monitoring Instrument (TROPOMI), to monitor atmospheric gases, assess air quality, and track climate-related changes globally (Okoduwa and Amaechi, 2024; Zhang *et al*., 2022; Mutanga and Kumar, 2019).

3.3.2 Selection of Aerosols, Carbon monoxide and Nitrogen dioxide as parameters

Aerosols, Carbon monoxide and Nitrogen dioxide are the most suited for this study, as they are the most commonly associated with urbanization, industrialization and vehicular emissions which are the major sources of air pollution in Bayelsa and Kano states. The use of these pollutants is also suitable as Aerosols adequately account for the air pollution resulting from dust storms which are frequent in Kano state, as well as pollution due to crude oil exploration and refining which occurs in Bayelsa state.

3.3.3 Timeframe of Analysis

The Sentinel-5P satellite which was used for this study was launched on October 13, 2017 (Kaplan *et al*., 2019). Nitrogen dioxide data was released from July 10, 2018 (Kaplan *et al*., 2019), and Carbon monoxide and Aerosol index data was similarly released within that period with its first successful use by scientists in November 2018 (European Space agency, 2024). This study uses air pollution data from January 1, 2019 to December 31, 2024, in order to ensure comprehensive temporal coverage for more reliable analysis. This is especially vital for analyzing trends and the significance of major events that may have affected air quality such as the COVID pandemic, the removal of fuel subsidy and the hike in fuel and transportation prices among other goods and services.

3.4 METHOD OF ANALYSIS

The data collected was analysed using ArcMap version 10.7.1, Google Earth Engine, Microsoft Excel and the Mann-Whitney U test. GEE provided satellite imagery of the study areas, Kano and Bayelsa states, showing concentration of the pollutants of interest in mol/m^2, except for Aerosols which has no SI unit. These images are referred to as Raster data, and were imported into ArcMap, where all irrelevant bits were extracted by mask using the shape files of the study areas. This refined data was edited and designed into maps that show variations in the concentration of the pollutants of interest using a colour grid (green, yellow, red) that indicates mild to severe concentrations, within the study areas over the period of 2019- 2024. Using Microsoft Excel, the trend of pollutant levels over the period of 2019-2024, was analysed and represented on graphs and the Mann-Whitney test was used to compare the pollutant levels between the two states.

3.4.1 Mann-Whitney U test

The Mann-Whitney U test is a non-parametric method used to assess differences between two independent groups when the data is not normally distributed, and serves as an alternative to the t-test, which assumes normality (Orcan, 2020). It ranks all data points from both groups (states in this study) and compares the sums of ranks (Orcan, 2020). The results are represented in a table showing 3 main value types. The Mann- Whitney U values represent the calculations for the comparison between the two states for each year and parameter, the Z-score indicates the deviation from the null hypothesis (no difference between the two states) and the asymptotic significance/p-value (2-tailed), indicates a significant difference between the two cities for each pollutant and year (Amaechi *et al.*, 2024). The Mann-Whitney U test is therefore an effective method for assessing differences in pollutant levels between the two states. The steps taken in this research is illustrated in Figure 3.2

3.5 RESEARCH DESIGN

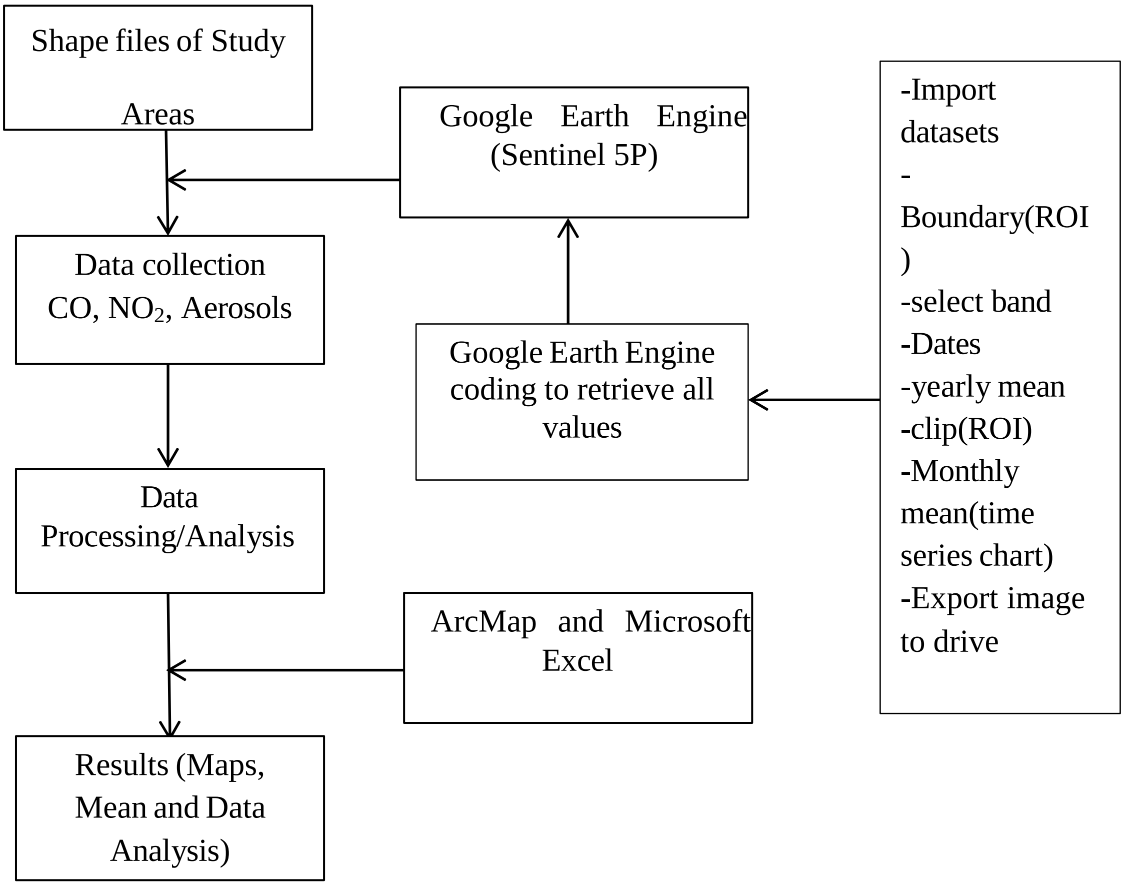


Figure 3.2: Illustration of the research design

CHAPTER FOUR

RESULTS

Table 4: Annual statistics extracted from the NO_2, CO and Aerosol maps of Kano and Bayelsa states (2019-2024)

	Kano State				Bayelsa State			
	CO (2019-2024)				CO(2019-2024)			
Year	Min	Max	Mean	Std dev	Min	Max	Mean	Std dev
2019	0.035	0.039	0.037	0.0028	0.047	0.051	0.049	0.0028
2020	0.036	0.04	0.038	0.0028	0.052	0.057	0.055	0.0035
2021	0.035	0.04	0.038	0.0035	0.049	0.054	0.052	0.0035
2022	0.034	0.04	0.037	0.0042	0.049	0.053	0.051	0.0028
2023	0.034	0.039	0.037	0.0035	0.046	0.052	0.049	0.0042
2024	0.036	0.041	0.039	0.0035	0.052	0.056	0.054	0.0028
	Kano State				Bayelsa State			
	NO_2 (2019-2024)				NO_2 (2019-2024)			
Year	Min	Max	Mean	Std dev	Min	Max	Mean	Std dev
2019	0.0000501	0.0000804	0.0000653	0.0000214	0.0000426	0.0000594	0.000051	0.0000119
2020	0.0000493	0.0000788	0.0000641	0.0000209	0.0000432	0.0000605	0.0000519	0.0000122
2021	0.0000543	0.0000547	0.0000545	0.0000003	0.0000473	0.0000637	0.0000555	0.0000116
2022	0.0000533	0.0000904	0.0000719	0.0000262	0.0000471	0.0000660	0.0000566	0.0000134
2023	0.0000553	0.0000919	0.0000736	0.0000259	0.0000446	0.0000640	0.0000543	0.0000137

2024	0.0000519	0.0000868	0.0000694	0.0000247	0.0000447	0.0000630	0.0000539	0.0000129

	Kano State				Bayelsa State			
	Aerosol (2019-2024)				Aerosol (2019-2024)			
Year	Min	Max	Mean	Std dev	Min	Max	Mean	Std dev
2019	-0.066	-0.746	-0.406	0.481	-0.887	-0.543	-0.715	0.243
2020	-0.914	-0.208	-0.561	0.499	-1.048	-0.655	-0.852	0.278
2021	-0.496	0.261	-0.118	0.535	-0.795	-0.509	-0.652	0.202
2022	0.175	0.887	0.531	0.503	-0.141	0.067	-0.037	0.147
2023	0.144	0.848	0.496	0.498	-0.243	-0.008	-0.126	0.166
2024	0.092	0.751	0.422	0.466	-0.203	-0.069	-0.136	0.095

4.1 DESCRIPTIVE ANALYSIS FOR MONTHLY CONCENTRATION OF PARAMETERS OF BAYELSA AND KANO STATES

4.1.1 Descriptive Analysis for Carbon Monoxide

From Appendix 1 and 2, one can observe that the concentration of Carbon Monoxide is significantly higher in Bayelsa state than in Kano state over the time period of 2019-2024, with its concentration reaching 0.075mol/m^2 in February, 2020. In Kano state, the highest Carbon Monoxide concentration was 0.046mol/m^2, which was reached in March for 2020 and 2021, in April of 2022 and May of 2024. This was likely influenced by oil exploration and refining activities, such as gas flaring and venting which is a major anthropogenic source of air pollution (Tran *et al*., 2024; Abaje *et al*., 2020; Soltanieh *et al*., 2016). Kano state having no oil does not carry out these activities, and evidently its higher population is not substantial enough to yield equal or higher CO pollution levels. It can also be observed that the lowest concentrations of CO occurred in October for Bayelsa state and in September for Kano state (except in 2024 when the concentration was 0.036mol/m^2 in September whereas the lowest was 0.035mol/m^2 which occurred in January, October and November) and the highest concentrations occurred in February for Bayelsa state and in the period of January to May for Kano state. This contrast can be attributed to more frequent biomass combustion, and low rainfall (no rainfall washout effect) which occurs in the dry season (de Sá *et al*., 2019; Simões Amaral *et al*., 2016; Yadav *et al*., 2019; Chen *et al*., 2019). This is extended for 5 months in Kano state, as the dry season lasts much longer there.

4.1.2 Descriptive Analysis for Nitrogen Dioxide

From Appendix 3 and 4, one can observe that the concentration of Nitrogen Dioxide is higher in Kano state than in Bayelsa state over the time period of (2019-2024), with its concentration reaching 0.0000768mol/m^2 in May, 2023. In Bayelsa state, the highest Nitrogen Dioxide concentration was 0.0000648mol/m^2, which was reached in December, 2021. This variance can be attributed to more severe vehicular emissions which is a major source of NO_2 in Kano state among other factors (Benazzi and Muhammad, 2019; Barau *et al*., 2023; Garba, 2016). The higher population in Kano state is one of such significant factors as it means more cars on the road and therefore more pollutant emissions (Jia *et al*., 2021; Willis *et al*., 2022), especially in the Kano metropolitan areas. It can also be observed that the lowest concentrations of NO_2 occurred in September for Bayelsa state with the exception of August and October of 2020 (concentrations of 0.0000399mol/m^2 and 0.0000398mol/m^2 respectively) and August, 2021 (0.0000468mol/m^2 in contrast to September's 0.0000489mol/m^2), while the highest concentrations occurred in November, December and

January, which are months of the dry season when there is increased burning of biomass and low rainfall (no rainfall washout effect) (de Sá *et al*., 2019; Simões Amaral *et al*., 2016; Yadav *et al*., 2019; Chen *et al*., 2019). In Kano state on the other hand, there is little variance in pollutant levels except in the months of April, May, June and July when there is a marked increase. This can be attributed to the planting season in Kano in which there is an increased use of fertilizers and pesticides which can lead to higher nitrogen dioxide emissions (Celikkol Erbas and Guven Solakoglu, 2017; Jote, 2023; Pathak *et al*., 2016; Sikora *et al*., 2020).

4.1.3 Descriptive Analysis Aerosols

From Appendix 5 and 6, one can observe that the concentration of Aerosols is significantly higher in Kano state than in Bayelsa state over the time period of (2019-2024), with its index reaching 1.792 in March, 2022. In Bayelsa state, the highest Aerosol Index was 1.357 in February, 2023. This was likely influenced by dust storms which are prevalent in Kano state (Ochiegbu, 2021; Aweda and Famoritade, 2018; Ogunjo *et al*., 2022), among other factors such as the higher population in Kano state. It can also be observed that the lowest concentrations of Aerosols occurred in May, 2021 for Bayelsa state (-1.571) and in September, 2020 for Kano state (-1.373) and the highest concentrations occurred in December, January, February and March for Bayelsa state and in the period of October to June for Kano state. This contrast is a result of the prevalent dust storms in Kano state which generate a lot of Aerosols (Ochiegbu, 2021; Aweda and Famoritade, 2018; Ogunjo *et al*., 2022).

4.2 CARBON MONOXIDE

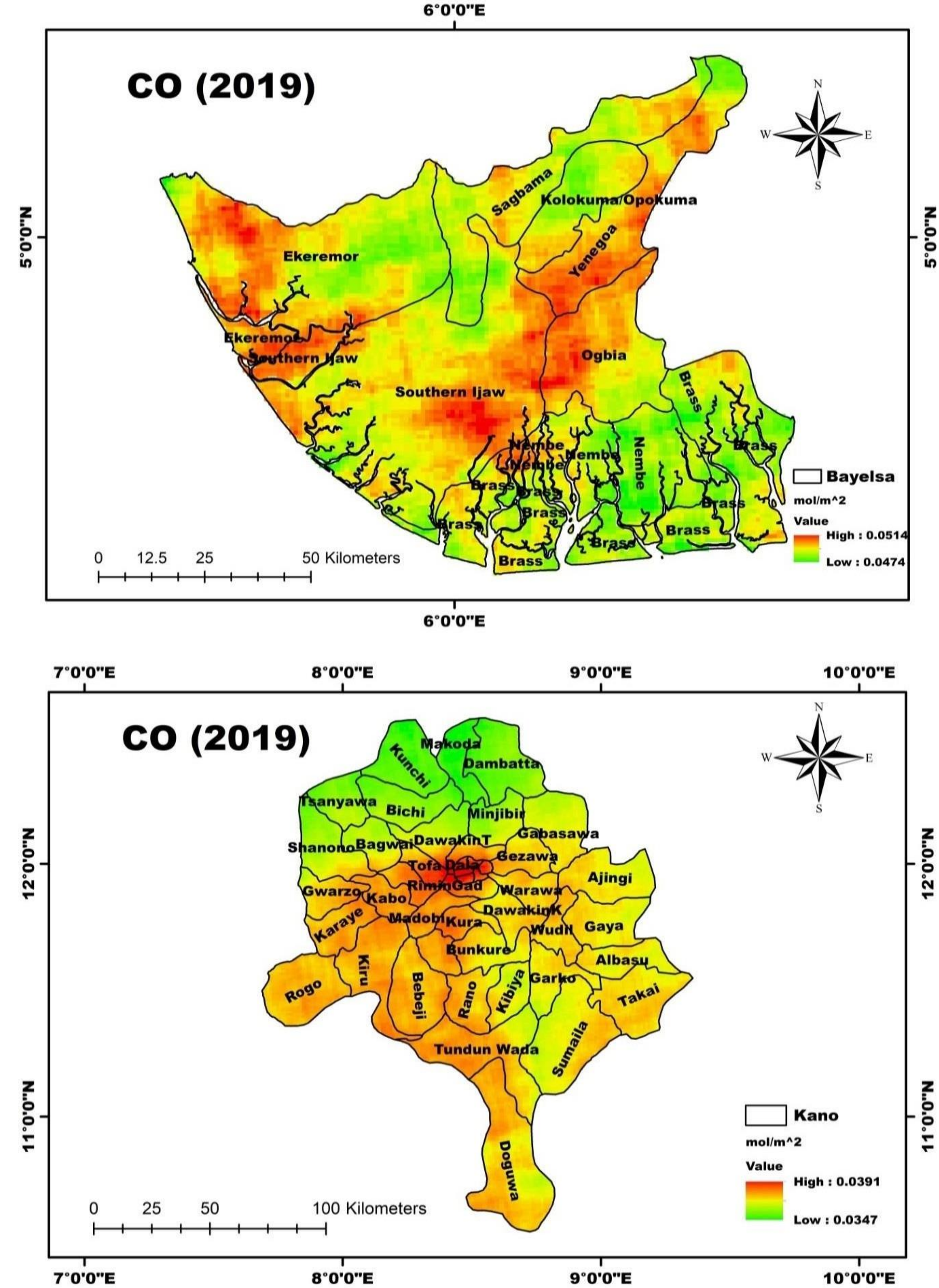


Figure 4.2.1: Carbon Monoxide concentrations in Bayelsa state and Kano state for 2019

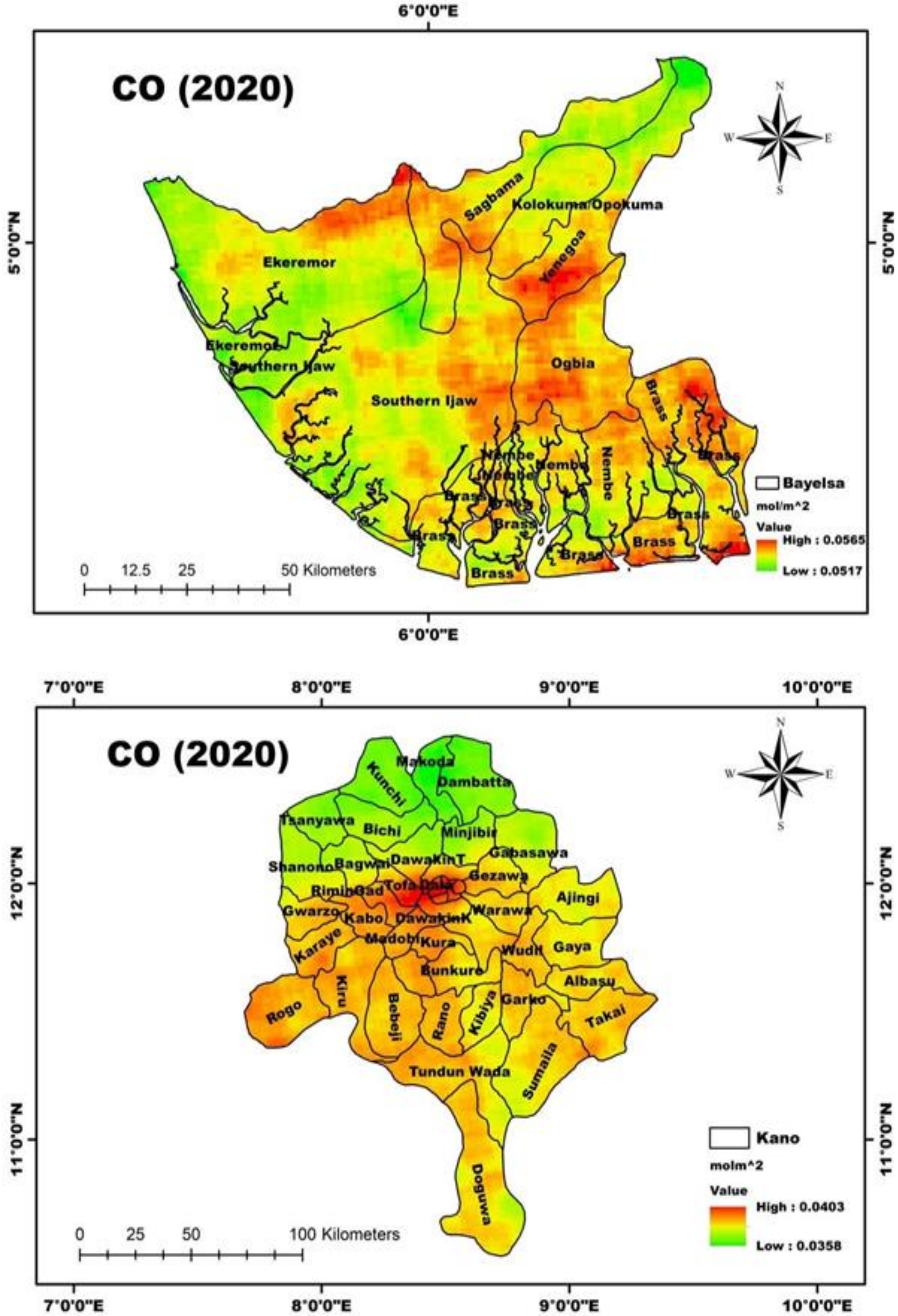


Figure 4.2.2: Carbon Monoxide concentrations in Bayelsa state and Kano state for 2020

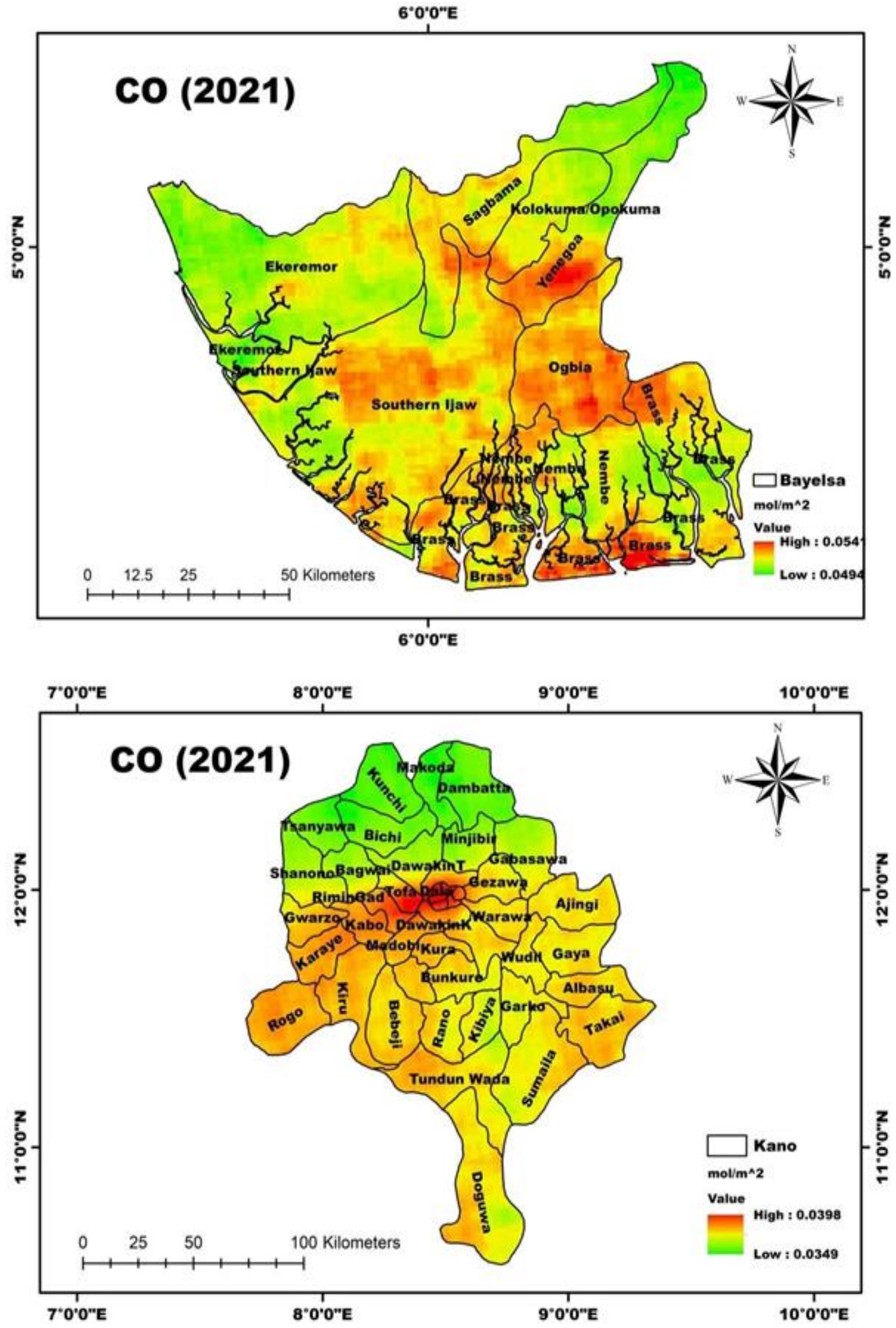


Figure 4.2.3: Carbon Monoxide concentrations in Bayelsa state and Kano state for 2021

