Too poor or too far?
Partitioning the variability in hospital birth by poverty and travel time in four sub-Saharan countries

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I, Kerry Wong, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Signature

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Date

Abstract

Poverty and long travel time are barriers to using skilled care at birth, especially care provided at hospitals which can be located far and result in high direct and indirect costs. In parts of sub-Saharan Africa, about one third of births occur in hospitals. This thesis aimed to assess the relative contributions of poverty and long travel time to the probability of giving birth in a hospital in Kenya, Malawi, Nigeria and Tanzania.

I first reviewed the literature related to measuring the distance/travel time between women and health facilities in sub-Saharan Africa. Although the measurements and standards adopted by included studies were diverse, the impeding effect of living far from health facilities on use of childbirth care was prominent.

In the second study, we compared two approaches to create high-resolution poverty maps in Kenya, Malawi, Nigeria and Tanzania. We found that the spatial variation in poverty and its determinants differed across countries, which should be considered when choosing the most suitable mapping approach. For each country, we used the better-performing approach to construct a national poverty map. These maps showed the highest concentration of poverty in remote locations, where population density was low and the allocation of resources potentially expensive.

Next, we assessed the wealth inequality in travel time to the nearest hospital and its trade-off against minimizing overall travel time in the four countries. Travel time was calculated by overlaying locations of the population, wealth subgroups and hospitals. We simulated alternative hospital locations to identify the shortest overall travel time and the narrowest equity gap possible. Results suggest that hospitals in the four countries are currently well placed to minimize overall travel time, but they create wide inequality gaps by wealth.

Lastly, we assessed the relative contributions of poverty, travel time, and other factors on the probability of hospital birth in the four countries. Poverty and travel time were important, and they played different roles within and across countries, meaning different strategies are needed to increase hospital-based childbirth. Nonetheless, these strategies alone do not address all barriers, and further research of where they do not lead to the desire result is required to help devise tailor-made actions.

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Abbreviations and acronyms used in this dissertation

ANC	Antenatal care
BEmONC	Basic emergency obstetric and newborn care
CEmONC	Comprehensive emergency obstetric and newborn care
CHAM	Christian Health Association of Malawi
CHEW	Community Health Extension Worker
DHS	Demographic and Health Survey
EA	Enumeration area
EmOC	Emergency obstetric care
EmONC	Emergency obstetric and newborn care
FBD	Facility-based delivery
FCT	Federal Capital Territory (in Nigeria)
FMCHP	Free Maternal and Child Health Program (in Nigeria)
FMS	Free Maternity Services
G	Goodness-of-prediction
GAM	Generalized additive model
GIS	Geographic information system
GNI	Gross National Index
HFR	Health Facility Registry
HSA	Health surveillance assistant
IDW	Inverse distance weighting
KEPH	Kenya Essential Package for Health
LGA	Local Government Authority
LMIC	Low- and middle-income country
MAE	Mean absolute error
MAP	Malaria Atlas Project
MBG	Model-based geostatistics
MDG	Millennium Development Goals
MFL	Master facility list
MICS	Multi-indicator Cluster Survey
MoH	Ministry of Health
OSM	OpenStreetMap
PCA	Principal component analysis
PFP	Private-for-profit
PNFP	Private-not-for-profit
PPP	Purchasing Power Parity
PSU	Primary sampling unit
RAI	Rural Access Index
RMSE	Root mean square error
SARA	Service Availability and Readiness Assessment
SBA	Skilled birth attendant
SD	Standard deviation
SDG	Sustainable Development Goals
SI	Spatial interpolation
SPA	Service Provision Assessment
SSA	Sub-Saharan Africa
TBA	Traditional birth assistant
UHC	Universal Health Coverage
UNFPA	United Nations Population Fund
UNICEF	United Nations Children's Fund,
WHO	World Health Organization
WI	Wealth index

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Chapter 1
Positioning the thesis

1 Positioning the thesis

1.1 Introduction

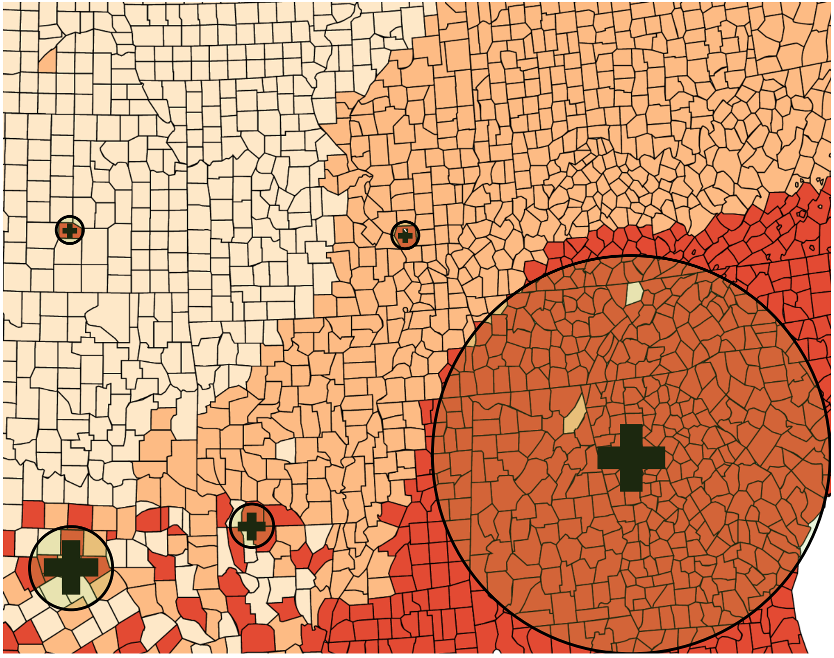
Between 1990 and 2015, the global maternal mortality ratio (MMR) dropped by 44% from 385 to 216 maternal deaths per 100,000 live births [1]. Despite this progress, it fell short of the Millennium Development Goal (MDG) target of a 75% reduction, and the number of maternal deaths remains unacceptably high. In 2015, which marked the end of MDGs, an estimated 303,000 women died of maternal causes. Almost all of these deaths occurred in low- and middle-income countries (LMICs), and more than half in sub-Saharan Africa (SSA). The global community is committed to further reducing maternal mortality, with a global target of less than 70 per 100,000 live births by 2030 as Goal 3.1 of the Sustainable Development Goals (SDGs). To tackle stark geographic disparities, and as part of the Ending Preventable Maternal Mortality Strategy, this target is expanded to require that no country has a MMR above 140 [2].

Most of the causes of maternal deaths are preventable by the timely use of evidence-based interventions [3]: all women need access to antenatal care, skilled care during childbirth, and care and support in the weeks after childbirth. Of these, it is particularly important that all births occur in a well-equipped environment, attended by health professionals with the right skills [4]. The health of women and newborns is also closely linked, and ensuring newborn health, in many cases, requires implementing these same interventions.

The use of appropriate and skilled childbirth care to meet the needs of pregnant women in LMICs faces critical inequity issues, with poorer women utilizing less care and less optimal care compared to more affluent women [5], [6]. Factors influencing underutilization of care among poorer women include, but are not limited to, a lack of financial resources, lack of information to identify the need for care, time constraints and high opportunity costs of care-seeking, cultural beliefs and norms, and concerns about mistreatment [7]. Furthermore, whether an individual could obtain care also depends on the service provision environment that they are situated within. Supply-side determinants driven by the health system can impose tremendous barriers to obtaining care [8].

Unlike some types of health services, the provision of high-quality lifesaving care at childbirth is largely immobile, i.e. the patient needs to receive health services at a fixed location, or in close proximity to it. This is because the provision of comprehensive emergency obstetric and newborn care functions requires fairly advanced equipment and supplies, such as a caesarean-section theatre and blood transfusion. At the same time, communities and human settlements tend to show some degree of segregation in geographical space by community members' sociodemographic characteristic such as their socioeconomic status (SES). The net effect of this phenomenon is the formation of clusters of people with similar SES who experience similar levels of geographic separation from services and infrastructure. It may therefore be reasonable to speculate that the east at which poor people and less poor people can physically access healthcare differ, and their opportunities for healthcare of any given quality also differ, and that this is ultimately reflected in the extent of service uptake between groups (Figure 1.1). The provision of adequate health services to guarantee all with a minimum level of physical accessibility to a relevant range of quality services, including skilled childbirth care, can therefore be seen as a geographic and resource-allocation issue optimizable at the system level.

Figure 1.1 Schematic diagram of the geographic relationship underlying residential segregation, physical accessibility to health services and service uptake (image sourced from: colorbrewer2.org)



People and communities of similar SES have greater tendency to cluster with those who are alike. They are thus subject to a similar level of physical accessibility to the services that are offered at fixed locations. Such spatial pattern of accessibility to services by SES may overlap with the inequality of service uptake by SES.

The spatial dimension of equitable healthcare access is of contextual importance to devising appropriate health system strategies to improve health and reduce inequalities. In a recent Lancet series, equitable provision of quality care to all people is enshrined as a feature of a high-quality health system [9], without which equity of health impact and health outcome become an unreachable goal. However, equitable provision and equitable service uptake are complementary ideas that are too often discussed in isolation [10].

This dissertation sets out to investigate the extent to which different levels of uptake of skilled childbirth care among population subgroups are due to inequitable geographic access to health services versus differences in SES. We focus on analyses of four countries in SSA – Kenya, Malawi, Nigeria and Tanzania – where poverty is highly prevalent, the world's maternal deaths concentrate, and the uptake of skilled childbirth care inequitable.

1.2 Research questions and thesis objectives

The overarching research question I address in this thesis is degree of inequity in physical accessibility to skilled childbirth care by wealth in the selected countries, and to quantify the relative contribution of such differentials to disparities seen in using hospital care for childbirth. In order to answer this question, I defined four study objectives, each of which answered in a study:

Study 1 To review the approaches used in the literature to measure physical accessibility, and to synthesize evidence on what is already known about the importance of physical accessibility to the use of skilled childbirth care in SSA.

Study 2 To create high-resolution national maps to identify the locations of low to high SES areas for the four study countries.

Study 3 To quantify the extent to which physical accessibility to the nearest hospital is inequitable by SES using the high-resolution maps created in Study 2; and to examine if the current health systems in the study countries have allocated resources to optimize equity in physical accessibility by SES as well as average physical accessibility for the whole population.

Study 4 To partition the variability of hospital birth by SES, physical accessibility and other relevant factors in the four study countries, and to provide answers to the overarching objective of this thesis, by building on the preceding 3 studies.

1.2.1 Thesis outline

The rest of this thesis is structured into 8 chapters:

Chapter 2 Background Chapter 2 provides background information outlining maternal health, the poverty- and geographic-related inequalities of childbirth service uptake, and where such inequalities may overlap in SSA. Chapter 2 also contains information on the context of Kenya, Malawi, Nigeria and Tanzania, including geography, population, economy, governance, the structure of the health system and the provision of childbirth care.

Chapter 3 Data and Methods Chapter 3 is an overview of the data sources and methods used for the four planned studies. Further details for each of the four studies is then provided in Chapters 4-7.

Chapter 4 Study 1	Study 1 is a systematic literature review and meta-analysis of the measurement approaches used in the literature to quantify physical accessibility of skilled childbirth care in SSA. It also investigates what is already known about the importance of physical accessibility for the use of skilled childbirth care in SSA.
Chapter 5 Study 2	Study 2 is the first of a two-part attempt to compare physical accessibility to health services in poor and non-poor areas in the selected countries. The objective of Study 2 is to create high-resolution gridded national poverty maps to identify the locations at which the poor and less poor live. We compare different spatial interpolation techniques for high-resolution map creation and identify factors that influence their respective performances.
Chapter 6 Study 3	In Study 3, we utilize the poverty maps created in Study 2 to locate where the poor and less poor live, and overlay their locations with locations of hospitals and grid-based data of population size in a geographic information system (GIS). Then, combining these layers with an accessibility surface, we calculate travel time to the nearest hospital for people at different levels of wealth. The objective of Study 3 was to quantify the difference in travel time to the nearest hospital by wealth subgroups. Alongside the equity assessment, we further explore whether the current health systems in the selected countries have efficiently allocated resources to minimize overall travel time across the whole population. The balance between equity and efficient will be explored.
Chapter 7 Study 4	In Chapter 7 (Study 4), we partition the variability of hospital birth by wealth, travel time and other relevant factors in the selected countries. By building on the preceding three chapters, this final study answers the overarching objective of this thesis.
Chapter 8 Discussion and Conclusion	Chapter 8 is the last chapter of this thesis. I discuss the findings from the four studies together, alongside the lessons learnt and recommendations. Lastly, I close this thesis with the conclusion and my final remark.

Each chapter ends with its references and supplementary materials.

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Chapter 2
Background

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2 Background

The aim of Chapter 2 is to present the background information needed to contextualize this dissertation. It is organized in two main parts. In Section 2.1, I discuss the research context by going into the current status of maternal health, the use of skilled care for childbirth and the associated pro-rich and pro-urban distributions usually seen in SSA. I also outline the relationship underpinning wealth and geographic location – an idea less considered in the maternal health epidemiology literature – and how such relationship may make it difficult to understand if women are too poor or living too far to use skilled care for childbirth. In Section 2.2, I describe the four study countries – Kenya, Malawi, Nigeria and Tanzania – in detail, including their geography, economy and population, governance, health provision and healthcare structure.

2.1 Research context

2.1.1 Maternal health in sub-Saharan Africa

Maternal health is referred to as "the health of women during pregnancy, childbirth and the postpartum period". Especially in LMICs, improving maternal health has fundamental importance to a country's ability to prosper. Investing in better maternal health improves the outcomes for the women and her children, potentially increases the number of women in the workforce and promotes the economic growth of communities and countries [1]. Maternal health has been recognized and discussed as a public health concern on global developmental agendas since the 1987 Safe Motherhood Conference, including at the 1994 International Conference on Population and Development, the 1995 Fourth World Congress on Women, and the 1997 Safe Motherhood Technical Consultation. Specific targets were put in place to improve maternal health around the world in the MDG: Target 5A – Reduce by three quarters, between 1990 and 2015, the MMR and Target 5B – Achieve, by 2015, universal access to reproductive health [2]. At the present time of the SDGs, good maternal health continues to be endorsed globally: the goal is to reduce the global MMR to fewer than 70 per 100,000 livebirths by 2030 [3]. At the national level, countries should aim to reduce their MMRs by at least two-thirds from their 2010 baseline, and no country should have an MMR greater than 140 per 100,000 livebirths [4].

To monitor countries' progress towards such goals, maternal health is closely tracked by the World Health Organization (WHO) and partners using the MMR, calculated as the number of maternal deaths per 100,000 livebirths, as an indicator [1], [5]–[11]. The definition of a maternal death is given as the "death of a woman while pregnant or within 42 days of delivery or termination of pregnancy, irrespective of the duration and site of pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accident or incidental causes" [12]. The major direct causes include haemorrhage, infection, obstructed labour,

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hypertensive disorders in pregnancy, and complications of unsafe abortion [12]. In 2015, an estimated 216 maternal deaths per 100,000 livebirths happened globally (Table 2.1) [1]. MMR in SSA was the highest of all world regions, 2.5 times the global average and three times above South Asia, the region with the second highest rate.

Table 2.1 Estimates of maternal mortality ratio per 100,000 livebirths in 2015 by world region [1]

World region	Maternal mortality ratio (MMR)
Sub-Saharan Africa	546
South Asia	182
Middle East and North Africa	110
Oceania	82
Latin America and Caribbean	68
East Asia and Pacific	62
Central and Eastern Europe and the Commonwealth of Independent States	25
Europe	13
Northern America	13
World	**216**

A maternal death is a tragedy wherever it happens and whomever it happens to. However, the long-term consequences are likely to be very different in SSA and LMICs compared to in a high-income setting. In LMICs, where there is a general lack of social security, a maternal death increases mortality risks (particularly for the newborns) and worse nutrition and survival for the newborn and the women's other children. In addition, other family members are also more hard-pressed with economic and productive activities and domestic duties. This means the education of the children may be compromised, with possible consequences of extending the poverty cycle by another generation [13]–[16]. On a macroeconomic level, healthier women and children contribute to more productive and better-educated societies, and are crucial to long-term productivity [17]. The development and economic performance of nations depends, in part, upon how each country protects and promotes the health of women [17]–[19].

2.1.2 Maternal healthcare

Major causes of maternal mortality (and morbidity) in SSA are considered preventable if women had adequate access to effective maternal health interventions, delivered via contacts such as regular and quality antenatal care (ANC), skilled care at childbirth and postnatal care (PNC). ANC can be defined as the care provided to women during pregnancy in order to ensure the best health conditions for both mother and baby. The components of ANC include: risk identification, prevention and management of pregnancy-related or concurrent diseases and health education and health promotion [20]. ANC improves health both directly, through detection and treatment of pregnancy-related complications, and indirectly, through the identification of pregnancies at increased risk of complications during childbirth, thus ensuring transfer to appropriate management at birth [20], [21]. Following childbirth, the postnatal period is a critical phase in the lives and mothers and newborn babies. Best PNC practices, including appropriate timing and place of care, and the content of care for all mothers and babies, can avert maternal and newborn mortality and morbidity [22]. Unlike skilled care at birth, the provision of a good quality ANC and PNC can happen in outpatient settings, and even during home-visits.

2.1.2.1 Skilled care at childbirth

While a maternal death can occur throughout pregnancy and the postnatal period, childbirth is by far the most dangerous time for mothers and newborns [23]. Complications that develop during and following childbirth are difficult to predict and might rapidly become fatal or lead to disabling problems [24]. In 1987, the Safe Motherhood Initiative was launched to raise awareness and stimulate action at the global and national levels to make pregnancy and childbirth safer for women and newborns [25]. A clear consensus emerged from an international conference convened by the group in 1997 that ensuring skilled care during childbirth is a critical intervention for making pregnancy and childbirth safer [26].

The notion of skilled care during childbirth encompasses care provision by a health provider with midwifery skills who has been trained to proficiency to provide competent care during pregnancy and childbirth. A competent provider, as stated in the 2018 joint statement by the WHO, United Nations Children's Fund (UNICEF) and United Nations Population Fund (UNFPA), is someone who (i) provides and promotes evidence and human rights-based, quality, socio-culturally sensitive and dignified care to women and newborns, (ii), facilitates physiological processes during labour and delivery to ensure a clean and positive childbirth experience and (iii) identifies and manages or refers women and/or newborns with complications [27]. The care provider should also be able to perform (as part of a team) all signal functions of emergency maternal and newborn care [27] (detailed below in Section 2.1.4).

In addition to the competency of the care provider(s), the provision of sufficient care is heavily dependent on the place of childbirth [27]. The requirement for such an environment is complex, but the critical “physical features” should include supportive supervision to birth attendant, support from other health personnel and informal care givers, essential drug supplies and equipment, and adequate systems for communication and referral [27]–[30].

2.1.2.2 Indicator for the use of skilled care at births

In many LMICs, where the routine data system is weak and measurement of the MMR indicator costly, the use of skilled care at birth is widely adopted as a proxy to indicate the status of a population’s maternal health. The indicator is calculated as the percentage of livebirths attended by a skilled birth attendant (SBA) [2], and the data required for this calculation is usually collected in population surveys, such as Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS). In these surveys, women are asked the cadres of health personnel who assisted the childbirth. Often, women are also asked to report the place where they gave birth, thus allowing for the calculation of another indicator of maternal health and maternal health utilization – the percentage of live birth that occurred in a health facility – “facility-based delivery” (FBD).

In their assessment of the validity of SBA and FBD data, Blanc and colleagues found evidence to suggest that women can report the type and level of facility where they delivered more accurately than the cadre of attendant [31]. Regardless of the conceptual and measurement limitations of capturing the two indicators, the estimates of FBD and SBA closely correlate with each other [31]. Whilst there are exceptions, in LMICs, care provided by an SBA outside of a health facility is unlikely to be sufficient to meet the standard required to ensure safety given the lack of the support and supply needed (and vice versa). For these reasons, unless otherwise noted (such as in Chapter 4), the focus of skilled care at birth is directed to the location of childbirth (e.g. facility-based versus. outside of a health facility) in the rest of this dissertation.

2.1.2.3 The place of childbirth

In much of SSA, a substantial proportion of women do not deliver in a health facility, indicating the lack of use of skilled care at childbirth. Figure 2.1, plotted using data made publicly available by UNICEF [32], shows that FBD is below 50% in 14 of the 48 countries in the region (as recognized by The World Bank [33]). FBD is also unevenly distributed across the population. The percentage of childbirth among the richest quintile of the population in SSA which occurred in a health facility was approximately 4 times higher when compared to the poorest quintile. The pro-rich pattern of using skilled care at birth appears even more pronounced when the population is further disaggregated by wealth [34]. In a study of 46 LMICs, the wealth gap between the extreme quintiles (poorest 20% versus richest 20%) to that between the extreme deciles (poorest 10% versus richest 10%) were compared against one another. The authors showed that in 28 of 46 countries, there was statistical evidence that the differences between extreme deciles were larger than between quintiles [34].

In addition to the strong pro-rich pattern of use, rates of FBD are consistently lower among childbirths in rural areas. In a review in 2011, Moyer and Mustafa showed that the uptake of FBD in SSA is a complex issue shaped by the characteristics of the pregnant woman, her immediate social circle and financial status, the facility that is closest to her, as well as the context of the community in which she lives [35]. The urban-rural gap in FBD in LMICs is influenced by many

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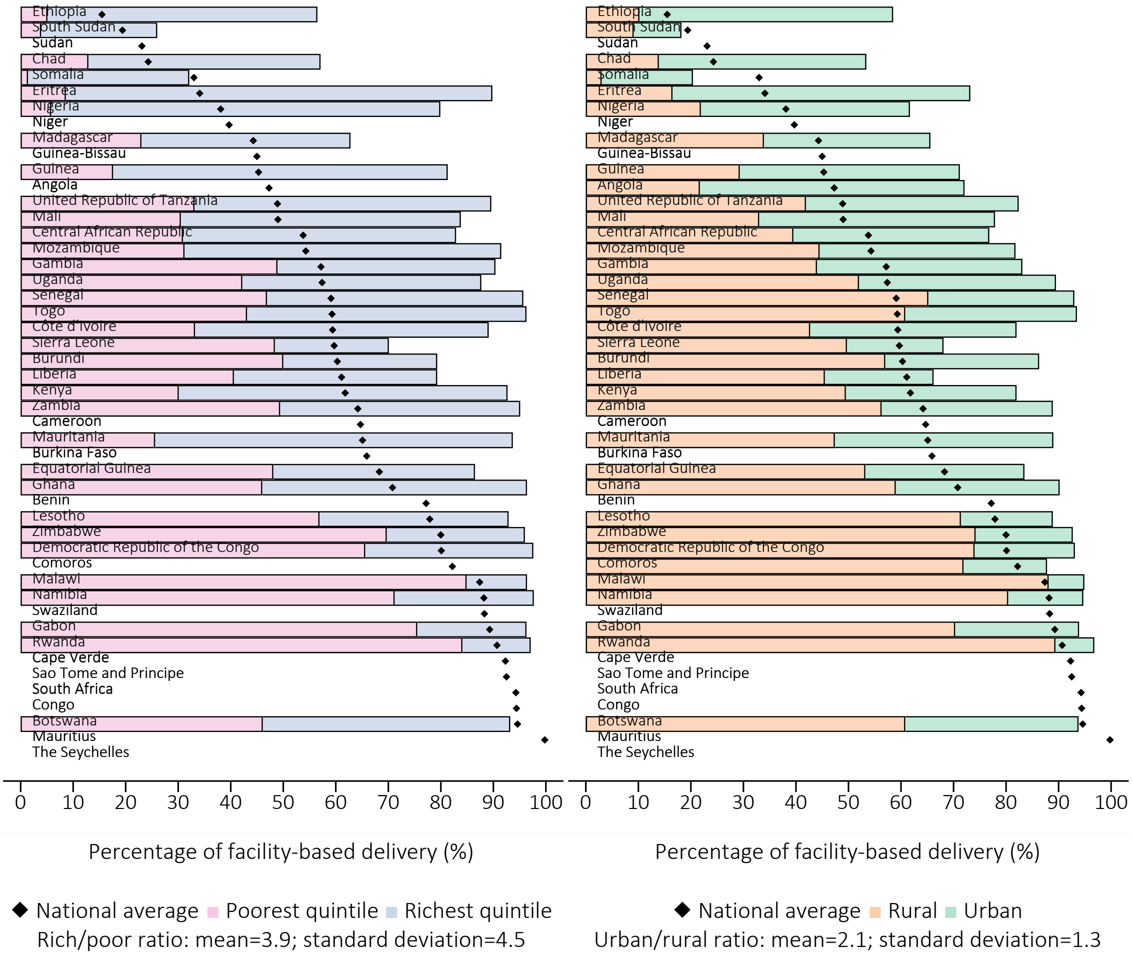
different factors. While higher concentration of poorer families (more below in Section 2.1.3.2) and important cultural and social/norms likely contribute, the geographic nature of the disparities in FBD between urban and rural areas raise a crucial question about a geographic explanation. If all births should take place in health facilities for optimal care, then rural dwellers in remote areas are inevitably more constrained in their ability to physically reach such facilities due to physical/geographic constrains, such as increased travel impedance and paucity of healthcare provision in/near the places where they live.

Figure 2.1 Facility-based childbirth by sociodemographic characteristics [31]



2.1.3 Access to health services

An individual's physical accessibility to health services is heavily conditioned by what the system provides them with. This is the notion of *access to* health services, and is referred to as the opportunity or ease with which people are able to obtain appropriate healthcare from a provider or institution to address health needs [36]–[38]. Aday and Andersen explicitly conceptualised access to health services in terms of the characteristics of the healthcare delivery system that affect the population's opportunity to utilize healthcare services as needs arise [39]. In this framework, access has three dimensions:

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- physical accessibility is understood as the availability of appropriate health services within a reasonable reach of those who need them, and are organized and delivered to suit the population for ease of actual use;
- financial affordability is a measure of people's ability to pay for services without financial hardship, including the direct cost of health services and indirect and opportunity cost (e.g., the cost of transportation to and from facilities and of taking time away from work);
- service acceptability represents people's willingness to seek services; acceptability is low when people perceive services to be ineffective, or feel discouraged to seek services for social and cultural factors, such as discrimination or disrespect, which might be based on language, age, sex, ethnicity or religion.

Physical accessibility, financial affordibility and service acceptability can enable or hinder people to use health services. Good access depends, among other factors, on the organizational aspects of healthcare provision [40], and is amendable to improvement through effective health planning and policymaking.

2.1.3.1 The physical (geographic) dimension of access to health services

The physical dimension of access to health services is determined by the geographic arrangement between the healthcare supplied and the population served [3], and may underpin the urban-rural gap shown in Figure 2.1. In the simplest form, the way in which physical accessibilty can create barriers to healthcare utilization can be illustrated by the "distance decay" problem [40]. The distance decay problem signifies the tendency for less interaction between two locales as distance increases [41], [42]. Distance decay is a consequence of the added cost, difficulty or time of having to travel long distances, and the assumed reduced willingness and ability to bear that cost of travel; leading to the use of suboptimal care (that are within closer reach), or in the worst case, unmet health need by forgoing use of care.

In the maternal and newborn health literature, this geographic explanation was first noted in the "three delays" framework by Thaddeus and Maine in 1994 [43], and later extended by Gabrysch and Campbell in 2009 [44]. In these frameworks, physical accessibility is considered to have a direct effect on a woman as she identifies and reaches a health facility for both uncomplicated childbirth and in an obstetric emergency. In addition, judgement about physical accessibility and the time and cost incurred to reach a facility indirectly impact the decision to seek preventive and emergency care both before and after labour begins (Figure 2.2) [44]. The effect of physical accessibility on the use of skilled care at birth is reviewed as part of Study 1 in Chapter 4 in this dissertation.

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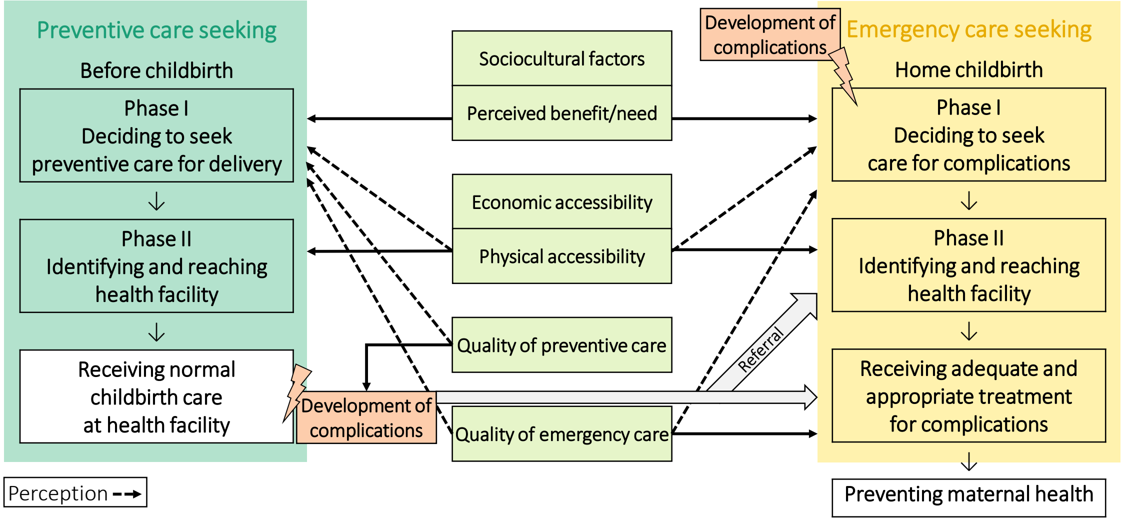
Figure 2.2 Factors affecting use of childbirth care and maternal mortality (recreated from Gabrysch and Campbell [44])



2.1.3.2 Physical accessibility to health services and wealth

Physical accessibility should be carefully accounted for when deciding about the geographic locations of healthcare provision (at least for those services that are not mobile and are provided at fixed locations) [3]. The provision of services, and therefore the population's physical accessibility to health services, is inevitably more difficult in remote areas of weak integration or connectedness, where the infrastructure, road networks, road conditions and options for transportation are suboptimal. Topographic constraints are crucial barriers here, as they make the introduction of resources and human power to these places challenging and expensive. Those residing in such settings are often poorer relative to others who live in other parts of the country; and also have a certain tendency to remain that way [45], [46].

The locational nature of environmental/topographic constraints and the resultant disadvantage in infrastructure and services are critical to explaining the spatial patterns of SES [47]. Bird and Shepherd, in their empirical study of semi-arid zones in Zimbabwe, identified a clear link between high levels of remoteness, low levels of public and private investment and high prevalence of chronic poverty [47]. Escobal and Torero found similar results in Peru in 2005; they identified a strong association between spatial pattern of SES and variation in private and public assets [48]. For SSA, a study conducted in 2010 found that the poor in Kenya were disproportionately more likely to be far from a motor-able road, and more likely to live in areas with relatively little access to education, especially higher education [49].

The spatial pattern of wealth or SES is perhaps due to the tendency for people to reside, and be found/seen to reside, in the same/nearby neighbourhoods and areas with others who are similar [50]. Clusters of people who are similar in wealth or SES may be expected to have a similar level of economic accessibility (or financial affordibility, see Section 2.1.3) and a similar level of physical accessibility to health services (at least for those services that are provided at fixed location in space). This adds difficulties to how we can understand whether people are too poor or too far to use health services, and potentially render the effectiveness of the strategies employed to increase service uptake. In the delay framework by Gabrysch and Campbell [44], the effect of economic accessibility and that of physical accessibility may overlap to certain extent.

It is worth noting, however, that there are important exceptions to the spatial overlapping of SES and physical accessibility to health care (and other services) described here. Wealth disparity is widely seen (and worsening) in expanding urban cities in LMICs. Inner-city, or intra-urban, residential segregation as defined by wealth may mean that the poor and the less poor are not necessarily very different in how far they are to health services. However, the poor may be less likely to own, drive or use cars, and the public transportation system may not be well-streamlined to meet their health needs [51], [52], especially for an event such as childbirth. The nearest healthcare provider may also be private and unaffordable. Depending on how physical accessibility is measured (which I investigate in Chapter 4), inequity by SES in an intra-urban setting may still exist. Rapid urban population growth and the development needed to cope with the rising demand of services may further exacerbate existing urban-rural disparities of both wealth and physical accessibility to healthcare (and other services), leading to a wider wealth gap across the whole population and marked differences in physical accessibility to healthcare (and other services) between wealth subgroups.

2.1.4 All health facilities are not made equal

Our conceptualization of skilled care at birth as measured by FBD has so far overlooked that health facilities typically differ from one another, and thus the care provided and the quality that can be expected in different health facilities may not be identical. LMIC governments mostly rely on deploying primary health care (PHC) to meet the health needs of those living in rural and hard-to-reach areas [53]. PHC is referred to as the basic level of a structured health system, which provides outpatient care for simple and common health problems [54]–[56]. Secondary and tertiary facilities can offer a fuller and more comprehensive range of health services, but are less seen in rural and hard-to-reach places. Secondary and tertiary facilities provide referral care and often serve as the primary contact point for their catchment population. The WHO defines PHC based on three components [57]:

- meeting people’s health needs through comprehensive promotive, protective, preventive, curative, rehabilitative, and palliative care throughout the life course, strategically prioritizing key health services aimed at individuals and families through primary care and the population through public health functions as the central elements of integrated health services;

- systematically addressing the broader determinants of health (including social, economic, environmental, as well as people's characteristics and behaviours) through evidence-informed public policies and actions across all sectors; and
- empowering individuals, families, and communities to optimize their health, as advocates for policies that promote and protect health and well-being, as co-developers of health and social services, and as self-carers and caregivers to others.

Especially in rural areas, a person usually first sees the local provider, typically from a lower-level, PHC facility such as a dispensary or health centre, when they have a health problem. A healthcare provision network including all levels of health facilities and a functional referral mechanism should help overcome the potential issue of poor physical accessibility by enabling people to meet their health needs with the most appropriate health services, regardless of their most convenient point of entry into the health system [58].

But health service provision assessments, such as Service Provision Assessment (SPA) and Service Availability and Readiness Assessment (SARA), often demonstrate that PHC faciliities lack the equipment and capacity to deliver the basic functions (usually confined to outpatient care) that they are expected to perform [59], [60]. A functioning referral system in many LMICs is also not in place to facilitate complicated and severe cases to be effectively and efficiently escalated. These referral systems are challenged with multiple issues – a small number of ambulances, unreliable logistics and communications, and inadequate community-based facilitated referral, resulting in excess morbidity and mortality from treatable conditions [61]–[64].

Concerns of low quality facility-based childbirth care in PHC facilities – suboptimal SBA staffing, and the lack of capacity for a SBA to perform essential interventions, start treatment and supervise referral due to limited equipment and medical supply [65], [66] – have prompted researchers to reflect on the provision of maternal health services in resource-limited settings. In a recent Lancet series, Campbell and colleagues argued that childbirth should occur in facilities providing emergency obstetric and newborn care (EmONC) – at the basic EmONC (BEmONC) level, with facilitated referral to comprehensive EmONC (CEmONC) where advanced services can be provided [66] (Table 2.2).

In many LMICs, this likely means that childbirths should take place in hospitals, as lower-level facilities are often ill-equipped or have low patient load so that health personnel do not intervene often enough (e.g. remove placenta/retained product) to stay well-practiced and maintain skills.

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At the county level in Kenya, for instance, 0-10% of health centres and dispensaries provide all seven BEmONC functions. Although in some cases still suboptimal, readiness of BEmONC is higher in hospitals across the country (0% in Nyamira County to 83% in Muranga County) [67]. Failure to acknowledge the type of care offered/can be expected when considering an individual's physical accessibility to health services can lead to serious misunderstanding of the service provision environment that women are situated within.

Table 2.2 Signal functions used to identify basic and comprehensive emergency obstetric care services

Basic emergency obstetric care services (BEmONC)	Comprehensive emergency obstetric care services (CEmONC)
(1) Administer parenteral antibiotics (2) Administer uterotonic drugs (i.e. parenteral oxytocin) (3) Administer parenteral anticonvulsants for pre-eclampsia and eclampsia (i.e. magnesium sulphate) (4) Manually remove the placenta (5) Remove retained products (6) Perform assisted vaginal delivery (7) Perform basic neonatal resuscitation	Perform signal functions 1-7, plus: (8) Perform surgery (e.g., caesarean-section) (9) Perform blood transfusion
A BEmONC facility is one in which all functions 1-7 are performed. A CEmONC facility is one In which all functions 1-9 are performed.	

The use of adequate health services, such as hospital-based care, at birth is inequitable in SSA, with the poorer and rural populations most affected. Low use among rural women may be due to suboptimal organizaiton of health services; factors amendable at the system level that individuals can do little about. Moreover, locational disadvantage may also reinforce, and be reinforced by, wealth disparities. As the call for all women to receive high-quality childbirth care in a well-equipped facility urgently rises, whether the "left behind" are too poor to use hospital-based childbirth care, or live too far from a hospital to go there for childbirth, ought to be better understood.

2.2 Study context

2.2.1 Geography

Kenya and Tanzania are in East Africa, Malawi is in southern Africa (sharing a border with Tanzania) and Nigeria in West Africa (

Figure 2.3). Kenya and Tanzania both have a coastline along the Indian Ocean to the east, and Nigeria along the Gulf of Guinea. The equator passes Kenya at the middle, separating upper and lower Kenya almost equally. Tanzania (officially the United Republic of Tanzania and Zanzibar) incorporates Mainland Tanzania and an offshore semi-autonomous region – Zanzibar. Due to a data limitation (see Section 3.3.1.1), the analyses in this dissertation exclude Zanzibar. The capital cities of these countries are Nairobi (Kenya), Lilongwe (Malawi), Dodoma (Tanzania), and Abuja (Nigeria).

Kenya borders with Tanzania in the south, and both countries are part of the East Africa Community (together with Burundi, Rwanda, South Sudan and Uganda). Kenya and Tanzania share some physical features, including Lake Victoria (the largest freshwater lake in Africa) and the Great Rift Valley. The highest mountain in the African continent, Mount Kilimanjaro, is in north-eastern Tanzania, whilst the second highest, Mount Kenya, is in Kenya. Malawi occupies a thin strip of land to the south of Tanzania. The Great Rift Valley also runs through Malawi (from north to south), and in this deep trough lies Lake Malawi, the third largest lake in Africa. In general, the topography of Nigeria consists of plains in the north and south interrupted by plateaus and hills in the centre of the country. Large areas of the coast of south-eastern Nigeria is a marsh/wetland without roads.

Figure 2.3 Geographic location of the study countries

2.2.2 Population

The population size and population density of the four countries in 2015 are given in Table 2.3 Country data and statistics in 2015, together with other data and statistics. Nigeria ranks as the most populated and densely populated country among the four studied here (and the most populated country in Africa) [68]. On the other hand, Tanzania is the least densely populated. The percentages of urban population in 2015 were 26% (Kenya), 16% (Malawi), 48% (Nigeria) and 32% (Tanzania). In all countries, the population age structure is young, with at least 40% of the population below 15 years of age (global average equals 26%). The annual rates of population growth exceed global average by 2-4 fold.

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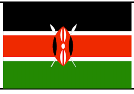
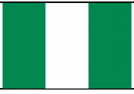
Table 2.3 Country data and statistics in 2015

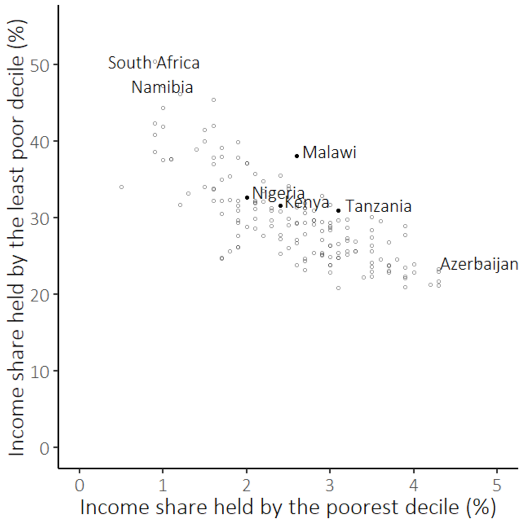
	Republic of Kenya (Kenya)	Republic of Malawi (Malawi)	Federal Republic of Nigeria (Nigeria)	United Republic of Tanzania and Zanzibar (Tanzania)	World
National flag [69]					
Total area (km^2)	580,367	118,484	923,768	947,300	NA
% land area (%)	98	79	99	94	NA
National population in 2015 (million)	47	18	181	54	7,341
Population density in 2015 (person/km^2 land area)	83	187	215	64	NA
% urban population in 2015	26	16	48	32	54
Percentage of population aged 0-14 in 2015 (%)	41	45	44	45	26
Annual population growth in 2015 (%)	2.3	2.6	2.6	3.0	1.2
Projected population in 2025 (million)	60	22	233	69	8,184
GNI per capita in 2015, Atlas method (current US$)	1,290	350	2,880	980	10,647
GNI per capita in 2018, Atlas method (current US$)	1,620	360	1,960	1,020	11,101
World Bank income classification in 2018	Lower-middle	Low	Lower-middle	Low	NA
% population at $1.90 a day in 2015 (2011 PPP)	37	72	54	49	10
Income share held by the poorest decile	2.4	2.6	2.0	3.1	NA
Income share held by the least poor decile	31.6	38.1	32.7	31.0	NA

NA: data is not available or not applicable. GNI = gross national income. PPP = purchasing power parity

2.2.3 Economy

The World Bank uses gross national income (GNI) per capita to classify countries into four income groups – lower, lower-middle, upper-middle and higher. In the most recent fiscal year, for which data from 2018 is used, Kenya and Nigeria were classified as lower-middle income countries, and Malawi and Tanzania lower-income countries [70]. The percentage of population considered in poverty using the $1.90/day (2011 purchasing power parity) threshold vary across the selected countries from 37% in Kenya to 72% in Malawi, but are high in all cases compared to the global average of 10% [71]. There was marked uneven distribution of income, with less than 2-3% of the total national income held by the poorest 10% of the population and over 30% held by the least poor (Table 2.3 Country data and statistics in 2015) [72]. Among 163 sovereign states for which this data is available, the selected countries rank midrange (Figure 2.4).

Figure 2.4 Income share held by the poorest and least poor deciles (plotted using data from 163 sovereign states)



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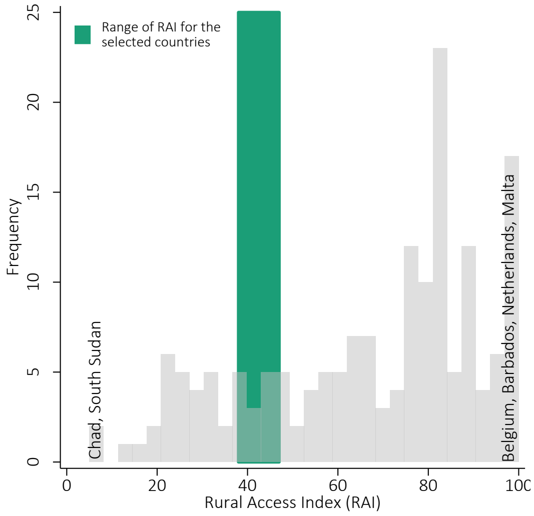
2.2.4 Transportation

The lack of transportation can isolate individuals from the services they need. Two SDG indicators directly refer to one's to ability to use transportation: 9.1.1 "Proportion of the rural population who live within 2km of an all-season road" and 11.2.1 "Proportion of population that has convenient access to public transport, by sex, age and persons with disabilities" [73]. The Rural Access Index (RAI), a measure for SDG indicator 9.1.1, was last globally revised in 2006 [73]. According to this revision, country RAIs ranged from 0% in Chad and Sudan to 100% in Belgium, Barbados, the Netherlands and Malta (Figure 2.5). RAIs of the four study countries were between 38% in Malawi and Tanzania to 47% in Nigeria.

Figure 2.5 Rural Access Index (RAI) of 174 sovereign states



In the study countries, the transportation infrastructure is weak and lacks good governance in urban areas. Most African cities have developed around individual transport and the public authorities often struggle to control the supply side of public transport and traffic management. Affordability and inclusiveness of available urban transport options are major concerns that lead to time-consuming and costly travels [74]. This appears where congestion gets out of control and where scheduled bus services are unavailable/unreliable, most often superseded by paratransit services (e.g., matatu in Nairobi) [74]. In Nairobi, matatus dominate the public transport supply system [74]. In Lagos, over 40% of commuter trips are undertaken using privately operated, and largely unregulated, minibus vehicles (danfos) and motorcycle taxis (okadas), closely followed by 40% non-motorised means [75]. In Dar es Salaam, close to 90% of travel is conducted using motorised public transport and non-motorised transport (approximately equal split) [75]. Motorised services are largely provided by a private operators, a number of informal daladala minibuses, and a growing bajaji rickshaw industry [75]. In Blantyre, the commercial and industrial capital of Malawi, the modes of transportation are largely by walking (77%) and public transport (26%) [76].

2.2.5 Governance

Before I outline the provision of healthcare in the four study countries, it is important to acknowledge that their governance is decentralized, and involves part of the public decision-making process, implementation and financing in health (and in other sectors) falling under subnational leadership(s).

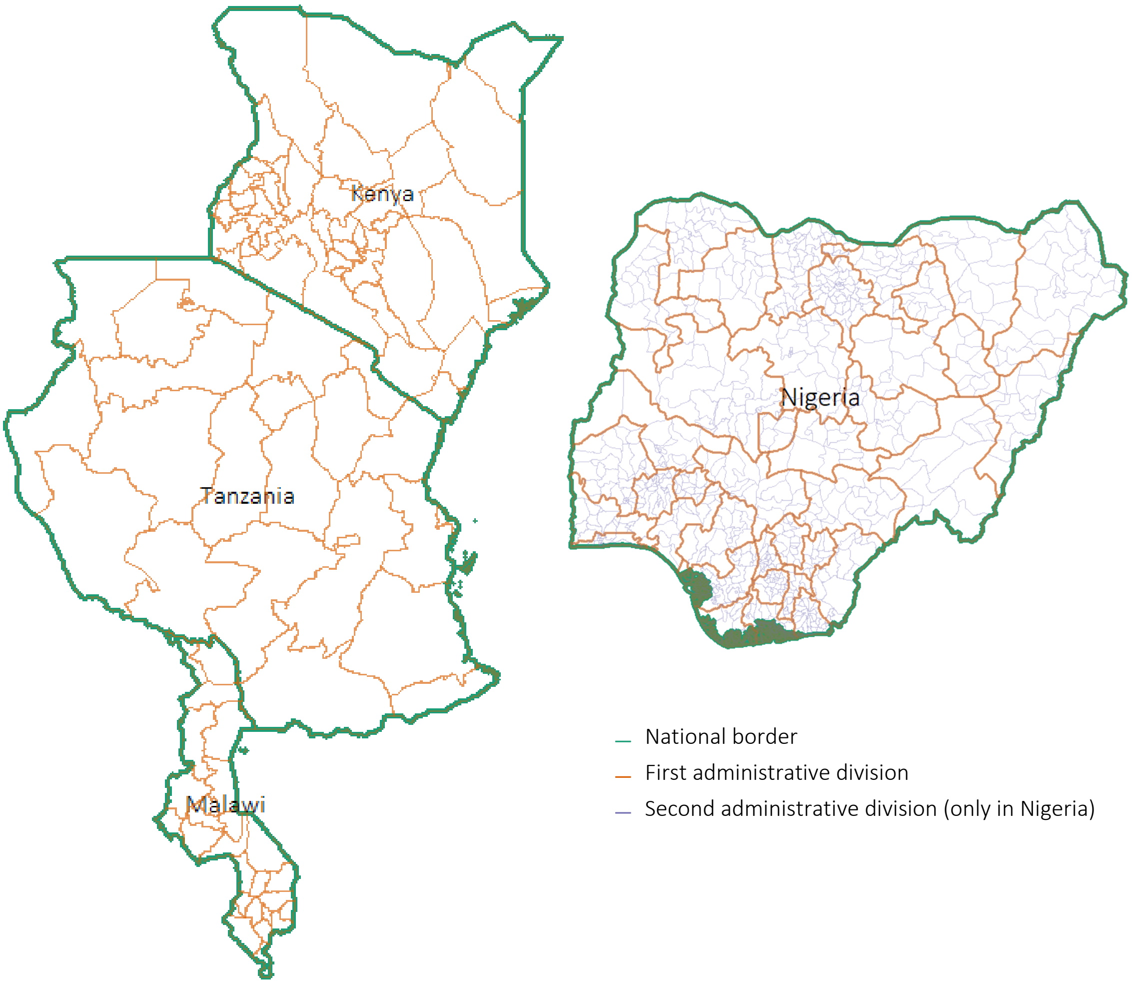
2.2.5.1 Kenya, Malawi and Tanzania

Kenya, Malawi and Tanzania operate a one-tier structure of decentralized governance. Subnational governments – 47 counties in Kenya, 28 districts in Malawi and 30 regions in Tanzania Mainland (Figure 2.6) – elect their own executives. The national constitution or the local government acts of a country typically states the division of the specific functions, powers and competencies of the national governments and the subnational governments. In Kenya, for instance, the Constitution introduces a principle of general jurisdiction that any responsibilities not specifically assigned to local governments by the constitution shall remain the competences of the national government [77]. According to the Local Government Act in Malawi, where well-justified, subnational governments can also jointly discharge a competence that could not be implemented locally [78], [79].

2.2.5.2 Nigeria

The Constitution of Nigeria, on the other hand, provides for the operation of the federal government at the top of a three-tier system. The second tier consists of 36 states and the Federal Capital Territory (FCT) under the direct control of the federal government. Local government exists in a single tier across all states. Altogether, there are 774 local government authorities (LGAs) (Figure 2.6). The 36 States take charge of all matters that affect their jurisdictions, while the federal government takes charge of a few exclusive matters of national interest (e.g., defence and foreign policy) [80]. Under the Nigerian Constitution, States have the power to ratify constitutional amendments. As sovereign entities, States of Nigeria also have the right to organize/structure their individual governments in any way within the parameters set by the Constitution of Nigeria.

Figure 2.6 Administrative division in Kenya, Malawi, Nigeria and Tanzania



2.2.6 Financing of the decentralized governments

The financing of the government systems in the one-tier structure of decentralization in Kenya, Malawi and Tanzania is similar. Subnational governments in Kenya are responsible for collecting taxes, user fees and charges; and, in addition, the constitution stipulates that a minimum of 15% of revenue raised nationally must be allocated to county governments. County governments also receive revenue from central government block grants through the Local Authority Transfer Fund. In Malawi, subnational governments have the responsibility to raise and collect local taxes and user fees and charges; however, majority of their revenue comes from national government grants, both conditional (sectoral funds) and unconditional (general resource funds) [79]. In Tanzania, subnational governments have the power to levy taxes, fees and charges; however, the majority of local authority revenue comes in the form of sector-specific conditional transfers from national government [81]. Local governments are not able to collect taxes besides those allocated to them by the central government [82].

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On the other hand, in Nigeria, the funds raised by taxes are collected by all levels of government. Federal and state governments are responsible for raising and collecting taxes. Local governments collect some local taxes, such as those for haulage, hawking and markets, as well as motor and commercial drivers' levies [83]. All federal revenue collected is pooled in the federal account which is in turn split across the three tiers of government based on an agreed formula [84].

2.2.7 Provision of healthcare in a decentralized government

Decentralization typically involves part of the public decision-making processes and a large part of implementation falling under subnational leadership. Subnational governments in Kenya, for instance, are responsible for the provision of health, water provision and distribution, commerce (markets, trade development and regulation, business licenses), public transport, education (pre-school and technical), and the implementation of national policies [72]. In line with the Constitution of Kenya 2010 [77], the Kenya Health Policy 2014-2030 sets out that each county establishes a health department whose role is to create and provide an enabling institutional and management structure responsible to coordinate and manage the delivery of healthcare mandates and services at the county level [85]. The policy also gives directions to the formation of county health management teams to provide technical and professional management structures in the county, and to coordinate the delivery of health services through the health facilities present in each county. Table 2.4 lists the responsibilities in the Kenyan health sector devolved to the subnational governments, and those that remain under the responsibility of the national government [77], [85].

Table 2.4 Responsibilities of the national and county government in health in Kenya [77], [85]

National ministry responsible for health	County department responsible for health
National referral hospitals	County health facilities and pharmacies
Healthy policy	Ambulance services
Financing	Licensing and control of agencies that sell food to public
Quality assurance and standards	Disease surveillance and response
Health information, communication and technology	Cemeteries, funeral homes and crematoria
National public health laboratories	Refuse dumps and solid waste disposal
Public-private partnerships	Control of drugs abuse and pornography
Monitoring and evaluation	Disaster management
Planning and budgeting for national health services	Public health and sanitation
Ports, borders and trans-boundary areas	Veterinary services (exc. regulation of veterinary professionals)
Major disease control (Malaria, TB, leprosy etc.)	

The national government is responsible for the healthcare provision in national referral hospitals. These hospitals are the highest level of health facilities providing the most advanced type of services in the government sector. There are currently four national referral hospitals – three in

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Nairobi and one in Eldoret. All other healthcare provided at a health facility in the country fall under the responsibilities of the county governments.

Similar to Kenya, in Malawi and Tanzania, the provision of health and other major services is also partially assigned as the responsibility of the subnational governments. In Nigeria, this responsibility is shared among the three-tier government.

2.2.8 Health system organization and healthcare structure

2.2.8.1 Kenya

Levels of care

Established under the Second National Health Sector Strategic Plan in 2007, the Kenya Essential Package for Health (KEPH) defines health service provision across a continuum of care. The KEPH consists of six service delivery levels and six age cohorts, specifying a defined set of interventions and services for each point of care. Figure 2.7 illustrates the six life-cycle cohorts/stages defined by KEPH: pregnancy and newborn up to 2 weeks; early childhood to 5 years; late childhood between 6 and 12 years; adolescence and youth between 13 and 24 years; adulthood between 25 and 59 years; and the elderly of 60+ years [86].

Figure 2.7 The life-cohort based approach to the delivery of healthcare services of the Kenya Essential Package for Health (KEPH) (adopted from the Clinical Guidelines for Management and Referral of Common Conditions at Levels 2-3: Primary Care [86])

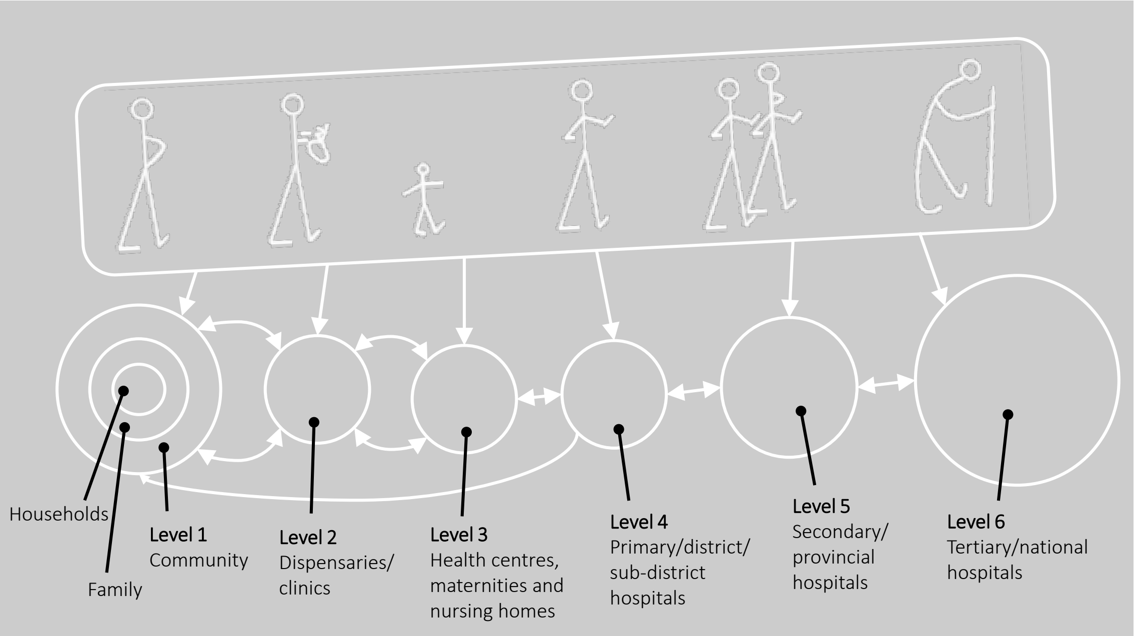

Figure 2.7 also depicts the linkages among care levels 1-6 of KEPH. Level 1, or the community level, is the first level care and entry into the health system. Together with levels 2 and 3, the general functions of pre-hospital care are health promotion and preventive care provided at

dispensaries, clinics, health centres, maternities and nursing homes. Hospital care offered at levels 4 and 5 are the intermediary between national referral hospitals and primary care. Level 4 and level 5 hospitals provide surgical services, internal medicine and some specialist services, such as EmONC. National referral hospitals, the responsibility of the national government, offer a comprehensive range of specialised services, sophisticated diagnostics, therapeutic and rehabilitative services. The expected services for the pregnant women and newborns up to 2 weeks (the first of six age cohorts in KEPH) across levels 1 to 6 care are outlined in the Clinical Management and Referral Guidelines (summarized in Table 2.5) [86].

Table 2.5 KEPH strategic interventions for pregnant women and newborn up to 2 weeks, by level of care [86]

Level 1	**Community: Village/households/families/individuals**
	Provide communities with current knowledge and facilitate appropriate practices and attitudes leading to safe pregnancy and childbirth
Level 2	**Dispensaries/clinics**
	Facilities are equipped to provide very basic antenatal care and refer all childbirths
Level 3	**Health centres, maternities, nursing homes**
	a) Ensure that health centres are equipped to provide basic essential obstetric care b) Enhance health systems support for delivery of quality obstetric and newborn care c) Establish a functional supportive supervision system to ensure quality assurance d) Develop outreach programs to serve “hard-to-reach” populations
Level 4	**Primary/district/sub-district hospitals**
	Equipped to provide comprehensive essential obstetric care
Level 5	**Secondary/provincial hospitals**
	Equipped to provide essential obstetric care
Level 6	**Tertiary/national hospitals**
	Provision of care to adequately manage mothers and newborn infants referred from lower level

Care at childbirth

The Clinical Management and Referral Guidelines set out that normal labour and childbirth should be managed by a skilled provider linked to EmOC facilities by an effective referral system. In addition, women should be referred to a level 4-6 facility (a hospital) before labour becomes obstructed [86], [87]. Health centres (level 3 facilities) in Kenya are required to provide basic EmOC signal functions and are “theoretically” and “automatically” classified as BEmOC facilities, but few actually offer all required signal functions [88]. Gaps in the referral system have also been identified, including (i) lack of clear guidelines on referral processes, (ii) lack of resources in health facilities, according to the national service standards and norms, (iii) lack of formal communication and transport mechanisms, (iv) poor relationships between referring and receiving facilities, (v) lack of pro–poor protection mechanisms for emergency referrals, (vi) inadequate capacity to monitor the referral system and provide feedback, and (vii) inaccurately reported referral data [89]. These concerning realities are thoroughly discussed in the Lancet Maternal Health Series 2016 [90].

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Non-government sector

In addition to the government sector, the Kenyan healthcare system also includes the non-government/private sector with private-for-profit (PFP) providers and the private-not-for-profit (PNFP) providers. Kenya's non-government health sector is one of the most developed in SSA [91]. About 38% and 14% of all health facilities in Kenya fall under the ownerships of the PFP and PNFP sectors, respectively [92]. While the government sector has levels 5 and 6 facilities, the non-government sector does not yet [92]. Non-government facilities are levels 1-4 and their locations are primarily in urban wealthy places where sufficient investment returns can be expected.

