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Taye Bayode

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Reducing Childhood Malaria Through Sustainable Urban Planning: A Spatial Risk Modelling Approach to Foster Public Health-Based Urban Structure and Infrastructure in Akure, Nigeria

Supervisor and Reviewer:
Prof. Dr. Alexander Siegmund (Heidelberg University & Heidelberg University of Education)

Co-supervisor and Reviewer:
Prof. Dr. Marcus Nüsser (Heidelberg University)

Dedication

To Davina Bayode and all the departed children who could not read this thesis because of malaria scourge.

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My deepest gratitude goes to my family and friends for their unwavering support. To my parents, Mr. and Mrs. David Ale Bayode, I extend my heartfelt thanks. Words cannot fully express how much you have supported me throughout my life's journey and instilled in me the value of education. I could not have wished for better parents. I express special thanks to my siblings – Kehinde, Seun, Teniola, Fisayo and Bukola for your love and support. You all never doubted my abilities and I am grateful for this. Olamide Aladetuyi and Oreoluwa Ajulo, Thank you for your support. To my wife, Oluwaseun – your patience, sacrifices, understanding and staying with our children in order for me to concentrate and complete the writing of this thesis are sincerely appreciated. Thank you for believing in me. During my doctoral programme, I took an extension because of my children – David and Jason. Thank you, David, for learning at an early age the meaning of 'Daddy is busy'. I may have taken some time off because of you; however, you became my motivation to complete this thesis.

My utmost appreciation to you all!

Taye Bayode

Heidelberg, 11 August 2024

Abstract

The health and wellbeing of inhabitants of cities in low- and middle-income countries like Nigeria are constantly threatened. Particularly, the striking urban health inequalities and the high burden of infectious diseases such as malaria with associated negative consequences. In addition to ill health among the malaria-infected individuals, other negative impacts of malaria include economic burden, loss of wages, and time away from school among children. However, these burdens are not evenly distributed in space and time. Existing studies on spatiality of malaria face three main shortcomings: They are done at a coarse scale resulting in the masking of local malaria hotspots, lacks important malaria socio-economic and socio-ecological variables essential for formulating tailored health policy interventions, and fall short in exploring the dynamics of city growth and its impact on impact on malaria in children under 5 years old (U5) given that the high level of urbanisation confronted by cities poses health risk on city inhabitants. Akure, Nigeria is an example of such city whereby the ongoing urbanisation processes with the potential to increase the risk of malaria among vulnerable groups has not been adequately investigated. Therefore, addressing these shortcomings are significant to improving health outcomes among city inhabitants in Nigeria.

This dissertation aims at closing these gaps by leveraging spatial and non-spatial cross-sectional mixed method approaches to answer two main questions: (i) What are the (spatial) growth dynamics and their impact on health in Akure? (ii) Where are the local pockets of U5 malaria, and what are their driving socio-economic and socio-ecological factors? These two main questions are further divided into nine sub-questions which were approached by gathering primary data from surveys and interviews as well as secondary data from policy documents and government repositories. The mixed methods used to analyse the data include descriptive and inferential statistics, machine learning and spatial data analysis.

The study reveals that Akure is rapidly urbanising, with a net increase of over 20 % in built-up areas between 1984 and 2023. However, the spatial growth of the city lacks formal urban planning, and its impact on health has been given little to no attention by local urban planning officials. Geostatistical modelling predicts that U5 malaria prevalence in Akure exceeds 35 % in certain locations. According to the exceedance probability model developed in line with the fifth National Malaria Strategic Plan of Nigeria, the study shows U5 malaria hotspots are primarily in peri-urban and informal settlements, suggesting the impact of urban structure on the malaria

burden. Finally, the dissertation identifies five critical social determinants of U5 malaria: window protection, distance to waste disposal sites, use of insecticide-treated nets, source of drinking water, and availability of health infrastructure.

In conclusion, this dissertation emphasises the need to include multiple actors beyond the public health sector as well as multidisciplinary approaches in generating place-based evidence for malaria reduction/elimination policy formulation. Such strategies are essential for cities like Akure to achieve the Sustainable Development Goals 3 and 11 in low- and middle-income countries, thereby sustainably improving their inhabitants' living conditions.

Zusammenfassung

Die Gesundheit und das Wohlbefinden der Bewohner von Städten in Ländern mit niedrigem und mittlerem Einkommen wie Nigeria sind ständig gefährdet. Insbesondere die eklatanten gesundheitlichen Ungleichheiten in den Städten und die hohe Belastung durch Infektionskrankheiten wie Malaria mit den damit verbundenen negativen Folgen. Zu den weiteren negativen Auswirkungen von Malaria zählen neben dem schlechten Gesundheitszustand der mit Malaria infizierten Personen auch die wirtschaftliche Belastung, Lohnausfälle und die Abwesenheit von der Schule für die Kinder. Allerdings sind diese Belastungen räumlich und zeitlich nicht gleichmäßig verteilt. Bestehende Studien zur Räumlichkeit von Malaria weisen drei Hauptmängel auf: Sie werden in einem groben Maßstab durchgeführt, was zur Maskierung lokaler Malaria-Hotspots führt, und es fehlen wichtige sozioökonomische und sozioökologische Variablen der Malaria, die bei der maßgeschneiderten Formulierung gesundheitspolitischer Interventionen helfen können. und fallen kurz in die Untersuchung der Dynamik des Stadtwachstums und seiner Auswirkungen auf die Malaria bei Kindern unter 5 Jahren (U5), da der hohe Grad der Urbanisierung, mit dem Städte konfrontiert sind, ein Gesundheitsrisiko für die Stadtbewohner darstellt. Akure, Nigeria, ist ein Beispiel für eine solche Stadt, in der die laufenden Urbanisierungsprozesse mit dem Potenzial, das Malariarisiko bei gefährdeten Gruppen zu erhöhen, nicht ausreichend untersucht wurden. Daher ist die Behebung dieser Mängel von entscheidender Bedeutung für die Verbesserung der Gesundheitsergebnisse der Stadtbewohner in Nigeria.

Diese Dissertation zielt darauf ab, diese Lücken zu schließen, indem räumliche und nicht-räumliche Querschnittsansätze mit gemischten Methoden genutzt werden, um zwei Hauptfragen zu beantworten: (i) Wie sind die (räumlichen) Wachstumsdynamiken und ihre Auswirkungen auf die Gesundheit in Akure? (ii) Wo sind die lokalen Nischen der U5-Malaria und was sind ihre treibenden sozioökonomischen und sozioökologischen Faktoren? Diese beiden Hauptfragen sind weiter in neun Unterfragen unterteilt, die durch die Erhebung von Primärdaten aus Umfragen und Interviews sowie Sekundärdaten aus Grundsatzdokumenten und Regierungsarchiven beantwortet wurden. Zu den gemischten Methoden zur Analyse der Daten gehören deskriptive und inferenzielle Statistik, maschinelles Lernen und räumliche Datenanalyse.

Die Studie zeigt, dass Akure sich rasch urbanisiert und zwischen 1984 und 2023 eine Nettozunahme der bebauten Fläche von über 20 % verzeichnet wird. Dem räumlichen Wachstum

der Stadt mangelt es jedoch an formeller Stadtplanung, und seine Auswirkungen auf die Gesundheit wurden kaum berücksichtigt Keine Beachtung durch örtliche Stadtplanungsbeamte. Geostatistische Modelle gehen davon aus, dass die U5-Malaria-Prävalenz in Akure an bestimmten Orten 35 % übersteigt. Gemäß dem Überschreitungswahrscheinlichkeitsmodell, das im Einklang mit dem fünften Nationalen Malaria-Strategieplan Nigerias entwickelt wurde, zeigt die Studie, dass U5-Malaria-Hotspots hauptsächlich in stadtnahen und informellen Siedlungen liegen, was auf den Einfluss der städtischen Struktur auf die Malariabelastung hindeutet. Schließlich identifiziert die Dissertation fünf kritische soziale Determinanten der U5-Malaria: Fensterschutz, Entfernung zu Mülldeponien, Verwendung von mit Insektiziden behandelten Netzen, Trinkwasserquelle und Verfügbarkeit von Gesundheitsinfrastruktur.

Zusammenfassend betont diese Dissertation die Notwendigkeit, mehrere Akteure außerhalb des öffentlichen Gesundheitssektors sowie multidisziplinäre Ansätze einzubeziehen, um ortsbezogene Beweise für die Formulierung von Richtlinien zur Malariareduzierung/-eliminierung zu generieren. Solche Strategien sind für Städte wie Akure unerlässlich, um die Nachhaltigkeitsziele 3 und 11 in Ländern mit niedrigem und mittlerem Einkommen zu erreichen und so die Lebensbedingungen ihrer Bewohner nachhaltig zu verbessern.

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Declaration

I, **Taye Bayode**, hereby declare that the thesis entitled "*Reducing Childhood Malaria Through Sustainable Urban Planning: A Spatial Risk Modelling Approach to Foster Public Health-Based Urban Structure and Infrastructure in Akure, Nigeria*" submitted for the degree of Doctor of Natural Sciences (Dr. rer. nat.) at Ruprecht-Karls-University of Heidelberg, Germany is the result of my original work and has not been submitted previously in whole or in part for the award of any other similar degree or diploma at any other institution. To the best of my knowledge, previously published or written material by another person have been duly acknowledged and referenced in this thesis.

This thesis was conceptualised by me with support from my supervisor – Professor Dr. Alexander Siegmund based on discussions we had during the early stages of the development of my thesis proposal. I designed the study and survey; gathered, and analysed the study data, drafted and reviewed the published manuscripts cumulating to this thesis. As a native speaker, Dr Maike Petersen helped me review the German version of my abstract. I have made clear my contributions and what was done by any other person, if any, in the parts of this thesis where the work has been jointly done.

Heidelberg, 11 August 2024

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List of abbreviations:

ANOVA: Analysis of Variance

AOR: Adjusted Odds Ratio

ArcGIS: Aeronautical Reconnaissance Coverage Geographic Information System

EP: Exceedance Probability

GIS: Geographic Information System

ITN: Insecticide-Treated Nets

IRS: Indoor Residual Spraying

LMICs: Low- and Middle-Income Countries

LLINs: Long-lasting Insectidal Nets

LULC: Land Use Land Cover

MBG: Model-Based Geostatistics

MIQ: Malaria Indicator Questionnaire

MPPUD: Ministry of Physical Development and Urban Development

NMSP: National Malaria Strategic Plan

OR: Odds Ratio

RBCs: Red Blood Cells

RS: Remote Sensing

SDCM: Social Determinants of Childhood Malaria

SDGs: Sustainable Development Goals

SDH: Social Determinants of Health

SSA: Sub-Saharan Africa

U5: Children Under Five Years

UN-Habitat: United Nations Human Settlements Programme

USGS: United States Geological Survey

Publications:

This doctoral dissertation is based on the following reputable and Scopus indexed publications. Indexes below are as of 05.06.2024.

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Publication 4

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Presentations:

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Talk Title: *Unequal Scene and Health Inequality in Rapidly Growing City of Akure: The Nigerian Reality.*

16th International Symposium on Geospatial Health, Enschede, The Netherlands. 13-16 November 2023.

Talk Title: *Modelling urban spatial structure and malaria: Empirical analysis from medium-sized city of Akure, Nigeria.*

18th International Conference on Urban Health (ICUH 2022) Valencia, Spain. 24-27 October 2022.

Talk Title: *Spatial analysis of childhood, malaria in Nigeria: A model-based geostatistical modelling approach.*

Deutsche Gesellschaft für Geographie (DGFG, GeoWoche 2021) Virtual. 5 -9 October 2021.

Talk Title: *Geostatistical analysis of malaria and risk factors among children under five years: A Case Study of Akure, Nigeria. (From Conventional to Contemporary Statistical Analysis Using Model-Based Geostatistical Approach)*

Deutsche Kongress für Geographie (DKG 2019), 25 – 30 September 2019, Kiel, Germany.

Talk Title: *Towards Improvement of Childhood Malaria through Spatial Planning in Akure, Nigeria: A Spatial Risk Modelling Approach for Population Health Promotion*

Arbeitskreis für Medizinische Geographie JAHRESTAGUNG, 27-27 September 2018. Remagen bei Bonn, Germany.

Talk Title: *Spatial distribution of childhood malaria incidence in Akure, Nigeria: Spatial Methods for Risk Modelling*

17th International Conference on Urban Health (ICUH 2021) Virtual. 6-8 July 2021.

Poster Title: *Spatio-temporal analysis of malaria prevalence in children under five years: A model-based geostatistical approach.*

Part I: Synopsis

1

“Children are one-third of our population and all of our future.”

Select panel for the promotion of child health, 1981.

I.1 Introduction

In modern human history, malaria has been one of the most important vector-borne parasitic diseases of public health concern. It is a serious, dangerous, and sometimes fatal illness, particularly among vulnerable groups, depending on the severity of the infection. The most vulnerable groups to malaria are children under five years of age (U5), pregnant women, HIV or AIDS infected individuals, and travellers from malaria free zones. Almost half of the world’s population from 85 countries are at risk of malaria infection recording a global estimate of 249 million malaria cases and 608,000 deaths from malaria in the year 2022 (Liu et al., 2021; World Malaria Report, 2023). Large proportion of the malaria burden are associated with U5 accounting for 76% (462,080) of global malaria deaths (World Malaria Report, 2023). It is important to note that the risk of malaria is not evenly distributed globally, with highest prevalence occurring in Africa (Figure I.1.1). Among the five World Health Organization (WHO) regions (African, South-East Asia, Eastern Mediterranean, Western Pacific, Americas), the highest burden can be found in WHO African Region with an estimate of 93.6% (233 million of 249 million) and nearly 95.4% (580,000 of 608,000) of the global malaria cases and death (World Malaria Report, 2023). Worse off, majority of the disease burden and death toll are peculiar with U5 children accounting for about 78.1% (~453 000 of 580,000) of malaria deaths in WHO African Region. Therefore, despite the extensive scientific research and developments in medical care and health care policies in the last decades to eradicate or eliminate malaria, the disease still greatly ravages residents of sub-Saharan Africa (SSA) making it one of her most important public health threats (Oladipo et al., 2022).

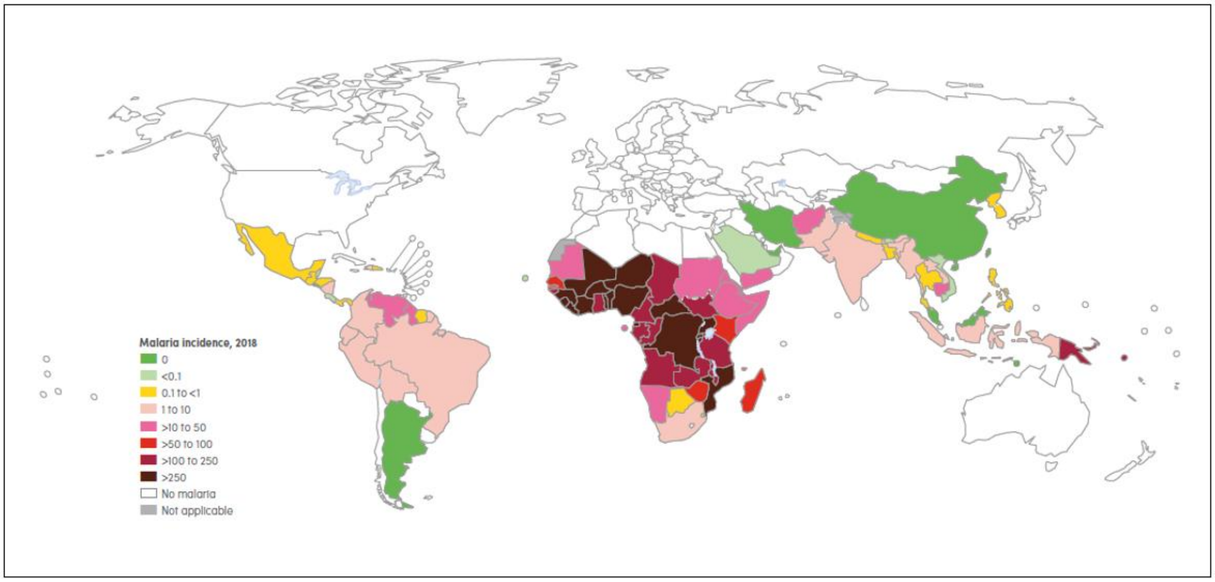

Figure I.1.1: Global malaria incidence rate i.e. cases per 1000 population at risk (Source: Adapted from World Malaria Report, 2019)

Nigeria, the most populous country in sub-Saharan Africa (SSA) stands out for its high prevalence of malaria compared to other countries worldwide. According to the (World Malaria Report, 2023) and Figure I.1.2, Nigeria accounted for about 26.8% (66.7 million) and 31.1% (~190,000) of global malaria cases and malaria deaths respectively. Of these worrisome figures, Nigeria accounted for 38.5% (~175,000) of global malaria deaths among children aged under 5 years thereby constituting a major public health problem with high morbidity and mortality. Thus, the burning question, which is influenced by this study by the author is “can sub-Saharan African countries particularly Nigeria, ever be free from the scourge of malaria, and how?” These questions are pertinent because the significant figures of malaria mortality and morbidity are crucial to the global fight against malaria. Successful elimination of malaria in Nigeria will not only be a significant achievement in Africa, but colossal and grand stride in public health, and the history of mankind.

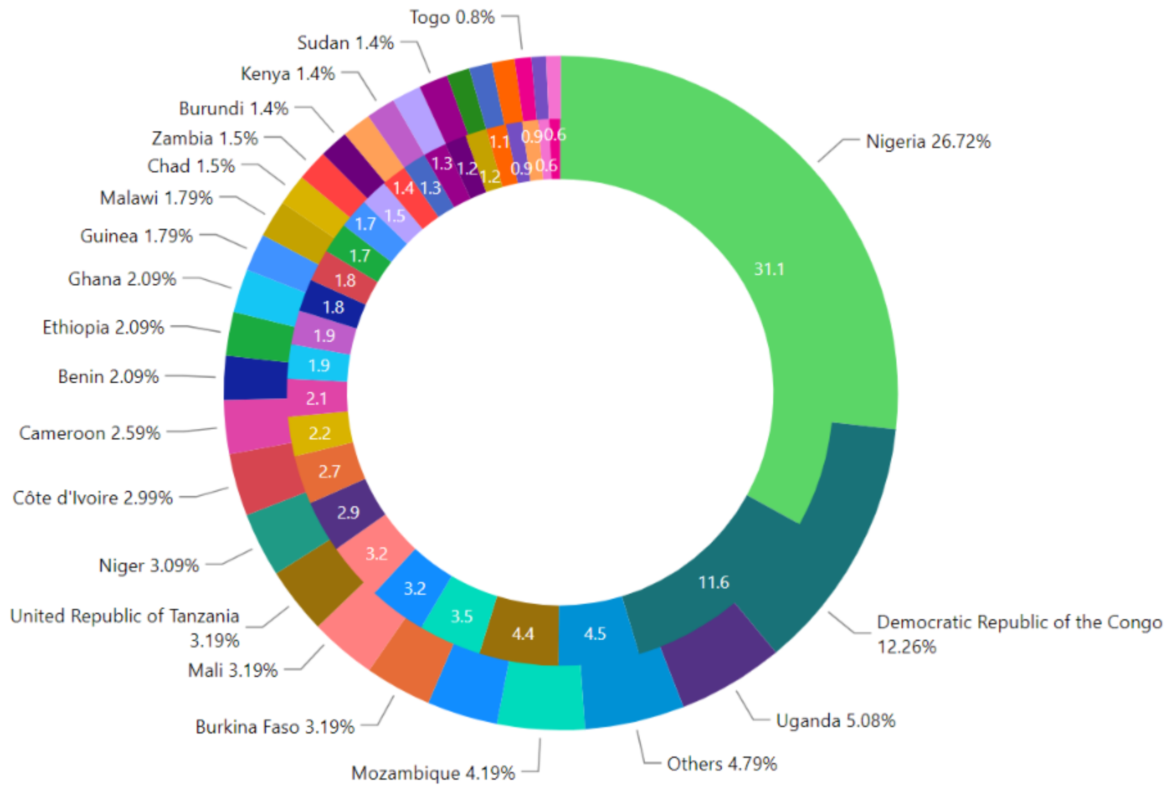

Figure I.1.2: Percentage global burden of malaria cases (outer ring) and malaria deaths (inner ring).

Good health is a fundamental universal-human right and a vital index to the sustainable development of any nation. For example, the fallouts from malaria cripple economic growth, thereby causing setback to national development; strains the residents' income and impairs early child development (Gallup & Sachs, 2001). These negative impacts are severe among poor households and households with children below the age of five years (Onwujekwe et al., 2013). In malaria endemic regions where residents are frequently exposed to malaria all year, U5 yet to develop substantial immunity to malaria are among the most vulnerable groups.

Poor health is associated with negative burdens, impairs child education, and reduces economic growth, thereby resulting in increased poverty within and between communities or countries around the world (SDG Compass, 2016). These disparities in poverty are exacerbated by the influence of the rapid urbanisation and the associated health challenges. Urbanisation is changing the landscape of disease patterns in SSA. For example, the prevalent infectious diseases risk such as malaria in the rural areas is now rampant in urban settings (Neiderud, 2015). One of the main reasons is because rapid population growth, if not planned, contributes to the emergence and proliferation of sub-standard shelter, degraded environment, derelict infrastructures, and poor spatial planning which are perfect conditions supporting the transmission of malaria. Furthermore, vulnerability to malaria disease is influenced by the environment due to the nature of disease transmission and propagation of malaria vectors. Environmental factors influence malaria, leading to variability in the under-five burden within and between regions. This also suggests the "spatiality" of malaria disease, which underscores the need to understand the spatial variability of malaria in SSA countries such as Nigeria. This is important most especially in this epoch of rapid urbanisation experienced in Nigeria that is characterised with deficit urban infrastructures, stressed healthcare resources, poor urban governance, and socio-political divide.

Historically, there are evidence-based examples of city planning to control the transmission of disease in the face of rapid urbanisation. During the 19th century industrial revolution in western cities; city planning restrained disease outbreaks through improvements in sanitation, housing and ensuring efficient buffer of residential areas from industrial pollution (Hall, 1996). As city continues to gain importance, due to its capacity to drive development and growth within national outlines, a focus on urban health through spatially planned urbanisation is crucial. Therefore, this study aims to examine the potential of sustainable urban planning as a tool to improve urban health and drive sustainable development in Akure, Nigeria. To enhance understanding on this issue, exploring sustainable urban planning as a means to reduce or eliminate malaria is particularly significant. This will ultimately lead to the promotion of good health; foster sustainable cities and communities; and sustainable development as asserted by Girardet in 1992 as "… a city whose population enjoys a high quality of life, and which takes care not to transfer socioeconomic and environmental health problems and costs to other places or future generations".

I.1.1 Malaria Elimination in Africa: A Mirage or Reality?

Malaria has a long history with humanity and has affected various civilizations throughout time. The writings of Hippocrates, as well as Lay and medical writers provided abundant evidence that malaria was endemic in many parts of the Greek world from 400 BC, by about 450 BC, malaria had arrived in Rome as described in the writings of Cicero, while early documentation of Chinese started description of malaria in 2700 BC with pernicious effect (Bisaccia et al., 2023; Ravenel, 1920). Despite the challenge to assert the earliest existence of malaria, no substantial evidence proves that it did not exist before, or that it was introduced about those times (Ravenel, 1920). Therefore, malaria has long been one of the main global health problems of our time with nearly half of the world's population at risk. Malaria is a major global public health issue with varying epidemiology and prevalence level across countries of the world (Rodríguez et al., 2024). The level of prevalence in place and time determines if the disease is epidemic or endemic. Malaria epidemic refers to acute outbreak upon a community often with little warning thereby resulting to a calamitous situation in which the functioning of a community or society is severely disrupted which can lead to humanitarian emergencies. Epidemic malaria signifies a periodic sharp increase in incidence. Simply put, the number of malaria cases or occurrence is highly in excess of that expected in a given place and time (World Health Organization, 2013). The WHO (2013) describes malaria endemicity as the malaria burden i.e., number of cases in an area. This degree of malaria transmission in an area is measured as the prevalence of peripheral blood stage infections in a population based on malaria testing. Based on the level of malaria burden, WHO has also classified endemicity into four. They are hypoendemic (child parasite rates below 10%), mesoendemic (10 -50%) , hyperendemic (> 50%) , or holoendemic i.e. child parasite rates above 75% (WHO Malaria Terminology, 2021; World Health Organization, 2013). It is also important to note that malaria epidemiology can be determined by the transmission of malaria in place and time. Malaria transmission can be Stable or Unstable. Stable malaria transmission is characterized with minimal fluctuations over the years. While unstable transmission are places in which transmission fluctuates from year to year (WHO Malaria Terminology, 2021; World Health Organization, 2013). Malaria epidemiology determine levels of immunity and risk of severe disease in a community at any given time. For example, people in areas of moderate or high transmission i.e., holoendemic and hyperendemic children below five years are particularly at high risk of severe malaria unlike older children. This is because of the partial immunity which is gradually developed after childhood from repeated exposure to malaria disease i.e., high and stable transmission. In places of unstable malaria transmission where transmission can be seasonal (mesoendemic) or very intermittent (hypoendemic) are places where populations may have low to no immunity. Such places are prone to malaria outbreaks which may affect all age and population groups with high mortality particularly in the hypoendemic regions.

Historical data shows there have been significant reduction in global malaria cases and death. However, from the year 2020, the trend changed due to the global COVID 19 epidemic (Figure I.1.3). Similarly, the global and regional trend correlates with the trend of malaria death in Nigeria but different for malaria cases (Figure I.1.4). In Nigeria, the burden of malaria has been increasing partly due to population growth.

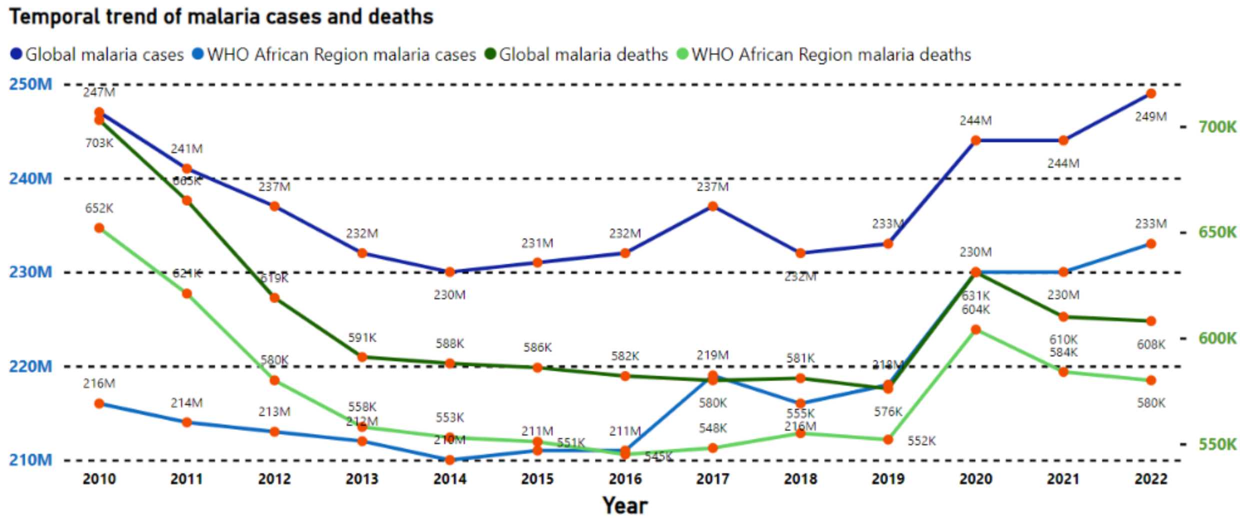

Figure 1.1.3: Global and WHO African Region malaria cases and deaths between 2010 and 2022.

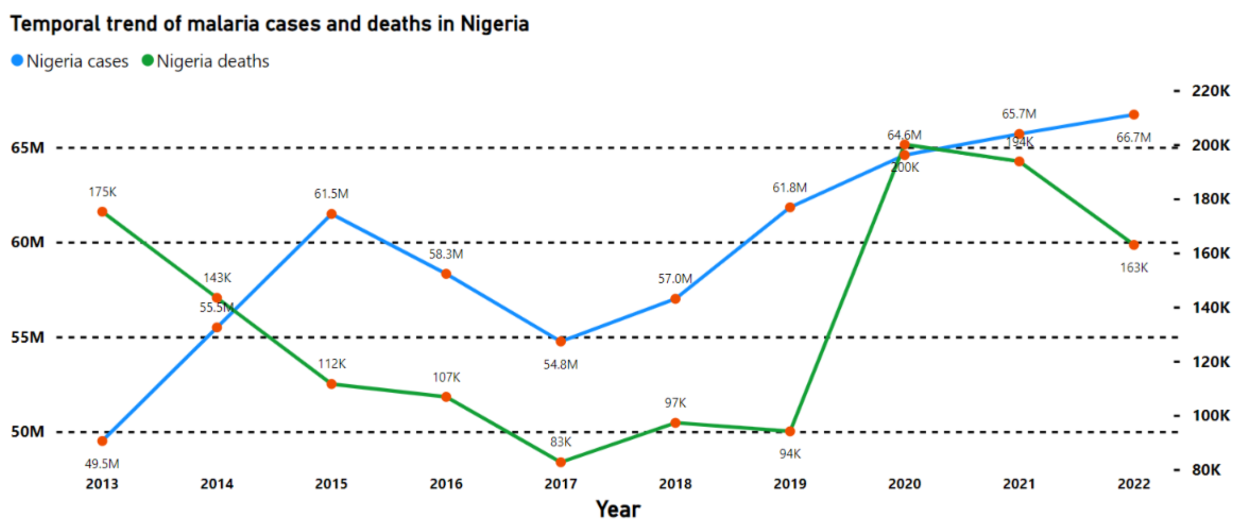

Figure I.1.4: Malaria cases and deaths in Nigeria between 2013 and 2022.

Malaria elimination is the sustainable interruption of local mosquito-borne malaria transmission. It not the same as, and does not require, the elimination of disease vectors or a complete absence of reported malaria cases in the country because imported malaria cases will continue to be detected due to international travel. Such international travel or migration can occasionally lead to the occurrence of introduced cases in which the infection is a first generation of local transmission after an imported case. Elimination of malaria can be envisaged when a successful malaria control programme is succeeding in reducing the burden of mortality and morbidity to a marginal level (World Health Organization, 2017). Areas with confirmed malaria cases during the last three years with evidence of local transmission are regarded as malaria-endemic areas. Conversely, countries that are non-endemic for malaria are paces with no record of local malaria transmission for at least the past three consecutive years. However, this can be hampered by environmental changes and political unrest which can negatively result to the emergence or re-emergence of malaria in areas where it was previously non-existent or well controlled. Environmental change such as climate change may be changing the distribution of malaria vectors, and therefore malaria transmission patterns and malaria burden globally. Warmer winter temperatures and prolonged amplification cycles may allow the establishment of imported mosquito-borne diseases in countries from which they have previously been absent. Increased rains and extreme precipitation events can lead to increased mosquito breeding sites, and therefore increased transmission risk. Political unrest like war disrupts the society and exacerbates health crises. It leads to the spread of malaria disease in overcrowded camps during displacement, limits access to healthcare infrastructures and destruction of infrastructures.

I.1.2 Lifecycle of Malaria

Malaria is an infectious disease caused by parasites of the *Plasmodium* genus through the bite of infected female Anopheles mosquitoes. The five major parasitic protozoa of the *Plasmodium* genus that causes malaria are: *falciparum, vivax, malariae, ovale, knowlesi*. *Plasmodium falciparum,* being the deadliest, poses greatest threat and it is the most prevalence in SSA (Gething et al., 2011). The intrinsic development of malaria parasite and infection is cyclical in nature between humans and the female Anopheles mosquitoes. Broadly, these cycles can be grouped into two with four stages (Figure I.1.5). The first cycle occurs within the human host while the second cycle takes place within the vector host.

First, the process starts with skin infection when malaria-infected female Anopheles mosquito bites a healthy human being, with a general purpose of sucking the human-blood as meal. Second, the inoculation of sporozoites into the human host takes place. This is the human liver stage where the sporozoites infect the liver cells hence infection starts here. Inside the hepatic cells in the liver, the sporozoites mature into schizonts which rupture and releases merozoites (Makanjuola & Taylor-Robinson, 2020). This stage or process is known as the exo-erythrocytic cycle or exo-erythrocytic schizogony.

The schizogony cycle continues where the parasites undergo asexual multiplication in the erythrocytes (erythrocytic schizogony). They are released into the blood vessel and invade the erythrocytes in which they grow and re-invade the fresh red blood cells (RBCs) for the completion of the erythrocytic cycle (Makanjuola & Taylor-Robinson, 2020; Neves Borgheti-Cardoso et al., 2020; Soni et al., 2016). Like the exo-erythrocytic cycle, the erythrocytic cycle involves several developments of the parasite. Third, the merozoites that has infected the red blood cells convert into ring-stage trophozoites which further mature or develops into schizonts. This further matures, rupture and releases merozoites. Afterwards, the released merozoites then invade the new RBCs and continue the cycle. At this stage, some of the merozoites differentiate into sexual erythrocytic stages i.e the male and female gametocytes. This process is called gametocytogenesis (Keleta et al., 2021; Tripathi et al., 2023). Also, the blood stage parasites are responsible for the clinical manifestation of malaria disease as well as an infective stage for mosquito (Keleta et al., 2021).

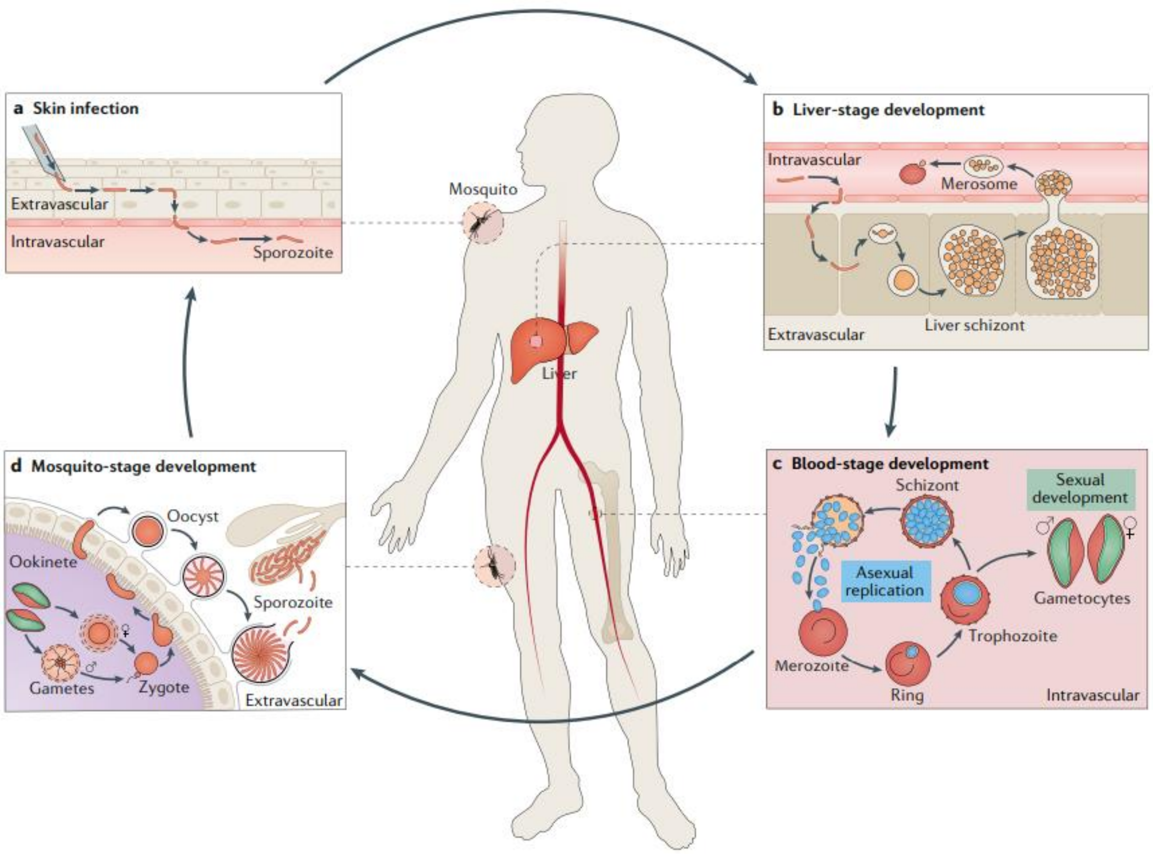

Figure I.1.5: Life cycle of malaria parasite in hosts (intermediate and definitive).
(Source: Venugopal et al., 2020)

The fourth stage (mosquito-stage development) which is also the second cycle is the Sporogony cycle. Here, a non-infected mosquito bites an infected human (i.e., with parasites in the human blood stage), gametocytes (male or female) are ingested by an Anopheles mosquito during the human-blood meal, then the parasite multiplication in the mosquito begins (sporogonic cycle). Inside the mosquito gut/stomach, the microgametocytes (male gamete) fuse with the macrogametocytes (female gamete) thereby generating zygotes (gametogenesis) (Keleta et al., 2021). The zygote becomes motile and elongated i.e. ookinetes. The ookinetes then develop into oocysts; this maturation occurs between the epithelium and basal lamina of the mosquito gut. The oocysts grow and rupture, releasing sporozoites (formed by asexual replication). The sporozoites migrate through the hemocoel to the mosquito's salivary glands which is then injected into new human host during blood meal thereby perpetuating the malaria life cycle (Figure I.1.5). The infected mosquito acts as vectors and carrier of the disease from one human to another. Unlike infected humans, the parasite does no harm to the mosquito.