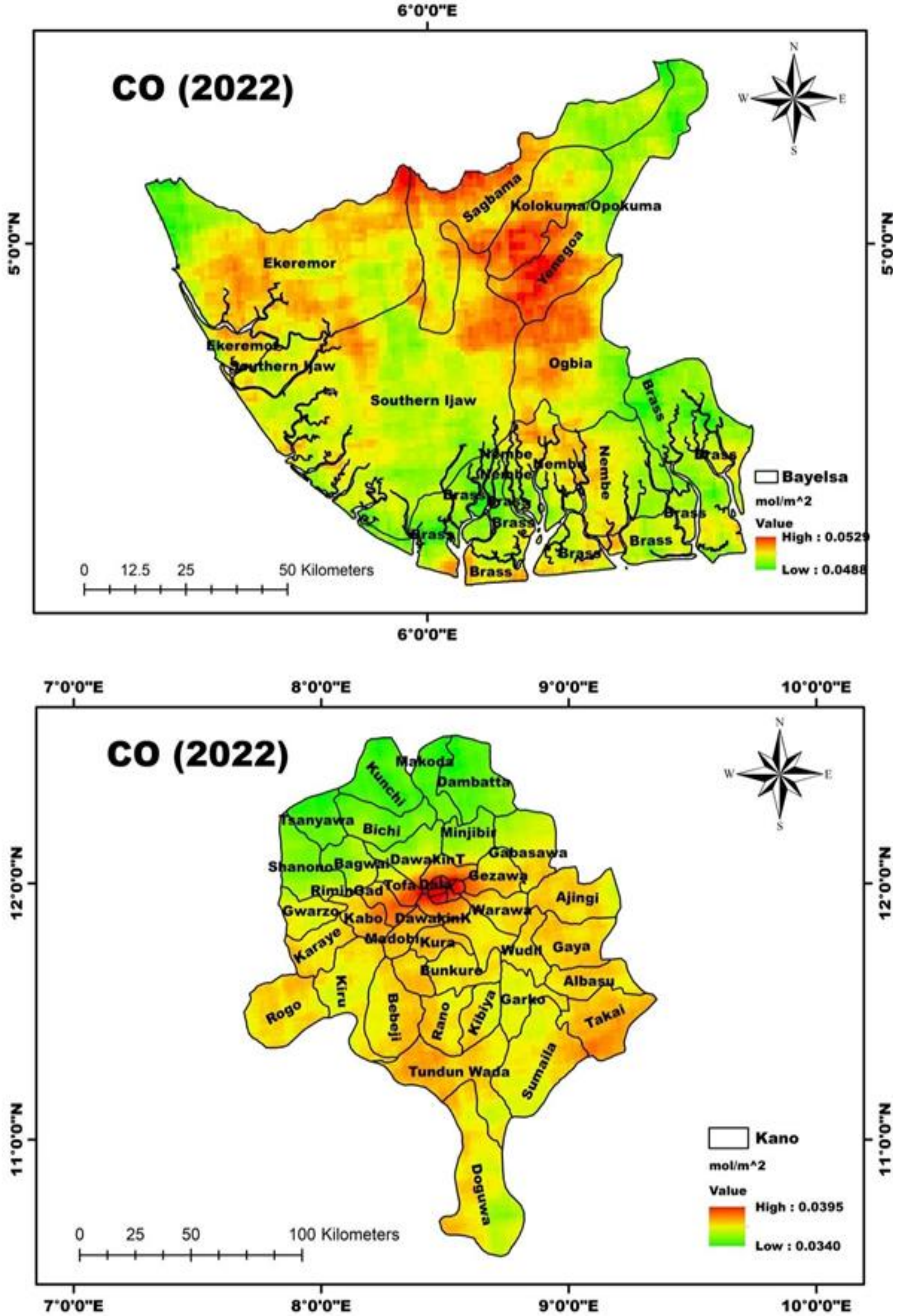


Figure 4.2.4: Carbon Monoxide concentrations in Bayelsa state and Kano state for 2022

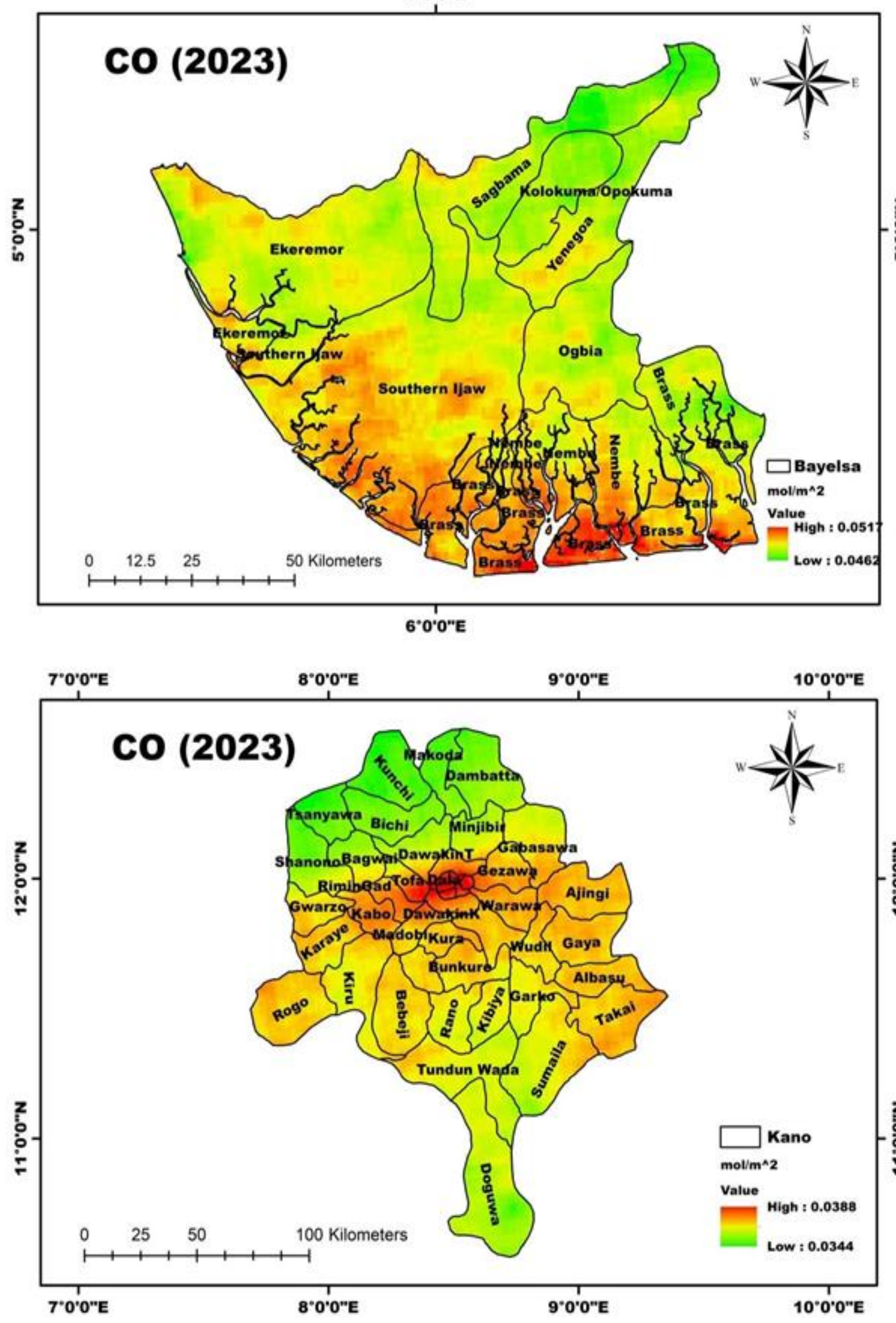


Figure 4.2.5: Carbon Monoxide concentrations in Bayelsa state and Kano state for 2023

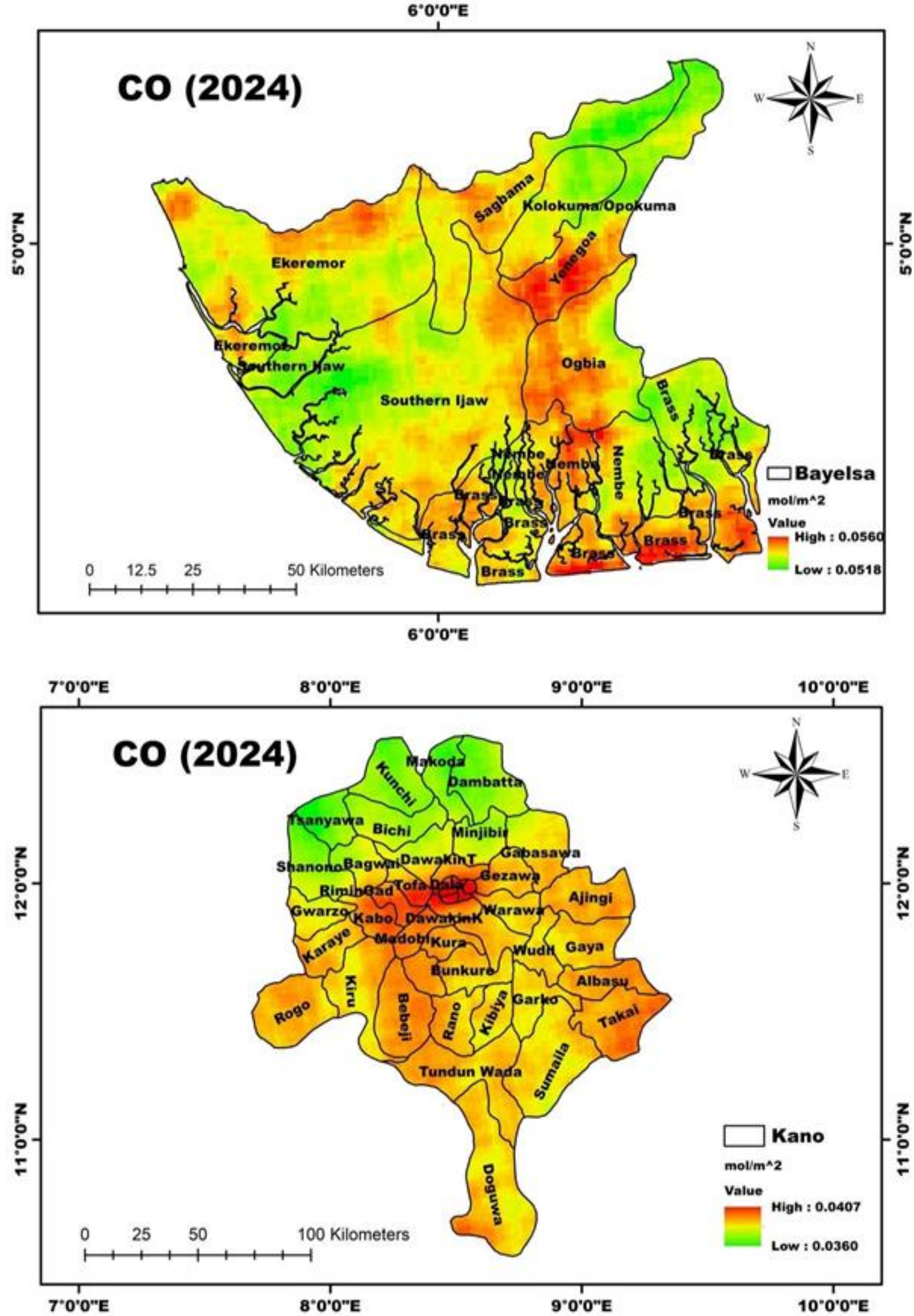


Figure 4.2.6: Carbon Monoxide concentrations in Bayelsa state and Kano state for 2024.

4.2.1 Spatial Distribution of CO in Bayelsa State and Kano State

For Kano State, CO concentrations are very high in the metropolitan areas which include Local Government Areas such as Dala, Tofa, Gezawa, Gabo, Dawakin Kudu, Dawakin Tofa and surrounding LGAs. Concentrations are also high in the South, Southeast and Southwest, whereas in the Northern part of the state, concentrations are relatively lower in places like Makoda, Kunchi, Dambatta, Tsanyawa, Bichi and Minjibir. This is observed for all the years (2019-2024) as shown in Figure 4.2.1-4.2.6, with only variances in mean concentrations as shown in Figure 4.2.8. In Bayelsa state, areas of high industrial activities such as Brass, Yenogoa, Nembe and Ogbia have high CO concentrations, with the highest found in Brass. This is because not only is Brass a hot spot for oil exploration it is also a community with significant Marine traffic (Adebangbe *et al*., 2025) and so more CO is emitted from Ship and oil tanker engines (Aakko-Saksa *et al*., 2023). Brass also has significant transportation activities. Places to the west such as Ekeremor and Southern Ijaw as well as in the Northeast particularly Sagbama, Opokuma/Kolokuma and the Northern most parts of Yenogoa have much lower levels of CO. Notably, Brass has much lower concentrations in 2019 and 2022 as shown in Figures 4.2.1 and 4.2.4 respectively. Additionally the western parts of Ekeremor and Southern Ijaw have much lower concentrations in 2020 and 2021 as shown in figures 4.2.2 and 4.2.3 respectively.

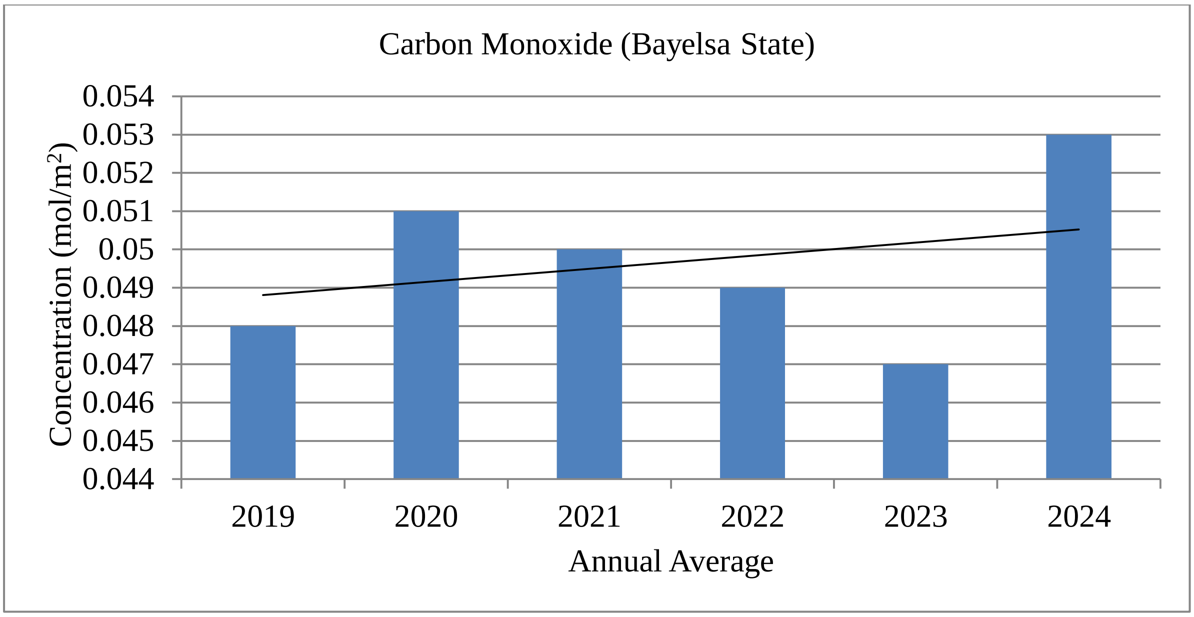


Figure 4.2.7: Graph showing CO trend in Bayelsa State from 2019 to 2024

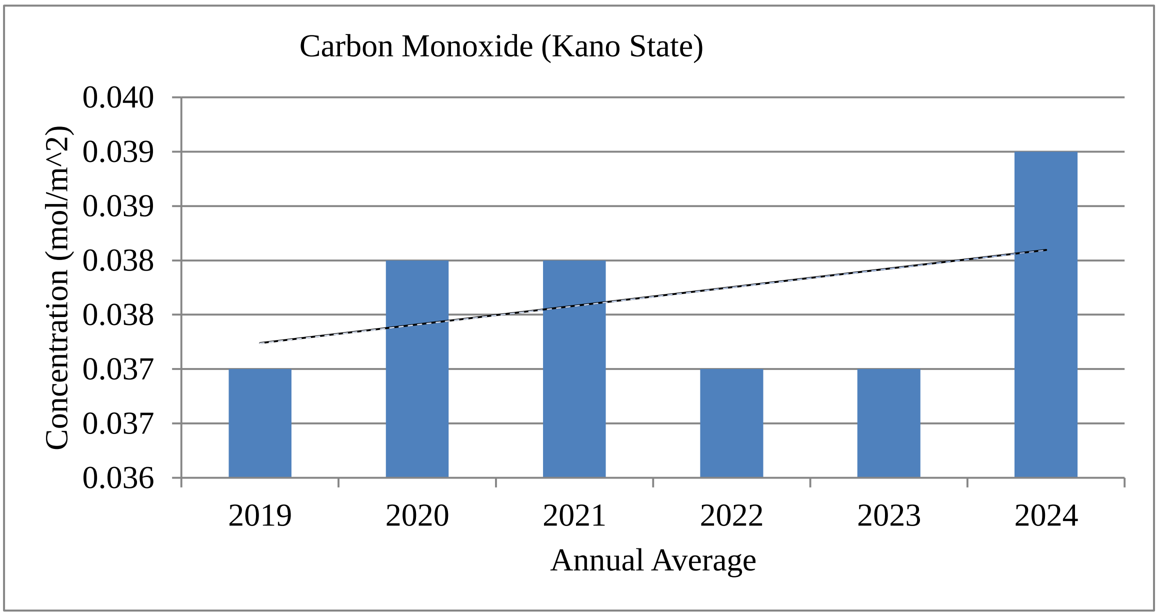
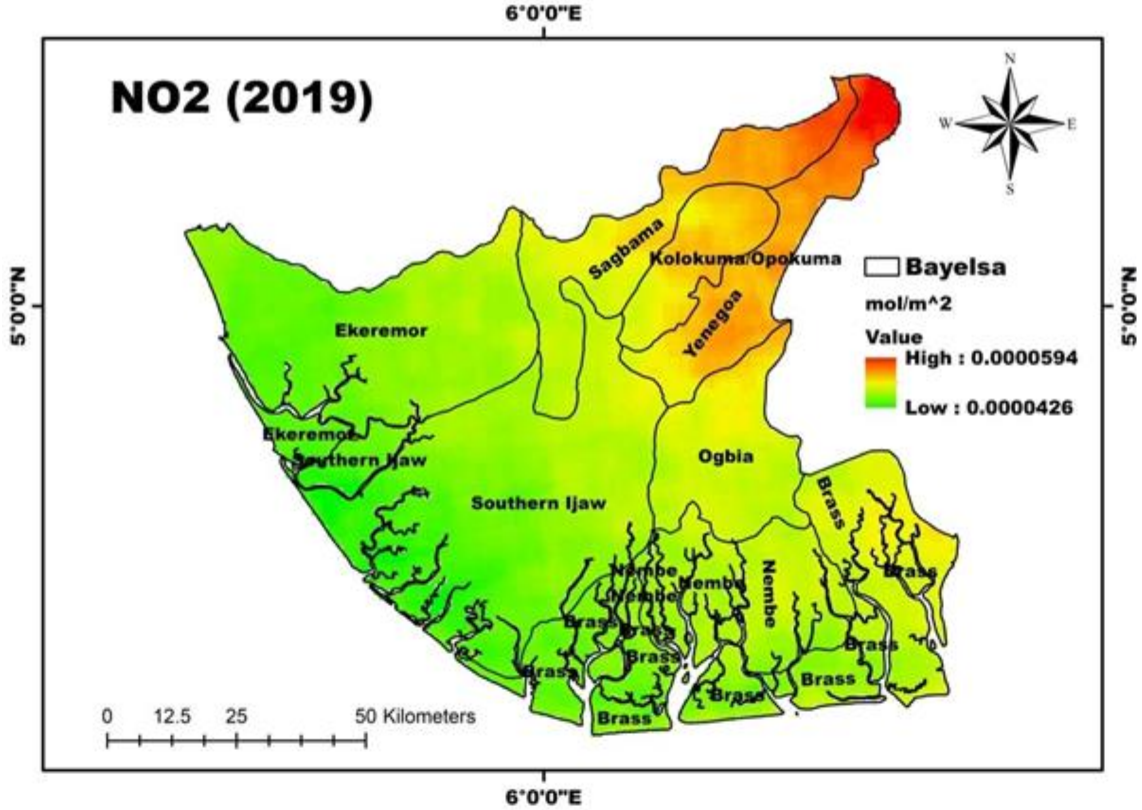


Figure 4.2.8: Graph showing CO trend in Kano State from 2019 to 2024

4.2.3 Descriptive Analysis of Annual CO Trend in Bayelsa and Kano states

In Bayelsa state (Figure 4.2.7), the mean CO concentrations in 2019 is relatively low (0.049mol/m^2), followed by a sharp increase in concentration in 2020 (0.055mol/m^2) which can be attributed to the COVID lockdowns (Olusola *et al.* 2020; Ogunjo *et al.*, 2022; Amaechi *et al.*, 2024; Oxoli *et al.*, 2020), where due to people being at home, more fossil fuels were combusted to generate electricity as well as increased biomass combustion (Oxoli *et al.*, 2020). From 2021, there is a gradual decline in CO levels and a significant drop in 2023 (Reduction of 0.002mol/m^2 over the previous year's reduction of 0.001mol/m^2) that is directly related to the removal of fuel subsidy which led to less combustion of petrol and subsequently less emission of CO (Amaechi *et al.*, 2023; Amaechi *et al.*, 2024). In 2024, there is a marked increase in CO concentrations from 0.049mol/m^2 of the previous year to 0.054mol/m^2, as the effects of fuel subsidy removal start to wear off, in addition to increased reliance on generators due to more severe inconsistent power issues among other factors (Ekeng *et al.*, 2024; Adebayo and Ainah, 2024). This rise in pollutant levels calls for a more strict approach in dealing with air pollution emission sources and enforcing relevant policies and regulations tailored to curb air pollution. In Kano state (Figure 4.2.8), the levels of CO for 2019, 2022 and 2023 are similar at 0.037mol/m^2 which may be attributed to relatively effective air pollution control measures or consistent emission levels. This changes in 2020 and 2021 (0.038mol/m^2), and can be attributed to COVID (Olusola *et al*. 2020; Ogunjo *et al.*, 2022; Amaechi *et al.*, 2024; Oxoli *et al.*, 2020). However, there is an increase in CO levels exceeding that of all previous years (0.039mol/m^2). Similarly to Bayelsa state, this can be attributed to increased reliance on generators (Ekeng *et al.*, 2024; Adebayo and Ainah, 2024), as well as growing industrial activities among other factors and highlights the urgent need for stricter air pollution measures.