The non-government sector is the larger employer of the Kenyan health workforce – almost 75% of the medical doctors and 66% of the nurses and clinical officers [93]. Approximately 47% of the poorest quintile of Kenyans will seek care from the PFP sector when a child is sick [94]. Services at PNFP facilities are generally considered as a good alternative at an affordable price [91].

2.2.8.2 Malawi

Levels of care

The organization of the health system and the healthcare structure in Malawi, and Tanzania (more below in Section 2.2.8.3) are very similar to those in Kenya. In Malawi, the Ministry of Health (MoH) and the Ministry of Local Government and Rural Development are jointly responsible for health service delivery in the government sector. The decentralized system has four tiers of service delivery – community, primary, secondary, and tertiary – linked through a referral system. As laid out in the Health Sector Strategic Plan II 2017-2022, community level, primary level and secondary level health services are delivered under the leadership at the District Health Office (subnational governance), controlled by their respective District Commissioners, with oversight of financial management coming from the national level. The public health functions of the central level further include agenda setting, policy making, standards setting, quality assurance, strategic planning, resource mobilization, technical support, monitoring and evaluation and international representation [95].

At the community level, services are provided by health surveillance assistants (HSAs), health posts, dispensaries, village clinics, and maternity clinics. HSAs mainly provide promotive and preventive care through door-to-door visits, village and outreach clinics and mobile clinics. At primary level, health services are provided at health centres and community hospitals. Health centres are staffed by nurses, clinical officers and medical assistants, and offer outpatient and maternity care [96]. Community hospitals are larger than health centres, and offer outpatient and inpatient services, and conduct minor procedures [95] (<20% provide caesarean-section [97]).

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The secondary level of care consists of district hospitals and Christian Health Association of Malawi (CHAM) hospitals of equivalent capacity. They provide catchment population with outpatient and inpatient care. The team at district hospitals (secondary level) generally comprises of 1-2 doctor(s), clinical officers/clinical associates and medical assistants. Lastly, central hospitals are tertiary level facilities. They provide specialist health services, referral services to district hospitals, and services in their region. Central hospitals also have the mandate to offer professional training, conduct research and support the districts.

Care at childbirth

The policy of the Malawi government mandates that all women should give birth in a health facility [98], and traditional birth attendants are outlawed [98]. In practice, fewer than 10% of childbirths occur outside a health facility [99]. The provision of BEmONC signal functions is the goal for all levels of health facilities in the country [100]. In practice, few health centres (5%) provide a full package of BEmONC or CEmONC services [95]. In addition to shortages of midwives and doctors to provide obstetric and neonatal services, there are also shortages of supplies and logistics in most health facilities and inadequate transport for referral of emergencies. An assessment of EmONC care provision in 2014 found that although almost all facilities surveyed reported having a functional mode of telecommunication, only a third of facilities had a functioning motor vehicle ambulance and 6% had a functioning motorcycle ambulance [100].

Non-government sector

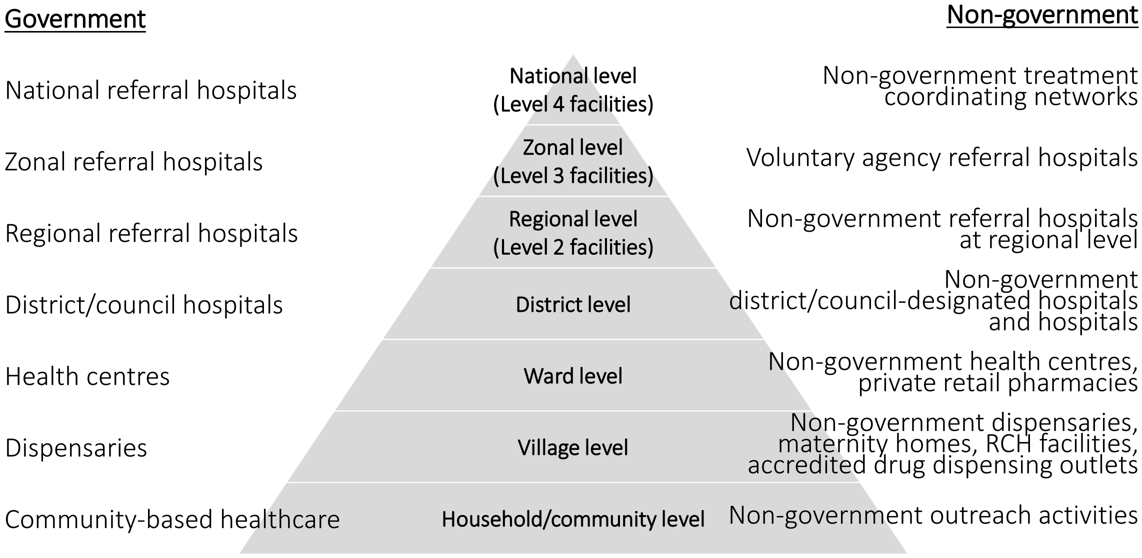
The government in Malawi, through the MoH, provides about 60% of health services, while the CHAM provides 39%, and a small contribution of 1% from the PFP sector [100]. CHAM is the largest PNFP provider in Malawi and is an important actor in the health system because of its large network of providers across the country, especially in rural places. About 80% of CHAM services are delivered in areas designated as hard-to-reach. CHAM boasts a vast health infrastructure with facilities at various levels of care, including health centres and hospitals. Approximately 40% of hospitals and 25% of health centres in the country are CHAM facilities [100]. The PFP sector is relatively small, and their facilities predominately located in urban areas. PFP facilities mainly serve the high-SES subgroup, and a small number of employees who purchase private health insurance [100].

2.2.8.3 Tanzania

Level of care

The Tanzanian government operates a decentralized, pyramidal health system (Figure 2.8, adapted from the Tanzania's Health Sector Strategy Plan IV). The districts are empowered to set priorities, and is responsible for health service implementation and the supervision of individual health facilities, including dispensaries, health centres, district hospitals and regional referral hospitals.

Figure 2.8 The health care pyramid in Tanzania (government and non-government equivalent), adopted from the Tanzania's Health Sector Strategy Plan IV



Dispensaries provide preventive and curative outpatient services, while health centres can also admit patients, and sometimes provide surgical procedures. Furthermore, conditions that require inpatient care should be referred from dispensaries to the nearest district hospital providing health services to referred patients. A district (subdivision of region) without a public district hospital enters into a service agreement with a hospital run by a faith-based provider, which is then designated as a district hospital. Regional referral hospitals function as referral hospitals to provide specialist medical care [100], and are in place in all 25 regions in mainland Tanzania. Above regional referral hospitals, there are zonal and national hospitals offering advanced medical care and are teaching hospitals for training purposes. Zonal and national hospitals are the responsibilities of the national government.

Care at childbirth

One explicit aim of Tanzania's policy is to increase access to childbirth care in PHC facilities – mainly by establishing one dispensary, that can provide basic antenatal, delivery, outpatient and postnatal care, for every village [101]. In Bintabara and colleagues' assessment, dispensaries generally scored <40/100 in availability and readiness to provide BEmONC [102]. The least available BEmONC signal function at health centres was parental administration of anticonvulsant (32%) [102]. Low levels of parental administration of antibiotics, manual removal of placenta and retained products of conception were other challenges also pointed out. The low availability of the BEmONC signal functions is further impacted by the long process of acquiring drugs and medical supplies due to logistic difficulties [102].

Non-government sector

The non-government health sector in mainland Tanzania comprises a wide range of actors engaged in a number of health activities, e.g., healthcare provision, pharmaceutical dispensing and laboratory diagnostics. The size of the private health sector has increased relatively quickly over the past 20 years in response to government policy changes (primarily the removal of the ban on private sector healthcare in 1991) [103]. The non-government health sector comprises PFP and PNFP entities. Public (or government), PFP and PNFP facilities are located throughout the mainland. According to Health Management Information System report 2013/14 by the Ministry of Health and Social Welfare [104], 16% of the 8,215 health facilities in the country are non-government, and approximately 14% of the 279 hospitals are non-government. The number of beds total 50,862, and the number of beds in hospitals is 34,017; in both cases, 4% of which are non-government.

2.2.8.4 Nigeria

Levels of care

The three tiers of the health system in Nigeria (federal, state and LGA) exercise considerable authority in the allocation and utilization of their resources. The National Health Policy, or the National Health Bill, ascribe roles and responsibilities to each level. The LGAs are responsible for primary healthcare, the State Governments are responsible for providing secondary care (at general hospitals) while the Federal Government is responsible for policy development, regulation, overall stewardship and providing tertiary care through the network of teaching hospitals and specialist hospitals, but several states manage and finance tertiary health care facilities within their state territories [105], [106].

Primary level facilities form the entry point into the healthcare system. They include health centres, clinics, dispensaries and health posts that provide preventive, curative, promotive and pre-referral care to the population [107]. PHC facilities are typically staffed by nurses, community health workers, community health extension workers (CHEWs), junior CHEWs, and environmental health officers [107]. The 774 LGAs are mandated by the constitution to finance and manage PHC facilities.

Secondary facilities are general hospitals providing general medical and laboratory services as well as specialized health services, such as surgery, paediatrics, obstetrics and gynaecology to patients referred from the PHC level. Medical officers, nurses, midwives, laboratory and pharmacy specialists, and community health officers typically staff general hospitals. Tertiary level facilities form the highest level of care in the country and include specialist and teaching hospitals and federal medical centres. Tertiary level facilities treat patients referred from the primary and secondary levels and have special expertise and full-fledged technological capacity that enable them to serve as resource centres for knowledge generation and diffusion. Each state has at least one tertiary facility [106], [107]. Most health services in the country are provided clinic-based, with minimal outreach, home and community-based services, mainly because of challenges with logistics [106].

Care at childbirth

In Nigeria, it is expected that pregnant women should receive antenatal care, delivery and postnatal care in the primary health centres closest to them [108], [109]. In case of pregnancy difficulties, women are referred to secondary care centres, under the management of state government, or tertiary facilities. There is a national referral system but its functionality has not been assessed [106].

Most PHC facilities are under-equipped. About three quarters of health facilities have <25% of minimal equipment package [110]. Less than half of PHC facilities have the listed essential drugs in stock [110]. A large proportion of these PHC facilities are in deplorable condition, due to poor funding at the state and local government levels [106]. The functionality of PHC facilities varies with geographic location. The capacity to provide BEmONC remains very limited – only around 20% PHC facilities have that capacity [110]. There is the perception that people have lost confidence in the PHC facilities, making bypassing a common practice [110].

Non-government sector

Makinde and colleagues studied the geographic and sectoral distribution of health facilities in Nigeria, and found 30,345 (88.2%), 3,993 (11.6%) and 85 (0.2%) at the primary, secondary and tertiary levels, respectively. Approximately 27% and 75% of primary health facilities and referral facilities, respectively, are private [111].

2.2.9 Financial risk protection for childbirth care

Many LMICs have adopted pro-poor policies to improve access to health services and accelerate progress towards maternal health for the poorer segment of the population. All four of the study countries have implemented different schemes to reduce users' out-of-pocket expenditure for using maternal health services.

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2.2.9.1 Kenya

The Kenyan government has implemented various pro-poor interventions to support the use of maternal health services since the early 2000 – including abolishing childbirth fees in 2007 in government dispensaries and health centres (with the replacement of a registration fee of 10-20 Kenya Shilings, or approximately 0.1-0.2 US dollars), and from 2006 to 2016 a reproductive health voucher program under which poor women could purchase subsidized vouchers for 200 Kenyan Shillings to cover the cost of antenatal care, facility childbirth and postnatal care.

In 2013, the President of Kenya announced free care for all women giving birth in all public health facilities under the Free Maternity Services (FMS) policy. The policy appears to have increased use of maternity services; but in some settings have led to confusion about what services were excluded whereby clients would still have to pay [112]. The policy was also not accompanied by supportive strategies to increase the capacity of health facilities, and the increased demand for services put a strain on health workers and compromised the quality of care received [112].

2.2.9.2 Malawi

All maternity-related services are offered free of charge in government facilities in Malawi. The major challenge, however, is an underfunded public health sector, which relies heavily on external donors to thrive. In some CHAM facilities, maternity services are free of charge due to service agreements between the government and non-government providers.

2.2.9.3 Tanzania

In the 2003 National Health Policy, Tanzania's government has declared maternal and child health services, including facility delivery, to be exempted from user fees in government facilities at the point of service delivery [101]. However, evidence from several studies suggest that the payments for giving birth in a facility were substantial, and were driven by high transport costs, unofficial provider payments, and preference for mission facilities, which levy user charges [113], [114].

2.2.9.4 Nigeria

In 2000, Kano State of Nigeria abolished the payment of user fees by pregnant women in its hospitals [115]. An evaluation carried out one year after revealed increased clinical attendance and decline in maternal mortality in the hospital. Adoption of free maternal and child healthcare policies began to emerge in other states [116], [117]. Referred to as the Free Maternal and Child Health Program (FMCHP), and tax-funded through State and Local Government contributions, childbirth services – such as vaginal and assisted vaginal delivery, caesarean-section and laparotomy for obstetric complications – are provided free of charge at point of service delivery

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at public primary and secondary health facilities in participating states [116]. However, operational issues related to human resources, funding, availability of drugs, infrastructure, and commitments of local governments have been raised, and available estimates indicate that FMCHP covers less than 0.01% of the poor (and the national insurance scheme covers only 3% of the population) [118].

2.2.9.5 To what extent did these policies provide risk protection?

In general, increases in uptake of facility-based care for childbirth have been demonstrated following policy interventions around user fees. A 2015 multi-country study (including Kenya, Nigeria, Tanzania and seven other sub-Saharan African countries) by McKinnon and colleagues showed an increase in skilled care at birth following the abolition of user fees for health facility childbirth – an increase of 3 facility-based childbirth per 100 livebirths (95%CI = 1,5), representing a 5% increase in relative terms [119]. In Malawi, user fee exemption at CHAM facilities led to a 11% increase in the mean proportion of pregnant women who gave birth at facilities [120].

User fee exemption has certain importance for increasing maternal healthcare utilization but may not have the same contribution to improving health outcomes. McKinnon and colleagues only found very weak evidence of an effect in reducing neonatal mortality across the countries included in their study – a reduction of 3 neonatal deaths per 1,000 livebirths (95%CI = -7,1) [119]. According to a 2018 study, no significant effects on maternal and neonatal mortality were identified following the free maternal service policy in Kenya [121].

In a 2014 systematic review of the impact of the removal or reduction of user fees on maternal health services, the authors identified six studies (in Nigeria, Ghana, Senegal and Nepal) that had shown an increased number of obstetric complications managed in health facilities [121]. The strength of the evidence presented in the included studies, however, was classified as “very low”. The review also identified one study that had reported effects of user fees on inequalities in the utilization of maternity service following free services in Ghana, and the results were variable. The difference in the proportion of facility-based childbirth between women in the richest and poorest wealth quintiles decreased by over 10% in parts of the country, whilst remaining unchanged elsewhere [122]. In Kenya, despite increase in overall access to skilled childbirth after the introduction of FMS in 2013, only a mild improvement in the rich-poor gap was achieved [123]. Similarly, in Nigeria, both the overall service uptake and wealth gap for the use of skilled care at birth stagnated between 2008 and 2013 [124], potentially suggesting poor effectiveness of strategies employed to increase care utilization and improve equity, including removal/reduction of fees.

Furthermore, fee-free policies should alleviate the direct service costs, but they rarely consider other costs associated with medicines, medical supplies and food associated with care-seeking. In some circumstances, for instance in Malawi, pregnant women are required to bring their own birth kits to CHAM facilities [23]. Indirect costs, such as that of other family caregivers attending the woman and transportation, have previously been reported to exceed the sum of the consultation or procedural fee [125]. All these remaining costs can be difficult to afford for service users, and have a negative impact on the intended program outcomes [126].

2.2.10 Summary of childbirth care provision in Kenya, Malawi, Nigeria and Tanzania

In summary, although the governance differs in Nigeria compared to the other three countries, adding confusion and complexity of the distribution of tasks, these health systems share several similarities, namely:

- the provision of health services is split between the national government (at the tertiary and/or national level) and the subnational government(s) (primary and secondary healthcare)
- overall recommendation for low-risk births to take place at PHC facilities, and the use of services at higher levels (presumably via referral) only for high-risk cases
- childbirth care readiness and capacity in PHC facilities is low, and often does not meet the standard for BEmONC, and
- some form of national financial protection schemes against out-of-pocket payments for using childbirth care in government facilities are in place (except for Nigeria where such policies differ across states); whilst these policies have been shown to be important to increasing the uptake of services, they may not have the same contribution to improving maternal and neonatal health outcomes and closing the associated inequality gaps.

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Chapter 3

Data and Methods

3 Data and methods

This chapter introduces the data and statistical methods used for the four studies in this dissertation, as summarized in Table 3.1. More details are provided in Chapters 4-7.

Table 3.1 Summary of the datasets and statistical methods used

Study	Chapter	Major objective	Description of data	Major methods
1	4	Systematic review of the methods used in the literature to quantify distance and travel time in SSA, and meta-analysis of the effect of long distance and travel time on using of skilled care at birth	Literature data collected from five online search engines	Narrative synthesis of methods and meta-analysis
2	5	Comparison of the performances of two multivariate spatial interpolation approaches to create high-resolution poverty maps	Secondary Data: 1. Demography and Health Surveys 2. Population density 3. Day-time land surface temperature 4. Vegetation index 5. Elevation 6. Potential Evapotranspiration 7. Aridity Index 8. Night-time light emission 9. Administrative region shapefiles	Spatial interpolation – generalized additive models and model-based geostatistics
3	6	Quantify the wealth-based inequality in travel time to the nearest hospital	Secondary Data: 1. High-resolution poverty map[1] 2. Country master health facility lists 3. Population density 4. Land surface friction 5. Administrative region shapefiles	Algorithm for finding the shortest paths between two points, simulations of alternative hospital locations
4	7	Partition the variability of hospital-based childbirth by wealth and travel time to the nearest hospital	Secondary Data: 1. Demography and Health Surveys 2. Country master health facility lists 3. Population density 4. Land surface friction 5. Administrative region shapefiles	Generalized additive models

[1] Outcome of Study 2

3.1 Study 1: Systematic review and meta-analysis

The aims of the systematic review and meta-analysis (Study 1) were two-fold: (i) to summarize the methods used to measure physical accessibility as the spatial separation between women and health services, and (ii) to establish the extent to which distance/travel time to skilled care for childbirth affects uptake of services in SSA.

3.1.1 Data

We searched and obtained data from five databases: Medline, Embase, Global Health, Africa Wide Information and POPLINE. These were selected based on recommendations made by the LSHTM library for reviews of topics related to epidemiology and reproductive health.

3.1.2 Methods

Search strategy, selection criteria, data extraction and study quality assessment are explained in Chapter 4. In the meta-analysis, only studies that fulfilled certain quality assessment criteria were included, and the included studies were further grouped by settings (urban/rural) and health facility type.

3.2 Study 2: Using spatial interpolation to create high-resolution poverty maps for the four countries

Data for high-resolution poverty maps are expensive to comprehensively collect, but spatial interpolation methods can be applied to estimate poverty for the whole study region using a sample of geo-referenced observations and appropriate covariate data. The aim of Study 2 was to compare the performances of two different multivariate spatial interpolation approaches to create high-resolution poverty maps for Kenya, Malawi, Nigeria and Tanzania.

3.2.1 Data

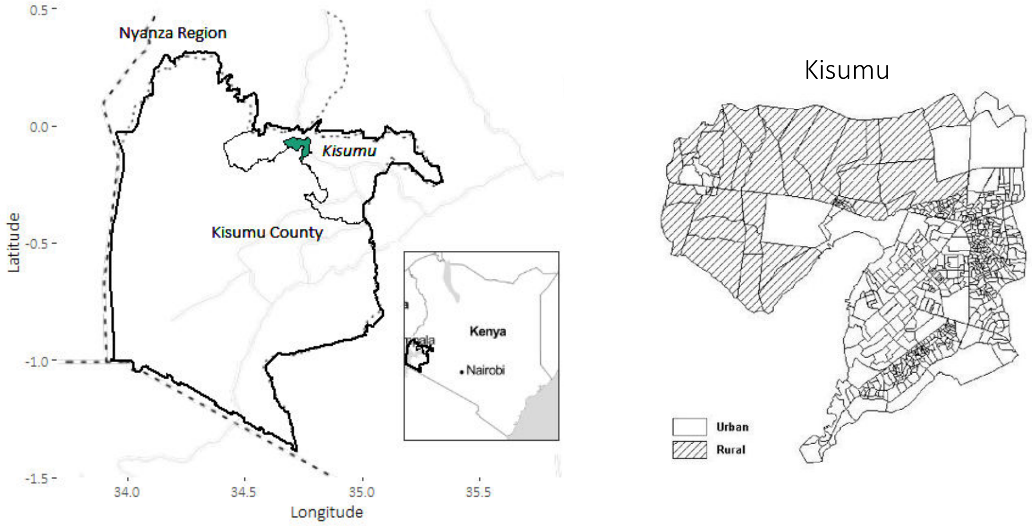
3.2.1.1 Demographic and Health Survey (DHS)

Since 1984, The DHS Program has provided technical assistance to more than 400 surveys in over 90 LMICs. The Program provides assistance to collecting and disseminating data from the Demographic and Health Surveys (DHS), which are nationally-representative household surveys that provide data for a wide range of monitoring and impact evaluation indicators in demography, reproductive health, child health and nutrition, living condition, among others. DHS uses a consistent sampling design across countries. In general, the study sample of DHS covers the entire population residing in non-institutional dwellings in the survey country.

The survey uses a list of non-overlapping enumeration areas (EA) as the sampling frame, often developed from a previous national census. Altogether, the EAs should cover the entire country, in geographical space, and its population. For instance, the 788 EAs in Kisumu (in the Kisumu County, Nyanza Region, Kenya) for the 1999 Census is shown in Figure 3.1 [1]. The EAs defines the primary sampling unit (PSU), also referred to as a “cluster” in DHS.

DHS samples are selected using a stratified multi-stage cluster design. Clusters are stratified by their urban/rural status using a country-specific classification (Figure 3.1). The Kenya National Bureau of Statistics, for instance, defines urban areas as “areas with increased density of human – created structures in comparison to the areas surrounding it and has a population of 2000 and above.”[2] Stratified sampling has three distinct advantages: (i) increased precision (smaller standard errors), (ii) the possibility of stratum-specific estimates with specified precision and (iii) administrative and logistical conveniences [3].

Figure 3.1 Urban/rural designation of census enumeration areas in Kisumu, Nyanza Region, Kenya as defined by the Kenya Central Bureau of Statistics during the decennial national census



Urban clusters and rural clusters are sampled with probability proportional to the EA's population size. For each sampled cluster, a complete listing and mapping exercise of households would be carried out, with the resulting lists of households serving as the sampling frame for the selection of households. A fixed number of households are then selected per cluster with a systematic sampling approach.

Locational data of the DHS

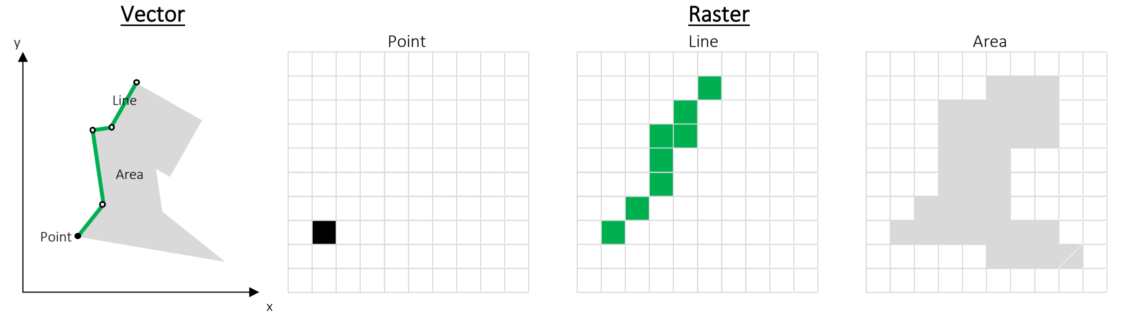
DHS enumerators record the geographic coordinates of the population centroid of each selected cluster as longitude and latitude (Box 3.A) using Global Positioning System (GPS) receivers. To ensure that households and respondents' confidentiality is maintained, especially in clusters with a small number of sampled households and respondents, the DHS apply a random displacement to the GPS latitude/longitude coordinates before releasing data externally. The displacement is carried out so that urban clusters contain an error of 0-2 km and for rural clusters 0-5km (and 1 in 100 rural clusters displaced by 0-10 km) at a direction randomly selected between 1-360^{o}. All households and individuals residing in the same DHS cluster are geo-referenced with the same longitude-latitude coordinates.

Based on an analysis of 40 national household surveys conducted by DHS Program, a 2013 DHS report [1] shows that the average displacement for urban clusters was 0.96 km; and the average displacement distances for our study countries but from different DHS Program surveys, were similar (Table 3.2). The average displacement for rural clusters were approximately 2.5 km.

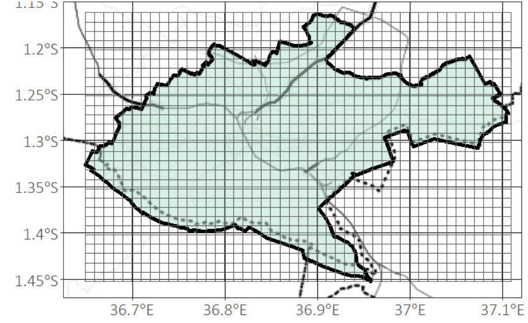
Box 3.A Types of spatial data

Spatial data is data with a geographic reference. The spatial data used in this analysis are referenced with their location on the Earth's surface in longitude and latitude. The 360 **longitude** lines runs north-south. The Greenwich /Prime Meridian is the 0° longitude line from which we measure east and west. **Latitude** lines run east-west and are parallel to each other. Equator is the 0° latitude line that cuts the Earth into the northern hemisphere and the southern hemisphere. Latitude values range between -90° at the South Pole to 90° at the North Pole. Longitude and latitude make up our geographic coordinate system. Every objects can be referenced with its own latitude and longitude coordinates, e.g., the London School of Hygiene of Tropical Medicine, in London, United Kingdom is at 51.5° North, 0.13° West – 51.5° north of the Equator and 0.13° west of Greenwich.

There are two **types of spatial data** – vector and raster. For **vector** data, geographic features are recorded individually with latitude and longitude coordinates. There are three subtypes of vector data: A point is defined by a single pair of coordinate values. A line is defined by a sequence of points through which the line is drawn. An area is defined similarly to a line, only with the first and last points joined to make an enclosure. For **raster** data, the entire area of a region is divided into non-overlapping grids, usually squares. A value is stored in each grid to represent certain attribute of that grid. The spatial resolution of raster data is determined by the size of the cells. Vector and raster data can be converted into one another, but depending on the grid size, some precision may be lost.



1km² grids over Nairobi County, Kenya (Area=696km²)



1km² grids over Lilongwe District, Malawi (Area=6,159km²)

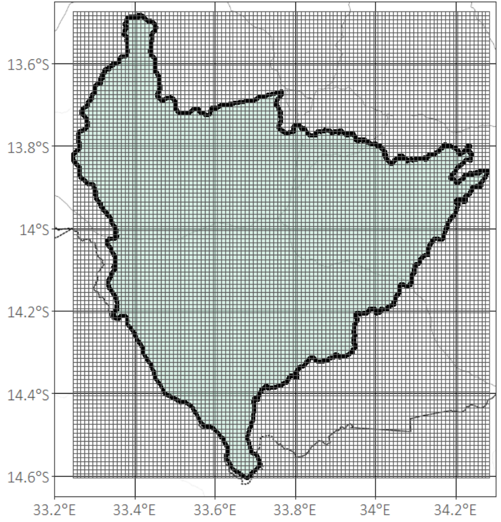


Table 3.2 Displacement distances in selected DHS Program surveys

	Kenya DHS 2003	Malawi DHS 2010	Nigeria DHS 2008	Tanzania AIS 2010
Urban clusters				
Number	129	151	279	133
Mean displacement distance (km)	0.97	1.00	1.03	0.98
Rural clusters				
Number	270	676	607	440
Mean displacement distance (km)	2.46	2.33	2.58	2.43

AIS: AIDS Indicator Survey

The DHS Program recommends for the impact of point displacements on raster-based analyses be moderated through averaging covariate values from neighbouring areas of the displaced points [4]. Details of using displaced coordinates and the associated impact are further discussed in Section 3.2.2.2 and Chapter 5.

The DHS Wealth index

Among other data, the DHS Household Questionnaire is used to collect information on the characteristics of the household's dwelling unit, such as source of water, type of toilet facilities, materials used for the floor of the house, ownership of various durable goods, ownership of agricultural land, ownership of livestock, farm animals, or poultry. Data on housing material, ownerships, possession and community infrastructure are used to derive a composite measure, referred to as the wealth index (WI) or asset index using a principal component analysis (PCA). PCA is a statistical procedure that converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables, referred to as "principal components" [5]. The first factor from the PCA, for instance, captures the largest percentage of the variance within the dataset [5].

Across LMICs, WI is often used as a measure to represent a mix of household- and community-effects on household SES to compare inequalities in a wide range of health impacts and health outcomes [6]–[8]. WI indicates the relative economic positions of households within a single survey and should not be used for external comparison. There are also other widely used indicators for poverty, including income and consumption expenditure [9]. However, they may be seen as less suited for LMICs. Income is the earning from productive activities [10]. In LMICs, many people do not know their income, or only know its broad ranges [9]. It is also subject to misreporting to survey interviewers, particularly misreporting of unearned income (e.g., gains through interest of loans, property rents or gambling winnings) [9], [11]. In addition, an earner may have different levels of income at different points in time; or their income may vary substantially by day, week or year [11]. Yet, care-seeking behaviours are probably more related to SES than current income [9].

Consumption (C) is defined as $C = Y - S - T$, where Y is income, S is savings and T is taxes [9]. Consumption, at least nondiscretionary expenditure, is considered more stable than income since households tend to "smooth" their consumption in periods of declining income [12]. Data collection for consumption, however, is lengthy, complex, and expensive. Respondents must recall their household's use/expenditure for many items. Prices differ across times and areas, necessitating adjustment of expenditure figures. Complex calculations and assumptions are required to include home-produced goods and assign the values of housing and consumer durables. There are, therefore, reliability, financial and logistical concerns with collecting consumption data in LMICs [8], [9], [12].

The strengths and limitations of any measure of wealth or financial position depend on the context and purpose for which it is being used. In this dissertation, the primary use of a measure is the distribution of services across the population (i.e. to assess equity gaps), and as a secondary use, to indicate the ability to afford health services. Based on the idea that possession of assets and access to infrastructure and amenities is related to the relative economic position of the household in the country [13], I rely on WI to quantify the state of being deficient in some desirable quality or constitute – the extent of poverty (or wealth). I assume that, compared to people in a wealthier household, those from poorer households have lower SES, and less means or agency to meet their material needs, including the need for childbirth care services, and the direct/indirect costs and, in some occasions, informal care payments incurred (see Section 2.2.9).

3.2.1.2 Other data

In Study 2, WIs of households in the same cluster (at which GPS coordinates are available) are aggregated to the cluster mean. Cluster median WI are then used as the outcome of interest. Outcome values at clusters/locations not sampled in the DHS were estimated from a set of covariates – population density, night-time light emission, day-time land surface temperature, vegetation, elevation, potential evapotranspiration and aridity (Table 3.3). These physical and environmental variables are thought to be able to capture information to indicate living condition and agricultural productivity [14]–[18]. Lastly, country administrative region shapefiles, as seen in Figure 2.6, were downloaded in July 2015 from the freely available gadm.org. All data used, except for DHS data and country administrative region shapefiles, are in raster format (see Box 3.A).

Table 3.3 Summary of the data used for Study 2

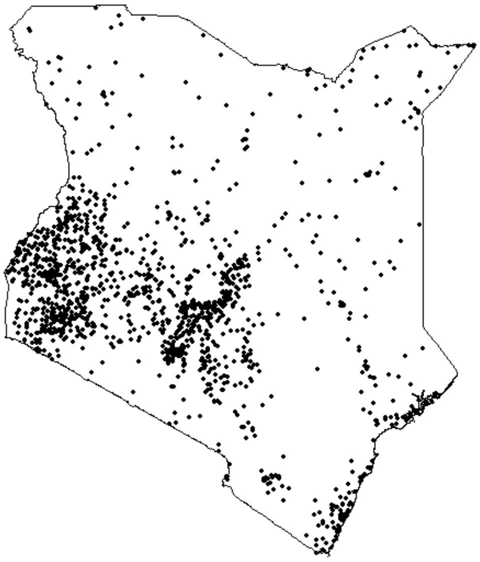
Name of data	Owner of data	Description
Demographic and Health Survey (DHS)	DHS Program	We used data from the following surveys: Kenya 2014, Malawi 2015-2016, Nigeria 2013, and Tanzania 2015-2016.
Gridded Population of the World (GPW), version 4	Socioeconomic Data and Applications Center (SEDAC)	Gridded population density for 2015
Night-time light (NTL) emission	National Oceanic and Atmospheric Administration (NOAA)/National Geophysical Data Center by the United States Air Force Weather Agency	The NTL data shows lights generated from electricity in 2013 (the most recent available), represented as a continuous variable. NTL have been proved to have a good ability to estimate various socioeconomic parameters [19]–[22] and urban structures [23]–[26].

Name of data	Owner of data	Description
Average day-time land surface temperature	NASA Earth Observations	Land surface temperature (LST) is how hot the ground feels to the touch. We used the average day-time land surface temperature for 2013. Previous research has found strong relationships between LST, vegetated areas, productivity and SES variables [27]–[29].
Vegetation index	NASA Earth Observations	Vegetation level shows changes in plant growth, primarily as a result of climate and environmental changes as well as human activity. We used the average value of daily vegetation index in 2013. In areas where livelihoods depend on livestock, potential for pasture is extremely important [30].
Elevation	United States Geological Survey (USGS)	Elevation represents height information about the surface of the Earth. Elevation, together with other environmental variables included here, are considered to be associated with the causes of poverty [16].
Potential evapotranspiration (PET)	Consortium for Spatial Information at the Consultative Group for International Agricultural Research (CGIAR-CSI)	PET is an index combining average rainfall, altitude and sun radiation and a likely indicator of available rainwater and agricultural potential, and thus productive activities [3].
Aridity index	Consortium for Spatial Information at the Consultative Group for International Agricultural Research (CGIAR-CSI)	An Aridity Index is used to quantify precipitation availability over atmospheric water demand. Aridity matters for primary production, and is considered to be associated with poverty [3].
Country administrative region shapefile	gadm.org	Map of countries and their sub-divisions.

3.2.2 Methods

DHS data on household WI is aggregated to the cluster level, however, there are many locations at which such data is not available. The locations for the 2014 Kenya DHS, clusters, for instance, is given in Figure 3.2.

Figure 3.2 Locations of 2014 Kenya DHS clusters



If we assume WI is available at every location in a country, where population count is greater than zero, then given the observed values at a set of sample locations, spatial analytical methods can be used to make better predictions at all unobserved locations. Before introducing spatial methods, I first explain why the frequently used simple linear regression is not suitable.

A simple linear regression can be used to explain a given variable as a linear function of a set of predictor variables; and since this is a probabilistic model, an error term that is assumed to be independent and identically distributed is also needed. If the set of predictor variables can fully capture the outcome, including its structure over space (if the predictors also present a similar spatial structure), the assumption of the distribution of the residuals is satisfied. On the other hand, if spatial structures in the outcome remains, the assumption of independently distributed error terms is violated [31]. The map of the residuals and formal tests can be used as diagnostics to detect residual spatial dependence, and whether explicit spatial approaches may lead to better predictions and more accurate estimation of predictors' effects.

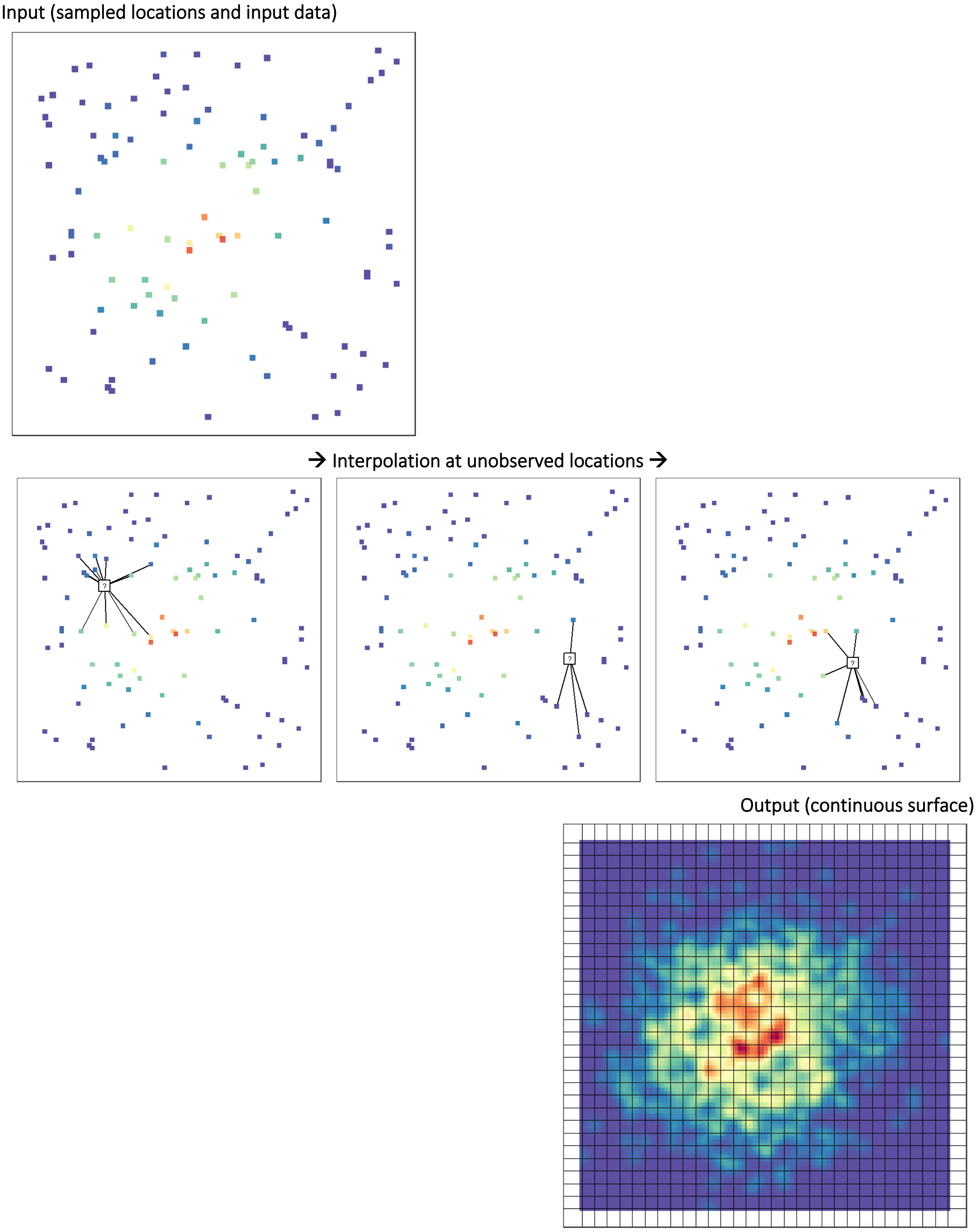
3.2.2.1 Univariate spatial interpolation

The basic premise behind spatial modelling is that "near things are more related than distant things" [32]. Such correlation in geographical space is known as (positive) "spatial autocorrelation". Spatial autocorrelation thus measures the similarity (or correlation) of the data with itself over distance/space. This correlation is useful for prediction making at locations where no measurements have been made. Most univariate SI methods take some form of a weighted average of the values at surrounding observed locations to inform about the unobserved locations (Figure 3.3). There are many ways in which this could be done. Three very common techniques of SI that are widely applied are described here: (i) local neighbourhood approach, (ii) geostatistical approach and (iii) variational approach.

Local neighbourhood approach

Local methods are simple and assume that each point influences the target point only up to a certain finite distance. Inverse distance weighting (IDW) is one of the simplest methods of this approach [33]. To predict a value for any unobserved location, IDW uses the observed values surrounding the prediction location. The observed values closest to the prediction location have a greater influence/weight on the predicted value than those farther away. IDW assumes that weights diminish proportionately to the inverse of distance (between the data point and the prediction location) raised to the power value p. When p = 2, the method is known as the inverse distance squared weighted interpolation.

Figure 3.3 Schematic diagram of the process of univariate spatial interpolation (SI)


Input (sampled locations and input data)

→ Interpolation at unobserved locations →

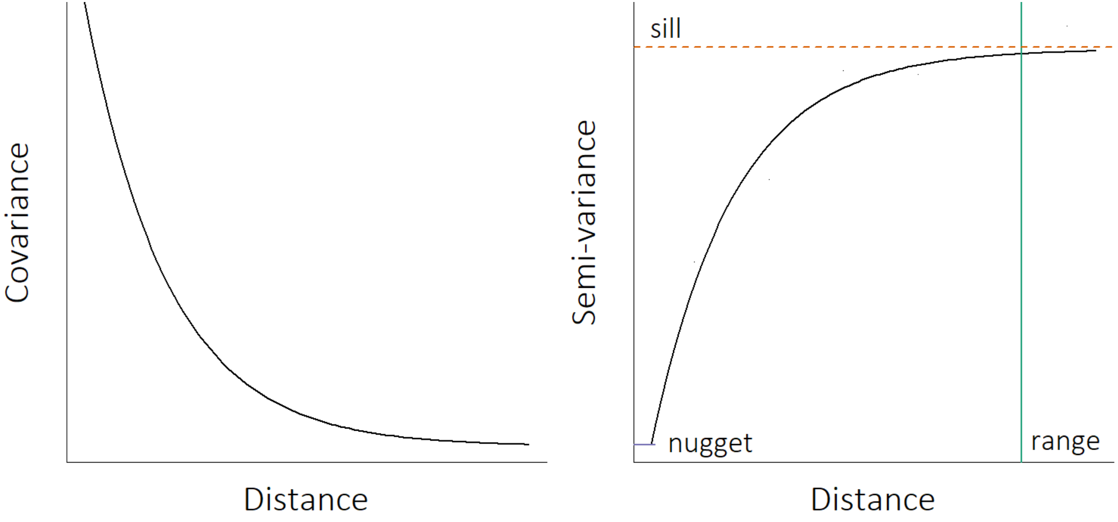
Output (continuous surface)

Geostatistical approach

The principles of geostatistics and interpolation by Kriging assumes the outcome being mapped has a certain spatial covariance/correlation [34]. There is said to be (positive) autocorrelation in a variable if observations that are closer to each other in space have related values, and it follows that as distances between points increases, the similarity (i.e., covariance or correlation) between the values at these points decreases. If we plot this out, with inter-point distance h on the horizontal axis, and covariance C(h) on the vertical axis (Figure 3.4), this representation of covariance as a function of distance is called covariogram. Geostatistical methods incorporate this covariance-distance relationship into the interpolation models. More specifically, this information is used to calculate the weights. As with IDW, geostatistical techniques is a weighted average of points in the proximity, whereby we calculate the distances between the unknown point at which we want to make a prediction and the measured points nearby, and use the value of the covariogram for those distances to calculate the weights needed. The covariogram, however, is often difficult to estimate [35], and a related function referred to as the semi-variogram (or simply the variogram) is calculated (from which the covariogram can be obtained, but not the other way around).

Given any pair of observations Z_1 and Z_2, their difference (also called the expected squared difference [35]) γ is calculated as $\gamma = \frac{(Z_1 - Z_2)^2}{2}$. We can obtain γ for all point pairs then plot these values as a function of the distances that separate these points. The resulting plot is the variogram (Figure 3.4). A variogram can be thought of as "dissimilarity between point values as a function of distance", such that the dissimilarity is greater for points that are farther apart.

Figure 3.4 A schematic covariogram and semi-variogram (variogram)



A model can be fitted to the empirical variogram based on its shape. A variogram model is a function of three parameters, known as the range, the sill and the nugget (where appropriate). The range is typically the level of h at the correlation between point values is zero (i.e., there is no longer any spatial autocorrelation). The value of γ at the range is called the sill. The nugget represents the small-scale variability of the data. A portion of that short-range variability can be the result of measurement error. The variogram may look differently for different data, and suppose it exhibits a wave pattern, geostatistical weights would take that into account whilst IDW weights based on distance would ignore it.

Variational approach (spline)

Lastly, the variation technique to interpolation takes a contrasting approach and assumes that the interpolation function should pass through (or close to) the data points and, at the same time, should be as smooth as possible [33]. These two requirements are combined into a single condition of minimizing the sum of the deviations from the measured points and the smoothness of the spline function. Conceptually, it is analogous to bending a sheet of rubber to pass through known points while minimizing the total curvature of the surface. This is a distinctive difference compared to kriging with which estimation is based on the spatial autocorrelation.

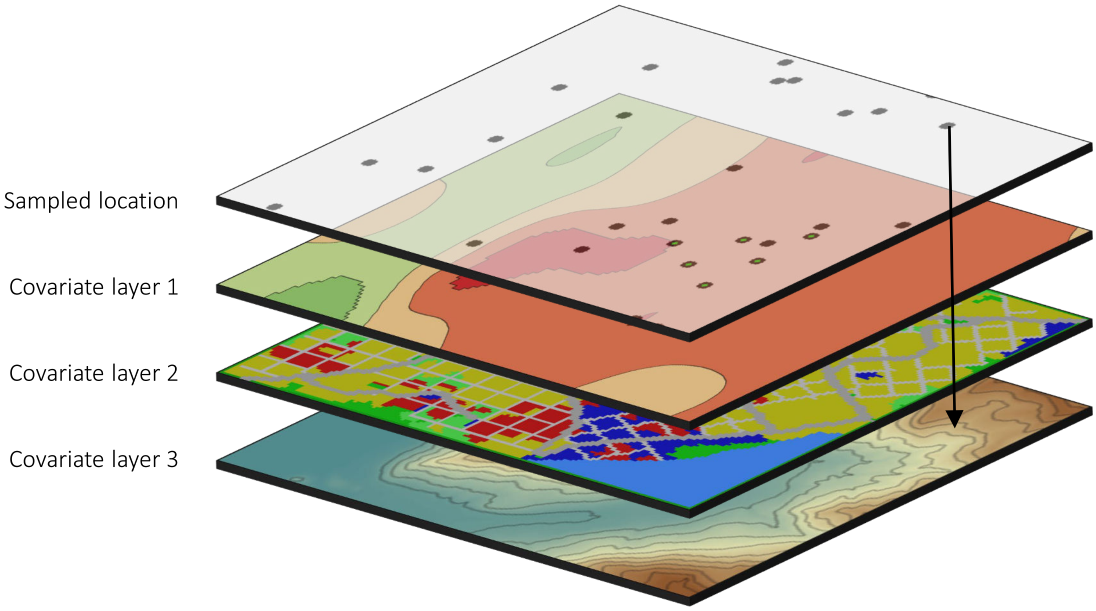
3.2.2.2 Multivariate spatial interpolation

Both geostatistical approach and the variation technique allow for easy incorporation of model covariates for prediction-making using modern statistical software packages [36]–[38]. These are the two approaches tested in Study 2. There is no consensus of which one method is most suitable for geo-referenced data [33]. Overall, SI methods should satisfy several important demands: accuracy and predictive power, robustness and flexibility in describing various types of phenomena, smoothing for noisy data, 2-dimensional formulation, direct estimation of derivatives (gradients, curvatures), applicability to large datasets, computational efficiency and ease of use [33]. The selection of an adequate method and appropriate parameters to best fulfil all of these requirements for a particular application is crucial. Different methods can produce quite different spatial representations and contextual understanding of the phenomenon is needed to evaluate which one is the closest to reality.

Using the predictors listed in Table 3.3, we compared the predictive performance of two robust multivariate SI methods – model-based geostatistics (MBG) and spline interpolation as part of a generalized additive models (GAM) – for Kenya, Malawi, Nigeria and Tanzania. Broadly, the two methods capture spatial variability in different ways. In the MBG framework for SI, it is typically assumed that the variance among observations between two areas is inversely related to their distance between one another. On the other hand, spline interpolation fits a smoothed curve through the set of known sampled points to estimate the unknown values. Applications of spline interpolation take a contrasting approach that an area's absolute location and its characteristics are more important for prediction than distance to, or characteristics of other locations.

Covariate values at DHS cluster locations were extracted via spatial overlaying in a geographic information system (GIS). A GIS is a system used to gather, manage and analyse geo-referenced data. Overlaying of geographic data enables data linkage via their locational references (Figure 3.5).

Figure 3.5 Overlaying in a geographic information system (GIS)



The displaced DHS cluster locations were used for covariate values extraction. However, the displacement procedure described in Section 3.2.1.1 means that a displaced location may be in a grid on the raster layer different from the true location of the cluster centroid, leading to the potential of extraction of values from a neighbouring grid. In their simulation study, Perez-Heydrich and colleagues showed that spatial smoothness/lumpiness – the extent to which a phenomenon varies in space – affects the extent of bias introduced through point displacement. For a smooth surface with a high level of spatial autocorrelation, averaging raster values from a <5km radius/buffer for urban areas and a <10km buffer for rural areas are considered reasonable because neighbouring values will be similar up to a large distance away from the true DHS location [39]. For a very noisy and unsmooth surface, point displacements can alter observed values, and the accuracy of buffer averaging is reduced [39].

Grace and colleagues tested different ways of adding environmental variables to DHS and other geocoded survey data that maintains confidentiality of survey respondents, and calculated the median vegetation index at buffer size 2km and 5km of the true DHS locations, and 5km and 10km of the displaced locations for Burkina Faso, Kenya and Tajikistan [40]. Their results are shown in

Table 3.4. In all settings, the vegetation indices obtained around the true locations differed by <0.01 unit when compared to those obtained from 5km and 10km buffers around the displaced locations. A neighbourhood approach, thus, seems sufficient to address the error that the random GPS displacement brings about when working with ancillary continuous surfaces (especially ones with high spatial autocorrelation).

Table 3.4 Mean and standard deviation (in parenthesis) of vegetation index calculated for the Demographic and Health Survey displaced cluster locations and for the true locations in Burkina Faso, Kenya and Tajikistan (extracted from Grace et al. 2019 [40])

	Displaced locations		True locations	
	5km buffer	10km buffer	2km buffer	5km buffer
Demographic and Health Survey				
Sub-Saharan Africa				
Burkina Faso (2010)	0.229 (0.047)	0.231 (0.047)	0.225 (0.047)	0.229 (0.047)
Kenya (2014)	0.604 (0.119)	0.603 (0.112)	0.603 (0.118)	0.603 (0.116)
Others				
Tajikistan (2012)	0.164 (0.121)	0.164 (0.124)	0.164 (0.018)	0.163 (0.120)

In this study, averages were obtained from the four nearest raster cells. We tested the value extracted using this method (approximately 3km buffer) and those from different buffer sizes: 5km, 10km and 20km. The extractions were highly corrected (see Table 3 in Section 5.1). Therefore, we do not expect the analytical results to differ by using alternative scales.

Prediction accuracy of the two SI methods was measured by the mean absolute error (MAE), root mean square error (RMSE), the goodness-of-prediction (G) statistics (also referred to as the predictive R-squared), and correlation coefficient between observed and predicted values. Further details of the theory and mechanism of MBG and GAM, and the metrics used for comparison are given in Chapter 5. The better-performing method for each country was then used to create a high-resolution map of wealth index for that country.

3.3 Study 3: Wealth inequality in travel time to the nearest hospitals

In Study 3, we used a raster file of travel cost/friction covering Kenya, Malawi, Nigeria and Tanzania, on which we overlaid the locations of all hospitals, to determine grid-level travel time to the nearest hospital with a shortest path algorithm. These travel time estimates were then combined with population raster data to determine the number of people subject to different travel time, and the mean travel time to the nearest hospital across the whole population. Moreover, we used the poverty maps generated in Study 2 to identify the poorest and least poor deciles of grids in each country. The difference in travel time between these populations was taken as the wealth-based inequality gap in travel time to the nearest hospital.

3.3.1 Data

3.3.1.1 Master facility list (MFL)

A master facility list (MFL) is a complete listing of health facilities in a country. One of the most important purposes of an MFL is to provide essential information to help health systems planning and management [32]. Many countries have multiple and fragmented lists of health facilities, with varying subsets of health facilities enlisted (primary versus secondary/tertiary; public versus private; functioning facilities versus all establishments), and different conventions and standards for naming and identifying the various health facilities by the various organizations at various points in time. In 2019, for instance, the Ministry of Health, Community Development, Gender, Elderly and Children in Tanzania counted over 10 different health facility lists managed by donors, government ministries, agencies and implementing partners [41]. These lists are costly to maintain and often contradict each other, leading to confusion and doubts for data users. The WHO encourages countries to compile and maintain one single MFL, from which all other lists can be derived.

MFLs should contain administrative information to identify the facility and information on the services they offer. It is an advantage to include only information that does not change too much over time, as information that varies a lot makes updating the list a challenge. The administrative information needed is the name of the facility, a unique identifying code, facility type/level, ownership and contact information. In addition, geographical coordinates, administrative affiliation, operational status, and which year the information refers to are also important.

Geographic coordinates can be measured using devices such as a GPS receiver. Having geographic coordinates in the MFL allows one to benefit from data visualization using maps and geospatial analyses. With geographic coordinates, it becomes possible to easily visualize, such as in a map, and query the data in a GIS. These maps can help identify areas of high or low concentration of activities and then making adjustments to service provision. Facility locational data can help examine questions related to access, equity, and gaps in service provision. Accurate location information about health allows health planners to target interventions, review and assess the impact of programs, and plan future activities.

Linking MFL data to other geo-coded datasets allows for greater insight into health programs and their interaction with factors that can influence program effectiveness. From a geographic perspective, it can be of value to understand the location of facilities and services relative to factors such as population distribution (overall population or key populations), transportation networks, road networks, climate or agricultural patterns. The key to this process is having the other datasets in question also stored as geographic data to allow linkage with the MFL in a GIS, A schematic of a GIS linkage via overlaying is given in Figure 3.5.

In recent years, progress has been made at both the national and international levels to develop methods of collecting and improving MFL data. In 2018, Ouma and colleagues assembled a geo-coded MFL of all public/government hospitals with emergency services across 48 countries and islands in SSA using data from various sources [42]. The authors provided the first spatial census of public hospital services in Africa, and made the first attempt to quantify the issue of poor and inequitable physical accessibility to government emergency hospital care by country and in the region as a whole. In addition, maps were drawn to show the populations most distant from these services. More recently in July 2019, but too late for use in this dissertation, Maina and colleagues published an important geo-referenced MFL of over 95,000 health facilities, including both hospitals and non- hospitals, across 50 countries and islands in SSA [43].

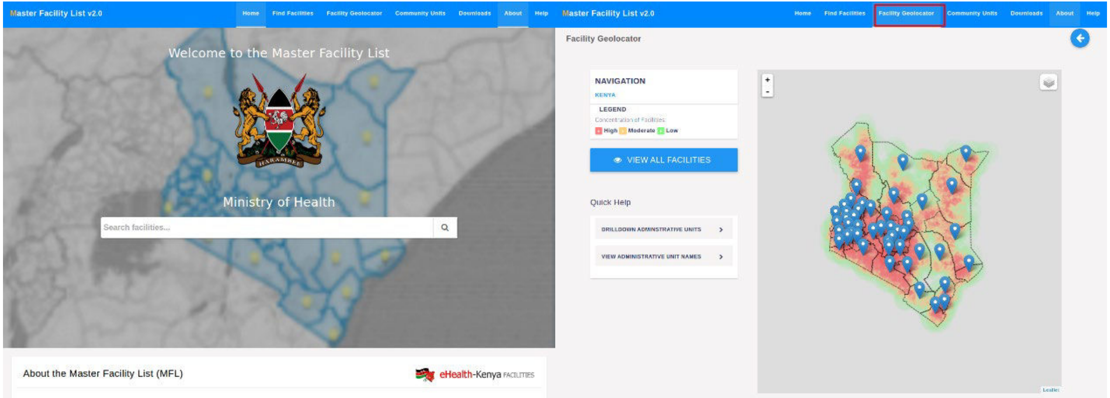
For Study 3, I obtained the geo-coded MFLs containing all health facilities in both the government and non-government sectors for the four countries online. All MFL data used in this dissertation was downloaded in March 2016. The Kenya Master Health Facility List (KMHFL) contains all health facilities in the country. Each health facility is identified with a unique code, with data on its geographical location, administrative location, ownership, type and the services offered. The MoH of Kenya has made the list available online at http://kmhfl.health.go.ke/#/home, including a map showing the concentration of facilities across the country (Figure 3.6). The locational data of the KMHFL was obtained from http://downloads.afyaresearch.org/mfl/Abridged eHealth Kenya Facilities Sept 2015.xls.

The 2013-14 Malawi SPA was designed to provide national and subnational information on the availability and quality of services from all functioning health facilities in the country. These facilities included hospitals, health centres, dispensaries, maternities, clinics, and health posts. The managing authorities of these facilities included the government, Christian Health Association of Malawi (CHAM), non-governmental organisations, private and faith-based organisations. The data was downloaded from https://dhsprogram.com.

The Nigeria MDGs Information System (NMIS) facility data is collected by the Office of the Senior Special Assistant to the President on the MDGs in partnership with the Sustainable Engineering Lab at the Columbia University. A rigorous, geo-coded baseline facility inventory across the country was created between 2009 and 2011, and later on in 2014, the first nation-wide full list of health facilities was completed [44]. The NMIS website (www.nmis.mdgs.gov.ng) has now become defunct (last attempted on 07/07/2019), but the Nigeria Health Facility Registry (https://hfr.health.gov.ng, last accessed on 07/07/2019) currently houses the MFL data.

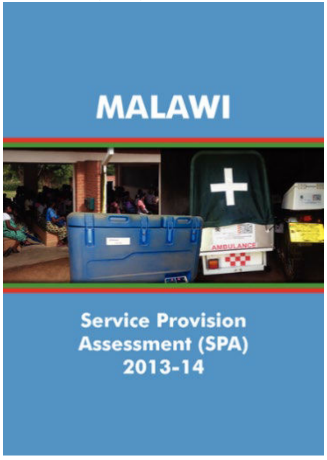
Figure 3.6 Data sources for the master facility list (MFL) in Kenya, Malawi, Nigeria and Tanzania used in Study 3

Kenya Master Health Facility List

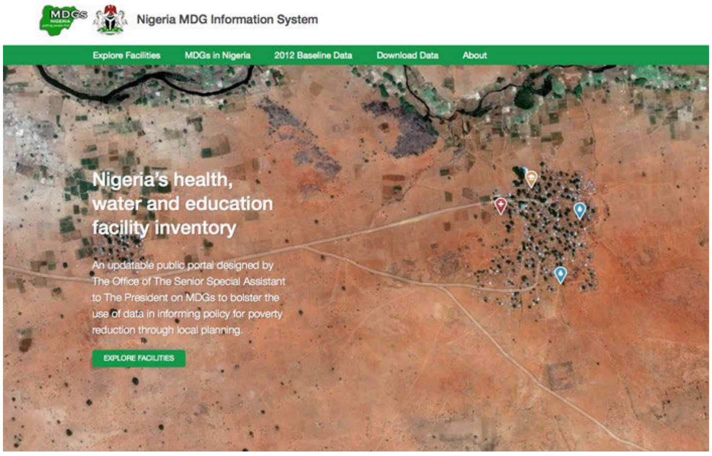


(Left: homepage of the Kenya Master Health Facility List; right: concentration of facilities in Kenya)

`Malawi Service Provision Assessment (SPA) 2013-14

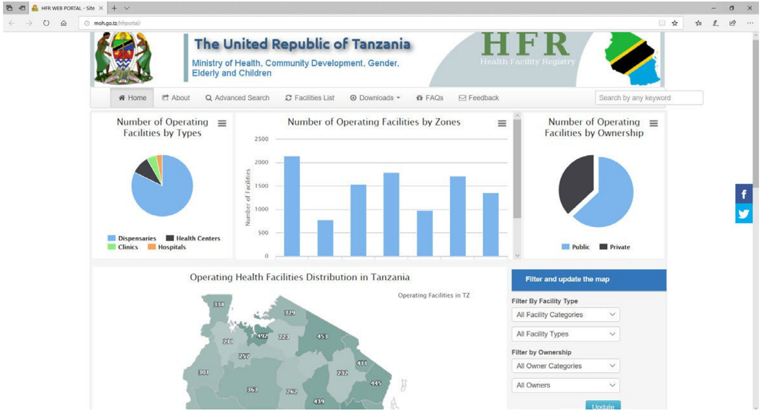


Nigeria Master Facility List (https://databox.worldbank.org/en/dataset/nigeria-nmis-health-facility-data-2014)



An updatable public portal designed by The Office of The Senior Special Assistant to The President on MDGs to bolster the use of data in informing policy for poverty reduction through local planning.

