SEASONAL GEOGRAPHICAL ACCESS TO HEALTHCARE IN CROSS RIVER STATE, NIGERIA

By:

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A thesis submitted in partial fulfilment of requirements for the Degree of Doctor of Philosophy

The University of Sheffield
Faculty of Medicine, Dentistry and Health
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July 2019

DECLARATION

I certify that this thesis submitted for the degree of Doctor of Philosophy is the result of my own research, except where otherwise acknowledged. No portion of the work presented in this thesis has been submitted for another degree or qualification to this, or any other, university or institution.

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ABSTRACT

Background: Geographical access to healthcare is a significant public health issue in developing countries. The problem becomes more complicated in the wet season when road transport is usually interrupted due to flooding. However, healthcare care accessibility studies have largely ignored the seasonality of geographical access let alone associating it with disease outcomes or accommodating it in the plan to increase access to health services. Therefore, this study carried out a community-level investigation of seasonal geographical access to health facilities, its influence on malaria outcomes and on the potential locations of new health facilities.

Method: A systematic review of geographical access to healthcare in Low-and-Middle-Income-Countries (LMICs) was conducted. Health facilities and road network data were obtained from the Local Authority. Facilities' locations were digitised from high-resolution Orthophoto Map and Google Map. Data on the geographical distribution of the population were projected from the community-level census record. A flood model was used to measure access in the wet season by driving and walking times. Trips to health facilities and potential locations of new facilities were assessed using the ArcGIS Network Analyst Tool. Logistic regression in SPSS was used to examine associations between drive times to health facilities and malaria outcomes.

Results: Average dry season drive times to Primary Health Care (PHC), hospitals and National Health Insurance Scheme (NHIS) in the Central Senatorial District (CSD) were 40, 132 and 92 minutes respectively. In the Southern Senatorial District (SSD), average drive times in the dry season were 30, 103 and 82 minutes to PHC, hospitals and NHIS respectively. In the wet season, average drive times to PHCs, Hospitals and NHIS in the CSD increased to 69, 230 and 139 minutes respectively. Average wet season drive times in the SSD also increased to 68, 160 and 142 minutes for PHCs, hospitals and NHIS respectively. While the whole population could access health facilities in the dry season, 70%, 37% and 68% of the population could access PHC, hospitals and NHIS in the wet season respectively. There was no compelling evidence that the odds of malaria increased in the wet season, although there were a few associations. The dry season Location-Allocation Models (LAMs) produced better population coverage than the wet season.

Conclusion: Measurement of geographical access without including the wet season can produce misleading results. Therefore, seasonal variability of geographical access should become an essential part of accessibility studies and healthcare planning.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

JOURNAL ARTICLE AND CONFERENCES

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LIST OF ABBREVIATIONS AND ACRONYMS

ACT – Artemisinin-based Combination Therapy
ANC – Antenatal Care
ART – Antiretroviral Therapy
CGH – Calabar General Hospital
CRGIA – Cross River Geographical Information Agency
CRS – Cross River State
CSD – Central Senatorial District
EFLAM – Existing Facilties Location Allocation Model
EmONC – Emergency Obstetric and Neonatal Care
EO – Edet Otu
ESRI – Environmental Systems Research Institute
FMC – Federal Medical Centre
FSHIP – Formal Sector Health Insurance Programme
GAS – Greedy Adding and Subtraction
GDP – Gross Domestic Product
GIS – Georgaphical Information Systems
GPS – Global Positioning System
HJ – Hannah Jordan
HLAM – Hierachical Location-Allocation Model
HMO – Health Maintenance Organization
HSRP – Health Sector Reform Programme
IRS – Indoor Residual Spray
ITN – Insecticide Treated Net
LAM – Location-Allocation Model
LLINs – Long-lasting Insecticide-treated mosquito nets
LMICs – Low-and Middle-income Countries
LSCP – Location Set Covering Problem
MASH – Mathematics and Statictics Help
MCH – Maternal and Child Health
MCLP – Maximal Covering Location Problem
MDI - Multiple Deprivation Indices
MeSH - Medical Subject Headings
MoH – Ministry of Health
NGSA – National Geological Surveys Agency
NHB – National Health Bill
NHIS – National Health Insurance Scheme
NHPR – National Health Policy Review

NIMET – Nigerian Meterological Agency
NMSP – National Malaria Strategic Plans
NPC – National Population Commission
NSD – Northern Senatorial District
NSHDP – National Strategic Health Development Plan
OSG-CRS – Office of the the Surveyor-General of Cross River State
PHC – Primary Health Centre
PPP – Public-Private Partnership
PWLAM – Population Weighted Location-Allocation Model
RM – Ravi Maheswaran
RPLAM – Random Points Location-Allocation Model
SLAM – Single-Level Location-Allocation Model
SSD – Southern Senatorial District
UGH – Ugep General Hospital
UK – United Kingdom
USA – United States of America
USAID – United States Agency for International Development
WHO – World Health Organisation

ACKNOWLEDGEMENTS

I am grateful to the Almighty God for the gift of life, protection and good health.

I would like to thank my supervisors; Professor Ravindra Maheswaran and Dr Hannah Jordan for their painstaking support in my PhD journey. I also want to thank my third supervisor Dr Mark Green for his great support during and after his time in the University of Sheffield. I also like to thank my Personal Tutor, Mr Dan Beever for his listening ears and efforts he made to pull me out of some of my challenges.

Many thanks to my professional colleagues and friends, especially Surv. Eyo Oku, Grace Ishatah, Surv. Edem Henshaw, Pst. Joseph Edet, Attai Abubakar, John Adesola, Josephine Akilamo, Dr Uyi, Kaiso Dahnyels and Dr Ibiwoye Busayo who helped in sourcing for the research data and proof-reading of my thesis.

I am indebted to my family, especially my late father, Ndabu Thomas Otu, for his indelible words of motivation; my mother, for her love and care; and my siblings, who always encourage me that everything would be okay in the hardest times of my PhD.

I like to thank my UK family, the Deeper Life Bible Church Sheffield for a great atmosphere of love and care. Special thanks to Pastor Victor Ebenuwa and Pastor Francis Owusu who supported me in every conceivable way.

I like to thank all my friends and colleagues at the University of Sheffield for giving me a great university experience. I want to thank the student finance office of the University of Sheffield for their understanding and bursaries I received when my PhD funding was cut. I would not be writing this page today if they did not rescue me.

I am grateful to the Niger Delta Development Commission for keeping the promise of sponsoring a part of my PhD. I like to also thank the Cross River State Government for the two years support they were able give to me.

Thanks to everyone, and all staff of the University of Sheffield.

CHAPTER ONE: INTRODUCTION

1. Chapter overview

Chapter One introduces the study of seasonal variation in geographical access to healthcare in Cross River State, Nigeria. It presents a brief introduction, research rationale, aims, objectives and research focus. It also discusses the potential impacts, plans of dissemination of findings and the structure of thesis. Overall, this chapter provides justification for the research and provides and describes to the overall body of the thesis.

1.1. Introduction to research

Geographical access to healthcare is a significant determinant of timely uptake of treatment and differential health outcomes (Alegana *et al.*, 2012; Blanford *et al.*, 2012). It has been established that long distances to health facilities increase the chances of delay in seeking effective treatment, the severity of the disease, hospital admission and mortality (O'Meara *et al.*, 2009; Schoeps *et al.*, 2011). However, accessibility measures have largely ignored the spatiotemporal dimension of geographical access especially in the sub-Saharan Africa where flooding poses a severe problem to transportation in the wet season (Stock, 1983; Ayeni, Rushton and McNulty, 1987).

Therefore, the effect of change in seasons on the proximity of health facilities and health outcomes remain under-researched. This study proposes an investigation of seasonal geographical access, and its effect on malaria outcomes and health facilities' location planning in Cross River State.

1.2. Rationale for study

Firstly, change in seasons affects every aspect of human life including mobility and proximity to health facilities (Blanford *et al.*, 2012; Ewing *et al.*, 2016). Geographical access is concerned with the means or ease of reaching a healthcare provider (Ribot and Peluso, 2003). The ease of reaching a healthcare provider is usually estimated by the cost of transport, distance or time taken to reach the facility. Travel times to health facilities may vary depending on the patient's origin of travel, time of the day and season of the year. The variation in proximity to facilities occurs because of how the population and facilities are distributed in geographical space and the impact of the environment on mobility (Delamater *et al.*, 2012). While snowfall in the winter interrupts travels in European countries (Johnsen *et al.*, 2017), heavy rainfalls in the wet season cause severe flooding which disrupts the road network and access to health services in sub-Saharan African countries (Vanguard Nigeria, 2013; Makanga *et al.*, 2017).

During that period, which is often between March and October (CometoNigeria, 2016), the affected population travels a longer distance to access healthcare in an attempt to avoid or use the flooded road segments while some lose access to healthcare for the whole period (Blanford *et al.*, 2012). Therefore, the healthcare inequality gap is expected to widen in the wet seasons, and a study of this kind is vital to quantifying the problem and finding solutions.

Secondly, changes in seasons may increase or reduce the prevalence and severity of some diseases, and most accessibility studies have ignored this problem (Kumar, 2004; Schoeps *et al.*, 2011; Alegana *et al.*, 2012). For instance, the prevalence of cold/flu is expected to rise in the winter and incidence of malaria is likely to upsurge in the wet season due to increased mosquito inoculation (World Health Organisation, 2017b; Iacobucci, 2018).

Malaria is a febrile disease that is transmitted by Anopheles mosquitos. The wet season provides extended breeding spaces for this species of mosquito in flooded areas (World Health Organisation, 2017b). Consequently, a significant number of people are expected to be sick of malaria at a time that mobility is limited by flood and distance to facilities has increased.

Although there has been a decline in the burden of malaria in the last decade, it remains one of the leading causes of hospital admissions and hospital deaths in Africa (Etyang and Scott, 2013). Annually, it accounts for 20% of hospital admissions, 17% of hospital mortality and 78% of death in children under the age of five in Africa (Etyang and Scott, 2013; World Health Organisation, 2014). Although distance and seasons may not have a direct effect on outcomes of malaria, both may cause a delay in seeking treatment. The delay in the uptake of effective treatment may lead to severe health outcomes (World Health Organisation, 2017b). In previous studies from Low-and Middle-Income Countries (LMICs), geographical access to health facilities had significant associations with severe malaria, hospital admissions and mortality (O’Meara *et al.*, 2009; Schoeps *et al.*, 2011).

Malaria prevention and treatment has received considerable attention (McCombie, 1996; Lengeler, 2004). A few studies have investigated the association between geographical access and malaria (Gething *et al.*, 2004; Alegana *et al.*, 2012), while seasonality of outcomes is often overlooked. This study proposes that the association between geographical access and malaria outcomes such as severity and hospital admission will be stronger in the wet season.

Lastly, seasonality of proximity to health facilities causes spatiotemporal inequality of geographical access to healthcare which is mostly unexplored in location-allocation measures (Oppong, 1996). The use of location-allocation models in health research and planning is gaining popularity (Rahman and Smith, 2000). However, the feasibility of the outcomes of such studies and plan is questioned on the grounds of limited finance, human resources, political interference and spatiotemporal inequality (Rahman and Smith, 2000). While recent models have been adapted to limit the number new health facilities' locations to the size of the budget, available health professionals and political plans (Verter and Lapierre, 2002; Kumar, 2004), the question of spatiotemporal inequality due to seasonal changes remain mostly unanswered by their methods. This problem may lead to an overestimation of geographical access and the potentials of a new facility in the wet season.

Since an intervention to increase access to healthcare must be adapted to the local setting (Goyder *et al.*, 2005), this study proposes the inclusion of spatiotemporal inequality in location-allocation in measures by incorporating the component of the wet season which is serious problem in Nigeria.

1.3. Aims

To explore seasonal geographical access to health facilities, examine seasonal associations between malaria outcomes and drive times to health facilities, and investigate the effect of wet season on location-allocation measures.

Objectives:

i. To review the literature on geographical access to health services in Low-and Middle-Income Countries (LMICs).
ii. To examine geographical access to healthcare in Cross River State in the wet and dry seasons.
iii. To investigate seasonal associations of drive times to healthcare, malaria severity and hospital admissions in selected Cross River State hospitals.

iv. To examine the effect of wet season on modelling method to support policy aimed at increasing geographical access to NHIS in Cross River State.

1.4. Research focus

This research examines seasonal geographical access to government-managed health facilities in the Cross River State of Nigeria. Apart from the introduction and discussion of relevant concepts, the entire study has four main components; a systematic review, seasonal geographical access to health facilities, seasonal associations of malaria outcomes and the effect of wet season on location-allocation measures.

Firstly, a systematic review of geographical access to healthcare was conducted to identify research gaps for this study. The review explored geographical access, utilisation of health services and the relationship between proximity to health services and health outcomes. Based on available knowledge at the time of this study, it was the first systematic review of evidence on geographical access in LMICs. The broad scope of the review extends the applications of its findings beyond Cross River State and provides public health decision-makers in Nigeria with comprehensive comparative knowledge of geographical access to healthcare in regions with similar characteristics.

Secondly, this research measured geographical access to all government-managed health facilities in Cross River State such as; Primary Health Centres (PHCs), Hospitals and National Health Insurance Scheme (NHIS) facilities in the wet and dry seasons. It produced comprehensive and empirical evidence of seasonal access to health facilities in the Cross River State of Nigeria which is useful for evidence-based planning of effective healthcare delivery.

The next core component was the investigation of seasonal associations between drive times to health services and malaria outcomes. The malaria outcomes in the study were severity, malaria admissions and malaria mortality in two major Cross River State hospitals. However, seasonal associations were limited to severity and admissions due to data limitations. The findings of the analyses produced the first evidence of the seasonal relationship between proximity to health services and malaria outcomes in Cross River State for planning of seasonal malaria intervention.

The last component examined the effect of wet season on the performance of NHIS facilities in Cross River State. It provides planners with an alternative method to consider in the plan to reduce inequality of access to healthcare in a location that experiences severe seasonal flooding. The study compared location-allocations in the wet and dry seasons to identify spatiotemporal potentials of health facilities which non-seasonal models cannot capture. This study supports planners' decision making on opening a new service, closing an existing service, relocating a service, expanding the capacity of an existing facility or modifying the services offered by an existing facility.

1.5. Plan of dissemination/implementation

This thesis was submitted to the University of Sheffield as part of the requirement for the award of a Ph.D. Apart from the thesis, the systematic review and the empirical chapters will produce at least three publications. One will come from the systematic review, one from the seasonal geographical access to healthcare and one from seasonal location-allocation analyses. The findings were presented in the form of a poster and oral presentations in conferences in the United Kingdom (UK) and more to be presented in Nigeria. An executive summary of this research finding will be made available to the Cross River State Ministry of Health (CRSMoH), the Department of Health, Education and Social Services (DHESS) of the

Niger Delta Development Commission (NDDC) and the Office of the Surveyor-General of Cross River State of Nigeria after the viva.

1.6. Structure of thesis

This thesis consists of nine themed chapters which were designed to cover the aims and objectives of the study. **Chapter One** introduces the research and discusses the research rationale, research focus, potential impacts of research, plan of dissemination of findings and thesis structure.

Chapter Two discusses healthcare in Cross River State and justifies the selection of the location for this study.

Chapter Three develops theoretical and conceptual framework for the study. It discusses relevant concepts of geographical access and seasonality of access to health services.

Chapter Four is the systematic review of the literature geographical access to health services in LMICs. It provides systematic focus on countries with similar characteristics. It also presents findings and research gaps for further studies. It satisfies the first objective of this study.

Chapter Five presents the research methodology and account of the strengths and weaknesses of the methods in the study.

Chapter Six focuses on geographical access to health facilities in the dry and wet seasons. It provides findings on seasonal inequality of geographical access to healthcare in Cross River State. It satisfies the second objective of this study.

Chapter Seven is dedicated to the study of the associations between distance to healthcare and malaria severity and hospital admissions in the wet and dry seasons. It satisfies the third objective of this study.

Chapter Eight is the last empirical chapter. It examines options for increasing seasonal geographical access to NHIS in Cross River State**.** It shows how an additional facility at an optimised location can boost population access to healthcare. It satisfies the fourth objective of this study.

Chapter Nine concludes this thesis with the discussion of findings, limitations, implications, recommendations and conclusion.

Except where otherwise cited, all tables, maps, graphs and charts used in the chapters of this thesis were produced by the author.

1.7. Chapter summary

In summary, Chapter One introduced the study of seasonal geographical access to healthcare in Cross River State and provided rationales for the research. It also presented the aims, objectives and the overview of the entire body of the thesis. The next is Chapter Two, which discusses background concepts of geographical access and builds upon the discussions in Chapter One.

CHAPTER TWO: BACKGROUND TO THE PROBLEM

2. Chapter overview

Whereas Chapter One introduced this research, Chapter Two discusses the study location and justifies its selection for the research.

2.1. Study location

The study location is Cross River State, one of the 36 states of the Federal Republic of Nigeria (Figure 2.1). It is in the South-South (i.e. Niger Delta) geopolitical zone which is one of the six (North Central, North East, North West, South East, South West and South-South) geopolitical zones in Nigeria. The estimated population of the state in the year 2015 was 3.6 million and the overall population growth rate that year was 2.7% (World Bank, 2015).

Like other states of Nigeria, the population of Cross River State is grouped into communities (villages), wards, Local Government Areas (LGAs) and senatorial districts for administrative purposes. The community is the smallest unit of settlement. These communities are grouped into wards which are further grouped into LGAs. There are 18 LGAs in Cross River State which are classified into three senatorial districts namely; the Northern Senatorial District (NSD), Central Senatorial District (CSD) and Southern Senatorial District (SSD) (Independent National Electoral Commission, 2015).

2.2. Socioeconomic characteristics

The senatorial districts of Cross River State have combinations of urban and rural characteristics, although their proportions vary. The SSD which houses the administrative capital (Calabar) is the most urbanised district while the NSD is least urbanised since it is the furthest from the state capital. Although there is no published spatial delineation of urban and rural areas in the state, the national classification of locations regards a location that has fewer than 20,000 people as rural while locations above that size as urban (Ofem, 2012). However, the classification does not account for typical urban communities that have less than 20,000 people and vice versa. Typically, urban areas where 35% of the population live have better infrastructures (e.g. roads, health facilities and schools) while rural areas having 65% of the population have poorer infrastructures (Governors' Climate and Forests, 2017).

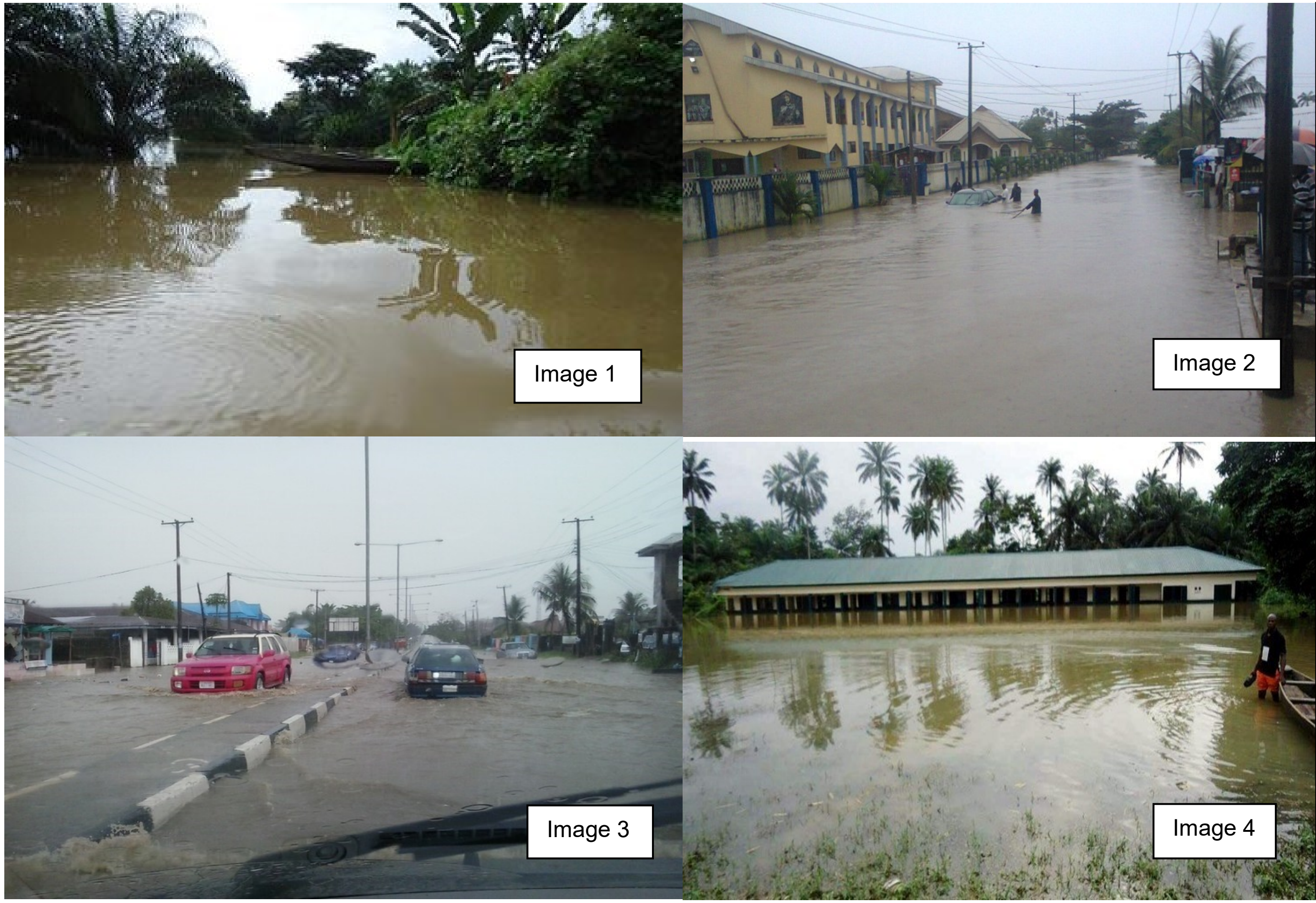
Figure 2.1: Map of Nigeria showing the study location (Adapted from OSG-CRS, 2015)

Economically, Cross River State is regarded as a ‘civil service state’ because it depends largely on the civil service and federal allocation for survival. Majority of the population are poor and educationally disadvantaged because the main occupation is farming, fishing and civil service (HFG Project, 2018). Therefore, excessive distance to health facilities which leads to additional cost of treatment may reduce the chances of healthcare utilisation.

2.3. Topography and climate

One commonality in both urban and rural areas is the complex topography that is characterised by low-lying undulating terrains with extensive floodplains along the course of Cross River and its major tributaries (Water Supply and Sanitation Sector Reform Programme, 2016). However, there are highlands of Oban massif in the south, Obudu Plateau and Obudu hills in the north rising to the heights of 1,600m (Water Supply and Sanitation Sector Reform Programme, 2016).

The state is within the tropical-humid, wet and dry seasons climate type with average temperatures ranging between 15-30°C and an annual rainfall of 1300-3000 mm (Njar *et al.*, 2013). Although, Obudu plateau has a distinct climate from the entire states with temperatures 4-10°C due to its high altitude (Njar *et al.*, 2013). The wet season spans from March to October with a short break in August while the dry season spans from November to February (CometoNigeria, 2016). The prolonged rainfalls during the wet seasons often lead to seasonal flooding in the low-lying parts of the state. During that period, the flood water remains unabated while road transportation and access to essential services including healthcare are usually interrupted in the affected areas for a short period of time or until the end of the season (Vanguard Nigeria, 2013). This situation underscores the importance of investigating seasonal geographical access to healthcare (Figure 2.2).



Legend
Image 1: Flooding in Okurikang Community, Cross River State (Vanguardngr, 2011)

Image 2: Flooding in Calabar Municipality: (CrossRiverWatch, 2013)

Image 3: Flooding in Calabar Municipality along parliamentary road (Nairaland, 2015)

Image 4: Flooding in Ikom Local Government area of Cross River State (Premium Times Nigeria, 2016)

Figure 2.2: Flooding in Cross River State

2.4. The Nigerian health system

The Nigeria health system is traced to the 10-year development plan (1946-1956) which came before independence in 1960 (Welcome, 2011). It gave birth to the various health institutions in Nigeria including schools, the ministry of health and clinics. The second National Development Plan of 1970-1974 provided the foundation for the primary health care policy which was implemented in 1980 (Uneke *et al.*, 2009). Nigeria's ambitious vision of becoming the world's 20th economy by the year 2020 (Vision 2020) of 2009 is the most followed-up of all National Development Plans. Since the wealth of a nation is sustained by the health of its workforce, the health of the population plays a significant role in the achievement and sustenance of the vision (National Planning Commission, 2009).

So far, Nigeria achieved a significant status as Africa's leading economy in 2014 (Africanranking, 2016). However, its economic position in Africa is not reflected in its health indicators. Nigeria has one of the lowest health indicators in sub-Saharan Africa (Uneke *et al.*, 2009) and is counted among the losers on international benchmarks like the Millennium Development Goals (MDGs). These failures may be blamed on the unclear position of healthcare in the Nigerian National Development Plans and the Constitution.

For a clearer delineation of the role of healthcare in the constitution, the Health Sector Reform bill was passed into law thereby giving birth to the Health Sector Reform Programme (HSRP) of 2004 – 2007 (Federal Ministry of Health, 2004).

2.4.1. Health Sector Reform Programme (HSRP)

The HSRP was initiated in 2004 to tackle organisational, financial and manpower challenges that limit the success of the Nigeria health system and the achievement of the Millennium Development Goals (Federal Ministry of Health, 2004). The comprehensive reform was set out to improve government participation in health services delivery; strengthen the system; lessen the burden of diseases; boost availability of health resources; improve access to quality health services, increase community education and involvement; and also promote partnership (Federal Ministry of Health, 2004). It also planned to improve information management through timely health data collection and management in the country's health information system.

Since geographical access to health services is one of the priorities of the HSRP, the federal government also planned to build and equip additional 200 primary health care facilities throughout the country through the Nigeria Debt Relief Fund (DRF) (Federal Ministry of Health, 2004). However, the method for distributing the facilities was not included in the reform and seasonality of access was overlooked. Since the HSRP did not include the use of location-allocation models in planning, there are chances that the facilities were distributed using mere discretion of politicians and planners.

Although there are numerous evidence source on the various areas of performance of government policies on health in the country such as; infrastructure, human resources development, clinical diagnostics and funding of health, there are few evidence sources on geographical access to health services (Welcome, 2011) and seasonality of healthcare delivery was never considered.

Though the HSRP was not very successful, it led to some reforms in the Nigerian health system. The most noted of them are the National Strategic Health Development Plan (NSHDP), National Health Policy Review (NHPR), the National Health Bill (NHB) and the National Health Insurance Scheme (NHIS) (Federal Ministry of Health, 2009).

2.4.2. Problems of the Nigeria health system

Theoretically, the structure of the Nigerian health system seems to be one of the best among many countries in the world in principles and policies (Abdulraheem, Olapipo and Amodu, 2012). In practice, the government shows its commitment to healthcare through a number of policies which some date back to the country's independence in 1960 (Iwuoha, 2013). However, the World Health Organization (WHO) ranking of 2000 which placed the Nigeria health system at 187th, 39 steps behind Uganda (149th) out of 191-member countries is paradox of its good structure and policies (Welcome, 2011; Iwuoha, 2013).

Nigeria has the one of the largest share of malaria mortality, under-five mortality and maternal mortality rates in the world (Abdulraheem, Olapipo and Amodu, 2012; Iwuoha, 2013). It also has one of the lowest levels of geographical access to healthcare in Africa, the highest burden of malaria in Africa and also accounts for 10% of global estimate of maternal mortality (Iwuoha, 2013). Although global maternal mortality dropped by 44% between 1990 and 2015, 814 in 100,000 women in Nigeria died of pregnancy and childbirth-related causes in 2015, amounting to the second highest maternal mortality ratio (MMR) in the world after India (World Health Organisation, 2015b). These problems are pointers to deeper issues in the country's health systems which include; seasonality of access, geographical accessibility, management, corruption and lack of sustainability which challenge health budgets and reduce the effectiveness of healthcare interventions.

2.4.3. Management of Nigeria health system

Nigeria operates a three-tier government administration; the federal, state and local government (Federal Ministry of Health, 2009). The federal government is the highest arm of government and it manages the affairs of the 36 states in the country. Every state government in turn manages the Local Government Areas (LGAs) within its administrative boundary and the LGA authority manages the ward and communities. The Nigeria health system was designed after the structure of government in the country. The Federal Government manages the teaching hospitals, federal specialist hospitals and the federal medical centres, and also provides budgetary allocations and national health policies through the Federal Ministry of Health (FMoH).

The state government manages secondary health services like in General and Cottage Hospitals which are available in most LGA headquarters and supervises the primary health care through the State Ministry of Health (SMoH). The LGA authority manages primary healthcare services which are available in most wards through the local Health Departments (Abdulraheem, Olapipo and Amodu, 2012). The primary health care was formed in the country in 1989 in line with the declaration of Alma-Ata of 1978 to provide basic healthcare services such as; health education, immunization, antenatal care, preventive and basic curative treatments (Federal Ministry of Health, 2004). Ideally, the primary health care is the entry point of the Nigerian health system, though patients are free to make self-referrals to any facility of choice.

Facilities that fall within the primary care category are health posts, health centres, dispensaries and Primary Health Centres (PHCs). Some PHCs also provide services like family planning, basic maternity services, management of chronic illnesses, distribution of essential drugs and Insecticide Treated Nets (ITN) and treatment of minor injuries (Federal Ministry of Health, 2009; Kress, Su and Wang, 2016). The PHC is supposed to serve between 5,000 to 20,000 people (Obembe, Osungbade and Ibrahim, 2017). However, some primary care facilities in Nigeria are not presently operational or lacking proper maintenance (Oyekale, 2017).

In principle, the roles of the three arms of the health system are defined but in practice there are several overlaps and duplications at various levels of management. Also, the system lacks proper administrative links, information management, good medical referral system and sufficient funding (Welcome, 2011).

2.4.4. Financing health care in Nigeria

Health care in Nigeria is financed by individuals, government and charities. Government's healthcare financing is guided by policies and plans such as; National Health Policy, Health Care Financing Policy, National Bill and National Strategic Health Development Plan (2010-2015) (Uzochukwu *et al.*, 2015). The national budget for health has not improved in the past three decades. The national Budget for healthcare were; 0.6%, 0.5%, 0.7%, 0.7% and 0.4% of Gross Domestic Product (GDP) in 2009, 2010, 2011, 2012 and 2013 respectively (Uzochukwu *et al.*, 2015). These are less than the 15% of annual budget which were agreed by the Abuja Declaration 2001 which Nigeria is a signatory (World Health Organisation, 2001). Since government budget for healthcare is low, households fund 69% of the national expenditure on health through out-of-pocket payments though 54% of the population live below poverty line (Uzochukwu *et al.*, 2015; World Bank, 2019).

Therefore, the cost of healthcare is expected to increase in locations that health facilities are not equitably distributed considering the additional cost of transport to the facilities. Health planners need to seek better ways of delivering healthcare with the limited resources.

2.4.5. Improving healthcare delivery in Nigeria

Some countries have made conscientious efforts in many areas to revamp their health systems. Some implemented complete privatisation, revamped the public sector to encourage competition and accountability while relinquishing some aspects of healthcare services to the private sector or form a partnership (Green, 2009). The two solutions adopted in Nigeria were revamping of the public sector and establishing a Public-Private Partnership (PPP) (Federal Ministry of Health, 2009). The PPP strategy was adopted for the National Health Insurance Scheme (NHIS).

2.4.6. National Health Insurance Scheme

The NHIS was first established by Decree 35 of 1999 as a response to the poor state of health in Nigeria. The scheme was implemented in 2005 to provide adequate funds, strengthen the weak healthcare system, improve access to health services and reduce out-of-pocket payment at the point of service delivery and financial burden of healthcare on the government (Welcome, 2011; Olakunde, 2012). In the NHIS strategy, FMoH formulates policies and manages the NHIS while the health services are provided by accredited private health insurance firms.

The goals of the scheme were to (Federal Republic of Nigeria, 1999):

- Ensure equity of access to good health services for every Nigerian.
- Shield Nigerians from the burden of medical expenses.
- Reduce the rise in the cost of healthcare.
- Ensure efficient healthcare delivery.
- Ensure equitable distribution of healthcare cost among various income groups and as well as the equitable use of all levels of healthcare.
- Maintain and provide a high standard of healthcare services.
- Improve and use private sector participation in healthcare delivery.
- Ensure that health facilities are adequately distributed in the country.
- Make sure funds are available for improved healthcare.

The NHIS is supposed to be a mandatory universal health insurance that eliminates barriers to access in the time of need. It is financed under a Public-Private Partnership (PPP) insurance scheme that is strictly controlled by the government (Olakunde, 2012). The components of the scheme are:

i. The Formal Sector Social Health Insurance Programme (FSHIP).
ii. The Urban Self-Employed Social Health Insurance Programme (USSHIP)
iii. The Rural Community Social Health Insurance Programme (RCSHIP).

FSHIP was the first among the three to be implemented in 2005 for the public sector, organised private sector (firms having more than ten employees), armed forces, Police and allied services, tertiary institution students and voluntary contributors (Olakunde, 2012; Odeyemi and Nixon, 2013). FSHIP is managed by Health Maintenance Organisation (HMOs), and NHIS accredited providers. HMOs may be for-profit or a non-profit organisation. HMOs are similar to private health insurance firms in the USA (Odeyemi and Nixon, 2013).

Contribution towards FSHIP is shared between the employer and the employee. The employer pays 10%, and the employee pays 5% of the employee's basic salary (Odeyemi and Nixon, 2013). An organisation is supposed to approach an HMO of choice for the health insurance of its employees. The HMO then presents the employer with the list of all accredited NHIS providers to choose. An employee can select any NHIS provider from the list and enrols himself/herself with the dependants. After registration, the employee and the dependants receive NHIS identity cards to be presented when accessing the service. The employee (contributor) has the liberty to change NHIS provider within three months if not satisfied with the service (Odeyemi and Nixon, 2013).

The USSHIP and RCSHIP are health insurance schemes for people with common economic activities or interests. Both are voluntary schemes that require some conditions that are different from the FSHIP which is compulsory. The two are still undergoing the process of full implementation (Olakunde, 2012; Odeyemi and Nixon, 2013), and consequently, no substantial information on users' participation and locations. Thus, the focus of this study will be limited to the FSHIP component of NHIS and 'NHIS' will be used instead of FSHIP in the remaining sections of this chapter for the sake of clarity.

2.4.7. The current state of the NHIS

Currently, participation in the NHIS is limited to public service workers being 40% of the working population and its success at the moment is limited due to inequitable distribution of facilities (Welcome, 2011). There are several inconsistencies in the literature and an overwhelming indication that there is inequitable access to NHIS in Cross River State and Nigeria at large. In 2011, only 3.5% (5.3 million) of the country's population had access to NHIS by enrolment to the scheme (Chukwu, 2013). Among the working class, only 40% of workers were using the scheme (Welcome, 2011). On the contrary, Olakunde (2012), reported 90% coverage of federal government workers in 2012 while Kannegiesser (2009), reported a full coverage in Cross River State. The NHIS coverage claim of Kannegiesser (2009) is refutable because the available NHIS enrolment data of 2015 that was received from the Cross River State NHIS office for this study was far less than findings of that study.

It is clear that the goal of equitable access to healthcare that was expected in the NHIS is still far from reach (Welcome, 2011; Olakunde, 2012; Odeyemi and Nixon, 2013). It is also evident that the rapid expansion of the NHIS coverage is presently not feasible as the scheme has not overcome its funding challenges (Mohammed, Sambo and Dong, 2011). As a way of overcoming the shortfall in the financing of the scheme, the government proposed a batch expansion in 2015. It was expected that national coverage of NHIS would reach 30% of the population by 2015 (National Health Insurance Scheme, 2015).

Although there is no publication to ascertain the level of achievement of that target, it is obvious that it was unsuccessful because the present low level of health indicators. Most of the government's concentration was on the registration of users and arbitrary accreditation of new facilities. Unfortunately, some people who registered for the service may not have used it because of excessive distance to the service. The current situation calls for a holistic and systematic plan to increase access to NHIS services in Cross River State.

At the present, there is limited evidence about access to NHIS in Nigeria and information about its geographical and seasonal accessibility is unavailable. Therefore, this study supports the Nigeria National Strategic Health Development Plan by including the component of season in the location-allocation analysis to tackle the problem of inequality of access to the NHIS.

2.5. Distribution of healthcare resources

Health resources like health facilities are usually distributed on demand. A community in need of a health service can send a request to the SMoH for approval (Ayeni, Rushton and McNulty, 1987). This method is mostly used in the allocation of primary health centres. When approval is given, the community is enlisted for implementation in the next budget that makes provision for it. The government may also site health facilities in locations that health planners consider suitable without any demand from the communities.

Although the current method seems appropriate and may be justified as the best way to match health need and demand with supply, it is possible that the communities that demanded the health facilities may not need them as much as those who could not make a request. The consequence is that communities with fewer health needs may have more facilities and vice-versa, hence inverse care (Hart, 1971). Healthcare facilities may be used as rewards for faithful voters and accessibility of such services may not be achieved.

2.5.1. Access to health facilities in Nigeria

People seeking healthcare and other public services such as schools or markets may walk, cycle or drive while some may have a combination of either two or more. While the population have the liberty to use any form of road transport, the roads in some localities are in deplorable states (Ekanem, Aboh and Okolisah, 2017). For instance, urban areas have better road network than the rural roads areas. Therefore, the use of public transport and car ownership is limited in rural areas compared to urban areas. As a result, transportation in most rural areas is mainly by walking. Residents of urban areas who have no private car and cannot afford public transport may also access health services on foot. This problem is expected to be worse in the wet season that flooding affect many communities. This problem highlights the need to use more than one travel scenario to estimate access to health services.

Human and material resources available for the Nigeria health system are grossly insufficient and unevenly distributed (Welcome, 2011; Abdulraheem, Olapipo and Amodu, 2012). The ratio of population to doctors, nurses, midwives and community health workers in the country remains one of the lowest in the world. There are 0.4 physicians to 1000 population in the country of which 88% work in hospitals (public and private) and only 12% in primary health facilities that serve approximately 20% of the population (Abdulraheem, Olapipo and Amodu, 2012) . According to the national health sector reform targets, there should be at least one comprehensive health centre (General Hospital) in a Local Government Area (LGA) with three serving doctors, one Basic Emergency Obstetric and Neonatal Care Centre (BEmONC) in a ward and one health post in a community (Federal Ministry of Health, 2004).

In 2000, the total number of health facilities in the country was 23,640 of which 61.8% belong to the public sector and 32% belong to the private sector who provides about 65% of health services in the country (World Health Organisation, 2004). The large number of health facilities and the report that 75% of households live within 5km to the closest health facilities, 53% of the population live within 1km and 47% live within 15km (World Health Organisation, 2004) may be mistaken for equitable access to healthcare. However, there are indications that some of the facilities are no more functional (Welcome, 2011). Since the distribution of health facilities in the country is uneven, the number may not make any significant impact on access and utilization health services (Iwuoha, 2013). In 2004, access to formal health services was 50.9% while utilization was 9.6% and residents in urban areas were more likely to use formal health services than those in rural areas (World Health Organisation, 2004). Access and utilisation of healthcare in Nigeria may have declined since that report considering the surge in the country's population growth and low funding of healthcare.

2.5.2. Seasonality of access to healthcare in Nigeria

Seasonality of geographical access to healthcare in Nigeria was observed in a previous study. In Kano State of Nigeria, one-third of the population lived in the riverine areas that are prone to flooding in the wet season, though seasonality of outpatients access was insignificant in the study (Stock, 1983). In Cross River State, the ratio of prenatal services to the maternal population was 12.4 per 100,000 in the dry season and 7.0 per 100,000 in the wet season (Otu, Maheswaran and Jordan, 2017). Like many other sub-Saharan African Countries, Nigeria suffers from severe flooding which affect transport and access to healthcare (Makanga *et al.*, 2017). In Cross River State, the problem is expected to be severer because the wet season period is longer than the dry season (CometoNigeria, 2016).

Therefore, the healthcare inequality gap is expected to be wider, malaria prevalence is likely to increase, and many health facilities may be inaccessible in the wet season due to flooding. Accessibility studies that excluded seasonality of services may have overestimated population access and potentials of the facilities.

2.6. Malaria in Nigeria

Nigeria's climate favours annual malaria transmission. A recent report shows that 85% of the population live in mesoendemic transmission area where a moderate proportion of the population is at risk, and 15% live in hyperholoendemic transmission areas where everyone is at risk (Malaria Elimination Programme, 2015). Cross River State is within the malaria mesoendemic transmission area where only a moderate proportion of the population is at risk (Adigun *et al.*, 2015; Malaria Elimination Programme, 2015). However, the state experiences the longest wet season and highest annual rainfall in Nigeria which favours high breeding of vectors and malaria transmission. Therefore, malaria transmission is expected to be higher in Cross River than many other states in the country.

In Figure 2.3, there is no marked variation in malaria transmission across the state, except in the highlands of Obudu Plateau where vector prevalence is less due to the sub-temperate climate with temperatures of 15 and 23°C (Njar *et al.*, 2013; Adigun *et al.*, 2015). A survey of LLINs coverage in 2011 by International Federation of Red Cross and Red Crescent Societies showed that the coverage in households was 87%, while 66% of the population had access to it and 60% of the population slept under it (Ugot *et al.*, 2011). Cross River State is suitable for this study because its climate favours moderate-high malaria transmission which can progress to severe malaria and death if prompt and effective treatment is not obtained.

According to the Nigeria Malaria Indicator Survey 2015 of the Malaria Elimination Programme women (Malaria Elimination Programme, 2015), malaria accounts for 60% of outpatient visits and 30% of admissions. It causes up to 11% of maternal mortality, 25% of infant mortality and 30% of under-five mortality. It also records 110 million clinically diagnosed cases and approximately 300,000 malaria-related childhood deaths yearly. Whereas malaria outcomes in Nigeria are widely studied (Ugot *et al.*, 2011; Njar *et al.*, 2013; Odu *et al.*, 2015), its association with drive times to health facilities is rarely adjusted and the investigation of seasonal associations is largely ignored.

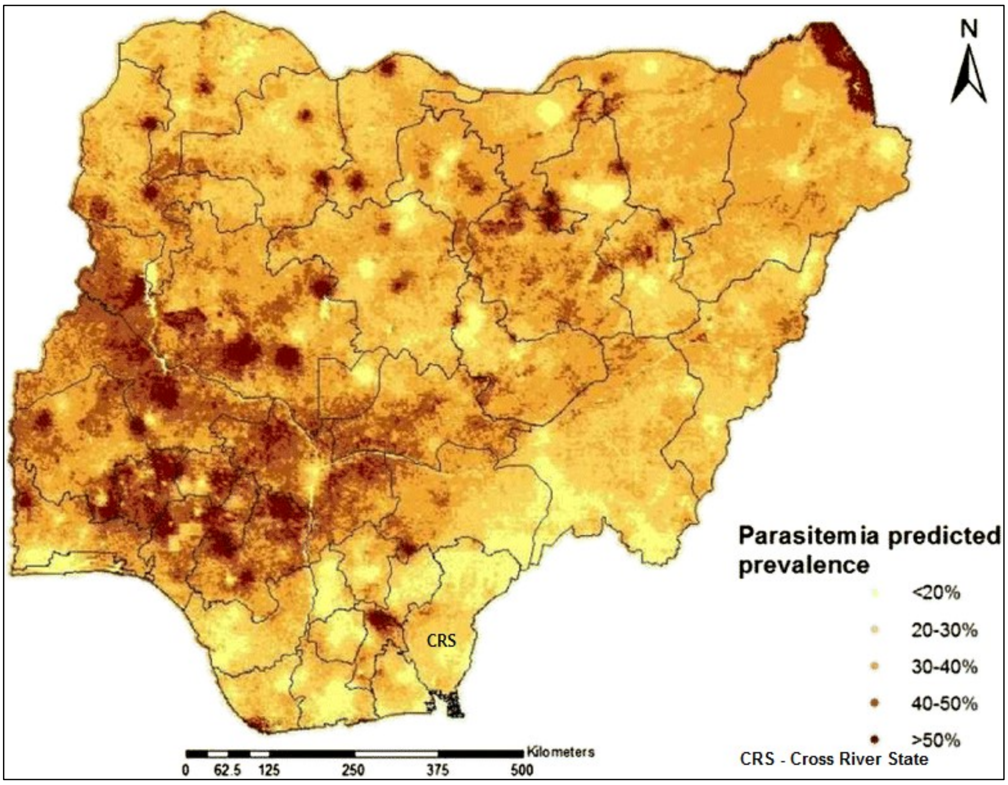


Figure 2.3: Predicted risk map of malaria among children under 5 in Nigeria (Adigun *et al.*, 2015)

2.7. Summary

Chapter Two discussed the background to the study. It covered study location, population, climate, topography, socioeconomic characteristics and the Nigeria health system. This study is suitable for Cross River State because its climate and topography favour high rainfall which leads to severe flooding and high malaria transmission. The problem causes spatio-temporal inequality and limited access to healthcare at the time it needed most by the population. The problem is further compounded by poverty and lack of evidence on the seasonal geographical access to healthcare. The next chapter presents the context of this study and discusses important concepts.

CHAPTER THREE: CONTEXT

3. Chapter overview

Chapter Three presents the conceptual and theoretical framework with a focus on seasonal geographical access to healthcare and its effect on health inequality.

3.1. Meaning of access

Access is a multidimensional concept that defines an individual's capacity to use a service in the time of need (Aday and Andersen, 1981). It is a multifaceted term that has no unanimous definition though defined in many ways depending on the context (Table 3.1). This study defines access in the framework of healthcare delivery. Health is "a state of complete physical, psychological, and social wellbeing and not simply the absence of diseases or infirmity" (World Health Organisation, 1948). One would need a sustained access to healthcare to attainment of this state of health. Healthcare is an organised delivery of medical care to an individual or a group of persons (English Oxford Living Dictionaries, 2015). Organised medical care is usually available in healthcare facilities (e.g. primary care centre and hospitals) or outside the health facility (e.g. health outreach services). This study considers access to healthcare services that are available in health facilities since their services are controlled by regulatory bodies and their locations are measurable.

3.2. Dimensions of access

Although there may be other contexts for the definition of 'access' in the literature, Table 3.1 shows the most common and relevant to this study. The general context of access from the English Oxford Living Dictionaries (2015) encapsulates the definitions of Ribot and Peluso (2003) and Penchansky and Thomas (1981). From the general perspective, access involves everything that is necessary for an individual to utilise available resources. The use of a health facility at any time requires eligibility in terms of insurance or ability to pay (i.e. financial power and permission), available transport system (i.e. opportunity), and ability to take the journey (i.e. personal mobility).

Table 3.1: Definition of access

Source	**Definition**	**Context**
(English Oxford Living Dictionaries, 2015)	"Power, opportunity, permission or right to come near or into contact with someone or something or opportunity to benefit from or use a system or service"	General
(Ribot and Peluso, 2003)	"possible means by which a person is able to benefit from things"	Physical and socio-economic
(Penchansky and Thomas, 1981)	"The degree of 'fit' between the clients and the system"	Physical

The various contexts in the definition of access gave birth to a formal classification of access into dimensions in accessibility studies (Penchansky and Thomas, 1981; George and Rubin, 2003; Chapman *et al.*, 2004; Peters *et al.*, 2008). However, all dimensions of access (Table 3.2) may be summarised into geographical accessibility, availability, acceptability and financial accessibility (Peters *et al.*, 2008).

The four dimensions of access by Peters *et al*. (2008) and the five dimensions of Penchansky and Thomas, (1981) are similar except for the absence of accommodation in the former (Table 3.2). Accommodation is the relationship between the ways in which health services are provided to the public (e.g. opening hours, walk in services, telephone services and suitability with cultural norms) and their feeling of satisfaction with the service

(Penchansky and Thomas, 1981). A customer's feeling of satisfaction after a first contact with the service may encourage or discourage further use of the service.

Chapman *et al.* (2004) and George and Rubin (2003) included utilisation which is the use of a health service. While the former also added relevance, effectiveness and equity, the latter included need and provision (Table 3.2). 'Relevance' is concerned with availability of the right services to the user. For instance, a nearby healthcare facility may be irrelevant to an uninsured person in the USA, if the service requires insurance. Thus, the relevance of a health service is related to financial accessibility. However, a health service may be relevant but not effective because of limited opening hours, low staffing and lack of medical equipment, which in turn lowers customers' satisfaction and hinders the chances of returning to use the service.

In some cases, 'relevant' and 'effective' healthcare services may be distributed in a manner that those who need them most have less and vice versa, hence inverse care (Hart, 1971). Equity of access to healthcare relates to 'need', 'provision', 'availability', 'accessibility' and 'geographical accessibility'. It is the role of the healthcare provider in the public or private sector to satisfy the healthcare needs of the population by making desired healthcare services equitably available and accessible to the population.

Table 3.2: Dimensions of access

Source	Dimensions
(Peters *et al.*, 2008)	geographical accessibility, availability, acceptability and financial accessibility
(Chapman *et al.*, 2004)	availability, utilisation, relevance, effectiveness and equity
(George and Rubin, 2003)	need, provision and utilisation
(Penchansky and Thomas, 1981)	availability, accessibility, accommodation, affordability and acceptability

3.3. Geographical access to healthcare and seasonal variability

Although the four dimensions of access (Peters *et al.,* 2008) have their roles in the healthcare system, this study focuses on geographical access because of its variability due to seasonal changes. Geographical access is concerned with the physical link between the user and the healthcare service (Penchansky and Thomas, 1981; Peters *et al.*, 2008). The link includes; transport networks like roads, rails and footpaths which connect people not just to healthcare but also to other essential services such as schools, markets and offices. Where the link is inaccessible, ineffective or longer than necessary as result of flooding or other factors, even a free, low-cost or high quality health care may be avoided (Feikin *et al.*, 2009; Alegana *et al.*, 2012; Makanga *et al.*, 2017). Therefore, geographical access is a pivot that sustains the effectiveness of other dimensions of access to healthcare and the consideration of its seasonality ensures all-year round healthcare delivery.

Guagliardo (2004) views geographical access as the ease of reaching available health facilities (Guagliardo, 2004). It takes into consideration the nature of human settlements, scarcity of health resources and how to effectively connect them. This makes geographical access an important part of the planning stage in any healthcare delivery if equity or equality of access is the goal. While it may be more difficult to achieve financial accessibility because of the socio-economic imbalance in the society or acceptability because of inability to completely measure individual preferences, geographical access is more stable and measurable.

Geographical access is also concerned with the demand and supply of health services (George and Rubin, 2003). Like the business supply chain, where a good haulage system is important in the prompt delivery of products to the consumers, geographical access is key to the timely supply of healthcare to the population. The demand for healthcare is usually followed by concerns over the travel time and convenience because of other important activities like work and family on the individual's priority list. Such concerns may result in a delay in seeking effective treatment if the facility is not 'nearby' or an inconvenience due to flooding is perceived (Stock, 1983; Noor *et al.*, 2003; Feikin *et al.*, 2009). On the part of the healthcare provider, the supply of healthcare becomes a responsibility and geographical access becomes a planning tool. Thus, the study of geographical access helps planners to decide the best location for a healthcare facility and the inclusion of seasonal variability ensures its sustainable access.

The distribution of health services tends to vary according to income distribution within a society (Peters *et al.*, 2008). Thus, high-income neighbourhoods tend to have better access to healthcare services than low-income areas. The situation may suggest that the poorer an individual becomes, the higher the likelihood of living far from healthcare. In the developing countries, urban areas which have better infrastructures like transportation, communication and water also have more health facilities than the rural areas who have less of infrastructure. In previous studies of geographical access to healthcare in LMICs, distances to healthcare facilities in the rural areas were longer than the distances in the urban areas (Noor *et al.*, 2003; Jain, Sathar and ul Haque, 2015). Such inequality in the access to healthcare can be minimised through the inclusion of geographical access in healthcare delivery. However, seasonal variability of geographical access widens healthcare inequality gap in the poor rural areas who experience severer flood impact due poor drainage.

Apart from the socio-economic imbalance in the society, the environment is a major determinant of human activities (Du *et al.*, 2004). The developed countries appear to be more prepared for adverse environmental problems than the developing countries. For instance, in Norway, helicopters services are mostly utilised for emergency healthcare during winter (Johnsen *et al.*, 2017). In Nigeria, prolonged rainfall in the wet season often leads to flooding in the lowland areas. Whereas, the socio-economic impact of flooding in Nigeria has been widely reported (Ajibade, McBean and Bezner-Kerr, 2013; Tawari-Fufeyin, Paul and Godleads, 2015), the impact of flooding on access to healthcare is largely underreported and planners are less prepared for healthcare delivery at such times.

In a study of seasonality of geographical access to healthcare in the neighbouring Niger, 15% of the population's access to healthcare facilities was lost in the wet season compared to the dry season (Blanford *et al.*, 2012). Therefore, the study of seasonal geographical access is important for effective healthcare delivery in the wet season considering that it is longer than the dry season in Cross River State.

The recent advancements in science and technology have transformed healthcare delivery in many countries in the last decade. Some developed countries in the last decade have overcome geographical barriers through the use of emergency helicopters and drones in the delivery of emergency healthcare services (Scott and Scott, 2017). Some have also taken advantage of mobile telecommunication and information technology by connecting patients via the internet and mobile phones to healthcare services (i.e. Telemedicine), thus, reducing the need to travel (Karp *et al.*, 2000), However, these technologies are presently unavailable or unreliable in many developing countries including Nigeria due to economic and political priorities of the government. Since the implementation of such technology is complex and cost-intensive (Larsen *et al.*, 2003) and the Nigeria's economy is struggling it way out of a recent recession, minimising distances to healthcare is essential.

3.3.1. Importance of measuring seasonal geographical access to healthcare

Geographical access measures potential or revealed access to healthcare (Joseph and Phillips, 1984). While potential access involves the estimation of geographical access of the entire population, revealed access measures the actual users or utilisation of the service. This study is concerned with potential access and measures the possibility of losing access to healthcare and experiencing poorer health outcomes due to a change in season.

The measurement of potential access to health services has been criticised on the grounds that it does not necessarily imply utilisation of healthcare (Akin and Hutchinson, 1999; Kahabuka *et al.*, 2011). Akin and Hutchinson (1999), demonstrated their support for the measurement of utilisation instead of potential access in the study of formal and informal health services in Sri Lanka which indicated that the 'phenomenon of bypassing' was common to all forms of health services since it is impossible to control patients' preferences. Nevertheless, the study did not consider that the same inability to control or measure patients' preferences in the choice of a preferred health facility is one of the many reasons why the measurement of potential geographical access is essential. Flooding in the wet season interrupts transportation and reduces the healthcare options as well as the chances of bypassing a facility.

Healy and McKee (2004) also argued that potential access is of no relevance because healthcare utilisation is associated with the type of service needed, physiological state, payment, perception of quality, satisfaction and service worth. For instance, an uninsured patient cannot use a nearby service that needs insurance, instead the patient will travel to a distant facility that offers free services. There is no doubt that healthcare facilities may be bypassed. However, the concern is the reasonable distance that a patient must travel to access the needed health service. Moreover, potential access is concerned with how potential users are linked to the right service and not any type of service near them. In locations that insurance is not a barrier to healthcare, ease of travel and proximity to a facility may encourage utilisation and service satisfaction (Baker and Liu, 2006; Feikin *et al.*, 2009). The study of seasonal accessibility introduces a time component into healthcare planning and delivery.

Another reason for measuring potential access is possibility of decline in healthcare utilisation due to distance (Maheswaran *et al.*, 2006; Adegoke, 2013). The phenomenon is called distance decay[1] effect (Fotheringham, 1981). Sensitivity to distance may differ according to individual's demographic and socioeconomic characteristics such as age, income and gender. Women may commit more time to job and family upkeep to the point that they have less time available to travel long distance to obtain personal healthcare (Cromley and McLafferty, 2002).

Also, family caregivers for the aged or patients with chronic illnesses may have to leave their jobs to keep up with healthcare appointments. The problem raises concerns of fairness in access to healthcare especially for socio-economically deprived households without a car or having one car with limited daytime access (Jordan *et al.*, 2004). Therefore, the presence of distance decay effect in the access to healthcare justifies the measurement of geographical access. Distance decay effect is expected to be stronger in the wet season because of travel inconveniences and safety concerns.

[1]Distance decay "A mathematical representation of the effect of distance on the accessibility of locations and the number of interactions between them, reflecting the notion that demand drops as distance increases" (ESRI, 2015)

Space-time constraints[2] of human activities also play a significant role in sensitivity to distance. People are more inclined to restrict themselves to the environment where they live, shop and work as a result of the cultural and social ties that they have built over time (Cromley and McLafferty, 2002). Since some communities do not have healthcare services nearby, effective healthcare may be delayed or avoided. When effective treatment is missed over a long period due to distance to the facility, the risk of illness severity, hospitalisation and death may increase (Rahaman *et al.*, 1982; Barker, Nthangeni and Millard, 2002; Schoeps *et al.*, 2011). The extended breeding space for mosquitoes and distance decay effect in the utilisation of health services may cause significant spatio-temporal associations between malaria outcomes and proximity to facilities.

The variation in preferred means of transport in the wet season also raises the need for distinct measurements of geographical access and comparison of findings for research and planning purposes. In developing countries, residents of urban areas have several options of transport such as private cars and public transport. In contrast, lack of good road networks and inefficient public transport system in the rural areas reduce mobility which is further deteriorated by seasonal flooding. Most people in the rural areas of Nigeria travel by walking, cycling or use animals such as camels and donkeys. Therefore, the use of a single method in measuring geographical access to healthcare which is found in most accessibility literature is insufficient for the comprehensive estimation of access across locations and socio-economic groups. The study of seasonal access allows planners to identify and provide mobile healthcare for population whose mobility is grossly affected by the wet season.

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[2]Space-time constraint implies restrain in the number of activities to be carried out as result of time limitation (Cromley and McLafferty, 2012, P. 235)

3.4. Geographical Information System (GIS) for Public Health

GIS is a computer application that acquires, compiles and manipulates spatial data by querying, modelling, sharing and archiving (Longley *et al.*, 1999). A GIS has the capabilities of data capture and preparation, management (including storage), manipulation and presentation (Huisman and By, 2009). It is a spatial decision-making tool whose application cuts across; housing, business, security, education and health. The use of GIS in healthcare has received various names such as; medical geography, health geography, spatial epidemiology, environmental health and public health GIS.

Although GIS as a field of study evolved in the 1960s, the application of GIS in public health dates back to 1948 in the work of an English physician, John Snow, in his study of a cholera outbreak in London (Environmental Systems Research Institute, 2018). Since then, both public and private health sectors have benefitted immensely from the use of GIS through spatial health data visualisation, modelling and planning (Cromley and McLafferty, 2002). In recent times, GIS has been used to study the distribution of health resources, maintenance of patients' databases, tracking of outcomes of diseases, monitoring of diseases outbreaks, identification of optimised locations for healthcare facilities, ambulance services and efficient healthcare delivery.

In practice or research, various healthcare providers and researchers have continued to find innovative ways of applying GIS to healthcare delivery. Some have used site analysis in the location-allocation model to determine suitable locations for health facilities (Berghmans, Schoovaerts and Teghem, 1984; Oppong, 1996). Demographic data have also been used to estimate health care need and match it with available physicians. An example is the Patient Location and Care Environment System (PLACES) of the Loma Linda University Medical

Center which allows users to view bed space and also access demographic and clinical information (Environmental Systems Research Institute, 2018).

Patients' addresses have been associated with utilisation and diseases outcomes to examine their interactions (Rutherford *et al.*, 2009; Alegana *et al.*, 2012). Some have also used GIS in the study and management of outbreaks of diseases (White *et al.*, 2013). Similarly, this study uses GIS to measure seasonal geographical access to health care, associates the place of residence with malaria outcomes and investigates seasonal interactions of health facilities' locations.

3.4.1. GIS data

The successful application of GIS in public health lies in its ability to combine and manipulate spatial and non-spatial datasets. Spatial data are directly or indirectly referenced to a location on the earth's surface while non-spatial data are not. Examples of non-spatial data include attributes or characteristics like date of hospital visit, height, medical diagnoses and admissions. Spatial data have location, shape and orientation. For instance, address, city and population would be considered as spatial data because they have a direct link to a location on the surface of the earth. These spatial datasets may come in the form of vector or raster model (Sutton, Dassau and Sutton, 2009).

A vector data model represents the world in the form of points, lines and polygons (Goodchild, 1992). The features that may be represented as a point include addresses like health facility, home address and centre of a locality. Roads, rails and power lines are usually represented by lines while administrative boundaries and parcels of land are often depicted as polygons. A raster model represents the world in the form of pixels which are also referred to as grid cells (Câmara *et al.*, 1996). Examples are; satellite images, digital orthophoto maps, elevation and population surface. This research links spatial (roads, health facilities, population, communities and flood regimes) and non-spatial datasets (health records) in the study of seasonal geographical access to health care.

3.5. Spatial organisation of society

Spatial organisation is as old as the history of humankind. Before research was ever conducted on this subject, humans have always arranged their immediate environment to suit their purposes (Klapka *et al.*, 2010). However, the clusters of people with similar race and culture, animal colonies and plants habitats speak of the natural spatial organisation. Research into spatial organisation began with the work of von Thünen (1826) on settlement systems in relation to agricultural production. After that was the work of Weber (1909) on industrial locations and resource distributions; and then to the works of Reilly (1931) and Christaller (1944) on commerce and services.

Christaller (1944) in the transportation principle of Central Place Theory believed that services should be arranged along transport routes in a matter that reduces transport cost and leaving out unwanted locations. The marketing principles of the same theory holds that the society is arranged in nodes such that the inner node provides first order, the next surrounding the inner node provides the second order and the outer node provides third order services. Christaller’s marketing principle can be seen in the arrangement of health services into tertiary, secondary and primary care. The transport principle provides a basic concept of planning with equity of service locations in mind.

(Hägerstrand, 1953) redirected of spatial organisation from mere economic focus to social and cultural problems. Since then, the study of spatial organisation has become a fundamental for understanding resource distribution, human society, cultures and behaviours.

The continual and inevitable change of the society from a collection of simple households and villages to urban and megacities with soaring population growth calls for the organisation of space through deliberate planning. For instance, an urban area having lost most of its vegetation and natural communal spaces to roads and housing requires a deliberate plan to create leisure locations and public places. Also, economic growth which is positive also comes with population surge, high car ownership, housing crises and accidents which indicate the need for reorganisation of space to accommodate the present need of the society. In healthcare, conscientious efforts will be required to keep up with healthcare delivery in the face of population growth, industrialisation, cultural diffusion and environmental disasters. Effective spatial organisation is directed to answer the question of accessibility of resources in space and accessibility is linked to transport (Christaller, 1944). Therefore, reorganisation of space to accommodate the wet season in healthcare delivery is important.

3.6. Transport and accessibility

Transport is concerned with the movement of people and goods from one place to another. It is one of many human inventions that has changed the world and its history is as old as human existence (Osman, 2011). Transport plays a significant role in our lives. Today, people rely on various means of transport to reach the shops, schools, work and health facilities. In the ancient times, the primitive population walked to preferred locations for hunting and gathering of wild fruits. Later, animals were used to lengthen the distance and increase the speed of travel. The advancement in technology gave birth to improved means of transport like canoe, ship, automobile and aviation which have increased speed and convenience when travelling. While these means of transport are available today, they are not all suitable for every purpose and location, and sometimes unaffordable. Therefore, the focus of transport has shifted from mere mobility to place accessibility (Morris, Dumble and Wigan, 1979; Cervero, 2005). That implies, transport in the context of accessibility considers other factors including; linking people to the right services, the quality of road, traffic condition, other land uses, distance to the service and usability at all times.

Accessibility is a combination of mobility and proximity (Cervero, 2005). Thus, one may decide to increase the speed between two points or find ways to make them closer to each other or implement both. Urban developers may use ‘trip-degeneration’ method to deliberately arrange services closer to the intended users (Whitelegg, 1993). Such arrangement seems to be a more sustainable way of planning land use in a manner that cares for the present and future needs of the population. Similarly, trip degeneration method can be used to provide seasonal mobile healthcare for remote localities that are disconnected from health services.

An example of ‘trip-degeneration’ method in planning is the Dutch A-B-C programme which classifies land use based on its accessibility and mobility profile (Cervero, 2005). The closer a land use to a means of transport, the higher its accessibility profile. Land use which are closer to more than one means of transport are considered more accessible than those that are less. In healthcare delivery, facilities that are closer to bus stops, train stations and major roads will be considered more accessible in this method. However, the profiling of land use base on proximity to transport alone may overestimate accessibility in locations with weak and unreliable transport system. For instance, a rural area may have good roads and rail networks with infrequent services or a segment that is impassable at some time of the year. In that case, accessibility of facilities in the rural areas will be overestimated. Therefore, beyond mobility and proximity is the reliability of transport which is an essential component of accessibility.

3.6.1. Micro-economic theory, travel demand and accessibility

An apparent change in accessibility may affect travel behaviour and reduce the level of satisfaction of a potential service (Morris, Dumble and Wigan, 1979). Therefore, transport planning for a specific service should be tailored toward customers' satisfaction because accessibility has a genuine influence on service delivery. The micro-economic theory that supports this relationship is the trip generation sub-model which is concerned with linking the right person to the right service (Morris, Dumble and Wigan, 1979). Linking users to the right service requires suitable accessibility measures.