4.3 NITROGEN DIOXIDE



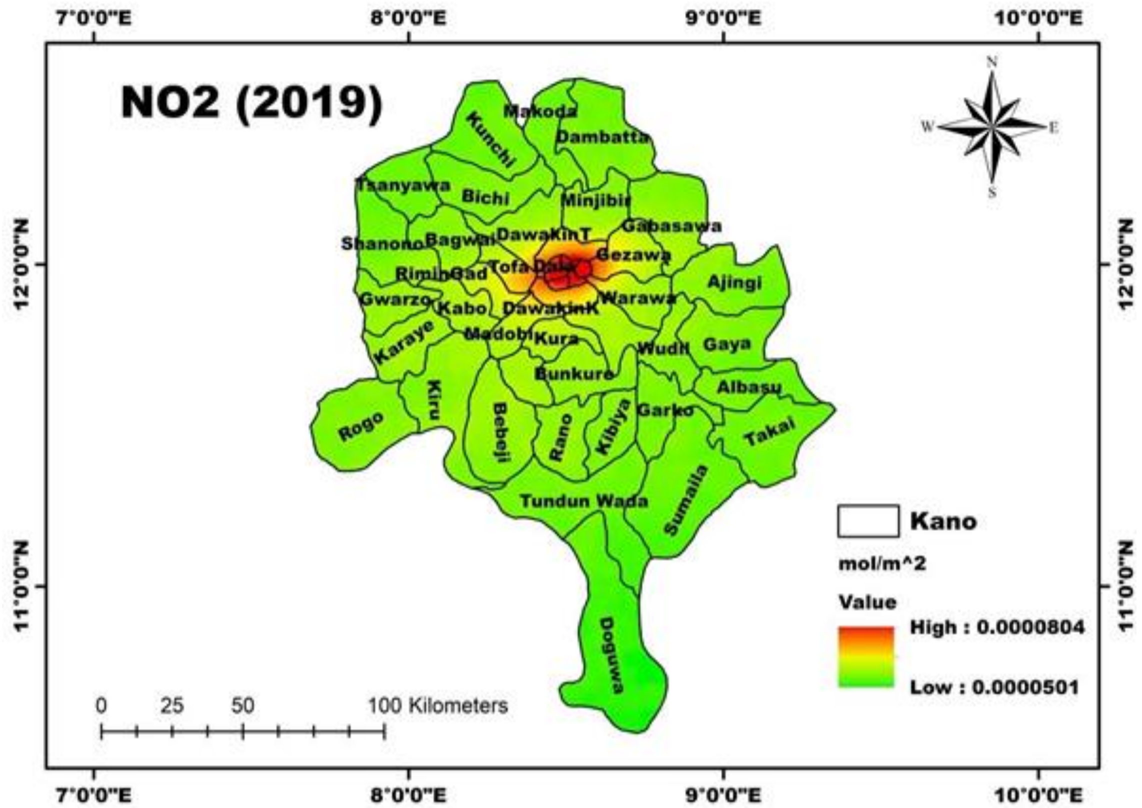


Figure 4.3.1: Nitrogen Dioxide concentrations in Bayelsa state and Kano state for 2019

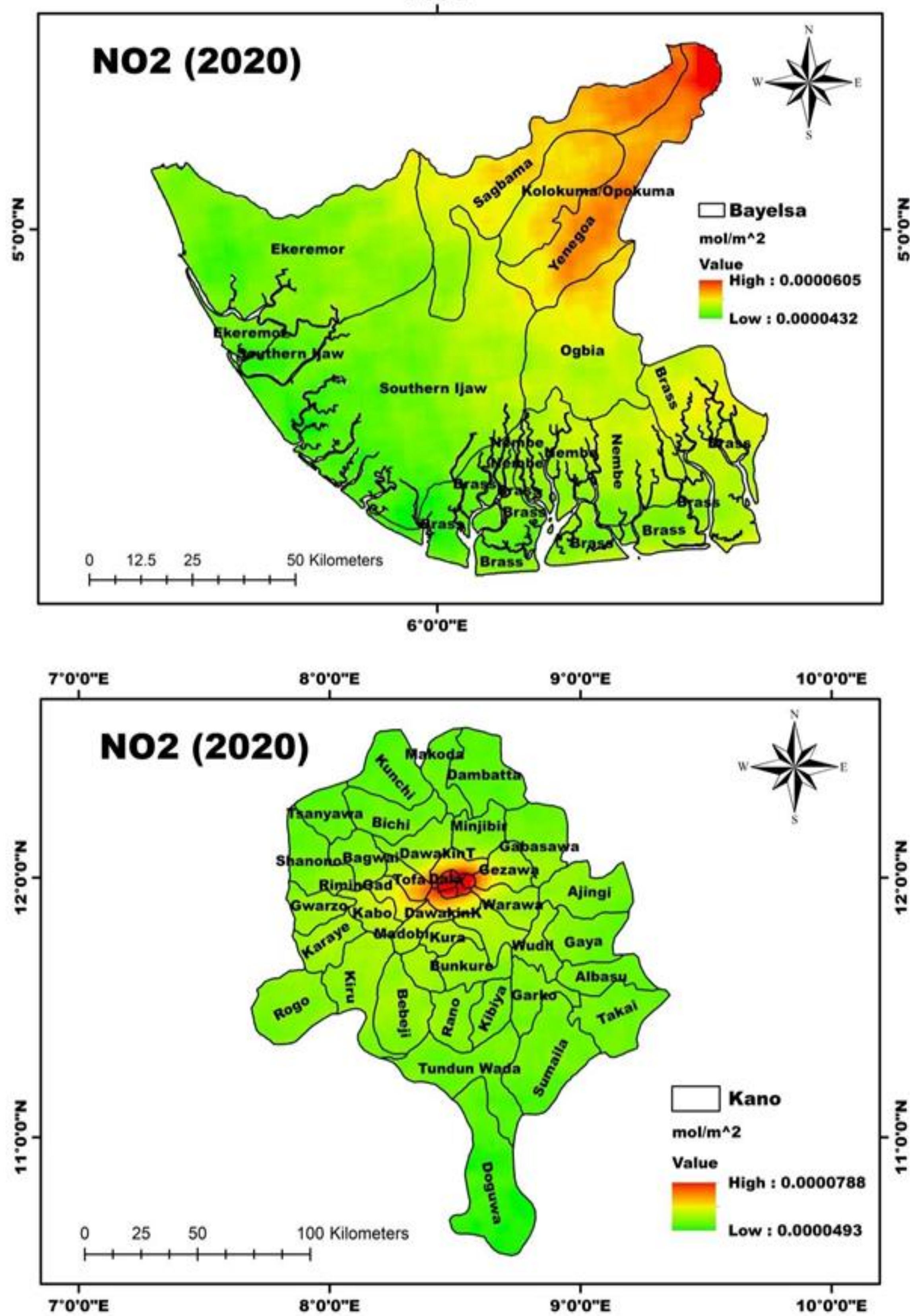
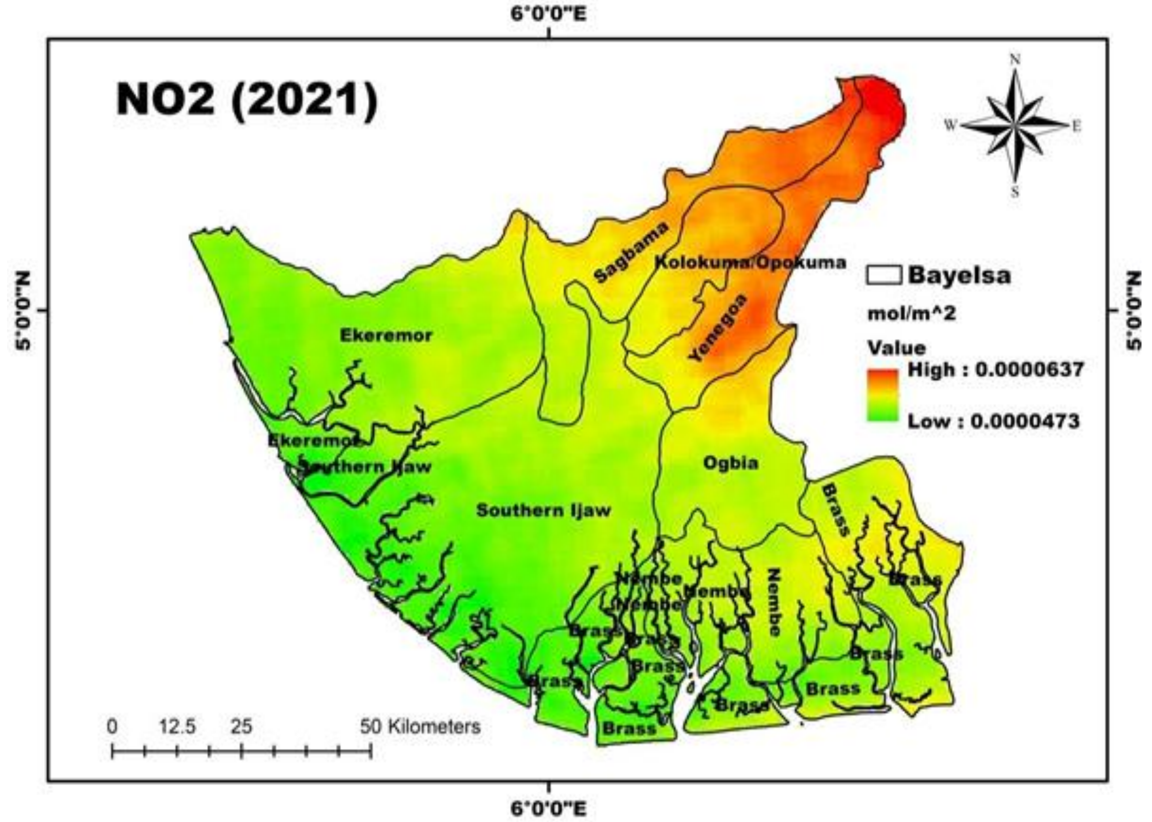


Figure 4.3.2: Nitrogen Dioxide concentrations in Bayelsa state and Kano state for 2020



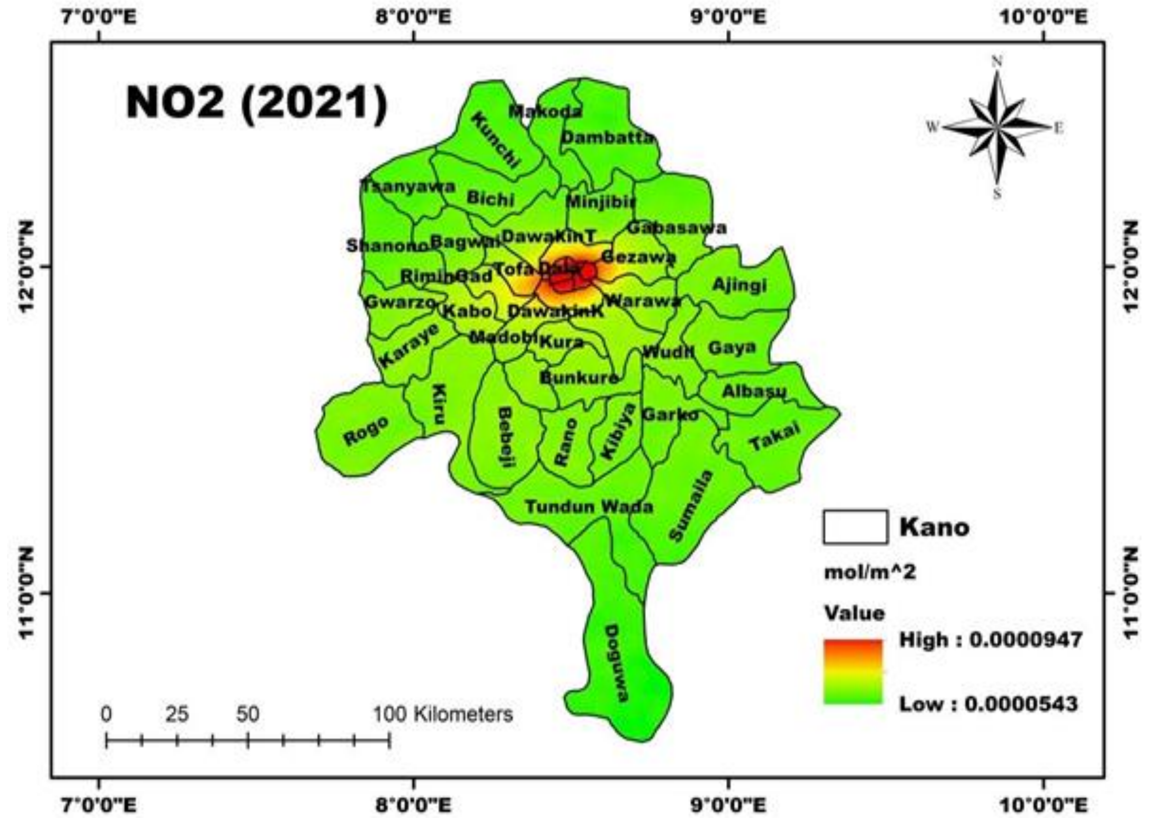


Figure 4.3.3: Nitrogen Dioxide concentrations in Bayelsa state and Kano state for 2021

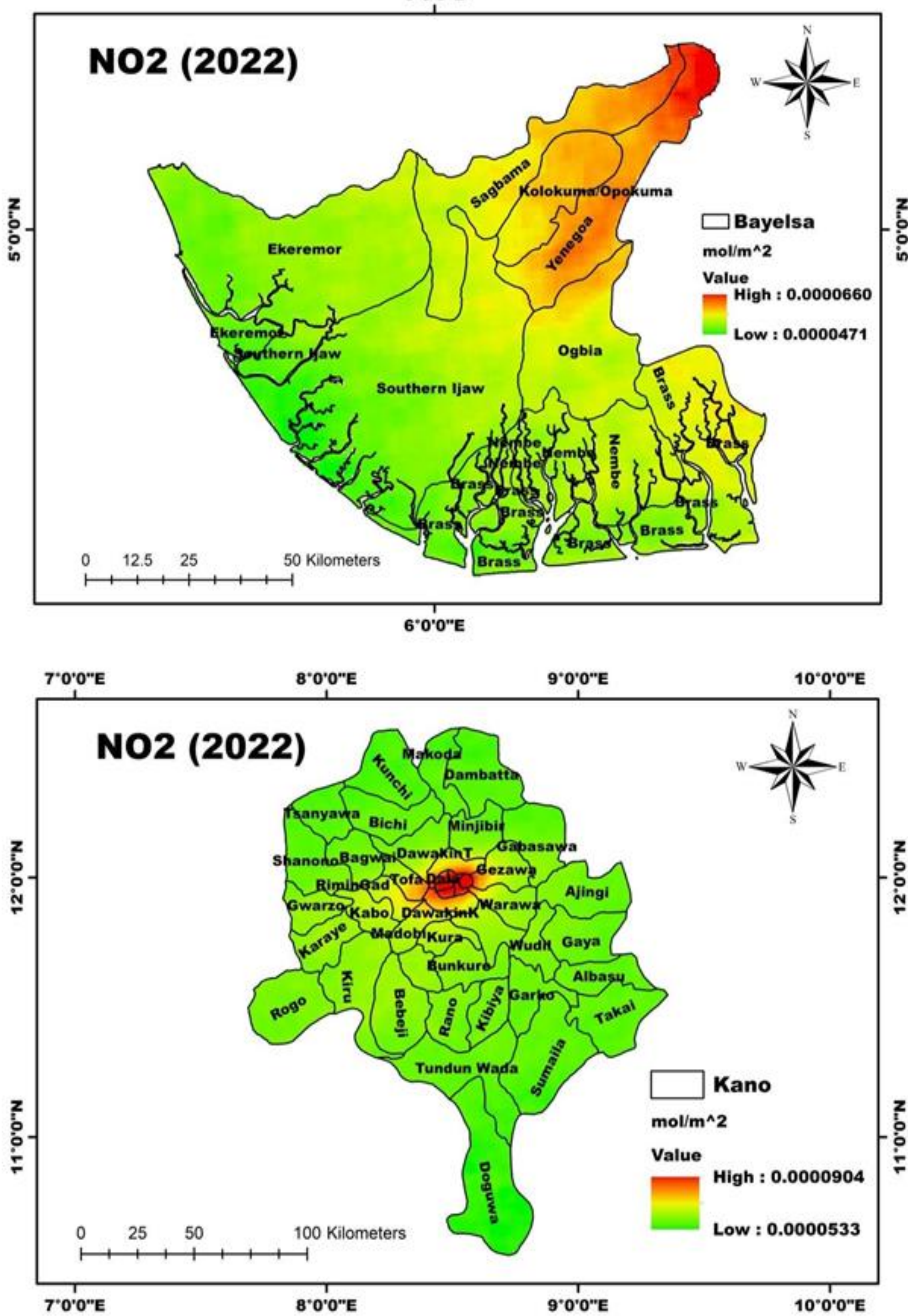


Figure 4.3.4: Nitrogen Dioxide concentrations in Bayelsa state and Kano state for 2022

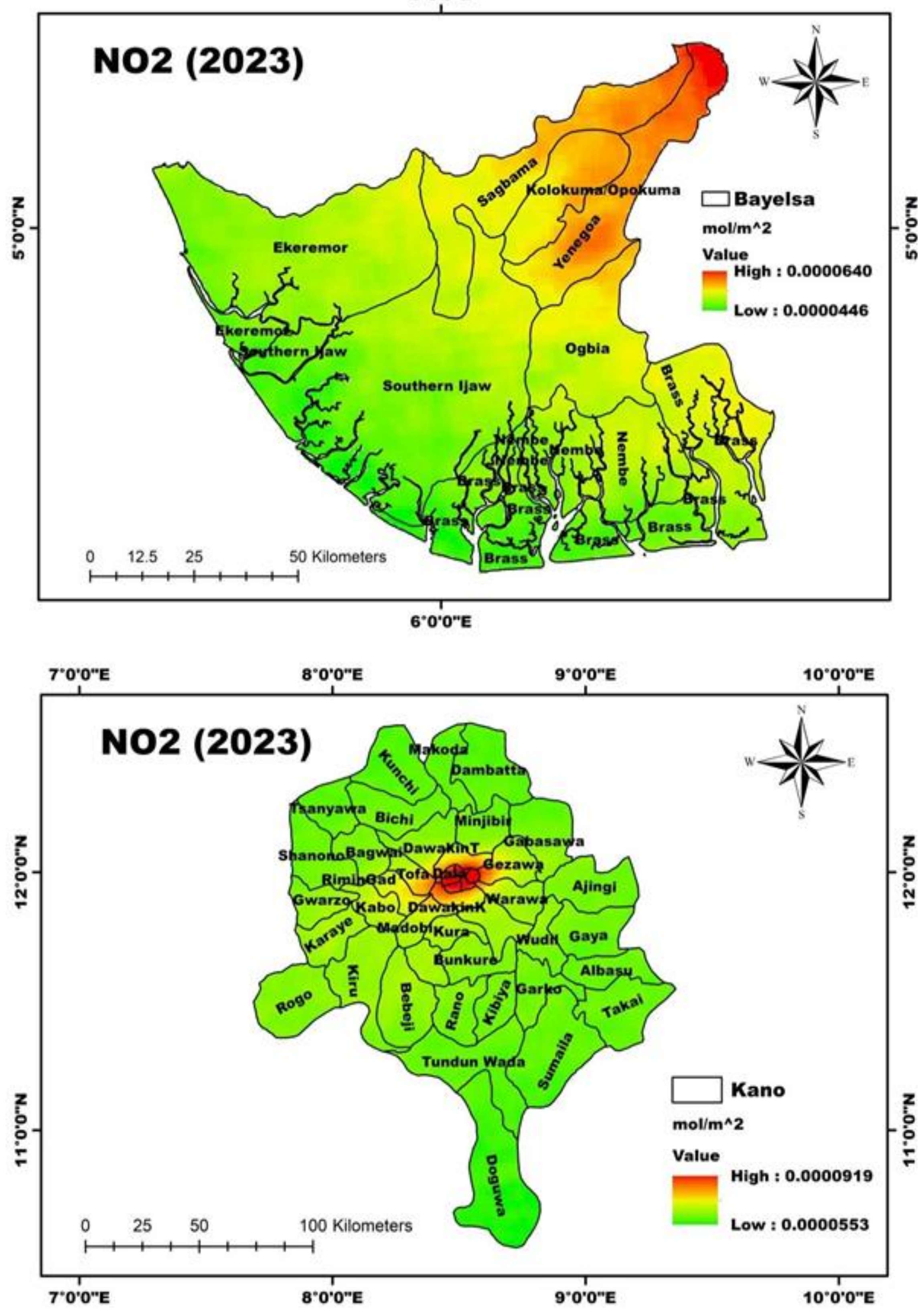


Figure 4.3.5: Nitrogen Dioxide concentrations in Bayelsa state and Kano state for 2023

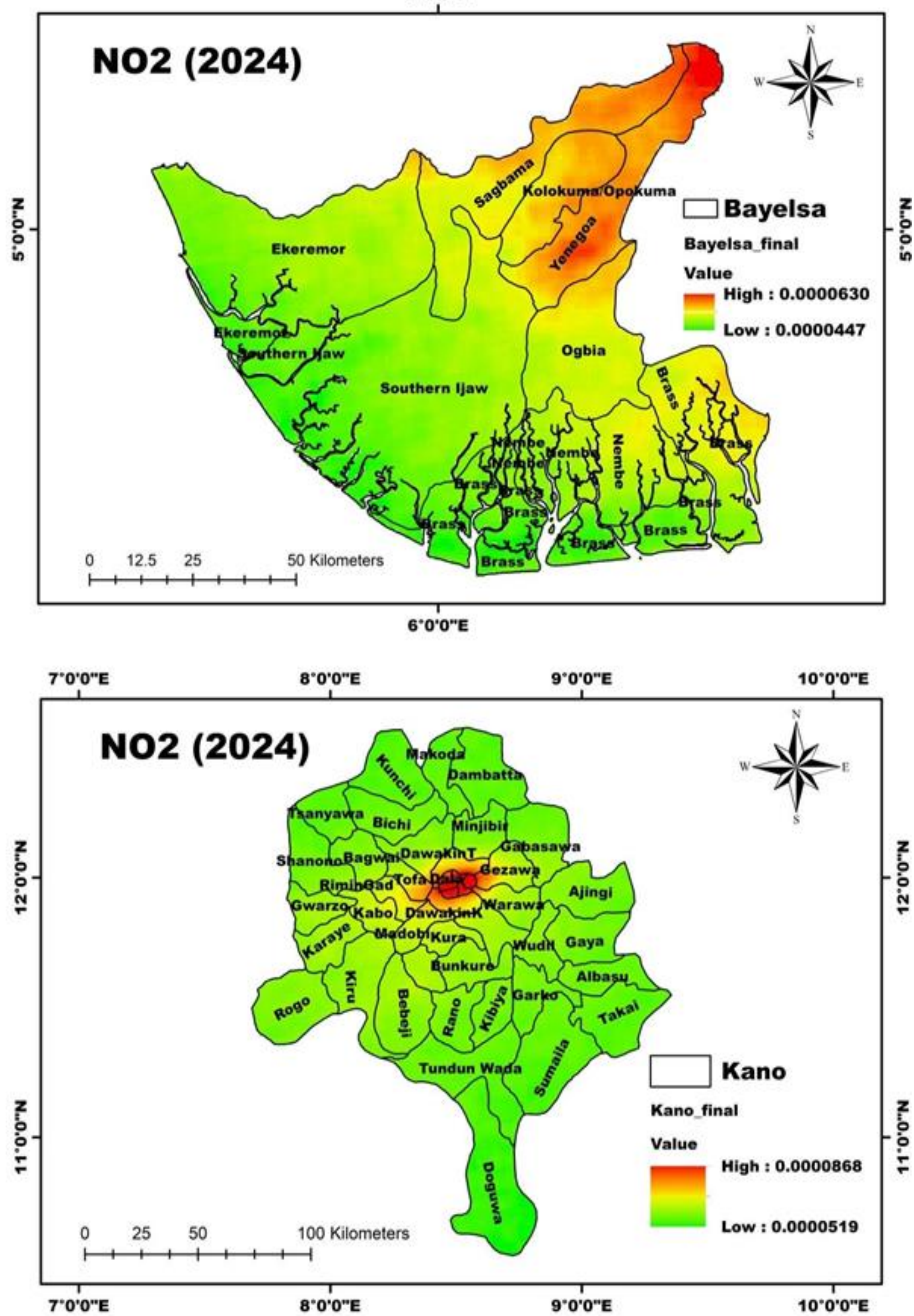


Figure 4.3.6: Nitrogen Dioxide concentrations in Bayelsa state and Kano state for 2024

4.3.1 Spatial Distribution of NO_2 in Bayelsa and Kano states

In Kano state, NO_2 levels are very high in the metropolitan areas such as Dala, Tofa, Gezawa, Dawakin Tofa and Dawakin Kudu. This is due to the concentration of vehicular activity in this region, which is a major source of NO_2 (Benazzi and Muhammad, 2019; Barau *et al*., 2023; Garba, 2016) among other possible contributing anthropogenic factors such as the concentration of the state's population in these parts. All other areas in Kano state have significantly lower concentrations of the pollutant. In Bayelsa state, NO_2 concentrations are highest in areas farther from the coast i.e north and northeast of the state particularly Yenogoa, Sagbama and Kolokuma/Opokuma. All other areas in the state such as to the west, the south and southeast have much lower concentration levels. The pollutant levels steadily reduce as we move closer to the coastal regions. These distributions continue in both states across all years (2019-2024) as shown in Figures 4.3.1-4.3.6.