Tanzanian Health Facility Registry

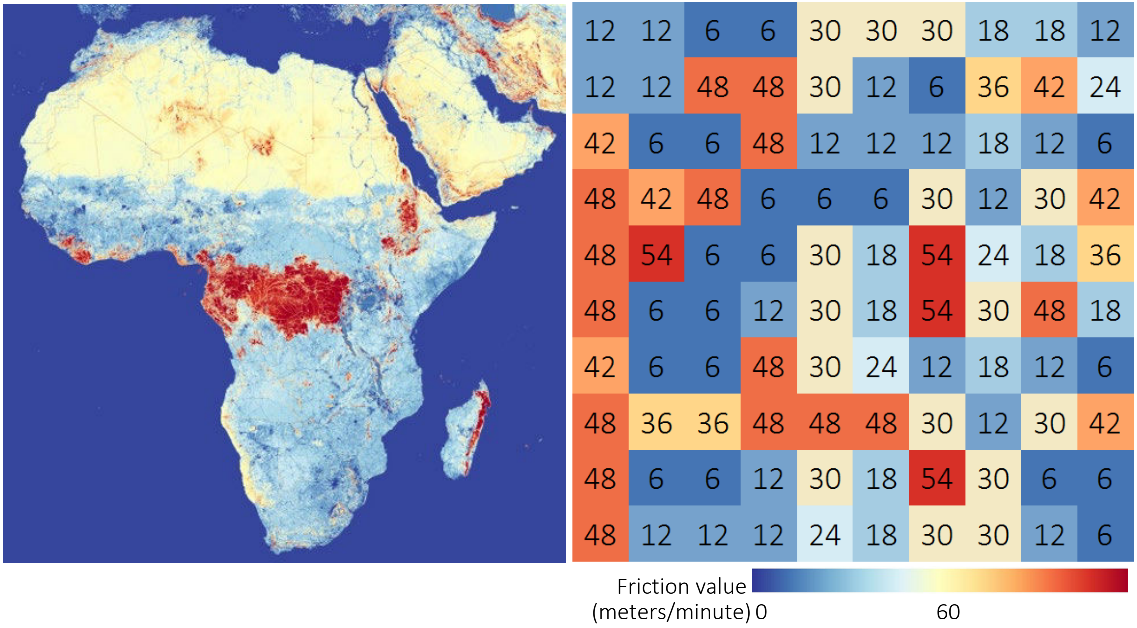


The Tanzania Health Facility Registry (HFR) is an effort to consolidate the different facility lists in Mainland Tanzania with official information on health facilities. The Tanzania HFR has its own website to provide the public with access to such information [41]: http://moh.go.tz/hfrportal (last accessed on 23/07/2019). Information about health facilities are collected by a member of Council Health Management Team or the Health Management Information System focal person of each council [41].

3.3.1.2 Global Surface friction 2015

The Global Surface Friction 2015 (the "friction surface" hereafter), created and made available by the Malaria Atlas Project (MAP), is a raster file that enumerates the average friction (or cost/difficulty) to move across each grid within the raster. Each grid is associated with a value that represents the average difficulty of moving from any point on one of the four edges to a point on one of the other three edges (Figure 3.7). This value represents the minimum time required to travel for one meter in a particular grid (grid size is approximately 1km^2 at the equator) – i.e. the smaller the value the less time required for movement. The value combines a wide range of information, such as the spatial locations and properties of roads, railroads, rivers, bodies of water, topographical conditions (elevation and slope angle), land cover, and national borders – each of which is a spatial layer on its own [45]. Where relevant, each grid cell in each layer should have a value that represents travel speed [45]. For instance, the OpenStreetMap database provided the necessary road information for assigning country- and road-type-specific speed data; and the movement speeds assigned to the waterbodies layers were 10 km/h for rivers and lakes and 19 km/h (or approximately 3 min per km) for oceans [46]. Slopes and elevation were also accounted for, whereby a speed adjustment factor was multiplied by the land-cover travel speed, thus lowering the speed of travel and increasing the time required to traverse. A slope adjustment factor of $1.016e^{-0.0001072\times\text{elevation}}$ was applied in the friction surface [46]. The different datasets/layers were then merged into a single friction surface, which enables the calculation of the cumulative time required to travel between two points along any path [45].

Figure 3.7 Global Friction Surface of the continent of Africa [47] and a schematic “zoom-in” of the gridded surface



12	12	6	6	30	30	30	18	18	12
12	12	48	48	30	12	6	36	42	24
42	6	6	48	12	12	12	18	12	6
48	42	48	6	6	6	30	12	30	42
48	54	6	6	30	18	54	24	18	36
48	6	6	12	30	18	54	30	48	18
42	6	6	48	30	24	12	18	12	6
48	36	36	48	48	48	30	12	30	42
48	6	6	12	30	18	54	30	6	6
48	12	12	12	24	18	30	30	12	6

3.3.2 Methods

3.3.2.1 Using the shortest path algorithm to find travel time to the nearest hospital

The path connecting two points that requires the least amount of total time is referred to, in this study, as the least-cost path or the shortest path. The shortest path problem can be solved using the shortest path algorithm, also known as the Dijkstra's algorithm. From any given original grid (origin), the shortest path algorithm starts by calculating the cumulative time required to reach all adjacent grids. We use eight neighbours/adjacent grids to allow for more flexible movement. From each of the eight adjacent grids, the algorithm then calculates the cumulative time required to reach all adjacent grids of this grid, and update the cumulative time required if it is an improvement (if the cumulative time is shorter). The process is repeated until the shortest times from the origin to all grids are identified; e.g., the least cost to reach the origin from the grid immediately above it in Figure 3.8 is calculated as (30+48)/2 = 39. We note that the algorithm assumes half of each of these two grids would need to be crossed.

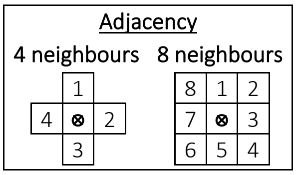
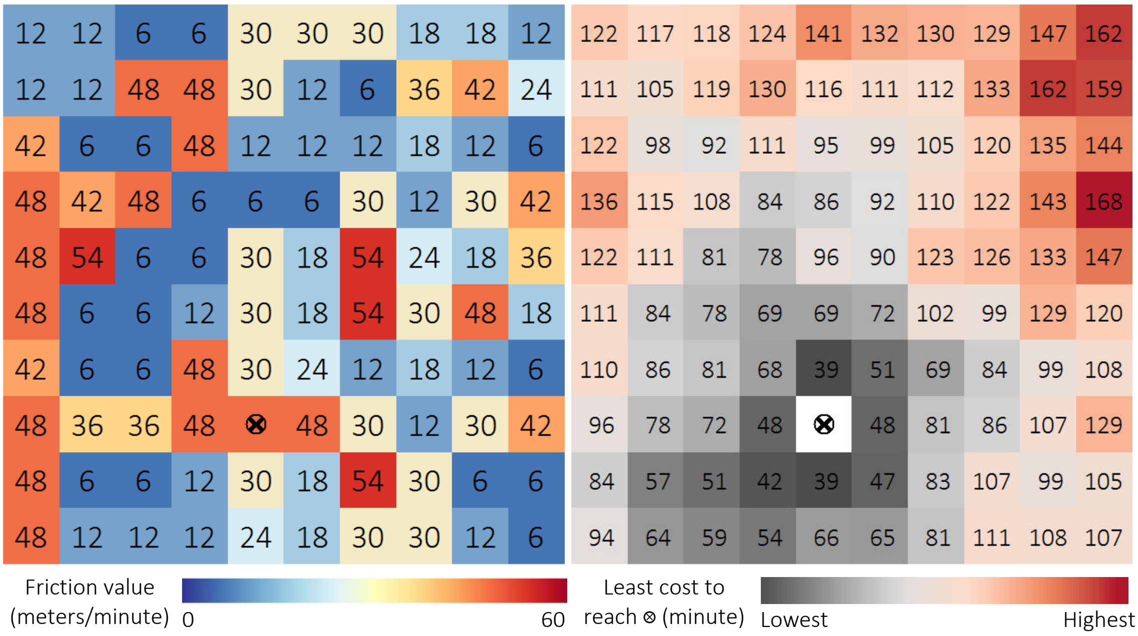


Figure 3.8 Schematic diagrams of a friction surface and the grid-level least-cost to reach ⊗



12	12	6	6	30	30	30	18	18	12
12	12	48	48	30	12	6	36	42	24
42	6	6	48	12	12	12	18	12	6
48	42	48	6	6	6	30	12	30	42
48	54	6	6	30	18	54	24	18	36
48	6	6	12	30	18	54	30	48	18
42	6	6	48	30	24	12	18	12	6
48	36	36	48	⊗	48	30	12	30	42
48	6	6	12	30	18	54	30	6	6
48	12	12	12	24	18	30	30	12	6

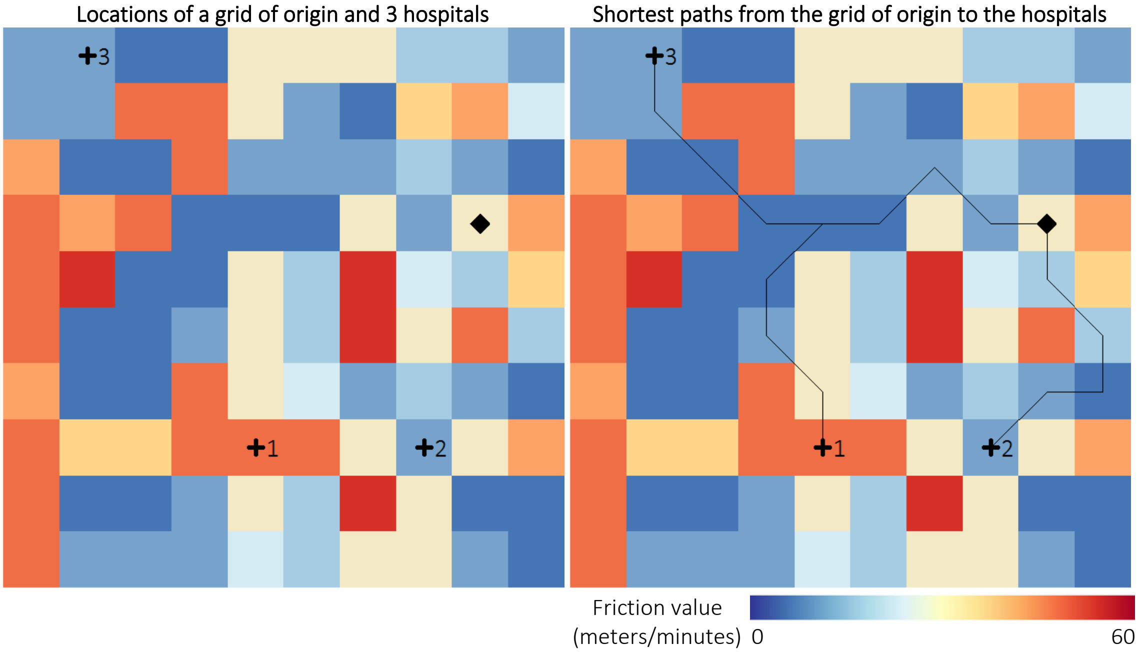
122	117	118	124	141	132	130	129	147	162
111	105	119	130	116	111	112	133	162	159
122	98	92	111	95	99	105	120	135	144
136	115	108	84	86	92	110	122	143	168
122	111	81	78	96	90	123	126	133	147
111	84	78	69	69	72	102	99	129	120
110	86	81	68	39	51	69	84	99	108
96	78	72	48	⊗	48	81	86	107	129
84	57	51	42	39	47	83	107	99	105
94	64	59	54	66	65	81	111	108	107

Note: the friction value at ⊗ is 48.

To calculate the grid-level travel time to reach the nearest hospital, we overlaid the friction surface with locations of all hospitals, and defined all grids with a hospital as the set of origins (see a schematic in Figure 3.9). Using the R package "gdistance", which applies the shortest path algorithm, the shortest path from every grid to every origin is calculated – giving rise to three paths to the hospitals for each grid in the schematic example below (Figure 3.9). For any given grid, the shortest cumulative time/cost of the three was then considered as the time needed to reach the nearest hospital.

This process was repeated for all grids to produce a raster file of travel time to the nearest hospital for each raster cell. We multiplied grid-level population count data by the corresponding shortest travel time, and then divided it by the total population headcount to obtain the national overall travel time to the nearest hospital. In addition, we identified those grid cells with WI in the lowest and highest 10th percentiles from the poverty map generated in Study 2. Separately, average travel time was calculated for grids of the poorest and least poor deciles, and the difference between them was taken as the wealth gap in travel time.

Figure 3.9 Schematic diagram of calculating travel time to the nearest hospital



♦ Origin
+ Hospitals

Cumulative travel time from the origin to the three hospitals are 143, 87 and 96 minutes. Travel time to the nearest hospital (hospital 2) from the origin is, therefore, 87 minutes.

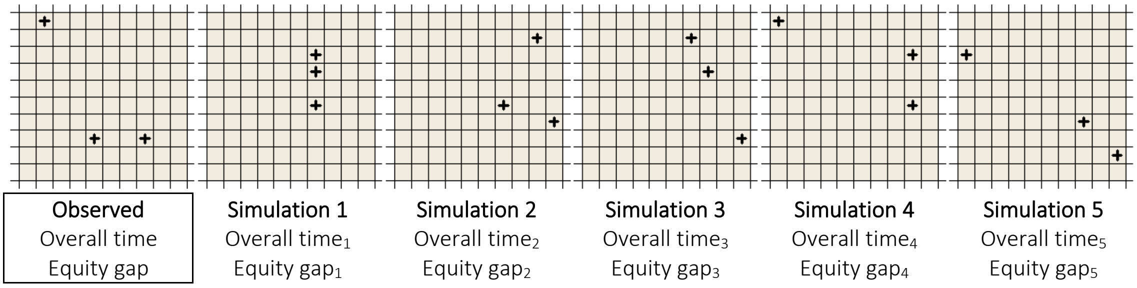
3.3.2.2 Comparing current hospital distribution with simulated distributions

The observed overall travel time and wealth gap in travel time quantified the current realities of hospital care provision. Typically, attaining the best values for both is a goal of a health system, as the wish for care provision is to minimize average travel time whilst being as equitable between SES subgroups as possible. Yet achieving such a balance is challenging, since overall travel time might be expected to be the shortest (optimal efficiency) when resources are allocated to populous (and often wealthier) locales, thus compromising equity of travel time between SES subgroups; while targeting rural, and generally poorer, populations comes at the expense of increased mean travel time and reduced efficiency. To assess the extent to which the two competing objectives (equity and efficiency) are balanced in the current health systems in the four study countries, we used a simulation exercise to find their respective theoretical optima.

The simulation exercise involved (i) assuming hospitals in the country were redistributed, (ii) recalculating overall travel time and the equity gap in travel time, and (iii) comparing these hypothetical values to the observed current distribution of hospitals (Figure 3.10). For each country, this process is repeated 7500 times, each with a different set of hospital locations, giving rise to the theoretical optimal efficiency and equity.

Constrained on having the same number of hospitals as found on the MFLs, the simulation exercise should allow us to identify the shortest overall travel time (and the equity gap associated with it), as well as the narrowest equity gap (and the overall travel time associated with it) possible. In addition, we identified the narrowest equity gap from the subset of simulations that had a shorter overall travel time to determine potential gain, or “losses incurred”, in equity at least at the current level of efficiency.

Figure 3.10 Simulation of alternative hospital locations



3.4 Study 4: Partitioning the variability of hospital birth by wealth index and travel time to the nearest hospital

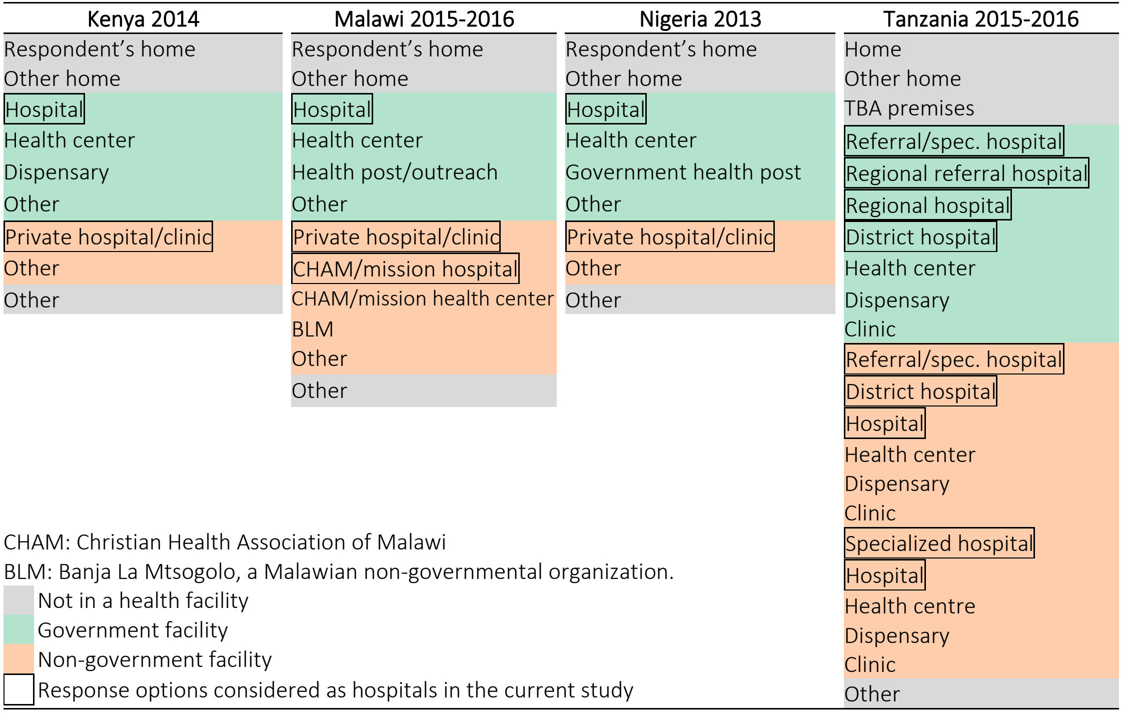
Having established and quantified the extent of inequity in travel time to hospital in Study 3, and acknowledging the wealth gap in hospital-based childbirth, the aim of Study 4 is to partition the variability in hospital birth between wealth and travel time in the selected countries.

3.4.1 Data

3.4.1.1 Place of childbirth

The DHS uses a stratified multi-stage sampling design (details described in Section 3.2.1.1), and each interviewed woman aged 15-49 in sampled households self-report the location of childbirth for all livebirths in the five years preceding the interview. These livebirths are nested on three levels – livebirths within women, women within households, households within clusters. DHS data on the location of all livebirths in the recall period is collected with the question “Where did you give birth to (NAME)?”, and women’s responses were coded based on a standardized list of response options. Across the surveys included in this analysis, the response options for childbirth location differ (Table 3.5). Broadly, the locations are categorized as non-facility and facility, the latter is either in the government sector or the non-government (or private) sector. “Private hospitals and clinics” are included in one category for Kenya, Malawi and Nigeria (Table 3.5). To determine whether this response option should be categorized as a hospital or not, Hanson and colleagues sought insights from country co-authors on whether the location has the capacity to provide comprehensive emergency obstetric care for women with complications [48]. Their approach was adopted in this dissertation.

Table 3.5 Response options for childbirth locations used in Demographic and Health Survey



Kenya 2014	Malawi 2015-2016	Nigeria 2013	Tanzania 2015-2016
Respondent’s home	Respondent’s home	Respondent’s home	Home
Other home	Other home	Other home	Other home
Hospital	Hospital	Hospital	TBA premises
Health center	Health center	Health center	Referral/spec. hospital
Dispensary	Health post/outreach	Government health post	Regional referral hospital
Other	Other	Other	Regional hospital
Private hospital/clinic	Private hospital/clinic	Private hospital/clinic	District hospital
Other	CHAM/mission hospital	Other	Health center
Other	CHAM/mission health center	Other	Dispensary
	BLM		Clinic
	Other		Referral/spec. hospital
	Other		District hospital
			Hospital
			Health center
			Dispensary
			Clinic
			Specialized hospital
			Hospital
			Health centre
			Dispensary
			Clinic
			Other

CHAM: Christian Health Association of Malawi
BLM: Banja La Mtsogolo, a Malawian non-governmental organization.
▒ Not in a health facility
🟩 Government facility
🟧 Non-government facility
☐ Response options considered as hospitals in the current study

3.4.2 Methods

3.4.2.1 Generalized additive model (GAM)

We used a generalized additive model (GAM) to account for the potential non-linear effects between the probability of hospital birth and the predictor variables – household wealth index, travel time from cluster centroid to the nearest hospital and maternal age at birth. The other predictor variables included were maternal education and birth order; they were included as linear terms. In addition, the survey cluster random effect was also accounted for.

3.4.2.2 Marginal and additive effects of poverty and long travel time

The extents to which poverty and travel time, as well as the cluster-level random effects, influence hospital birth are compared against one another. The comparison of these marginal effects is highly dependent on the choice of unit of change used across the predictors. Whilst some predictor covariates have an easily interpretable unit of measure – e.g., year for maternal education and maternal age at birth, and every one increment for birth order – the “best” unit of measure may be less tangible for wealth index and travel time, and is undefined for the cluster-level random effect. In light of this, one standard deviation (SD) around the mean (μ) and the associated predicted probabilities of hospital birth for each predictor variable was used to enable comparability. The effect sizes of the predictor variables all refer to a 1SD-change from mean in their respective scale and is thus informative about relative changes in utilization among the population of each country. For normally-distributed data, with a mean and median being the same and 68% of the data falling within 1SD from the mean value, the comparison between μ-1SD, μ, μ+1SD is equivalent to comparing the 16th, 50th and 84th percentiles.

The marginal effect of the survey cluster random effect was obtained from the distribution of predicted values with all model predictor variables set to the sample mean. We then calculated the predicted probabilities of 1SD around the model mean predicted probabilities of hospital birth as the marginal effect.

3.5 Closing remarks

Further details of data and methods are covered in each of the four studies in Chapter 4 to Chapter 7.

3.6 References

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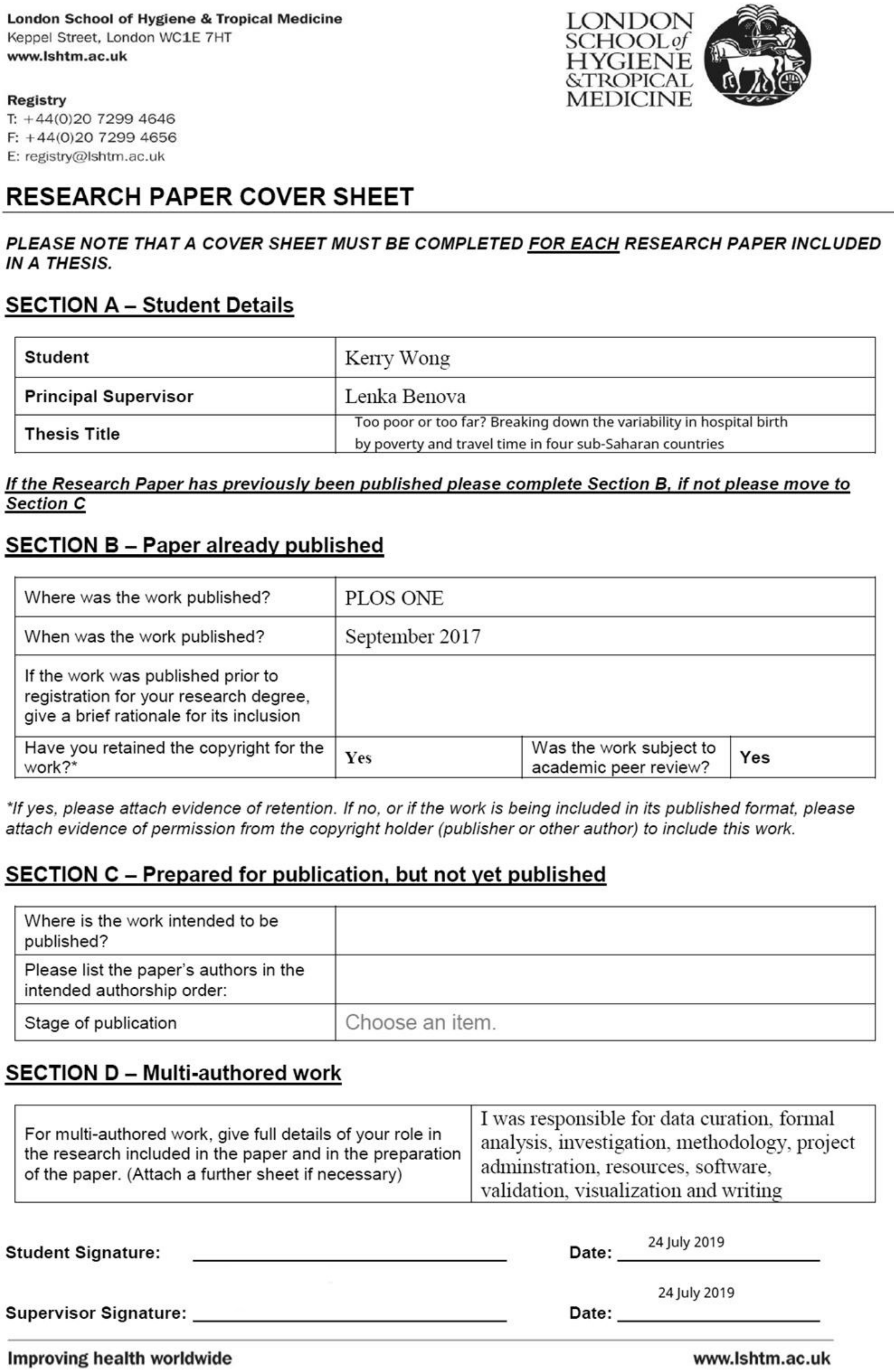
Chapter 4

Study 1: A look back on how far to walk: systematic review and meta-analysis of physical accessibility to skilled care for childbirth in sub-Saharan Africa



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Student	Kerry Wong
Principal Supervisor	Lenka Benova
Thesis Title	Too poor or too far? Breaking down the variability in hospital birth by poverty and travel time in four sub-Saharan countries

If the Research Paper has previously been published please complete Section B, if not please move to Section C

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4 Study 1: A look back on how far to walk: systematic review and meta-analysis of physical access to skilled care for childbirth in Sub-Saharan Africa

Physical accessibility of health services refers to the ease at which services can be physically reached by those who needs them. Good physical accessibility in the population is an important aspect of healthcare provision. A variety of measures of physical accessibility exist. Briefly, distance and travel time are simple ways to quantify potential accessibility. In addition, density refers to the intensity of provision in a localized area. All three measures can be obtained relatively easily. More developed approaches that incorporate the intensity of demand from nearby locations and the capacity of health facilities are also available.

Currently, eight indicators are used to measure the availability and use of facilities and the performance of health-care systems in saving the lives of women with obstetric complications [1]. None of them, however, specifically accounts for the physical accessibility of service provision as distance, travel time, or the intensities of supply and demand [1]. The set of eight indicators, also known as the UN Process Indicators, were developed by Columbia University and UNICEF in the early 1990s, and adopted by UNICEF, WHO and UNFPA in 1997 [2]. The premise of these indicators is that for women to receive prompt, adequate treatment for complications of pregnancy and childbirth, facilities for providing emergency obstetric care (EmOC) services must (i) exist and function, (ii) be geographically and equitably distributed, (iii) be used by pregnant women, (iv) be used by women with complications, (v) provide sufficient life-saving services, and (vi) provide good-quality care. The eight indicators and are:

(1) Availability of EmOC: basic and comprehensive care facilities
(2) Geographic distribution of EmOC facilities
(3) Proportion of all births in EmOC facilities
(4) Meeting the need for EmOC: proportion of women with major direct obstetric complications who are treated in such facilities
(5) Caesarean sections as a proportion of all births
(6) Direct obstetric case fatality rate
(7) Intrapartum and very neonatal death rate
(8) Proportion of maternal deaths due to indirect causes in emergency obstetric care facilities

The first indicator focuses on the availability of EmOC services. The updated guideline from 2009 suggests that, at the national level, there should be at least 5 EmOC facilities per 500,000 population of which at least one should be a comprehensive EmOC facility [1]. The second

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[1] WHO, UNFPA, UNICEF, and AMDD, Monitoring Emergency Obstetric Care: a Handbook. Geneva: World Health Organization, 2009, p. 161.

[2] D. Maine et al., “Guidelines for Monitoring the Availability and Use of Obstetric Services,” 1997.

indicator is calculated in the same way as the first, with an acceptance level of 5 EmOC facilities per 500,000 population in all subnational areas. It takes certain considerations of the geographic distribution and accessibility of facilities into account, but falls short to indicate the physical aspect of service provision.

Nonetheless, the physical aspect of service provision is somewhat recognized across the multiple revisions of the EmOC guidelines as a "supplementary" issue. The 1997 guidelines suggest the maximum of 3 hours of travel and 12 hours of travel to BE(m)OC and CE(m)OC, respectively, for most women [2]. These recommendations were based on estimates of the average time interval between onset of major obstetric complications to death in the absence of medical intervention (Table 4.1) [3]. Maine asserted that for most complications, the average time is 12 hours or more, with the exception of postpartum haemorrhage which can "kill a woman in less than one hour" [3]. In the 2009 update of the guidelines, these travel time thresholds were revised, such that a reasonable standard for the availability of basic and comprehensive EmOC facilities should be "within 2-3 hours of travel for most women" [1]. In a setting where the population walks, and assuming a general walking speed of 5km/h or a driving speed of 60 km/h, 2-3 hours of travel translate to 10-15km and 120-180km, respectively [2].

Table 4.1 Estimated average interval from onset to death for major obstetric complications, in the absence of medical intervention

Complication	Time from onset to death
Postpartum haemorrhage	2 hours
Antepartum haemorrhage	12 hours
Ruptured uterus	1 day
Eclampsia	2 days
Obstructed labour	3 days
Infection	6 days

Source: Maine, Deborah. Prevention of maternal deaths in developing countries: program options and practical considerations. Center for Population and Family Health, Columbia University, 1986.

In light of the different measures for physical accessibility available, and the insufficiency of the current EmOC process indicators to directly address the critical issue of physical accessibility, I decided to review the approaches used to quantify physical accessibility in the relevant literature. The results were valuable for evaluating how physical accessibility had been measured by researchers, and choosing a measure in subsequent analyses in this dissertation. I also take this

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[1] WHO, UNFPA, UNICEF, and AMDD, Monitoring Emergency Obstetric Care: a Handbook. Geneva: World Health Organization, 2009, p. 161.
[2] D. Maine et al., "Guidelines for Monitoring the Availability and Use of Obstetric Services," 1997.
[3] D. Maine et al., "Prevention of maternal deaths in developing countries : program options and practical considerations." 1987.

review opportunity to synthesize evidence on what is known about the effect of physical accessibility to the use of skilled care at birth in SSA.

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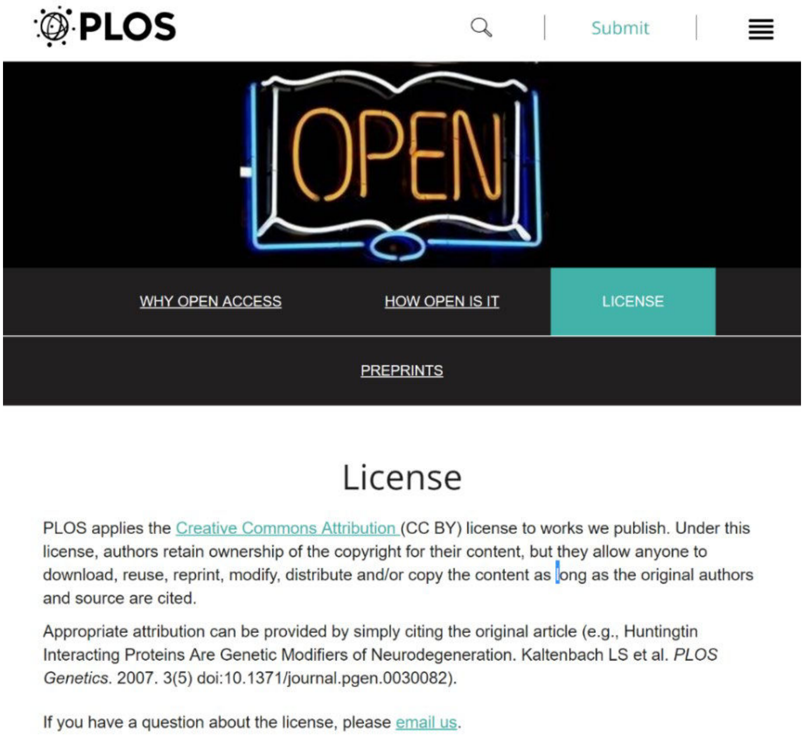

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RESEARCH ARTICLE

A look back on how far to walk: Systematic review and meta-analysis of physical access to skilled care for childbirth in Sub-Saharan Africa

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Abstract

Objectives

To (i) summarize the methods undertaken to measure physical accessibility as the spatial separation between women and health services, and (ii) establish the extent to which distance to skilled care for childbirth affects utilization in Sub-Saharan Africa.

Method

We defined spatial separation as the distance/travel time between women and skilled care services. The use of skilled care at birth referred to either the location or attendant of childbirth. The main criterion for inclusion was any quantification of the relationship between spatial separation and use of skilled care at birth. The approaches undertaken to measure distance/travel time were summarized in a narrative format. We obtained pooled adjusted odds ratios (aOR) from studies that controlled for financial means, education and (perceived) need of care in a meta-analysis.

Results

57 articles were included (40 studied distance and 25 travel time), in which distance/travel time were found predominately self-reported or estimated in a geographic information system based on geographic coordinates. Approaches of distance/travel time measurement were generally poorly detailed, especially for self-reported data. Crucial features such as start point of origin and the mode of transportation for travel time were most often unspecified. Meta-analysis showed that increased distance to maternity care had an inverse association with utilization (n = 10, pooled aOR = 0.90/1km, 95%CI = 0.85–0.94). Distance from a hospital for rural women showed an even more pronounced effect on utilization (n = 2, pooled aOR = 0.58/1km increase, 95%CI = 0.31,1.09). The effect of spatial separation appears to level off beyond critical point when utilization was generally low.

Conclusion

Although the reporting and measurements of spatial separation in low-resource settings needs further development, we found evidence that a lack of geographic access impedes use. Utilization is conditioned on access, researchers and policy makers should therefore prioritize quality data for the evidence-base to ensure that women everywhere have the potential to access obstetric care.

Introduction

Place forms part of the construct of social and physical interactions and resources, which influence health and wellbeing [1,2]. Geocoding, residential mobility, record linkage and data integration, spatial cluster detection, small area estimation and Bayesian applications mapping are examples of methodologies used to investigate health-related issues from a geographic perspective [3–5]. Increasingly, spatial thinking and geographic information system (GIS) tools are being applied to different public health and epidemiological topics, including global maternal, newborn and child health [6–8].

In the post-2015 era, the international communities continue to prioritize reducing preventable maternal and newborn deaths in low- and middle-income countries (LMICs) [1,5]. As part of the effort to achieve Sustainable Development Goal (SDG) 3.1 of reducing global maternal mortality ratio (MMR) to <70 per 100,000 live births by 2030, researchers and policy makers call specifically for equitable, within-country improvement [1,5]. The United Nations Sustainable Development Summit held in 2015 promoted mapping and other GIS tools be used to address localized health inequalities, targeting the hard-to-reach population at the subnational scale [9].

Accounting for a mere 13% of the global population, Sub-Saharan Africa (SAA) is home to two thirds of women who died of maternal causes globally [10]. Most maternal deaths in SSA are preventable [11]. The World Health Organization (WHO) has advocated for skilled care at every birth as one of the main strategies to ensure safe motherhood and combat maternal mortality [12]. In much of the region, however, fewer than half of all women received skilled care at birth [13]. Utilization is a complex issue driven by different personal, behavioural and cultural factors [14,15]. It has also been argued that universal healthcare utilization (including that of delivery care) is conditioned on everyone having potential access to health services [16–18]. Potential access has three system-level dimensions—services must be physically accessible, financially affordable and acceptable to those who require care if universal coverage is to be attained [18].

The effect of each of the three dimensions on usage of skilled care at birth in SSA and other resource-limited settings have been discussed in previous literature reviews. The most recent systematic review, found physical distance between health facilities and service user's residence to be one of the most significant barriers [19], confirming findings from earlier reviews [14,15]. Ongoing global attention on the SDG, coupled with technological advancements in GIS tools have driven researchers to better quantify and examine the impact of physical accessibility, mostly capturing it as the spatial separation between women and health services [3]. This calls for an effort to synthesize available evidence to appraise the different measurement approaches used, reassess spatial separation between women and available health services, and to better understand the effect of increased spatial separation on skilled delivery care utilization in SSA.

The objectives of this systematic review are to (i) provide an overview of the approaches undertaken to measure spatial separation (as distance and travel time) between women and health services and (ii) establish to extent to which spatial separation deters utilization of skilled care for childbirth in Sub-Saharan Africa using existing quantitative evidence.

Methods

Review question and search strategy

A systematic review was conducted to search, summarize and synthesize evidence using five databases—Medline, Embase, Global Health, Africa Wide Information and Popline. The search was performed in March 2016 for materials published between January 1986 and February 2016. The year cut-off of 1986 was chosen as it was the time when activists and professionals first started mobilizing around safe motherhood [20]. Using both MeSH terms and free-text terms, the search was designed to identify articles covering all three themes—(i) SSA, (ii) distance or travel time and (iii) utilization of skilled care at birth. A sample of search terms used is given in Box 1 and the complete search strategies for each database used is given in S1 Table.

Selection criteria, data extraction and study quality assessment

We removed duplicated records. Abstracts of unique studies identified were screened and discarded if they were irrelevant to the study question. We included studies that quantified the relationship between the magnitude of distance or travel time and women's actual use of skilled care at birth. Studies that only reported women's plan to use skilled care for future childbirths and studies that only reported women's opinion or perception on physical access as a reason for where or with whom to give birth were excluded. Reference lists of included papers were reviewed to identify additional studies, which were subjected to the same review process.

Descriptive information abstracted from the final list of included studies were study design, study objective, study sample and data source. We extracted studies' mean distance/travel time. If the mean was not provided, we approximated it as the product of the midpoint of each category (midpoint of last category with an unspecified upper bound is given as the lower bound + 0.5 × width of second last category). We also extracted the mean level of skilled care at birth. Information on the approaches taken to measure exposure (distance and travel time)

Box 1. Keywords and phrases for searching

(i) **Sub-Saharan Africa**
Individual country name; Sub-Saharan Africa; Africa South of the Sahara; multi-country; cross-culture; developing countries

(ii) **Geographic access**
Geospatial; geographic information system; kilometre; physical access; distance; travel; transport

(iii) **Skilled care at birth**
Facility birth; hospital birth; skilled birth attendant; traditional birth attendant; trained assistant

were also extracted; this included the data collection method and the definition of spatial separation—start point of origin, ending destination and type of line distance (straight or road network) or the mode of transportation for travel time (e.g., walking, driving). We also abstracted studies' outcome definition of skilled care at birth (delivery location and/or attendant). Crude and adjusted parameter estimates of effect sizes, and the confounding variables used in adjusted analysis (if available) were abstracted.

The quality assessment of the studies was carried out using a modified version of the National Heart, Lung and Blood Institute's Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies [21]. We assessed sample representativeness, sources of selection and location bias, whether exposure had been clearly defined and accurately measured. The assessment of outcome quality was based on whether the type of delivery location/attendant considered to be skilled and unskilled was clearly defined and accurately measured. We also recognize that some determinants of skilled facility-based delivery in SSA identified in previous literature reviews may confound the association between spatial separation and use of skilled care. Specifically, low financial means and low education both influence one's place of residence and healthcare use, and an individual in a more serious (self-assessed or otherwise informed) health situation might be more inclined to use healthcare given the same distance [22]. Therefore, multivariate analyses were considered as adequately-adjusted if affordability, education and need (or perceived need) for skilled care at birth were controlled for. We considered adjustment for parity, pregnancy complications, previous stillbirths, among others, as suitable proxy for (perceived) need for skilled care at birth.

All studies were reviewed by KLMW, and a 5% sample of studies was independently reviewed by LB and OMRC. Conflicts were resolved by discussions among KLMW, LB and OMRC.

Synthesis of data and meta-analysis

We created typology of distance and travel time measurement on the basis of data collection method and the definition used. According to the type of end location, studies results from adequately-adjusted analyses were first presented in a narrative format. The use of any nearest health facility (HF) regardless of its capacity to provide maternity care may bias women's true separation from skilled care provision. Meta-analysis is therefore restricted to adequately-adjusted results that defined the destination as a location with maternity care provision. To combine effect estimates referring to both a continuous variable and a categorical variable, results of the latter—where three or more levels were used—were converted with trend estimation technique proposed by Greenland and Longnecked (trend estimation is not possible for dichotomous comparisons) [23]. Estimated trends and adjusted odds ratios (AORs) of other studies that considered distance as a continuous variable were pooled in meta-analyses to test the effect of physical accessibility on the use of skilled care at birth. We were not able to retrieve unreported insignificant adjusted effects from some qualifying studies from the corresponding authors, in which case we included the unadjusted results that were presented to minimize biases in the pooled estimate [24].

Results

Study identification

Initial search results obtained from the databases totalled 14,412 articles. After de-duplication, 10,444 remained, of which 10,118 were discarded for irrelevance following title and abstract screening. The 326 potentially relevant articles were retained for full-text review, and 57 met the inclusion criteria. A flow diagram detailing the number of studies screened and assessed

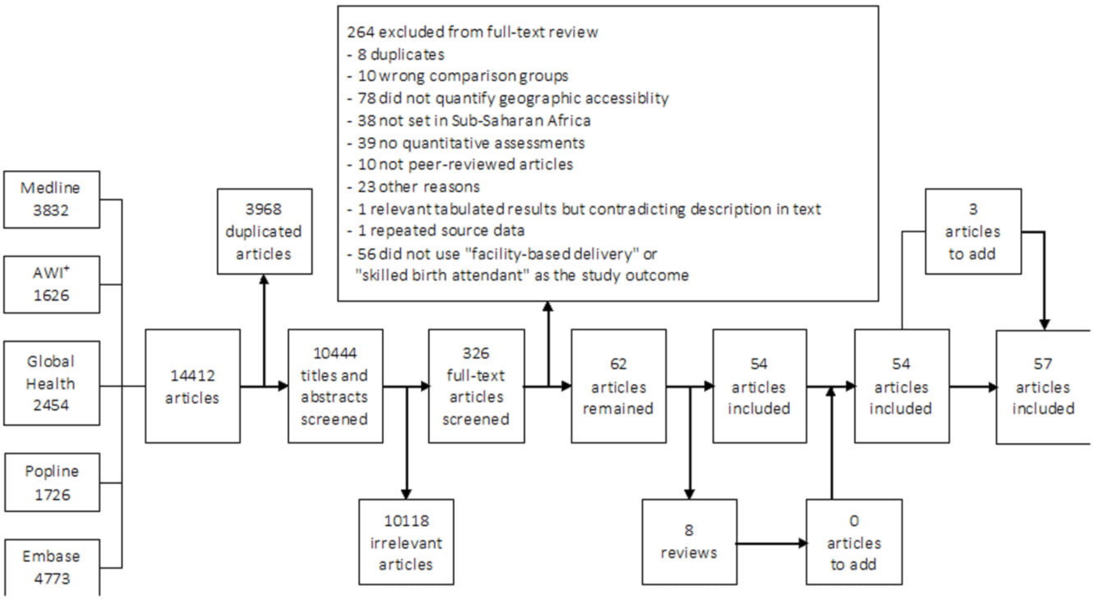

Fig 1. Flow chart of study selection for inclusion in the systematic review. +AWI = Africa Wide Information.

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for eligibility, with reasons for exclusion at each stage of the review process, is provided in Fig 1.

Characteristics of included studies

Out of 57 studies, 30 were conducted in Tanzania, Ethiopia and Kenya (S2 Table). No studies were found in 33 of 48 countries in SSA [25], including, for instance, the whole sub-region of Central Africa (Fig 2(a)). Eight studies (14%) were conducted at a national scale. The oldest identified article was published in 1991, but over two thirds of all included studies emerged since 2010 (Fig 2(b)). All included studies were cross-sectional. De Groot et al. 1993 [26] interviewed women as they attended a health facility (HF) for childbirth during the study period; the remaining 56 studies were retrospective. Esimai et al. 2007 [27] was set in urban Nigeria, 18 studies were set in both urban (or semi-urban) and rural areas, 34 studies were in rural area only, one was in a conflict context in Uganda and three did not provide clear information. Fourteen of 57 (25%) studies examined distance or travel time as a primary objective. The numbers of distance and travel time measurements were 40 and 25, including eight studies that measured both.

The results of the quality assessments are summarized in Table 1. Selection bias was identified in 28 studies. Particularly, sample selection in 14 of these 28 studies were confined to the easier-to-reach subpopulations, such as women living inside the catchment area of a HF. The other 14 study samples were drawn from existing health-seekers or registered residents who might have higher tendency to utilize skilled care.

Outcome (self-reported in 95% of the included studies) was considered clearly and well defined in 26 (46%) studies. The rest were unclear or prone to misidentifying the use of skilled care at birth by, for instance, not considering non-home births and births at HFs of any level as unskilled. Quality assessment of exposure measurement as well as confounding is presented in the following section together with examination of measurement approaches and effect of exposure. Overall, we did not find a high quality study that had an unbiased sample, a well-defined exposure and outcome, and adequate adjustment for all of affordability, education and (perceived) need for skilled care at birth.

Fig 2. (a) Geographic coverage^{+} and (b) year of publication of 57 included studies

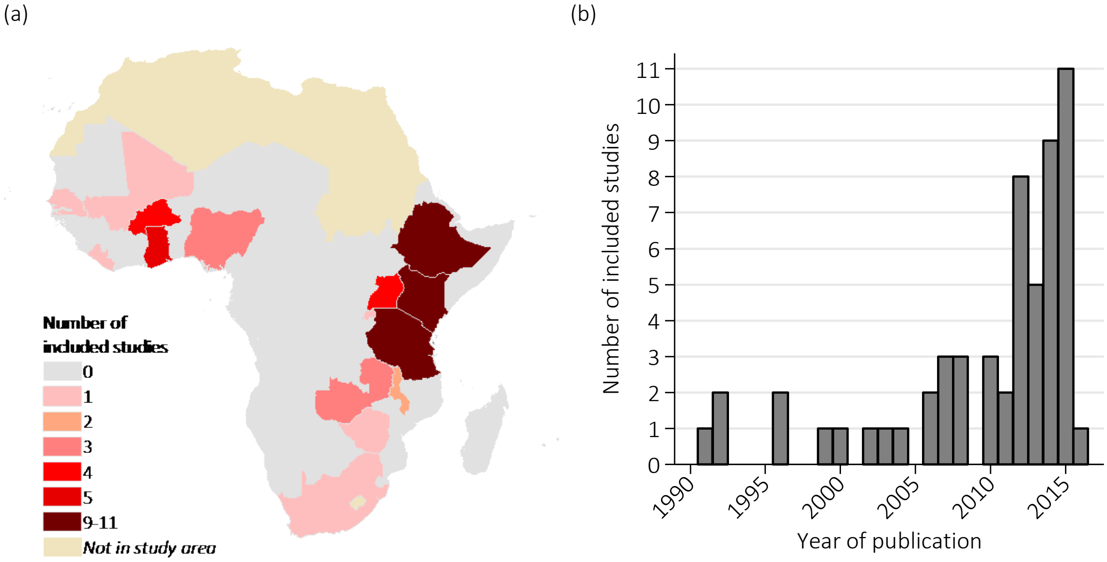

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Table 1. Quality assessment of 57 included studies

	Yes	No	Unclear
Potential selection bias (n=57)			
Study sample subject to greater physical accessibility (location bias)	14 (25%)	43 (75%)	0 (0%)
Study sample more likely to delivery with skilled care	14 (25%)	43 (75%)	0 (0%)
Study outcome (n=57)			
Self-reported data of type of care used	54 (95%)	2 (4%)	1 (2%)
Clearly defined as source of skilled obstetric care	26 (46%)	29 (51%)	2 (4%)
Adjustment for potential confounder (n=57)			
Affordability or financial means	37 (65%)	20 (35%)	0 (0%)
Education	41 (72%)	16 (28%)	0 (0%)
Need or perceived need of skilled care at birth	37 (65%)	20 (35%)	0 (0%)
All of the above	29 (51%)	28 (49%)	0 (0%)
Study exposure – measurements of distance (n=40)^			
Self-reported data only	22 (55%)	14 (35%)	4 (10%)
Clearly defined with start and end points and distance/transportation type	12 (30%)	28 (70%)	0 (0%)
Defined as starting from women's home and ending at a specified facility	2 (5%)	10 (25%)	28 (70%)
Study exposure – measurements of travel time (n=25)^			
Self-reported data only	22 (88%)	2 (8%)	1 (4%)
Clearly defined with start and end points and distance/transportation type	3 (12%)	22 (88%)	0 (0%)
Defined as starting from women's home and ending at a specified facility	1 (4%)	2 (8%)	22 (88%)
High-quality study (n=57)			
Sample selection unlikely to be biased, well-defined exposure and outcome and adequately adjusted for all three potential confounders	0 (0%)	57 (100%)	0 (0%)

^The numbers of distance and travel time measurements are 40 and 25, including eight studies that measured both.

Measuring distance

Quality of distance measurements. Among 40 studies with distance measurements, 12 were clearly defined with the start and end points as well as the distance type as straight-line or one along road (Table 1). Two of these 12 were well-defined as ending at certain specified locations likely to be able to offer labouring women skilled delivery care.

Typology of distance measurements. Table 2(a) presented the typology of the 40 studies with distance measurements. Twenty-two (55%) studies collected self-reported data only; 9 of which measured distance to any nearest HF regardless of its capacity to provide maternity care, while another 13 used one or more specified HFs as the end. All 22 studies conducted a survey and interviewed women about their distance to healthcare as part of a structured questionnaire; six of which stated a start point of origin (home or women's communities) and none of which detailed whether distance was straight-line or travelled along a road. The three studies with unclear data collection methods also provided little information on how distance was defined (Table 2a).

In the remaining 15 studies which did not use self-reported exposures, distance was measured or estimated using geographic data, including one (De Groot et al. 1991 [26]) that interviewed women attending a HF for childbirth about their distance from home village, whilst address and other data for women with non-facility births were calculated using local census data. Among the other 14 studies, Nwakoby 1992 [28] measured distance directly on a printed map; and Kenny et al. 2015 [29] tracked distance with a handheld positioning device during field workers' travels to the communities for household interviews. The rest integrated geolocated data of women's home or communities and a complete listing of HFs of the study area in a GIS. Seven of these then estimated straight-line distance from geospatial coordinates; and four others—Mills et al. 2008 [30], Joharifard et al. 2012 [31], Nesbitt et al. 2014 [32] and Johnson et al. 2015 [33]–estimated road network distance by further adding a shape file of vector data (a file to store geometric data of geographic features represented by points, lines or shapes) of the study area's road systems in their GISs.

Effects of distance on skilled care at birth. The effects of distance across the 40 studies were first summarized by their sample-level mean proportions of skilled care at birth and mean distances (Fig 3(a)). Multi-site studies, or studies reporting distances to more than one end points are represented separately. Fig 3(a) suggested that there was little to no difference in use as distance from specified HFs changed within the 40km-bound across all included studies. As distance from specified HFs increased beyond this threshold, however, a drop in skilled care utilization was observed, suggesting certain non-linear effect. This pattern appeared to be driven heavily by only one multi-site study (Kruger et al. 2011 [34]), however, another two studies stratified their study subjects into living "closer" and "further away" from health services (Hounton et al. 2008 [35] and Mwaliko et al. 2014 [36]) and their results were in line with this observed non-linearity, as they both found a negative effect of distance on use only among women who lived "closer".

Across all studies, women's mean distances to their nearest HF of any level and specified HFs was 4km and 15km, respectively. Anastasi et al. 2015 [37] found no crude association between distance to the nearest HF with maternity care and use (S2 Table). Seven and 14 studies evaluating distance to the nearest HF and distance to one or more specified HF(s) reported effects controlled (or at least tested) for affordability, education and (perceived) need, respectively (Table 3). Among these 22 studies, four found distance to have no significant effect on use of skilled care at birth. The rest concluded that increased distance was at least marginally significantly associated with reduced use of skilled care at birth ($p<0.1$). From adequately-adjusted studies, meta-analysis indicated that every kilometre increase in distance to a source

Table 2. Typology of (a) measurements of distance in 40 studies and (b) measurements of travel time in 25 studies

(a) Endpoint	Data collection method													Total
		Self-reported			Measured or estimated			Both			Unclear			
		Start point			Start point			Start point			Start point			
	Line type	Home	Community	Unclear	Home	Community	Unclear	Home	Community	Unclear	Home	Community	Unclear	
Nearest health facility only	Unclear	1	1	7				▨	▨	▨		1		12
	Straight line				1			▨	▨	▨				
	Road network						1	▨	▨	▨				
	Both							▨	▨	▨				
Health facility equipped to provide skilled care for childbirth	Unclear	2	2	9		1	1					1		23
	Straight line					3			1					
	Road network					2								
	Both					1								
Both nearest & equipped health facility	Unclear	▨	▨	▨				▨	▨	▨			1	5
	Straight line	▨	▨	▨	2	1		▨	▨	▨				
	Road network	▨	▨	▨		1		▨	▨	▨				
	Both	▨	▨	▨				▨	▨	▨				
Total		22			14			1			3			40

(b) Endpoint	Data collection method													
		Self-reported			Measured or estimated			Both			Unclear			
		Start point			Start point									
	Line type	Home	Community	Unclear	Home	Community	Unclear							
Nearest health facility only	Unclear			4	▨	▨	▨	▨	▨	▨	▨	▨	▨	13
	Walking		1	8	▨	▨	▨	▨	▨	▨	▨	▨	▨	
	Mechanized				▨	▨	▨	▨	▨	▨	▨	▨	▨	
	Both				▨	▨	▨	▨	▨	▨	▨	▨	▨	
Health facility equipped to provide skilled care for childbirth	Unclear			6				▨	▨	▨	▨	▨	▨	12
	Walking	1		3				▨	▨	▨	▨	▨	▨	
	Mechanized					1		▨	▨	▨	▨	▨	▨	
	Both					1		▨	▨	▨	▨	▨	▨	
Total		23			2			0			0			25

		Average Distance (km)	Average Use (%)
+	Any nearest facility	4	54
o	Other specified facilities	15	46

		Average Time (min)	Average Use (%)
○	Walking time to any nearest facility	68	40
●	Walking time to specified facilities	108	37

Fig 3. Summary of included studies' mean levels of use of skilled care at birth against (a) average distance to health services in kilometres (km) and (b) average travel time to health services in minutes (min).

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of maternity care was associated with a reduction in the odds of using skilled care at birth (pooled OR = 0.90, 95%CI = 0.85–0.94) (Fig 4). There was, however, evidence of high heterogeneity (I^2 = 96%, p-value<0.001).

Hounton et al. 2008 [35], Mills et al. 2008 [30] and Kruk et al. 2015 [38] presented adjusted results and provided an opportunity to assess the effects of distance when different types of end location were compared. After controlling for distance to the nearest HF, increased distance to a higher-level HF remained strongly associated with a reduced likelihood of skilled care at birth in all three studies. However, meta-analysis of studies from rural areas of (Hounton et al. 2008 [35] and Kruk et al. 2015 [38]) showed no effect of increased distance (pooled aOR = 0.58, 95%CI = 0.31–1.09) and strong evidence of heterogeneity (I^2 = 87.9%, p-value = 0.004) (Fig 4). Meta-analysis was also conducted on five estimates of distance to lower-level HFs (all set in rural areas). The result suggested a small but significant effect of distance (pooled aOR = 0.97, 95%CI = 0.96–0.99) with no evidence of heterogeneity (I^2 = 41.7%, p-value = 0.143) (Fig 4).

Measuring travel time

Quality assessment. The numbers of travel time measurements totalled 25, three of which were clearly defined with the start and end locations as well as the mode of transportation. Of these, one was well-defined as the walking time from women's home to their nearest point of maternity care provision (Table 1).