I.1.3 Urbanisation and Urban Transmission of Malaria

There is no universal definition for rurality (rural area) because different institutions, organizations and nation adopts varying approaches to the definition. In Nigeria, single criterion i.e. population threshold of < 20,000 is defined as rural while places with population of more than 20,000 is urban (Madu, 2010; Okali et al., 2021). Predominantly, malaria risk in higher in the rural areas compared to peri-urban and urban areas. The later are considered to be at lower risk of malaria because of improved housing condition, better socioeconomic status and limited number of breeding sites (Mathanga et al., 2016). However, the tide turned when urban malaria cases accounted for about 6 - 28% of estimated global incidence of malaria disease (Hassen & Dinka, 2022; Wilson et al., 2015). This is further complicated by the impact of urban agricultural practices as significant drivers of malaria illness and vector breeding sites according to the reports of Awosolu et al. (2021) and De Silva & Marshall (2012). Additionally, it has now been noted that malaria vectors have adapted and propagates in polluted water. For example, (Killeen et al., 2019) and (Pulford et al., 2011) reported that most effective malaria vectors Anopheles gambiae, Anopheles coluzzii, and Anopheles arabiensis, notably for their strong preference in unpolluted water, now show a great adaptation pattern to polluted waters in urban cities, and breed in a variety of human-made habitats such as containers filled with water, swimming pools and tire tracks. Given the dynamics of malaria vectors, urban malaria therefore remains a concern in the context of elimination efforts.

Urbanisation, which is movement of population from rural to urban places (Kuddus et al., 2020) or process through which cities grow and become urban (Bayode & Siegmund, 2024), is another complex and critical factor that impacts malaria transmission. Rapid urbanisation increases the demand for health and housing infrastructures which can result to unequal distribution of healthcare resources and emergence of substandard housing and increases vulnerability to malaria transmission. Earlier, (Pindolia et al., 2012) had found uncontrolled urbanisation as a plausible risk factor for the spread of malaria and arboviral infections in urban areas. Recently, (Mathanga et al., 2016) described the possible explanation to more intensive malaria transmission in cities and peri-urban areas. In their opinion, the pace of public health interventions could not match the rate or urbanisation thereby creating favourable condition to the reproduction of Anopheles mosquitoes especially in the outskirts of the cities in SSA. This supports the notion that rapid urbanisation in SSA will lead to increased incidence and prevalence of malaria, with its attendant negative impacts. Therefore, factors that contribute to urban malaria will become more important as SSA gets more urbanised. Hence, this study seeks to explore the complex dynamics of rapid urbanisation and its impact on health burden in a medium-sized city in Nigeria. This is important as there are limited studies in SSA that has explored this complexity and previous studies on spatiality of malaria are done on coarse scale leading to masking of important local hotspot of malaria.

I.1.4 Malaria Vaccine

Malaria represents a critical public health problem with enormous complexity to eradicate. There are multi-plethora challenges to the eradication of malaria which are: insecticide and drug resistance, socio-cultural hindrances, malaria importation and climate change (Dhiman, 2019). However, malaria vaccine seems to be very viable. For decades, there have been numerous efforts to develop an effective malaria vaccine. Malaria vaccine efforts can be traced to early 1960s where the history of modern malaria vaccine began particularly to the works of immunologist - Dr. Ruth Nussenzweig in 1965 with experimental studies on primates, rodents and humans to test irradiated sporozoites as potential vaccine approach (El-Moamly & El-Sweify, 2023; Nussenzweig et al., 1967). However, promising results emerged in the 1970s when Clyde et al.m(1973) discovered high protective efficacy from radiation-attenuated sporozoites in individuals exposed to a significant number of infectious mosquito bites.

The quest or pursuit for malaria vaccine has been a long and challenging journey for medical scientists. The development of malaria vaccine faced numerous hurdles due to the complex biology, life cycle, pathophysiologic complexity, genetic diversity, and genome of the malaria parasite. (Lorenz & Karanis, 2011; Rénia & Goh, 2016). The diverse immune escape mechanisms from the parasites ability to evade the human immune system, antigenic variations and the absence of sterile immunity are problematic and complicated for the development of malaria vaccine (Rénia & Goh, 2016).

Malaria vaccines are categorized based on the targeted developmental stage of the parasite. The vaccines can broadly be grouped into pre-erythrocytic vaccines (anti-infection), erythrocytic vaccines, and transmission-blocking vaccines. While most malaria vaccines are developed to target one of these three parasite stages, it invariably means that *Plasmodium* genus such as *vivax* and *ovale* which have the ability to produce dormant hypnozoite stages in the liver cannot be combated with blood-stage vaccine candidates (Lorenz & Karanis, 2011). However, some malaria vaccine target two or the three development stages of the malaria parasite life cycle (Hill, 2011; Matuschewski, 2017).

Despite these challenges, 6th October 2021 was landmark day when the World Health Organization (WHO) approved the RTS,S malaria vaccine - specifically RTS,S/AS01 also known as Mosquirix™ - with strong safety, high impact for widespread use (Björkman et al., 2023). RTS,S was developed by GlaxoSmithKline (GSK). It is a recombinant protein malaria vaccine that targets the circumsporozoite protein of *Plasmodium falciparum* parasite at the pre-erythrocytic stage (‘Efficacy and Safety of RTS,S/AS01 Malaria Vaccine with or without a Booster Dose in Infants and Children in Africa’, 2015). RTS,S/AS01 is administered in a schedule of four doses from 5 months of age for the reduction of malaria disease and burden in sub-Saharan Africa and other regions with moderate to high *Plasmodium falciparum* malaria transmission (World Health Organization, 2021). The vaccine significantly reduces total malaria cases, and the deadly form of the disease among young children, and evidence base included phase 3 trials among African children and an ongoing malaria vaccine implementation programme (MVIP) in Ghana, Kenya and Malawi (Björkman et al., 2023). The R21 with adjuvant Matrix-M (R21/Matrix-M) vaccine is described as the “next generation RTS,S like vaccine”. It represents an advancement over the RTS,S vaccine developed by the Jenner Institute in Oxford, UK. The four-dose cheaper new vaccine offers 75% efficacy, higher protection rate compared to its predecessor (El-Moamly & El-Sweify, 2023; World Health Organization, 2021). Malaria vaccine is not a replacement of other malaria interventions but rather an added tool in malaria combating arsenal.

I.1.5 Malaria Interventions in Endemic Regions

Malaria is an old disease that has negatively impacted nations. There are various public health interventions to prevent and manage malaria disease. Broadly, public health interventions for malaria can be grouped into three which are prevention, treatment, and control strategies. An example of prevention intervention is the development of malaria vaccine. The development of safe, effective, and affordable vaccine is critical for the fight against malaria. Malaria vaccine has been discussed extensively in the previous section. The common malaria treatment intervention is the development of antimalarial drug which plays a key role in the fight against malaria. Though in the last decade, there have been spread of drug-resistant parasites which has impact the progress on malaria control efforts. Malaria control strategies are malaria diagnosing and vector management approaches. Malaria diagnosing can be case management of malaria in health facilities or community based. Health facility case management of malaria is important. Case management focuses on the diagnosis and prompt treatment of malaria with effective anti-malarial medicines according to WHO guidelines (WHO, 2010). This approach highlights the WHO 3Ts Campaign – Test, Treat and Track – as a cornerstone for guiding health workers to treat only confirmed malaria cases rather than presumptively (Ruizendaal et al., 2014; WHO, 2010). Artemisinin-Combination Therapy (ACTs) are recommended for malaria treatment alongside the use of Rapid Diagnostic Tests (RDTs) kits in most countries in Sub-Saharan Africa. Some of such combinations include artemether plus lumefantrine, artesunate plus amodiaquine, artesunate plus mefloquine, and artesunate plus sulfadoxine-pyrimethamine. Case management treatment is influenced by the nature or severity of the malaria disease.

Community case management plays critical and vital role in SSA where majority of children with malaria disease are treated at home. Therefore, reaching the homes and communities with anti-malarial treatment thus have impact on malaria control and reduction of malaria morbidity and mortality (Patouillard et al., 2017; Ruizendaal et al., 2014). The WHO proposed community case management of malaria in areas lacking medical facilities or communities where medical facilities are inaccessible (WHO, 2021). In this approach, community-based trained volunteers offer prompt access to effective anti-malarial drugs (Patouillard et al., 2017; Tizifa et al., 2018).

Vector and biological control are directed towards the mosquitoes i.e. carrier of the malaria parasite. Long-Lasting Insectidal-Treated Nets (LLIN) and Indoor Residual Spraying (IRS) are the two most common biological and vector control methods used in SSA. Despite the insecticide resistance in mosquitoes, vector control remains the one of the most effective measures to prevent malaria transmission (Orok et al., 2021). Good and adequate shelter are some of the basic requirements that sustains vector control strategy because the human shelter that have walls need to be sprayed including interior walls of the houses. Consequently, culture, tradition and religion could serve as an impediment. For example, in Nigeria particularly in the North, there are inscriptions boldly written on door post such as “ba shiga” meaning “visitors are not allowed”. Such act can prevent vector control officers from carrying out the required vector control intervention (Badolo et al., 2012). Larval control with the use of larval control agents such as larvivorous fishes, and the bacterial pathogens (*Bacillus thuringiensis israelensis* and *Bacillus sphaericus*) is also another type of vector control, but this can be categorised as secondary control measure (Maheu-Giroux & Castro, 2013). The Nigerian government is committed to the elimination of malaria. The fifth National Malaria Strategic Plan 2021–2025, gives a roadmap on how the Nigerian government aims to eliminate malaria in Nigeria. The document illustrates intervention strategies to combat malaria which include improving everyone’s access to vector control interventions such as LLINs, IRS, Larval Source Management. Among the strategies is to ensure that at least 80% of the target population at malaria risk is provided with intermittent preventive treatment for all pregnant women (IPTp), vector surveillance and monitoring of resistance (National Malaria Elimination Programme, 2020).

I.1.6 Historical development of spatial modelling of infectious disease

The history and applications of spatial analytical techniques to disease monitoring can be traced to the works of John Snow in Victorian London, especially the cholera disease map (Figure I.1.6). The rapid urbanisation experienced in the 19th century in London resulted into overcrowding, large inadequacy of city’s facilities amenities and increasing amounts of sewage flowed into cesspits. In 1831 cholera arrived due to the contaminated water source (well) from sewage. It was an appalling situation where tens of thousands of Londoners lost their lives to the four major cholera outbreaks between 1831 and 1866 (Davenport et al., 2019). Following the third outbreak in 1854, the pioneering investigation by John Snow on the cholera epidemics in the Soho district of London led to his conclusion that contaminated water from the Broad Street pump was the source of the cholera outbreak which killed about 500 residents within 10 days (Barnett, 2013; Tulchinsky, 2018). Based on the evidence-based result of John Snow's investigation, John Snow recommended and convinced the local authority to disable the pump by removing its handle which led to the containment of the disease (Barnett, 2013). During his investigation, he created a dot map depicting the proliferation of cholera cases and found them to be clustered around a one water pump on Broad Street (Mitali, 2009). The cholera map is a landmark in epidemiology, and his approach marked a transformative moment in the study of how disease spread across space and time.

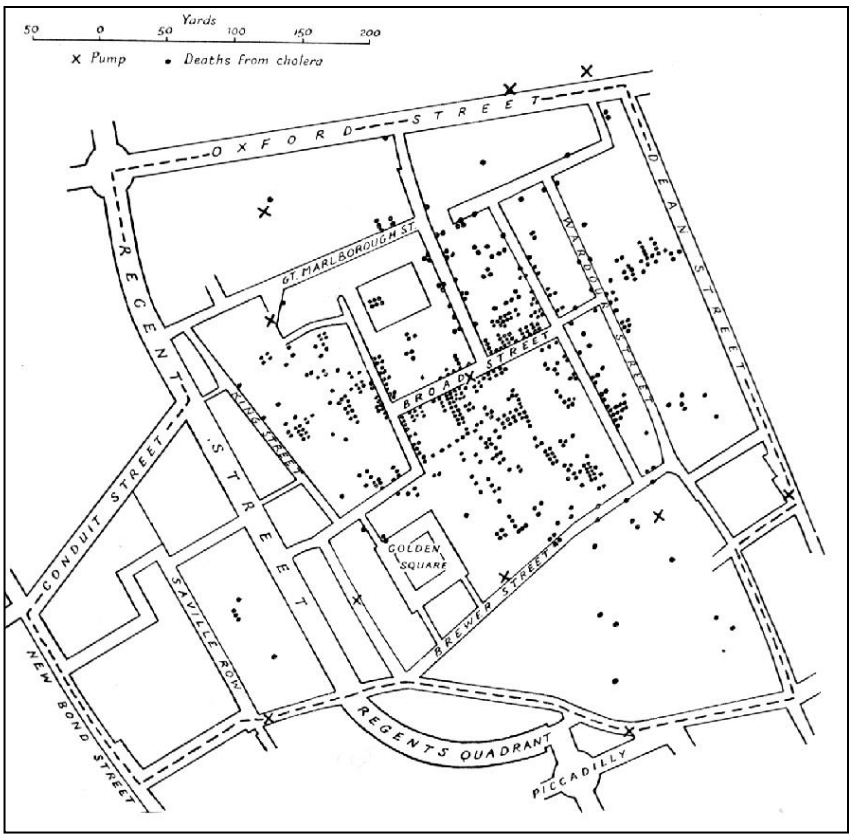

Figure I.1.6: Map of contaminated water pump in Broad Street.
(Source: Stamp, L. D. 1964)

Spatial epidemiologists perceive the severity and propagation of infectious diseases as a product of the spatial and temporal interaction between human and the physical environment upon which scholars have been able to develop complex spatial models to understand these dynamic interactions. In the last three decades, there have been rapid increase in the data-driven spatial modelling techniques part due to the improvements in data availability and computational capacity (Chowell & Rothenberg, 2018). Spatial modelling for infectious disease is quantitatively driven involving spatiotemporal data which can be classified into two research methods. They are statistical modelling method (Anselin et al., 2006; Kulldorff & Nagarwalla, 1995), and spatial transmission dynamic modelling approaches (Eubank et al., 2004; Heesterbeek et al., 2015; Riley, 2007). The former are often used to explore the relationships between spatiotemporal infectious disease patterns, host or environmental characteristics through the generation of maps to determine and visualize the distribution of disease morbidity or mortality and identification of infectious disease hotspots or clusters (Lawson, 2018; Zulu et al., 2014), while the latter is useful in generation of scenario analyses of the potential course and severity of infectious disease epidemics (Balcan et al., 2009; Chowell et al., 2017; Ferguson et al., 2005; Riley, 2007), characterising and forecasting the spatiotemporal transmission patterns of epidemic outbreaks, or assessing the effectiveness of interventions and the feasibility of achieving elimination target (Chowell & Rothenberg, 2018).

I.1.7 State of the Art on Malaria Studies

The malaria parasite was discovered by Charles Louis Alphonse Laveran in 1880 and documentations on mosquitoes as malaria transmission vectors was by Ronald Ross in 1897 (Cox, 2010). Since the discovery of malaria, novel attempts to stop its transmission have been the focus of humanity from different fields of study, including geography.

The ecology of malaria is a complex relationship between the host, vectors and the environment thereby attracting diverse specialties in malaria studies such as vector control. A notable example is the extensive research conducted by Dambach et al., (2012, 2014). Another aspect is geographic correlation studies which explain the spatial-temporal variability of malaria transmission and ecological interactions acting at different scales (Grillet et al., 2010). In the last decade, datasets have been produced on sub-Saharan Africa to explain the spatial distribution and prediction of malaria occurrence. The geographical outline of the analysis determines the nature of the model and calibrated variables, such as the studies of (Kleinschmidt et al., (2000, 2001); Omumbo et al., (2005); Garske et al., (2013) and Colón-González et al., (2021). These studies were conducted on national and intercontinental outlines mainly driven by climatic or environmental variables. The shortcomings of these regional or broad-scale studies include but are not limited to the masking of local or fine-scale heterogeneity of malaria transmission.

Therefore, the roles of local contextual factors such as household characteristics, local mobility patterns, land use and health-seeking behaviour are not rigorously investigated (Bannister-Tyrrell et al., 2019). Some scholars characterized malaria risk based on empirical evidence using a malaria-specific indicator such as socio-economic variables, assessed its relationship with environmental risk factors to understand the complexity of malaria transmission as well as prevention strategies of malaria within a local spatial limit (Kazembe & Mathanga, 2016; Ngom & Siegmund, 2010, 2015). However, these studies did not explore the impact of urban growth dynamics on malaria or examined spatial planning as determinants of health outcomes.

In the last decade and as malaria-endemic countries transitioned to lower levels of malaria transmission, the occurrence of malaria has exhibited a patchy distribution, which cannot be effectively identified using coarse datasets. The scientific exploration of intra-urban malaria transmission to provide direction on how to maximise the scarce available resources is therefore important.

In the 21st century, cities of lower- and middle-income countries (LMICs) or global south are confronted by significant global health challenges because of rapid urbanisation. This has prompted the need to rethink approaches to disease prevention (Giles-Corti et al., 2016). A viable approach is sustainable city planning because it is a veritable tool to manage development and liveability in cities and rural counterparts (Badland et al., 2014). There are several documentations of studies on the impact of city planning on urban health, especially in the global north with focus on chronic diseases. For example, design of the urban environment and urban planning has been linked to physical inactivity, obesity, and cardiovascular diseases, among others as prevalent health problem in global north (Ewing, 2005; Northridge & Freeman, 2011; Osayomi & Orhiere, 2017). In contrast, LMICs are threatened with a double burden of diseases owing to its highly heterogeneous social population. Nigeria like other African countries, seldom integrate city planners to help solve specific health problems such as malaria in an era of the willingness and awareness of city planners to address health problems in cities (Lowe et al., 2022). Some studies in Africa, such as (Gonçalves et al., 2015), identified urban planning and health inequities of some selected non-communicable diseases on a small-scale city in Cape Verde. However, their study did not systematically infer the types of spatial units (structure) and engagement of spatial statistical methods. Specifically, Kabaria et al., (2016), engaged the spatial statistical methods to map the intra-urban malaria risk in Dar es Salaam between 2006 and 2014.

However, the built-up places were not classified according to their level of sustainable spatial planning developments.

This study is the first spatial micro-epidemiology of malaria to be conducted in Nigeria engaging the use of advanced spatial methods; and the first of its kind that will systematically integrate the structure of urban environment influence into the spatial profile of childhood malaria epidemiology. To further reduce malaria within cities in Nigeria, there is need to integrate sustainable city planning into geospatial studies of malaria; especially, among U5 because their susceptibility to malaria is critical in places of stable malaria transmission. This study is set to fill the identified gap within a local context of medium-sized city such as Akure being a rapidly urbanizing city in Nigeria.

The next section of this thesis discusses the research goal and objective. Each of the research objectives were achieved according to the formulated research questions. Furthermore, the section also discusses how the study have been designed to achieve the set goals and objectives.

2

"I think you can have a ridiculously enormous and complex data set, but if you have the right tools and methodology then it's not a problem."

Aaron Koblin.

I.2. Research Objectives, Data and Methodology.

This is a pioneer study in rapidly growing medium-sized city in Nigeria to unveil the masked local pockets of disease burden like U5 malaria. This research aims enhance our understanding on how childhood malaria burden differs within the spatial outline of Akure, Nigeria. Particularly, what are the driving factors for U5 malaria transmission and how can sustainable urban planning be an enabler to improved health outcomes in Akure, Nigeria.

I.2.1 Specific objectives and research questions:

1. The first objective of this thesis is to explore the complex relationship between urban planning and health as a critical driver for sustainable development in Akure, Nigeria. The results of the study to achieve this first objective are contained in a published peer-reviewed paper summarised in Section three. The first objective answers the following research questions (RQs):
   - RQ1. What are the urban and spatial growth characteristics of Akure?
   - RQ2. What is the spatial growth trend and its relationship with other land use or land cover types in Akure?
   - RQ3. How can the observed spatial growth characteristics and trend impact the health of the inhabitants? In addition, are there working relationship between the health experts across various institutions in combating the health treats of rapid urbanisation in Akure?
2. The second objective pursued within this thesis is to determine the risk factors for childhood malaria in Akure within the framework of social determinants of health (SDH). The results are presented in another published peer-reviewed paper summarised in Section three of this thesis. The objective answered the following questions:
   - RQ4. What are the social determinants of childhood malaria (SDCM)?
   - RQ5: What are the risk factors of childhood malaria in Akure, Nigeria based on the itemised SDCM?

3. The third objective of this thesis is to determine the spatial hotspots of childhood malaria in Akure. To investigate this objective, two questions were proposed, which were answered, and their results were presented in a published peer-reviewed article. The summary of this published article is in Section three and answers the following questions:
   - RQ6. Where are the hotspots of U5 malaria in Akure?
   - RQ7. How can practical and viable public health policy be formulated based on U5 malaria prevalence predictive tool?
4. The fourth objective of this thesis explores the effect (indirect) of urban structure on malaria prevalence in Akure. The fourth objective answered two questions in peer-reviewed article summarised in Section three. The research questions are:
   - RQ8. What are the different types of urban structures in Akure?
   - RQ9. Is there a statistical difference in U5 malaria prevalence based on the identified urban structures?

I.2.2 Thesis Contribution

This thesis contributes to improving the frontiers of spatial health research from a multidisciplinary lens by drawing strength from three broad subject domains which are geography, urban planning, and public health. Particularly, this thesis explores the risk exposure of childhood malaria based on location, social and built-environmental/contextual characteristics of the study population that are essential for effective design of policy recommendations.

From the standpoint of the ongoing urbanisation trend in cities of LMICs like Akure, Nigeria, the control of communicable diseases such as malaria deserves special attention because its increasing high population density could cluster vulnerable populations around malaria risk. These clusters or local pockets of malaria risk can be investigated with the capabilities of spatial modelling techniques such as model-based geo-statistics (MBG) without undermining the ability to explore and determine the impact of social risk factors on U5 malaria in Akure. Furthermore, the study objectives were explored based on the tenets of urban planning which include making cities liveable, healthy, and sustainable. Urban planning can foster high quality of life through the exploration of the complex dynamic relationship of city's spatial growth and the impact on health. This study contributes to literature by exploring such complex relationships and the roles of urban planning in ameliorating these health impacts which is yet to gain appropriate interest among cities in LMICs like Nigeria.

Succinctly, this thesis enables deeper understanding of the significant causal factors of childhood malaria; improves capabilities for malaria prediction among vulnerable U5 population and effective place-based policy formulation for malaria elimination while drawing the attention of urban planners as health practitioners in LMICs.

I.2.3 Study Area, Population and Sampling Technique

Since 1976, Akure comprises two local governments, North and South, collectively as the capital of Ondo State. Ondo State is a south-western part of Nigeria and one of the 36 states in Nigeria (Figure I.2.1). Akure lies between 5°06‟E to 5°38‟E longitude and 7°07‟N to 7°37‟N latitude in Nigeria. Despite Akure being a medium-sized city, the city is strategically located within a 48-kilometer radius of major towns – Owo to the East and Iju/Ita Ogbolu to the North (Usman et al., 2018). Furthermore, Akure is located approximately 350 and 700 Kilometers to Lagos state (former Nigerian capital and the largest city in West Africa) and Southwest of Abuja (the Federal Capital of Nigeria) respectively (Emmanuel & Fasakin, 2017) The dual political role of Akure as the provincial headquarters of old Ondo province in 1939 and capital of Ondo State in addition to its proximity to major towns and cities has resulted in the influx of people to the city (Olamiju & Olujimi, 2011).

Akure is relatively a flat land. The city is about 250 meters above sea level and the land towards the North is hilly, studded with large granite formations of volcanic origin (Bayode, 2014). Like most tropical places, Akure has two distinct seasons which are: (1) dry season from November to March with the average minimum and maximum daily temperature of 32^{o}C and 34^{o}C. (2) rainy or wet season from April to October with the average minimum and maximum daily temperature of 27^{o}C and 31^{o}C. The average annual rainfall is within the range of 140.5 mm and 240 mm (Daniel, 2015; Makinde et al., 2021). The climatic characteristics of Akure is perfect and sustainable for the propagation of malaria parasites and mosquito vectors.

The population of the city grew from 38,852 in 1952 to 71,106 in 1963 while in 1980, the population was estimated to be 112, 850 (Emmanuel & Fasakin, 2017) . The establishment of a federal tertiary institution like the Federal University of Akure (FUTA) in 1981 made Akure more attractive and ever since the rate of population growth has been more rapid. For example, the population of Akure almost tripled from 157,947 to 500,000 between 1990 and 2006 (Balogun et al., 2011). Population census in Nigeria sometimes comes with uncertainty therefore contributing to the difficulty in obtaining reliable estimates of population data in Nigeria

(Tofowomo, 2008). For this study, the population data from Geographic, Population and Demographic Data (GEOPODE, a kick polio project sponsored by the Bill & Melinda Gates Foundation) which estimated the population of Akure in 2022 to be over one million inhabitants (1,283,541) was adopted. Among this estimated population, U5 accounted for 12.7% of the total population i.e 162,975 thousand. For this study, approximately 0.6% of the U5 population was sampled i.e 1000 children. The sampling technique for the study followed the path of spatial-reference stratified sampling by Ngom & Siegmund (2010).

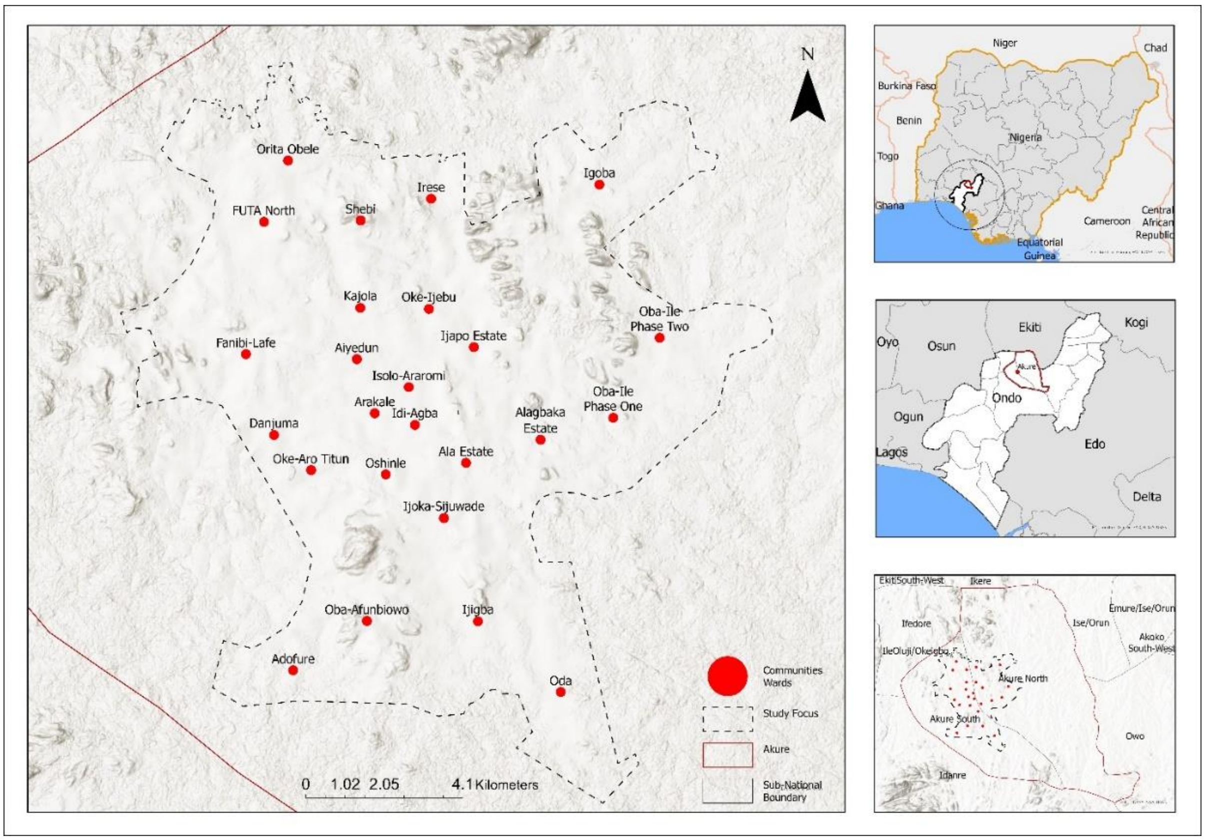

Figure I.2.1: Study focus in sub-national and national context.

I.2.4 Spatial Method Framework and Spatial Data Analysis.

The methodology and conceptual flow for this study are divided into three stages or parts which are data acquisition, statistical (spatial and non-spatial) modelling and visualisation (Figure I.2.2). Each stage of part involves various overlapping steps associated with the collection, cleaning, analysis, interpretation, and visualisation of the study data.

Data acquisition. For this study, three groups of data from different sources were used for the study analyses. They are:

- Satellite imageries - Landsat & WorldView2,
- Field survey (Malaria indicator questionnaire, Key Informant Interview),
- Administrative data

The Landsat Imagery is multi-spectral, open-source satellite data with a 30m spatial resolution, sourced from the United States Geological Survey (USGS) Earth Explorer data portal. The Landsat Imagery was used to explore the temporal spatial growth and land use land cover (LULC) characteristics in Akure. The acquired WorldView2 which is a high spatial resolution – 0.46m imagery with three bands (RGB), was used to develop the spatial structure for Akure. Furthermore, this study leveraged Artificial Intelligence methods from the Picterra platform (https://picterra.ch/geospatial-imagery-analysis) to extract the building footprints from the WorldView2. These building footprints were used as surrogate for U5 children during the field survey. This is because of the lack of prior knowledge of household with U5 children. The geocoded sampled houses were visited to obtained malaria epidemiologic data using Malaria Indicator Questionnaire (MIQ). In addition to the MIQ, Key Informant Interviews (KIIs) were carried out to obtain information within the purview of urban planning and public health in Akure. The participant of the KIIs were officials/employees of the Ministry of Physical Planning and Urban Development (MPPUD) via snowball sampling. The MIQ for this study is not limited to malaria epidemiology; rather it also contains factors relating to social determinants of health such as individual characteristics, social and economic characteristics, and housing characteristics. After the development of the questionnaire, it was pretested and vetted by the researchers in Research Group for Earth Observation and Institutional Review Board at Heidelberg University, Germany for final approval before the commencement of field survey. Selected participants or respondents for the study were randomly selected from households within each stratum according to the spatial structure of the study area. The household heads were interviewed retrospectively along with the geo-coded MIQ. The field survey is necessary because accurate health statistics are almost non-existent in informal settlements and the lack of data has masked health disparities within cities (Kjellstrom & Mercado, 2008; WHO, 2008; Unger & Riley, 2015). Furthermore, there is low reporting of disease burden such as malaria in Akure because the people largely engage in self-medication (informality). The acquired administrative data contains the absolute locations of available health facilities and administrative boundary of the study area. The health facilities are additional data to assess the level of infrastructure in study area.

Prior to the next stage, basic social statistics, and data cleaning were be carried out. They include the data distribution of the social variables, checking for outliers and missing values. In respect to the satellite image and administrative data, geodata preprocessing such as area of interest (AOI), was determined. Other preprocessing includes clipping of the AOI with the available health facilities.

Spatial and non-spatial data modelling. The second stage is dedicated for spatial and non-spatial data modelling. The activities here include utilisation of spatial and aspatial statistical concepts. The LULC modelling was done using various remote sensing (RS) and geographic information systems (GIS) techniques. The appropriate bands were selected and classified using the Support Vector Machine (SVM) classifier in Aeronautical Reconnaissance Coverage Geographic Information System Professional (ArcGIS Pro). Other steps include model validation with accuracy assessment and Pearson's correlation. For the urban structure modelling, the variables considered are texture, geometry, neighbourhood density and vegetation indices computed from the available bands. Expert system object-oriented classification algorithm in eCognition software and Momepy tool in python was adopted for this study to classify Akure into different strata as a reflection of its level of city planning. This was achieved through rule-set development in line with the works of Kohli et al., 2012. Other spatial statistical concepts include cluster and spatial regression statistics (model-based geostatistics). Furthermore, the spatial statistical model was calibrated with the relevant associated variables while observing for necessary diagnostic checks with the residuals using the empirical variogram.

The non-spatial statistical techniques include Chi-Square and Multivariable logistics regression, and analysis of variance (ANOVA). With the Chi-Square, associated variables or factors driving the burden of malaria were determined. Furthermore, the multivariable logistics regression was used to determine the impact of the associated causal factors of U5 malaria. Lastly, the ANOVA statistical tool was used to explore difference in mean of malaria burden among identified spatial structures in Akure.

Data visualisation. The third stage is for data visualisation and result interpretation which could serve as a tool to guide policy formulation and direct engagement of scarce resources for malaria elimination. The derived results serve to inform and improve urban planning practices that can contribute to equitable and healthy living in cities. As such, this will improve city sustainability and foster community health in Akure.

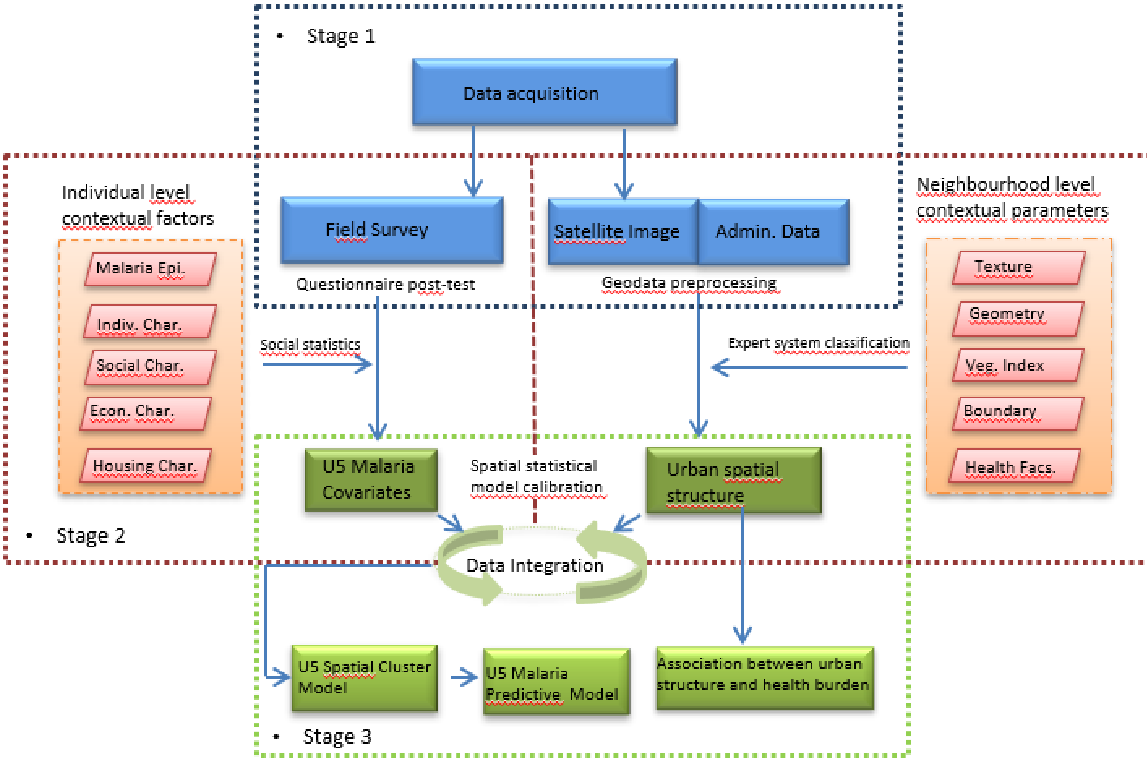

Figure I.2.2: Schematic overview of the spatial method framework and data analysis of childhood malaria based on spatial structures in Akure, Nigeria.

3

"One can measure the importance of a scientific work by the number of earlier publications rendered superfluous by it?"
~ David Hilbert

I.3. Publication Summaries

This section provides summaries of the four peer-reviewed articles that address all the research questions for this study. Each manuscript has been summarised separately, in the order in which it answers the study's research questions.

Tripartite Relationship of Urban Planning, City Growth and Health for Sustainable Development in Akure, Nigeria.

Rationale for the study. This manuscript is concerned with the intricate relationships between urban planning, city growth, and health as critical components and drivers of sustainable development in a rapidly growing city like Akure, Nigeria. These relationships have been conceptualized in Figure I.3.1. The city of Akure is becoming more urban because of the multitude of push and pull factors from nearby settlements. The rapid urbanisation phenomenon in Akure has the potential to generate urban health crises among the city dwellers with more consequences on vulnerable populations like children, senior citizens/older persons, pregnant women and poor residents (Aliyu & Amadu, 2017).

Cities play a critical role as engines of economic growth. World Bank figures show that 80% of global gross domestic product (GDP) is generated in cities (Kilroy et al., 2015). However, the associated prosperity with cities can also be a blessing in disguise. In 2016, the United Nations Human Settlements Programme (UN-Habitat) unequivocally reported that the current urbanisation trend is unsustainable in many respects, puts many people at risk, creates unnecessary costs, negatively affects the environment, and is intrinsically unfair (UN-Habitat, 2016). In Nigeria, for example, one of the most notable environmental changes is the phenomenal growth of urban centres posing a threat to the ecosystem (Alabi, 2022; Ikhuoria, 1987). Others include the precarious living conditions in city centres like Akure (Akinbamijo & Fasakin, 2006), and unequal or unfair distribution of healthcare resources and infrastructures (Aliyu & Amadu, 2017). Given these fallouts, the impact of urban planning on sustainable growth of cities and improved health outcomes is more critical than ever before. The importance of urban development that supports the health and well-being of city dwellers is paramount. Akure, a rapidly growing medium-sized city, provides a case study for understanding these dynamics.

Figure I.3.1: Conceptual model of the threefold relationship between urban planning, city growth and health for sustainable development.

Data and Methods. The paper builds on a multimethodology approach which involves the use of more than one method for data collection and analysis. This approach is pivotal to the utilisation of the potential strengths of both qualitative and quantitative methods of data collection and analysis (Greene et al., 1989). For this study, it is crucial to explore diverse thematic themes which are urban planning, health, growth, and sustainability. Therefore, this approach provided the opportunity to explore diverse perspectives, uncover relationships and insights that exist between the intricate layers of our multifaceted research questions (Shorten & Smith, 2017).