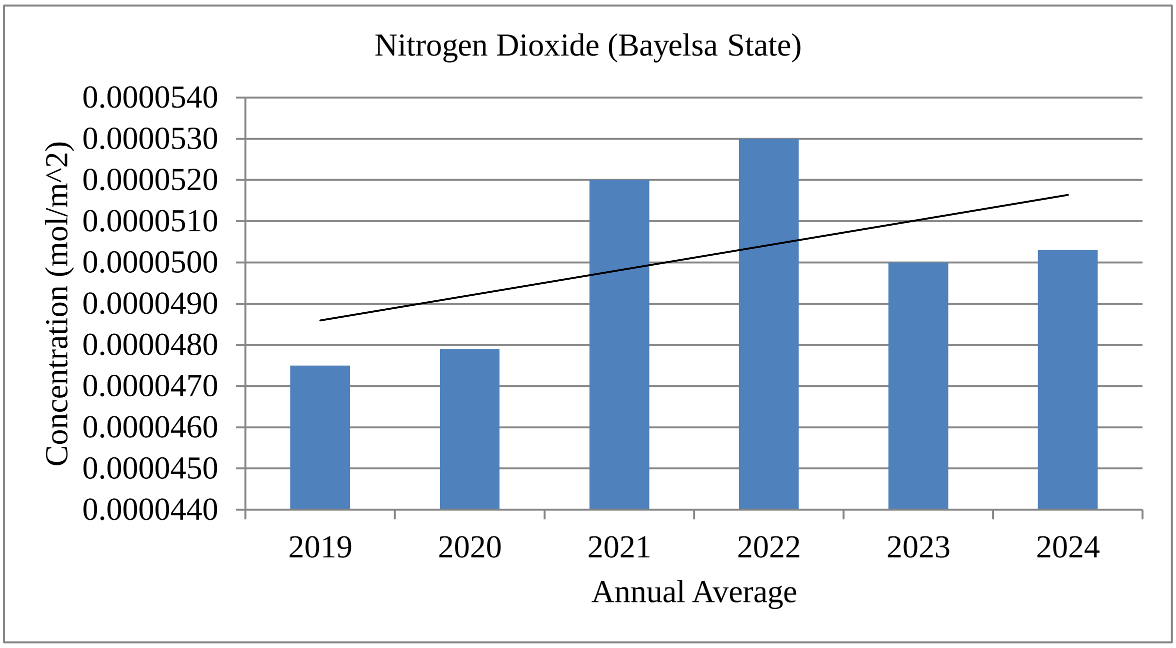


Figure 4.3.7 Graph showing NO_2 trend in Bayelsa state from 2019 to 2024

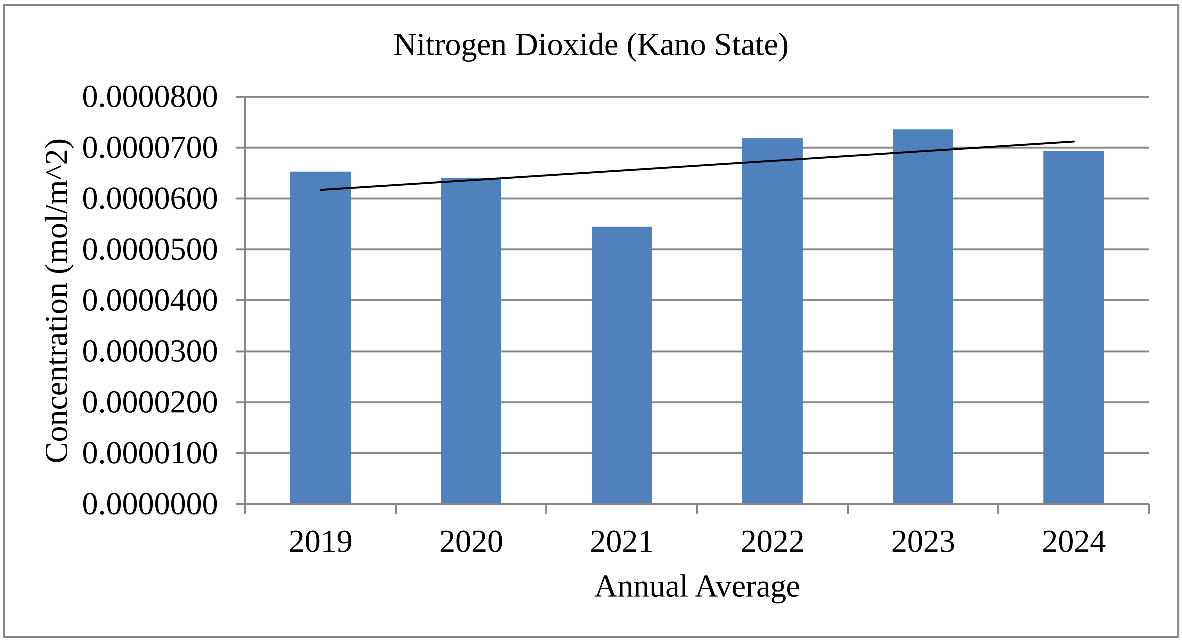


Figure 4.3.8: Graph showing NO_2 trend in Kano state from 2019 to 2024

4.3.2 Descriptive Analysis of Annual NO_2 Trend in Bayelsa and Kano states

In Bayelsa state (Figure 4.3.7), the lowest concentration of nitrogen dioxide within the studied period (2019-2024) is in 2019 (0.0000510mol/m^2), it gradually increases up to 2022 reaching 0.0000566mol/m^2 and steadily declines for the following 2 years. The gradual increase in concentration can be attributed to growing industrial activities among other factors, and the subsequent decline can be linked to fuel subsidy removal (Amaechi *et al*., 2023; Amaechi *et al*., 2024), and possibly better air pollution control measures as pertains to nitrogen dioxide. The trend in nitrogen concentration levels in Kano state (Figure 4.3.8) across the years is more inconsistent, starting with a concentration of 0.0000653mol/m^2 in 2019 and gradually declines until 2021 (0.0000545mol/m^2), There is then a significant increase in 2022 (0.0000719mol/m^2), which continues in 2023 (0.0000736mol/m^2) and then declines to 0.0000694mol/m^2 in 2024. The initial decrease in concentrations in 2020 and

2021 can be attributed to COVID (Olusola *et al*. 2020; Ogunjo *et al*., 2022; Amaechi *et al*., 2024; Oxoli *et al*., 2020). In the following years there was an observed increase in NO_2 concentrations as the lockdowns ended coupled with other factors. The subsequent decline in 2024 may be attributed to several anthropogenic factors.