Typology of travel time measurements. Table 2(b) shows the various travel time measurements identified. Two studies (Masters et al. 2013 [39] and Nesbitt et al. 2014 [32]) measured and estimated the travel time required to reach a HF by mapping population locations, health service locations, land-cover and detailed road networks in the study areas in GIS. Travel times from different locations where subpopulations resided to health services were then estimated on the basis of empirically derived driving/walking speed [40,41]. The rest of travel time measurements (n = 23) were self-reported data collected from surveys, where women were asked the time they would need to reach their nearest HF (n = 13) and a specified

Table 3. Effect estimates of multivariate association adjusted for affordability, education and need or perceived need for skilled care for childbirth

	Study	Settings	(Reference)	Multivariate association with using skilled care for childbirth (95% confidence interval if available)					
Distance to the nearest facility	De Allegri et al. 2011	Rural Burkina Faso	(≤5km)	>5km	0.035**				
	Johnson et al. 2015	Rural Ghana	(≤8km)	>8km	0.74 (0.62-0.88)**				
	Lwelamira and Safari 2012	Rural Tanzania	(<5km)	5-10km	0.87 (0.73-1.04)	>10km	0.62 (0.47-0.81)*		
	Nakua et al. 2015	Rural Ghana	(≤5km)	6-10km	0.32 (0.13-0.74)*	11-15km	0.40 (0.11-1.46)		
	Mageda et la. 2015	Rural Tanzania	(<5km)	5-10km	0.43 (0.5-1.7)	≥10km	0.43 (0.3-0.8)**		
	O'Meara et al. 2014	Rural Kenya (multi-site)							
		- Butula	Every one kilometre increment: 1.33 (1.00-1.69)*						
		- Bunyala	Every one kilometre increment: 0.80 (0.60-1.07)						
		- Teso North	Every one kilometre increment: 1.14 (0.79-1.64)						
		- Bungoma East	Every one kilometre increment: 1.18 (0.93-1.51)						
	Ndao-Brunblay et al. 2014	Rural Tanzania	Every one kilometre increment: 0.89 (p-value=0.085)						
Distance to health facilities equipped to provide skilled care for childbirth	Mpembeni et al. 2007	Rural Tanzania	(0-5km)	6+km	0.25 (0.16-0.37)***				
	De Allegri et al. 2015	Rural Burkina Faso	(≤6km)	7km	(0.01-0.30)*				
	Moran et al. 2006	Rural Burkina Faso	(<22.8km)	≥22.8km	0.39 (0.202-0.759)*				
	Mills et al. 2008	Urban and rural Ghana	(0-9km)	10-19km	0.54 (0.37-0.79)*	20+km	0.31 (0.23-0.43)*		
	Magadi et al. 2000	Urban and rural Kenya	(<5km)	5-10km	0.47*	>10km	0.38*		
	Gage 2007	Rural Mali	(<1km)	1-4km	0.526 (0.277-1.001)	5-9km	0.491 (0.277-0.871)*	10-14km	0.418 (0.212-0.825)*
				15-29km	0.403 (0.209-0.779)***	30+km	0.623 (0.262-1.480)		
	Okafor 1991	Rural Nigeria	Every one kilometre increment: -0.097*						
	Lohela et al. 2012	Rural Malawi	Every one$^{\$}$ kilometre increment: 0.90 (0.87-0.93)***						
	Kruk et al. 2015	Rural Tanzania	Every one kilometre increment to dispensary (equipped to provide maternity care): 0.93 (0.84-1.04) Every one kilometre increment to primary health clinics (equipped to provide maternity care): 1.07 (0.97-1.19) Every one kilometre increment to hospital (higher-level and provide maternity care): 0.40 (0.26-0.63)***						
	Hounton et al. 2008	Rural Kenya	Every one kilometre increment to health centre (lower-level and usually led by a nurse) for <7.5km: 0.77 (0.75-0.79)*** Every one kilometre increment to health centre (lower-level and usually led by a nurse) for ≥7.5km: 0.97 (0.95-0.98)*** Every one$^{\$}$ kilometre increment to hospital (higher-level and the main source of surgical care): 0.97 (0.97-0.99)***						
	Joharifard et al. 2012	Rural Rwanda	Every one kilometre increment (up to 14): 0.909 (0.608-1.907) **INSIGNIFICANT**						
	Kitui et al. 2013	Urban and rural Kenya	Adjusted effect of distance to the nearest HF offering maternity care is insignificant (results not presented in original study) **INSIGNIFICANT**						
	Anyait et al. 2012	Mostly rural Uganda	Adjusted effect of distance to the nearest HF offering maternity care is insignificant (results not presented in original study) **INSIGNIFICANT**						
	Nuwaha and Amooti-kaguna 1999	Mostly rural Uganda	Adjusted effect of distance to the nearest HF offering maternity care is insignificant (results not presented in original study) **INSIGNIFICANT**						
Travel time	Wado et al. 2013^{+}	Urban and rural Ethiopia	(<60min)	>60min	0.55 (0.34-0.89)*				
	Hailu et al. 2014^{+}	Urban and rural Ethiopia	(<60min)	≥60min	0.3 (0.11-0.87)*				
	Gebru et al. 2014^{+}	Ethiopia	(≤60min)	>60min	0.249 (0.143-0.434)**				
	Abikar et al. 2013	Kenya	(<60min)	>60min	0.26 (0.08-0.81)*				
	Van Eijk et al. 2006^{+}	Rural Kenya	(<60min)	60min	0.58 (0.33-1.05)	>60min	0.36 (0.18-0.75)*		
	Spangler and Bloom 2010^{+}	Rural Tanzania	(<30min)	30-60min	0.45 (0.31-0.64)***	≥60min	0.26 (0.18-0.38)***		
	Kawakatse et al. 2014^{+}	Rural Kenya	(<20min)	21-40min	0.547 (0.536-0.558)	41-60min	0.533 (0.515-0.554)	>60min	0.403 (0.282-0.573)***
	Masters et al. 2013^{++}	Rural Ghana	Every one hour increment: 0.801 (0.69-0.93)***						
	Teferra et al. 2012^{+}	Urban and rural Ethiopia	Adjusted effect of walking time is insignificant (results not presented in original study) **INSIGNIFICANT**						
	Amano et al. 2012^{+}	Urban and rural Ethiopia	Adjusted effect of walking time is insignificant (results not presented in original study) **INSIGNIFICANT**						
	Nuwaha and Amooti-kaguna 1999^{+}	Mostly rural Uganda	Adjusted effect of motorized travel time is insignificant (results not presented in original study) **INSIGNIFICANT**						

Reverse associations shown if original results were presented with greater distance or travel time as reference category or unskilled care for childbirth as the outcome of interest.

$^{\$}$ Association shown was converted from a 10-km increment by raising the original estimate to the power of 0.1.

$^{+}$ Walking time; $^{++}$ Motorized travel time; * $p<0.05$; ** $p<0.01$; *** $p<0.001$

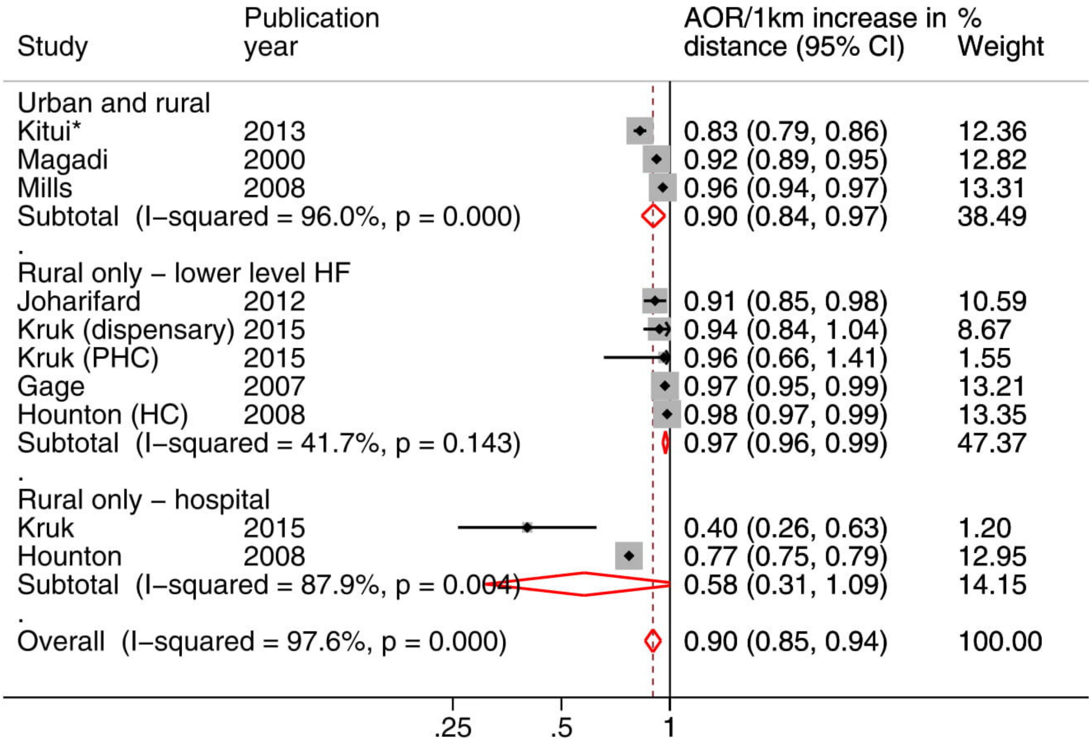

Fig 4. Forest plot showing the adjusted odds ratios (AORs) for every 1km increase in distance to maternity care on the use of skilled care at birth from adequately-adjusted analyses. Weights are for random-effects meta-analysis. PHC = primary health care; HC = health center; HF = health facility. *Unadjusted estimate used as adjusted estimate was unavailable.

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HF (n = 12). The start point of origin and the mode of transportation were unreported in 21 and 10 studies, respectively.

Effects of travel time. Fig 3(b) plots the 25 studies using the sample mean levels of skilled care utilization and mean travel times. No specific pattern emerged from these observations. The average walking time to the nearest HF was 68 minutes and time to reach all other specified facilities was 108 minutes.

Anastasi et al. 2015 [37] and Anyait et al. 2012 [42] found no crude relationship between travel time and utilization of skilled care at birth. Results of the 11 studies that reported the mode of transportation, a crucial element in understanding travel time, and were adequately-adjusted are shown in Table 3. Teferra et al. 2012 [43], Amano et al. 2012 [44], Nuwaha and Amooti-kaguna 1999 [45] found no significant adjusted association between walking time and utilization of skilled care at birth. Van Eijk et al. 2005 [46] and Kawakatse et al. 2014 [47] compared more than two categories of travel time and only found significant difference between the reference category and the furthest (longest time) category. The other six studies found significant reduced use of skilled care as travel time increased in every comparison made, including four studies (Wado et al. 2013 [48], Hailu et al. 2004 [49], Gebru et al. 2014 [50] and Abikar et al. 2013 [51]) that looked at times less than 60 minutes versus above, Spangler and Bloom 2010 [52] who compared <30 minutes, 30–60 minutes and ≥60 minutes, and lastly, Masters et al. 2013 [39] who considered motorized travel time as a continuous variable. Meta-analysis was not possible as only one study—the authors showed a reduced of 24% in odds of FBD in rural mothers per hour increase in motorized travel time [39].

Discussion

Summary of findings

In this systematic review we found evidence suggesting that increased distance and travel time to health facility were inversely correlated with the utilization of skilled care at childbirth in SSA. The details required for a meaningful and thorough understanding of the effect of spatial separation between women and health service were clearly provided by 12 of the 57 included studies and the effect of travel time by three studies. In addition, a few studies suggested that the negative effect of spatial separation waned for women who live very far from health services. For these populations who are perhaps "too" separated from healthcare provision, utilization of skilled birth attendance was generally very low and further increase in distance had no significant effect on skilled care utilisation.

Limitations of existing evidence

These findings should be interpreted with certain limitations in mind. The 57 included studies were predominately retrospective and cross-sectional, and only one quarter of them primarily focused on physical accessibility. Many countries in SSA, including the whole sub-region of Central Africa, where within-country, urban-rural disparities in delivery care utilization have been noted [53,54], is entirely unrepresented. Substantial amount of included studies is prone to location and selection biases, considered non-home births (albeit some of these studies intended to examine the determinant of home deliveries) and childbirths in HFs of any level, or those attended by medical personnel of any qualifications as "skilled" care. However, these limitations likely result in an underestimate of the observed effect in the current review. Moreover, almost all studies relied on self-reported data for place of and attendant at childbirth, which could cause misclassification as respondents may not know or recall correctly the level of HF and the medical qualification of the birth attendant.

Findings from systematic review

This review has identified two major ways to measure distance and travel time in the literature of maternity care utilization—self-reported data and GIS-based estimation using overlaid coordinates of the population and health services. In the former, the details required to thoroughly comprehend physical accessibility are often unreported. Kabakyenga and colleagues [55], for instance, did not report the mode of transportation although the questionnaire they had adopted included a question on how women went to the HF for labour [56]. Absence of such details could also be rooted in the lack of clarity in the survey instrument itself. An unclear question would lead to increased variability in the data as people interpret the question differently. Readers of these studies cannot reach a meaningful understanding without making strong assumptions, thus hindering the translation of quantitative findings to actionable information.

The more rigorous distance and travel time estimation techniques performed in a GIS are less prone to error induced from respondents not having a concrete idea of geographical space, and does not depend on people knowing where the nearest health facility/maternity care/hospital is located. However, its application would depend on the availability of geocoded study sample and the local healthcare infrastructure—data often unavailable or costly to obtain in low-resource settings. To determine network distance would further require geospatial data of the road system. Nesbitt et al. 2014 [32] found no significant difference in the effects on facility-based delivery between straight line and road distances. Adaptation of similar investigation in a greater variety of contexts can strengthen such evidence base and justify the use of road distance in studies attempting to answer other related questions.

Researchers should avoid asking for self-reported distance and travel time as they can be difficult to conceptualize. Researchers of population-based study should capitalize on fieldworkers' travels to collect location data, either as travel routes or fixed-point coordinates. For facility-based study, addresses should be collected and manually referenced on hardcopy maps or satellite imageries. It is surprising that the use of addresses and printed maps as means of assessing distance was scarce. In the current review, only the older studies quantified women's physical accessibility to healthcare on printed maps [26,28]. Quality of the measurements made would depend on map resolution and the accuracy of manual referencing of addresses and locations (of women's home/community and HFs). Nonetheless, this approach is particularly feasible for small-scale regional studies with engagement of the local communities. While detailed maps used to be difficult to obtain, the open-source community has started to address this challenge by making topographic information and crowdsourced map available [57]. Key features and landmarks are digitized to create shapefiles and vector layers of spatial objects that can then be imported and analysed in major analytical software packages broadly used in epidemiological studies (such as Stata, R, ArcGIS and QGIS). Multiple studies of maternity care determinants set in LMICs have already adopted this approach [33,58–61]. Prioritizing accurate, up to date, and reliable geospatial data availability has been highlighted in expert group meetings [62], but the compilation of geospatial data of health facility census and other ancillary data (e.g., road network) remains a challenge for local teams. Digitization of satellite imagery requires basic computational skills and is responsive to changes on the ground, offering an opportunity to fill current data gap.

On average, women from the identified studies live 15km and 108 minutes of walking time to a health facility likely to be equipped for skilled delivery. These levels are above the 5km threshold of what is considered walkable for a heavily pregnant woman [63], and the one-hour travel time to the nearest obstetric care recommended by the WHO [64]. Meta-analysis of adequately-adjusted results demonstrated that increased distance from maternity care provision deters use of maternity care for those with such intention and financial ability. Distance to a higher-level facility might have additional appeal to labouring women, despite accessibility to a nearby facility of lower-level (although unsupported by our meta-analysis possibly due to between-study heterogeneity and high within-study uncertainty in some instances). In addition to maternal and other individual and community factors, studies of bypassing front-line facilities for childbirth in LMICs have identified perceived higher quality of care, availability of drugs and medical equipment, and additional obstetric care functionality at higher-level HF as important determinants [65–71]. Investing in frontline facilities to ensure they have the appropriate equipment, drugs and medical personnel for their intended roles could increase met need for obstetric care within minimal travel time, especially in rural settings.

A few studies identified in the current review suggested distance and travel time to be influential only within a certain threshold, beyond which utilization is universally low and any extra spatial separation ceases to have an effect. Non-linearity should therefore be noted when analysing the effect of distance and travel time. We are unable to identify one universal critical threshold from available evidence. This is due to context-specificity, the many ways in which spatial separation has been captured, the different analytical approaches used in individual studies, as well as a lack of a reporting standard in the current literature.

Overcoming spatial separation requires bringing people to healthcare or healthcare to people [72]. From a policy-making perspective, modifiable health system factors such as, but not limited to, physical accessibility have contextual importance in prioritizing action and devising appropriate health system responses. Relevant strategies have been proposed in SSA and other LMICs [72–77]. Governments and their partners should prioritize the provision of better measurement to ensure countries have quality data to make informed decisions.

Limitation of the systematic review

Physical accessibility, financial affordability and service acceptability form the basis of potential access [18,78]. To certain extent, affordability enables physical accessibility and service acceptability may change individuals' perception of distance/travel time. We accounted for financial means directly, but not for service acceptability. This is because service acceptability is in part, among others, users' social status and perception of need, which we have already addressed [79]. We omitted the grey literature and so might have missed some relevant studies. However, these are also the ones unlikely to (i) have novel approaches or tools not already identified and (ii) included a well-adjusted analysis. Only a small proportion of the included studies (25%) primarily addressed physical inaccessibility, which suggests possible publication bias from studies that intended to assess the influence of distance and travel time but did not find any significant association.

Conclusion

Higher reporting standard of distance and travel time is needed to help understand and device appropriate strategies to overcome the persisting spatial separation between women and maternity care in SSA. Utilization is not possible without access and current evidence, while not without limitations, shows that suboptimal physical inaccessibility impedes use. In light of the global effort to reduce preventable maternal and newborn mortality and morbidity, researchers and policy makers should prioritize the provision of better measurement and information to ensure countries have quality data to make informed decisions on the spatial distribution of health facilities that provides physically accessible skilled delivery care to all women.

Supporting information

S1 Table. Complete search strategy.
(DOCX)

S2 Table. Summary of 57 included studies.
(DOCX)

S3 Table. PRISMA 2009 checklist.
(DOC)

S1 Document. Copyright permission from original copyright holder.
(MSG)

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4.2 Supplementary materials

4.2.1 Supplementary material A. Complete search strategy

4.2.1.1 Medline

a. Sub-Saharan Africa

Africa, Western/ or Africa, Central/ or "Africa South of the Sahara"/ or Africa, Eastern/ or Africa, Southern/	16650	OR 471187
Angola or Benin or Botswana or Burkina Faso or Burundi or Cameroon or Cape Verde or Central African Republic or CAR or Chad or Comoros or Congo or Cote d'Ivoire or cote dIvoire or Ivory Coast or DRC or Djibouti or Equatorial Guinea or Eritrea or Ethiopia or Gabon or Gambia or Ghana or Guinea or Guinea-Bissau or Kenya or Lesotho or Liberia or Madagascar or Malawi or Mali or Mauritania or Mauritius or Mozambique or Namibia or Niger or Nigeria or reunion or Rwanda or "Sao Tome and Principe" or Senegal or Seychelles or Sierra Leone or Somalia or South Africa or Sudan or Swaziland or Tanzania or Togo or Uganda or Western Sahara or Zambia or Zimbabwe or SSA or "sub-saharan Africa"	366661	
Cross-culture comparison/ or developing countries/ or multicentre studies/ or multicountry or multi-country or multiple countries or multicentre or multicentre or multi-center or multi-centre	111314	

b. Geographic access

"Catchment area (health)"/ or Geographic information systems/ or Geographic mapping/ or Time factors/ or Travel/ or health service accessibility/	1093409	OR 2035284
Geospatial or spatial or gis or "geographic information system" or "geographic information systems" or distance* or travel* or transport*	918903	
time* adj5 (birth* or childbirth? or deliver* or labo?r or parturition? or obstetric* or gyn?ecology or facilit* or hospital* or institut* or clinic? or center? or centre? or department? or unit? or ward?)	69453	
(km? or m? or kilometer? or meter? or mile?) adj2 (at least or more or less or within or from or to or away or walk or drive or ride or bike or cycle or commut*)	58058	
(physical or geograph*) adj1 (inaccess* or access*)	824	

c. Skilled care at birth

fbd or sba	2600			OR 237791
(birth* or childbirth? or deliver* or labo?r or parturition?) adj5 (facilit* or non-facilit* or nonfacilit* or hospital* or institut* or non-institut* or noninstitut* or clinic? or center? or centre? or department? or unit? or ward? or place or home* or domicile* or village* or domestic or community or assist* or attend)	41330			
(village or tradition* or skill* or train*) adj1 (attend* or birth attend* or health or assistant* or care or manpower or delivery or staff or midwif* or professio*)	16173			
Birthing centers/ or Delivery rooms/ or Delivery, obstetric/ or Home childbirth/	27142			
Birth* or Childbirth? or Deliver* or Labo?r or Parturition or Pregnan* or Obstetrics/ or Parturition/ or Pregnancy/	1434254		AND 176186	
Physicians/ or doctor* or physician* or Midwifery/ or midwi* or nurses/ or nurse* or obstetrical nursing/ or Professional practice/ or Health personnel/ or ((clinical or health of medical) adj1 (officer* or auxiliary*))	783285	OR		
"Delivery of Health Care"/ or "Obstetrics and Gynecology Department, Hospital"/ or Health Behavior/ or Health facilities/ or Health Facility Closure/ or Health Personnel/ or Health Services/ or Healthcare Disparities/ or Maternal Health Services/ or Maternal-Child Health Centers/ or Universal Coverage/	190269			
((health* or medical) adj3 (utiliz* or utilis* or use* or uptake* or access*))	141332			

(a AND b AND c) OR (b AND c [reviews only])

4.2.1.2 Africa Wide Information

b. Geographic access

Geospatial or spatial or travel or gis or "geographic information system" or "geographic information systems" or distance* or travel* or transport*	136078	OR 141818
(time*)	3376	
W5		
(birth* or childbirth? or deliver* or labo?r or parturition? or obstetric* or gyn?ecology or facilit* or hospital* or institut* or clinic? or center? or centre? or department? or unit? or ward?)		
(km? or m? or kilometer? or meter? or mile?) W2 (at least or more or less or within or from or to or away or walk or travel or drive or ride or bike or cycle or commut*)	2808	
(physical or geograph*)	271	
W1		
(inaccess* or access*)		

c. Skilled care at birth

fbd or sba	3482			OR 354294
(birth* or childbirth? or deliver* or labo?r or parturition?) adj5 (facilit* or non-facilit* or nonfacilit* or hospital* or institut* or non-institut* or noninstitut* or clinic? or center? or centre? or department? or unit? or ward? or place or home* or domicile* or village* or domestic or community or assist* or attend)	63404			
(village or tradition* or skill* or train*) adj1 (attend* or birth attend* or health or assistant* or care or manpower or delivery or staff or midwif* or professio*)	32082			
Birth* or Childbirth? or Deliver* or Labo?r or Parturition or Pregnan* or Birth/or Childbirth/ or Obstetrics/ or Parturition/ or Pregnancy/	1721875		AND 285872	
Physician/ or doctor* or physician* or Midwife/ or Nurse/ or Nurse midwife/ or Nurse midwifery/ or midwi* or nurse* or Health auxiliary/ or Health care manpower/ or Health care personnel/ or Medical personnel/ or Professional practice/ or ((clinical or health of medical) adj1 (officer* or auxiliary*))	1100487	OR		
Health care delivery/ or Health care facility/ or Health care utilization/ or Health care/ or Health center/ or Health service/ or Hospital service/ or Hospital utilization/ or Medical service/ or Public health service/ or Maternal care/ or Maternal treatment/ or Maternity ward/	538964			
((health* or medical) adj3 (utiliz* or utilis* or use* or uptake* or access*))	197683			

b AND c

4.2.1.3 Global health

a. Sub-Saharan Africa

Africa, Western/ or Africa, Central/ or "Africa South of the Sahara"/ or Africa, Eastern/ or Africa, Southern/	165042	OR 803358
Angola or Benin or Botswana or Burkina Faso or Burundi or Cameroon or Cape Verde or Central African Republic or CAR or Chad or Comoros or Congo or Cote d'Ivoire or cote dIvoire or Ivory Coast or DRC or Djibouti or Equatorial Guinea or Eritrea or Ethiopia or Gabon or Gambia or Ghana or Guinea or Guinea-Bissau or Kenya or Lesotho or Liberia or Madagascar or Malawi or Mali or Mauritania or Mauritius or Mozambique or Namibia or Niger or Nigeria or reunion or Rwanda or "Sao Tome and Principe" or Senegal or Seychelles or Sierra Leone or Somalia or South Africa or Sudan or Swaziland or Tanzania or Togo or Uganda or Western Sahara or Zambia or Zimbabwe or SSA or "sub-saharan Africa"	221215	
Developing countries/ or least developed countries/ or international comparisons/ or multicountry or multi-country or multiple countries or multicentre or multicentre or multi-center or multi-centre	787861	

b. Geographic access

Access/ or Distance travelled/ or Geographical information systems/ or Mapping/ or Travel/	9712	OR 130848
Geospatial or spatial or travel or gis or "geographic information system" or "geographic information systems" or distance* or travel* or transport*	101663	
(time*) adj5 (birth* or childbirth? or deliver* or labo?r or parturition? or obstetric* or gyn?ecology or facilit* or hospital* or institut* or clinic? or center? or centre? or department? or unit? or ward?)	14216	
(km? or m? or kilometer? or meter? or mile?)	13051	
adj2		
(at least or more or less or within or from or to or away or walk or travel or drive or ride or bike or cycle or commut*)		
(physical or geograph*) adj1 (inaccess* or access*)	460	

c. Skilled care at birth

fbd or sba	497			OR 43473
(birth* or childbirth? or deliver* or labo?r or parturition?) adj5 (facilit* or non-facilit* or nonfacilit* or hospital* or institut* or non-institut* or noninstitut* or clinic? or center? or centre? or department? or unit? or ward? or place or home* or domicile* or village* or domestic or community or assist* or attend)	13049			
(village or tradition* or skill* or train*) adj1 (attend* or birth attend* or health or assistant* or care or manpower or delivery or staff or midwif* or professio*)	6248			
Birth* or Childbirth? or Deliver* or Labo?r or Parturition or Pregnan* or Birth/or Childbirth/ or Obstetrics/ or Parturition/ or Pregnancy/	212185		AND 30082	
physicians/ or doctor* or physician* or midwives/ or midwi* or nurses/ or nurse* or medical auxiliaries/ or health care workers/ or ((clinical or health of medical) adj1 (officer* or auxiliary*))	86456	OR		
Institutions/ or Health services/ or Hospitals/ or Health centres/ or Maternity service/ or Health care utilization/	84166			
((health* or medical) adj3 (utiliz* or utilis* or use* or uptake* or access*))	34561			

d. Review

review or literature reviews/ or systematic reviews/ or reviews/	251068

(a AND b AND c) OR (b AND c AND d)

4.2.1.4 Popline

a. Sub-Saharan Africa

Angola OR Benin OR Botswana OR Burkina Faso OR Burundi OR Cameroon OR Cape Verde OR Central African Republic OR CAR OR Chad OR Comoros OR Congo OR Cote d'Ivoire OR IvORy Coast OR DRC OR Djibouti OR Equatorial Guinea OR Eritrea OR Ethiopia OR Gabon OR Gambia OR Ghana OR Guinea OR Guinea-Bissau OR Kenya OR Lesotho OR Liberia OR Madagascar OR Malawi OR Mali OR Mauritania OR Mauritius OR Mozambique OR Namibia OR Niger OR Nigeria OR reunion OR Rwanda OR "Sao Tome and Principe" OR Senegal OR Seychelles OR Sierra Leone OR Somalia OR South Africa OR Sudan OR Swaziland OR Tanzania OR Togo OR Uganda OR Western Sahara OR Zambia OR Zimbabwe OR SSA OR "sub-saharan Africa"	OR
multicountry OR multi-country OR multiple countries OR multicentre OR multicentre OR multi-center OR multi-centre	
LITERATURE REVIEW	

b. Geographic access

Geospatial OR spatial OR travel OR gis OR "geographic information system" OR "geographic information systems" OR distance* OR travel* OR transport* or "geographic access" OR "geographic accessibility" OR "geographic inaccess" OR "geographic inaccessibility" or "geographical access" OR "geographical accessibility" OR "geographical inaccess" OR "geographical inaccessibility" or "physical access" OR "physical accessibility" OR "physical inaccess" OR "physical inaccessibility"	OR
DISTANCE OR GEOGRAPHIC FACTORS OR TRANSPORTATION OR COMMUTING OR PROGRAM ACCESSIBILITY	

c. Skilled care at birth (i)

"facility-based delivery" OR "facility based delivery" OR "facility-based birth" OR "facility based birth" OR "institutional delivery" OR "institutional birth" OR "skilled birth" OR "skilled attendant" OR "skilled attendants" OR "skilled assistant" OR "skilled assistants" OR "skilled assistance" OR "traditional birth" OR "traditional attendant" OR "traditional attendants" OR "traditional assistant" OR "traditional assistants" OR "traditional assistance" OR SBA OR FBD OR homebirth	OR
TRADITIONAL BIRTH ATTENDANTS	

d. Skilled care at birth (ii)

labour* OR labor* OR birth* OR childbirth* OR intrapartum OR intra-partum OR parturition*	OR
UTILIZATION OF HEALTH CARE	

e. Skilled care at birth (iii)

labour* OR labor* OR birth* OR childbirth* OR intrapartum OR intra-partum OR parturition*	OR
DELIVERY OF HEALTH CARE	

(a AND b AND c) OR (a AND b AND d) OR (a AND b AND e)

4.2.1.5 EMBASE

a. Sub-Saharan Africa

Africa, Western/ or Africa, Central/ or "Africa South of the Sahara"/ or Africa, Eastern/ or Africa, Southern/	12547	OR 548123
"Africa south of the Sahara"/ or “Central Africa”/ or “North Africa”/	428257	
Angola or Benin or Botswana or Burkina Faso or Burundi or Cameroon or Cape Verde or Central African Republic or CAR or Chad or Comoros or Congo or Cote d'Ivoire or Ivory Coast or DRC or Djibouti or Equatorial Guinea or Eritrea or Ethiopia or Gabon or Gambia or Ghana or Guinea or Guinea-Bissau or Kenya or Lesotho or Liberia or Madagascar or Malawi or Mali or Mauritania or Mauritius or Mozambique or Namibia or Niger or Nigeria or reunion or Rwanda or "Sao Tome and Principe" or Senegal or Seychelles or Sierra Leone or Somalia or South Africa or Sudan or Swaziland or Tanzania or Togo or Uganda or Western Sahara or Zambia or Zimbabwe or SSA or "sub-saharan Africa"	129953	
Developing countries/ or “multicentre study (topic)” or multicountry or multi-country or multiple countries or multicentre or multicentre or multi-center or multi-centre		

b. Geographic access

"traffic and transport"/ or Geographic information system/ or geographic mapping/ or geography/ or spatial analysis/ or travel/	86661	OR 1440775
Geospatial or spatial or travel or gis or "geographic information system" or "geographic information systems" or distance* or travel* or transport*	124408	
(time*) adj5 (birth* or childbirth? or deliver* or labo?r or parturition? or obstetric* or gyn?ecology or facilit* or hospital* or institut* or clinic? or center? or centre? or department? or unit? or ward?)	108745	
(km? or m? or kilometer? or meter? or mile?) Adj2 (at least or more or less or within or from or to or away or walk or travel or drive or ride or bike or cycle or commut*)	77517	
(physical or geograph*) adj1 (inaccess* or access*)	1079	

c. Skilled care at birth

fbd or sba	3482			OR 354294
(birth* or childbirth? or deliver* or labo?r or parturition?) adj5 (facilit* or non-facilit* or nonfacilit* or hospital* or institut* or non-institut* or noninstitut* or clinic? or center? or centre? or department? or unit? or ward? or place or home* or domicile* or village* or domestic or community or assist* or attend)	63404			
(village or tradition* or skill* or train*) adj1 (attend* or birth attend* or health or assistant* or care or manpower or delivery or staff or midwif* or professio*)	32082			
Birth* or Childbirth? or Deliver* or Labo?r or Parturition or Pregnan* or Birth/or Childbirth/ or Obstetrics/ or Parturition/ or Pregnancy/	1721875		AND 285872	
Physician/ or doctor* or physician* or Midwife/ or Nurse/ or Nurse midwife/ or Nurse midwifery/ or midwi* or nurse* or Health auxiliary/ or Health care manpower/ or Health care personnel/ or Medical personnel/ or Professional practice/ or ((clinical or health of medical) adj1 (officer* or auxiliary*))	1100487	OR		
Health care delivery/ or Health care facility/ or Health care utilization/ or Health care/ or Health center/ or Health service/ or Hospital service/ or Hospital utilization/ or Medical service/ or Public health service/ or Maternal care/ or Maternal treatment/ or Maternity ward/	538964			
((health* or medical) adj3 (utiliz* or utilis* or use* or uptake* or access*))	197683			

(a AND b AND c) OR (b AND c [reviews only])

4.2.2 Supplementary material B. Summary of 57 included studies

4.2.2.1 Distance to any nearest health facility

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Sample selection									Afford-ability	Education	(Perceived) need
De Allegri et al. 2011 Burkina Faso Nouna (Rural)	Multi-stage cluster random sample; first, clusters were defined according to the catchment area of each first-line HF. Second, one village where the HF was located, and another village randomly drawn from the list of all the villages in the HF catchment area were selected. In the third stage, 20 households in each village were randomly selected. N=435 women pregnant within a one-year recall period	✓	×	Distance	Unclear	Unclear TO Any nearest HF	SR	Location	HF (first-line HF or hospital)	Others	Adjusted; negative; living <5km from a HF was associated with delivering in a HF – AOR=28.42, p-value<0.001	Household asset index quintile	Maternal and paternal literacy	Parity
Johnson et al. 2015 Ghana Ghana (Rural)	Multi-stage cluster random sample from the 2003 and 2008 Ghana DHSs, rural clusters only. The births recorded in the two surveys cover the periods 1999-2003 and 2004-2008. Geo-referenced database of HFs, Community-based Health Planning and Services (CHPS) compounds and digitised topographic databased of national road network. N=4349 births from the two DHSs within each of the two five-year recall periods	×	×	Distance	Road	Unclear TO Any nearest HF for CHPS compound (where provision of skilled delivery care is not stated as a core activity)	Est.	Attendant	People with midwifery skills (e.g. doctors, midwives, nurses)	Others	Adjusted; negative; access to HF and CHPS (<8km) have a significant impact on the uptake of skilled birth care: the odds of skilled birth care increased by 35% (p<0.01) for those with access to HF, the odds of skilled care increased by 51% (p<0.05) for those with access to HF and CHPS. But living close to CHPS only showed no significant effect (p>0.05)	Household wealth status	Maternal education	Parity

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Sample selection										Education	(Perceived) need
Lwelamira and Safari 2012 Tanzania Bahi (Rural)	Random selection of households from all households in the study area. Obstetric history of all women from sampled households were obtained. N=984 women given birth within the two-year recall period	×	×	Distance	Unclear	Unclear TO Any nearest HF	SR	Location	HF	Others	Adjusted; negative; Women >10km were 38% less likely to deliver in a HF compared to those <5km (AOR=0.62, 95%CI=0.47-0.81). But odds of facility delivery for those living 5-10km to the nearest HF were not significantly different from women <5km.	Annual household income	Maternal education	Perceived quality of maternity services
Nakua et al. 2015 Ghana Amansie West (Rural)	The eligible study sample was respondents attending post-partum care identified by a sample of local health officials, and may not include mothers who were not engaged with the health system. N=400 women given birth within the one-year recall period	×	✓	Distance	Unclear	Unclear TO Any nearest HF	SR	Attendant	Persons with midwifery skills (doctor, nurse, midwives and health officer)	Others	Adjusted; negative; compared to <5km, living 6-10km to the nearest HF was associated with reduced odds of delivering in a HF – AOR=0.32 (95%CI=0.13,0.74). Living 11-15km to the nearest HF, however, did not show any significant effect.	Average household income per day	Maternal education	Ever used unskilled care, knowledge about benefits of skilled delivery
Mageda et al. 2015 Tanzania Biharamula (Unclear)	Multi-stage cluster random sample N=598 women given birth within the one-year recall period	×	×	Distance Time	Unclear Walking	Unclear TO Any nearest HF	SR	Location	HF	Others	Adjusted; negative; women living <5km were more likely to have an institutional delivery than those living >10km, AOR=2. (95%CI=2.3-3.9). Odds for those living 5-10km were not significantly different from those living >10km. No result was presented.	Regularity of maternal and paternal sources of income	Maternal and paternal education	Parity

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Sample selection									Afford-ability	Education	(Perceived) need
O'Meara et al. 2014 Kenya Bunyala (Rural)	Multi-stage cluster random sample data were collected from four districts within the Academic Model Providing Access to Healthcare (AMPATH) Primary Health Care catchment area and may not represent household located outside of any catchment area. GPS coordinates were captured for every household and HF. N=1987 women who delivered in the last five years	✓	×	Distance	Straight	Home TO 1 Any nearest HF 2 Hospital	Est.	Location	Hospital/ Nursinghome, Health centre/ Dispensary, and private clinics	Home	(Any nearest HF) Adjusted; mixed; effect of distance differed across the four districts – in Bunyala, Teso North and Bungamo East, distance was insignidicant but in Butula, distance was associated with delivery in a facility, AOR=1.33, 95%CI=1.00-1.69. (Hospital) Crude; mixed; significant only in Bunyala – COR=0.79, 95%CI=0.74-0.87.	Household SES index quartiles	Maternal education	Parity
Ndao-Brumblay et al. 2013 Tanzania Kasulu (Rural)	Multi-stage cluster random sample; individual responses for distance to any nearest HF were aggregated at the village level and corresponding village estimates were assigned to individual respondents. N=1183 women given birth within a five-year recall period	×	×	Distance	Unclear	Village TO Any nearest HF	SR	Location	Any government, mission or private HF	Friend's home or own home	Adjusted; marginally negative; distance from had a marginal negative association with institutionalized delivery (AOR=0.89, p=0.085).	Household asset index quintile	Maternal education	Parity

4.2.2.2 Distance to one or more specific health facility

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Mpembeni et al. 2007 Tanzania Mtwara (Rural)	A random sample HF was first selected. For each of the selected HF, one village in its catchment area was selected randomly. In the selected village, a house to house survey was conducted and all women who had given birth within the previous one year were interviewed. N=974 women given birth within the one-year recall period	✓	✕	Distance	Unclear	Unclear TO Nearest HF with maternity care	SR	Attendant	Doctor, nurse, midwife, MCHA (TBA unclear)	Untrained relatives or friends (TBA unclear)	Adjusted; negative; distance to the HF providing maternity care (AOR=4.09, 95%CI=2.72–6.16) were significant associated with use of skilled care at birth.	Household asset index quintile	Maternal education	Advised where to deliver during ANC and knowledge of pregnancy danger signs
De Allegri et al. 2015 Burkina Faso Nouna (Rural)	Multi-stage cluster random sample with women who resided within the catchment areas of front-line health facilities only. N=420 women given birth within the one-year recall period	✓	✕	Distance	Unclear	Village TO Specified front-line HF equipped as BEmOC	Unclear	Location	Others	Home	Adjusted; negative; there were significant association between home delivery and greater distance to preassigned front-line HF (AOR=19.33, 95%CI=3.37-110.88).	Household asset index quintile	Maternal and household head's literacy	History of miscarriage
Moran et al. 2006 Burkina Faso Koupela (Rural)	The study area comprised 145 villages in 13 health facility catchment areas. Within each catchment area, villages were stratified as further than or within the average distance to the HF. Villages from stratum were randomly selected, and women were then random selected from chosen villages. N=180 women given birth within the one-year recall period	✓	✕	Distance	Unclear	Unclear TO Preassigned health centre	Unclear but likely to be measured	Attendant	Doctor, nurse, midwife or auxiliary nurse	Others	Adjusted; negative; women living further away were 61% (95%CI=24.4-79.8) less likely to use a skilled provide at delivery.	Plan for saying money for emergency	Maternal education	Plan for birth assistant

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Mills et al. 2008 Ghana Kassena-Nankana (Urban and rural)	All mothers with recorded birth in the local Health and Demographic Surveillance Site. The NDSS has a geographical information system with a geo-reference of roads, HFs rivers, and households/compounds.	✗	✓	Distance	Road	Cluster TO 1 Nearest HF 2 District hospital	Est.	Attendant	Health professional (doctor, midwife or nurse)	Others	Adjusted; negative; distance to the district hospital showed significant association with use of health professionals at last delivery – AOR for >20km compared to <10 km was 0.31 (95%CI=0.33,0.43) and AOR for 10-19km compared to <10km was 0.54 (95%CI=0.34-0.79). Effect of distance to nearest HF was insignificant.	Household asset index quintile	Maternal education	Parity
Magadi et al. 2000 Kenya Kenya (Urban and rural)	Multi-stage cluster random sample from the 1993 Kenya DHS N=5,290 births occurred within the five-year recall period	✗	✗	Distance	Unclear	Unclear TO Nearest HF with maternity care	SR	Location	Others	Home	Adjusted; negative; for births occurring 5-10km or >10km away, the average odds of home births are more than double, compared to births occurring <5km from maternity care.	Household asset index tercile	Maternal education	Birth Order
				Time	Unclear						Adjusted; negative; the average odds of home births >2h from maternity care are almost double the odds of births <1h from a HF offering maternity care.			
Gage 2007 Mali Mali (Rural)	Multi-stage cluster random sample from the 2001 Mali DHS, including a community questionnaire that collected data from key informants on the socioeconomic, and health and other infrastructure of enumeration areas selected for interview. N=6,178 most recent births within the five-year recall period	✗	✗	Distance	Unclear	Unclear TO Nearest HF with maternity care	SR (by community informants)	Attendant	Trained health worker (doctor, nurse, auxiliary nurse or midwife)	Others	Adjusted; negative; Distance had strong effects on the odds of both facility-based delivery and delivering with a trained health worker.	Household asset index	Maternal education	Mother told about pregnancy complications
								Location	HF	Others				

Citation Country Region (Settings)	Study sample		Distance/travel time (exposure) measurement				Study outcome			Results				
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Okafor 1991 Nigeria Udi (Rural)	One-stage sample of town in part based on interviewers' convenience and all women residing were interviewed. N=498 women given birth within the two-year recall period	✓	×	Distance	Unclear	Town TO Nearest HF with maternity care	SR	Both	In a HF with at least a midwife or a trained and state licenced auxiliary/ TBA	Others	Adjusted; negative; effect of distance was significant at p<0.05 level.	Husband's occupation	Maternal education	Parity
Lohela et al. 2012 Malawi Malawi (Rural) Note: We also included Gabrysch et al. 2011 which covered the analysis for Zambia in Lohela et al. 2012.	Multi-stage cluster random sample from the 2004 Malawi DHS, rural clusters only. Births that occurred before the mothers moving to the current location were excluded. Facility data on all public and semi-public and major private HFs were obtained from national Health Facility Censuses conducted in Malawi in 2002. N=8842 children born within the five-year recall period	×	×	Distance	Straight	Cluster TO Nearest HF with maternity care	Est.	location	HF	Others	Adjusted; negative; the odds of facility delivery decreased by 65% for every 10 km increase in distance to the closest facility (AOR=0.35, p=0.001).	Household asset index quintile	Paternal education	Women's modern attitudes (in cluster)

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Selection										Education	(Perceived) need
Kruk et al. 2015 Tanzania Pwani (Rural)	The study population is women with deliveries in the past year who live in catchment areas of 24 study health facilities: government primary care clinics with at least one medically trained staff member who were trained in basic obstetric care and were actively providing delivery services. Enumerators collected locations of all HFs in the study area and sub-village centres using GPS receivers. N=3,019 women given birth between six weeks and one year before interview	✓	×	Distance	Straight	Village TO 1 Primary clinic 2 Health centre 3 Hospital	Est.	Location	HF	Home (own or that of someone else)	Adjusted; negative; women's distance from the nearest hospital was strongly associated with an increased likelihood of home delivery (AOR=2.49, 95%CI=1.60,3.88). Distance from the nearest health center and dispensary were not associated with likelihood of home delivery.	Household asset index quintile	Maternal education	Primipara
Hounton et al. 2008 Burkina Faso Ouargaye (Rural)	A census was conducted to cover the total population in the study area. All 43 health facilities in the two districts were surveyed, each of which typically led by a nurse and maternity care typically provided by an auxiliary midwife, except for in remote centres where TBA are the main givers of maternity care. N=81,539 women given birth within the five-year recall period.	×	×	Distance	Unclear	Unclear TO 1 Preassigned health centre (typically led by a nurse) 2 Preassigned hospital	Unclear	Location	Health centre or hospital	Others	Adjusted; negative; the effect of distance to the health centre was very pronounced up to about 7 km from the health centre (AOR 0.77/km, 95%CI=0.75-0.79), levelling off beyond that (AOR 0.97/km, 95%CI=0.95-0.98). Distance to the district hospital remained an important predictor of institutional birth – AOR 0.83/10km, 95%CI=0.77-0.91)	Household asset index quintile	Maternal education	Parity

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Selection										Education	(Perceived) need
Joharifard et al. 2012 Rwanda Bugesera (Mostly rural)	From each selected villages, 40 women were to be interviewed. Enumerators stood from the main road at the edge of each village, approached the closest households consecutively until they had either approached all households or interviewed 40 women. N=959 women given birth within the three-year recall period	✓	×	Distance	Road	Village TO 1 Each village's designed health centre (staffed exclusively by nurse) 2 Nyamata District Hospital (result not presented)	Est.	Location	Health centre, hospital	Others	Adjusted; negative; Greater distance between the respondents'' village and her designated HC was negatively associated with facility delivery – AOR=0.909 (95%CI=0.846-0.976) per additional kilometre.	Covered by health insurance	Maternal education	Next-to-last delivery at HF, past intra/post-partum problems
Kitui et al. 2013 Kenya Kenya (Urban and rural)	Multi-stage cluster random sample of the 2008-2009 Kenya DHS; HF data from the 2008 Kenya Health Facility Database N=5857 live births within a five-year recall period	×	×	Distance	Straight	Cluster TO Nearest HF with maternity care	Est.	Location	Any HF	Home or on the way	Adjusted; insignificant; results not presented.	Household asset index quintile	Maternal education	Parity
Anyait et al. 2012 Uganda Busia (Mostly rural)	The study population was restricted to women residing within 5km of a HF providing delivery services. N=500 women given birth within a twp-year recall period	✓	×	Distance Time	Unclear Unclear	Unclear TO Nearest HF with maternity care	SR	Location	Public and private HF	Others	Crude; negative; living <3km of a HF offering maternity care increased the likelihood of HF delivery (COR=1.9, 95%CI=1.2-3.1) Adjusted; insignificant; result not presented Crude; insignificant; Time taken to reach maternity HF did not influence the place of delivery (COR=0.8, 95%CI=0.5-1.3).	▨	▨	▨

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Nuwaha and Amooti-kaguna 1999 Uganda Rakai (Mostly rural)	Villages were selected proportional to population size, then standing in the centre of each village. In addition, about 80% of the study population lived <5km from a HF N=211 women given birth within the one-year recall period	×	×	Distance	Unclear	Unclear TO 1 Nearest HF with maternity care 2 Nearest HF offering caesarean section (CS)	SR	Location	TBA's place or HF	Home	Crude; negative; 39% of mothers <5km to a maternity centre delivered at home, compared with 66% who lived >5km (COR=0.35, 95%CI=0.17-0.71). 26% of the mothers who were <5km to a health unit that could do CS delivered at home, compared to 65% who were >5km (COR=0.21, 95%CI=0.11-0.40) Adjusted; insignificant, result not presented.	▨	▨	▨

4.2.2.3 Walking or motorized travel time to any end location

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Wado et al. 2013 Ethiopia Gilgel Gibe (Urban and rural)	Multi-stage cluster random sample of women taken from mothers with recorded birth in the Gilgel Gibe Health and Demographic Surveillance Site. N=1,456 women given birth within the two-year recall period	×	✓	Time	Walking	Home TO Nearest HF with maternity care	SR	Location	HF	Others	Adjusted; negative; women living >1h walking time from a health HF offering maternity care were 45% less likely to delivery in a HF (AOR=0.55, 95%CI=0.34-0.89).	Household asset index tercile	Maternal education	Parity; pregnancy related morbidity

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Hailu et al. 2014 Ethiopia Tsegedie (Urban and rural)	Multi-stage cluster random sample N=485 women given birth within a two-year recall period	✕	✕	Time	Walking	Unclear TO Any nearest HF	SR	Location	HF (health centres and hospitals)	Home	Adjusted; negative; women living <1h from the nearest HF were three times (AOR=3.3, 95%CI=1.15-9.52) more likely to deliver in a HF compared to women living <1h from the nearest HF.	Household monthly income	Maternal education	Parity
Gebru et al. 2014 Ethiopia Tigrey (Urban and rural)	Facility-based study, all women who visited the selected HFs for child immunization services during the study period were included N=911 women who gave birth within a one-year recall period	✕	✕	Time	Walking	Unclear TO Any nearest HF	SR	Attendant	Skilled birth attendant (no other specifications given)	Others	Adjusted; negative; women living <1 hour to HF were more likely to utilize SBA – AOR=4.017, 95%CI=2.302-7.009)	Family monthly income	Maternal education	Parity
Van Eijk et al. 2006 Kenya Asembo and Gem (Rural)	Multi-stage cluster random sample of women taken from mothers with recorded birth in the local Health and Demographic Surveillance Site. N=730 women given birth within the	✕	✓	Time	Walking	Unclear TO Any nearest HF	SR	Location	HF	Others (own house, TBA's house, on the way to a HF)	Adjusted; negative; women who delivered outside of a HF were more likely to delivery outside of a HF than women <1h walking time to antenatal care (AOR=2.75, 95%CI=1.33-5.68). But living exactly 1h from, or used bus/bicycle instead showed no difference compared to walking <1h.	Household asset index status	Maternal education	Parity
Spangler and Bloom 2010 Tanzania Kilombero and Ulanga (Rural)	All mothers with recorded birth in the local Health and Demographic Surveillance Site. N=1,150 women given birth within the 42-60 days recall period	✕	✓	Time	Walking	Home TO Any nearest HF	SR	Location	In a HF, on the way to a HF	Others	Adjusted; negative; compared to women <30min of a HF, those living 30-60 min away were much less likely to use obstetric care (AOR=0.45, 95%CI=0.31-0.64), as were those >60min (AOR=0.26, 95%CI=0.18-0.38).	Household head's occupation and household asset/ possession	Maternal education	Perceived problems with labour

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Kawakatsu et al. 2014 Kenya Nyanza (Rural)	A total of 11,906 mothers who had children aged 12–23 months were identified by community health workers in 64 sub-locations in the study area; 40 mothers in each sub-location were selected using random-sampling methods. N=2,560 mothers of children aged 12-23 months	×	✓	Time	Walking	Unclear TO Any nearest HF	SR	Location	Any HF (dispensary/ health centre/ hospital or higher-level)	Others	Adjusted; negative; using >60min as the reference category, women living near a health facility (<20min walk) have 2.482 times higher odds of giving birth in a HF (95%CI=1.735-3.549). Odds of skilled care for women living 21-40 min and 41-60 min were insignificant.	Household asset index quintile	Maternal education	Parity
Masters et al. 2013 Ghana Ghana (Rural)	Multi-stage cluster random sample from the 2008 Ghana DHS. Facility data, including GPS coordinates, was obtained from the 2010 Emergency Obstetric Needs Assessment Facility Census. All HFs were considered birthing facilities. Travel time were generated for every 1km-by-1km grid covering the whole of Ghana from road network maps, land-cover spatial later and empirically derived. Travel time were calculated from all DHS clusters to its nearest source of maternity care. N=1,384 births occurred within the five-year recall period	×	×	Time	Motorized	Cluster TO Nearest HF with maternity care	Estimated	Location	HF	Home	Adjusted; negative; An increase of travel time of one hour reduced the odds of facility birth by 20% (AOR=0.0801, 95%CI=0.69,0.93)	Household asset index tercile	Maternal and paternal education	Parity; ever had a terminated pregnancy

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Teferra et al. 2012 Ethiopia Sekela (Urban and rural)	Multi-stage cluster random sample N=371 women who gave birth within a one-year recall period	×	×	Time	Walking	Unclear TO Any nearest HF	SR	Location	HF	Home	Crude; negative; women living <1h were more likely to use skilled care compared to women living further away (COR=6.2, 95%CI=1.87,20.5) Adjusted; insignificant, result not presented.	Family income (not significant)	Maternal education	Knowledge of delivery service
Amano et al. 2012 Ethiopia Munisa Woreda (Urban and rural)	Multi-stage cluster random sample N=855 women who gave birth within a one-year recall period	×	×	Time	Walking	Unclear TO Any nearest HF	SR	Location	HF (hospitals and health centres)	Home	Crude; negative; women living <30min were more likely to use skilled care compared to women living further away (COR=2.04, 95%CI=1.26,3.30) Adjusted; insignificant, result not presented.	Paternal job type	Maternal education	Parity
Nuwaha and Amooti-kaguna 1999 Uganda Rakai (Mostly rural)	Villages were selected proportional to population size, then standing in the centre of each village. In addition, about 80% of the study population lived <5km from a HF N=211 women given birth within the one-year recall period	×	×	Time	Walking	Unclear TO 1 Nearest HF with maternity care 2 Nearest HF offering caesarean section (CS)	SR	Location	TBA's place or HF	Home	Crude; negative; 26% of mothers <1h walking time to maternity centre delivered at home, compared to 56% of those who were >1h (COR=0.27,95%CI=0.14-0.65) Adjusted; insignificant, result not presented.	▨	▨	▨

4.2.2.4 Inadequately adjusted or crude analysis (distance only)

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Selection										Education	(Perceived) need
Hodgkin 1989 Kenya South Nyanza (Rural)	Cross-sectional multi-stage cluster random sample of households N=149 deliveries within the one-year recall period from 552 households	×	×	Distance	Unclear	Home TO Nearest HF with maternity care	SR	Location	Hospital and health centre in government, in missionary and in the private sector	TBA's place, home, others	Adjusted; negative; every 1km increment → -3.4% in the probability of delivering in a HF	Worth of house	Household lead's education	×
Gitimu et al. 2015 Kenya Makueni (Urban and rural)	Multi-stage cluster random sample N=1,212 women's latest deliveries	×	×	Distance	Unclear	Unclear TO Any nearest HF	SR	Attendant	People with midwifery skills (doctors, midwives and nurses)	Others	Adjusted; negative; living <5km from a HF was associated with a higher likelihood of SBA – AOR=1.594, ,95% CI, 1.071- 2.371 – compared to living >6km	×	Maternal education	Parity
Faye et al. 2011 Senegal Gossas (Urban and rural)	Sample was selected from all women who gave birth during the period July 2006 to June 2007 and who previously had given birth in a HF during the five years preceding the study period. N= 373 women	×	✓	Distance	Unclear	Home TO Any nearest HF	SR	Location	HF	Outside of HFs	Adjusted; negative; Giving birth outside of HFs were more frequent more women living >5km from a HF (AOR=2.24, 95%CI=1.21,4.15).	×	Maternal education	Parity

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Selection										Education	(Perceived) need
Van den Broek et al. 2003 Malawi Unclear (Rural)	Study sample is the entire population living in the catchment area of the Namitambo health centre. The HF is staffed by a clinical assistant and five to seven nurses. The two nearest hospitals (staffed by medical doctors) are >1h via untarred tracks away. N=2179 childbirths within the one-year recall period	✓		Distance	Unclear	Unclear TO Namitambo Health Centre	SR	Attendant	Trained healthcare workers (doctor, nurse and midwives)	TBAs, unskilled female relatives and others	Adjusted; negative; as distance increased, assistance at childbirth is more likely to be given by a TBA or female relative than by a trained midwife ($p<0.0001$).	×	Maternal education	×
Moindi et al. 2016 Kenya Kilifi (Rural)	Facility-based study of women attending who had invited to participate. N=410 given birth within the six-month recall period	×	✓	Distance	Unclear	Household TO Nearest hospital	SR	Location	HF	Home	Adjusted; negative; living >10km away from the nearest hospital was associated with adjusted RR of 3.86 (95%CI=2.13-7.02).	×	Own and partner's education	Parity
Van Rijsbergen and D'Exelle 2012 Tanzania Lake Zone (Urban and rural)	Multi-stage cluster random sample N=518 women's latest deliveries	×	×	Distance	Unclear	Community TO Any nearest HF	Unclear	Location	1 Local HF (dispensary/ health centre) 2 Hospital	Home or on the way	Adjusted; mixed; multinomial probit regression models gave coefficient of the distance variable is negative ($p<0.1$) for hospital delivery and negative ($p<0.01$) for delivery at a local HF. Notes: distance was zero if any HF was available in the community	Wealth	×	Parity

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Selection										Education	(Perceived) need
Mwaliko et al. 2014 Kenya Webuye (Rural)	The study included all households (residing within the Webuye HDSS) registered during census and had reported at least one birth within one year preceding the census. N=3255 households reported at least one birth within the two-year recall period	×	✓	Distance	Straight	Home TO 1 Any nearest HF 2 hospital	Est.	Location	Others	Home	Adjusted; negative; distance to the hospital strongly negatively correlated with home births; AOR of home births for women living >4km from a hospital was 2.07, 95%CI=1.08–1.60. In another model with distance to the nearest any HF instead, AOR=1.32 (p=0.006) comparing <2km and >2km.	Household lead's employ-ment status	Household lead's education	×
McLaren et al. 2014 South Africa South Africa (Urban and rural)	Multi-stage cluster random sample from the first wave of the National Income Dynamics Study. GPS coordinates of the household were taken using handheld GPS units. Data on HFs were shared by five public sources, which were combined to create a master list of all HFs. N=3003 children <5 years old	×	×	Distance	Straight	Home TO Nearest public HF	Est.	Attendant	Doctor or nurse	Others	Adjusted; negative; children in households >2km from the nearest pubic HF are 3 percentage points less likely to have had a doctor or nurse present at their birth ($p < 0.05$).	Household per capita income quintile	×	×
Kenny et al. 2015 Liberia Konobo and Glio-Twarbo (Rural)	Multi-stage cluster random sample, but excluded villages that either could only be reached on foot or only accessible by canoe, or had less than 20 households. Distance was measured with handheld GPS devices by enumerators during travel to each cluster using recorded GPS tracks. Distance was then divided into quartiles and analysed as a categorical variable. N=600 women given birth within the five-year recall period	✓	×	Distance	Road	Cluster TO Konobo Health Centre (the only formal HF to the study area)	Measured	Location	HF (with any provider)	Others	Adjusted; negative; women at farther distances were less likely to have a facility–based delivery (AOR = 0.41, P=0.006 for the most distant vs nearest quartile; p=0.04 for trend).	×	Maternal education	×

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Gabrysch et al. 2011 Zambia Zambia (Rural)	Multi-stage cluster random sample from the 2007 Zambia DHS. The Zambia Health Census 2005 provided facility data, including GPS coordinates, on all public, semi-public as well as larger private for-profit HFs in the country. N=4,146 births occurred within the five-year recall period	×	×	Distance	Straight	Cluster TO Nearest HF with maternity care	Estimated	Location	HF	Home	Adjusted; negative; the final, fully adjusted model showed a 29% decrease in odds of facility delivery for every doubling of distance, and a 26% increase in odds of facility delivery for every step increase in level of EmOC, assuming a linear effect.	Household asset	Maternal education	×
Kruger et al. 2011 Tanzania Mbulu (Rural)	Facility-based study, data on all children attending the eight reproductive and child health (RCH) clinics during the study period were included. N=3868 infants registered at RCH clinics in 1998, 1999, 2006 and 2007	×	✓	Distance	Unclear	RCH clinic of birth TO Haydom Lutheran Hospital (HLH) or another high-level HF	SR (by RCH staff)	Location	Hospital, health centre, dispensary	Home	Crude; negative; Shorter distance to a higher-level HF with maternity care was a significant predictor in 1999, 2006 and 2007 and for all years combined (COR=1.02, 95%CI=1.01-1.02) Adjusted; insignificant; AOR for all years combined was 1.65, 95%CI=1.04-2.61.	▨	▨	▨
Esmai et al. 2002 Nigeria Ile-Ife (Urban)	A systematic sample of women residing in the urban town of Ile-Ife. N=117 women given birth	×	×	Distance	Unclear	Unclear TO Approved health facilities	SR	Location	Hospital or health centre	Home	Crude; negative; distance >5km was associated with reduced use of skilled care at birth (p-value<0.05)	▨	▨	▨

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Nwakoby 1992 Nigeria Obukpa Town (Rural)	Multi-stage cluster random sample N=488 women given birth within the two-year recall period	×	×	Distance	Unclear	Village TO Comprehensive health centre in Obukpa Town	Measured directly from a map	Location	Compre-hensive health centre in Obukpa Town	Home	Crude; inconclusive; (no test was performed to assess the strength of evidence of the bivariate relationship) 87% of the women living <1km used the facility for delivery. The percentage fell as the distance between the facility and place of residence increased. At >3km, only 24% of the women used the comprehensive health centre for delivery.	▨	▨	▨
De Groot et al. 1990 Tanzania Sengerema (Unclear)	Women were interviewed at birth at the Sengreme District Hospital. All births outside of this facility were considered non-hospital (unskilled) births. Total number of non-hospital births was estimated from local population data. N=179 deliveries at the Sengreme District Hospital and 957 expected deliveries estimated using local population data	×	×	Distance	Straight	Village TO Sengreme District Hospital	SR for facility births and est. for non-facility births	Location	Sengreme District Hospital	Others	Crude; negative; 98% of all deliveries within 5km took place in hospital, including both high and low risk pregnancies. Only 21% of high risk pregnancies beyond 5km came to hospital for delivery.	▨	▨	▨