3.6.2. Place accessibility measures

The advancement in GIS has led to the development of advanced spatial tools for data collection, integration and analyses of patterns of geographical access to health services (Cromley and McLafferty, 2002). In a review of place accessibility measures, the common measures of accessibility were distance measures, gravity-based measures, cumulative opportunity measures and Utility-based measures (Makri and Folkesson, 1999). However, the most common measures adopted in healthcare accessibility studies are distance measures, gravity-based measures and cumulative opportunity measures (Chapter Four).

3.6.3. Distance measures

Distance is a numeric description of the space between two objects or locations (Environmental Systems Research Institute, 2015). It is the simplest accessibility measure and most widely used (Makri and Folkesson, 1999). It determines the degree of spatial separation (i.e. distance apart) between two nodes[3] known as origin and destination (Ingram, 1971). It describes the space between two locations by the distance, travel cost or

[3]Node is "the beginning or ending point of an arc (line), topologically linked to all the arcs that meet there" (ESRI, 2015)

travel time from the origin (i.e. the residence of potential user) to the destination (i.e. the location of healthcare facility) (Pooler, 1995). The principle is that the further away a location is, the less accessible it becomes (Makri and Folkesson, 1999).

Distance measures range from simple straight-line (Euclidean) distance to complex network distance measurement. In any case, it computes the shortest, average, weighted or maximum distance to one or many locations in the study. The shortest distance measures the proximity of one origin to many destinations and describes the closeness of an individual (i.e. patient) to many opportunities (i.e. healthcare facilities). Average distance is the 'middle' distance in the distribution that is usually expressed in the form of mean, median and mode. The most commonly used of them is the mean which is the sum of distances to all destinations divided by the number of distances to destinations. Mean distance can also be weighted to produce mean weighted distance which reflects the attractiveness of locations. Maximum distance is a measure of the farthest journey from an origin to many destinations. It measures the longest distance an individual in the population would travel to access a service.

3.6.3.1. Euclidean distance

Euclidean distance is widely used in the measurement of geographical access to healthcare (Chapter Four). It connects the origin of the journey to the destination of opportunity with a straight line (Cromley and McLafferty, 2002). The origin of travel can be individuals' locations of residence or a central position (centroid) in the region of study. It does not take into consideration factors such as speed, road type and time or season associated with the journey, hence it may underestimate travel distance in some locations (Jordan *et al.*, 2004; Delamater *et al.*, 2012). Euclidean distance was not chosen for this study because of its inability of measure seasonality of access.

3.6.3.2. Network distance

It is unlikely that every patient will travel in a straight-line to a health facility as assumed by the Euclidean model. Actual travel to health facilities is usually along available transport network such as paths, roads and rail tracks. Unlike the Euclidean distance, the network models incorporate real world features along the transport network into analyses of geographical access. It takes into consideration the type of road and travel impedance such as speed which varies according to road type (Delamater *et al.*, 2012). Seasonality as well as different modes of travel such as walking, animal, cycling and vehicle (public or private transport) can be combined to form a single journey to a health facility.

However, this method is more complex and computationally intensive compared to the Euclidean distance (Jordan *et al.*, 2004; Haynes *et al.*, 2006). It requires spatial data about real world phenomenon and general assumptions about the population to be represented in the spatial model which may not be available for every individual or location (Baradaran and Ramjerdi, 2001). The travel experience of the population is generalised such that every person in the population has similar travel experience of walking, cycling or driving (Curtis and Scheurer, 2010).

Another assumption is that every member of the population travels at the same time (day or night), irrespective of weather condition, personal ability and traffic pattern. Every member of the population is also expected to have the same knowledge of the way and chooses the shortest path which is unlikely (Curtis and Scheurer, 2010). The network-based tool in many software can model individual or group travel patterns, but the challenge in such analysis is the lack of georeferenced data, computation time and unpredictable potential factors associated with every journey.

3.6.4. Comparing Euclidian and network distance measures

Comparing Euclidean distance with road network distance, the former saves time because the model is simple and does not need large datasets. Unlike the road network, results of Euclidean distance measures are reproducible because the distance of journey does not change over time. Thus, the findings are less affected by frequent structural changes such urban renewal in the region (Delamater *et al.*, 2012). Despite the weaknesses of the network distance measure, it remains a better approximation of seasonal geographical access compared to Euclidean distance (Delamater *et al.*, 2012).

The seasonal component of accessibility was modelled into the network analysis and results were presented for the dry and wet seasons. Mean and maximum distances are also adopted in the presentation of findings because they explain the middle points and extremes in healthcare accessibility (Chapter Four).

3.6.5. Gravity-based measures

The gravity-based measure is a popular measure of accessibility, though it is more complex than the distance measure (Curtis and Scheurer, 2010). It combines network distance with measure of opportunity or attractiveness (Hansen, 1959). The attractiveness or number of opportunities reduces as the distance, time and generalised cost of reaching the node increases (Joseph and Bantock, 1982). In healthcare, the opportunities can be the quality of services, type of service, opening times and cost of service. Accessibility is modelled to show distance decay effect which reduces the number of available opportunities or attractiveness as distances, time and generalised cost increases (Schuurman, Bérubé and Crooks, 2010).

Gravity measures is more suitable than distance measures if the characteristics of destinations (e.g. health facilities) are available and the goal is to measure geographical accessibility by the attractiveness (i.e. characteristics) of healthcare facilities. However, the challenge of obtaining healthcare facilities' characteristics and developing appropriate weights limit its application (Curtis and Scheurer, 2010). Also, it may overestimate travel in the densely populated areas with little potential for expansion and underestimate trips in underdeveloped zones with the probability of future expansion. Since this study is concerned with the locations of health facilities and not its characteristics, a gravity-based measure was not used. However, further studies of geographical access to healthcare in Cross River State may use gravity-based measures in measuring geographical accessibility by facility sizes, number of medical personnel, number of beds, free facilities and high traffic facilities if data are available.

3.6.6. Cumulative opportunity measures

Cumulative opportunity is one of the earliest measures of accessibility (Wachs and Kumagai, 1973). It counts the number of opportunities that are available within a given time and distance (Kwan, 1998). Every opportunity (e.g. health facility) in this measure has equal weight and the only weight factor that determines accessibility is the length of distance or the duration of time required to reach the facility. Cumulative opportunity estimates the proportion of the population that can reach health facilities within fixed travel times (e.g. 10, 20 and 30 minutes). Such findings are useful for the estimation of potential users of health facilities. It can also estimate choice of health facilities by identifying the number of health facilities that are available within 10 minutes' drive time from a single position. However, it requires the knowledge of the number of people within the region of study which may be unavailable, outdated or unreliable (Curtis and Scheurer, 2010). In this study, cumulative opportunity measure was used because of its ability to estimate the proportion of potential users of health facilities.

3.7. Transport and access to healthcare

Like in every other service, transport plays a significant role in healthcare accessibility. The problem of poor transport system is exacerbated in the rural and sub-urban locations especially among the elderly, disabled people, low-income households and people with terminal illnesses that need regular access to health services (Jordan *et al.*, 2004).

A review of transportation barriers to healthcare access for chronic illnesses that require multiple visits to health facilities in the USA showed that lack of access to good transport led to failure in keeping hospital appointments, delay in seeking care and low medication adherence (Syed, Gerber and Sharp, 2013). In that review, owning a car or having access to a car had strong influence on the utilisation of health services in nine studies and the effect was stronger in the rural areas.

HIV patients in rural California who faced great transportation challenges while accessing health services also missed 35% of hospital appointments (Sarnquist *et al.*, 2011). From the analysis of USA national data, access to transportation varied according to ethnic groups (Wallace *et al.*, 2005). Ethnic minorities who lacked good access to transportation also lacked access to health services and most affected of them were older, poorer, less educated and females (Wallace *et al.*, 2005).

Though the impact of transportation on healthcare accessibility is well documented in the literature, most of them use single travel scenarios and seasonality of travel was rare. Where comparison was made, it was often limited to car ownership and public transport (Jordan *et al.*, 2004). Hence, the poorest that do not own a car and cannot also afford public transport are often underrepresented by those studies. Although there are no published statistics, personal knowledge show that a reasonable proportion of rural dwellers in Nigeria depend on walking and cycling. Since these travel scenarios are rarely measured, there exists a gap in the studies of access to healthcare among those who have no private car and cannot afford public transport.

3.8. Healthcare planning

Planning is a decision-making process towards the future (Green, 2009). It is an essential component of the health system which is usually in the form of activity planning or allocative planning (Green, 2009). Activity planning is concerned with the monitoring of scheduled events in the healthcare ‘calendar’ to ensure that everything works according to plan. Allocative planning which is the focus of this study is concerned with the allocation of health resources to improve service delivery. Allocative planning consists of five components: objectives, resources, implementation, future and method.

A ‘good’ allocative planner sets out achievable objectives bearing in mind the scarcity of resources, applicability of methods within the host health system, the strategy for implementation and future changes. There has been a debate over the years on who should be the ‘good’ allocative planner (Buse, Mays and Walt, 2012). Some groups have argued in favour of the state (government) and some in favour of the private sector.

3.8.1. Management of healthcare planning

Until 1980, the government was mostly responsible for managing health systems in most LMICs (Buse, Mays and Walt, 2012). The roles of the state included policy formulation, financing, service provision and regulation (Green, 2009). The state designs a ‘suitable’ healthcare system and formulates policies that govern it. Hence, the state controls policies implementation, the supply and quality of healthcare services by capping the number licenses to private practitioners, moderating the size of medical schools and providing incentives to health workers in the rural areas. In some countries, the UK for instance, government regulates the prices for health services, drugs and also provides amenities (e.g. water, energy and telecommunication) for the smooth operation of the various healthcare facilities (Buse, Mays and Walt, 2012). As a result, the type of health care that an individual can access is mostly determined by the government. The leading role of the state is justified under the premise of equity and justice and the need for intervention for the sake of efficiency.

As enshrined in the constitution of most countries, everyone has the right to equal treatment irrespective of any form of personal differences or circumstances. By inference, it suffices to argue that everyone has the right to equitable healthcare regardless of the ability to pay for the service. However, such law is difficult to enforce in LMICs. Unlike the UK 1944 White Paper that grants every citizen fair access to health care, fairness in access to health care falls outside the enforceable laws of Nigeria since it is not within Chapter IV (Fundamental Rights) of the 1999 Constitution (Olajide, 2016). Thus, the argument that healthcare under the management of government grants equitable access is flawed in Nigeria. Also, if payment for health services is removed even when government revenue is low, health care providers may compromise the quality, and the health system may collapse.

However, some groups still argue that the efficiency of healthcare delivery can be achieved through coordination of practice, proper dissemination of information, elimination of competition and coordination of prices which are only possible with state's management (Emmerson, Frayne and Goodman, 2000; Buse, Mays and Walt, 2012). As opposed to the state, the private sector discriminates according to purchasing power as services are only available in locations with greater market value. The result is a deliberate denial of access to health care in deprived areas. In that case, most people will not have information about new interventions that are beneficial to their health (Emmerson, Frayne and Goodman, 2000;

Green, 2009). This weakness of the private sector lends support to the argument that favours state-managed health system.

Unfortunately, since the global economic recession of 1980, governments in LMICs suffered a fall in revenue and a drop in quality of health care delivery (Lagarde and Palmer, 2011). Health systems were underfunded, overstaffed or having several bureaucracies that reduced efficiency. In Nigeria, illicit fees were charged on the health care services that were purported to be free. Having noted the appalling state of the health systems, the United Nations advised LMICs countries to adopt the 'structural adjustment programmes', which relinquishes some of its roles to the private sector and also enforce user fees at the point of using the service (Lagarde and Palmer, 2011).

Besides the global economic recession, the weakness of state-managed health systems is explained in the 'public choice' and 'property right' theories of neoliberal economic thinking. The theory of 'public choice' explains that politician and bureaucrats will likely spend on projects that favour their political ambitions and personal interests (Bole, 1991; Green, 2009). Besides, government expenditure on projects is sometimes limited by wastefulness and some form of corruption that makes the outcome ineffective. The 'property right' proponents believe that the state failed due to lack of ownership right in the public sector (Bole, 1991). Thus, a documented "grand plan" may be abandoned or not implemented after extensive publicity or implemented in a manner that fails to meet the need of the population (Uneke *et al.*, 2009).

In comparison with the public sector, owners of private firms may be more efficient in management because they want to maximise returns on investment. While in the public sector, civil servants and politicians have less motivation to perform maximally on their jobs since 'it does not belong to anyone' and the result may lead to the ineffectiveness of the system. Despite the weaknesses of the state-managed health systems, the state remains an inevitable manager of health care delivery in Nigeria.

3.9. Increasing accessibility of health service

One of the major goals of the public and private sector is to make its services more accessible to the public. Increasing access to a service requires robust decision-making tools that treats the service locations and the customers as parts of a system in which they belong. Therefore, most planners are gradually moving away from the use of mere discretion in determining the best location for a service to the use of spatial decision-making tools like the location-allocation models (LAMs).

3.9.1. Location-allocation model

A LAM is a decision-making algorithm for identifying an optimal location(s) for one or more facilities with the intention of improving geographical accessibility and location efficiency (Kumar, 2004). The LAM algorithm assigns demand points (e.g. residential areas) to one or more facilities according to certain measurable criterion (e.g. the number of proposed or existing facilities, travel cost or distance). The two most important issues that arise in the selection of an optimum location are suitable criterion and objective function (Rahman and Smith, 2000). Suitable criterion refers to a condition that a site must fulfil before it is selected. For instance, the planner may say a primary health facility must not be more than 5km from the community centroid. However, the objective function depends on the type of organisation (i.e. private or public) that is planning the new location.

While the primary objective of the private sector is clear and that is to minimise cost, or maximise profit for every new facility location, the objective of the public sector is not very specific for every type of facility. For instance, if the government wants to locate emergency ambulance for accident rescue points, the criterion would be to minimise mean travel distance of the ambulance to emergency call locations or to maximise distance to a rescue point (Rahman and Smith, 2000). In Cross River State for instance, government's criterion would be to minimise maximum drive time to health facilities and the objective function would be to maximise population coverage.

3.9.2. Categories of LAM

Rahman and Smith (2000) in the review of LAMs used in developing countries identified two main categories. They are the Single-Level Location-Allocation Models (SLAMs) and the Hierarchical Location-Allocation Models (HLAM). SLAMs locate a single type facility or a component of a health system (e.g. clinics only or hospitals only) without considering other higher or lower levels of facilities (Patel, 1979; Berghmans, Schoovaerts and Teghem, 1984). The time-saving advantage of modelling a single type of facility at a time makes SLAM the most suitable for this study. HLAM is useful for addressing problems at regional level since it locates facilities in a manner that reflects the hierarchical structure of the system (Harvey, Hung and Brown, 1974). For instance, HLAMs may be used to locate various levels of healthcare facilities (i.e. from community clinics to specialist hospitals). Since this study plans examine individual facilities, SLAM was considered the most suitable.

Many location-allocation problems have been formulated from SLAMs for maximum public welfare depending on the interpretation of goal. These are p-median, Location Set Covering Problem (LSCP), pq-median problem and Maximal Covering Location Problem (MCLP) (Rahman and Smith, 2000). Since these problem formulations have been discussed extensively in a review elsewhere (Rahman and Smith, 2000), only relevant ones will be discussed in this section.

Among the four problem formulations, the p-median is the most widely used (Rahman and Smith, 2000; Kumar, 2004; Karatas, Razi and Tozan, 2016). The aim of the p-median problem is to find the locations of *p* facilities among *n* candidate location in a manner that the total weighted distance between demand points and nearest facilities is minimised (Tansel, Francis and Lowe, 1983). However, the model assumption does not account for remote users who may not travel to the nearest facility and the decreasing tendency of utilisation after a certain threshold of distance (Rahman and Smith, 2000). If the planner does not have enough resources to provide services for the entire population but wants to achieve maximum coverage with limited resources, as in the case of the NHIS, the p-median becomes unsuitable for such planning (Karatas, Razi and Tozan, 2016). The MCLP overcomes that limitation by enforcing distance constraints which leave some demand locations unassigned (Church and ReVelle, 1974). Therefore, the MCLP was considered the most suitable for this study.

3.9.2.1. Maximal Covering Location Problem (MCLP)

MCLP is used to identify 'optimal' location patterns based on some realised objectives that can be quantified (Church and Davis, 1992). It aims to maximise total number of demand points considering a certain number of facilities and fixed budget (Balcik and Beamon, 2008). In solving for a site for the public facility, the objective function is embedded in two proxy measures. There are the total weighted distance or time taken to reach the facility and the farthest distance that a user must travel to use the facility which is also regarded as the 'maximal service distance' (Church and ReVelle, 1974).

The only cost factor is the number of facilities which shows the required level of expected expenditure. Considering the required level of spending on a fixed number of health facilities, the planner may decide the 'smallest maximal service distance' from the demand points. In another case, the planner may try to cover the entire population with the minimal service distance. However, if faced with the reality of inadequate facilities, the planner may decide to locate the facilities in a manner that only a few lay outside the desired service distance.

Several levels of expenditure over a certain maximum coverage distance can be represented using a “trade-off” curve. The curve can be developed by solving several MCLP for a fix distance with varying number of facilities (Church and ReVelle, 1974). For instance, ten facilities can be located to cover 70% of the population meanwhile 15 facilities could give 100% coverage. This type of planning provides the planner with the leverage to spend the extra funds on other beneficial projects.

Another case is the desire to cover maximum possible population with desirable distance (S) such that no one travels further than a certain distance (T) to the closest facility in a solution where T is greater than S (T>S) (Church and ReVelle, 1974). In that case, the planner is not only interested in the maximum distance but also interested in the quality of services for those outside the maximum distance. It brings a certain amount of equity in the solution through a manner of total coverage. This problem is called MCLP with mandatory closeness constraints.

Solution techniques of the MLCP are heuristic approaches and linear programming (Church and ReVelle, 1974; Chaudhary and Pujari, 2009). The most popular of them are the heuristic approaches which is also called the Greedy Adding (GA) Algorithm (Church and ReVelle, 1974). For the maximal cover of *n* facilities under a certain distance, the solution starts with an empty solution set and then adds a single best facility site at a time. The GA algorithm continues to pick one facility at a time until the required number of facilities is selected, or the desired population is covered. The weakness of the GA is the inability to move facilities’ sites around as new facilities are being added especially when the site is no more optimal or justified (Church and ReVelle, 1974).

The weakness of GA was improved in the second heuristic solution called the Greedy Adding and Subtraction (GAS) Algorithm. The algorithm replaces one facility at a time and moves the locations about until the objective is achieved. The GAS calculates coverage for the required number of facilities like the GA and guarantees global optimality. In concept, the GAS algorithm is similar to the Ignizio heuristic (Shannon and Ignizio, 1970; Church and ReVelle, 1974). However, while the GAS replaces any facility in the model by another facility with higher potential coverage, the Ignizio heuristic replaces only facility site that makes less contribution to total coverage when compared with the last added facility.

The GAS provides the best algorithm for solving the NHIS location problem since it can provide optimal coverage according to budget and adjust replacing facilities with one that has the potential to increase overall population coverage. Another advantage is its availability on the University of Sheffield’s licensed ArcGIS 10.4 software package.

Some studies in the past have demonstrated the use of MCLP in health planning. Verter and Lapierre (2002), demonstrated the use of MLCP in the location public healthcare facilities in Fulton County, Georgia and mammography screening centres in Montreal, Quebec. Oppong (1996), also used the MCLP in the planning of seasonal access to Primary Health Care delivery in Suhum District, Ghana. However, the implementation of LAMs with seasonal constraints is largely underrepresented in the literature. Therefore, such LAMs results produce locations whose potentials are overestimated in the wet season in which access is limited by severe flooding (Oppong, 1996).

3.10. Inverse care law

Inverse care law proposed by Julian Tudor Hart in 1971 states that: "The availability of good medical care tends to vary inversely with the need for it in the population served" (Hart, 1971). Inverse care law is a serious issue in recent discussions about health inequality. Globally, better health systems and quality care tend to reside in the high-income countries while worse health system and low-quality care are available in poorer countries who have higher disease burden (Peters et al., 2008). Within a country, the more impoverished population who often live in rural areas with limited infrastructures and poor environmental conditions have limited access to healthcare compared to those in the urban areas which are well off. In countries that have no universal healthcare insurance, the law becomes more prominent. In sub-Saharan African countries, inverse care becomes spatiotemporally evident because of the deprivation of access to healthcare due to flooding in the wet season.

3.11. Equity of access to health services

Equity of access to health care is a common objective of every healthcare systems (Goddard and Smith, 2001). However, it appears to be more realistic in developed countries than developing countries. Equity in this context is concerned with the supply side of the health system and implies making equal services available to equal needs (Sowney and Barr, 2004). Equity is either vertical or horizontal. Vertical equity is justified based on morally relevant factors such as need, ability and merit while horizontal equity of access is concerned with equal access and fair distribution of health resources (Culyer, 1995). Since reliable measurement of need, ability and merit are rarely available, horizontal equity (equality) is deemed most suitable for this study.

Although it may be implausible to fashion a healthcare system that eliminates inequality, the margin among social groups and geographical locations can be reduced if the problem is identified. Although inequality is generally assumed to be fixed, this study believes that it is spatiotemporal, varying in magnitude according to time, month and season. For instance, if the distance to a healthcare double in the wet season compared to the dry season, the outcomes of inequality by whatever measurements are expected to be twofold. Therefore, this kind of study is a prerequisite for planning a sustainable and all-inclusive health service delivery.

3.11.1. Need, demand and supply of healthcare services

According to Fries *et al.* (1998), healthcare need represents the burden of illness in the population while healthcare demand is the request for a health service. Demand is an expressed need which is usually identified when the service is about to be used while supply is concerned with the provision of the service. Healthcare needs include health education, disease prevention, diagnosis, treatment, rehabilitation and terminal care. Everyone has healthcare needs but where demand is made, there is rarely a guarantee of supply. The inability of the service provider to match healthcare need with supply is termed deprivation.

Deprivation “is the denial of something considered to be a necessity” (English Oxford Living Dictionaries, 2015). Deprivation is a multi-dimensional issue that spans across health, finance, education and infrastructure (Townsend, 1987; Payne and Abel, 2012). In healthcare, it can be identified at individual, group or location level. Location deprivation is a higher level of deprivation that can be determined using average deprivation indices of individuals living in a location. For instance, a rural area may be considered as a deprived locality because of unemployment, poor transport systems and long travel distance to health facilities (Jordan *et al.*, 2004). Consequently, an urban area may be classified as less deprived because of the availability of infrastructures that are lacking in the rural area.

Measurement of deprivation at location level may result in the underestimation of the needs of the poor that are living within a wealthy locality and vice-versa. The reliability of such indices is further questioned on the grounds of political influence and relevance of date (Townsend, 1987). An example is the population census statistics which are often conducted after 10 years. Decisions that are made based on such statistics may lack the ability to satisfy the current needs of the population. However, location deprivation indices remain the most widely used because of the lack of current and reliable deprivation data in many countries. Also, population projection methods are widely used make census data relevant. Several indices of location deprivation have been used over the years in the developed countries. In the UK for instance, Townsend scores (Townsend, 1987) and Multiple Deprivation Indices (MDI) (Payne and Abel, 2012) have been widely used. Conversely, Nigeria and most sub-Saharan African countries do not have any published deprivation indices. Since indices of developed countries are rarely useful in the developing countries, indicators of socio-economic imbalance are often used as a proxy for individual deprivation while availability of certain infrastructures is used as a proxy for location deprivation.

In some studies of geographical access to health services in LMICs, deprivation indices were derived from a range of indicators including education, occupation, income, car ownership, availability of certain appliances in the home (e.g. television and telephone) and location of residence (Bailey and Phillips, 1990; Al-Taiar *et al.*, 2008). Although, these indicators represent the current deprivation state of an individual, they are rarely available in most published secondary data. Hence, the location of residence which is easier to determine becomes the best available indicator of deprivation for this research. Thus, this research limits location deprivation to the variations in urban and rural area characteristics, the latter being more deprived because of its lack of infrastructures. In the context of this study, communities whose access to healthcare is disrupted in the wet season without temporary provisions from the government are considered deprived.

3.12. Concept of season

A season is a the period of the year that is identified by unique climate conditions (National Geographic, 2019). According to National Geographic, the four seasons of the world are spring, summer, fall and winter; each are distinguished by its peculiar characteristics. In the Northern Hemisphere, winter starts on December 21 or 22, the summer starts on June 20 or 21, spring begins on March 20 or 21 and fall (autumn) begins on September 22 or 23. The seasons in the Northern Hemisphere are in opposite of the Southern Hemisphere. For instance, Australia winter begins in June and the summer solstice is December 21 or 22.

Africa lies mainly within the intertropical zone between the Tropic of Cancer and the Tropic of Capricorn with the equator running through the middle (Beck *et al.*, 2018). It is the most tropical continent characterised by hot climate, high precipitation and humidity. The climates of Africa include; the tropical monsoon climate, the subtropical highland climate, equatorial climate, the semi-desert climate (semi-arid), the desert climate (hyper-arid and arid) and the tropical wet and dry climate. Temperate climates are experienced only on the high altitudes. Africa is known for climate variability and high rainfall (Figure 3.1). Nigeria has a combination of tropical rainforest, tropical monsoon, tropical savanna and arid steppe climates (Beck *et al.*, 2018). Annual precipitation varies across the country though it increases up to 3000mm in the south (Njar *et al.*, 2013). Further details about rainfall in Nigeria are available in Chapter Two (Section 2.3).

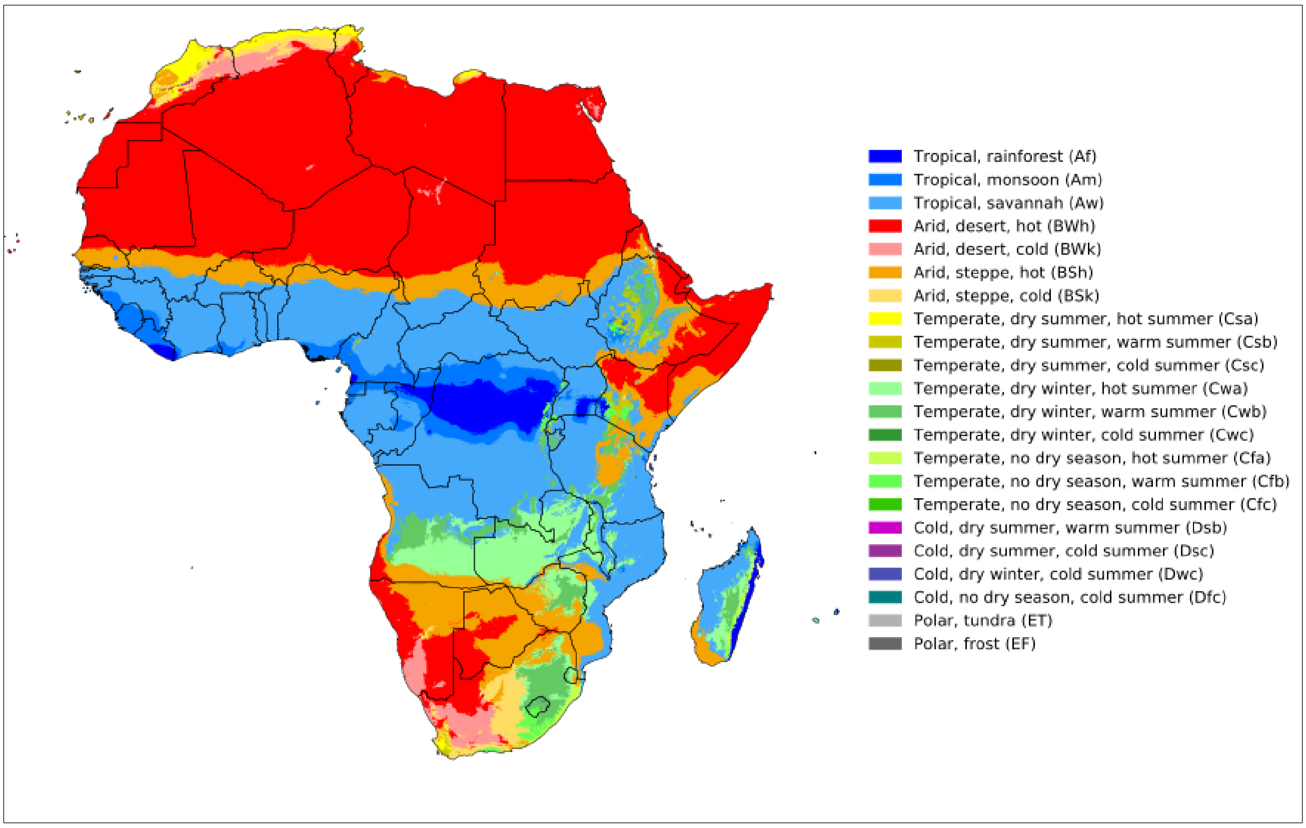

Figure 3.1: Köppen–Geiger climate classification map for Africa (Beck *et al.*, 2018)

Change in season is a natural phenomenon and its impact is felt in every country (Parmesan and Yohe, 2003). Season is an important determinant of human activities including agriculture, housing, clothing, transport, healthcare and investment (Bosello, Roson and Tol, 2007; Morton, 2007). However, many developed countries such as the UK and USA have overcome some of the brute impacts of seasonal changes using advanced technologies and adaptable infrastructures. In a developing country like Nigeria, lack of good infrastructures like drainage and roads lead to flooding in the wet season which limits road transport and mobility in the affected localities (Adelekan, 2011). Therefore, studying geographical access without considering its seasonal variability is a deliberate rejection of the impact of seasons on human lives.

3.13. Malaria

Malaria is a life-threatening disease which can be prevented and cured (World Health Organisation, 2017b). In 2016, the estimated malaria cases were 216 million in 91 countries, representing additional 5 million cases over 2015 (World Health Organisation, 2017b). African countries had the highest share (90%) of malaria cases recorded in 2016. Despite the successes achieved in the last decade in many countries, malaria is a major public health problem in Nigeria with the greatest toll on under-five children and pregnant women (Malaria Elimination Programme, 2015). According to the Nigeria Malaria Indicator Survey 2015, malaria accounts for 60% of outpatient visits and 30% of admissions (Malaria Elimination Programme, 2015). It causes up to 11% of maternal mortality, 25% of infant mortality and 30% of under-five mortality. It also records 110 million clinically diagnosed cases and approximately 300,000 malaria-related childhood deaths yearly.

Malaria causes loss of productive hours as a result of medical leave from school or work and thus impedes economic growth (Gallup and Sachs, 2001; Sachs and Malaney, 2002; Chima, Goodman and Mills, 2003; Jobin, 2014). In 2014, malaria exerted additional burden on the already-weakened health system, retarded gross domestic product (GDP) by 40 percent annually, leading to 480 billion naira in out-of-pocket treatments, preventions and loss of work hours (Malaria Elimination Programme, 2015).

International organisations including WHO and USAID have taken major steps to curb malaria morbidity and mortality (Malaria Elimination Programme, 2015; Odu *et al.*, 2015). One of the major malaria programmes in Nigeria is the National Malaria Strategic Plans (NMSP) which is currently in its fourth stage covering 2014 – 2020 (Malaria Elimination Programme, 2015). The aim of the plan is to reduce malaria morbidity and malaria-related death to zero by 2020. This study was designed with the NMSP actualisation in mind since most of the earlier studies focussed on factors unrelated to seasonal geographical access to malaria treatment.

3.13.1. Malaria transmission

Malaria is caused by Plasmodium parasites which are transmitted to people through the bites of infected female *Anopheles* mosquitoes called malaria vectors (Centre for Disease Control and Prevention, 2015; World Health Organisation, 2017b). Malaria parasites that infect humans are *Plasmodium falciparum (P. falciparum), Plasmodium vivax, Plasmodium ovale, Plasmodium malaria, and Plasmodium knowlesi*. The deadliest of them is the *P. falciparum* which is mostly found in Africa (World Health Organisation, 2017b).

Anopheles mosquitoes breed by laying their eggs in water, which hatch into larvae and eventually become adult mosquitoes (World Health Organisation, 2017b). The female mosquitoes use blood meal to nurture their eggs. Some species of Anopheles mosquito breed in aquatic habitats like small or shallow water connecting fresh water which is abundant in the rainy season in tropical countries. The longer the mosquito lifespan in a location, the more intense its transmission in that area. African vector species have a long lifespan and strong human-biting habit, that is why 90% of world's malaria cases occur in Africa (World Health Organisation, 2017b).

3.13.2. Malaria symptom

Malaria is an acute febrile illness in which symptom usual start 10 – 15 days in a non-immune individual after an infective mosquito bite (World Health Organisation, 2017b). It usually begins with fever, headache and chills which may be difficult to recognise as malaria (Centre for Disease Control and Prevention, 2015). If treatment delays beyond 24 hours, P. falciparum malaria may progress to severe illness which may lead to death (World Health

Organisation, 2017b). Severe malaria in children often shows up in the form of one or more of severe anaemia, cerebral malaria or respiratory distress related to metabolic acidosis. Adults may also have multi-organ involvement. Asymptomatic infections may also occur in people who have developed partial immunity in malaria endemic areas.

3.13.3. Malaria: prevention, diagnoses and treatment

Presently, WHO recommended forms of preventing malaria vector transmission are insecticide-treated mosquito nets and indoor spraying with residual insecticides. Long-lasting Insecticide-treated mosquito nets (LLINs) are most preferred because it is provided free of charge (Ugot *et al.*, 2011). Indoor residual spraying (IRS) is a powerful and rapid way of reducing malaria transmission. Travellers can also prevent malaria through chemoprophylaxis (World Health Organisation, 2017b). The WHO also recommends preventive treatment with sulfadoxine-pyrimethamine for pregnant women living in moderate-to-high transmission regions.

Early malaria treatment is essential for reducing the disease, prevention of deaths and reduction of transmission. The WHO recommended treatment for *P. falciparum* malaria is Artemisinin-based Combination Therapy (ACT) (World Health Organisation, 2015a). Parasite-based diagnostic testing (either microscopy or rapid diagnostic test) is recommended before administering the drug. However, treatment based on symptoms may be considered if a parasitological diagnosis facility is unavailable.

3.13.4. Access to malaria prevention, diagnoses and treatment

In Nigeria, LLINs are usually available in all health facilities, though it may not be supplied free of charge in private health facilities. LLINs are sometimes given house-to-house by mobile health workers, especially in the rural areas (Ugot *et al.*, 2011). IRSs are sold in local shops. Parasite-based diagnostic testing is usually available in hospitals or private parasitological diagnosis facility. Malaria treatment is available at all levels of health facilities (including PHCs, hospitals and NHIS), though comprehensive treatment for severe malaria involving diagnostics and admissions are only available in the hospitals and NHIS facilities.

The use of effective malaria prevention, diagnoses and treatment depends on accessibility of the facility. The systematic review of literature in Chapter Four shows that the use of malaria treatment tends to decline with increasing distance to the nearest health facility (Gething *et al.*, 2004; Alegana *et al.*, 2012). Since a delay in treatment of malaria symptoms up to 24 hours may lead to severity and death, significant associations between drive time to healthcare and malaria outcomes (i.e. severity and hospitalisation) are expected. Alegana *et al. (*2012) found that fever in children doubled as travel time to the nearest health facility increased from 30 minutes to 60 minutes. This study proposes that malaria associations with drive times will be stronger in the wet season.

3.14. Summary

Chapter Three discussed the background concepts of this study with links on healthcare. The focus of this chapter was on accessibility, though it was linked to healthcare, organisation of society, transport and health outcomes. Other areas covered were; meaning of access, measurements of access, increasing accessibility, spatial organisation, transportation, healthcare planning, equity of access, seasons and malaria. It builds a foundation for concepts that will be used in the remaining chapters of this thesis and will support the interpretation of the results of the review and primary studies. The next chapter presents a systematic review of the literature on geographical access to healthcare in LMICs.

CHAPTER FOUR: A SYSTEMATIC REVIEW OF GEOGRAPHICAL ACCESS TO HEALTHCARE IN LMICS

4. Chapter overview

Chapter One introduced this thesis and justifies the aims of the study. Chapter Two discussed provided a background to the study and rationalises the suitability of the study location. Chapter Three presented relevant concepts and context of this research. This chapter provides a systematic focus of the literature on geographical access on countries with similar characteristics. It fills research gaps in the literature on geographical access to healthcare, provides evidence for planning and research gaps for further studies. The included studies (n=80) were peer-reviewed research articles from 40 countries, extracted from 4 electronic databases and reference lists of included studies.

This review found an unequal geographical access to healthcare in urban and rural areas. It also found compelling evidence of a decline in the utilisation of healthcare services and increase in illness outcomes as travel distance or time to health facilities increased. Studies on the seasonality of geographical access were scarce (n=3) and the focus of most studies was on paediatric and obstetric care.

4.1. Background to review

LMICs share the greater burden of morbidity and mortality in the world (Bright *et al.*, 2017; World Health Organisation, 2017a). Some of the deaths may be avoided through access to low-cost healthcare (World Health Organisation, 2017b, 2017a). However, access to healthcare in the LMICs is weakened by poverty and inadequate public health infrastructures (Nantulya and Reich, 2002; Peters *et al.*, 2008). Previous healthcare accessibility studies found inequity of access to healthcare in the LMICs with the least access among the poorer population (Noor *et al.*, 2003; Bright *et al.*, 2017). The relationship between poverty and access to healthcare in LMICs was captured in four dimensions namely; geographical accessibility, availability, financial accessibility and acceptability (Peters *et al.*, 2008).

Whereas previous reviews gave considerable attention to availability, financial accessibility and acceptability of healthcare (Lagarde and Palmer, 2011; Asante *et al.*, 2016; Strasser, Kam and Regalado, 2016; Bright *et al.*, 2017), geographical accessibility has received less attention let alone its seasonality. Therefore, this review examines geographical access to healthcare which is also the focus of this thesis. Since previous studies found that an increase in distance to healthcare led to a significant decline in the utilisation of healthcare and an increase in disease outcomes (Schoeps *et al.*, 2011; Alegana *et al.*, 2012), this review also investigates associations between geographical access to healthcare, utilisation of healthcare and illness outcomes. Although this thesis focuses on Cross River State of Nigeria, the review provided a broader focus on countries with similar characteristics for the sake of policy and research.

<u>Objective:</u>

To examine geographical access to healthcare in LMICs.

This review objective covers;

i. Distance to health facilities.
ii. Association between distance to facility and utilisation of health services.
iii. Relationship between distance to health facility and diseases outcomes.

4.2. Methods

4.2.1. Protocol and registration

The protocol for this review is registered with PROSPERO international prospective register of systematic reviews (Registration number: CRD42018084251).

4.2.2. Study eligibility criteria

Studies that had the following criteria were included in the review:

4.2.2.1. Types of participants

Studies were included if they considered participants of any age or gender. That implies, there were no restrictions on studies participants provided access to healthcare was reported or measured in distance or time travel as one of the major outcomes or factors considered in the study.

4.2.2.2. Types of health facilities

The review included studies which examined access to healthcare for a part or the whole of the population by Peters *et al*. (2008) framework of geographical accessibility. Access to healthcare for this study was defined as the physical link between a potential user or an actual user and healthcare services including immunisation, maternal care, malaria treatment and chronic illnesses. Studies in such categories must include patients' trips to healthcare facilities reported in time or distances travelled. Included healthcare facilities should fall into at least one of primary care, hospital or specialist health services categories.

4.2.2.3. Types of outcome measures

Studies that reported at least one of the following were included in the review if they also considered patient's trips by distance or time to travel:

- **Access to health facility**: e.g. patients' actual or potential trips to the nearest health facility or any facility of choice which was reported in minimum, mean, median and maximum time or distance travelled.
- **Utilisation of health services:** e.g. proportion of women seeking antenatal care and/or facility delivery, children taken to health facilities for treatments and use of antiretroviral treatment facility. This also includes compliance with treatment for chronic illnesses like cancer, tuberculosis and Human Immunodeficiency Virus (HIV).
- **Health outcomes:** e.g. malaria severity in children, malaria hospitalisation and child mortality.

4.2.2.4. Types of study

The study designs included in this review were cohort studies, cross-sectional studies, case-control and non-epidemiological study designs (i.e. intervention and field of geography) which were mere measurements of distances to facilities (Carneiro and Howard, 2011).

4.2.3. Information sources

Four electronic databases were searched (MEDLINE via OvidSP, CINAHL via EBSCO, POPLINE and Sociological Abstracts via ProQuest). The search strategy covered the population, intervention, outcome and study setting. Search terms were prepared using Medical Subject Headings (MeSH) (Appendix II). The search range was from January 1980 – May 2019, and language was limited to English. Reference lists were also checked to find relevant studies. Reviews were not included though their reference lists were also inspected for relevant studies. To ensure that a similar review was not published, and protocol was not registered, the title of this review was searched on Cochrane database and PROSPERO and there was no similarity with existing protocol or review.

4.2.4. Search

The search strategy for MEDLINE is shown in the Appendix II. The search strategy was applied to all databases, though where necessary it was adapted to fit relevant subheadings in the affected database. The search strategy was inspected and approved by the ScHARR library, University of Sheffield. The search was conducted initially in 2015 but was updated in 2018 and 2019.

4.2.4.1. Study selection

All studies identified in the databases and reference lists were exported to a bibliographic database (Endnote version X7) for duplicate removal and screening. After duplicates removal, eligibility criteria were used to inspect suitable articles for inclusion in the review. The entire process of study selection was carried out by the author (EO) and checked by PhD supervisors (RM and HJ).

4.2.4.2. Data extraction and analysis

Data used in this review were findings of the included studies. Data were extracted into a Microsoft Excel workbook which was designed particularly for this review. The relevant data extracted from the studies into the review extraction sheet was adapted from Bright *et al.* (2017).

Data extracted included the following:

1. Publication details: author, year and journal.
2. Method: study design and year of study.
3. Study location: region, country and setting (urban/rural).
4. Participants: age, sex and sample size.
5. Health facility: Primary care, hospital and specialist facility
6. Outcomes: study outcome(s) including method of measurement.

7. Results: including relevant effects and distribution (e.g. Risk ratio, Odds ratio, mean, median and maximum).

A narrative approach was adopted in the synthesis of results as recommend for systematic reviews with complex interventions (Petticrew *et al.*, 2015). Meta-analysis was not conducted because of the variation in the included study designs, interventions types and outcomes.

4.2.5. Risk of bias

The author independently assessed the risk of bias as required by the standard of a PhD, with oversight and recommendations from PhD supervisors. A low-level quality assessment was used in this review. That implies, every study that showed a clear description of measuring of geographical access to healthcare was included in this review because of the need to gather enough information about geographical access to healthcare in the LMICs. Therefore, no study was rejected on basis of quality.

4.3. Results

A total of 846 records were initially identified by the electronic databases, 565 studies being unrelated to the review objective were removed and 55 relevant studies (Appendix IV) were saved for further consideration (Figure 4.1). Reference lists of relevant studies were scanned for studies not in the databases and 84 studies were extracted. Studies were also sourced from the author's personal library (n=41). All studies retrieved for consideration (n=180) from search and reference lists were exported to Bibliographic software (Endnote X7) for further inspection. Of the considered studies, 68 studies being duplicates were removed and 32 studies were excluded. Reasons for exclusion of the studies are shown in Figure 4.1. A total of 80 eligible studies were included in the review. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart is shown in Figure 4.1.

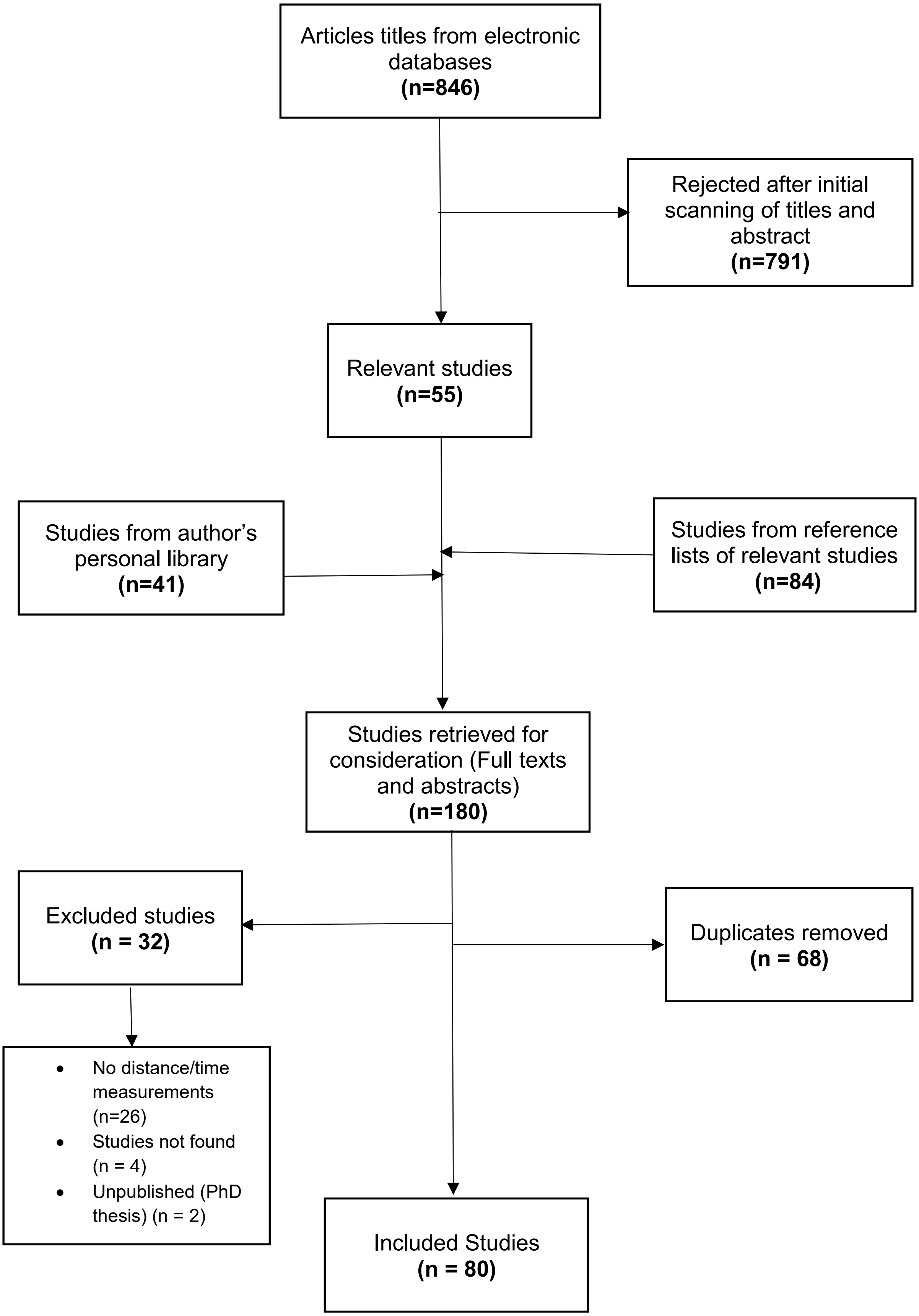

Figure 4.1: Search results showing included and excluded studies

4.3.1. Study characteristics

The characteristics of the studies are shown in Table 4.1. The included studies were published between 1981 and 2019 (Figure 4.2). The highest number of studies was recorded between 2010 and 2019 (n=45, 56%). Study designs were cohort (n=6, 8%), case-control (n=4, 5%), cross-sectional (n=42, 54%) and non-epidemiological study designs (n=28, 33%). More than half of the studies (n=49, 61%) were conducted in Africa, 10 (13%) from Latin America/Caribbean and 21 (26%) from Asia.

4.3.2. Outcome categories

The outcome categories are shown in Table 4.1. Some studies focussed on geographical access to healthcare (n=28, 35%), while some associated access with either utilisation/treatment compliance (n=43, 54%) or access/illness outcomes (n=5, 6%). Only a small number of studies investigated access, utilisation and illness outcomes (n=4, 5%).

4.3.3. Health facilities

Studies conducted in primary care facilities were 26 (33%), hospitals 15 (15%), specialist (tertiary) facilities 3 (4%), primary care/hospital 26 (33%) and any facility 13 (16%) (Table 4.1).

4.3.4. Healthcare services

Healthcare services are shown in Table 4.1. Many studies examined any form of healthcare service in the facilities (n=31, 39%), especially those whose outcomes were on access to healthcare. Other health services were Antiretroviral treatment (ART), cancer, family planning, malaria treatment, obstetric care, paediatric care, substance abuse, tuberculosis and trypanosomiasis. Obstetric care (n=20, 25%) had the highest number of studies among those that considered a single health service and was followed by paediatric care (n=16, 20%). Studies that looked at obstetric services considered either one or all of antenatal care, facility delivery, maternal mortality and neonatal mortality. Studies on paediatric care also looked at fever, malaria, cough, immunization and mortality in under-five children.

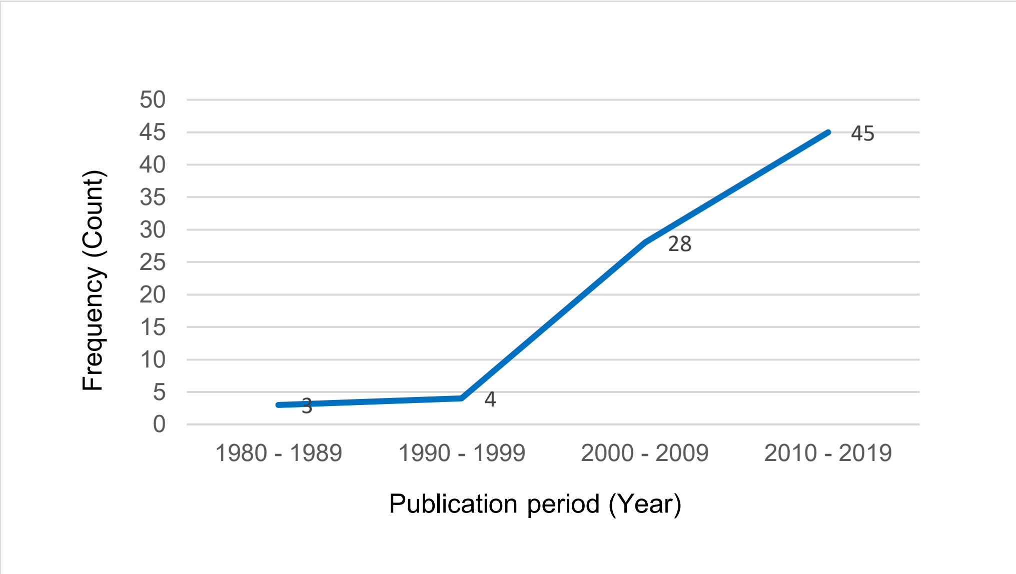

Figure 4.2: Publications of geographical access studies in LMICs decades

Table 4.1: Characteristics of included studies

Characteristics of included studies	Number	%		Healthcare Service	Number	%
Variables				Any healthcare service	31	39
Location				Antiretroviral treatment (ART)	3	4
Urban or peri-urban	11	14		Cancer	1	1
Rural or semi-rural	34	42		Family planning	1	1
Mixed	35	44		Malaria	1	1
Decade of publication				Obstetric care	20	25
1980 - 1989	3	4		Obstetric/Paediatric care	2	3
1990 - 1999	4	5		Paediatric care	16	20
2000 - 2009	28	35		Substance abuse	1	1
2010 - 2019	45	56		Tuberculosis/ Trypanosomiasis	2	3
Study design				Surgery	2	3
Cohort	6	8		**Spatial measurements of outcome**		
Case-control	4	5		Distance	46	58
Cross-sectional	42	54		Time	23	28
Non-epidemiological designs	28	33		Distance/time	11	14
				Specific spatial measurements		
Region				Euclidean distance	16	20
Latin America/Caribbean	10	13		Drive time (road only)	7	9
Asia	21	26		Drive time (road and water)	1	1
Africa	49	61		Drive time/road distance	4	5
Outcome category				Walk time	1	1
Access to healthcare	28	35		Road distance	6	8
Access/Utilisation/treatment compliance	43	54		Euclidean/road distance	4	5
Access/illness outcome	5	6		Euclidean/drive time	2	3
Access/Utilisation/illness outcome	4	5		Euclidean/road distance/drive times	1	1
Health facilities				Euclidean/road distance/walking	1	1
Primary healthcare	26	33		Euclidean/self-reported distance	1	1
Hospital (Secondary care)	12	15		self-reported distance	29	36
Tertiary/specialist facility	3	4		self-reported time	2	3
Primary/secondary	26	33		Walking/cycling	1	1
Any facility	13	16		Walking/driving	4	5

4.3.5. Measurements of geographical access to health facilities

The summary of measurements of geographical access are presented in Table 4.1. Geographical access to health facilities were measured by actual or potential time and distance to the nearest facility. Most of the studies (n=46, 58%) used distance measurements, 23 (28%) used time measurements while 11 (14%) combined distance and time measurements in a single study. In the distance category, the two types of distance measurements employed were Euclidean and road network though the derivation of these distances varied in the studies. Euclidean distance was measured from the source of travel to the destination via a straight line except for one study that employed hexagons of 500m radius (Islam and Aktar, 2011).

Road distances were mainly measured along existing road network by network analysis or self-reported by users or potential service users. Most of the distances were self-reported (n=29, 37%) (Table 4.1). Distance and time travels were either measured along road network or self-reported by the service users. Travel times were measured by driving, walking or/and cycling. Only one study measured time travel with a combination of road and water (Vadrevu and Kanjilal, 2016).

The results from the measurements of geographical access were reported as mean, median and maximum time/distance travelled. Not all studies reported the distribution of time/distance travel. In this review, the units for time and distance are minutes and kilometres respectively. Where a study provided findings in a different unit of measurement, the values were converted to the required unit using the SI unit conversion factors (by MobiTrenz) in HTC One M8 mobile phone. Table 4.1. provides further details about the included studies.

4.3.6. Risk of bias in included studies

All studies were included provided they had a clear method of measuring geographical access to healthcare. This review included only findings that were judged to be relevant in the primary studies. If a study considered more than one health facility (e.g. primary care and hospital) or health outcome (e.g. utilisation and illness outcomes), the findings were separated into the respective categories. If a study which measured association between geographical access and utilisation also provided mean distance or the population living near healthcare facilities, such findings were also included.

4.4. Description of studies

4.4.1. Comparison group

In Table 4.1, most of the studies compared facilities or health outcomes. In the outcome categories, 43 (54%) studies compared decline in the utilisation and compliance to treatment between the population that lived near the service and those that lived far away. Five studies (5%) compared illness outcome (e.g. severity, hospitalisation and mortality) in the population that lived closer to the service and those who lived far from the service. Also, geographical access, utilisation and illness outcomes were compared in 4 (5%) studies. In the health facility category, 26 (33%) of the studies compared healthcare access in primary care and hospital facilities while 13 (16%) measured access to any health facility within the study area.

In the measurements of geographical access to healthcare, studies that compared effectiveness of measurements were 18 (23%). Euclidean distance was mostly compared with other methods of measurements like road distance, drive time and self-reported distance. Although, Euclidean distance was found to underestimate trips to health care in all the studies, it was argued to be the best method if road network data was not available.

4.5. Geographical access to health facilities

Health facilities identified in the included studies were grouped into primary care, hospital and tertiary/specialist facilities.

4.5.1. Primary care

Primary care facilities were named primary health centres, clinic, dispensary or health centre in the included studies. These facilities were all recognised to be the entry points of the health systems.

4.5.2. Distance to primary care

In the primary care category, 6 studies reported the distribution of distance to PHCs (Table 4.2). Among them, no study reported minimum distance, 4 studies (Ayeni, Rushton and McNulty, 1987; Noor *et al.*, 2003; Yao, Murray and Agadjanian, 2013) reported mean distance, 3 studies (Kumar, 2004; Siedner *et al.*, 2013; Yao, Murray and Agadjanian, 2013) reported median distance and 2 studies (Ayeni, Rushton and McNulty, 1987; Kumar, 2004) reported maximum distance. One of the studies (Noor *et al.*, 2003) reported mean distance to dispensaries and health centres in multiple locations by Euclidean distance and the shortest mean distance (2.4km) to primary care in the review.

Another study (Ayeni, Rushton and McNulty, 1987) reported mean Euclidean distance to MCW (Maternity and Child Welfare centres) and dispensaries. A study (Kumar, 2004) reported historic mean access to primary health centres between 1981 – 1996. One study (Yao, Murray and Agadjanian, 2013) reported mean Euclidean distance to primary health clinics and HIV testing centres as well as the longest mean distance (22.98km) to primary care among the studies. Mean distance to primary care was between 2.4km to 22.98km.

Median distance to primary health care was between 2.4km – 9.0km (Table 4.2). In the group that reported median distance, Kumar, (2004) reported median distance for historic access to primary health centres between 1981 – 1996 by Euclidean distance. While the other reported median distance to primary health centres in a single year by Euclidean distance and road network (Al-Taiar *et al.*, 2010). One study (Siedner *et al.*, 2013) reported median Euclidean distance to clinics and the longest median distance (9.6km) in this category.

Maximum distance to primary care was between 11.1km – 23.8km (Ayeni, Rushton and McNulty, 1987; Kumar, 2004). Ayeni, Rushton and McNulty (1987) reported maximum Euclidean distance to maternal and child welfare centres and dispensaries while Kumar (2004), reported maximum distance to primary health centres.

4.5.2.1. Distance to public and private primary care

Distance to public and private primary care facilities were considered in 2 studies (Ayeni, Rushton and McNulty, 1987), but only one (Kumar, 2004) separated the findings. Kumar 2004 found that private primary care was more accessible to the population (Table 4.2).

4.5.2.2. Distance to urban and rural primary care

A few studies (n=2) reported findings for access to primary care in urban and rural areas (Table 4.2). One of them (Noor *et al.*, 2003) reported the difference between rural and urban areas while the other (Kumar, 2004) did not. Noor *et al.* (2003), found that mean Euclidean distances to primary care and dispensaries in rural areas doubled compared to urban areas.

4.5.2.3. Distance and population coverage of primary care

Eight studies in the primary care category presented findings of the proportion of population living within certain distances to the services (Table 4.3). One study (Islam and Aktar, 2011) reported the population within Euclidean distance to primary care, 2 studies (Buor, 2002; Nteta, Mokgatle-Nthabu and Oguntibeju, 2010) presented self-reported distance to health centres. Another study (Annis, 1981) reported population within road distance to health posts. One study (Rosero-Bixby, 2004) presented findings for the population within Euclidean distance to outpatient facilities. Two studies (McLaren, Ardington and Leibbrandt, 2014; Mazzi *et al.*, 2019) also reported the population within Euclidean distance to public clinics/Community Health Worker (CHW) and another (Reshadat *et al.*, 2015) reported a historic road distance (1997 – 2012) to health centres. In Figure 4.3, the highest population coverage was at 10km (99%) and the points showed no particular pattern of population coverage except for the little cluster at distance below 1km.

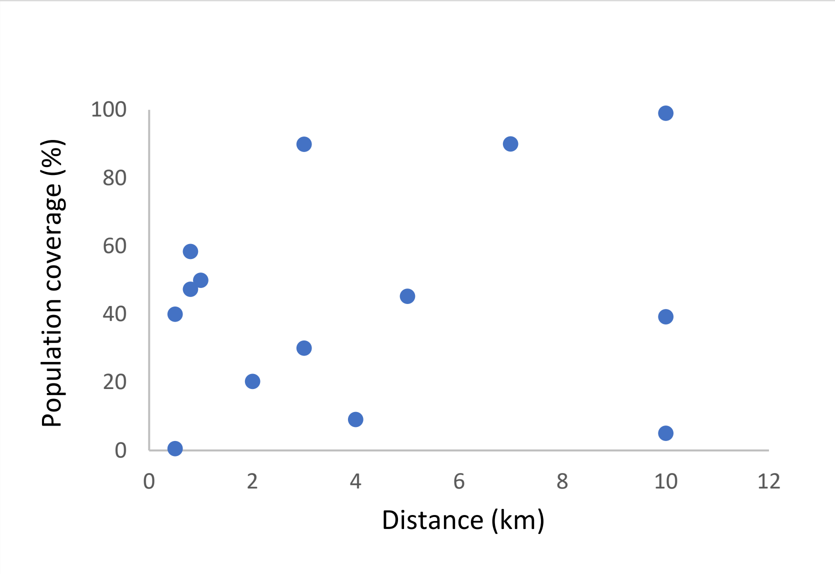

Figure 4.3: Distance to primary and population coverage

4.5.3. Travel time to primary care

Travel time to primary care was reported by 3 studies (Table 4.2). One of the 3 studies (Moïsi *et al.*, 2010) reported median drive and walk time (47 minutes) to vaccine centre and 2 studies (Tanser, Gijsbertsen and Herbst, 2006; Steinhardt, 2010) reported mean travel time to primary care. Tanser, Gijsbertsen and Herbst (2006) reported mean drive time (73.6

minutes) to clinics while Steinhardt (2010) reported mean self-reported travel time (120.2 minutes) to primary health centres. No study reported results on minimum time or maximum time travelled to primary care.

4.5.3.1. Time travel to public and private primary care

As shown in Table 4.2, no study distinguished the findings of public primary care facilities from the private facilities.

4.5.3.2. Travel times to urban and rural primary care

One of the studies (Tanser, Gijsbertsen and Herbst, 2006) was conducted in urban, peri-urban and rural population while 2 studies (Moïsi *et al.*, 2010; Steinhardt, 2010) were in rural areas (Table 4.2). The study that involved urban, peri-urban and rural population did not present separate findings.