The quantitative data i.e satellite data were critical to the study. Landsat satellite images from 1984 to 2023 were obtained from the United States Geological Survey (USGS) Earth Explorer data portal. These images, covering various Landsat missions, provided a detailed spatio-temporal view of land use and land cover (LULC) changes in Akure. This was achieved based on image classification using the support vector machine classifier. The images were classified into five LULC which are water body, developed, rock outcrop/barren, dense forest and disturbed vegetation/cultivated. The model was validated to determine the accuracy of the LULC classification. The classified image validation result was quantified based on Kappa coefficient while Pearson's correlation was used to quantify relationship among various LULC classes. The data analysis involved GIS and RS technologies. Spatial analysis was performed using ArcGIS Pro, and gap filling for Landsat 7 images was done using Quantum GIS.

The qualitative data was obtained through Key informant interviews conducted with officials from the Ministry of Physical Planning and Urban Development in Akure, employing snowball sampling to gather insights on health within urban planning. The collected KII responses were transcribed and reported accordingly.

Findings and Discussion. Findings on the spatial growth pattern of Akure which involves the spatio-temporal analysis of the LULC classes show that over the past four decades (1984 – 2023), the city of Akure has urbanized rapidly at the expense of the forest or natural land covers. Forest land decreased by 46.16%. Conversely, developed land increased by 18.6% hectares in the same period. Cultivated land also saw a substantial increase of 27,853.65 hectares. Furthermore, the study reveals strong positive relationship between the years and developed LULC ($r = 0.93$, $p = .00224$). This phenomenon is different with the forest LULC. According to the result in Figure I.3.2, forest land is negatively correlated with the year and developed land respectively ($r = -0.97$, $r = -0.94$; $p = 0.000277$, $p = 0.00193$). This highlights the temporal rapid urban expansion phenomenon in Akure which is likely to continue. Conversely, the green space is more likely to continue to be depleted based on the study result. This can impact the health of the city and ecosystem negatively. Given the impact of the city growth on health and sustainable development in Akure, the integration of urban planning and public health was explored. Interviews with urban planning officials reveals lack of synergy between urban planners and public health practitioners in Akure. This disconnect limits the effectiveness of urban planning in addressing health impacts associated with rapid urban growth. This is further supported by the obsolete usage of a master plan to guide development of the city. The current master plan was developed in the 1980's. The continuous and unregulated expansion of Akure requires attention of the urban planners in the city while noting that to ensure high quality of life and sustainable city, positive residents' health outcomes is germane. Importantly, combating health issues should not be left only to the public health practitioners but a collaborative effort across other institutions like urban planning should be encouraged.

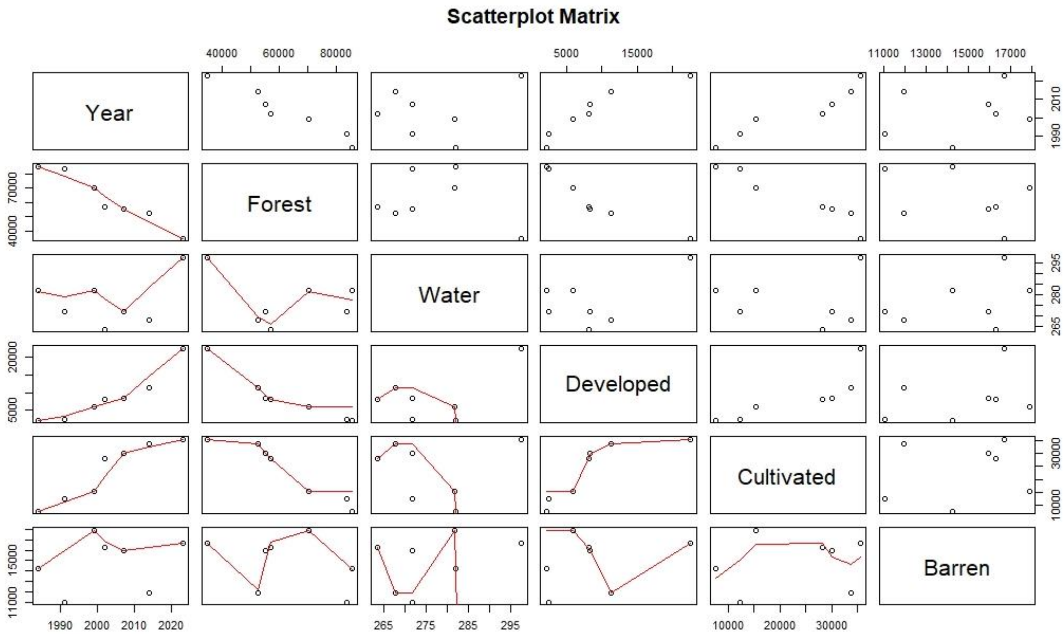

Figure I.3.2: Nexus among LULC and years

Conclusion and Recommendations. The study underscores the necessity of integrating urban planning with public health to manage the rapid urban growth in cities and foster sustainable development in Akure. This is important given the health of city residents, city-health and healthy ecosystems are interlinked and intricate to sustainable development. By utilising both qualitative and quantitative data, this manuscript provides a comprehensive view of how urban expansion impacts land use and public health, advocating for more collaborative planning efforts to achieve sustainable development goals. In Akure, the focus of the Ministry of Physical Development and Urban Development is physical urban development thereby undermining the health-focused role of urban planners. Furthermore, the physical development in Akure is unprecedented and lacks robust control due to lack of poor monitoring due to lack of robust data, finance, human resources, poor capacity building, tools, and technologies. The unprecedented pattern of urbanisation experienced in Akure needs to be taken with utmost importance. This is essential in order to better respond to the challenges and address issues such as inequality, climate change, informality, insecurity, and the unsustainable forms of urban expansion (UN-Habitat, 2016). The study acknowledges some limitations due to the medium quality of freely available Landsat images and the seasonal timing of image acquisition, which could affect the accuracy.

Social Determinants of Malaria Prevalence Among Children Under Five Years: A Cross-Sectional Analysis of Akure, Nigeria.

Rationale for the study. This paper explores the Social Determinants of Childhood Malaria based on the framework of Social Determinants of Health. SDH encompasses factors that are related to the social, physical, economic, and environmental characteristics of individuals that shapes their health outcomes. These collective factors known as SDH are where health begins. In the concrete, SDH is largely the reason why people inherit disease-morbidity status since it accounts for about 80% of health outcomes excluding medical care (Greer et al., 2023). SDH is critical to health outcomes and amplifies health inequality among populations in a geographic space and time.

Despite various studies focusing on malaria prevalence, there is lack of comprehensive research on the social determinants of health (SDH) influencing childhood malaria, particularly, in medium-sized city like Akure, Nigeria. This is vital as WHO identified and stressed the importance of creating social and physical environments that promotes good health for all i.e. SDG3 (Marmot et al., 2008). This study aims to fill the identified gap by exploring the impacts of SDH on malaria occurrence among children under five years old in Akure, Nigeria.

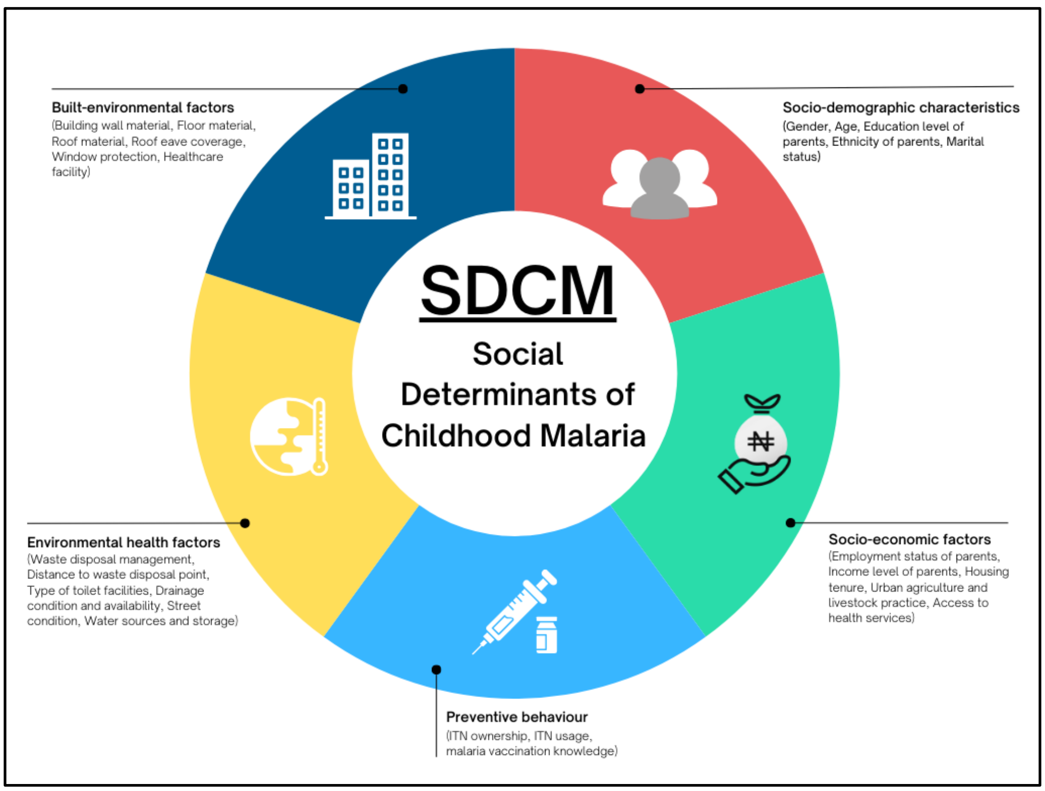

Figure I.3.3: Social determinants of childhood malaria

Data and Methods. For this study, data were collected using a pretested Malaria Indicator Questionnaire through a retrospective survey conducted from October to December 2019. The MIQ are designed into sections of variables encompassing social determinants of health. For this study, we further extended these variables covering all possible social determinants of childhood malaria – a concept that is fundamental to the study analysis (Figure I.3.3). These variables were grouped into different sections fashioned after (Hasyim et al., 2019). About 1000 building were randomly sampled as representation of the study population (0.6%), and coordinates of the building were noted for targeted visitation and information gathering. The survey targeted households with children under five years old, focusing on five broad social determinants of childhood malaria which are: socio-demographic, socio-economic, preventive behaviours, built-environmental, and environmental health factors.

The collected data were analysed using R statistical programming. The analysis involved both bivariate (Chi-square (x^2) and Fisher's exact test) and multivariate logistic regression methods to identify and model the risk factors associated with U5 malaria. The significant association were measured at 5% alpha level ($p < 0.05$) along with backward elimination based on Schwartz's Bayesian information criterion to determine the best fit model. The significant predictors from the bivariate analysis were included in the multivariable logistic regression model, with results presented as odds ratios (OR) and adjusted odds ratios (aOR). The former is the likelihood of child contracting malaria excluding other factors while the latter depicts chances of successful malaria transmission given other conditions i.e variables. The likelihood or chances increases if OR is greater than one (OR > 1) otherwise the risk of malaria is reduced.

Findings and Discussion. According to the study findings factors such as Age, window protection, availability, and usage of ITN, source of drinking water, employment of mother, availability of health infrastructure are determinants of U5 malaria in Akure, Nigeria. The multivariable logistics regression analysis revealed several significant determinants of U5 malaria in Akure. Key findings and risk factors of U5 malaria were observed within various SDCM factors. For example, socio-demographic factors such as the Age of Children are drivers of malaria prevalence. According to the study findings, children aged 12-47 months are significantly more likely to contract malaria compared to those below 11 months. This is because of the fizzling out of the passive immunity from mother to child in the early months of life. In respect to preventive behavioural factors, the usage of insecticide-treated nets (ITNs) significantly reduces the risk of malaria. ITN and good window protection serves as protective mechanism to block out mosquito vectors. According to the study result, children not using ITNs are 3.09 times more likely to have malaria. In addition, healthcare infrastructure is a determinant of U5 malaria. The absence of nearby health infrastructure significantly increases the risk of malaria (aOR = 1.84). Within the physical/built environmental factors, window protection is critical to reducing malaria morbidity. Households with unprotected or broken windows have higher likelihood of malaria, with an aOR of 2.44. Proximity to waste disposal sites and sources of drinking water are the environmental health predictors on U5 malaria in Akure. Living closer than 10 metres to waste disposal sites increases the risk of malaria (aOR = 2.11) because waste disposal sites can serve as breeding sites for mosquitoes. Households relying on dug wells or other non-piped sources of water are at higher risk of malaria compared to those with piped water. This explains wealth index in Akure as households that use dug wells are poor households. These findings highlight that factor beyond direct healthcare interventions, such as environmental and infrastructural conditions, play critical roles in malaria prevalence among U5 children in Akure. Therefore, policy recommendations directed at improving these conditions are important to achieve good health in Akure.

Conclusion and Recommendations. The study underscores the complexity of malaria transmission, emphasizing the importance of addressing social determinants of health in malaria prevention strategies. Effective malaria control in Akure requires a multifaceted approach that includes improving housing conditions, increasing the use of ITNs, enhancing waste management practices, and ensuring the availability of health infrastructure. By targeting these significant predictors, interventions can be more effective in reducing the malaria burden among children under five years old in Akure. This approach aligns with broader public health goals and contributes to sustainable development promoting healthier living environments especially in LMICs. The study acknowledges the limitation caused by retrospective method of obtaining epidemiological data resulting to recall bias, and definition of malaria disease. However, this was managed through the introduction of additional cross-checked questions to limit such bias.

Identifying Childhood Malaria Hotspots and Risk Factors in a Nigerian City Using Geostatistical Modelling Approach.

Rationale of the study. Malaria remains a significant public health challenge in sub-Saharan Africa, particularly affecting vulnerable populations such as children under five years old and pregnant women. Furthermore, small, or fine scale (e.g cities) level variations in the burden of malaria and malaria risk factors are not yet sufficiently understood despite its importance to unveil the local pockets of disease burden that could have been masked from National studies. This manuscript aims to explore the spatial variability of U5 malaria prevalence in Akure, Nigeria using model-based geostatistical techniques. The study predicts U5 malaria burden at a fine spatial resolution, identifying hotspots where the disease prevalence exceeds 10%. A 10% probability threshold was adopted to align this study with Nigeria's fifth National Malaria Strategic Plan from 2021 - 2025, which aims to achieve a parasite prevalence of less than 10%. This target therefore formed the conceptual frame for the study (Figure I.3.4). The insights from the study are crucial for guiding policy development and targeted interventions to reduce malaria burden and improve urban health.

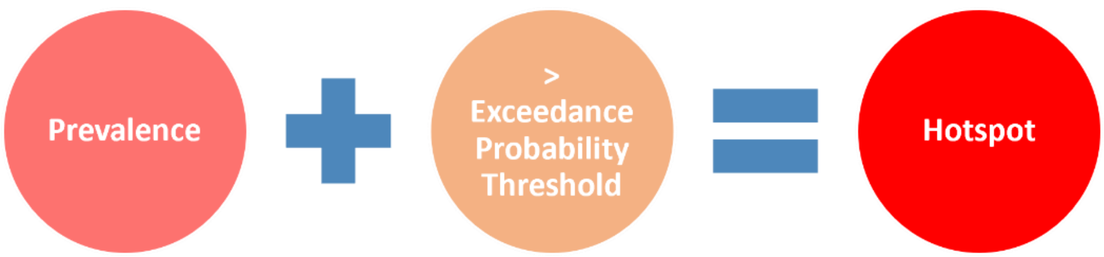

Figure I.3.4: Conceptual chart for identification of malaria hotspots

Data and Methods. The study employs a comprehensive geostatistical modelling approach to analyse U5 malaria prevalence. Data were collected through the MIQ during field survey carried out between October and December 2019. The study analysis involves several steps staring with exploratory data analysis to understand the relationships between U5 malaria prevalence and various covariates. Chi-square tests and non-spatial generalized linear models (GLM) were used to identify significant associations and guide the selection of variables for the geostatistical model. Geostatistical modelling is core to the study which involves spatial data analysis using MBG techniques within the generalised linear mixed model framework or spatial generalised linear mixed models. A binomial geostatistical model was developed, incorporating spatially correlated random effects to account for spatial dependency. The model parameters were estimated using Monte Carlo maximum likelihood methods, and the effectiveness of the model was validated through cross-validation techniques. Exceedance Probability (EP) modelling was carried out to identify malaria hotspots. This method provided spatial predictions of U5 malaria prevalence and identified areas where the likelihood of prevalence exceeded predefined thresholds (10%) with high certainty. This did not only result to the determinants of U5 malaria hotspots but serves as practical and viable guide upon which public health policy can be formulated.

Findings and Discussion. The study findings reveal significant spatial variability of U5 malaria prevalence across Akure including associated variables. Key findings include the use of insecticide-treated nets significantly reduce the likelihood of malaria, with a 56% reduction in odds. Households with piped water and good housing conditions also show lower malaria prevalence. The burden of malaria increased with age, potentially due to reduced use of ITNs among older children. The study was able to determine the high-risk area of malaria MBG predicted prevalence of more than 35% in certain areas. These areas are poor and low-income communities such as Arakale, Isolo-Araromi, Ayedun, and Oda exhibiting higher malaria transmission rates. This phenomenon can be attributed to substandard housing and poor drainage facilities. Newly emerging suburbs also show high prevalence due to poor urban planning and suitable mosquito breeding conditions. The EP modelling result using 80% and above as certainty level, and 10% as cut off further reveals U5 malaria hotspots in places like Isolo-Araromi, Oda, Arakale, Aiyedun, Kajola, Idi-Agba, Oba-Ile Phase Two, Orita Obele and Fanibi-Lafe. These hotspots are critical targets for intensified malaria control efforts to meet the fifth NMSP targets. The study observes lower transmission in affluent neighbourhoods such as Oba-Ile Phase One, Ijapo and Alagbaka Estate. These areas are characterised with high standard building structures and better facilities such as good rood conditions, drainage, a good water supply and less vegetationand robust development control.

Conclusion and Recommendations. This study underscores the importance of spatial analysis in understanding and addressing the burden of malaria in urban settings. The identification of specific high-risk areas through geostatistical modelling provides valuable insights for targeted malaria interventions. Key protective measures, such as the use of ITNs and improving housing conditions, are essential for reducing malaria transmission. The findings emphasise the need for spatially targeted public health policies and interventions to achieve significant reductions in malaria burden and improve urban health outcomes in Akure, Nigeria.

City Classification and Health Burden: Evidence from U5 Malaria in Rapidly Growing city of Akure, Nigeria.

Rationale of the study. Cities are pivotal to attaining the Sustainable Development Goal 3, which targets health and well-being for all. This is however challenging to attain in Nigeria because of the rapid and uncontrolled urbanisation which has created urban health disparities. The type of urbanisation and structure of cities have the potency to affect health of the city residents. Yet, little is known about the interplay between urban structure and health in rapidly urbanising Nigerian cities. This study examines malaria prevalence among children under five years old in various settlement types in Akure, Nigeria, using acquired primary healthcare data and Very High-Resolution satellite imagery. Urban structure refers to the patterns within cities (Figure I.3.5) and Akure, a medium-sized capital city in southwestern Nigeria, exemplifies the dynamic economic and spatial changes impacting urban areas.

Figure I.3.5. Urban structure types in Akure Nigeria.

Data and Methods. This research employed MIQ to collect data on malaria prevalence through household sampling. Satellite imagery was used to classify Akure into four settlement types: informal, medium density, formal/planned, and peri urban. Two settlements were selected from each classification type and the malaria data were aggregated according to the selected neighbourhoods. ANOVA was used to determine the differences in malaria burden between the selected settlements.

Table 1: List of settlements and zonation in Akure

Settlement classification			
Informal	**Medium-density**	**Planned**	**Peri-Urban**
Arakale	Fanibi/Lafe	Ijapo	Igoba
Erekesan	Ijomu	Alagbaka	Shagari
Isolo	Oke-Aro Titun	Oba-Ile Phase One	Owode
Isikan	Oke-Ogba	Oke-Ijebu	Adofure

Finding and Discussion. Studies have examined the correlation between socio-economic characteristics and residential quality in Akure (Akinbamijo & Fasakin, 2006; Emmanuel & Fasakin, 2017), but few have investigated the direct or indirect impacts on residents' health. According to the study finding, the ANOVA results show significant differences ($p = 1.118e{-}05$) in malaria prevalence among settlement types with higher malaria burdens in informal and peri-urban settlements compared to lower prevalence in formal settlements. Akure's rapid urbanisation reflects continuous growth trend, leading to challenges such as service shortages and inadequate infrastructure in new urban areas. The growth of Akure (spatial and population) has increased rapidly in the past four decades (Figure 14). This growth has not been controlled with elements of informality in the peri urban areas. According to Bayode & Siegmund (2024), these areas are characterised with fragmented landscapes and weak urban planning with potential negative impact on health outcomes. In agreement to this, the study shows higher burden of malaria in the peri-urban settlement.

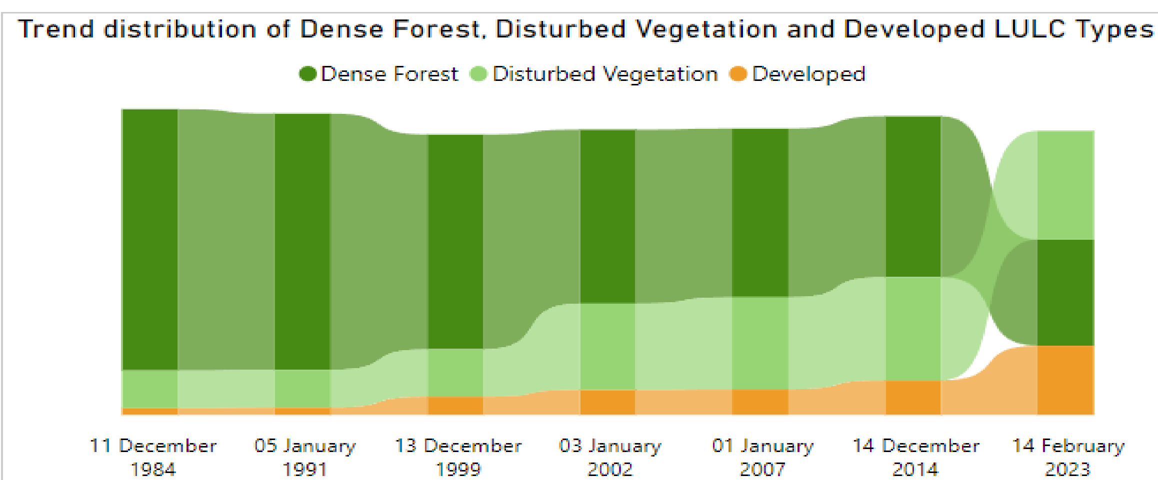

Figure I.3.6: Trend distribution of grey and green infrastructures in Akure

Conclusion and Recommendation. Spatial science tools have revolutionized city management, yet cities in LMICs to lag far behind in the studying and modelling urban spatial forms. This research provides a platform for social and environmental investigations in Akure, highlighting the challenges of managing population growth, urban development, and socio-economic gradients. The study underscores the need for urban planning approach to address these issues and promote equitable development. The study calls for improved urban development policies to address the high malaria burden in informal and peri-urban areas, emphasizing the need for better infrastructure and planning to ensure health equity and sustainable growth in rapidly urbanizing cities like Akure.

4

"Growth is inevitable and desirable, but destruction of community character is not. The question is not whether your part of the world is going to change. The question is how."

Edward T. McMahon

I.4 Conclusions

This thesis presents work on malaria burden in rapidly growing cities, with a focus on Akure, Nigeria. The research aims to enhance understanding of the risk factors and spatial inequality of childhood malaria by employing qualitative, quantitative, and geostatistical methods. These approaches uncover spatial patterns and explore urban planning strategies that promote urban health and drive sustainable development. This research is particularly relevant in an increasingly urbanised world, where the growing pace of urbanisation poses challenges to human health and environmental sustainability. The study objectives and research questions addressed by the thesis leads to the following conclusions:

Human health is deeply interconnected with the health of the environment. The well-being of children and the health of the natural environment are deeply interconnected and mutually dependent. A healthy environment directly enhances human health by reducing the prevalence of diseases. Conversely, environmental degradation, such as deforestation, negatively impacts human health and contributes to the spread of waterborne diseases like malaria. In sub-Saharan Africa (SSA), increasing population growth has led to the expansion of cities and urban development, often at the expense of the environment. Effective urban development requires adequate monitoring to ensure the sustainability of cities. For instance, urban trends and projections are vital tools for policymakers to plan and provide infrastructure that meets the demands of a growing population. This thesis highlights the interconnection between the environment and health. Remarkably, despite their clear relationship, little research has been conducted to explore this connection in low- and middle-income countries (LMICs).

Social determinants are important to positive health outcomes. Social and economic factors have a significant influence on whether people live healthy or unhealthy lives, often outweighing the impact of genetics or medical care. Consequently, these factors are crucial to achieving positive health outcomes. Social determinants such as economic stability, education, healthcare access and quality, neighbourhood and built environment, and social and community context collectively shape health outcomes. These conditions play a critical role in influencing people's health and well-being, as they encompass the environments in which people are born, live, work, and age. Addressing these social determinants is essential for improving public health and reducing health disparities.

Urban planners are in fact health professionals. Even if urban planners are not formally trained in healthcare, their decisions significantly shape the environments where people live, work, and play. Consequently, the decisions of urban planners in city management and development directly impact the physical, mental, and social well-being of city residents. Urban planners can help mitigate health disparities by ensuring equal access to healthcare facilities and safe housing. For example, effective waste disposal can reduce diseases like malaria, as demonstrated by this thesis. The health challenges of the 21st century are complex and require interdisciplinary collaboration. Beyond the place-based evidence of malaria burden presented in this thesis, the importance of urban planning in achieving positive health outcomes has been firmly established.

Unequal scene implies unequal health outcome. There is a noticeable socio-economic divide reflected in health outcomes among different settlements. Locations with evidence of adequate urban planning exhibit better well-being compared to those with poor planning, as indicated by this thesis. Examples of urban planning elements include the physical layout of the city and the availability of infrastructure, such as resource allocation and the provision of services in deprived communities. Without these, the quality of life in cities will be compromised. Inequities in the distribution and allocation of infrastructure exacerbate social injustice, resulting in inequalities in many areas, such as wealth, well-being, education, and employment. This thesis highlights the connection between health, the visible conditions of the environment (i.e., scenery), and the disparities in the quality of life in Akure, Nigeria.

Spatial targeting of health interventions saves resources and lives. A strategic focus on specific geographic areas is essential to ensure the efficient dissemination and utilisation of healthcare resources. This approach is critical for targeted policy formulation and the optimisation of scarce resources for malaria elimination in Akure. Healthcare resources are limited, and this strategy will address the healthcare needs of populations where they are most urgently required, as demonstrated by this thesis.

I.4.1 Recommendations

Based on the findings of this thesis, the following recommendations are proposed to mitigate the burden of malaria and enhance the sustainability of Akure. These recommendations aim to address the need for improved health outcomes in the city of Akure, Nigeria.

1. **Creation of inclusively developed master plan.**

This can be achieved by implementing an appropriate master plan to serve as a blueprint for guiding the development of Akure. The study emphasises the importance of professional inclusion in the development process, promoting improved synergy and collaboration among allied health institutions in Akure. For instance, a master plan can provide direction for proper waste management and ensure timely clearance of drainages, particularly during the rainy season. Effective urban planning in residential areas could significantly reduce the incidence of uncleared drainages, lower population density, and improve access to clean water for domestic use and consumption. Proper planning would also enhance the efficacy of vector control measures. Additionally, a well-designed master plan supports the effective distribution of health resources, which is critical for reducing malaria prevalence. For example, planning for the creation of healthcare facilities to serve every 1,000 persons per square kilometre could ensure improved access to healthcare centres. The strategic placement of these facilities would enable timely treatment and significantly improve malaria control outcomes.

2. **Robust and periodic health surveillance through geospatial assessment of malaria.**

A geo-spatial surveillance program could provide valuable insights into the current transmission and distribution patterns of malaria in the area. This is crucial for identifying local hotspots and ensuring the spatially targeted use of scarce health resources. Such an approach would enable the timely implementation of appropriate intervention and control measures. Additionally, it would facilitate the monitoring and evaluation of the malaria control program, allowing for improvements in the most affected areas.

3. **Robust and periodic urban growth surveillance.**

Growth is an inevitable and natural phenomenon. However, it can be planned strategically to enhance the prosperity of the city. This requires robust monitoring using quality GIS and RS techniques. Therefore, capacity development is essential in this regard. Effective monitoring, in line with the master plan, is both necessary and highly recommended. Additionally, this approach can help assess the effectiveness of urban planning controls in Akure.

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Part II: Publications

“Neither cities nor places in them are unordered, unplanned; the question is only whose order, whose planning, for what purpose?”

~ Peter Marcuse

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*CORRESPONDENCE
Taye Bayode
bayode@stud.uni-heidelberg.de

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Tripartite relationship of urban planning, city growth, and health for sustainable development in Akure, Nigeria

Taye Bayode[1,2]* and Alexander Siegmund[1,2]

[1]Institute of Geography and Heidelberg Centre for Environment (HCE), Heidelberg University, Heidelberg, Germany, [2]Department of Geography – Research Group for Earth Observation (rgeo), UNESCO Chair on World Heritage and Biosphere Reserve Observation and Education, Heidelberg University of Education, Heidelberg, Germany

We live in an urban planet. As the world continues to urbanize, urban development that support the health and wellbeing of city dwellers is far more important than ever before to achieve sustainable development targets. This study explores the complex relationship among urban planning, city growth, and health as critical drivers of sustainable development in the rapidly growing nodal city of Akure, Nigeria. The study provides a four-decade spatio-temporal model of urban Land Use Land Cover (LULC) changes in Akure between the years 1984 and 2023 from acquired Landsat satellite imageries. The result shows more than 20% net change increase in developed LULC classes between the study years. A strong positive correlation exists between the years covered in the analyses and urban development (r = 0.93, p = 0.002), and a strong negative relationship with the forest land use (r = –0.94, p = 0.002) with potential debilitating impacts on residents' health, green infrastructures and the city's sustainability in the future. Furthermore, results of key informant interviews (KIIs) of officials of the Ministry of Physical Planning and Urban Development (MPPUD) in Akure, Ondo State, unveil various views on the "place of health" in urban planning practices in Akure. A lack of synergy between urban planners and public health practitioners in the city and limiting scope of functions of urban planning on the impact of health in Akure were observed. Thus, we recommend the integration of a sustainable urban planning approach as a guide to manage the city.

KEYWORDS

sustainable development, sustainable urban planning, urban health, urban growth, Nigeria

1 Introduction

There is no doubt we live on an urban planet due to the rapid and ongoing urbanization phenomenon the world is experiencing. Urbanization is a process through which the cities grow. Kuddus et al. (2020) refer to urbanization as a mass movement of populations or population shifts from rural to urban settings. The turning point in world history was in 2007 when, for the first time, more people lived in cities compared to rural areas (Aliyu and Amadu, 2017).

The United Nations estimated that 55% of the world's population resided in urban areas in 2018; while this figure was 30% in 1950, and it is expected to increase to 68% by 2050

(United Nations Department of Economic and Social Affairs, Population Division, 2015). Furthermore, this implies that the number of urban dwellers will grow by 2.5 billion between 2018 and 2050, and two-thirds of all humans will live in cities (United Nations Department of Economic and Social Affairs, Population Division, 2015). Hence, the future is urban.

The projected population growth in cities and urbanization levels vary among regions of the world. United Nations Department of Economic and Social Affairs, Population Division (2015) asserted that most of the population growth will occur in the lower-income regions of Africa and Asia while the urban population will triple and double in Africa and Asia, respectively. Although Northern America and Europe are mostly urbanized, Africa and Asia are rapidly catching up and urbanising faster compared to other regions, with the possibility to become 56 and 64% urban, respectively (Alirol et al., 2011; Aliyu and Amadu, 2017). Notably, Nigeria in West Africa, China and India in Asia are expected to experience the highest level of urbanization and urban growth by 2050 (Aliyu and Amadu, 2017).

Urbanization is majorly a result of economic development and industrialization, which often result in changes in urban settings (Keivani, 2009; Kuddus et al., 2020). Some of these changes (positive) can be physical, such as the development of infrastructures to service the urban residents; economic changes, such as increased wages, and socio-economic changes, such as increased living standards in urban places (Chen et al., 2013; Ya-Feng et al., 2020). Contrarily to the positive changes, substantial and severe problems induced by urbanization, such as the unreasonable layout of urban spaces and uncontrolled and extensive urban physical development, are notable in urban areas (Jiao, 2015; Liu and Wang, 2016).

Nigeria is not left out from rapid urbanization processes and associated uncontrolled urban expansion. According to Urbanization Research Nigeria, the urbanization rate in Nigeria was projected to be approximately 52% in 2020 based on the report compiled in 2015 (Bloch et al., 2015). Further to their findings, the urban growth (spatial) and physical development in Nigeria are increasing and concentrated around four major urban fields, among which are the south-western conurbation that stretches from Lagos in the south to Ilorin in the north and Akure in the east. Particularly in Akure, (Owoeye and Ibitoye, 2016) averred that the economic factor is the major driver of the city's urbanization because Akure is part of crude oil producing regions in Nigeria. Other factors are the educational and nodality of the city with respect to transportation (Owoeye and Ibitoye, 2016; Bayode and Siegmund, 2022).

Associated with rapid population growth and urbanization is the expansion of existing built-up/developed land area and land cover. Seto et al. (2012) asserted that urban land cover will increase by 1.2 million km^2 by the year 2030, which is approximately three times the urban land cover in 2000. This phenomenon contributes to urban sprawl, which calls for monitoring (Alabi, 2022). Therefore, it is important to study how cities' spatial extent increases and how cities are planned and sustainably managed. Geographic information systems (GIS) and remote sensing have proved to be valuable tools for monitoring urban land cover and use (Younes et al., 2023).

Rapid urbanization can hinder human and sustainable development by predisposing urban residents to negative health outcomes and increasing vulnerability to health risks. For example, unequal distribution of health infrastructures and social and economic inequities can exacerbate health inequalities (Aliyu and Amadu, 2017). Cities in low-income and middle-income countries (LMICs), such as Nigeria, are breeding grounds for poverty, inequality, environmental hazards, increased traffic accidents and injuries, spread of communicable diseases, and air pollution, among others (Moore et al., 2003; Kuddus et al., 2020). Therefore, rapid urbanization and the scale of the urban population constitute major public health challenges of the twenty-first century for urban planners and governments (Aliyu and Amadu, 2017).

Urban environmental conditions and the quality of built environments are important to the health and quality of life of a city's inhabitants. Northridge and Freeman (2011) and Carmichael et al. (2019) posited that urban (spatial) planning systems have the capacity to reduce urban health inequalities as an enabler of urban health. Through impacting the physical urban environment, urban planning and design processes can directly impact physical and mental health and social wellbeing and reduce health inequities in various ways (Smit et al., 2011). For example, the works of Jackson (2003) and UN-Habitat (2007) show the impact of built environment, urban planning policy, and city design on the mental and physical health of urban residents. However, limited consideration has been given to the impact of urban planning on urban health, thereby hindering sustainable development in LMICs (Smit et al., 2011; Tuhkanen et al., 2022).

A number of scholars alluded the complex relationship among sustainability, urban planning, and health in cities; nonetheless, these relationships have not been sufficiently explored in LMICs such as Nigeria (Northridge and Freeman 2011; Siri, 2016; Vardoulakis and Kinney, 2019; UN-Habitat and World Health Organization, 2020). Earlier studies in LMICs explored urban growth without drawing a nexus to the health impacts of urban growth (Hassan et al., 2016; Owoeye and Ibitoye, 2016; Mohammadi and Sharifi, 2021; Moradi and Sharifi, 2023; Seyam et al., 2023; Younes et al., 2023).

Akure is a medium-sized city that is rapidly growing among Nigerian cities, whose residents' health and urban growth (spatial) have been explored by several researchers (Bloch et al., 2015). With respect to urban (spatial) growth and modeling, Owoeye and Ibitoye (2016) explored land use change detection in Akure using remote sensing. Consequently, Usman et al. (2018) investigated the impact of urban sprawl in Akure with geospatial assessment, while Eke et al. (2017) analyzed the urban expansion of Akure using geographic information systems (GIS). Exploring the relationship between urban health and city growth, Alabi (2022) observed the financial and health toll of urban sprawl on residents of Akure, while Popoola et al. (2020) investigated how micro-climate is influenced by urban growth in Akure. Akinbamijo and Fasakin (2006) and Bayode and Siegmund (2022) explored determinants and disparities in the health status of Akure residents. These previous studies collectively lack comprehensive validation through statistical modeling and accuracy assessment, which limits the robustness of their findings. Moreover, theses previous studies have also failed to explore the complex relationships among city growth, urban planning, and health or investigate health concerns within the urban planning practices of Akure by incorporating the perspectives of experienced and active city planning officials. Thus, our study aims to fill the identified gaps by conducting a large-scale spatio-temporal urban growth modeling in Akure and investigating concerns for health issues by urban planners as the city experiences rapid urban growth yet not planned.

The objectives of this study are as follows: (a) explore and model the urban growth characteristics of Akure, Nigeria; (b) determine the temporal relationship between urban growth and other land use land cover classes; and (c) investigate if there are synergies between urban planners and public health officials in Akure on how to tackle potential health problems emanating from rapid urban expansion.

1.1 Urban planning and public health in cities

The health-focused origins of urban/town planning and public health can be traced to ideas and vision of planning pioneers and urban reformers—Ebenezer Howard and Patrick Geddes in Britain, Lewis Mumford in the United States, and Gräfin Dohna and James Hobrecht in Germany—more than a century ago over how urbanization was affecting the health of impoverished city residents, especially during the industrial revolution (Duhl and Sanchez, 1999; Northridge and Freeman, 2011; Baumgart, 2017). For example, the 1848 Public Health Act was put in place to combat infectious diseases in the crowded cities of Britain and building codes and emphasis on the efficient design and usage of public sewage were considered to reduce health inequalities (Peterson, 1979; Garb, 2003).

Despite the close tie, common origin and objectives between public health and urban planning, the two professional disciplines have had a roller-coaster relationship even after 1900 (Hebbert, 1999). The two professions parted ways in the early twentieth century when medical practice/public health professionals turned their attention from the environment and sanitarium to the science of bacteriology, i.e., biomedical causes of disease and disability (Hebbert, 1999; Northridge and Freeman, 2011). However, both disciplines are re-converging due to the complex health challenges of the twenty-first century.