4.2.2.5 Travel time with an unspecified mode of transportation or inadequately adjusted or crude analysis only

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Afford-ability	Adjustment	
		Location	Selection										Education	(Perceived) need
Wilunda et al. 2015 Ethiopia South West Shoa Zone (Urban and rural)	Multi-stage sample; in the first stage, villages were selected at random. In the second stage, enumerators walked down a randomly selected direction (method unspecified), visiting consecutive households whilst other enumerators walked from the end of village along this direction, visiting consecutive houses. N=500 women given birth within a two-year recall period	×	×	Time	Unclear	Unclear TO Nearest HF with maternity care	SR	Attendant	Doctor, nurse, midwife, or a health officer	Others	Adjusted; negative; the odds of delivery by a SBA decreased with increasing time to the nearest HF with maternity care – <30min as base, AOR for 30-59 min = 0.48 (95%CI=0.23-.96) and AOR for >60min = 0.35 (95%CI=0.15-0.82).	Household asset index quintile	Maternal and paternal education	Had a pregnancy/ delivery related problem
Habte et al. 2015 Ethiopia Cheha (Urban and rural)	Household having eligible women were identified by house to house visit made by local health officials. From this compilation, the final study sample was randomly selected. N=816 women who gave birth within a two-year recall period	✓	×	Time	Unclear	Unclear TO Nearest HF with maternity care	SR	Both	In a HF attended by skilled birth attendants	Others	Adjusted; negative; Women who should travel >60 min and 30-60 min were less likely to deliver at health facility than women living <30 min AORs were 0.22 (95%CI=0.09,0.55) and 0.42 (95%CI=0.18,0.95).	Able to afford a facility-based delivery	Paternal education (not significant)	Maternal and paternal attitudes towards facility-based delivery
Tadese and Ali 2014 Ethiopia Raya Alamata (Urban and rural)	Multi-stage cluster random sample N=600 women given birth within the one-year recall period	×	×	Time	Unclear	Unclear TO Any nearest HF	SR	Attendant	Health professionally trained health worker having the essential midwifery skills	Others	Adjusted; insignificant; comparison of women living <30 minute to >30 minute showed no significant effect on skilled care at birth	Monthly expendi-ture	Maternal and paternal education	Knowledge about obstetric complica-tions

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Alemayehu and Mekonnen 2015 Ethiopia Akansha Guagusa (Urban and rural)	Multi-stage cluster random sample; study participants were identified by health services extension workers as field guides. N=373 women given birth within the one-year recall period	×	✓	Time	Unclear	Unclear TO Any nearest HF	SR	Attendant	with nursing and above level of training	Others	Adjusted; insignificant; comparison of women living <1 hour and 1 hour to >1 hour showed no significant effect on skilled care at birth	×	×	Ever given birth at HF
Kabakyenga et al. 2012 Uganda Mbarara (Semi-urban and rural)	Households in which there was a women who had recently delivered or currently was pregnant were identified with assistance of local health officials. First two women from each village who met this criteria were interviewed. N=750 who given birth within the one-year recall period	×	✓	Time	Unclear	Unclear TO Nearest HF with maternity care	SR	Attendant	Persons with midwifery skills (doctor, nurse, midwives and health officer)	Others	Crude; negative; women >1h from a HF offering childbirth services were less likely to choose assistance by skilled birth attendant (COR=0.7, 95%CI=0.5,1.0).	▨	▨	▨
Stekelenburg et al. 2004 Zambia Kalabo (Rural)	HFs in the study area were randomly selected and women living within the catchment areas of selected HFs were selected. N=322 women's last delivery	✓	×	Time	Walking	Home TO HF of actual childbirth	SR	Location	Hospital, clinics	Others	Crude: negative; 71% of those <2h walk delivered in a HF, but only 35% of those living >2h did (COR=4.7, 95%CI=2.6-8.3) Note: the question about walking time to the clinic was only put to those who did walk there.	▨	▨	▨

4.2.2.6 Others

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.[1]	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results		Adjustment	
		Location	Selection									Afford-ability	Education	(Perceived) need
Feyissa and Genemo 2014 Ethiopia East Wollega (Urban and rural)	The source population for the study was all women who gave birth in last five years; the study sample was selected by consecutive sampling technique. N=320 women's latest deliveries	×	×	Distance	Unclear	Unclear TO Any nearest HF	SR	Location	Any HF	Others	Adjusted; negative; adjusting for time to reach HF, among variables, distance >10km (AOR: 0.665, 95% CI:.173–.954) compared to <5km was significantly associated with institutional delivery	×	×	×
				Time	Unclear						Adjusted; insignificant; adjusting for distance from HF and mode of travel (foot vs. others), among others, the effect of time to reach HF was insignificant	×	×	×
Anastasi et al. 2015 Uganda Gulu District (Conflict conditions)	Women attending ANC at one HF were interviewed and asked about their previous birth. N=130 currently pregnant women previously given birth within the two-year recall period	×	✓	Distance	Unclear	Unclear TO Nearest HF with maternity care	SR	Location	HF	Others	Crude; insignificant; p=0.44	▨	▨	▨
				Time	Unclear	Unclear TO 1 Nearest HF with maternity care 2 A specifically named HF					1 Nearest HF with maternity care - crude; insignificant; p=0.14 2 a specifically named HF - crude; insignificant; p=0.45	▨	▨	▨

Citation Country Region (Settings)	Study sample			Distance/travel time (exposure) measurement				Study outcome			Results			
	Sampling design, health facility data (where applicable) and sample size	Potential bias		Distance vs. time	Line/ Transport type	Start-end	SR vs. Est.^{1}	Birth location/ attendant	Skilled care	Unskilled care	Crude/Adjusted analysis; summary of key results	Adjustment		
		Location	Selection									Afford-ability	Education	(Perceived) need
Nesbitt et al. 2014 Ghana Brong Ahafo (Rural)	Surveillance of all women of reproductive age in the study area through monthly visits was undertaken as part of health and demographic surveillance for several field studies. The surveillance included taking GPS coordinates of 433 village centroids and, in 173 larger villages, coordinates of 47,537 compounds. A health facility assessment of all HFs were conducted and geographic coordinates were obtained. A detailed road network of all roads in the study area was created using GPS trackers. The road network was then integrated into a spatial layer of land-cover for additional information on road condition, surface type and etc. Travel time by vehicle were obtained for 88 journey segments to calibrate road speeds. N=9306 births in 2009	×	×	Distance ________ Time	Straight and road ________ Non-motorized and motorized	1 Compound 2 Village TO 1 Nearest HF with maternity care 2 Nearest CEmOC	Est. Travel time were obtained for roads (network time), and from available land-cover speed map (raster time)*. *GlobCover 2009, GEM European Commission project	Location	HF	Others	Crude; negative; ORs for facility use were the same for all four of straight-line and road distances, as well as non-motorized network and raster time: the odds of women delivering in a HF decreased by 67% (OR=0.33) per standard deviation (SD) increase in each measure (to the nearest HF with maternity care). There was a smaller effect with motorized measures from both origins – CORs range between 0.71-0.91. The odds of women delivering in a HF decreased by 55-60% per SD increase in each distance and non-motorized travel time measure (to the nearest CEmOC). The authors also noted that multivariate analysis adjusted for age, parity and wealth quintile gave similar results, but these results were not shown.	▨	▨	▨
Mwaniki et al. 2002 Kenya Mbeere (Rural)	Cross-sectional descriptive survey, whose study population comprised mothers bringing their children to the child welfare clinics. N=200 women given birth	×	✓	Distance ________ Time	Unclear ________ Unclear	Unclear TO Any nearest HF	SR	Location	HF	Others	Crude; negative; More of those who lived <5km to a HF delivered in a HF compared to women living >5km (X2=7.57; p=0.0059; df=1) ______________________________ No results on travel time and use of skilled care at birth were presented.	▨	▨	▨

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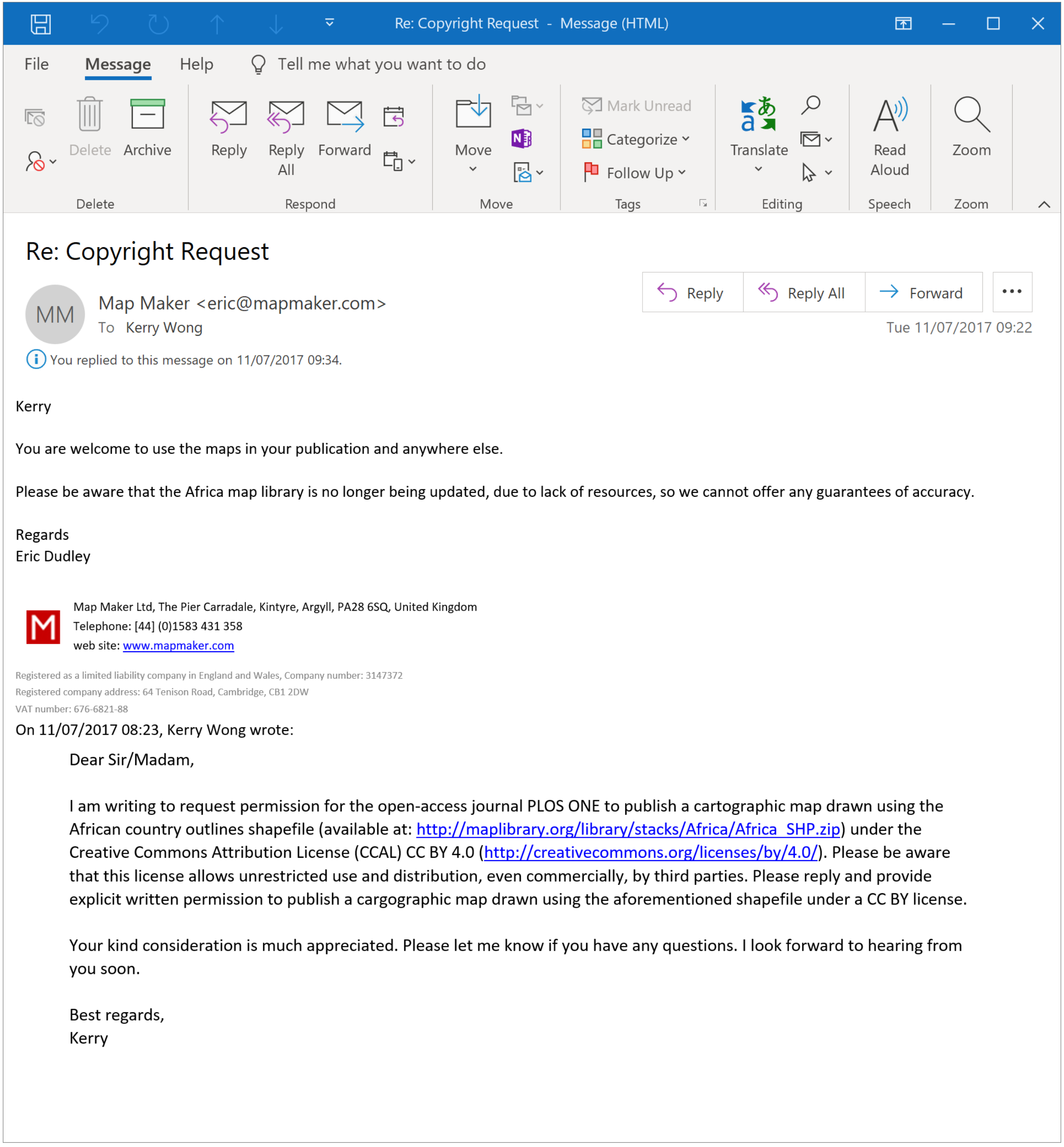

Re: Copyright Request

Map Maker <eric@mapmaker.com>
To Kerry Wong
Tue 11/07/2017 09:22

You replied to this message on 11/07/2017 09:34.

Kerry

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Please be aware that the Africa map library is no longer being updated, due to lack of resources, so we cannot offer any guarantees of accuracy.

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On 11/07/2017 08:23, Kerry Wong wrote:

> Dear Sir/Madam,
>
> I am writing to request permission for the open-access journal PLOS ONE to publish a cartographic map drawn using the African country outlines shapefile (available at: http://maplibrary.org/library/stacks/Africa/Africa_SHP.zip) under the Creative Commons Attribution License (CCAL) CC BY 4.0 (http://creativecommons.org/licenses/by/4.0/). Please be aware that this license allows unrestricted use and distribution, even commercially, by third parties. Please reply and provide explicit written permission to publish a cargographic map drawn using the aforementioned shapefile under a CC BY license.
>
> Your kind consideration is much appreciated. Please let me know if you have any questions. I look forward to hearing from you soon.
>
> Best regards,
> Kerry

4.3 Poster

A look back on how far to walk: systematic review of distance and travel time as barriers of attaining skilled care at birth in Sub-Saharan Africa

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Background

Prominent inequitable coverage of skilled care at birth persists despite continuous effort, particularly in Sub-Saharan Africa. Universal use is at least partially dependent on all women having sufficient geographic access. In this regard, remote dwellers are most affected and spatial approaches and tools have been called upon. Coupled with recent technological advancements, researchers are increasingly quantifying and examining the impact of physical accessibility on the use of skilled care at birth.

Aim

This systematic review focuses on the geographic barriers to skilled, facility-based delivery in Sub-Saharan Africa. The specific objectives are to:

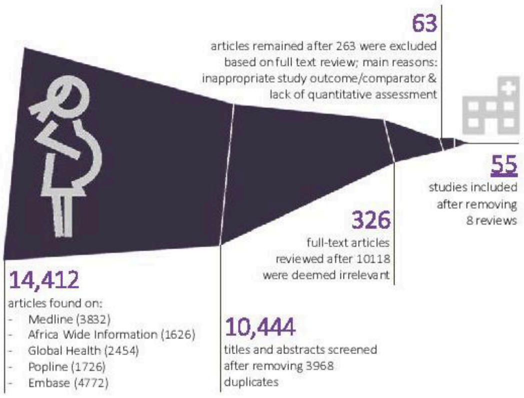
(a) review the methods and metrics used in assessing geographic barriers (defined as distance and travel time)
(b) synthesize quantitative evidence of the effect of increased geographic barriers on skilled care at birth.

Search methods

Search themes (a) Sub-Saharan Africa (b) facility-based delivery (FBD) or skilled birth attendant (SBA) at delivery (c) distance or travel time **Inclusion criteria** (a) English language (b) January 1986-March 2016 (c) any study type/design (d) peer-reviewed **Exclusion criterion** no quantitative assessment of the effect of distance/travel on actual (vs. planned) use of FBD/SBA **Analysis and synthesis strategy** results from multivariate analyses adjusted for the potential confounding effects of affordability, education and (perceived) need for care are presented.

Results

Systematic review flowchart



14,412 articles found on:
- Medline (3832)
- Africa Wide Information (1626)
- Global Health (2454)
- Popline (1726)
- Embase (4772)

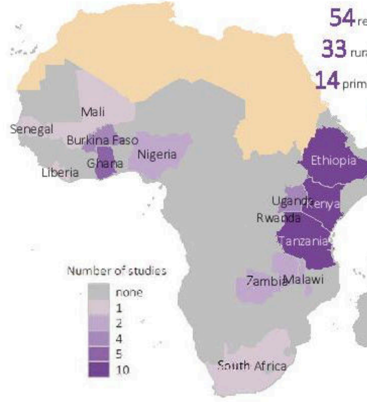
10,444 titles and abstracts screened after removing 3968 duplicates

326 full-text articles reviewed after 10118 were deemed irrelevant

63 articles remained after 263 were excluded based on full text review; main reasons: inappropriate study outcome/comparator & lack of quantitative assessment

55 studies included after removing 8 reviews

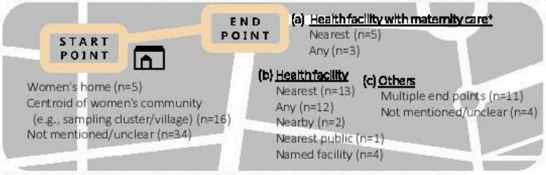
Overview of included studies (N=55)



54 retrospective, cross-sectional
33 rural/mostly rural settings only
14 primarily focus on spatial access
39 published since 2010

Study definitions of spatial separation

Included studies considered spatial separation between women and maternity care differently in **start and end points definition** (left panel) and **data collection method and connection type** (right panel):

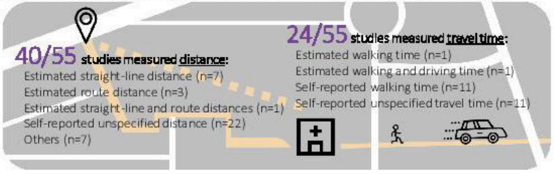


Women's home (n=5)
Centroid of women's community (e.g., sampling cluster/village) (n=16)
Not mentioned/unclear (n=34)

(a) Health facility with maternity care[+]
Nearest (n=5)
Any (n=3)

(b) Health facility
Nearest (n=13)
Any (n=12)
Nearby (n=2)
Nearest public (n=1)
Named facility (n=4)

(c) Others
Multiple end points (n=11)
Not mentioned/unclear (n=4)



40/55 studies measured distance:
Estimated straight-line distance (n=7)
Estimated route distance (n=3)
Estimated straight-line and route distances (n=1)
Self-reported unspecified distance (n=22)
Others (n=7)

24/55 studies measured travel time:
Estimated walking time (n=1)
Estimated walking and driving time (n=1)
Self-reported walking time (n=11)
Self-reported unspecified travel time (n=11)

[+]Refers to health facilities with skilled birth assistants or maternity beds, among others.

Spatial access and skilled care at birth

The effects of distance across the 40 studies were first summarized by their sample mean proportion of skilled care at birth and mean distance in Figure 1. Overall, there seemed to be little to no difference in use as distance changed within the 40km-bound.

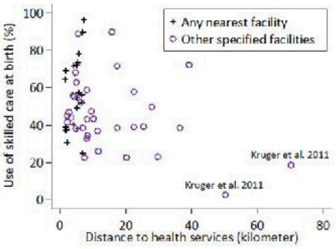


Figure 1 Mean distance against use of skilled care at birth

Distance to the nearest facility, regardless of its capacity to provide skilled care at birth, likely underestimates women's true separation from skilled care. Of studies that evaluated distance to specified health facilities, nine reported effects on skilled care utilization for childbirth controlled (or at least tested) for affordability, education and (perceived) need (Table1).

Table 1 Adjusted odds ratios and 95%CI of skilled care utilization

Mpembeni et al. 2007			
<6km	6+km		
Reference	0.24 (0.16-0.37)**		
De Allegri et al. 2015			
≤6km	7+km		
Reference	0.05 (0.01,0.30)*		
Moran et al. 2006			
<22.8km	22.8+km		
Reference	0.39 (0.20-0.76)*		
Mills et al. 2008			
<10km	10-19km	20+km	
Reference	0.54 (0.37-0.79)*	0.31 (0.23-0.43)*	
Mdegi et al. 2000			
<5km	5-10km	10+km	
Reference[1]	0.37*	0.37*	
Reference[2]	0.54*	0.53*	
Reference[3]	0.34*	0.46*	
Gage 2007			
<1km	1-4km	5-9km&	30+km
Reference	0.53 (0.28,1.00)	0.49 (0.28,0.87)*	0.62 (0.26-1.48)
Okafor 19911	Every 1km increase: -0.097*^		
Joharifard et al. 2012	Every 1km increase (up to 14km): 0.91 (0.61-1.91)		
Hounton et al. 2008	Every 10km increase: 0.83 (0.77-0.91)**		

*p<0.05; ** p<0.001; & Odds ratios for 10-14km and 15-29km are similar and omitted here; ^parameter estimate of multinomial logistic regression; [1]qualified medical professional vs. TBA; [2]qualified medical professional vs. relative; [3]qualified medical professional vs. no one

Among the nine studies shown in Table 1, three considered distance as a continuous variable and two concluded with negative effects; the rest used distance as a categorical variable with varying breakpoints and all found reduced odds in use of skilled care at birth as distance increased.

The effect of travel time, from analyses adjusted for affordability, educated and (perceived) need, on use of skilled care at birth was similar to that of distance and is omitted here.

Summary of findings

We conducted an extensive systematic search and identified a wealth of studies on the impact of increased distance and travel time on use of skilled care at birth in SSA. Few studies (14/55) focused primarily on the spatial dimension of healthcare access. Almost all were retrospective, cross-sectional and relied on self-reported data. Evidence is heavily concentrated in Ethiopia, Kenya and Tanzania. The operational definitions of distance and travel time varied; and were frequently poorly reported.

Results from well-adjusted studies assessing distance to specified health facilities showed **association between increased distance and reduced used of care**. There is also some indication of a waning effect of distance among those living further away from healthcare provision. For these women, utilization is generally low and changes in distance cease to have an effect.

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Chapter 5

Study 2: Comparison of spatial interpolation methods to create high-resolution poverty maps for low- and middle-income countries

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RESEARCH PAPER COVER SHEET

PLEASE NOTE THAT A COVER SHEET MUST BE COMPLETED FOR EACH RESEARCH PAPER INCLUDED IN A THESIS.

SECTION A – Student Details

Student	Kerry Wong
Principal Supervisor	Lenka Benova
Thesis Title	Too poor or too far? Partitioning the variability in hospital birth by poverty and travel time in four sub-Saharan countries

If the Research Paper has previously been published please complete Section B, if not please move to Section C

SECTION B – Paper already published

Where was the work published?	J R Soc Interface		
When was the work published?	October 2018		
If the work was published prior to registration for your research degree, give a brief rationale for its inclusion			
Have you retained the copyright for the work?*	**No**	Was the work subject to academic peer review?	**Yes**

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5 Study 2: Comparison of spatial interpolation methods to create high-resolution poverty maps for low- and middle-income countries

The lessons learnt about measuring physical accessibility in Study 1 will be revisited in Study 3, which aims to assess the extent to which physical accessibility to the nearest hospital is inequitable by SES (and for which a measure for physical accessibility would be required). In order to carry out Study 3, a map showing the locations of different SES is required. The aim of Study 2 is to support this need by creating a high-resolution gridded map of the locations of the poor and the less poor in the four study countries – Kenya, Malawi, Nigeria and Tanzania.

The use of maps to track of poverty, health and other developmental goals across LMICs for advocacy, project planning, and monitoring and evaluation of programs has rapidly increased in recent years. The relevant data typically come from population survey, such as the DHS, which enables disaggregation by first to second level of administrative division. To gain a complete understanding of the spread and distribution of the problem, e.g., poverty, valid approaches to estimating health and population indicators in smaller geographic scale is needed. However, increasing the sample size big enough for such estimation is resource-intensive. Spatial interpolation (SI) using modelling techniques, DHS geo-references and appropriate remote-sensed covariate data to predict values at all unsampled locations, thereby creating a gridded-maps, becomes a highly useful tool.

SI is the process of using points with known values to estimate values at other unknown points, and is suited for the purpose of Study 2. As is the case with measuring physical accessibility, a number of different SI methods can be applied. Previous studies have shown that their comparative predictive performances varies due to a variety of factors. In this study, we compare two multivariate SI methods – model-based geostatstics (MBG) and spline in a generalized additive model (GAM) formulation – for the four study countries. We based our selection of method to create the best high-resolution poverty map for use in Study 3 with empirical results on a country-by-country basis. The potentially generalizable factors that influence predictive performances of MBG and GAM are also explored.

This chapter presents the manuscript of Study 2 published in the Journal of Royal Society Interface in September 2018 (doi: 10.1098/rsif.2018.0252). The ownership was retained and no permission to reuse was required (Figure 5.1).

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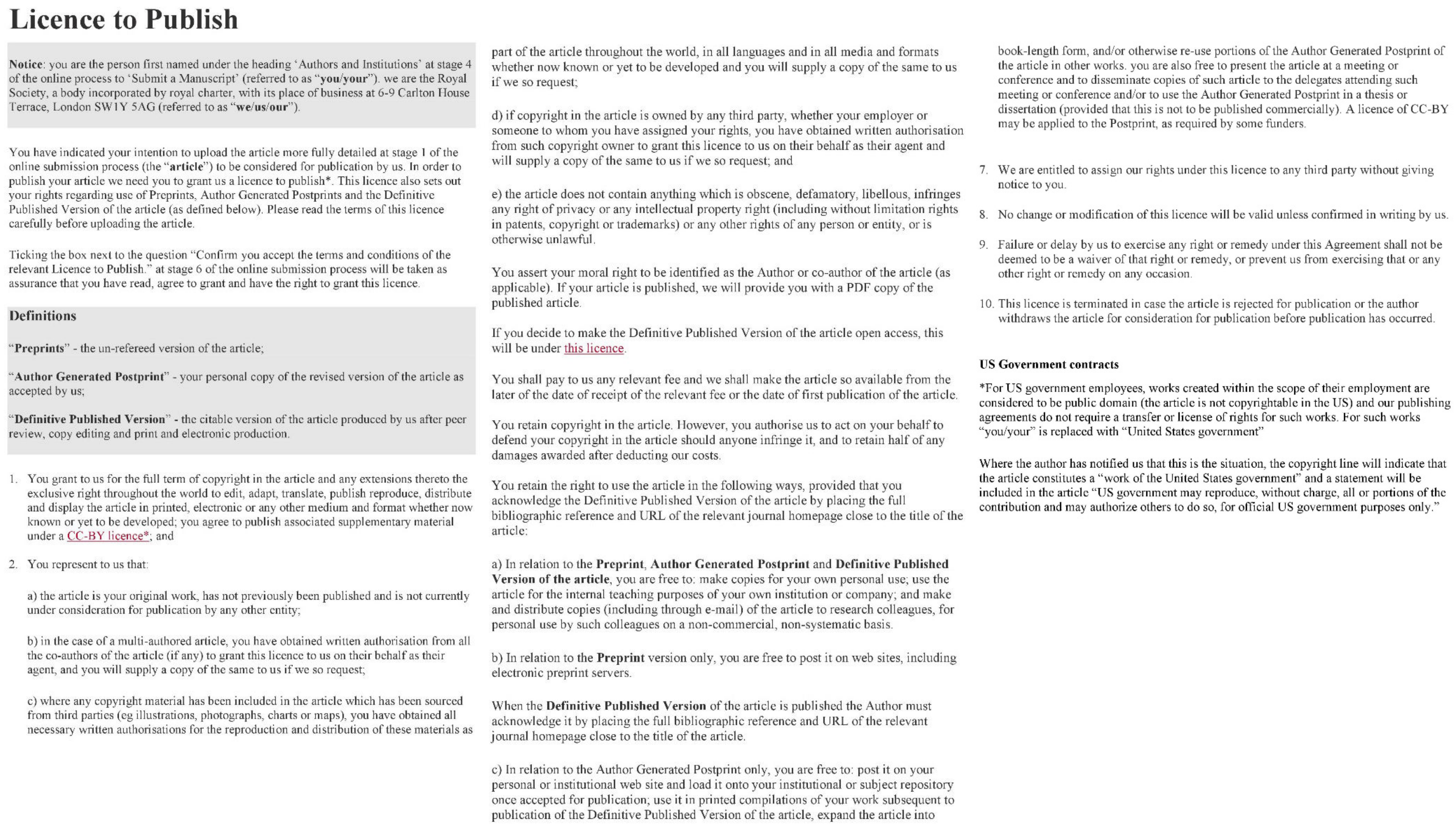

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INTERFACE

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Comparison of spatial interpolation methods to create high-resolution poverty maps for low- and middle-income countries

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High-resolution poverty maps are important tools for promoting equitable and sustainable development. In settings without data at every location, we can use spatial interpolation (SI) to create such maps using sample-based surveys and additional covariates. In the model-based geostatistics (MBG) framework for SI, it is typically assumed that the similarity of two areas is inversely related to their distance between one another. Applications of spline interpolation take a contrasting approach that an area's absolute location and its characteristics are more important for prediction than distance to/characteristics of other locations. This study compares prediction accuracy of the MBG approach with spline interpolation as part of a generalized additive model (GAM) for four low- and middle-income countries. We also identify any potentially generalizable data characteristics influencing comparative accuracy. We found spatially scattered pockets of wealth in Malawi and Tanzania (corresponding to the major cities), and overarching spatial gradients in Kenya and Nigeria. Spline interpolation/GAM performed better than MBG for Malawi, Nigeria and Tanzania, but marginally worse in Kenya. We conclude that the spatial patterns of wealth and other covariates should be carefully accounted for when choosing the best SI approach. This is particularly pertinent as different methods capture geographical variation differently.

1. Introduction

Poverty has strong associations with adverse health outcomes, lost human potential and societal instability [1,2]. The international community and national governments that signed on to the Sustainable Development Goals are committed to eradicating poverty in all its forms. To achieve this goal, it is helpful to have information on where affected individuals and communities reside at refined spatial scales since aggregate data can conceal heterogeneity and any underlying patterns. Subnational poverty maps that describe spatial patterns of poverty and inequality across a country can help more effectively allocate resources and implement targeted interventions to attain higher levels of wealth and welfare among the most deprived.

Data on poverty indicators at refined geographical scales across a country are regularly collected via censuses. However, decennial censuses are too infrequent to enable timely monitoring and tracking. National surveys are generally more frequent but representative only for coarse spatial units. To overcome these constraints, Elbers and colleagues extended the techniques of small area estimation (SAE) to both types of data in 2000 [3]. The SAE method for area-unit mapping identifies comparable census and survey variables, models the desired attribute (e.g. poverty) using the survey variables common to the census, and computes poverty on small geographical partitions (e.g. enumeration area, village or hamlet) across the country based on the model obtained and the census predictor variables. Poverty/welfare is assumed to be uniform within each target region. The method has been widely used to produce subnational choropleth maps of poverty indicators in many low- and middle-income countries (LMICs) [4–7]. Other areal interpolation techniques include the dasymetric modelling method, which takes advantage of ancillary data to better approximate and redistribute count data within each target area [8]. This method has been demonstrated for accurate population mapping by age, sex and race [9], and may be extended to other socioeconomic characteristics.

The availability of georeferenced data has drastically increased in recent years. The Demographic and Health Survey (DHS) Program, for instance, has gained a reputation for collecting and providing georeferenced data on core development indicators in LMICs over the last few decades. Better data, coupled with new geographical information system (GIS) analytical techniques, have fuelled interests among researchers to improve output quality, including using spatial interpolation (SI) modelling techniques to create high-resolution gridded map surfaces. We assume that the variable of interest (e.g. poverty) has a meaningful value at every location within a study region, which is typically divided into non-overlapping small grid squares. SI techniques are then employed to predict values at every grid based on the sampled data and, where applicable, auxiliary covariates. Many multivariate spatial statistical methods have been applied in studies using DHS georeferenced data for spatial modelling and interpolation, such as SAE, kriging, autoregressive methods and model-based geostatistics (MBG) [10]. In 2013, The DHS Spatial Interpolation Working Group assessed various properties of these SI methods, e.g. computational efficiency, account for non-stationary variance and inclusion of optimal covariate selection procedures. The Working Group proposed the MBG approach as the most suitable for creating interpolated surfaces [10–12]. The incorporation of uncertainty into the modelling framework was seen as a compelling strength of MBG [10].

In 2014, the WorldPop project and partners pioneered the creation of high-resolution gridded map surfaces of the estimated proportions of people living under the USD1.25 and USD2.00 poverty thresholds with DHS data using a Bayesian MBG approach [13]. Poverty map surfaces were drawn for Kenya, Tanzania, Uganda and Pakistan, among others [13]. Furthermore, maps of population age structure [14], fertility indicators [15], malaria indicators [16,17] and other health indicators (e.g. childhood vaccination, childhood malnutrition, household access to improved source of drinking water and sanitation [12,18]) were also produced using the same framework.

The MBG methodology is detailed elsewhere [19]. Briefly, it divides spatial variation into three components—deterministic variation, spatial autocorrelation and random noise [20]. The deterministic variation of the phenomenon of interest is modelled as a set of covariates, while spatial autocorrelation refers to a variable's relationship with itself in space [21]. It is generally assumed that nearer neighbours are more related to each other than more distant counterparts. Such positive autocorrelation structure is defined and used as part of the MBG approach to explain variation in the data and make more accurate predictions at unsampled locations across the map region. Non-stationarity and other localized effects can be dealt with when implementing MBG via, for instance, optimal estimation of the covariance matrix or a Bayesian partition model [22], but the method remains most widely used for phenomena that are more similar as a function of the distance separating the sampled locations in practice [23–25].

On the other hand, spline interpolation is grounded in a slightly different theoretical viewpoint. Spline interpolation assumes that the interpolation function should pass through (or close to) the data points while being as smooth as possible. Spline interpolation can be conceptualized as bending a sheet of rubber through the observations in three-dimensional space. In this method, the geographical structure of the mapped phenomenon is not explicitly formulated. Researchers have incorporated spline spatial interpolation in a generalized additive model (GAM) formulation with the geographical coordinates (e.g. longitude and latitude) and other covariates to create interpolated map surfaces. In this GAM framework, each predictor variable is related to the outcome via a smoothed function, then all functions are added to predict the link function. Insurance pricing [26], property pricing [27], lexical data [28] and fish ecology [29,30], just to name a few different outcomes, have been mapped using this robust method in the literature.

The assumptions about the underlying variation in the sampled data, the choice of method and the parameters used can be critical to SI prediction accuracy [20]. Individuals and households with common characteristics sometimes cluster together either by choice or due to social, economic, geographical or political forces [31]. The assumption of spatial autocorrelation in wealth may be valid, as poverty tends to concentrate in mountainous regions, arid land, land-locked areas, and levels-off closer to the national/financial capitals, bodies of water and coastal areas [32]. In recent years however, the emergence of secondary cities in many LMICs may have led to certain degree of within-country redistribution of the population, economic opportunities and wealth [33]. Secondary cities are fast-developing regional hubs that provide critical support functions for governance, production services and transportation. Sometimes the locations of these cities are deliberately planned for deprived regions. Thus, a rather complex spatial structure of towns and cities might be expected, and raises concerns regarding the quality of interpolation when (positive) spatial autocorrelation is assumed and used for prediction making.

The way in which wealth is distributed across the map region likely affects prediction accuracy of the poverty maps made using existing SI approaches to different extents. We present an analysis comparing the performance of spline interpolation as part of GAM-based fitting with multivariate MBG for four LMICs in sub-Saharan Africa. The result of this comparative analysis will empirically reveal the data characteristics that contribute to any discrepancies in prediction accuracy found between methods. This will in turn shed light on the suitability of the two methods for the creation of interpolated poverty maps.

Table 1. Country data and statistics in 2016. GDP, gross domestic product; PPP, purchasing power parity.

	Kenya	Malawi	Nigeria	Tanzania
total area (km^2)	580 367	118 484	923 768	947 300
% land area	98.1	79.4	98.6	93.5
national population (million)[a]	47.2	17.6	181.2	53.9
% urban population[a]	26	16	48	32
population annual growth rate (%)[a]	2.6	2.9	2.6	3.1
unemployment rate (%)[a]	11.9	6.4	4.3	2.1
GDP *per capita*, PPP (international dollar)[a]	3020	1159	6039	2653
GDP annual growth rate (%)[a]	5.7	2.8	2.7	7.0
GDP composition (%)[a]				
agriculture	33.3	29.7	20.9	31.5
industry	19.1	16.0	20.4	26.4
services	47.6	54.3	58.8	42.2
labour force by occupation (%)[b]				
agriculture	38.0	84.7	2.1	66.7
industry	14.3	8.4	19.5	6.0
services	47.8	6.9	78.5	27.3
Gini index[c]	48.5	46.1	43.0	37.8

[a]Data for 2015.

[b]International Labour Organization modelled estimates for 2017.

[c]Most recent data available from http://databank.worldbank.org (last accessed: 31 March 2018).

2. Data and methods

2.1. Study area

We studied four LMICs in sub-Saharan Africa—Kenya, Malawi, Nigeria and Tanzania. These countries were selected based on available data and variability in terms of geography and economy. National statistics on wealth and economics of the four countries according to The World Bank [34] and International Labour Organization [34] are presented in table 1.

2.2. Data

We used the most recent DHS as of October 2017. The DHS collects nationally representative data on population health and sociodemographic characteristics using a multi-stage cluster sampling design with enumeration area as the primary sampling unit (PSU). As part of the DHS sampling procedure, a list of established households in each sampled PSU is obtained and used as the sampling frame for household selection [35]. The surveys include the longitude and latitude coordinates of the population centroids of sampled PSUs. The accuracy of these locations is estimated within 15 m [36]. For anonymity considerations, urban clusters are displaced up to 2 km and rural clusters up to 5 km [37]. The displaced point is then checked to ensure that it falls within the boundaries of the first administrative region, and re-displaced if necessary [37].

For each DHS, a household wealth index (WI) is computed from a range of consumer durables, access to services and housing materials via a principal component analysis [38]. The WI is widely adopted in LMICs as an indicator of socioeconomic position that describes a household's cumulative living standard within an individual survey [39]. The index is also broadly used for assessing pro-poor targeting and inequality, and, where relevant, for controlling for socioeconomic confounding [40]. To approximate poverty at the PSU level, we used the average household WI (rescaled by a factor of 10^{-6}) with adjustment for survey-specific weights as outlined by DHS manuals. We present descriptive results of the data distribution and spatial pattern of WI of the four study countries.

2.3. Model covariates

We identified and assembled a collection of remote sensing covariates based on those used by others to generate maps of multidimensional poverty [13]. In general, the accuracy of these data to provide up-to-date indication on welfare and living conditions is considered acceptable [13,41–45]. We included data on population density from version four of the Gridded Population of the World (GPW) [46], on daytime land surface temperature [47] and vegetation index [48] from the NASA Earth Observations (NEO), on elevation data from the United States Geological Survey (USGS) [49], rasterized surfaces of Global Potential evapotranspiration and Global Aridity Index from the Consortium for Spatial Information at the Consultative Group for International Agricultural Research (CGIAR-CSI) [50–52], and on night-time light emission from the National Oceanic and Atmospheric Administration (NOAA)/National Geophysical Data Center by the United States Air Force Weather Agency [53,54]. At their finest resolutions, the land surface temperature layer and the vegetation index layer were 0.1 degree grids (approximately 11 km at the equator), while the other covariate layers were 30 arc second grids (approximately 1 km at the equator). Using these files, we extracted covariate values from each raster layers at the georeferenced PSUs, represented as spatial points, via spatial overlaying [55]. That is, we superimposed a spatial layer of the georeferenced PSUs over different covariate layers and obtained covariate values at the corresponding locations. To account for PSU location displacement, averages were obtained from the four nearest raster cells. As a check of sensitivity to alternative analytical scales, these averages were compared to those resulting from applying buffer sizes of 5, 10 and 20 km using Pearson correlation coefficients.

We updated accessibility measures for the current analysis with Natural Earth's free data on 'populated places' (v. 4.0.0, released in October 2017), which included national and subnational capitals, as well as places with a population size of at least 50 000 [56]. We calculated the straight-line distance from every included DHS PSU to the nearest populated place. We opted for straight-line distance for its comparability to proxy accessibility with more complicated metrics such as mechanized and non-mechanized estimated travel time in LMIC settings [57]. Country administrative areas shapefiles were obtained from the freely available Database of Global Administrative Areas [58].

We found missing data in the spatial coordinates of 9 of 1594 PSUs from the Kenya DHS and 7 of 896 PSUs from the Nigeria DHS. These PSUs were removed from the analysis [59]. There were no other missing data. In addition, one PSU data point was removed from the analysis in the Southern Region in Malawi as it had an extreme value of 41 453 for population density, while the median and 75th percentile were 267 and 579 and observations of the nearest neighbours were below 10 000.

2.4. Methods of interpolation

2.4.1. Model-based geostatistics

The MBG model is a class of generalized linear mixed models with an approximation of a multivariate stationary Gaussian Process for outcome z at location s_i with mean μ and covariance C for the spatial component, as well as an unstructured component $\varepsilon(s_i)$ represented as Gaussian with zero mean and variance [19]. The mean μ is modelled using a linear function of the predictor variables, while spatial covariance is written as

$$C(Z(s_1), Z(s_2)) = E[(Z(s_1) - \mu)(Z(s_2) - \mu)],$$

where s_1 and s_2 are a pair of sampled locations of distance h units apart. Covariance expresses the amount of variation in the observed Z values at s_1 and s_2. We separately modelled the spatial dependency structure using a spherical covariance function for each included survey. The spherical covariance function is written as $\rho(h)$: $C(h) = \sigma^2\rho(h)$, where

$$\rho(h) = \begin{cases} 1 - 1.5\phi h + 0.5(\phi h)^3, & \text{if } h < \dfrac{1}{\phi} \\ 0, & \text{otherwise} \end{cases}$$

and ϕ the decay parameter [60].

2.4.2. Generalized additive model using spline spatial interpolation

The spline interpolation consists of polynomials that describe pieces of a surface and are fitted together so that they join smoothly [20]. The Akima method was developed to implement bivariate interpolation onto a grid for irregularly spaced point data using bivariate smoothing techniques [61,62]. The interpolation function should pass through or nearby the observed values at all sampled locations.

For each survey, the interactions between latitude and longitude of the DHS PSUs are used as a predicator variable together with the aforementioned in a GAM as smooth functions. The GAM regression technique supports non-Gaussian error distributions and nonlinear relationships between the outcome and predictor variables [63]. GAMs are nonparametric extensions of linear model regressions that apply nonparametric smoothers to each predictor and additively calculate the component outcome [63]. A GAM is expressed as

$$g(E(Z)) = \alpha + \sum_{i=1}^{p} f(X_i) + \varepsilon.$$

We use the identity link $g(.)$ to relate the linear predictor with the expected value of the response Z. For each predictor variable X_i, a smoothing function f_i is found. GAM can provide fit for a linear, nonlinear and non-monotonic relationship. We specified each term as a penalized thin plate regression spline. A truncated eigen-decomposition is used to achieve the rank reduction [64].

2.4.3. Linear models

Lastly, we compared the spatial methods with a multivariable linear regression, which estimates WI by exploiting its dependency on population density and other covariates as outlined earlier. The equation used is

$$E(Z) = \alpha + \sum_{i=1}^{p} \beta_i X_i + \varepsilon.$$

The regression coefficients β_i are constant over the whole study area and can be estimated using the least square method, from a set of covariates at N observed locations.

2.5. Assessment of predictive performance

We randomly divided the PSUs of each selected survey into a training set of 80% and a holdout of 20% for validation. We used the training set to build the models with all predictor variables, which was then used to make predictions for the holdout locations. This enabled us to directly assess prediction accuracy of the three methods compared to the observed values. We conducted the process for 100 randomly selected training and testing datasets and compared the mean values of four accuracy metrics for each method. We further repeated the process with three different proportions of holdout—30%, 40% and 50%—to examine the potential impact on prediction accuracy, as data availability changes.

Prediction accuracy was measured by the mean absolute error (MAE), root mean square error (RMSE), the goodness-of-prediction (G) statistics (also referred to as the predictive R-squared), and correlation coefficient between observed and predicted values. The MAE was used to detect bias, and should be zero if the predictions were unbiased. RMSE was used to measure the average magnitude of the squared error. Smaller MAE and RMSE values would indicate few errors and more accurate predictions from the model. The two are calculated as follows:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|p_i - o_i|$$

$$\text{RMSE} = \left[\frac{1}{n}\sum_{i=1}^{n}(p_i - o_i)^2\right]^{1/2},$$

where n is the number of predictions made, p_i the predicted value at point s_i and o_i the observed value at location s_i.

The G-value is a measure of the effectiveness of model estimates relative to estimating with just the sample mean. The G-value is written as

$$G = 1 - \left[\frac{\sum_{i=1}^{n}(p_i - o_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o})^2}\right].$$

A G-value of 1 indicates perfect prediction, a positive value indicates a more reliable model than if the sample mean had been used, a negative value indicates a less reliable model than if the sample mean had been used.

We used Stata/SE 14 data management and R v. 3.4.1 for all the statistical analyses. MBG and GAM-based fitting were performed using the R packages spBayes [65] and mgcv [64], respectively.

3. Results

The number of georeferenced PSUs across the four study surveys ranged from 605 in Tanzania and 1585 in Kenya (figure 1). The number of sampled households ranged from 12 558 in Tanzania to 38 021 in Nigeria. The average number of PSU per 1000 km^2 was higher in Malawi than in the other countries—9 compared to 1–3 (figure 1). The average numbers of households per PSU in Kenya, Malawi, Nigeria and Tanzania, respectively, were 23, 28, 43 and 21, and of de-jure household members per PSU were 91, 141, 199 and 104.

The distributions of PSU mean WI for each country are shown in figure 1*b–e*. In Tanzania and Malawi, majority of PSUs were relatively poor and the distributions of the WI were heavily right-skewed. The spatial distribution of PSU mean WI is also presented and showed good survey coverage in all areas (figure 1*a* and electronic supplementary material A).

The spatial pattern of PSU mean WI varied across countries. In Malawi, concentrations of wealthy PSUs were observed in Mzuzu, Lilongwe and Blantyre, among others. In Tanzania, we found relatively wealthy PSUs in Dar es Salaam, Arusha, Mwanza and Zanzibar. On the other hand, prominent spatial gradients were observed in Kenya and Nigeria. In Kenya, majority of the north and northeast was poor except for a few larger towns and the regional capitals. The wealthiest PSUs were found in the Nairobi and Central Kenya provinces. Most mid-WI PSUs were found to the west and east sides of Central Kenya Province. Northern Nigeria was predominantly poor. The majority of relatively rich PSUs were located in the southern part of the country, and one cluster at the centre in Abuja. In the south, a substantial number of mid-WI PSUs were seen the Enugu and Makurdi states.

Table 2 shows the four accuracy metrics for all results. Across all study countries, both SI approaches performed better than the linear fit. For both MBG and GAM, mean errors generally increased from lower to higher holdout proportions, and the opposite was observed for G-value and correlation. This indicated a greater probability that inaccurate predictions occurred in models with larger holdouts. Regardless of the SI method used, G-value and correlation were the lowest for Malawi which reflected worst prediction effectiveness when compared with the other three countries.

The GAM fit performed better at all holdout proportions for Malawi, Nigeria and Tanzania based on all four metrics. In Kenya, mixed results were observed—MBG interpolations were comparatively better for RMSE, G-value and correlation between predicted WI and observed WI at 20–40% holdout. The relative performance of the GAM in Kenya improved as holdout proportions increased to 50%.

The spatial patterns of the covariates are illustrated in electronic supplementary material B, and we explored the effects of the covariates by country using the full datasets (electronic supplementary material C). Night-time light emission most consistently showed an association with WI across all countries, followed by population density. Overall, night-time light was positively associated with WI, while the opposite was observed for population density. In the GAM fits, in all cases except for population density in Tanzania, the curves were significant at the 0.001% level.

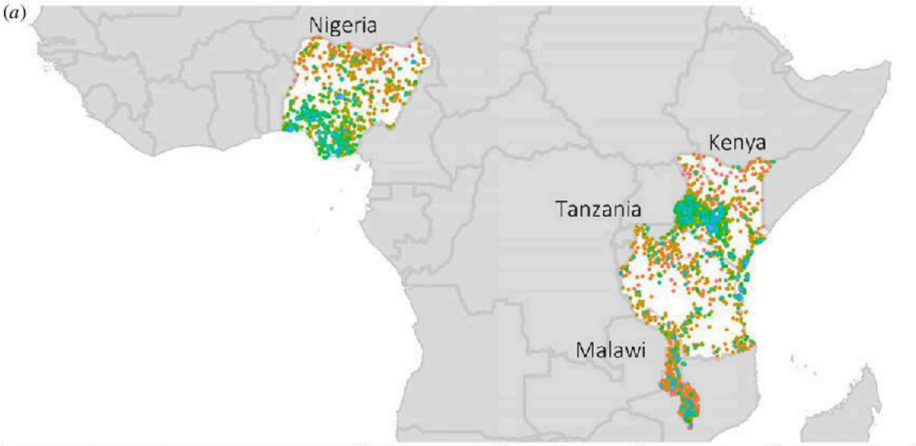
Finally, Pearson correlation coefficients between the average values used for our analysis and those resulting from using buffer sizes of 5, 10 and 20 km showed strong correlations across different extractions methods (table 3), thus we do not expect the analytical results to differ by using alternative scales.

4. Discussion

In this study, we assessed the performances of two spatial methods to predict poverty for four countries in sub-Saharan Africa. We compared a Bayesian multivariable MBG approach with spline interpolation as part of a GAM to predict WI at holdout locations using DHS data. We observed better predictive performances of these spatial methods when compared to non-spatial models. Our results revealed marked differences in the shape of the distribution and spatial pattern of WI across the four countries. We found that predictive performance was the lowest in Malawi compared to the other three countries regardless of the method used. GAM-based fitting of smoothed functions of the spatial coordinates and WI, adjusted for other predictor variables, generally performed better than MBG in Malawi, Nigeria and Tanzania. In Kenya, on the other hand, the GAM fit resulted in marginally worse prediction accuracy than the MBG approach.

4.1. Study limitations

Our findings have important implications but should be understood within certain limitations. First, the random displacement applied to the GPS coordinates of the DHS PSUs could have misclassified assignment of predictor variables [66]. The extent of misclassification depends on the smoothness of the surface from which data are being linked [66]. We attempted to mitigate the effects of potential bias of rough/unsmooth surfaces by integrating from raster cells close to the displaced locations. Second, as we conducted



	2014 Kenya	2015 Malawi	2013 Nigeria	2015 Tanzania
number of primary sampling unit (PSU)	1585	850	889	608
average number of PSU per 1000 km^2 (land area)	3	9	1	1
average number of households per PSU	23	28	43	21
average number of de jure members per PSU	91	141	199	104

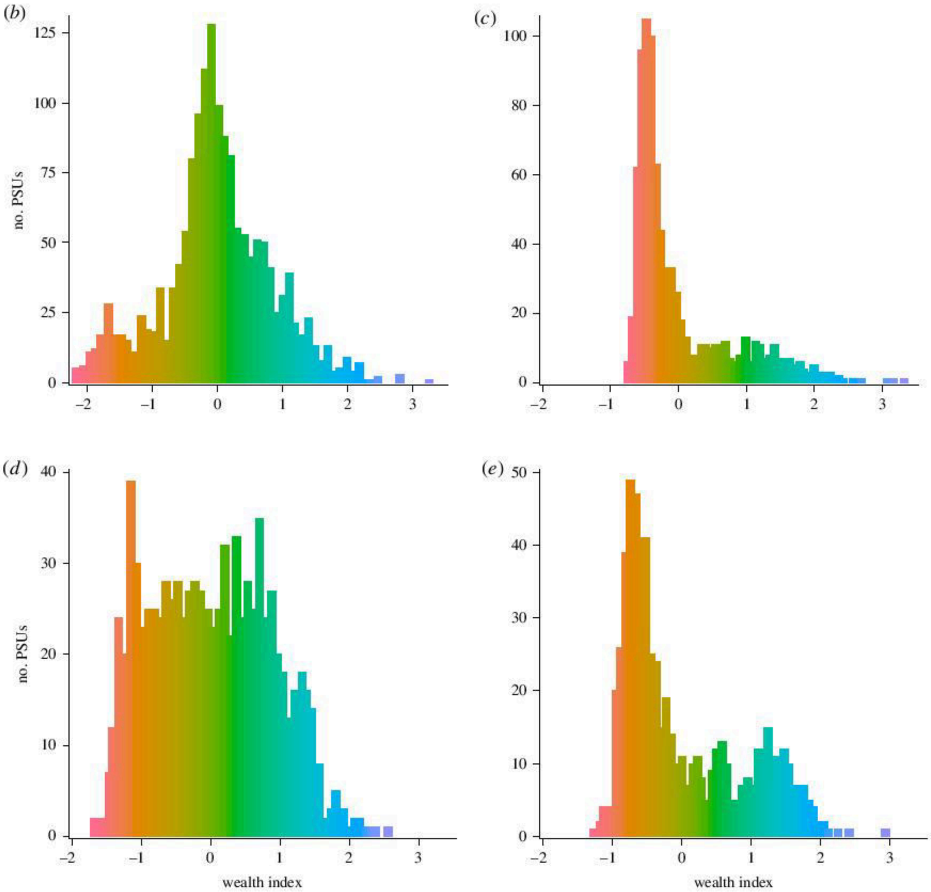


Figure 1. Study region. (*a*) Geographical location of the study countries and DHS PSUs. (*b*) 2014 Kenya DHS. (*c*) 2015 Malawi DHS. (*d*) 2013 Nigeria DHS. (*e*) 2015 Tanzania DHS. Note: the original values of wealth index have been rescaled by a factor of 10^{-6}.

an out-of-sample validation based on sampled data, the comparative performance between MBG and GAM if 100% of the data were used to make predictions at unsampled locations is uncertain. Third, we did not use the revised global map of travel time to cities estimated by Weiss and colleagues [67] which was published after we analysed our data. Fourth, we opted for a straight-line measure for accessibility as it is unclear that more sophisticated methods are better [57,68].

Table 2. Performance assessment of the non-spatial and spatial interpolation methods for 20–50% of data holdout. Note 1: the more optimal value is shaded for each comparison. Note 2: each value is calculated as the mean of 100 random model runs. OLS, ordinary least squares; MBG, model-based geostatistics; GAM, generalized additive model; MAE, mean absolute error; RMSE, root-mean-square error; *G*-value, goodness of fit value.

holdout		Kenya			Malawi			Nigeria			Tanzania		
		OLS	MBG	spline based GAM	OLS	MBG	spline based GAM	OLS	MBG	spline based GAM	OLS	MBG	spline based GAM
20%	MAE	0.487	0.399	0.392	0.403	0.385	0.324	0.487	0.429	0.387	0.475	0.453	0.364
	RMSE	0.651	0.531	0.540	0.575	0.548	0.513	0.619	0.551	0.506	0.595	0.581	0.499
	G-value	0.441	0.604	0.589	0.416	0.464	0.528	0.487	0.594	0.657	0.535	0.535	0.656
	correlation	0.668	0.780	0.772	0.656	0.691	0.741	0.703	0.775	0.816	0.737	0.742	0.816
30%	MAE	0.490	0.403	0.395	0.404	0.388	0.328	0.489	0.435	0.391	0.478	0.458	0.371
	RMSE	0.655	0.537	0.544	0.576	0.552	0.520	0.623	0.559	0.512	0.597	0.584	0.509
	G-value	0.438	0.596	0.585	0.420	0.456	0.516	0.489	0.587	0.655	0.541	0.541	0.649
	correlation	0.665	0.775	0.769	0.658	0.685	0.732	0.703	0.771	0.813	0.740	0.744	0.812
40%	MAE	0.487	0.407	0.396	0.402	0.393	0.334	0.488	0.440	0.395	0.479	0.462	0.377
	RMSE	0.651	0.543	0.545	0.575	0.558	0.537	0.622	0.564	0.518	0.599	0.591	0.518
	G-value	0.441	0.585	0.581	0.420	0.451	0.488	0.491	0.581	0.647	0.537	0.529	0.638
	correlation	0.667	0.767	0.766	0.657	0.681	0.722	0.704	0.766	0.809	0.737	0.736	0.805
50%	MAE	0.487	0.413	0.400	0.402	0.397	0.340	0.487	0.446	0.399	0.478	0.465	0.385
	RMSE	0.651	0.552	0.553	0.575	0.565	0.547	0.622	0.571	0.524	0.599	0.594	0.531
	G-value	0.441	0.571	0.569	0.417	0.437	0.469	0.491	0.571	0.638	0.533	0.521	0.612
	correlation	0.667	0.758	0.760	0.655	0.672	0.710	0.704	0.760	0.803	0.734	0.731	0.795

Fifth, the use of asset-based indices to assess poverty may be affected by the choice of components and poor comparability between urban and rural areas [69,70], but such indices are easy to compute and compare well to more complex indicators of wealth [71–73]. Sixth, we only used four case countries, and our results may have limited generalizability to LMICs. Last, the wealth index data used for modelling were aggregated to the PSU from household-level data, and the covariates exploited were provided at different grid sizes. Grid size of the land surface temperature layer and the vegetation index layer, in particular, are larger and have potential within-grid variations that cannot be accounted for in the current analysis.

4.2. Model-based geostatistics and generalized additive model

Comparison based on goodness-of-fit value and correlation showed that predictive performance was lowest in Malawi, indicating neither model was sufficient to address the spatial variability of WI. The covariate datasets used were provided as raster objects at set grid size. Within each grid, covariate values are considered constant. Given that Malawi has a substantially smaller land area compared to the other three countries, every grid on a Malawi covariate layer covers a larger proportion of the country's surface area, leading to higher levels of aggregation. At higher levels of aggregation, there is greater potential for information loss [74]. Night-time light emission, one of the strongest predictors found in this study (see electronic supplementary material C), ranged between zero and approximately 60 units across all four countries. If the spatial scale of covariate effect in Malawi was also similar to the other countries, higher levels of aggregation may not lead to greater information loss. On the other hand, if the spatial scale of covariate effect for night-time light in the smaller country and economy was as least as rapid as the other three countries, greater potential for information loss might be expected [74]. This may have contributed to the reduced model performance and prediction accuracy in Malawi.

While the two SI methods explored in this analysis offer different ways of capturing the underlying spatial pattern, they share certain mathematical connection as previously discussed by Cressie and Wahba [75,76]. Cressie, for instance, demonstrated commonalities between the two-dimensional Laplacian smoothing spline of degree two and the universal kriging predictor [76]. Nonetheless, the two methods remain 'practically very different' [76], and the predictive performances resulting from the typical ways in which these methods are applied are the main interest of the current analysis.

Many factors affect the predictive performance of different SI methods, and our study did not yield a consistent 'best method'. Rather, each approach offers different ways of capturing different data structure, and in line with previous studies [77–79], we found different methods performed better under different conditions. Our results revealed four possible factors for the performance of the methods: (i) data density, (ii) normality of data, (iii) the underlying spatial wealth pattern and (iv) the choice of covariates.

Firstly, the comparative performance of the two approaches might be sensitive to data density. Our results across a range of holdout proportions demonstrated that predictive performances reduced for both methods when sparse datasets were used. While this may not be surprising, the more optimal SI method for Kenya changed from MBG to GAM when data density decreased from 80 to 50%.

Secondly, non-spatial exploratory data analysis indicated that the WI values at the PSU level for Kenya (figure 1*b*) followed a normal distribution. On the other hand, the distributions for Malawi, Nigeria and Tanzania were right-skewed

Table 3. Pearson correlation coefficients between extractions averaged from the four nearest grids and buffers of 5, 10 and 20 km. Note 1: population data were excluded as the original data were collected at the highest resolution available from population censuses in vector format, and then uniformly distributed to a raster pixel or grid. The method adopted is detailed elsewhere [46].

	Kenya			Malawi			Nigeria			Tanzania		
	5 km	10 km	20 km	5 km	10 km	20 km	5 km	10 km	20 km	5 km	10 km	20 km
night-time light	0.978	0.933	0.859	0.958	0.863	0.673	0.976	0.914	0.802	0.966	0.891	0.812
aridity	0.997	0.989	0.964	0.995	0.988	0.974	1.000	1.000	1.000	0.996	0.983	0.958
potential evapotranspiration	0.996	0.989	0.968	0.989	0.970	0.940	1.000	0.999	0.999	0.995	0.982	0.948
land surface temperature	0.978	0.994	0.970	0.956	0.988	0.946	0.995	0.997	0.972	0.960	0.986	0.906
vegetation index	0.948	0.988	0.961	0.926	0.979	0.933	0.974	0.992	0.961	0.928	0.982	0.929
elevation	0.998	0.994	0.984	0.990	0.974	0.949	0.996	0.991	0.984	0.998	0.993	0.981

(figure 1*c–e*). This empirical difference across countries coincided with MBG performing more optimally for Kenya. Although normality in the outcome is not required for MBG, second order variation is structured as a multivariate normal-distributed random field. The influence of data normality, together with the choice of covariates (more below), on the suitability of different SI methods should be carefully accounted for. This may be particularly pertinent as top inequality—large and slowly declining top wealth shares as indicated by right skew—is rising both globally and in many countries [80–82]. It is also unlikely to be solely due to our use of WI as a measure of wealth, since previous studies have also found a similar distribution in other wealth indicators in Malawi [83] and Tanzania [84].