4.4 AEROSOL

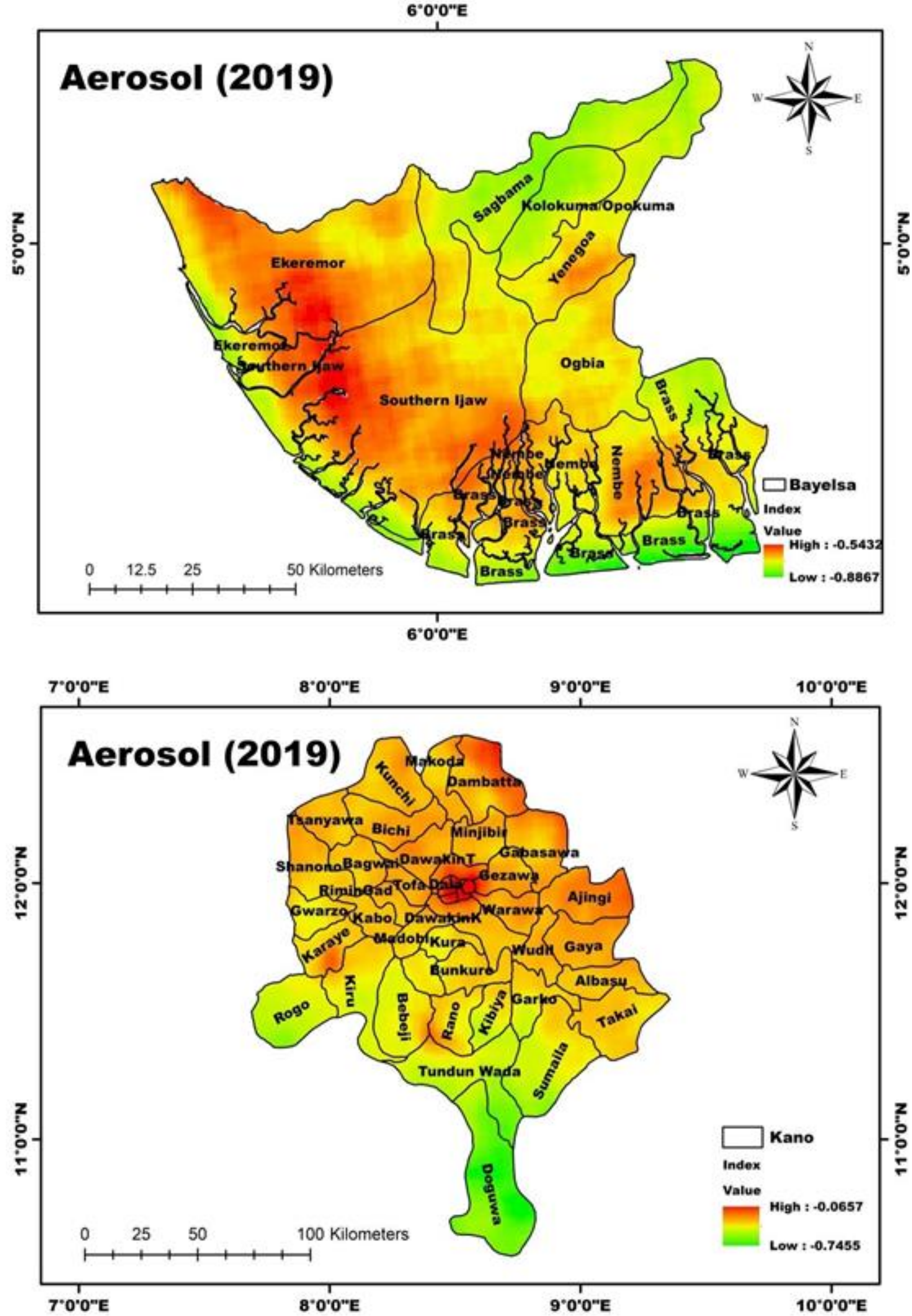


Figure 4.4.1: Aerosol levels in Bayelsa state and Kano state for 2019

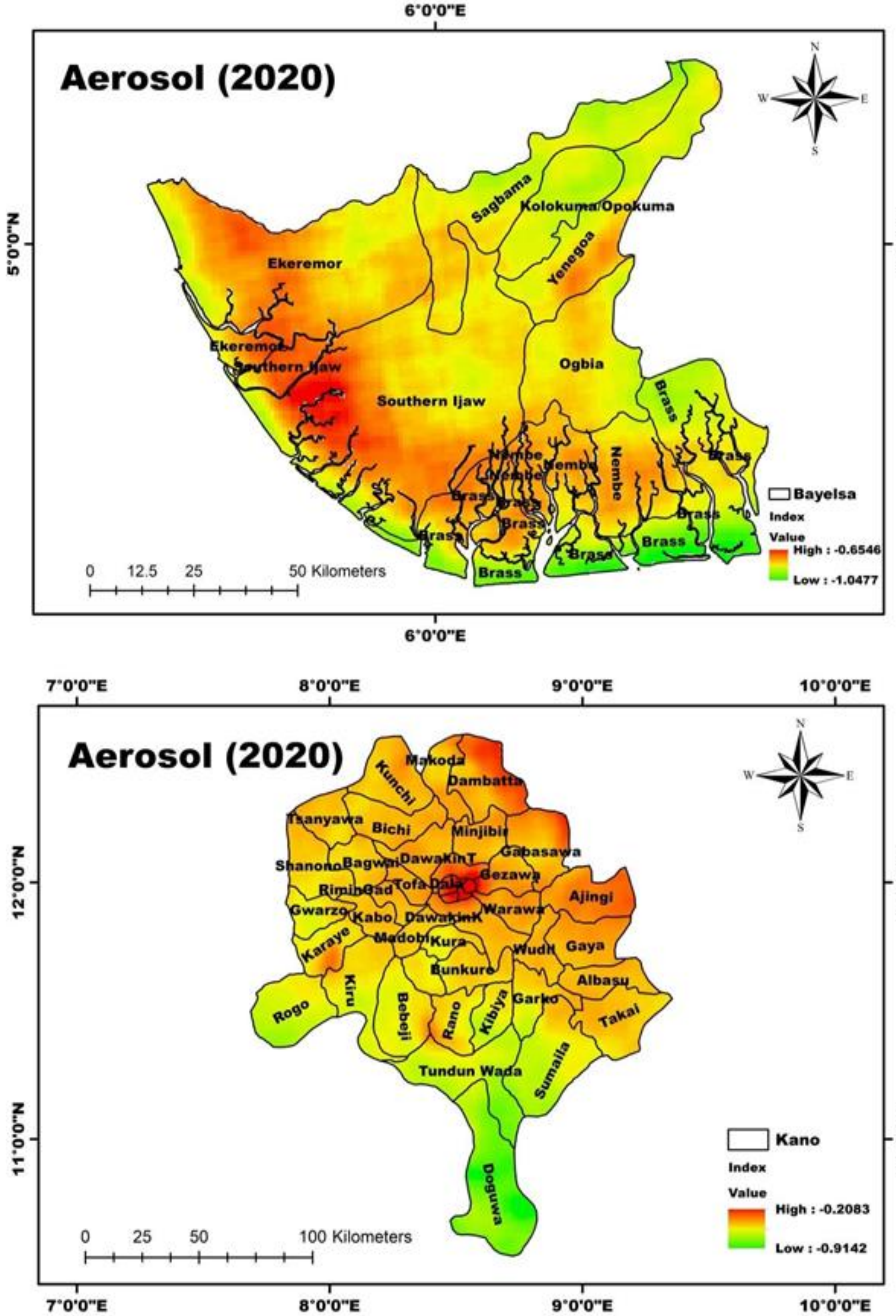


Figure 4.4.2: Aerosol levels in Bayelsa state and Kano state for 2020

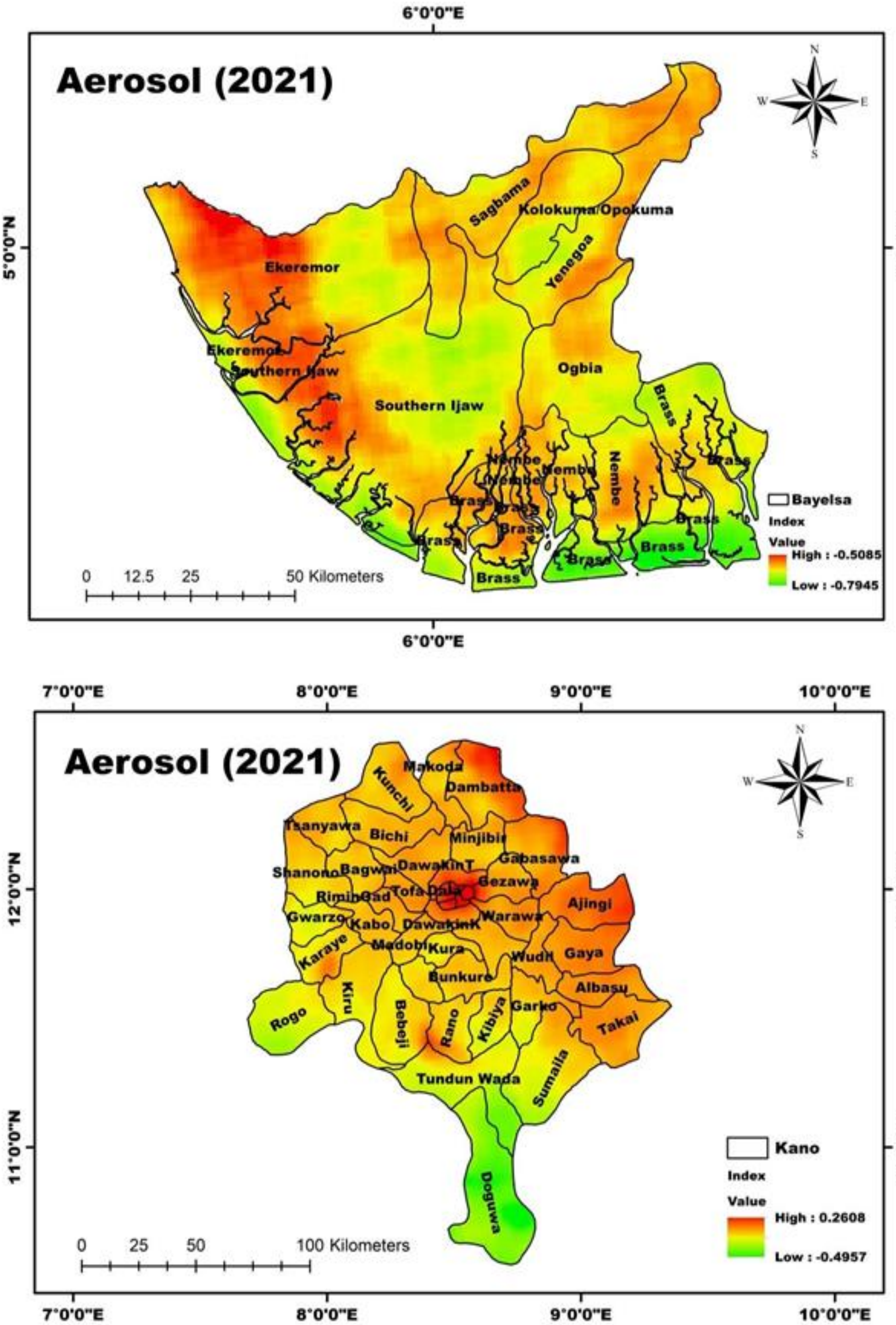


Figure 4.4.3: Aerosol levels in Bayelsa state and Kano state for 2021

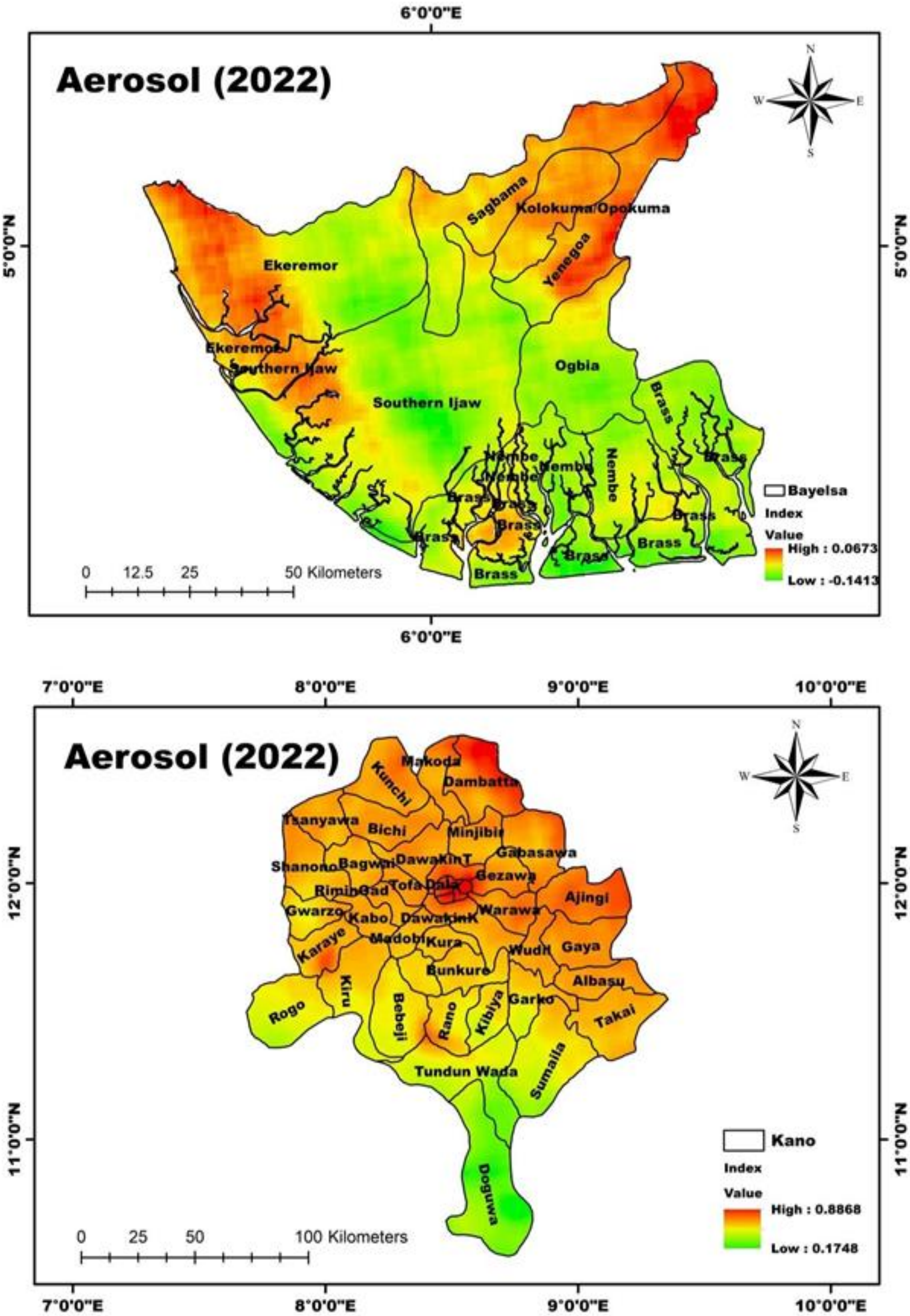


Figure 4.4.4: Aerosol levels in Bayelsa state and Kano state for 2022

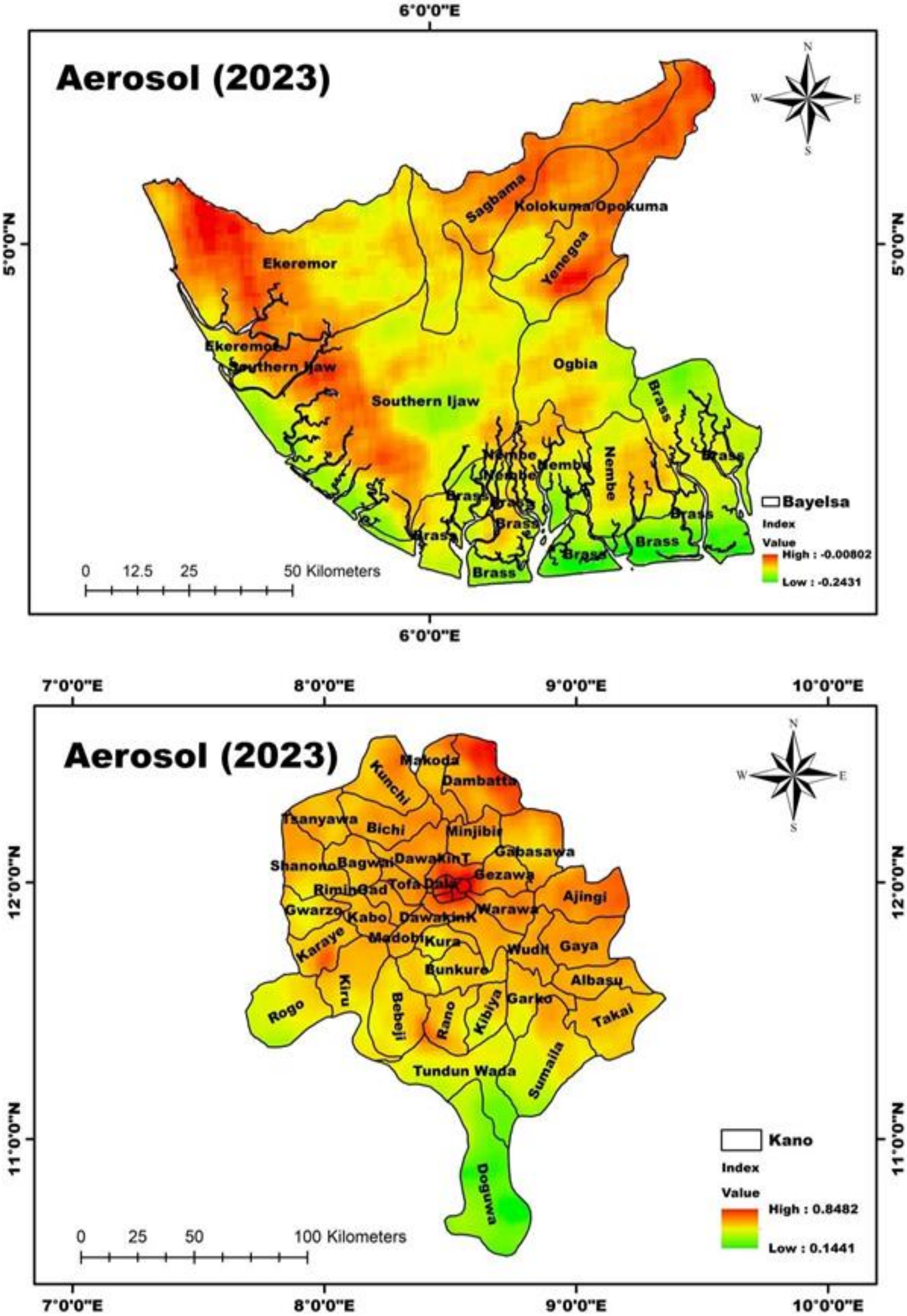


Figure 4.4.5: Aerosol levels in Bayelsa state and Kano state for 2023

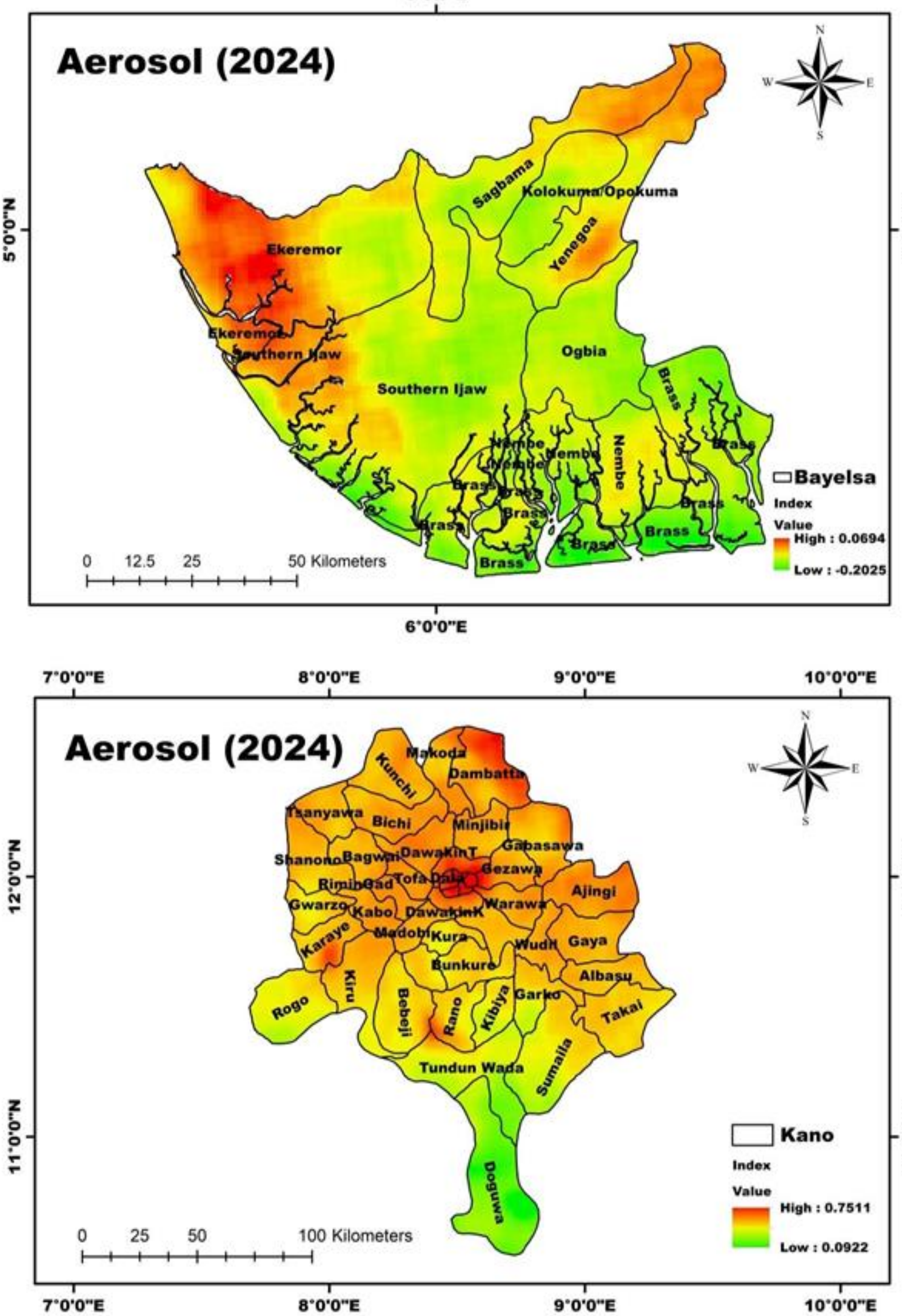


Figure 4.4.6: Aerosol levels in Bayelsa state and Kano state for 2024

4.4.1 Spatial Distribution of Aerosols in Bayelsa and Kano states

In Kano state, the Metropolitan areas such as Dala, Tofa, Gezawa, Dawakin Tofa, Dawakin Kudu, have the highest levels of Aerosols. High concentrations are also present in every other place except for the far south particularly Doguwa. The closer one moves to the south the lower the aerosol index, this is observed for all years (2019-2024) as shown in Figures 4.4.1-4.4.6, with variances only in mean concentrations as shown in Figure 4.4.8. In Bayelsa state, the western part of the state which includes the northwestern parts of Ekeremor and Southern Ijaw, as well as the northern parts of the state such as Yenogoa, Sagbama and Kolokuma/Opokuma, have the highest Aerosol values. This changes in 2022 and 2024 when the Eastern parts of Ekeremor and Southern Ijaw, and the greater part of Ogbla, Nembe and Brass have much lower concentrations as shown in Figures 4.4.4 and 4.4.6 respectively. All other regions have relatively lower Aerosol values across all years. It is also important to note that the Aerosol values gradually decreases as one approaches the shoreline, such that the parts of brass which are closest to the shore have the lowest Aerosol levels. This is because of rainfall washout, which is more prominent in coastal regions, as they have more rainfall (de Sá *et al*., 2019; Simões Amaral *et al*., 2016; Yadav *et al*., 2019; Chen *et al*., 2019).

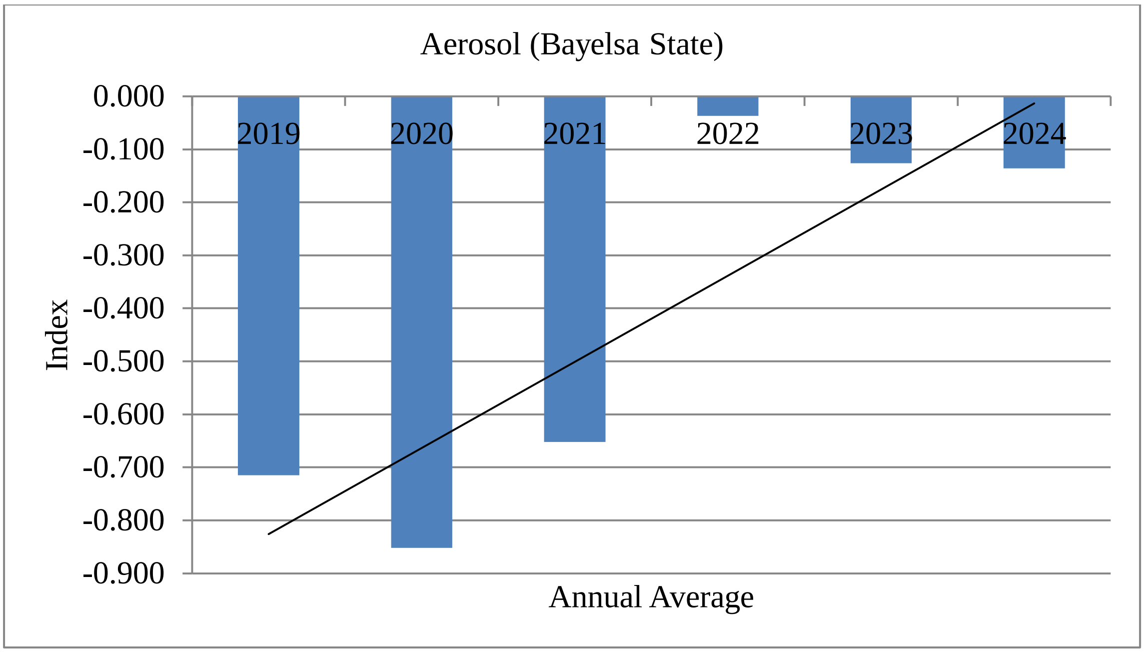


Figure 4.4.7: Graph showing Aerosol trend in Bayelsa state from 2019 to 2024

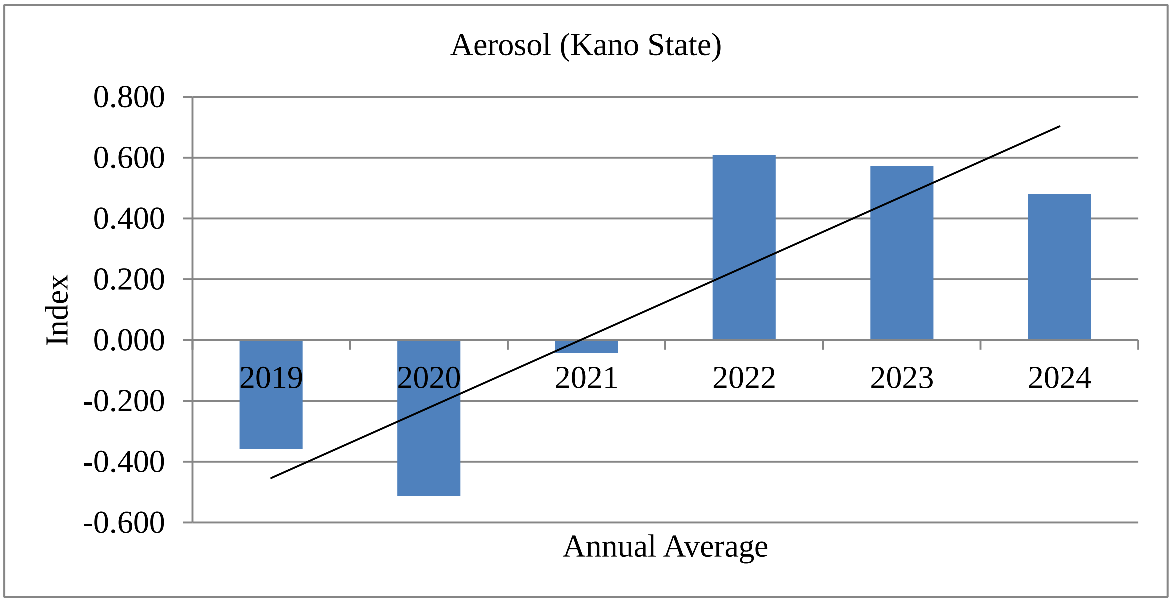


Figure 4.4.8: Graph showing Aerosol trend in Kano state from 2019 to 2024

4.4.2 Descriptive Analysis of Annual Aerosol trend in Bayelsa and Kano states

In Bayelsa state (Figure 4.4.7), Aerosol levels are relatively low remaining negative throughout the studied period (2019 to 2024), with the highest value being -0.037 in 2022. There is a steady rise in index levels from 2020 (-0.852) to 2022, after the previous year's low (-0.715 in 2019). This is followed by a gradual reduction in 2023 and 2024. This is the same pattern observed in Kano state (Figure 4.4.8) although the aerosol levels are much higher. COVID along with some other factors contribute to this (Olusola *et al*. 2020; Ogunjo *et al*., 2022; Amaechi *et al*., 2024; Oxoli *et al*., 2020).

Table 4.5: Mann-Whitney U test statistics for comparative assessment

	NO_2 2019	NO_2 2020	NO_2 2021	NO_2 2022	NO_2 2023	NO_2 2024	CO 2019	CO 2020	CO 2021	CO 2022	CO 2023	CO 2024	Aerosol 2019	Aerosol 2020	Aerosol 2021	Aerosol 2022	Aerosol 2023	Aerosol 2024
Mann-Whitney U	25.5	23.5	20.5	26	14	31	22.5	25.5	17	19.5	14.5	29	49	58	26.5	35	28	39
Z	-2.686	-2.801	-2.975	-2.656	-3.349	-2.369	-2.863	-2.69	-3.181	-3.036	-3.328	-2.491	-1.328	-0.808	-2.628	-2.136	-2.54	-1.905
Asymp. Sig. (2-tailed)	0.007	0.005	0.003	0.008	0.001	0.018	0.004	0.007	0.001	0.002	0.001	0.013	0.184	0.419	0.009	0.033	0.011	0.057

Test Statistics[b] (Grouping Variable: States (Bayelsa and Kano)

4.5 COMPARATIVE ASSESSMENT BETWEEN BAYELSA STATE AND KANO STATE

Table 4.5 shows the Mann-Whitney U test for all pollutants from 2019 to 2024, and the p-values gotten indicate when there is a significant difference (less than 0.05) in the pollutant concentration between the two states for that year. From the table we observe that all the p-values for CO and NO_2 are below 0.05, meaning for all the years (2019-2024), there is a significant difference between the CO and NO_2 levels in the two states, with Bayelsa state having higher CO levels and Kano state having higher NO_2 levels. For Aerosols on the other hand, the p-values are only below 0.05 in 2021, 2022 and 2023, which means there is a significant difference in aerosol levels between the two states for those years, with Kano state consistently higher across all years. For 2019, 2020 and 2024, the aerosol levels in the two states are close with no significant difference. These results further highlight the variation in factors affecting or contributing to air pollution in these states and show that population may not be so much of a key factor as are others such as oil exploration and gas flaring, industrial activities and vehicular emission.

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 Summary of Findings

This study was done to carry out a comparative assessment of air quality in Kano and Bayelsa states which are the most populated and the least populated states in Nigeria respectively (National Bureau of Statistics, 2020), and to discuss the significance of population to the air quality of these states. Studies have shown that population can either have a positive impact (Sterling, 2017; Cheng *et al*., 2016: Chen *et al*., 2020; Castells- Quintana *et al*., 2021; Fuladlu and Altan, 2022) or a negative impact (Carozzi and Roth, 2023; Sun *et al*., 2023; Zhang *et al*., 2021; Borck and Schrauth, 2021; Yuan *et al*., 2014) on air quality, with the outcome depending on the presence, application or effects of other factors such as cleaner energy alternatives and more effective forms of public transportation (Sterling, 2017, Chen *et al*., 2020). The data obtained from this study show that population may in fact negatively affect air quality. CO concentrations were found to be consistently higher in Bayelsa state than in Kano state, with the p-value from the comparative analysis indicating a significant difference for each year. This is expected as Bayelsa state is a location of oil exploration and gas flaring activities, it also shares borders with the Atlantic ocean and thus has significant marine traffic which is another contributor to CO pollution (Vohra *et al*., 2021; Abaje *et al*., 2020; Adebangbe *et al*., 2025), and thus, the much higher population in Kano state is not enough to produce nearly as much CO pollutant levels. However this plays a role in the concentrations of NO_2 which are higher in Kano state than in Bayelsa state. Pollutant emissions from vehicles, which is a major source of NO_2 pollution (Benazzi and Muhammad, 2019; Barau *et al*., 2023; Garba, 2016; Cheng *et al*., 2016), is also a major pollution source in Kano state (Idris *et al*., 2022), especially in the metropolitan areas as shown in the spatial analysis of this study. With the higher population of Kano state contributing to more vehicles on the road and subsequently more emissions, it is not surprising that NO_2 levels are much higher in Kano than in Bayelsa. The p-values also show a significant difference across all the years for NO_2 between the states, further buttressing this. There are also similar fluctuations in NO_2 levels across the studied period as shown in the trend analysis. For aerosols, although the values are generally higher in Kano state, there is a significant difference only in 2021, 2022 and 2023, with the other years having no significant differences. One major contributing factor to this is the oil exploration and gas flaring activities prevalent in Bayelsa state (Tran *et al*., 2024; Abaje *et al*., 2020; Soltanieh *et al*., 2016). Apart from CO emissions, combustion of fossil fuels through such activities also yields aerosol, however the prevalent dust storms in Kano (given that it is close to the Sahara desert), coupled with extended dry seasons and higher population as well as emissions from traffic results in higher aerosol values (Benazzi and Muhammad, 2019; Barau *et al*., 2023; Garba, 2016; Cheng *et al*., 2016; Ochiegbu, 2021; Aweda and Famoritade, 2018; Ogunjo *et al*., 2022). Notably, as we move southward in Kano (away from the Sahara), the aerosol levels begin to decline as seen in the spatial analysis of this study. In summary, the levels of NO_2 and Aerosols are higher in Kano state than in Bayelsa state, with Bayelsa state having higher CO levels. This study thus finds that the higher population in Kano state does not improve air quality based on the data obtained.

5.2 Influence of Population on Air quality

The population size of an area can impacts its urbanization, traffic and industrial activities, leading to more pollutant emissions (Carozzi and Roth, 2023; Sun *et al*., 2023; Zhang *et al*., 2021; Borck and Schrauth, 2021). A higher population leads to increased rate of urbanization, which if not properly managed can lead to congestion and subsequently higher emissions and pollution (Yuan *et al*., 2014). A large population size can also mean increased traffic, as there would be more vehicles on the road when not properly managed. Studies however show that if alternate forms of public transportation as well as more effective structuring of transit systems are employed, Population increase can lead to a reduction in pollutant emissions (Cheng *et al*., 2016; Sterling, 2017; Chen *et al*., 2020). One of such studies even finds that higher population results in lower Vehicle Miles Travelled (VMT) (Sterling, 2017). However in a place like Kano state where these measures are yet to be employed, its high population corresponds to increased traffic and subsequently more pollutant emissions. The high population of Kano also corresponds to increased industrial activities as there would be an increased demand for goods and services leading to more production, abundant workforce and infrastructure development, and industrial activities yield more pollutant emissions. Additionally, deforestation and urban expansion in Kano state due to the high population and high urbanization rates may also worsen air pollution (Heald and Spracklen, 2015; Andrée *et al*., 2019)). In Bayelsa state which has a much lower population, the impact on urbanization, traffic and industrial activities is not as significant, and so there tends to be less human activity and less pollutant emissions. However the oil exploration activities is a driver for urbanization and other industrial activities (Numbere, 2021; Avtar *et al*., 2019), in that these activities lead to development of infrastructure (oil companies often invest in infrastructure such as roads, bridges and housing to support their operations, which can also benefit local communities), in-migration of oil workers, growth of supporting industries such as manufacturing, construction, petrochemical and transportation. These activities lead to increased pollutant emissions in addition to the emissions from the oil exploration activities.

5.3 Implications of Findings

Air pollution in densely populated areas such as in Kano state increases the risks of respiratory diseases and cardiovascular diseases among other issues (Manisalidis *et al*., 2020; Lee *et al*., 2015; Lee *et al*., 2020), and the elevated levels of air pollutants in Kano state especially NO_2 and Aerosols emphasizes the need for much more attention to be given to mitigating air pollution through the enforcement of effective policies and regulations as well as the establishment of more urban green spaces (which is especially effective in dealing with Aerosol pollution) and the use of better transportation options (which is effective especially for NO_2). Aerosols have been linked to various health problems which range from respiratory and cardiovascular problems to more systemic issues (Sangkham *et al*., 2024), and therefore is a major risk factor for mortality and morbidity (Orellano *et al*., 2020; Burnett *et al*., 2018). Short term and long term exposure to nitrogen dioxide have also been linked to various health issues. Short-term NO_2 exposure has been linked to increased mortality risk in multi-location studies (Wang *et al*., 2021; Meng *et al*., 2021). Long-term exposure to NO_2 is associated with an increased risk of respiratory mortality (Chen *et al*., 2024; Huangfu and Atkinson, 2020). Cardiovascular impacts have also been observed, with research demonstrating an association between ambient NO_2 exposure and the severity of coronary atherosclerosis, as well as an increased risk of myocardial infarctions (Wang *et al*., 2019; Newby *et al*., 2015). CO which has higher concentration levels in Bayelsa state also has several health effects. The dangers of CO exposure have been well documented, particularly in relation to cardiovascular and neurological health risks (Savioli *et al*., 2024; Lee *et al*., 2015). Studies consistently show that short-term exposure to CO is associated with increased risks of myocardial infarction and emergency hospital admissions for cardiovascular diseases (Lee *et al*., 2015; Lee *et al*., 2020; Liu *et al*., 2024). Therefore there is an urgent need for attention to air quality in both states. High concentration of these pollutants is also detrimental to the environment. For example high concentrations of NO_2 leads to the formation of acid rain which corrodes surfaces and damages soil and crops, this reduces the fertility of the soil and can subsequently affect agriculture in the region (Mehta, 2015; Weldeslassie *et al*., 2018). Economically, the increased industrial activities which lead to more pollutant emissions can also benefit the economy, however at the expense of public health and the environment.

5.4 Recommendations

In Kano state, strengthening of public transport to reduce vehicle emissions is vital in dealing with pollutant emissions and this can be done by following the findings of Sterling (2017), Cheng *et al*. (2016) and Chen *et al*. (2020). They found that the use of cleaner transportation alternatives such as electric vehicles (buses and cars), and encouraging the public to utilize public transportation more frequently corresponds to a decline in air pollutant emissions. Proper enforcement of industrial pollution control measures can also prove instrumental in reducing pollutant emissions from industrial activities. Additionally, an increase in the number of green spaces, as well as afforestation programs is also important for absorbing pollutants. In Bayelsa state, there is a need for better monitoring and regulation of emissions from oil exploration. The adoption of cleaner energy alternatives by individuals and companies especially oil companies would also significantly reduce emission levels.

Additionally, more severe fines should be placed on gas flaring activities, making treating of harmful emissions and finding alternative uses to gases that are flared a cheaper/ more attractive alternative. This would discourage the flaring of gases. In both states there is a need for further strengthening of air quality monitoring systems, implementation of public awareness programs on pollution reduction and development of state-specific policies for pollution control.