In spite of the increasing number of urban dwellers globally, projections by the United Nations indicate that 75% of the infrastructure to service the projected population has not yet been built (UN-Habitat and World Health Organization, 2020). Communicable and infectious diseases thrive in overcrowded cities, slums, and places characterized by inadequate access to clean water, sanitation, and hygiene facilities. WHO and UN-Habitat (2020) noted that working and living in an unhealthy environment reportedly killed 12.6 million people in 2012, and approximately 4 years later, an estimated 7 million mortality cases were attributed to air pollution because only 1 in 10 cities worldwide meet standards for healthy air. Specifically, most of these challenges are more serious among cities in the Global South, where the confronted public health challenges and threats can be linked to urban and territorial planning (UN-Habitat and World Health Organization, 2020). Therefore, the increasing complexity of the urban environment and health in cities worldwide has once again steered the need for the convergence of the two disciplines (urban planning and public health) to proffer solutions to urban health challenges (Northridge and Freeman, 2011).

Rapid population growth and spatial expansion are some of the results of urbanization, which could birth poor urban physical development, weak urban planning control and poor sanitation, thereby making the urban environment incapable of providing the need for healthy shelter, potable water, waste disposal, and health service. The consequence of this led to the spread of diseases and the enactment of decrees to guide the use of land (Oyewale, 2003). This shows that the quality of the urban environment and urban health status are influenced by urban planning decisions (Didier et al., 2009).

There are direct and indirect health risks posed by the urban environments. Direct risks occur when people are inadequately protected against or exposed to disease-inducing agents, such as polluted air, soil, or water. Indirect health risks can occur through the degradation of urban and hinterland resources, depletion of green infrastructures and forest covers, low-quality urban spaces, ecosystem disruptions, inadequate waste management, and poor transportation infrastructures (Didier et al., 2009). Collectively, these risks affect both the health of urban residents and the health of the city since these urban health and environmental challenges are fallouts of how we organize, develop, manage, and live in the cities (Dodman, 2009).

Rapid urbanization and urban life are characterized by high health inequality, and the urban poor bear the brunt of the health challenges (Elsey et al., 2019). The urban poor, who are often the residents of slums and squalor or densely populated places, are vulnerable to high disease transmission, illness resulting from proximity to toxic and hazardous wastes, lack of clean water and sanitation, and water, air, and noise pollution (Satterthwaite, 1997). Urban poor are at risk of infectious diseases of poverty, such as typhoid, diarrhea, cholera, and intestinal worms from contaminated water and food, as well as waterborne diseases associated with malaria because of poor drainage and garbage collection (Meikle et al., 2001). Urban poor are restricted to geographically dangerous areas such as hillsides, riverbanks, and water basins subject to landslides, flooding, or industrial hazards (Kuddus et al., 2020). To address these health disparities in cities, urban planners are increasingly being called on by public health professionals (Corburn, 2005).

Public health issues ravaging cities identified at the 8th Global Conference on Health Promotion (2013), include obesity, diabetes, asthma, heart disease, cancer, communicable disease from overcrowding, malaria, pollution, traffic crashes, stress, industrial risk, and violence. However, several important aspects have been identified to tackle these public health issues. Some of the identified aspects include improved housing quality; equitable access to and improved coverage of basic services, recreational facilities, and regeneration of green spaces; transport options, including cycling and walking infrastructures; security from urban violence; and implementation of environmental laws to address environmental hazards and curb sprawling suburbs (UN-Habitat, 2007). To address these public health issues in cities, urban planning was therefore described as a vehicle that can aid the improvement of urban dwellers' health and achieve the New Urban Agenda targeting two of the 17 Sustainable Development Goals (SDGs), which are (i) ensure healthy lives and promote wellbeing for all at all ages, i.e., SDG 3 and (ii) make cities and human settlement inclusive, safe resilient, and sustainable, i.e., SDG 11 (WHO and UN-Habitat, 2020).

Human health and the physical environment are intricately linked. From the perspectives and tenets of public health planning, the physical environment is seen as having attributes that can be managed through social intervention that aims at enhancing the overall health and wellbeing of the entire urban system (Didier et al., 2009). This, therefore, requires cooperation and synergies between public health experts and urban planners, within and at the level of national and municipal authorities, communities, international organizations, non-governmental organizations, and researchers.

1.2 Urban planners as health experts

Lakshmanan (2012) asserted that urban and regional planning is an art of shaping and guiding the physical growth of towns and cities to meet the diverse needs of the public and to provide healthy conditions where people can live, work, and thrive physically, socially, and economically in an urban environment. Therefore, urban and regional planning can be described as a discipline that contains all elements—be it physical, social, cultural, economic, political, and ecological—of a town and other urban environment.

Urban planners, sometimes also called city and regional planners, are professionals who facilitate decision-making. Their role involves coordinating, facilitating, and creating a logical, systematic decision-making process that results in the best actions for urban or town dwellers (Litman, 2020). They also help a city to solve problems in the environment such as inadequate housing, traffic congestion, and the location of new schools and parks (Porter, 1999).

The practice of urban health promotion by controlling exposure to the agents of disease first came to fruition in the mid-nineteenth century, which provides the initial indication that urban planning is directly associated with health, in part due to the appalling effects from the fall outs of industrialization and urbanization (Duhl and Sanchez, 1999). During this period, urban planners took on the responsibilities of public health experts. Some of their objectives were the removal of unsanitary conditions and the beautification of cities; the main objectives of urban planning were functionality and public health or health promotion in cities as documented in the works and efforts of several pioneers such as Ebenezer Howard, Patrick Geddes, and Lewis Mumford who helped to shape and further the tenets of social and health planning (Egunjobi and Ogunmodede, 2019). Ever since, the goal and sole aim of urban planning has not changed.

According to Agbola and Oladoja (2003), urban planners make every person in a society realize his/her full human potential in a wholesome environment by creating a healthy, agreeable, and sustainable environment for everyday life through functional arrangement and location of facilities in space.

Urban planners, especially in the Global South, need to adopt new skills and revisit their ethical commitment. There is a need to incorporate these new demands and approaches into urban planning curricula and education (UN-Habitat, 2010). Relatively recently, new opportunities for increased collaboration between urban planning and health have emerged. Planners are increasingly involved in the preparation of joint strategic needs assessments and joint health and wellbeing strategies with health boards (Pineo, 2022).

2 Materials and methods

2.1 Study area

This study area, Akure, is located in the south-western part of Nigeria (see Supplementary Figure 1). It is a medium-sized capital city of Ondo State, and it lies in the tropics between E 5°04′42″--E 5°29′45″/N 7°26′43″--N 7°03′50″. Akure city is made up of two local Governments—Akure South and Akure North—which is relatively approximately 370 m above sea level in altitude. The city is experiencing rapid population increase and urban growth. Since Akure became the administrative capital of Ondo State, the population has increased tremendously and more than tripled. In 1963, the population of Akure was approximately 71,106, which rose to 239,124 in 1976, 239,124 in 1991, and 360,268 in 2006 (Owoeye and Ibitoye, 2016). Studies averred that the national census led to an underestimation of the population in some parts of Nigeria for political reasons, while alternative and objective population estimates from aerial imagery estimated the population of Akure to be over one million—1,283,541 (Tofowomo, 2008; Bayode and Siegmund, 2022). More about the study area have been discussed in Bayode and Siegmund (2022).

2.2 Data sources

2.2.1 Qualitative data and sampling technique

To augment the robustness of the dataset for this study, qualitative data were gathered by conducting key informant interviews (KIIs) with the officials/employees of the Ministry of Physical Planning and Urban Development (MPPUD).

Snowball sampling was adopted as the study qualitative data sampling technique to gather information about health within the scope of urban planning and growth in Akure. Snowball sampling is commonly engaged in qualitative research (Browne, 2005; Noy, 2008). It is particularly useful in registering "hidden populations," "very seldom" population, or "difficult to encounter" population (Dragan and Isaic-Maniu, 2022). The population is referred to as hidden in this context due to the low numbers of potential participants or the sensitivity of the topic (Browne, 2005). It is a recruitment method whereby one interviewee gives the researcher the name or contact of at least one or more potential persons who are eligible to be interviewed and so on (Browne, 2005; Kirchherr and Charles, 2018; Dragan and Isaic-Maniu, 2022).

According to the snowball technique, we were able to locate and interview a total of four officials between October and December 2021. They include two senior officers, one mid-level, and a junior officer. The KII was recorded and transcribed.

2.2.2 Satellite data

Satellite datasets are one of the new and effective methods of urban land use land cover or field monitoring (Zamani et al., 2022). The satellite data used for this study are Landsat satellite images from 1984 to 2023. They include Landsat 4 and Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 and Landsat 9 Operational Land Imager (OLI), and Thermal Infrared Sensor (TIRS). Landsat 4–5 consist of seven spectral bands with spatial resolution between 30 meters (Bands 1–5 and 7) and 120 meters (Band 6). Band 6 is thermal infrared but is resampled to 30-m pixels. Landsat 7 images consist of eight spectral bands with a spatial resolution of 30 m, excluding band 8, which is a panchromatic band with a spatial resolution of 15 m. Landsat 8 images consist of nine spectral bands with a spatial resolution of 30 m for Bands 1–7 and 9. Band 8 is 15-m panchromatic band, while the thermal bands 10 and 11 are collected at 100 m. The Landsat bands selected for this study all have a spatial resolution of 30 m.

Landsat images used for this study are open-source remote sensing images (data) obtained from the United States Geological

TABLE 1 Description of Landsat satellite images used for LULC analysis.

Year	Landsat satellite	Sensor	Composite bands	Spatial resolution (m)	Date of acquisition
1984	L5	Thematic mapper (TM)	Bands 4,3,2	30	11/12/1984
1991	L4	Thematic mapper (TM)	Bands 4,3,2	30	05/01/1991
1999	L7	Enhanced thematic mapper plus (ETM+)	Bands 4,3,2	30	13/12/1999
2002	L7	Enhanced thematic mapper plus (ETM+)	Bands 4,3,2	30	03/01/2002
2007	L7	Enhanced thematic mapper plus (ETM+)	Bands 4,3,2	30	12/12/2007
2014	L8	Operational land imager (OLI) and thermal infrared sensor (TIRS)	Bands 5,4,3	30	14/12/2014
2023	L9	Operational land imager (OLI) and thermal infrared sensor (TIRS)	Bands 5,4,3	30	14/02/2023

Survey (USGS) earth explore data portal.[1] The USGS data portal contains an extensive collection of publicly available geospatial datasets. We extracted the Landsat satellite imageries for Path 190 Row 055, wherein our study area is located.

Table 1 describes the Landsat sensors used for this study, their spatial resolution (i.e., pixel size), selected bands, and the date the images were captured. The Landsat images have different bands with varying wavelengths, as explicitly documented on https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites.

Before downloading the raster datasets from the portal, we developed a pragmatic search criterion to filter the datasets that have <10% cloud cover. Images between the months of December and February for each selected year were downloaded to minimize bias introduced to our results from seasonal variation and impacts of cloud cover (Taiwo et al., 2023). These months are part of the dry season months in Akure, Nigeria.

2.3 Data analysis

The data analytical techniques adopted for this study involve different tools, software, and stages. They are generally combinations of geographic information systems (GIS) and remote sensing (RS) technologies, as illustrated in Figure 1. GIS represents a combination of science and application (Laplante, 2015). It is a comprised system concerned with the organization, handling, manipulating, processing, and retrieving data whose spatial position or geographic pattern is of concern (Classen, 1977). RS is a method of collecting data at a distance from the object (earth's surface and atmosphere) under study through the use of electromagnetic sensors often by the use of satellites or aircraft (Schowengerdt, 2007). GIS and RS have been widely used in urban mapping and monitoring of urban development (Owoeye and Ibitoye, 2016; Usman et al., 2018; Popoola et al., 2020; Sharifi, 2020; Mohammadi and Sharifi, 2021; Saha et al., 2022; Moradi and Sharifi, 2023). After the pragmatic selection of the Landsat images (raster datasets) for this study, the image processing started with band combinations to develop a False Color Composite (FCC) of the images. The selected bands for composite bands/stacked bands vary from one sensor to another depending on the spectral characteristics. Bands 4, 3, and 2 were selected from Landsat 4, 5, and 7, while Bands 5, 4, and 3 were selected from Landsat 7 and 8. The analysis of the study's spatial extent was determined by clipping the FCC with the study area boundary shapefile.

The raster data processing was carried out in ArcGIS Pro. Furthermore, raster analysis such as fill gap was performed in QGIS to fill the data gaps in Landsat 7 image for the year 2007 because of Scan Line Corrector (SLC) failure in ETM+ in 2003.

2.3.1 Land use classification

Land use classification provides information on land cover and the various types of human activities for which land can be used (Karan and Samadder, 2018). The classification of land cover and use can be supervised or unsupervised. According to Richards (2013), supervised classification, the most frequently used for quantitative analysis of remote sensing data, was adopted for this study. It is a pixel-based classifier that classifies satellite image pixels based on spectral reflectance properties or multispectral composition that are similar or identical (Bayarsaikhan et al., 2009; Islami et al., 2022). The supervised classification process is mainly conducted in three steps, which are training sample selection, classification, and accuracy assessment (Seyam et al., 2023).

First, the training samples were created according to the default classification schema from the 2011 National Land Cover Database (Jin et al., 2019). Approximately 25 training samples were created for each LULC class. The five LULC classes in this study are forest, developed, water body, disturbed vegetation/cultivated, and barren/rock outcrop. The LULC is differentiated by colors to avoid confusion. This process was done using on-screen digitized features.

Second, image classification was carried out. A support Vector Machine (SVM) classifier was engaged to classify the images into five LULC classes. SVM is a supervised classification method commonly used in the LULC research community with associated advantages

1 https://earthexplorer.usgs.gov/

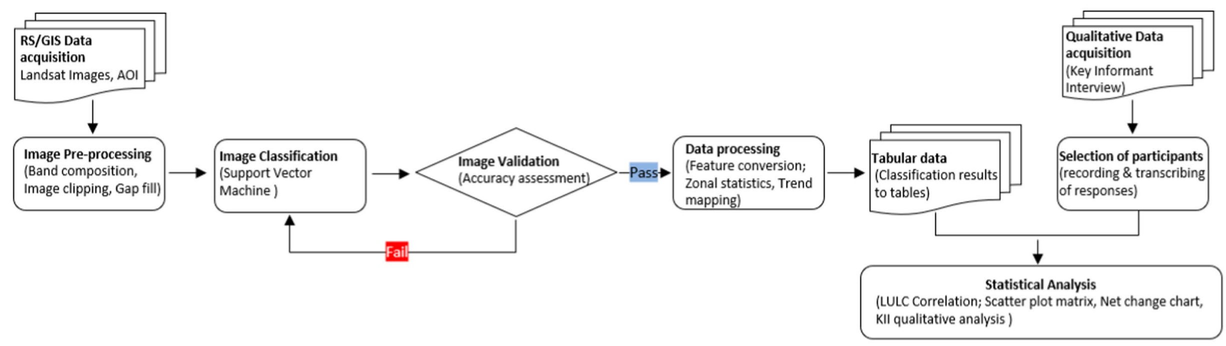

FIGURE 1
Data analysis workflow of the methodology.

such as requirements of fewer samples, less susceptibility to noise, and correlated bands (Mohammadi and Sharifi, 2021; AlDousari et al., 2022; Rahaman et al., 2022).

Based on the classification schema and classification grouping in the study by Rahaman et al. (2022), the following features can be found in the following classes. Forest area includes concentrated trees, dense plantation, gardens, and large parks. Developed areas include built-up residential, industrial, and commercial areas, impervious surfaces, and transportation networks. Water body includes ponds, lakes, wetlands, rivers, streams, and canals. Disturbed vegetation/cultivated area includes fragmented forest areas, croplands, grazing lands, etc. Barren/rock outcrop includes rocks, impervious areas, etc.

Third, data validation or evaluation for this study was conducted. This is further discussed in the next section (model validation). It is an interactive process of comparing classified LULC to the true value, i.e., ground truthing. The results for the data validation were quantified based on the Kappa assessment, and a decision was made. If the results were erroneous with a low score (i.e., fails), the data processing was carried out again till the results pass validation with high Kappa values.

2.3.2 Statistical analysis

The classified raster image was converted to polygon features upon which the Zonal Statistics as table was used to compute the area coverage (quantification) of LULC classes in square meters $\left(m^2\right)$. The tables were exported for further data statistical analysis—correlation—in R version 3.6.3. The correlation method adopted for this study is Pearson's Product Moment Correlation (Equation 1).

$$\rho_{x,y} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{1}$$

Where $\rho_{x,y}$ represent the covariance between the two variables, σ_x represent the standard deviation of a land use land cover type/element, and σ_y represent the standard deviation of other land use land cover type/element. Pearson's correlation is widely used in LULC correlation analysis and some previous LULC studies (Awuh et al., 2019; Zhu et al., 2019; Maishella et al., 2020; Jamei et al., 2022; Aka et al., 2023; Yao et al., 2023) all adopted Pearson's correlation for their analysis.

Pearson's correlation is a parametric statistical test that measures the degree of linear association between two quantitative variables with association value results ranging from plus one (+1) to minus one (−1) in decreasing order of strength. A correlation value of +1 indicates a perfect positive relationship, a value of −1 indicates a perfect negative relationship, while 0 indicates no relationship/correlation (Lee Rodgers and Nicewander, 1988; Yim et al., 2010). Furthermore, Cohen et al. (2013) grouped correlation coefficients as follows: 0.10–0.29 indicate a weak/small relationship, 0.30–0.49 indicate a moderate/medium relationship, while values between 0.5 and 1.00 indicate a strong/large relationship. The key informant interview was recorded and transcribed for this study. Figure 1 shows the data analysis workflow methodology.

2.4 Model validation

It is crucial to carry out an assessment or validate the performance of the model, i.e., to test the reliability of the result or predicted land use land cover based on the training samples. The most common method of accuracy assessment to determine the accuracy result of land use classification is the contingency method (Islami et al., 2022). This is also known as a contingency matrix, confusion matrix, or error matrix.

For this study, the accuracy was assessed using an average of 267 ground truth data points (validation) or reference points. The reference points/data for this study were based on prior knowledge of the study area, field visits, and retrospective observations from Google Earth images according to studies by Aka et al. (2023) and Seyam et al. (2023). In addition to this, archives and classified maps of the study area were also considered. The distribution of the point follows a stratified random method, according to Hassan et al. (2016). In addition to quantitatively comparing classification results and reference data, other components of the confusion matrix, such as producer accuracy, user accuracy, overall accuracy, and non-parametric Kappa statistical test (coefficient), were performed to further quantify or measure the degree of the classification accuracy. Producer's accuracy and user's accuracy estimate overall accuracy (Islami et al., 2022). Particularly, overall accuracy represents the number of accurately classified pixels (LULC) of the Landsat imagery. Producer's accuracy is a false negative, i.e., errors of omission, while

User's accuracy depicts false positives, also referred to as errors of commission. The overall degree of agreement or classification precision is determined by the Kappa coefficient in Equation (2).

$$Kappa\ coefficient = \frac{(T\ x\ C) - D}{T^2 - D} \qquad (2)$$

Where T is the test pixels, i.e., the total number of reference pixels, C is the total number of correctly classified pixels (Diagonal), and D is the sum of multiplied values of row and column. The accuracy assessment was carried out using Image analyst tools—segmentation and classification in ArcGIS Pro, while for explicit computation on producer's accuracy, user's accuracy, and overall accuracy (see Rwanga and Ndambuki, 2017; Talukdar et al., 2020; Islami et al., 2022).

3 Results

3.1 Spatio-temporal changes in LULC classes

The land use type for Akure since inception and from the processed Landsat image of 1984 shows that it was predominately forest land (Figure 2). According to Table 2, the spatial coverage of forest LULC in 1984 was approximately 85,513.68 hectares and 34,797.42 hectares by the year 2023, indicating a decrease of 46.16% in approximately four decades. This is contrary to the developed LULC class. Between the study years, developed land use shows an increasing trend. According to Table 2, developed land use land cover increased from 2,158.56 hectares to 22,591.53 hectares between the years 1984 and 2023, respectively, depicting a percentage increase of 18.6%. Increasing area coverage of developed land phenomenon is similar to the disturbed/cultivated land use land cover type. Based on our study analysis, the cultivated land increased from 7,652.34 hectares in 1984 to 35,505.99 hectares between 1984 and 2023. This depicts the highest increase, i.e., 27,853.65 hectares among the land use land cover classes. Developed land increased by 20,432.97 hectares, while forest land decreased by 50,716.3 hectares.

There was no distinctive increment in the values of rock outcrops and water bodies between the study periods. The values for the latter are low, likely because of the period (dry season) in which the imageries were captured.

3.2 Accuracy assessment and kappa coefficient

Supplementary Table 1 represents the result of the confusion matrix. The table also includes results of the user's accuracy (U_Accuracy), producer's accuracy (P_Accuracy), overall accuracy, and Kappa coefficient (Kappa). The Kappa index of agreement represents an overall assessment of the classification accuracy. The Kappa coefficients for the years 1984, 1991, 1999, 2002, 2007, 2014, and 2023 are 0.75, 0.77, 0.75, 0.86, 0.97, 0.74, and 0.96, respectively. According to rating criteria developed by Talukdar et al. (2020), Kappa coefficient values between 0.70 and 0.85 indicate very good or substantial agreement, while Kappa results higher than 0.85 indicate excellent or almost perfect agreement. Based on this criterion, the Kappa coefficient for this study is reliable, and classification accuracy is satisfactory. The image analysis for this study was done with freely available Landsat images of medium quality, and the season of acquisition has some ramifications in terms of accuracy, as noted by Seyam et al. (2023). This could have contributed to the discrepancies in the Kappa coefficients between the study years. We obtained some of the reference points from retrospective Google Earth images with dates that are not the same as Landsat image acquisition dates but very close. However, there are no discrepancies in the user's accuracy for

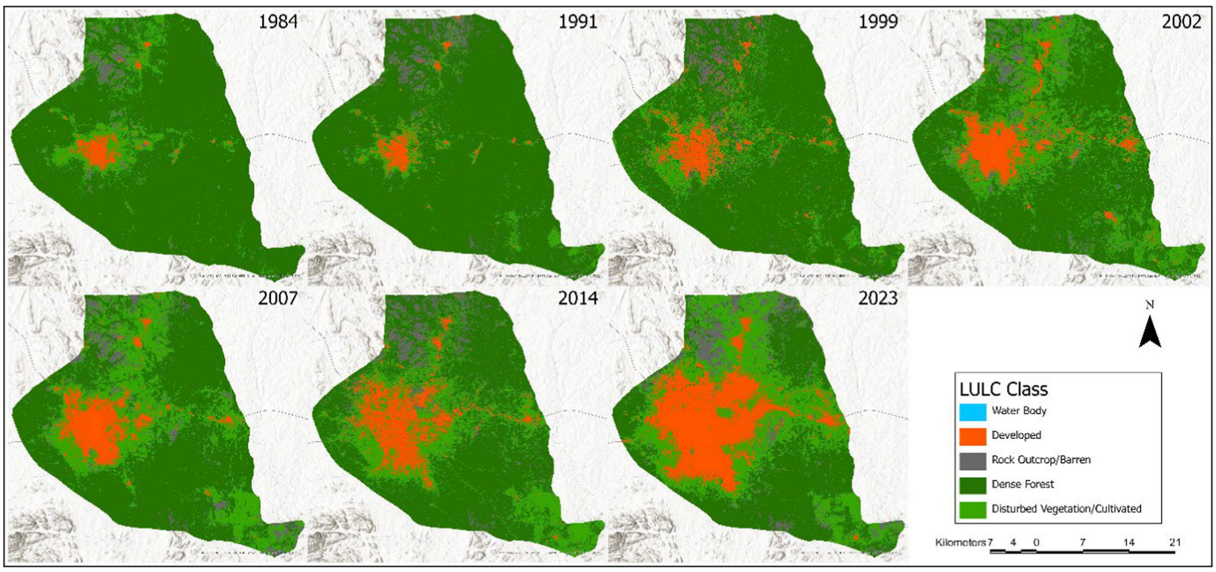

FIGURE 2
LULC classification for the years 1984, 1991, 1999, 2002, 2007, 2014, and 2023.

TABLE 2 LULC spatial coverage for the years 1984, 1991, 1999, 2002, 2007, 2014, and 2023.

LULC	Area (hectares)							
	1984 (%)	1991 (%)	1999 (%)	2002 (%)	2007 (%)	2014 (%)	2023 (%)	Increase or decrease (%)
Developed	2,158.56 (1.96%)	2,433.24 (2.21%)	5,934.78 (5.4%)	8,189.28 (7.45%)	8,387.91 (7.64%)	11,295.18 (10.28%)	22,591.53 (20.56%)	20,432.97 (18.6%)
Forest	85,513.68 (77.84%)	83,777.4 (76.26%)	70,275.06 (63.97%)	56,942.55 (51.83%)	55,251.72 (50.3%)	52,669.53 (47.94%)	34,797.42 (31.68%)	−50716.3 (−46.16%)
Cultivated	7,652.34 (6.97%)	12,317.67 (11.21%)	15,483.69 (14.09%)	28,179.9 (25.65%)	30,000.15 (27.31%)	33,687 (30.67%)	35,505.99 (32.32%)	27,853.65 (25.35%)
Water	281.89 (0.26%)	271.86 (0.25%)	281.64 (0.26%)	263.45 (0.24%)	271.88 (0.25%)	267.79 (0.24%)	297.45 (0.27%)	15.56 (0.01%)
Barren	14,249.7 (12.97%)	11,054.21 (10.06%)	17,879.21 (16.28%)	16,279.20 (14.82%)	15,942.72 (14.51%)	11,934.88 (10.86%)	166,661.99 (15.17%)	2,414.08 (2.2%)

TABLE 3 Correlation matrix between different LULC classes and time.

	Year+	Developed	Forest	Cultivated	Water	Barren
Year+	1	0.932	−0.971	0.942	0.275	0.256
Developed	0.932	1	−0.936	0.824	0.538	0.338
Forest	−0.971	−0.936	1	−0.957	−0.259	−0.39
Cultivated	0.942	0.824	−0.957	1	−0.0038	0.196
Water	0.275	0.538	−0.259	−0.0038	1	0.398
Barren	0.256	0.338	−0.39	0.196	0.398	1

+Signifies the capturing period of the Landsat satellite images used for the study's analyses.

this study. According to Rwanga and Ndambuki (2017), the user's accuracy reflects the reliability of the classification of the user.

3.3 Relationship between LULC classes

The correlation results are presented in Table 3, Supplementary Figure 2 and Supplementary Table 2. The results show a strong positive and significant correlation between the years and developed land LULC ($r = 0.93$, $p = 0.00224$). Conversely, forest land is negatively correlated with the year and developed land ($r = -0.97$, $r = -0.94$; $p = 0.000277$, $p = 0.00193$). Similarly, the cultivated land is negatively correlated with the forest land ($r = -0.96$, $p = 0.000731$). Furthermore, the cultivated land is positively correlated with the year and developed land ($r = 0.942$, $r = 0.824$; $p = 0.00151$, $p = 0.0226$). Water body and rock outcrops/barren land are not significant and, therefore, not discussed in this section.

3.4 Urban planning practices and health in Akure

The findings from the key informant interview are presented under the following questions and responses. According to the KII that was conducted, the study was able to gather succinct information about planning practices and approaches in Akure particularly if concern for health issues is well considered as the city rapidly expands. This study endeavors to seek information broadly about the master plan and synergies between the Ministry of Health (MoH) and the Ministry of Physical Planning and Urban Development (MPPUD) in Akure.

The participants expressed similar views that the overarching goal of MPPUD is to monitor physical development in Akure. However, less importance is placed on the health of residents with respect to the functions of the ministry.

> *"The ministry monitors physical development in Akure which are done by different departments. The ministry places less importance on improvement of health outcomes among the residents of Akure."*

Most participants agreed that the current master plan was last updated over 21 years, but there was no agreed date among the participants on when the master plan was developed. However, reference was made to 1984 and 1986.

> *"The current master plan was developed in the 1980's. It is the document that guides development of Akure, but it is long overdue because the built-up extent of Akure has changed tremendously. It is germane for the institute to update the master plan. The master plan was last updated in 2001."*

The participants agreed on consultation with other ministries during the development of the master plan. Nevertheless, most participants further agreed there is no synergy between the Department of Public Health in MoH and departments in MPPUD, while one of the interviewees is not sure of the relationship between the two ministries.

> *"During the development of master plan, other ministries in Ondo State were involved. We consider the MoH as a stakeholder in this regard. Despite the involvement of other ministries, particularly MoH, there is no synergy or overlapping functions focused on health issues between both ministries."*

In addition to the above findings, the participants agreed that house visitation and environmental health factors that determine health outcomes in Akure are not within the purview of MPPUD.

> *"It is not the responsibility of any department in MPPUD to check compliance with environmental health factors that influences health outcomes in Akure. This is the responsibility of public health department at health ministry."*

Furthermore, the officials interviewed in the MPPUD collectively agreed on the need to train urban planners not only in Akure but also in Nigeria on urban health issues.

> *"Urban planners are health experts. It is necessary to stress the importance and need for training on health issues in urban places by urban planners in Akure and Nigeria. Furthermore, there should be close working relationship or establishment of health department in MPPUD in Akure."*

The participants agreed on the rapid expansion of Akure and the non-usage of modern spatial technologies (e.g., GIS and RS) for monitoring the spatial growth by the MPPUD. Furthermore, the dominant views about the challenges of using GIS centers around financial cost, human resources, and political will.

> *"The use of modern spatial technologies are rarely integrated as part of the tools and necessary skillset in the ministry. Urban growth modelling are seldom carried out. Some of the barriers confronted by the ministry in respect to the use of modern spatial technologies are financial/economic hardship; lack of human resources and political will."*

4 Discussion

The study shows a continuous increase in the spatial extent of built-up/developed land use while the spatial extent of forest land use is decreasing. For example, between the years 1984 and 2023, the developed land percentage increase is approximately 946.6% while the cultivated land percentage increase is approximately 364%. Contrarily, the forest land percentage decrease is approximately 59.31% in the same period. In terms of net change, the built-up/developed land use land cover increased by 20,432.97 hectares while the net loss of forest land is 50,716.30 hectares, as shown in Figure 3.

The observed trends are similar to the studies by Owoeye and Ibitoye (2016), Popoola et al. (2020), and Alabi (2022) conducted in West African countries, study by Rwanga and Ndambuki (2017) in South Africa, and studies conducted in some Asian countries by Hassan et al. (2016), Arumugam et al. (2021), Islami et al. (2022), and Seyam et al. (2023). The study by Owoeye and Ibitoye (2016) averred the factors responsible for this trend in Akure. According to them, some of the factors are the construction of buildings, provision of public utilities, and other developmental projects embarked on by the Ondo State government at different periods due to the economic situation in that period, especially from 2002 onwards when Ondo State is classified as one of the mineral endowed regions in Nigeria. The land use change over time in Akure is periodic with a steady increase. However, the change pre-2000s is slower compared to post-2000s. Using the year 2002 as a reference, the net change in developed LULC between 2002 and 2023 is 144,022 ha. This is two times more than the net change between 1984 and 2002 (60,307 ha), as illustrated in Figure 4.

Nevertheless, the staggering figure from this analysis shows that the ongoing phenomenon is a threat to the sustainability of green infrastructures, residents' health, and environmental and ecological stability of Akure.

The monitoring of forest cover is crucial due to its impact on climate change, desertification, soil erosion, and flooding, especially when this ecosystem loses millions of hectares each year (Moradi and Sharifi, 2023). The outward growth and depletion of forest cover

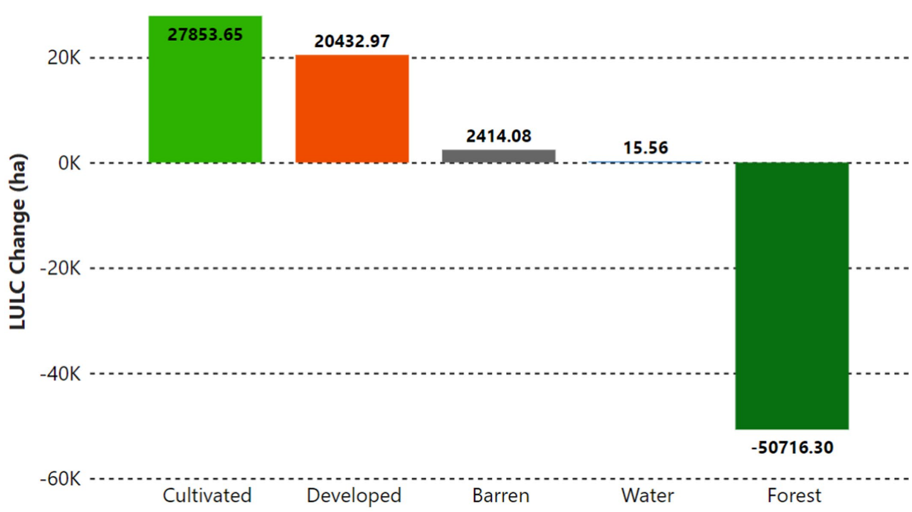

FIGURE 3
Net change of each LULC in Akure between the study years.

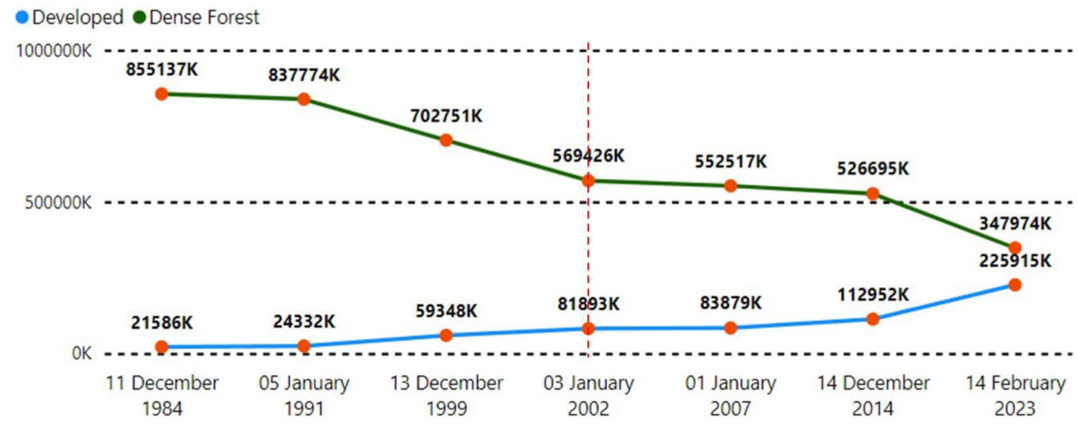

FIGURE 4
Temporal pattern of forest and developed LULC between 1984 and 2023.

contribute to ecological imbalance, changes to micro-climate, and loss of green-infrastructure investment in Akure. Vardoulakis and Kinney (2019) stressed the importance of urban green infrastructure and associated societal, environmental, and health benefits. Vegetation cover, for example, forest land use land cover, serves as a coolant to reduce the increasing global warming and as carbon sinks for carbon emission from other land use types (industrial and transportation). Therefore, continuous reduction in green spaces will predispose the population to increasing micro-climatic conditions, accelerate the thermal environment, and contribute to environmental degradation (Popoola et al., 2020; Saha et al., 2022). Consequences of environmental degradation include soil erosion and increased vulnerability to flooding.

The urban growth pattern in Akure follows the concentric ring spatial expansion along transportation routes to the east, as depicted in Figure 2. This phenomenon was observed in the LULC study of another city—Ibadan, Nigeria (Taiwo, 2022). Land use land cover changes are characterized by urban sprawl, similar to the studies by Owoeye and Ibitoye (2016) and Alabi (2022) in Akure and other African countries such as Egypt, which often leads to the depletion of parcels of land for agricultural purposes (Salem et al., 2020).

Cities and the process that drives urbanization are critical moderators of the interplay between human health and sustainability or urban space (Siri, 2016). Verburg et al. (2004) attempted to identify some of the factors/processes that drive urbanization and urban growth. According to their extensive study, urban expansion forces are probably classified into five categories, which are environmental characteristics, social factors, spatial neighbourhood factors, economic factors, and spatial policies. Their classification is in agreement and overlaps with the inferences from studies by Usman et al. (2018) on Akure. Specifically, Usman et al. (2018) noted the availability of robust social and infrastructural facilities in Akure compared to the hinterlands as drivers of the city's growth. Other factors that drive Akure's urban growth are natural population increase (increased births compared to deaths), nurturing business climate, and establishment of educational institution (Bayode, 2014; Bayode and Siegmund, 2022). The effect of these factors can be seen as the built-up LULC of the city experiences continuous expansion in time. Another reason for the outward expansion, emergence, and growth of suburbs in Akure is the social problems of the core region of Akure (Popoola et al., 2020). Furthermore, the study by Bayode and Siegmund (2022) on social determinants of infectious disease outcomes (malaria) among children below the age of five shows that poor housing characteristics, which are predominantly in the core region of Akure, is a factor, while Akinbamijo and Fasakin (2006) highlight poor waste management practices, e.g., littering of residential areas as contributing factors to the spatial disparities in health negative outcomes in Akure with high incidences in the core and suburbs. Despite scholars in Akure having echoed health issues relating to socio-environmental conditions in Akure, ways to tackle these challenges are not yet fully integrated into urban planning practices in Akure.

According to the KII with the officials of MPPUD, there is divergence in the function of public health discipline and urban planning despite the two professional disciplines sharing common origins. Among the identified Global North countries, such as the United Kingdom, one of the major reforms gave local authorities responsibility for the health of their local population. Furthermore, this development brought public health and urban planners under the same local authority, thereby creating a platform that supports closer working relationships (Carmichael et al., 2019).

MPPUD in Akure is focused on physical urban development. This undermines the relevance or "place of health" in urban planning. According to Barton and Tsourou (2013), a city is much more than physical structures such as buildings, connectors such as streets, and green infrastructures such as open spaces; a city is a dynamic, complex social space in which the health is closely linked to that of its residents. Healthy people make healthy cities. Therefore, approaches and investments that not only elevate the health of the planet but also people should be at the heart of the city's internal and external policies.