Thirdly, the underlying spatial pattern in the data is important to choosing the 'best' performing SI method in a given map region. MBG predictive maps are typically based on the assumptions of stationarity of the spatial process, as the approach accounts for the covariance of the residuals between any two locations by modelling it as dependent on the distance and direction between them, and is independent of the location itself. In the presence of good global spatial autocorrelation, such as the case of Kenya, where the global spatial pattern of wealth appears to decrease over distance from Nairobi (figure 1*a*), MBG performed marginally better than GAM. In 1969, the post-colonial Kenyan government selected seven cities around Nairobi to develop as secondary cities to decongest urban conditions [85]. While Nairobi remains economically dominant in Kenya, the seven cities have developed a sizable economic base over the last few decades [85]. Except for Mombasa, these cities span across the Kenyan savannah in the southwest [86]. The rest of the country is predominately arid land where livelihoods are generally challenging [87,88]. The geographical pattern of wealth in Kenya may thus be more parsimoniously explained by spatial autocorrelation compared to the other study countries. The tendency for poverty rates to be more similar in nearby locations has also been shown in other LMICs [89,90].

In other settings, pairs of locations distant from each other may be more similar than nearby neighbours although local spatial autocorrelation is observed, in which case the assumption of stationarity may not be optimal when considering spatial processes over the whole map region. One practical way to take non-stationarity into account in an MBG framework is by partitioning the study area into disjoint regions and define a separate stationary process in each region [91]. Other non-stationary models may also be appropriate. The GAM formulation, for instance, allows the outcome to vary smoothly in space instead of assuming locations' predictive power on one another to be dependent on distance. In our study, the GAM approach provided better predictions than MBG at all holdout proportions for Malawi and Tanzania, where we observed spatial scatter of concentrations of wealthy locations across the national extents. The pattern observed in Malawi and Tanzania may not be unique. In Ethiopia and Rwanda, for instance, a secondary cities development component involving collections of locations that form a spatially multi-centred network has been proposed as part of a strategy to attain inclusive growth and build resilience [92,93]. The identification and inclusion of these secondary cities were partially based on their institutional capacity at the time of selection. Moreover, there were also the intentions to relieve urban conditions in primary cities, promote a spatial balance and equity and transform the economic geography of the countries through redistributing resources [92,93].

As development of secondary cities continues to be the focus of sustainable growth, it is important to account for the geographical organization of these emerging cities when constructing smoothed map surfaces of wealth and other development indicators using SI techniques. Researchers, planners and development agencies have conceived several types of theoretical city/settlement patterns, including nucleated, clustered, dispersed and random [33,94,95]. Depending on the spatial processes of the outcome and available covariates, the assumption of spatial stationarity in the SI model formulation may or may not be suitable. The potentials for the similarities between a distant pair of locations, or any pair of locations, to be used as an input for poverty mapping warrant further research. In particular, the application of some non-spatial methods for interpolation, including machine learning techniques, without the constraint of using neighbouring data to make prediction at an unsampled or unobserved location offers new opportunities to capturing more complex spatial patterns [41]. With these methods, an algorithm is used to decide which observations should be leveraged for a certain prediction, allowing the inclusion of data from any other sample points if the model finds them similar to the location being interpolated in terms of the predictor variables.

Lastly, the choice of predictor variables and their relationships with the outcome is a strong factor influencing the predictive performance and the choice of SI method. The outcome being mapped may be spatially correlated, and largely due to certain spatial trends in the covariates. In which case, accounting for covariate effects and examining whether any residual spatial correlation remains are crucial. The current analysis was performed using the full model formulation with all covariates included. Overall, the curvatures for night-time light emission and population density showed the strongest effects across study countries, while the other climatic and environmental features have moderate effects in Kenya and Nigeria, and weak effects in Malawi and Tanzania. This is an important point to note for two reasons: (i) the spatial processes of WI in Malawi and Tanzania are less stationary compared to Kenya and Nigeria and (ii) remotely sensed data are generally less costly to collect on a vast scale compared to other data collection efforts, making them suitable for the use of SI, but their availability is usually higher for natural conditions in LMICs where the determinants of the spatial structure of wealth are becoming more complex. Non-stationary spatial processes that lack suitable and readily available predictors (e.g. wealth/poverty in Malawi and Tanzania) can limit the predictive performance of SI methods that rely on good spatial stationarity. Different groups around the world are working on producing high resolution data on 'man-made' features for large geographical areas—anonymised mobile data [96], human settlement pattern [97], urban–rural classification [97], which are potentially more closely associated with the spatial process of wealth for some settings. Although mostly confined to smaller geographical areas such as subnational administrative regions, the number of studies on high or very high resolution of urban slum mapping have also been increasing [98]. The use of these data as covariates may mean that spatial autocorrelation would become more or less informative, and have potential influence on the comparative performance of different SI methods. In future attempts to create a smoothed poverty surface for a given region, one may wish to explore method-specific, contextually relevant covariates/interactions, perform variable selection as well as allowing for a more flexible predictor–outcome structure to find the best SI method and model formulation.

5. Conclusion

MBG and spline interpolation offer different ways of capturing spatial variability in the data. Our results shed light on four factors relevant to selecting a suitable method when interpolating poverty for an LMIC from sampled data and other covariates. These factors include data density, normality of data, the underlying geographical pattern of wealth and the choice of covariates. As part of the progress towards inclusive growth and resilience, governments and policymakers in some LMICs are beginning to aim for a spatial economic balance by redistributing resources within the national extent instead of having one primary city. This likely impacts the spatial autocorrelation structures of welfare, health and demographic indicators, leading to deviations from the most ideal conditions for some SI methods to perform optimally. The use of covariates further influences the extent to which residual spatial correlation can be informative in the prediction making process. In future attempts to create an interpolated poverty surface for an LMIC, researchers and analysts should carefully explore the structure of the possible covariates and the outcome in order to identify the most suitable SI method.

Data accessibility. All datasets generated and analysed during the current study are available from the following repositories: https://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD11C1_M_LSTDA, https://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD_NDVI_M, https://lta.cr.usgs.gov/GTOPO30, http://www.cgiar-csi.org/data/global-aridity-and-pet-database, https://ngdc.noaa.gov/eog/dmsp/downloadV4compo sites.html, http://sedac.ciesin.columbia.edu/data/collection/gpw-v4, http://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-populated-places/ and https://dhsprogram.com/data/available-datasets.cfm.

Authors' contributions. K.L.M.W. and O.J.B. conceptualized the study. K.L.M.W undertook data processing and assembling. K.L.M.W. conducted the analysis, with supervision from O.J.B. and L.B. O.J.B., L.B. and O.M.R.C. contributed to interpretation of the findings. K.L.M.W. drafted the manuscript, with contributions from L.B., O.J.B. and O.M.R.C. All authors read and approved the final manuscript.

Competing Interests. We declare we have no competing interests.

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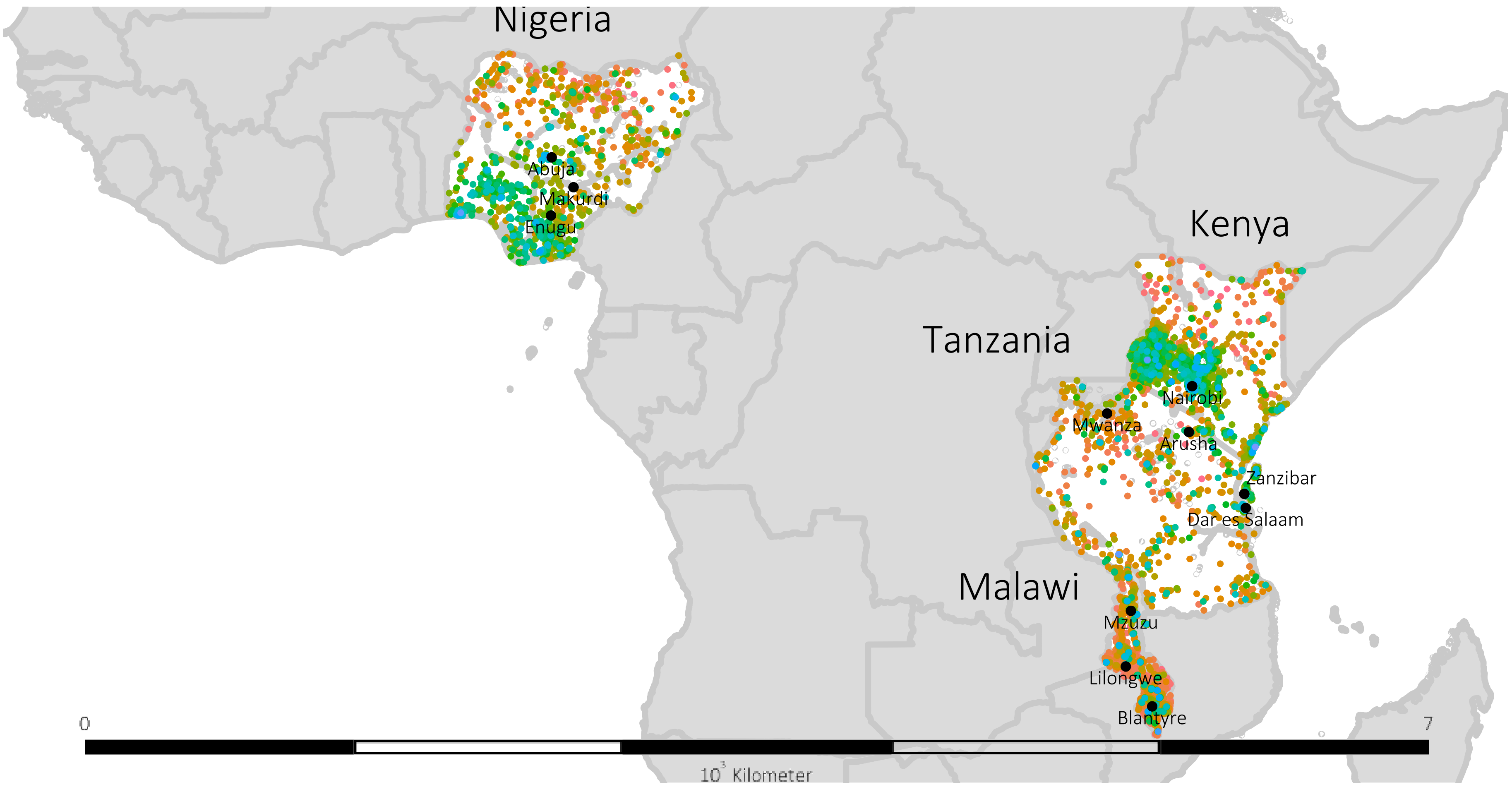
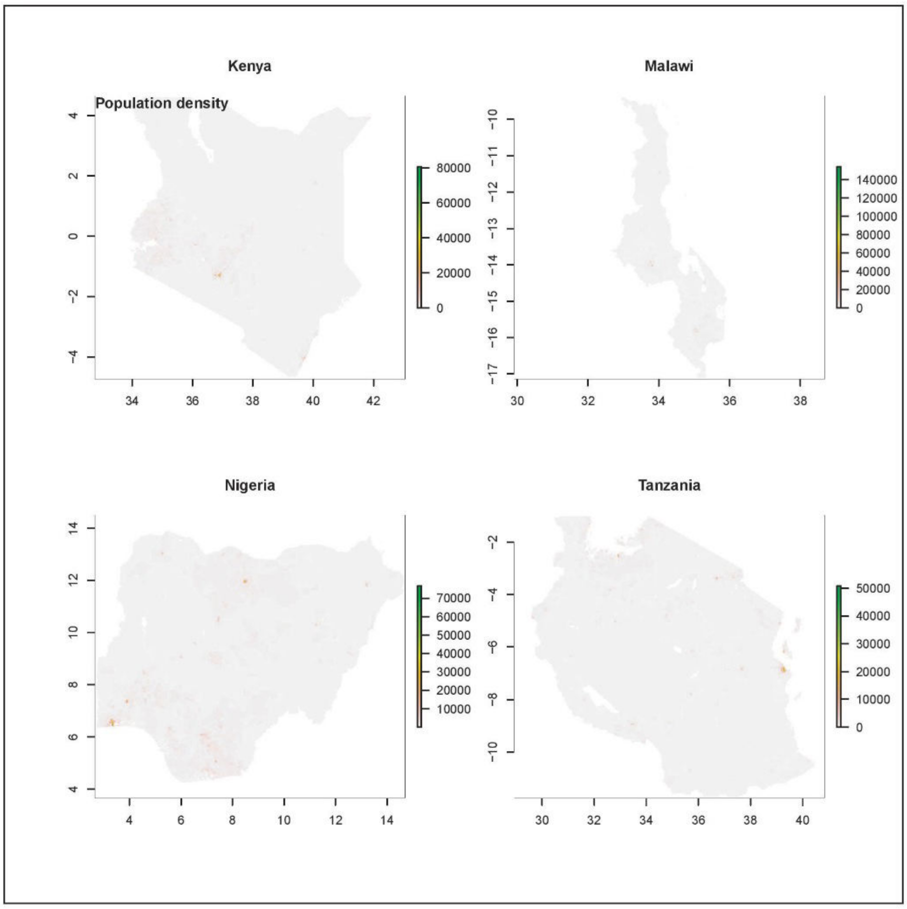
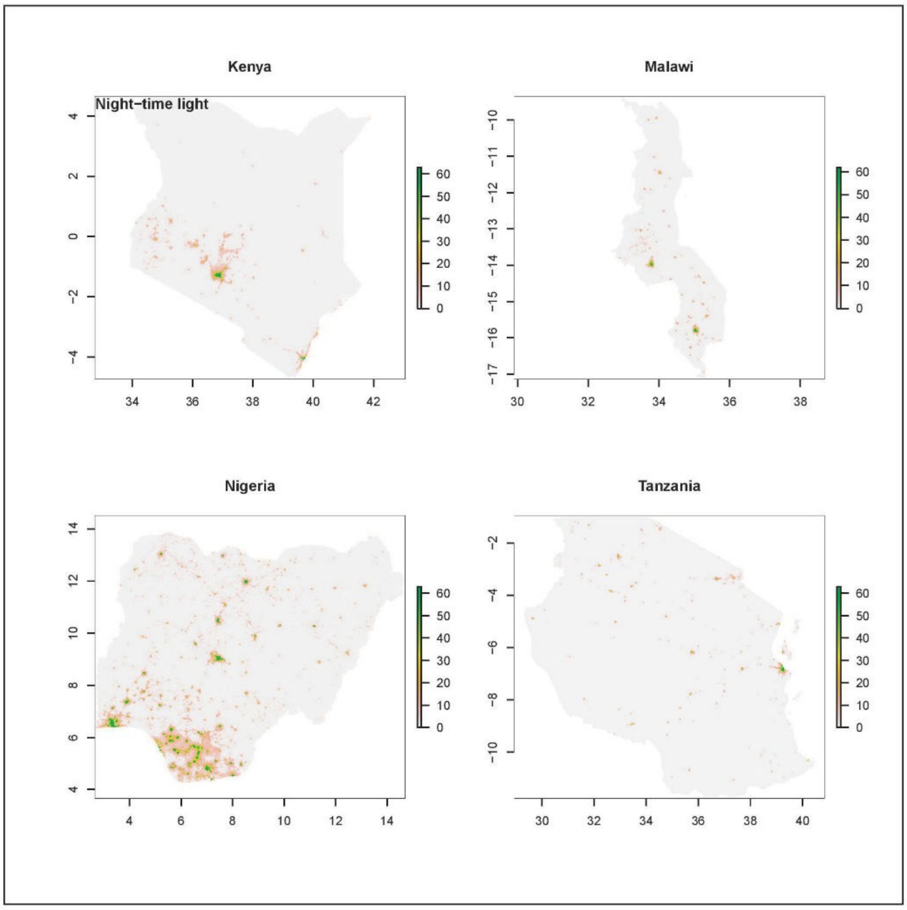
5.2 Supplementary materials

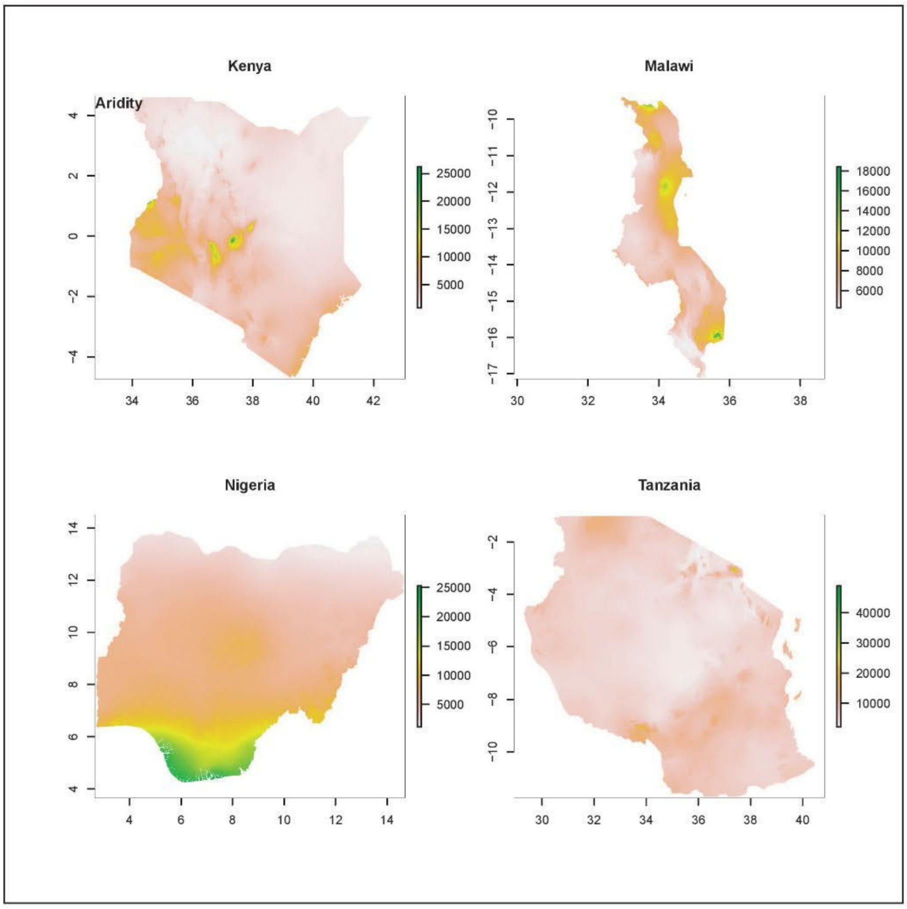
5.2.1 Supplementary material A. Study region



5.2.2 Supplementary material B. Model covariates






Kenya
Aridity
4
2
0
-2
-4
34
36
38
40
42
25000
20000
15000
10000
5000
Malawi
-10
-11
-12
-13
-14
-15
-16
-17
30
32
34
36
38
18000
16000
14000
12000
10000
8000
6000
Nigeria
14
12
10
8
6
4
4
6
8
10
12
14
25000
20000
15000
10000
5000
Tanzania
-2
-4
-6
-8
-10
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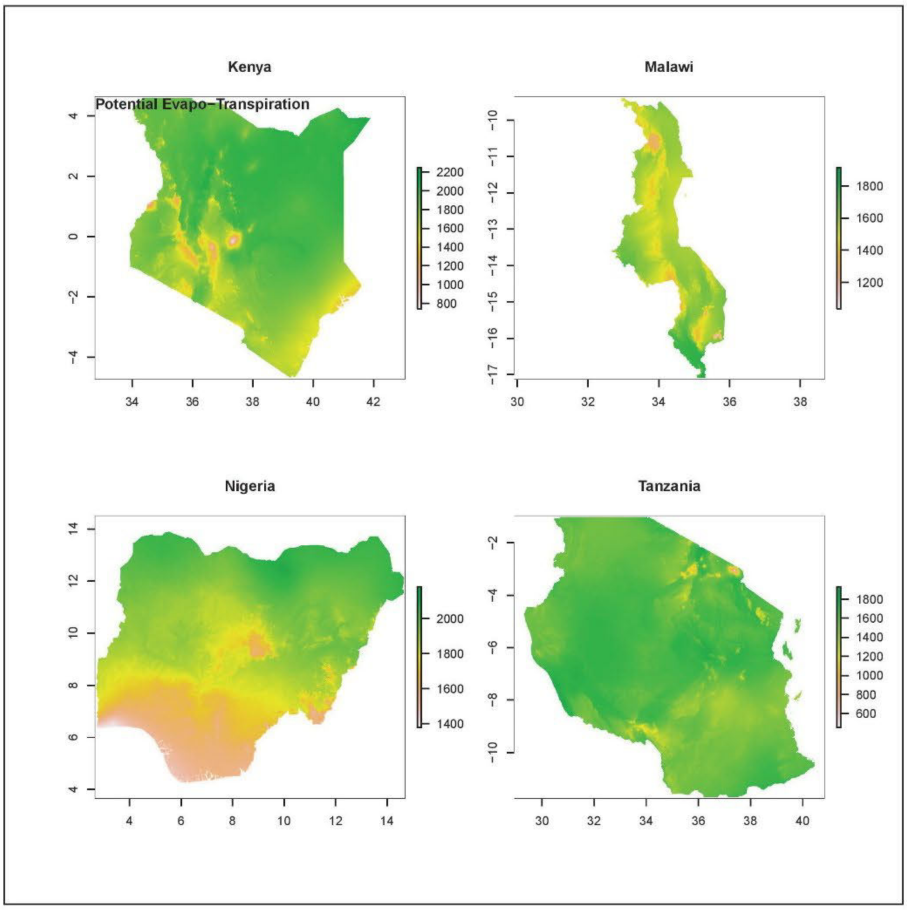
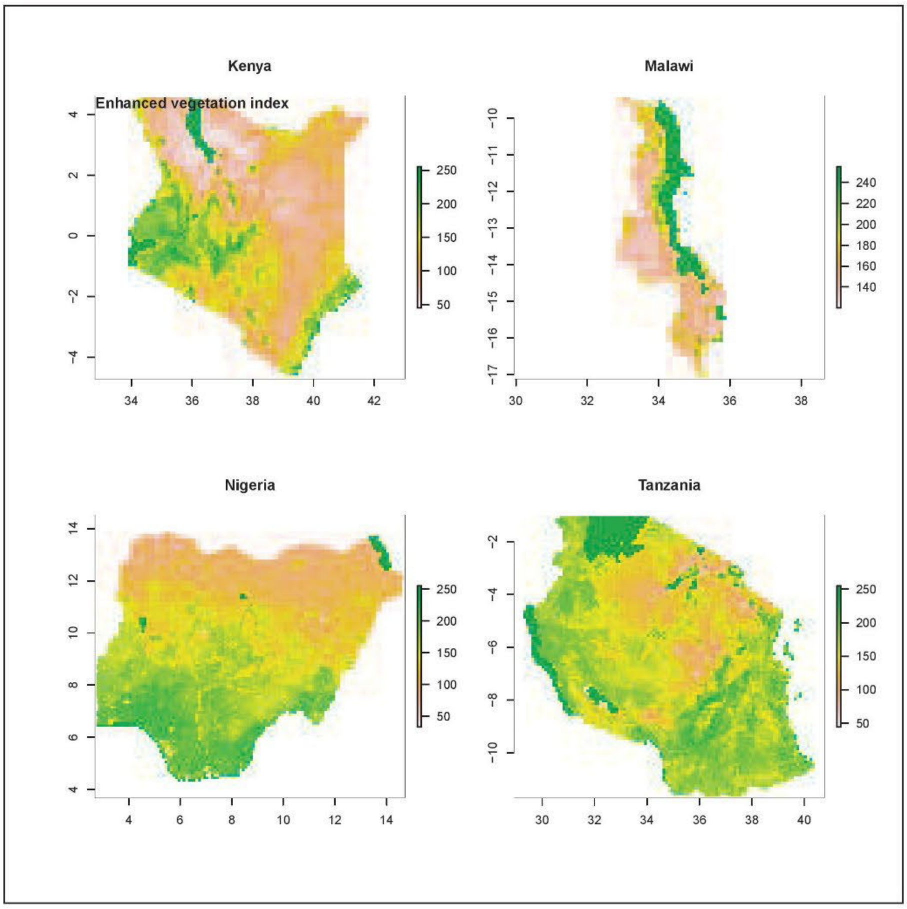
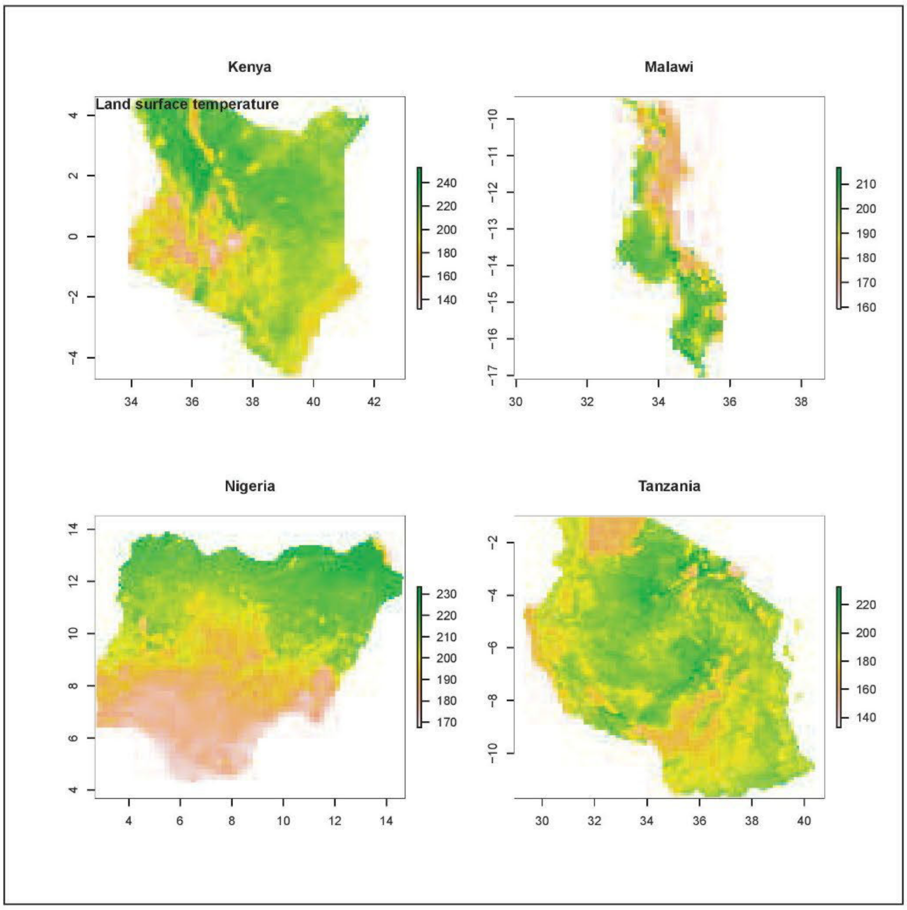
38
40
40000
30000
20000
10000


Kenya
Potential Evapo−Transpiration
4
2
0
-2
-4
34
36
38
40
42
2200
2000
1800
1600
1400
1200
1000
800
Malawi
-10
-11
-12
-13
-14
-15
-16
-17
30
32
34
36
38
1800
1600
1400
1200
Nigeria
14
12
10
8
6
4
4
6
8
10
12
14
2000
1800
1600
1400
Tanzania
-2
-4
-6
-8
-10
30
32
34
36
38
40
1800
1600
1400
1200
1000
800
600


Kenya
Enhanced vegetation index
4
2
0
-2
-4
34
36
38
40
42
250
200
150
100
50
Malawi
-10
-11
-12
-13
-14
-15
-16
-17
30
32
34
36
38
240
220
200
180
160
140
Nigeria
14
12
10
8
6
4
4
6
8
10
12
14
250
200
150
100
50
Tanzania
-2
-4
-6
-8
-10
30
32
34
36
38
40
250
200
150
100
50


Kenya
Land surface temperature
4
2
0
-2
-4
34
36
38
40
42
240
220
200
180
160
140
Malawi
-10
-11
-12
-13
-14
-15
-16
-17
30
32
34
36
38
210
200
190
180
170
160
Nigeria
14
12
10
8
6
4
4
6
8
10
12
14
230
220
210
200
190
180
170
Tanzania
-2
-4
-6
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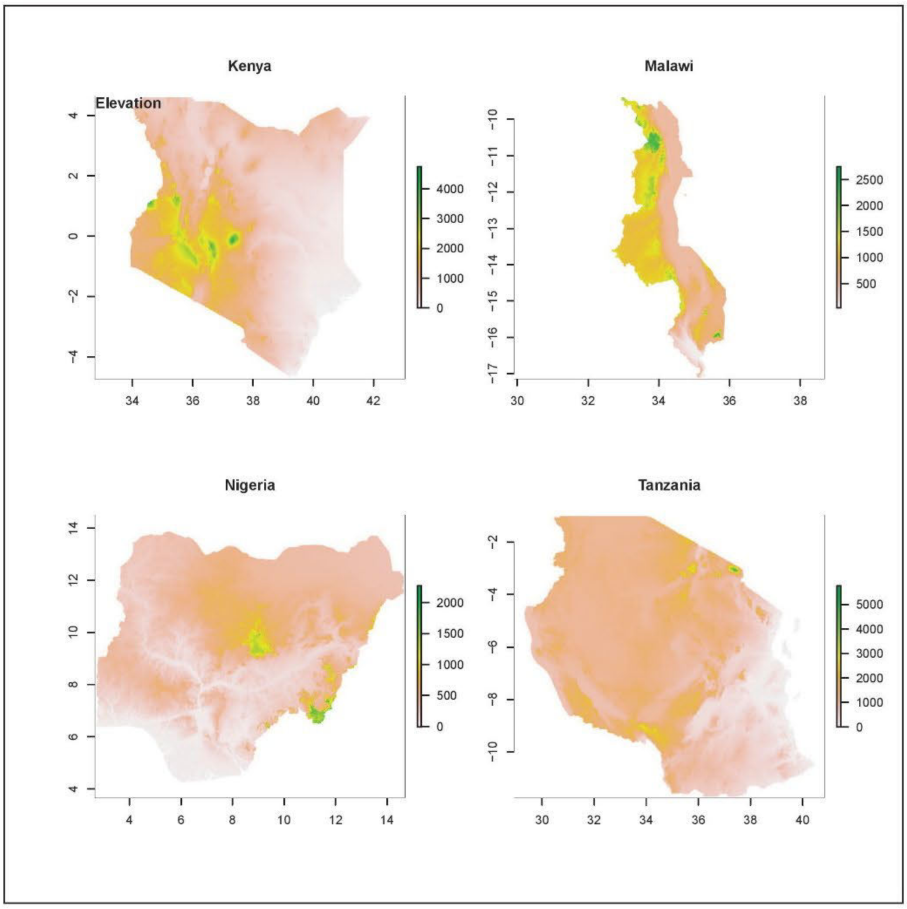
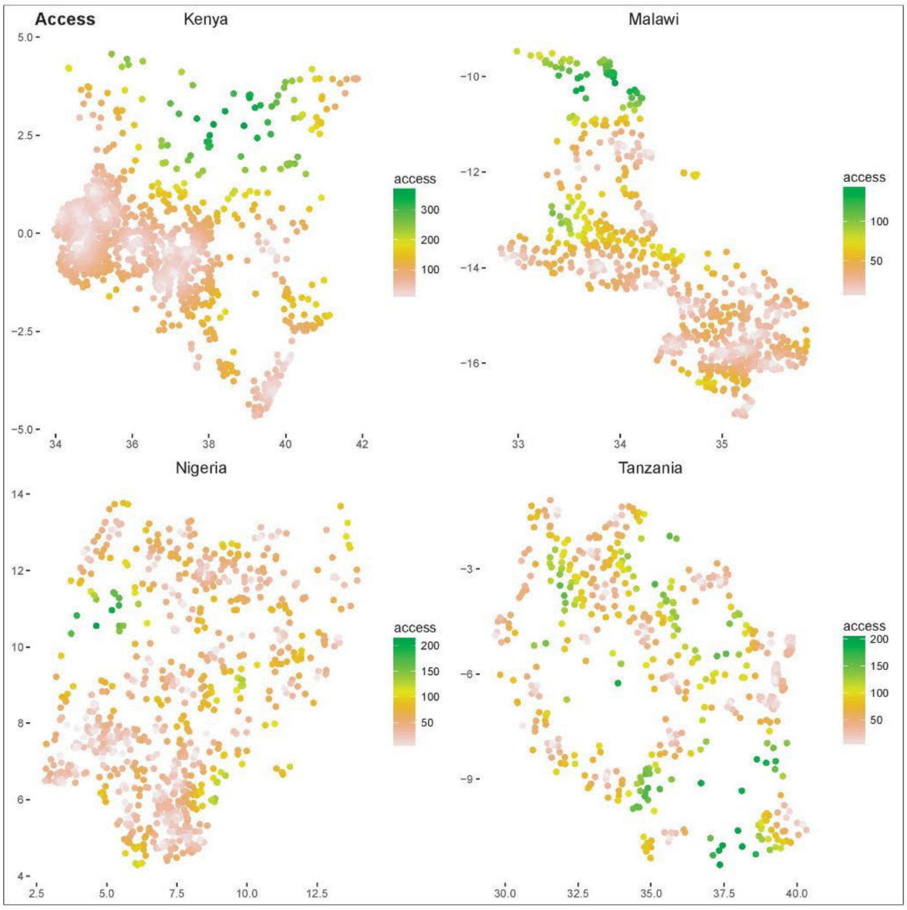
38
40
220
200
180
160
140

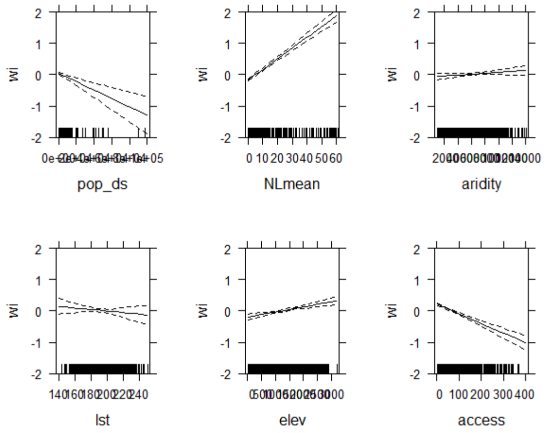

Kenya
Elevation
4000
3000
2000
1000
0
Malawi
2500
2000
1500
1000
500
Nigeria
2000
1500
1000
500
0
Tanzania
5000
4000
3000
2000
1000
0


Access
Kenya
access
300
200
100
Malawi
access
100
50
Nigeria
access
200
150
100
50
Tanzania
access
200
150
100
50

5.2.3 Supplementary material C: covariate effects from full model formulation with no hold-out data

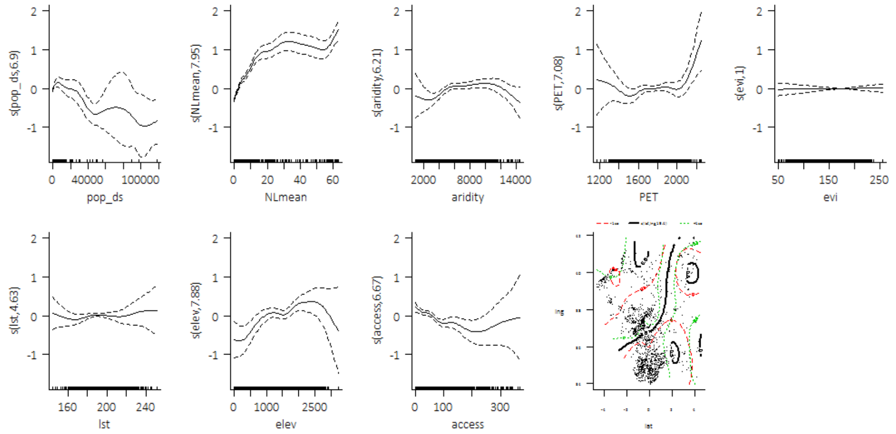
5.2.3.1 Kenya

MBG



```
Empirical mean and standard deviation for each variable, plus 2.5% and 97%
quantiles:
                                          2.5%     97.5%
                   Mean       SD   quantiles  quantiles
(Intercept)     -0.6280   0.7170     -1.8900     0.7130
pop_ds           0.0000   0.0000      0.0000     0.0000  ***
NLmean           0.0374   0.0023      0.0345     0.0416  ***
aridity          0.0000   0.0000      0.0000     0.0000
PET              0.0002   0.0002     -0.0001     0.0004
evi              0.0016   0.0008      0.0001     0.0029  *
lst             -0.0017   0.0030     -0.0074     0.0035
elev             0.0003   0.0001      0.0002     0.0003  ***
access          -0.0024   0.0004     -0.0029    -0.0016  ***
```

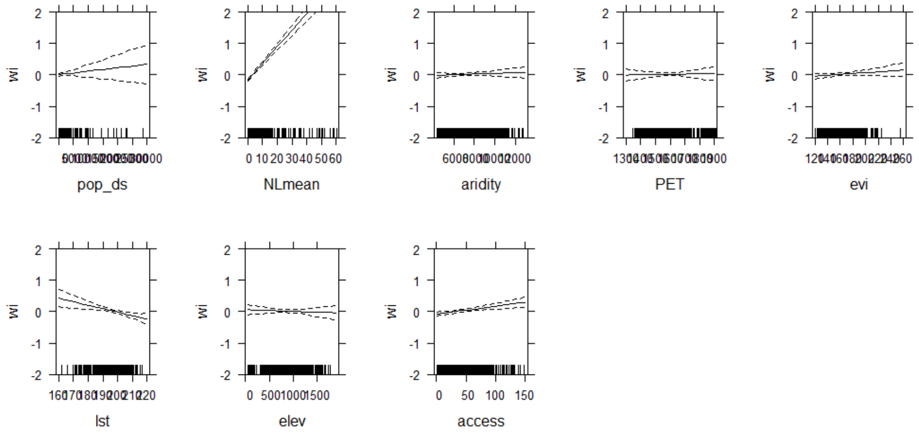
GAM



```
Approximate significance of smooth terms:
              edf  Ref.df      F  p-value
s(pop_ds)   6.903  7.828  6.054 1.75e-07 ***
s(NLmean)   7.945  8.695 38.921  < 2e-16 ***
s(aridity)  6.214  7.348  2.799 0.005740 **
s(PET)      7.081  8.080  2.724 0.005092 **
s(evi)      1.000  1.000  0.059 0.808913
s(lst)      4.631  5.759  1.008 0.459754
s(elev)     7.878  8.634  3.391 0.000492 ***
s(access)   6.666  7.763  3.577 0.000482 ***
s(lat,lng) 19.398 23.770  4.804 2.44e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

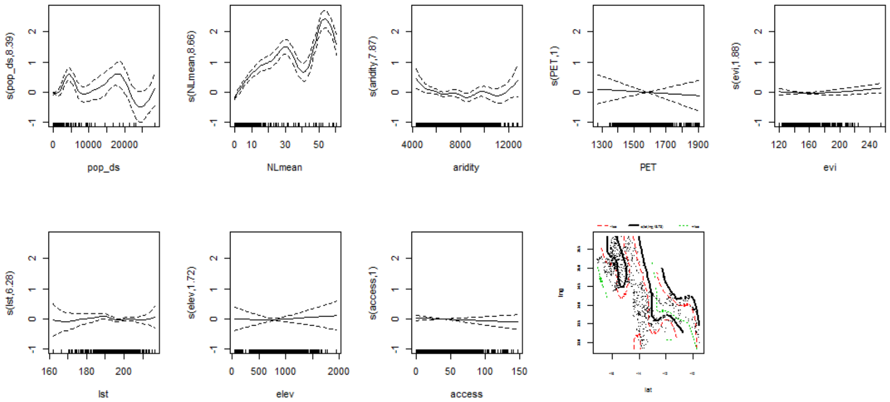
5.2.3.2 Malawi

MBG



```
Empirical mean and standard deviation for each variable, plus 2.5% and 97%
quantiles:
                                         2.5%      97.5%
                  Mean        SD    quantiles  quantiles
(Intercept)     1.9800    1.2700      -0.3400     4.3300
pop_ds          0.0000    0.0000       0.0000     0.0000
NLmean          0.0526    0.0037       0.0454     0.0586  ***
aridity         0.0000    0.0000       0.0000     0.0000
PET             0.0000    0.0004      -0.0006     0.0008
evi             0.0009    0.0011      -0.0011     0.0027
lst            -0.0121    0.0032      -0.0180    -0.0076  **
elev           -0.0001    0.0001      -0.0003     0.0001
access          0.0023    0.0009       0.0009     0.0039  ***
```

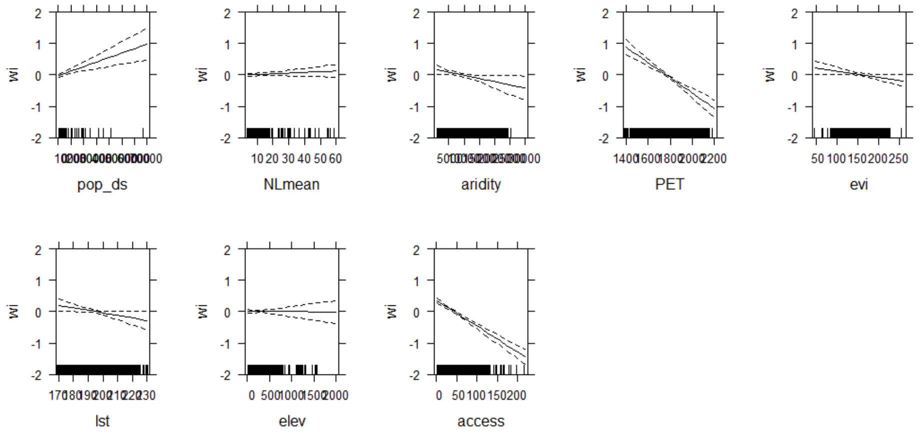
GAM



```
Approximate significance of smooth terms:
               edf Ref.df      F  p-value
s(pop_ds)    8.394  8.870  5.139 9.00e-07 ***
s(NLmean)    8.660  8.960 49.908  < 2e-16 ***
s(aridity)   7.875  8.646  2.220   0.0192 *
s(PET)       1.000  1.000  0.193   0.6608
s(evi)       1.878  2.314  2.302   0.1091
s(lst)       6.280  7.407  0.919   0.4778
s(elev)      1.716  2.157  0.518   0.6080
s(access)    1.000  1.000  0.707   0.4008
s(lat,lng) 18.726 23.276  2.682 3.32e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

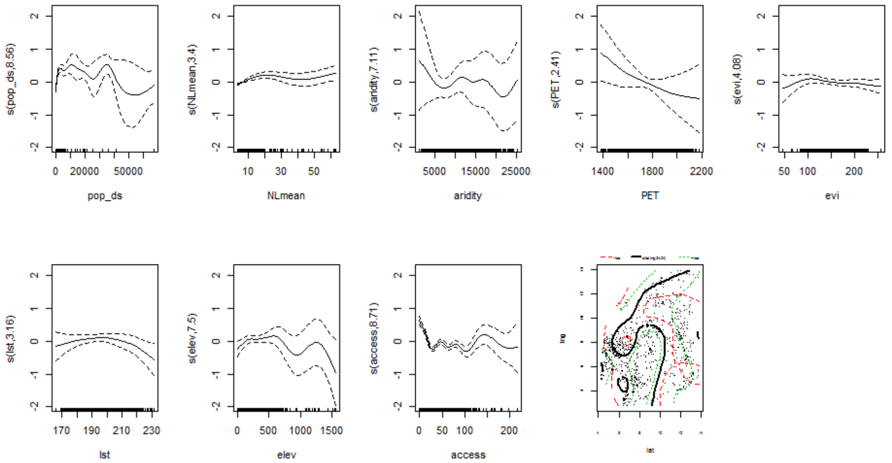
5.2.3.3 Nigeria

M
B
G



```
Empirical mean and standard deviation for each variable, plus 2.5% and 97%
quantiles:
                                         2.5%       97.5%
                  Mean        SD    quantiles   quantiles
 (Intercept)     6.6500   0.7750      5.3800      7.8500    ***
 pop_ds          0.0000   0.0000      0.0000      0.0000    ***
 NLmean          0.0032   0.0025     -0.0015      0.0063
 aridity         0.0000   0.0000      0.0000      0.0000    *
 PET            -0.0031   0.0004     -0.0038     -0.0025    ***
 evi            -0.0025   0.0009     -0.0038     -0.0008    *
 lst            -0.0018   0.0039     -0.0097      0.0030    .
 elev           -0.0001   0.0001     -0.0003      0.0000
 access         -0.0084   0.0006     -0.0095     -0.0073    ***
```

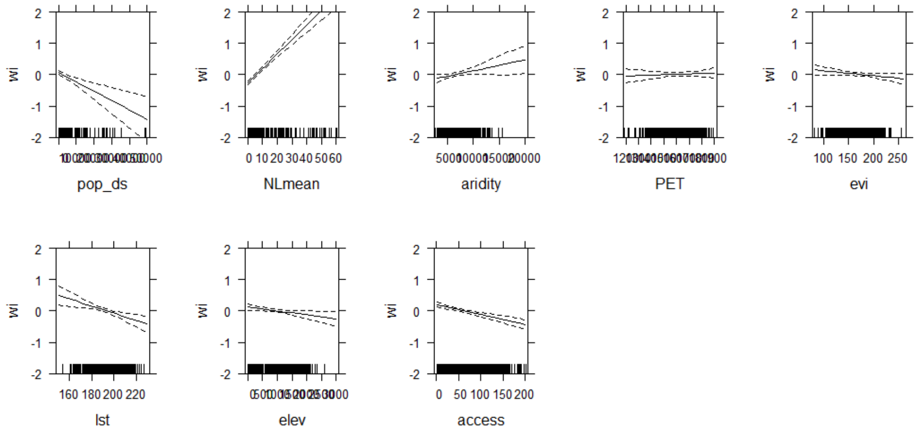
G
A
M



```
Approximate significance of smooth terms:
              edf  Ref.df      F  p-value
s(pop_ds)   8.557   8.923  8.129 1.76e-11 ***
s(NLmean)   3.399   4.164  6.618 2.38e-05 ***
s(aridity)  7.110   8.041  1.367  0.30236
s(PET)      2.406   3.109  1.639  0.22241
s(evi)      4.079   5.140  0.934  0.44031
s(lst)      3.156   4.102  2.299  0.05336 .
s(elev)     7.503   8.414  2.384  0.00948 **
s(access)   8.706   8.969 15.692  < 2e-16 ***
s(lat,lng) 24.237  27.118  4.461 2.30e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

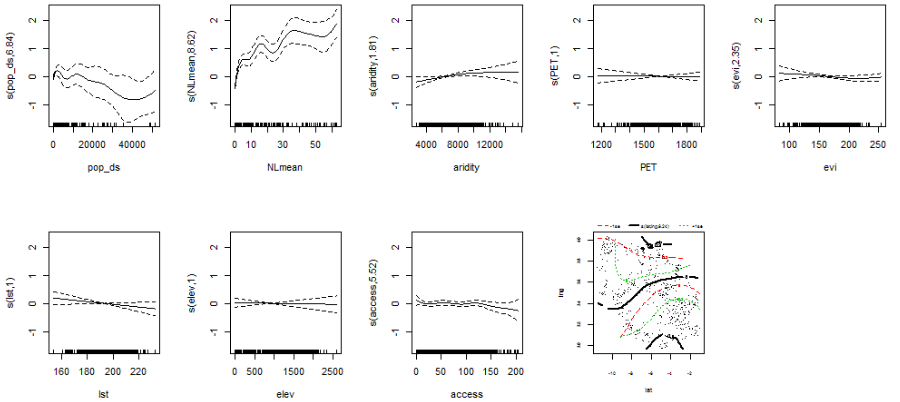
5.2.3.4 Tanzania

MBG



```
Empirical mean and standard deviation for each variable, plus 2.5% and 97%
quantiles:
                                          2.5%       97.5%
                    Mean        SD   quantiles   quantiles
 (Intercept)      3.0000    0.8470      1.7400      4.4000   *
 pop_ds           0.0000    0.0000      0.0000      0.0000   ***
 NLmean           0.0469    0.0032      0.0413      0.0525   ***
 aridity          0.0000    0.0000      0.0000      0.0001   *
 PET             -0.0001    0.0003     -0.0005      0.0003
 evi             -0.0023    0.0009     -0.0039     -0.0009   .
 lst             -0.0133    0.0045     -0.0200     -0.0050   **
 elev            -0.0002    0.0000     -0.0003     -0.0001   *
 access          -0.0031    0.0007     -0.0042     -0.0020   ***
```

GAM



```
Approximate significance of smooth terms:
              edf Ref.df      F  p-value
s(pop_ds)   6.837  7.596  2.081 0.06297 .
s(NLmean)   8.616  8.949 14.584 < 2e-16 ***
s(aridity)  1.811  2.283  2.428 0.07777 .
s(PET)      1.000  1.000  0.026 0.87297
s(evi)      2.346  2.898  0.767 0.54251
s(lst)      1.000  1.000  2.513 0.11344
s(elev)     1.000  1.000  0.066 0.79742
s(access)   5.521  6.678  0.958 0.45336
s(lat,lng)  6.242  8.799  2.684 0.00494 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Chapter 6

Study 3: Current realities versus theoretical optima: quantifying efficiency and sociospatial equity of travel time to hospitals in low- and middle-income countries

6 Study 3: Current realities versus theoretical optima: quantifying efficiency and sociospatial equity of travel time to hospitals in low- and middle-income countries

The aim of Study 3 is to assess physical accessibility to the nearest hospital by wealth subgroups in the population. We locate all hospitals in Kenya, Malawi, Nigeria and Tanzania using data from their respective MFLs. Then, for every non-overlapping grid cell within the national extents, travel time to the nearest hospital are estimated from a cost-friction surface. Together with gridded maps of population size, the high-resolution gridded poverty maps created for the four study countries in Study 2 are then incorporated in a GIS to help locate where the relative poor and less poor live, thus allowing the estimation of travel time by wealth subpopulation.

As discussed in Study 1, an ideal measure of physical accessibility of facility-based childbirth care should reflect real-life travel to a place where appropriate care, e.g., adequate care to ensure a safe childbirth, can be sought. In Study 3 and Study 4, we use travel time along the road network to the nearest hospital to quantify women's physical accessibility to facility providing such care.

We obtain the equity gap as the difference in travel time between subpopulations at the poorest and least poor locations. Furthermore, overall travel time across the whole population is also determined. A health system that has allocated resources efficiently (focussing on reducing travel time for the average person) should enable the shortest overall travel time across the whole population. Yet such ways to allocate resources may put remote, low population density, and often poorer places in a lower priority, leading to systematic difference in travel time between them and their wealthier counterparts. To assess whether the current distribution of hospitals in each of the four study countries is equitable and efficient, we use a simulation approach to hypothesize alternative locations for hospitals. The observed equity gap and efficiency are compared to the theoretical optima realized through the simulation.

The remainder of this chapter presents the manuscript of Study 3 published in BMJ Global Health in August 2019 (doi: 10.1136/bmjgh-2019-001552).

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Student	Kerry Wong
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Thesis Title	Too poor or too far? Partitioning the variability in hospital birth by poverty and travel time in four sub-Saharan countries

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Research

BMJ Global Health

Current realities versus theoretical optima: quantifying efficiency and sociospatial equity of travel time to hospitals in low-income and middle-income countries

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ABSTRACT

Background Having hospitals located in urban areas where people, resources and wealth concentrate is efficient, but leaves long travel times for the rural and often poorer population and goes against the equity objective. We aimed to assess the current efficiency (mean travel time in the whole population) and equity (difference in travel time between the poorest and least poor deciles) of hospital care provision in four sub-Saharan African countries, and to compare them against their theoretical optima.

Methods We overlaid the locations of 480, 115, 3787 and 256 hospitals in Kenya, Malawi, Nigeria and Tanzania, respectively, with high-resolution maps of travel time, population and wealth to estimate current efficiency and equity. To identify the potential optima, we simulated 7500 sets of hospitals locations based on various population and wealth weightings and percentage reallocations for each country.

Results The average travel time ranged from 38 to 79 min across countries, and the respective optima were mildly shorter (<15%). The observed equity gaps were wider than their optima. Compared with the best case scenarios, differences in the equity gaps varied from 7% in Tanzania to 77% in Nigeria. In Kenya, Malawi and Tanzania, narrower equity gaps without increasing average travel time were seen from simulations that held 75%–90% of hospitals at their current locations.

Interpretations Current hospital distribution in the four sub-Saharan African countries could be considered efficient. Simultaneous gains in efficiency and equity do not necessarily require a fundamental redesign of the healthcare system. Our analytical approach is readily extendible to aid decision support in adding and upgrading existing hospitals.

Key questions

What is already known?

- ► The populations is typically heterogeneously distributed in space. The efficiency of healthcare provision can be optimised by choosing populous locations, especially in densely-populated urban cities, as health facility sites. This generally minimises average travel time, thus meeting the efficiency objective; but leaves long travel times for the rural and often poorer population and decreases equity.
- ► Especially in low-resource settings, the healthcare system is often challenged by the tension of balancing the efficiency and equity objectives.

What are the new findings?

- ► Through quantifying the efficiency and equity of travel time to hospital in Kenya, Malawi, Nigeria and Tanzania, we found that current spatial distribution of hospital in these countries was close to optimally efficient, but tended to be inequitable and pro-rich, and often unnecessarily so.
- ► We showed that the current spatial distribution of hospital in most countries is 75%–90% similar to the hypothetical optimised scenarios.

What do the new findings imply?

- ► While it is unrealistic to imagine moving hospitals, our analytical approach can readily be extended to aid decision support in placing new health facilities and upgrading existing ones while optimising the efficiency and equity objectives.
- ► Maximising total beneficiaries and accounting for those in hard-to-reach areas can be balanced, and achieving gains in both priorities does not necessarily involve a fundamental redesign of the healthcare system.

BACKGROUND

Health services are often provided in relation to population density for efficiency and other economic and political reasons described below. More recently, interests in ensuring equitable access and achieving universal health coverage (UHC)—the aspiration that all people obtain access to the health services they need without risking financial hardship—had grown. While the concept of equitable access is multifaceted, most studies measure the equity of use of key services; nevertheless, physical accessibility remains a fundamental consideration in many low-income and middle-income countries (LMICs) and may be a key factor underpinning inequitable service use. It would be useful to have a tool that assesses both efficiency and equity of existing service locations. This could ultimately be used to identify options which compensate for inequitable physical locations, including by adding facilities or in which locations to best upgrade facilities.

A good level of physical accessibility is attained when healthcare is available and located within reasonable reach to people. Physical accessibility is often expressed as the travel time or distance between healthcare and the population.[1] Service provision strategies that aim to optimise physical accessibility are most efficient when the population's average travel time is minimised for a given total provision cost.[2] Selecting densely populated urban cities to locate health facilities is a good way to achieve the efficiency objective.

Two determinants of hospital locational preference related to population and population density are the economy and politics.[3] Healthcare providers tend to locate in areas with good markets. The private sector is a case in point, but in the public decision-making process of establishing a new hospital or renovating an existing one, location also plays an important role specifically with regard to guaranteeing the profit return on investment.[4 5] The impact of politics on the spatial distribution of healthcare is also recognised. Friedmann examined the effect of geopolitics, observing that power is concentrated in the capital cities and to a lesser extent in provincial headquarters.[6] Such concentration makes urban locations the locus of political power and the homes of the elite, who often have mechanisms working to influence the process of locational and allocational decision-making to their advantage.[7 8] In Nigeria, for instance, it has been argued that the location of public facilities could be affected by reasons including community monetary contributions and political considerations, such as when a commissioner or minister influences the selection of their home-town in health facility site selection.[9] The net effect of all this is that privileged people and places are better served, and rural and remote places less populated, poorer and with worse physical access to health services. Such unequal opportunities to accessing health services can exacerbate existing inequalities in healthcare utilisation, with the marginalised and vulnerable faring the worst.

In most LMICs, governments aim to meet the health needs of those living in rural and hard-to-reach areas with health centres and health posts. If such facilities are considered, then average travel time are reduced, and equity improved. However, many of these facilities only provide outpatient care,[10–12] and the fuller range of life-saving health services—caesarean section, treatment of postpartum haemorrhage, emergency operations, specialised therapies, gynaecology/paediatric inpatient care, just to name a few—are generally only available in hospital settings.[10–12] Health service provision assessments, such as Service Provision Assessment or Service Availability and Readiness Assessment, also often demonstrate that health centres and health posts are underequipped and understaffed for the basic functions that they are expected to perform.[13–15] Equitable distribution of higher-level care is therefore paramount to ensure accessibility to a broad range of services; yet the challenge of which lies in a relatively small effective geographic coverage for the high-cost professionals, equipment and interventions required.

Inequity of physical access to surgical care and emergency obstetric care (services usually provided only in hospital settings) in poorer areas/subpopulations has been shown suboptimal compared with wealthier areas/subpopulations in LMICs in a few national and subnational studies.[16–18] However, there is still a distinct lack of nationally-representative and generalisable studies in the literature. This calls for a better understanding of the trade-off between efficiency and equity intrinsic to public decision-making for higher-level care. The aim of this study is to develop an approach to examine the balance between efficiency and equity of physical accessibility to hospital in four LMICs in sub-Saharan Africa. We calculate the current levels of efficiency and equity, and compare them to their theoretical maxima realised through a simulation exercise. Future applications of our approach could be used to decide where best to upgrade or add facilities.

DATA AND METHODS

Study settings

We studied four LMICs in sub-Saharan Africa—Kenya, Malawi, Nigeria and Tanzania. These countries were selected because they had a complete georeferenced listing of hospitals (master facility list, MFL) and were variable in terms of demography, geography, healthcare financing and health service delivery. National statistics are presented in table 1.

Data

We used five sources of data in this study: MFL, population, friction, Demographic and Health Survey (DHS) and country administrative areas boundary data. MFL data were obtained online.[19–23] All hospitals with recorded geographic coordinates within the corresponding national extents were included (online supplementary A). Hospitals were classified according to the respective MFLs. As the Tanzanian MFL did not include hospitals in Zanzibar, this subregion was excluded. We also excluded one hospital on Likoma Island in Malawi.

We used the Gridded Population of the World population estimate (version 4) for every 1×1 km^2 non-overlapping pixel across the study countries.[24] The Malaria Atlas Project's land surface friction file for all land pixels between

Table 1 Country data and statistics in 2016 (unless otherwise stated)

	Kenya	Malawi	Nigeria	Tanzania
Total area (km^2)[43]	580 367	118 484	923 768	947 300
% land area[43]	98	79	99	94
National population (million)[43]*	47	18	181	54
% urban population[43]*	26	16	48	32
Gini Index[44]†	48	44	49	38
GDP per capita, purchasing power parity (current US$)[43]*	3020	1159	6039	2653
Health expenditure per capita, purchasing power parity (current US$)[43]	157	108	215	97
% out-of-pocket	33	11	72	26
% external	18	54	10	37
% birth registration coverage[45]	67	67	30	26
Number of hospital beds per 10 000 population[45]	14	13	5	7
% population >2 hour travel time to public emergency hospital care[30]	7	7	8	25

*Data from 2015.
†Data from 2013.
GDP, gross domestic product.