Table 4.2: Distribution of travel distance and time to primary health care

Distribution of distance travel to primary health care (km)							
Author(s)	**Geography**	**Destination**	**Locality**	**Median**	**Mean**	**Maximum**	**Method**
Noor *et al.* (2003)	Greater Kisii, Bondo, Kwale and Makueni districts, Kenya	Dispensary	Rural		3.8		Euclidean
		Health centre	Rural		4.4		
		Dispensary	Urban		2.8		
		Health centre	Urban		2.4		
Ayeni, Rushton and McNulty (1987)	Ogun State, Nigeria	MCW	Rural		2.7	13.5	Euclidean
		Dispensary	Rural		2.5	13.7	
Kumar (2004)	North-western India	Primary health centre (private)	Rural/urban	3.5 (1981) 2.5 (1991)	3.7 (1981) 2.7 (1991)	13.9 (1981) 11.1 (1991)	Euclidean
		Primary health centre	Rural/urban	7.4 (1981) 4.5 (1991) 4.3 (1996)	7.7 (1981) 4.5 (1991) 4.3 (1996)	23.8 (1981) 13.7 (1991) 13.7 (1996)	Euclidean
Al-Taiar *et al.* (2010)	Taiz province, Yemen.	Primary health centre	Rural	2.4			Euclidean
				7.0			Road distance
Yao, Murray and Agadjanian (2013)	Gaza Province, Mozambique	Nearest primary health clinic	Rural		5.5		Euclidean distance
		Nearest HIV testing clinic	Rural		22.9		
Siednera *et al.* (2013)	Uganda	Clinic	Rural	9.6			Euclidean distance
Distribution of travel time to primary health care (minutes)							
Tanser, Gijsbertsen and Herbst (2006)	Hlabisa health sub-district South Africa	Clinic	Rural/urban/peri-urban		73.6		Road network
Steinhardt (2010)	Afghanistan	Primary health centre	Rural		120. 2		Self-reported
Moïsi et al. (2010)	Kilifi District, Kenya	Vaccine centre	Rural	47			Walking and driving

Table 4.3: Population coverage of primary care in distance

Population coverage of primary care facilities by distance travel						
Author(s)	**Location**	**Facility**	**Locality**	**Proportion (%)**	**Distance (km)**	**Method**
Islam and Aktar (2011)	Khulna, India	Primary care	Urban	40.0	0.5	Euclidean
Buor (2002)	Kumasi metropolis, Ghana	Health centre	Urban	5.0	10.0	Self-reported
Annis (1981)	Western Guatemala-Sololá, Totonicapán, and San Marcos	Health post	Rural	0.5 20.3 30.0 99.0	0.5 1.0 – 2.0 2.0 – 3.0 10.0	Transport network
Rosero-Bixby (2004)	Costa Rica (National)	Outpatient facility	Urban/rural	50.0	1.0	Euclidean
Nteta, Mokgatle-Nthabu and Oguntibeju (2010)	Tshwane Region of Gauteng Province, South Africa	Community Health Centres	Urban/rural	45.3 39.2	5.0 10.0	Self-reported
McLaren, Ardington and Leibbrandt (2014)	South Africa	Public clinics	Urban/rural	90.0	7.0	Euclidean
Reshadat *et al.* (2015)	Iran	Health centres	Urban	47.3 (1997) 58.4 (2012)	0.8+ 0.8+	Road distance
Mazzi et al., (2019)	Sheema District, Uganda	Community Health Worker	Rural	89.9 9.1	<3 ≥3	Road Distance

Table 4.4: Population coverage of primary care by travel time

Population coverage of primary care facilities by time travel						
Author(s)	**Location**	**Facility**	**Locality**	**Proportion (%)**	**Time (min)**	**Method**
Tanser (2006)	KwaZulu-Natal, South Africa	Primary healthcare	Rural	91.0 65.0 50.0 81.0	50.0 <60.0 81.0 150.0	Transport network
Munoz and Kallestal (2012)	Western province, Rwanda	Primary healthcare	Urban/rural	2.6	60.0	Walking
				58.0	60.0	Walking cycling
				34.3	60.0	Public transport
Perry and Gesler (2000)	Carabuco, Bolivia	Primary healthcare	Rural	51.0	60.0	Euclidean
	AmbanaÂ, Bolivia	Primary healthcare	Rural	50.1	60.0	
	Charazani, Bolivia	Primary healthcare	Rural	16.0	60.0	
Annis (1981)	Western Guatemala-Sololá, Totonicapán, and San Marcos	Health post	Rural	2.0	60.0	Road network
Jin *et al.* (2015)	Deqing County, Zhejiang, China	Clinics	Urban/rural	57.9	5.0	Drive time
				92.7	10.0	
Makanga *et al.* (2017)	Mozambique	Primary care	Urban/rural	46 (dry) 87 (dry)	60.0 60.0	Walking Drive time
				9 (wet) 5 (wet)	60.0 60.0	Walking Drive time

Table 4.5: Distribution of travel distance and time to hospitals and specialist care

Distribution of travel distance to hospital and specialist care (km)							
Author(s)	**Location**	**Destination**	**Locality**	**Median**	**Mean**	**Maximum**	**Method**
Sabde, De Costa and Diwan, (2014)	Madhya Pradesh, India	EmONC hospital	Urban/rural	9.5			Self-reported
Noor *et al.* (2003)	Greater Kisii, Bondo, Kwale and Makueni districts, Kenya	Greater Kisii district hospitals	Urban		2.6		Euclidean distance
			Rural		5.9		
		Bondo district hospitals	Urban		1.2		
			Rural		5.8		
		Kwale district hospital	Urban		3.4		
			Rural		8.1		
		Makueni district hospital	Urban		0.4		
			Rural		6.5		
Vora *et al.,* 2015	India	Free comprehensive emergency obstetric care	rural		15.3 - 28.3 (2005-2006) 15.5 - 28.4 (2012-2013)		Road distance
Distribution of travel time to hospital and specialist care (mins)							
Ahamad (2011)	Trinidad and Tobago	Cancer care hospital	Urban/rural	225.0			Self-reported
Silal *et al*. (2014)	Kwa-Zulu Nata, South Africa	Maternity hospital	Urban/rural		109.0		Self-reported
Moïsi *et al.* (2010)	Kilifi District, Kenya	Hospital for under-five years treatment	Rural	193.0			Transport network (walking and driving)
Vadrevu and Kanjilal (2016)	India	Maternal health service	Rural		33.8		Road and water

Table 4.6: Population coverage of hospital and specialist care in distance and time

Population coverage of hospitals and specialist care (km)						
Author(s)	**Location**	**Destination**	**Locality**	**Proportion**	**Distance (km)**	**Method**
Islam and Aktar (2011)	Khulna, India	Government hospital	Urban	15.3	0.5	Euclidean
		Private hospital	Urban	22.6	0.5	
Rosero-Bixby (2004)	Costa Rica (National)	Hospital	Urban/rural	8.0 12.0	1.0 12.0	Euclidean
Vora *et al.* (2015)	Sabarkantha, India	Emergency obstetric care	Rural	61.1 (2006-2007) 60.3 (2012-2013)	15.0	Road distance
	Dahod, India	Emergency obstetric care	Rural	42.2 (2006-2007) 44.5 (2012-2013)		
	Surendranagar, India	Emergency obstetric care	Rural	22.3 (2006-2007) 22.1 (2012-2013)		
Cooke *et al.* 2010	South Africa	ART facility	Rural	31.0	4.8+	Euclidean
Population coverage of hospitals and specialist care (mins)				**Proportion**	**Time (min)**	**Method**
Gething *et al.* (2012)	Ghana (national)	EmONC hospital	Urban/rural	20.0 50.0	120.0 240.0	Driving and walking
Sabde, De Costa and Diwan (2014)	Madhya Pradesh, India	EmONC hospital	Urban/rural	43.0	120.0	Self-reported
Jin *et al.* (2015)	Deqing County, Zhejiang, China	Town hospital County hospital	Urban/rural	50.0 55.1	15.0	Drive time
		Town hospital County hospital	Urban/rural	95.8 98.0	30.0	
Hu *et al.* (2013)	China	Hospitals	Rural (mainly)	9.0 36.0	15.0 30.0	Drive time
Premkumar *et al.*, (2018)	North Region, Tanzania	Orthopaedic surgery	Urban/rural	68.0	240.0	Drive time
Juran *et al.* (2018)	Sub-Saharan Africa	Essential surgery	Urban/rural	92.5	120.0	Drive time

Table 4.7: Distribution of distance and time to any health facility

Distribution of distance to any health facility (km)							
Author(s)	**Location**	**Facility**	**Locality**	**Median**	**Mean**	**Maximum**	**Method**
Guenther et al. (2012)	Malawi (national)	Any facility	Rural		5.0		Self-reported
	Zambia (national)	Any facility	Rural		8.0		
	Mali (national)	Any facility	Rural		10.0		
Buor (2004)	Ahafo-Ano South District, Ghana	Any facility	Urban		4.6		Self-reported
			Rural		20.27		
Buor (2003)	Ahafo-Ano South District, Ghana	Any facility	Rural		19.7		Self-reported
Jain, Sathar and ul Haque (2015)	Pakistan	Any institutional delivery	Urban/rural		7.0		Euclidean
		Normal delivery	Rural		8.0		
			Urban		1.0		
Mazzi *et al.* (2019)	Sheema district, Uganda	Any public facility	Rural		1.6		Road
Distribution of travel time to any health facility (min)							
Blanford *et al.* (2012)	Niger (national)	Any facility	Urban/rural			14400.0	Transport network – walking/Carmel
O'Meara *et al.* (2009)	Kilifi district, Kenya	Any facility	Rural		73.0		Transport network – walking
Buor (2005)	Ahafo-Ano South District, Ghana	Any facility	Urban		15.67		Self-reported
			Rural		34.71		
Buor (2003)	Ahafo-Ano South District, Ghana	Any facility	Rural		32.0		Self-reported

Table 4.8: Population coverage of any facility by distance and time

Population coverage of any facility by distance travel						
Author(s)	**Location**	**Facility**	**Locality**	**Proportion (%)**	**Distance (km)**	**Method**
Kesterton *et al.* (2010)	East India	Any public facility	Urban/rural	40	5	Self-reported
Buor (2003)	Ahafo-Ano South District, Ghana	Any public facility	Rural	47	10	Self-reported
Buor (2002)	Kumasi metropolis, Ghana	Any public facility	Rural	75	5	Self-reported
Jain, Sathar and ul Haque (2015)	Pakistan	Any maternal health facility	Urban/rural	25	10+	Euclidean distance
Mazzi *et al.* (2019)	Sheema district, Uganda	Any public facility	Rural	<5 ≥5	98.5 1.5	Road distance
Population coverage of any facility by time travel				**Proportion (%)**	**Time (min)**	
Blanford *et al.* (2012)	Niger (national)	Any public facility	Urban/rural	39 (dry) 24 (wet) seasons	60	Transport network - walking
Noor *et al.* (2006)	Greater Kisii, Bondo, Kwale and Makueni, Kenya	Any public facility	Urban/rural	63 83	60	Transport network Euclidean
Okwaraji *et al.* (2012)	North-western Ethiopia	Any public facility	Rural	90.4	>90	Self-reported
Buor (2003)	Ahafo-Ano South District, Ghana	Any public facility	Rural	17	60	Self-reported

4.5.3.3. Population coverage of primary care by travel time

As shown in Table 4.4, population coverage by time travel to primary care was reported by 6 studies. Three studies (Annis, 1981; Tanser, 2006; Munoz and Kallestal, 2012) reported population coverage (2.0%, 34.3% and 65.0% respectively) of primary health centres at 60 minutes' drive time. One of the studies (Perry and Gesler, 2000) reported population coverage of primary health centres by Euclidean time in three rural locations (51.0%, 50.1% and 16.0%) at 60 minutes. Another study (Jin *et al.*, 2015) reported the population within 5 minutes (57.9%) and 10 minutes (92.7%). A study found that population access to maternal health services within 60 minutes decreased by 5 times (walking) and 17 times (driving) in the wet season compared to dry season (Makanga *et al.*, 2017). Table 4.4 shows that the population within 60 minutes' drive time to rural primary care were between 2.0% - 65.0%. Most of the population lived within 60 minutes to the nearest primary care facility (Figure 4.4).

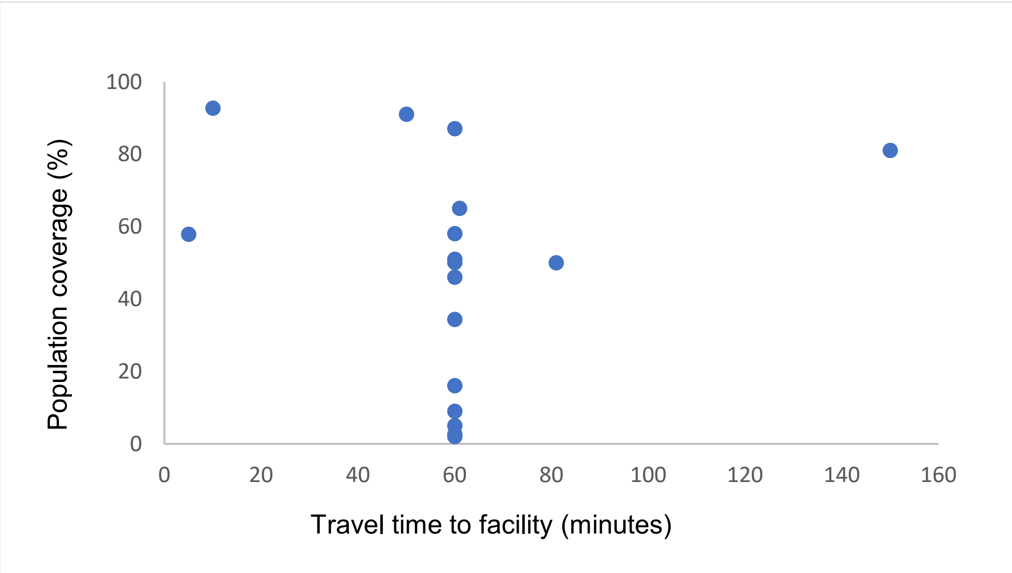

Figure 4.4: Travel time to primary care facilities and population coverage

4.6. Geographical access to hospitals/specialist health services

Healthcare facilities in this category were named hospitals, Emergency Obstetric and Neonatal Care (EmONC) hospitals, comprehensive emergency obstetric care, cancer care hospitals, maternity hospitals and hospital for under-fives (paediatric hospital) in the respective studies.

4.6.1. Distance to hospitals/specialist health services

As shown in Table 4.5, the distribution of travel distance to hospitals and specialist health services were reported by 3 studies. One of the studies (Sabde, De Costa and Diwan, 2014) presented median self-reported distance (9.5km) to EmONC hospitals. Another reported mean Euclidean distance (0.4km-3.4km in urban and 5.8km-8.1km in rural) to hospitals in four districts (Noor *et al.*, 2003). The third study (Vora *et al.*, 2015) presented a historic (2005-2013) access to free comprehensive emergency obstetric care services in 3 locations. In the three locations, average distance to the service was between 15.3 - 28.3km (2005-2006) at the introduction of the service and between 15.5 - 28.4km (2012-2013) at the end of the study. There was no remarkable improvement of geographical access over the study period. The 2 studies (Noor *et al.*, 2003; Vora *et al.*, 2015) conducted in multiple locations reported unequal geographical access to hospitals and specialist health services.

4.6.1.1. Distance to public and private hospitals/specialist healthcare services

There was no distinction between private and public hospitals/specialist healthcare services in the distance travel category (Table 4.5).

4.6.1.2. Distance to urban and rural hospitals/specialist healthcare services

As shown in Table 4.5, there was urban-rural inequality in the distance to hospitals/specialist healthcare services. Of the three studies that reported distance access to hospitals/specialist health services, 2 studies (Noor *et al.*, 2003; Sabde, De Costa and Diwan, 2014) included urban and rural areas while one study (Vora *et al.*, 2015) was conducted in rural areas. While De Costa and Diwan (2014), did not distinguish urban and rural findings, Noor *et al.* (2003), found that mean Euclidean distance to hospitals doubled in most rural areas except in one location in which the rural population travelled 16 times (6.5km) the mean distance (0.4km) of the urban population (Noor *et al.*, 2003).

4.6.1.3. Population coverage of hospital/specialist health services by distance

From Table 4.6, the population coverage of hospitals and specialist healthcare services by travel distance was reported by 4 studies (Rosero-Bixby, 1997; Cooke *et al.*, 2010; Islam and Aktar, 2011; Vora *et al.*, 2015). One of the studies (Islam and Aktar, 2011) found that urban private hospitals (22.5%) were closer to the population than urban public hospitals (15.3%). In both urban and rural areas, the population within Euclidean distances to hospitals were 8.0% and 12.0% at 1km and 12km respectively (Rosero-Bixby, 2004). In the rural areas, population access to emergency obstetric care within 15km was 22.3% - 61.1% between 2006-2007 and 22.1% - 60.3% between 2012-2013 (Vora *et al.*, 2015). Although, no remarkable improvement was found over the period in that study, there was inequality in the distribution of the Emergency obstetric care facilities. In another rural area, 31% of the population lived over 4.8km to the nearest Antiretroviral Treatment (ART) facility (Cooke *et al.*, 2010). There was no specific pattern in the population coverages of hospitals in the studies (Figure 4.5).

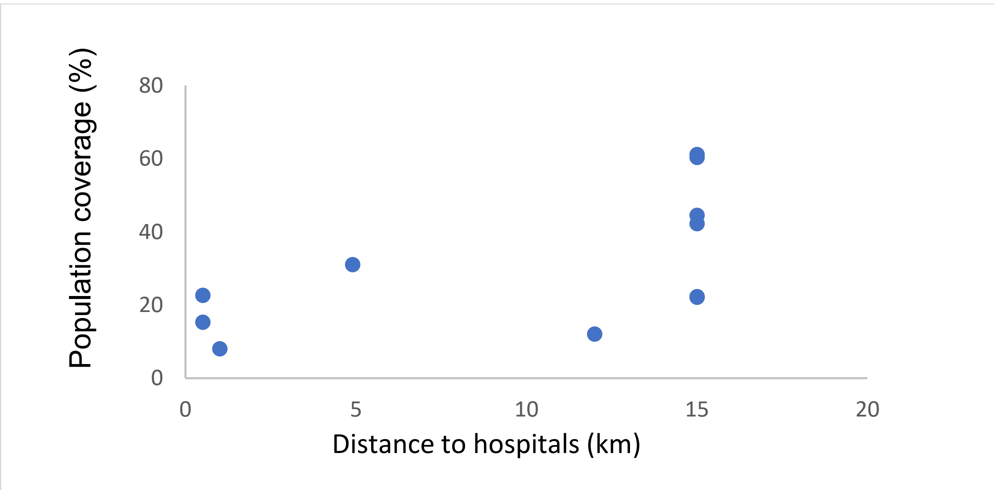

Figure 4.5: Distance to hospitals and population coverage

4.6.2. Travel time to hospitals/specialist health services

As shown in Table 4.5, 4 studies (Moïsi *et al.*, 2010; Ahamad, 2011; Silal *et al.*, 2014; Vadrevu and Kanjilal, 2016) provided findings for mean and median travel times to hospitals/specialist healthcare facilities. The differences in the methods of measurement and presentation of results made the findings incomparable. In one of the studies (Ahamad, 2011), median self-reported time to a cancer care hospital was 225 minutes. Mean self-reported time to the nearest maternity hospital was 109 minutes in another study (Silal *et al.*, 2014). Median walking and driving time to the children's hospital was 193 minutes (Moïsi *et al.*, 2010). The mean travel time by water and road to the nearest maternal health service provider was 33.8 minutes in another study (Vadrevu and Kanjilal, 2016).

4.6.2.1. Travel time to public and private hospitals/specialist health services

From Table 4.5, no study reported the difference in travel times to public and private hospitals/specialist healthcare services.

4.6.2.2. Travel time to urban and rural hospitals/specialist healthcare services

As presented in Table 4.5, 2 studies (Ahamad, 2011; Silal *et al.*, 2014) were conducted in urban and rural areas, while 2 other studies (Moïsi *et al.*, 2010; Vadrevu and Kanjilal, 2016) were conducted in rural areas. The variation in urban and rural travel time access to hospitals/specialist healthcare facilities was not reported in studies.

4.6.2.3. Population coverage of hospital/specialist by travel time

From Table 4.6, population coverage of hospitals and specialist healthcare was reported by 6 studies (Gething *et al.*, 2012; Hu *et al.*, 2013; Sabde, De Costa and Diwan, 2014; Jin *et al.*, 2015; Juran *et al.*, 2018; Premkumar *et al.*, 2018). Travel times were reported at 15, 30, 120 and 240 minutes. The findings were dissimilar in presentation, lacking a relevant pattern (Figure 4.6). In one of the studies (Gething *et al.*, 2012), the population within drive times to the nearest EmONC in both urban and rural areas were 20% (120 minutes) and 50% (240 minutes).

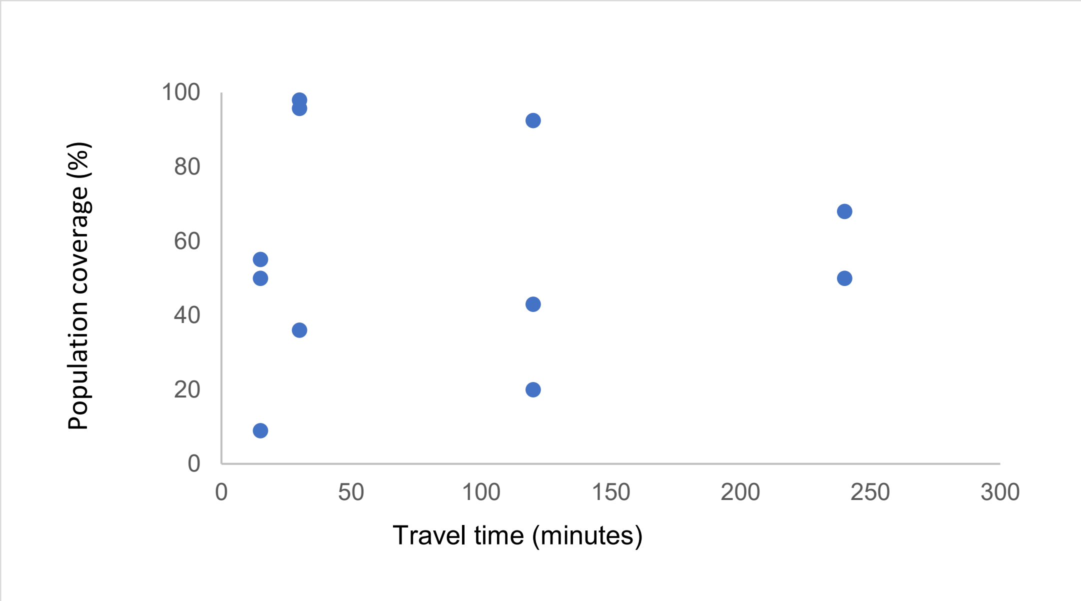

Figure 4.6: Travel time hospitals and population coverage

Another study (Sabde, De Costa and Diwan, 2014) found that the population who lived within 120 minutes (self-reported travel time) to EmONC hospital in both urban and rural areas was 43%. In another location, the population could access town (50.0%) and county hospitals (55.1%) within 15 minutes and within 30 minutes, access to town and county hospitals increased to 95.8% and 98.0% respectively (Jin *et al.*, 2015). Rural hospitals were also available to 9% of the population at 15 minutes' drive and 36% of the population at 30 minutes' drive (Hu *et al.*, 2013). Two recent studies measured access to surgical services in hospitals and reported population coverage of 68 – 93% % at 120 – 240 minutes.

4.7. Geographical access to any health facility

The studies in this category estimated the travel times or distances to available facilities in the locality with the assumption of no user restrictions to the services.

4.7.1. Distance to any facility

As shown in Table 4.7, the distribution of distances to any facility was reported by 5 studies (Buor, 2003, 2005; Guenther *et al.*, 2012; Jain, Sathar and ul Haque, 2015; Mazzi *et al.*, 2019). Only mean distances were reported in this category. Mean self-reported distances to any health facility in the rural areas were between 5.0km – 20.3km. In a study conducted across three countries, self-reported mean distances to any facility in rural areas were 5.0km (Malawi), 8.0km (Zambia) and 10.0km (Mali) (Guenther *et al.*, 2012). In another study, mean self-reported distances to any facility were 4.6km and 20.3km in urban and rural areas respectively (Buor, 2005). Another study which was conducted in a rural area found that the population travelled an average of 19.7km (self-reported distance) to any health facility (Buor, 2003). Average Euclidean distance to any institutional delivery facility was 7.0km in urban and rural areas (Jain, Sathar and ul Haque, 2015). In the same study, average Euclidean distance to normal deliveries was 8.0km in rural areas and 1.0km in urban areas. Mean distance to any public facility in Uganda was 1.6km (Mazzi *et al.*, 2019)

4.7.1.1. Distance to any public or private healthcare services

In this category, the differences between public and private facilities were not reported (Table 4.7).

4.7.1.2. Distance to any facility in urban and rural areas

From Table 4.7, two studies (Buor, 2003; Guenther *et al.*, 2012) were conducted in rural areas and the other two studies (Buor, 2005; Jain, Sathar and ul Haque, 2015) were conducted in urban and rural areas. One of studies reported that mean Euclidean distance to normal deliveries was 8 times longer in the rural (8.0km) areas than the urban areas (1.0km) (Jain, Sathar and ul Haque, 2015). In another study, mean self-reported distance to any facility in the rural area (20.3km) was 4 times longer than the urban area (4.6km) (Buor, 2005).

4.7.1.3. Population coverage of any facility by distance travel

As shown in Table 4.8, five studies reported population coverage by distance (Buor, 2002, 2003; Kesterton *et al.*, 2010; Jain, Sathar and ul Haque, 2015). Three of the studies measured self-reported distances, one measured Euclidean distance and one road distance. A study found that 40% of urban and rural population lived within 5km to any facility (Kesterton *et al.*, 2010). One study reported 47% population coverage within 10km in rural areas (Buor, 2003) and another reported 75% coverage within 5km in another rural area (Buor, 2002). In another study, 25% of women lived beyond 10km to any maternal health service provider (Jain, Sathar and ul Haque, 2015). In rural Uganda, 99% of the population lived within 5km of road distance to the nearest public facility (Mazzi *et al.*, 2019).

4.7.2. Travel time to any facility

Four studies provided findings from the measurement of travel time to any healthcare facility (Table 4.7). Average self-reported travel time to any healthcare facility in rural areas was between 32.0 minutes and 34.7 minutes (Buor, 2003, 2005). In another study, maximum travel time by road transport network including walking and use of camel was 14,440 minutes (Blanford *et al.*, 2012). Mean walking and driving time in another study was 73.0 minutes (O'Meara *et al.*, 2009).

4.7.2.1. Time travel to any public or private healthcare services

There was no report of the difference in travel times to any public and private healthcare facilities (Table 4.7).

4.7.2.2. Travel times to any facility in urban and rural areas

As shown in Table 4.7, among the four studies that reported the distribution of travel times to health facilities, two studies were conducted in urban and rural areas (Buor, 2005; Blanford *et al.*, 2012) and two were conducted in rural areas (Buor, 2003; O'Meara *et al.*, 2009). One of the two studies conducted in urban and rural areas found that average self-reported travel times in rural areas (34.7 minutes) was 2.2 times longer than urban areas (15.7 minutes) (Buor, 2005).

4.7.2.3. Population coverage of any facility by time travel

The population within travel times to any facility was reported by 4 studies (Table 4.8). A meaningful comparison of the findings in the four studies was unlikely because of the variations in measurement methods and presentation of findings. One of the studies measured seasonal variability in travel times to any health facility (Blanford *et al.*, 2012) and others did not indicate seasons. The study that considered seasonal variability in travel times found 15% loss of population access to any facility in the wet season (Blanford *et al.*, 2012). In another study of urban and rural areas, 83% and 63% of the population lived within 60 minutes' drive and Euclidean times respectively (Noor *et al.*, 2006). A study also found that 9.6% of the population lived within 90 minutes to any health facility (Okwaraji *et al.*, 2012). In another study, 17% of the population in the rural area reported that they lived 60 minutes to any healthcare facility (Buor, 2003).

4.8. Geographical access and utilisation of health services

The studies that reported the association between geographical access and utilisation of healthcare compared the outcomes of healthcare utilisation in the baseline group with other groups in the study. The baseline group were patients who lived nearer to the service. The studies in this category examined the utilisation of primary care and hospital or both facilities. The dominant healthcare services in this category were paediatric and obstetric care.

4.8.1. Geographical access and utilisation of primary care

Primary care services in the studies were mostly utilised for paediatric and obstetric care. In the primary care category, some reported general use of the service (n=7), a few reported uses of paediatric care (n=3) and majority reported the use of obstetric care (n=14) (Table 4.9).

Table 4.9: Access and utilisation

Health service	Findings	References
Primary care		
General care	sd	Nteta, Mokgatle-Nthabu and Oguntibeju (2010), Tanser, Gijsbertsen and Herbst (2006), Baker, Bazemore and Jacobson (2008), Cooke *et al. (*2010), Müller *et al. (*1998), Stock (1983), Baker and Liu (2006)
Paediatric care	sd	Feikin *et al*. (2009), Noor *et al*. (2003), Ewing *et al*. (2011)
	mf	NoorAli *et al*. (1999)
Obstetric care	sd	De Allegri *et al*. (2011), Phiri *et al. (*2014), Heard *et al*. (2004), Matsuoka *et al*. (2010), Gabrysch *et al*. (2011), Agha and Carton (2011), Acharya and Cleland (2000), Wagle *et al. (*2004), Hounton *et al*. (2008), Gage & Calixte (2006), Jain *et al*. (2015), Mwaliko *et al. (*2014)
	nd	Kesterton *et al*. (2010)
	mf	Okafor (1991)
Hospitals		
	sd	Stock (1983)
	nd	Carlucci *et al*. (2008)
Any facility		
Paediatric care	sd	Alegana *et al*. (2012), Blanford *et al*. (2012), Al-Taiar *et al*. (2010), Gething *et al*. (2004), Ustrup *et al*. (2014)
Any care	sd	Buor (2003), Myers *et al. (*2010), Buor (2002), Amaghionyeodiwe (2008), Harris *et al. (*2011)
Code for findings: sd – significant decrease, nd – no significant decrease, mf – mixed findings		

4.8.1.1. Utilisation of general primary health care

'General primary health care' is a term used in this review to describe primary healthcare services that were not given a specific name or were unrelated to obstetric and paediatric care. The findings of associations between geographical access and utilisation of general primary care were reported by 7 studies and all found significant declines in utilisation with increasing distance. One of the studies reported a decline in the utilisation of clinics as walking time from home to the facility increased (Baker and Liu, 2006). In another study, 90.2%, 69.0% and 14.0% declines in the utilisation of community health centres were found in the groups who reported that they lived within 0 – 30, 31 – 60 and beyond 60 minutes respectively (Nteta, Mokgatle-Nthabu and Oguntibeju, 2010).

Another study also found that the adjusted odds of decline in utilising public primary healthcare was 10 times higher in the group who lived within 30 minutes' drive time than the group that lived

90-120 minutes from the facility (Tanser, Gijsbertsen and Herbst, 2006). A study also reported 50% decline in the utilisation of primary care facilities after 4km road distance from home (Baker, Bazemore and Jacobson, 2008). A study also reported a significant decline in the utilisation of ART in rural primary health centres as the distance to the facilities increased (Cooke *et al.*, 2010). In one of the studies, the use of a single rural mission health sub-centre suffered 50% decline in utilisation at a self-reported distance of 3.5km (Müller *et al.*, 1998). Another study also reported 25% decline rate per kilometre (Euclidean distance) in the utilisation of dispensaries in rural areas (Stock, 1983).

4.8.1.2. Utilisation of paediatric care in primary health care facilities

The association between geographical access and utilisation of paediatric healthcare in primary health care facilities was reported by 4 studies (Table 4.9). Three of the studies reported declines in utilisation while one had mixed findings. One of the studies reported 34% decline in the utilisation of out-patient paediatric clinic when self-reported road distance to the facility exceeded 1km (Feikin *et al.*, 2009). Another study found a steady decline in the utilisation of public health centres and dispensaries for paediatric fever treatment at 1km interval (Noor *et al.*, 2003). A study also found that the group who lived in the "hard-to-reach" (remote) villages were less likely to use health facilities for the treatment of childhood fever in the dry and wet season (Ewing *et al.*, 2011).

In a study with mixed findings, caregivers of children with fever, diarrhoea or upper respiratory tract infection who lived less than 4km to the facility were 22% less likely to use the facility (NoorAli, Luby and Rahbar, 1999). However, when the distance to the closest private facility was controlled, children living 4km away from government facilities were less likely to use the facilities.

4.8.1.3. Geographical access and utilisation of obstetric care in primary health care facilities

The studies (n=14) in this category reported the use of obstetric healthcare service in primary healthcare facilities (Table 4.9). The services include antenatal care, immunisation and new-born delivery. Most of the studies (n=12) in this category reported significant declines in the utilisation of obstetric care as distance to the facilities increased. Women who lived within 5km of self-reported distance to the closest facility were more likely to use antenatal care and also deliver in a healthcare facility than those who lived beyond 5km (De Allegri *et al.*, 2011). Another study also found a significant association between self-reported distance and the utilisation of public and private healthcare facilities for new-born deliveries (Phiri *et al.*, 2014). A study reported a significant decrease in the use of family planning, HIV testing and counselling by women in public or private facilities due to proximity to facilities (Heard, Larsen and Hozumi, 2004).

Another study found that women in the rural areas were more likely to avoid the use of healthcare facilities because of distance (Matsuoka *et al.*, 2010). It was also found that every twofold increase in Euclidean distance to the nearest facility led to a 29% decline in facility delivery (Gabrysch *et al.*, 2011). A study also found the effect of self-reported travel time on the use of antenatal (ANC), postnatal care, institutional delivery and family planning services (Agha and Carton, 2011). In another study, the use of Bacillus Calmette–Guérin (BCG) vaccine among mothers doubled where health post was located within the community of residence (Acharya and Cleland, 2000). It was also found that distance was the most significant predictor of home delivery and women were more likely to deliver at home if the self-reported distance to the nearest maternity facility was up to 60 minutes away from home (Wagle, Sabroe and Nielsen, 2004).

A study reported a significant effect of self-reported distance on institutional delivery (Hounton *et al.*, 2008). It was also found that having a maternal health facility within 5km significantly increased the odds of institutional delivery (Gage and Calixte, 2006). Another study reported a 3% decrease in the odds of utilisation of institutional delivery per 1km increase in Euclidean and road distance to the facility after controlling for household wealth (Jain, Sathar and ul Haque, 2015). Another study also showed that 30-80% of women were more likely to deliver new-born at home if they lived 2km (Euclidean distance) to the facility, however, distance was not effective after 2km (Mwaliko *et al.*, 2014).

In a study with a mixed finding, there was a significant association between self-reported distance to Maternal and Child Health (MCH) and use of prenatal care, deliveries and postnatal service but after controlling for location difference, service type and locations without the service, distance was no longer significant (Okafor, 1991). In a neutral study, Kesterton *et al.* (2010) reported no significant relationship between distance and institutional deliveries in public and private facilities.

4.8.1.4. Utilisation of primary health care in urban and rural

Apart from a study (Phiri *et al.*, 2014) which found that distance decay in the utilisation of primary care was likely to occur in both urban and rural areas, other studies did not differentiate the findings.

4.8.1.5. Utilisation of public and private primary health care

There was no distinction between the findings of public and private primary health care in this category.

4.8.2. Geographical access and utilisation of hospitals

The association between geographical access and utilisation of hospitals was reported by two studies. One of them reported a 20% decline in utilisation per kilometre (Stock, 1983), while one found no significant association of distance with the utilisation of hospitals (Carlucci *et al.*, 2008).

4.8.3. Geographical access and utilisation of any healthcare facility

The studies in this category associated travel distance or time to any healthcare facility in the study location with the outcomes of healthcare utilisation. There were 10 studies in this category and all of them reported distance decay effect in the utilisation of the services (Table 4.9). The discussion of findings is grouped into paediatric care and other healthcare services because many studies considered paediatric care.

4.8.3.1. Utilisation of any healthcare facility for paediatric care

Five studies reported the association between geographical access and the utilisation of paediatric care in any healthcare facility. One of the studies reported a high utilisation of facilities for under-five fever treatment in urban and rural areas within 3km (walking and cycling) to the facilities and a steady decline afterwards (Alegana *et al.*, 2012). Another study reported twofold odds of complete vaccination among children that lived within 1-hour walking time to the facilities against the group that lived further away and accessibility declined in the wet season compared to the dry season (Blanford *et al.*, 2012). In another study, unvaccinated children travelled longer road distance (median 8.0km, 21 minutes) to the facilities than the vaccinated children (6km, 16 minutes) (Al-Taiar *et al.*, 2010). It was also found that the utilisation of government health centres for fever treatment in children decreased steadily as distance to the facilities increased up to 6km (Gething *et al.*, 2004).

Among many factors including household income, cost of treatment and choice of formal health service, distance was the major predictor of a patient's utilisation of a health facility for the treatment of under-five fever and cough (Ustrup *et al.*, 2014).

4.8.3.2. Utilisation of any health facility for any care

All facilities in this group reported significant declines in the utilisation of facilities (Table 4.9). A study reported 60-80% loss of utilisation of any facility at 60 minutes and 30-50% loss of utilisation at 11km to the facilities (Buor, 2003). Distance also had a significant influence on the utilisation of health facilities for substance abuse treatment (Myers, Louw and Pasche, 2010). Two studies also found distance decay effects in the utilisation of health facilities (Buor, 2002; Amaghionyeodiwe, 2008). In another study, at travel times 38.2 minutes in rural areas and 20.2 minutes in urban, choice of health facility was influenced by distance among other factors (Harris *et al.*, 2011). The study showed that urban population were more sensitive to distance than the rural population.

4.9. Geographical access and health outcomes

Studies in this category examined the association between the outcomes of a disease and travel distance or time to the nearest healthcare facility (Table 4.10). The diseases in the studies included malaria/fever and Tuberculosis (TB). The outcomes considered were severity, hospital admissions and mortality. Diseases outcomes in the groups who lived near healthcare facilities were compared with the groups who lived far away from the facilities. There were 10 studies in this category and the majority (n=9) reported findings for differential health outcomes in children and one study (Barker, Nthangeni and Millard, 2002) reported TB mortality. Most of the studies (n=7) in this category found significant associations between geographical access and diseases outcomes.

Table 4.10: Access and illness outcomes

Health service/Outcome	**Finding**	**Reference**
Paediatric care	-	-
Malaria hospitalisation	sd	O'Meara *et al.* (2009)
Malaria severity	sd	Al-Taiar *et al.* (2008), Alegana *et al. (*2012)
Child mortality	sd	Schoeps *et al. (*2011), Målqvist *et al. (*2010), Almeida and Szwarcwald (2011)
	nd	Rutherford *et al. (*2009), Moïsi *et al. (*2010), Adedini *et al.* (2014)
TB mortality	sd	Barker *et al*. (2002)
Code for findings: sd – significant decrease, nd – no significant decrease, mf – mixed findings		

Studies concerned with paediatric health either studied malaria/fever severity (n= 2), malaria admission (n=1) or mortality (n=6) in children. For malaria admissions in children, a study reported a twofold increase in urban and rural areas when travel times increased from 10 minutes to 2 hours (O'Meara *et al.*, 2009). There was a significant association between distance to healthcare and malaria severity when the distance to facility exceeded 2km (Al-Taiar *et al.*, 2008). The number of children who had fever doubled as travel time to the nearest health facility increased from 30 minutes (32%) to 1 hour (60%) (Alegana *et al.*, 2012).

Among the studies (n=6) that examined mortality in children, half (n=3) found no effect of geographical access on the outcomes of mortality in children. Among the group who found associations between geographical access and child mortality was 50% higher when the distance to the nearest health facility was 4km (Schoeps *et al.*, 2011). Mothers who lived beyond 1.3km of Euclidean distance from the nearest health facility had about 2 times higher risk of neonatal mortality than mothers who lived closer to the health facility (Målqvist *et al.*, 2010). There was also a significant association between infant mortality and distance to hospital after controlling for income, geographical region, population size and factors relating to the supply of health services (Almeida and Szwarcwald, 2012).

In the group of studies that found no associations between geographical access and child mortality (n=3), one study conducted in urban and rural areas found that child mortality was 5 times more likely to occur in rural areas, but distance to health facility had no direct significant association with mortality (Rutherford *et al.*, 2009). The other 2 study also found that child mortality was explained by other factors (e.g. cultural barriers and availability of resources) other than distance to the nearest vaccination centre and hospital (Moïsi *et al.*, 2010; Adedini *et al.*, 2014). The only study on TB mortality found a significant association between geographical access and mortality especially in the group that lived over 60km to the nearest healthcare facility (Barker, Nthangeni and Millard, 2002).

4.10. Discussion

Based on Cochrane and PROSPERO databases search for review similarity, this is the first systematic review of geographical access to healthcare in LMICs. The review comprises 80 peer-reviewed studies from 40 countries (Figure 4.1). The study of geographical access to healthcare gained prominence in 2000 and continued to rise until 2019 (Figure 4.2), which implies the subject is fairly new in LMICs. In all the studies, geographical access was measured to the nearest healthcare facility with the assumption that users would use the nearest healthcare facility.

Although the assumption that patients would use the nearest healthcare facility may be challenged on the grounds of cultural barriers, service quality and eligibility, it is still the most reliable assumption in the measurement of potential healthcare access.

The review identified two broad healthcare facilities (i.e. primary care and hospitals) in the studies of geographical access to healthcare in LMICs. In the primary care intervention, health facilities were those that provided basic outpatient services like immunisations, treatment of illness in children, antenatal care and basic maternal deliveries. There were name variations for primary care facilities in the various studies, though the descriptions indicated that they provided similar services. The names found in the studies were clinics, dispensaries, primary health centres, polyclinics, maternal and child welfare centre and health centres.

Hospitals were mostly named ‘hospitals’ and provided all the services that are offered in the primary care as well as comprehensive and emergency health care which included inpatient and outpatient services. Unlike the primary care, there were fewer studies on hospital access. Although two groups of facilities were identified, some studies examined geographical access to any nearest facility (primary care or hospital) regardless of the patient’s ability to use it. Such studies may have overestimated access to healthcare in neighbourhoods that had facilities open to only a specific class of people (e.g. military clinics) or a defined health condition (e.g. mental health care).

It was also found that no study considered geographical access to specialist health care services provided by dentists, opticians or physiotherapists. However, two recent studies considered access to essential and orthopaedic surgeries in hospitals (Juran *et al.*, 2018; Premkumar *et al.*, 2018). This indicates a gap in the study of geographical access.

The utilisation and health outcomes categories also measured geographical access to primary health care and hospital services. For instance, some studies considered the utilisation of health services offered in primary care facilities or hospitals while some considered the differential health outcomes of users of the services. Studies that examined utilisation or illness outcomes focused on paediatric and obstetric care while a few studies considered access to healthcare for the entire population. Although a handful of studies considered utilisation or outcomes of ART, TB and cancer care, no study measured access, utilisation or outcomes of chronic medical conditions that require regular medical check-ups like asthma and diabetes.

4.10.1. Travel modes to health facilities and distance intervals

The broad methods of measuring geographical access to health care in the studies were distance and time travel (Table 4.1). Trips to healthcare facilities were obtained by actual measurements, self-report or perceived by the patient. Most of the studies used self-reported distance (n=29, 36%), probably because of the difficulty in accessing and analysing spatial datasets. Among the studies that measured trips to health facilities, the majority used Euclidean distance (n=16, 20%) and only a few estimated access by road distance. No study considered specific use of rail or public transport with bus times, though a single study included water transport (Vadrevu and Kanjilal, 2016). The distribution of geographical access to healthcare was reported by mean, median and maximum distance or time, however, the majority reported the mean.

The choice of travel modes and distance/time intervals in the studies were determined by the discretion of the authors considering the research gap to addressed and availability of data. Therefore, every study used what was most suitable for them. Locations that had planning goals (i.e. PHC should be within 5km), used them as a bench mark for determining underserved population. Where such benchmarks were not available, researchers adopted a bench mark that was deemed suitable to present their results. The variation in travel/time intervals adopted made it difficult to compare findings. However, common time intervals used were; 5, 10 and 30 minutes and common distance interval used were; 1, 2, 3 and 5km.

The distance/time interval indicated accessibility which shows the progressive trip of the population from the facility to the fringes. Those who lived near the facility were considered well served and those who lived beyond the defined accessibility distance/time were considered underserved.

4.10.2. Types of healthcare facilities

The dominant healthcare facility in this review was primary care. Mean distance to primary care was 2.4km – 22.9km by Euclidean distance (Table 4.2). The shortest mean distance was recorded in the access to health centres while the longest mean distance was recorded in the access to HIV testing centres. In the time travel category, mean travel time was 73.6 minutes – 120.2 minutes (Table 4.2). The least recorded in the drive time to clinics and the longest was self-reported travel time to primary health centres.

In the hospital category (Table 4.5), mean Euclidean distance in the year, 2003 was 0.4km – 3.4km in the urban area and 5.8km – 8.1km in rural areas (Noor *et al.*, 2003). In another study, mean road distance in the rural areas was 8.4km – 56.7km in 2000-2006 and 15.5km – 28.4km in 2012-2013 (Vora *et al.*, 2015). The findings obtained in distance measurements were much similar to those of time measurements. A meaningful comparison of the findings was unlikely considering the diversities in measurement methods and presentation of findings. However, it is safe to conclude that geographical access was better in some countries and primary health care facilities were closer to the population than hospitals.

4.10.3. Geographical access to public and private health care

Most of the studies measured access to public healthcare facilities. A few who included both types of facilities did not distinguish the findings. However, two studies (Tables 4.2 and 4.6) from India found that private healthcare facilities were more accessible to the population than public healthcare facilities (Kumar, 2004; Islam and Aktar, 2011). Although the limited attention on private healthcare delivery downplays the important roles of private medical practice in LMICs, factors like data availability, affordability and the proportion of population served by private facilities may have been the limitations.

4.10.4. Urban and rural access to health care

Geographical accessibility of urban and rural healthcare facilities were proxy indicators of inequality since standard deprivation indices were rarely used in the studies. However, the findings for urban and rural areas were rarely reported separately, but where it was separated, the rural population travelled twice the distance of urban areas (Tables 4.5 and 4.7). Urban-rural inequality in the access to healthcare may not be eliminated because healthcare facilities are usually sited in large population clusters which are often in urban areas. The infrastructure in urban areas such as water, road and electricity which support those facilities are also better in the urban areas. Thus, having more healthcare facilities in urban areas may be justified under the context of equity. However, the study of geographical access would help planners to identify healthcare accessibility problems in the rural areas and also find ways to reduce them. Thus, the measurement gap of urban and rural access to healthcare should form a part of future studies of geographical access.

4.10.5. Population coverage of healthcare facilities

The population coverage of facilities was provided by studies that measured only geographical access to healthcare. Those findings were useful in understanding the service coverage of health facilities in LMICs. However, the findings were not provided in a uniform manner which makes them incomparable. Although incomparable, it was observed that urban populations were closer to health facilities than the rural population. It was also observed that the population in the various studies were closer to primary care than hospitals as it was expected. There was no specific pattern in the studies except that primary care facilities were closer to the population than the hospitals (Figure 4.7)

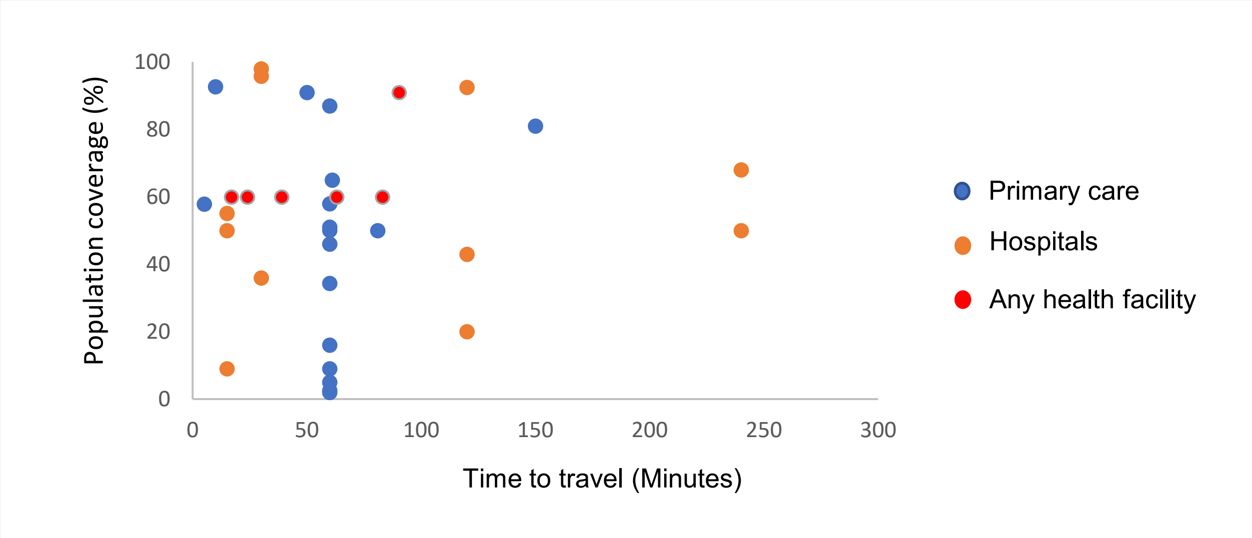

Figure 4.7: Population coverage of health facilities in LMICs

4.10.6. Geographical access and utilisation of healthcare

Most of the healthcare services in this category were paediatric and obstetric care in primary care facilities (Table 4.9). This review found compelling evidence of distance decay effect in the utilisation of healthcare services. All the studies in the general category of utilisation of primary care reported distance decay in the use of the services. Distance decay was also reported in 2 out of 3 studies on access to paediatric care and 12 of 14 studies in the obstetric care category. Patients were likely to delay utilisation of paediatric care if the facility was up to 1km or 30 minutes' walk or drive from home. In the hospital category, 1 out of 2 studies reported distance decay effect. The finding implies that distance decay effect was common to both primary care and hospitals. However, a firm conclusion on the difference between the two types facilities was not possible since hospitals had fewer studies. A convincing evidence of distance decay effect was also found in the utilisation of any facility where all 12 studies in that category reported significant effects.

Considering the similarity of findings from studies conducted in different countries, the association between geographical access and utilisation of healthcare services in LMICs cannot be refuted. However, the level of association varies according to location, characteristics of the population and type of health facilities. The residents of urban areas may delay utilisation of healthcare because of the busy urban lifestyle and the rural residents may also delay utilisation because of long travel times to facilities which are often in the urban areas (e.g. hospitals). Thus, healthcare facilities in urban areas may suffer decline in utilisation as those in the rural areas. However, the education level of users and access to information in urban and rural areas may cause a difference in urban and rural utilisation of healthcare services. Unlike primary care, hospitals may experience a lesser effect of distance decay because they are fewer and serve as the last resort of health care in LMICs. Since ambulance services are not readily available most LMICs, patients arrange their travel to the hospitals.

4.10.7. Geographical access and illness outcomes

There were 10 studies in this category and 7 studies reported significant association of disease outcomes or mortality with geographical access to healthcare (Table 4.10). Although the effects varied from one study to the other, there was compelling evidence that fever/malaria severity, malaria hospitality, child mortality and TB mortality were associated with distance to the nearest healthcare facility. Three of the studies on child mortality found no effect of distance, thus signifying mortality in children were explained by other factors other than distance to healthcare.

One of the studies which found no effect of distance in urban and rural areas also reported that child mortality was 5 times more likely to occur in the rural areas (Rutherford *et al.*, 2009). Although that study found no association of child mortality and distance, child mortality in the rural areas may be indirectly linked to the long distance to healthcare. The study is also a pointer to the fact that distance is not the only factor influencing health outcomes. Therefore, healthcare interventions targeted at the reduction of child mortality in the rural areas should in addition to proximity of healthcare consider other factors such as education, hygiene, nutrition and cultural practices.

The large number of studies on paediatric and obstetric care shows a great response to the problem of child and maternal mortality in LMICs. However, the findings are insufficient for making reliable conclusions about the effect of geographical access in the entire population. Therefore, future studies should not be limited to a gender or age group.

4.10.8. Recommendations

The study of geographical access to healthcare in LMICs is relatively new considering that there were few studies before year 2000. However, the persistent rise in the number of studies since 2000 presents encouraging opportunities to fill the gaps in the literature which include;

- Measurement of geographical access.
- Reporting of findings.
- Seasonality of geographical access to healthcare.
- Healthcare providers (Public and private healthcare access).
- Location (urban and rural access).
- Health outcomes.

Since most of the studies used self-reported and Euclidean measurements which are less reliable, further studies may consider more reliable methods like measured road distance and travel time (including walking and driving) if the data is available. Studies should also use more than one method of measurement and the findings should be compared. Comparison of findings would enable future studies to use one method of measurement to predict another in similar locations if the required data for a new measurement is not available.

For the sake of uniformity and ease of future reviews, a standard should be developed for reporting of the findings of geographical access to healthcare. In this review, it was difficult to synthesize the findings for discussion. If all future studies would report population access by travel distance at 1km and 3km intervals and travel time at 30 minutes and 60 minutes intervals, it would be easier to synthesize the findings of future studies.

A gap was also found in the measurement of seasonal geographical access to healthcare. Three studies who measured seasonality of access found that population access declined in the wet season (Ewing *et al.*, 2011; Blanford *et al.*, 2012; Makanga *et al.*, 2017). These studies demonstrated how seasonal variability led to 37% loss of access to life-saving maternal healthcare within 2 hours' drive (Makanga *et al.*, 2017) and 15% decline of access to vaccines within 1 hour walking in the wet season. These studies captured spatiotemporal variations in access to healthcare in a way that the traditional measurements of geographical access cannot. Nigeria is currently experiencing one of the highest maternal and child mortalities in the world, yet no study considered the impact of seasons in the country on those health outcomes. The lack of studies in this area and the similarity of Nigeria's environmental characteristics with those in the seasonal studies make this thesis timely.

Another area that received less attention in the studies was the private medical practice and hospital care. The poor representation of private practice in the study of geographical access underestimates its importance in the LMICs. Since the lack of data may constitute a major limitation in the study of healthcare in the private sector, healthcare system managers should consider the coordination of private medical practice in the LMICs. Further studies should include private healthcare practice and findings should be reported separately if public and private healthcare services are examined. Also, more studies on hospitals and specialist services delivered by opticians, dentists and physiotherapists in public and private healthcare facilities are also needed.

This review also found a gap in the reporting of urban-rural access to healthcare. Many studies that were conducted in urban and rural areas did not separate the findings. Where data is available, future studies should provide independent findings for the two locations. Such findings would serve as a proxy for measuring healthcare deprivation since standard deprivation indices are lacking in most LMICs.

This review also found a gap in the association of geographical access with utilisation and illness outcomes. Most of the studies in these categories considered paediatric and obstetric care, probably as a response to the burden of child and maternal mortality in LMICs. Since studies have established the association of geographical access with paediatric and obstetric care, further studies should consider including the whole population without limit to gender or age. It should also examine chronic conditions such as asthma, diabetes and cancers that need regular medical check-ups.

Such measurements would also refine or tell more about the findings obtained from studies that examined utilisation of health facilities and differential outcomes of illnesses. Also, instead of measuring access to a single type of health facility in a study, all health facilities in the location should be measured and compared if the data is available.

The number of studies in this review represents a small fraction of countries in the LMICs. For instance, a few studies (n=7) were conducted in different locations in Nigeria but there was no study from Cross River State. Therefore, more studies of geographical access in LMICs are expected. Since, all the gaps identified in this review cannot be filled in a single study, this thesis measures seasonal variability in geographical access to healthcare (including primary care, hospitals and NHIS) using road network (walking and driving) and examines association between malaria outcomes and drive times to healthcare without a limit on age or gender.

4.10.9. Strengths and limitations

A systematic approach was used in searching, screening, appraisal and data extraction for this review. Reference lists of included studies were also searched for relevant studies to minimise citation bias. However, some limitations should be considered while interpreting the findings of this review. This review included only studies that were published in English from 1980 to 2019, which means relevant studies that were published in other languages or outside the period of this review were excluded. While the findings of this review remain valid for the chosen language and time, further reviews may be needed for non-English language studies that were conducted in African francophone countries, Asia and Latin America.

This review included only peer-reviewed studies that used cohort, cross-sectional, case-control and non-epidemiological study designs. Included studies were single year studies or time-series which were conducted in a single location, across locations or countries. However, there is an awareness that the review does not cover all LMICs, some study designs, studies published in databases not linked to the ones used and grey literature. Another limitation of this review is the sample sizes of the studies. While some used large sample sizes some were small. Some studies were hospital-based and some were national studies. The generalisation of findings from studies that were conducted in a hospital for the entire population may increase the risk of bias.

Furthermore, considering the complexities of studies, the uniqueness of study designs, variations in measurements and methods of presenting findings, there was a challenge of synthesizing all findings in the primary studies. The solution was to extract only findings that matched the review template. Consequently, findings that may have been of interest to the original authors but could not fit into the template were not included. It was practically impossible to report all the findings in the included primary studies.

A low-level quality assessment was used in this review and study that had a clear method of measuring geographical access was scrutinised before inclusion. There is an awareness that some of the studies were low in quality. However, considering the challenges of conducting a research in the LMICs and the need to gather sufficient information about geographical access, every study that met the inclusion criteria was included in this review.

4.10.10. Conclusion

This study examined geographical access to healthcare in LMICs. It found inequality in geographical access. It also found compelling evidence of decline in utilisation of healthcare services and increase in diseases outcomes as distance to healthcare facilities increased. Among the gaps identified in this review, seasonal geographical access matches the interest of this thesis and will become the focus of the empirical chapters of this thesis. The next chapter (Five) presents research methodology.

CHAPTER FIVE: METHODOLOGY

5. Chapter overview

This chapter discusses methodological approach in the primary studies. It covers data collection, processing and analyses as well as the strengths and weaknesses of methods used. The objective of this chapter is to discuss methods and justifications for the primary studies.

The methodology addressed three main problems which are interconnected. They are; seasonal geographical access to healthcare, its association with malaria outcomes and its effect on NHIS location planning. The methods incorporated flooding which was identified as a serious problem in the study location (Chapter Three). Therefore, drive times to health facilities were expected increase in the wet season due to potential flooding of some road segments. The odds of malaria outcomes such as severity and hospital admission were also expected to increase at the same time due to extended breeding spaces for mosquito and reduced access to healthcare. Within the same period, the expected performance of health facilities, for instance the NHIS was expected to decline.

To achieve the study objectives (Chapter One), a methodology workflow comprising three main components namely; data collection, data cleaning and analyses was designed (Figure 5.1). Data were selected to address the research aims and objectives (Chapter One). Data including health facilities, roads, communities, population and malaria were collected from trusted government sources. Health facilities were government managed PHCs, hospitals and NHIS. The road data comprised major and minor roads. Communities were locations of the smallest units of population settlements. Population figures were community level aggregates of 1991 census figures. Malaria data were 2015 record of patients who were diagnosed with malaria in two selected government hospitals.

The data were cleaned and stored in the right file type for analyses. Health facilities were assigned coordinates, unwanted variables were removed, road network was created, and a custom flood model was developed.

The measurement of seasonal geographical access to healthcare comprised dry and wet seasons analyses. Geographical accessibility of health facilities for both seasons were measured by driving and walking times to the nearest health facility. It was expected that drive times to health facilities will be longer in the wet season compared to the dry season because of patients' attempt to avoid the flooded road segments. Unequally access to healthcare was also expected in the rural areas due to bad roads and poor drainage. Travel time was measured in this study because it takes into consideration the condition of roads at the time of travel. The analyses of seasonal geographical access to healthcare satisfied the second objective of this research.

The malaria study comprised of descriptive analyses and association of seasonal geographical access with malaria outcomes. Malaria outcomes and dependent variables in the study were diagnosis, admissions and mortality. Independent variables were drive times to the nearest health facility and hospital attended, gender and months of hospital visit. Association between dependent and independent variables were analysed using logistic regression because of the binary variables in the data. The analyses of malaria data satisfy the third objective of this research.

MCLP, a model for selecting optimal locations was used to study the NHIS performance in the wet and dry seasons. Three sub-models were created from the MCLP; Existing Facilities Location Allocation Model (EFLAM), Population Weighted Location Allocation Model (PWLAM) and the Random Points Location Allocation Model (RPLAM). The models were used to identify potential locations for increasing population access to the NHIS using drive times. It was expected that the wet season models will perform less than the dry season models. The location-allocation analyses of NHIS satisfies the fourth objective of this research.

The results of the analysis were presented in tables, graphs, maps and charts. The findings of seasonal geographical access are discussed in Chapter Six. Malaria study is discussed in Chapter Seven and location-allocation findings are presented in Chapter Eight. The summary and recommendations based on the findings are presented in Chapter Nine.

5.1. Data and method

The datasets used in this study were road network, healthcare facilities, communities, population and malaria records (Figure 5.1). Drive and walking time travels were used to measure geographical accessibility of facilities and regression method was used to investigate associations. However, where necessary original datasets and methods were updated before using them.

5.1.1. Data collection

This study used secondary datasets that were collected from reliable government sources. However, primary data were also collected to update the secondary datasets and establish suitable conditions for the models used in data analyses where necessary.

5.1.2. Road data

The measurement of travel time depend heavily upon a detailed and accurate representation of road segments (length) and travel speed Impedance (Delamater *et al.*, 2012). The road network of Cross River State was acquired free of charge from the Office of the Surveyor-General of Cross River State (OSG-CRS) in a pen drive. It was provided with locations of road segments, incomplete road names, incomplete length and no speed attribute.

The road dataset was checked for topology issues, ensuring that every line ended at a junction, no breaks in between and no segment crossed a junction that has no over-head bridge. Road segments that had problems such as overlaps, breakage and multiple lines were edited.

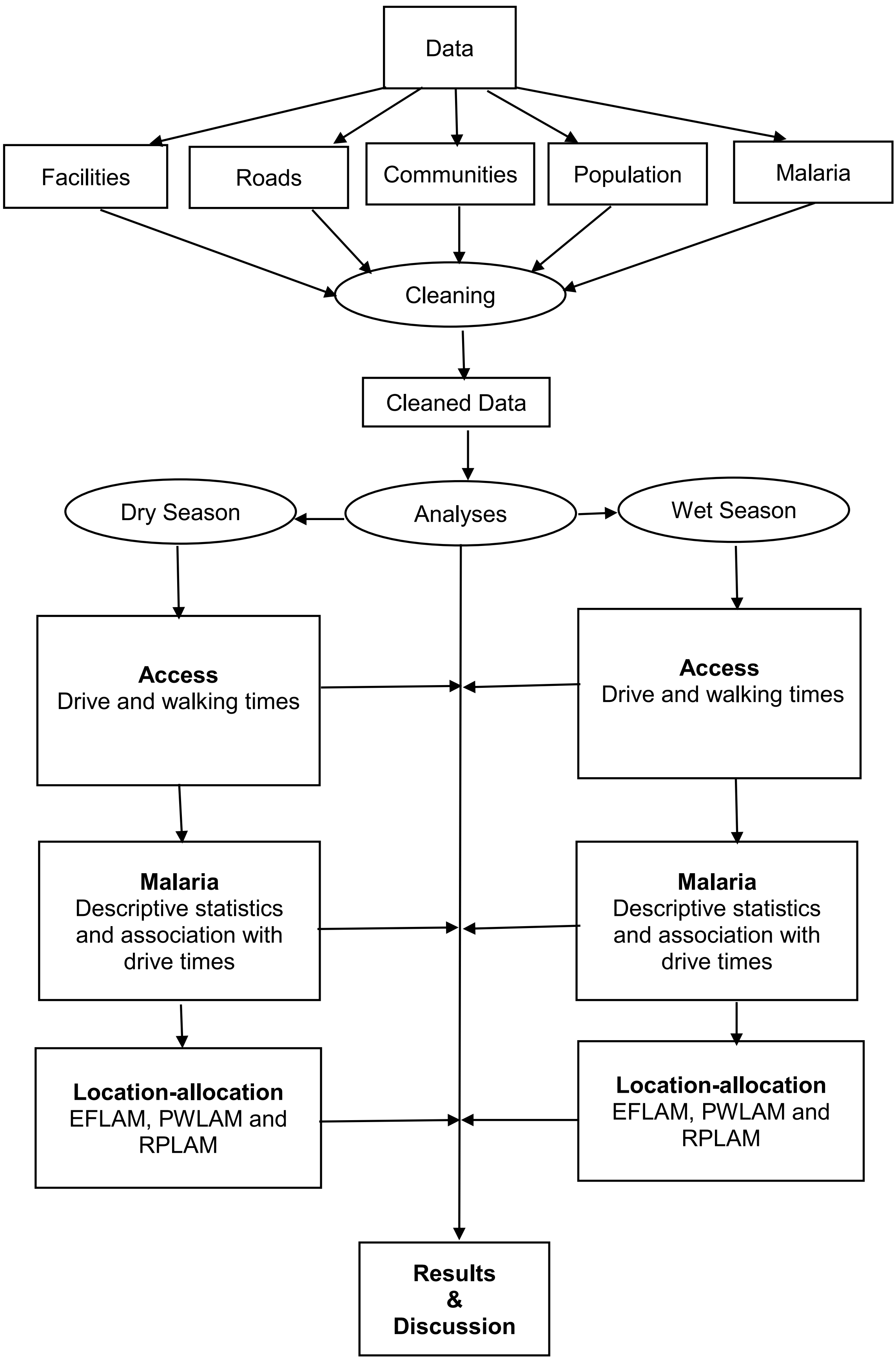

Figure 5.1: Key diagram showing methodology

5.1.2.1. Speed limit classification

Road segments in Nigeria are classified into various speed limits (Table 5.1) according to the hierarchy of roads and types of vehicles (Nigeria Highway Code, 2015). The published speed limits were not used because the hierarchies of roads were not provided along with the road data and it would be time-consuming to assign travel speed to each road segment. Another reason was the understanding that most people will not travel at the maximum speed limits considering traffic congestions at certain times of the day, the bad condition of some roads and safety.

Table 5.1: Maximum speed limits and actual average driving speed (km/hr)

Types of vehicles	Built-up	Highway	Expressway	Actual (all roads)
Private cars	50	80	100	20
Taxis & buses	50	80	90	20

Instead of using the maximum speed limits, the measured average walking and driving speed within the city of Calabar was used. A Land Surveyor was consulted to walk 1km from one point to another through as many streets as possible. A Garmin e-trek Global Positioning System (GPS) equipment was used to track the distance, start time and end time of each trip. The process was repeated for three days in different road segments and the average walking speed was calculated from the data obtained (Table 5.2). To ensure that road conditions were accounted for, each trip comprised tarred and earth road. The calculated average walking speed was 3.1km/hr.

Table 5.2: Average walking speed in Calabar

Person walk	Start – End time	Distance	Time lapse (min)
Point A – B	06:56pm - 07:12pm	1km	16
Point C – D	7:14pm - 7:34pm	1km	20
Point E – F	8:01pm- 8:23 pm	1km	22
Sum	58 mins		
Average walking speed	= Total Distance/Time = 3km / 58min = 0.052km/min (3.12km/hr)		

The same process of measuring walking speed was repeated for average driving speed (Table 5.3) at an interval of 3km. A private car was hired to drive for 3km along 3 distinct routes. Start and end time of each trip were measured, and distance was calculated using GPS. The calculated average driving speed was 19.3km/hr. It was assumed that public and private cars would travel at the same speed since there are no timetables for public transport in Nigeria and waiting times vary depending on the time and location.

It was also necessary to assign river crossing speed to road segments without bridges. Since there was no published boat sailing speed for this purpose, a custom speed was derived by paying canoe-men to sail across the cross river in Calabar city. The crossing time was recorded at the shore and the width of the river was extracted from the digital orthophoto map of Cross River State. Average boat sailing speed was computed and assigned to relevant road segments. The computed average boat sailing was 3.3km/hr (Table 5.4).

Table 5.3: Average driving speed in Calabar

Car Drive	Start – End Time	Distance	Time lapse (min)
Point A – B	4:36pm-4:47pm	3km	11
Point C – D	5:33pm-5:43pm	3km	10
Point E – F	4:43pm- 4:50pm	3km	7
Total Time	28 mins		
Total driving distance	9 km		
Average driving speed	Total Distance/Time = 9km / 28min = 0.32km/min (19.26km/hr)		

Table 5.4: Average boat sailing speed along cross river

Vessel	From shore A – B	Time Lapse (min)	From shore B – A	Time lapse (min)
Boat A	10:38 – 10:52am	14	10:53 – 11:08am	15
Boat B	11:12 – 11:31am	19	11:33 – 11:47am	14
Sum	14+19+15+14 = 62			
Width of river on Orthophoto map	Measurement A = 848m, B = 856m, C = 835m and D = 846m Total Distance = 3385m (3.4km)			
Crossing Speed	Average Speed = (Total Distance/Time) = 3.4km/62mins = 0.06km/min (3.3km/hr)			

5.1.2.2. Road hierarchy

Ideally, the average speed is supposed to be assigned according to the hierarchy of road. However, it was not feasible since the hierarchy of each road segment was not provided in the original file. In like manner, urban and rural roads were assigned the same travel speed because the roads in the two localities were not distinguished in the original data. Urban/rural overlay was not was not possible because there was no data delineating urban and rural areas. Moreover, the assignment of a uniform travel speed to all road segments was deemed the best solution since some expected high-speed roads in Cross River State are not in good condition (Premium Times, 2015; Ekanem, Aboh and Okolisah, 2017). Since the roads are not in good condition (Figure 5.2), driving speed may not differ much in the state.