Urban planners should be perceived as de facto health professionals who should work collaboratively with other institutions to tackle health challenges in Akure, as agreed by the KII participants. This is extremely important because urban planning should no longer be seen as a unidimensional, static, technocratic activity, but rather a process of bringing together various perspectives and sectoral priorities to develop the common future of a city (UN-Habitat, 2007).

Our findings also elucidate the challenges confronted by the MPPUD on the applications of modern geospatial technologies to the modeling of urban spatial growth. In Akure, the department rarely uses these modern technologies because of financial implications, human resources with the skillset, and investments by the government. Among the arguments of Northridge and Freeman (2011), political will/power is essential to attain increased health equity in urban places. The lack of urban growth modeling indicates growth as unguided and not planned.

5 Limitations and future research

Despite the study's attempt to explore the nexus of urban planning, city growth, and health toward the sustainability of Akure, this study is characterized by or had some limitations. The first limitation is related to data availability, particularly empirical public health indicators, to further support our findings. However, we referenced previous studies on exacerbated public health challenges due to poor urban planning and built urban environments in the context of this manuscript. We therefore strongly recommend extensive future research with the inclusion of data on public health indicators to be conducted.

The second limitation is related to the qualitative sampling technique. Snowballing is a non-probability sampling technique with no sampling frame. Therefore, individuals cannot be randomly sampled, which questions the generalisability of a snowball sample (Given, 2008). This should be considered in the study interpretation, and we hope future research will employ a parametric sampling technique.

Third, rainfall is vital for vegetation. This implies that most urban green spaces are more visible and better captured by the Landsat satellite during the rainy season. The study's interpretation on forest land use should be taken with caution, and we hope that future studies will investigate the effect of seasonality LULC analysis.

Finally, more robust classifiers and algorithms can be considered in future research. Mohammadi and Sharifi (2021) elaborated on other classification algorithms such as Relevant Vector Machine (RVM), Bagging Trees (BT), Random Forest (RF), and Convolutional Neural Network (CNN). Specifically, Moradi and Sharifi (2023) observed that the CNN method outperforms existing classification methods based on the accuracy of the results. The results of SVM can be unsuitable, especially when a number of features is much more than the number of samples training referred to as the "curse of dimensionality," and ways to deal with this have been discussed by Mohammadi and Sharifi (2021). These other methods require technical know-how, and they are computationally intensive while we hope they are considered in future research. Nevertheless, Nadzri et al. (2023) observed SVM outperformed RF in their study based on the obtained Kappa results.

6 Conclusion

Our study explored the potential sustainable development impediments in Akure from the complex relationship of three tripartite sustainability wicked problems (urban growth, urban planning, and urban health). As the world continues to urbanize, urban development that supports the health and wellbeing of city dwellers is far more important than ever before to achieve sustainable development targets.

The spatial footprint of developed LULC is increasing rapidly with little regard to its impact on the city residents' health, according to our study. In addition to this, the growth of the city is poorly controlled and unplanned. The impact of this phenomenon was observed from the encroachment into the green space/forested land cover between the years of study. This can also induce environmental problems such as urban heat islands. There is a lack of close working relationships between public health professionals and urban planners in Akure, which could be from the limited urban planning functions with respect to urban health and health issues. The study calls for pragmatic and sustainable urban management approaches in Akure. For example, urban physical development control and regulations to curb urban sprawl in Akure are vital. Therefore, the use of geospatial technologies should be encouraged, and periodic training of urban planners is crucial, which can improve the effectiveness of urban growth monitoring in Akure. Furthermore, importance should be given to health in the urban planning profession in Akure. This can start with education and capacity building in various departments of ministry.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

Ethics statement

Informed consent was obtained from the staff of MPPUD who participated in the KII. Furthermore, we adhered to the anonymity of data and presented results.

Author contributions

TB: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. AS: Supervision, Writing – review & editing.

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Conflicts of interest

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

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frsc.2023.1301397/full#supplementary-material

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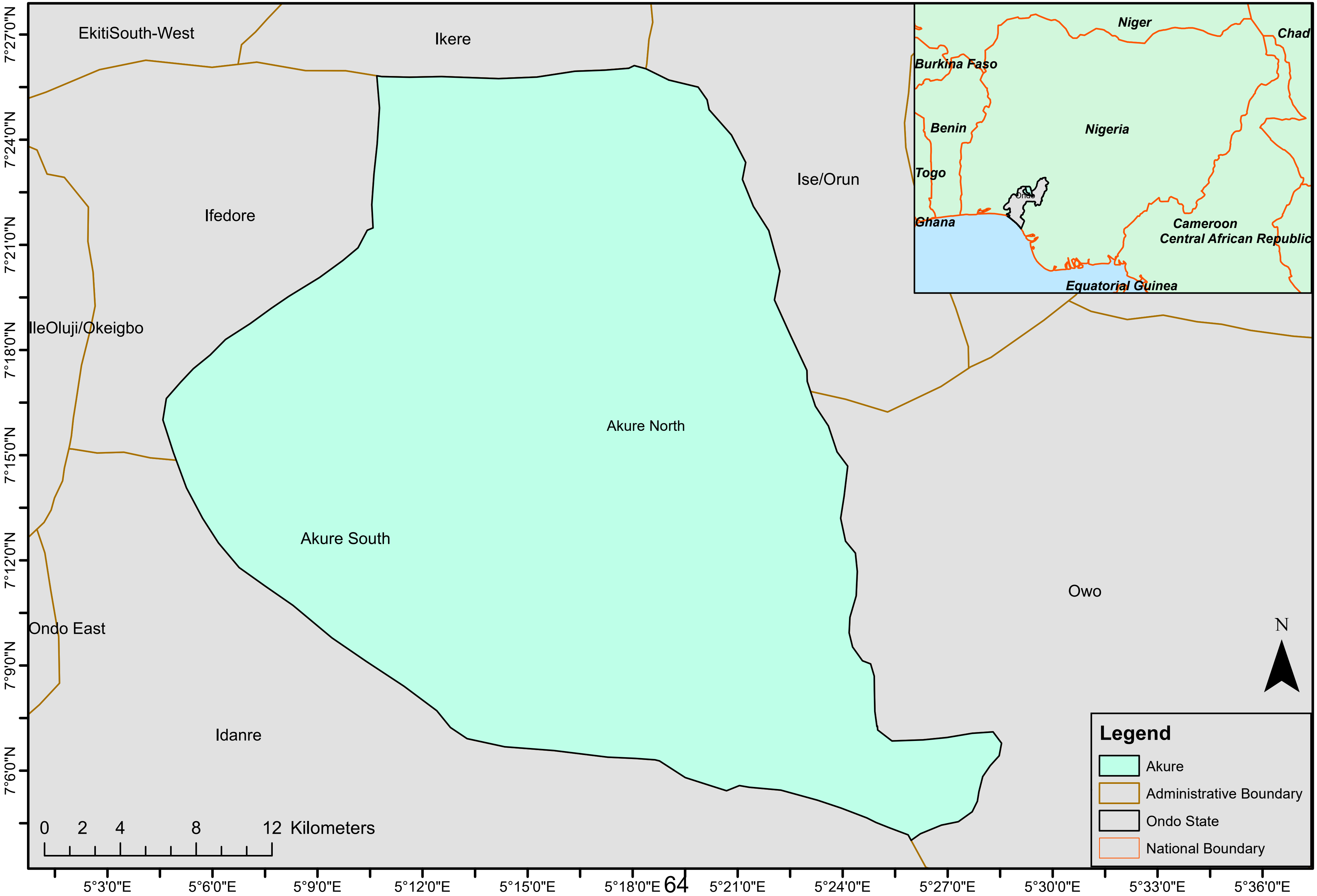
Supplementary Figure 1. Study area map of Akure, Ondo State, Nigeria



Supplementary Material

Supplementary Table 1: Confusion matrix for classified years 1984, 1991, 1997, 2022, 2007, 2014 and 2023.

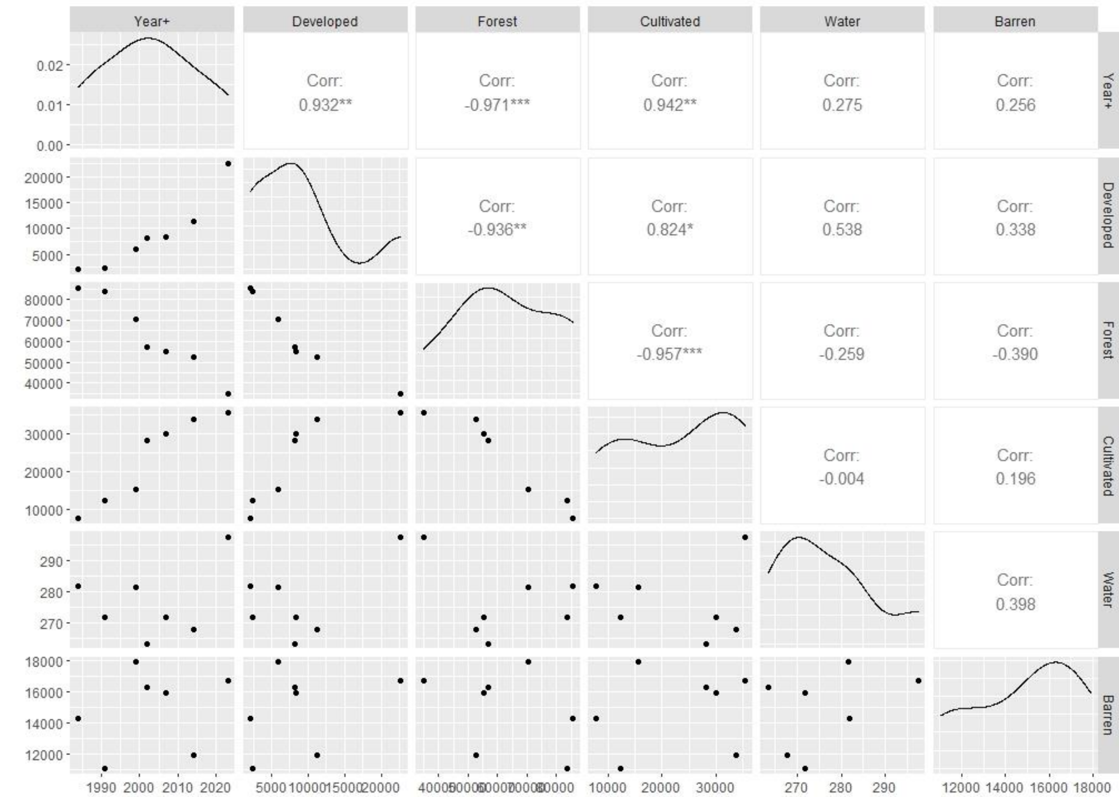
Year	1984							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	202	0	0	8	0	210	0.961905	0
Developed	0	10	0	1	0	11	0.909091	0
Water	0	0	0	0	0	0	0	0
Cultivated	5	0	0	23	1	29	0.793103	0
Barren	0	0	10	1	9	20	0.45	0
Total	207	10	10	33	10	270	0	0
P_Accuracy	0.975845	1	0	0.69697	0.9	0	**0.903704**	0
Kappa	0	0	0	0	0	0	0	**0.750737**
Year	1991							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	211	0	0	4	0	215	0.981395	0
Developed	0	9	0	2	0	11	0.818182	0
Water	1	0	4	0	0	5	0.8	0
Cultivated	7	0	0	25	0	32	0.78125	0
Barren	4	0	4	1	4	13	0.307692	0
Total	223	9	8	32	4	276	0	0
P_Accuracy	0.946188	1	0.5	0.78125	1	0	**0.916667**	0
Kappa	0	0	0	0	0	0	0	**0.765028**
Year	1999							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	159	0	0	16	0	175	0.908571	0
Developed	0	11	0	2	3	16	0.6875	0
Water	0	0	7	6	1	14	0.5	0
Cultivated	2	0	0	40	0	42	0.952381	0
Barren	0	0	3	2	8	13	0.615385	0
Total	161	11	10	66	12	260	0	0
P_Accuracy	0.987578	1	0.7	0.606061	0.666667	0	**0.865385**	0
Kappa	0	0	0	0	0	0	0	**0.748487**
Year	2002							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	133	0	0	3	0	136	0.977941	0
Developed	0	20	0	0	0	20	1	0
Water	0	0	3	0	0	3	1	0
Cultivated	8	2	5	72	1	88	0.818182	0
Barren	0	0	2	1	10	13	0.769231	0
Total	141	22	10	76	11	260	0	0
P_Accuracy	0.943262	0.909091	0.3	0.947368	0.909091	0	**0.915385**	0
Kappa	0	0	0	0	0	0	0	**0.860905**

Year	2007							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	177	2	0	0	0	179	0.988827	0
Developed	0	30	0	0	0	30	1	0
Water	0	0	0	1	0	1	0	0
Cultivated	0	0	1	73	0	74	0.986486	0
Barren	0	0	0	0	11	11	1	0
Total	177	32	1	74	11	295	0	0
P_Accuracy	1	0.9375	0	0.986486	1	0	0.986441	
Kappa	0	0	0	0	0	0	0	**0.969415**

Year	2014							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	121	0	0	13	0	134	0.902985	0
Developed	0	24	2	1	3	30	0.8	0
Water	0	1	4	0	0	5	0.8	0
Cultivated	8	0	1	55	0	64	0.859375	0
Barren	2	0	4	6	7	19	0.368421	0
Total	131	25	11	75	10	252	0	0
P_Accuracy	0.923664	0.96	0.363636	0.733333	0.7	0	**0.837302**	0
Kappa	0	0	0	0	0	0	0	**0.742697**

Year	2023							
Class Value	Forest	Developed	Water	Cultivated	Barren	Total	U_Accuracy	Kappa
Forest	86	1	0	1	1	89	0.966292	0
Developed	0	55	1	0	0	56	0.982143	0
Water	0	0	9	3	0	12	0.75	0
Cultivated	0	0	0	83	0	83	1	0
Barren	0	0	0	1	18	19	0.947368	0
Total	86	56	10	88	19	259	0	0
P_Accuracy	1	0.982143	0.9	0.943182	0.947368	0	**0.969112**	0
Kappa	0	0	0	0	0	0	0	**0.957284**

Supplementary Material



Supplementary Figure 2. Scatter plot correlation matrix of LULC classes and time/year

Supplementary Material

Supplementary Table 2: Correlation matrix p-values between different LULC classes and time/year

	Year^{+}	Developed	Forest	Cultivated	Water	Barren
Year^{+}	0.000000000	0.002240077	0.0002770810	0.0015103005	0.5504714	0.5795302
Developed	0.002240077	0.000000000	0.0019329069	0.0226149665	0.2133149	0.4588206
Forest	0.000277081	0.001932907	0.000000000	0.0007312806	0.5746650	0.3876267
Cultivated	0.001510301	0.022614967	0.0007312806	0.000000000	0.9935124	0.6734934
Water	0.550471406	0.213314948	0.5746650441	0.9935123554	0.000000000	0.3761651
Barren	0.579530153	0.458820575	0.3876266636	0.6734933895	0.3761651	0.000000000

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Name, first name	Taye Bayode	Alexander Siegmund	
Methodology	☑	☐	☐
Software	☑	☐	☐
Validation	☑	☐	☐
Formal analysis	☑	☐	☐
Investigation	☑	☐	☐
Resources	☑	☑	☐
Data Curation	☑	☐	☐
Writing-Original Draft	☑	☐	☐
Writing-Review&Editing	☑	☑	☐
Visualization	☑	☐	☐
Supervision	☐	☑	☐
Project administration	☑	☑	☐
Funding acquisition	☑	☑	☐

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Prof. Dr. Alexander Siegmund | | 23.01.2025
Name/*Name* | Unterschrift/*Signature* | Datum/*Date*

"Health inequalities and the social determinants of health care are not footnote to the determinants of health. They are the main issue."

Michael Marmot

II.2 Social determinants of malaria prevalence among children under five years: A cross-sectional analysis of Akure, Nigeria.

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Social determinants of malaria prevalence among children under five years: A cross-sectional analysis of Akure, Nigeria

Taye Bayode [a,b,*], Alexander Siegmund [a,b]

[a] Institute of Geography & Heidelberg Centre for Environment, Heidelberg University, Germany
[b] Department of Geography – Research Group for Earth Observation (rgeo), UNESCO Chair on World Heritage and Biosphere Reserve Observation and Education, Heidelberg University of Education, Germany

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ABSTRACT

The global fight towards the reduction of malaria burden in the last decade has indeed attained great strides. Conversely, and in recent times, the African region especially Nigeria is characterised with increasing malaria burden. With focus on childhood malaria, this paper explores the impact of social determinants of health on malaria occurrence among children under the age of five years old (U5) in emerging city of Akure. Retrospective survey was conducted from October to December 2019 with the aid of pretested Malaria Indicator Questionnaire (MIQ). First, bivariate analysis (Chi-square) was employed to identify and select predictor variables associated with U5 malaria occurrence. Second, social model of malaria was developed engaging the multivariable logistic regression method to model the risk of U5 malaria in Akure. The U5 malaria occurrence was significantly influenced by window protection and netting [Adjusted odds ratios (aOR): 2.44, 95%CI: 0.32 – 1.51, $p < 0.01$]; distance to waste disposal sites (aOR = 2.11, 95%CI: 0.21 – 1.32, $p < 0.01$); usage of insecticides treated nets — ITNs (aOR = 3.09, 95%CI: 0.67 – 1.59, $p < 0.01$); and availability of health infrastructures (aOR: 1.84, 95%CI: 0.13 – 1.10, $p < 0.05$). The study demonstrated that factors outside the healthcare sector are important drivers of U5 malaria in Akure. As a result, U5 children with frequent usage of ITN, protected window and residents more than 10 metres away to waste disposal sites are less likely to suffer from malaria blight. This paper recommends that interventions should be directed towards the significant predictors as part of malaria reduction strategies in Akure.

Introduction

Within the last decade, the world has experienced reduction of malaria burden [1]. However, these achievements are disproportionate among the countries and regions of the world with increasing burden in recent times. According to the World Health organization (WHO) report in 2019, there were about 228 million global cases of malaria in 2018 compared with 219 million in penultimate year. While most of the malaria cases were experienced in the African Region, Nigeria exclusively shared about 25% (57 million) and 24% (97 000) of the global malaria morbidity and mortality [1]. The worrisome large

* Corresponding author.
E-mail address: bayode@stud.uni-heidelberg.de (T. Bayode).

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number of malaria prevalence impacts the nation negatively. The negative impacts of malaria burden are multidimensional and deters the nation from achieving the sustainable development goals. The human and economic costs associated with malaria are enormous and often lead to low productivity and loss of incomes from malaria treatment or inability to work [2]. Irrespective of the direct and indirect cost of malaria, its complex interaction with national development results in a vicious circle of poverty. Therefore, malaria is not only a public health problem but also impediment to the growth and the development of malaria endemic countries [3,4]. Particularly in Nigeria, the estimated cost of malaria prevention, treatment and loss of income due to inability to work is about 132 billion naira i.e. ∼ US$ 835 million [5]. This reality is not farfetched since an estimated 97% of Nigerians are at risk of malaria [1].

Malaria burden disproportionately affects population groups. Studies of [1,6] have pointed that the burden of malaria are more prevalent among children, pregnant woman, and travellers from non-endemic areas. For example, U5 children accounted for about 67% (272 000) of global malaria deaths [1]. This gross statistical value is because: infant and young children (U5) are at high risk of clinical episodes from their low or no protective immune mechanism to malaria infection [1,7,8]. The negative impact of malaria among U5 children in devastating. In some instances, the deleterious effect of malaria among children results to low level of cognitive development, severe disease such as anemia and malnourishment [9–12]. In Nigeria, childhood malaria accounts for 25% and 30% of infant and childhood mortality [5,13]. Malaria is an infectious disease caused by any of the five parasitic protozoa of the Plasmodium genus through female Anopheles mosquitoes bites [14–16]. Among these five parasitic species (P. *falciparum*, P. *vivax*, P. *malariae*, P. *ovale* and P. *knowlesi*), P. *falciparum* poses greatest threat and prevalence in Africa with about 2.57 billion people at risk globally [14]. Climatic and environmental variables such as temperature, humidity, rainfall, and wind speed modulates the life cycles of malaria vectors and parasites [17–19]. The complexity of weather variables constitutes some of the underlying forces of malaria in Nigeria which lies in the heart of the tropics on the west coast of Africa [20].

Beyond malaria-weather complexity, social factors and physical conditions of the environment such as poor governance, sub-optimal health infrastructure, socioeconomic characteristics of the population, environmental conditions, poor health seeking and preventive behavior are found to drive malaria occurrence in Nigeria [20–22]. Collectively, these factors are the social determinant of health (SDH). SDH is a relatively new term in healthcare. They are "the condition in which people are born, grow, live, work and age that shape the health. Further, these conditions are shaped by the distribution of money, power, and resources at global, national, and local level" [23]. They lie outside the health sector — however, they are where health begins. Healthy People 2020 and WHO stressed the need to create social and physical environments that promotes good health for all i.e. SDG3 [24]. This can be achieved within policy-based driven approach within five key determinants. They include: Economic stability, Education, Social and Community Context, Health and Health Care, Neighborhood and Built Environment. SDH approach has been applied in malaria studies around the world [25–29]. Nevertheless, there remains paucity of studies in Nigeria which explored the impacts of SDH on malaria. More importantly, on U5 malaria in a local context.

Preventive behavior is an important driver of malaria prevalence. In Nigeria, [21,30] explored the preventive behavior — knowledge, attitudes and practices (KAP) and risk factors for malaria transmission in north and north central parts of Nigeria. Focusing on children under five years of age. [31] investigated the individual and household-level determinants of malaria infection from northwest and southern Nigeria. In the south-western part of Nigeria, most studies on malaria have been focused on malaria – weather interactions. Specifically, in Ondo State, [32] observed clinical-reported malaria cases and meteorological data across. [33] further highlighted the impact of climate change on malaria transmission in Akure, Nigeria. The study went further beyond the ambit of weather–malaria relationships and included physio-environmental factors such as distance to dumpsites. Despite these attempts to understand malaria transmission, no comprehensive study has been conducted on relationships between SDH and malaria transmission in Akure. modeling U5 malaria occurrence in Akure as a function of SDH will serve as a support tool for the fight towards malaria eradication in Nigeria. This will move the country towards good health for all as well as maintaining inclusive, safe, resilient, and sustainable city as part of the broad sustainable development goals. This study marks a landmark investigation on the complexity and impact of SDH on U5 malaria transmission in Akure.

Materials and methods

Study area

Akure is a medium-sized city in the south-western part of Nigeria (Fig. 1), comprising two Local Government Areas — LGAs (Akure South and North). The availability of tertiary education, nurturing commercial climate and the attainment of administrative capital city of Ondo State since 1976 have collectively strengthened her migration pull factors from hinterlands such as Ifedore and Idanre [34] and therefore population rise. According to the [35], the population of Akure was about 239,124 in 1991 and estimated as 353,211 in 2006. Notably, it is difficult to estimate a reliable population of Nigerian cities from census figures. The national census of 1991 encountered uncertainty, which led to underestimation of the number of inhabitants in many parts of Nigeria based on political reasons [36]. An alternative to population estimates is the augmentation of aerial imagery with limited survey data [37]. A demonstration in Nigeria is the Geographic, Population and Demographic Data project sponsored by the Bill and Melinda Gates Foundation (http://geopode.world). According to the project results, Akure is estimated to have over one million inhabitants (1, 283, 541). Among this estimated population, U5

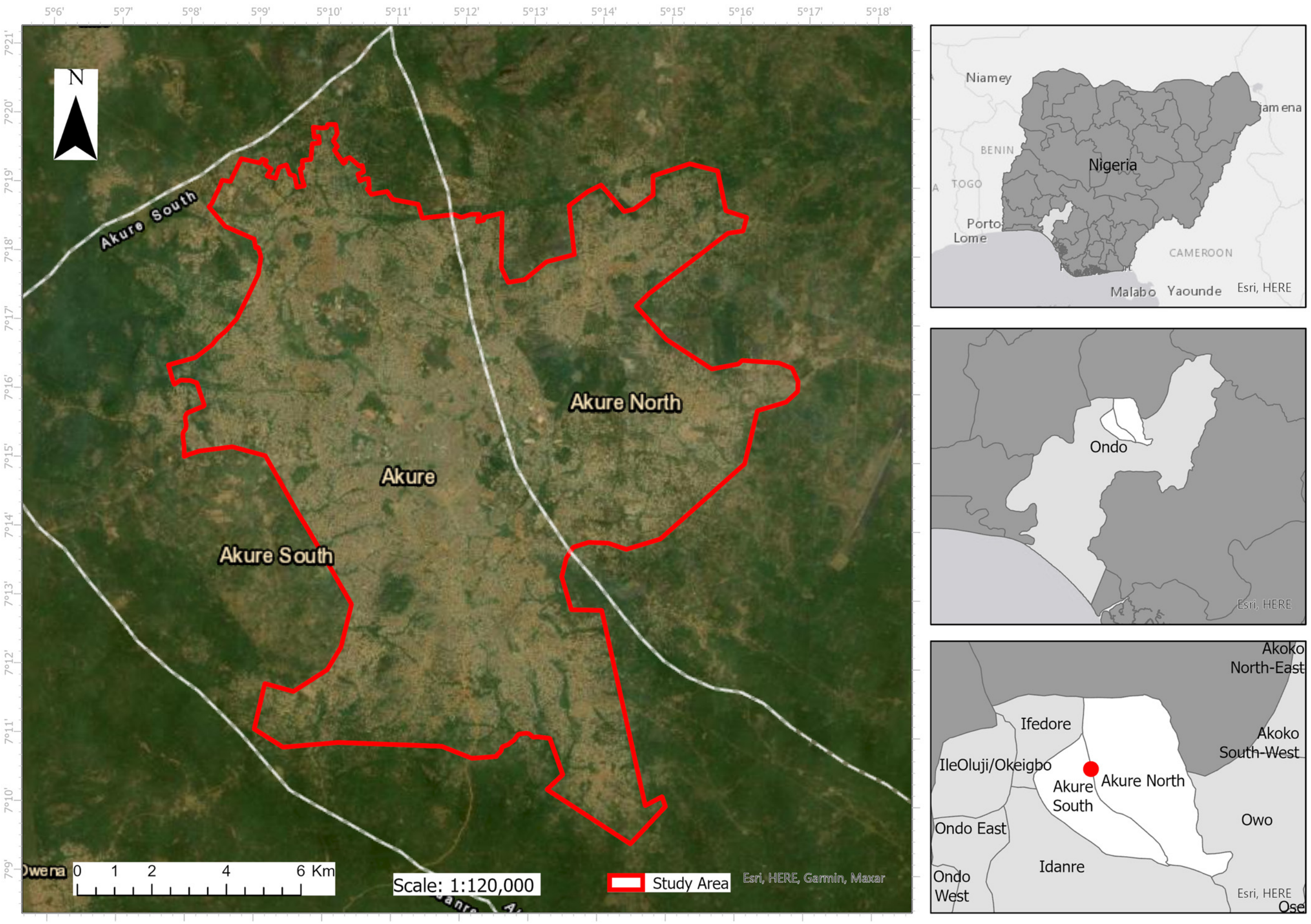

Fig. 1. Map of Akure city, Ondo State, Nigeria.

accounted for 12.7% (162,975) of the total population in Akure. This estimate was adopted for this study. The climatic and environmental condition in Akure are contributory factors to malaria infection [22,32]. Akure has two distinct seasons — that is a relatively dry season from November to March and rainy season from April to October [22]. Due to the tropical and humid climatic condition in Akure, the average annual rainfall is within the range of 1405 mm and 2400 mm, while the average minimum and maximum daily temperature of Akure are 27 C and 38 C in the wet season and 23 C and 39 C in the dry season, respectively.

Study design

This paper documents social determinants associated with childhood malaria occurrence in Akure, Nigeria. The Malaria Indicator Questionnaire (MIQ) was used to derive active malaria data. MIQ is a standardized structured survey questionnaire with wide usage in malaria studies [29]. It is a critical instrument in the absence of fine scale malaria data because of low disease reporting/documentation rate. Particularly in Akure, available malaria data from Demographic Health Information System (DHIS) lacks the crucial demographic and socioeconomic characteristics — therefore, not suitable for childhood malaria modeling. For detailed and guided dissemination of MIQ, the buildings in Akure were extracted with Artificial Intelligence methods on the Picterra platform (https://picterra.ch/geospatial-imagery-analysis). 1000 random buildings were sampled as surrogate for the study population (0.6%). The coordinates of the buildings were registered in a Global Positioning System (GPS) and each sampled house was visited. This afforded the ability to retrospectively obtain 12 months (December 2018 to November 2019) inventory of malaria burden among the study participants. Verbal informed consents were obtained from the parents or guardian before the interview was conducted. The survey took place between October and December 2019 with the help of five trained field assistant from Federal University of Technology, Akure. In the case of non-availability of household head/guardian, a matured member of the household was interviewed. The study questionnaire was reviewed and approved by institutional review board from Heidelberg University, Germany.

Malaria epidemiology variable

The epidemiological or dependent variable for this study is the occurrence of malaria among U5 children in Akure. The popular methods of malaria parasite detection in humans include the Rapid Diagnostic Tests (RDTs) and microscopy tests [28]. RDTs technique requires little technical knowhow but its parasite detection capability is low. RDTs does not detect malaria parasite itself, rather the Plasmodium falciparum specific protein [38]. This will ultimately increase the rate of malaria false positives. This makes microscopy test more reliable. To minimize the fallouts from RDTs and retrospective identification of malaria occurrence, verbal report based on obtained microscopy test, clinical test and response to malaria drugs were adopted as definition of malaria disease. To further minimize bias of comorbidities from the later, series of cross-checked questions were further engaged. This is pertinent to avoid false confirmation of other diseases that share malaria clinical symptoms as malaria. The dependent variable (presence or frequency of malaria) was categorized into two outcomes and inputted in spreadsheet. A child with presence of malaria is coded as 1, while the child with absence of malaria is coded as 0.

Malaria explanatory variables

The explanatory or independents variables regarded in this study are within the frame of SDH. They include socio-demographic characteristics (gender, age, education level of parents, ethnicity, marital status,) socioeconomic factors (employment status, income level, housing tenure, urban agriculture and livestock), preventive behavior (ownership and usage of insecticide treated bed nets - ITN, malaria vaccination knowledge), built-environmental factors (materials of building wall, floor and roof, window protection, coverage of roof eave) and environmental health factors (distance to waste disposal site, type of toilet facilities, availability and condition of drainage, street condition). These variables were grouped into different sections fashioned after [28]. This is similar to the criteria for environmental health in Riskedas 2013 (joint monitoring program World Health Organization – the United Nations Children's Fund criteria). These broad determinants were obtained with the MIQ created in English language. In situation whereby the respondents do not understand English, the interview was conducted in Yoruba language. This is possible because the interviewee (field assistants) understands the native Yoruba language of Akure residents. The independents variables were transformed to categorical variables. The inputted data in spreadsheet were double checked to enhance data cleansing. All the response was converted into dummy variable for U5 malaria modeling.

Statistical data analysis

The obtained data were processed in R statistical programming (R version 3.6.3) and significant associations have been measured at 5% alpha level ($p < 0.05$). Both bivariate and multivariable statistical analyses were conducted. Bivariate analysis such as Chi-square ($\chi 2$) and Fisher's exact test were utilised to determine significant dependence between the categorical independent variables and U5 malaria outcomes. This connotes the first stage of variable selection for statistical model building as demonstrated in the works of [25,39,40]. The dependent variables with significant relationship with malaria outcomes were selected for the development of bivariate and multivariate regression models. Since the dependent variable is binary, the binary logistics regression model was further engaged. Logistics regression is an extension of generalized linear model (GLM) with capabilities to explore the nexus between a binary response variable and collection of explanatory variables [38]. In multivariable analysis, it is important to find a parsimonious model. To unravel this, backward elimination based on Schwartz's Bayesian information criterion (BIC) with coefficient to the log of the sample size (k=log(n)) as described by [41] was carried out. It is a stepwise iterative process of removal of non-significant variables ($P > 0.05$) until the sample sized (k) is reached. The results of the bivariate and multivariate logistics regression were presented in Odds Ratio (OR) and adjusted Odds Ratio (aOR) respectively. These ratios represent the magnitude of malaria risk. OR, which is also known as crude odds ratio represents the likelihood of an event when other variables are not taken into consideration. The adjusted OR, which is also known as the conditional odds ratio are presented when controlling for other confounders. The likelihood of contracting malaria increases when the OR is higher than one (OR > 1). In situation when the OR is lesser than 1 (OR < 1), the chance of having malaria reduces. All results were presented with 95% confidence interval. This suggests certainty range of the generated results.

Results

Prevalence of malaria

The percentage of valid response for our analysis is about 60% ($n = 568$) having purged for all forms of malaria misconstrued status. The obtained relatively low value is because we do not have a prior knowledge of buildings with U5 children. The association between malaria prevalence and social determinants of health is represented in Table 1 . It is a summary statistic to gain first insights and familiarize oneself with the dataset. Comparatively, the prevalence of malaria is higher among the male children (54.5%) compared to female children (45.5%). Nonetheless, malaria prevalence increases with increasing age of the children in the study population. The children below 11 months constituted 5.3%; between 12 and 23 months make up 18.9% and children above 24 months shared above 20% each of U5 malaria prevalence. Children of married parents shared most (88.8%) of the malaria burden in relation to other marital status bracket. However, irrespective of the marital status of the parents, children whose father and mother are from the *Yoruba* tribe had 89% and 84.6% of malaria prevalence, respectively. Akure being a south-western city, the major tribe is Yoruba. The education level among parents' sex in Akure vary as shown in table (1). While the men are more educated, malaria prevalence increases with education level of the father. The children whose father has a tertiary education shared 53% of malaria burden followed by secondary education (23.5%), Apprentice (18%), primary education (4.2%) and no education (1.3%). In respect to education of mother, children whose mother had secondary education shared 40.2%, followed by tertiary education (25.5%), apprentice (21.1%), primary education (8.6%) and no education (4.6%). Apparently, most of Akure residents work in informal sector. The prevalence of U5malaria is highest (60.7%) among children whose father works in informal sector. This is followed by formal sector (36.7%), others (1.5%) and 1.1% for unemployed. In a similar vein and in respect to mothers, informal sector constituted 74.3%, formal sector (19.6%), unemployed (5.9%) and others (0.2%). Comparatively, children from poor household contacted malaria more. From table (1), poor household that collects less than ₦50,000 are attributed with almost 50% of U5 malaria prevalence. Household income between ₦50,000 to ₦100,000 associates with 24% of U5 malaria burden, while 29.2% of children who contracted malaria were from household whose income is more than ₦100,000. The usage of Insecticide Treated Net (ITN) appeared to be an important tool to control malaria. However, some households do not use ITN despite its availability. 54.5% of children who owned ITN had malaria while children who does not use ITN shared 65.3% of malaria burden. Apparently, allocation of ITN is the major ways of acquiring ITN. Most of the households (85.1%) got their ITN through mass distribution, while few about 8.4% got it through antenatal care visit. Approximately, 55.6% of U5 children from locality with available health infrastructure had malaria and 44.4% did not. Our study reveals a higher prevalence of U5 malaria among households whose major source of drinking water is the dug well. Those whose water source is piped water makes up 32.3%, surface water (0.9%) and others (14.1%). The category of others includes those who purchase sachet water and vendor services. However, most (95.4%) of household with covered water storage container had malaria and 4.6% did not. The coverage of drainage channel is also an essential element to be considered as malaria transmission factors. From our study, Akure operates open drainage system – as such, 84.4% U5 with open drainage contacted malaria while about 20% with closed drainage contacted malaria. Over the years, and being a capital city, the standard of living and development in Akure has improved. Most households had a toilet facility. U5 from household with flush toilet had highest (80.2%) prevalence of malaria, followed by pit latrine (16.3%); bucket toilet (2.9%) and no facility (0.7%).

In a similar vein, pick up service for waste by the waste management institutions has improved. Nevertheless, 53% of U5 from households that benefits from pick up service had malaria. This is followed by burning (29.9%); vacant plot (15.6%); moving water body (1.3%) and others (0.2%). Furthermore, our study reveals higher prevalence (67.5%) of malaria prevalence among U5 whose waste disposal point is greater than 10 metres from dwelling unit, while less than 10 metres constituted 32.5%. As regarding routine check by town planners, almost 60% of U5 who had malaria fell into the category of residents who are not sure if there is routine check. The emergence of some sort of agricultural practice in Akure is gradually gaining momentum. Among household with presence of livestock, 35.6% U5 had malaria, while 64.4% with no presence of livestock. This phenomenon is synonymous with urban agricultural (UA) practice. The prevalence of U5 malaria among household that practice UA is 29% and 71% with households with no UA practices. Comparatively, more of the sampled houses are self-

Table 1
Distribution of the social determinants of U5 malaria prevalence.