5.5 Limitations of the Study

The major limitation of the study is that though the influence of population on the air quality of the study areas was discussed, there was no analysis carried out to quantify the significance of population on the air qualities of Kano and Bayelsa states, therefore further study will be required to obtain that information. Other limitations could be those frequently associated with the use of Sentinel-5P for analysis, mainly discrepancies can arise due to differences in spatial resolution and the influence of local meteorological conditions (Verhoelst *et al*., 2021)

5.6 Conclusion

This study compared air quality in Kano and Bayelsa states using Sentinel-5P data from 2019 to 2024 and examined how population influences pollution. Kano, the most populated state, shows higher NO_2 and aerosol levels driven by traffic, industrial activities, and dust events. Bayelsa, despite its lower population, registers higher CO levels from oil exploration, gas flaring, and marine traffic. These findings show that population influences air quality through the type of human activities present rather than through population size alone. The study stresses the need for state-specific interventions. In Kano, strengthening public transport, enforcing emission controls, and expanding green spaces may reduce NO_2 and aerosol pollution. In Bayelsa, stricter monitoring of oil-related emissions and the adoption of cleaner energy alternatives can help lower CO levels. The study also notes that effective urban planning can lessen pollution even in highly populated areas. Based on the limitations of this study, future research should measure the impact of population more precisely and consider additional local factors. This study provides a basis for policymakers to develop targeted strategies for improving air quality in both states. It underlines that population effects on pollution vary with the types of human activities and that tailored interventions are needed to protect public health and the environment.

REFERENCE LIST

Aakko-Saksa, P. T., Lehtoranta, K., Kuittinen, N., Järvinen, A., Jalkanen, J-P., Johnson, K., Jung, H., Ntziachristos, L., Gagné, S., Takahashi, C., Karjalainen, P., Rönkkö, T. and Timonen, H. (2023). Reduction in greenhouse gas and other emissions from ship engines: Current trends and future options. *Progress in Energy and Combustion Science*. **94**: 101055.

Abaje, I.B., Bello, Y. and Ahmad, S.A. (2020). A review of air quality and concentrations of air pollutants in Nigeria. *Global Journal of Applied Science and Environmental Management*. **24**: 373–379.

Abera, A., Friberg, J., Isaxon, C., Jerrett, M., Malmqvist, E., Sjöström, C., Taj, T. and Vargas, A.M. (2021). Air quality in Africa: public health implications. *Annual Review of Public Health*. **42**: 193–210.

Abhijith, K.V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., Broderick, B., Di Sabatino, S. and Pulvirenti, B. (2017). Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments: a review. *Atmospheric Environment*. **162**: 71–86.

Abulude, F.O., Arifalo, K.M., Kenni, A.M., Akinnusotu, A., Oluwagbayide, S.D. and Sunday, A. (2022). Air quality index levels of particulate matter (PM2.5) in Yenagoa, Nigeria. *Jurnal Geografi Gea*. **22**: 95–105.

Adamu, H. and Oji, S. (2021). Air pollution exposure mapping by GIS in Kano metropolitan area. *Pollution.* **7**(1): 101–112.

Adebangbe, S. A., Dixon, D. and Barrett, B. (2025). Geocomputation techniques for identifying spatio- temporal patterns of reported oil spills along crude oil pipeline networks. *International Journal of Digital Earth.* **18**(1): 2448218.

Adebayo, A. and Ainah, P.K. (2024) Addressing Nigeria's electricity challenges: Past, present, and future strategies. *American Journal of Applied Sciences*. **2**(5): 1-16.

Agbo, K.E., Walgraeve, C., Eze, J.I., Ugwoke, P.E., Ukoha, P.O. and Van Langenhove, H. (2020). A review on ambient and indoor air pollution status in Africa. *Atmospheric Pollution Research.* **12**(2): 333- 357.

Ahmed, A.A.M., Jui, S.J.J., Sharma, E., Ahmed, M.H., Raj, N. and Bose, A. (2024). An advanced deep learning predictive model for air quality index forecasting with remote satellite-derived hydro- climatological variables. *Science of The Total Environment*. **906**: 167234.

Ahmed, Y.Y., Mohd Shafrib, Z.H., Binti Roslan, S.N.A. and Gambo, J. (2024). Urban heat island and outdoor air quality: A remote sensing/machine learning approach for sustainable environmental management in Kano Metropolis. Available at https://ssrn.com/abstract=4790416 (Accessed 29th November, 2024)

Ai, H., Zhang, X. and Zhou, Z. (2023). The impact of greenspace on air pollution: Empirical evidence from China. *Ecological Indicators*. **146**: 109881.

Aliyu, M.A., Maharazu, A.Y., Suleiman, K. and Lawan, B.Y. (2021). Biophysical mapping and land use attributes of Kano ecosystems. North-Western Nigeria. *Bayero Journal of Pure and Applied Sciences*. **14**(2): 115–124.

Alvarado, M., Gonzalez, F., Fletcher, A. and Doshi, A. (2015). Towards the development of a low-cost airborne sensing system to monitor dust particles after blasting at open-pit mine sites. *Remote Sensing*. **15**(8): 19667–19687.

Amaechi, C.F., Enuneku, A., Omatsola, O.P. and Okoduwa, A.K. (2024) Evaluation of fuel subsidy removal policy on air quality: A case study on Federal Capital Territory, Abuja, Nigeria. *Malawi Journal of Science and Technology*. **16**(1): 85-99.

Amaechi, C.F., Ezenwa, J., Okoduwa, A.K., Emejulu, J.M. and Biose, E. (2024). Comparative assessment of air quality between the two major commercial states in Nigeria, sub-Saharan Africa. *Ethiopian Journal of Environmental Studies and Management.* **17**(5): 596-622.

Amaechi, C.F. and Biose, E. (2016). Gas flaring: carbon dioxide contribution to global warming. *Journal of Applied Sciences and Environmental Management*. **20**(2): 309-317.

Amaechi, C.F., Enuneku, A., Amadi, U.S. and Okoduwa, A.K. (2024). Effects of COVID-19 policy on air quality in Lagos State, Nigeria. *Applied Environmental Research*. **46**(1): 1-8.

Amaechi, C.F., Nzeagwu, O.F. and Okoduwa, A.K. (2023) Effect of fuel subsidy removal on air quality in Lagos State, South Western, Nigeria. *Ethiopian Journal of Environmental Studies and Management*. **16**(6): 816-829.

Amegah, A. K. and Agyei-Mensah, S. (2017). Urban air pollution in Sub-Saharan Africa: time for action. *Environmental Pollution*. **220**: 738-743.

Andrée, B. P. J., Chamorro, A., Spencer, P., Koomen, E. and Dogo, H. (2019). Revisiting the relation between economic growth and the environment: A global assessment of deforestation, pollution, and carbon emission. *Renewable and Sustainable Energy Reviews.* **114**: 109221.

Anejionu, O.C.D., Blackburn, G.A. and Whyatt, J.D. (2015). Detecting gas flares and estimating flaring volumes at individual flow stations using MODIS data. *Remote*

Sensing of Environment. **158**: 81– 94.

Anenberg, S.C., Henze, D.K., Tinney, V., Kinney, P.L., Raich, W., Fann, N., Malley, C.S., Roman, H., Lamsal, L., Duncan, B., Martin, R.V., van Donkelaar, A., Brauer, M., Doherty, R., Jonson, J.E., Davila, Y., Sudo, K. and Kuylenstierna, J.C.I. (2018) Estimates of the global burden of ambient $PM_{2.5}$, ozone, and NO_2 on asthma incidence and emergency room visits. *Environmental Health Perspectives*. **126**(10): 107004.

Angelova, P.R., Myers, I. and Abramov, A.Y. (2023). Carbon monoxide neurotoxicity is triggered by oxidative stress induced by ROS production from three distinct cellular sources. *Redox Biology*. **60**: 102598.

Apte, J.S., Marshall, J.D., Cohen, A.J. and Brauer, M. (2015). Addressing Global Mortality from Ambient PM2.5. *Environmental Science and Technology*. **49**(13): 8057–8066.

Asubiojo, O.I. (2016). Pollution Sources in the Nigerian environment and their health implications. *Ife Journal of Science*. **18**(4): 974–980.

Avtar, R., Tripathi, S., Aggarwal, A. K. and Kumar, P. (2019). Population–urbanization–energy nexus: a review. *Resources*. 8(3): 136.

Aweda, E. D. and Famoritade, M. B. (2018). Evaluation of harmattan dust events over Kano, Nigeria. *Monograph of Atmospheric Research*. **1**: 52-56.

Baek, J.I. and Ban, Y.U. (2020). The impacts of urban air pollution emission density on air pollutant concentration based on a panel model. *Sustainability*. **12**(20): 8401.

Baklanov, A., Molina, L.T. and Gauss, M. (2014). Megacities, air quality and climate. Atmospheric Environment. **94**: 52-61.

Barau, A.S., Kafi, K.M., Mu'allim, M.A., Dallimer, M. and Hassan, A. (2023). Comparative mapping of smellscape clusters and associated air quality in Kano City, Nigeria: an analysis of public perception, hotspots, and inclusive decision support tool. *Sustainable Cities and Society*. **96**: 104680.

Bede-Ojimadu, O. and Orisakwe, O.E. (2020). Exposure to wood smoke and associated health effects in Sub-Saharan Africa: A systematic review. *Annals of Global Health*. **86**(1): 1–27.

Bekkar, A., Hssina, B., Douzi, S. and Douzi, K. (2021). Air-pollution prediction in smart city, deep learning approach. *Journal of Big Data*. **8**(1): 1–21.

Bello, Y.A., Adzandeh, E.A. and Fabiyi, O.O. (2014). Statistical analysis of urban growth in Kano metropolis. *Environmental Monitoring and Analysis*. **2**(1): 50–56.

Benazzi, K. and Muhammad, I. (2019). Assessment of the pollution extent of sulphur dioxide (SO_2) and nitrogen dioxide (NO_2) in ambient air within Kano Metropolis, Kano State, Nigeria. *Journal of Environmental Science Computer Science and Engineering and Technology*. **8**(4): 396–404.

Berezi, O.K. and Nwankwoala, H.O. (2023). Application of geo-information technologies for flood vulnerability mapping in Bayelsa state, southern Nigeria. *Journal of Engineering and Applied Sciences Technology*. **1**(1): 1-11.

Bodah, B.W., Neckel, A., Maculan, L.S., Milanes, C.B., Korcelski, C., Ramírez, O., Mendez-Espinosa, J.F., Bodah, E.T. and Oliveira, M.L.S. (2022). Sentinel-5P TROPOMI satellite application for NO2 and CO studies aiming at environmental valuation. *Journal of Cleaner Production*. **357**: 131960.

Borck, R. and Schrauth, P. (2021). Population density and urban air quality. *Regional Science and Urban Economics*. **86**(C): 103596.

Borge, R., Lange, S., and Kehew, R. (2023). Analysis of air quality issues and air quality management status in five major African cities. *Clean Air Journal*. **33**(2): 1–22.

Boudalia, C., Kasmi, A.M. and Alili, A. (2023). Is a dense city a healthy city? A preliminary study on the interplay between urban density and air quality in Oran, Algeria. *Cybergeo: European Journal of Geography*. **1054.**

Brocato, J., Sun, H., Shamy, M., Kluz, T., Alghamdi, M.A., Khoder, M.I., Chen, L.C. and Costa, M. (2014). Particulate matter from Saudi Arabia induces genes involved in inflammation, metabolic syndrome, and atherosclerosis. *Journal of Toxicology and Environmental Health A*. **77**: 751–766.

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C.A. 3rd, Apte, J.S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S.S., Kan, H., Walker, K.D., Thurston, G.D., Hayes, R.B., Lim, C.C., Turner, M.C., Jerrett, M., Krewski, D., Gapstur, S.M., Diver, W.R., Ostro, B., Goldberg, D., Crouse, D.L., Martin, R.V., Peters, P., Pinault, L., Tjepkema, M., van Donkelaar, A., Villeneuve, P.J., Miller, A.B., Yin, P., Zhou, M., Wang, L., Janssen, N.A.H., Marra, M., Atkinson, R.W., Tsang, H., Thach, T.Q., Cannon, J.B., Allen, R.T., Hart, J.E., Laden, F., Cesaroni, G., Forastiere, F., Weinmayr, G., Jaensch, A., Nagel, G., Concin, H. and Spadaro, J.V. (2018). Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences*. **115**(39): 9592- 9597.

Carozzi, F. and Roth, S. (2023). Dirty density: air quality and the density of American cities. *Journal of Environmental Economics and Management*. **118**(2): 102767.

Castells-Quintana, D., Dienesch, E. and Krause, M. (2021). Air pollution in an urban world: A global view on density, cities and emissions. *Ecological Economics*. **189**: 107153.

Celikkol Erbas, B. and Guven Solakoglu, E. (2017). In the presence of climate change, the use of fertilizers and the effect of income on agricultural emissions. *Sustainability*. **9**(11): 1989.

Chaudhuri, S. and Roy, M. (2024). Global ambient air quality monitoring: can mosses help? A systematic meta-analysis of literature about passive moss biomonitoring. *Environment Development and Sustainability*. **26**: 5735–5773.

Chen, F., Lao, Q., Jia, G., Chen, C., Zhu, Q. and Zhou, X. (2019) Seasonal variations of nitrate dual isotopes in wet deposition in a tropical city in China. *Atmospheric Environment*. **196**: 1-9.

Chen, J., Wang, B., Huang, S. and Song, M. (2020). The influence of increased population density in China on air pollution. *Science of the Total Environment*. **735**: 139456.

Chen, X., Qi, L., Li, S. and Duan, X. (2024). Long-term NO_2 exposure and mortality: A comprehensive meta-analysis. *Environmental Pollution*. **341**: 122971.

Cheng, H., Madanat, S. and Horvath, A. (2016). Planning hierarchical urban transit systems for reductions in greenhouse gas emissions. *Transportation Research Part D: Transport and Environment*. **49**: 44-58.

Cheng, Z., Luo, L., Wang, S., Wang, Y., Sharma, S., Shimadera, H., Wang, X., Bressi, M., de Miranda, R.M., Jiang, J., Zhou, W., Fajardo, O., Yan, N. and Hao, J. (2016). Status and characteristics of ambient PM2.5 pollution in global megacities. *Environment International*. **89–90**: 212–221.

Chu, L.M., Shaefi, S., Byrne, J.D., Alves de Souza, R.W. and Otterbein, L.E. (2021). Carbon monoxide and a change of heart. *Redox Biology*. **48**: 102183.

Compernolle, S., Argyrouli, A., Lutz, R., Sneep, M., Lambert, J.C., Mari Fjæraa, A., Hubert, D., Keppens, A., Loyola, D., O'Connor, E., Romahn, F., Stammes, P., Verhoelst, T. and Wang, P. (2021). Validation of the Sentinel-5 Precursor TROPOMI cloud data with Cloudnet, Aura OMI O2-O2, MODIS, and Suomi-NPP VIIRS. *Atmospheric Measurement Techniques*. **14**: 2451–2476.

Crippa, M., Janssens-Maenhout, G., Dentener, F., Guizzardi, D., Sindelarova, K., Muntean, M., Van Dingenen, R. and Granier, C. (2016). Forty years of improvements in European air quality: regional policy-industry interactions with global impacts. *Atmospheric Chemistry and Physics.* **16**: 3825– 3841.

Croitoru, L., Chang, J. and Akpokodje, J. (2020). The health cost of ambient air pollution in Lagos. *Journal of Environmental Protection*. **11**(9): 753–765.

de Jesus, A. L., Rahman, M. M., Mazaheri, M., Thompson, H., Knibbs, L. D., Jeong, C., Evans, G., Nei, W., Ding, A., Qiao, L., Li, L., Portin, H., Niemi, J. V., Timonen, H., Luoma, K., Petäjä, T., Kulmala, M., Kowalski, M., Peters, A., Cyrys, J., Ferrero, L., Manigrasso, M., Avino, P., Buonano, G., Reche, C., Querol, X., Beddows, D., Harrison, R. M., Sowlat, M. H., Sioutas, C. and Morawska, L. (2019). Ultrafine particles and PM2.5 in the air of cities around the world: Are they representative of each other? *Environmental International*. **129**: 118-135.

de Sá, S.S., Rizzo, L.V., Palm, B.B., Campuzano-Jost, P., Day, D.A., Yee, L.D., Wernis, R., Isaacman- VanWertz, G., Brito, J., Carbone, S., Liu, Y.J., Sedlacek, A., Springston, S., Goldstein, A.H., Barbosa, H.M.J., Alexander, M.L., Artaxo, P., Jimenez, J.L. and Martin, S.T. (2019) Contributions of biomass-burning, urban, and biogenic emissions to the concentrations and light-absorbing properties of particulate matter in central Amazonia during the dry season. *Atmospheric Chemistry and Physics*. **19**(12): 7973-8001.

Di, Q., Wang, Y., Zanobetti, A., Wang, Y., Koutrakis, P., Choirat, C., Dominici, F. and Schwartz, J.D. (2017). Air pollution and mortality in the Medicare population. *New England Journal of Medicine*. **376**(25): 2513-2522.

Diener, A. and Mudu, P. (2021). How can vegetation protect us from air pollution? A critical review on green spaces' mitigation abilities for air-borne particles from a public health perspective - with implications for urban planning. *Science of The Total Environment*. **796**: 148605.

Dijkema, M.B.A., van Strien, R.T., van der Zee, S.C., Mallant, S.F., Fischer, P., Hoek, G., Brunekreef, B. and Gehring, U. (2016). Spatial variation in nitrogen dioxide concentrations and cardiopulmonary hospital admissions. *Environmental Research*. **151**: 721-727.

Dondi, A., Carbone, C., Manieri, E., Zama, D., Del Bono, C., Betti, L., Biagi, C. and Lanari, M. (2023). Outdoor air pollution and childhood respiratory disease: The role of oxidative stress. *International Journal of Molecular Sciences*. **24**(5): 4345.

Donovan, G.H., Gatziolis, D., Longley, I. and Douwes, J. (2018). Vegetation diversity protects against childhood asthma: results from a large New Zealand birth cohort. *Nature Plants*. **4**(6): 358-364.

Echendu, A.J., Okafor, H.F. and Iyiola, O. (2022). Air pollution, climate change, and ecosystem health in the Niger Delta. *Social Sciences.* **11**(11): 525.

Ede, P.N. and Edokpa, D.O. (2015). Regional air quality of Nigeria's Niger Delta. *Open Journal of Air Pollution*. **4**(1): 7–15.

Ekeng, L., Ahiakwo, C., Amadi, H. and Obuah, E. (2024) Voltage collapse in Nigeria power system— causes and remedies. *IOSR Journal of Electrical and Electronics*

Engineering, **19**(1): 54-63

Ephraim-Emmanuel, B.C., Enembe, O. and Ordinioha, B. (2023). Respiratory health effects of pollution due to artisanal crude-oil refining in Bayelsa, Nigeria. *Annals of Global Health.* **89**(1): 1–11.

European Space Agency. (2024). Sentinel-5P operations. Available at https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-5P (Accessed 6th February 2025)

Evangelopoulos, D., Perez-Velasco, R., Walton, H., Gumy, S., Williams, M., Kelly, F.J. and Künzli, N. (2020). The role of burden of disease assessment in tracking progress towards achieving WHO global air quality guidelines. *International Journal of Public Health* **65**(8): 1455–1465.

Evangelopoulos, D., Katsouyanni, K., Keogh, R.H., Samoli, E., Schwartz, J., Barratt, B., Zhang, H. and Walton, H. (2020). PM2.5 and NO2 exposure errors using proxy measures, including derived personal exposure from outdoor sources: A systematic review and meta-analysis. *Environmental International*. **137**: 105500.

Fowler, D., Brimblecombe, P., Burrows, J., Heal, M. R., Grennfelt, P., Stevenson, D. S., Jowett, A., Nemitz, E., Coyle, M., Liu, X., Chang, Y., Fuller, G. W., Sutton, M. A., Klimont, Z., Unsworth, M. H. and Vieno, M. (2020). A chronology of global air quality. *Philosophical Transactions of the Royal Society A.* **378**(2180): 20190314.

Fuladlu, K. and Altan, H. (2022). Examination of the population density impact on major air pollutants: A study in the case of Germany. In: Piselli, C., Altan, H., Balaban, O., and Kremer, P. (eds.), *Innovating strategies and solutions for urban performance and regeneration*. Springer, Cham. pp. 211-218.

Fussell, J.C. and Kelly, F.J. (2021). Mechanisms underlying the health effects of desert sand dust. *Environment International*. **157**: 106790.

Garba, M. and Yunusa, M. (2016). Assessing gaseous pollutants and air quality in some areas of Kano metropolis, Kano, Nigeria. *Emerging Infectious Diseases*. **203**: 125–134.

Goh, C.C., Kamarudin, L.M., Zakaria, A., Nishizaki, H., Ramli, N., Mao, X., Zakaria, S.M.M.S., Kanagaraj, E., Sukor, A.S.A. and Elham, M.F. (2021). Real-time in-vehicle air quality monitoring system using machine learning prediction algorithm. *Sensors*. **21**(15): 1–16.

Goshua, A., Akdis, C. A. and Nadeau, K. C. (2022). World Health Organization global air quality guideline recommendations: executive summary. *Allergy*. **77**(7): 1955-1960.

Guerreiro, C., Foltescu, V. and de Leeuw, F. (2014). Air quality status and trends in Europe. *Atmospheric Environment*. **98**: 376–384.

Gulia, S., Nagendra, S.S., Khare, M. and Khanna, I. (2015). Urban air quality management: a review. *Atmospheric Pollution Research*. **6**(2): 286–304.

Han, S. and Sun, B. (2019). Impact of population density on PM2.5 concentrations: a case study in Shanghai, China. *Sustainability*. **11**(7): 1968.

Hassaan, M.A., Abdallah, S.M., Shalaby, E.A. and Ibrahim, A.A. (2023). Assessing vulnerability of densely populated areas to air pollution using Sentinel-5P imageries: a case study of the Nile Delta, Egypt. *Scientific Reports*. **13**(1): 17406.

Haq, E.U., Waseem, F. and Baqi, A. (2021). Appraisal of temporal variations in atmospheric compositions over South Asia by addition of various pollutants in recent decade. *International Journal of Innovations in Science and Technology*. **3**(1): 1–15.

Hayes, E.K. and Gagnon, G.A. (2024) From capture to detection: A critical review of passive sampling techniques for pathogen surveillance in water and wastewater. *Water Research.* **261**: 122024.

Heald, C. L. and Spracklen, D. V. (2015). Land use change impacts on air quality and climate. *Chemical Reviews*. **115**(10): 4476-4496.

Hernández-Gordillo, A., Ruiz-Correa, S., Robledo-Valero, V., Hernández-Rosales, C. and Arriaga, S. (2021). Recent advancements in low-cost portable sensors for urban and indoor air quality monitoring. *Air Quality, Atmosphere and Health.* **14**(9): 1489–1506.

Holloway, T., Miller, D., Anenberg, S., Diao, M., Duncan, B., Fiore, A.M., Henze, D.K., Hess, J., Kinney, P.L., Liu, Y., Neu, J.L., O'Neill, S.M., Odman, M.T., Pierce, R.B., Russell, A.G., Tong, D., West, J.J. and Zondlo, M.A. (2021). Satellite monitoring for air quality and health. *Annual Review of Biomedical Data Science*. **4**: 417–447.

Holman, C., Harrison, R. and Querol, X. (2015). Review of the efficacy of low emission zones to improve urban air quality in European cities. *Atmospheric Environment*. **111**: 161-169.

Holub, F., Hospido, L. and Wagner, U.J. (2021). Urban air pollution and sick leaves: evidence from social security data. Available at: https://ssrn.com/abstract=3572565 (Accessed 24th November 2024).

Hossain, M. S., Frey, H. C., Louie, P. K. K. and Lau, A. K. H. (2021). Combined effects of increased O_3 and reduced NO_2 concentrations on short-term air pollution health risks in Hong Kong. *Environmental Polluion.* **270:** 116280.

Huang, C., Shan, W. and Xiao, H. (2018). Recent advances in passive air sampling of volatile organic compounds. *Aerosol and Air Quality Research*. **18**(3): 602-622.