Figure 5.2: Bad road conditions of a highway in Cross River State (Premium Times, 2015)

5.1.2.3. Building road network

Basic road network datasets were built for this study due to data limitations. The ArcMap network analyst tool in ArcGIS 10.4 software was used to build the road network. The road datasets were built without any fixed turn restriction since the attribute was not provided. It was built to allow connectivity via any vertex since all vertices were at the road junctions. To ensure the use of appropriate cost in the final analyses, separate road networks were built for walking, driving and road distance. For walking and driving, the cost was time and the unit was minutes and for road distance road dataset, the cost was the length and the unit was Kilometres. Driving directions were not established in the dataset because they were not supplied with the original data.

5.1.3. Sensitivity

The average speeds obtained from actual measurements were compared with the average speeds obtained from Google Map for sensitivity checks. The starting point (A) on Google Map was Kent Street in Calabar city while the Endpoint (B) was University of Calabar (Figure 5.3). The direction was solved, and three best routes were provided for driving and walking from Point A to B. The actual measured average walking and driving speeds were 0.32km/min and 0.05km/min respectively (Tables 5.2, 5.3). The Google Map measured average driving and walking speeds were 0.36km/min and 0.08km/min respectively (Table 5.5). The differences in average driving and walking speeds in the two measurements were 0.04km/min and 0.03km/min respectively.

The differences were expected because the routes used in the actual measurements were different from that of Google Map. Moreover, the road network in Google Map is incomplete, and it is unaffected by traffic at certain times of the day and road restrictions. In a previous study, average walking speed in the cities was 4km/h (0.07km/min) (Blanford *et al.*, 2012). Thus, average walking or driving speed may vary depending on topography, individual, time of the day and traffic situation of the location. Therefore, the method used is accurate for the location.

Table 5.5: Google map average driving and walking speed in Calabar (Google Map, 2016)

Average driving and walking speed in Calabar		
Driving	Time A – B (min)	Distance (km)
Point A – B	8	2.9
Point A – B	10	3.7
Point A – B	10	3.6
Total	28	10.2
Average driving Speed	0.36km/min	
Walking	Time A – B (min)	Distance (km)
Point A – B	52	4.1
Point A – B	54	4.3
Point A – B	54	4.3
Total	160	12.7
Average walking Speed	0.08km/min	

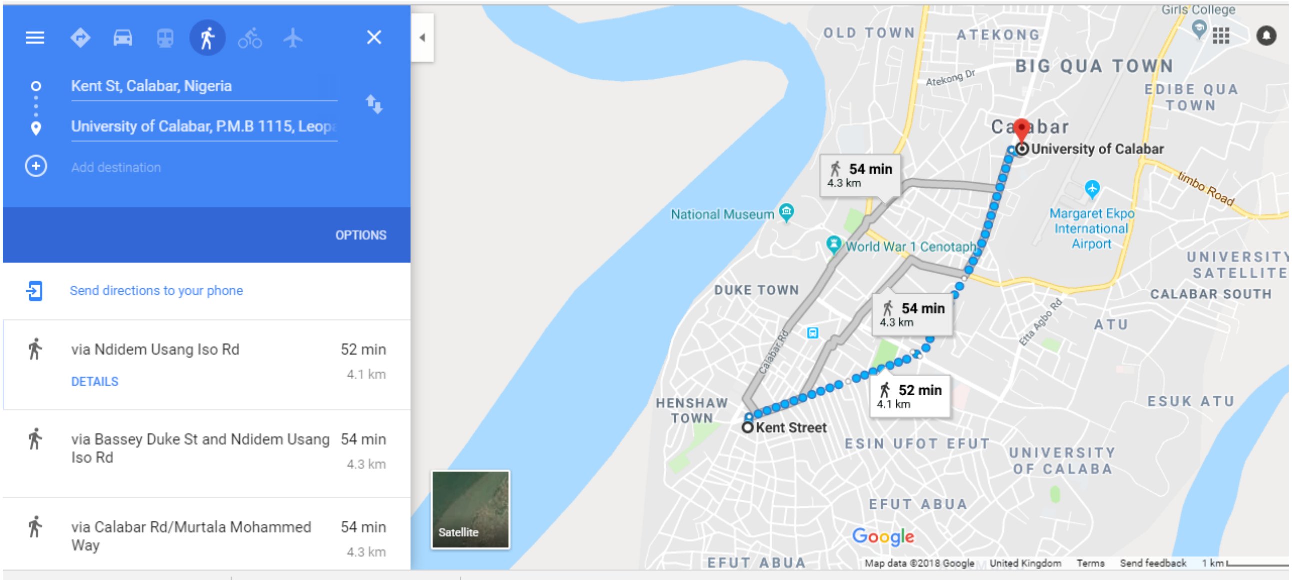

Figure 5.3: Walking time in Calabar (Google Map, 2016)

5.1.4. Communities and population

The analysis of trips to facilities requires geocoded communities' points that have population attributes (Blanford *et al.*, 2012). Community level population data was needed for the estimation of population access to healthcare at a micro level. Unlike some developed countries where this type of data can be downloaded from the internet, the data were held at different offices in Cross River State. Applications were sent to the National Population Commission (NPC) and OSG-CRS and followed up with telephone calls for about six months before the datasets were delivered. The population data were obtained from the NPC and geocoded communities were obtained from the OSG-CRS.

Since the 2006 population census data was not available at the community level, the 1991 population census data which had communities' level figures were scanned from the NPC office in Calabar, Cross River State (Appendix V). Attributes supplied with the data were community name, the number of males, number of female and total for both sexes. The data entered into Excel workbook and checked to ensure no errors or omissions were made by comparing the original (scanned copies) with the Excel copy.

5.1.4.1. Population projection

Population data was projected from 1991 to 2015 using population growth rates obtained from the World Bank website, since the original population data was too old for this study. The population growth rates were 2.5% (1992 – 2005), 2.6% (2005 – 2007) and 2.7% (2007 – 2015) (World Bank, 2015). The World Bank population growth rates were used, because they were the most reliable projection parameter at the time of this study. The values were programmed into Excel sheet and projection was computed for each year from 1992 to 2015 using the projection formula: $Nt=Pe^{rt}$ (Kennan, 2016). Where (Nt) represents the population at a future date, (P) is the present population, (e) represents the natural logarithm base of 2.71828 and (r) is the rate of increase divided by 100 and (t) represents the time period. The accuracy of the projection computation was checked by the Mathematics and Statistics Help (MASH) centre at the University of Sheffield.

Although population projections from growth rates may vary according to administrative level (Population Reference Bureau, 2015), the projection from national growth rates was the only feasible approach. Further discussions on strengths and weaknesses are presented in Chapter Nine of this thesis (Page 240).

5.1.4.2. Geocoding of population data

Community points were matched to population file to produce geocoded communities with population attributes (Figure 5.4). The community shapefile from the OSG-CRS contained 1034 communities while the population file from NPC contained 1396 communities. The variation was partly because of the purpose for which the data were created. While OSG-CRS identified a single community point for planning purposes, NPC split some communities into two or more units for census enumeration (i.e. Ofombongha 1A, 1B, 2, 3 and 4). The solution was to identify the 'duplicates' in the NPC data and sum the values and give it one name (i.e. Ofombongha).

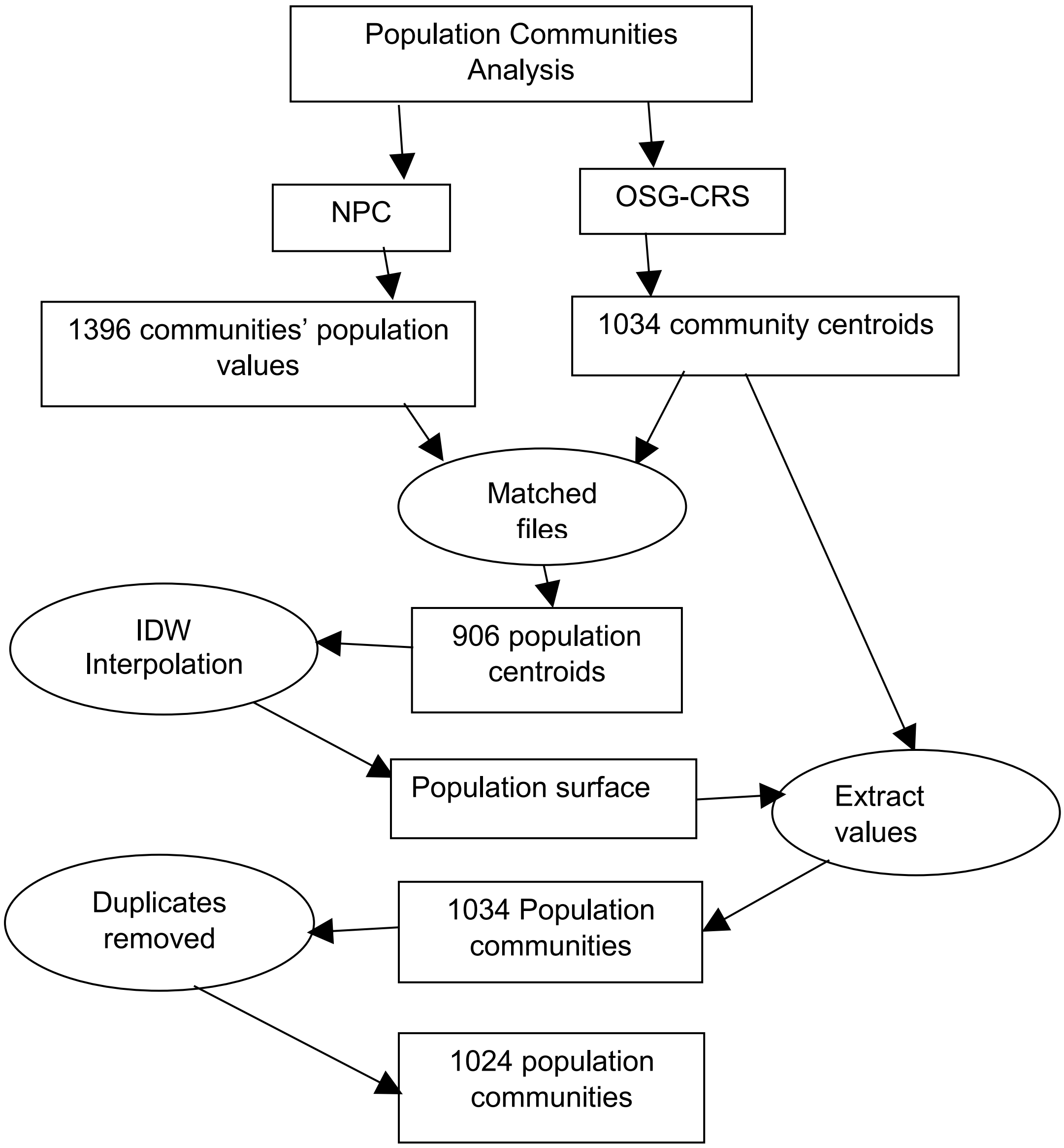

Figure 5.4: A flow chart showing the processing of population communities

Names variations in the two (population and communities) files were managed by comparing the two files, and one name was saved for each community in a new file that was created. The problem of missing communities in either population or communities file was solved by extracting from the population file 906 entries whose communities' names were also available in the main communities file. Population values were assigned to community centroids and a GIS tool (the IDW[4]) was used to estimate population around that point, assuming an inverse distance weighted

[4] Inverse Distance Weighted (IDW) interpolation.

effect (Environmental Systems Research Institute, 2016a). The original communities file containing 1034 communities was used to extract population values from the population surface. After removing duplicates, the final number of communities used in the study was 1024 and the projected population value for the year 2015 was 3,628,810 (Figure 5.5).

Table

Comm_and_pop_updated06022017

FID	Shape *	NAME	LGA	RASTERVALU	2015Pop
0	Point	Adim	Biase	17588.378906	17588.4
1	Point	Biakpan	Biase	6371.371582	6371.37
2	Point	Ikun	Biase	5322.015625	5322.02
3	Point	Etono Central	Biase	5752.641602	5752.64
4	Point	Agwagune	Biase	8405.150391	8405.15
5	Point	Abini	Biase	8915.886719	8915.89
6	Point	Akpet I	Biase	4940.304688	4940.3
7	Point	Orira	Biase	5222.322266	5222.32
8	Point	Ikot Okpora	Biase	477.736114	477.736
9	Point	Ikot Ana	Biase	6192.022949	6192.02
10	Point	Iwuru Obiontan	Biase	8723.018555	8723.02
11	Point	Betem	Biase	3459.79126	3459.79
12	Point	Ehom	Biase	4498.858398	4498.86
13	Point	Idomi	Yakurr	14235.958984	14236
14	Point	Mkpani	Yakurr	25802.820313	25802.8
15	Point	Ekori	Yakurr	31507.113281	31507.1
16	Point	Nko	Yakurr	23320.207031	23320.2
17	Point	Anong	Abi	3638.087158	3638.09
18	Point	Adadama	Abi	1723.363159	1723.36
19	Point	Ebom	Abi	9903.046875	9903.05
20	Point	Ediba	Abi	10564.175781	10564.2
21	Point	Igoni - Igoni	Abi	5258.814941	5258.81
22	Point	Usumutong	Abi	14360.537109	14360.5
23	Point	Egboro Enyi	Abi	2469.799805	2469.8
24	Point	Agbara Igbo	Abi	1440.802734	1440.8
25	Point	Igbo Imabana	Yakurr	2859.76123	2859.76
26	Point	Asiga	Yakurr	5487.578125	5487.58
27	Point	Oyadama	Obubra	3635.739014	3635.74
28	Point	Oderiga	Obubra	6534.835449	6534.84
29	Point	Iyamayong	Obubra	5369.770996	5369.77
30	Point	Ochon	Obubra	9000.337891	9000.34
31	Point	Iyamitet	Obubra	7327.022461	7327.02
32	Point	Onyene Okpon	Obubra	1521.376465	1521.38
33	Point	Ofonbonga	Obubra	930.483154	930.483
34	Point	Ogurude	Obubra	3561.696533	3561.7
35	Point	Isobo Otaka	Biase	1954.050659	1954.05

1 (0 out of 1024 Selected)

Figure 5.5: An extract of the processed population and community data

5.1.5. Health facilities

The study was limited to government-managed health facilities because the aim of the study is to inform policy, and this is the area in which government policy has some leverage. Health facilities' files were obtained from the Cross River State Ministry of Health (CRSMoH) and the NHIS office in Calabar, Cross River State. The data from the CRSMoH were supplied in an Excel file with the names of facilities, types and location names. Scanned copies of NHIS data comprising facilities' names and incomplete location attributes were obtained from the NHIS office. Each type of health facility was entered into a new Excel file for geocoding. Health facilities obtained were 19 hospitals, 119 PHCs and 67 NHIS facilities, making a total of 205 facilities. Since some government hospitals operate as public hospitals as well as NHIS facilities, some government hospitals were also included in the NHIS facilities data. Those facilities were not considered as duplicates because their NHIS services are only opened to insured users.

5.1.5.1. Geocoding of health facilities

At that stage, location coordinates were assigned to all health facilities since they were not supplied in the original files. A unique approach was adopted in the geocoding of each type of facility. PHCs were assigned the point coordinates of their communities (Figure 5.6) since their actual locations could not be traced on any of the reference map files (Autophoto map and Google Map), and a field survey was not possible considering the cost and time involved. Coordinate locations of hospitals were extracted from the digital Autophoto map of Cross River State since they were marked (Figure 5.7). NHIS facilities coordinate positions were obtained from the reference map files and additional location information was obtained sources who know the locations (Figure 5.8).

5.1.6. Roads, communities and facilities data checks

After processing, the datasets were displayed together on ArcGIS software for visualisation and checks to ensure accuracy and consistency, and there was no issue with the processed datasets (Figure 5.9).

Table

CRS_PHC

FID	Shape *	Id	PHC_Name	LGA
0	Point	0	Afafanyi PHC	Abi
1	Point	0	Igbo-Imabana Model Primary Health Centre	Abi
2	Point	0	Adadama Primary Health Centre	Abi
3	Point	0	Ebom/Ebijakara Primary Health Centre	Abi
4	Point	0	Ediba Comprehensive Health Centre	Abi
5	Point	0	Ediba PHC	Abi
6	Point	0	Anong/Ezeke PHC	Abi
7	Point	0	Usumutong Primary Health Centre	Abi
8	Point	0	Akamkpa Primary Health Centre	Akamkpa
9	Point	0	Old Netim Primary Health Centre	Akamkpa
10	Point	0	Nsan Primary Health Centre	Akamkpa
11	Point	0	Osomba Primary Health Centre	Akamkpa
12	Point	0	Nyaje Primary Health Centre	Akamkpa
13	Point	0	Mbarakom Primary Health Centre	Akamkpa
14	Point	0	Aningeje Primary Health Centre	Akamkpa
15	Point	0	Uyanga Primary Health Centre	Akamkpa
16	Point	0	Ikot Offiong Ambai PHC	Akpabuyo
17	Point	0	Ikot Efanga Primary Health Centre	Akpabuyo
18	Point	0	Idundu Primary Health Centre	Akpabuyo
19	Point	0	Ikot Nakanda PHC	Akpabuyo
20	Point	0	Ekpene Esuk Primary Health Centre	Bakassi
21	Point	0	Esighi Primary Health Centre	Bakassi
22	Point	0	Ikang Primary Health Centre	Bakassi
23	Point	0	Nsidung PHC	Bakassi
24	Point	0	Anyikang Primary Health Centre	Bekwarra
25	Point	0	Abuochiche Model Primary Health Centre	Bekwarra
26	Point	0	Afrike Ochagbe Primary Health Centre	Bekwarra
27	Point	0	Gakem Primary Health Centre	Bekwarra
28	Point	0	Nyanya 1 Primary Health Centre	Bekwarra
29	Point	0	Utukwe Primary Health Centre	Bekwarra
30	Point	0	Ukpah Primary Health Centre	Bekwarra
31	Point	0	Ijom-Abayong Primary Health Centre	Biase
32	Point	0	Adim Primary Health Centre	Biase
33	Point	0	Agwagune Primary Health Centre	Biase
34	Point	0	Abini Primary Health Centre	Biase
35	Point	0	Akpet Primary Health Centre	Biase

1 (0 out of 119 Selected)

Figure 5.6: An ArcGIS extract of Cross River State PHCs

GH_CRS

FID	Shape *	Id	Name	LGA
0	Point	0	General Hospital	Akamkpa
1	Point	0	St Joseph Hospital Ikot Eneyo	Akabuyo
2	Point	0	General Hospital Abuochiche	Bekwarra
3	Point	0	Model General Hospital Obanliku	Obanliku
4	Point	0	General Hospital Ugep	Yakurr
5	Point	0	Eja Memorial Hospital Itigidi	Abi
6	Point	0	Oban Cottage Hospital	Akamkpa
7	Point	0	Akpet Central Cottage Hospital	Biase
8	Point	0	Calabar General Hospital	Calabar South
9	Point	0	Calabar Naval Hospital	Calabar Municipality
10	Point	0	University of Calabar Teaching Hospital	Calabar Municipality
11	Point	0	Calabar Police Clinic	Calabar Municipality
12	Point	0	Eburutu Brigade Medical Centre	Calabar Municipality
13	Point	0	Dr Lawrence Henshaw Memorial Hospital	Calabar South
14	Point	0	Holy Family Catholic Hospital	Ikom
15	Point	0	Obubra General Hospital	Obubra
16	Point	0	Obudu Sacred Heart Hospital	Obudu
17	Point	0	General Hospital Ogoja	Ogoja
18	Point	0	Ofoboche Specialist Hospital Okuku	Yala

Figure 5.7: An ArcGIS extract of Cross River State hospitals

Edit View Bookmarks Insert Selection Geoprocessing Customize Windows Help

Table

NHIS_Facilities_complete

CODE	NAME_OF_FA	ADDRESS
CR/0058/P	UNIVERSITY OF CALABAR TEACHING HOSPITAL	Moore Road, Calabar, Cross River State.
CR/0125/PULTIMATE MEDICAL AND CONSUTANT	USSY MEDICAL CONSULTING ROOM	Isong Inyang Junction, Akamkpa
CR/0076/P	VICTORIA ITAM HOSPITAL	4 Ediba Lane, Calabar Municipal, Cross River, Nigeria
CR/0061/P	13 BDE MC CALABAR	Brigade Medical Centre, Eburutu Barrack, Calabar Municipal, Cross River, Nigeria
CR/0064/P	130 BN MRS OGOJA	Army Barracks, Ogoja
CR/0062/P	146 BN MRS, CALABAR	Eburutu Barracks, Calabar
CR/0063/P	245 RECCE BN MRS, IKOM	Army Barracks, Ikom
CR/0065/P	341 AR MRS OGOJA	Ogoja
CR/0060/PULTIMATE MEDICAL AND CONSUTANT	ADI SPECIALIST CLINIC	7A Otop Abasi Street, Calabar
CR/0086/PULTIMATE MEDICAL AND CONSUTANT	AMAZING GRACE SPT CLINIC	45, Ikot Uduak Street, Off MCC Road
CR/0007/P	BAKOR MEDICAL CENTRE	Block 1 Plot 7 Federal Housing Estate, Ikot Ansa, Calabar Municipality
CR/0074/PULTIMATE MEDICAL AND CONSUTANT	BASSEY ENON MEDICAL CENTRE	11B Yellow Duke Street, Calabar
CR/0033/P	BENSON CLINIC AND MATERNITY	Opp. Motor Park, Four Corners, Ikom
CR/0012/P	CANNAN MEDICAL CENTRE	20b Iso Oqua, Big Qua Town,Calabar
CR/0006/P	CITY CLINIC	101 Ndidem Isang, Isong Road, Calabar
CR/0048/P	COMPREHENSIVE HEALTH CENTRE	(Poly Clinics) Ooba Okpoma, Yala
CR/0092/PULTIMATE MEDICAL AND CONSUTANT	COMPREHENSIVE HEALTH CENTRE (UCTH) (ANNEX)	Okoyong, Odukpani
CR/0100/PULTIMATE MEDICAL AND CONSUTANT	COTTAGE HOSPITAL AKPET CENTRE	Akpet Central
CR/0051/P	COUNTRY SPECIALIST HOSPITAL	18 Calabar Road, Ikom
CR/0046/P	DANEX MEDICAL CENTRE	5 Danex Road Edenkokol, Ijiman, Ugep
CR/0069/PULTIMATE MEDICAL AND CONSUTANT	DYNASTY CLINIC	73 Edim-Otop Street, Calabar,
CR/0083/PULTIMATE MEDICAL AND CONSUTANT	DSS CLINIC	Calabar, Cross River State
CR/0010/PULTIMATE MEDICAL AND CONSUTANT	EFKAM CLINIC	94 Ndidem Usang Iso Road, Calabar
CR/0004/P	FAITH FOUNDATION SPECIALIST CLINIC	57 Ndidem Isang, Isong Road, Calabar
CR/0126/PULTIMATE MEDICAL AND CONSUTANT	FIRST FOUNDATION CLINIC	Ikom-Abakaliki Road
CR/0093/P	GENERAL HOSPITAL AKAMKPA	Akamkpa
CR/0001/P	GENERAL HOSPITAL MARY SLESSOR AVENUE	Mary Slessor Road, Calabar
CR/0095/P	GENERAL HOSPITAL OBUBRA	Obubra
CR/0094/P	GENERAL HOSPITAL UGEP	Ugep
CR/0042/P	GENERAL HOSPITAL, IGOLI OGOJA	Ogoja
CR/0009/P	GOLDIE CLINIC	137, Goldie Street, Calabar
CR/0123/PULTIMATE MEDICAL AND CONSUTANT	GROUP SPECIALIST CLINIC	5 Edet Eyo Crescent, (Off Ndidem Usang Iso)
CR/087/PULTIMATE MEDICAL AND CONSUTANT	HERITAGE SPECIALIST CLINIC	64, Ekpo Abasi Street, Calabar, Cross River State
CR/0096/P	HOLY FAMILY CATHOLIC HOSPITAL	Ikom
CR/0127/PULTIMATE MEDICAL AND CONSUTANT	IBIM MEDICAL CENTRE	Plot 70 ,G.R.A, Agric Road, Ikom,

Figure 5.8: An ArcGIS extract of Cross River State NHIS

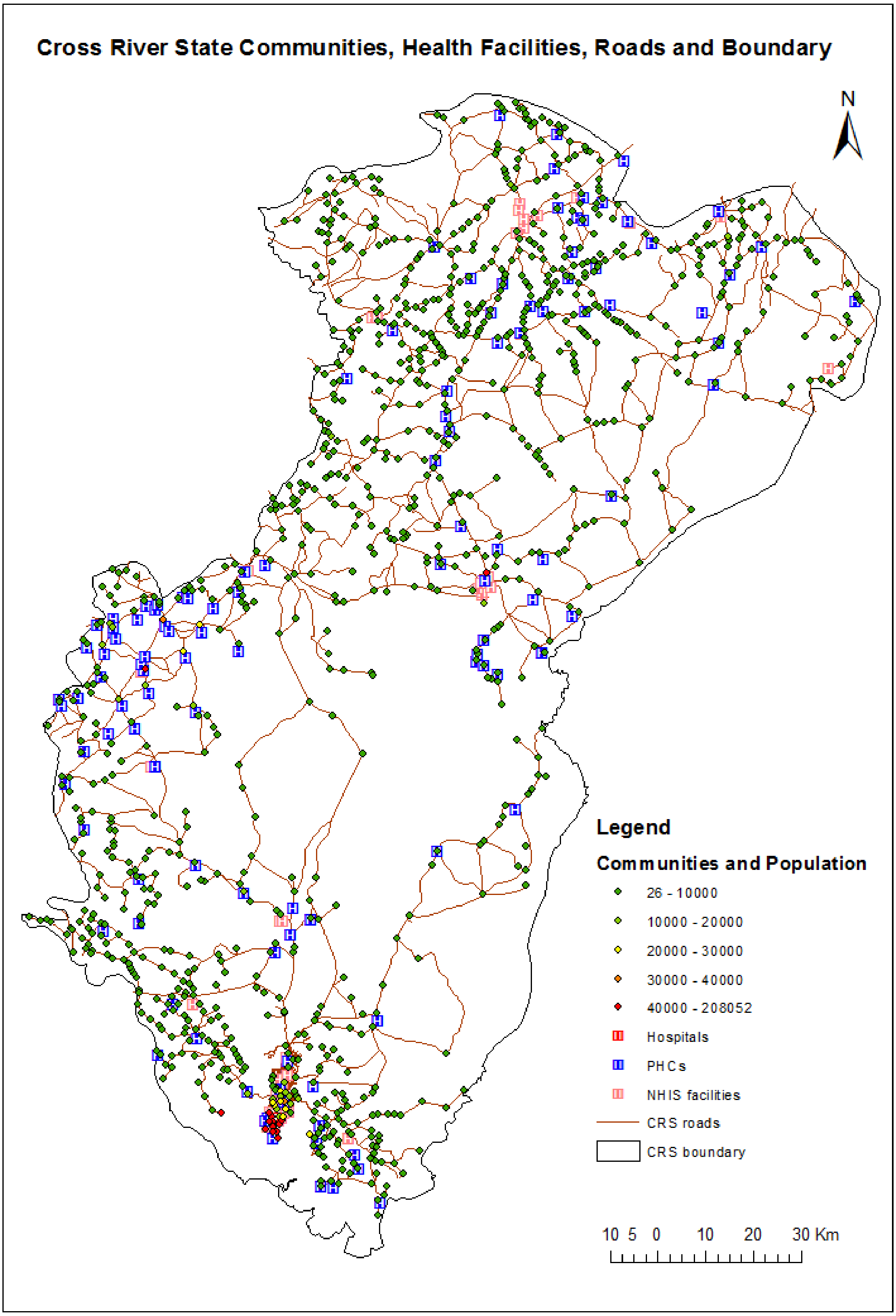

Figure 5.9: Communities, health facilities and roads in Cross River State

5.1.7. Malaria data

Anonymised records of patients who were diagnosed with malaria by parasite-based diagnostic testing in 2015 were obtained from the Calabar General Hospital (CGH) and the Ugep General Hospitals (UGH). The former is in the SSD, and the latter is in the CSD. The hospitals are state-owned and the largest in the two districts. Two districts in the state were used in this study because of the inability to get data from any hospital in the NSD. Hospitals were considered the best sources for the malaria data because of the availability of malaria diagnostics and treatments services.

Scanned records of patients holding address, gender, age, the month of hospital visit, malaria diagnoses, hospitalisation and mortality were received from the Record Officers in the respective hospitals (Appendix VI). Address attribute was either name of the street (CGH) or the community's (UGH). The month of hospital visit was from February to December because of the national doctors' strike which shut down the hospitals in January. Malaria diagnoses were recorded as simple, acute, uncomplicated, complicated, mild, severe, serious, cerebral and malaria in pregnancy. Case hospitalisation was recorded as admitted, not admitted or left blank. Patient's condition at the time of discharge was blank for patients who survived, and dead was entered for cases who died of the disease. Although socio-economic attributes were requested, it was not provided because the malaria surveillance database in the state does not capture it.

5.1.8. Processing of malaria data

The records from CGH (n= 4339) and UGH (n=1447) were entered into Ms Excel files. Consistency in the address attribute was ensured by assigning community names to streets in the CGH file since the UGH file had only names of communities (Figure 5.10). The street names in the CGH data were traced on Google Map, and their locations were used to find the right community. Where a street location could not be found on the map, the location description was obtained over the phone from someone who knows it. Gender was entered as male or female as it was in the original file. Actual ages in the original files were grouped into five years range (i.e. 0 – 4, 5 – 9, etc.) to match Nigeria Population Commission data. Malaria diagnoses were grouped into mild and severe. Mild malaria cases were those written originally as simple, malaria, uncomplicated, mild or malaria in pregnancy. Severe malaria cases were those entered initially as severe, acute, complicated, cerebral or serious. Malaria in pregnancy diagnosis, which was only common to CGH, was considered mild case as directed by the Record Officer.

Hospitalisation was grouped into admission and no admission. Mortality attribute was grouped into mortality (dead) and no mortality (alive). New attribute fields (drive times to CGH, UGH and nearest health facility) were added. The dry and wet seasons drive times from the communities to the respective health facilities were calculated. Other public facilities in the districts were included to examine how proximity to them would affect malaria outcomes in the hospitals the patients visited. Cases with incomplete entries or who lived outside the hospital's catchment areas in UGH (n=1) and CGH (n=228) were excluded. The boundaries of the senatorial districts in which the hospitals were found were used to define the catchment.

5.1.9. Ethical approval

The ethical approval for this study was obtained from the Cross River State Ministry of Health, Nigeria before data collection (Appendix I).

	A	B	C	D	E	F	G	H
1	ID	AGE	SEX	DIAGNOSIS	HOSPITAL ADMISSION	DISCHARGE_REPORT	VISIT_MONTH	COMMUNITY
8	1007	50-54	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Ekondo
9	1008	30-34	Female	Mild	Not Admitted	Alive	01/02/2015	Nyakasang
10	1009	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Efut Abua
11	1011	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Ekondo
12	1012	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Ikot Ishie
13	1013	5-9	Female	Mild	Not Admitted	Alive	01/02/2015	Ekpo Abasi
14	1014	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Ikot Ansa
15	1015	5-9	Male	Mild	Not Admitted	Alive	01/02/2015	Ikot Ansa
16	1016	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Efut Abua
17	1017	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Ekorinim
18	1018	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Uwanse
19	1019	10-14	Male	Mild	Not Admitted	Alive	01/02/2015	Efut Abua
20	1020	25-29	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Abua
21	1021	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Ekpo Abasi
22	1022	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Ekpo Abasi
23	1023	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Ekpo Abasi
24	1024	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Efut Ekondo
25	1026	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Ayanganse/Idundu
26	1027	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Ekondo
27	1028	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Uwanse
28	1029	0-4	Male	Mild	Not Admitted	Alive	01/02/2015	Atakpa
29	1030	0-4	Female	Mild	Not Admitted	Alive	01/02/2015	Efut Abua

Figure 5.10: An extract of the processed malaria data from CGH

5.1.10. Software

The main software applications used in this study were the University of Sheffield's licensed versions of ESRI ArcGIS 10.4, Microsoft (Ms) Word 2010, Excel 2010, SPSS 25, Endnote and Mendeley. All spatial analyses were conducted in ArcGIS being the most widely used and most suitable for the purpose. Ms Word 2010 was used for word processing while Ms Excel was used for data preparation and basic statistical analyses. Statistical analyses were conducted in SPSS 25 and Mendeley was used for referencing. However, the first referencing software was Endnote, but the database was moved to Mendeley because of license issues in Endnote which did not support thesis writing on the home Personal Computer (PC). The University of Sheffield's YOYO Desktop PC was used for all computer-based processing since it has larger storage space compared to other computers in the University.

5.2. Data analyses

Data analyses were conducted in three groups to fulfil the objectives of the primary studies in this thesis. The first group was seasonal geographical access to healthcare and the findings are presented in Chapter Six. The second group was the analyses of malaria in selected hospitals and the findings are in Chapter Seven. The last group was the use of location-allocation models to increase access to the NHIS and the findings are discussed in Chapter Eight. Each group of analysis was further subdivided into wet and dry seasons to fill the research gap in seasonal geographical access to healthcare.

5.3. Group one analysis: seasonal geographical access to healthcare

Objective: To examine geographical access to healthcare in Cross River State in the wet and dry seasons. This analysis satisfies the second objective of this thesis.

Subsections:

i. Geographical access in the dry season comprising drive time and walking time.

ii. Geographical access in the wet season comprising drive times and walking times.

Based on findings of the literature review (Chapter Four), this study assumes that travel times to health facilities will be longer and population access will decrease in the wet season compared to the dry season.

5.3.1. Analysis of geographical access in the dry season

Dry season access assumes normal trips from communities' centroids to health facilities without disruptions on the road network. The travel scenarios were drive and walking times. In the models, trips were computed from communities to the nearest health facility because people tend to use the closest healthcare facilities (Chapter Four).

5.3.1.1. Travel time analyses

Walking and driving times were calculated separately using the Closest Facility Solver of the ArcGIS network analyst tool. Travel time cut-off was not used since the longest travel time was unknown before the analyses. All processed healthcare facilities were included in the analyses. No barrier or restriction was modelled since none was known at the time. The algorithm was set to model travel from communities to healthcare facilities since patients were expected to travel from home to health facilities. The walking time analysis was like the drive time except for the variation in travel speed which was different in the models. The cost was time and unit was in minutes. The results were retrieved and saved.

5.3.2. Analysis of geographical access in the wet season

The dry season data and measures were used except for the road network that was adjusted to reflect trips in the wet season. For that reason, this section discusses the adjustments that were made on the road network to estimate wet season access and the development of a suitable flood regime for the study.

5.3.2.1. Developing the flood regime

Unlike some developed countries, it was difficult to gather information about flood in Cross River State and suitable data was not available. There were scant literature and all lacked coherence and fitness for this purpose. Offices contacted for flood data were the OSG-CRS, Nigerian Ministry of Environment, Cross River State Geographical Information Agency (CRGIA), National Geological Surveys Agency (NGSA) and the Nigerian Meteorological Agency (NIMET). Unfortunately, there was no flood data from any of them after several phone calls and many months of direct contacts.

The available solution was in producing a custom flood model for this study. The best approach for creating a custom flood model at that time was a fall back to the scant literature on flooding and wet season access to healthcare. In a previous study, average walking speed in the wet season was 3km/hr (Blanford *et al.*, 2012). The challenge of adopting a wet season walking speed from another study is the locational variability of flood impact since no two countries have the same flood experience. Therefore, it was considered necessary to produce a custom model for this study from the scant flood information in Cross River State.

Moses (1987), in the study of fishing along the cross river basin stated that the flood-prone areas are the low-lying regions along the cross river and its tributaries. However, the study did not provide the names of the communities within the flood-prone areas. Vanguard Nigeria (2013), in the national news, reported that 212 Cross River State communities were affected by flooding in 2013. However, there was no mention of the names of the affected communities in that report.

Since the area liable to flood and the number of communities in that area were known, the next task was to identify the communities that were reported by Vanguard Nigeria (2013). An ArcGIS buffer tool was used to create buffers 1km, 2km, 3km, 4km and 5km along the Cross River (Figure 5.12) and the results were used to delineate the communities within those buffers. A buffer tool was used in a study elsewhere to create flood boundaries (Zhang, 2012). The number of communities bound within the buffer results was 142, 203, 246, 310 and 351 for 1km, 2km, 3km, 4km and 5km respectively. Since none of them matched the Vanguard's report, the 3km buffer was deemed the most suitable flood regime for this study because all flood-prone communities would likely be included. If the 2km buffer result were used, some of the flood-prone communities would be left out. Although similar studies (Qi *et al.*, 2009; Zhang, 2012) used elevation data, it was unnecessary in this case because the number of flood-prone communities and their location description were available and enough to map the location of interest. The buffer analyses produced a potential flood regime and locations of flood-prone communities for this study (Figure 5.11).

At the data processing stage, it was found that the Northern Central District (NSD) was unaffected by seasonal flooding based on the adopted model. Therefore, further analysis of wet season analysis did not include the NSD.

5.3.2.2. Creating wet season road network

After determining a suitable flood regime, the next task was to convert the dry season roads to wet season roads by applying the wet season parameters to the network. The potential flood regime was overlaid on the road network and intersected road segments were manually marked and assigned average water crossing speed. It can be recalled from the dry season that all roads had the same speed except the segments that crossed a water body that had no bridge analysis. In the wet season, the average river crossing speed was applied to the road segments within the potential flood regime, because it was assumed that people would alight from their cars at the beginning of the flooded road segment and cross with a boat or average driving and walking speed would reduce to average boat sailing speed.

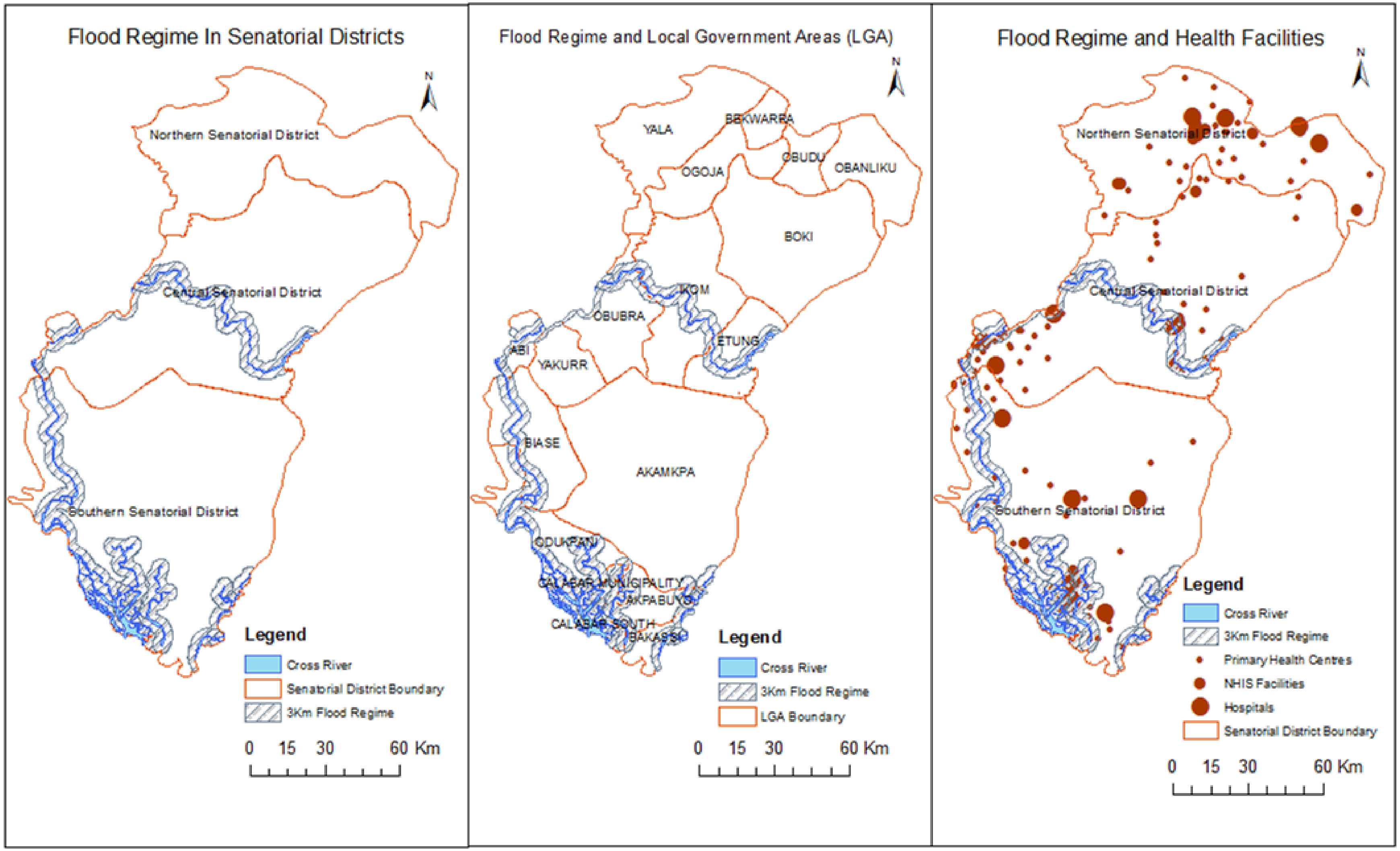

Figure 5.11: Flood regime in Cross River State

5.3.2.3. Analysis of wet season access

As for the dry season access analysis, ArcGIS Network Analyst tool was used to model three travel scenarios in the wet season to PHCs, hospitals and NHIS facilities at community level. The travel scenarios were walking time and drive time. The analyses of walking and drive times were equivalent to the dry season except for the adjustment that reduced travel speed in the potentially flooded road segments. In the modification, average canoe sailing speed (0.06km/min) was applied to the potentially flooded road segments assuming no access to the affected roads except by canoe, or that cars would drive as slow a canoe.

5.4. Group two analysis: malaria and drive times to health facilities

Objective: To examine seasonal associations between drive times to healthcare, malaria severity and hospital admissions in selected Cross River State hospitals.

Subsections:

i. Descriptive analysis: sum, percentages and crude rates.

ii. Regression analysis: odds ratios and test of significance.

iii. Seasonal analysis: relate findings of dry and wet seasons.

Hypothesis: From the findings the literature review (Chapter Four), this study hypothesizes that:

i. “Severe” or admitted malaria cases live further away from health facilities than the “mild” cases.

ii. Odds of malaria severity and hospital admissions are stronger in the wet season.

This study investigates the outcomes of malaria reported in two hospitals. It examines the association between drive times to health facilities and malaria outcomes. Cases (severe malarias) and controls (mild malarias) were compared with exposure of interest (drive times to healthcare facilities). Malaria outcomes in the association were limited to severity and hospital admissions since mortality cases were insufficient for a meaningful regression analysis.

Cases were defined as patients who were diagnosed with severe malaria or admitted due to malaria either in the CGH or UGH hospitals between February and December 2015. Controls were diagnosed with mild malaria or not admitted in the hospital over the same period in the two hospitals.

According to WHO guidelines, malaria symptoms are to be treated within 24 hours of the onset of symptoms irrespective of the age of the patient (World Health Organisation, 2015a). Therefore, this study examined malaria outcomes that were reported in the selected Cross River State hospitals without any restriction on age. The crude rates of malaria attendance and malaria outcomes (severity, admissions and mortality) were calculated.

Descriptive statistics were used to explore the data by age, gender, diagnoses, admission status, month of hospital visit and drive times to facilities. The association between malaria outcomes (dependent variable) and drive time to the nearest health facility (independent variable) were investigated using Binomial logistic regression in the SPSS 25 software package. Logistic regression was successfully used to investigate similar associations in related studies (O'Meara *et al.*, 2009; Al-Taiar *et al.*, 2010). Drive time of cases to the closest health facilities were grouped into 30 minutes intervals to minimise zeros in the groups.

The odds ratio (OR) of malaria in the groups was determined as the association between an exposure (i.e. distance) and an outcome (i.e. malaria severity) (Szumilas, 2010). Odds ratios in the results were explained as;

- OR=1 Exposure does not affect odds of malaria outcome
- OR>1 Exposure associated with higher odds of malaria outcome
- OR<1 Exposure associated with lower odds of malaria outcome

The 95% Confidence Interval (CI) was used to estimate the precision of the OR. The p-value was set at ≤ 0.05 to test the significance of the OR. The adjusted odds ratios were calculated using the multivariate regression model.

5.4.1. Confounding

A confounding variable is an external variable that may distort a true association between the exposure and outcome of interest (Skelly, Dettori and Brodt, 2012). The review in Chapter Four suggested that potentially confounding variables include age, education, co-morbidity, socio-economic indicator and environment can influence study findings. However, this study was unable to gather enough data on potential confounding variables. Therefore, potentially confounding variables could not be matched. Nevertheless, the available variables were stratified to reduce the risk confounding (Szumilas, 2010). For instance, age was grouped into intervals of 5 years and drive time was set at 30 minutes' interval.

5.5. Group three analysis: location-allocation of NHIS

Objective: To investigate the effect of wet season on location-allocation of National Health Insurance Scheme (NHIS) facilities in Cross River State.

Subsections:

i. Location-allocation of NHIS facilities in the dry and wet dry seasons.
ii. Compare existing and potential locations.
iii. Measure difference between dry and wet season findings.

Assumption: As suggested by literature (Oppong, 1996), this study assumes that wet season reduces the potential of service coverage of new NHIS locations produced by LAMs.

The datasets in this study were NHIS facilities, roads network, communities and population. The collection and processing of these datasets were discussed in the earlier sections of this chapter. Only NHIS was selected for the LAM analysis because it is a pilot study. This study required the locations of existing NHIS facilities. Patients' enrolments in the various facilities were not necessary since the interest was in the entire population. The quality of facilities was not necessary as well since there are set standards of quality every facility must satisfy before its accreditation. Characteristics of the facilities such as capacity, staffing and equipment were not included in the study, since data were not available at the time this research was conducted. A total of 67 NHIS facilities were included in the study of which 40 were private, and 27 were public.

Another useful dataset was the road network since most people travel by road in Cross River State. Since some studies found variations between wet and dry season access in accessibility and LAM findings, the LAM analysis was split into seasons (Oppong, 1996; Ewing *et al.*, 2016). Travel by public transport and private transport were treated as the same since there is no public transport timetable in the state and transporters can load passengers from any point along the road. Drive time was preferred above walking time since NHIS is a high-level facility. Drive time was also more suitable than road distance since distance does not consider the speed of the journey. Another required data was the population of the communities. The population of the communities are necessary to establish demand points for the facilities and calculate population coverage per maximum drive time to the facilities.

5.5.1. MCLP problem formulation for NHIS

This section discusses the use of MCLP algorithm to increase access to NHIS services. Instead of merely increasing the number of registered users of the service to a value that is equivalent to 30% of the population or fixing facilities arbitrarily as usual to achieve that plan, this solution set offers a better method for increasing population coverage. The MCLP takes into consideration the locations of existing facilities, the proximities of the communities to facilities and the population of each community (if available) before assigning a new facility.

One of the key advantages of the MCLP is that the solution produced has a potential of overcoming the challenge of low utilisation due to excessive travel time which is one of the current problems of the NHIS. The model is also adjustable and can be designed to fit any size of government budget on health care. It is also suitable for a short or long-term health care planning. In the short-term, it may be extended to tackle seasonal access to health care while in the long term, it may be used for sustainable healthcare planning.

MCLP application in the NHIS planning requires the measurement of the current population coverage of facilities before the choice of new facilities' locations. It was necessary to compare the old and proposed systems to examine the changes that are expected in the new system. To achieve that, the first step was to define the problems. The problems were defined as:

i. Maximize the population coverage of NHIS within a desired service drive time given a fixed number of health facilities.
ii. Locate a fixed number of NHIS facilities to maximize the population covered within a service drive time, while maintaining the mandatory coverage within drive time.

The problems were grouped into existing and proposed facilities MCLP models. The existing facilities analysis depicts the current population access to NHIS facilities while proposed facilities analyses show the improvements in the systems when new facilities are placed in optimal locations. For this study, the existing facilities model is named ‘Existing Facilities Location-Allocation Model’ (EFLAM). This model shows the current state of population coverage of NHIS facilities over desirable drive times. Two other models were also customised for increasing population access to NHIS.

The models were Population Weighted Location-Allocation Model (PWLAM) and Random Points Location-Allocation Model (RPLAM). These names formed for this study. PWLAM is a type of MCLP that allows the planner to control the choice of a new location based on population attributes. After satisfying the drive time condition in the model, the new location is weighted by the potential number of people that will use. The attractiveness of a new site depends on the population sizes of nearby communities and priority is given to highly populated neighbourhoods.

In practice, the PWLAM is justifiable because it is a frequent practice in Nigeria to site health facilities in highly populated areas (e.g. urban areas). The PWLAM model also fits into government’s goal of the NHIS, which is to increase population access to NHIS. In this study, the conditions used in the PWLAM model were the weight (i.e. population) and distance since the actual plot of land may vary depending on other factors that were not known at the time of this study.

The RPLAM was implemented by selecting 100 random points from the 1024 communities in Cross River State using the “Create Random Points” tool in ArcGIS. Since health facilities are supposed to be sited within population clusters, the default zero distance setting was used to create the random points. If a fixed distance (e.g. 1km) were used, the points would have been placed outside the population clusters. There was no need for the calculation of sample size before random point’s selection since all the 100 points were not to be used at the same time in the solutions.

The RPLAM gives the planner options to test the model with varying number of random points until a suitable number is achieved. This model was designed with healthcare planners in mind. For instance, with limited resources and 1024 communities demanding for NHIS facilities, planners may use this method to choose unbiased 100 potential communities to focus on while making plans for others. This model allows the planner to narrow down the choice of location to a few since it is unlikely that every community in the state would be given a NHIS facility. The model was set to select suitable locations for new NHIS facilities from the sampled points. In this study, 100 points’ sample was used as an example since it represents about 10% of the communities.

Comparing the two models, the PWLAM gives every community the chance of being selected while the RPLAM can only select from the pre-sampled 100 communities. However, the PWLAM may not select a low weighted community while the RPLAM may not include all locations with high population since the population is not an input in the location sampling. While PWLAM would fail where the population of each community is not available, the RPLAM can be implemented where population data are not available. Each of the two models selects distinct locations since the MCLP algorithm moves all candidate locations about when a new facility is added or removed. In this study, the two models are used to check their suitability for NHIS planning in Cross River State.

5.5.1.1. Implementing LAMs for NHIS

The models were implemented in the University of Sheffield’s licensed version of ESRI ArcGIS 10.4. The location allocation model tool in ArcGIS consists of seven problem types namely (Environmental Systems Research Institute, 2016b);

- Minimize impedance
- Maximize coverage
- Maximize capacitated coverage
- Minimize facilities
- Maximize attendance
- Maximize market share
- Target market share

Minimize Impedance (P-median) chooses facilities in manner that the sum of weighted impedances (demand location multiplied by impedance to the facility) is minimised. Maximize Capacitated Coverage choses facilities such that maximum demand locations can be served without exceeding the capacity of facilities. Minimize Facilities algorithm chooses as many facilities as possible within the impedance cutoff of facilities while minimising the number of required facilities. Maximize Attendance algorithm selects facilities such that as much demand weight as possible is allocated with the assumption that demand weight decreases with distance. Maximize Market Share algorithm selected facilities with the largest amount allocated demand before the presence of competitors based on the selection of the analyst. Target Market Share chooses the fewest number of facilities needed to capture the market in the presence of competitors.

Out of the seven, the relevant problem types were maximum coverage and maximum capacitated coverage. Since all facilities were expected to have the same quality and capacity data was unavailable, the maximum capacitated coverage was considered unsuitable for this study. The maximum coverage problem was considered most suitable because it allows facilities to be located in a manner that sufficient demand points as possible are located within the maximum travel drive time (Environmental Systems Research Institute, 2016b; Figure 5.12).

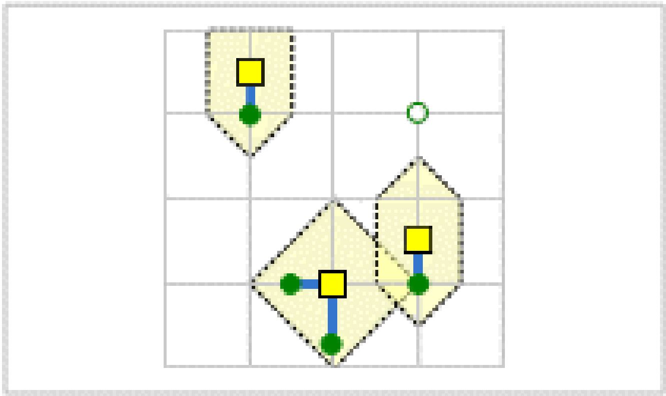

Figure 5.12: An illustration of maximize coverage algorithm (Environmental Systems Research Institute, 2016b)

The conditions of maximize coverage algorithm were:

i. A demand point (i.e. community location) outside the impedance cut-off was not allowed in the solution.
ii. A demand point within the impedance cut-off was located to the nearest facility.
iii. Where more than one facility is near a demand point within the impedance cut-off, only one facility, and the closest will be located.

In the existing facilities solution (i.e. EFLAM), data inputs were existing NHIS facilities, road network and community points (demand points). A total of 67 existing NHIS facilities were used in the analysis and with maximum drive times of 15, 30, 45, 60, 75, 90, 105 and 120 minutes. This analysis needed no new facility as all existing facilities in the EFLAM were mandatory. However, in the PWLAM, 67 optimal facilities' locations were selected from 1024 communities while in the RPLAM 67 potential facilities points were chosen from 100 sampled communities.

Since it was expected that the population would travel from their homes to the facilities and not the other way around, travel direction was set to flow from demand to the facility. Time of the day was not included in the analysis because road data did not have traffic flow information. The result of each solution set was saved, and the population coverage for each maximum drive time was extracted from the results. In the proposed facilities solutions, the models were used to predict proposed optimal locations for new NHIS facilities and facilities' coverage. In both models (PWLAM and RPLAM), existing NHIS facilities were mandatory in the selection of new sites since there was no intention of moving existing services to new locations. The models could only move new facilities locations about as more facilities were added.

The proposed facilities models were set to select 5, 10 and 15 additional optimised locations at 15, 30, 45, 60, 75, 90, 105, and 120 minutes' drive time. The choice of the number of new facilities to add or the maximum drive time in each solution in this study followed no laid-down rule as there is none. However, the target of 5 new facilities may be used as a short-term plan while 10 to 15 may be used as a long-term plan. Modelling of NHIS coverage at increasing drive time of 15 minutes allows planners to have a detailed knowledge of population access to the facility. The results also provide options for selecting the number of facilities to add at a preferred drive time with the desired population coverage. It also allows planners to measure and understand the implication of adding or removing a service from a location.

5.6. Reflection on data collection

Unlike in the UK and some developed countries where conducting a Public Health GIS research using secondary data is automated, in Nigeria it requires a lot of manual processes and is quite time-consuming. Although these problems were considered before the start of this PhD, it was impossible to have a full estimate of its magnitude before the data collection stage.

After confirmation review, government offices that promised to provide data were contacted by emails and followed up by phone calls and visits. The National Population Commission reported that they had only hard copies of 1991 census data and that the digital copies of the healthcare facilities' data from a recent survey by their office were deleted from the computer because of some maintenance issues. Other offices had data that needed editing and update.

At that point, it became clear that the success of this research would need more than the standard data collection time for a PhD research. The problem areas were:

- Geocoding of healthcare facilities.
- Developing a suitable flood model.
- Checking of the road network.
- Processing of population data.
- Collection of flood data.
- Processing of malaria data.

Since there was no geocoded healthcare facilities' data, all healthcare facilities were geocoded by the author. A total of 205 healthcare facilities were geocoded using the Cross River State orthophoto map, Google map, Google Earth and location information obtained over the phone. In some instances, it took up to a week or more to find someone who knew the location. After geocoding, the locations were validated to ensure accuracy.

The road dataset needed an update since they were mere line features. The data were tested for road network analysis and all incorrect junctions and broken road segments were corrected manually. The road network was built, and average travel speeds were applied to the road segments.

Since there were no recent census data, the 1991 population census data were projected to

2015. However, the major problem was not in projection of the population but in the assigning of population values to communities. Since there was no automatic method, population values were assigned manually to 906 communities.

The processing of malaria data consumed a substantial portion of the PhD time. The address variables in the malaria data were either street names or names of the communities. A total of 5557 malaria cases were geocoded; 1446 from UGH and 4111 from CGH. The hospitals were also geocoded for the study. Distances from the communities to the nearest healthcare facilities were also calculated and assigned to each patient.

In this study, flood data was needed to estimate geographical access to healthcare in the wet season. The Cross River State Ministry of Environment handles flood prevention, erosion management and natural disasters management. However, due to an overlap of duties, the Office of the Surveyor-General and the Cross River State Geographic Information Agency also keep some spatial data about the environment in Cross River State. Unfortunately, none of these offices had flood data despite the annual reports of flooding and financial budgets for emergency relief and flood protection in the state.

The solution was to produce a custom model from the scant literature about flooding in Cross River State. Previous publications showed that the major source of the flood in Cross River State is the river that flows from the south through the central through the state and communities around it are at risk. It was assumed that the population would cross the flooded road segments by canoe or drive through if the flood level was low. Since there was no standard canoe sailing speed. Canoe-men were paid to sail across the Cross River and were asked to pluck a leaf on the other shore to show that they arrived. The start and finishing times were recorded, average canoe sailing speed was thus calculated, and the values were applied to flooded road segments and rivers without a bridge.

Over 13 months of this PhD time were spent on data collection and processing. Although part of my PhD funding was cut in the second year and it was difficult to cope with financial difficulties, the work continued because of the personal motivation to apply GIS to healthcare. Many lessons were learnt during this research and they may be useful for those who will study that location or a similar place in the future.

In a future research, the following precautionary measures would be adopted:

- Data will be collected and saved before the start of the research if it is a secondary research and ethical approval is not required.
- If ethical approval is required, there would be no acceptance of a promise of data for availability. There would have to be a certain level of proof of availability before commissioning the research.
- Support the collection and preservation of spatial and non-spatial research data in LIMCs because most research data are often deleted after the study or stored privately in an inaccessible location.
- These problems motivated the development of Africa Research Database (www.afredat.com) with a colleague.

Considering the PhD time frame, the amount of work and limited funding, it suffices to say that significant effort and time was given to this thesis.

5.7. Summary of Chapter Five

Chapter Five discussed the study methodology and reflection on data collection. The datasets in the study were health facilities, road network, population, communities and malaria cases. Access was measured by travel times in the wet and dry seasons. Binary logistic regression was used to examine seasonal associations between malaria outcomes and drive times to health facilities. Location allocation models adapted for the study were EFLAM, PWLAM and RPLAM. All analyses were split into wet and dry seasons to examine seasonality of findings. The results of the analyses in this chapter are presented in Chapters Six, Seven and Eight for seasonal geographical access, malaria associations and LAMs respectively.

CHAPTER SIX: GEOGRAPHICAL ACCESS TO HEALTHCARE IN THE DRY AND WET SEASONS

6. Chapter overview

Chapter Six is the first of the three empirical results chapters of this thesis. It presents findings and discusses geographical access to healthcare in the wet and dry seasons. This chapter fills the research gap in the seasonality of geographical access identified in Chapter Four. The gap in the presentation of the results was filled by presenting findings for each type of health facility according to their distributions and population coverage. This chapter satisfies the second objective of this thesis which is “to examine geographical access to healthcare in Cross River State in the wet and dry seasons”. The assumption in this study is that drive and walking times will increase and population coverage of facilities will decrease in the wet season.

6.1. Results

Although the analyses were conducted at community level, the findings were aggregated into district and state output levels for ease of presentation and clarity. Population access by travel time was grouped into intervals of 60 minutes intervals. However, the population living less than 60 minutes were also taken into consideration in the presentation. Although there is no acceptable interval for presenting this kind of findings, the systematic review in Chapter Four showed that the use of health facilities tends to decline after 60 minutes travel from home in some studies (Wagle, Sabroe and Nielsen, 2004). Intervals of 60 minutes were used to group the findings into 5 groups for the sake of presentation. Mean and maximum travel times to healthcare were also calculated. The findings are presented in tables, graphs and maps.

Ideally, the baseline for underserved population is usually derived from national standard travel times to health facilities (Mazzi *et al.*, 2019). However, not every country has such standards and in that case, proxy baselines were used (Jordan *et al.*, 2004). Since there is no known national or state baseline for travel times to healthcare in Nigeria, the proxy baseline for the underserved population in this study was fixed at 90 minutes' walk to all health facilities, 30 minutes' drive to PHCs and 90 minutes' drive to hospitals and NHIS facilities. It implies that the population who lived beyond the proxy baseline were underserved.

6.2. Seasonal distribution of facilities and population access

As shown in Table 6.1, the population of Cross River State was unevenly distributed across the senatorial districts with the Southern Senatorial District (SSD) having the highest population density as well as the highest number of communities (Figures 6.1, 6.2). The findings were expected since the state capital, Calabar is in the SSD. The SSD population density (244.7/sqkm) was also 1.4 times the density of Cross River State (172.7/sqkm) (Table 6.2). In the dry season, 119 PHCs, 19 hospitals and 67 NHIS facilities were accessible (Table 6.1). In the wet season, accessible PHCs, hospitals and NHIS facilities in CRS dropped to 67 (56.3%), 11 (57.9%) and 23 (34.3%) respectively (Table 6.1, Figure 6.1). Access to other health facilities are expected to be interrupted at some point in the wet season because of their locations.

Table 6.1: Distribution of health facilities in Cross River State

Seasons	Dry season				Wet season			
Locality	SSD	NSD	CSD	CRS	SSD (%)	NSD (%)	CSD (%)	CRS (%)
PHCs	40	26	53	119	13 (32.5)	26 (100.0)	28 (52.8)	67 (56.3)
Hospital	10	5	4	19	5 (50.0)	5 (100.0)	1 (25.0)	11 (57.9)
NHIS	42	12	13	67	7 (16.7)	12 (100.0)	4 (30.8)	23 (34.3)
Total facilities	92	43	70	205	25 (27.2)	43 (100.0)	33 (47.1)	101 (49.3)

Key: SSD – Southern Senatorial District, NSD – Northern Senatorial District, Central Senatorial District, CRS – Cross River State

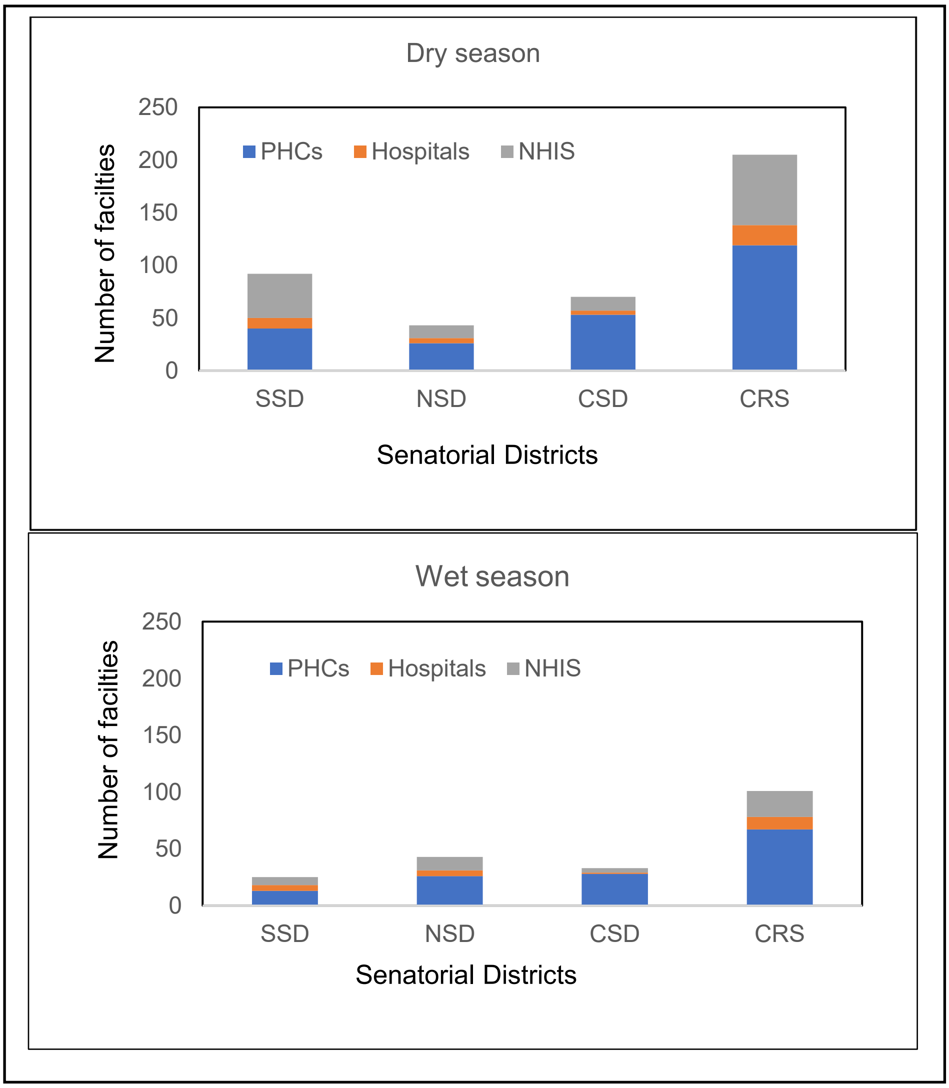

Figure 6.1: Accessible facilities

Health facilities distribution tends to follow the pattern of population distribution in the dry seasons. Districts with greater population density also had higher number of health facilities (Tables 6.1, 6.2). Also, in the dry season, it was found that higher number of health facilities or population in a district did not translate into a higher facility to population ratio. For instance, the SSD with the highest number of facilities (n = 92) had PHCs (1.9 per 100,000) and hospitals (0.5 per 100,000) to population ratios that were lower than CSD, NSD and CRS (Table 6.2). On the contrary, the NSD had the lowest population density, number of health facilities and the highest ratios of facilities to population except for PHCs (Table 6.2). Among the districts, the CSD had the most crowded hospitals (0.4 per 100,000) and NHIS (1.4 per 100,000) facilities except for PHCs (Table 6.2).