Research variables	No. examined (%)	U5 malaria prevalence (%)	P value
Socio-demographic			
Child Sex			0.945
Female	258 (45.4%)	207 (45.5%)	
Male	310 (54.6%)	248 (54.5%)	
Age range			< 0.001
< 1year	43 (7.6%)	24 (5.3%)	
1–2 years	102 (18.0%)	86 (18.9%)	
2–3 years	120 (21.1%)	103 (22.6%)	
3–4 years	134 (23.6%)	114 (25.1%)	
4–5 years	169 (29.8%)	128 (28.1%)	
Marital status			0.389
Divorced	12 (2.1%)	12 (2.6%)	
Married	506 (89.1%)	404 (88.8%)	
Separated	23 (4.0%)	19 (4.2%)	
Single	21 (3.7%)	15 (3.3%)	
Widowed	6 (1.1%)	5 (1.1%)	
Ethnicity of father			0.354
Hausa	8 (1.4%)	7 (1.5%)	
Igbo	39 (6.9%)	32 (7.0%)	
Others	11 (1.9%)	11 (2.4%)	
yoruba	510 (89.8%)	405 (89.0%)	
Ethnicity of mother			0.112
Hausa	9 (1.6%)	9 (2.0%)	
Igbo	59 (10.4%)	49 (10.8%)	
Others	12 (2.1%)	12 (2.6%)	
yoruba	488 (85.9%)	385 (84.6%)	
Education of father			0.047
Apprentice	104 (18.3%)	82 (18.0%)	
No education	8 (1.4%)	6 (1.3%)	
Primary	20 (3.5%)	19 (4.2%)	
Secondary	122 (21.5%)	107 (23.5%)	
Tertiary	314 (55.3%)	241 (53.0%)	
Education of mother			0.055
Apprentice	123 (21.7%)	96 (21.1%)	
No education	24 (4.2%)	21 (4.6%)	
Primary	44 (7.7%)	39 (8.6%)	
Secondary	219 (38.6%)	183 (40.2%)	
Tertiary	158 (27.8%)	116 (25.5%)	
Employment of father			0.131
Formal sector	220 (38.7%)	167 (36.7%)	
Informal sector	331 (58.3%)	276 (60.7%)	
Others	10 (1.8%)	7 (1.5%)	
Unemployed	7 (1.2%)	5 (1.1%)	
Employment of mother			0.005
Formal sector	125 (22.0%)	89 (19.6%)	
Informal sector	409 (72.0%)	338 (74.3%)	
Others	3 (0.5%)	1 (0.2%)	
Unemployed	31 (5.5%)	27 (5.9%)	
Household income			0.334
< ₦20,000	47 (8.3%)	38 (8.4%)	
₦20,000 - ₦50,000	213 (37.5%)	175 (38.5%)	
₦50,000 - ₦100,000	133 (23.4%)	109 (24.0%)	
₦100,000 - ₦150,000	90 (15.8%)	72 (15.8%)	
> ₦150,000	85 (15.0%)	61 (13.4%)	
Preventive behavior			
ITN Ownership			< 0.001
No	234 (41.2%)	207 (45.5%)	
Yes	334 (58.8%)	248 (54.5%)	
ITN Usage			< 0.001
No	341 (60.0%)	297 (65.3%)	
Yes	227 (40.0%)	158 (34.7%)	
ITN Acquisition			0.091
Antenatal care visit	54 (9.5%)	38 (8.4%)	
Mass distribution	473 (83.3%)	387 (85.1%)	
Other	20 (3.5%)	16 (3.5%)	
Postnatal care visit	21 (3.7%)	14 (3.1%)	
Availability of health infrastructure			0.025
No	239 (42.1%)	202 (44.4%)	
Yes	329 (57.9%)	253 (55.6%)	

(*continued on next page*)

Table 1 (*continued*)

Research variables	No. examined (%)	U5 malaria prevalence (%)	P value
Environmental health			
Drinking water source			< 0.001
Dug well	275 (48.4%)	240 (52.7%)	
Other	86(15.1%)	68 (14.9%)	
Piped water	207 (36.4%)	147 (32.3%)	
Household water storage covered			0.066
No	22 (3.9%)	21 (4.6%)	
Yes	546 (96.1%)	434 (95.4%)	
Drainage Covered			0.753
No	478 (84.2%)	384 (84.4%)	
Yes	90 (15.8%)	71 (15.6%)	
Toilet Facility			0.205
Bucket toilet	13 (2.3%)	13 (2.9%)	
Flush toilet	462 (81.3%)	365 (80.2%)	
No facility	3 (0.5%)	3 (0.7%)	
Pit laterine	90 (15.8%)	74 (16.3%)	
Mode of waste disposal			0.571
Burning	170 (29.9%)	136 (29.9%)	
Moving water body	6 (1.1%)	6 (1.3%)	
Others	2 (0.4%)	1 (0.2%)	
Pick up	299 (52.6%)	241 (53.0%)	
Vacant plot	91 (16.0%)	71 (15.6%)	
Distance to waste disposal site			0.007
< 10 metres	170 (29.9%)	148 (32.5%)	
> 10 metres	398 (70.1%)	307 (67.5%)	
Routine check by Town planners			0.086
I dont know	348 (61.3%)	271 (59.6%)	
Never	147 (25.9%)	119 (26.2%)	
Quarterly	34 (6.0%)	28 (6.2%)	
Yearly	39 (6.9%)	37 (8.1%)	
Presence of livestock			0.568
No	369 (65.0%)	293 (64.4%)	
Yes	199 (35.0%)	162 (35.6%)	
Urban agriculture practice			0.278
No	409 (72.0%)	323 (71.0%)	
Yes	159 (28.0%)	132 (29.0%)	
Physio/built environment			
Housing tenure			0.755
Tenantship	264 (46.5%)	210 (46.2%)	
Self owned	304 (53.5%)	245 (53.8%)	
Roof eave covered			0.634
No	68 (12.0%)	53 (11.6%)	
Yes	500 (88.0%)	402 (88.4%)	
Window protection			< 0.001
No	181 (31.9%)	164 (36.0%)	
Yes	387 (68.1%)	291 (64.0%)	
Roof materials			0.276
Finished	491 (86.4%)	389 (85.5%)	
Natural	4 (0.7%)	4 (0.9%)	
Others	2 (0.4%)	1 (0.2%)	
Rudimentary	71 (12.5%)	61 (13.4%)	
Wall materials			0.033
Finished wall	506 (89.1%)	399 (87.7%)	
Rudimentary walls	62 (10.9%)	56 (12.3%)	
Floor materials			0.346
Finished floor	509 (89.6%)	405 (89.0%)	
Rudimentary floor	59 (10.4%)	50 (11.0%)	
Street condition			0.004
Bad	478 (84.2%)	393 (86.4%)	
Good	90 (15.8%)	62 (13.6%)	

owned, among which 53.8% of U5 had malaria, while the guardian/parents of 46.2% U5 had malaria. 88.4% of U5 who had malaria lives in houses with uncovered roof eave while 11.6% lives in covered roof eave. Regarding the protection from house elements such as window. Prevalence of U5 malaria is 64% with homes with window protection and 36% with homes with no window protection. Most building in Akure are made of non-rudimentary building materials. Particularly, prevalence of U5 malaria is about 86% with houses with modern roof materials. In a similar vein, almost 88% and 89% are respectively

Table 2
Bivariate and multivariable logistics regression model on social determinants of U5 malaria.

Research variables	Bivariate model Odds Ratio (95%CI)	Multivariate model Adjusted OR (95%CI)
Age of Children (months)		
< 11	Ref	Ref
12–23	4.26*** (0.65 – 2.27)	3.20*** (0.29 - 2.05)
24–35	4.80*** (0.78 – 2.37)	3.66*** (0.43 – 2.18)
36–47	4.51*** (0.74 – 2.28)	3.65*** (0.45 – 2.14)
48–59	2.47** (0.20 – 1.60)	1.56 (−0.3 – 1.22)
ITN Usage		
Yes	Ref	Ref
No	2.95*** (0.66 – 1.51)	3.09*** (0.67 – 1.59)
Health Infrastructure		
Yes	Ref	Ref
No	1.64** (0.07 – 0.94)	1.84** (0.13 – 1.10)
Source of drinking water		
Piped	Ref	Ref
Dug well	1.82* (−0.05 – 1.22)	2.54*** (0.42 – 1.46)
Others	0.65 (−1.05 – 0.15)	1.83* (−0.05 – 1.29)
Window Protection		
Yes	Ref	Ref
No	3.18*** (0.63 – 1.74)	2.44*** (0.32 – 1.51)
Distance to Waste disposal point		
< 10 metres	1.99*** (0.20 – 1.22)	2.11 *** (0.21 – 1.32)
> 10 metres	Ref	Ref

*$p<0.1$; **$p<0.05$; ***$p<0.01$.

associated with modern wall and floor materials. In our study, the street condition was also considered. Prevalence of U5 malaria is higher (86.4%) with bad street condition compared to good condition (13.6%).

Risk factors associated with U5 malaria

Table 2 represents the logistic regression modeling results of the social factors influencing the prevalence of U5 malaria in Akure. Broadly, variables of socio-demographic characteristics (age of the children); preventive behavior (mosquito bed net usage - ITN); environmental health (availability of health infrastructure, source of drinking water and distance to waste disposal point) and built-environment (window protection) were observed as significant determinants of U5 malaria by the *generalised linear model* with effects directly predicted in both odds ratio and adjusted odds ratio. According to our findings, the children between the ages 12 – 47 months are particularly susceptible to malaria compared to children below 11 months. A child between 12 and 23 months (aOR = 3.20; 95% CI = 0.29 –2.05), between 23 – 35 months (aOR = 3.66; 95% CI = 0.43 – 2.18) and 36 – 47 months (aOR = 3.65; 95% CI = 0.45 – 2.14) are each 3 times more likely to have malaria than children below the age of 1 year. Furthermore, the children who do not frequently use insecticide treated bed net (ITN) are prone to having malaria. The children in this category are 3.09 times more likely to have malaria (aOR = 3.09; 95% CI = 0.67- 1.59) compared to the children in the usage group.

The likelihood of having malaria is 1.86 times more when there is no available health infrastructure within the neighbourhood (aOR = 1.84; 95% CI = 0.13 – 1.10) unlike when there is availability of health infrastructure. The analysis of the odds ratio demonstrated that households whose source of drinking water is dug well are 2.54 times more likely to have malaria (aOR = 2.54; 95% CI = 0.42 – 1.46) compared to household with piped/tap water. Similarly, household with other sources of drinking water such as purchase of sachet water or vendor are 1.83 times more likely to have malaria (aOR = 1.83; 95% CI = −0.05 – 1.29). It was also discovered that children in houses with broken or vector-proofed windows are 2.44 times more likely to have malaria (aOR = 2.44; 95% CI = 0.32 – 1.51) compared to windows in good condition.

Discussion

Eradication of malaria has been on the agenda of global health actors for decades. Undoubtedly, the global and scientific health communities have made tremendous achievements toward these specific goals at all levels of organization. However, the quest is inundated with challenges which have slowed down the progress in some regions of the world like Nigeria for example. As a result, the need for continuous examination on ways to reduce the burden of malaria in Nigeria is paramount. More so, malaria occurrence is complex with varying interplay of factors in different places and regions of the world [25]. This peculiarity suggests that effective policies and interventions in a particular place might under-perform in other places.

Based on the result of this study, age of children is a significant predictor of U5 malaria. The risk of malaria increases with increasing age among the participants compared to children below 11 months (<1 year). In the multivariate model, children between 48 and 59 months are however not significant. The studies of [40,42] conducted in Malawi and Ethiopia both found age as significant predictor of U5 malaria respectively. This is also in accordance to the study of [38] in Uganda.

What is however common about this study is the un-stratification of the children's age. The high prevalence found among children above 12 months might be because of the reduced transferred passive immunity from mother to child. According to [43], this protective mechanism actsas a buffer in the first half year of life, which fizzle out afterwards. Another reason could be attitudinal visit of the mother to the hospital. In Akure, pre and postnatal care are free. During this stage, mothers visit the hospital regularly thereby getting information and necessary aid on how to prevent their babies from mosquito bites. In most cases, they receive bed nets as shown in the study that exiguous 3.5% did not freely acquire their bed nets. Mosquito bed net (ITN) has been reported as effective measures to control the transmission of malaria in SSA [29]. This is made possible through the reduction of vector-human interaction, thereby limiting the number of mosquito bites. The higher the exposure of individuals to mosquito bites per day, the higher the likelihood of malaria infection [44]. Accordingly, this study showed that the relative risk of malaria was higher among U5 children that rarely use ITN compared the usage group. This is similar to earlier studies of [21,25,39,42,45], which collectively substantiated ITN as preventive measure against malaria among U5 children. Several reasons impel the non-usage of ITN which include but not limited to non-availability of ITN, lack of purchasing power, discomfort, and poor health education. These determinants are as well influenced by the availability of health care infrastructure, accessibility to media and improved malaria knowledge. Availability and access to health infrastructure is important to population health. In SSA, malaria transmission is purported to be determined by knowledge of and access to healthcare services [46,47]. The availability of healthcare service significantly influence care-seeking behavior of individuals in formal healthcare sectors [48]. This study revealed fold increase of malaria risk among U5 in households with available healthcare facility in their district. This is consistent with previous study in India [28], where malaria risk was predicted by availability of healthcare facilities. This however sets a draw back on the knowledge of malaria prevention and treatment such as the proper usage of ITN and administered drugs. Another reason might be because non-awareness of healthcare service in a district increases the distance to healthcare facility of choice located in another district. [25] asserted that proximity to healthcare facility would increase the knowledge of individuals about malaria as they interact with health staff frequently. Additional malaria control supplement to ITN usage is window screening and protection. Window screening, ceilings and closed eaves have been deemed as sustainable measure of malaria control in SSA [49,50] further argued the cost-effectiveness of mosquito-proofed housing over the usage of ITN. When it is permanently fixed, it prevents exposure from all other types of vectors. In our study, we observed that households with poorly screened windows experience higher episodes of malaria, which is in accordance to the studies of [51,52]. One of the characteristics of jerry-built houses are broken or poorly screened windows. Intuitively in Akure, the health impact of such houses should be minimal as they are expected to be clustered in a minor (core) part of the city. [53] stressed the proliferation of substandard 'modern buildings' in Akure. Such buildings are characterized with poor drainage and sewage system, lack of portable water and poor sanitation. Water, sanitation, and hygiene has been alluded to be critical to healthy living [1]. The intricate relationships between access to portable water and malaria was shown in our study — U5 malaria risk increases greatly in household whose source of drinking water is dug-well compared to piped water. This is in accordance to the recent and holistic study of [54]. Good water informs good nutrition which enhance disease resistance among U5 children. Furthermore, the likelihood of open dug well is high among the residents of Akure. As countries in SSA are experiencing rapid urbanization, the increased and poor management of solid waste are now of consequential environmental and health concern [55,56]. Interestingly in this study, the odds of U5 malaria were higher among households with less than 10 m to waste disposal point. The findings support the arguments of [57,58] on health impacts of waste disposal practice in Nigeria. According to this study, the increased vulnerability may be because waste disposal points are breeding sites for vector and pull factors for rodents. Additionally, the illegal and indiscriminate usage of nearby bush or drainage as informal waste disposal point are common in Akure. This contributes to the poor sanitary condition of the environment.

Conclusion

The effective monitoring, evaluation and eradication of malaria cannot be actualised without understanding the determinants of malaria. This study shows the importance, and effect of non-medical factors on the prevalence of U5 malaria in Akure. Results of the analysis carried out on these determinants show that: age of children, mosquito bed net usage, availability of health infrastructure, window screening, source of drinking water and distance to waste disposal point are significant predictors of malaria among U5 children. Therefore, intervention towards these predictors is necessary to achieve the target goals within the broad frame of sustainable development goals 3 and 11. For example, there is need for more commitment towards wider coverage of ITN, reinforced with quality dissemination of information on its proper usage. This can be achieved with improved accessibility to health care infrastructure. Such accessibility should address the salient issues of un-marginalised distribution of such critical infrastructure. Furthermore, the health gains from good drinking water are beyond reduced malaria risk but also the prevention of other allied illness that shares symptoms with malaria such as diarrhea and anemia. Beyond doubt, the need for coordinated synergy between public health and town planning boards at a local level is much needed than ever before in this epoch of rapid urbanization. The health challenges of the 21st century has shown outrightly that Town planners are not pseudo-health experts, but De-facto health professionals. Therefore, the overlaps and effect of housing characteristics on health outcomes should not be addressed with triviality — as it is paramount to improving the household living condition. Succinctly, the identified factors serve as tools in the arsenal toolbox to combat malaria in Akure. This will go a long way to improving the wellbeing of the residents with associated ripple effect on the national development of Nigeria as well.

Limitations

This study is fraught with challenges which includes the following: The study design is cross-sectional in approach, thereby posing a drawback on the ability to investigate the incidence of U5 malaria in Akure. Nonetheless, we examined the burden of U5 malaria. During this examination, we took 12 months inventory of malaria burden among the study participants. This may be subject to recall bias from the participants. Another limitation is that place of residence (rural vs urban) was not accounted for. This is not a comparative study, however, several studies suggested that the prevalence of malaria is higher in rural places compared to urban places [39,59,60]. Being a study conducted solely in Akure (urban), the level of urbanity can serve as surrogate for residence classification like in the study of [61]. In the further analysis of U5 malaria in Akure, this can be assessed with geographical and environmental covariates such as temperature, altitude, water bodies, vegetation and spatial structure using spatial modeling techniques for optimization of place-based interventions.

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Declaration of Competing interest

The authors declare that they have no conflicts of interest.

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Name, first name	Taye Bayode	Alexander Siegmund	
Methodology	[x]	[ ]	[ ]
Software	[x]	[ ]	[ ]
Validation	[ ]	[ ]	[ ]
Formal analysis	[x]	[ ]	[ ]
Investigation	[x]	[ ]	[ ]
Resources	[x]	[x]	[ ]
Data Curation	[x]	[ ]	[ ]
Writing-Original Draft	[x]	[ ]	[ ]
Writing-Review&Editing	[x]	[x]	[ ]
Visualization	[x]	[ ]	[ ]
Supervision	[ ]	[x]	[ ]
Project administration	[x]	[x]	[ ]
Funding acquisition	[x]	[x]	[ ]

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Prof. Dr. Alexander Siegmund		23.01.2025
Name/*Name*	Unterschrift/*Signature*	Datum/*Date*

“The goal of the agenda for action on global health is clear: to reduce the number of people, particularly children, dying unnecessarily from ill-health and disease.”

~ Aileen Carroll

II.3 Identifying childhood malaria hotspots and risk factors in a Nigerian city using geostatistical modelling approach.

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Identifying childhood malaria hotspots and risk factors in a Nigerian city using geostatistical modelling approach

Taye Bayode[1,2]✉ & Alexander Siegmund[1,2]

Malaria ranks high among prevalent and ravaging infectious diseases in sub-Saharan Africa (SSA). The negative impacts, disease burden, and risk are higher among children and pregnant women as part of the most vulnerable groups to malaria in Nigeria. However, the burden of malaria is not even in space and time. This study explores the spatial variability of malaria prevalence among children under five years (U5) in medium-sized rapidly growing city of Akure, Nigeria using model-based geostatistical modeling (MBG) technique to predict U5 malaria burden at a 100 × 100 m grid, while the parameter estimation was done using Monte Carlo maximum likelihood method. The non-spatial logistic regression model shows that U5 malaria prevalence is significantly influenced by the usage of insecticide-treated nets—ITNs, window protection, and water source. Furthermore, the MBG model shows predicted U5 malaria prevalence in Akure is greater than 35% at certain locations while we were able to ascertain places with U5 prevalence > 10% (i.e. hotspots) using exceedance probability modelling which is a vital tool for policy development. The map provides place-based evidence on the spatial variation of U5 malaria in Akure, and direction on where intensified interventions are crucial for the reduction of U5 malaria burden and improvement of urban health in Akure, Nigeria.

Keywords Urban health, Spatial variability, Childhood malaria, Geostatistics, Exceedance probability

Abbreviations

AIC	Akaike information criterion
EP	Exceedance probability
ITN	Insecticide-treated nets
MBG	Model-based Geostatistics
MCML	Monte Carlo maximum likelihood
MIQ	Malaria Indicator Questionnaire
MIS	Malaria Indicator Survey
NMSP	National Malaria Strategic Plan
OR	Odds ratio
SES	Socio-economic status
SDH	Social determinants of health
SGLMMs	Spatial generalised linear mixed models
SSA	Sub-Saharan Africa
U5	Children under five years
VIF	Variance Inflation Factor
WHO	World Health Organization

Infectious disease like malaria has been a public health burden for generations. Though there have been tremendous advances in its management and treatment, but the public health challenge still lingers. According to the recent World Malaria Report[1] progress towards fighting malaria is being stalled as there was an increase

[1]Institute of Geography & Heidelberg Centre for Environment (HCE), Heidelberg University, Heidelberg, Germany. [2]Department of Geography-Research Group for Earth Observation (rgeo), UNESCO Chair on World Heritage and Biosphere Reserve Observation and Education, Heidelberg University of Education, Heidelberg, Germany. ✉email: bayode@stud.uni-heidelberg.de

in malaria cases for the second consecutive year. However, some improvement of 1% fewer malaria-related deaths were recorded in 2021. In 2018, Sub-Saharan Africa (SSA) accounted for 94% of global malaria deaths. Furthermore, children under the age of five (U5) accounted for 70% of malaria-related mortality in the SSA region[2,3]. An increase to 96% of malaria-related death is recorded in WHO African Region in 2021, and the top 16 malaria-affected countries are all situated in SSA. While pregnant women are at heightened malaria exposure risk, about 80% of malaria deaths were from U5 in WHO African Region[1].

From these worrisome malaria burden statistics, Nigeria takes a large share of the global numbers. In 2021, Nigeria accounted for about 26.6% of malaria cases and 31.3% of malaria-related deaths globally[1]. Descriptively, this amounts to over 50 million and 100,000 of malaria cases and deaths respectively in Nigeria. As averred by[4,5], about 60% of outpatient hospital visits can be attributed to malaria in Nigeria. In Nigeria, U5 children are the most vulnerable group—they experience about an average of 2–4 bouts per year, and account for about 90% of national mortality from malaria[6]. Furthermore, Nigeria accounted for 38.4% of global malaria deaths in children under five[1]. In case of severe type of malaria, comorbidity such as anaemia, respiratory distress and prostration can be experience by the child[6].

Coupled with the recent slow progress in malaria reduction in SSA, the recent global pandemic—coronavirus disease (COVID-19)—has further contributed to the interruption of malaria control undertakings in malaria endemic regions of the world. Park et al.[7] reported the high levels of surfeit malaria morbidity and mortality in Low and Middle Income Countries (LMICs), which could be attributed to poor community engagement and limited malaria tests. For example, the work of Ilesanmi, Afolabi and Iyiola[8] identifies limited acquisition of malaria tests to healthcare providers as a barrier against visiting health facilities. This could have been because of less funding going towards malaria control because of COVID-19[8]. Thus, the pandemic worsened the healthcare problems such as already weak health systems, ineffective and inefficient health management, and inequitable distribution of human resources between urban and rural areas in Nigeria identified by[9].

This study sets out to estimate the burden of U5 malaria and variability in the rapidly urbanising medium-sized city of Akure. Overcrowding, environmental degradation, and likely substantial increase in malaria transmission are challenges of rapidly urbanising areas or places in Nigeria such as Akure[10,11]. In Nigeria, small or fine scale (e.g. cities) level variations in the burden of malaria and malaria risk factors are not yet sufficiently understood. National or regional-level surveys may not capture intra-urban specific characteristics and risks of malaria burden[10]. Furthermore, national or regional surveys may miss out on adequate sample sizes or tilt to those who use public health facilities and largely exclude socioeconomic data, behaviours, and a well-defined catchment population[12]. Some studies have explored the risk factors of malaria in Nigeria, however, mostly with the use of descriptive and regression statistical techniques to assess a combination of data from blood testing and questionnaires[13,14]. A few studies have attempted spatial risk analyses of malaria in Nigeria. For example, using Kriging to develop predictive risk factor maps,[15] assessed the spatial distribution and socio-demographic risk factors of U5 malaria in Nigeria. A close attempt at spatial statistical modelling of malaria incidence and hotspots was made by[16]. These authors used Moran's diagram, index of local Moran's I, and spatial regression models to conduct a spatiotemporal analysis of the association between malaria incidence and environmental predictors in Nigeria. In particular[17], applied Bayesian geostatistical technique to model malaria risk in Nigeria using malaria indicator survey (MIS) data and environmental/climatic data. These studies have all been done at national level which could mask small/local scale spatial variation. Hence, there is sparse use of spatial predictive modelling and the development of probability models with certainty levels to guide the deployment of limited public health resources at sub-national scales in Nigeria which is one of the vital applications of Model-Based Geostatistics (MBG). MBG is a known risk mapping approach which provides robust information on the spatial distribution of infections and facilitates the design and implementation of intervention or control programmes[18]. In addition, MBG modelling method have the capacity to deliver expected precision result for improved decision-making[19]. According to literatures, Model-Based Geostatistics (MBG) is considered as well-established statistical tool for modelling spatial correlation generated by unmeasured risk factors to predict disease prevalence in location of interest or investigation[20,21]. MBG is a principled likelihood-based approach with effective applicability in low resource settings and places characterised with incomplete or non-existent disease registries. With MBG, it is possible to provide probability metrics or quantification for pragmatic policy relevant thresholds. Furthermore, MBG allows for quantification of uncertainty and intrinsic variability in small area predictions[22]. Hence, our assessment is sacrosanct and provides city-level information that contributes to understanding specific characteristics of the area (place) and the people (residents) of such places. Till date and to the authors knowledge, no known works have used MBG explicitly to model the fine scale spatial variation of malaria risk and estimation particularly in Nigeria. Our study aims to fill this gap with the aim of identifying U5 malaria prevalence hotspots while considering the social determinants of malaria which are often not available because of incomplete or lack of health registry especially when local scale is concerned. Our study is significant in supporting public health planning by unveiling areas of high malaria prevalence and associated risk factors. This will lead to allocating already scarce resources necessary to reduce malaria's burden in malaria hotspots.

We recognise that spatial dimensions are crucial when managing infectious diseases. Also, as countries are experiencing a reduction in malaria burden, spatial targeting of the disease control efforts towards malaria risk factors and high-risk locations, which our study supports, is pertinent. Identifying hotspots based on the level of certainty and uncertainty, which the MBG affords us, increases our findings' usefulness for further research, health policy formulation, decision-making, resource planning, allocation, and implementation. Specific gains include the distribution of limited health resources in particular places where they are most required. We expect that our study will create the needed awareness of using MBG in disease modelling for resource-scarce regions to identify disease hotspots and probability levels for increased attention.

Methods

Study setting

The study area, Akure is a medium-sized rapidly urbanising city of Ondo State, which is one of the south-western states of Nigeria as shown in Fig. 1. The fusion of two Local Government Areas (LGA)—Akure North and Akure South—makes up Akure. Since the city became the capital of Ondo State in 1976, several other factors such as being the seat of government, home to the Federal-government owned tertiary institutions such as University of Technology and a College of Agriculture, well-connected transportation routes with proximity to Idanre Hills (a famous tourist centre), have collectively attributed to making Akure the most populated and developed city in Ondo State.

According to (*Population and Housing Census 2006*, n.d.), the population of Akure increased from 239,124 in 1991 to 353,211 in 2006[23]. Since the 2006 census is not reliable[24], we adopted a practical and reliable estimation from the place-based Geographic, Population and Demographic Data project (https://geopode.world). Based on derived estimate, the city has over one million residents (1,283,541). From the estimate, U5 comprises of about 12% (162,975) of the estimated population. Akure like Ondo State lies in the tropics which is characterised with humid and derived savanna agroecological zones; dry and wet seasons climate[25] making it a perfect condition for the propagation of vectors (mosquitoes) and transmission of malaria.

Epidemiologic data and explanatory variables

Epidemiologic data (U5 malaria) for this study was obtained with the aid of a Malaria Indicator Questionnaire (MIQ). U5 malaria was determined by a verbal report based on obtained microscopy/clinical test from health centres/laboratories and response to malaria prescribed treatment. We strictly adopted combinations of these two criteria to reduce our bias about the definition of malaria since we do not have the ethical right, qualification, and skills to carry out malaria test on our study participants. To further reduce bias in our studies, cross-checked questions were included. The purpose of some of these questions is to limit the chances of false confirmation of diseases with similar malaria symptoms according to the studies of[26,27]. Furthermore, the MIQ was utilised to capture malaria explanatory variables within the frame of social determinants of health (SDH) similar to the study of[28]. The considered SDH variables are within the scope of socio-demographic characteristics (child sex, child age, ethnicity etc.); socioeconomic characteristics (household income, father's education, mother's education etc.); preventive behaviour (insecticide-treated bednets—ITN, availability of health infrastructure etc.); built-environmental factors (Window protection, covered roof eaves etc.); and the environmental health factors (drainage condition and covering, toilet facility, proximity to waste disposal point etc.). The considered variables

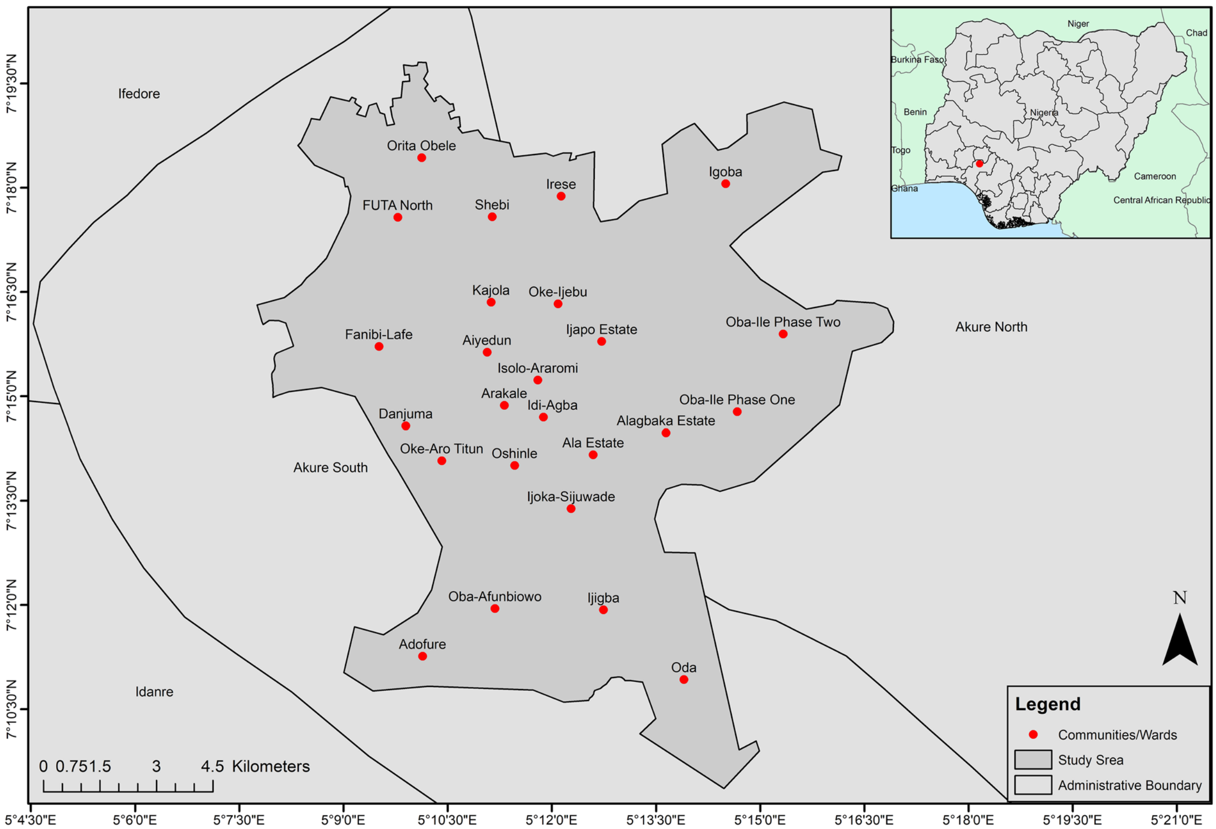

Figure 1. The city of Akure and communities in national context. (Note: The map was drawn by the author with ArcGIS 10.4.1, Esri Inc, http://ww.esri.com. The Nigeria administrative boundaries were gotten from https://datacatalog.worldbank.org/search/dataset/0039368; the boundaries for other countries were gotten from https://datacatalog.worldbank.org/search/dataset/0038272/World-Bank-Official-Boundaries).

for the analysis were determined after considering the extensive works of[28–30]. MIQ is known to be effective in places of low disease reporting rate and paucity of malaria data[29,31].

Sample size and sampling technique

In most cases, available secondary malaria data from hospital visits lack the important characteristics (socio-economic status (SES) and sociodemographic) and absolute spatial reference (coordinates) thereby making such data unsuitable for our study objectives. These peculiarities are prevalent in SSA particularly in local settings/scale and Akure is no exception. To deal with this challenge, we randomly sampled 1000 buildings like in the study of[32], with the hope that we would be able to obtain about 600 valid study participants. The estimation of Nigeria's population, particularly children below the age of five, poses challenges due to infrequent and biased government censuses[24]. Additionally, identifying households with young children in the country beforehand is nearly unfeasible due to lack of antecedent knowledge of houses or households with U5 children. To address these constraints, our study leveraged previous research to determine the sample size, taking budgetary limitations into account. We utilized building sampling as a spatial reference to locate households during our field visits. By importing the extracted building data into ArcGIS Pro, we were able to generate accurate locations of the sampled buildings in relation to the GPS coordinates used during our field survey. The buildings in Akure were extracted following the methodology described on the Picterra platform with a paid subscription (https://picterra.ch/geospatial-imagery-analysis).

The study samples are within the scope of other cross-sectional studies and population proportion sampling method of[33,34]. According to our knowledge of local demography, most households with U5 children have only one child under five years. In rare cases where there were more than one U5 child i.e. two, we selected the youngest and subsequently selected the eldest in next household with such a similar characteristic as our aim is to model individual-level variability of childhood malaria in Akure. With random sampling, each child, house, or household has equal chances of being selected thereby reducing the risk of selection bias.

Data collection and informed consent

The lead author assisted with five research assistants visited each of the pre-identified houses with the MIQ to gather evidence on active malaria cases after the rainy season. The survey period for this study was between October and December in the year 2019. According to[35], dry season in Akure is from November to March while the rainy season is from April to October. The sampled houses (families) were visited between 4:30 pm and 6:00 pm to enhance effective targeting of the respondents. Upon visiting a sampled location, the guardian, parents, or adult relative (> 18 years) with the child's health history was interviewed. Privacy and ethical consent procedures were observed and strictly followed. We obtained informed consent from guardians, parents or adult relative to participate in the study or partake in the interview. Furthermore, we assured, maintained, and adhered to the anonymity of the data and presentation of results obtained from analyses of collected data. The MIQ for the study was created in English language, however, with the option of conducting the interview in Yoruba language (native language in Akure) in case a guardian/parent has a low level of English literacy. This approach ultimately improved the level of inclusion in this study since the lead author and field assistants understands English and Yoruba language. This research was performed in accordance with relevant guidelines and regulations. The methods of data collection and interpretation are in accordance to declaration of Helsinki ethical principles and codes.

Exploratory analysis

Before the development of the geostatistical models for this study, we preliminarily carried out an exploratory analysis of the data. The purpose of this is to provide insights and guides into development of best fit geostatistical model for U5 malaria prevalence[36]. The objectives and focus on this stage of analysis are:

(i) Establish the determinants variables or factors of U5 malaria prevalence. This can be accomplished by utilisation of bivariate analysis such as Chi-square ($\mathcal{X}^2$) to build a table summary of the association between U5 malaria and the covariates. This formed the basis of non-spatial analysis discussed in the later section of this paper.

(ii) Explore the association between U5 malaria prevalence and covariates i.e. explanatory or independent variables. In this stage, we fitted a non-spatial generalised linear model (GLM) to observed and assess the relationship (magnitude and direction) of the covariates with U5 malaria prevalence. The selected model has the least Akaike Information Criterion (AIC) from the stepwise forward approach that was conducted. In addition, Variance Inflation Factor (VIF)/generalized Variance Inflation Factor (GVIF) was used as regression diagnostic measure to detect the presence of collinear variables in order to avoid multicollinearity in our model and reduce standard error of model coefficients according to the works of[37,38]. Furthermore, we evaluated our designed model accuracy using cross-validation (*k*-fold) technique. The purpose of this is to test the effectiveness of our model against data points which were not used during the training of the model (new data sets). During the model training randomly selected subset of the data (training set) is used to inform predictions at location of remainder of the data (test set)[36]. The combination of these methods (GVIF and cross-validation) guide against correlation among model explanatory variables, overfitting of our model, evaluate prediction accuracy, and provide insight on variable importance and selection asides the retention of variables based on their p-values ($p < 0.05$). In the final step, the odds ratio (OR) which determines risk factors of U5 was computed. Given the exposure or factor, OR greater than 1 means the U5 malaria is likely to occur; OR less than 1 means the event (U5 malaria) is less likely to occur while OR equals 1 means the likelihood of malaria does not change.

(iii) Examine spatial dependency of U5 malaria by testing for spatial correlation on the residuals i.e. to examine spatial dependency in step (ii). The focus is to determine if variation in the residuals i.e. variation that is not captured by the retained variables reveal evidence of spatial correlation by using empirical variogram[36]. The choice of spatial model is determined by the detection of spatial correlation in the residual.

Geostatistical modelling

Unlike non-spatial/standard statistical modelling, spatial data and modelling observe the assumption of spatial dependence (autocorrelation) between neighbouring locations due to observed common exposure[39–41]. Spatial autocorrelation in this context refers to the relationship between U5 malaria of a child (Y_{ij}) in location j with itself in another neighbouring location within the same geographical space[39]. Spatial autocorrelation expresses the degree of similarity among the observation values within the geographical space of interest[42]. Therefore, to account for spatial dependency, we formulated a geostatistical model which follows the geostatistical model for prevalence surveys by[43]. The model is within the generalised linear mixed model framework or spatial generalised linear mixed models (SGLMMs) which relates disease prevalence data with potential linear predictors, binomial error distribution, logistic-link function and latent Gaussian process by adding random effects at the observed locations[43,44]. Model-based geostatistics has its origin from Kriging which is a method of interpolating (predicting values at unmeasured locations) or smoothing spatial data. Particularly, MBG is termed as application of explicit parametric stochastic models and likelihood-based methods of inference to geostatistical problems[45]. The interpolation is based on observation data pairs while correlation is a function of distance between the data pairs[43,46].