85° north and 60° south for a nominal year 2015 was used to enumerate land-based travel speed.[25] The friction value, given as the time (in minutes) needed to travel one metre, represents the generalised difficulty of crossing a pixel depending on factors such as types of road, water bodies and terrain with slopes.[25] In the study region, the minimum and maximum friction values to travel 1 meter were 0.0005 min and 0.3 min—equivalent to travelling at the speed of 120 km/hour and 0.2 km/hour—respectively.

We estimated median household wealth index—a composite measure of a household's cumulative living standard—with DHS data as means of assessing pixel-level wealth. Wealth index was modelled based on a suite of covariates—population density, day-time land surface temperature and vegetation index, elevation, potential evapotranspiration, aridity index and night-time light emission. To derive high-resolution poverty maps, we used model-Based Geostatistics for Kenya and a generalised additive model for each of Malawi, Nigeria and Tanzania. Our choices of modelling methods were based on a previous analysis that compared the performances of these approaches.[26] Lastly, we sourced country administrative areas boundary files from the freely available Database of Global Administrative Area (www.gadm.org).[27]

Calculating travel time to the nearest hospital, efficiency and equity

For each country, travel time to the nearest hospital was computed for every 1×1 km^2 pixel using an algorithm that Weiss and colleagues devised to identify the path that requires the least time through the friction surface between two points.[25] The application of the algorithm on the friction surface to construct an accessibility map enumerating travel time to the nearest hospital has been performed in a previous study.[28] Once travel time to the nearest hospital from all pixels was obtained, we superimposed data on population count and estimated wealth to produce estimates of the average travel time to the nearest hospital (time_{all}) and the same for just the poorest and richest 10% of pixels—$\text{time}_{\text{poor}}$ and $\text{time}_{\text{rich}}$—respectively.

Conceptual and operational definitions

The definition of efficiency in economics is mainly as allocative efficiency and pertains to the optimal distribution of resources for maximum production of health, while technical efficiency refers to the production of health at minimum costs.[29] In this study, we defined efficiency as a function of the average travel time (time_{all}) to the nearest hospital across the population by country, assuming maximum access to care will facilitate the maximum production of health. Optimal efficiency was attained when time_{all} was minimised. On the other hand, equity is often considered in terms of systematic differences that are unjust or unfair, implying a value judgement.[29] For the purpose of this study, we looked at equity from a distributional perspective alongside socioeconomic status, with the aim of achieving equal access to available care for equal need. Our operational definition of equity is then measured as the excess in travel time of the poorest decile compared with the richest decile ($\text{time}_{\text{poor}} - \text{time}_{\text{rich}}$). Optimal equity is characterised by a minimum absolute value of the equity gap—equal physical access to the nearest hospital regardless of the status of wealth. Our calculation and optimisation are summarised in table 2. We compared the observed average travel time and the observed equity gap against their optimal values.

Identifying optimising efficiency and equity through a simulation

For each country, we identified the optimal levels for efficiency and equity using a simulation approach. Conditioned on the observed number of hospitals, and excluding all unpopulated places, we simulated hospital sites from every 1×1 km^2 non-overlapping pixel within the study

Table 2 Study metrics and optimisations

Metrics definition	
Time$_{all}$	Average travel time to the nearest hospital in the population
Time$_{poor}$	Average travel time to the nearest hospital for the poorest 10% of pixels
Time$_{rich}$	Average travel time to the nearest hospital for the richest 10% of pixels
Optimisations	
Efficiency	min(time$_{all}$)
	Minimise overall travel time to the nearest hospital in the population
Equity gap	min(abs(time$_{poor}$ – time$_{rich}$))
	Minimise absolute difference between travel time to the nearest hospital for the poorest and for the richest decile

region. We sampled hospitals locations with five weighting schemes—probability directly proportional to population count and the square of population count, wealth index, inverse of wealth index and unweighted. These weights were chosen based on their potentials to optimise average travel time and the equity gap. We anticipated that, for instance, weighting by population count should minimize average travel time, i.e.,optimise overall efficiency. Moreover, we relocated three different proportions of current hospital sites. The first batch of simulations relocated a random sample of 10% of hospitals from the current MFL using each of the five weights with 500 replicates. The second batch relocated a random 25% of hospitals, and the third with all 100% hospitals relocated. This totalled 7500 simulated scenarios for each study country (500 replicates×5 probabilistic weighting schemes×3 relocation proportions). We calculated time$_{all}$, time$_{poor}$, time$_{rich}$ and the equity gap for each simulated scenarios, and identified the best cases that optimised efficiency and equity. Conditioned on not increasing the observed time$_{all}$, we then identified the best simulation for minimising the absolute value of the equity gap to determine the potential of improving equity of physical access without compromising efficiency.

We also conducted the same analysis using only government/public hospitals, since provision of private sector care may not be efficiency or equity driven, data are likely more credible and complete for public sector facilities, and private hospitals are likely to be particularly unaffordable to the least wealthy subpopulation.

Patient and public involvement statement

We did not involve patients or the public in our work.

RESULTS

Current spatial distribution of hospitals, optimal efficiency and optimal equity

The observed spatial distributions of hospitals in Kenya (n=480), Malawi (n=115), Nigeria (n=3787) and Tanzania (n=256) are presented in figure 1(i)A–D. The observed average travel times to the nearest hospital (time$_{all}$) were 44, 38, 46 and 79 min for the four countries. In Kenya, for instance, average travel time ranged from 11 min for the richest 10% decile to 130 min for the poorest 10% decile (figure 1(i)A)—an equity gap of 119 min. The observed equity gaps of Malawi, Nigeria and Tanzania were 42, 46 and 167 min, respectively.

Maps of simulated hospital locations resulting in optimal efficiency are shown in figure 1(ii)A–D. In Kenya, the most efficient simulation resulted in time$_{all}$ of 43 min (figure 1(ii)A), 2% better than the observed. Time$_{poor}$ of the most efficient simulation for Kenya was 115 min, 11% less than the observed 130 min. The percentages of reduction in time$_{all}$ comparing the observed distribution against the most efficient simulations for Malawi, Nigeria and Tanzania were 4, 13 and 1, respectively; and time$_{poor}$ of these most efficient simulations were also lower than their respective observed values.

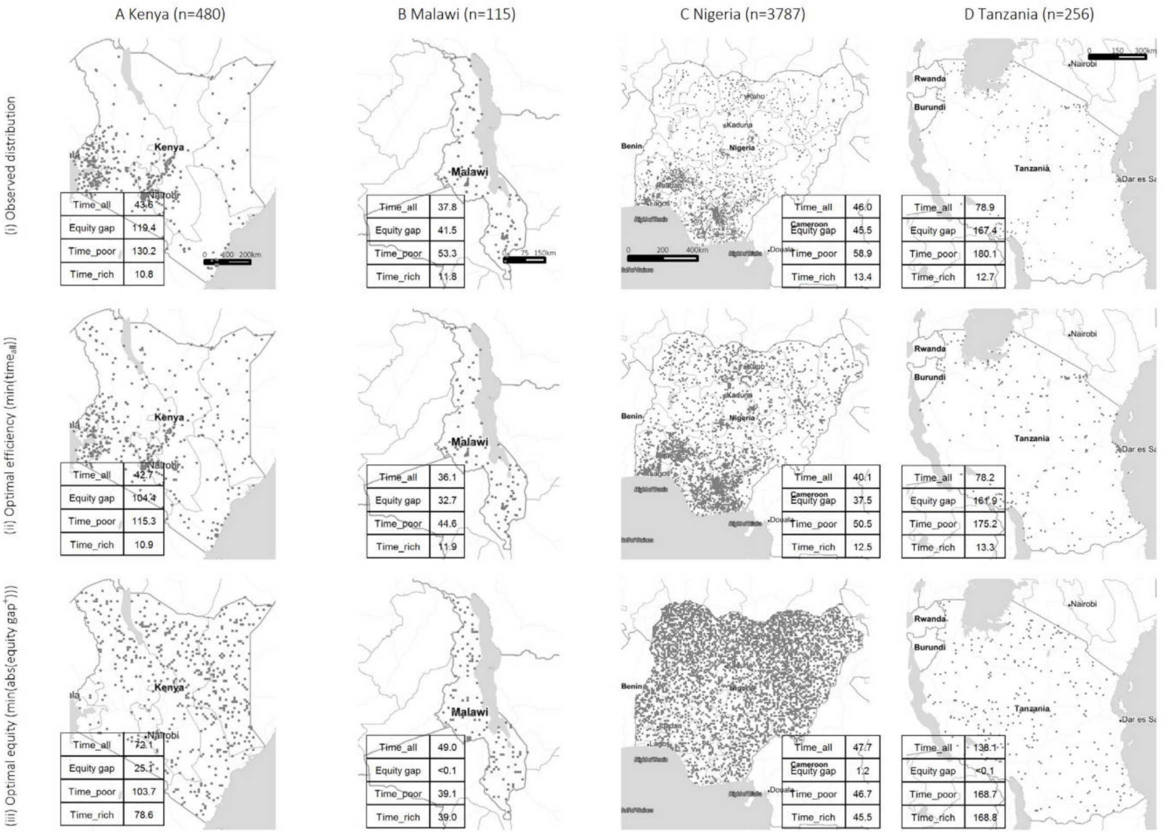
Figure 1(iii)A–D illustrates simulated hospitals locations with optimal equity (minimum absolute value of time$_{poor}$-time$_{rich}$). The equity gap of the most equitable simulation for Kenya was 25 min—79% narrower than the observed. However, time$_{all}$ increased to 72 min and time$_{rich}$ to 79 min. In the other three countries, the equity gaps could almost be fully eliminated, and increases in both time$_{all}$ and time$_{rich}$ from their observed values were also seen.

Online supplementary B shows time$_{all}$ and the equity gap of the observed spatial distributions of public hospitals in Kenya, Malawi, Nigeria and Tanzania. Similar comparisons were seen when these observed values were compared with their respective optima.

More efficient and more equitable

Figure 2 summarises the results of all 7500 simulations for each study country. The numbers of simulation that decreased time$_{all}$ (more efficient) and narrowed the equity gap (more equitable) were 887 for Kenya, 425 for Malawi, 2711 for Nigeria and 81 for Tanzania. Restricting to these subsets which improved equity without compromising on efficiency, the most equitable simulations for Malawi and Nigeria, for instance, narrowed the equity gaps to 29 min (30% reduction) and 10 min (77% reduction), respectively. The associated increase in time$_{rich}$; compared with the observed was small in Malawi (and also in Kenya and Tanzania), but was more substantial for Nigeria (from 13 to 37 min). Lastly, 34, 79, 2070 and 2 simulations remained for Kenya, Malawi, Nigeria and Tanzania, respectively, when further conditioned on not increasing time$_{rich}$.

The 887 simulations with reduced time$_{all}$ and the equity gap for Kenya are shown in the lower-left quadrants (grey area) in figure 3. In Kenya, Malawi and Tanzania, redistributing 10%–25% of hospitals (or holding 75%–90% of hospitals at their current locations) accounted for all those simulations that decreased time$_{all}$ and narrowed the equity gap. In Nigeria, however, simulations that



$^{+}$equity gap=time$_{poor}$-time$_{rich}$

Figure 1 Observed and simulated hospital locations and travel time to the nearest hospital (in minutes).

relocated 100% of hospitals accounted for majority (2274 of 2711, or 84%) of those simulations that were more efficient and more equitable (figure 3).

DISCUSSION

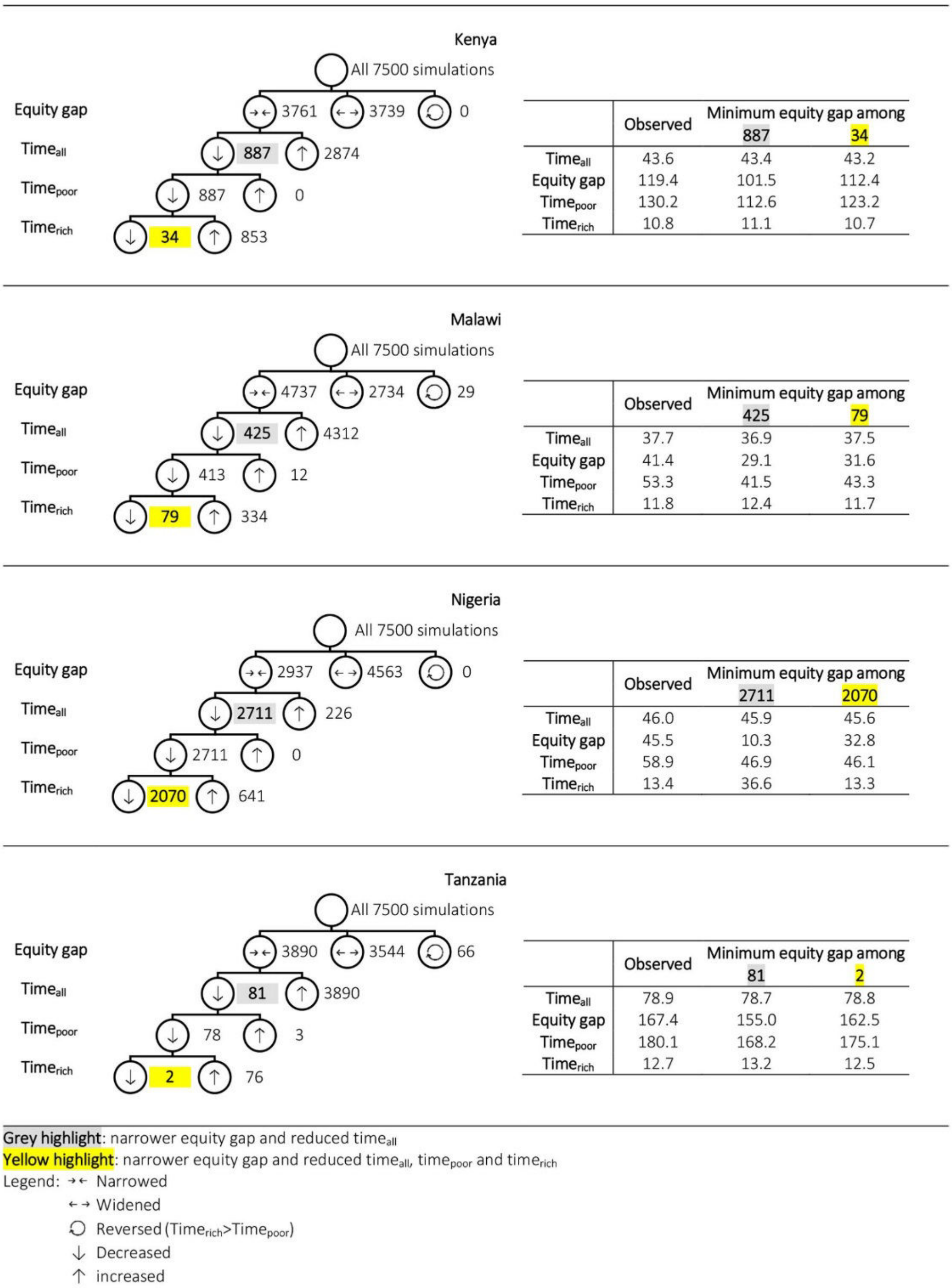
Summary

We conducted a multicountry simulation study to examine the trade-offs between efficiency (average travel time) and sociospatial equity (absolute difference in travel time between the poor and least poor deciles) of physical access to the nearest hospital in Kenya, Malawi, Nigeria and Tanzania. As means of assessing current system performance, we compared current efficiency and equity with their theoretical optima, obtained through a simulation exercise that relocated hospitals and thus provided alternative values for efficiency and equity.

Across the study countries, the average travel time was very close to their respective theoretical optima, but the observed travel time for the least poor tended to be too high for optimal efficiency. Compared with the observed, the best cases for efficiency for Kenya, Malawi and Tanzania were only mildly better (<5%); the best case for Nigeria was 13% more efficient. In all countries but Kenya, the equity gaps in travel time could almost be completely closed, although this would have required the whole population, and especially those living in the least poor places, to travel for longer. Without compromising efficiency, we still found simulations with narrower equity gaps. The potential extent of equity gap reduction varied across countries from being almost negligible in Tanzania to being prominent in Nigeria. Furthermore, simultaneous improvements in efficiency and equity were found from simulations that held 75%–90% of hospitals at their current locations for Kenya, Malawi and Tanzania, while more substantial reorganisation involving up to 100% of hospitals were required in Nigeria.

Strengths and limitations

Empirical research of health service provision across key dimensions of inequality have not been widely conducted due to the lack of suitable data. To our knowledge, this is the first multicountry study to quantify the trade-offs between the conflicting goals of hospital care provision efficiency and sociospatial equity, and to identify current areas of substandard performance in sub-Saharan Africa. Using the Malaria Atlas Project's Friction Surface 2015, we were able to refine the scale of results and generalisability



Kenya

	Observed	Minimum equity gap among 887	Minimum equity gap among 34
Time$_{all}$	43.6	43.4	43.2
Equity gap	119.4	101.5	112.4
Time$_{poor}$	130.2	112.6	123.2
Time$_{rich}$	10.8	11.1	10.7

Malawi

	Observed	Minimum equity gap among 425	Minimum equity gap among 79
Time$_{all}$	37.7	36.9	37.5
Equity gap	41.4	29.1	31.6
Time$_{poor}$	53.3	41.5	43.3
Time$_{rich}$	11.8	12.4	11.7

Nigeria

	Observed	Minimum equity gap among 2711	Minimum equity gap among 2070
Time$_{all}$	46.0	45.9	45.6
Equity gap	45.5	10.3	32.8
Time$_{poor}$	58.9	46.9	46.1
Time$_{rich}$	13.4	36.6	13.3

Tanzania

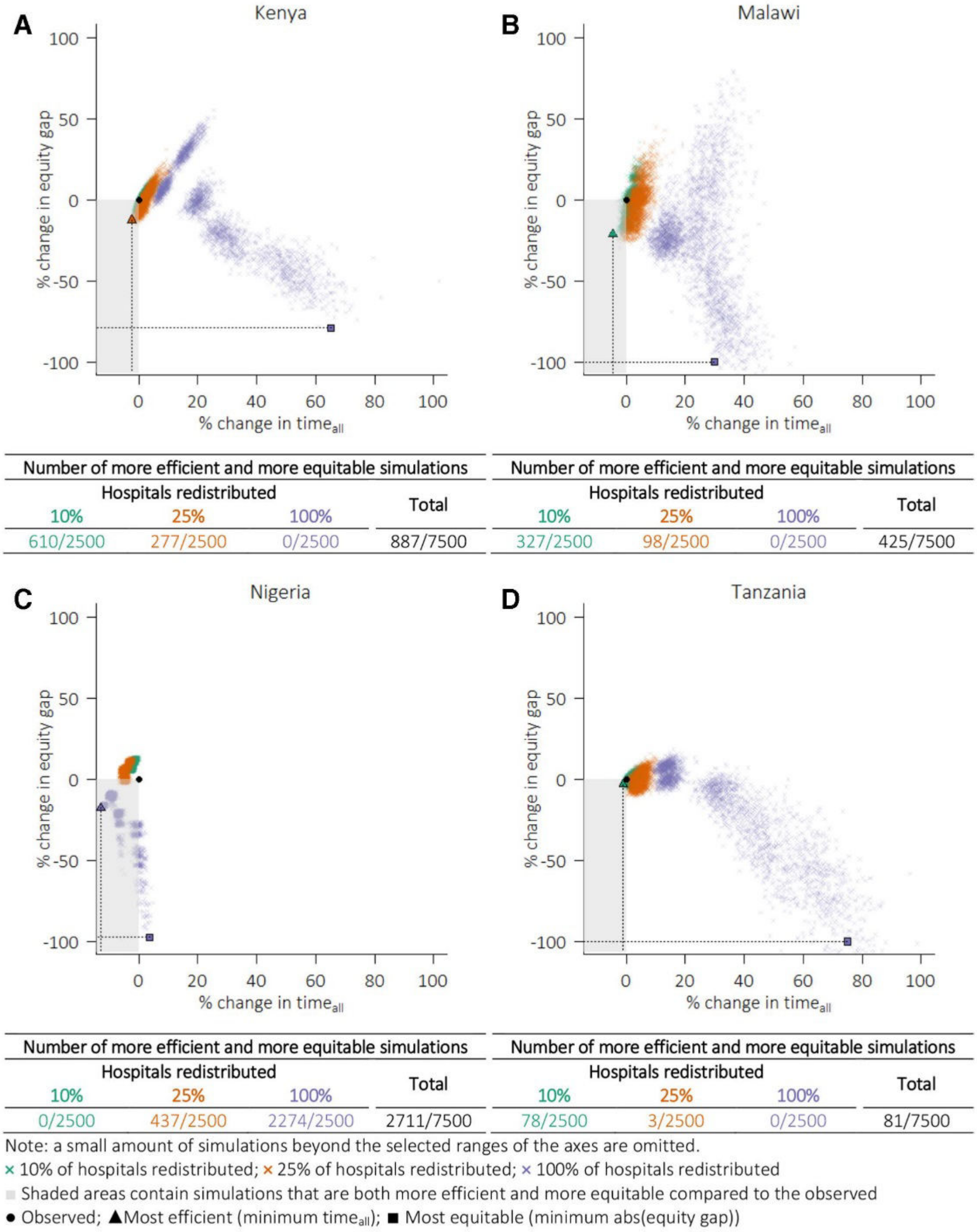
	Observed	Minimum equity gap among 81	Minimum equity gap among 2
Time$_{all}$	78.9	78.7	78.8
Equity gap	167.4	155.0	162.5
Time$_{poor}$	180.1	168.2	175.1
Time$_{rich}$	12.7	13.2	12.5

Grey highlight: narrower equity gap and reduced time$_{all}$
Yellow highlight: narrower equity gap and reduced time$_{all}$, time$_{poor}$ and time$_{rich}$
Legend: →← Narrowed
←→ Widened
↻ Reversed (Time$_{rich}$>Time$_{poor}$)
↓ Decreased
↑ increased

Figure 2 Summary of simulation results in minutes (hospitals in all sectors).

compared with previous studies conducted at the county and sub-district levels.[16–18]

Our results have important implications but should be interpreted in light of their limitations. First, our theoretical optimisation approach did not account for key factors of the possibility and practicability of hospital care provision, including physical environment and the supporting infrastructure. Second, enlisting, georeferencing and validating MFL data require an extensive effort and are prone to error. When compared with Ouma and colleagues' inventory of public emergency hospital care delivery points, we noted certain mismatches in numbers—for example, 399 public hospitals in Kenya from Ouma *et al*[30] against



A — Kenya

Number of more efficient and more equitable simulations			
Hospitals redistributed			Total
10%	25%	100%	
610/2500	277/2500	0/2500	887/7500

B — Malawi

Number of more efficient and more equitable simulations			
Hospitals redistributed			Total
10%	25%	100%	
327/2500	98/2500	0/2500	425/7500

C — Nigeria

Number of more efficient and more equitable simulations			
Hospitals redistributed			Total
10%	25%	100%	
0/2500	437/2500	2274/2500	2711/7500

D — Tanzania

Number of more efficient and more equitable simulations			
Hospitals redistributed			Total
10%	25%	100%	
78/2500	3/2500	0/2500	81/7500

Note: a small amount of simulations beyond the selected ranges of the axes are omitted.
× 10% of hospitals redistributed; × 25% of hospitals redistributed; × 100% of hospitals redistributed
▨ Shaded areas contain simulations that are both more efficient and more equitable compared to the observed
● Observed; ▲Most efficient (minimum time$_{all}$); ■ Most equitable (minimum abs(equity gap))

Figure 3 Relative changes in equity gap and average travel time comparing the observed from simulation results.

390 as obtained from the MFL used in this analysis. These discrepancies may be partially due to different inclusion criteria, such as the provision of emergency services at a facility. We did not make consolidating the whole list a high priority as the small differences found would unlikely affect our results substantially; however, validity check and data completeness assessment might be relevant in future work where manual checking of facilities becomes a feasible task. Third, travel times were derived by varying speeds of travel based on land cover characteristics and topography, and travel time estimates (and wealth estimates) assumed homogeneity among individuals located in the same pixel. Perceived physical barriers, actual travel pattern, road conditions, time spent in transit and so on likely vary among people living in the same pixel and are unaccounted for. Other assumptions of travel friction (eg, the impact of seasonal and temporal variabilities) and wealth (eg, displacement of DHS geocodes) have been detailed elsewhere.[25 26] Lastly, our definition for hospital was based on data on the type of health facility as given in the MFLs; and these hospitals may vary somewhat in

capacity, quality of care and the range of health services that they provide.

Service provision efficiency versus equity

Equity in health service provision seeks a distribution so that everyone has a 'fair' opportunity to access healthcare, and that no sociodemographic subgroup is disadvantaged and left behind. In this study, equity was defined as equal travel time to the nearest hospitals regardless of geographic location and wealth. When compared with the actual geographic locations of hospitals, the best simulated cases for equity across the study countries all had greater numbers of hospitals locating in poorer places, and smaller numbers of hospitals locating in richer places. Because wealth and people typically concentrate at the same places and poverty in others, average travel time on the whole would increase, and overall efficiency compromised.

Compromising efficiency to redress inequity is a distributional issue with geographic, economic and political dimensions.[31] However, without notably increasing average travel time, or reducing efficiency, we still found 'excess' hospital care provision in richer locations in all study countries from our simulation. The equity corrections identified relative to the observed mildly curtail physical accessibility for the rich and shortened travel time for the poor; thereby improving overall access and narrowing the equity gap simultaneously. For Kenya, Malawi and Tanzania, a small difference in the current system involving 10%–25% of hospitals in simulated alternative hospitals locations resulted in gains in both efficiency and equity. Such a small difference indicates the closeness between the current system and the theoretical best scenario. In Nigeria, however, the equity correction involves relocating a larger proportion of hospitals (from south to north, qualitatively). We observed similar results in our sensitivity analysis with public-sector hospitals only, so current equity gap does not appear to exist solely because private healthcare providers concentrate in more profitable populated, urban and rich places. Possible explanations are that Nigeria has too few numbers of hospitals in the north with respect to the number of people supposed to benefit from such services, and somewhat populous settlement patterns in semi-urban places, where sizeable populations are affected by suboptimal physical accessibility. Gaps in service coverage studied here may partially be filled by the provision of pre-hospital care at lower-level facilities and a high-functioning referral system, but in settings such as those studied here, lower-level facilities are often limited in their capacity to manage sick individuals and effectively refer complicated cases upwards, thus rendering people's chances to healthcare utilisation to meet their health needs.[32–34] Expanding the provision of care without consideration of its quality and adequacy to meet the needs of the target population may create a fragmented system that stratify people into tiered benefits.[35]

In this study, we assessed how close the current distribution of hospitals is to the theoretical best scenarios. While existing hospitals are unlikely to be relocated, our simulations help quantify the best cases for efficiency and equity with provision fixed at its current level. The national health sector plans in many LMICs overtly display their commitment to advancing service provision/delivery at both the national and subnational levels as means of moving towards achieving UHC and access to safe, effective, quality and affordable essential health services for all.[36–39] Potential policy approaches to increase access may involve building better road networks and strengthening interfacility communication and transportation services. Building new hospitals is also an attractive project for governments and international funders[40]; and strategies to ensure their integration with the existing system and overall functioning are essential.[40] In LMICs, where the physical and human resources needed to sustain the structure of a comprehensive healthcare system are limited, decision-makers may be interested in the spatial decision mechanism developed here as it provides insights into where a hospital might be added/upgraded to improve existing levels of efficiency and equity. The method presented in this study can be used to support such spatial decision-making by conditioning on all existing hospitals and simulating new locations. The efficiency-equity balance might be particularly pertinent to emergency health services planning due to the critical role of travel time. Some solutions also extend to a hierarchy of health facilities of varying levels,[41] and are suitable for ensuring the population's accessibility to a whole network of both primary healthcare and the wider range of other health services.[40]

A holistic approach to equitable healthcare provision should also take into consideration the rapid population and economic shifts. Urbanisation, secondary cities development and internal migration (rural to urban) amplify the ever-increasing healthcare demand in populated and urban areas. Moreover, rural places are often characterised by topographic and logistical constraints, where adequate healthcare provision requires investment in basic infrastructure (roads, water and sanitation networks, electricity grid) that is difficult for the health sector to finance alone. In many LMICs, there has only been slow to modest progress in meeting the health needs of 'everyone, everywhere'.[42] The preference to perform efficiently, and the maximisation of total beneficiaries, over equity concerns has also been explicated in some policy-making arenas.[42] This raises concerns around structuring the health system so that no one is left behind; and unless health interventions are designed to promote equity, movement towards UHC may lead to improvements at the national level while continuing to exclude the marginalised by reinforcing existing distributional imbalance. This is of particular importance to countries with a low overall access quotient.[30] Analysis similar to that presented in this paper, when a country-geocoded MFL becomes ready to a country, can play an integral role in making sure that the provision of all types and levels of services in local areas are not left behind from the effort of making national improvements.

CONCLUSION

Our results suggest that the goal of bringing hospitals within the reach of the largest proportion of the population is satisfactorily attained. This is probably due to the commendable effort to prioritise healthcare in populated areas. However, current hospital distribution falls short to be equitable, with the health needs of those living in remote and hard-to-reach places most neglected, especially since they also tend to have greater unmet needs of healthcare. A separate set of criteria for establishing new hospitals in scarcely populated and poor places may be needed, despite expected lower cost-effectiveness of such locations compared with urban locales. Our results suggest the possibility of dual optimisation of efficiency and sociospatial equity compared with the current system. Encouragingly, achieving the two goals simultaneously does not necessarily require a fundamental redesign of the current system, and strategies to optimising placement of new facilities are available to help drive future decisions.

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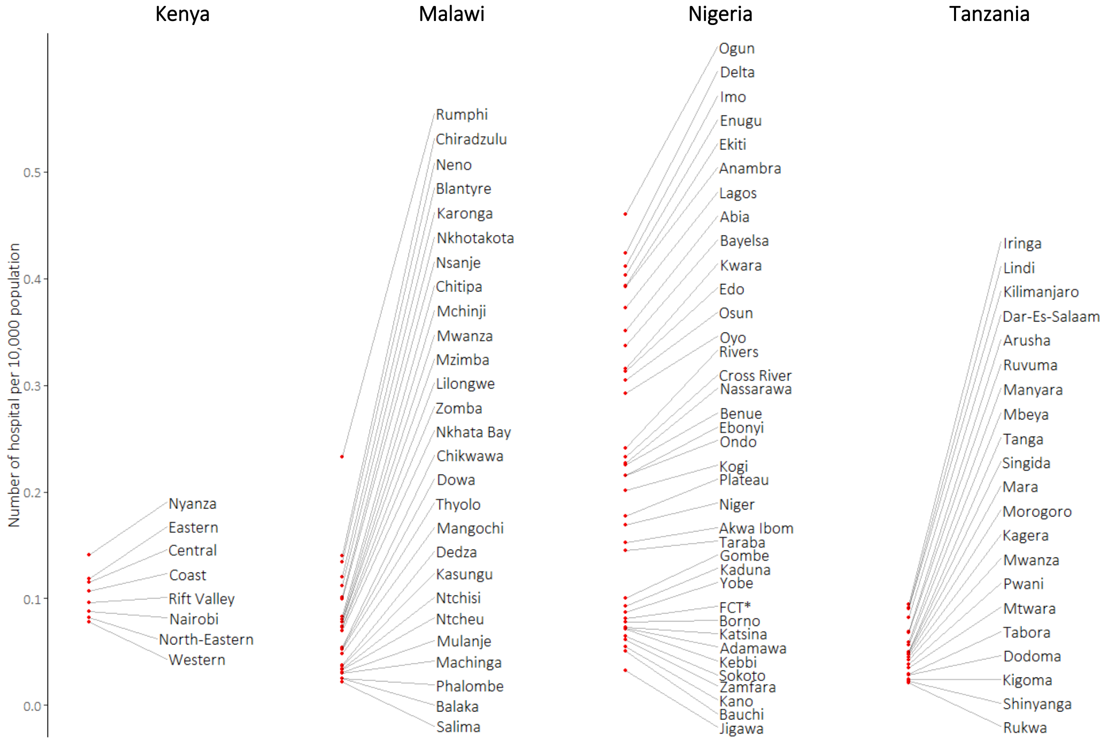
6.2 Supplementary material

6.2.1 Supplementary material A. Facility data from Master Facility List (MFL)

	Kenya	Malawi	Nigeria	Tanzania
Number of facilities	9430	977	33850	7783
Number of hospitals	485	116	3787	265
Number of hospital per 1,000 km^2 land area	0.85	1.23	4.16	0.30
Number of hospital per 10,000 population	0.10	0.07	0.21	0.05
Number of hospitals with no geographic coordinates	5	0	0	9
Number of hospitals included in the main analysis	480	115[+]	3787	256
Number of public hospitals included in the main analysis	390	50	1244	119

[+] One hospital on Likoma Island was excluded from the analysis.

Number of hospitals per 10,000 population by first administrative division



*FCT = Federal Capital Territory

6.2.2 Supplementary material B. Observed and simulated hospitals locations and travel time to the nearest hospital (in minutes)

			All hospitals					Public hospitals only			
			Time$_{all}$	Equity	Time$_{poor}$	Time$_{rich}$		Time$_{all}$	Equity	Time$_{poor}$	Time$_{rich}$
Kenya	Observed	(n=480)	43.6	119.4	130.2	10.8	(n=390)	43.9	118.8	130.2	11.4
	Most efficient (min time$_{all}$)		42.7	104.4	115.3	10.9		43.2	110.5	122.0	11.5
	Most equitable (min(abs(equity gap))		72.1	25.1	103.7	78.6		79.5	24.0	108.7	84.7
	Pro-poor (min(time$_{poor}$))		70.2	26.5	101.0	74.5		69.0	68.0	106.2	38.3
	Pro-rich (min(time$_{rich}$))		44.6	123.4	133.9	10.5		44.6	123.7	134.8	11.1
Malawi	Observed	(n=115)	37.7	41.4	53.3	11.8	(n=50)	44.0	52.3	66.3	13.9
	Most efficient (min time$_{all}$)		36.1	32.7	44.6	11.9		42.5	37.9	51.9	13.9
	Most equitable (min(abs(equity gap))		49.0	<0.1	39.1	39.0		70.4	<0.1	56.5	56.5
	Pro-poor (min(time$_{poor}$))		52.9	-3.8	37.8	41.6		63.1	3.8	45.5	41.7
	Pro-rich (min(time$_{rich}$))		38.5	41.5	53.0	11.5		45.5	49.7	62.4	12.8
Nigeria	Observed	(n=3787)	46.0	45.5	58.9	13.4	(n=1244)	48.3	44.7	60.1	15.5
	Most efficient (min time$_{all}$)		40.1	37.5	50.0	12.5		47.5	50.6	61.7	11.1
	Most equitable (min(abs(equity gap))		47.7	1.2	46.7	45.5		63.6	0.1	60.2	60.1
	Pro-poor (min(time$_{poor}$))		46.0	32.0	45.8	13.9		61.8	26.5	58.9	32.4
	Pro-rich (min(time$_{rich}$))		45.1	49.9	59.0	9.1		49.3	52.1	63.1	10.9
Tanzania	Observed	(n=256)	78.9	167.4	180.1	12.7	(n=119)	92.3	183.6	198.4	14.8
	Most efficient (min time$_{all}$)		78.2	161.9	175.2	13.3		90.6	186.1	201.5	15.3
	Most equitable (min(abs(equity gap))		138.1	<0.1	168.7	168.8		168.7	0.1	198.2	198.1
	Pro-poor (min(time$_{poor}$))		129.5	55.7	150.2	94.5		168.1	96.8	183.8	87.0
	Pro-rich (min(time$_{rich}$))		83.3	174.1	186.3	12.1		96.9	188.0	201.4	13.4

Chapter 7

Study 4: Too poor or too far? Partitioning the variability of hospital-based childbirth by poverty and travel time in Kenya, Malawi, Nigeria and Tanzania

7 Study 4: Too poor or too far? Partitioning the variability of hospital-based childbirth by poverty and travel time in Kenya, Malawi, Nigeria and Tanzania

Study 3 established the extent to which current provision of hospital care is pro-rich in Kenya, Malawi, Nigeria and Tanzania. Such relationship, coupled with the concentration of wealth in urban populous places raises speculation of the potential overlap of the negative effects of poverty and long travel times on the use of hospital-based care, including that for childbirth.

This chapter presents a study that aimed to assess the proportion of variability of hospital-based childbirth in the population that can be explained by variation in poverty and travel time in Kenya, Malawi, Nigeria and Tanzania. At the time of the submission of this dissertation, this manuscript is under review with the International Journal of Equity in Health (submitted in June 2019).

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Student	Kerry Wong
Principal Supervisor	Lenka Benova
Thesis Title	Too poor or too far: Partitioning the variability of hospital-based childbirth by poverty and travel time in Kenya, Malawi, Nigeria and Tanzania

If the Research Paper has previously been published please complete Section B, if not please move to Section C

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Student Signature: ______________________ **Date:** 25 July 2019

Supervisor Signature: ______________________ **Date:** 25 July 2019

7.1 Abstract

Background

In sub-Saharan Africa, women are most likely to receive skilled and adequate childbirth care in hospital settings, yet the use of hospital for childbirth is low and inequitable. The poorest and those living furthest away from a hospital are most affected. But the relative contribution of poverty and travel time is convoluted, since hospitals are often located in wealthier urban places and are scarcer in poorer remote area. This study aims to partition the variability in hospital-based childbirth by poverty and travel time in four sub-Saharan African countries.

Methods

We used data from the most recent Demographic and Health Survey in Kenya, Malawi, Nigeria and Tanzania. For each country, geographic coordinates of survey clusters, the master list of hospital locations and a high-resolution map of land surface friction were used to estimate travel time from each DHS cluster to the nearest hospital with a shortest-path algorithm. We quantified and compared the predicted probabilities of hospital-based childbirth resulting from one standard deviation (SD) change around the mean for different model predictors.

Results

The mean travel time to the nearest hospital, in minutes, was 27 (Kenya), 31 (Malawi), 25 (Nigeria) and 62 (Tanzania). In Kenya, a change of 1SD in wealth led to a 33.2 percentage points change in the probability of hospital birth, whereas a 1SD change in travel time led to a change of 16.6 percentage points. The marginal effect of 1SD change in wealth was weaker than that of wealth in Malawi (13.1 vs. 34.0 percentage points) and Tanzania (20.4 vs. 33.7 percentage points). In Nigeria, the two were similar (22.3 vs. 24.8 percentage points) but their additive effect was twice stronger (44.6 percentage points) than the separate effects. Random effects from survey clusters also explained substantial variability in hospital-based childbirth in all countries, indicating other unobserved local factors at play.

Conclusions

Both poverty and long travel time are important determinants of hospital birth, and the extent to which they determine whether women give birth in a hospital vary within and across countries, meaning different strategies are needed.

7.2 Background

Ensuring skilled care at birth, with the right person in an enabled environment, can prevent mortality and morbidity in women and newborns. In high-burden and resource-scarce settings, such as countries of sub-Saharan Africa, the use of skilled care at birth is still far from universal [1]. A wide range of different social, woman, birth-related, and macro-level barriers to using skilled care at birth have been identified in the literature [2]–[4]. Low household wealth/socioeconomic status (SES) and problematic physical accessibility to an adequate provider are amongst the most persistent barriers. A number of studies have shown that wealthier women consistently report higher use of skilled care at childbirth than their poorer counterparts [5]–[7]. For the poor, the direct (e.g. medical bills) and indirect (e.g. transportation, lost earnings) costs associated with seeking and using skilled childbirth care may be unaffordable [8], [9].

In addition to financial affordability, the lack of physical accessibility to health services also imposes tremendous barriers to using skilled care at birth. Physical accessibility is determined by one's geographic location, and is captured by factors such as the distribution of facilities, travel time or distance from home to facility, availability of transportation, and the condition of roads. It shapes people's options for care-seeking and their decision making [10], and can cause delays in reaching an adequate provider when needs arise[3]. The negative effect of poor physical accessibility on the use of skilled care at birth was first reviewed by Thaddeus and Maine in 1994 [4], and reaffirmed in systematic reviews, including Gabrysch and Campbell 2009 [3], Moyer and Mustafa 2013 [2], Wong et al. 2017 [11] and Tegegne et al. 2018 [12].

Removing financial and accessibility barriers maybe complicated by the correlation between them [13], since resource and infrastructure often concentrate in wealthier urban places, and are scant in poorer and remote areas. Higher availability and better accessibility to healthcare in urban wealthier places may exacerbate the inequity gap in health service uptake between people living in such places and their counterparts in poorer and remote areas. A recent study of wealth inequalities in travel time to the nearest hospital in Kenya, Malawi, Nigeria and Tanzania found dramatic differences between wealth subgroups. Average travel time to the nearest hospital for the wealthiest decile was <15 minutes – 4-14 times shorter compared to the poorest deciles in these countries [14]. Such gap in travel time raises questions regarding the potential overlap of the negative effects of poverty and travel time on use of skilled care at birth, in other words – are women too poor or too far to use skilled care at birth? This question exposes a gap in the current literature about the separate and combined contributions of these two barriers.

To address this question, we propose to examine the variability in the proportion of births occurring in hospitals (rather than in any health facility), since the full range of life-saving "skilled" childbirth services, such as caesarean section and blood transfusion, are typically only available in hospital settings if at all [15]; and equipment and staffing at lower-level, primary facilities (e.g., health centres/posts/huts and dispensaries) are often inadequate for the basic functions that they are expected to provide [16]–[18]. In this study, we quantify the relative contribution of poverty and travel time on rates of hospital birth in sub-Saharan African countries. We also aim to test if poverty and travel time interact. Our results generate insights that can be used for health policy making to ensure that the most left behind expectant mothers receive skilled and adequate care for childbirth.

7.3 Data and methods

7.3.1 Study settings

We studied four LMICs in sub-Saharan Africa – Kenya, Malawi (excluding Likoma Island), Nigeria and Tanzania (excluding Zanzibar). These countries were selected over others in the sub-Saharan African region because they had a recent complete list of hospitals with geographic coordinates, and represented different contexts in terms of demography, geography, travel time to the nearest emergency care and facility-based childbirth. National statistics according to the World Bank[19],the Demographic and Health Surveys Program [20], and the 2015 geocoded inventory of emergency hospitals in sub-Saharan Africa by Ouma and colleagues [21] are presented in Table 7.1.

Table 7.1 Country data and statistics

	Kenya	Malawi	Nigeria	Tanzania
Total area (km^2)[19]	580,367	118,484	923,768	947,300
National population in 2015 (million)[19]	47	18	181	54
% urban population in 2015[19]	26	16	48	32
% of all births in health facilities[a] [20]	61.2	91.4	35.8	62.6
% population >2 hours travel time to public emergency hospital care [21]	7	7	8	25

[a] The most recent Demographic and Health Survey as of January 2019 for each country – Kenya 2014, Malawi 2015/16, Nigeria 2013 and Tanzania 2015/16.

7.3.2 Data and measurement

We used four data sources: (i) Demographic and Health Surveys (DHS) to determine place of childbirth, household location, household wealth and other potential confounders, (ii) a master list of all health facilities with geographic coordinates for each country, (iii) the Global Friction Surface 2015 by the Malaria Atlas Project (MAP) is used in conjunction with (i) and (ii) to determine travel time from household to hospital, and (iv) country administrative boundary files (version 2.5, July 2015) downloaded from the GADM database on gadm.org [22].

First, we used the most recent DHS as of January 2019 for each study country – Kenya 2014, Malawi 2015/16, Nigeria 2013 and Tanzania 2015/16. The DHS collect nationally representative data on population health and sociodemographic characteristics using a multi-stage cluster sampling design with enumeration area as the cluster, or primary sampling unit (PSU). As part of the DHS sampling procedure, a list of established households in each sampled cluster is obtained and used as the sampling frame for household selection [23]. All women aged 15-49 in selected households were interviewed with a standardized questionnaire with questions on all their livebirths in the five years before the survey. All these births were considered in the current analysis.

In each survey, a household wealth index was constructed by the DHS using household asset data via a principal component analysis [24]. Each livebirth is assigned its household's wealth index. The outcome of interest is hospital-based childbirth. For each livebirth, place of childbirth was based on women's answer to: "Where did you give birth to [name of child]?" in the Women's Questionnaire. The major categories of response options were domestic environments (home of respondent, family member, or traditional birth assistant (TBA)), public/government sector health facilities and private/non-government sector health facilities. The DHS conflated clinics and hospitals as one response option for health facilities in the non-government sector for Kenya, Malawi and Nigeria. In line with the approach taken by Hanson and colleagues [25], the categorisation of facility delivery locations into hospital was done in consideration of the local context and health system in each country, and the response options on the survey. Data on other potential predictors of hospital birth, including maternal education, maternal age at birth and birth order, were also sourced from the DHS. We captured the context-specific barriers associated with the lived environment beyond the predictor variables described here by including a random effect at the level of survey cluster.

The DHS include the longitude and latitude coordinates of the population centroids of sampled clusters. All individuals residing in the same cluster have the same geo-referenced location. For anonymity reasons, urban clusters are displaced up to 2 km and rural clusters up to 5 km[26]. We excluded nine clusters in Kenya and seven clusters in Nigeria with missing coordinates from our analysis.

Second, master lists of health facilities were obtained online [27]–[31]. These lists are inventories of all government and non-government health facilities in the country, with data on facility type – hospital vs. others – and geographic coordinates. These lists contain facility data from 2015 (Kenya), 2013 (Malawi), 2010-2014 (Nigeria) and 2016 (Tanzania).

Third, we quantified physical access as the travel time required to travel from the displaced cluster centroid to the nearest hospital using the MAP Global Friction Surface (the friction surface below) 2015. The friction value represents the generalized difficulty to cross a pixel depending on land surface condition, such as the type of roads, water bodies, terrain with slope. Travel time to the nearest hospital was computed for every 1×1km^2 pixels covering the study region using an algorithm devised by Weiss and colleagues [32]. This algorithm identifies the path that requires the least time through the friction surface between two points [32], and has been used to construct accessibility maps enumerating travel time to the nearest hospital in previous studies [14], [33]. DHS suggests generating average values using neighbourhood buffers to moderate the potential impact of point displacements [34]. In this study, we extracted travel time values for each DHS cluster as the average of the four nearest pixels.

7.3.3 Statistical analysis

We tested travel time estimated from the MAP friction surface by comparing 20% of DHS clusters (selected at random) against travel time estimates obtained using data from the OpenStreetMap (OSM) project [35]. We used Pearson correlation coefficient to assess the linear correlation between the two sets of values.

Generalized additive models (GAMs) were used to assess the effects of wealth, travel time to the nearest hospital and other predictor variables on hospital birth [36]. The "mgcv" package for the R statistical package [37] was used to construct mixed-effects GAM models with the application of survey sampling weights. A different GAM was constructed for each country. A GAM model is expressed as

$$\boxed{\mathit{logit(hospital\ birth)} = f_1(\mathit{wealth\ index, travel\ time}) + f_2(\mathit{maternal\ age\ at\ birth}) + \mathit{maternal\ education} + \mathit{birth\ order}}$$

We used the logit link *logit(.)* to relate the predictors with the expected value of the response. Smoothing functions f_i are found for the different predictor variables. We tested whether the effect of travel time varied by wealth using an interaction term specified as a scale invariant tensor product smooth. For this term, we tested two different numbers of knots for smoothing – 5 and 10. A penalized thin plate regression spline was fitted to maternal age at birth, as very young and very old women may use hospital childbirth care differently [38]. A truncated eigen-decomposition is used to achieve the rank reduction [37]. Linear terms were used for maternal education and birth order. We applied survey-specific weighting to account for the sampling procedures used in the surveys.

We present the marginal effects of all predictors from the fully-adjusted mixed-effects GAMs. For each model predictor, we calculated the predicted probabilities of hospital birth for every standard deviation (SD) change from mean – μ±1SD – whilst holding other predictors at the respective sample mean. These predictions showed the effect that varying each predictor variable within a country's population would result in. For normally-distributed data, with a mean and median being the same and 68% of the data falling within 1SD from the mean value, the comparison between μ-1SD, μ, μ+1SD is equivalent to comparing the 16th, 50th and 84th percentiles. The marginal effect of the survey cluster random effect was obtained from the distribution of predicted values with all model predictor variables set to the sample mean. Again, we calculated the predicted probabilities of 1SD around the model mean predicted probabilities of hospital birth.

We further used a response surface to show the additive effect of DHS wealth index and travel time on hospital birth. The predicted probabilities were represented by a colour gradient. Model residuals were plotted as heat maps to show the locations at which the variability of hospital birth was well explained by the fully-adjusted mixed-effects GAM models.

7.3.4 Ethics approval

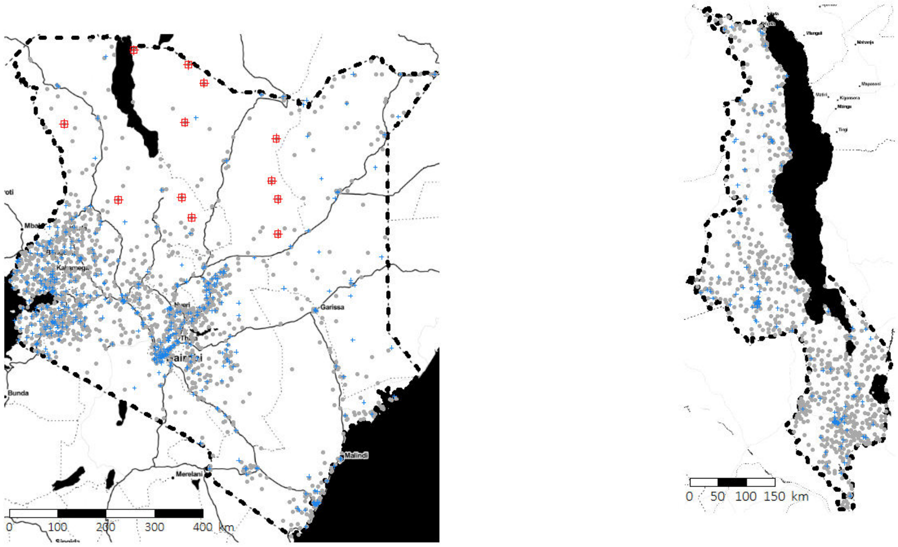
The DHS receive government permission and follow ethical practices including informed consent and assurance of confidentiality. The authors requested and received approval to download and use the data from the DHS websites as detailed under the data sharing page. Master facility lists were publicly available [23]. The Research Ethics Committee of the London School of Hygiene and Tropical Medicine approved our secondary-data analysis (Ethics Ref.: 11890).

7.4 Results

7.4.1 Descriptive

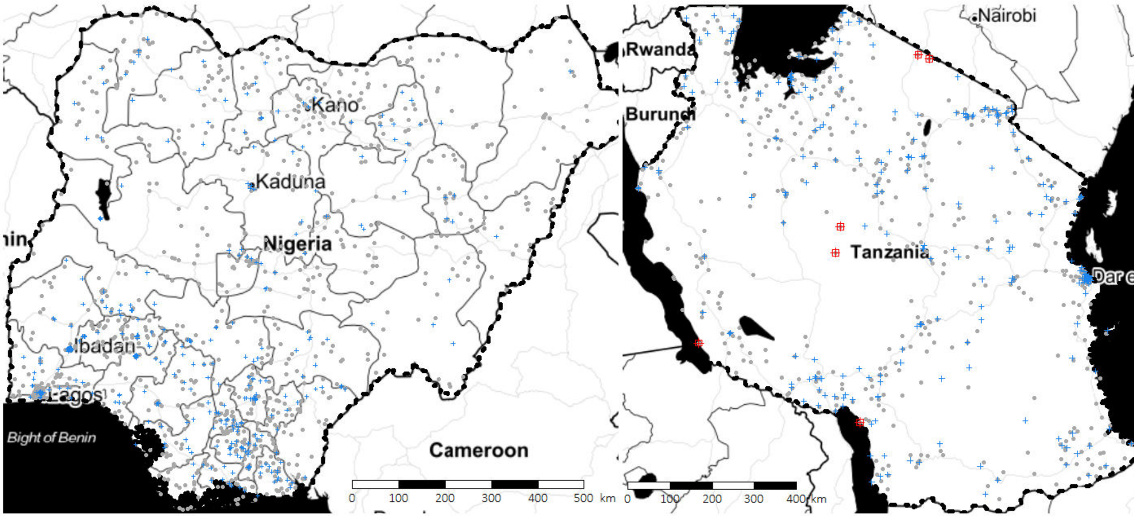
Across the study countries, the numbers of DHS clusters identified were 1565 (Kenya), 828 (Malawi), 889 (Nigeria), and 527 (Tanzania). Travel time estimated from the MAP friction surface and that obtained using OSM data showed good alignment (Pearson correlation coefficients over 0.75 in all countries, see Section 7.8.1), apart from a few clusters with long travel time of ≥5 hours estimated using the MAP friction surface. For this reason, we then excluded 12 and 6 clusters from Kenya and Tanzania from the final analysis (Figure 7.1).

Figure 7.1 Map of the study region, hospitals and DHS clusters



a. Kenya

b. Malawi



c. Nigeria

d. Tanzania

+ Hospital; ● DHS clusters in the study region; ⊞ DHS clusters excluded from the final analysis due to high estimated travel time (see Section 7.8.1).

The numbers of DHS clusters, livebirths and hospitals used in our final analysis are shown in Table 7.2, together with summary statistics of travel time to the nearest hospital and the percentage of births in hospitals by country. Overall, Kenya and Nigeria had the shortest mean travel time from clusters to the nearest hospital (about 25 minutes), and Tanzania the longest (62 minutes). Travel time was highly right-skewed, and a cube-root transformation was used in subsequent analyses. The percentage of births in hospitals ranged between 27% in Nigeria to 39% in Kenya. Majority of hospital births occurred in government hospitals, except in Nigeria, where the shares of government hospital births and non-government hospital births were similar (Table 7.2).

Table 7.2 Summary statistics in study countries

		Kenya	Malawi	Nigeria	Tanzania
DHS survey year		2014	2015/16	2013	2015/16
Number of DHS clusters		1,585	828	889	527
Number of DHS clusters⁺ <5 hours from a hospital		1,573	828	889	521
Number of livebirths included in the final analysis$		19,463	17,384	31,828	8,317
Year of master facility list data		2015	2013	2010-2014	2016
Number of hospitals in the master facility list		485	116	3787	265
Number of geo-referenced hospitals		480	115	3787	265
Travel time to the nearest hospital in minutes					
Mean (standard deviation)		26.6 (40.5)	30.9 (28.5)	25.2 (33.5)	61.7 (58.4)
Standard deviation					
Median (interquartile range)		12.7	24.9	14.2	45.1
Interquartile range		4.1-29.8	10.7-40.7	3.7-34.1	16.9-87.9
Maximum		291.2	268.3	293.9	296.0
Percentage distribution of place of childbirth among livebirths included in the final analysis$					
Hospital	Government sector	30.3	27.4	14.1	23.0
	Non-government sector	9.1	7.9	13.0	8.3
Other health facilities	Government sector	15.8	51.4	8.5	27.1
	Non-government sector	6.1	4.8	0.2	3.6
Not in a health facility (own/TBA/other home)		37.2	7.1	63.2	37.9
Unknown/missing		1.5	1.5	1.0	0.0
Total percentage of hospital childbirth		39.4	35.3	27.1	31.4
Total percentage of facility childbirth		61.3	91.4	35.8	62.1

TBA: Traditional birth attendant

⁺ Excluding Likoma Island in Malawi (22 DHS clusters) and Zanzibar in Tanzania (81 DHS clusters), and DHS clusters without geographic coordinates (9 in Kenya and 7 in Nigeria).

$ The final analysis comprised live births from geo-referenced survey clusters <5 hours from a hospital, and with the same residence at the time of survey and birth (where data was available).

7.4.2 The association of wealth, travel time, other covariates with hospital birth

The deviances explained by the fully-adjusted mixed-effects GAMs were similar using both 5 and 10 knots for smoothing on the interaction term between travel time and wealth (Section 7.8.2). We present results from the simpler models with 5 knots. Results of the fully-adjusted mixed-effects GAMs are shown in Table 7.3. All predictor variables were significant. The mean predicted probabilities of hospital birth obtained from these models were 33.2% (Kenya), 32.7% (Malawi), 26.6% (Nigeria) and 29.6% (Tanzania).

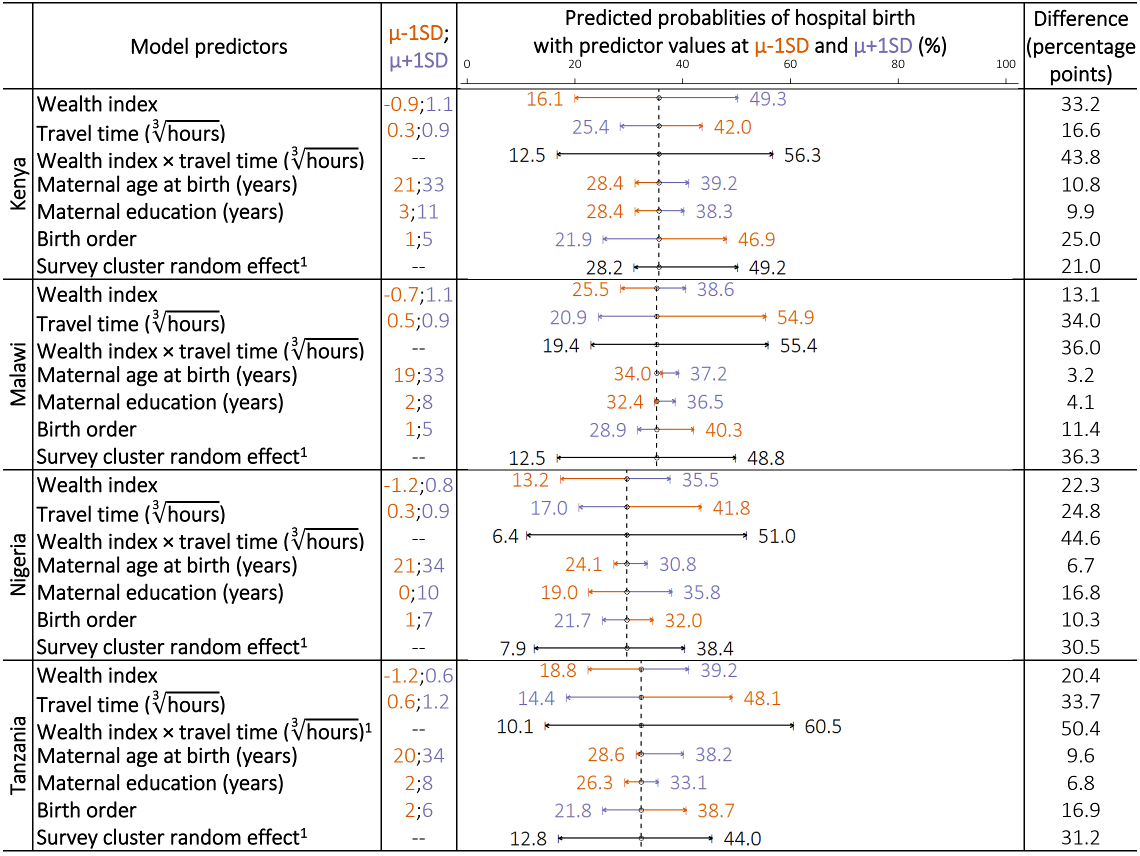
Table 7.3 Results of generalized additive models of hospital-based childbirth by country

	Kenya			Malawi			Nigeria			Tanzania		
Approximate significance of smooth terms	EDF	RDF	p-value	EDF	RDF	p-value	EDF	RDF	p-value	EDF	RDF	p-value
Wealth index × travel time ($\sqrt[3]{\text{hours}}$)	6.48	7.31	<0.00	10.71	24.00	<0.00	11.77	24.00	<0.00	8.37	24.00	<0.00
Maternal age at birth (years)	2.36	2.96	<0.00	2.89	9.00	<0.00	2.54	9.00	<0.00	3.79	6.00	<0.00
Parametric coefficients of linear terms	EST	SE	p-value	EST	SE	p-value	EST	SE	p-value	EST	SE	p-value
Maternal education (years)	0.06	0.01	<0.00	0.03	0.01	<0.00	0.09	0.00	<0.00	-0.05	0.01	<0.00
Birth order	-0.28	0.02	<0.00	-0.12	0.02	<0.00	-0.10	0.01	<0.00	-0.16	0.03	<0.00
Random effects	EDF	RDF	p-value	EDF	RDF	p-value	EDF	RDF	p-value	EDF	RDF	p-value
Survey cluster	515	1052	<0.00	482	609	<0.00	575	701	<0.00	319	481	<0.00
Mean of predicted probability of hospital birth (%)	33.2			32.7			26.6			29.6		

EST = estimate; SE = standard error; EDF = estimated degrees of freedom; RDF = reference degrees of freedom

Figure 7.2 shows the marginal effect of 1 SD change from mean for each predictor variable whilst holding other model covariates at sample mean. In Kenya, compared to the average model-predicted value of 33.2%, a decrease in wealth index by 1SD from the mean reduced the predicted probability of hospital birth to 16.1%, and an 1SD increase from mean brought the predicted probability of hospital birth to 49.3% – a difference of 33.2 percentage points between the 16th and 84th percentiles. The marginal effect of μ±1SD change for travel time was weaker than that of wealth index (16.6 percentage points). The overall additive effect between wealth index and travel time by 1SD around the mean was 43.8 percentage points. The marginal effect of μ±1SD change for maternal age at birth, maternal education and birth order were 10.8, 9.9 and 25.0 percentage points, respectively. Lastly, the survey cluster random effect for 1SD change from mean was obtained from the distribution of predicted probabilities of hospital birth, whilst holding all other predictor variables at the sample mean. Comparing survey clusters 1SD below and above the mean led to a change of 20.0 percentage points in the predicted probability of hospital birth.