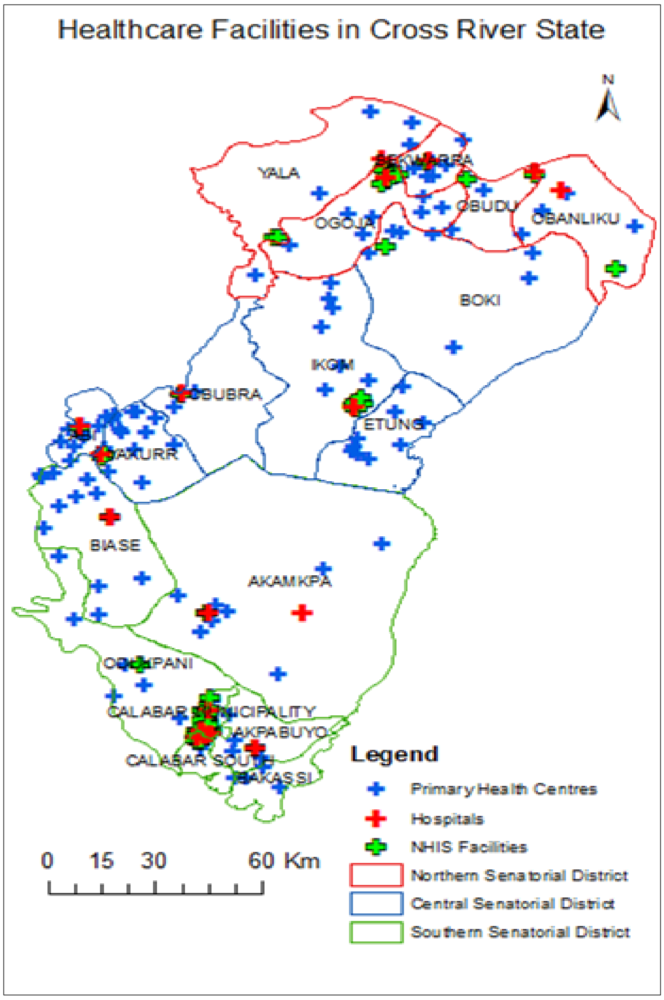

Figure 6.2: Health facilities in Cross River State

Table 6.2: Facilities to population

Seasons	Dry season				Wet season			
Districts	SSD	NSD	CSD	CRS	SSD	NSD	CSD	CRS
PHC per 100,000	1.9	5.2	5.5	3.3	0.6	5.2	2.9	1.8
Hosp per 100,000	0.5	1.0	0.4	0.5	0.2	1.0	0.1	0.3
NHIS per 100,000	2.0	2.4	1.4	1.9	0.3	2.4	0.4	0.6
Total facilities per 100,000	4.2	8.5	7.3	5.6	1.2	8.5	3.4	2.8
Population	2165103	503040	960667	3628810	x	x	x	x
Pop. Density (sqkm)	244.7	111.3	125.7	172.7	x	x	x	x

In the wet season, CRS PHCs, hospitals and NHIS per 100,000 people were 1.8, 0.3 and 0.6 respectively while it was 3.3, 0.5 and 1.9 respectively in the dry season (Table 6.2). The SSD had the least facility density in the wet season because total number of facilities per 100,000 persons dropped from 4.2 in the dry season to 1.2 in the wet season. The model showed that 95 (30.4%), 266 (49.1%) and 98 communities (31.1%) in CSD have difficulty accessing PHCs, hospitals and NHIS respectively in the wet season (Table 6.3). In the SSD, 185 (85%), 231 (61.3%) and 206 (54.6) communities were shown to have difficulty accessing PHCs, hospitals and NHIS respectively (Table 6.3). Although, the NSD was unaffected by severe flooding in the wet season, the effect of wet season on access in the SSD and CSD reduced the overall accessibility of health facilities at the state level.

6.3. Seasonal drive times to health facilities

The findings of driving times to health care in the dry and wet seasons are presented separately with a summary discussion of the both findings at the end of the chapter.

6.3.1. Dry season drive times to health facilities in Cross River State

This section presents the findings of drive time access to healthcare in the dry season. The results are shown in two groups; the state (Table 6.4, Figure 6.3) and senatorial district levels (Table 6.5). In the drive times category, the baseline for the underserved population was set at 30 minutes' drive time for PHCs and 90 minutes for hospitals because the latter is expected to be further to the communities than the former. There were also more PHCs than hospitals in the study.

Table 6.3: Population and communities affected by wet season

Facilities	PHC		Hospitals		NHIS		All Facility	
Districts	CSD (%)	SSD (%)	CSD (%)	SSD (%)	CSD (%)	SSD (%)	CSD (%)	SSD (%)
Communities with access	218 (69.6)	192 (15)	47 (50.9)	146 (38.7)	215 (68.7)	171 (45.4)	218 (69.6)	193 (51.2)
Affected communities	95 (30.4)	185 (85)	266 (49.1)	231 (61.3)	98 (31.3)	206 (54.6)	95 (30.4)	184 (48.8)
Total number of Communities	313 (100)	377 (100)	313 (100)	377 (100)	313 (100)	377 (100)	313 (100)	377 (100)
Population with access	668624 (69.6)	437351 (36.8)	353525 (20.2)	348582 (16.1)	649411 (67.6)	363737 (16.8)	668624 (69.6)	454672 (21)
Affected Population	292043 (30.4)	1727752 (63.2)	607142 (79.8)	1816521 (83.9)	311256 (32.4)	1801366 (83.2)	292043 (30.4)	1710431 (79)
Total Population	960667 (100)	2165103 (100)	960667 (100)	2165103 (100)	960667 (100)	2165103 (100)	960667 (100)	2165103 (100)

In Table 6.4, 72.8% of Cross River State population could access the nearest PHC at less than 30 minutes' drive. The underserved population in Cross River State was 27.2% in the access to PHCs, and that implies about 73% of the people in the communities had 'good' access if they drove to the facilities. The average drive time to PHCs was 41.1 minutes while the maximum drive time to the nearest PHC was 156.5 minutes. Hospital care was available to 48.2% of the population within 30 minutes' drive and the underserved population was 32.3%. The average drive time to the nearest hospital was 120 minutes and the maximum drive was 367.7 minutes.

In the NHIS category, 47.9% of the population lived within 30 minutes' drive to the nearest facility while 25.5% of the population of Cross River State lived within the underserved region of over 90 minutes (Table 6.4). Comparing the findings of the hospital and the NHIS, the NHIS reduced the underserved population by 1.3%. The NHIS facilities also reduced the mean drive time by 30.5 minutes and maximum drive time to higher order facilities by 9.2 minutes.

Table 6.4: Drive times to health facilities in Cross River State

Population within drive times to health facilities in Cross River State (%)				
Time (Min)	PHC	Hospital	NHIS	Any Facility
0 - 29.999	72.8	48.2	47.9	74.9
30 - 89.999	22.0	19.4	26.5	21.3
90 - 149.999	5.2	16.3	16.9	3.8
150 - 209.999	-	9.8	5.0	-
>209.999	-	6.2	3.6	-
Total	100.0	100.0	100.0	100.0
Distribution of Time to healthcare (Min)				
Mean	41.1	120.4	89.9	36.9
Maximum	156.5	367.7	358.5	156.5

6.3.1.1. Dry season drive times to health facilities in the senatorial districts

The findings of dry season drive times to healthcare in the senatorial districts are presented in Table 6.5. Drive time access to PHCs in the senatorial districts was shorter than Cross River State. Within the 30 minutes' drive to PHCs, population access was 65.5% in CSD, 62.5% in the NSD and 85.4% in the SSD respectively. Comparing the senatorial districts with the state, the proportions of PHCs underserved population in CSD and NSD increased by extra 7.3% and 10.3% respectively, but 12.6% decline in the SSD. Using the mean drive time as a yardstick, PHCs access in the SSD were 1.4 times and 1.2 times better in the CSD and NSD respectively. At the state and senatorial district, every member of the population could access PHCs within 150 minutes' drive. Mean drive times to PHCs in the senatorial districts were 40.2 minutes, 35.0 minutes and 29.6 minutes for CSD, NSD and SSD respectively. Mean drive times to PHCs in the senatorial districts were lower than Cross River State (41.0 minutes).

In Table 6.5, population drive time access to hospitals in the SSD (66.6%) within 30 minutes was approximately 3 times longer than CSD and NSD. At about 90 minutes' drive cap for the underserved population, cumulative population access to hospitals were 60.5%, 75.8% and

80.4% in CSD, NSD and SSD respectively. In comparison with the state level, the differences were 7.1% more (CSD), 8.2% less (NSD) and 12.7% less (SSD). Mean drive time to hospitals in the senatorial districts were 132.7 minutes, 85.4 minutes and 103.2 minutes in the CSD, NSD and SSD respectively. The mean drive times to hospitals in the senatorial districts were shorter than the state level except in the CSD (132.7 minutes).

In Table 6.5, there was no marked difference between drive times to NHIS facilities and hospitals within 30 minutes except in the NSD where 5% of the population lost access to NHIS. However, within 30 minutes' drive to NHIS, CSD gained 3.2% while SSD gained 0.4% and NSD lost 5% of population access in comparison with hospitals. Cumulative population drive access to NHIS within 90 minutes in the senatorial districts were 72.0%, 70.9, 82.3 in CSD, NSD and SSD respectively. The underserved population in the NHIS category were 28%, 29.1% and 17.7% in the CSD, NSD and SSD respectively. The SSD had the best drive time access to healthcare facilities while the NSD and SSD were fairly similar.

6.3.2. Wet season drive time access to healthcare in the wet season

Since the NSD is unaffected by seasonal flooding, the discussion in this section focusses on SSD and CSD only. The findings of wet season drive times to healthcare are presented in Table 6.6 and Figure 6.4. Mean drive time to PHCs in the CSD (68.8 minutes) and SSD (67.6 minutes) were about the same. However, maximum drive time in the CSD (493.9 minutes) was longer than that of SSD (327.3 minutes) by 166.6 minutes. Within 30 minutes, more people in the CSD (56.1%) could access PHCs compared with the SSD population (36.3%). Using drive time beyond 30 minutes as a reference for the underserved population, the underserved population in the SSD (63.7%) was 1.5 times higher than those of CSD (43.9%) in the wet season. However, most of the people lived within 0 – 90 minutes' drive to the nearest PHC in both districts.

In Table 6.6, drive time access to hospitals was unequal between 0 – 30 minutes in the two districts as the residents of SSD (34.7%) had 3 times higher hospital access than the CSD (11.4%). At 90 minutes' drive reference for the underserved population for higher order facilities, 41.3% of CSD had access to the hospitals against 73.1% in the SSD. Thus, the underserved population living beyond 90 minutes' drive to hospitals was 2.1 times higher in the CSD (58.7 minutes) than the SSD (26.9 minutes). Mean drive time to the hospital in the CSD (230.1 minutes) was also longer than that of SSD (159.5 minutes) by 70.6 minutes while maximum drive time to hospital was longer in the SSD by 39.5 minutes.

Table 6.5: Dry season drive times to health facilities in senatorial districts

Population access by drive time to health facilities in senatorial district (%)												
Facilities	PHC			Hospital			NHIS			Any Facilities		
Time (Min)	CSD	NSD	SSD	CSD	NSD	SSD	CSD	NSD	SSD	CSD	NSD	SSD
0 - 29.999	65.5	62.5	85.4	23.1	24.2	66.6	26.3	19.2	67.0	65.5	76.8	86.0
30 - 89.999	27.5	34.1	13.2	37.4	51.6	13.8	45.7	51.7	15.3	27.5	21.3	12.5
90 - 149.999	7.0	3.4	1.4	18.5	17.3	7.2	17.5	28.5	9.9	7.0	1.9	1.4
150 - 209.999	-	-	-	9.9	6.3	7.2	9.0	0.6	6.1	-	-	-
>209.999	-	-	-	11.2	0.6	5.2	1.5	-	1.6	-	-	-
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Distribution of Time to healthcare (Min)												
Mean	40.2	35.0	29.6	132.7	85.4	103.2	91.7	71.7	82.1	37.0	29.8	27.6
Maximum	134.0	142.2	146.9	318.3	235.0	289.8	279.6	167.0	354.7	134.0	142.2	146.9

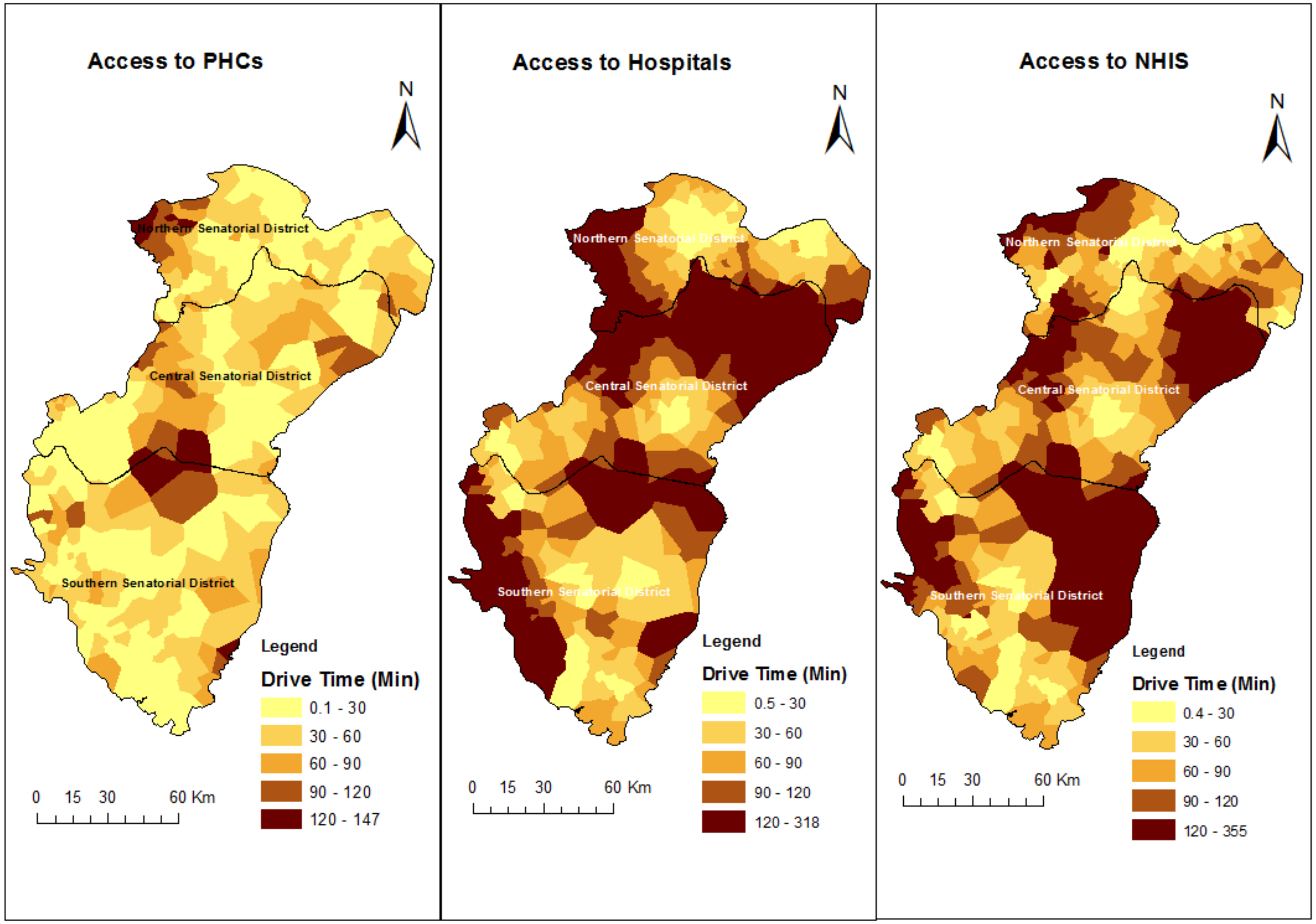

Figure 6.3: Thiessen maps showing dry season drive time accessibility of health facilities in Cross River State

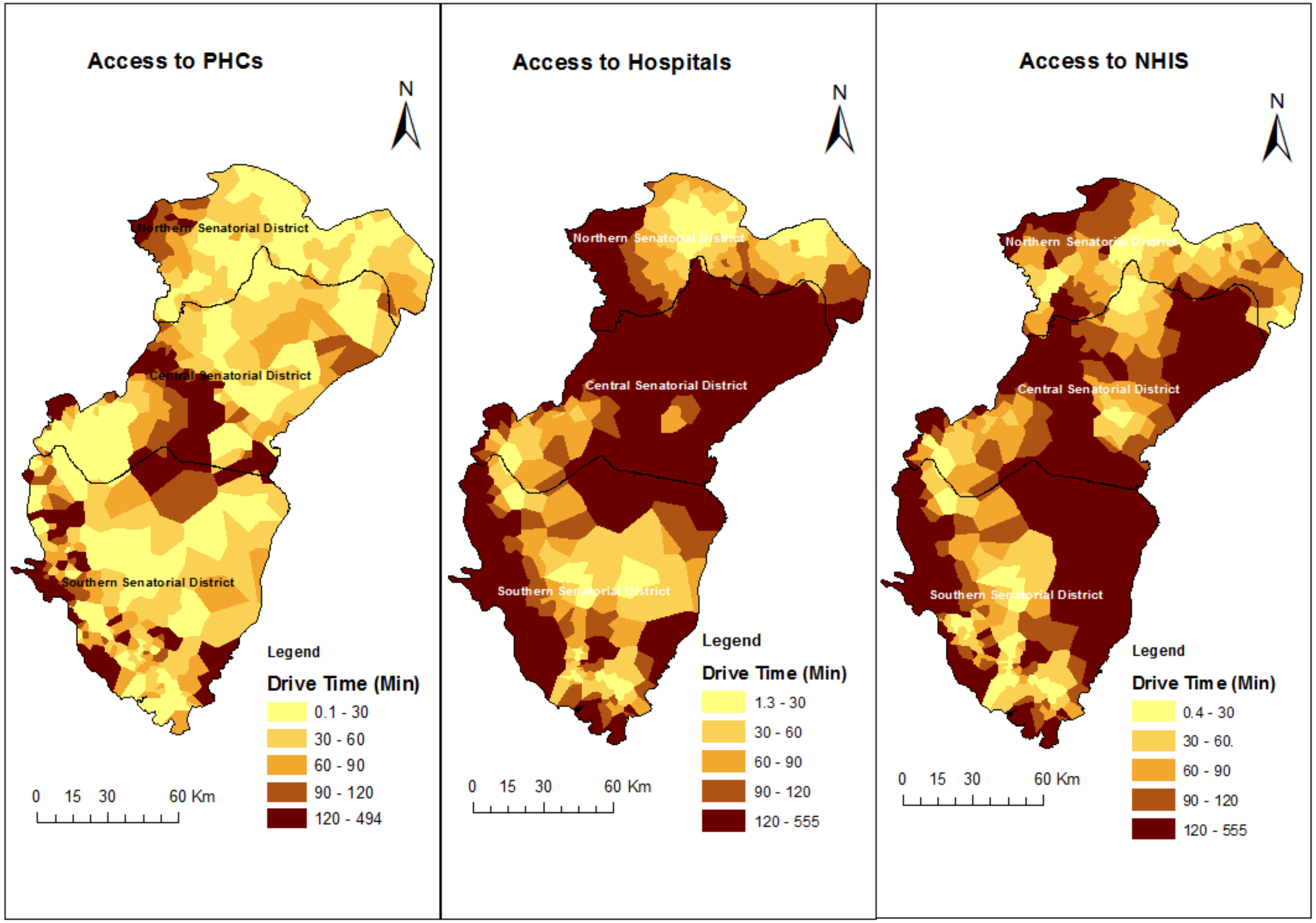

Figure 6.4: Thiessen maps showing wet season drive time accessibility of health facilities in Cross River State

Comparing NHIS with hospital services, NHIS doubled population access to higher order healthcare within 30 minutes in the CSD and increased by 1.6 times in the SSD (Table 6.6). The cumulative populations who lived within 0 – 90 minutes to NHIS were 55.4% and 77.2% in the CSD and SSD respectively. The underserved population in the NHIS category were also 44.6% (CSD) and 22.8% (SSD). Comparing mean drive times to hospitals with the NHIS facilities, it was found that NHIS reduced mean drive times to higher order healthcare by 91.6 minutes in the CSD and 17.1 minutes in the SSD.

If the population could access any of the three health facilities in the study by driving, population access in the CSD was determined by access to PHCs (Table 6.6). Meanwhile, population access to any facility in the SSD within approximately 30 minutes' drive doubled (70.4%) compared with the PHC (36.3%). However, beyond 90 minutes' drive, there was no difference between PHCs and any facilities' access. Average drive time to any facility in the CSD was also like PHCs (0.5 minutes difference), although it reduced average drive time by 6 minutes and maximum drive time by 21.3 minutes in the SSD.

Table 6.6: Drive time access to healthcare in the wet season

Population access by drive time to facilities in the wet season (%)											
Facilities	PHC			Hospital			NHIS			Any Facility	
Time (Min)	CSD	SSD		CSD	SSD		CSD	SSD		CSD	SSD
0 - 29.999	56.1	36.3		11.4	34.7		21.1	55.7		56.1	70.4
30 - 89.999	25.5	53.1		29.9	38.4		34.3	21.5		26.5	19.0
90 - 149.999	11.5	5.6		16.7	10.1		22.0	7.1		10.5	5.6
150 - 209.999	3.5	1.5		9.8	2.5		12.1	2.2		3.5	1.5
>209.999	3.4	3.5		32.3	14.3		10.5	13.6		3.4	3.5
Total Population	100.0	100.0		100.0	100.0		100.0	100.0		100.0	100.0
Distribution of Time to healthcare (Min)											
Mean	68.8	67.6		230.1	159.5		138.5	142.4		69.3	61.6
Maximum	493.9	327.3		515.3	554.8		504.4	554.6		493.9	306.0

6.4. Seasonal walking time to health facilities in Cross River State

As expected, walking times to health facilities were longer than drive times. This mode of travel was more suitable for access to PHCs because hospitals and NHIS facilities were fewer. There was no marked difference between the dry and wet seasons' walking times to health facilities (Figures 6.5, 6.6).

6.4.1. Dry season walking time to health facilities in Cross River State

The findings from the analyses of walking time to health facilities are presented in Table 6.7 and 6.8 for state level and senatorial districts respectively. Walking time accessibility map is shown in Figure 6.5. In the findings of population coverage (Table 6.7), when walking time was less than 30 minutes, 20.3% of the population of Cross River State could access the nearest PHC. Cumulatively, 56.8% of the population in Cross River State could walk to the nearest PHC in 90 minutes. Thus, 43.2% of the population was underserved primary care services. PHCs recorded the shortest mean (244.2 minutes) among the three types of health facilities while hospitals had the highest mean (694.2 minutes) and maximum walking time (2284.7 minutes) (Table 6.7).

Hospital access in Cross River State population within 30 minutes' walk was 12.2% (Table 6.7). A fall in hospital coverage was expected since it is a higher order facility that is expected to serve a larger population, unlike the PHC (Figure 6.5). The proportion of population within the underserved neighbourhood of hospitals was 67%. NHIS access was better than hospitals since 34.2% of the population walked less than 30 minutes to the service. The proportion of underserved population to NHIS services (56.4%) was also less than the hospital (Table 6.7). At less than 30 minutes' walk, 41% of Cross River State population could reach any of the three health facilities while 39.6% lived in the underserved region.

Table 6.7: Dry season walking times to health facilities in Cross River State

Population access by walking times to health facilities in Cross River State (%)				
Time (Min)	Percentage population to facilities			
	PHC	Hospital	NHIS	Any Facility
0 - 29.999	20.3	12.2	34.2	41.0
30 - 89.999	36.5	20.8	9.3	19.4
90 - 149.999	11.5	12.3	3.4	9.8
150 - 209.999	7.7	4.5	3.5	8.7
>209.999	24.1	50.2	49.5	21.1
Total	100.0	100.0	100.0	100.0
Distribution of time to healthcare (min)				
Mean	244.2	694.2	546.0	223.3
Maximum	974.4	2284.7	2201.1	974.4

6.4.1.1. Dry season walking times to health facilities in the senatorial districts

The findings of walking time access to health facilities in the senatorial districts are presented in Table 6.8. In the three districts, the SSD had the shortest mean walking time to PHCs (177.6 minutes) while a longest mean walking time was recorded in the CSD though it has the highest number of PHCs. Mean walking time to PHCs in the CSD was similar to the state level findings. The SSD had a relatively better access to PHCs with mean walking time that is 1.4 times shorter than the state's mean walking time to PHCs. However, the SSD (914.4 minutes) had the longest maximum walking time to PHCs in the senatorial districts, which was 60 minutes shorter than the state level.

The SSD (25.2%) had the highest population access while the NSD (9.2%) had the least access to PHCs within 30 minutes' walk (Table 6.8). At 90 minutes' walking baseline, the underserved population were 47.4%, 69.6% and 23.8% for CSD, NSD and SSD respectively. The population living in underserved areas of SSD was 1.8 times less than the state level, two times less than the CSD and 2.9 times less than the NSD. The findings show that walking access to PHCs in SSD was better than the state level and other senatorial districts.

In the hospital category (Table 6.8), while no one lived within 30 minutes' walk to any hospital in the CSD, 0.9% of NSD and 26.1% of SSD population could access PHCs within that walking time. The population living in the underserved localities in the three senatorial districts were 91.1% (CSD), 91.6% (NSD) and 40.8% (SSD). The values were found to be higher than the state level (67%) except for SSD.

In Table 6.8, NHIS facilities improved walking access to health services below 30 minutes although it was about the same as hospitals at 210 minutes. Within 30 minutes' walk, NHIS access was better than hospitals because it gave extra 15.2% (CSD), 0.7% (NSD) and 24.4% (SSD) population access to higher order care. The underserved NHIS population were 78.4%, 95.5% and 35.4% for CSD, NSD and SSD respectively. If the communities in the senatorial districts had the liberty to access any of the three facilities on foot, the overall outcome would resemble walking access to PHCs except in the SSD (Table 6.8).

Overall, the SSD had the best access to healthcare facilities by walking times and population coverage. The values recorded in the SSD were higher than other senatorial districts as well as the state level.

Table 6.8: Dry season walking times to health facilities in senatorial district in the dry season

Population access by walking time to health facilities in senatorial district (%)												
Facilities	PHC			Hospital			NHIS			All Facilities		
Time (Min)	CSD	NSD	SSD	CSD	NSD	SSD	CSD	NSD	SSD	CSD	NSD	SSD
0 - 29.999	21.8	9.2	25.2	0.0	0.9	26.1	15.2	1.6	50.5	27	11.7	56.6
30 - 89.99	30.8	21.1	50.9	9.0	7.6	33.1	6.3	3.1	14.1	27.2	27.2	20.6
90 - 149.99	9.8	19.5	6.1	11.8	8.2	6.2	4.3	7.8	1.0	8.4	24.4	5.6
150 - 209.99	6.8	18.5	5.2	2.4	10.4	2.0	2.1	11.9	2.4	7.3	16.5	5.7
>209.99	30.8	31.6	12.5	76.9	73.0	32.6	72.1	75.7	32.0	30.1	20.2	11.5
Total	100	100	100	100	100	100	100	100	100	100	100	100
Distribution of time to healthcare (min)												
Mean	243.2	218	177.6	816.4	531.8	627.6	562.1	446.2	492.8	241.6	185.8	165.5
Maximum	833.9	885.1	914.4	1981.9	1463.1	1778.4	1740.6	1039.8	2208.4	833.9	885.1	914.4

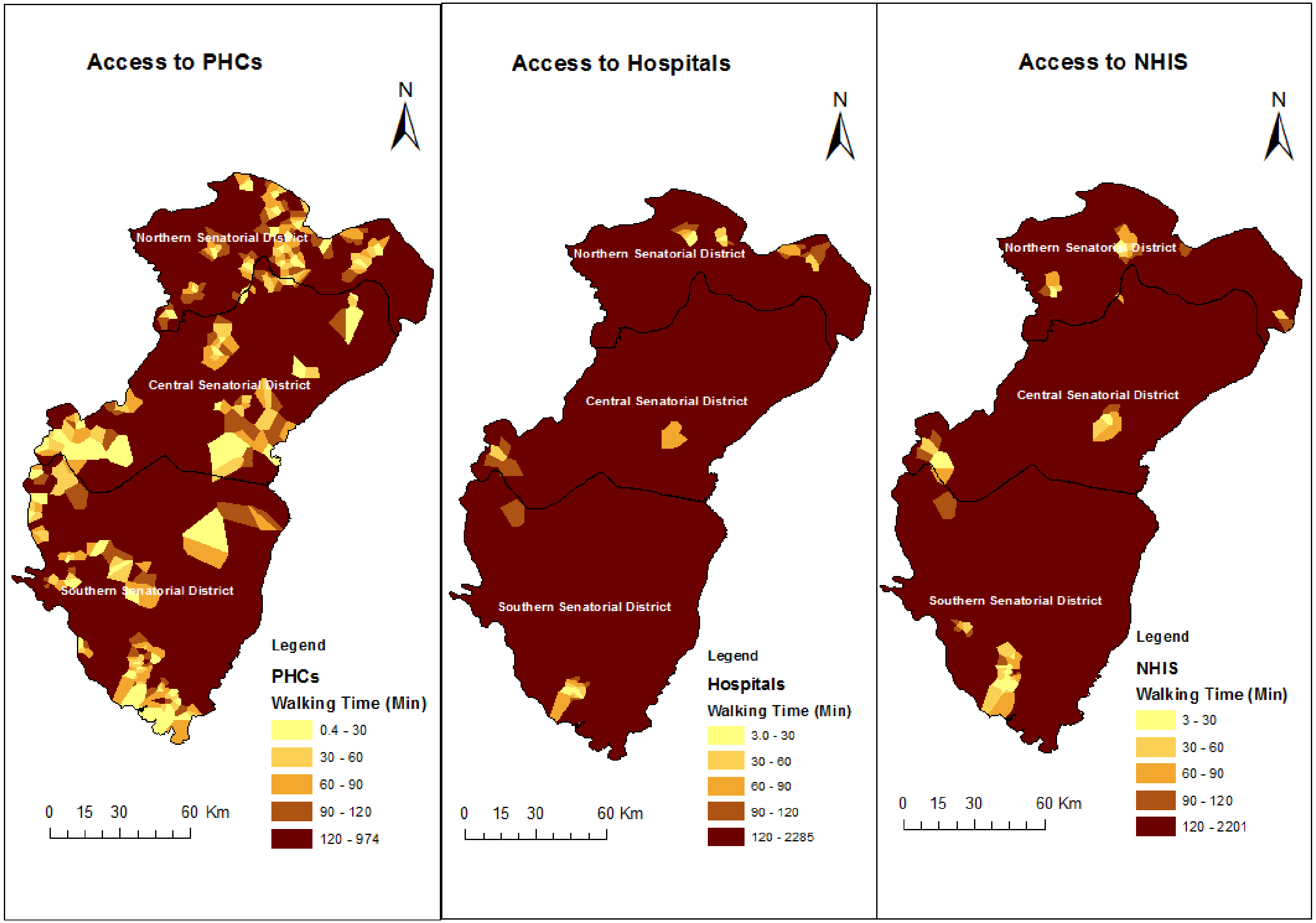

Figure 6.5: Thiessen maps showing dry season walking times access to health facilities in Cross River State

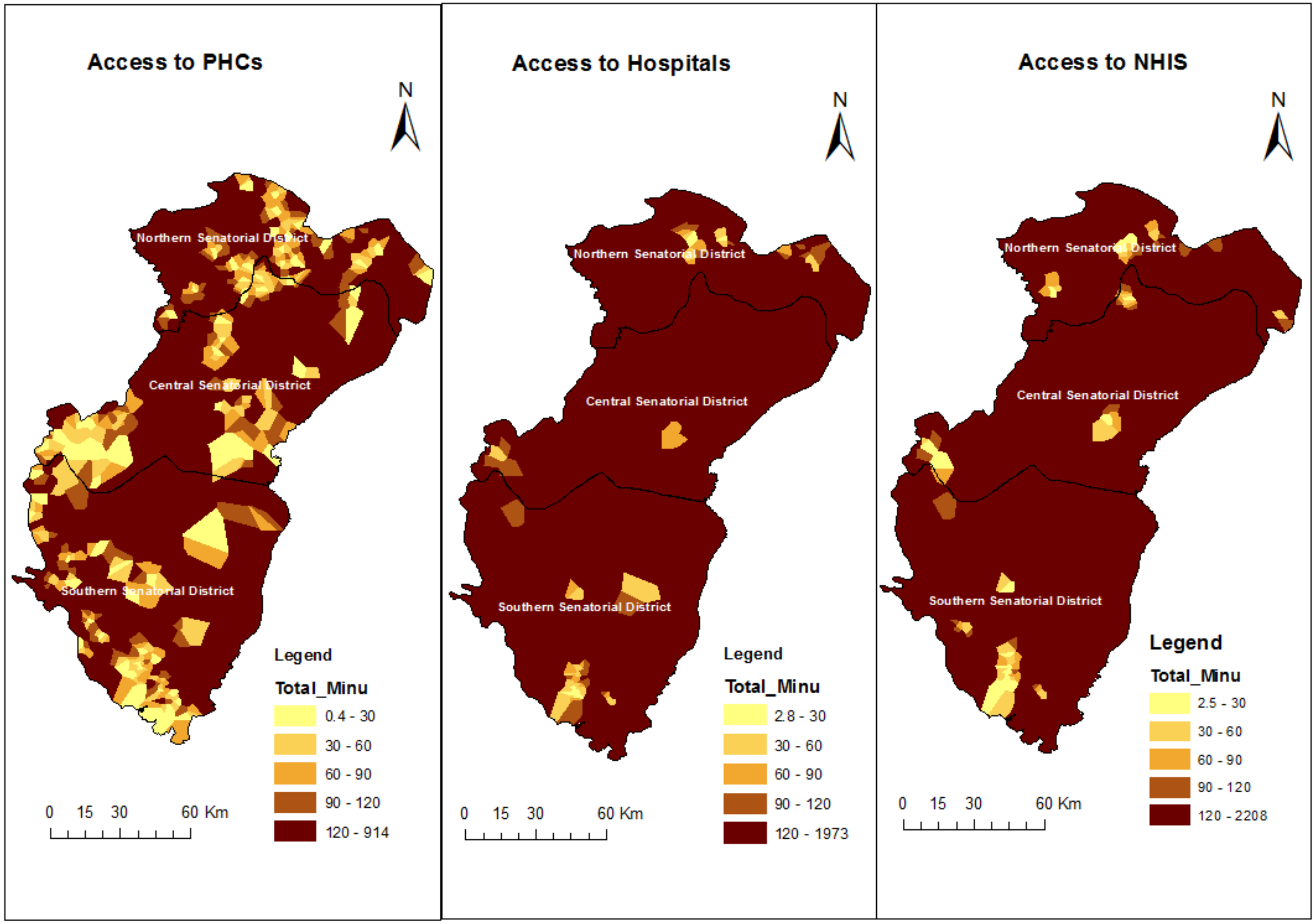

Figure 6.6: Thiessen maps showing wet season walking times access to health facilities in Cross River State

6.4.1.2. Walking time to healthcare in the wet season

Table 6.9 shows the findings of walking access to health facilities in SSD and CSD and Figure 6.6 presents the state level walking access. Mean walking time to PHCs in the wet season was 240 minutes in the CSD and 174 minutes in the SSD. Although the SSD had a shorter mean walking time, it also had the longest walk to PHCs (914.4 minutes) in the wet season. Within 30 minutes' walk from the communities, there was no wide margin of difference (3.7%) in population access between CSD and SSD. However, at 90 minutes' reference walking time for the underserved population, the gap was widened as cumulative population access was 53.1% and 76.2% in the CSD and SSD respectively. Thus, the PHCs underserved population by walking time in the CSD (46.9%) doubled the figure in the SSD (23.8%).

As reported in dry season access, no one lived within 30 minutes' walk to the nearest CSD hospital in the wet season, although 31.7% lived within that time range in the SSD (Table 6.9). It was found that the underserved population within walking times (90 minutes) to hospitals in the CSD (91%) was 2.2 times higher than the SSD (40.6%). Cumulatively, 24.6% of the CSD population lived within 0 – 210 minutes' walk to the nearest hospital unlike the SSD (67.4%). Thus, the population who lived beyond 210 minutes' walk to the nearest hospital were 2.3 times higher in the CSD in comparison with the SSD. The SSD also had a lower mean (623.2 minutes) and maximum (1761.1 minutes) walking time access to hospitals in the wet season.

Walking access to NHIS (16.5%) improved comparatively against hospitals (0.0%) access within 30 minutes in the CSD (Table 6.9). SSD also gained additional 21.2% of population access within 30 minutes when compared with hospitals. The NHIS underserved populations were 78.5% and 35.4 for CSD and SSD respectively, indicating service improvement over the hospitals. Average walking times to NHIS were 557.8 minutes and 487.1 minutes in the

CSD and SSD respectively. However, some locations in the SSD were within 2208.4 minutes (about 37 hours) walk to the nearest NHIS facility.

If the population could use any of the three health facilities in the study without restrictions, overall walking access between 0 – 90 minutes would have improved and become as good as access to PHCs. Fewer members of the population would have also lived beyond the 210 minutes to higher order facilities. Access to any of the three healthcare facilities led to a minor decrease in the mean walking access to healthcare, although the maximum walking times were similar to that of the PHCs. Population access to any health facility was identical to PHC access, probably because PHCs were the most accessible facilities.

Table 6.9: Walking access to healthcare in the wet season

Population access by walking time to health facilities in the wet season (%)								
Facilities	PHC		Hospital		NHIS		Any Facility	
Time (Min)	CSD	SSD	CSD	SSD	CSD	SSD	CSD	SSD
0 - 29.999	21.8	25.5	0.0	31.7	16.5	52.9	27.0	59.1
30 - 89.999	31.3	50.7	9.0	27.7	5.0	11.7	27.4	18.0
90 - 149.999	9.6	6.2	11.8	5.9	4.3	1.0	8.5	5.7
150 - 209.999	6.6	5.3	3.8	2.0	2.6	2.4	7.1	5.8
>209.999	30.7	12.3	75.4	32.6	71.6	32.0	30.0	11.3
Total Population	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Distribution of Time to healthcare (Min)								
Mean	240.0	174.0	808.2	623.2	557.8	487.1	238.4	162.4
Maximum	832.1	914.4	1973.2	1761.1	1740.6	2208.4	832.1	914.4

6.5. Summary of findings

Seasonal geographical access to health facilities was measured by driving and walking times. Euclidean distance measure was not included because it is unaffected by seasons. Road distance was excluded because it cannot account for additional travel times to facilities in the wet season. The analyses were conducted at the community level, but the results were presented at senatorial districts and state levels considering the large number of communities (n=1024) in the study. The baseline for underserved population was fixed at 90 minutes' walk to all health facilities, 30 minutes' drive to PHCs and 90 minutes' drive to hospitals and NHIS facilities. The people who lived beyond those times to facilities were assumed to travel too far to health facilities.

There were 205 health facilities in the study comprising PHCs (n=119), hospitals (n=19) and NHIS (n=67) (Table 6.1). The SSD had nearly half (45%) of the health facilities while the rest was shared unevenly between CSD (34%) and NSD (21%). It was found that health facilities in Cross River State were unintentionally or deliberately distributed according to population density. The SSD had a population density of approximately 245, CSD had 126 and NSD had 111 persons per square km (Table 6.2). However, the NSD with the lowest population density and number of health facilities also had the highest population to facilities ratios except for PHCs (Table 6.2).

Although the NSD had the highest population to facilities ratio, travel times were better in the SSD (Table 6.5, Figure 6.3). The disparities in the results would have resulted from the nature of settlements and infrastructural developments in the two districts. For instance, the NSD had a higher population to facilities ratio, but the communities may be dispersed with a poorer road network. Unlike the NSD, the SSD is the most urbanised district with lower facilities to population ratio, and a better road network to link the population to health services and the result was better access to healthcare. This situation points to a planning problem which can be solved with the use of LAMs in health planning (Chapters Three and Eight). PHCs were more accessible to the population than hospitals and NHIS facilities. Travel time to NHIS were also shorter than hospitals, showing an improvement in the access to health care if there was a universal access to the NHIS service.

6.5.1. Seasonal accessibility of health facilities

The NSD was excluded from wet season analysis because it is not within the flood regime. However, its dry season findings were included in the Thiessen maps and some graphs for comparison of seasonal access in Cross River. This study found that in comparison to the dry season, travel times increased, population access decreased, and some healthcare facilities were inaccessible in the wet season.

While all health facilities were accessible in the dry season, some were inaccessible in the wet season due to flooding (Table 6.1). Approximately 47% (CSD) and 68% (SSD) of PHCs were inaccessible in the wet season. The effect of wet season on access to hospitals was more severe in the CSD as 75% of hospitals were potentially out of reach against 50% in the SSD. NHIS access in the wet season increased against the hospitals in the same season in the CSD (30.8%) while SSD (16.7%) decreased. Also, 59% and 71% of any of the three facilities in the CSD and SSD respectively (Table 6.3). The study found that there were more inaccessible facilities in the SSD than the CSD.

6.5.2. Seasonality of communities and population access

The study revealed that some communities were unable to access health facilities in the wet season while everyone could access healthcare in the dry season (Table 6.3, Figure 6.7). Communities whose PHCs access was affected in the wet season were 30.4% (n = 95) in the CSD and 49.1% (n = 185) in the SSD. Also, 85% (n = 266) and 61.3% (n = 231) of the communities in the CSD and SSD respectively were also disconnected from hospitals services in the same period. The communities that lost access to NHIS were 98 (31.3%) and 206 (54.6%) in the CSD and SSD respectively.

Figure 6.7 shows that the communities who would lose access to healthcare were within or close to the potential flood regime. However, in the access to hospitals, all the communities in the northern part of the CSD were potentially disconnected from hospital access. The third map in Figure 6.8 shows that the northern part of the CSD was reconnected again to higher order healthcare through the NHIS.

While the entire population could access healthcare in the dry season, some locations could not get healthcare in the wet season (Table 6.3). The results show that the population who lived in the affected communities will be unable to access healthcare if the road segments leading to health facilities were impassable. From Table 6.3, it is shown that 30.4% (n = 292,043) of CSD population lost access to PHC in the wet season, that percentage increased by 2.6 times in the SSD (79.8%, n = 1,727,752). The population access in the CSD was also 1.3 times and 2.6 times higher in the access to hospitals and NHIS respectively. Therefore, the impact of seasonal variability of population access to healthcare was stronger in the SSD.

6.5.3. Seasonal variation in drive and walking time access

Figures 6.9 are graphical representations of the variations in population access to healthcare in the wet and dry seasons by drive times. The bars within 30 minutes' drive were longer in the dry season for all the health facilities. At drive time greater than 210 minutes where the dry season had no or low values, the bars emerged or increased in the wet season indicating longer drive times. It was also found that more people drove over 120 minutes to health facilities in the wet season (Figures 6.10, 6.11, 6.12).

Average drive times to PHCs increased by 28.6 minutes and 38.0 minutes in the CSD and SSD respectively in the wet season compared to the dry season (Figure 6.13, Tables 6.5, 6.6). The extra mean travel time to hospitals was 97.4 minutes in CSD and 56.3 minutes in

SSD. Average drive time to NHIS also increased by 46.8 minutes (CSD) and 60.3 minutes (SSD). Mean drive times to PHCs and any health facility in the wet season were 2.3 times and 2.2 times longer respectively in the SSD. Maximum drive times to PHCs in CSD and SSD also increased by 359.9 minutes and 180.4 minutes respectively. Extra maximum drive times required to reach any health facility in the wet season were 359.9 minutes and 159.1 minutes in CSD and SSD respectively. These values provide an estimated budget of extra time needed to access health facilities by driving in the wet season.

There was no obvious difference between walking time access in the two seasons since water crossing speed which is equivalent to walking speed was also used in potentially flooded road segments in the wet season (Figures 6.5, 6.6). Walking time in the wet season may be longer or shorter than the dry season depending on the decision of the traveller. People may use longer walking routes to health facilities to avoid the flooded road segments or use a canoe or a car to cross if it is unsafe to walk. Therefore, these findings would represent walking times access in Cross River State.

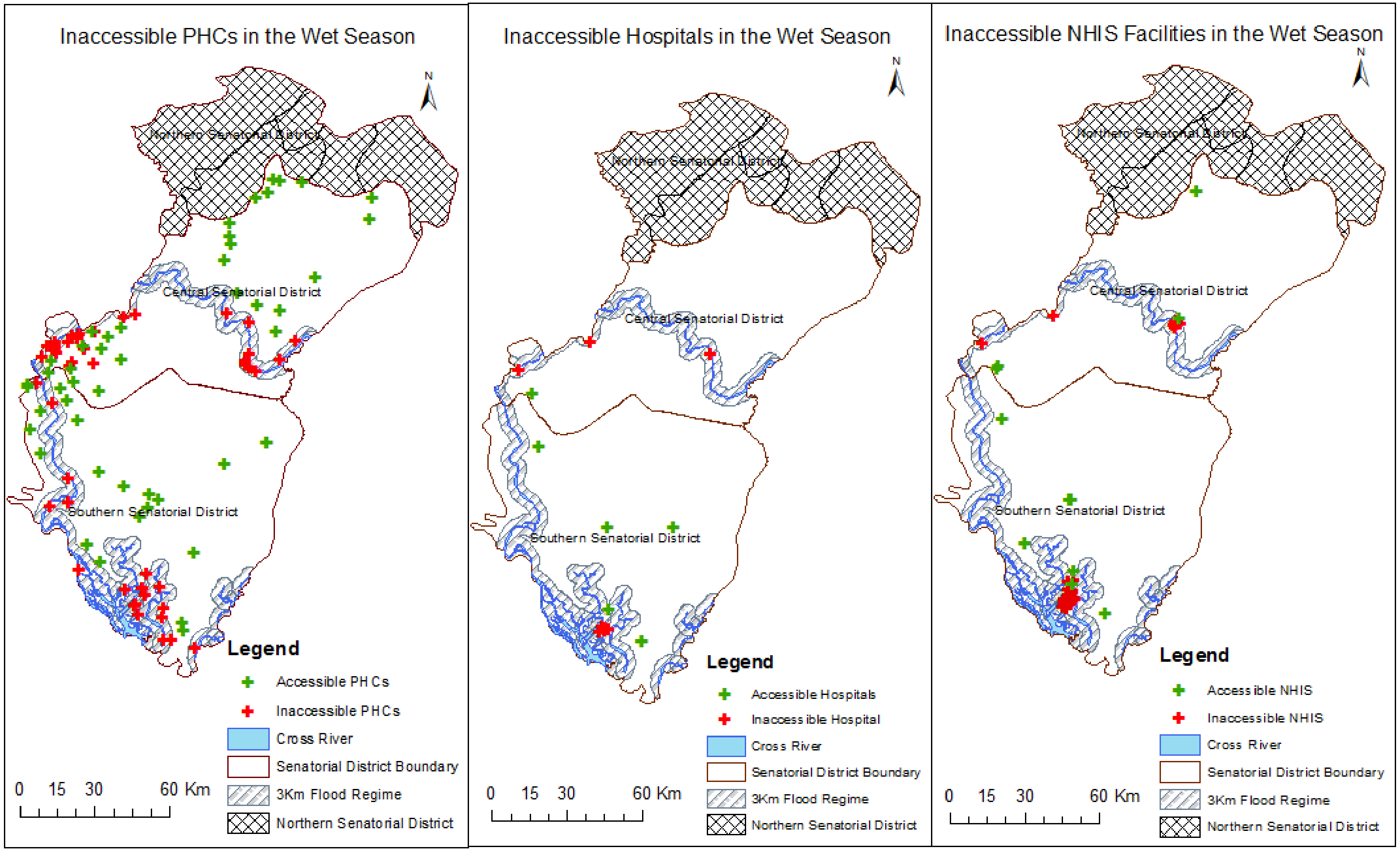

Figure 6.7: Seasonal accessibility of health facilities

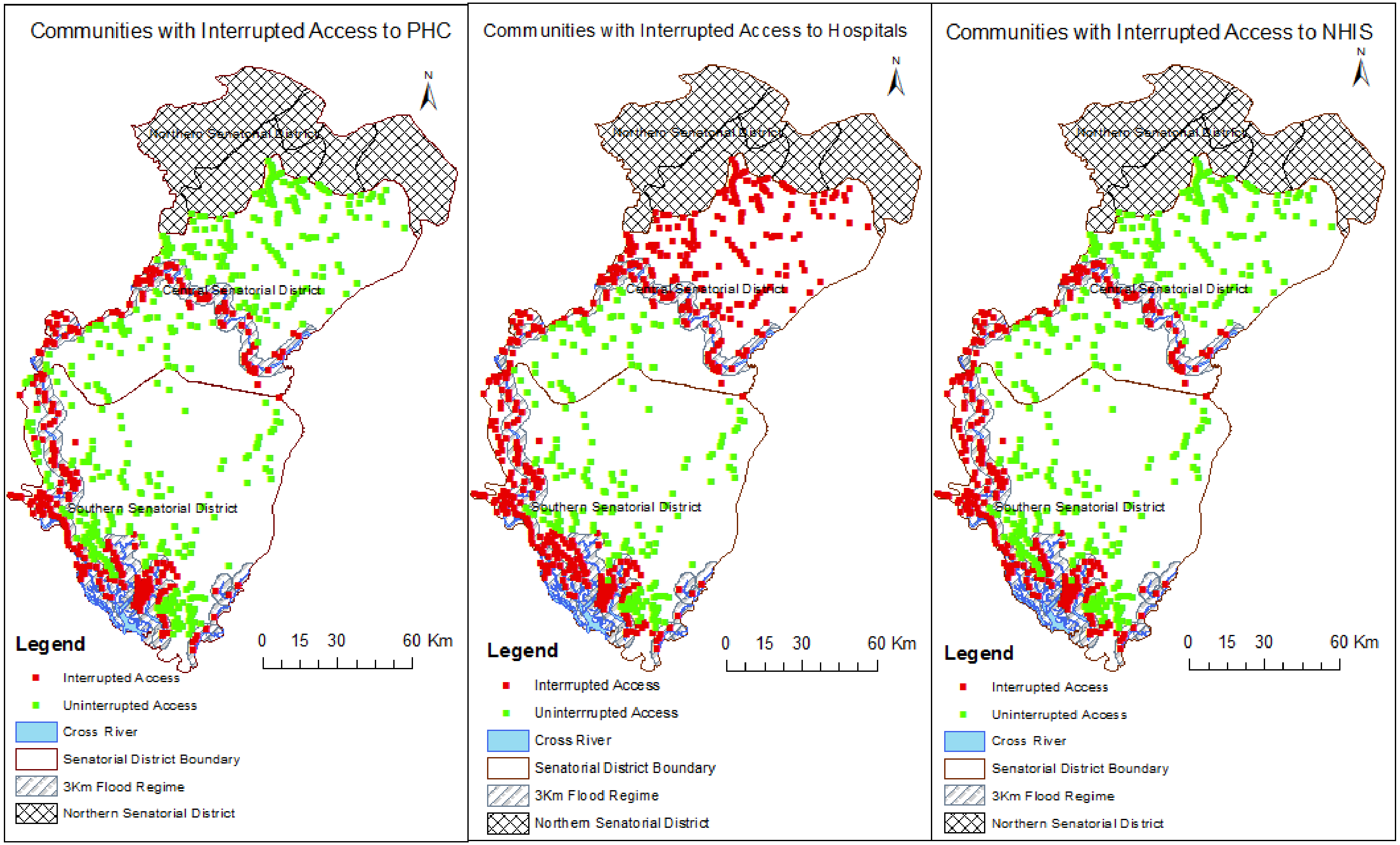

Figure 6.8: Communities with interrupted access to health facilities

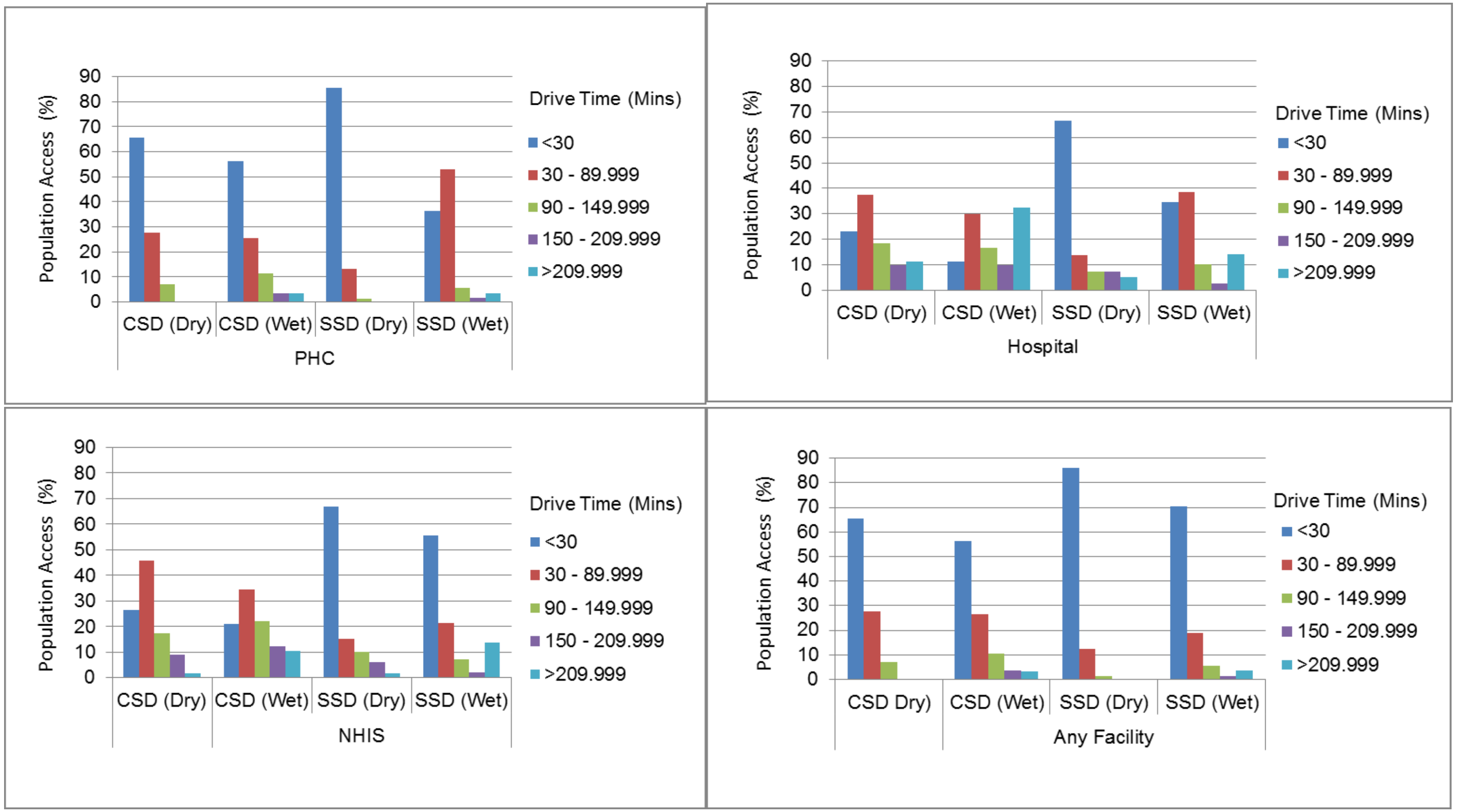

Figure 6.9: Population drive time access in dry and wet season

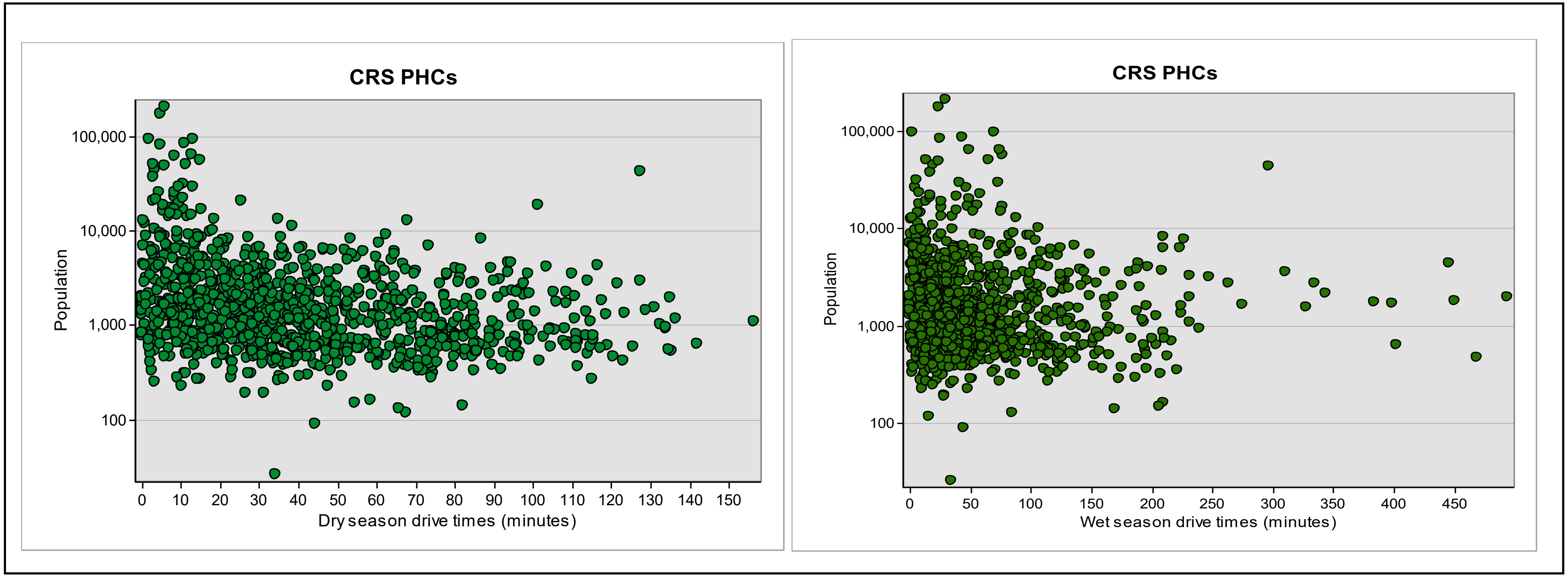

Figure 6.10: Population and drive times to PHCs in the wet and dry seasons

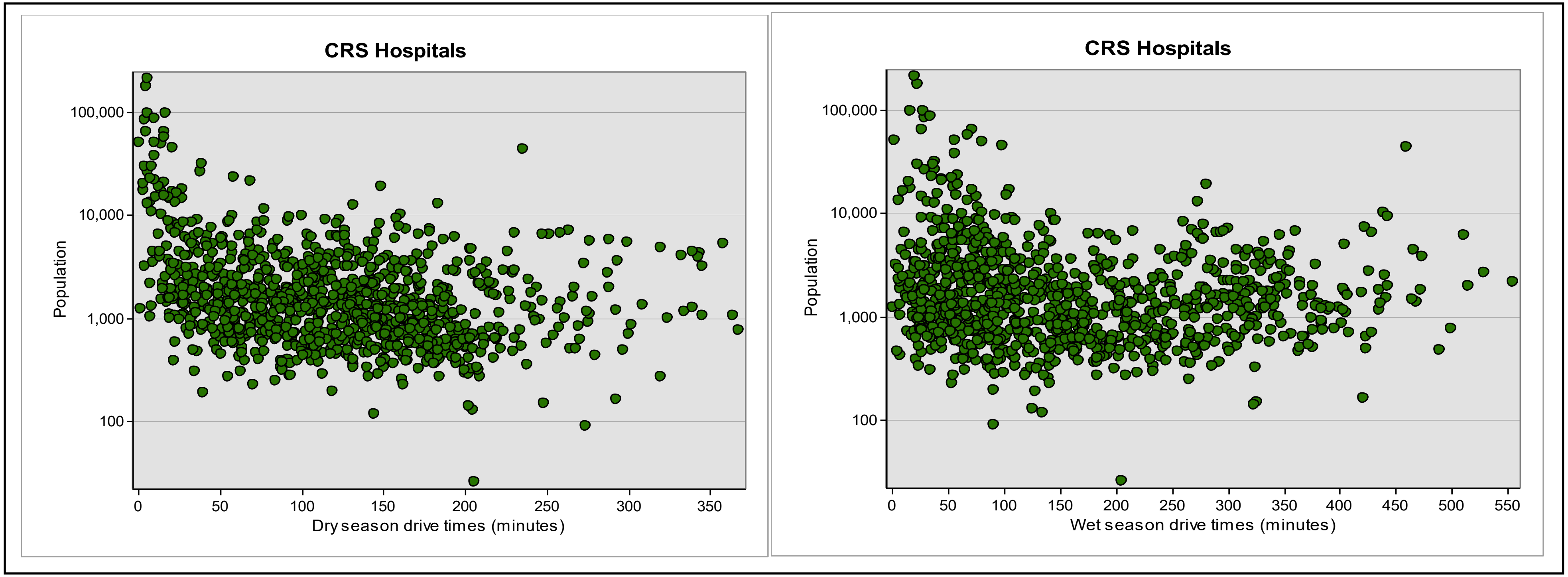

Figure 6.11: Population and drive times to Hospitals in the wet and dry seasons

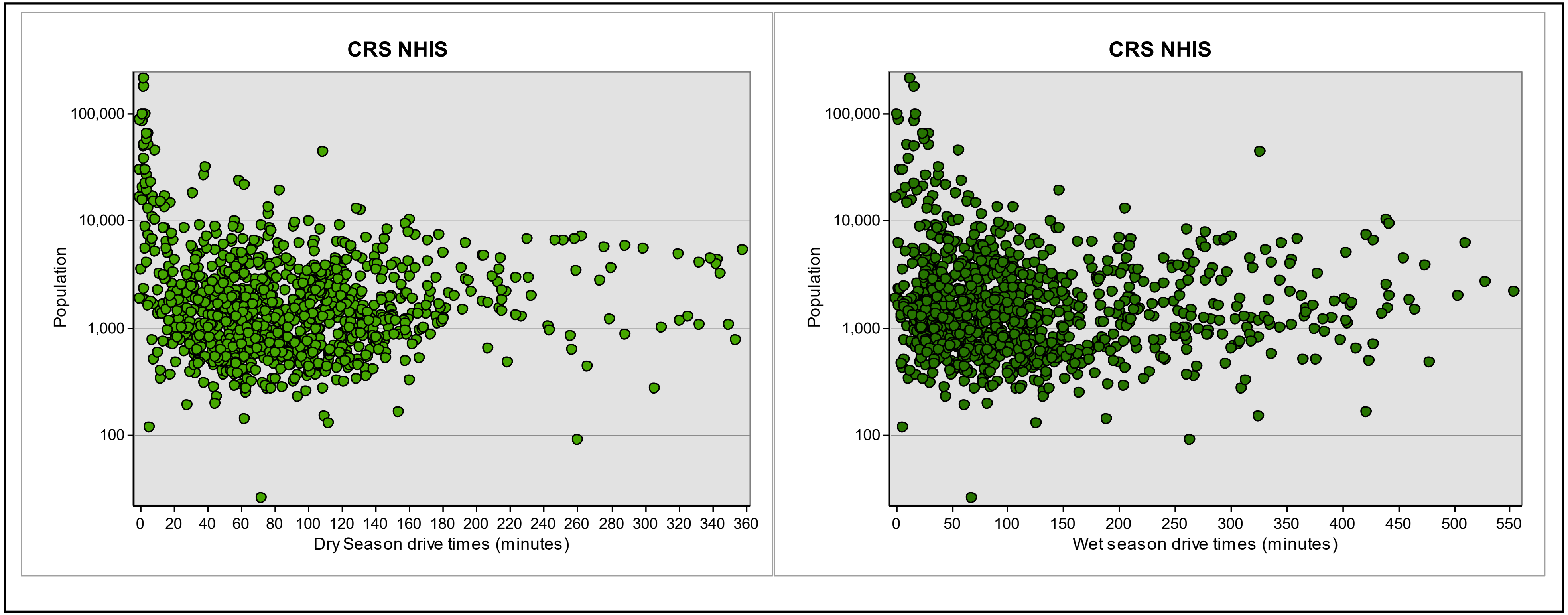

Figure 6.12: Population and drive times to NHIS in the wet and dry seasons

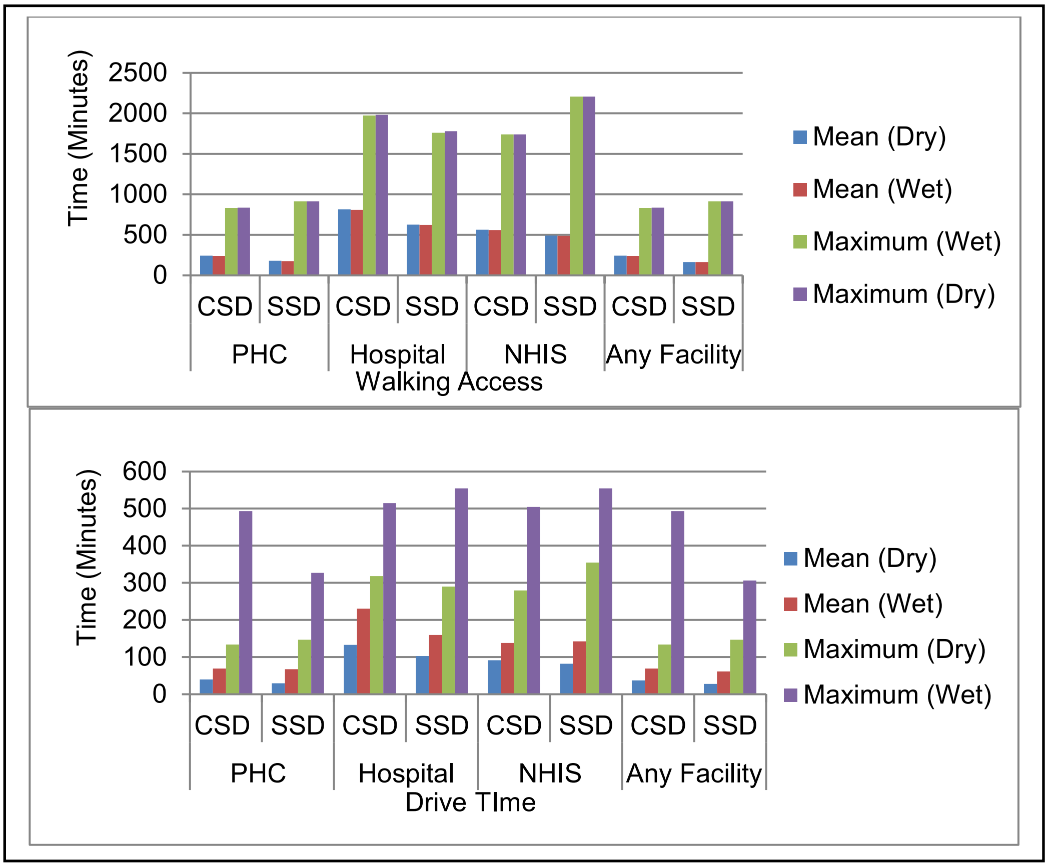

Figure 6.13: Distribution of travel time in wet and dry season

6.6. Summary

The objective of this chapter was to examine seasonal geographical access to healthcare in Cross River State. Health facilities in the study were PHCs, hospitals and NHIS. Results were presented for wet and dry season access and the findings were discussed. Driving and walking times to facilities were adopted for this study because they are more suitable for measuring seasonality of access. The NSD was unaffected and the SSD was the most affected district in the state. The results revealed a marked increase in average drive times to all forms of health services in the wet season in comparison with the dry season. It was also found that if patients were to use any of the three facilities, more than half of them may be unavailable at some point in the wet season.