Equation (1) describes the likelihood-based Binomial Geostatistical Model adopted for this study. This is an extension of a binary logistic regression model by the inclusion of random effects and spatially correlated random effects i.e. spatial Gaussian process. Hence, let U5 malaria status Y_{ij} of a child i at location j take the value of 1 if a child has malaria, and 0 otherwise. The dependent variable—Yij follows a Bernoulli probability distribution with $P(Y_{ij}=1)=\mathcal{P}_{ij}$ which is conditional on a stationary Gaussian process (x) and an additional set of study location specific and unobserved random effects Z_i, the linear predictor of the model assumes the form:

$$\log\left(\frac{P_{ij}}{1-P_{ij}}\right) = d(\mathcal{X}_i)'\beta + (\mathcal{X}_i) + Z_i \tag{1}$$

where $\mathcal{X}_i$ is the vector of a child, with individual-level covariates with associated regression coefficient β; $S=\{(x): x\in R^2\}$ is a Gaussian process with mean zero, variance σ^2, and correlation function $p(x,x')=\text{Corr}\ \{(x),S(x')\}$. The Gaussian process (S) is stationary and isotropic, while the correlation function is a function of euclidean distance[47]. The aim of study location random effects Z_i is to account for the unexplained nonspatial variation which could be small scale spatial variation or measurement error. This is also known as the nugget effect (τ^2). The random effects are independent normal, (i.e. $Zi \sim N\ (0, \tau^2)$) variates.

In Eq. (1), we write τ^2 for the variance of Z_i and model $S\ (x)$ as a stationary Gaussian process with variance σ^2 and matérn correlation function[48]. Matérn model is an efficient method for modelling correlation function as strongly recommended by[45,49,50]. It contains kappa (k) which determines the smoothness of the process. The matérn correlation function is given by:

$$\rho(u;\emptyset,\kappa) = \frac{2^{\kappa-1}\Gamma_{(\kappa)}}{(u|\emptyset)^{\kappa}\kappa_{\kappa}(u|\emptyset)},\quad u>0, \tag{2}$$

where $\emptyset > 0$ is a scale parameter which regulates the rate at which the spatial correlation goes to zero or decays as the distance increases[51,52]; $k>0$ is the shape parameter which determines the smoothness of (x). Kk (.) is the modified Bessel function of the second kind of order $k>0$, and u is the distance between two sampled locations. Kappa is difficult to estimate reliably since this will involve large data collected at small distances. Hence three discrete set of values (0.5, 1.5, 2.5) corresponding to different level of smoothness have been defined for Kappa[44]. These values correspond to the discontinuity of the different level of smoothness. For this study, we adopted 0.5 for Kappa according to the documentation and works of[36,44]. Kappa of 0.5 corresponds to exponential correlation function i.e. the Matérn covariogram becomes the exponential one[44,53]. Furthermore, most functions available in PrevMap package in R, the Matérn shape parameter κ is treated as fixed because not all parameters in the Matérn class can be estimated consistently. Matérn class has the capacity to model the behaviours of variogram and it consists of exponential variograms as a special case unlike other popular covariograms such as exponential, powered-exponential, gaussian or spherical covariograms. For more technical details, we refer the reader to the works of[44,46,53].

Monte Carlo maximum likelihood and spatial prediction

In this study, Monte Carlo maximum likelihood methods (MCML) was utilised for parameter estimation as documented in the PrevMap package in R[44]. MCML is based on importance sampling techniques approximation of the high-dimensional intractable integral that defines the likelihood function[54]. It enables flexibility in fitting complex models and avoids asymptotic inference and computational challenges encountered in solely likelihood-based fitting[55]. The likelihood function for parameters β and $\theta^T=(\sigma^2,\emptyset,\tau^2)$ is obtained by integrating out the random effects included in Eq. (1), where σ^2 is the variance, $\emptyset$ is the range, and τ^2 is the nugget effect. We map the risk of U5 malaria over 100×100 m grid. Spatial distribution maps of U5 malaria prevalence, likelihood-based geostatistical modelling and spatial prediction were developed in R statistical programming (R version 3.6.3). To improve the model predictions, the covariates are included. The selected covariates for the spatial model were carefully considered according to their significance level as discussed in earlier section i.e. Exploratory analysis.

Often, the development of public health policies are based on the exceedance, or non-exceedance of a predefined prevalence or incidence thresholds say t[36]. Therefore, the exceedance probability (EP) of U5 malaria prevalence predictions in each location above the predefined thresholds t can be expressed or defined as:

$$\mathrm{EP}(\mathcal{X}) = \mathrm{Probability}[\mathcal{P}(\mathcal{X}) > \mathrm{t}|\mathrm{Y}_1, \ldots, \mathrm{Y}_\mathrm{N}]. \tag{2}$$

It is necessary to note that the resulting estimates at each locations have uncertainties that need to be taken to consideration[52]. The exceedance probability can help to overcome this challenge and prevent unjustifiable policy decisions by quantifying how likely $\mathcal{P}(\mathcal{X})$ is to be above a threshold t as shown in Eq. (3). For this study, we set prevalence threshold to be 10% (0.1) which can be categorised as hotspots of U5 malaria in Akure. According to[56], places with annual malaria prevalence of 10–35% have moderate transmission while area of high transmission are above 35%. However, the recently implemented fifth National Malaria Strategic Plan (NMSP) covering the period of 2021–2025 in Nigeria aims to achieve parasite prevalence of less than 10%[57]. We therefore adopted 10% as our exceedance threshold to determine hotspots of malaria prevalence in Akure. If EP is close to 100%, this shows that U5 malaria prevalence to be above the threshold t is very high*;* if EP is close to 0%, the prevalence of U5 malaria is highly likely to be below t*.* EP close to 50% suggests high level of uncertainty which means that prevalence of U5 malaria is equally likely to be above or below t*.*

Ethical approval

We received ethical approval from the institutional review board at the Institute of Geography, Heidelberg University, Germany. We obtained informed consent from parents, guardians or adult relative who participated in the interview, and we adhered to the anonymity of the data and presented results. Before the interview was carried out, ethical clearance was obtained from the Ondo State Ministry of Health.

Results

Non- spatial analysis

We effectively obtained about 60% valid responses (n = 568). As mentioned earlier, we do not have previous knowledge of houses or households with U5 children. This has contributed to the low responses coupled with budget constraints to sample more houses. Furthermore, we expunged participants who had spent less than two weeks in the location depending on the week of survey to reduce risk of imported malaria. Nevertheless, the obtained valid responses were deemed sufficient after carrying out statistical power analysis with open source G*Power tool, version 3.1.9.6[58]. The point prevalence of U5 malaria in Akure, Nigeria based on verbal confirmation according to the study definition of positive malaria was 22.5%. Malaria prevalence among the female children (23.3%) is higher compared to malaria prevalence among male children (21.9%) according to Table 1. According to the study, about 40% of the children have ITN. Further to the study findings in Table 1 on the usage of ITN and its impact on malaria prevalence, children who sleep under ITN have lower prevalence of malaria (16.7%) compared to children who do not sleep under ITN (26.4%). This further implies that usage of ITN is malaria risk factor with significant reduced odds of U5 malaria and serves as protection against mosquito bites.

The study findings show that vector-proof houses are determinant factor of malaria. Vector-proof houses protect against malaria. The houses in good condition characterised with good window screening have a lower prevalence of malaria (18.6%), while children living in substandard houses characterised with poor or defected window covering recorded higher prevalence of malaria (39.9%). The condition and source of drinking water also plays significant role in the burden of malaria. According to the study findings, almost half (48%) of the survey households depend on Dug well as water source. Despite this large figure, the burden of U5 malaria is higher (28%) among households with Dug wells compared to affluent households that depends on piped water source (15.9%). As shown in Table S1 (supplementary file), drainage with covering is a determinant and risk factor of malaria. U5 children living in places with covered drainage records less burden of malaria (13.3%) compared with U5 children dwelling in places with poor drainage facilities (24.3%). According to Table S1 (supplementary file), Education, Income and type of employment further illustrate effect of social determinants or socioeconomic characteristics on health. U5 children whose fathers are employed in the formal sector have lower burden of malaria (18.2%) compared with U5 children whose fathers are either work in informal sector (26%) or unemployed (28.6%). This phenomenon is similar to the study findings on effect of income level on U5 malaria. According to our study findings, the burden of malaria reduces as income level increases (Table S1 as supplementary file). U5 malaria prevalence is lower among mothers who have obtained tertiary education (18.4%) compared to mothers with no education (33.3%).

Supplementary Table S1 online contains additional table summary of mostly non-significant covariates in this study. We have discussed some selected covariates in the manuscript.

Model results

The results reported in Table 2 describes the significant predictors and parameter estimates from the binomial logistic model for this study as documented in Eq. (1). The sigma sq (σ^2) is the variance of the Gaussian process, Ø is the scale parameter which represents the extent of the spatial correlation in metres, while tau sq (τ^2) is the non-spatial variation. After further exploration of the model results particularly because of the binary response at each sampled locations we fitted the model without Z terms i.e. tau sq (τ^2). This pragmatic decision further led to the improvement of the model fit. According to the model result, the model accuracy from the k-fold cross-validation was 0.75 (75%) and Cohen's kappa was 0.01, which could be considered "slight" given the thresholds of[59] relatively indicating good performance. ITN, window protection and piped water source are significant with high variable importance. In addition, these variables are not correlated to each other according to the GVIF values (see Table 2). Therefore no added uncertainty in the model estimates and almost

Factors	Negative (N = 440)	Positive (N = 128)	OR (95% CI)	p value
Child sex				0.708
Female	198 (76.7%)	60 (23.3%)	1.00	
Male	242 (78.1%)	68 (21.9%)	0.93 (0.62–1.37)	
ITN				0.007
No	251 (73.6%)	90 (26.4%)	1.00	
Yes	189 (83.3%)	38 (16.7%)	0.56 (0.36–0.86)	
Urban agriculture				0.351
No	321 (78.5%)	88 (21.5%)	1.00	
Yes	119 (74.8%)	40 (25.2%)	1.23 (0.79–1.88)	
Waste disposal				0.457
Burning	128 (75.3%)	42 (24.7%)	1.00	
Water body	4 (66.7%)	2 (33.3%)	1.52 (0.27–8.61)	
Others	1 (50%)	1 (50%)	3.05 (0.19–49.8)	
Pick up	231 (77.3%)	68 (22.7%)	0.90 (0.58–1.39)	
Vacant plot	76 (83.5%)	15 (16.5%)	0.60 (0.31–1.16)	
Child age				0.352
< 1 year	38 (88.4%)	5 (11.6%)	1.00	
1–2 years	79 (77.5%)	23 (22.5%)	2.21 (0.78–6.27)	
2–3 years	94 (78.3%)	26 (21.6%)	2.10 (0.75–5.88)	
3–4 years	98 (73.1%)	36 (26.9%)	2.79 (1.02–7.64)	
4–5 years	131 (77.5%)	38 (22.5%)	2.20 (0.81–5.99)	
Window protection				0.001
No	125 (69.1%)	56 (39.9%)	1.00	
Yes	315 (81.4%)	72 (18.6%)	0.51 (0.34–0.77)	
Water source				0.007
Dug well	198 (72%)	77 (28%)	1.00	
Other	68 (79.1%)	18 (20.9%)	0.68 (0.38–1.22)	
Piped water	174 (84.1%)	33 (15.9%)	0.48 (0.31–0.77)	

Table 1. Description of U5 malaria with considered covariates.

Factors	Estimate	StdErr	p value	GVIF
ITN	− 0.5159	0.1004	2.779e−07***	1.005669
Window protection	− 0.9137	0.1116	2.586e−16***	1.064548
Piped water source	− 0.3985	0.1074	0.0002063***	1.068029
Spatial covariance parameters				
Log σ^2	− 0.2242	0.0696		
Log Ø	6.4724	0.2191		

Table 2. Monte Carlo maximum likelihood estimates for the binomial logistic model. ***$p < 0.001$; **$p < 0.01$; *$p < 0.5$. The units of the scale parameter ∅ is in metres.

non-multicollinearity have been maintained since the VIF values are very close to 1 and lower than threshold of 5 as explicitly discussed in[60,61]. The usage of ITN reduces the risk of malaria burden. Concurrently, vector-proof houses with good window protection have a negative relationship with the likelihood of positive malaria outcomes. Water sources (i.e. piped) have a negative association with the probability of malaria, while other sources of water are non-significant.

For this study, point referenced U5 malaria prevalence data were analysed using MBG models to outline and map areas where prevalence of U5 malaria is above or below a set policy threshold. We predicted the prevalence of U5 malaria at a fine scale (100 × 100 m resolution map). The predictive power of the model increases when disease predictors are considered. According to Fig. 3 (left panel), the predicted prevalence of U5 malaria in Akure is slightly above 35%, while it is about 35% when the predictors are not considered as seen in the left panel of Fig. 2. Furthermore, the probability that U5 malaria prevalence is above 10% is shown in the right panel of Fig. 3. We used the 10% exceedance threshold to determine hotspots for this study associated with the level of certainty. Therefore, areas with ≥ 80% probability of exceeding the threshold were considered hotspots. The certainty level is captured with the contour lines. The uncertainty in the estimates is quantified using the standard

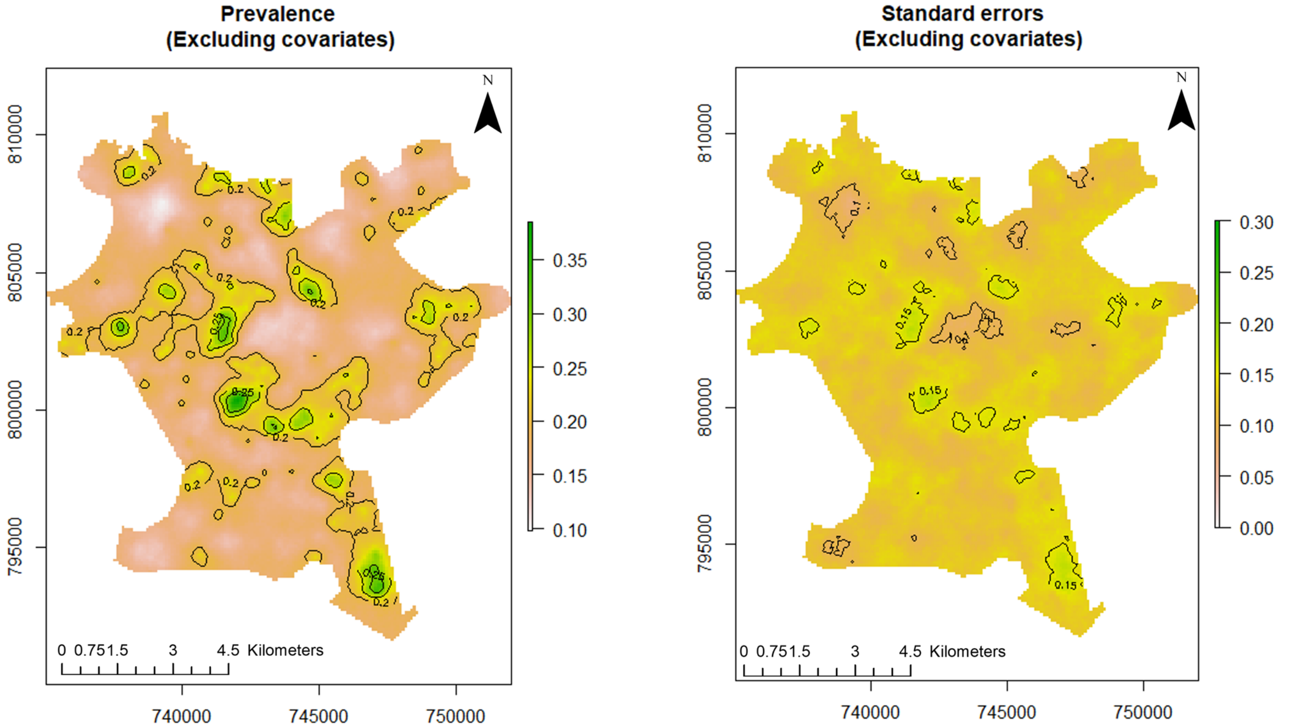

Figure 2. Predictive distribution of U5 malaria in Akure (left panel) and standard errors of the predictions (right panel). The figure was created with R version 3.6.3, https://cran.rstudio.com/.

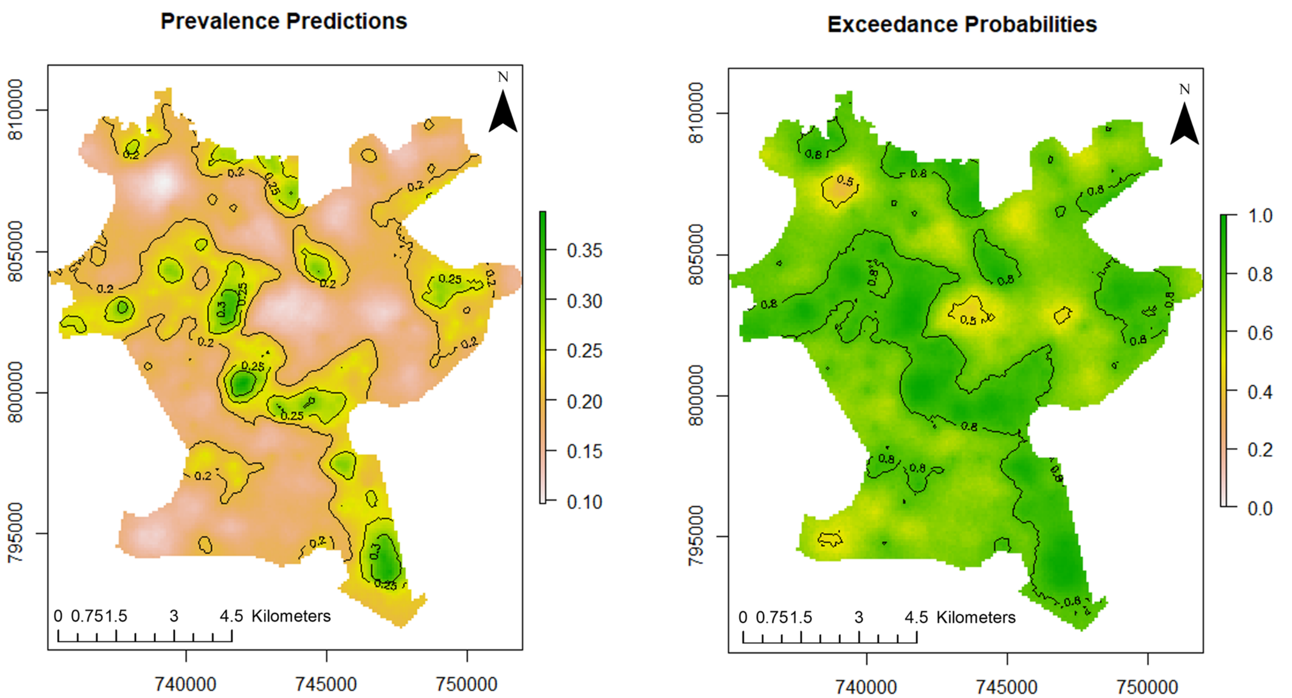

Figure 3. Predictive distribution of U5 malaria in Akure (left panel) and exceedance probabilities (right panel). The figure was created with R version 3.6.3, https://cran.rstudio.com/.

errors as shown in right panel of Fig. 2. A set of diagnostic plots that provide checks on the convergence of the MCMC is provided in Fig. S1 (supplementary file).

Discussion

Spatially targeted policy and healthcare intervention are pertinent to eradicating disease transmission. e.g., malaria. Therefore, spatial modelling of disease remains an important public health tool. Through disease models, hotspots can be determined for prioritising timely intervention in resources-scarce contexts.

The reduction in malaria burden has stalled. The recent figures of global malaria burden according to[1] is the same level as before 2011, with much increase in the last two years. Furthermore, the national-level statistics may not reflect what is obtainable at lower administrative levels. Since countries are experiencing reduction in malaria burden between 2010 and 2019 as reported by[1], coupled with the scarce availability of health resources, spatial targeting of intervention for maximum utilisation of resources is essential. Geostatistical methods as seen in this study provides the opportunity for precision in hotspot determination.

There is variability in U5 malaria spatial distribution in Akure. The spatial predicted burden of U5 malaria is higher in the poor and low-income communities such as Arakale, Isolo-Araromi, Ayedun, and Oda. The high malaria transmission might have been due to the lack of suitable housing infrastructure. Based on the morphology of Akure as documented by[62], Arakale and Isolo-Araromi are communities in the city centre characterised by old and substandard buildings, poor drainage facilities and below-minimum space between buildings. Collectively, these features aid high transmission of malaria. Conversely, Oba-Ile Phase Two and Oda which are newly emerging areas (suburbs) and outlying districts of Akure are also characterised with high burden of malaria as shown in the exceedance probability model (right panel of Fig. 3). These places have prevalence greater than 10% with 80% certainty. These newly emerging places show element of poor planning control[11,24] with fragmented sites which are suitable vector breeding sites[63]. Lower transmission of U5 malaria was observed in affluent neighbourhoods such as Oba-Ile Phase One, Ijapo Estate and Alagbaka Estate. These areas have standard building structures and better facilities such as good rood conditions, drainage, a good water supply and less vegetation[62] and robust urban planning development control.

Local spatial estimations of disease allow us to identify locations of disease clusters where disease prevalence is above the geographical average (hotspots). In this study, U5 malaria hotspots were determined through the exceedance probability model as shown in the right panel of Fig. 3. 10% cut off was adopted as the threshold to identify malaria hotspots which is in accordance with the NMSP target set by the Nigerian government. According to the exceedance probabilities model, the dark green areas show locations where U5 malaria prevalence is above 10% with certainty level of 80% and above. These places such as Isolo-Araromi, Arakale, Aiyedun, Kajola, Idi-Agba, Fanibi-Lafe, Oba-Ile Phase Two, Oda, Orita Obele and Irese. The identified places require targeted malaria control effort by the health authorities towards malaria elimination in order to meet the NMSP target.

The study analyses elucidate the risk factors of U5 malaria prevalence. Based on our model results, several factors determine the risk of malaria among U5 in Akure. Although not significant, child's gender is one of these factors. Male children exhibited a slightly lower malaria burden than their female counterparts. A similar study conducted in Cameron shows a non-significant association between child sex and malaria with a lower burden among male children[64], while the studies of[65,66] show significant lower burden of malaria among males compared to females. However, among older children, males are more prone to malaria because of their higher engaging outdoor activities compared to female[13,67]. The reason for our findings could be difference in background immunity between male and female children.

The availability and usage of ITNs is another significant and important factor that affects malaria exposure. According to our study, the usage of ITNs reduces the likelihood of childhood malaria by 56% (OR = 0.56; 95% CI = 0.36–0.86) in Akure, Nigeria compared the children who do not sleep under ITN. Our findings agrees with the following studies in Ghana[30], Nigeria[68], Uganda[69], and Kenya[70]. Good ITN protects against mosquito vectors by reducing the vector-to-human contacts. This mechanically prevents or stops mosquito bites.

The impact of urban agriculture on the susceptibility of malaria among children under five was not significant which is in agreement to the studies of in Ibadan Nigeria[13] and[71] in Malawi. According to our study, households that practice urban agriculture are 1.23 times likely to have malaria (OR = 1.23; 95% CI = 0.79–1.88) compared to household who do not practice urban agriculture. Few studies have investigated intra-urban impact of urban agriculture on U5 malaria unlike rural–urban studies. For example[52], found a positive association between positive malaria outcome and children living in rural areas of Ghana, as well as[40] in Mozambique. Rural areas are usually highly vegetated, serving as a suitable habitat for the breeding of mosquitoes. In addition, we do not find an association between the adopted mode of waste disposal method and U5 malaria prevalence. One of the challenges of urbanisation is increasing waste generation as this has consequences on the health of urban residents. Good waste management practices such as regular trash disposal reduce the risk of malaria as there would be less mosquito breeding, clogging and flooding[72].

Also, the study findings show a non-significant increasing trend in the burden of malaria with each increasing age categories similar to the outcomes observed in the studies of[13,52]. The lower risk of malaria burdens in younger children could be because of the passive immunity acquired from mothers through breastfeeding as observed in the studies of[2,52]. Intuitively, this observed phenomenon might also be due to the fact that older children are less likely to sleep under ITN when there are not enough ITN to serve the younger and older children among poor households.

Lower risk of malaria exists among U5 children in vector-proof houses such as window protection (OR = 0.51; 95% CI = 0.34–0.77). Similar findings are reported by[28,73]. Houses in good condition i.e. mosquito-proofing houses offer significant advantage of equitably protecting all members of particular households even those that are not sleeping under a bed net[73]. Window screening prevent mosquitoes from entering the houses or places of abode. According to our study, households with a piped source of water have reduced odds of U5 malaria (OR = 0.48; 95% CI = 0.31–0.77). In this study, since wealth index was not considered access to piped water is used as a surrogate for wealth index, which explains the reduced odds for households with a piped source of water and window protection. Poor households are likelier to live in substandard houses with avenues for malaria vectors to find their way into the building. These findings are in agreement with the studies of[17,69,74–76] where highest wealth status households or better off households are noted to afford malaria preventive measures. Some of these measures include appropriate housing facilities with screens that block or hinder vectors resulting in reduced vector-human contact, insecticide-treated bed nets to reduce malaria transmission, quick diagnosis and acquiring of drugs in case of infection without depending on public facilities. Moreover, malaria in Africa have been described as a disease of rural population and communities which are homes of the poorest of the poor[77], as further illustrated by income level in Table S1 (supplementary file). The higher the income level, the lower the odds of U5 malaria.

Study limitations and future research

There are some limitations in this study that should be considered when interpreting the study findings. The epidemiologic variable—presence or absence of malaria—retrospectively determined by verbal report might lead to recall bias. Furthermore, not all research variables that influences the transmission of malaria are considered in this study. Therefore, robust health routine survey data with associated environmental factors and SES void of bias should be considered in future study. Nevertheless, this research primarily considered social factors and cross-checked questions on definition of malaria to limit bias was maintained.

It is pertinent to note that the study's sample size is relatively small with potential to introduce some biases in the study results such as the low proportion of malaria-positive cases. This might have impacted the low Cohens kappa measure i.e. measurement of agreement of the two categorical variable outcomes (positive and negative malaria outcome). However, the obtained results from statistical power analysis test and cross-validation model accuracy have led to improvement of the study validity. Therefore, an extensive future study with more samples should be strongly considered. Lastly, since this is a cross-sectional study, the impact of seasonality on malaria prevalence should be considered while interpreting the results since the burden of malaria varies seasonally.

Conclusions

This study demonstrated steps toward understanding the spatial structure of U5 malaria through the application of Model-based Geostatistical modelling to a very-fine scale mapping in places of low resource settings such as Akure, Nigeria. The map provides place-based evidence on the spatial variation of U5 malaria in Akure and serves as a guide to locations that require crucial and intensified interventions for the reduction of malaria burden.

The study shows spatially predicted variability of U5 malaria risk in Akure, with high prevalence within the centre of the city, transition zone, and newly developed places/suburbs which are characterised with low urban planning development control. The study further shows low prevalence of U5 malaria burden in the affluent communities such as Alagbaka, Oba-ile etc. According to our findings, the usage of ITNs, window protection, and a piped-water source reduces the risk of U5 malaria. Therefore, interventions addressing these risk factors are germane while also ensuring continuous monitoring of malaria prevalence and intervention assessment should be considered. This is however predicated on the availability of malaria covariates data especially at local level. Hence, barriers on data availability should be addressed. The health challenges of the twenty-first century are complex and requires multiple discipline and approaches to tackle these challenges. Therefore, urban planning control and development in the city core and outlying districts should be intensified.

Geographical or spatial targeting of public health control efforts in U5 malaria hotspots developed in accordance to the exceedance probability model will aid the elimination of malaria in Akure, Nigeria. The evidence-based policy formulation and implementation directed towards places of high malaria risk and transmission can lead to malaria elimination and achieving set target according to the Nigeria's NMSP. In addition, this can also contribute towards Nigeria's achievement of Sustainable Development Goals 3 and 11 which are to: (1) Ensure health lives and promote well-being for all at all ages and (2) Making cities and human settlement inclusive, safe resilient and sustainable.

Data availability

Data can be made available from the corresponding author upon reasonable request. However, the R scripts for the exploratory analysis, cross-validation, parameter estimation and spatial prediction are freely available at: https://github.com/Taye20/MBG/tree/main.

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Author contributions
T.B: conceptualisation; data curation; formal analysis; methodology; validation; visualisation; writing—original draft, writing—review & editing; project administration. A.S: supervision; project administration; writing—review & editing.

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The authors declare no competing interests.

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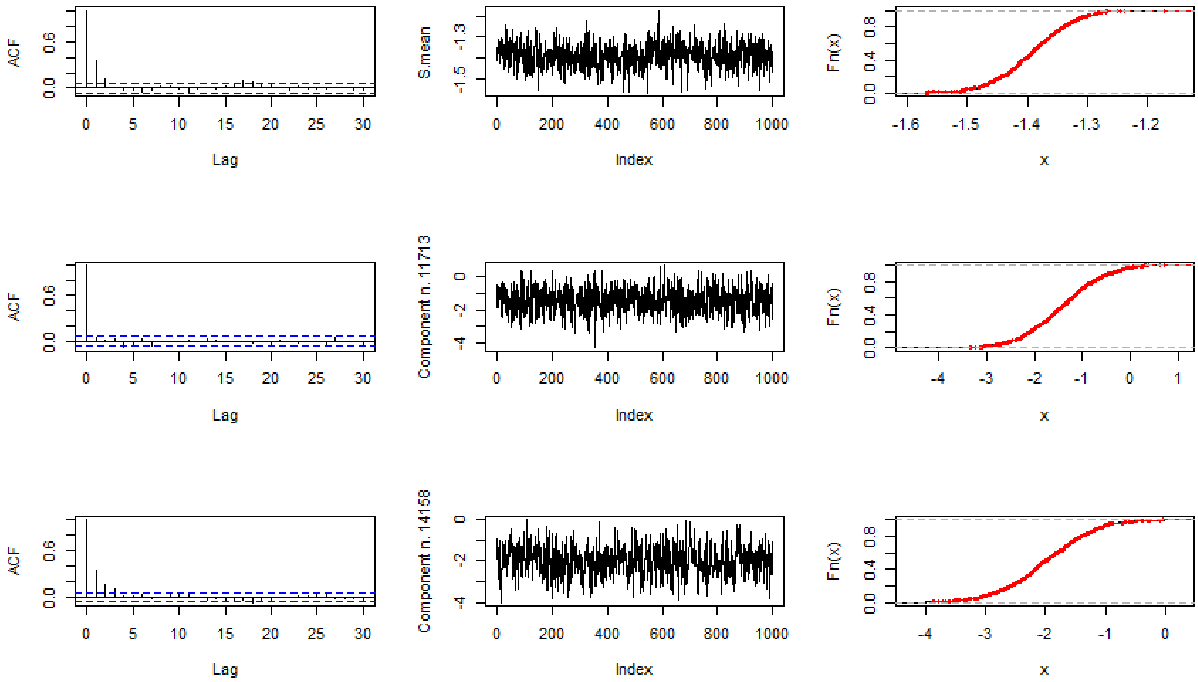
Correspondence and requests for materials should be addressed to T.B.

Supplementary Table S1: Description of U5 malaria with considered covariates.

Factors	Negative (N = 440)	Positive (N = 128)	OR (95% CI)	p value
Drainage Covered				0.023
No	362 (75.7%)	116 (24.3%)	1.00	
Yes	78 (86.7%)	12 (13.3%)	0.48 (0.25 – 0.91)	
Toilet Facility				0.229
Flush toilet	361 (78.1%)	101 (21.9%)	1.00	
Bucket toilet	11 (84.6%)	2 (15.4%)	0.64 (0.14 – 2.97)	
No facility	1 (33.3%)	2 (66.7%)	7 (0.64 – 79.64)	
Pit latrine	67 (74.4%)	23 (25.6%)	1.23 (0.73 – 2.07)	
Health Infrastructure				0.372
No	151 (77%)	45 (23%)	1.00	
Not Sure	37 (86%)	6 (14%)	0.54 (0.22 – 1.37)	
Yes	252 (76.6%)	77 (23.4%)	1.03 (0.67 – 1.56)	
HouseTenure				0.074
Individual ownership	214 (78.1%)	60 (21.9%)	1.00	
Inherited	23 (76.6´7%)	7 (23.3%)	1.09 (0.44 – 2.65)	
Others	0 (0%)	2 (100%)	17.72 (0.84 – 374.24)	
Rented	203 (77.5%)	59 (22.5%)	1.04 (0.69 – 1.56)	
Marital Status				0.489
Divorced	10 (83.3%)	2 (16.7%)	1.00	
Married	387 (76.5%)	119 (23.5%)	1.54 (0.33 – 7.11)	
Separated	19 (82.6%)	4 (17.4%)	1.05 (0.16 – 6.77)	
Single	18 (85.7%)	3 (14.3%)	0.83 (0.12 – 5.85)	
Widowed	6 (100%)	0 (0%)	0.32 (0.01 – 7.84)	
Father’s Ethnicity				0.292
Hausa	4 (50%)	4 (50%)	1.00	
Igbo	31 (79.5%)	8 (20.5%)	0.26 (0.05 – 1.27)	
Others	8 (72.7%)	3 (27.3%)	0.38 (0.05 – 2.55)	
Yoruba	397 (77.8%)	113 (22.2%)	0.28 (0.07 – 1.16)	
Mother’s Ethnicity				0.123
Hausa	4 (44.4%)	5 (55.6%)	1.00	
Igbo	46 (78%)	13 (22%)	0.23 (0.05 – 0.97)	
Others	9 (675%)	3 (25%)	0.27 (0.04 – 1.70)	
Yoruba	381 (78.1%)	107 (21.9%)	0.22 (0.05 – 0.85)	
Father’s Education Level				0.297
Apprentice	84 (80.8%)	20 (19.2%)	1.00	
No education	5 (62.5%)	3 (37.5%)	2.52 (0.56 – 11.43)	

Primary	14 (70%)	6 (30%)	1.80 (0.62 – 5.27)	
Secondary	88 (72.1%)	34 (27.9%)	1.62 (0.87 – 3.04)	
Tertiary	249 (79.3%)	65 (20.7%)	1.10 (0.63 – 1.92)	
Mother’s Education Level				0.158
Apprentice	95 (77.2%)	28 (22.8%)	1.00	
No education	16 (66.7%)	8 (33.3%)	1.70 (0.66 – 4.38)	
Primary	29 (65.9%)	15 (34.1%)	1.75 (0.83 – 3.72)	
Secondary	171 (78.1%)	48 (21.9%)	0.95 (0.56 – 1.62)	
Tertiary	129 (81.6%)	29 (18.4%)	0.76 (0.43 – 1.37)	
Father’s Employment Status				0.053
Formal sector	180 (81.8%)	40 (18.2%)	1.00	
Informal sector	245 (74%)	86 (26%)	1.58 (1.04 – 2.41)	
Others	10 (100%)	0 (0%)	0.21 (0.01 – 3.70)	
Unemployed	5 (71.4%)	2 (28.6%)	1.80 (0.34 – 9.61)	
Mother’s Employment Status				0.051
Formal sector	107 (85.6%)	18 (14.4%)	1.00	
Informal sector	305 (74.6%)	104 (25.4%)	2.03 (1.17 – 3.50)	
Others	3 (100%)	0 (0%)	0.83 (0.04 – 16.74)	
Unemployed	25 (80.6%)	6 (19.4%)	1.43 (0.51 – 3.96)	
Income Level				0.103
< ₦20,000	33 (70.2%)	14 (29.8%)	1.00	
₦20,000 - ₦50,000	162 (76.1%)	51 (23.9%)	0.74 (0.37 – 1.50)	
₦50,000 - ₦100,000	100 (75.2%)	33 (24.8%)	0.78 (0.37 – 1.62)	
₦100,000 - ₦150,000	70 (77.8%)	20 (22.2%)	0.67 (0.30 – 1.50)	
> ₦150,000	75 (88.2%)	10 (11.8%)	0.31 (0.12 – 0.78)	
Floor covering material				
Finished floor	398 (78.2%)	111 (21.8%)	1.00	
Natural floor	22 (81.5%)	5 (18.5%)	0.81 (0.30 – 2.20)	0.105
Rudimentary floor	20 (62.5%)	12 (37.5%)	2.15 (1.02 – 4.54)	
Roof covering material				
Finished Roof	388 (70%)	103 (21%)	1.00	
Natural Roof	2 (50%)	2 (50%)	3.77 (0.52 – 27.07)	0.103
Others	1 (50%)	1 (50%)	3.77 (0.23 – 60.74)	
Rudimentary Roof	49 (69%)	22 (31%)	1.69 (0.98 – 2.93)	



Supplementary Figure S1: Autocorrelation plot of a thinned sequence of 10000 MCMC samples (left panels), trace plot of the same sequence (central panels) and empirical commulative distribution plots for the first 5000 and second 5000 samples (right panels), for the spatial average of predicted logit-transformed prevalence (first row) and for the predicted logit-transformed prevalence at two randomly selected locations (second and third rows). The figure was created with R version 3.6.3, https://cran.rstudio.com/

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4. Beteiligungen/*Contributions***

Contributor Role	Doktorand/in/ *Doctoral student*	Co-Autor/in 1/ *Co-author 1*	Co-Autor/in 2/ *Co-author 2*
Name, first name	Taye Bayode	Alexander Siegmund	
Methodology	☑	☐	☐
Software	☑	☐	☐
Validation	☑	☐	☐
Formal analysis	☑	☐	☐
Investigation	☑	☐	☐
Resources	☑	☑	☐
Data Curation	☑	☐	☐
Writing-Original Draft	☑	☐	☐
Writing-Review&Editing	☑	☑	☐
Visualization	☑	☐	☐
Supervision	☐	☑	☐
Project administration	☑	☑	☐
Funding acquisition	☑	☑	☐

***Kategorien des CRediT (Contributor Roles Taxonomy, https://credit.niso.org/)*

Hiermit bestätige ich, dass alle obigen Angaben korrekt sind/*I confirm that all declarations made above are correct.*

Unterschrift/*Signature* ____________ ____________ ____________

Doktorand/in/*Doctoral student* Co-Autor/in 1/*Co-author 1* Co-Autor/in 2/*Co-author 2*

Betreuungsperson/*Supervisor:*

Hiermit bestätige ich, dass alle obigen Angaben korrekt sind und dass die selbstständigen Arbeitsanteile des/der Doktoranden/in an der aufgeführten Publikation hinreichend und signifikant sind/*I confirm that all declarations made above are correct and that the doctoral student's independent contribution to this publication is significant and sufficient to be considered for the cumulative dissertation.*

Prof. Dr. Alexander Siegmund		23.01.2025
Name/*Name*	Unterschrift/*Signature*	Datum/*Date*

"The way a city is structured affects the quality of life of its citizens."