Huangfu, P. and Atkinson, R. (2020). Long-term exposure to NO_2 and O_3 and all-cause and respiratory mortality: A systematic review and meta-analysis. *Environmental International*. **144**: 105998.

Idris, M., Muhammad, A. G., Said, R. S. and Akpootu, D. O. (2022). Effect of meteorological parameters on the dispersion of vehicular emission in some selected areas in Kano State-Nigeria. *Bayero Journal of Pure and Applied Sciences*. **13**(1): 517-524.

Isah, H.M., Sawyerr, H.O., Raimi, M.O., Bashir, B.G., Haladu, S. and Odipe, O.E. (2020). Assessment of commonly used pesticides and frequency of self-reported symptoms on farmers' health in Kura, Kano State, Nigeria. *Journal of Education and Learning Management*. **1**(1): 31–54.

Izah, S.C. and Seiyaboh, E.I. (2018). Impact of Land-Use Change from 2000-2020 on Environmental Resources in Bayelsa State, Nigeria. *Journal of Applied Sciences and Environmental Management*. **28**(5): 1519–1525.

Jack, J.T. and Tokpo, C.E. (2021). Insecurity in the Niger Delta: A report on emerging threats in Akwa Ibom, Bayelsa, Cross River, Delta, Edo and Rivers states. 76-82. Available at https://www.researchgate.net/profile/Tarila-Ebiede/publication/349637474_Insecurity_in_the_Niger_Delta_A_Report_on_Emerging_Threats_i n_Akwa_Ibom_Bayelsa_Cross_River_Delta_Edo_and_Rivers_States/links/603927e4a 6fdcc37a855 862c/Insecurity-in-the-Niger-Delta-A-Report-on-Emerging-Threats-in-

Akwa-Ibom-Bayelsa-Cross- River-Delta-Edo-and-Rivers-States.pdf#page=70 (Accessed 1st December, 2024).

Javaid, A., Creutzig, F. and Bamberg, S. (2020). Determinants of low-carbon transport mode adoption: systematic review of reviews. *Environmental Research Letters*. **15**: 103002.

Jerrett, M., Turner, M.C., Beckerman, B.S., Pope, C.A., van Donkelaar, A., Martin, R.V., Serre, M., Crouse, D., Gapstur, S.M., Krewski, D., Diver, W.R., Coogan, P.F., Thurston, G.D. and Burnett, R.T. (2017). Comparing the health effects of ambient particulate matter estimated using ground-based versus remote sensing exposure estimates. *Environmental Health Perspectives*. **125**(4): 552–559.

Jia, C., Li, W., Wu, T. and He, M. (2021) Road traffic and air pollution: Evidence from a nationwide traffic control during coronavirus disease 2019 outbreak. *Science of The Total Environment*. **781**: 146618.

Jote, C. A. (2023). The impacts of using inorganic chemical fertilizers on the environment and human health. *Organic and Medicinal Chemistry International Journal*. **13**: 555864.

Kaginalkar, A., Kumar, S., Gargava, P. and Niyogi, D. (2021). Review of urban computing in air quality management as smart city service: An integrated IoT, AI, and cloud technology perspective. *Urban Climate*. **39**:100972.

Kalantari, E., Gholami, H., Malakooti, H., Nafarzadegan, A.R. and Moosavi, V. (2024). Machine learning for air quality index (AQI) forecasting: shallow learning or deep learning? *Environmental Science and Pollution Research International.* **31**(54): 62962-62982.

Kaplan, G. and Yigit Avdan, Z. (2020). Space-borne air pollution observation from Sentinel-5P TROPOMI: Relationship between pollutants, geographical and demographic data. *International Journal of Engineering and Geosciences*. **5**(3): 130–137.

Katoto, P.D., Byamungu, L., Brand, A.S., Mokaya, J., Strijdom, H., Goswami, N., De Boever, P., Nawrot, T.S. and Nemery, B. (2019). Ambient air pollution and health in Sub-Saharan Africa: current evidence, perspectives and a call to action. *Environmental Research*. **173**: 174–188.

Khadija, B.U. and Muhammad, I. (2019). Assessment of the pollution extent of sulphur dioxide (SO_2) and nitrogen dioxide (NO_2) in ambient air within Kano metropolis, Kano state, Nigeria. *Journal of Environmental Chemical and Ecotoxicology*. **8**: 396–404.

Khreis, H., Kelly, C., Tate, J., Parslow, R., Lucas, K. and Nieuwenhuijsen, M. (2017). Exposure to traffic- related air pollution and risk of development of childhood asthma: A systematic review and meta- analysis. *Environment International*. **100**: 1-31.

Khreis, H., Johnson, J., Jack, K., Dadashova, B. and Park, E.S. (2022). Evaluating the performance of low- cost air quality monitors in Dallas, Texas. *International Journal of Environmental Research and Public Health.* **19**(3): 1647.

Khuriganova, O. I., Obolkin, V. A., Golobokova, L. P., Bukin, Y. S. and Khodzher, T. V. (2019). Passive Sampling as a Low-Cost Method for Monitoring Air Pollutants in the Baikal Region (Eastern Siberia). *Atmosphere*. **10**(8): 470.

Kim, K-H., Kabir, E. and Kabir, S. (2015). A review on the human health impact of airborne particulate matter. *Environment International*. **74**: 136-143.

Kim, H.J., Lee, H.W., Park, J., Lee, C.H. and Lee, C.H. (2020). Short-term exposure to fine particulate matter and pneumonia-related hospitalizations: A systematic review and meta-analysis. *Environmental Research Letters*. **15**(12): 123012.

Kojima, S., Michikawa, T., Matsui, K., Ogawa, H., Yamazaki, S., Nitta, H., Takami, A., Ueda, K., Tahara, Y., Yonemoto, N., Nonogi, H., Nagao, K., Ikeda, T., Sato, N. and Tsutsui, H. (2020). Association of fine particulate matter exposure with bystander-witnessed out-of-hospital cardiac arrest of cardiac origin in Japan. *Journal of the American Medical Association Network Open*. **3**(4): e203043.

Kök, İ., Şimşek, M. U. and Özdemir, S. (2017). A deep learning model for air quality prediction in smart cities. *2017 IEEE International Conference on Big Data (Big Data).* Boston, MA, USA. **1:** 1983-1990. Available at: https://ieeexplore.ieee.org/document/8258085 (Accessed 20th November, 2024).

Kolawole, O.M., Omole, O.O. and Adesina, O.A. (2023). Assessment of Suspended Particulate Matter (SPM) and Toxicity Potential (TP) of emissions from different power generating sets in Ado-Ekiti, Nigeria. *ABUAD Journal of Engineering Research and Development.* **6**(2): 50-56.

Kumar, P., Skouloudis, A.N., Bell, M., Viana, M., Carotta, M.C., Biskos, G. and Morawska, L. (2016). Real-time sensors for indoor air monitoring and challenges ahead in deploying them to urban buildings. *Science of the Total Environment*. **560-561**: 150–159.

Landrigan, P.J., Fuller, R., Acosta, N.J.R., Adeyi, O., Arnold, R., Basu, N., Baldé, A.B., Bertollini, R., Bose-O'Reilly, S., Boufford, J.I., Breysse, P.N., Chiles, T., Mahidol, C., Coll-Seck, A.M., Cropper, M.L., Fobil, J., Fuster, V., Greenstone, M., Haines, A., Hanrahan, D., Hunter, D., Khare, M., Krupnick, A., Lanphear, B., Lohani, B., Martin, K., Mathiasen, K.V., McTeer, M.A., Murray, C.J.L., Ndahimananjara, J.D., Perera, F., Potočnik, J., Preker, A.S., Ramesh, J., Rockström, J., Salinas, C., Samson, L.D., Sandilya, K., Sly, P.D., Smith, K.R., Steiner, A., Stewart, R.B., Suk, W.A., van Schayck, O.C.P., Yadama, G.N., Yumkella, K. and Zhong, Ma. (2017). The Lancet Commission on pollution and health. *The Lancet*. **391**(10119): 462-512.

Languille, B., Gros, V., Bonnaire, N., Pommier, C., Honoré, C., Debert, C., Gauvin, L., Srairi, S., Annesi- Maesano, I., Chaix, B. and Zeitouni, K. (2020). A methodology for the characterization of portable sensors for air quality measure with the goal of deployment in citizen science. *Science of The Total Environment.* **708**: 134698.

Lanzafame, R., Monforte, P. and Scandura, P.F. (2016). Comparative analyses of urban air quality monitoring systems: passive sampling and continuous monitoring stations. *Energy Procedia*. **101**: 321–328.

Larkin, A., Geddes, J.A., Martin, R.V., Xiao, Q., Liu, Y., Marshall, J.D., Brauer, M. and Hystad, P. (2017). Global land use regression model for nitrogen dioxide air pollution. *Environmental Science and Technology*. **51**(12): 6957–6964.

Lee, F.Y., Chen, W.K., Lin, C.L. and Kao, C.H. (2015). Carbon monoxide poisoning and subsequent cardiovascular disease risk: A nationwide population-based cohort study. *Medicine*. **94**(10): e624.

Lee, K. K., Spath, N., Miller, M. R., Mills, N. L. and Shah, A. S. V. (2020). Short-term exposure to carbon monoxide and myocardial infarction: a systematic review and meta-analysis. *Environment International*. **143**: 105901.

Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D. and Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*. **525**(7569): 367-371.

Liu, C., Yin, P., Chen, R., Meng, X., Wang, L., Niu, Y., Lin, Z., Liu, Y., Liu, J., Qi, J., You, J., Kan, H. and Zhou, M. (2018). Ambient carbon monoxide and cardiovascular mortality: a nationwide time-series analysis in 272 cities in China. *Lancet Planetary Health*. **2**(1): e12–e18.

Liu, Y., Guo, M., Wang, J., Gong, Y., Huang, C., Wang, W., Liu, X., Liu, J., Ju, C., Ba, Y., Zhou, G. and Wu, X. (2024). Effect of short-term exposure to air pollution on hospital admission for cardiovascular disease: A time-series study in Xiangyang, China. *Science of The Total Environment*. **918**: 170735.

Liu, M., Li, Z., Lu, F., Guo, M., Tao, L., Liu, M., Liu, Y., Deginet, A., Hu, Y., Li, Y., Wu, M., Luo, Y., Wang, X., Yang, X., Gao, B., Guo, X. and Liu, X. (2021). Acute effect of particulate matter pollution on hospital admissions for cause-specific respiratory diseases among patients with and without type 2 diabetes in Beijing, China, from 2014 to 2020. *Ecotoxicology and Environmental Safety*. **226**: 112794.

Liu, Y., Pan, J., Fan, C., Xu, R., Wang, Y., Xu, C., Xie, S., Zhang, H., Cui, X., Peng, Z., Shi, C., Zhang, Y., Sun, H., Zhou, Y. and Zhang, L. (2021). Short-term exposure to ambient air pollution and mortality from myocardial infarction. *Journal of the American College of Cardiology*. **77**(3): 271-281.

Lu, H., Wang, R., Li, J., Tong, M., Cao, M., Liu, H., Xiao, Q., Zheng, Y., Liu, Y., Guan, T. and Xue, T. (2023). Long-term exposure to the components of fine particulate matters and disability after stroke: Findings from the China National Stroke

Screening Surveys. *Journal of Hazardous Materials*. **460**: 132244.

Mahmud, K., Mitra, B., Uddin, M.S., Hridoy, A.-E.E., Aina, Y.A., Abubakar, I.R., Rahman, S.M., Tan, M.L. and Rahman, M.M. (2023). Temporal assessment of air quality in major cities in Nigeria using satellite data. *Atmospheric Environment: X*. **20**: 100227.

Mehta, P. (2015). A conceptual understanding of scientific and legal perspective of acid precipitation and its impacts: a review. *Journal of Applied Science And Research*. **3**(2): 54-75.

Manibusan, S. and Mainelis, G. (2022). Passive bioaerosol samplers: A complementary tool for bioaerosol research. A review. *Journal of Aerosol Science.* **163**: 105992.

Manisalidis, I., Stavropoulou, E., Stavropoulos, A. and Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: a review. *Frontiers in Public Health*. **8**: 1-13.

Mansfield, T., Rodriguez, D., Huegy, J. and Gibson, J. (2014). The effects of urban form on ambient air pollution and public health risk: a case study in Raleigh, North Carolina. *Risk Analysis*. **35**(5): 901– 918.

Marć, M., Zabiegała, B. and Namieśnik, J. (2015). Current air quality analytics and monitoring: a review. *Analytica Chimica Acta.* **853**: 116–126.

Masiol, M. and Harrison, R.M. (2015). Quantification of air quality impacts of London Heathrow Airport (UK) from 2005 to 2012. *Atmospheric Environment*. **116**: 308–319.

Meng, X., Liu, C., Chen, R., Sera, F., Vicedo-Cabrera, A.M., Milojevic, A., Guo, Y., Tong, S., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P.H.N., Lavigne, E., Matus

Correa, P., Valdes Ortega, N., Osorio-Garcia, S., Kyselý, J., Urban, A., Orru, H., Maasikmets, M., Jaakkola, J.J.K., Ryti, N., Huber, V., Schneider, A., Katsouyanni, K., Analitis, A., Hashizume, M., Honda, Y., Ng, C.F.S., Nunes, B., Teixeira, J.P., Holobaca, I.H., Fratianni, S., Kim, H., Tobias, A., Íñiguez, C., Forsberg, B., Åström, C., Ragettli, M.S., Guo, Y.L.L., Pan, S.C., Li, S., Bell, M.L., Zanobetti, A., Schwartz, J., Wu, T. and Gasparrini, A. (2021). Short-term associations of ambient nitrogen dioxide with daily total, cardiovascular, and respiratory mortality: Multilocation analysis in 398 cities. *British Medical Journal*. **372**: n534.

Meseke, A.B., Indabawa, I.I., Bello, U., Sanda, A.H., Adamu, A.A., Garba, N.N., Abdullahi, I.S., Bala, M., Umar, I., Aliyu, A.S. and Muhammad, S. (2021). Comparative assessment of particulate matter concentrations in urban and rural areas in Kano state, Nigeria, using a low-cost air quality monitor: a pilot study. *Pollution*. **7(**1): 101-112.

Mir Alvarez, C., Hourcade, R., Lefebvre, B. and Pilot, E. (2020). A scoping review on air quality monitoring, policy and health in West African cities. *International Journal of Environmental Research and Public Health*. **17**(23): 9151.

Moderato, L., Aschieri, D., Lazzeroni, D., Rossi, L., Biagi, A., Binno, S. M., Monello, A., Pelizzoni, V., Sticozzi, C., Zanni, A., Capucci, A., Nani, S., Ardissino, D., Nicolini, F. and Niccoli, G. (2023). Air pollution and out-of-hospital cardiac arrest risk: A 7-year study from a highly polluted area. *European Heart Journal: Acute Cardiovascular Care*. **12**(12): 810–817.

Mohammed, A., Buba, L.F., Kodiya, M.A. and Oluwatosin, O.L. (2021). Assessment of air quality improvement potentials of urban trees in Kano metropolis, Kano state, Nigeria. *Bima Journal of Science and Technology*. **5**: 174–184.

Morakinyo, B.O. (2015). Flaring and pollution detection in the Niger Delta using remote sensing. Available at: https://api.semanticscholar.org/CorpusID:130536717. (Accessed: 29th November, 2024)

Morawska, L., Thai, P.K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., Bedini, A., Chai, F., Christensen, B., Dunbabin, M., Gao, J., Hagler, G.S.W., Jayaratne, R., Kumar, P., Lau, A.K.H., Louie, P.K.K., Mazaheri, M., Ning, Z., Motta, N., Mullins, B., Rahman, M.M., Ristovski, Z., Shafiei, M., Tjondronegoro, D., Westerdahl, D. and Williams, R. (2018). Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: how far have they gone? *Environment International*. **116**: 286–299.

Moshammer, H., Poteser, M., Kundi, M., Lemmerer, K., Weitensfelder, L., Wallner, P. and Hutter, H.P. (2014). Nitrogen dioxide remains a valid air quality indicator. *International Journal of Environmental Research and Public Health.* **11**(5): 4582–4596.

Muhammad, I., Raimi, M. and Sawyerr, H. (2021). Probabilistic assessment of self-reported symptoms on farmers' health: A case study in Kano State for Kura Local Government Area of Nigeria. *Isotopes in Environmental and Health Studies*. **9**(975): 975-985.

Mukherjee, A. and Agrawal, M. (2017). World air particulate matter: sources, distribution and health effects. *Environmental Chemistry Letters*. **15**(2): 283-309.

Mutanga, O. and Kumar, L. (2019). Google Earth Engine applications. *Remote Sensing*. **11**(5): 591.

Mzid, N., Cantore, V., De Mastro, G., Albrizio, R., Sellami, M.H. and Todorovic, M. (2020). The application of ground based and satellite remote sensing for estimation of biophysiological parameters of wheat grown under different water regimes. *Water*. **12**(8): 2095.

Nalakurthi, N.V.S.R., Abimbola, I., Ahmed, T., Anton, I., Riaz, K., Ibrahim, Q., Banerjee, A., Tiwari, A. and Gharbia, S. (2024). Challenge and opportunities in calibrating low-cost environmental sensors. *Sensors*. **24**(11): 3650

National Bureau of Statistics. (2020). Demographic statistics bulletin. Available at https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://nigerianstat.gov.ng/download/1241121&ved=2ahUKEwjh763i4tmJAxVTVKQEHQIdKBkQFnoECB8QAQ&usg= AOvVaw3nVhakifrlB86oNATttS0J (Accessed 13th November, 2024).

Navares, R. and Aznarte, J.L. (2020). Predicting air quality with deep learning LSTM: towards comprehensive models. *Ecological Informatics.* **55**: 101019.

Newby, D.E., Mannucci, P.M., Tell, G.S., Baccarelli, A.A., Brook, R.D., Donaldson, K., Forastiere, F., Franchini, M., Franco, O.H., Graham, I., Hoek, G., Hoffmann, B., Hoylaerts, M.F., Künzli, N., Mills, N., Pekkanen, J., Peters, A., Piepoli, M.F., Rajagopalan, S. and Storey, R.F. (2015). Expert position paper on air pollution and cardiovascular disease. *European Heart Journal*. **36**(2): 83–93.

Numbere, A. O. (2021). Impact of Urbanization and Crude oil exploration in Niger delta mangrove ecosystem and its livelihood opportunities: a footprint perspective. *Agroecological Footprints Management for Sustainable Food System*. **1**: 309-344.

Ochiegbu, D.C. (2021) Event of harmattan dust transport in Kano State of Nigeria. *International Journal of Scientific and Research Publications*. **11**(8): 205-210.

Official website of Bayelsa state government. (2024). History & Culture - Bayelsa state government. Available at https://bayelsastate.gov.ng/our-history/#:~:text=The%20state%20is%20made%20up,the%20Government%20and%20private%20in stitutions. (Accessed 1st December, 2024).

Ogunjo, S., Olaniyan, O., Olusegun, C.F., Kayode, F., Okoh, D. and Jenkins, G. (2022). The role of meteorological variables and aerosols in the transmission of COVID-19 during Harmattan season. *GeoHealth*. **6**(2): 1-14

Ogunsola, O.E., Njoku, E.I. and Ayokunnu, O.D. (2023). Industrial air pollutants investigation in the Niger Delta region of Nigeria. *Open Access Library Journal*. **10**(7): 1–15.

Okoduwa, A. and Amaechi, C.F. (2024). Exploring Google Earth Engine, machine learning, and GIS for land use land cover change detection in the Federal Capital Territory, Abuja, between 2014 and 2023. *Applied Environmental Research*. **46**(2): 1–10.

Okoduwa, K.A. and Amaechi, C.F. (2023). Monitoring and Mapping of Atmospheric Concentration of Carbon Monoxide (CO), Sulphur Dioxide (SO2), and Nitrogen Dioxide (NO2) from 2019–2022 in Benin City, Southern Nigeria. *Journal of Applied Sciences and Environmental Management.* **27**(12): 2715–2722.

Olawade, D.B., Wada, O.Z., Ige, A.O., Egbewole, B.I., Olojo, A. and Oladapo, B.I. (2024). Artificial intelligence in environmental monitoring: advancements, challenges, and future directions. *Hygiene and Environmental Health Advances.* **12**: 100114.

Olusola, J.A., Shote, A.A., Ouigmane, A. and Isaifan, R.J. (2021). The impact of COVID-19 pandemic on nitrogen dioxide levels in Nigeria. *PeerJ*. **9**: e11387.

Omokpariola, D., Nduka, J. and Omokpariola, P. (2024). Short-term trends of air quality and pollutant concentrations in Nigeria from 2018–2022 using tropospheric Sentinel-5P and 3A/B satellite data. *SN Applied Sciences*. **6**(182): 1–23.

Orcan, F. (2020). Parametric or non-parametric: Skewness to test normality for mean comparison. *International Journal of Assessment Tools in Education*. **7**(2): 255-265.

Orellano, P., Reynoso, J., Quaranta, N., Bardach, A. and Ciapponi, A. (2020). Short-term exposure to particulate matter (PM10 and PM2.5), nitrogen dioxide (NO2), and ozone (O3) and all-cause and cause-specific mortality: Systematic review and meta-analysis. *Environment International*. **142**: 105876.

Oxoli, D., Cedeno, R. and Brovelli, M. (2020). Assessment of Sentinel-5P performance for ground-level air quality monitoring: Preparatory experiments over the COVID-19 lockdown period. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. **XLIV-3/W1-2020**: 111–118.

Park, Y.M., Chavez, D., Sousan, S., Figueroa-Bernal, N., Alvarez, J.R. and Rocha-Peralta, J. (2023). Personal exposure monitoring using GPS-enabled portable air pollution sensors: a strategy to promote citizen awareness and behavioral changes regarding indoor and outdoor air pollution. *The Journal of Exposure Science and Environmental Epidemiology*. **33**(3): 347-357.

Parmar, T. K., Rawtani, D. and Agrawal, Y. K. (2016). Bioindicators: the natural indicator of environmental pollution. *Frontiers in Life Science*. **9**(2): 110–118.

Patel, H., Talbot, N., Dirks, K. and Salmond, J. (2023). The impact of low emission zones on personal exposure to ultrafine particles in the commuter environment. *Science of the Total Environment*. **874**: 162540.

Pathak, H., Jain, N., Bhatia, A., Kumar, A. and Chatterjee, D. (2016). Improved nitrogen management: a key to climate change adaptation and mitigation. *Indian Journal of Fertilisers*. **12**(11): 151-162.

Pipa, S.P., Oyedeji, A.A. and Angaye, T.C. (2024). The evaluation of suspended particulate matter (SPM) associated with artisanal refineries in Bayelsa State, Nigeria. *International Journal of Innovative Biosciences Research.* **12**(3): 15–20.

Piracha, A. and Chaudhary, M.T. (2022). Urban air pollution, urban heat island, and human health: a review of the literature. *Sustainability*. **14**(15): 9234.

Qian, Y., Li, H., Rosenberg, A., Li, Q., Sarnat, J., Papatheodorou, S., Schwartz, J., Liang, D., Liu, Y., Liu, P. and Shi, L. (2021). Long-term exposure to low-level NO_2 and mortality among the elderly population in the southeastern United States. *Environmental Health Perspectives*. **129**(12): 127009.

Ravina, M., Caramitti, G., Panepinto, D. and Zanetti, M. (2022). Air quality and photochemical reactions: analysis of NOx and NO2 concentrations in the urban area of Turin, Italy. *Air Quality, Atmosphere and Health*. **15**: 541–558.

Requia, W.J., Vicedo-Cabrera, A.M., Amini, H., da Silva, G.L., Schwartz, J.D. and Koutrakis, P. (2023). Short-term air pollution exposure and hospital admissions for cardiorespiratory diseases in Brazil: A nationwide time-series study between 2008 and 2018. *Environmental Research*. **217**: 114794.