Both CSD and SSD experienced a decline in population access to healthcare in the wet season, but the impact was stronger in the SSD though it's the most urbanised district in the state. The disruption of health care access affected not only the population within the potential flood regime but also the population who lived outside the regime and needed to cross the flooded area.

Therefore, the assumption that geographical access to healthcare decreases in the wet season is supported by the findings of this study. Thus, accessibility studies that do not consider the seasonality of access may be misleading. The population is expected to budget extra travel time when planning to use a healthcare facility in the wet season. Further discussions on the findings, limitations and implications of the study this chapter are presented in Chapter Nine. The next chapter presents the seasonal association between drive times to healthcare and malaria outcomes in selected Cross River State hospitals.

CHAPTER SEVEN: SEASONAL GEOGRAPHICAL ACCESS TO HEALTHCARE AND MALARIA OUTCOMES

7. Chapter overview

In Chapter Four, a systematic review of geographical access to healthcare in LMICs was presented. Chapter Five discussed the study methodology. Chapter Six filled a gap in the literature with the study of seasonal geographical access to healthcare. This chapter links seasonal geographical access in Chapters Six with the differential malaria outcomes in selected hospitals. It shows the findings of the analysis that was discussed in Chapter Five. This study hypothesises that severe or admitted malaria cases live further away from health facilities than the "mild" cases and that the odds of malaria severity and hospital admissions are stronger in the wet season. This chapter fulfils the third objective of this thesis.

7.1. Results

The results of the analyses of the malaria data are presented in charts and tables. The first part shows the findings of the descriptive analyses and the second part presents the findings of the binary logistic regression. The findings are presented separately by seasons and hospital locations for comparison.

7.2. Description of malaria variables

The description of malaria in CGH and UGH are shown in Tables 7.1 and 7.2 respectively. There were 5557 included malaria cases in the study (Figure 7.1, Tables 7.1, 7.2). The majority (n=4111) were registered in CGH, and the rest were from UGH (n=1446). CGH serves mainly urban population while UGH serves mostly rural areas. Seasonal malaria attendance in both hospitals was dissimilar. Malaria attendance in CGH doubled in the wet season (n=2789) compared to the dry season (n=1322). In UGH, the number of malaria cases tripled in the dry season (n=1109) compared to the wet season (n=337). Considering the effect of the wet season and rurality of UGH catchment, the low attendance in the wet season may have resulted from poor transport and lack of access to the hospital. Meanwhile, the CGH may have enjoyed continual patronage in the wet season due to better road infrastructure.

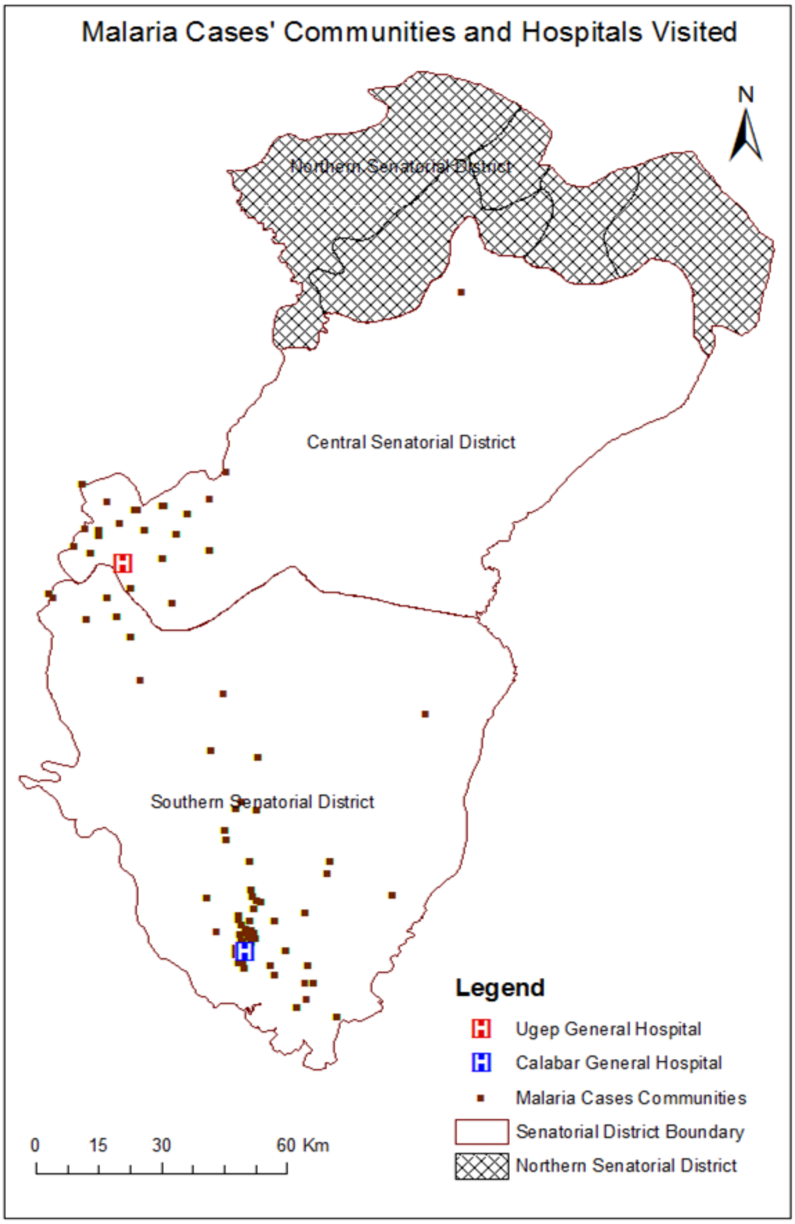

Figure 7.1: Malaria communities and hospitals attended

7.2.1. Malaria by gender

There were more females than males in the study although the difference was small (Tables 7.1, 7.2). In CGH, 55.0% (n=2263) were male and 45.0% (n=1848) were female. Similarly, UGH had 51.3% (n=742) females and 48.7% (n=704) males. The proportion of males who attended UGH in the wet season was higher than females; but in the dry season, the proportion of females was higher. In CGH, there were more females in the wet (difference = 301) and dry (difference = 114) seasons. The findings may not indicate that females were more likely to be diagnosed with malaria. Rather, it may indicate that there were more females in the population, or they were more likely to seek healthcare than males. At UGH, the wet season would have limited travels of females because of the potential problems like bad roads, the crossing of water, accidents and long distance associated with the journey to the hospital at that time of the year.

7.2.2. Malaria by age

Most cases in the study were under-five children (Tables 7.1 and 7.2). They constituted 43% of malaria attendance in CGH and 50% in UGH. For UGH, the value was 2.5 times higher in the dry season, and in CGH it was 1.5 times less compared to the wet season. The pattern of malaria attendance by age in the two hospitals were similar. It may indicate that the 0-4 age group was not just the most susceptible to malaria, but the findings could reflect the population structure in the state (Figure 7.2). However, other age groups did not show very close similarity with the population structure of Cross River State.

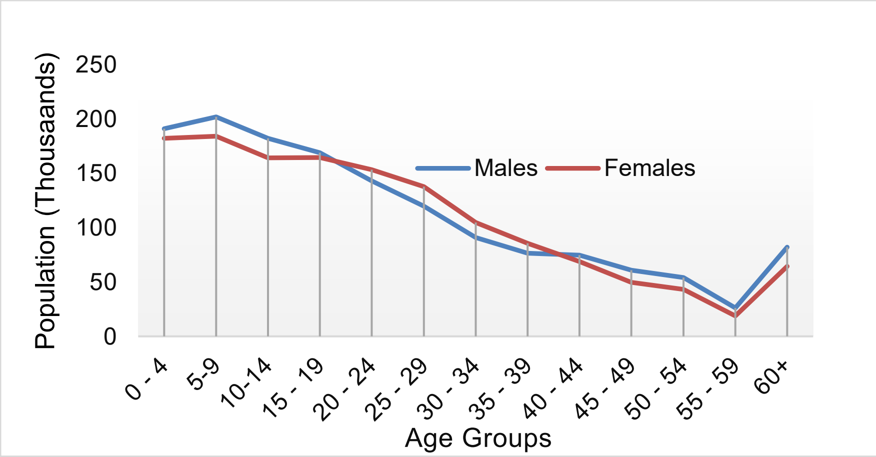

Figure 7.2: Cross River State 2006 population census by age and gender (National Population Commission, 2006)

7.2.3. Malaria diagnoses

Most of the malaria diagnoses in the two hospitals were mild (Tables 7.1, 7.2). In CGH, there were 3406 (82.9%) mild and 705 (17.1%) severe cases (Table 7.1). However, nearly half (41.4%) of the cases in UGH were severe (Table 7.2). Severe malaria was 2.5 times more in CGH and 3.5 times less in UGH in the wet season compared to the dry season. The study found that more severe malaria cases were recorded in UGH which serves a rural population. Therefore, for every 1000 malaria cases in UGH, 414 of them were severe (Table 7.3). However, the chances of being diagnosed with severe malaria in the wet season (407 per 1000) were as high as the dry season (417 per 1000) at UGH. Similarly, the chances of having severe malaria diagnosis in CGH in the dry season (156 per 1000) was nearly as high as the wet season (179 per 1000).

Table 7.1: Characteristics malaria cases in CGH

	Wet Season		**Dry Season**		**Wet/Dry Seasons**
Variables	N	n (%)	N	n (%)	Total (%)
Gender of cases	2789		1322		4111 (100)
Male		1244 (44.6)		604 (45.7)	1848 (45.0)
Female		1545 (55.4)		718 (54.3)	2263 (55.0)
Age of cases (years)	2789		1322		4111 (100)
0-4		1066 (38.2)		698 (52.8)	1764 (42.9)
5-9		177 (6.3)		68 (5.1)	245 (6.0)
10-14		102 (3.7)		44 (3.3)	146 (3.6)
15-19		88 (3.2)		25 (1.9)	113 (2.7)
20-24		185 (6.6)		44 (3.3)	229 (5.6)
25-29		221 (7.9)		84 (6.4)	305 (7.4)
30-34		178 (6.4)		71 (5.4)	249 (6.1)
35-39		151 (5.4)		53 (4.0)	204 (5.0)
40-44		134 (4.8)		50 (3.8)	184 (4.5)
45-49		127 (4.6)		55 (4.2)	182 (4.4)
50-54		115 (4.1)		44 (3.3)	159 (3.9)
55-59		87 (3.1)		31 (2.3)	118 (2.9)
60+		158 (5.7)		55 (4.2)	213 (5.2)
Malaria diagnoses	2789		1322		4111 (100)
Mild		2290 (82.1)		1116 (84.4)	3406 (82.9)
Severe		499 (17.9)		206 (15.6)	705 (17.1)
Malaria admission	2789		1322		4111 (100)
No admission		2641 (94.7)		1161 (87.8)	3802 (92.5)
Admission		148 (5.3)		161 (12.2)	309 (7.5)
Malaria mortality	2789		1322		4111 (100)
No mortality		2786 (99.9)		1321 (99.9)	4107 (99.9)
Mortality		3 (0.1)		1 (0.1)	4 (0.10)
Drive time to CGH (minutes)	2789		1322		4111 (100)
0 - 30		500 (17.9)		1246 (94.3)	1746 (42.5)
30 - 60		936 (33.6)		40 (3.0)	976 (23.7)
60 - 90		536 (19.2)		5 (0.4)	541 (13.2)
90+		817 (29.3)		31 (2.3)	848 (20.6)
Mean drive time to CGH (mins)		79.3 (SD 72.1)		15.8 (SD 22.8)	58.9 (SD 67.6)
Drive time to nearest facility (mins)	2789		1322		4111 (100)
0 - 30		251 (90.2)		1305 (98.7)	3821 (92.9)
30 - 60		215 (7.7)		17 (1.3)	232 (5.6)
60 - 90		51 (1.80)		0 (0.0)	51 (1.2)
90+		7 (0.30)		0 (0.0)	7 (0.2)
Mean drive time to nearest facility (mins)		17.6 (SD 13.6)		3.5 (SD 4.6)	13.0 (SD 13.3)

Table 7.2: Characteristics malaria cases in UGH

	Wet Season		Dry Season		Wet/Dry Seasons
Variables	N	n (%)	N	n (%)	Total (%)
Gender of cases	337		1109		1446 (100.0)
Male		172 (51.0)		532 (48.0)	704 (48.7)
Female		165 (49.0)		577 (52.0)	742 (51.3)
Age of cases (years)	337		1109		1446 (100.0)
0-4		201 (59.6)		518 (46.7)	719 (49.7)
5-9		24 (7.1)		93 (8.4)	117 (8.1)
10-14		27 (8.0)		81 (7.3)	108 (7.5)
15-19		17 (5.0)		63 (5.7)	80 (5.5)
20-24		11 (3.3)		34 (3.1)	45 (3.1)
25-29		9 (2.7)		62 (5.6)	71 (4.9)
30-34		6 (1.8)		34 (3.1)	40 (2.8)
35-39		3 (0.9)		29 (2.6)	32 (2.2)
40-44		5 (1.5)		29 (2.6)	34 (2.4)
45-49		12 (3.6)		86 (7.8)	98 (6.8)
50-54		4 (1.2)		33 (3.0)	37 (2.6)
55-59		5 (1.5)		18 (1.6)	23 (1.6)
60+		13 (3.9)		29 (2.6)	42 (2.9)
Malaria diagnoses	337		1109		1446 (100.0)
Mild		200 (59.3)		647 (58.3)	847 (58.6)
Severe		137 (40.7)		462 (41.7)	599 (41.4)
Malaria admission	337		1109		1446 (100.0)
No admission		272 (80.7)		766 (69.1)	1038 (71.8)
Admission		65 (19.3)		343 (30.9)	408 (28.2)
Malaria mortality	337		1109		1446 (100.0)
No mortality		335 (99.4)		110 (99.7)	1441 (99.7)
Mortality		2 (0.6)		3 (0.3)	5 (0.3)
Drive time to UGH (minutes)	337		1109		1446 (100.0)
0 - 30		199 (59.1)		580 (52.3)	779 (53.9)
30 - 60		84 (24.9)		266 (24.0)	350 (24.2)
60 - 90		39 (11.6)		32 (2.9)	71 (4.9)
90+		15 (4.5)		231 (20.8)	246 (17.0)
Mean drive time to UGH (mins))		38.6 (SD 47.6)		59.6 (SD 89.8)	54.7 (SD 82.4)
Drive time to nearest facility (mins)	337		1109		1446 (100.0)
0 - 30		325 (96.4)		1057 (95.3)	1382 (95.6)
30 - 60		11 (3.3)		5 (0.5)	16 (1.1)
60 - 90		0 (0.0)		1 (0.1)	1 (0.1)
90+		1 (0.3)		46 (4.1)	47 (3.3)
Mean drive time to nearest facility (mins)		5.4 (SD 12.2)		15.9 (SD 47.9)	13.4 (SD 42.6)

Table 7.3: Crude rates of malaria outcomes

Crude Rates for malaria outcomes in CGH (per 1000)			
	Wet season	**Dry Season**	**Wet/Dry seasons**
	n (Crude rate)	n (Crude rate)	Total (Crude rate)
Case diagnoses	2789	1322	4111
Mild	2290 (821.1)	1116 (844.2)	3406 (828.5)
Severe	499 (178.9)	206 (155.8)	705 (171.5)
Case admission	2789	1322	4111
No admission	2641 (946.9)	1161 (878.2)	3802 (924.8)
Admission	148 (53.1)	161 (121.8)	309 (75.2)
Case mortality	2789	1322	4111
No mortality	2786 (998.9)	1321 (999.2)	4107 (999.0)
Mortality	3 (1.1)	1 (0.8)	4 (1.0)
Crude Rates for malaria outcomes in UGH (per 1000)			
Case diagnoses	337	1109	1446
Mild	200 (593.5)	647 (583.4)	847 (585.8)
Severe	137 (406.5)	462 (416.6)	599 (414.2)
Case admission	337	1109	1446
No admission	272 (807.1)	766 (690.7)	1038 (717.8)
Admission	65 (192.9)	343 (309.3)	408 (282.2)
Case mortality	337	1109	1446
No mortality	335 (994.1)	110 (99.2)	1441 (996.5)
Mortality	2 (5.9)	3 (2.7)	5 (3.5)

7.2.4. Malaria admissions

Admitted malaria cases in the hospitals were fewer than unadmitted cases. A total of 717 (12.9%) malaria cases were admitted in both hospitals (Tables 7.1, 7.2). Therefore, the crude rate of hospital admission due to malaria was 129 per 1000 cases who reported malaria in both hospitals. In CGH, 7.5% (n=309) of the cases were admitted while 28.2% (n=408) were admitted in UGH. The crude rates of malaria admissions were 75 per 1000 and 282 per 1000 cases for CGH and UGH respectively (Table 7.3). That implies, the chances of a patient having hospital admission after being diagnosed with malaria was approximately 4 times higher in UGH compared to CGH.

The rates of malaria admissions varied in the wet and dry seasons. In CGH, it was 53 per 1000 (n=148) and 122 per 1000 (n=161) for wet and dry seasons, respectively (Table 7.3). Therefore, the chances of having malaria admission in CGH was 2.3 times higher in the dry season. In UGH, malaria admission rates were 193 per 1000 (n=65) and 309 per 1000 (n=343) for the wet and dry seasons, respectively. The chances of having malaria admission in UGH was 1.6 times higher in the dry season. Typically, malaria admissions were expected to be higher in the wet season due to the long distance to health facilities and increased mosquito bites during that period. However, that assumption does not hold in this case.

7.2.5. Malaria mortality

Only a few cases (n=9, 0.2%) were reported dead due to malaria in both hospitals (Tables 7.1, 7.2). Four of the cases were from CGH, and 5 were registered in UGH. The crude malaria mortality rates for the year were 1 per 1000 and 4 per 1000 in CGH and UGH, respectively. Therefore, the chances of dying from malaria that year were 4 times higher in UGH in comparison with CGH. In the wet season, 3 (0.1%) cases died in CGH while 2 (0.6%) died in the UGH. In the dry season, only one (0.1%) dead was recorded died in CGH and 3 (0.2%) in UGH.

However, the crude rates of malaria mortality in CGH for the wet season (1 per 1000) and dry season (1 per 1000) were similar. In UGH, the rate of malaria mortality was two-fold in the wet season (6 per 1000) compared to the dry season (3 per 1000). Therefore, comparing the two hospitals in the study, malaria cases were 6 times more likely to die in UGH during the wet season.

In UGH, all cases who died were in the age groups 0-4 years (n=4) and 40-44 (n=1). In CGH, the 4 cases who died were spread across four age groups (0-4, 25-29, 30-34 and 40-44). Crude malaria mortality for the year in the age group 0-4 years was 9.3 times higher in UGH (5.6 per 1000) than CGH (0.6 per 1000).

7.2.6. Drive time to hospital attended

There was no marked difference in the mean drive times of malaria cases to the two hospitals. Mean drive time of malaria cases to CGH was 58.9 minutes (SD 67.6) (Tables 7.1, 7.2). Mean drive time of cases who registered in UGH was 54.7 minutes (SD 82.4) (Table 7.2). However, there was a remarkable difference between mean drive times to the two hospitals in the wet and dry seasons. Malaria patients in CGH travelled a mean drive time of 79.3 minutes (SD 72.1) in the wet season and 15.8 minutes (SD 22.8) in the dry season. Therefore, the difference between means of patients' travel times to CGH for both seasons was 63.5 minutes, indicating 5 times increase in the wet season. Mean drive times of cases who registered in UGH were 38.6 minutes (SD 47.6) and 59.6 minutes (SD 89.8) in the wet and dry seasons, respectively. The difference between means of patients' travel times to UGH was 21 minutes, amounting to approximately two-fold increase.

Nearly half (n=1746, 42.5%) of the malaria cases who visited CGH that year lived within 30 minutes' drive to the facility (Table 7.1). In the wet season, cases who travelled within 30 minutes' drive to CGH were 17.9% (n=500) while 94.3% (n=1246) travelled the same time to the facility in the dry season. There was no increasing trend of malaria cases as drive times to CGH increased, although most of the patients lived beyond 30 minutes' drive to the facility in the wet season.

In UGH, 53.9% (n=779) of malaria cases who visited the facility that year lived within 30 minutes' drive (Table 7.2). However, there was no remarkable difference between the proportions of cases who lived within 30 minutes' drive to the facility in the wet (n=199, 59.1%) and dry seasons (580, 52.3%). Like the CGH, malaria cases did not increase as drive times to facilities increased.

7.2.7. Drive time to nearest health facility

It was assumed that proximity to the nearest health facility would increase chances of using the hospital for malaria treatment. Therefore, it was expected that most of the cases would live beyond the baseline drive time of 30 minutes' drive to the nearest health facility. This study computed the nearest drive times to PHC, NHIS and other public hospitals within the study catchment areas for the respective facilities (i.e. UGH and CGH), and the shortest of them was matched as the patient's nearest facility.

The overall mean drive time to the nearest health facility in CGH was 13.0 (SD 13.3) (Table 7.1). Malaria cases' mean drive times were 17.6 minutes (SD 13.6) and 3.5 minutes (SD 4.6) in the wet and dry seasons, respectively. Also, 92.9% (n=3821) of all cases in CGH lived within 30 minutes' drive to the nearest health facility (Table 7.1). The disaggregated results for CGH showed that over 90% of the cases lived within 30 minutes' drive to the nearest facility in the wet (n=251, 90.2%) and dry seasons (n=1305, 98.7%).

In UGH, mean drive time to the nearest health facility (13.4 minutes, SD 42.6) was similar to that of CGH (Tables 7.1, 7.2). However, the findings of seasonal disaggregation of results were dissimilar. Mean drive times to the nearest health facility within UGH catchment area were 5.4 minutes (SD 12.2) 15.9 minutes (SD 47.9) in the wet and dry seasons respectively. These results show that mean drive times to the nearest health facility within UGH catchment was shorter in the wet season. Like the CGH, over 90% of the population lived within 30 minutes' drive to the closest facility. Therefore, it can be deduced that proximity was probably not the reason for reporting malaria in the study hospitals. Other reasons like preferences, quality of service and availability of diagnostic facilities could have been the motivating factors.

7.3. Univariate associations of malaria diagnoses with patients' attributes

The results of univariate associations of malaria diagnoses are presented in Tables 7.4 and 7.5 for CGH and UGH, respectively. Each table shows results for the wet and dry seasons as well as the combined results for the year.

7.3.1. Association of malaria diagnosis in the wet and dry seasons

From the combined analysis of malaria severity in age groups in the two hospitals, the highest proportion of severe cases were found among ages 0-4 years (CGH = 36.8%, UGH = 55.6%). Apart from the age group 0-4 years, a minor peak was found in the UGH and CGH at age group 25-29 years (Figures 7.3 and 7.4). In both hospitals, more females than males were diagnosed with severe malaria except in age group 0-4 years, though not with a wide margin.

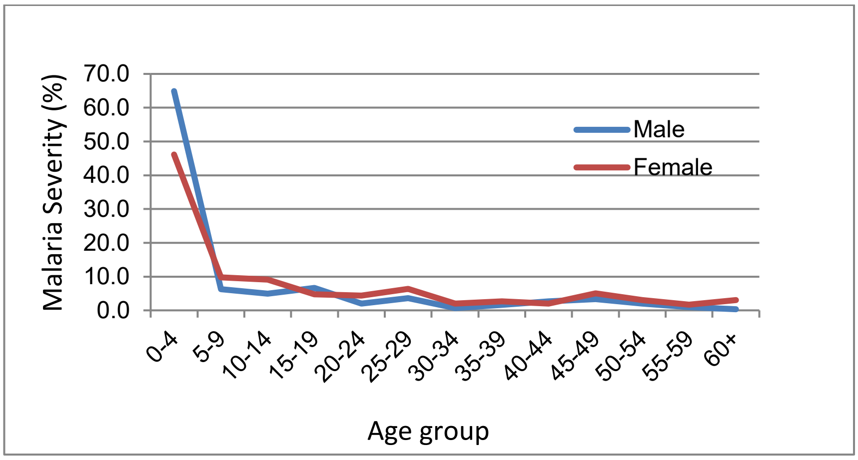

Figure 7.3: Malaria severity in UGH

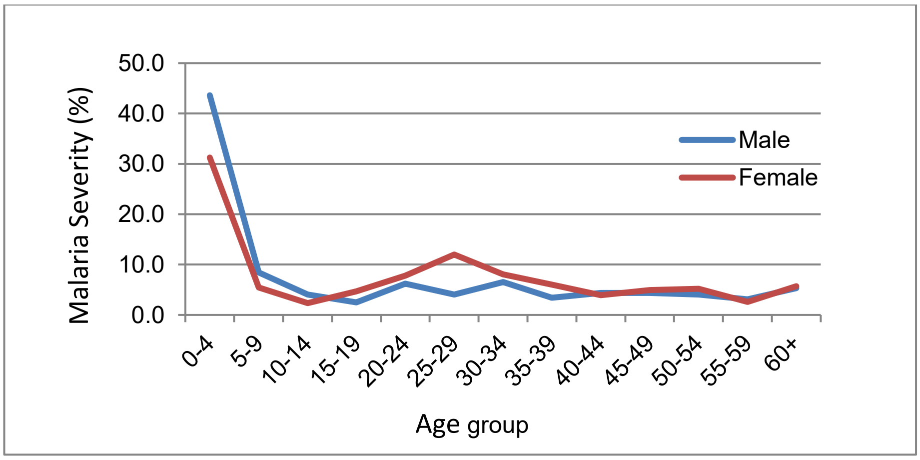

Figure 7.4: Malaria severity in CGH

In UGH, the associations between malaria diagnosis and age groups were only significant at age groups 30-34 (OR 0.3), 45-49 (OR 0.4) and 60+ (OR 0.4), indicating that patients in the baseline group (0-4 years) were more likely to develop severe malaria (Table 7.5). In CGH, significant findings were in age groups 15-19 (OR 1.7), 20-24 (OR 1.6), 25-29 (OR 1.4) and 30-34 (OR 1.5), implying the baseline group was less likely to be diagnosed of severe malaria (Table 7.4). In the gender analysis, there was no significant relationship between gender and malaria severity was found in the two hospitals.

The number of severe malaria cases did not increase as drive times to CGH and UGH increased (Tables 7.4, 7.5). The proportion of severe cases who lived within 30 minutes' drive were 37.6% (n=265) and 53.6% (n=321) for CGH and UGH, respectively. It was found that 91.5% of the severe cases who registered at CGH lived within 30 minutes' drive to the nearest health facility (Table 7.4). Similarly, 94.5% of severe malaria cases at UGH lived within 30 minutes' drive to the nearest health facility (Table 7.5). Therefore, the use of the CGH and UGH for malaria treatment would have resulted from other reasons other than the distance to the nearest health facility. The associations between malaria severity and seasons were not significant in the two hospitals.

7.3.2. Association of malaria diagnosis in the wet season

In CGH, there was no significant results from any of the variables, except for age groups 15-19 (OR 1.8) and 30-34 (OR 1.6) (Table 7.4). Therefore, the odds of severe malaria were in the two groups (15-19 and 30-34) were like the dry season. In UGH, there was no significant results in any of the variables in the wet season analysis (Table 7.5).

7.3.3. Association of malaria diagnosis in the dry season

The odds of severe malaria in CGH were 3.2 and 2.0 in age groups 20-24 and 25-29, respectively, in the dry season (Table 7.4). There were no other significant results in any of other variables except for the group who lived 30-60 minutes' drive to UGH in which the odds of severe malaria doubled. Also, in the dry season, the odds of severe malaria were 0.2 and 0.3 in age groups 30-34 and 45-49, respectively. The odds of severe malaria among the group who lived 60-90 minutes' drive (OR 2.2) to UGH was significantly higher. Drive times to the nearest health facility had no significant findings.

Table 7.4: Univariate association of malaria diagnoses in CGH

Malaria Diagnosis in CGH												
	Wet Season				**Dry Season**				**Wet/Dry Seasons**			
Risk Factor	Severe malaria (%)	Mild malaria (%)	Odd ratio (95% CI)	p-value	Severe malaria (%)	Mild malaria (%)	Odd ratio (95% CI)	p-value	Severe malaria (%)	Mild malaria (%)	Odd ratio (95% CI)	p-value
Age groups (year)												
0-4	164 (32.9)	902 (39.4)	1		96 (46.6)	602 (53.9)	1		260 (36.8)	1504 (44.2)	1	
5-9	36 (7.2)	141 (6.2)	1.4 (1.0-2.1)	0.10	12 (5.8)	56 (5.0)	1.3 (0.7-2.6)	0.38	48 (6.8)	197 (5.8)	1.4 (1.0-2.0)	0.05
10-14	14 (2.8)	88 (3.8)	0.9 (0.5-1.6)	0.66	8 (3.2)	36 (3.2)	1.4 (0.6-3.1)	0.41	22 (3.1)	124 (3.6)	1.0 (0.6-1.7)	0.91
15-19	22 (4.4)	66 (2.9)	1.8 (1.1-3.1)	0.02	4 (1.9)	21 (1.9)	1.2 (0.4-3.6)	0.75	26 (3.7)	87 (2.6)	1.7 (1.1-2.7)	0.02
20-24	35 (7.0)	150 (6.6)	1.3 (0.9-1.9)	0.23	15 (7.3)	29 (2.6)	3.2 (1.7-6.3)	0.00	50 (7.1)	179 (5.3)	1.6 (1.2-2.3)	0.01
25-29	39 (7.8)	182 (7.9)	1.2 (0.8-1.7)	0.40	20 (9.7)	64 (5.7)	2.0 (1.1-3.4)	0.02	59 (8.4)	246 (7.2)	1.4 (1.0-1.9)	0.04
30-34	40 (8.0)	138 (6.0)	1.6 (1.1-2.4)	0.02	12 (5.8)	59 (5.3)	1.3 (0.7-2.5)	0.47	52 (7.4)	197 (5.8)	1.5 (1.1-2.1)	0.01
35-39	27 (5.4)	124 (5.4)	1.2 (0.8-1.9)	0.43	7 (3.4)	46 (4.1)	1.0 (0.4-2.2)	0.91	34 (4.8)	170 (5.0)	1.2 (0.8-1.7)	0.47
40-44	26 (5.2)	108 (4.7)	1.3 (0.8-2.1)	0.23	3 (1.5)	47 (4.2)	0.4 (0.1-1.3)	0.13	29 (4.1)	155 (4.5)	1.1 (0.7-1.6)	0.71
45-49	24 (4.8)	103 (4.3)	0.3 (0.8-2.1)	0.31	9 (4.4)	46 (4.1)	1.2 (0.6-2.6)	0.59	33 (4.7)	149 (4.4)	1.3 (0.9-1.9)	0.22
50-54	25 (5.0)	90 (3.9)	1.5 (1.0-2.5)	0.08	8 (3.9)	36 (3.2)	1.4 (0.6-3.1)	0.41	33 (4.7)	126 (3.7)	1.5 (1.0-2.3)	0.05
55-59	18 (3.6)	69 (3.0)	1.4 (0.8-2.5)	0.19	2 (1.0)	29 (2.6)	0.4 (0.1-1.8)	0.26	20 (2.8)	98 (2.9)	1.2 (0.7-1.9)	0.51
60+	29 (5.8)	129 (5.6)	1.2 (0.8-1.9)	0.34	10 (4.9)	45 (4.0)	1.4 (0.7-2.9)	0.37	39 (1.7)	174 (2.4)	1.3 (0.9-1.9)	0.17
Total	499 (100)	2290 (100)			206 (100)	1116 (100)			705 (100)	3406 (100)		
Gender												
Female	272 (54.5)	1273 (55.6)	1		112 (54.5)	606 (54.3)	1		384 (54.5)	1879 (55.2)	1	
Male	227 (45.5)	1017 (44.4)	1.1 (0.9-1.3)	0.66	94 (45.6)	510 (45.7)	1.0 (0.7-1.3)	0.99	321 (45.5)	1527 (44.8)	1.0 (0.9-1.2)	0.73
Total	499 (100)	2290 (100)			206 (100.0)	1116 (100.0)			705 (100)	3406 (100)		
Drive time to CGH (minutes)												
0 - 30	78 (15.6)	422 (18.4)	1		187 (90.8)	1059 (94.9)	1		265 (37.6)	1481 (43.5)	1	
30 - 60	174 (34.9)	762 (33.3)	1.2 (0.9-1.7)	0.16	11 (5.3)	29 (2.6)	2.2 (1.1-4.4)	0.04	185 (26.2)	791 (23.2)	1.3 (1.1-1.6)	0.01
60 - 90	86 (17.2)	450 (19.7)	1.0 (0.7-1.4)	0.85	1 (0.5)	4 (0.4)	1.4 (0.2-12.7)	0.76	87 (12.3)	454 (13.3)	1.1 (0.8-1.4)	0.61
90+	161 (32.3)	656 (28.6)	1.3 (1.0-1.8)	0.06	7 (3.4)	24 (2.2)	1.7 (0.7-3.9)	0.25	168 (23.8)	680 (20.0)	1.4 (1.1-1.7)	0.00
Total	449 (100.0)	2290 (100.0)			206 (100.0)	1116 (100.0)			705 (100.0)	3406 (100.0)		

Drive time to Nearest Health facility (minutes)												
0 - 30	442 (88.6)	2074 (90.6)	1		203 (98.5)	1102 (98.7)	1		645 (91.5)	3176 (93.2)	1	
30 - 60	44 (8.8)	171 (7.5)	1.2 (0.9-1.7)	0.29	3 (1.5)	14 (1.3)	1.2 (0.3-4.0)	0.81	47 (6.7)	185 (5.4)	1.3 (0.9-1.7)	0.19
60 - 90	11 (2.2)	40 (1.7)	1.3 (0.7-2.5)	0.46	-	-	-	-	11 (1.6)	40 (1.2)	1.4 (0.7-2.7)	0.38
90+	2 (0.4)	5 (0.2)	1.9 (0.4-9.7)	0.45	-	-	-	-	2 (0.3)	5 (0.1)	2.0 (0.4-10.1)	0.42
Total	499 (100)	2290 (100)			206 (100)	1116 (100)			705 (100)	3406 (100)		
Seasons												
Wet season	-	-		-	-	-		-	499 (70.8)	2290 (67.2)	1	
Dry season	-	-		-	-	-		-	206 (29.2)	1116 (32.8)	0.9 (0.7-1.0)	0.67
Total	-	-		-	-	-		-	705 (100)	3406		

Table 7.5: Univariate association of malaria diagnoses in UGH

Malaria Diagnoses in UGH												
	Wet Season				**Dry Season**				**Dry/Wet seasons**			
Risk Factor	Severe malaria	Mild malaria	Odd ratio (95% CI)	p-value	Severe malaria	Mild malaria	Odd ratio (95% CI)	p-value	Severe malaria	Mild malaria	Odd ratio (95% CI)	p-value
Age group (year)												
0-4	84 (61.3)	117 (58.5)	1		249 (53.9)	269 (41.6)	1		333 (55.6)	386 (45.6)	1	
5-9	12 (8.8)	12 (6.0)	1.4 (0.6-3.3)	0.44	36 (7.8)	57 (8.8)	0.7 (0.4-1.1)	0.10	48 (8.0)	69 (8.1)	0.8 (0.5-1.2)	0.29
10-14	8 (5.8)	19 (9.5)	0.6 (0.3-1.4)	0.23	34 (7.4)	47 (7.3)	0.8 (0.5-1.2)	0.31	42 (7.0)	66 (7.8)	0.7 (0.5-1.1)	0.15
15-19	4 (2.9)	13 (6.5)	0.4 (0.1-1.4)	0.15	30 (6.5)	33 (5.1)	1.0 (0.6-2.0)	0.95	34 (5.7)	46 (5.4)	0.9 (0.5-1.4)	0.52
20-24	6 (4.4)	5 (2.5)	1.7 (0.5-5.7)	0.41	13 (2.8)	21 (3.2)	0.7 (0.3-1.4)	0.27	19 (3.2)	26 (3.1)	0.9 (0.5-1.6)	0.59
25-29	4 (2.9)	5 (2.5)	1.1 (0.3-4.3)	0.88	26 (5.6)	36 (5.6)	0.8 (0.5-1.3)	0.36	30 (5.0)	41 (4.8)	0.9 (0.5-1.4)	0.51
30-34	2 (1.5)	4 (2.0)	0.7 (0.1-3.9)	0.68	6 (1.3)	28 (4.3)	0.2 (1.0-0.6)	0.00	8 (1.3)	32 (3.8)	0.3 (0.1-0.7)	0.00
35-39	3 (2.2)	0 (0.0)	-	-	10 (2.2)	19 (2.9)	0.6 (0.3-1.3)	0.16	13 (2.2)	19 (2.2)	0.8 (0.4-1.6)	0.53
40-44	3 (2.2)	2 (1.0)	2.1 (0.3-12.8)	0.43	11 (2.4)	18 (2.8)	0.7 (0.3-1.4)	0.29	14 (2.3)	20 (2.4)	0.8 (0.4-1.6)	0.56
45-49	7 (5.1)	5 (2.5)	2.0 (0.6-6.4)	0.27	18 (3.9)	68 (10.5)	0.3 (0.2-0.5)	0.00	25 (4.2)	73 (8.6)	0.4 (0.3-0.6)	0.00
50-54	2 (1.5)	2 (1.0)	1.4 (0.2-10.1)	0.74	13 (2.8)	20 (3.1)	0.7 (0.3-1.4)	0.34	15 (2.5)	22 (2.6)	0.8 (0.4-1.6)	0.49
55-59	0 (0.0)	5 (2.5)	-	-	8 (1.7)	10 (1.5)	0.9 (0.3-2.2)	0.76	8 (1.3)	15 (1.8)	0.6 (0.3-1.5)	0.28
60+	2 (1.5)	11 (5.5)	0.3 (0.6-1.2)	0.08	8 (1.7)	21 (3.2)	0.4 (0.2-1.0)	0.04	10 (1.7)	32 (3.8)	0.4 (0.2-0.8)	0.01
Total	137 (100.0)	200 (100)			462 (100.0)	647 (100)			599 (100.0)	847 (100)		
Gender												
Female	67 (48.9)	98 (49.0)	1		230 (49.8)	347 (53.6)	1		297 (49.6)	445 (52.5)	1	
Male	70 (51.1)	102 (51.0)	1.0 (0.7-1.6)	0.99	232 (50.2)	300 (46.4)	1.2 (1.0-1.5)	0.21	302 (50.4)	402 (47.5)	1.1 (0.9-1.4)	0.27
Total	137 (100.0)	200 (100.0)			462 (100.0)	647 (100.0)			599 (100.0)	847 (100.0)		
Drive time to UGH (min)												
0 - 30	84 (61.3)	115 (57.5)	1		237 (51.3)	343 (53.0)	1		321 (53.6)	458 (54.1)	1	
30 - 60	29 (21.2)	55 (27.5)	0.7 (0.4-1.2)	0.23	101 (21.9)	165 (25.5)	0.9 (0.7-1.2)	0.43	130 (21.7)	220 (26.0)	0.8 (0.7-1.1)	0.20
60 - 90	15 (10.9)	24 (12.0)	0.9 (0.4-1.7)	0.66	19 (4.1)	13 (2.0)	2.2 (1.03-4.4)	0.04	34 (5.7)	37 (4.4)	1.3 (0.8-2.1)	0.28
90+	9 (6.6)	6 (3.0)	2.1 (0.7-6.0)	0.19	105 (22.7)	126 (19.5)	1.2 (1.0-1.6)	0.23	114 (19.0)	132 (15.6)	1.2 (0.9-1.6)	0.16
Total	137 (100)	200 (100)			462 (100)	647 (100)			599 (100)	847 (100)		

Drive time to Nearest Health Facility (minutes)												
0 - 30	131 (95.6)	194 (97.0)	1		435 (94.2)	622 (96.1)	1		566 (94.5)	816 (96.3)	1	
30 - 60	5 (3.6)	6 (3.0)	1.2 (0.4-4.1)	0.73	5 (1.1)	0 (0.0)	-	-	10 (1.7)	6 (0.7)	2.4 (0.9-6.7)	0.91
60 - 90	0 (0.0)	0 (0.0)	-	-	1 (0.2)	0 (0.0)	-	-	1 (0.2)	0 (0.0)	-	-
90+	1 (0.7)	0 (0.0)	-	-	21 (4.5)	25 (3.9)	1.2 (0.7-2.2)	0.55	22 (3.7)	25 (3.0)	1.3 (0.71-2.3)	0.42
Total	137 (100)	200 (100)			462 (100)	647 (100)			599 (100)	847 (100)		
Seasons												
Wet Season	-	-		-	-	-		-	137 (22.9)	200 (23.6)	1	
Dry season	-	-		-	-	-		-	462 (77.1)	647 (76.4)	1.0 (0.8-1.3)	0.74
Total	-	-		-	-	-		-	599 (100)	847 (100)		

7.4. Univariate associations of malaria admission with patients' attributes

Univariate analysis of the association between malaria admissions and attributes of patients are presented in Tables 7.6 and 7.7. The former shows findings for CGH and the latter shows results for UGH.

7.4.1. Associations of malaria admissions in the wet and dry seasons

In Table 7.6, like malaria diagnoses, malaria admissions in CGH were highest in the age group 0-4 years. The odds of having hospital admission due to malaria was significantly lower in age groups 45-49 (OR 0.3), 50-54 (OR 0.3) and 55-59 (OR 0.2) compared to the baseline group. There was no significant difference between the male and female groups. The odds of severe malaria were also significantly lower among all the groups who lived beyond 30 minutes' drive to CGH. Therefore, patients who lived within 30 minutes' drive to CGH were more likely to be admitted for malaria treatment. There were no significant findings for drive time to the nearest health facility.

In UGH, malaria admissions were more likely to occur in the baseline age group, except for age group 20-24, which was insignificant (Table 7.7). In the gender analysis, there was no significant difference between the male and female groups. The odds of malaria admission in the male group (OR 0.8) was significantly lower than the female group. The chances of having malaria admission were significantly lower among cases who lived 30-60 (OR 0.4) and over 90 minutes' drive (OR 0.7) to UGH. Like CGH, the chances of being admitted in the hospital was higher among the group who lived within 30 minutes' drive to the facility. Drive times to the nearest health facility had no significant findings.

7.4.2. Association of malaria admissions in the wet season

In CGH, the odds of malaria admissions were significantly less in the age groups 45-49 (OR 0.2) and 50-54 (OR 0.2) compared to the baseline group (Table 7.6). There was no significant difference between male and female groups. However, the odds of malaria admissions were approximately 2 times higher among the groups who lived 30-90 minutes' drive to the nearest health facility (OR 2.3).

It was found that 67.7% (n=44) and 95.4% (n=62) of the admitted malaria cases lived within 30 minutes' drive time to UGH and the nearest facility within that catchment area, respectively (Table 7.7). There were no significant findings in any of the analyses of the variables except for drive time 30-60 minutes (OR 0.4) to UGH (Table 7.7).

7.4.3. Association of malaria admissions in the dry season

More than half (55.9%) of malaria admissions in CGH occurred among age group 0-4 years in the dry season (Table 7.6). However, there was no significant association in the age and gender analyses. There was also no significant association between malaria admissions and drive times to facilities except at drive times 30-90 minutes (OR 2.2) to CGH. The study showed that over 90% of the cases who admitted in CGH lived within 30 minutes' drive to health facilities in the dry season. The odds of malaria admission in CGH (OR 2.5) and UGH (OR 1.9) were significant in the dry season, indicating that cases were more likely to be admitted in the dry season (Tables 7.6 and 7.7).

In UGH, 80% (n=275) of the admitted cases were within 0-4 years (Table 7.7). The odds of malaria admission were significantly lower in all age groups compared to the baseline group except for the 60+ group, which was insignificant. The odds of admission were twofold in the male group (OR 1.5) compared to the female group. The proportion of admitted cases who lived within 30 minutes to UGH was 62.1% (n=213). The odds of malaria admission were significantly lower among groups who lived beyond 30 minutes to the facilities. Also, 94.2% (n=323) of admitted cases lived within 30 minutes' drive to the nearest health facility, and associations of that variable were insignificant due to data limitations.

7.5. Multivariate associations of malaria diagnoses

The findings of the multivariate analysis of malaria diagnoses in CGH and UGH are presented in Tables 7.8 and 7.9, respectively. In the combined wet/dry season analysis of malaria diagnoses by age groups in CGH (Table 7.8), the adjusted odds of severe malaria were significant in age groups 15-19 (OR 1.7), 20-24 (OR 1.6), 25-29 (OR 1.4), and 30-34 (OR 1.5). In the wet season, the adjusted odds were significant in age groups 15-19 (OR 1.8) and 30-34 (OR 1.6). In the dry season, the adjusted odds were significant in age groups 20-24 (OR 3.2) and 25-29 (OR 2.0). These results show that malaria outcomes varied in the age groups depending on seasons and cases within 19-34 years were affected significantly.

Unlike CGH, the adjusted odds of severe malaria for the wet/dry season in UGH were significant in age groups 30-34 (OR 0.3), 45-49 (OR 0.4), and 60+ (OR 0.4) (Table 7.9). There were no significant findings from the age analysis in the wet season. In the dry season, the results were significant among age groups 30-34 (OR 0.2) and 45-49 (OR 0.3). Therefore, the odds of severe malaria in UGH was significantly higher in the baseline group.

Gender was not significant with malaria severity in either of the hospitals in the study. In CGH, the adjusted odds of severe malaria at drive times 30-60 (OR 1.3) and 90+ minutes (OR 1.4) was significantly higher than the baseline group in the combined wet/dry season analysis (Table 7.8). However, the individual analysis of malaria severity and drive times in wet and dry seasons produced no significant results. Similarly, drive times to the nearest facility within CGH catchment area and season were not significant (Table 7.8). In UGH, none of the analysis of drive times to UGH, drive time to the nearest health facility and seasons was significant (Table 7.9).

Table 7.6: Univariate association of malaria admissions in CGH

Malaria admissions in CGH												
	Wet Season				**Dry Season**				**Dry/wet seasons**			
Risk Factor	Admitted malaria (%)	Non-admitted malaria (%)	Odd ratio (95% CI)	P-value	Admitted malaria (%)	Non-admitted malaria (%)	Odd ratio (95% CI)	P-value	Admitted malaria (%)	Non-admitted malaria (%)	Odd ratio (95% CI)	P-value
Age groups (year)												
0-4	76 (51.4)	990 (37.5)	1		90 (55.9)	608 (52.4)	1		166 (53.7)	1598 (42.0)	1	
5-9	11 (7.4)	166 (6.3)	0.9 (0.5-1.7)	0.66	11 (6.8)	57 (4.9)	1.3 (0.7-2.6)	0.45	22 (7.1)	223 (5.9)	1.0 (0.6-1.5)	0.83
10-14	5 (3.4)	97 (3.7)	0.7 (0.3-1.7)	0.40	6 (3.7)	38 (3.3)	1.1 (0.4-2.6)	0.89	11 (3.6)	135 (3.6)	0.8 (0.4-1.5)	0.45
15-19	5 (3.4)	83 (3.1)	0.8 (0.3-2.0)	0.61	0 (0.0)	25 (2.2)	-	-	5 (1.6)	108 (2.8)	0.5 (0.2-1.1)	0.08
20-24	7 (4.7)	178 (6.7)	0.5 (0.2-1.0)	0.10	11 (6.8)	33 (2.8)	2.3 (1.1-4.6)	0.03	18 (5.8)	211 (5.5)	0.8 (0.5-1.4)	0.45
25-29	10 (6.8)	211 (8.0)	0.6 (0.3-1.2)	0.16	13 (8.1)	71 (6.1)	1.2 (0.7-2.3)	0.51	23 (7.4)	282 (7.4)	0.8 (0.5-1.2)	0.30
30-34	8 (5.4)	170 (6.4)	0.6 (0.3-1.1)	0.20	8 (5.0)	63 (5.4)	0.9 (0.4-1.9)	0.70	16 (5.2)	233 (6.1)	0.7 (0.4-1.1)	0.13
35-39	7 (4.7)	144 (5.5)	0.6 (0.3-1.4)	0.26	4 (2.5)	49 (4.2)	0.6 (0.2-1.6)	0.26	11 (3.6)	193 (5.1)	0.6 (0.3-1.0)	0.06
40-44	7 (4.7)	127 (4.8)	0.7 (0.3-1.6)	0.42	2 (1.2)	48 (4.1)	0.3 (0.1-1.2)	0.08	9 (2.9)	175 (4.6)	0.5 (0.3-1.0)	0.05
45-49	2 (1.4)	125 (4.7)	0.2 (0.1-0.9)	0.03	3 (1.9)	52 (4.5)	0.4 (0.1-1.3)	0.12	5 (1.6)	177 (4.7)	0.3 (0.1-0.7)	0.01
50-54	2 (1.4)	113 (4.3)	0.2 (0.0-1.0)	0.04	3 (1.9)	41 (1.9)	0.5 (0.2-1.6)	0.25	5 (1.6)	154 (4.1)	0.3 (0.1-0.8)	0.01
55-59	0 (0.0)	87 (3.3)	-	-	2 (1.2)	29 (1.9)	0.5 (0.1-2.0)	0.30	2 (0.6)	116 (3.1)	0.2 (0.0-0.7)	0.01
60+	5 (5.4)	150 (5.7)	0.7 (0.3-1.5)	0.34	8 (5.0)	47 (5.0)	1.2 (0.5-2.5)	0.73	16 (5.2)	197 (5.2)	0.8 (0.5-1.3)	0.37
Total	148 (100)	2641 (100)			161 (100)	1161 (100)			309 (100)	3802 (100)		
Gender												
Female	73 (49.3)	1472 (55.7)	1		85 (52.8)	633 (54.5)	1		158 (51.1)	2105 (55.4)	1	
Male	75 (50.7)	1169 (44.3)	1.2 (1.0-1.8)	0.13	76 (47.2)	528 (44.3)	1.1 (0.8-1.5)	0.68	151 (48.9)	1697 (44.6)	1.2 (1.0-1.5)	0.15
Total	148 (100.0)	2641 (100.0)			161 (100.0)	1161 (100.0)			309 (100.0)	3802 (100.0)		
Drive time to CGH (minutes)												
0 - 30	25 (16.9)	475 (18.0)	1		145 (90.1)	1101 (94.8)	1		170 (55.0)	1576 (41.5)	1	
30 - 60	46 (31.1)	890 (33.7)	1.0 (0.6-1.6)	0.94	9 (5.6)	31 (2.7)	2.2 (1.0-4.7)	0.04	55 (17.8)	921 (24.2)	0.6 (0.4-0.8)	0.00
60 - 90	22 (14.9)	514 (19.5)	0.9 (0.5-1.5)	0.49	0 (0.0)	5 (0.4)	-	-	22 (7.1)	519 (13.7)	0.4 (0.3-0.6)	0.00
90+	55 (37.2)	762 (28.9)	1.4 (0.9-2.2)	0.20	7 (4.3)	24 (2.1)	2.2 (0.9-5.2)	0.07	62 (20.1)	786 (20.7)	0.7 (0.6-1.0)	0.04

Total	148 (100.0)	2641 (100.0)			161 (100.0)	1161 (100.0)			309 (100.0)	3802 (100.0)		
Drive time to Nearest Health Facility (minutes)												
0 - 30	120 (81.1)	2396 (90.7)	1		159 (98.8)	1146 (98.7)	1		279 (90.3)	3542 (93.2)	1	
30 - 60	22 (14.9)	193 (7.3)	2.3 (1.4-3.7)	0.00	2 (1.2)	15 (1.3)	1 (0.2-4.4)	1.00	24 (7.8)	208 (5.5)	1.5 (0.9-2.3)	0.90
60 - 90	5 (3.4)	46 (1.7)	2.2 (0.9-5.6)	0.11	-	-	-	-	5 (1.6)	46 (1.2)	1.4 (0.5-3.5)	0.50
90+	1 (0.7)	6 (0.2)	3.3 (0.4-27.9)	0.27	-	-	-	-	1 (0.3)	6 (0.2)	2.1 (0.3-17.6)	0.49
Total	148 (100)	2641 (100)			161 (100)	1161 (100)			309 (100)	3802 (100)		
Seasons												
Wet season	-	-		-	-	-		-	148 (47.9)	2641 (69.5)	1	
Dry season	-	-		-	-	-		-	161 (52.1)	1161 (30.5)	2.5 (2.0-3.1)	0.00
Total	-	-		-	-	-		-	309 (100)	3802 (100)		

Table 7.7: Univariate association of malaria admissions in UGH

Malaria admissions in UGH												
	Wet season				**Dry season**				**Dry/wet seasons**			
Risk Factor	Admission (%)	No Admission (%)	Odd ratio (95% CI)	P-value	Admission (%)	No Admission (%)	Odd ratio (95% CI)	P-value	Admission (%)	No Admission (%)	Odd ratio (95% CI)	P-value
Age groups (year)												
0-4	43 (66.2)	158 (58.1)	1		275 (80.2)	243 (31.7)	1		318 (77.9)	401 (38.6)	1	
5-9	8 (12.3)	16 (5.9)	1.8 (0.7-4.6)	0.19	15 (4.4)	78 (10.2)	0.2 (0.1-0.3)	0.00	23 (5.6)	94 (9.1)	0.3 (0.2-0.5)	0.00
10-14	2 (3.1)	25 (9.2)	0.3 (0.7-1.3)	0.11	12 (3.5)	69 (9.0)	0.2 (0.1-0.3)	0.00	14 (3.4)	94 (9.1)	0.2 (0.1-0.3)	0.00
15-19	-	17 (6.3)	-	-	2 (0.6)	61 (8.0)	0.0 (0.0-0.1)	0.01	2 (0.5)	78 (7.5)	0.0 (0.0-0.1)	0.01
20-24	1 (1.5)	10 (3.7)	0.4 (0.1-3.0)	0.35	-	34 (4.4)	-	-	1 (0.2)	44 (4.2)	0.0 (0.0-0.2)	0.28
25-29	2 (3.1)	7 (2.6)	1.1 (0.2-5.2)	0.95	9 (2.6)	53 (6.9)	0.2 (0.1-0.3)	0.00	11 (2.7)	60 (5.8)	0.2 (0.1-0.5)	0.00
30-34	2 (3.1)	4 (1.5)	1.8 (0.3-10.4)	0.49	7 (2.0)	27 (3.5)	0.2 (0.1-0.5)	0.00	9 (2.2)	31 (3.0)	0.4 (0.2-0.8)	0.00
35-39	1 (1.5)	2 (0.7)	1.8 (0.2-20.7)	0.62	1 (0.3)	28 (3.7)	0.0 (0.0-0.2)	0.00	2 (0.2)	30 (2.9)	0.1 (0.0-0.4)	0.00
40-44	1 (1.5)	4 (1.5)	0.9 (0.1-8.4)	0.94	2 (0.6)	27 (3.5)	0.1 (0.0-0.3)	0.00	3 (0.7)	31 (3.0)	0.1 (0.0-0.4)	0.00
45-49	-	12 (4.4)	-	-	2 (0.6)	84 (11.0)	0.0 (0.0-0.1)	0.00	2 (0.5)	96 (9.2)	0.0 (0.0-0.1)	0.01
50-54	-	4 (1.5)	-	-	5 (1.5)	28 (3.7)	0.2 (0.1-0.4)	0.00	5 (1.2)	32 (3.1)	0.2 (0.1-0.5)	0.00
55-59	-	5 (1.8)	-	-	3 (0.9)	15 (2.0)	0.2 (0.0-0.6)	0.01	3 (0.7)	20 (1.9)	0.2 (0.1-0.6)	0.00
60+	5 (7.7)	8 (2.9)	2.3 (0.7-7.4)	0.16	10 (2.9)	19 (2.5)	0.5 (0.2-1.0)	0.06	15 (3.7)	27 (2.6)	0.7 (0.4-1.3)	0.00
Total	65 (100)	272 (100)			343 (100)	766 (100)			408 (100)	1038 (100)		
Gender												
Female	38 (58.5)	127 (46.7)	1		154 (44.9)	423 (55.2)	1		192 (47.1)	550 (53.0)	1	
Male	27 (41.5)	145 (53.3)	0.6 (0.4-1.1)	0.09	189 (55.1)	343 (44.0)	1.5 (1.2-2.0)	0.00	216 (52.9)	488 (47.0)	0.8 (0.6-1.0)	0.04
Total	65 (100.0)	272 (100.0)			343(100.0)	766 (100.0)			408 (100.0)	1038 (100.0)		
Drive time to UGH (minutes)												
0 - 30	44 (67.7)	155 (57.0)	1		213 (62.1)	367 (47.9)	1		257 (63.0)	522 (50.3)	1	
30 - 60	9 (13.8)	75 (27.6)	0.4 (0.2-1.0)	0.03	52 (15.2)	214 (27.9)	0.4 (0.3-0.6)	0.00	61 (15.0)	289 (27.8)	0.4 (0.3-0.6)	0.00
60 - 90	7 (10.8)	32 (11.8)	0.8 (0.3-1.9)	0.56	19 (5.5)	13 (1.7)	2.5 (1.2-5.2)	0.01	26 (6.4)	45 (4.3)	1.2 (0.7-2.0)	0.54
90+	5 (7.7)	10 (3.7)	1.8 (0.6-5.4)	0.32	59 (17.2)	172 (22.5)	0.6 (0.4-0.8)	0.00	64 (15.7)	182 (17.5)	0.7 (0.5-1.-)	0.04
Total	65 (100.0)	272 (100.0)			343 (100.0)	766 (100.0)			408 (100.0)	1038 (100.0)		

Drive time to Nearest Health Facility (minutes)												
0 - 30	62 (95.4)	263 (96.7)	1		323 (94.2)	734 (95.8)	1		385 (94.4)	997 (95.6)	1	
30 - 60	3 (4.6)	8 (2.9)	1.6 (0.4-6.2)	0.50	5 (1.5)	0 (0.0)	-	-	8 (2.0)	8 (0.8)	2.7 (1.0-7.0)	0.06
60 - 90	0 (0.0)	0 (0.0)	-	-	1 0.3)	0 (0.0)	-	-	1 (0.2)	0 (0.0)	-	-
90+	0 (0.0)	1 (0.4)	-	-	14 (4.1)	32 (4.2)	1.0 (0.5-1.9)	0.99	14 (3.4)	33 (3.2)	1.1 (0.6-2.1)	0.77
Total	65 (100)	272 (100)			343 (100)	766 (100)			408 (100)	1038 (100)		
Seasons												
Wet season	-	-	-	-	-	-	-	-	65 (15.9)	272 (26.2)	1	
Dry season	-	-	-	-	-	-	-	-	343 (84.1)	766 (73.8)	1.9 (1.4-2.5)	0.00
Total	-	-	-	-	-	-	-	-	408 (100)	1038 (100)		

Table 7.8: Multivariate analysis of malaria diagnosis in CGH

Multivariate association of malaria Diagnosis in CGH						
	Wet Season		**Dry Season**		**Wet/Dry Seasons**	
Risk Factor	Odds ratio (95% CI)	p-value	Odds ratio (95% CI)	p-value	Odds ratio (95% CI)	p-value
Age groups (year)						
0-4	1		1		1	
5-9	1.4 (1.0-2.1)	0.11	1.4 (0.7-2.6)	0.37	1.4 (1.0-2.0)	0.07
10-14	0.9 (0.5-1.6)	0.69	1.4 (0.6-3.1)	0.40	1.0 (0.6-1.7)	0.91
15-19	1.8 (1.1-3.1)	0.02	1.2 (0.4-3.6)	0.73	1.7 (1.1-2.8)	0.02
20-24	1.3 (0.9-1.9)	0.21	3.2 (1.7-6.4)	0.00	1.6 (1.1-2.2)	0.01
25-29	1.2 (0.8-1.8)	0.33	2.0 (1.2-3.5)	0.01	1.4 (1.0-1.9)	0.03
30-34	1.6 (1.1-2.4)	0.02	1.3 (0.7-2.6)	0.43	1.5 (1.1-2.1)	0.01
35-39	1.2 (0.8-1.9)	0.37	1.0 (0.4-2.2)	0.94	1.2 (0.8-1.7)	0.46
40-44	1.3 (0.9-2.2)	0.19	0.4 (0.1-1.3)	0.13	1.1 (0.7-1.6)	0.68
45-49	0.3 (0.8-2.1)	0.28	1.3 (0.6-2.7)	0.53	1.3 (0.9-1.9)	0.22
50-54	1.5 (1.0-2.5)	0.08	1.5 (0.7-3.2)	0.37	1.5 (1.0-2.3)	0.06
55-59	1.4 (0.8-2.5)	0.18	0.5 (0.1-2.0)	0.29	1.2 (0.7-2.0)	0.50
60+	1.2 (0.8-2.0)	0.31	1.3 (0.7-2.9)	0.44	1.3 (0.9-1.9)	0.19
Total						
Gender						
Female	1		1		1	
Male	1.1 (0.9-1.3)	0.41	1.1 (0.8-1.5)	0.69	1.1 (1.0-1.3)	0.36
Total						
Drive time to CGH (minutes)						
0 - 30						
30 - 60	1.2 (0.9-1.7)	0.16	2.0 (1.0-4.0)	0.08	1.3 (1.0-1.7)	0.04
60 - 90	1.1 (0.8-1.5)	0.78	1.9 (0.1-34.0)	0.67	1.1 (0.8-1.5)	0.55
90+	1.3 (1.0-1.8)	0.13	2.3 (0.8-6.6)	0.11	1.4 (1.0-1.9)	0.04
Total						
Drive time to Nearest Health facility (minutes)						
0 - 30	1		1		1	
30 - 60	1.1 (0.7-1.6)	0.63	0.5 (0.1-3.1)	0.43	1.1 (0.7-1.5)	0.75
60 - 90	1.2 (0.5-2.4)	0.65	-	-	1.2 (0.6-2.4)	0.67
90+	1.7 (0.3-9.1)	0.52	-	-	1.6 (0.3-8.5)	0.57
Total						
Season						
Wet season	-	-	-	-	1	
Dry season	-	-	-	-	1.1 (0.8-1.4)	0.53

Table 7.9: Multivariate analysis of malaria diagnosis in UGH

Multivariate associations of Malaria Diagnosis in UGH						
	Wet Season		**Dry Season**		**Dry/Wet seasons**	
Risk Factor	Odd ratio (95% CI)	p-value	Odd ratio (95% CI)	p-value	Odd ratio (95% CI)	p-value
Age group (year)						
0-4	1		1		1	
5-9	1.3 (0.5-3.2)	0.55	0.7 (0.4-1.1)	0.12	0.8 (0.5-1.2)	0.23
10-14	0.6 (0.3-1.5)	0.28	0.8 (0.5-1.3)	0.34	0.7 (0.5-1.1)	0.15
15-19	0.5 (0.1-1.5)	0.19	1.0 (0.6-1.7)	1.00	0.9 (0.5-1.4)	0.53
20-24	1.6 (0.5-5.7)	0.47	0.7 (0.3-1.4)	0.29	0.9 (0.5-1.6)	0.64
25-29	1.3 (0.3-5.0)	0.73	0.8 (0.5-1.6)	0.39	0.8 (0.5-1.4)	0.49
30-34	0.7 (0.1-4.1)	0.70	0.2 (1.0-0.6)	0.00	0.3 (0.1-0.7)	0.00
35-39	-	-	0.6 (0.3-1.3)	0.22	0.8 (0.4-1.7)	0.58
40-44	2.3 (0.4-14.3)	0.37	0.7 (0.3-1.5)	0.37	0.8 (0.4-1.7)	0.62
45-49	2.3 (0.7-7.7)	0.17	0.3 (0.2-0.5)	0.00	0.4 (0.3-0.7)	0.00
50-54	1.3 (0.2-9.6)	0.80	0.7 (0.4-1.5)	0.42	0.8 (0.4-1.6)	0.55
55-59	-	-	0.9 (0.4-2.4)	0.87	0.6 (0.3-1.5)	0.28
60+	0.3 (0.1-1.3)	0.09	0.4 (0.2-1.0)	0.05	0.4 (0.2-0.8)	0.01
Total						
Gender						
Female	1		1		1	
Male	1.0 (0.6-1.6)	0.98	1.1 (0.8-1.4)	0.69	1.4 (0.8-1.3)	0.73
Total						
Drive time to UGH (min)						
0 - 30	1		1		1	
30 - 60	0.7 (0.4-1.2)	0.17	0.9 (0.7-1.3)	0.61	0.9 (0.7-1.2)	0.37
60 - 90	0.8 (0.4-1.7)	0.52	2.0 (1.0-4.3)	0.06	1.3 (0.8-2.2)	0.25
90+	5.4 (0.6-48.3)	0.13	1.2 (0.8-1.7)	0.34	1.2 (0.9-1.7)	0.27
Total						
Drive time to Nearest Health Facility (minutes)						
0 - 30	1		1		1	
30 - 60	0.3 (0.0-3.4)	0.33	-	-	2.1 (0.7-6.2)	0.18
60 - 90	-	-	-	-	-	1.00
90+	-	-	1.0 (0.5-2.0)	0.96	1.0 (0.5-2.0)	0.94
Total						
Season						
Wet season	-	-	-	-	1	
Dry season	-	-	-	-	1.0 (0.8-1.3)	0.73

7.6. Multivariate associations of malaria admissions

The adjusted odds of malaria admissions in the combined wet/dry season for CGH were significant in age groups 45-49 (OR 0.3), 50-54 (OR 0.3) and 55-59 (OR 0.4) implying lower chances of admissions compared to the baseline group (Table 7.10). In the wet season, the odds of malaria admission were significantly lower among cases in age group 45-49 (OR 0.2). In the dry season, it was significantly higher in the age group 20-24 (OR 2.3). The findings from the analysis by gender and drive times to UGH were not significant in either season. The adjusted odds of malaria admission doubled at 30-60 minutes to the nearest health facility in the wet season (OR 2.2) and combined wet/dry season analysis (OR 1.8). The adjusted odds of malaria admission were significant in the dry season (OR 2.8).