Enrique Penalosa

II.4 City Classification and Health Burden: Evidence from U5 Malaria in Rapidly Growing city of Akure, Nigeria.

Published, IJID Regions

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City classification and health burden: Evidence from U5 malaria in the rapidly growing city of Akure, Nigeria

Taye Bayode [1,2,*], Olumuyiwa Bayo Akinbamijo [3], Alexander Siegmund [1,2]

[1] Institute of Geography & Heidelberg Centre for Environment, Heidelberg University, Heidelberg, Germany
[2] Department of Geography – Research Group for Earth Observation (rgeo), UNESCO Chair on World Heritage and Biosphere Reserve Observation and Education, Heidelberg University of Education, Heidelberg, Germany
[3] Department of Urban and Regional Planning, School of Environmental Technology, Federal University of Technology Akure, Nigeria

A R T I C L E I N F O

Keywords:
ANOVA
Cities
Informal settlement
Urban development
Nigeria

A B S T R A C T

Objectives: Little is known about the complex interplay between urban structure and health in rapidly urbanizing cities in Nigeria.
Methods: The study broadly used very high-resolution satellite imagery and gathered primary data. With the aid of the very high-resolution imagery and identified neighborhoods, two neighborhoods each were sampled based on their classified urban structure characteristics. The obtained malaria epidemiologic data were aggregated according to stratified neighborhoods. Analysis of variance was used to determine the mean difference of malaria burden between the spatial structure.
Results: The study shows that under 5 malaria varies significantly among the settlement classes (P = 1.118e-05) with highest difference between peri-urban settlement and medium-density settlement (P = 0.0000988). The study shows higher malaria burden in the informal and peri-urban settlement compared with the lower prevalence in formal settlements.
Conclusions: The study findings underscore the urgent need for comprehensive urban development policies to address health inequities by prioritizing physical infrastructure improvements in marginalized areas. Such improvements will translate to enhanced health equity for rapidly growing informal, poor, and deprived settlement areas and ultimately promote sustainable urban development efforts.

Introduction

Cities play important and critical role in the achievement of Sustainable Development Goal 3. However, the urbanization trend in low- and middle-income countries, such as Nigeria, presents significant sustainable development challenge, particularly, the striking urban health inequalities. It is well-known that factors such as geography, socio-ecological characteristics, and health policies influence health inequality; little is known about the complex interplay between urban structure and health in rapidly urbanizing cities in Nigeria.

Urban structure, also known as urban spatial structure (USS), illustrates the structural patterns in cities and extended urban areas. It is of note that within a city, the spatial structure landscape can vary dramatically from the Central Business District to the suburbs. This is often as a result of dynamic economic structures with accompanied transformation in the city's socio-spatial organization [1]. Urban economists model USS based on the complex and interacting economic forces of decentralization, dispersion, and multiple employment [2]. This analogy is not far dissimilar from the tenets of the Chicago school's description of city growth and development patterns. A simpler illustration was inferred by Zhang et al. [3] as changing distribution of population in the urban space as a result of economic activities and average decline in urban density gradient within enlarged urban spatial limit [4]. Urban population and density, economic activities, level of education, health, and segregation are some of the key determinants of urban structure, thereby forming the theoretical conceptualization of neighborhoods [5,6]. This holds true in Akure, with diverse urban density structure. Classification pattern of Akure into residential structures dates to the work of Olorunfemi where housing in Akure were characterized due to the rapid development, population growth, and changing political status [7]. The rapid development and population growth of Akure is asserted to be a continuous phenomenon. According to the study by Urbanization Research Nigeria in 2015, Akure is identified as a city that will experience major concentration of urban spatial growth and physical development because Nigeria's urbanization rate was projected to be about 52% in the year 2020 [1].

* Corresponding author.
E-mail address: bayode@stud.uni-heidelberg.de (T. Bayode).

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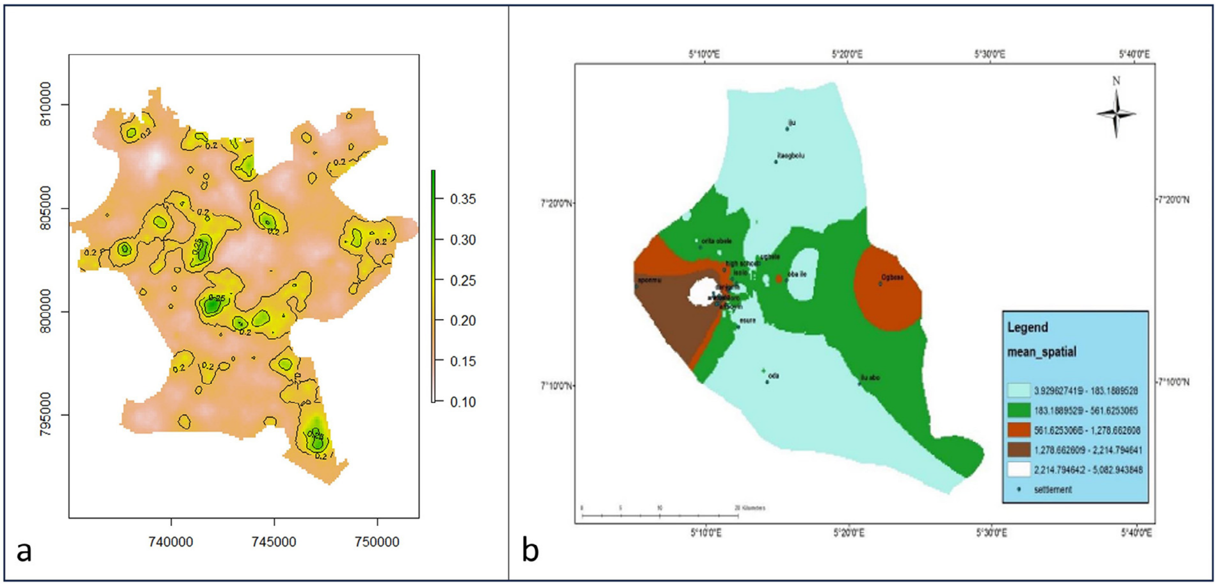

Figure 1. (a) Spatial pattern of under 5 malaria prevalence in Akure [11]. (b) Mean spatial distribution of malaria prevalence in Akure [12].

Furthermore, the complex interaction between population increases and skewed distribution of services exacerbates the inflow impact of population from rural hinterlands around Akure to the city of Akure. This has resulted in the emergence of new places in the suburbs. However, these newly emerged urban areas often experience shortages of services and infrastructure due to demographic demands and population density [8]. Ultimately, the new urban areas and/or urban expansion is likely to increase in Nigeria, with profound consequences for the physical configuration of Nigerian urban settlements and impacts on the health of urban residents [9,10]. For example, [11] identification of children below the age of 5 years (U5) malaria variability in Akure reveals the enormous burden in poor and low-income residential communities, i.e. city centers (Arakale, Araromi) and newly emerging areas (suburbs such as Oba Ile), as shown in Figure 1. Similarly, Abdulkareem et al. [12] observed the highest burden of malaria in core areas of Akure such as Araromi, Arisoyin, High School, and Ogbese, followed by relatively high burden in the suburbs such Orita Obele, Esure, and Oba Ile.

Scholars have investigated impacts of residential or spatial structure in Akure on various aspects. For example, Olujimi [13] explored how disparities in infrastructure between different zones in Akure impacts rental values of residential properties, and Emmanuel [14] explored socio-economic gradient along residential densities in Akure, whereas Olayiwola [15] explored the correlation between socio-economic characteristics and quality of residential neighborhoods in Akure. Akinbamijo and Fasakin [16] explored spatial disparities of health among residential zones (core, transition, and peripheral) in Akure. However, the study does not empirically classify these residential neighborhoods and did not investigate the impact (direct/indirect) on residents' health. Earlier, Alex et al. [2] pointed out the need to study urban structure because city growth pattern is experiencing qualitative change. However, to date and to the best of the authors' knowledge, no studies have explored the impact (direct or indirect) on health of Akure residents. Our study aims to fill this identified gap using childhood malaria prevalence as a proxy for health condition in Akure. To date, malaria remains a significant public health problem in Nigeria. Nigeria records the highest cases of malaria and deaths worldwide. Worse, the burden of malaria and death toll are higher among U5 [17,18].

Urban land use model: a brief overview

Historically, USS widely spread model with more applicability in urban land use planning and distribution of population are the ecological models—concentric zone, sector, and multiple nuclei models. Other approach includes economic model and activity models as rightly put forward by Carter [19]. The concentric zone model was developed by Burgess [20,21] to explain urban social structures in cities as increasing socio-economic status with distance from the city center—a concept adopted from plant ecological framework (competition, dominance, invasion, and succession). Alternatively, Adams and Hoyt [22] described urban structure and city growth pattern based on residential rent pattern and impacts of transportation development with the sector model, a theory propounded by Hoyt, H. in 1939. Sector and concentric zone models overlap. Although both models explain the outward growth of cities, their practicality, structure of growth, and land use patterns differ. The former has practical application in real estate management with radial outward growth and non-random land use pattern, whereas the latter has a sociological application, with ring-like outward growth and random land use pattern. Often, large cities do not grow a single nucleus. Thus, formal and more effective generalization of urban land uses were developed by Harris and Ullman in 1945 [23]. The basic assumption is that city's mini nuclei was originally developed independently with the specialized advantages that they offered [6]. The delineation or classification of neighborhoods based on morphological characteristics is complex, multidimensional, and nebulous [5]. Nevertheless, the emergence of new data sources and availability of increased computational power has enabled urban geographers and spatial scientist to quantitatively classify neighborhoods based on arrangement, shape, and structure of the built environment [24,25].

Methodology

Study area

This study area, Akure, is located in the south-western part of Nigeria. It is a medium-sized capital city of Ondo State, and it lies in the tropics at E 5°04′42"–E 5°29′45"/N 7°26′43"–N 7°03′50". Akure City, being the regional capital of Ondo State since 1976 is one of the emerging prominent urban centers. The city has a long history dated back to pre-colonial era, making it a traditional city with attractive responsibilities, such as the main base for Benin's trade and western frontier of Benin, and notably emerged as the headquarters of Ondo Province in 1915. The city has witnessed rapid population growth in the last twenty years. According to earlier study of Emmanuel [14] and Akinbamijo and Fasakin [16], Akure has three distinct morphological

Table 1
List of settlements and zonation in Akure.

Settlement classification			
Informal	Medium-density	Planned	Peri-Urban
Arakale	Fanibi/Lafe	Ijapo	Igoba
Erekesan	Ijomu	Alagbaka	Shagari
Isolo	Oke-Aro Titun	Oba-Ile Phase One	Owode
Isikan	Oke-Ogba	Oke-Ijebu	Adofure
Eruoba	Oke Padi	Ala	Ijoka Road
Odo Ikoyi	Aiyedun		Aule Road
Oritagun	Oke Isinkan		Gaga Area
Erekefa	Oke Arata		Ologede Area
Immagun			
Igann			

structures (zones), which are the core, transition, and peripheral. Further details about Akure have been discussed [10,11,26,27].

Data and method

The study broadly used very high-resolution satellite imagery and gathered primary data from field survey. According to the field survey, malaria indicator questionnaire was used to gather malaria prevalence on U5. Details on the sampling and method of primary data collection have been discussed [27]. With the aid of the very high-resolution imagery, first, this study modeled and classified the urban structure of Akure based on building morphological characteristics, such as building size, building orientation, and density using the Momepy tool (https://docs.momepy.org/en/stable/) in python, according to the works of Fleischmann and Taubenböck et al. [28,29]. This was also augmented with expert classification, historical maps, and visual classification (qualitative). Second, this study used analysis of variance to statistically determine the difference in the mean of U5 malaria among the selected settlement classes. In this study, we randomly selected two settlements from each residential zones from the list of zones in Akure, as shown in Table 1.

Results

The objectives of this study are to classify Akure into different morphological characteristics and to determine if disease burden (U5 malaria) is significantly different among the classified settlements. Based on the morphological characteristics, the study classified the settlements into four, which are medium-density, informal, peri-urban, and planned settlement, represented by letters A, B, C, and D, respectively, as shown in Figure 2. In a bid to test the significance difference of U5 malaria burden among the selected settlements, the analysis of variance result (Figure 3), according to the study analysis, shows that U5 malaria varies significantly among the settlement classes (P = 1.118e-05), with highest difference between peri-urban settlement and medium-density settlement (P = 0.0000988). There is no difference between planned and medium-density settlement and informal and medium settlement (P = 0.3091361 and P = 0.1440773, respectively). The study further shows that the highest burden of U5 malaria is associated with the peri-urban settlement. These areas are characterized with fragmented landscapes and weak urban planning [10,30].

Discussion

The informal settlements are the core area or inner city. They represent the Central Business District, where the market, *Obas* palace, and earliest residential structures are located. These places lack formal or modern form of urban planning. Owoeye and Omole [31] argued that Akure follows Burgess' concentric zone theory, where medium-density developments bridges informal and formal settlements. Our study supported this with distinct density characteristics between these settlements. The medium-density settlements are often occupied by middle-class residents [15,31]. The medium-density zone is followed by government residential estates earmarked for the affluent residents. This zone is also regarded as the high-class residential areas [31,32]. However, according to our study, we observed a distinction between the high-class residential areas (D) and characteristics of newly emerging areas (C), as shown in Figure 2. The newly emerging areas are the peri-urban settlements found at the outskirts of the city.

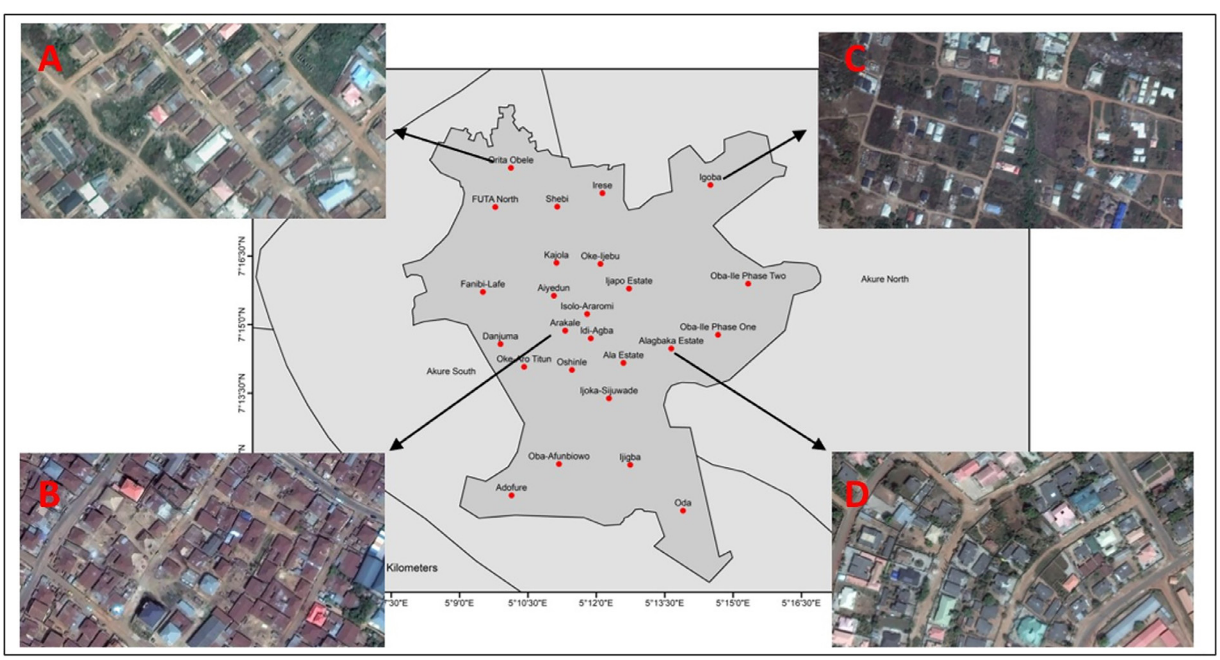

Figure 2. Study area with selected settlements.

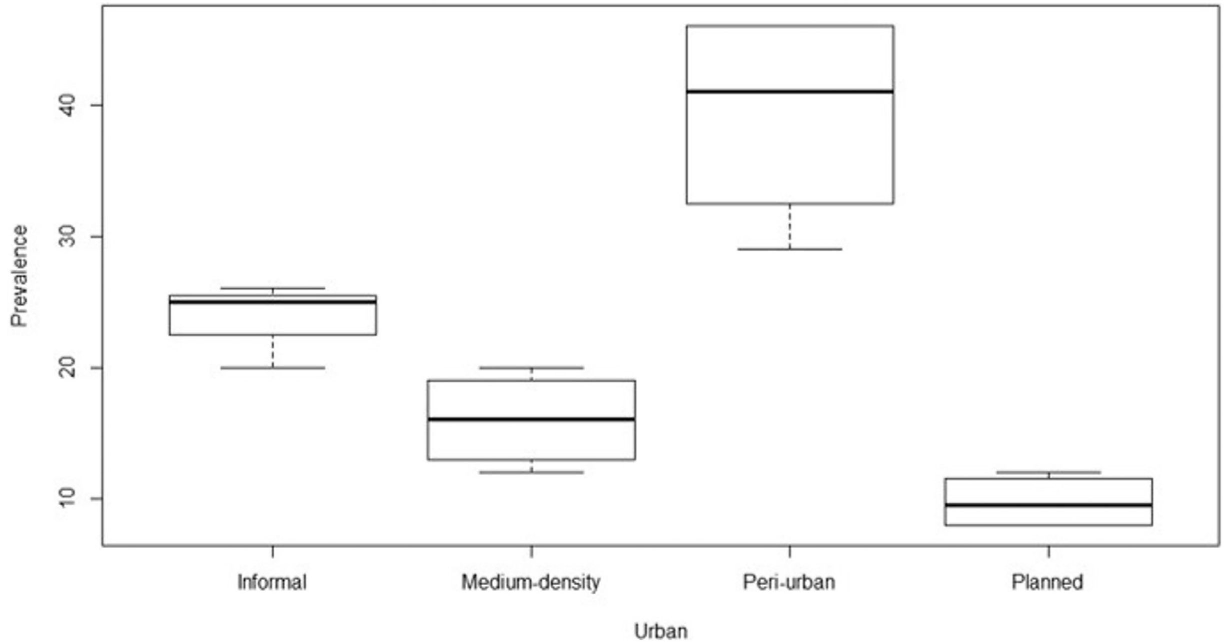

Figure 3. Analysis of variance result for the study.

The core/informal and peri-urban settlements have higher burden of malaria than the medium-density and planned settlements. This is because much of urban expansion in Africa is characterized by unplanned and unregulated growth, exacerbated by the legacy of colonialism, structural adjustment, and neo liberalism that spawned weak urban planning institutions [33]. The unequal distribution and pattern of infrastructure are fallouts of weak planning controls in Akure. Infrastructures improve livability in communities and urban experiences. However, the study of Akinbamijo and Aladetuyi [34] on the state of infrastructure in Akure reveals that road, water, and health infrastructures are subpar. With focus on spatial distribution of health facilities in Akure, Oyinloye and Olugbamila [35,36] highlighted the inadequate distribution of health facilities among localities at the central wards. Furthermore, Olugbamila [36] echoed the need for town planners to ensure equitable distribution of health facilities in Akure while putting into consideration the location of existing functional health infrastructures. This is vital because since the birth of Akure, its development has been guided by an obsolete master plan, which was produced in 1980 [10].

Recommendations and conclusion

The last two decades have witnessed enormous revolution in application of spatial science tools to city management, particularly, due to improved software computational capabilities, hardware, the fine scale resolution, and ubiquity of earth observation (EO) data. Despite these many advantages, cities in low- and middle-income countries lag in the study and modeling of the city spatial form. In this article, we modeled the urban residential structure of Akure using geographic information system technology and EO data sets. Furthermore, the study investigated the variability of malaria burden as a proxy for health outcome among the identified residential zones. The study identified variability in health outcomes, implying the indirect impact of urban structure on health outcome in Akure.

Paucity of data, such as EO, health, and location of health infrastructure, is a challenge and has limited the analytics of the study. However, this study highlights previous works done in Akure in this regard. We, therefore, strongly recommend extensive research with inclusion of the aforementioned data in their analysis.

Declarations of competing interest

The authors have no competing interests to declare.

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Ethical approval statement

Ethical clearance was obtained from the Ondo State Ministry of Health before interview was carried out.

Author contributions

TB conceived and conceptualised the study, obtained, analysed the data, interpreted the results, drafted, and revised the manuscript. OBA revised the manuscript. AS revised the manuscript.

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Name, first name	Taye Bayode	Olumuyiwa Akinbamijo	Alexander Siegmund
Methodology	☑	☐	☐
Software	☑	☐	☐
Validation	☑	☐	☐
Formal analysis	☑	☐	☐
Investigation	☑	☐	☐
Resources	☑	☑	☑
Data Curation	☑	☐	☐
Writing-Original Draft	☑	☐	☐
Writing-Review&Editing	☑	☑	☑
Visualization	☑	☐	☐
Supervision	☐	☐	☑
Project administration	☑	☐	☐
Funding acquisition	☑	☐	☑

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Hiermit bestätige ich, dass alle obigen Angaben korrekt sind/*I confirm that all declarations made above are correct.*

Unterschrift/*Signature* ______ Doktorand/in/*Doctoral student* ______ Co-Autor/in 1/*Co-author 1* ______ Co-Autor/in 2/*Co-author 2*

Betreuungsperson/*Supervisor:*

Hiermit bestätige ich, dass alle obigen Angaben korrekt sind und dass die selbstständigen Arbeitsanteile des/der Doktoranden/in an der aufgeführten Publikation hinreichend und signifikant sind/*I confirm that all declarations made above are correct and that the doctoral student's independent contribution to this publication is significant and sufficient to be considered for the cumulative dissertation.*

Prof. Dr. Alexander Siegmund		23.01.2025
Name/*Name*	Unterschrift/*Signature*	Datum/*Date*

INTRODUCTION AND CONSENT

Dear Participants,

We are grateful for your attentiveness to this study.

Spatial profile of childhood malaria occurrence can significantly provide support on how to maximize the limited resources for malaria control in Akure. Information on socio-economic factors as well as malaria epidemiology and preventive behaviour within different spatial settings may be useful to guide public health response, monitor, plan and evaluate malaria control programmes and health services. Furthermore, obtaining information on the aforementioned indicators is important for the successful completion of this study.

Our study focused on children under 5 years of age. Your household was selected for this survey. However, you don't have to be in the survey, but we hope you will agree to answer the questions since your views are important for this study. If you don't want to answer a particular question, please let me know. The questions usually take about 15 to 20 minutes. Please turn to the back page for other questions.

For this study, your identity remains incognito and the processed results are liable for academic purpose and scientific use only. Therefore, there are no financial benefits involved; and the entry of your name and cell phone number are primarily for revisit/follow up purposes if need be.

Supervisor:

Prof. Dr. Alexander Siegmund
Department Geography – Research Group for Earth Observation (rgeo)
UNESCO-Chairholder on World Heritage and Biosphere Reserve Observation and Education

Taye Bayode (Scientific Researcher)
Department Geography – Research Group for Earth Observation (rgeo)
UNESCO-Chairholder on World Heritage and Biosphere Reserve Observation and Education

1. How long have you been residing here?

- less than 6 months
- between 6 months and 1 year
- between 1 and 2 years
- more than 2 years

2. What is your household size?

3. How many of this household's child/children are less than five years old?

1	2	3	4

4. What is/are their age range?

- less than 1 year
- between 1 and 2 years
- between 2 and 3 years
- between 3 and 4 years
- between 4 and 5 years

5. Sex of child / children

Male	Female

6. Which month did your child or any of your children had malaria between November 2018 and November 2019? (If none, skip to question 14)

7. Was clinical result obtained for the malaria illness?

Yes	No

8. What he or she means in another neighborhood for at least two weeks before the materialization of malaria?

Yes	No
○	○

If yes, where?

9. Did he / she vomit during this period?

Yes	No
○	○

10. Did he/she have diarrhoea during this period?

Yes	No
○	○

11. What other symptoms did you notice?

12. How much do you spend on malaria treatment whenever you have the illness?

- less than ₦500
- between ₦500 - ₦1000
- between ₦1000 - ₦2,000
- between ₦2,000 - ₦3,000
- more than ₦3,000
- No expenses

13. How many bedrooms are available for use in your household?

1	2	3	4	5	6
○	○	○	○	○	○

14. Do you have mosquito bed nets for your children?

- Yes
- No (If No, skip to question 23)

15. Do you use mosquito bed nets for your children

- Yes
- No
- If No, why?

16. How old is/are the mosquito bed nets?

17. How often do you replace/treat your mosquito bed nets?

- ◯ Every 6 months
- ◯ Every 12 months
- ◯ Every 2 years
- ◯ Never
- ◯ Others, specify:

18. How did you get the mosquito bed nets?

- ◯ Mass distribution campaign
- ◯ Antenatal care visit
- ◯ Postnatal care visit
- ◯ Procured with personal cost of:

19. What time do you mount the mosquito bed nets?

- ◯ Permanently fixed
- ◯ Before 5pm
- ◯ Between 5pm and 7pm
- ◯ Between 7pm and 9pm
- ◯ After 9pm

20. Do you think your child/children find it comfortable sleeping under the mosquito bed nets?

- ◯ Yes
- ◯ No
- ◯ If No, why?

21. Do you know of any malaria vaccine? (Ask for examples)

- ◯ Yes
- ◯ No
- ◯ If Yes, how did you know about it?

22. Has your child/children been vaccinated against malaria?

- ◯ Yes
- ◯ No
- ◯ If No, why?

23. Would you accept malaria vacination for your child?

- ◯ Yes
- ◯ No
- ◯ If No, why?

24. What actvities and time do you think your child/children often exposed to mosquito bites?...............................

- ◯ Before 6am
- ◯ Between 6am - 7am
- ◯ Between 7am - 5pm
- ◯ Between 5pm - 6pm
- ◯ Between 6pm - 7pm
- ◯ After 7pm

25. Observe the weight of the child

26. Observe the height of the child

27. What is the main source of drinking water for members of your household?

- Piped water
- Dug well
- Surface water
- Others, specify:

28. Is your water storage covered?

Yes	No
○	○

29. Is your drainage channel covered?

Yes	No
○	○

Describe condition of drainage channel eg often blocked etc

30. Describe the street condition in your neighbourhood? (eg, not tarred with potholes)

31. What kind of toilet facility is available for use in your household?

- Flush toilet
- Pit laterine
- Bucket toilet
- No facility
- Others, specify:

32. Do you have healthcare infrastructures in this neighbourhood?

Yes	No	Not sure
○	○	○

33. How do you transport and what is the average travel time from your house to nearest health facility?

	Less than 30minutes	Between 30 minutes and 1 hour	More than 1 hour	Not sure	Never
By foot	◯	◯	◯	◯	◯
Motorbike	◯	◯	◯	◯	◯
Car	◯	◯	◯	◯	◯
Bus	◯	◯	◯	◯	◯
Others:	◯	◯	◯	◯	◯

34. How do you dispose your soild waste?

◯ Moving water body

◯ Burning

◯ Vacant plot

◯ Pick up

◯ Others, specify:

35. How far is your house to waste dump site?

◯ Less than 10 metres

◯ Between 10 - 20 metres

◯ Between 20 - 30 metres

◯ More than 30 metres

36. How often does Town Planning Officers scrutinize developmental activities in this neighborhood?

◯ Monthly

◯ Quarterly

◯ Yearly

◯ Never

◯ I don't know

37. What is your housing tenure type?

◯ Inherited

◯ Individual ownership

◯ Rented

◯ Others, specify

38. Marital status of parent/guardian

- ◯ Single
- ◯ Married
- ◯ Separated
- ◯ Divorced
- ◯ Widowed

39. Ethnicity of parents/guardian

	yoruba	Igbo	Hausa	Others, specify:
Father	◯	◯	◯	◯
Mother	◯	◯	◯	◯

40. Highest education status of parents/guardian

	No education	Primary	Secondary	Apprentice	Tertiary (i.e higher education)
Father	◯	◯	◯	◯	◯
Mother	◯	◯	◯	◯	◯

41. Employment status of parents

	Unemployed	Informal sector	Formal sector	Others, specify:
Father	◯	◯	◯	◯
Mother	◯	◯	◯	◯

42. Household monthly income

- ◯ less than ₦20,000
- ◯ between ₦20,000 - ₦50,000
- ◯ between ₦50,000 - ₦100,000
- ◯ between ₦100,000 - ₦150,000
- ◯ more than ₦150,000

43. Do you have / own livestock, farm animals or poultry in this household?

- ◯ Yes
- ◯ No
- ◯ If yes, specify type and numbers:

44. Do you practice urban agriculture or any form of horticulture?

Yes	No
◯	◯

45. Observe the floor material of the building

- ○ Natural floor (earth, dung)
- ○ Rudimentary floor (wood, bamboo)
- ○ Finished floor (ceramic, cement, carpet)
- ○ Others, specify:

46. Observe if the roof eave is covered

Yes	No
○	○

47. Observe if the window has protection against vectors

Yes	No
○	○

48. Observe the type of material of exterior wall and roof

- ○ Natural walls (dirt, palm)
- ○ Rudimentary walls (bamboo with mud; stone with mud; plywood)
- ○ Finished wall (cement, bricks, wood planks, stone with lime)
- ○ Others, specify:

49. Do you experience any form of mental disorder such as the following?

	Yes	No
Depression	○	○
Anxiety	○	○
Social intolerance	○	○
irritability	○	○

50. If yes, are they attributed to the condition of your house or neigbourhood?

	Yes	No
Neighbourhood condition	○	○
House condition	○	○

Taye Joshua BAYODE

PERSONAL DETAILS

ORCID:	https://orcid.org/my-orcid?orcid=0000-0002-4331-4961
Nationality:	Nigerian

EDUCATION

07/2017 – 04/2025	**Doctoral Candidate in Geography (Medical geography)** *Universität Heidelberg, Heidelberg, Germany*
03/2013 – 02/2015	**Master of Science in Urban and Regional Planning** *University of Ibadan, Ibadan, Nigeria*
10/2006 – 09/2011	**Bachelor of Technology in Urban and Regional Planning** *Federal University of Technology Akure, Nigeria*

WORK EXPERIENCE

07/2022 – Present

Junior Data Consultant (Anaylst)
Environmental Systems Research Institute (Esri UK), United Kingdom

- Sourcing, processing, and QA of third-party data products.
- Perform data processing tasks to maintain Esri UK's statistical data services (National Data Service)
- Perform routine operations to update and support the standard reports which are part of Esri UK's statistical data service.
- Authoring, reviewing, and updating work instructions in OneNote to improve delivery of data orders, workflows, and updates for customers.
- Provide second line support for data as a service.

05/2026 – 06/2022

GIS Data Analyst (EMEA)
JLL (Jones Lang LaSalle), United Kingdom

- Visualisation of warehouse labour availability in Europe, Middle East, and Africa
- Web scrapping and (Geo)data cleaning in Excel
- Processing geographical data and mapping locations of warehouses
- Updating images, maps, and coordinate on the database.

06/2021 – 01/2022

Data Analyst
The Binding Site Group Limited, United Kingdom.

- Participated in system development of special projects (antibody detection and monitoring) and performed other duties as assigned.
- Collaborated with different teams using the Enterprise Resource Planning (ERP) software on different projects.
- Complied structure and unstructured data and verified their quality, accuracy, and usability i.e data verification and validation.

09/2020 – 06/2021

Werk student (Data labelling)
Viscan Solutions GmbH, Germany.

- Labelling images for the development of artificial intelligence as part of the AI4INFRA research project
- Controlling of labelled images
- Participation in internal conferences

10/2018 – 05/2021	**Student Research Assistant** **GIS Station, Department of Geography, Heidelberg University of Education, Germany.**

- Management of publication database for the research group.
- Supported the research group at various and assigned capacities such as conference organisation.
- Supported by gathering essential data for the tutorial development for geo:spektiv online learning platform.
- Collaborated with other researchers (local and international) to author and publish articles on disease prevalence

PROFESSIONAL CONTINUING EDUCATION AND CERTIFICATES

09/2021	**Certificate of Lean Competency (Level 1 – Awareness)** *Binding Site & Cardiff University, United Kingdom*
11/2020	**Topics in Digital and Computational Demography.** *International Max Planck Research School for Population, Health, and Data Science (IMPRS-PHDS), Rostock, Germany.*
09/2019	**6th Trifels Summer School on Global Challenges and Systems Thinking.** *University of Koblenz-Landau, Landau, Germany*
09/2018	**10th International Summer School on Spatial Epidemiology, Social Media and Urban Health** *Humboldt University, Berlin, Germany*
08/2018	**The CODATA-RDA Research Data Science Summer School** *The Abdus Salam International Centre for Theoretical Physics (ICTP), Trieste, Italy*
2018 - 2019	**Advanced Epidemiology and Biostatistics for Doctoral Students.** *Institute of Public Health, Heidelberg University, Germany.*

Awards, Scholarships and Grants

2022	International Society of Urban Health (ISUH) travel scholarship award for 18th International Conference on Urban Health
2021	DAAD - Scholarship and Mentoring Programme (STIBET) - Graduation assistance
2018-2024	Kurt-Hiehle Stiftung Conference Travel Grant, Heidelberg University, Germany
2015	Group on Earth Observation Conference Attendance Scholarship, Geneva, Switzerland, for the 5th Geographic Object Based Image Analysis (GEOBIA) conference, Thessaloniki, Greece
2011	Best Graduation Student of the Department – Federal University of Technology Akure
2006 - 2011	Ondo State Scholarship award for bachelor’s degree

Additional Skills

Languages	English (Native) German (Intermediate)
Software	Microsoft Office 365: Microsoft Word, Excel, PowerPoint & Outlook Programming language: R, Python Visualization: R, Tableau Relational database management: SQL Spatial data processing and analysis: R, ArcGIS Pro/Online, QGIS & SatScan, GeoDa, GWR4, AutoCAD Image Processing: eCognition, ERDAS Imagine

Volunteer

04/2020 - Present

Convener — Virtual Teaching
Dept. of Urban and Planning, Federal University of Technology Akure, Nigeria

- Tutor on Introduction to Data Science and Spatial Data Science
- Developed syllabus on the Applications of Modern Geospatial Technologies to City Planning

Professional and private interests

Professional	Statistical learning; Spatial Data Science; Public health in low- and middle-income countries; Tropical disease propagation; Field survey
Private	Nature-photography; Freelance Writing; Urban Tourism.

Heidelberg, 27.01.2025

GESAMTFAKULTÄT FÜR MATHEMATIK,
INGENIEUR- UND NATURWISSENSCHAFTEN

COMBINED FACULTY OF MATHEMATICS,
ENGINEERING AND NATURAL SCIENCES

RUPRECHT-KARLS-
UNIVERSITÄT
HEIDELBERG

Eidesstattliche Versicherung gemäß § 8 der Promotionsordnung für die Gesamtfakultät für Mathematik, Ingenieur- und Naturwissenschaften der Universität Heidelberg / Sworn Affidavit according to § 8 of the doctoral degree regulations of the Combined Faculty of Mathematics, Engineering and Natural Sciences at the Heidelberg University

1. Bei der eingereichten Dissertation zu dem Thema / The thesis I have submitted entitled

   Reducing childhood malaria through sustainable urban planning: A spatial risk modelling approach to foster public health-based urban structure and infrastructure in Akure, Nigeria

   handelt es sich um meine eigenständig erbrachte Leistung / is my own work.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht. / I have only used the sources indicated and have not made unauthorised use of services of a third party. Where the work of others has been quoted or reproduced, the source is always given.

3. Die Arbeit oder Teile davon habe ich wie folgt/bislang nicht[1)] an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt. / I have not yet/have already[1)] presented this thesis or parts thereof to a university as part of an examination or degree.

   Titel der Arbeit / Title of the thesis: None

   Hochschule und Jahr / University and year: None

   Art der Prüfungs- oder Qualifikationsleistung / Type of examination or degree: None

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich. / I confirm that the declarations made above are correct.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt. / I am aware of the importance of a sworn affidavit and the criminal prosecution in case of a false or incomplete affidavit

Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe. / I affirm that the above is the absolute truth to the best of my knowledge and that I have not concealed anything.

27.01.2025
Ort und Datum / Place and date

Unterschrift / Signature

[1)] Nicht Zutreffendes streichen. Bei Bejahung sind anzugeben: der Titel der andernorts vorgelegten Arbeit, die Hochschule, das Jahr der Vorlage und die Art der Prüfungs- oder Qualifikationsleistung. / Please cross out what is not applicable. If applicable, please provide: the title of the thesis that was presented elsewhere, the name of the university, the year of presentation and the type of examination or degree.

The German text is legally binding.

Instruction concerning the

Sworn Affidavit

The German text is legally binding.

The universities in the state of Baden-Württemberg request a sworn affidavit concerning the sole authorship of the scientific achievements, in assurance that the doctoral student’s work is his or her own individual research.

The legal system associates a particular meaning and serious consequences with a sworn affidavit, and thus penalizes false sworn affidavits. Intentional (consciously made) false affidavits can be punished with up to 3 years of imprisonment or a fine.

A negligent offence (an affidavit made in spite of the fact that you should have noticed that the declaration is not true) can result in imprisonment for up to one year or a fine.

The corresponding penal provisions to be found in § 156 StGB (German Criminal Code) for false sworn affidavits and § 161 StGB for negligent offences.

§ 156 StGB: False sworn affidavits

Whosoever before a public authority competent to administer sworn affidavits, falsely makes such an affidavit or falsely testifies while referring to such an affidavit shall be liable to imprisonment of not more than three years or a fine.

§ 161 StGB: Negligent offences

(1) If a person commits one of the offences listed in §§ 154 to 156 negligently the penalty shall be imprisonment of not more than one year or a fine.

(2) The offender shall be exempt from liability if he corrects his false testimony in time. The provisions of § 158 (2) and (3) shall apply accordingly.

Acknowledged on 27.01.2025 ______________________ ______________________

Date Signature