Reshi, A., Pichuka, S. and Tripathi, A. (2024). Applications of Sentinel-5P TROPOMI satellite sensor: A review. *IEEE Sensors Journal*. **PP**(99): 1.

Rider, C.F. and Carlsten, C. (2019). Air pollution and DNA methylation: effects of exposure in humans. *Clinical Epigenetics*. **11**(1): 131.

Rose, J.J., Wang, L., Xu, Q., McTiernan, C.F., Shiva, S., Tejero, J. and Gladwin, M.T. (2017). Carbon monoxide poisoning: Pathogenesis, management, and future directions of therapy. *American Journal of Respiratory and Critical Care Medicine*. **195**(5): 596–606.

Salisu, A.B. (2023). Comparative mapping of smellscape clusters and associated air quality in Kano City, Nigeria: An analysis of public perception, hotspots, and inclusive decision support tool. *Sustainable Cities and Society*. 96: 104680.

Sangkham, S., Phairuang, W., Sherchan, S.P., Pansakun, N., Munkong, N., Sarndhong, K., Islam, M.A. and Sakunkoo, P. (2024). An update on adverse health effects from exposure to PM2.5. *Environmental Advances*. **18**: 100603.

Sarmiento, L., Wägner, N. and Zaklan, A. (2023). The air quality and well-being effects of low emission zones. *Journal of Public Economics*. **227**: 105014.

Savenets, M. (2021). Air pollution in Ukraine: A view from the Sentinel-5P satellite. *Időjárás*. **125**(2): 271– 290.

Savioli, G., Gri, N., Ceresa, I. F., Piccioni, A., Zanza, C., Longhitano, Y., Ricevuti, G., Daccò, M., Esposito, C. and Candura, S. M. (2024). Carbon Monoxide Poisoning: From Occupational Health to Emergency Medicine. *Journal of Clinical Medicine*. **13**(9): 2466.

Schwarz, M., Peters, A., Stafoggia, M., de'Donato, F., Sera, F., Bell, M.L., Guo, Y., Honda, Y., Huber, V., Jaakkola, J.J.K., Urban, A., Vicedo-Cabrera, A.M., Masselot, P., Lavigne, E., Achilleos, S., Kyselý, J., Samoli, E., Hashizume, M., Ng, C.F.S., Pereira da Silva, S.N., Madureira, J., Garland, R.M., Tobias, A., Armstrong, B., Schwartz, J., Gasparrini, A., Schneider, A. and Breitner, S. (2024). Temporal variations in the short-term effects of ambient air pollution on cardiovascular and respiratory mortality: a pooled analysis of 380 urban areas over a 22-year period. *The Lancet Planetary Health*. **8**(9): e657-e665.

Seesaard, T., Kamjornkittikoon, K. and Wongchoosuk, C. (2024). A comprehensive review on advancements in sensors for air pollution applications. *Science of The Total Environment.* **951**:175696.

Seihei, N., Farhadi, M., Takdastan, A., Asban, P., Kiani, F. and Mohammadi, M. J. (2024). Short-term and long-term effects of exposure to PM10. *Clinical Epidemiology and Global Health*. **27**: 101611.

Shabani, N.B. (2023). A comparative evaluation of AI-based methods and traditional approaches for air quality monitoring: analyzing pros and cons. Available at SSRN: https://ssrn.com/abstract=4680965 (|Accessed 20th November, 2024).

Shikwambana, L., Mhangara, P. and Mbatha, N. (2020). Trend analysis and first-time observations of sulphur dioxide and nitrogen dioxide in South Africa using TROPOMI/Sentinel-5P data. *International Journal of Applied Earth Observation and Geoinformation*. **91**: 102130.

Sikora, J., Niemiec, M., Szeląg-Sikora, A., Gródek-Szostak, Z., Kuboń, M. and Komorowska, M. (2020). The impact of a controlled-release fertilizer on greenhouse gas emissions and the efficiency of the production of Chinese cabbage. *Energies*. **13**(8): 2063.

Singh, D., Dahiya, M., Kumar, R. and Nanda, C. (2021). Sensors and systems for air quality assessment monitoring and management: a review. *Journal of Environmental Management*. **289**: 112510.

Simões Amaral, S., Andrade de Carvalho Jr, J., Martins Costa, M. A. and Pinheiro, C. (2016). Particulate matter emission factors for biomass combustion. *Atmosphere*. **7**(11): 141.

Soltanieh, M., Zohrabian, A., Gholipour, M.J. and Kalnay, E. (2016) A review of global gas flaring and venting and impact on the environment: Case study of Iran. *International Journal of Greenhouse Gas Control*. **49**: 488-509.

Song, X., Hu, Y., Ma, Y., Jiang, L., Wang, X., Shi, A., Zhao, J., Liu, Y., Liu, Y., Tang, J., Li, X., Zhang, X., Guo, Y. and Wang, S. (2022). Is short-term and long-term exposure to black carbon associated with cardiovascular and respiratory diseases? A systematic review and meta-analysis based on evidence reliability. *British Medical Journal Open*. **12**(5): e049516.

Sterling, M. (2017). Air Quality: Population Density and Transportation Emissions. *The Equilibrum*. **3**(1): 11-15.

Suku, P.G., Ugwoha, E. and Orikpete, O.F. (2024). Artisanal crude oil refining in the Niger Delta: Environmental impacts, health outcomes, and strategies for sustainable mitigation. *Journal of Earth and Environmental Science Research*. **6**(220): 2-9.

Sun, B., Fang, C., Liao, X., Guo, X. and Liu, Z. (2023). The relationship between urbanization and air pollution affected by intercity factor mobility: A case of the Yangtze River Delta region. *Environmental Impact Assessment Review*. **100**: 107092.

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S. and Brisco, B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*. **164**: 152–170.

Tanko, I.A., Suleiman, Y.M., Yahaya, T.I. and Kasim, A.A. (2017). Urbanisation effect on the development of urban heat island over Kano Metropolis Nigeria. *International*

Journal of Scientific and Engineering Research. **8**(9): 293–299.

Tasic, V., Bozilov, A., Misic, N., Topalovic, D., Randjelovic, I., Mirkov, N. and Kamenovic, V. (2023). Portable air quality monitor based on low-cost sensors. *Thermal Science.* **27**: 107.

Thompson, J.E. (2016). Crowd-sourced air quality studies: A review of the literature and portable sensors. *Trends in Environmental Analytical Chemistry.* **11**: 23–34.

Tikader, M., Mukhopadhyay, D. and Davadkar, D. (2024). Remote sensing and GIS in air pollution mitigation: A bibliometric review of Chhattisgarh, India. *International Journal of Environment and Climate Change*. **14**(4): 174–193.

Torretta, V., Rada, E. and Capodaglio, A. (2015). An example of the use of bio-indicators for air quality assessment in areas with high industrial presence. *Environmental Engineering and Management Journal.* **14**: 2679-2687.

Tran, H., Polka, E., Buonocore, J.J., Roy, A., Trask, B., Hull, H. and Arunachalam, S. (2024) Air Quality and Health Impacts of Onshore Oil and Gas Flaring and Venting Activities Estimated Using Refined Satellite-Based Emissions. *Geohealth*. 8(3): e2023GH000938.

Ulpiani, G. (2021). On the linkage between urban heat island and urban pollution island: three-decade literature review towards a conceptual framework. *Science of the Total Environment*. **751**: 141727.

Van der Wat, L. and Forbes, P. B. C. (2015). Lichens as biomonitors for organic air pollutants. *TrAC Trends in Analytical Chemistry.* **64**: 165–172.

van Donkelaar, A., Martin, R.V., Brauer, M., Hsu, N.C., Kahn, R.A., Levy, R.C., Lyapustin, A., Sayer, A.M. and Winker, D.M. (2016). Global estimates of fine particulate matter using a combined geophysical- statistical method with information from satellites, models, and monitors. *Environmental Science and Technology*. **50**(7): 3762–3772.

Verhoelst, T., Compernolle, S., Pinardi, G., Lambert, J.-C., Eskes, H.J., Eichmann, K.-U., Fjæraa, A.M., Granville, J., Niemeijer, S., Cede, A., Tiefengraber, M., Hendrick, F., Pazmiño, A., Bais, A., Bazureau, A., Boersma, K.F., Bognar, K., Dehn, A., Donner, S., Elokhov, A., Gebetsberger, M., Goutail, F., Grutter de la Mora, M., Gruzdev, A., Gratsea, M., Hansen, G.H., Irie, H., Jepsen, N., Kanaya, Y., Karagkiozidis, D., Kivi, R., Kreher, K., Levelt, P.F., Liu, C., Müller, M., Navarro Comas, M., Piters, A.J.M., Pommereau, J.-P., Portafaix, T., Prados-Roman, C., Puentedura, O., Querel, R., Remmers, J., Richter, A., Rimmer, J., Rivera Cárdenas, C., Saavedra de Miguel, L., Sinyakov, V.P., Stremme, W., Strong, K., Van Roozendael, M., Veefkind, J.P., Wagner, T., Wittrock, F., Yela González, M. and Zehner, C. (2021). Ground-based validation of the Copernicus Sentinel-5P TROPOMI NO2 measurements with the NDACC ZSL-DOAS, MAX-DOAS and Pandonia global networks. *Atmospheric Measurement Techniques*. **14**: 481–510.

Vîrghileanu, M., Săvulescu, I., Mihai, B.A., Nistor, C. and Dobre, R. (2020). Nitrogen dioxide (NO2) pollution monitoring with Sentinel-5P satellite imagery over Europe during the coronavirus pandemic outbreak. *Remote Sensing*. **12**(21): 3575.

Vohra, K., Vodonos, A., Schwartz, J., Marais, E. A., Sulprizio, M. P. and Mickley, L. J. (2021). Global mortality from outdoor fine particle pollution generated by fossil fuel combustion: Results from GEOS-Chem. *Environmental Research*. **195**: 110754.

Wakawa, L.D., Uzairu, A. and Harrison, G.F.S. (2016). Air pollution tolerance and dust particulate matter accumulation capacities of trees in Kano, North-West Nigeria. *Open Access Library Journal*. 10: e10319.

Wang, S., McGibbon, J. and Zhang, Y. (2024). Predicting high-resolution air quality using machine learning: Integration of large eddy simulation and urban morphology data. *Environmental Pollution*. **344**: 123371.

Wang, M., Li, H., Huang, S., Qian, Y., Steenland, K., Xie, Y., Papatheodorou, S. and Shi, L. (2021). Short- term exposure to nitrogen dioxide and mortality: A systematic review and meta-analysis. *Environmental Research*. **202**: 111766.

Wang, M., Hou, Z.H., Xu, H., Liu, Y., Budoff, M.J., Szpiro, A.A., Kaufman, J.D., Vedal, S. and Lu, B. (2019). Association of estimated long-term exposure to air pollution and traffic proximity with a marker for coronary atherosclerosis in a nationwide study in China. *Journal of the American Medical Association Network Open*. **2**(6): e196553.

Waqas, M., Nazeer, M., Wong, M.S., Shaolin, W., Hon, L. and Heo, J. (2024). Impact of urban spatial factors on NO_2 concentration based on different socio-economic restriction scenarios in U.S. cities. *Atmospheric Environment*. **316**: 120191.

Weichenthal, S., Pinault, L., Christidis, T., Burnett, R. T., Brook, J. R., Chu, Y., Crouse, D. L., Erickson, A. C., Hystad, P., Li, C., Martin, R. V., Meng, J., Pappin, A. J., Tjepkema, M., van Donkelaar, A., Weagle, C. L. and Brauer, M. (2022). How low can you go? Air pollution affects mortality at very low levels. *Science Advances*. **8**(39): eabo3381.

Weldeslassie, T., Naz, H., Singh, B. and Oves, M. (2018). Chemical contaminants for soil, air and aquatic ecosystem. *Modern age environmental problems and their remediation*. **1**: 1-22.

West, J.J., Cohen, A., Dentener, F., Brunekreef, B., Zhu, T., Armstrong, B., Bell, M.L., Brauer, M., Carmichael, G., Costa, D.L., Dockery, D.W., Kleeman, M., Krzyzanowski, M., Künzli, N., Liousse, C., Lung, S.-C.C., Martin, R.V., Pöschl, U., Pope, C.A. III, Roberts, J.M., Russell, A.G. and Wiedinmyer, C. (2016). What we breathe impacts our health: improving understanding of the link between air pollution and health. *Environmental Science and Technology*. **50**(10): 4895–4904.

Willis, M.D., Schrank, D., Xu, C., Harris, L., Ritz, B.R., Hill, E.L. and Hystad, P. (2022) A population- based cohort study of traffic congestion and infant growth using connected vehicle data. *Science Advances*. **8**(43): eabp8281.

Wong, P.P., Lai, P.C., Allen, R., Cheng, W., Lee, M., Tsui, A., Tang, R., Thach, T.Q., Tian, L., Brauer, M. and Barratt, B. (2019). Vertical monitoring of traffic-related air pollution (TRAP) in urban street canyons of Hong Kong. *Science of the total environment*. **670**: 696-703.

World Health Organization (2021). WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide, and carbon monoxide. Geneva: World Health Organization. Available at https://www.who.int/publications/i/item/9789240034228 (24th November 2024).

World Health Organization (2021). Air pollution is responsible for 6.7 million premature deaths every year. Available at https://www.who.int/teams/environment-climate-change-and-health/air-quality-and- health/health-impacts/types-of-pollutants (5th February 2025).

Wu, B., Wu, C., Ye, Y., Pei, C., Deng, T., Li, Y.J., Lu, X., Wang, L., Hu, B., Li, M. and Wu, D. (2024). Long-term hourly air quality data bridging of neighboring sites using automated machine learning: a case study in the Greater Bay area of China. *Atmospheric Environment*. **321**: 120347.

Xu, C., Fan, Y.N., Liang, Z., Xiao, S.H., Huang, L., Kan, H.D., Chen, R.J., Liu, X.L., Yao, C.Y., Luo, G., Zhang, Y., Li, Y.F., Ji, A.L. and Cai, T.J. (2020). Unexpected association between increased levels of ambient carbon monoxide and reduced daily outpatient visits for vaginitis: A hospital-based study. *Science of The Total Environment*. **723**: 137923.

Yadav, R., Sahu, L.K., Beig, G., Tripathi, N., Maji, S. and Jaaffrey, S.N.A. (2019) The role of local meteorology on ambient particulate and gaseous species at an urban site of western India. *Urban Climate*. **28**: 100449.

Yang, B., Ding, L. and Tian, Y. (2021). The influence of population agglomeration on air pollution: an empirical study based on the mediating effect model. *IOP Conference Series: Earth and Environmental Science*. **687**: 012014.

Yitshak-Sade, M., Bobb, J. F., Schwartz, J. D., Kloog, I. and Zanobetti, A. (2018). The association between short and long-term exposure to PM2.5 and temperature and hospital admissions in New England and the synergistic effect of the short-term exposures. *Science of The Total Environment*. **639**: 868- 875.

Yuan, C., Ng, E. and Norford, L.K. (2014). Improving air quality in high-density cities by understanding the relationship between air pollutant dispersion and urban morphologies. *Building and Environment*. **71**: 245-258.

Yu, H. and Stuart, A.L. (2017). Impacts of compact growth and electric vehicles on future air quality and urban exposures may be mixed. *Science of the Total Environment*. **576**: 148–158.

Zang, X., Zhang, Z., Zhao, Y., Li, G., Xie, H., Zhang, W., Wu, G., Yang, X. and Jiang, L. (2024). Effects of NO_2 and SO_2 on the secondary organic aerosol formation from β-pinene photooxidation. *Journal of Environmental Sciences*. **136**: 151-160.

Zhang, B., Wu, Y., Zhao, B., Chanussot, J., Hong, D., Yao, J. and Gao, L. (2022). Progress and challenges in intelligent remote sensing satellite systems. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. **15**: 1814–1822.

Zhang, M., Buekens, A. and Li, X. (2017). Dioxins from Biomass Combustion: An Overview. *Waste Biomass Valor*. **8**: 1–20

Zhang, Y., Eastham, S., Lau, A., Fung, J. and Selin, N. (2021). Global air quality and health impacts of domestic and international shipping. *Environmental Research Letters*. **16**(8): 084055.

Zhao, Q., Yu, L., Li, X., Peng, D., Zhang, Y. and Gong, P. (2021). Progress and trends in the application of Google Earth and Google Earth Engine. *Remote Sensing*. **13**(18): 3778.

Zhao, Y., Hu, J., Tan, Z., Liu, T., Zeng, W., Li, X., Huang, C., Wang, S., Huang, Z. and Ma, W. (2019). Ambient carbon monoxide and increased risk of daily hospital outpatient visits for respiratory diseases in Dongguan, China. *Science of the Total Environment*. **668**: 254–260.

Zhou, S., Wang, W., Zhu, L., Qiao, Q. and Kang, Y. (2024). Deep-learning architecture for PM2.5 concentration prediction: A review. *Environmental Science and Ecotechnology*. **21**: 100400.

APPENDIX

Appendix 1: Carbon Monoxide monthly concentration for Bayelsa State

Month	2019	2020	2021	2022	2023	2024
January	0.065	0.068	0.065	0.065	0.061	0.063
February	0.067	0.075	0.065	0.064	0.063	0.072
March	0.055	0.064	0.056	0.059	0.054	0.058
April	0.045	0.047	0.048	0.046	0.044	0.046
May	0.038	0.041	0.04	0.038	0.039	0.046
June	0.043	0.043	0.042	0.039	0.039	0.045
July	0.046	0.045	0.052	0.046	0.044	0.052
August	0.043	0.049	0.052	0.05	0.05	0.059
September	0.039	0.042	0.043	0.043	0.038	0.046
October	0.037	0.037	0.037	0.035	0.036	0.041
November	0.041	0.047	0.045	0.045	0.044	0.047
December	0.053	0.056	0.055	0.055	0.054	0.057
Mean	0.048	0.051	0.05	0.049	0.047	0.053
Standard deviation	0.010	0.012	0.009	0.010	0.009	0.009

Appendix 2: Carbon Monoxide monthly concentration values for Kano State

Month	2019	2020	2021	2022	2023	2024
January	0.04	0.037	0.037	0.038	0.039	0.035
February	0.04	0.043	0.04	0.038	0.037	0.043
March	0.044	0.046	0.046	0.044	0.041	0.045
April	0.045	0.044	0.041	0.046	0.042	0.044
May	0.042	0.042	0.039	0.04	0.041	0.046
June	0.035	0.036	0.036	0.035	0.035	0.038
July	0.033	0.033	0.034	0.033	0.033	0.036
August	0.033	0.035	0.036	0.036	0.035	0.039
September	0.031	0.032	0.033	0.03	0.032	0.036
October	0.033	0.032	0.034	0.03	0.033	0.035
November	0.034	0.036	0.035	0.034	0.037	0.035
December	0.034	0.039	0.035	0.034	0.036	0.036
Mean	0.037	0.038	0.037	0.037	0.037	0.039
Standard deviation	0.0049	0.0048	0.0037	0.0050	0.0034	0.0043

Appendix 3: Nitrogen Dioxide monthly concentration values for Bayelsa State

Month	2019	2020	2021	2022	2023	2024
January	0.0000588	0.0000546	0.0000588	0.0000647	0.0000628	0.0000588
February	0.0000577	0.0000494	0.0000525	0.0000588	0.0000556	0.0000546
March	0.0000527	0.0000475	0.0000499	0.0000558	0.0000444	0.0000563
April	0.0000482	0.0000435	0.0000482	0.0000522	0.0000494	0.0000525
May	0.0000459	0.0000439	0.0000449	0.000053	0.000055	0.0000521
June	0.0000426	0.0000478	0.0000488	0.0000463	0.0000467	0.0000485
July	0.0000448	0.0000433	0.0000495	0.0000464	0.0000489	0.0000438
August	0.0000399	0.0000456	0.0000468	0.0000481	0.0000492	0.0000433
September	0.0000410	0.0000431	0.0000489	0.0000453	0.0000456	0.0000427
October	0.0000398	0.0000463	0.0000513	0.0000491	0.0000467	0.0000450
November	0.0000476	0.0000519	0.0000599	0.0000524	0.0000483	0.0000492
December	0.0000515	0.0000583	0.0000648	0.0000644	0.0000472	0.0000569
Mean	0.0000475	0.0000479	0.0000520	0.0000530	0.0000500	0.0000503
Standard deviation	0.00000653	0.00000485	0.00000600	0.00000672	0.00000527	0.00000572

Appendix 4: Nitrogen Dioxide monthly concentration values for Kano State

Month	2019	2020	2021	2022	2023	2024
January	0.0000538	0.0000456	0.0000549	0.0000550	0.0000613	0.0000510
February	0.0000563	0.0000457	0.0000515	0.0000552	0.0000553	0.0000525
March	0.0000588	0.0000525	0.0000577	0.0000577	0.0000548	0.0000550
April	0.0000636	0.0000576	0.0000613	0.0000677	0.0000680	0.0000624
May	0.0000663	0.0000600	0.0000657	0.0000682	0.0000768	0.0000749
June	0.0000652	0.0000652	0.0000740	0.0000653	0.0000723	0.0000745
July	0.0000638	0.0000610	0.0000659	0.0000615	0.0000675	0.0000650
August	0.0000525	0.0000525	0.0000610	0.0000592	0.0000638	0.0000525
September	0.0000502	0.0000550	0.0000600	0.0000573	0.0000623	0.0000538
October	0.0000488	0.0000552	0.0000599	0.0000574	0.0000540	0.0000565
November	0.0000502	0.0000548	0.0000577	0.0000589	0.0000577	0.0000533
December	0.0000473	0.0000551	0.0000549	0.0000584	0.0000530	0.0000560
Mean	0.0000564	0.0000550	0.0000604	0.0000602	0.0000622	0.0000590
Standard deviation	0.00000692	0.00000571	0.00000602	0.00000456	0.00000772	0.00000842

Appendix 5: Aerosol monthly concentration values for Bayelsa State

Month	2019	2020	2021	2022	2023	2024
January	0.004	0.39	-0.436	0.789	0.855	0.939
February	0.297	0.552	-0.164	1.336	1.357	1.033
March	-0.372	-0.618	-0.597	0.542	-0.196	0.217
April	-0.586	-1.04	-1.12	-0.271	-0.131	-0.277
May	-1.021	-1.384	-1.571	-0.496	-0.52	-0.529
June	-0.871	-1.134	-1.535	-0.715	-0.582	-0.582
July	-0.8	-1.106	-0.301	-0.432	-0.622	-0.252
August	-0.835	-0.946	-0.681	0.088	-0.167	0.087
September	-1.086	-1.091	-0.774	-0.534	-0.519	-0.585
October	-1.205	-1.371	-0.751	-0.649	-0.701	-0.777
November	-1.127	-1.351	-0.463	-0.415	-0.58	-0.58
December	-0.61	-0.818	0.72	0.313	0.551	0.372
Mean	-0.684	-0.826	-0.639	-0.037	-0.105	-0.078
Standard Deviation	0.463	0.647	0.618	0.653	0.669	0.611

Appendix 6: Aerosol monthly concentration values for Kano State

Month	2019	2020	2021	2022	2023	2024
January	0.175	0.224	-0.448	1.128	1.086	0.917
February	0.444	0.487	0.089	1.486	1.309	1.144
March	0.465	-0.124	0.251	1.792	0.738	1.369
April	0.349	0.115	-0.252	1.171	0.912	0.989
May	0.008	-0.261	-0.623	1.092	0.896	1.002
June	-0.416	0.028	-0.597	0.602	0.371	1.007
July	-0.724	-1.167	-0.144	-0.128	-0.078	-0.276
August	-1.144	-1.38	-0.386	-0.564	-0.294	-0.601
September	-0.943	-1.373	0.098	-0.344	-0.023	-0.387
October	-1.122	-1.153	0.108	0.119	0.727	-0.176
November	-0.844	-0.875	0.416	0.367	0.485	0.416
December	-0.542	-0.673	0.984	0.574	0.749	0.365
Mean	-0.358	-0.513	-0.042	0.608	0.573	0.481
Standard deviation	0.617	0.669	0.466	0.746	0.494	0.686