In UGH, the adjusted odds of malaria admission were significantly lower in all age groups except for cases who were above 60 years compared to the baseline group. Gender produced no significant results in the analysis (Table 7.11). Unlike CGH, adjusted odds of malaria admission were significantly lower within 30-60 minutes' drive in both seasons. In the dry season, the adjusted odds of malaria admission were 3.3 among cases who lived within 30-90 minutes' drive from CGH. Malaria cases who lived within 30-60 minutes from the nearest health facility within UGH catchment area also had higher chances of malaria admissions (OR 4.4). The adjusted odds of malaria admissions in the dry season (OR 3.2) was also higher than the wet season.

Table 7.10: Multivariate analysis of malaria admissions in CGH

Multivariate analysis of Malaria admissions in CGH						
	Wet Season		**Dry Season**		**Dry/wet seasons**	
Risk Factor	Odd ratio (95% CI)	P-value	Odd ratio (95% CI)	P-value	Odd ratio (95% CI)	P-value
Age groups (year)						
0-4	1		1		1	
5-9	0.9 (0.4-1.6)	0.63	1.3 (0.7-2.6)	0.43	1.1 (0.7-1.7)	0.83
10-14	0.7 (0.3-1.8)	0.45	1.1 (0.4-2.6)	0.86	0.9 (0.5-1.6)	0.69
15-19	0.8 (0.3-2.1)	0.68	-	-	0.5 (0.2-1.3)	0.18
20-24	0.5 (0.2-1.2)	0.12	2.3 (1.1-4.7)	0.03	1.0 (0.6-1.7)	0.97
25-29	0.7 (0.3-1.2)	0.23	1.3 (0.7-2.5)	0.43	0.9 (0.6-1.5)	0.70
30-34	0.6 (0.3-1.3)	0.22	0.9 (0.4-1.9)	0.76	0.7 (0.4-1.3)	0.27
35-39	0.7 (0.3-1.5)	0.34	0.6 (0.2-1.6)	0.27	0.6 (0.3-1.2)	0.16
40-44	0.8 (0.3-1.7)	0.49	0.3 (0.1-1.2)	0.08	0.6 (0.3-1.1)	0.11
45-49	0.2 (0.1-0.9)	0.03	0.4 (0.1-1.3)	0.14	0.3 (0.1-0.7)	0.01
50-54	0.2 (0.1-1.0)	0.05	0.5 (0.2-1.8)	0.30	0.3 (0.1-0.8)	0.02
55-59	-	-	0.5 (0.1-2.0)	0.35	0.2 (0.1-0.8)	0.02
60+	0.7 (0.3-1.5)	0.34	1.0 (0.7-1.5)	0.83	0.9 (0.5-1.5)	0.66
Total						
Gender						
Female	1		1		1	
Male	1.2 (0.9-1.7)	0.27	1.0 (0.7-1.5)	0.81	1.1 (0.9-1.4)	0.39
Total						
Drive time to CGH (minutes)						
0 - 30	1		1		1	
30 - 60	1.0 (0.6-1.6)	0.93	2.0 (1.0-4.5)	0.07	1.2 (0.8-1.9)	0.36
60 - 90	0.7 (0.4-1.4)	0.40	-	-	0.9 (0.5-1.6)	0.69
90+	1.0 (0.5-1.7)	0.96	2.6 (0.9-7.5)	0.07	1.3 (0.8-2.1)	0.34
Total						
Drive time to Nearest Health Facilities (minutes)						
0 - 30	1		1		1	
30 - 60	2.2 (1.2-3.9)	0.01	0.6 (0.1-4.0)	0.61	1.8 (1.1-3.2)	0.03
60 - 90	2.1 (0.8-5.8)	0.15	-	-	1.9 (0.7-5.2)	0.19
90+	3.3 (0.4-29.0)	0.29	-	-	2.7 (0.3-23.6)	0.36
Total						
Season						
Wet season	-	-	-	-	1	
Dry season	-	-	-	-	2.8 (2.0-4.2)	0.00

Table 7.11: Multivariate analysis of malaria admissions in UGH

Multivariate analysis of Malaria admissions in UGH						
	Wet season		**Dry season**		**Dry/wet seasons**	
Risk Factor	Odd ratio (95% CI)	P-value	Odd ratio (95% CI)	P-value	Odd ratio (95% CI)	P-value
Age groups (year)						
0-4	1		1		1	
5-9	1.5 (0.6-4.0)	0.37	0.2 (0.1-0.3)	0.00	0.3 (0.2-0.4)	0.00
10-14	0.3 (0.1-1.2)	0.09	0.2 (0.1-0.3)	0.00	0.2 (0.1-0.3)	0.00
15-19	-	-	0.0 (0.0-0.1)	0.00	0.0 (0.0-0.1)	0.00
20-24	0.3 (0.0-2.5)	0.26	-	-	0.0 (0.0-0.2)	0.00
25-29	1.1 (0.2-5.6)	0.93	0.2 (0.1-0.3)	0.00	0.2 (0.1-0.4)	0.00
30-34	1.8 (0.3-10.8)	0.54	0.2 (0.1-0.6)	0.00	0.3 (0.1-0.7)	0.00
35-39	2.3 (0.2-29.4)	0.51	0.0 (0.0-0.2)	0.00	0.1 (0.0-0.3)	0.00
40-44	1.0 (0.1-10.0)	0.97	0.1 (0.0-0.3)	0.00	0.1 (0.0-0.4)	0.00
45-49	-	-	0.0 (0.0-0.1)	0.00	0.0 (0.0-0.1)	0.00
50-54	-	-	0.2 (0.1-0.5)	0.00	0.2 (0.1-0.5)	0.00
55-59	-	-	0.2 (0.1-0.8)	0.02	0.2 (0.1-0.7)	0.01
60+	2.0 (0.6-7.0)	0.29	0.5 (0.2-1.1)	0.12	0.8 (0.4-1.5)	0.48
Total						
Gender						
Female	1		1		1	
Male	0.6 (0.3-1.2)	0.13	1.1 (0.8-1.5)	0.45	0.8 (0.8-1.3)	0.92
Total						
Drive time to UGH (minutes)						
0 - 30	1		1		1	
30 - 60	0.4 (0.2-1.0)	0.04	0.4 (0.3-0.6)	0.00	0.4 (0.3-0.6)	0.00
60 - 90	0.8 (0.3-1.9)	0.51	3.3 (1.4-7.9)	0.01	1.7 (1.0-3.1)	0.07
90+	2.3 (0.4-14.9)	0.38	0.6 (0.4-0.9)	0.02	0.6 (0.4-1.0)	0.03
Total						
Drive time to Nearest Health Facility (minutes)						
0 - 30	1		1		1	
30 - 60	0.6 (0.1-6.0)	0.64	-	-	4.4 (1.4-14.4)	0.01
60 - 90	-	-	-	-	-	-
90+	-	-	1.0 (0.4-2.2)	0.96	1.0 (0.4-1.9)	0.78
Total						
Season						
Wet season	-	-	-	-	1	
Dry season	-	-	-	-	3.2 (2.3-4.6)	0.00

7.7. Summary

The objective of Chapter Seven was “to investigate seasonal associations between drive times to healthcare, malaria severity and hospital admissions in selected Cross River State hospitals.” The selected hospitals were CGH and UGH. The two facilities are important to this study because the findings of Chapter Six show that geographical access to healthcare within their catchment areas is usually limited in the wet season. Therefore, the chances of being diagnosed with severe malaria and having admissions due to the disease were expected to be higher in the wet season. Severe malaria and admitted cases were also expected to live further away from hospitals they attended and the nearest government health facility.

A total of 5557 malaria cases were included in the study of which 4111 were registered at the CGH and 1446 from UGH (Tables 7.1 and 7.2). Both hospitals are owned and managed by the government, and most people are expected to use them because their services are cheaper than private hospitals and the availability of diagnostic equipment. All cases included in the study were diagnosed with malaria by laboratory testing in 2015. The data in the research cover 11 months instead of 12 because the hospitals were shut down in January 2015 due to the national labour strike. The results presented here may not represent all malaria in the entire population since other cases would have used either private health care, self-care, or traditional healers.

Although both hospitals are in urban areas, CGH serves mostly urban population while UGH serves mainly rural areas. Therefore, access to malaria treatment was expected to be lower, and the chances of having severe malaria, hospital admission, and dying from the disease was supposed to be higher in the UGH. Malaria cases who registered in CGH were expected to travel shorter distances to healthcare compared to UGH, considering that Chapter Six found that health facilities in SSD were more accessible than those in CSD, except in the wet season.

7.7.1. Core findings

The following are the main findings of this study;

i. CGH had more malaria cases in the wet season, and UGH had more in the dry season.

ii. The difference between male and female groups was insignificant for severity and admission analyses of both facilities. However, fewer females used UGH in the wet season.

iii. Approximately half of the malaria cases in the study were below five years, and the value was smaller for CGH in the wet season but higher for UGH in the dry season.

iv. Most of the malaria cases were mild, although nearly half of all the cases in UGH were severe.

v. The crude rate of severe malaria in the dry season was like the wet season in the two hospitals, and the association was not significant.

vi. The chances of having hospital admission were significantly higher in the dry season even after adjusting for age, gender, drive time to the hospital of admission, drive time to the nearest health facilities and season.

vii. Malaria cases were 6 times more likely to die, and mortality among under-five children was 9.3 times higher in UGH compared to CGH.

viii. The number of severe malaria or admitted cases did not increase with distance to facilities, and there was no compelling effect of wet season on malaria outcomes. Therefore, the hypothesis that malaria outcomes increases in the wet season and worse outcomes live far from the health facilities is refuted in this study.

7.7.2. Discussion of main findings

CGH recorded more malaria cases than UGH because it serves a larger population (Table 7.1 and

7.2). The estimated population of CGH catchment area is 2,165,103, and that of UGH is 960,667. Considering transport issues in the wet season, fewer people would have used the UGH in the wet season. Therefore, the low malaria attendance from UGH in the wet season would have resulted from inadequate access to the facility in the wet season.

There was no significant difference between male and female groups in either severity or admission analysis. However, there were fewer females than males who used UGH in the wet season. This result provides a further explanation of the low utilization of UGH in the wet season for malaria treatment. The number of females who used the facility would have declined due to safety concerns in the wet season, considering the bad roads and the likelihood of flooding during that period.

This study found that malaria remains a significant health problem for children under the age of five. However, the effect was different in the two hospitals. While the odds of severe malaria in CGH were higher in other age groups than the baseline group, it was less in UGH. There were a few associations in the seasonal analysis but not enough to make a firm conclusion about the effect of seasons on malaria outcomes in the various age groups.

Although UGH had fewer malaria cases than CGH, the proportion of severe cases was higher in UGH (41%) (Tables 7.1 and 7.2). The finding may indicate that the patients may have delayed effective treatment until it was severe before they visited the hospital. There was no significant effect of seasons on malaria diagnoses and crude rates for wet and dry seasons were similar for both hospitals.

Contrary the hypothesis of this study, the odds of hospital admission were significantly higher in the dry season even after adjusting for age, gender, drive time to the hospital of admission, drive time to the nearest health facilities and season. This result may reflect a limitation in the data or the possibility that most cases were admitted in the hospitals during the dry season for other factors other than malaria.

Although malaria mortality data were insufficient for a substantial analysis, this study found that the chances of dying of malaria were higher in UGH compared to CGH. Again, access to health care is expected to be poorer in the UGH catchment areas considering its rurality. This result indicates a serious healthcare inequality problem with a greater impact on children below five years.

In overall, the study found no compelling evidence that cases with worse outcomes lived far from the hospitals they attended or the nearest health facility. It was found that approximately 90% of the patients lived within 30 minutes' drive (baseline group) to the nearest health facility. However, there were a few significant associations among other drive time groups. However, because the population of the hospital catchment areas is likely to decrease within distance from the facility, the proportion of malaria attendance and outcomes may decrease in that manner.

It was also found that the size of the data makes it difficult to measure the impact of season on malaria outcomes. When the data was split into seasons, either the significance level dropped, or some groups had no values.

7.7.3. Conclusion of Chapter Seven

This study investigated malaria outcomes in two hospitals. Although more cases were recorded in the wet season, there was no compelling effect of wet season on malaria severity and admission. Instead, malaria admissions were more likely to occur in the dry season. Therefore, the hypothesis that malaria outcomes will be worse in the wet season is rejected in this study. The limitations and strength of the study are discussed in Chapter Nine. Next chapter presents findings for the study on the use of location-allocation models.

CHAPTER EIGHT: SEASONALITY OF GEOGRAPHICAL ACCESS AND LOCATION-ALLOCATION MODELS

8. Chapter overview

Chapter Eight is the last of the empirical results chapters. It builds on the concept of the seasonality of geographical access to health services which was measured in Chapters Six and Seven. It relates the problem of the seasonality of access to the application of LAMs in healthcare planning. The assumption is that if geographical access to healthcare is reduced in the wet season due to flooding, proposed plans for new facilities, locations should accommodate seasonality in their models. Therefore, it was expected that the "viability" of proposed facilities' locations in terms of population coverage would decrease in the wet season compared to the dry season. The findings of this chapter satisfy the fourth objective of this thesis, "to examine the effect of wet season on location-allocation of National Health Insurance Scheme (NHIS) facilities in Cross River State".

8.1. Results

The models in the study were EFLAM, RPLAM, and PWLAM. EFLAM measures the performance of existing NHIS facilities. RPLAM selected new locations from preselected sample points, and PWLAM chose new sites based on the population sizes of demand points. The performance of each model was examined using the wet and dry seasons' drive times. Details of the analyses were discussed in methodology chapter. This results chapter presents findings in three sections. The first section sections present findings for the dry season. The second section shows the wet season results. The third section discusses the similarities and differences in the performances of the models in the two seasons. There were 67 existing facilities in the study and Figure 8.1 shows their locations.

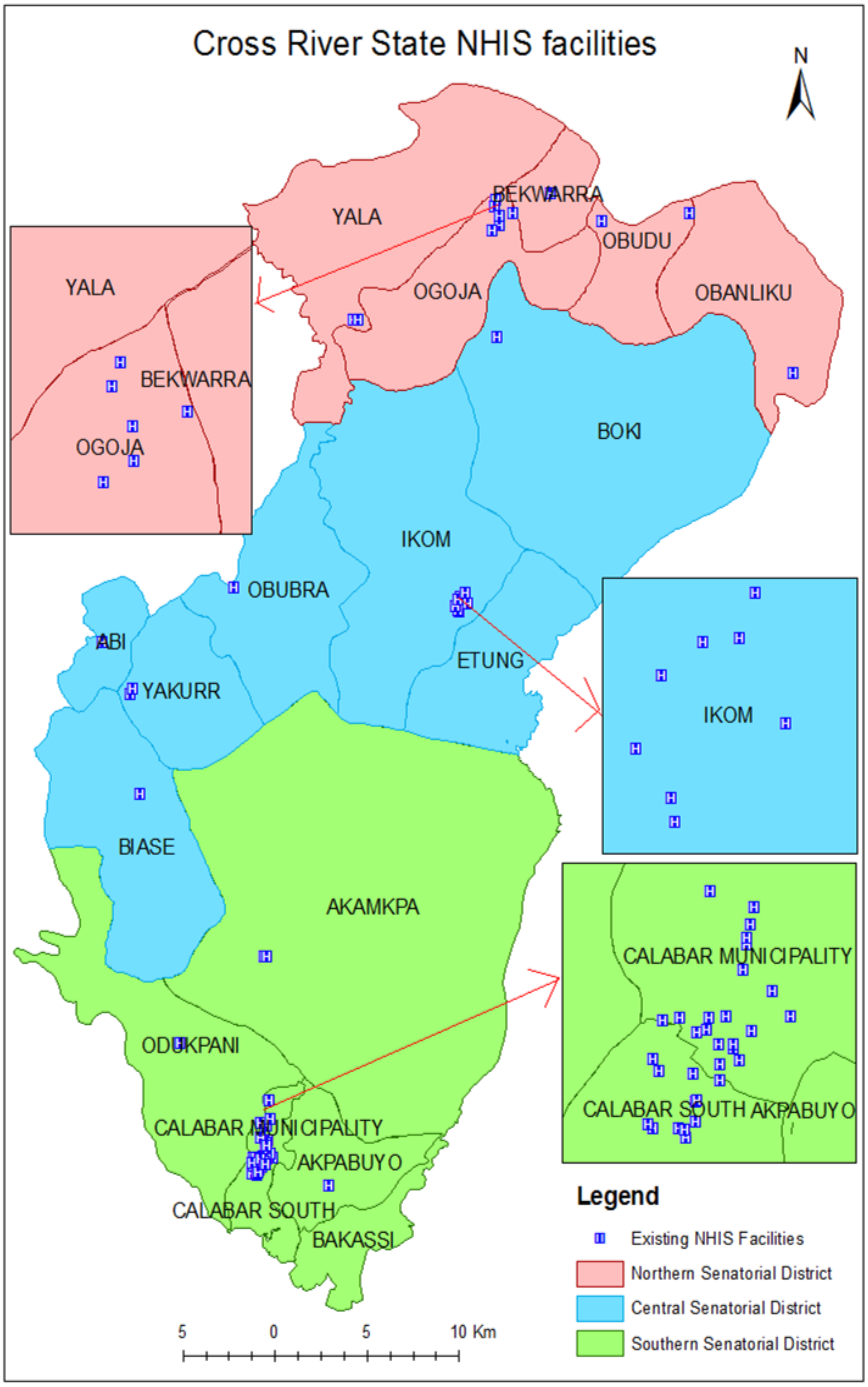

Figure 8.1: Existing NHIS facilities in Cross River State

8.2. Location-allocation of NHIS in the dry season

Table 8.1 shows the results of the dry season LAMs analyses. In each analysis, 67 facilities were selected at various drive times to serve 1024 communities whose total population was 3,628,810. EFLAM produced the current communities and population coverage of the existing 67 NHIS facilities in Cross River State. PWLAM selected 67 optimised locations for the proposed NHIS facilities from 1024 population weighted communities. RPLAM also chose 67 optimised locations for NHIS facilities from 100 spatially sampled and non-weighted community locations.

Table 8.1 shows a marked difference in the results that were produced by the three models. At 15 minutes' drive time, the proportions of communities covered were 7.2%, 33.1% and 27.8% for EFLAM, PWLAM, and RPLAM respectively. That implies PWLAM and RPLAM could cover 4.6 and 3.9 times more communities than EFLAM respectively at 15 minutes. When maximum drive time was increased to 60 minutes from the closest facility, EFLAM could cover 44.6% of communities; PWLAM covered 100% while SPLAM covered 85.6%. At 60 minutes' drive, PWLAM covered 2.2 times more communities than EFLAM, while RPLAM covered 1.9 times more than EFLAM (Figure 8.2). Since PWLAM could reach all communities within 60 minutes' drive, it is considered the best of the three models.

As shown in Table 8.1, the three models were also tested using population coverage because it is possible for a model to cover more communities but less population. The reason is that some communities are sparsely populated, and there is a tendency that the model may have selected most of them. From Table 8.1, EFLAM covered 45.2% of Cross River State population at 15 minutes' maximum drive to the closest facility, while PWLAM covered 74.2% and RPLAM covered 29.8% over the same drive time. At 15 minutes' drive time, PWLAM could make NHIS facilities available to an extra 29% (1,052,355) of the population compared with EFLAM. RPLAM also denied 15.4% (558,937) of the population access to NHIS services compared to EFLAM. At 60 minutes' drive, PWLAM's NHIS locations covered the entire population, while EFLAM's performance was short of RPLAM's population coverage by 18.8% (682,216) (Figure 8.3).

Comparing the findings at 15 and 60 minutes' drive time threshold to the closest facility, PWLAM was the most attractive while EFLAM performed better at 15 minutes and RPLAM at 60 minutes (Table 8.1). Although RPLAM could reach more communities with the service than the EFLAM at

15 minutes, it was also unable to serve communities with high population density effectively in the model (Figures 8.2, 8.3). EFLAM could not increase population coverage at 60 minutes' drive time since some of the existing facilities were clustered, and the model had no option of moving them about like other models (Figure 8.3). PWLAM and RPLAM did not only vary for population or communities covered, but they also varied in the selection of communities. However, both models selected similar locations in some places (Figures 8.4, 8.5).

Table 8.1: Service coverage of existing and optimised models in the dry season

Drive time (min)	**15**	**30**	**45**	**60**	**75**	**90**	**105**	**120**
EFLAM communities and population coverage								
No of comm. (%)	74 (7.2)	165 (16.1)	310 (30.3)	457 (44.6)	589 (57.5)	702 (68.6)	790 (77.1)	852 (83.2)
Pop. Coverage	1641353 (45.2)	1870921 (51.6)	2263779 (62.4)	2569708 (70.8)	2785628 (76.8)	2987270 (82.3)	3116475 (85.9)	3257917 (89.8)
PWLAM communities and population coverage								
Comm. Coverage (%)	339 (33.1)	685 (66.9)	940 (91.8)	1024 (100.0)	-	-	-	-
Pop. Coverage (%)	2691467 (74.2)	3224397 (88.9)	3555996 (98.0)	3628810 (100.0)	-	-	-	-
RPLAM communities and population coverage								
Comm. Coverage (%)	285 (27.8)	541 (52.8)	752 (73.4)	877 (85.6)	941 (91.9)	983 (96.0)	1000 (97.7)	1010 (98.6)
Pop. Coverage (%)	1080011 (29.8)	2404620 (66.3)	2821863 (77.8)	3249921 (89.6)	3425314 (94.4)	3517287 (96.9)	3587063 (98.8)	3602028 (99.3)

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 67

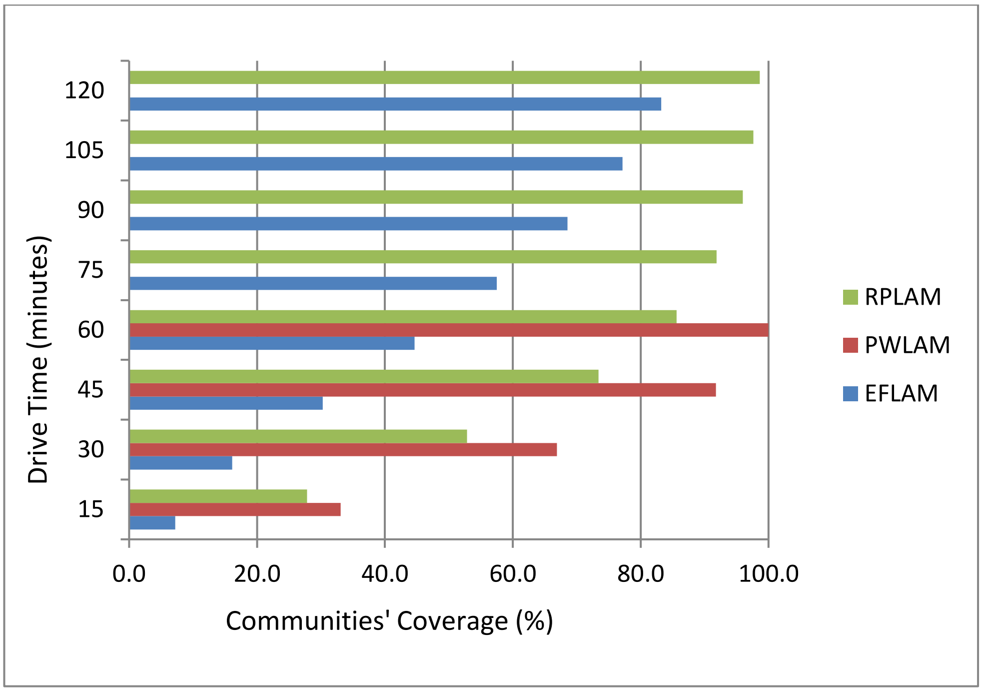

Figure 8.2: Comparison of communities' coverage of RPLAM, PWLAM and EFLAM in the dry season

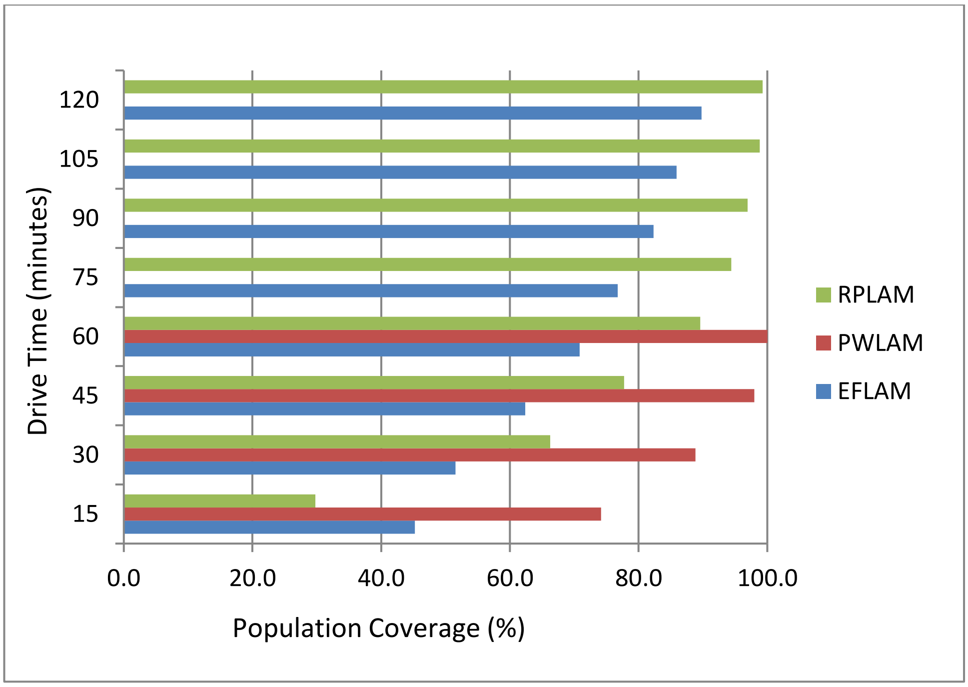

Figure 8.3: Comparison of population coverage of RPLAM, PWLAM and EFLAM in the dry season

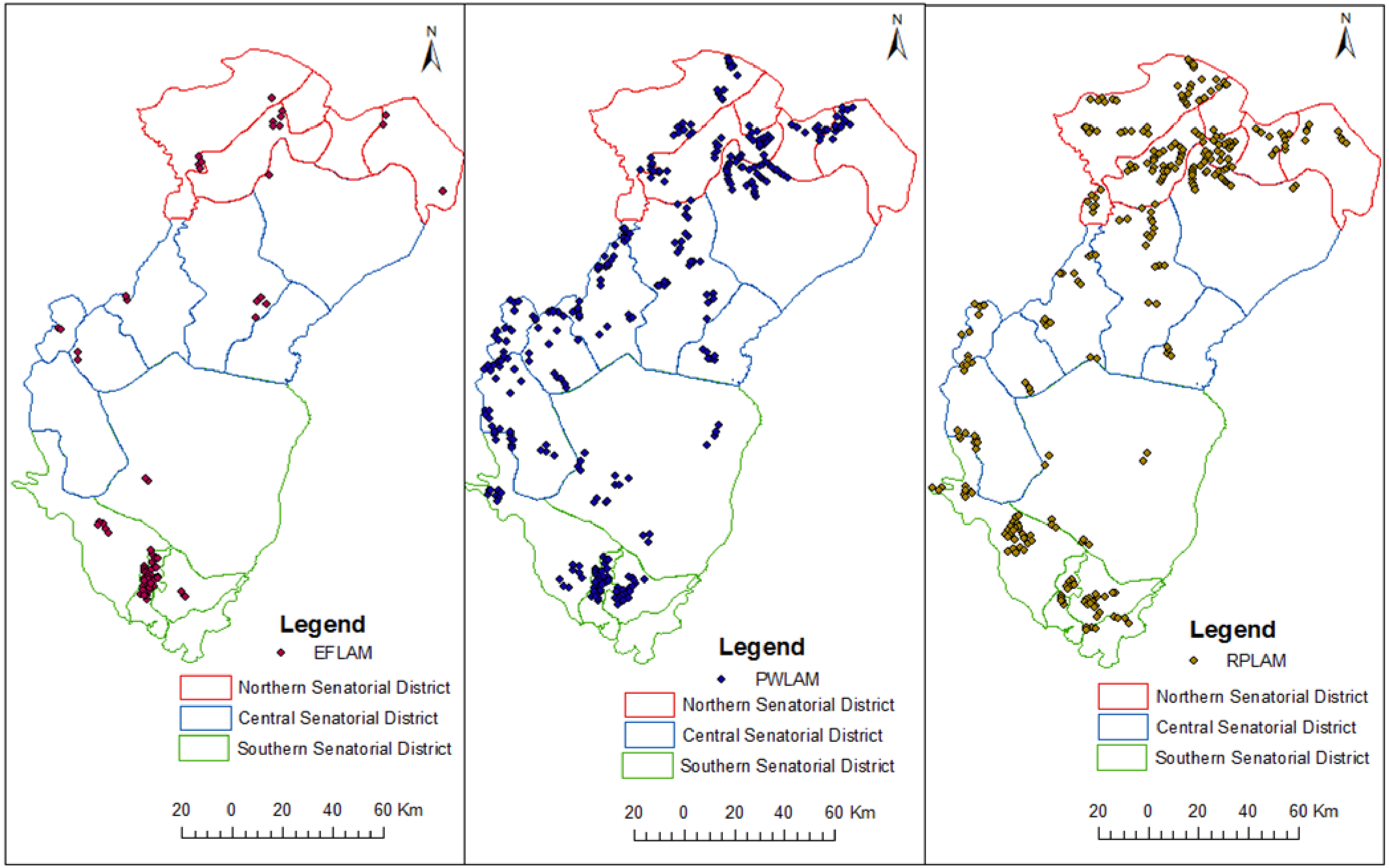

Figure 8.4: Communities served within 15 minutes' maximum drive in the dry season

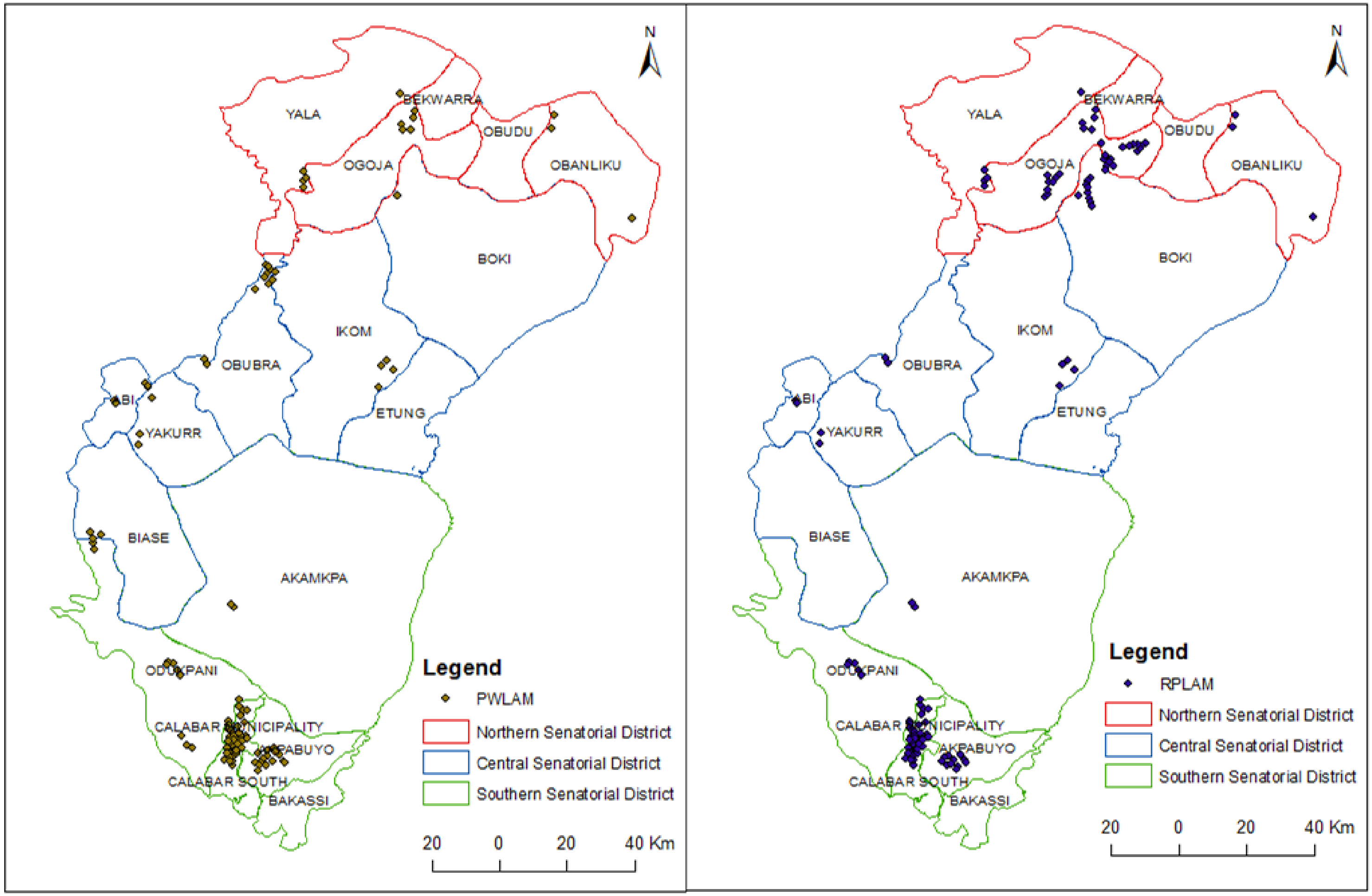

Figure 8.5: Comparing population coverage with 5 new optimised locations at 15 minutes' maximum drive time in the dry season

8.2.1. Increasing population coverage of NHIS in the dry season

Based on the initial comparison of the performances of the three models, PWLAM and RPLAM would be preferred to EFLAM since they covered more communities and facilities (Table 8.1). Although these two models prove to be better than the EFLAM which portrays the current situation of NHIS facilities coverage in the State, it is unlikely that health care planners would be able to move the locations of the existing facilities. Therefore, PWLAM and RPLAM were used to select potential communities for future facilities, and the findings served as a sensitivity analysis of the two selected models. The performance of the two models was tested to see which of them would be more effective in the increase of NHIS coverage when new facilities are added to the systems. The findings are presented in Tables 8.2 – 8.4 as well as Figures 8.6 – 8.8.

8.2.1.1. Adding 5 new facilities using the dry season LAMs

Table 8.2 shows findings for the proposed addition of 5 new NHIS facilities to the system. Therefore, the number of facilities was increased to 72, and the models were set to select 67 required (existing facilities) plus 5 new optimal locations. The drive times thresholds, total population, and communities included in the model were the same as that of Table 8.1.

From Table 8.2, it was observed that RPLAM could cover additional 3.8% of the communities in comparison with PWLAM at 15 minutes' maximum drive to the closest facility while PWLAM could cover extra 4.2% of the population than the RPLAM. At 60 minutes' maximum drive to the nearest facility, the difference in communities' coverage was 3.5% in favour of RPLAM (60.4%) while the gap in population coverage was 5.1% in support of PWLAM (81.3%). It was also noted that there was no marked difference between the two models at 120 minutes' maximum drive since the gap in communities' coverage was 0.6% and the difference in population coverage was 0.8%.

Figure 8.6 shows a steady rise in communities and population coverage as drive time increased from 15 to 120 minutes. The gap between communities and population though wider at 15 minutes was closed at 120 minutes. The results show no difference in the two models at 120 minutes' drive to facilities.

Table 8.2: Dry season LAMs with 5 additional facilities

Drive time (min)	15	30	45	60	75	90	105	120
PWLAM communities and population coverage								
Communities' coverage (%)	105 (10.3)	217 (21.2)	412 (40.2)	583 (56.9)	735 (71.8)	832 (81.3)	914 (89.3)	978 (95.5)
Population coverage (%)	1844802 (50.8)	2179151 (60.1)	2572396 (70.9)	2950250 (81.3)	3189915 (87.9)	3367218 (92.8)	3495213 (96.3)	3579970 (98.7)
RPLAM communities and population coverage								
Communities' coverage (%)	144 (14.1)	256 (25.0)	438 (42.8)	619 (60.4)	751 (73.3)	857 (83.7)	928 (90.6)	972 (94.9)
Population coverage (%)	1684759 (46.4)	2010670 (55.4)	2445040 (67.4)	2764367 (76.2)	3067160 (84.5)	3252258 (89.6)	3364856 (92.7)	3552417 (97.9)

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 72

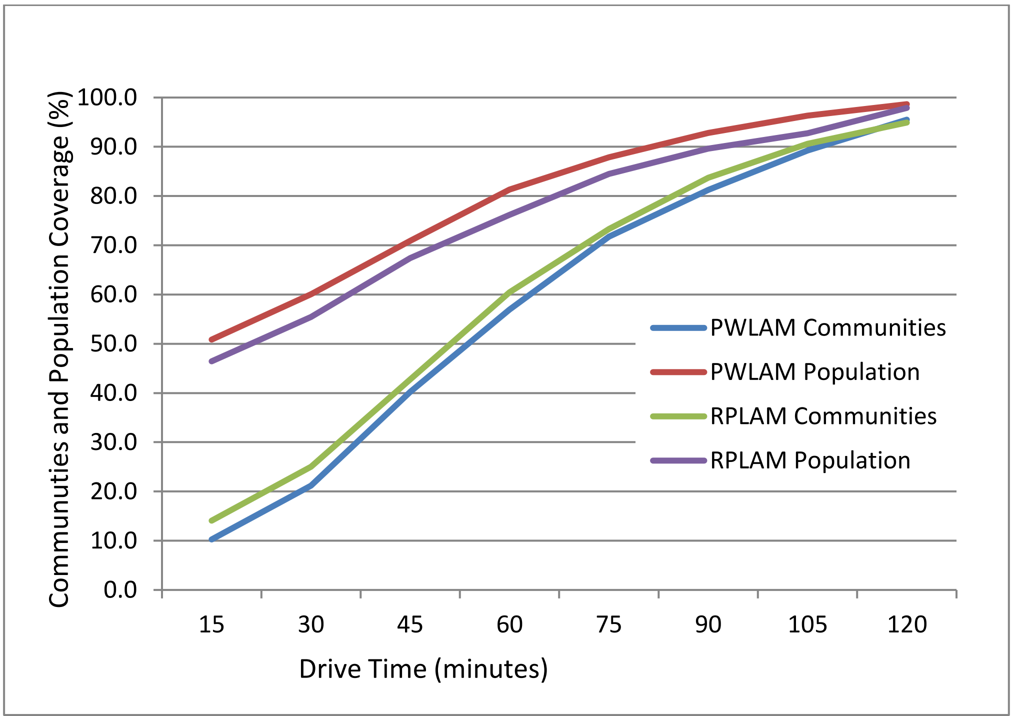

Figure 8.6: Dry season trade-off curves for communities and population coverage with 5 new facilities

8.2.1.2. Adding 10 new facilities using the dry season LAMs

RPLAM and PWLAM were also compared after adding 10 new proposed locations to the existing 67 NHIS facilities. From Table 8.3, the total number of health facilities to be selected in the model was increased to 77 (67 existing NHIS facilities and 10 new locations). When the maximum drive time was 15 minutes, PWLAM communities' coverage was 13.3%, and RPLAM communities' coverage was 14.2%, making a difference of 0.9%. Also, at 15 minutes, population coverage was 55.0% for PWLAM, and RPLAM was 48.4%, making a difference of 6.6% (239,502).

In Table 8.3, when maximum drive time was increased to 60 minutes, PWLAM covered 68.9% of the communities while RPLAM could cover 69.2%. At the same drive time, PWLAM coverage was 86.9% of the population while RPLAM's coverage was 81.3% of the population. At 60 minutes' drive to the nearest facility, the differences in coverage for the two models were 0.3% and 5.6% for communities and population coverage, respectively. Unlike Table 8.2, the PWLAM exceeded RPLAM's communities and population coverage at 120 minutes' drive time, though with a small margin (Table 8.3, Figure 8.7).

Table 8.3: Dry season LAMs with 10 additional facilities

Drive time (min)	15	30	45	60	75	90	105	120
PWLAM communities and population coverage								
No of communities (%)	136 (13.3)	271 (26.5)	506 (49.4)	706 (68.9)	836 (81.6)	931 (90.9)	981 (95.8)	1017 (99.3)
Population coverage (%)	1996392 (55.0)	2381246 (65.6)	2778511 (76.6)	3152822 (86.9)	3364194 (92.7)	3507121 (96.6)	3590421 (98.9)	3620025 (99.8)
RPLAM communities and population coverage								
Communities' coverage (%)	145 (14.2)	320 (31.3)	519 (50.7)	709 (69.2)	892 (87.1)	930 (90.8)	982 (95.9)	1009 (98.5)
Population coverage (%)	1755069 (48.4)	2071773 (57.1)	2571241 (70.9)	2950095 (81.3)	3235278 (89.2)	3419216 (94.2)	3510878 (96.8)	3602385 (99.3)

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 77

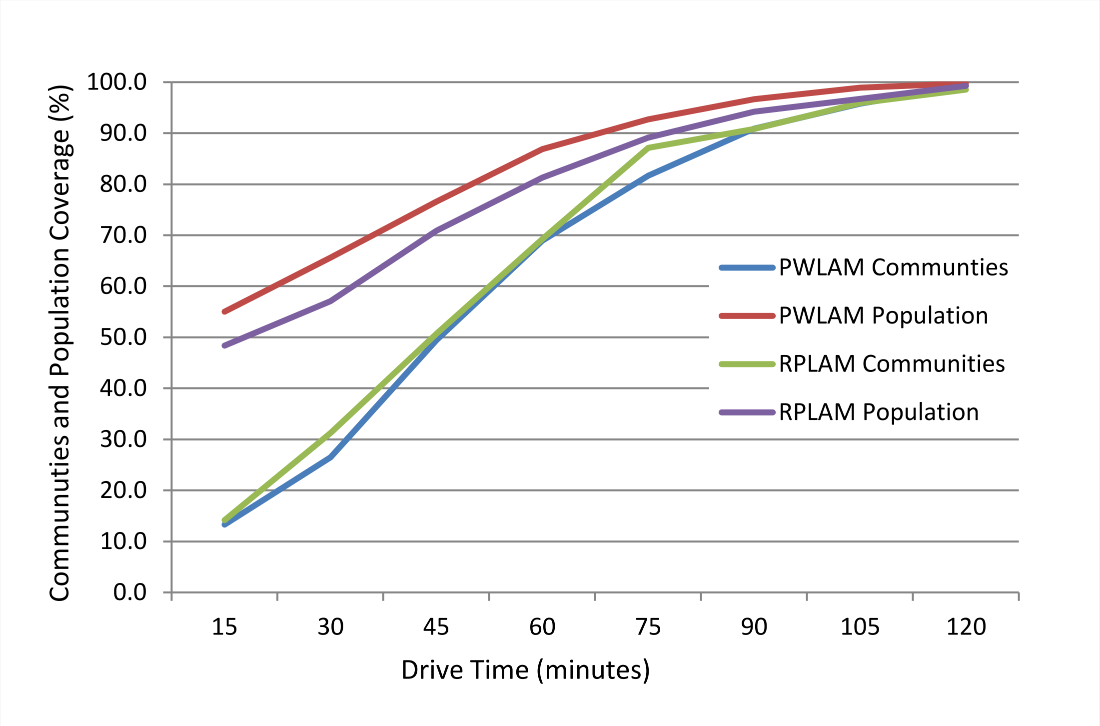

Figure 8.7: Dry season trade-off curves for communities and population coverage with 10 new facilities

8.2.1.3. Adding 15 new facilities using the dry season LAMs

PWLAM and RPLAM were also used to select 15 additional suitable locations for new NHIS in addition to the existing ones (Table 8.4). The difference in communities' coverage between the two at 15 minutes maximum drive time was 0.9% in favour of RPLAM and the gap in population coverage at the same time was 8% in favour of PWLAM. When the threshold was fixed at 60 minutes, the differences were 0.5% and 5.3% for communities and population coverage respectively in favour of PWLAM. At 120 minutes threshold, PWLAM was also higher as it could cover every community and the entire population while RPLAM could cover 99% of the communities and 99.5% of the population.

Figure 8.8 shows no major difference in communities' coverage between the two models, especially between 45 – 75 minutes' drive time. In the population coverage, there is a gap between the two models from 15 minutes until it was closed at 120 minutes. With an additional 15 facilities to existing NHIS, PWLAM covered more population and communities between 60 – 120 minutes.

Table 8.4: Dry season LAMs with 15 Additional facilities

Drive time (min)	15	30	45	60	75	90	105	120
PWLAM communities and population coverage								
No of communities (%)	162 (15.8)	316 (30.9)	588 (57.4)	775 (75.7)	895 (87.4)	978 (95.5)	1016 (99.2)	1024 (100.0)
Population coverage (%)	2122963 (58.5)	2524928 (69.6)	2939040 (81.0)	3289087 (90.6)	3475940 (95.8)	3576765 (98.6)	3621811 (99.8)	3628810 (100.0)
RPLAM communities and population coverage								
Communities' coverage (%)	171 (16.7)	374 (36.5)	577 (56.3)	770 (75.2)	877 (85.6)	967 (94.4)	1001 (97.8)	1014 (99.0)
Population coverage (%)	1831478 (50.5)	2157066 (59.4)	2658702 (73.3)	3094944 (85.3)	3328355 (91.7)	3483358 (96.0)	3544903 (97.7)	3609033 (99.5)

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 82

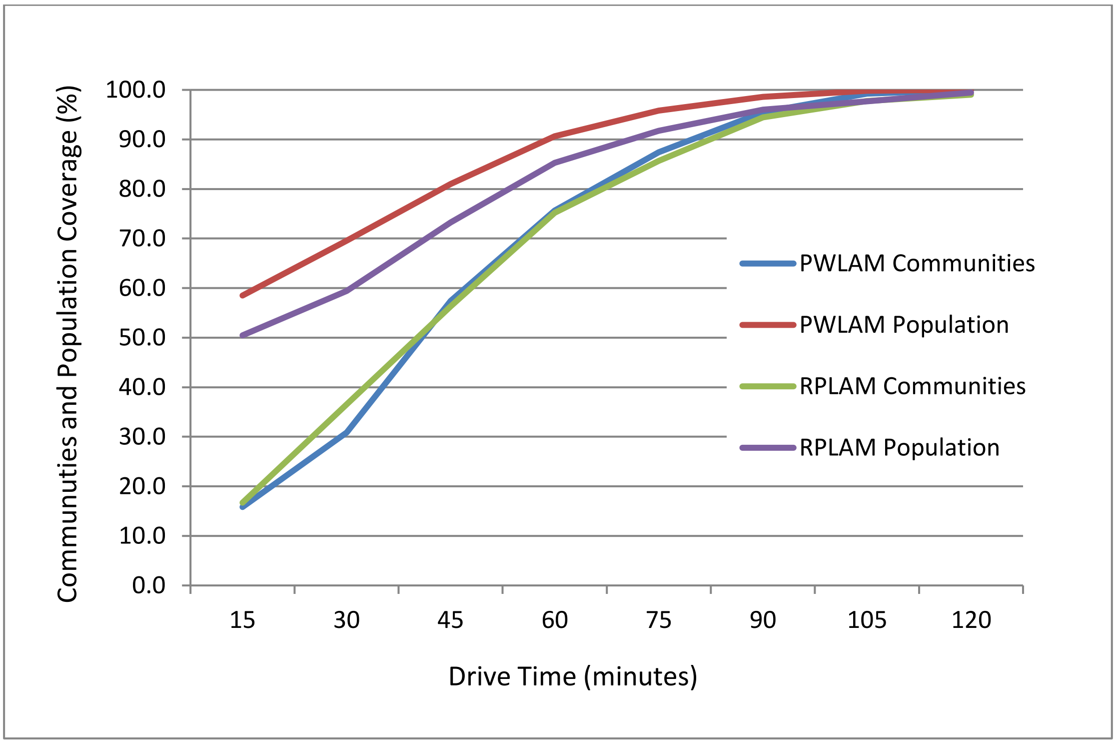

Figure 8.8: Trade-off curve for communities and population coverage with 15 new facilities

8.3. Location-allocation of NHIS in the wet season

Wet season results are presented in Tables 8.5 – 8.8. In overall, the models' performances decreased in the wet season compared to the dry season. For communities' coverage, EFLAM performed better than the PWLAM at 15 minutes' drive, but less than RPLAM (Table 8.5). While EFLAM covered 4.7% of communities at 15 minutes, PWLAM was 1.5%, and RPLAM was 24.4%. Like, the dry season results, the effectiveness of EFLAM within 15 minutes' drive to NHIS could have resulted from the clustering of the facilities. Although EFLAM was the best at 15 minutes, communities' coverage of PWLAM was 3 times higher than EFLAM at 60 minutes. At 120 minutes, communities' coverage was 69%, 100% and 86% for EFLAM, PWLAM, and RPLAM, respectively. It was observed EFLAM's communities' coverage increased by 10% per additional 15 minutes' drive. However, PWLAM and RPLAM had no pattern of increase.

Population coverage was 18.7%, 62.9% and 12.7% for EFLAM, PWLAM, and RPLAM, making RPLAM the least at 15 minutes (Table 8.5). Like, the communities' coverage, PWLAM covered the whole population at 120 minutes while EFLAM covered 81% and RPLAM 83%. In overall, PWLAM was the best model, followed by the RPLAM.

Table 8.5: Service coverage of existing and optimised models in the wet season

Existing facilities								
Drive time (min)	15	30	45	60	75	90	105	120
EFLAM communities and population coverage								
No of comm.	48	145	246	347	445	534	629	708
(%)	4.7	14.2	24.0	33.9	43.5	52.2	61.4	69.1
Pop. Coverage	677202	1506641	1896311	2193674	2430533	2587705	2791311	2937898
(%)	18.7	41.5	52.3	60.5	67.0	71.3	76.9	81.0
PWLAM communities and population coverage								
Comm. Coverage	15	482	738	868	936	982	1020	1024
(%)	1.5	47.1	72.1	84.8	91.4	95.9	99.6	100
Pop. Coverage	2281098	2782068	3188937	3410399	3535163	3597441	3626588	3628810
(%)	62.9	76.7	87.9	94.0	97.4	99.1	99.9	100
RPLAM communities and population coverage								
Comm. Coverage	250	459	605	699	750	803	844	880
(%)	24.4	44.8	59.1	68.3	73.2	78.4	82.4	85.9
Pop. Coverage	462080	933307	1165586	1498121	1818232	2254547	2618770	2996465
(%)	12.7	25.7	32.1	41.3	50.1	62.1	72.2	82.8

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 72

8.3.1. Adding 5 new facilities using the wet season LAMs

Table 8.6 shows the situation of the NHIS in the wet season after 5 proposed facilities were added using PWLAM and RPLAM. Both models were more suitable than EFLAM. Like the dry season analysis, all locations of existing facilities were maintained. It was observed that PWLAM covered more population while RPLAM covered more communities. Communities' coverage at 15, 60 and 120 minutes were 5.2%, 45.5% and 76.4% respectively for PWLAM and 9.0%, 49.2% and 80.1% for RPLAM respectively. However, the margin of difference was not very large, except at 15 minutes where RPLAM was higher by 3.8%. Population coverage at 15, 60 and 120 minutes were 31.9%, 68.8% and 88.5% for PWLAM respectively, while it was 19.7%, 66.4 and 85.9% respectively for RPLAM. Like the communities' coverage, the margin of difference between the two models was small except at 15 minutes where PWLAM was higher by 12.2%.

Table 8.6: Wet season LAMs with 5 additional facilities

Additional 5 facilities								
Drive time (min)	15	30	45	60	75	90	105	120
PWLAM communities and population coverage								
Comm. coverage	53	182	352	466	571	671	735	782
(%)	5.2	17.8	34.4	45.5	55.8	65.5	71.8	76.4
Pop. coverage	1158502	1834870	2195752	2496656	2765432	2922214	3074402	3211564
(%)	31.9	50.6	60.5	68.8	76.2	80.5	84.7	88.5
RPLAM communities and population coverage								
Comm. coverage	92	240	374	504	611	680	757	820
(%)	9.0	23.4	36.5	49.2	59.7	66.4	73.9	80.1
Pop. coverage	715079	1661836	2077636	2409065	2653933	2830023	2998592	3116712
(%)	19.7	45.8	57.3	66.4	73.1	78.0	82.6	85.9

8.3.2. Adding 10 new facilities using the wet season LAMs

From Table 8.7, an additional 10 facilities were added to the wet season's PWLAM and RPLAM. Although PWLAM's communities' coverage was lower at 15 minutes (5.2%), it equaled RPLAM at 105 and 120 minutes. In the population coverage, PWLAM could reach more communities than the RPLAM. Communities coverage at 15, 60 and 120 minutes were 5.2%, 52.7% and 83.0% respectively for PWLAM, and 11.3%, 56.5% and 83.4% respectively for RPLAM. Population coverage at 15, 60 and 120 minutes were 31.9%, 75.1% and 92.8% respectively for PWLAM, and 22.1%, 70.1% and 87.6% respectively for RPLAM.

8.3.3. Adding 15 new facilities using the wet season LAMs

Table 8.8 shows the addition of 15 proposed facilities to the existing NHIS facilities. Unlike previous results, the addition of 15 facilities brought the model outputs very close. For instance, communities' coverage in PWLAM and RPLAM were similar from 30 minutes to 120 minutes. The finding indicates that the higher the number of facilities added, the closer the performances of the two models. However, population coverage at 15, 60 and 120 minutes were 43.3%, 79.9%, and 95.6% respectively for PWLAM, and 22.9%, 72.2% and

89.1% respectively for RPLAM.

Table 8.7: Wet season LAMs with 10 additional facilities

Additional 10 facilities								
Drive time (min)	15	30	45	60	75	90	105	120
PWLAM communities and population coverage								
Comm. coverage	53	239	379	540	631	720	801	850
(%)	5.2	23.3	37.0	52.7	61.6	70.3	78.2	83.0
Pop. coverage	1158502	2032469	2414952	2724169	2953584	3108483	3273026	3369174
(%)	31.9	56.0	66.6	75.1	81.4	85.7	90.2	92.8
RPLAM communities and population coverage								
Comm. coverage	116	288	435	578	684	748	802	854
(%)	11.3	28.1	42.5	56.5	66.8	73.1	78.3	83.4
Pop. coverage	800834	1723957	2152648	2545151	2809253	2937332	3062759	3179299
(%)	22.1	47.5	59.3	70.1	77.4	81.0	84.4	87.6

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 77

Table 8.8: Wet season LAMs with 15 Additional facilities

Additional 15 facilities								
Drive time (min)	15	30	45	60	75	90	105	120
PWLAM communities and population coverage								
Comm. coverage	88	278	471	609	716	773	856	908
(%)	8.6	27.1	46.0	59.5	70.0	75.5	83.6	88.7
Pop. coverage	1571749	2222590	2599670	2897548	3098190	3227218	3385413	3470238
(%)	43.3	61.3	71.6	79.9	85.4	89.0	93.3	95.6
RPLAM communities and population coverage								
Comm. coverage	141	336	494	623	722	785	833	875
(%)	13.8	32.8	48.2	60.8	70.5	76.7	81.3	85.5
Pop. coverage	830449	1811955	2223349	2620039	2882392	3005578	3119541	3234091
(%)	22.9	49.9	61.3	72.2	79.4	82.8	86.0	89.1

Total Population = 3,628,810, Total number of Communities = 1024, Number of facilities = 82

8.4. Performances of LAMs in the wet and dry seasons

Apart from identifying potential location options for increased geographical access to the NHIS facilities, this study also tested the performances of the models in the dry and wet seasons. Since drive times to the NHIS in the wet season are longer than the dry season because of the flooding on some road segments (Chapter Six), the performances of new locations selected by LAMs were expected to decline in the wet season.

8.4.1. Performance of EFLAM

The analysis of EFLAM showed that more population and communities were reached in the dry season (Figure 8.9). There was no major wet-dry season difference between the communities and population from 0 – 30 minutes' drive. However, the gap began to widen steadily after 30 minutes until to 120 minutes. That implies, seasonal variation in communities' coverage was only effective after 30 minutes and the longer the distance, the wider the margin of difference in seasons. Unlike communities, population coverage gap was wider at 0 – 30 minutes, but it maintained a steady gap of approximately 10% difference until 120 minutes. Therefore, the wet-dry season performance difference of EFLAM was 10%. That implies the population coverage performance of EFLAM would be overestimated by 10% if the wet season was not accommodated in the model.

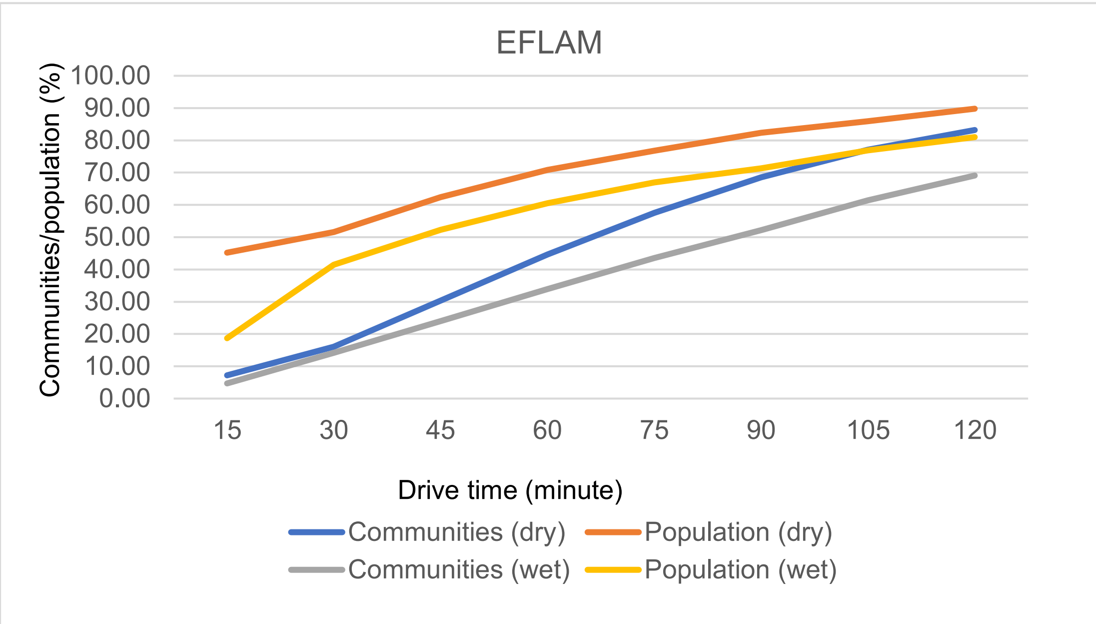

Figure 8.9: EFLAM in the dry and wet seasons

8.4.2. Performance of PWLAM

From Figure 8.10, there was a marked variation in the wet and dry season PWLAMs. While the all communities and population were reached within 60 minutes' drive in the dry season, all were reached at 120 minutes in the wet season. Unlike the dry season which access was 100% at 60 minutes, the wet season's PWLAM could reach only 85% of the communities and 94% of the population within the same drive time. That implies a loss of 15% communities and 6% of population access in the wet season. It also lost 32% and 11% of communities and population access respectively at 15 minutes' drive time. However, unlike EFLAM, it was found that the longer the drive time, the smaller the difference between wet and dry season access to NHIS. Therefore, if the wet season is not accommodated in the PWLAM model, its performance will be overestimated by 6% of the population and 15% of community access after 60 minutes' drive. The population coverage of model will also be overestimated by 11% at 15 minutes' drive.

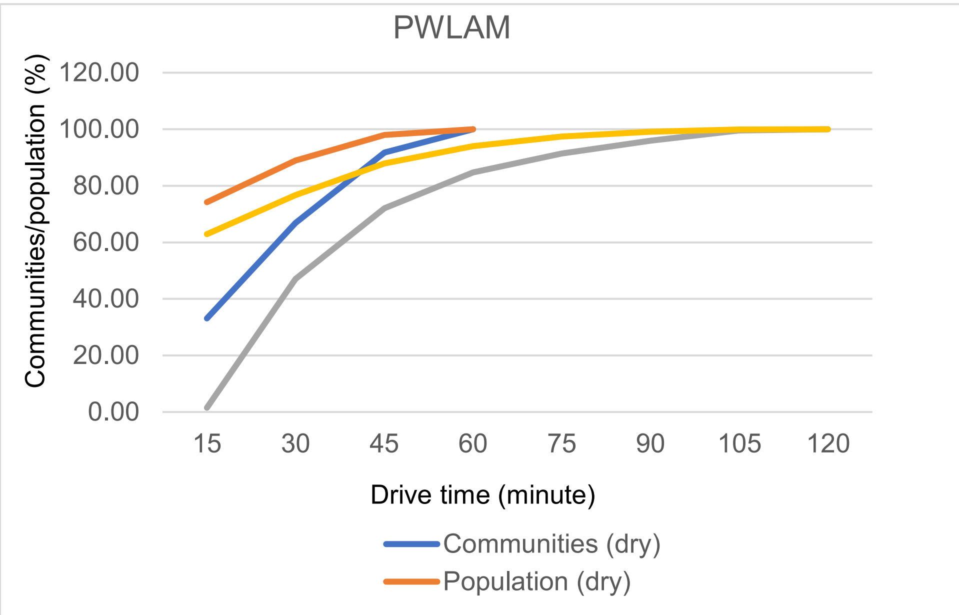

Figure 8.10: PWLAM in the dry and wet seasons

8.4.3. Performance of RPLAM

The RPLAM was quite different from the EFLAM and the PWLAM. It lost 3.4% of community access and 17.1% of population access in the wet season at 15 minutes' drive (Figure 8.11). At 60 minutes' drive, the loss increased to 17.3% and 48.3% for communities and population respectively. RPLAM suffered more loss of population access than communities' access in the wet season while the opposite was the case with the PWLAM. Therefore, executing the RPLAM without considering the wet season could lead to an overestimation of the model's performance by nearly 50% at 60 minutes' drive.

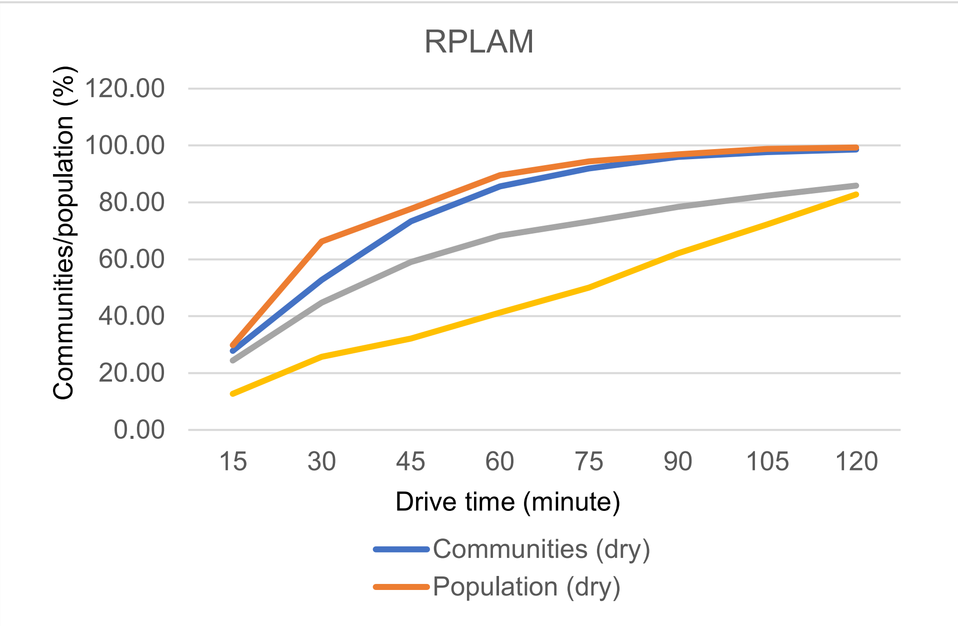

Figure 8.11: RPLAM in the dry and wet seasons

8.4.4. Seasonality of model performance with additional facilities

The seasonality of PWLAM and RPLAM performances in the wet and dry seasons were examined (Figures 8.12 and 8.13). With additional 5 facilities, both models lost 5.1% of communities access in the wet season at 15 minutes' drive compared to the dry season. However, population coverage declined by 18.9% in the PWLAM and 26.7% in the RPLAM, making a difference of 7.8%. At 60 minutes' drive time, PWLAM's wet/dry season differences were 11.4% and 12.5% for communities and population respectively. The difference was also 11.2% and 9.8% for communities and population respectively for RPLAM at 60 minutes. The two models performed differently in the wet season. However, the PWLAM was better than the RPLAM because it covered more communities than the latter in the wet season.

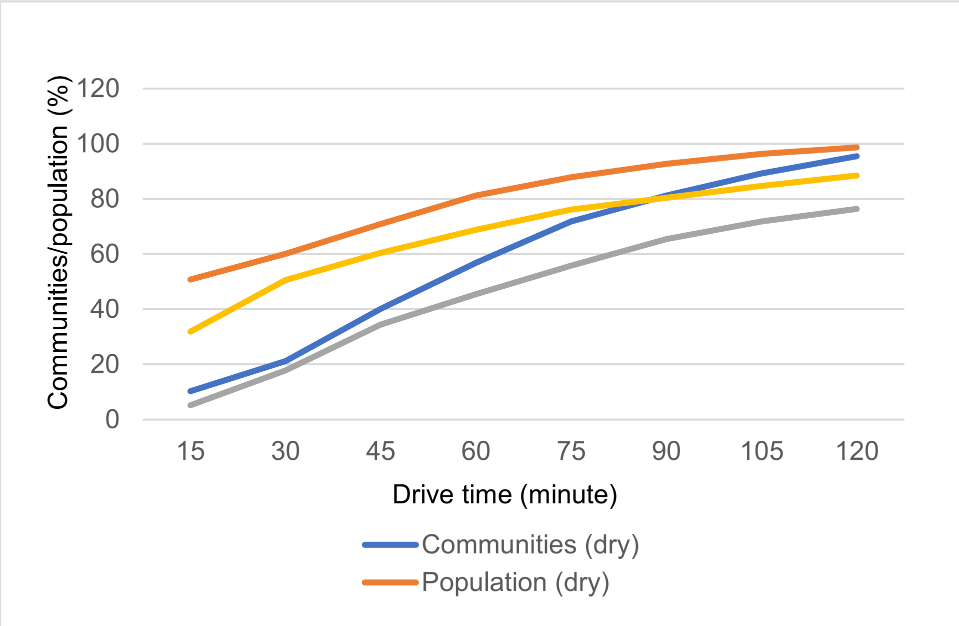

Figure 8.12: PWLAM and 5 additional facilities the dry and wet seasons

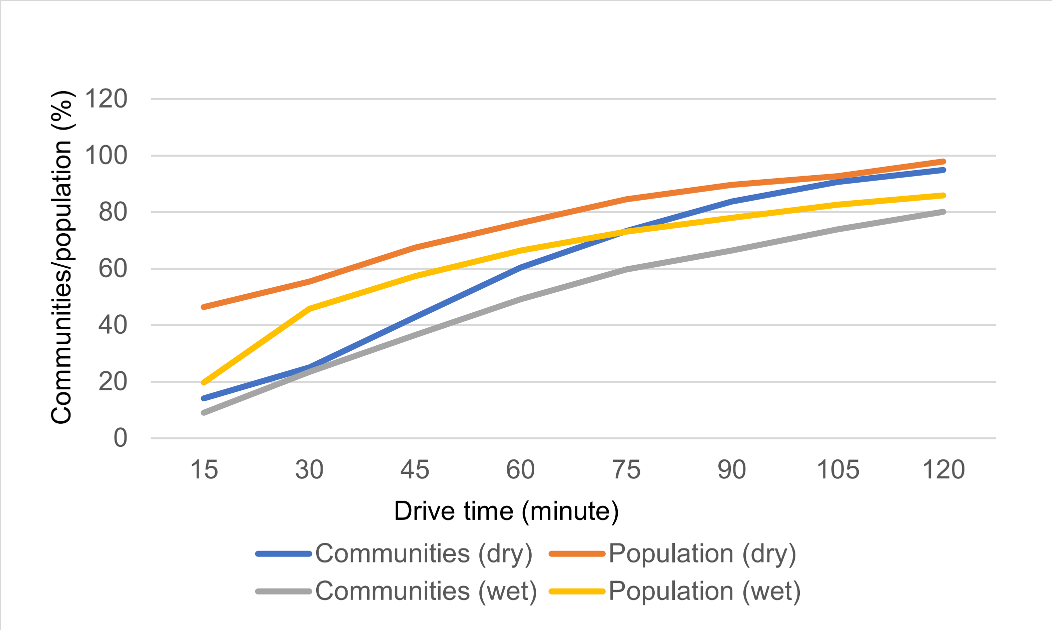

Figure 8.13: RPLAM and 5 additional facilities the dry and wet seasons

8.5. Summary

Chapter Eight examined the seasonality of LAMs performances using EFLAM, RPLAM and PWLAM. Since seasons are rarely considered in LAMs for healthcare planning, this study fills the gap in the literature by fulfilling the fourth objective of this thesis. NHIS was used in this study to demonstrate the application of LAMs and the same method can be used to locate any form of health service.

Core findings:

i. The performances of LAMs decreased in the wet season when compared to the dry season.

ii. RPLAM and PWLAM performed differently but the PWLAM was better in the wet season.

iii. EFLAM which shows the present situation of NHIS facilities was most effective within 15 minutes' drive because the facilities are clustered.

This study demonstrated the importance of accommodating seasonal variability of geographical access in LAMs for healthcare. The performances of the three models decreased in the wet season in terms of population and communities reached. EFLAM was overestimated by at least 10% when the wet season component was not in the model. PWLAM lost 6% of the population and 15% of communities in the wet season after 60 minutes' drive to facilities. At 15 minutes', the population reached by PWLAM also decreased by 11%. RPLAM population access decreased by approximately 50% at 60 minutes' drive in the wet season. Therefore, the study or use of LAMs for healthcare without including seasonality of geographical access may produce misleading results.

PWLAM exceeded the performance of RPLAM when examined with 5 additional facilities in the wet season. PWLAM covered 7.8% more of the population than RPLAM at 15 minutes' drive with 5 new facilities although both model performances decreased in the wet season. However, the difference between the two models decreased as the drive times to facilities increased.

Since most existing NHIS facilities were clustered in the densely populated urban areas, EFLAM was most effective within 15 minutes' drive. PWLAM and RPLAM exceeded the performance of the EFLAM after 15 minutes since their models selected optimised locations that could enhance population coverage. Although the performance of EFLAM was low, it is good to note that the facilities were situated in the urban areas to maximise population coverage. The plan seems to be the ideal at the time since every healthcare planner would aim at the highest population coverage for any facility. It can also be recalled that NHIS facilities are managed in partnership with the private sector. The private sector would locate a facility based on the estimated profit margin. Although the reason looks justifiable, if the PWLAM were used in the planning, the private sector would still maximise profit since it targeted highly populated communities.

This chapter also showed that instead of increasing population coverage by mere registration to the service, planners could use the MCLP models to estimate population coverage over desired travel distance or time. The population coverage could then become the target of the government. In that way, planners may be spared the enticement of setting an arbitrary NHIS registration goal which may be achieved without improving access to healthcare services. It is obvious that registration to the service may not translate into utilisation if the distance to the service is not favourable. The MCLP models can address this challenge of lack of utilization of the service after registration due to excessive travel time. Also, the registration target of the service may be difficult to achieve if the users are not sure of the ability to use the service afterwards.

Conclusively, this chapter demonstrated the importance of considering the seasonality of geographical access in the use of LAMs for healthcare research or planning. LAMs performances decreased in the wet season, indicating a spatiotemporal difference in their abilities to select optimised locations or increase population access to healthcare. The limitations and implications of this study are discussed in the next chapter (Chapter Nine). The next chapter brings the major findings of this thesis together to make conclusions and recommendations about seasonal geographical access to healthcare.

CHAPTER NINE: SUMMARY, RECOMMENDATIONS AND CONCLUSION

9. Chapter overview

This chapter is the last of this thesis, which examined seasonal geographical access to healthcare. Being the concluding chapter, it synthesises the introductory chapters, literature review, and empirical chapters to draw some conclusions and makes recommendations about the seasonality of geographical access to healthcare. The chapter presents the summary of research findings, limitations of the study, and links with the broader perspective of spatial access to healthcare in LMICs and similar locations. It provides generalisable findings and implications for policymakers and researchers.

9.1. Summary of research findings

This study was designed to examine seasonal geographical access to healthcare. The research was timely because of the research gap on seasonality of geographical access to health services, which the systematic review in Chapter Four identified. The gap was filled by measuring drive and walking times to health facilities in the dry and wet seasons, investigating seasonal associations of drive times and malaria outcomes in selected hospitals, and examining the effects of seasons on the use of LAMs for healthcare planning.

The objectives of the study were:

v. To review the literature on geographical access to health services in Low-and Middle-Income Countries (LMICs).

vi. To examine geographical access to healthcare in Cross River State in the wet and dry seasons.

vii. To investigate seasonal associations of drive times to healthcare, malaria severity and hospital admissions in selected Cross River State hospitals.

viii. To examine the effect of wet season on modelling method to support policy aimed at increasing geographical access to NHIS in Cross River State.

The first objective was fulfilled in Chapter Four in a systematic review of geographical access to healthcare in LMICs. The review found compelling evidence of the importance of geographical access to health services. Some of the studies did demonstrate inequality in access to health care between urban and rural areas. It was found that distance to health facilities in urban areas was half of the distance in rural areas in some studies. Most of the studies found a decrease in the utilisation of health facilities after certain distance thresholds. Most of the studies also found that diseases outcomes like severity, admissions and mortality increased with distance to the nearest health facilities with a stronger effect in the rural areas. However, considering the heterogeneity in the studies, quantitative synthesis to produce a summary measure of the impact of distance on healthcare was not appropriate. Although a few studies also found that distance was unrelated to the outcomes, overall, the review justifies the need to strive for equitable geographical access to healthcare.

The gaps identified in the review were; lack of evidence on empirical measurements of geographical access to healthcare, limited evidence on seasonal geographical access to healthcare, insufficient evidence on the association between distance to healthcare and differential malaria outcomes, use of less optimised methods in health facilities location planning and limited data.

The second objective was fulfilled in Chapter Six by examining geographical access to healthcare in the wet and dry seasons. The travel scenarios in the study were walking and drive times because they were the most suitable because of their ability to track travel time and journey delays. The study found that average drive time to all health facilities increased in the wet season while population access decreased. Also, 30% of CSD and 79% of SSD population lost access to healthcare at some point in the wet season. However, the impact would vary depending on infrastructural development in a community and proximity to the flood regime.

Nearly half of the CSD and 70% of SSD health facilities were potentially affected by seasonal flooding. Average drive times to PHCs in the wet season increased by 29 and 38 minutes in CSD and SSD, respectively compared to the dry season. Average drive times to hospitals were also increased by 97.4 minutes in CSD and 56.3 minutes in SSD in the wet season. Average drive time to NHIS also increased by 46.8 minutes (CSD) and 60.3 minutes (SSD). Although the study may not be very effective in measuring walking time access in the wet season, the findings indicate that people who walk will reach the facilities faster during that period if they cross the flooded road segments by car or canoe. This study justifies the need for infrastructural development as a way of sustaining all-year round population access to healthcare and the inclusion of seasonal variability of geographical access in healthcare planning and research.

In the wet and dry seasons, it was observed that health facilities were distributed deliberately or by chance according to the population density of senatorial districts. More facilities were in the SSD, which also had the highest population density. However, the ratio of facilities to population showed a marked inequity in that distribution as the district with the lowest population density (NSD) had the highest ratio of hospitals and NHIS services. Although the SSD had a low ratio of population to facilities, it also had the shortest average distances to most healthcare facilities and better population coverage. The findings were probably due to a better road network in the SSD and because that it is the most urbanised district, the communities tend to be closer to each other. It was also found that the introduction of NHIS in the state increased access to higher-order government-managed health facilities since it was more accessible than hospitals.

The third objective was fulfilled in Chapter Seven with an investigation of the seasonal association of drive times to healthcare and differential malaria outcomes in two public hospitals (CGH and UGH). Children under five years were more likely to develop severe malaria, have hospital admission and die of the disease in the rural hospital (UGH). Malaria patients in UGH were six times more likely to die, and mortality among under-five children was 9.3 times higher than CGH. These findings point to the problem of healthcare inequality in rural areas. While the seasonal association of malaria severity was insignificant, the chances of having malaria admission in both hospitals were higher in the dry season even after adjusting for age, gender and drive times to health facilities. It could mean that fewer admittable malaria cases were reported in hospitals in the wet season due to transport issues, or some would have used private facilities and self-medication.

The study found no compelling evidence of an association between drive times and malaria outcomes in the selected hospitals even after analysing the data by seasons. However, there were a few significant associations which indicated higher odds of malaria severity and admissions within 30-60 minutes' drive time to CGH and 60- 90 minutes' drive to UGH. Therefore, the hypothesis that malaria outcomes increases in the wet season and worse outcomes live far from the health facilities is refuted in this study. Data was a major problem in this study. The data lacked the statistical power to detect seasonal differences in malaria outcomes because some of the drive times groups had no values.

The last objective was fulfilled in Chapter Eight by examining the effect of wet season on modelling method to support policy aimed at increasing geographical access to NHIS in Cross River State. The MCLP was further customised into three models, namely; EFLAM.

RPLAM and PWLAM. The performances of the three models in terms of communities and population coverage in the dry season were higher than the wet season. EFLAM had a 10% steady decline of population coverage after 30 minutes' drive in the wet season. The population and communities' coverage of PWLAM also decreased by 6% and 15% respectively after 60 minutes' drive time in the wet season. Similarly, RPLAM population coverage dropped by 50% at 60 minutes' drive in the wet season. These findings imply that healthcare accessibility methods that exclude the seasonality of geographical access are likely to produce misleading results.

9.2. Limitations of the study

There is an awareness that data limitations, model assumptions, research method and possible confounding variables may influence the outcome of this study. Therefore, this section discusses those limitations and how this study overcame them.

9.2.1. Data limitations

One outstanding problem of research in the developing countries including Nigeria is the lack of data. Unlike some developed countries where secondary research data may be easily accessible, in the developing countries the opposite is the case. In this study, datasets including the location of health facilities, population data, malaria data and the road network were sourced from various sources and received in different formats. Such datasets may have problems including positional accuracy, missing data, incompleteness and human errors which the user of this research should be aware of.

9.2.2. Positional accuracy of health facilities and patients' addresses

The original health facilities datasets and malaria records had no spatial coordinate for the intended analyses. Since each facility or patient in the record had an address variable being either a street name or community name, the address variable was used to trace and extract the coordinate point (Easting and Northing) for each facility or patient from the Cross River State digital orthophoto map and Google Map. The potential issues with that operation are map error, location approximation and crowdsourcing of unknown locations.

Map error might influence measurements and the outcomes of this study if there were variations between the coordinates obtained from the map and the coordinates that would have been obtained from actual ground measurements. However, the actual ground measurements could not be obtained because of the time limit of the PhD research and high financial cost. However, the chances of having map error would have been eliminated or reduced to the barest minimum by repeated measurements. Also, the local projection datum (WGS 84 Zone 32N) was used in the extraction of data from the reference map files. The coordinates were plotted to the administrative map of the state and communities' data were used to check the accuracy of the points and all the points fell within the expected locations. That was possible because the process involved extracting a point from a polygon feature in each case and the point would be accurate wherever it is taken within the polygon.

Apart from map error, when the location of a facility was not found in any of the reference map files, the coordinate point of the community centroid in the address was used instead. This problem was only peculiar to PHCs. The coordinates of communities were used as address coordinates for all PHCs for consistency sake. Such approximation of locations might be a problem if the community's centroid coordinate was obtained from the centre of the community while the actual location of PHC is at the fringes. However, that may not constitute a major problem because the communities are small especially in the rural areas. It is also unlikely that PHCs would be sited extremely far from the centre of population which was the community centroid.

Data crowdsourcing was also necessary at the preparation stage when more than one facility was to be extracted from a community or when the street address could not be traced on the reference map. Unlike the PHCs which had a facility to a community, the NHIS had more than one facility within a community. Crowdsourcing of location was peculiar to private NHIS facilities. The descriptions of those addresses that could not be obtained from Google Map were received by phone calls from people who were familiar with those locations. Data crowdsourcing might affect the findings of this study if the location descriptions obtained were inaccurate. However, the chances of receiving inaccurate descriptions were reduced since the descriptions were provided by current residents of communities and the location points were also extracted from the map during the phone call. Data crowd-sourcing is the cheapest and a time-saving method of collecting geospatial data for research and planning purposes (Heipke, 2010).

Although it may be argued that the data extraction processes were less precise than actual measurements, it is also important to note that the methods used were the best as at the time of this research. Since the level of positional accuracy expected of this study is not as high as that of a cadastral boundary (i.e. measuring a small parcel of land), the chances of having an error that may cause a massive deviation from the results obtained is slim.

9.2.3. Missing population communities

It can also be recalled that population datasets were scanned copies of the 1991 population census which were projected to the year 2015 during this study. The main challenge was not in the projection since projected population datasets are widely used in research. However, some communities that came with the original population datasets had no location coordinates. Out of 1396 communities that were represented in the population file, only 906 communities that had location coordinates were interpolated to produce a population surface. The surface gave population values to locations that had no values using the population of communities around it. The population values of the 1024 communities in the studies were extracted from that interpolated population surface.

The close estimation of the community level projection (3,628,810) of this study with the state level projection of the Nigeria National Bureau of Statistics (3,755,757) for the same year eliminates the chances of gross error in the population data. The world population projection of Population Reference Bureau since 1950 was inaccurate by 4% in 12 projections and high accuracy is not to be expected at country and smaller levels (Population Reference Bureau, 2015). With the 3.4% (community to state) projection difference, it seems reasonable to say that the population projection used in this study was within the acceptable error limit.

9.2.4. Incomplete attributes of malaria cases and data processing

Another limitation was data incompleteness of the malaria files that were supplied by the Calabar General Hospital. While the UGH data was complete, 228 cases (5.3%) who had incomplete attributes from the CGH were excluded from the study because they did not have complete attributes for the analysis. The implication is that the excluded cases may have either made significant associations insignificant or vice-versa, and the effect of that in the study is unknown. The problem raises the need for the improvement of health surveillance databases in hospitals. Also, the chances of having human error when converting the malaria data are unlikely since discrepancies in the records were resolved with the hospitals' record officers over the phone.

9.2.5. Confounding

Confounding in this study is only relevant to the examination of the association between malaria outcomes and proximity to health facilities that were examined in Chapter Seven.

The presence of unmeasured confounders may have limited the power of this study to detect significant associations between malaria outcomes and proximity to health facilities. However, this study could not match potentially confounding variables including education, comorbidity and socio-economic status because of lack of data.

Age groups were stratified into intervals of 5 years to reduce confounding by age and drive times to health facilities were grouped into 30 minutes' intervals to reveal a progressive increase of health outcome as distance increases from the health facilities. Age, gender and drive times to facilities were included in multivariate analyses of malaria outcomes.

9.2.6. Choice of method

Although the best methods were used in this study, users must be aware of the limitations of those methods. The assumption that patients would use the nearest health facility is used in most studies of geographical accessibility. This study also used the same assumption in the measurement of the population access to healthcare and modelling of new proposed locations for the NHIS. However, there is an awareness that some patients may not always use the nearest health facility because of personal preferences.

That may not affect the findings of this study because the focus of this research was on potential access and not revealed access. Moreover, the overwhelming evidence of distance decay effect in the utilisation of health facilities in LMICs that was reported in Chapter Four further strengthens the assumption that most patients in Cross River State would likely use the nearest health facility.

The measurement of wet season access to healthcare is new in literature, and the methods often used in the studies are rarely transferable. As far as it is known, its earliest study in Africa was in the planning of primary health care locations in Ghana (Oppong, 1996). In this study, the methods used in flood modelling, crossing of flooded road segments and estimation of the population affected by seasonal flooding were customised for this study. Standard flood models are usually produced from a robust simulation of measurable flood variables like elevation model, yearly flood regimes and estimated impact (Soares-Frazão *et al.*, 2008).

However, a standard flood model was not available for this study, and it was unrealistic to create one due to lack of data, time and funds. As a result, this study utilised published evidence of estimated communities at risk flooding and the main source flooding (cross river) in the estimation of a suitable flood regime for the study. Since the flood regime produced was based on published evidence about flooding, the findings thereof being the first of its kind in that location remains the most valid evidence.

After producing the custom flood model for this study, there was a need to estimate patients' travels across the potentially flooded road segments. Again, there were no relevant river crossing data as available published canoe sailing speed was that of professional sports. The gap was filled by measuring river crossing speed using a traditional canoe, and that speed was applied to the potentially flooded road segments. Average road driving speed was also modelled to change to river crossing speed as soon as the patient enters the flooded road segment. The assumption is that a patient would alight from the car at the beginning of the flooded part and use a canoe to cross and then continues with a car on the other side or average driving speed would reduce to average canoe sailing speed in the flooded segments if the segment is navigable by car.

Crossing of the flooded road segment with canoe was applicable to the rural areas who may not alternative routes to the health facility. Those in urban areas were expected to drive through the flooded segment if it is safe or use an alternative route to the hospital. In either of the options, the model calculates the shortest drive time from the community to the closest facility. The implication of that assumption is the exclusion of waiting times at the entrance and exit of the flooded road segment as it is unlikely that a patient would find a canoe immediately at the entrance and car at the exit. Thus, the model used may have underestimated travel times in the wet season. Waiting time was excluded because it is likely to vary from one location to another and the data was unavailable at the time of this study and the possibility of measuring it was unlikely. Also, flood impact in the rural areas may be severer than the urban areas, but such variations were not captured because of data limitations. This methodological issue leaves a gap for further studies on seasonal access to healthcare.

The last methodological issue to consider is the selection of an optimised location for new facilities in LAM. The LAM used in this study does not suggest a specific parcel of land for the construction of a new NHIS facility, like other similar models. Instead, it shows optimum communities that the facilities can be located. The findings may not pose any major problem since the points selected were communities' centroids which are supposed to be within the densely populated areas of the selected communities. During implementation, the planner would have to decide the actual parcel of land or a facility within the designated community, hence its flexibility. Planners would also take into consideration the variation between wet and dry season access.

9.3. Implications of this study

This section discusses the implications of the findings of this research with links to the broader perspective of geographical access to health services. For clarity, the discussion is subdivided into three to reflect the core components of empirical chapters of this thesis.

9.3.1. Seasonal geographical access to healthcare

This study began with a systematic review of the literature on geographical access to healthcare in LMICs. It was important to review studies from LMICs, to have a wider perspective of the subject in locations that have similar socio-economic and environmental characteristics to Nigeria. Since evidence on the seasonality of geographical access scarce in the review, the gap was filled in the empirical chapters.

The conventional methods of measuring geographical access to health care were the Euclidean distance (Ayeni, Rushton and McNulty, 1987; Noor *et al.*, 2003; Kumar, 2004), transport network (Al-Taiar *et al.*, 2010), and self-reported distance/time (Buor, 2002; Steinhardt, 2010). The most widely used of the three methods were Euclidean distance and self-reported distance/time, probably due to the ease of measurement. However, they may underestimate trips to health facilities and are also incapable of measuring seasonal geographical access. For instance, it is unlikely that people would travel along a straight line to health facilities as assumed by the Euclidean distance measurement. Thus, access to health care in the densely populated urban areas and flood-prone locations may be underestimated by such assumptions. Similarly, the self-reported measurement may produce unreliable findings because it is subjective and depends on the level of knowledge of the service user.

Therefore, this study measured geographical access to healthcare by road transport because of its suitability for modelling seasonal geographical access. Trips to health facilities were estimated along the road by walking and driving for wet and dry seasons. However, there was no separation between trips made by private car or public transport, and footpaths were not included because of data limitations.

In the literature review, the distribution of trips to healthcare were commonly presented using the minimum, median, mean and maximum time. The most widely used of these distributions is the mean (Noor *et al.*, 2003; Kurihara and Kato, 2007; Silal *et al.*, 2014). While the mean and maximum are easier to measure, the minimum and median distributions are not widely used because of relevance. This study used the mean and maximum distribution because those were the most relevant outputs for this study. The minimum distribution was not used because it was deemed unreasonable since distances were measured from communities' centroid to the facilities and some communities' centroids (e.g. PHCs) were also used as health facilities locations. Median distribution was not used as well because the study was interested in the average and maximum travel time.

This study found that geographical access to healthcare varies depending on the means of transport used. Thus, those who drove (private/public transport) spent a shorter time than those who walked. That is why the Euclidean distance measurement is insufficient in the comprehensive estimate of trips to health facilities because of its inability to capture the variations in the travel scenarios. Other studies also confirmed the differences in access by the means of transport. One of such studies is Munoz and Kallestal (2012), in Western province, Rwanda in the study of PHCs where walking access was 2.6% within 60 minutes of urban and rural areas. Where walking access could not be measured independently from driving, some combined walking with driving, (O'Meara *et al.*, 2009; Moïsi *et al.*, 2010; Blanford *et al.*, 2012) to produce access estimate by the transport network. This study overcomes this gap in the literature by measuring and producing findings of walking and drive time separately since walking time was underreported in the literature review.

Previous studies have also shown that geographical access varies according to the level of neighbourhood deprivation (Jordan *et al.*, 2004; Peters *et al.*, 2008). However, the major challenge about the adaptation of such studies is the availability of deprivation indices in

Nigeria. This study measured deprivation by geographical access to healthcare. It was found that the most urban district (i.e. SSD) also had shorter mean travel time to health facilities than districts that were more rural in characteristics (i.e. CSD and NSD). Rural areas that are characterised by poor infrastructures and poverty also travelled a long distance to health facilities. Low infrastructure in the rural areas may increase the severity of flood in the wet season, and the poor population may incur an extra cost of healthcare due to additional transport time. Healthcare was therefore inversely distributed according to need (Hart, 1971).

In the study of access to hospitals in Greater Kisii, Bondo, Kwale and Makueni districts in Kenya (Noor *et al.*, 2003). The study found that Euclidean mean distance was 0.4km – 3.4km in urban areas while it was 5.8km – 8.1km in the rural areas. In the same study, mean Euclidean distances to rural dispensary and health centres were 3.8km and 4.4km respectively and in the urban areas it was 2.8km and 2.4km for dispensary and health centres respectively. Although it is established in the literature and in this study that residents of urban areas travel shorter distances to healthcare, some studies did not report the differences. Some of such studies include Kumar (2004), in the study of PHCs in India by Euclidean distance and Tanser, Gijsbertsen and Herbst (2006), in the study of road network travel to clinics in Hlabisa health sub-district South Africa. The challenge of such studies is in the underestimation of the population with least access who are usually in the rural areas. However, reporting separate findings for urban and rural areas is sometimes limited by the research data.

This study also showed the proportion of the population living within set travel time bands to health facilities. While there are no universally accepted distance or time bands for this type of study, authors of various studies adopted suitable groups depending on the nature of the study location. Owen, Obregón and Jacobsen (2010), in the study of Alta Verapaz, Guatemala, showed that 56.2% of the rural population lived within 60 minutes' travel on transport network to hospitals while 38.1% lived within the same time travel to tertiary facilities by transport network. This study also used a 60 minutes' time band with an initial consideration of a 30 minutes' interval in order examine population's nearness to health facilities.

As observed in the literature review, this study found that geographical accessibility varies depending on the level of health care. That means lower order facilities (e.g. primary health centres) were closer to the population than higher order facilities (e.g. hospitals). Therefore, the maximum tolerable walking time all facilities was set at 90 minutes. Maximum tolerable drive times to PHCs and hospital/NHIS were also set at 30 and 90 minutes respectively. The population who lived beyond those travel limits were considered underserved. The values used in this study to decide the underserved population were only examples for planning since there are no standards of such in the Nigeria healthcare system. The only standard that is widely seen in the literature is the population coverage of PHCs. The government expects a PHC to serve between 5,000 to 20,000 people.

This study found that PHC to population ratios in the dry season were 1.9, 5.2, 5.5 and 3.3 per 100,000 for SSD, NSD, CSD and CRS respectively (Table 6.2). In the wet season, the ratios were 0.6, 5.2, 2.9 and 1.8 per 100,000 for SSD, NSD, CSD and CRS, respectively (Table 6.2). Therefore, one PHC in SSD served 52,632 people in the dry season and 166,667 people in the wet season. At the state level, a PHC served 30,303 people in the dry season and 55,556 people in the wet season. It shows that the expected accessibility standard of the PHC was not achieved SSD and CRS and the pressure on the facilities doubled in the wet season. In the wet season, people are likely to use mostly those facilities whose accessibility is not affected by the flood. The problem is expected to increase pressure not just on the health facilities and equipment but the health workers as well.

Although the comparison of health facilities in a single study is not very common in literature, a few studies compared access to two or more healthcare facilities. In the study of Greater Kisii, Bondo, Kwale and Makueni districts, Kenya, mean Euclidean distance to hospitals was between 0.4 – 3.4km in urban areas and 5.8 – 8.1km in the rural areas (Noor *et al.*, 2003). Meanwhile, in the same study, mean Euclidean distances to rural dispensary and health centres were 3.8km and 4.4km respectively. In the urban areas, distances were 2.8km and 2.4km for dispensary and health centres respectively. In Alta Verapaz Guatemala, 56.2% of the rural population lived within 60 minutes to the nearest hospital while population access to tertiary facilities within the same travel time dropped to 38.1% (Owen, Obregón and Jacobsen, 2010). This study also compared travel times to the various healthcare facilities. Travel times to PHCs were shorter those of hospitals and NHIS. NHIS facilities were also more accessible than hospitals.

Although rarely considered in most accessibility studies, this study found seasonal variability in geographical access to healthcare. A similar finding was obtained in a study of the urban and rural population access to any public healthcare facilities by road in Niger (Blanford *et al.*, 2012). In that study, population coverage of facilities within 60 minutes in the dry season was 39% while it was 24% in the wet season over the same travel time leading to 15% loss of population access in the wet season. This study also found that drive times to all health facilities were longer and population access decreased in the wet season. In some locations, average drive times and facility-to-population ratios doubled. PHCs were least affected in the wet season because they are more than other facilities and sited closer to the population. NHIS facilities were more accessible than hospitals in the wet season because they had a higher number of facilities. However, the accessibility of NHIS in the wet season may not make much difference if the potential user is not insured.

This study estimated extra travel times to healthcare facilities in the wet season and the affected population. The additional drive times to PHCs were 28.6 minutes and 38.0 minutes in the CSD and SSD, respectively. For hospitals, extra drive times were 97.4 and 56.3 minutes in the CSD and SSD, respectively. It implies that the cost of healthcare is likely to increase in the wet season because of the additional transport fare that may be required. Healthcare users are also expected to allow adequate time when planning to use health services considering that there is no ambulance.

It is estimated that approximately 30% and 80% of CSD and SSD population respectively, are potentially at risk of losing access to healthcare at some point in the wet season. The findings do not imply that the people lacked access throughout the wet season, but it shows that they are likely to be affected because of their locations, which are within or near the flood regime. The severity of flood impact on access to healthcare may vary depending on the location's proximity to the flood regime, amount of rainfall and the level of infrastructural development. However, patronage of private healthcare may increase in the wet season, if the people can pay for the services.

Apart from showing variability in population access to health care, this study also improved upon previous findings by identifying the communities and facilities whose accessibility may be interrupted at some point in the wet season. Since this is the first comprehensive study of seasonal access to healthcare in Nigeria, it sets a foundation and paves the way for more studies of this kind in the future. Future studies may use the concept in this study to plan mobile healthcare delivery for the population during the wet season. Researchers and planners may estimate the additional number of patients that may visit each facility in the wet season if data is available.

9.3.2. Proximity to health facilities and malaria outcomes

This thesis also examined the seasonal associations of malaria outcomes and geographical access to healthcare in two selected hospitals (Chapter Seven). Malaria outcomes in the associations were severity and admissions. Geographical access was measured by drive times to health services. The study found no substantial evidence of association to confirm the hypothesis that long distance to healthcare was associated with worse malaria outcomes in the selected hospitals, though there were a few significant associations. It was expected that associations would be stronger in the wet season; however, the odds of malaria admissions were significant in the dry season after adjusting for age, gender and drive times distance to facilities. The crude rate of malaria admissions was higher in the rural hospital (UGH) and children under five years had the highest proportion.

The findings of this study do not necessarily rule out the fact that there is an association between geographical access and differential health outcomes which have been established in previous studies. Instead, the lack of significant association could have resulted from data limitations which was insufficient for a meaningful seasonal analysis. The findings would only hold for the two hospitals and not the entire state.

Previous studies found significant associations between distance to health facilities and severity of malaria. The progression from mild to severe malaria in Taiz province of Yemen was significantly associated with travel distance above 2km to the nearest health facility (Al-Taiar *et al.*, 2008). In Northern Namibia, 32.3% of children with fever lived less than 30 minutes to the nearest health facility while 60% lived one hour to the nearest health service (Alegana *et al.*, 2012). Therefore, the number of fever cases doubled after 30 minutes. In this study, there was no progressive increase in malaria cases or outcomes as drive time to facilities increased. The possible reason would be the nature of settlements. If fewer people live in remote communities, the number of malaria cases from there will be less.

Although this thesis found no significant associations between drive time to health facilities and malaria hospitalisation, significant associations were recorded in a previous study. The incidence of hospitalised malaria in under-five children in urban and rural Kilifi, Kenya doubled as travel time to the closest primary care facility progressed from 10 minutes to 2 hours (O'Meara *et al.*, 2009).

While this study could not examine associations between distance to health facilities and malaria mortality due to the nature of data (i.e. power), some studies found significant associations between geographical access and death due to disease while some did not. There was a significant association between walking time and infant/child mortality in rural Nouna district, Burkina Faso. After adjusting for confounding in the study, under-five mortality was 50% higher at a distance of 4 hours to the health facility (Schoeps *et al.*, 2011). A significant association was also found in the study of rural north-western Ethiopia in which children who lived beyond 90 minutes' walk from the health facility had over 2 times greater risk of death than those who lived below that time (Okwaraji *et al.*, 2012).

Conversely, a study conducted in North Bank of River Gambia for both rural and urban areas found no significant association between distance and child mortality; although, it also found that children in the rural areas were about 5 times more likely to die than children in urban areas (Rutherford *et al.*, 2009). This thesis found that under-five children who reported malaria in the rural hospital were 9.3 times more likely to die compared to the urban hospital, although, drive times associations were not significant.

9.3.3. Seasonality of LAMs in healthcare planning

The last focus area of this thesis demonstrated the potential of LAMs in the planning of increase of population access to health services as a way of proffering a solution to the problem of inequality of access to healthcare. NHIS facilities were used in the study because of the government's target of increasing NHIS access to 30% of the population. A review of the use of LAMs for healthcare planning in developing countries (Rahman and Smith, 2000) showed that LAM solutions had been widely studied and used. However, the seasonality of geographical access is rarely considered in any of the models. A study found that the performance of LAMs in locating PHCs decreased in the wet season compared to the dry season (Oppong, 1996). This thesis found that the performance of the RPLAM and PWLAM in locating proposed NHIS decreased in the wet season compared to the dry season. With an additional five locations to existing locations, both models lost 5.1% of communities' access at 15 minutes' drive in the wet season.

The most popular model in public sector planning over the years is the p-median (Osleeb and McLafferty, 1992; Kumar, 2004). Osleeb and McLafferty (1992), used p-median in the planning of the control of (dracunculiasis) disease while Kumar (2004), used p-median to study the locations of primary health care facilities in India. However, in this study, the Maximum Coverage model was used instead because the government objective was batch covering (of 30% of the population) of the NHIS, unlike the p-median which is most suitable where the objective is to cover the entire population. Whatever the model adopted, LAMs have been implemented by Euclidean distance or road network travel. Although, previous studies implemented LAM using Euclidean distance measurements (Ayeni, Rushton and McNulty, 1987; Kumar, 2004), this study used drive time considering the limitations of the Euclidean distance.

LAMs are often used to measure the effectiveness of past locations. This study used LAM to measure the effectiveness of current locations of NHIS which were established by bureaucratic and political interventions. It found that the present locations of NHIS are not optimal and that more people would have had access to NHIS if the facilities were located at optimal locations identified using either PWLAM or RPLAM. It was observed that if PWLAM fixed the existing 67 NHIS facilities, population coverage within 15 minutes could have increased from the current 1,641,353 to 2,691,467 in the dry season (Table 8.1). In the wet season, population access could have been 3.4 times higher (2,281,098) than the current coverage (667,202). These findings show that the optimised models are least affected by the seasonality of geographical access compared to the unsystematic methods.

In the past, Rahman and Smith (1996) studied the effectiveness of locations for Health and Family Welfare Centres (HFWC) in Tangail Thana in Bangladesh using the p-median. The facilities were to be used for immunisations, diarrhoeal diseases, fever and family planning programmes in the rural areas. The study revealed that optimal locations would have kept average distance to the services at 1.9km while the existing average distance to the service was 3.1km in the dry season. It also showed that 4 facilities placed in optimal location instead of arbitrary 7 existing facilities would have provided the population coverage per kilometre of the existing facilities. Ayeni, Rushton and McNulty (1987) in the study of hospitals maternities and child welfare centres in Ogun state showed that mean distance to maternity and child-welfare centres decreased from 3.8km in existing locations to 2.7km in the optimal locations.

Previous studies have also demonstrated the use of LAMs in locating facilities in proposed new areas. LAMs like other decision support systems can be useful for the planning and identification of optimal locations for public services including healthcare (Longley *et al.*, 2011). The availability of software packages like the ESRI ArcMap simplifies the process and methods of integrations of such tools in planning. In Saudi Arabia, Location Set Covering Problem (LSCP) was used to locate health centres in a new city, Yanbu al Sinaya (Berghmans, Schoovaerts and Teghem, 1984). The estimated population was divided into

36 vertices (regions) of equal weight, and the model was used to find a suitable number of centres for health centres considering the ratio of population to doctors.

In this study, new locations were identified using the population of the community as a weight (PWLAM) or sampled community location (RPLAM). However, in this study, the sites identified and the communities in the study are not entirely new because the government has no plan of constructing new NHIS facilities but plans to upgrade existing facilities to the required standard before accreditation. Also, instead of having a specific point to site the facility like in the conventional LAM solution, the government will have a community to accredit a facility in any location of their choice. Thus, the models in this study are more flexible than those used in previous studies.

The potential use of LAMs to improve an existing system was found in previous studies. An example is the work of Okafor (1981), in a study aimed at expanding the network of public facilities using fixed supply points. The problem was solved using the transportation formulation model which is rarely used in healthcare planning. Four possible sites were added to improve the existing hospital system in the then Bendel State of Nigeria. Although, it was later thought that p-median would have provided a better solution in that study (Rahman and Smith, 2000). Oppong (1996), used MCLP to identify suitable locations for seasonal primary care delivery in Ghana.

Similarly, since this study was aimed at increasing population coverage of NHIS, the MCLP method was used to identify new locations in addition to the existing 67 NHIS facilities. For instance, if five additional facilities were accredited in addition to the 67 existing facilities using the PWLAM at 15 minutes' drive time, 50.8% of the population and 10.3% of the communities would have lived closer to NHIS services in the dry season. In the wet season, access decreased to 31.9% and 5.2% for population and communities respectively over the same drive time. However, since the current population estimate for each community was not available until this study, RPLAM would be a useful alternative since it requires only community locations. If RPLAM was used to site additional 5 facilities at 15 minutes' drive time, NHIS service coverage would have increased to 46.4% of the population and 14.1% of the communities in the dry season. In the wet season, it would be 19.7% and 9.0% for population and communities, respectively. If planners decided to increase the preferred drive time in the model depending on available resources, population coverage would have increased by 10% per additional 15 minutes (e.g. 15, 30, 45, 60) in either PWLAM or RPLAM in the dry season.

Unlike most studies of this kind, this study also measured seasonal variability in the performance of LAMs used in the study. Oppong (1996), demonstrated that the outcomes of LAM in the planning of primary care in Ghana varies according to seasons and it was confirmed by this study. However, there was not difference between dry and wet season within 30 minutes' drive in the EFLAM model. The study found that the variation in communities and population coverage ranged between 6% and 48%. Although, the more the number of facilities, the smaller the difference between the two seasons.

The use of LAMs in the past yielded direct benefit by saving capital budget on healthcare. A typical example was the case of Massachusetts, USA. The health authorities used LAMs to redistribute dialysis facilities according to population need but in favour of the sparsely populated areas. Two years after implementation, the plan saved the authorities the sum of $5.1 million (USD) (Pliskin and Tell, 1981). In like manner, proper use of location-allocation model in planning the distribution of NHIS facilities may save a substantial cost of healthcare delivery. If new NHIS facilities in Cross River State were sited in optimal locations through a long-term batch implementation plan, that would reduce clustering of the service in urban areas while giving access to the sparsely populated communities. The extra funds that would be recovered may be used for the expansion of the service capacity of NHIS or other services like the PHCs and hospital.

Despite the numerous benefits that are associated with the use of LAM in healthcare planning, a few challenges may hinder the implementation process if they are not given adequate consideration. Like other essential services, healthcare planning may be partly or wholly influenced by several factors including the shortage of funds, human resources, profit margin of the private sector, political ambitions, accreditation model and sustainability.

If those factors are managed well with the seasonality of geographical access in consideration, equitable access to NHIS or any form of healthcare in the world would reduce patients' overall cost of treatment, increase personal savings, improve safety and sustain the environment in the long-run. Equitable distribution of health facilities would save the overall cost of transportation since long-distance travel to health facilities would be unnecessary, and the patients cost would be released. Less road travel also means fewer road accidents, less use of fuel, less pollution of the environment and improved air quality. Siting a few facilities at optimised locations would also save our forest and land from unnecessary extraction and processing of construction materials. It would reduce patients' traffic in the peak of health crises like the wet season. Productivity would also increase as patients and caregivers will travel less, thus having more time for other essential aspects of their lives like family, education, career and recreation.

9.4. Contributions to research

The key contributions of this research are in the demonstration of the theoretical and practical possibilities of measuring seasonal geographical access to health services despite the lack of data. These contributions have been studied and presented comprehensively and uniquely in a way that no previous study has captured.

Firstly, this thesis fills a gap in the literature by producing the first systematic review of the literature on geographical access to healthcare in LMICs. The broad scope of the review and its findings makes it a useful tool not just for research but evidence-based healthcare planning and delivery as well.

Secondly, the thesis contributes to research method by developing a custom flood model for measuring seasonal geographical access to healthcare. It provides an understanding of the potential health impact of seasonal flooding by estimating the population, communities and health facilities that are usually affected by seasonal flooding. The concepts used in the flood model is adaptable for further planning and studies beyond the field of public health and geography. For instance, the concept can be used to study flood mitigation intervention and provision of relief to potential flood communities.

Thirdly, it improves upon research data collection by using mobile phone technology for spatial data crowdsourcing. The use of mobile phones for spatial data collection and validation is not common in the literature. This time and cost-saving method implemented in this thesis is useful for future collection and updating of spatial and non-spatial research data where it is unavailable or insufficient. Since the traditional spatial data collection method by measuring instruments is laborious, expensive and time-consuming researchers may crowdsource research data and validate them using free reference data like the Google Map. This study used the Google Map to validate and obtain coordinates from locations of health facilities that were obtained over the phone.

Fourthly, this study improves upon the methods for locating new healthcare services to increase geographical accessibility by introducing the RPLAM. The sub-models in this study were RPLAM and PWLAM. Most location-allocation studies use PWLAM because of its population component. However, RPLAM, which uses sample points, is rarely available in location-allocation literature. RPLAM population coverage was only 5% less than PWLAM, indicating its suitability for health services location.

Fifthly, this thesis contributes to the study of healthcare accessibility by expanding on the measurement of seasonal geographical access. The focus areas of this thesis have generated three papers to be submitted to peer-reviewed journals. The first paper will publish the results of the systematic review. Another publication will come from the seasonal geographical access to health facilities in Cross River State, and the last paper will publish the findings of seasonal LAMs for NHIS. The publications will fill gaps in the literature on seasonal geographical access to healthcare and open opportunities to extend the study to locations with similar environmental and socioeconomic characteristics. An executive summary and a copy of this thesis will be submitted to the Cross River State Ministry of Health as agreed during ethical approval.

Lastly, this study updated existing data and produced new datasets, which are useful for further research and planning. This study produced community-level population estimates for the year 2015, which was last available in the 1991 population census data. It has also provided health facilities location data, updated street network, river crossing speed and flood regime, which were not available before this study. The data will be made available for public access in an open-access data repository with permission from the NPC and OSG-CRS.

9.5. Implication for planning

This study showed the impact of seasons on geographical access to health services. Planners may use the findings of this study to identify affected locations and plan seasonal healthcare delivery, especially for the remote communities. Mobile clinics and health workers should be available for healthcare delivery during the peak of the wet season. Better roads and drainage construction will increase the geographical accessibility of health facilities.

The limitations of research data in this study raise the need to maintain open-access databases for planning and research. Such databases should hold relevant data such as health records, road network, environmental conditions, and administrative boundaries. Health surveillance records should capture not just medical information but socio-economic and geospatial information as well.

This study showed that locating a health facility by mere discretion does not produce optimum geographical accessibility. It also demonstrated that with RPLAM, health planners could use limited data such as facilities and demand locations to achieve better healthcare coverage. Therefore, attaining adequate healthcare coverage is possible with limited data. LAMs have the potential of saving government budget on healthcare, increasing collaboration and protecting the environment; therefore, it should become an essential part of healthcare planning.

9.6. Recommendation for research

This study serves as a foundation for further studies of geographical access to healthcare. In this study, for instance, there was no distinction between private car access and public transport while footpaths were not available for the walking access analysis. Future studies of geographical access may consider those areas if data is available.

Beyond the study of geographical access to health services is the possibility of adapting the methods used in the study to examine seasonal access to other essential services like schools, banks, markets and security. Also, further studies on seasonal access may improve upon the flood model using more precise data.

This study serves as a basis for further malaria studies in hospitals as health surveillance databases improve. Future research may limit malaria analysis to children because they were the majority in the data. This study can also be extended to examine other serious health outcomes in the developing countries such as; cancer, child mortality and maternal mortality.

Future studies can improve upon the findings of this study by including capacity, equipment, available services and opening hours as weights in the location models if the data are available. Research data sharing after studies completion should be encouraged among researchers because it will save time and cost of a future study.

9.7. Conclusion

Finally, this PhD research achieved its aims and objectives in nine themed chapters and made significant contributions to seasonal geographical access to healthcare. The wet season flood model, which was developed during this study, was used to measure geographical access, the associations of malaria outcomes in hospitals and location-allocation of health facilities. This study also demonstrated the use of crowdsourcing for research and planning, where secondary data is unavailable. It is expected that planners and researchers will find this study useful.

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APPENDICES

Appendix I: Ethical Approval Certificate

GOVERNMENT OF CROSS RIVER STATE OF NIGERIA
MINISTRY OF HEALTH, CALABAR
HEALTH RESEARCH ETHICS COMMITTEE
E-mail: crsmohresearchethics@yahoo.com
+234 08034047926

CRS/MH/HREC/016/Vol.V/008 — 25th February, 2016

Edet Otu
University of Sheffield
United Kingdom

CERTIFICATE OF ETHICAL APPROVAL

The Cross River State Health Research Ethics Committee (CRS-HREC) having reviewed your application for Ethical Approval of the Research titled **"Examining Geographical Access to Health Care in Cross River State"** *with REC No. RP/REC/2015/328* has granted **FULL ETHICAL APPROVAL**.

This approval is valid for **ONE YEAR** from the date of its issuance.

You may proceed with your study in accordance with the protocol. You are requested to abide by every professional and ethical code for the conduct of this research, including advising the CRS-HREC of any changes to your protocol in advance.

The CR-HREC reserves the right to request an audit of this research at any time during or post implementation. ***A copy of the completed research (Results) should be submitted*** *to* the Department of Clinical Governance, SERVICOM and E-Health for policy and decision making in the State Ministry of Health.

Yours sincerely,

Dr. Bassey Ikpeme
Ag. Chairman CR-HREC

Appendix II: Systematic review search strategy 1980 – 2017

Medline search strategy translated across all databases.

1. Access*.mp.
2. limit 1 to (abstracts and english language and yr="1980 - 2017")
3. Utili*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
4. limit 3 to (abstracts and english language and yr="1980 - 2017")
5. Use*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
6. limit 5 to (abstracts and english language and yr="1980 - 2017")
7. Geograph*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
8. limit 7 to (abstracts and english language and yr="1980 - 2017")
9. Spatial*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
10. limit 9 to (abstracts and english language and yr="1980 - 2017")
11. Location*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
12. limit 11 to (abstracts and english language and yr="1980 - 2017")
13. Distance*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
14. limit 13 to (abstracts and english language and yr="1980 - 2017")
15. Travel time*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
16. limit 15 to (abstracts and english language and yr="1980 - 2017")
17. Walk*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
18. limit 17 to (abstracts and english language and yr="1980 - 2017")

19. Optim*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
20. limit 19 to (abstracts and english language and yr="1980 - 2017")
21. Equ*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
22. limit 21 to (abstracts and english language and yr="1980 - 2017")
23. Low income.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
24. limit 23 to (abstracts and english language and yr="1980 - 2017")
25. Middle income.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
26. limit 25 to (abstracts and english language and yr="1980 - 2017")
27. LMICs.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
28. limit 27 to (abstracts and english language and yr="1980 - 2017")
29. Developing.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
30. limit 29 to (abstracts and english language and yr="1980 - 2017")
31. Africa*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
32. limit 31 to (abstracts and english language and yr="1980 - 2017")
33. Asia*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
34. limit 33 to (abstracts and english language and yr="1980 - 2017")
35. Caribbean.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
36. limit 35 to (abstracts and english language and yr="1980 - 2017")
37. Latin America.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

38. limit 37 to (abstracts and english language and yr="1980 - 2017")
39. Third world*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
40. limit 39 to (abstracts and english language and yr="1980 - 2017")
41. Less develop*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
42. limit 41 to (abstracts and english language and yr="1980 - 2017")
43. Emerging econom*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
44. limit 43 to (abstracts and english language and yr="1980 - 2017")
45. Health Service*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
46. limit 45 to (abstracts and english language and yr="1980 - 2017")
47. Health Facilit*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
48. limit 47 to (abstracts and english language and yr="1980 - 2017")
49. Healthcare.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
50. limit 49 to (abstracts and english language and yr="1980 - 2017")
51. Health care.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
52. limit 51 to (abstracts and english language and yr="1980 - 2017")
53. 4 or 6
54. 8 or 10 or 12
55. 14 or 16 or 18
56. 20 or 22
57. 24 or 26 or 28 or 30 or 32 or 34 or 36 or 38 or 40 or 42 or 44
58. 46 or 48 or 50 or 52
59. 1 and 53 and 54 and 55 and 56 and 57 and 58
60. from 59 keep 1-28

Appendix III: Systematic review search strategy 2018 – 2019

Medline search strategy translated across all databases

1. Access*.mp.
2. limit 1 to (abstracts and english language and yr="2018 - 2019")
3. Utili*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
4. limit 3 to (abstracts and english language and yr="2018 - 2019")
5. Use*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
6. limit 5 to (abstracts and english language and yr="2018 - 2019")
7. Geograph*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
8. limit 7 to (abstracts and english language and yr="2018 - 2019")
9. Spatial*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
10. limit 9 to (abstracts and english language and yr="2018 - 2019")
11. Location*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
12. limit 11 to (abstracts and english language and yr="2018 - 2019")
13. Distance*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
14. limit 13 to (abstracts and english language and yr="2018 - 2019")
15. Travel time*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
16. limit 15 to (abstracts and english language and yr="2018 - 2019")
17. Walk*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
18. limit 17 to (abstracts and english language and yr="2018 - 2019")

19. Optim*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
20. limit 19 to (abstracts and english language and yr="2018 - 2019")
21. Equ*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
22. limit 21 to (abstracts and english language and yr="2018 - 2019")
23. Low income.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
24. limit 23 to (abstracts and english language and yr="2018 - 2019")
25. Middle income.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
26. limit 25 to (abstracts and english language and yr="2018 - 2019")
27. LMICs.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
28. limit 27 to (abstracts and english language and yr="2018 - 2019")
29. Developing.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
30. limit 29 to (abstracts and english language and yr="2018 - 2019")
31. Africa*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
32. limit 31 to (abstracts and english language and yr="2018 - 2019")
33. Asia*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
34. limit 33 to (abstracts and english language and yr="2018 - 2019")
35. Caribbean.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]
36. limit 35 to (abstracts and english language and yr="2018 - 2019")
37. Latin America.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

38. limit 37 to (abstracts and english language and yr="2018 - 2019")

39. Third world*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

40. limit 39 to (abstracts and english language and yr="2018 - 2019")

41. Less develop*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

42. limit 41 to (abstracts and english language and yr="2018 - 2019")

43. Emerging econom*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

44. limit 43 to (abstracts and english language and yr="2018 - 2019")

45. Health Service*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

46. limit 45 to (abstracts and english language and yr="2018 - 2019")

47. Health Facilit*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

48. limit 47 to (abstracts and english language and yr="2018 - 2019")

49. Healthcare.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

50. limit 49 to (abstracts and english language and yr="2018 - 2019")

51. Health care.mp. [mp=title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms]

52. limit 51 to (abstracts and english language and yr="2018 - 2019")

53. 4 or 6

54. 8 or 10 or 12

55. 14 or 16 or 18

56. 20 or 22

57. 24 or 26 or 28 or 30 or 32 or 34 or 36 or 38 or 40 or 42 or 44

58. 46 or 48 or 50 or 52

59. 1 and 53 and 54 and 55 and 56 and 57 and 58

60. from 59 keep 1-7

Appendix IV: Search results from electronic databases

Search Results Database	Search Date	Period	Results	Relevant Titles
Cochrane Library	02/12/2017	1991 - current	0	0
MEDLINE via OvidSP	02/12/2017	1980 - current	28 (with 3 duplicates)	9
CINAHL, EBSCO	02/12/2017	1982 - current	464	18
POPLINE	02/12/2017	1980 - current	0	0
Sociological Abstract via ProQuest	02/12/2017	1980 - current	42	7
Total studies				75
Studies considered after initial scanning				52

Search results from electronic databases (2018 – 2019)

Search Results Database	Search Date	Period	Results	Relevant Titles
Cochrane Library	06/05/2019	2018 – 2019	0	0
MEDLINE via OvidSP	06/05/2019	2018 – 2019	59	7
CINAHL, EBSCO	06/05/2019	2018 – 2019	175	4
POPLINE	06/05/2019	2018 – 2019	0	0
Sociological Abstract (Social Science Database) via ProQuest	06/05/2019	2018 – 2019	0	0
Total studies				
Studies considered after initial scanning				11

The relevant papers were sorted at this stage and only new papers (n=3) were added to the review. Duplicates were dropped at this stage.

Appendix V: Community level population figures (National Population Commission, 1991)

cross river

NATIONAL POPULATION COMMISSION

NATIONAL POPULATION COMMISSION

Locality Summary Listing

State: CROSS-RIVER Lga: AKAMKPA

Locality	Males	Females	Both-Sexes
OZU-ABAM	1,083	1,246	2,329
NDI-INYA	284	309	593
AMAOGU	188	219	407
IKOT EFFIOM EYAMBA	341	320	661
EFFIOFIOM UWET	105	105	210
OKOPEDI	370	346	716
UWET	330	348	678
BUDENG	115	73	188
EKPRI IBAMI	127	127	254
AKWA IBAMI	209	145	354
AKWA IBAMI CAMP	323	266	589
BUDENG CAMP	342	326	668
CALABAR RIVER CAMP	458	404	862
HEADQUARTER CAMP	386	359	745
DUKWE CAMP	491	410	901
OJO CAMP	449	421	870
IGBOFIA CAMP	539	446	985
DUWANG	458	408	866
UYANGA	3,969	4,001	7,970
SMALL IWURU	823	803	1,626
OJOR	1,509	1,468	2,977
IFUMKPA	641	543	1,184
ERENYA	180	203	383
IKO EKPEREM	1,003	1,014	2,017
IKO ESAI	1,300	1,393	2,693
OWAI	606	609	1,215
NEW EKURI	351	412	763
OLD EKURI	463	442	905
AWANEYEN & OTHERS	241	211	452
OBUTONG & OTHERS	157	160	317
MKPOT	852	833	1,685
EKANG	237	181	418
MFAMENYIN	434	400	834
NKAME	246	205	451
MBEBAN	290	271	561
OJOK	333	288	621
OLD OJOK	104	89	193
OLD NDEBIJI	451	443	894
OWOM	287	258	545
IKPAI	72	72	144
NYAJE	939	1,017	1,956
NTEBACHOT	277	182	459
OREM	216	199	415
AKOR	1,111	953	2,064
NEW NDEBIJI	228	218	446
IKU	33	15	48
ABUNG	202	137	339
OKARARA	362	318	680
AYIP EKU ESTATE	363	289	652
OSOMBA	389	321	710
AKING	401	428	829
MANGHO	104	95	199
ONREL CAMP II	742	634	1,376
NKOROKUM	1,242	1,097	2,339
ISOBA	1,122	1,076	2,198

NATIONAL POPULATION COMMISSION

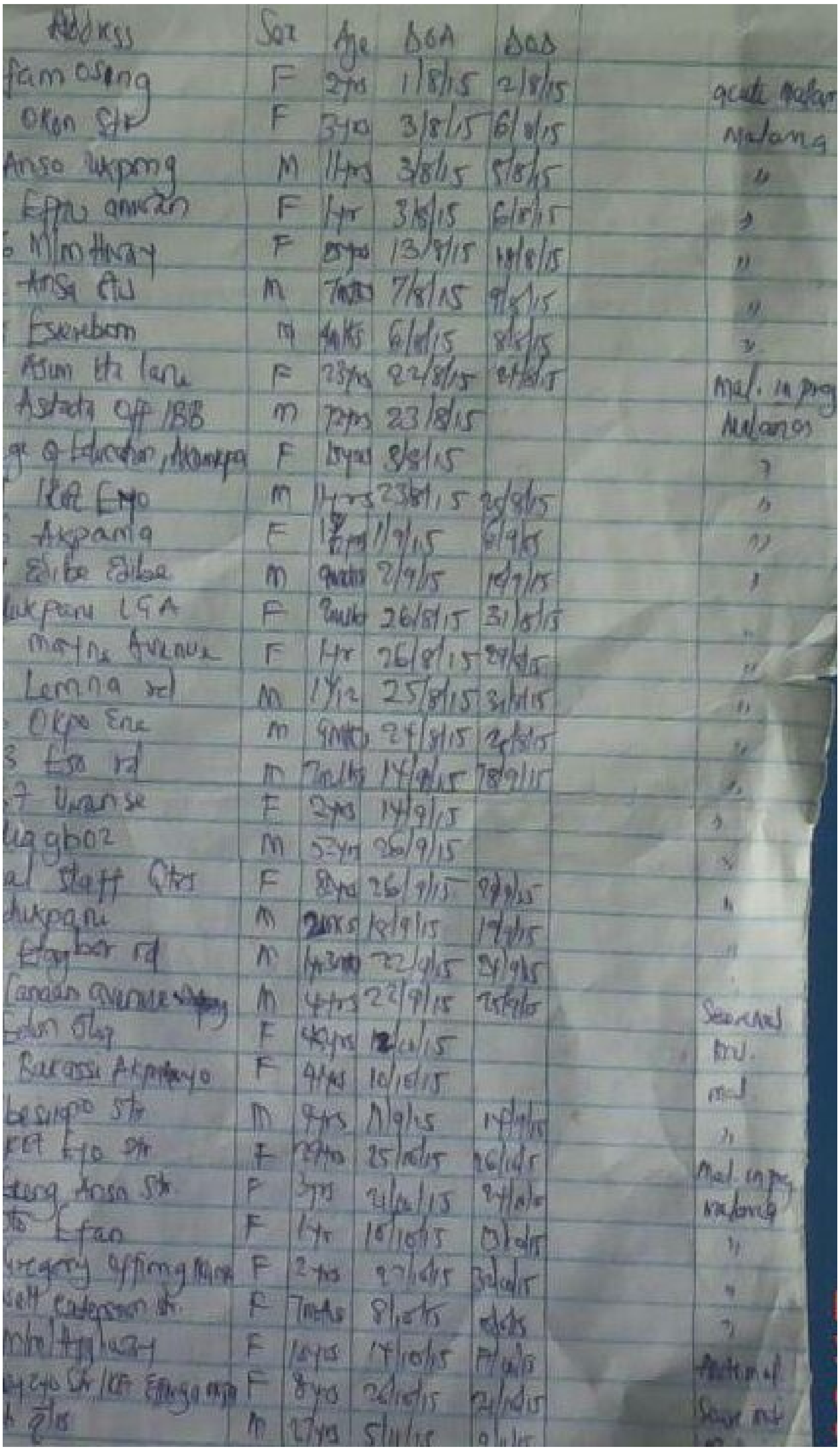
NATIONAL POPULATION COMMISSION

Locality Summary Listing

State: CROSS-RIVER Lga: AKAMKPA

Page 1

Appendix VI: An extract of original malaria data scanned from the CGH



Address	Sex	Age	DOA	DOD	
fam Osong	F	2yrs	1/8/15	2/8/15	acute malaria
Okon St	F	3yrs	3/8/15	6/8/15	Malaria
Anso Ukpong	M	11yrs	3/8/15	5/8/15	"
Efiom Amazon	F	1yr	3/8/15	6/8/15	"
Mm Henry	F	8yrs	13/8/15	14/8/15	"
Ansa Eta	M	7mths	7/8/15	9/8/15	"
Esserebom	M	4mths	6/8/15	8/8/15	"
Asim Eta lane	F	23yrs	22/8/15	24/8/15	Mal. in preg
Atakpa off IBB	M	7yrs	23/8/15		Malaria
ge of Education, Akamkpa	F	13yrs	8/8/15		"
Ikot Enyo	M	14yrs	23/8/15	25/8/15	"
Akpania	F	1½yrs	1/9/15	6/9/15	"
Edibe Edibe	M	9mths	2/9/15	14/9/15	"
ukpani LGA	F	2mths	26/8/15	31/8/15	"
Marina Avenue	F	1yr	26/8/15	29/8/15	"
Lemna rd	M	1½yrs	25/8/15	31/8/15	"
Okpo Ene	M	9mths	24/8/15	26/8/15	"
Eso rd	M	7mths	14/9/15	18/9/15	"
Uwanse	F	2yrs	14/9/15		"
ugboz	M	5yrs	26/9/15		"
al Staff Qtrs	F	8yrs	26/9/15	29/9/15	"
ukpani	M	2yrs	16/9/15	19/9/15	"
Edgerber rd	M	1yr 3mths	22/9/15	25/9/15	"
Canaan Avenue [illegible]	M	4yrs	22/9/15	25/9/15	Severe
Eden Oku	F	40yrs	[illegible]/10/15		Mal.
Bakassi Akpabuyo	F	4yrs	10/10/15		mal
besiipo St	M	9yrs	11/9/15	14/9/15	"
Ekpo Efio St	F	29yrs	25/10/15	26/10/15	Mal. in preg
Etang Ansa St	F	3yrs	24/10/15	27/10/15	malaria
Efan	F	1yr	18/10/15	21/10/15	"
Gregory offiong [illegible]	F	2yrs	27/10/15	30/10/15	"
Calt Anderson St	F	7mths	8/10/15	10/10/15	"
[illegible]	F	10yrs	14/10/15	17/10/15	Auction of
[illegible] St / [illegible]	F	8yrs	26/10/15	29/10/15	Sever mal
[illegible]	M	27yrs	5/11/15	9/11/15	