Figure 7.2 Marginal effects of one standard deviation (SD) change from mean (μ) of the predictor variables on the predicted probabilities of hospital birth



	Model predictors	μ-1SD; μ+1SD	Predicted probablities of hospital birth with predictor values at μ-1SD and μ+1SD (%)	Difference (percentage points)
Kenya	Wealth index	-0.9;1.1	16.1 49.3	33.2
	Travel time ($\sqrt[3]{\text{hours}}$)	0.3;0.9	25.4 42.0	16.6
	Wealth index × travel time ($\sqrt[3]{\text{hours}}$)	--	12.5 56.3	43.8
	Maternal age at birth (years)	21;33	28.4 39.2	10.8
	Maternal education (years)	3;11	28.4 38.3	9.9
	Birth order	1;5	21.9 46.9	25.0
	Survey cluster random effect[1]	--	28.2 49.2	21.0
Malawi	Wealth index	-0.7;1.1	25.5 38.6	13.1
	Travel time ($\sqrt[3]{\text{hours}}$)	0.5;0.9	20.9 54.9	34.0
	Wealth index × travel time ($\sqrt[3]{\text{hours}}$)	--	19.4 55.4	36.0
	Maternal age at birth (years)	19;33	34.0 37.2	3.2
	Maternal education (years)	2;8	32.4 36.5	4.1
	Birth order	1;5	28.9 40.3	11.4
	Survey cluster random effect[1]	--	12.5 48.8	36.3
Nigeria	Wealth index	-1.2;0.8	13.2 35.5	22.3
	Travel time ($\sqrt[3]{\text{hours}}$)	0.3;0.9	17.0 41.8	24.8
	Wealth index × travel time ($\sqrt[3]{\text{hours}}$)	--	6.4 51.0	44.6
	Maternal age at birth (years)	21;34	24.1 30.8	6.7
	Maternal education (years)	0;10	19.0 35.8	16.8
	Birth order	1;7	21.7 32.0	10.3
	Survey cluster random effect[1]	--	7.9 38.4	30.5
Tanzania	Wealth index	-1.2;0.6	18.8 39.2	20.4
	Travel time ($\sqrt[3]{\text{hours}}$)	0.6;1.2	14.4 48.1	33.7
	Wealth index × travel time ($\sqrt[3]{\text{hours}}$)[1]	--	10.1 60.5	50.4
	Maternal age at birth (years)	20;34	28.6 38.2	9.6
	Maternal education (years)	2;8	26.3 33.1	6.8
	Birth order	2;6	21.8 38.7	16.9
	Survey cluster random effect[1]	--	12.8 44.0	31.2

⌽ National average

[1] The survey cluster random effect for one standard deviation change from mean was obtained from the distribution of the marginal effects with all other predictor variables held at the sample mean.

In Malawi, the marginal effect of 1SD change in wealth was weaker than that of travel time (13.1 versus 34.0 percentage points), and additive effect between wealth and travel time was not notably stronger (36.0 percentage points) than individual effect of travel time alone. In Nigeria, the marginal effects of wealth and travel time was similar (25.3 and 26.1 percentage points), and their additive effect was considerably stronger (48.2 percentage points). In Tanzania, the marginal effect of wealth was weaker than that of travel time (20.4 versus 33.7 percentage points), and their additive effect was stronger (50.4 percentage points). In all three countries, the marginal effects of maternal education, maternal age at birth and birth order were weaker than that of wealth and travel time. Survey clusters 1SD below and above the mean led to a change of approximately 30 percentage points in the predicted probability of hospital birth.

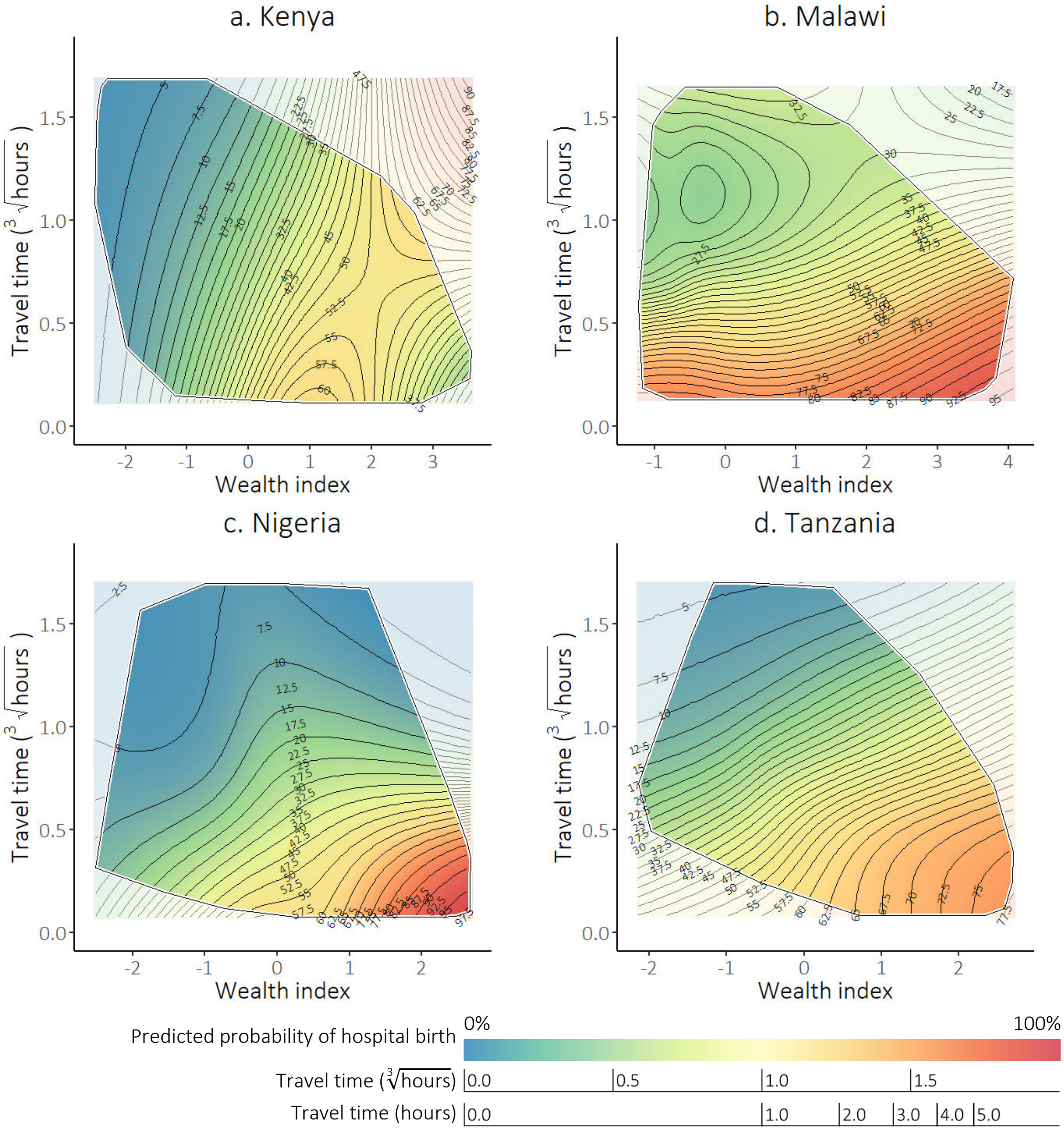
7.4.3 The additive effect of wealth and travel time

We then plotted the additive effects between wealth and travel time as response surfaces, with the other model predictors held at the sample mean (Figure 7.3). The response surfaces show the predicted probabilities as a function of travel time and wealth. In all four countries, livebirths to women who lived closer to a hospital and were from the least poor (lower right corner of the graph) had the greatest predicted probability of hospital birth; whilst the poorest who lived furthest away (top left corner) had the lowest. In Kenya, however, the predicted probability of hospital birth was low for the poorest, regardless of travel time. In addition, the increase in predicted probability of hospital birth with wealth index levelled off for the least poor. On average, in Malawi the predicted probability of hospital birth was high only for those living close to a hospital, regardless of wealth. In Nigeria, the predicted probability of hospital birth was low for those with either a long travel time or a low wealth index.

The angle of the contour lines represents the responsiveness of predicted probabilities of hospital birth to changes in the two predictor variables. Contour lines angled close to being vertical in Kenya show that the predicted probabilities of hospital birth were more responsive to changes in wealth, and the effect of travel time was relatively weaker – in line with results shown in Figure 7.2. In Malawi, contour lines were angled more horizontally, indicating responsiveness of hospital birth to changes in travel time. In Nigeria, hospital birth was most responsive to changes in travel time among those who were far and poor, and less so for those who were far but less poor. The predicted probabilities of hospital birth were more responsive to changes in travel time for those living very far away in Tanzania.

The spaces between contour lines are widest among those who have the lowest predicted probability of hospital birth in Kenya, Nigeria and Tanzania, thus for them a fixed unit decrease in travel time and a fixed unit increase in wealth would have the smallest effect on the outcome. In Malawi, on the other hand, the widest gaps between contour lines were seen for those who have the highest predicted probability of hospital birth, for whom decreasing travel time or improving wealth would have the smallest increase in likelihood of hospital birth.

Figure 7.3 Predicted probability of hospital birth by travel time to the nearest hospital and household wealth index^



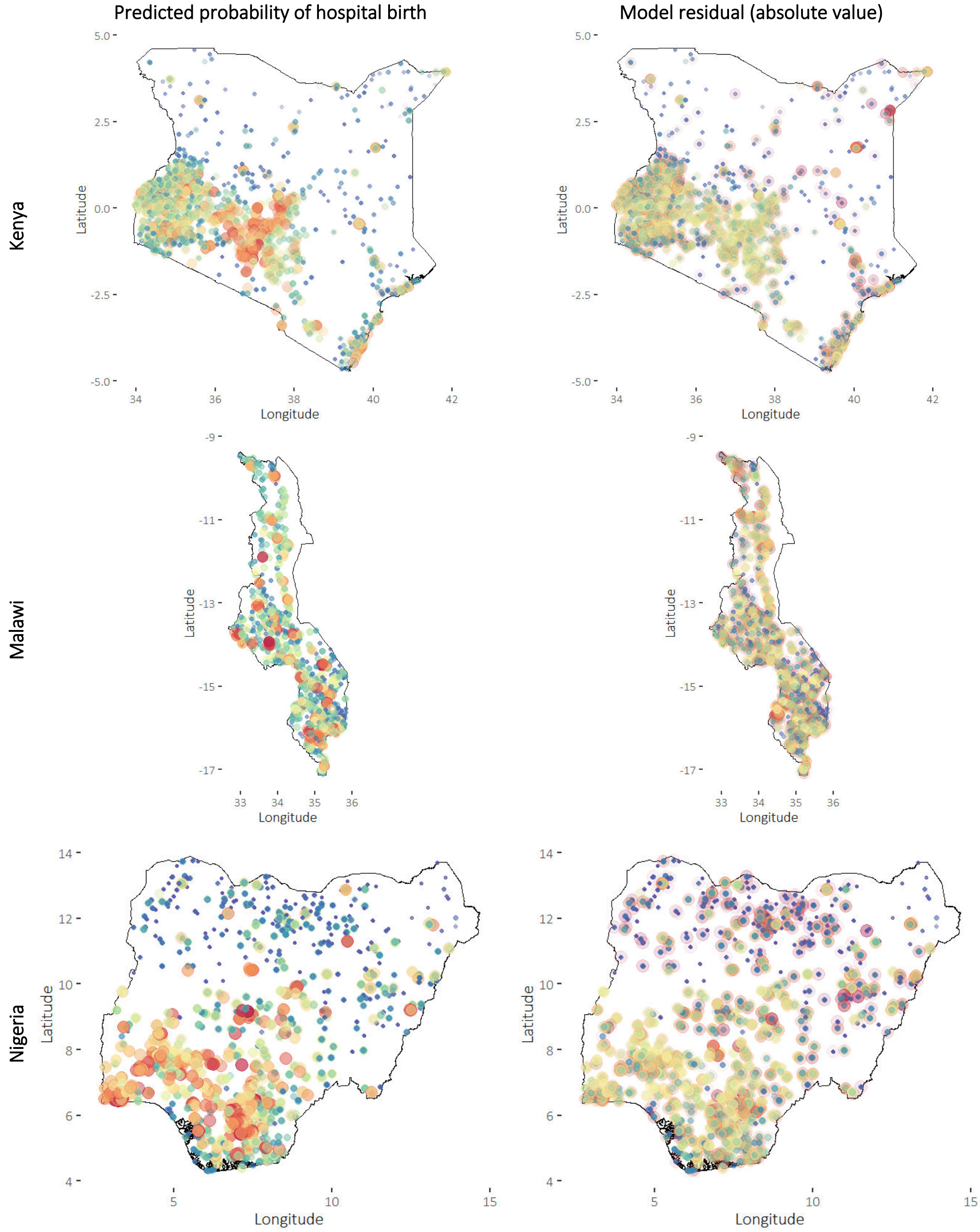
^ Model covariates – maternal education, maternal age at birth and birth order – were set to sample mean. Random effect at the survey cluster level was applied.

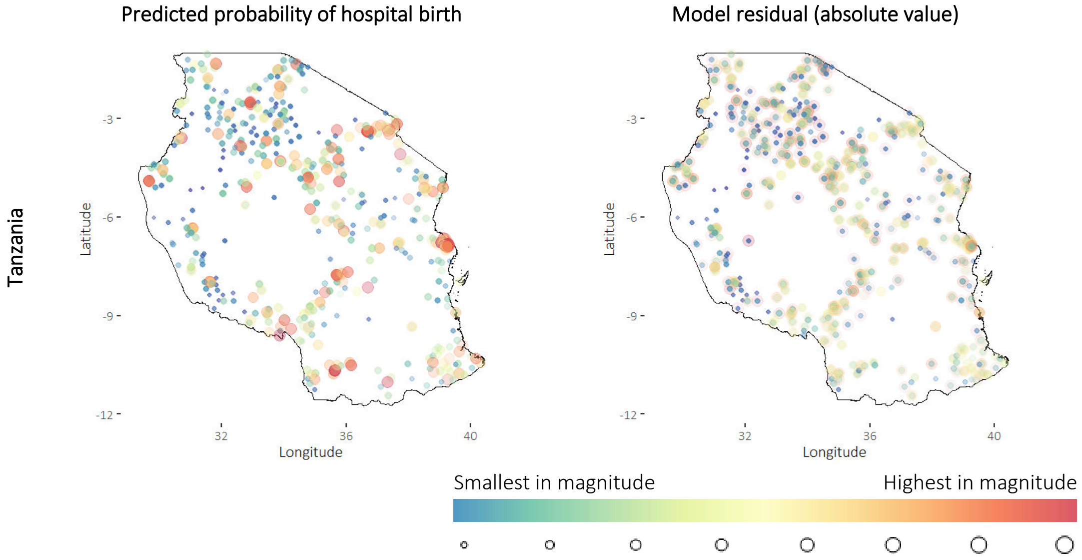
All the observed combinations of values between travel time and wealth index were contained within the border. The colour gradient represents the value of the predicted probability of hospital birth (red: highest probabilities; blue: lowest probabilities). Contour lines are drawn to connect points that have the same predicted values. We drew contour lines for each 2.5 percent point increment in the predicted probabilities of hospital birth.

7.4.4 GAMs residuals

Model residuals can show the extent of the variance in the data not explained by the model, with higher values indicating worse model fit. Model residuals were generally smallest when the predicted probability of hospital birth was low (Figure 7.4), estimated travel time was short and wealth index was low to medium (Section 7.8.3). But there are exceptions; some groups of DHS clusters with low-to-medium predicted values stand out with large residuals, such as in Elwak, Bella Wagberi and Zubak in Kenya, Lilongwe in Malawi, and Kano and Gombe in Nigeria. In Nigeria, both high proportion of predicted hospital birth and high model residuals were mostly in the south, except for some costal clusters in southern Delta and Bayelsa States along the Gulf of Guinea.

Figure 7.4 Model predicted probabilities of hospital birth and model residuals





7.5 Discussion

7.5.1 Summary of study results

Poverty and long travel time to health services are important barriers of maternity care-seeking in LMICs. They are commonly treated as colinear, and their separate effects have not been studied extensively. To our knowledge, this is the first study to partition their effects on hospital-based childbirth. We confirmed the substantial barriers posed by poverty and long travel time in Kenya, Malawi, Nigeria and Tanzania. By separating the effects of poverty and travel time, we found that the situation differed by country. The marginal effect of wealth on hospital birth was stronger than that of travel time in Kenya; the opposite was observed in Malawi and Tanzania. In Nigeria, the two were similar but their additive effect was twice as influential as their separate effects. Also, in Nigeria, hospital birth was generally most responsive to changes in travel time for women who were poor and lived the furthest away from a hospital. In most cases, women who were already least likely to give birth in a hospital would benefit the least from changes in wealth and travel time. Although both poverty and travel time were important, the random effects of survey clusters explained a substantial extent of between-cluster variability in hospital birth in all countries, indicating other unobserved local factors were at play.

7.5.2 Interpretation of results

The differences in the relative contribution of poverty and long travel time on giving birth in a hospital within and across countries identified in our results require a context-specific interpretation. In Kenya, we found that wealth index was the predominant determinant of hospital birth for those from low- and middle-SES households. The Kenyan government has implemented various pro-poor interventions to support the use of maternal health services since the early 2000 – including childbirth fees abolishment in 2007 in government dispensaries and health centres (with the replacement of a registration fee of 10-20 Kenyan Shillings, ≈ 0.1-0.2 US dollars) [39], [40], and from 2006 to 2016 a reproductive health voucher programme under which poor women could purchase subsidized vouchers for 200 Kenyan Shillings to cover the cost of antenatal care, facility childbirth and postnatal care [41], [42]. In 2013, the government extended the abolishment of maternity services (including childbirth) fees in all levels of government health facilities under the Free Maternity Services (FMS) policy [43]. Data used in our analysis primarily included childbirth prior to this change; other studies conducted afterwards have shown positive overall results – including sustained increase in hospital-based childbirth (1-2 years post implementation) [44], [45], higher rates of childbirth in hospitals than in lower-level facilities [46], greater increase of childbirth than antenatal care in hospitals [47], and a mild decline in the use of low-cost private hospital for childbirth [47] – but a 2019 study found small gains in the wealth-inequality of skilled childbirth services following the announcement of the FMS policy due to a relatively small increase in service uptake among low SES women to catch up with existing inequality gap [48].

In Tanzania, where both the number of hospitals by land area and average travel time to the nearest hospital were the least optimal among countries studied here [14], [21], we found that the effect of travel time was greater than that of wealth. Hospitals in Tanzania are primarily located in the southern and northern regions, with lower-level facilities serving rural areas in the central region. The Tanzanian government is committed to expanding service coverage so that people “don’t have to travel long distance to access the services in distant facilities”, putting forward projects to adding and renovating government health facilities in recent health policy plans [49], [50]. Both the Kenyan and Tanzanian governments have shown commendable attempts to support the use of maternal healthcare (including for childbirth) by removing user fees in public health facilities (Kenya and Tanzania) and making services geographically closer to the population (Tanzania) [49], [50]. The implementation of these different strategies, however, seems to face similar challenges. In Kenya, limited pre-existing health infrastructure and other supply-side capacity to match the increased workload following fee removal and insufficient referral and emergency obstetric care capacities contribute to persisting poor maternal (and newborn) health and its inequalities [51], [52]. Indeed, decline in maternal/neonatal mortality and stillbirths does not appear to have followed as a result of increase in facility utilization for childbirth [44], [53]. FMS in Kenyan government facilities may also have limited impact on increasing hospital birth for the poorest and the most remote women/families (among whom mortality and morbidity are typically the highest) due to the small number of hospitals that are within their reach [52]. For Tanzania, some findings suggest that policies directed at reducing distance or travel time, by expanding service provision, deteriorate service quality when scarce resources are diluted. This may put the poorest people who cannot pay the toll to bypass their nearest facility at higher risk of receiving suboptimal care [54], [55]. To ensure adequate care and safe motherhood for all, concerted effort and innovative targeting is required, including strategically merging resources from existing facilities and upgrading service provision in facilities in remote settings. Promising outcomes in physical accessibility and quality of care received have been shown in Tanzania and other LMICs when decisions are supported by the right tools and approaches [55]–[58].

The government of Malawi promotes childbirth at primary health facilities, with referral to hospitals for women known to be at high risk [59], [60]. As part of the Banda era legacy, Malawi had a reasonably strong health centre system, and in a relatively well populated small rural country this meant that most women were not geographically too far from one of these facilities. Health services in the government sector are free-of-charge at the point of use in the country [59]. Since 2006, the government has also been progressively exempting childbirth fees for catchment populations of Christian Health Association of Malawi (CHAM) health facilities (often located in remote area; approximately 40% and 25% of hospitals and health centres in the country are CHAM facilities, respectively [61]). Malawi has attained a near universal facility childbirth rate – 91% of livebirths in the 5 years before the 2015-16 DHS were delivered in a health facility [62] – yet only an estimated 25% of obstetric complications occurred in facilities with the capacity to provide the level of obstetric and newborn care required (such as in a hospital) [63], [64]. In pre-hospital settings, the median distance to the nearest point of obstetric surgical care is over 30km. In *The Lancet*'s Maternal Health series in 2016, Campbell and colleagues called for all women to give birth in health facilities that can guarantee at least basic emergency obstetric care standard and timely referral for women with complications to reach higher-level care to ensure safe motherhood [1]. Our results suggested that the overall effect of travel time on hospital birth was greater than that of wealth, and their additive effect did not substantially explain further variability. Measures should be put in place to improve physical accessibility to EmONC services, including strengthening the capacity of health centres (to which some solutions are available to strategically select locations for facility upgrading that balances travel time across the whole population and equity as defined by wealth subgroups [14]); and expanding the provision of free maternal healthcare at more CHAM hospitals, especially those that are in very remote locales. However, recent reduction of development partners' contribution to the Malawian total health budget has impaired the fee exemption mechanism with CHAM, resulting in certain facilities re-introducing user fees to cope with the financial setback. Such reduction is speculated to be related to internal political instability, scandals and poor governances [59], [65]. Strategies that include fee-based, non-profitable health providers working in rural areas mitigates financial barriers to use of care and expands the options for higher-level health providers that poor remote dwellers are otherwise unable to use, thus shortening the travel time required to obtain and receive adequate care [66], [67]. Long-term implementation of these strategies should not be hampered by unfavourable policy environment and government challenge.

In Nigeria, women who either had to travel for long or were poor were very unlikely to give birth in a hospital. These women concentrated in specific geographic settings, with the poorest being largely in the north, especially in Yobe State, while women travelling for long were mostly in the southern coastal areas in Delta and Bayelsa States. For those in Yobe State, the effect of travel time appeared to be very strong. The state has one of the lowest levels of skilled care for childbirth in the country [68], and while several studies have found ethnicity, social norm and religion as fundamental reasons for homebirths, there were also very few health facilities in the region [69]. Lembani and colleagues further posited that the Boko Haram Insurgency in the area since 2011 has resulted in the destruction and closing of many health facilities, with health personnel preferring to relocate in other areas [68]. The general lack of service provision in the area may have strongly affected the population’s ability to access health services. On the other hand, for those in the south who are approximately equally far but are relatively less poor, wealth played a relatively stronger role. Difficult riverine terrains in Bayelsa State pose additional impediments to overcoming travel-related barriers [70]. Although the area’s energy sector has generated interest among multi-national companies [71], most Bayelsans remain poor, while the state’s public infrastructure is underdeveloped [72], [73]. The proportion of women in Bayelsa who cited financial reasons for homebirth is higher than the national average [74]. Under such special economic and environment conditions, wealth may be additionally helpful for overcoming cost of transport, as well as trade-offs in time and financial loss from daily/productive activities.

In the context of health equity, horizontal equity refers to the principle that people with the same needs should have a similar level of access to the required health services; this contrasts to vertical equity which denotes unequal access to healthcare for people with different needs [75]–[77]. Assuming the need for skilled and adequate care for childbirth is universal or somewhat even across all population subgroups by sociodemographic characteristics (e.g., wealth and place of residence), the principle of horizontal equity is met if service uptake is also similarly distributed. In many LMICs, however, this is not the case. Wealth and physical accessibility of individuals continue to act as drivers of inequitable uptake of health services. Partitioning the variability of hospital birth by poverty and travel time can be useful for broad policy development towards reducing inequity, as a clearer understanding could help focus efforts on bringing the “left behind” and hospital closer to each other, or making childbirth services free of charge/financially affordable. It is also worth noting that our analysis revealed substantial survey cluster random effects, demonstrating local factors other than wealth and travel time are at play, and may limit the impact of strategies that are aimed at removing financial and accessibility barriers. Future studies are required to identify such local factors and how they can be overcome.

7.5.3 Study Limitations

Our results have important implications but should be interpreted with a few limitations in mind. First, the estimation of travel time from DHS cluster centroids to the nearest hospital using the MAP friction surface assumes a generalized travel speed for each type of land surface, which does not account for temporality, seasonality, and transportation used by the individuals. In rural areas characterized by a high level of poverty, walking and non-motorized vehicles remain the major means of transportation, with the adoption of motorized transportation only by those who can afford them [78]–[81]. In urban settings, a wider range of transportation is available to the population. Of these, private mid-sized vehicles – such as matatus in Kenya – have become very common. In poorer urban areas, however, many people still struggle to afford the fees to take these private vehicles and walk, whilst others who can afford them face challenges due to poor road networks of where they live, which can impede matatus from entering [82]–[84]. The additional cost, time and difficulty of movement likely mean that we may have underestimated travel time for poor households, and the true negative effect of long travel time on hospital-based childbirth may be stronger than the effect estimated. Second, accuracy of our distance effect estimate is influenced by DHS coordinates displacement. Applying Karra and Canning's proposed method to correct the biased estimator with the expected minimum distance [85], Sato and colleagues found larger corrected effects than the uncorrected effects for distance on facility-based childbirth and attendance by doctor in Tanzania[86]. The difference, however, were small (<2 percentage points) [86]. Third, we excluded DHS clusters for which travel time estimated from the MAP friction surface was over 5 hours. In checking our travel time estimates against those obtained from OSM Routing Services, larger discrepancies tended to come from long travel time estimates using the MAP friction surface. This only affected a small number of data points (12 in Kenya, 6 in Tanzania and none in Malawi and Nigeria), but more detailed validity assessment of travel time estimates might be relevant in future work where manual checking becomes a feasible task. Fourth, this analysis employed data on livebirths in the five years preceding survey interviews and hospital data at given timespans. Although their occurrences are rare, we may have missed a very small number of hospitals due to their opening, closing, upgrading and downgrading. Fifth, the use of wealth index as measure of poverty at the national level may not accurately identify the very poor [7]; this may be particularly true for Malawi where the data appears to be considerably right-skewed. Sixth, we used one standard deviation around the mean as a consistent unit of change in our comparison of marginal effects of the model predictors.

Other choices of unit (e.g. 5- or 10-year increment in maternal age at birth and maternal education, 60-minute change in travel time) may vary the comparison and lead to different results. Last, our definition for hospital was based on data on the type of health facility as given in the MFLs; and these hospitals may vary in capacity, quality of care, and the range of health services that they provide. Such unmeasured attributes may be confounded with the exposure and outcome of our study.

7.6 Conclusion

By assessing the relative contribution of poverty and long travel time, we found that these two factors determine whether women give birth in hospitals to different extents within and across the four study countries. For the poor and remote who do not give birth in hospitals, the effect of poverty was stronger in some cases, while the effect of long travel time was stronger in others. Given the focus of "leaving no one behind" in the Universal Health Coverage agenda, more precise identification of women and families who are most left behind warrants further research. Such additional understanding can help inform the financial and geographic barriers that people face, device tailor-made system-wide strategies in bringing skilled care to meet health needs, and ultimately contribute to attaining the desired improvements in maternal and newborn health, and the associated inequalities, in resource-limited settings.

7.7 References

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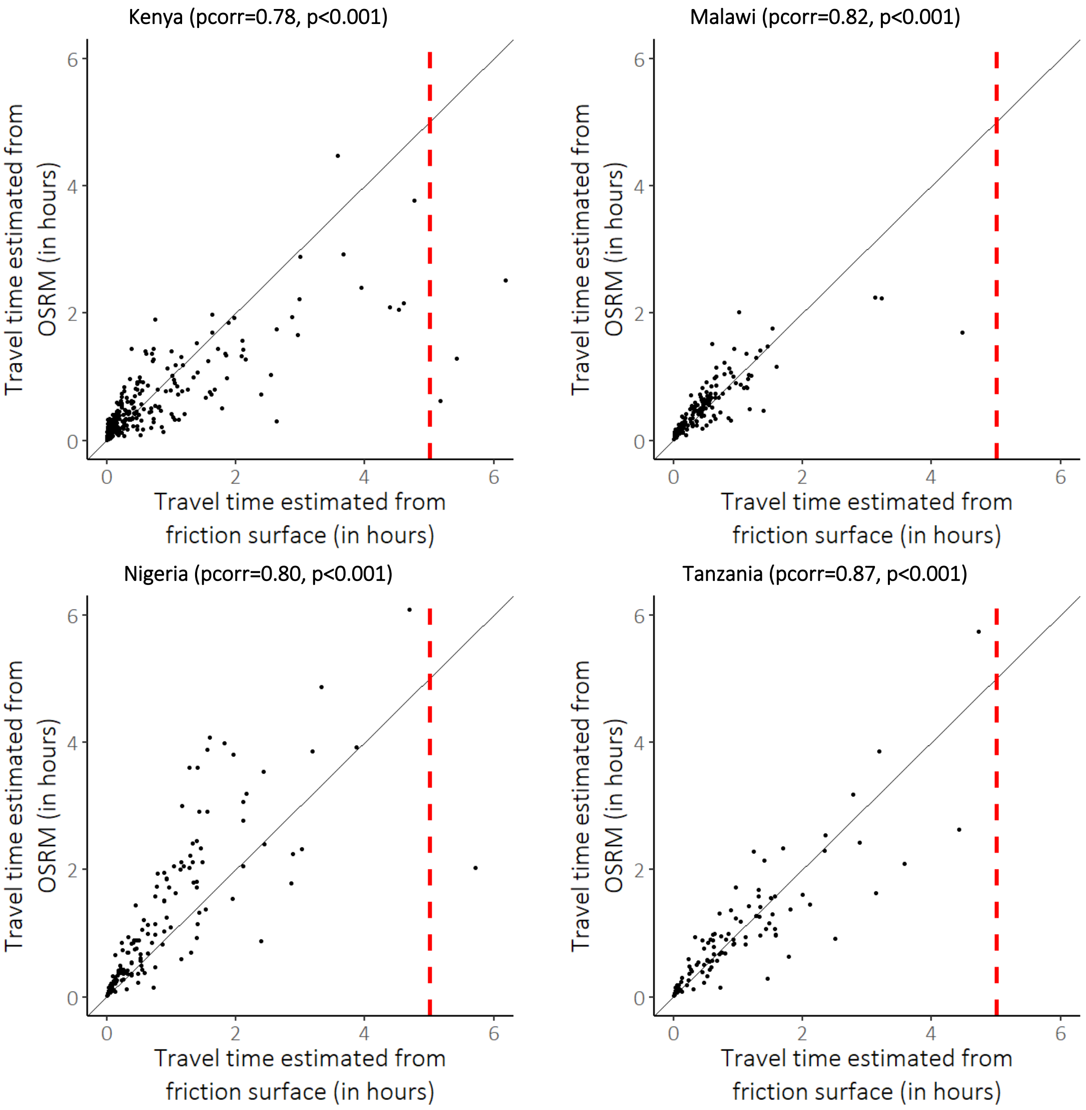
7.8 Supplementary material

7.8.1 Supplementary material A. Checking travel time estimates

Travel time estimated from the friction surface and that obtained from the OpenStreetMap project via the “osrm” package in R are shown in the plots below. Pearson correlation coefficients of the two sets of estimates in all countries are above 0.75. This suggests good alignment of the two. Larger discrepancies between the two sets of estimates arise from longer travel time estimated using the friction surface, with low corresponding OSRM estimates, especially for Kenya and Malawi.



7.8.2 Supplementary material B. Model deviance and model results

Deviance explained (DE) and %DE of different model formulations

Structure of random effects		DHS clusters only			
k used for travel time × wealth index[a]		k=5		k=10	
		DE[b]	% DE[c]	DE[b]	% DE[c]
Kenya	null	21958	--	--	--
	travel time	1388	6.3	--	--
	wealth index	2659	12.1	--	--
	travel time × wealth index	2780	12.7	2787	12.7
	travel time × wealth index + covariates[d]	3435	15.5	3441	15.7
Malawi	null	15472	--	--	--
	travel time	1299	8.4	--	--
	wealth index	645	4.2	--	--
	travel time × wealth index	1443	9.3	1445	9.3
	travel time × wealth index + covariates[d]	1560	10.1	1561	10.1
Nigeria	null	37383	--	--	--
	travel time	5483	14.7	--	--
	wealth index	8785	23.5	--	--
	travel time × wealth index	9157	24.5	9178	24.5
	travel time × wealth index + covariates[d]	10136	27.1	10151	27.2
Tanzania	null	9985.6	--	--	--
	travel time	1633.8	16.4	--	--
	wealth index21.0	1439.4	14.4	--	--
	travel time × wealth index	1889.7	18.9	1895.7	19.0
	travel time × wealth index + covariates[d]	2096.6	21.0	2080.8	20.8

[a] k = number of knots used on the smoothed term for the travel time × wealth interaction

[b] Deviance explained (DE) = DN – DR, where DN is the null deviance and DR = Σ[residuals(MODEL, type="deviance")^2]

[c] %DE = DE * 100/DN, where DN is the null deviance.

[d] Model covariates were maternal education, maternal age at birth and birth order.

Model results for Kenya

```
> summary(gam)
Family: quasibinomial
Link function: logit

Formula:
hosp ~ eduyears + s(ageatbirth) + bord + te(timecube, v191, k = 5) +
    s(v001, bs = "re")

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.182297   0.107594  -1.694   0.0902 .
eduyears     0.064933   0.009418   6.894 5.62e-12 ***
bord        -0.281132   0.017320 -16.231  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                      edf   Ref.df      F p-value
s(ageatbirth)       2.356    2.963 28.950  <2e-16 ***
te(timecube,v191)   6.479    7.306 83.953  <2e-16 ***
s(v001)           514.876 1052.000  1.482  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.305   Deviance explained = 26.8%
-REML = 7062.2  Scale est. = 1.048     n = 15585


> gam.check(gam)
Method: REML   Optimizer: outer newton
full convergence after 6 iterations.
Gradient range [-0.00212677,0.001021191]
(score 7062.243 & scale 1.048045).
Hessian positive definite, eigenvalue range [0.002112653,5803.807].
Model rank =  1532 / 1532

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                       k'     edf k-index p-value
s(ageatbirth)        9.00    2.36    1.00    0.62
te(timecube,v191)   24.00    6.48    0.97    0.01 **
s(v001)           1496.00  514.88      NA      NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Model results for Malawi

```
> summary(gam)
Family: quasibinomial 
Link function: logit 

Formula:
hosp ~ eduyears + s(ageatbirth, bs = "cs") + bord + te(timecube, 
    v191, k = 5, bs = "cs") + s(v001, bs = "re")

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.551906   0.109263  -5.051 4.45e-07 ***
eduyears     0.028308   0.009371   3.021  0.00253 ** 
bord        -0.120546   0.021231  -5.678 1.39e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                      edf Ref.df       F  p-value    
s(ageatbirth)       2.885      9   4.368 4.99e-06 ***
te(timecube,v191)  10.707     24 306.642  < 2e-16 ***
s(v001)           482.247    609   4.064  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.333   Deviance explained = 30.5%
-REML = 5940.8  Scale est. = 1.0127    n = 14047

> gam.check(gam)
Method: REML   Optimizer: outer newton
full convergence after 7 iterations.
Gradient range [-0.004679196,0.004154062]
(score 5940.844 & scale 1.012713).
Hessian positive definite, eigenvalue range [0.4965591,5450.065].
Model rank =  864 / 864 

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                      k'    edf k-index p-value
s(ageatbirth)       9.00   2.88    1.00    0.55
te(timecube,v191)  24.00  10.71    1.01    0.90
s(v001)           828.00 482.25      NA      NA
```

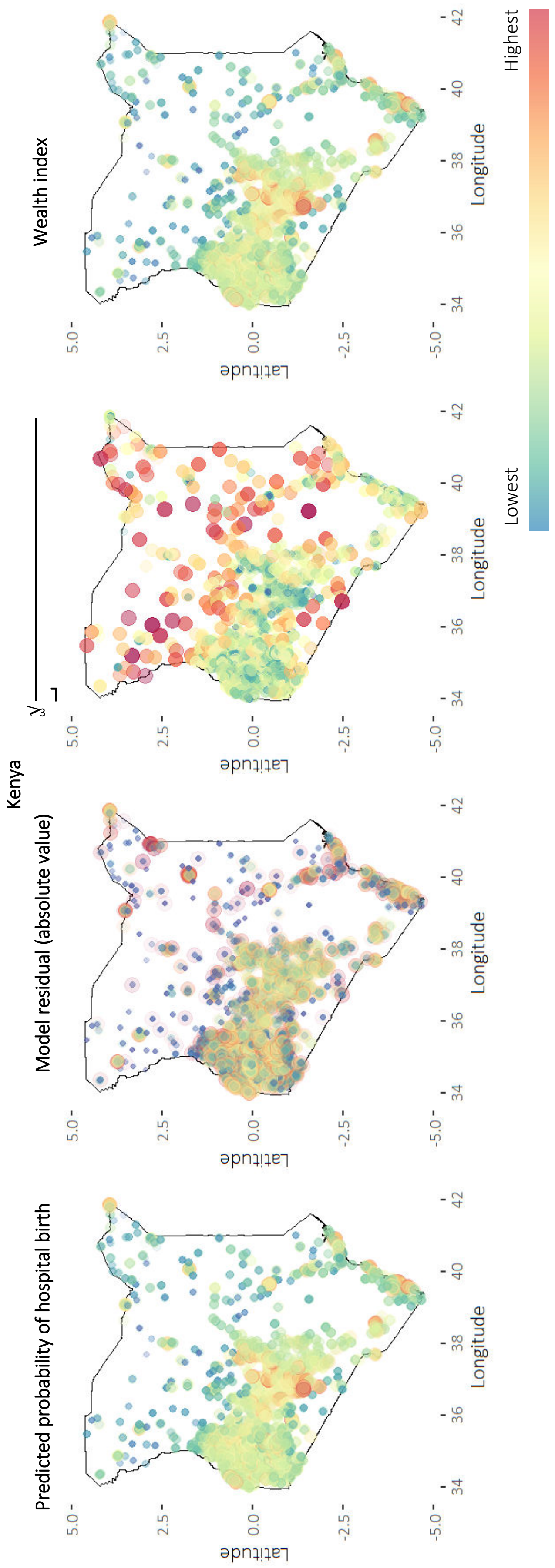
Model results for Nigeria

```
> summary(gam)
Family: quasibinomial
Link function: logit

Formula:
hosp ~ eduyears + s(ageatbirth, bs = "cs") + bord + te(timecube,
    v191, k = 5, bs = "cs") + s(v001, bs = "re")

Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.563824   0.079401 -19.695   <2e-16 ***
eduyears     0.086800   0.004891  17.745   <2e-16 ***
bord        -0.103559   0.011888  -8.711   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                      edf Ref.df        F  p-value
s(ageatbirth)       2.539      9   13.406 1.57e-11 ***
te(timecube,v191)  11.773     24 1023.667  < 2e-16 ***
s(v001)           574.575    701    4.616  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.434   Deviance explained = 41.1%
-REML = 9617.1  Scale est. = 1.0181    n = 31208

> gam.check(gam)
Method: REML   Optimizer: outer newton
full convergence after 7 iterations.
Gradient range [-0.002203074,0.001675076]
(score 9617.06 & scale 1.018132).
Hessian positive definite, eigenvalue range [1.053828,12668.04].
Model rank =  925 / 925

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                      k'    edf k-index p-value
s(ageatbirth)       9.00   2.54    0.99    0.46
te(timecube,v191)  24.00  11.77    0.96    0.01 **
s(v001)           889.00 574.58      NA      NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

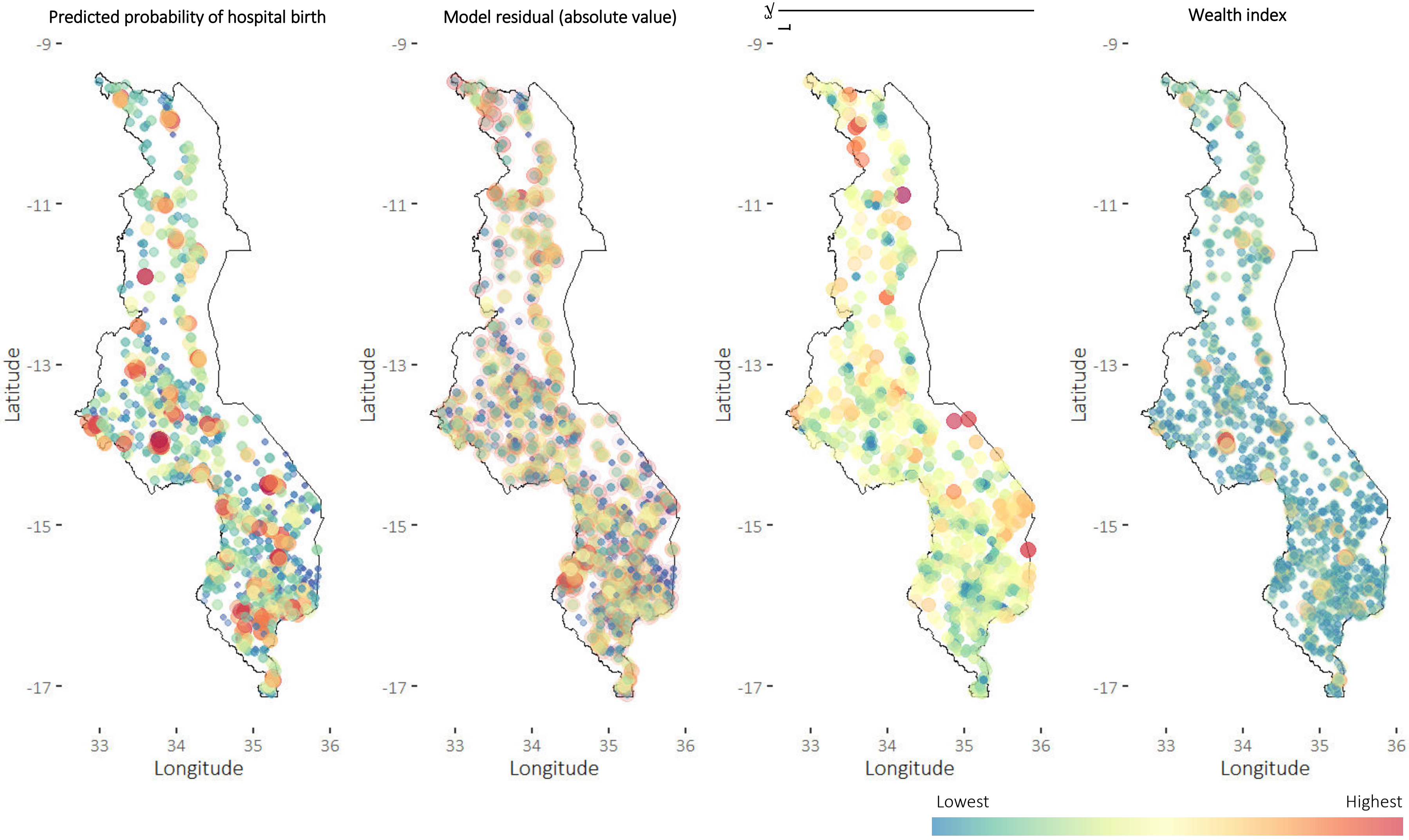
Model results for Tanzania

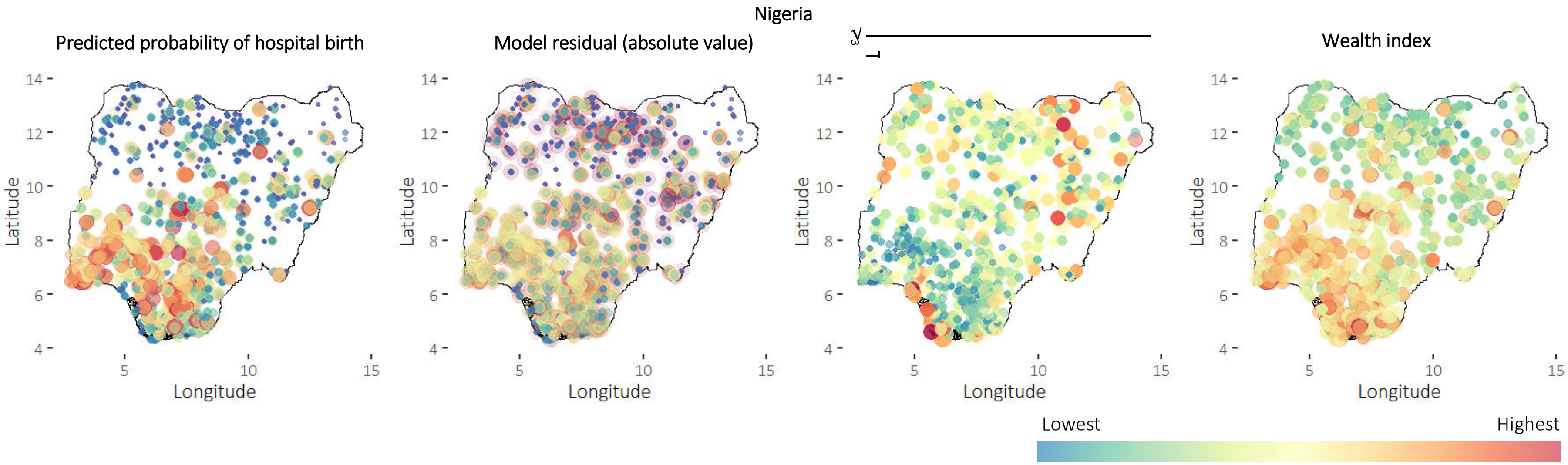
```
> summary(gam)
Family: quasibinomial
Link function: logit

Formula:
hosp ~ eduyears + s(ageatbirth, bs = "cs") + bord + te(timecube,
    v191, k = 5, bs = "cs") + s(v001, bs = "re")

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.79500    0.14563  -5.459 4.96e-08 ***
eduyears     0.05399    0.01145   4.716 2.46e-06 ***
bord        -0.16420    0.02799  -5.866 4.68e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                      edf Ref.df       F  p-value    
s(ageatbirth)       3.791      9   4.985 4.01e-06 ***
te(timecube,v191)   8.373     24 145.732  < 2e-16 ***
s(v001)           318.895    481   1.899  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.374   Deviance explained = 35.5%
-REML = 3242.3  Scale est. = 1.2177    n = 7187

> gam.check(gam)
Method: REML   Optimizer: outer newton
full convergence after 9 iterations.
Gradient range [-1.782754e-05,2.637179e-05]
(score 3242.262 & scale 1.217685).
Hessian positive definite, eigenvalue range [0.9157861,3285.951].
Model rank =  557 / 557

Basis dimension (k) checking results. Low p-value (k-index<1) may
indicate that k is too low, especially if edf is close to k'.

                      k'    edf k-index p-value   
s(ageatbirth)       9.00   3.79    0.98   0.135   
te(timecube,v191)  24.00   8.37    0.96   0.005 **
s(v001)           521.00 318.90      NA      NA   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

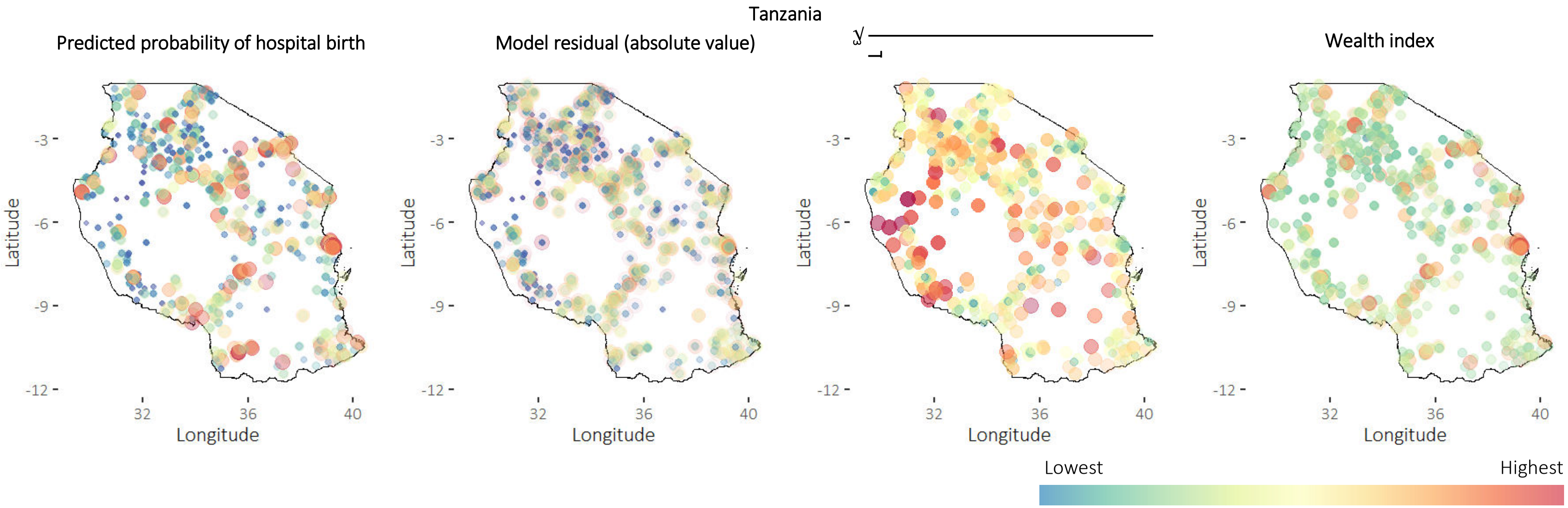
7.8.3 Supplementary material C. Model residuals



Malawi


Predicted probability of hospital birth
Model residual (absolute value)
Wealth index
Latitude
-9
-11
-13
-15
-17
Longitude
33
34
35
36
Lowest
Highest


Nigeria
Predicted probability of hospital birth
Model residual (absolute value)
Wealth index
Latitude
14
12
10
8
6
4
Longitude
5
10
15
Lowest
Highest


Tanzania
Predicted probability of hospital birth
Model residual (absolute value)
γ3
Wealth index
Latitude
-3
-6
-9
-12
Longitude
32
36
40
Lowest
Highest

Chapter 8

Discussion and conclusion

8 Discussion and conclusion

8.1 Summary of key findings

The aim of this dissertation was to assess and partition the contributions of SES and physical accessibility to underutilization of childbirth care in hospitals in SSA. I designed four consecutive studies to investigate this relationship. Their objectives and key findings are shown in Table 8.1.

First, in the systematic review, I found that although some included studies employed more rigorous methods to measure distance/travel time, the standard and quality of most measurements taken were poor. Nonetheless, from those studies that met our inclusion criteria for meta-analysis, we were able to confirm the strong association between increasing distance/travel time and lower use of skilled care at birth (Study 1).

Next, in testing the predictive performances of two multivariate spatial interpolation methods to create high-resolution gridded map of SES in Study 2, neither showed consistent advantages over the other. Rather, their predictive performances differed by a few aspects of the outcome being mapped and the predictors used (e.g., sample density and data distribution). The MBG approach showed better predictive performance in Kenya, which had a nucleated pattern of high SES. On the other hand, spline interpolation as part of a GAM model performed better in Nigeria (prominent north-south divide of SES), and Malawi and Tanzania (pockets of concentration of high SES and no other identifiable global patterns).

Third, building on the poverty maps created in Study 2, travel time to the nearest hospital from lower SES areas was found to be longer than that from higher SES areas in Study 3 – approximately 4.5 times longer in Malawi and Nigeria, 12 times longer in Kenya and 14 times longer in Tanzania. The wealth gap in travel time was partly due to high population density at high SES places, and the preference to select these places as hospital sites to more efficiently maximize the production of health for the same cost. In some occasions, however, the geographic distribution of hospitals was too pro-rich and exceeded the level needed for optimal efficiency.

Finally, the effects of low SES and long travel time on the probability of hospital birth differed within and across countries (Study 4). In Kenya, the marginal effect of μ±1SD of wealth on hospital birth was stronger than that of travel time (33.2 vs. 16.6 percentage points); whilst the opposite was observed in Malawi (13.1 vs. 34.0 percentage points) and Tanzania (20.4 vs. 33.7 percentage points). In Nigeria, the two were similar (22.3 vs. 24.8 percentage points) but their additive effect was twice as strong. Mixed-effects models showed substantial variability in hospital-based childbirth at the level of survey clusters, indicating other unobserved local factors at play.

Table 8.1 Summary of findings in this dissertation

	Objective(s)	Data	Methods	Summary of key findings
Study 1	To systematically review the measurement approaches used in the literature to measure physical accessibility, and to synthesize evidence on what is already known about the importance of physical accessibility to the use of skilled childbirth care (all sub-Saharan African countries)	Primary data collected from five online literature search engines	Narrative synthesis of methods and meta-analysis	Distance and travel time have been measured in many different ways in the 57 articles identified. Some measures, e.g, straight-line distance to the nearest facility, do not meaningfully indicate women’ s physical accessibility to adequate and skilled childbirth care. Furthermore, the details required for a comprehensive understanding of the effect of distance/travel time were only clearly given in a small percentage of the included studies (12 of 57 studies, or 21%). Meta-analysis of 10 studies showed that increased distance to maternity care had an inverse association with utilization (pooled aOR = 0.90/1km, 95%CI = 0.85–0.94); and utilization was universally very low for those who live “ too far” , for whom a further increase in distance/travel time does not have significant effects.
Study 2	To create high-resolution national poverty maps to identify the locations at which the poor and less poor live; to prepare input data for Study 3 (Kenya, Malawi, Nigeria and Tanzania)	DHS, gridded population size, a suite of satellite images, administrative region shapefiles	Spatial interpolation – generalized additive models and model-based geostatistics	Using a hold-out approach, two mapping methods than can both be applied to produce high accuracy, high resolution maps (MBG and GAM) but differ in the ways they capture spatial patterns were empirically compared against one another. Depending on a few factors, including sample density, data distribution, and the underlying spatial pattern of the outcome, their predictive performances differ. The MBG approach showed better predictive performance in Kenya, which had a nucleated pattern of high SES. On the other hand, spline interpolation as part of a GAM model performed better in Nigeria (where SES showed a prominent north-south divide), and Malawi and Tanzania (pockets of concentration of high SES and no other identifiable global patterns).
Study 3	To calculate efficiency and equity of travel time to the nearest hospital; and to develop an approach to compare the observed efficiency and equity to their theoretical maxima with a simulation, in order to examine current balance between the efficiency and equity objectives (Kenya, Malawi, Nigeria and Tanzania)	High-resolution poverty map, country MFL, gridded population size, land surface friction, administrative region shapefiles	Algorithm for finding the shortest paths between two points, simulations of hospital locations	Using a simulation exercise, we were able to make a “ judgement call” about where countries sit on the trade-off between efficiency and equity. We found that the geographic distribution of hospitals is largely efficient in minimizing overall travel time, but leaves a wide inequality gap between wealth subgroups. Those of lower SES always have longer to travel to reach their nearest hospital. Of the four study countries, Nigeria was the most inequitable/pro-rich; the potential loss of efficiency in overall travel time in Nigeria was 13%, compared to 1-5% in Kenya, Malawi and Tanzania. The approach developed here is useful to identify gaps in system performance, and can be extended to select locations most suited for adding/upgrading health facilities.
Study 4	To quantify and compare the contributions of low SES and long travel time on hospital birth (Kenya, Malawi, Nigeria and Tanzania)	DHS, country MFL, gridded population size, land surface friction, administrative region shapefiles	Generalized additive models	Both SES and travel time were important determinants of hospital birth. In Kenya, the marginal effect of SES was stronger than that of travel time (33.2 vs. 16.6 percentage points difference for every ±1 standard deviation around the mean); whilst the opposite was observed in Malawi (13.1 vs. 34.0 percentage points) and Tanzania (20.4 vs. 33.7 percentage points). In Nigeria, they were similar (22.3 vs. 24.8 percentage points) but their additive effect was twice as strong.

The remainder of this chapter is structured as follows – I will first discuss the major strengths and limitations of this dissertation. Thereafter, I review the various lessons learnt across the four studies, alongside a discussion of recommendations for data and measurement, and planning and policy considerations for health service provision. Lastly, this chapter ends with a final conclusion of the dissertation.

8.2 Strengths and limitations

A major strength of this dissertation lies in its approach to provide a perspective for how inequities in healthcare utilization are produced. The concept of "health equity" is multifaceted. Especially in large-scale, multi-LMICs studies which rely on household survey data (e.g., DHS and MICS data), health equity is often measured through health impact and health outcome, with the variability in the population described by the sociodemographic characteristics of people [1]–[5]. Yet an individual's uptake of services is conditioned on their health service provision – the availability of affordable and acceptable health services within reasonable reach – which should be duly considered and acknowledged. Inequality analyses of service uptake that fail to account for the underlying inequalities in the distribution of healthcare provision are confounded by environmental variables separate from the individuals. To my knowledge, this dissertation is the first to quantify the extent to which the poor and non-poor differ in their physical accessibility to health services using existing nationally-representative secondary data from multiple SSA countries. The analytical approaches used in this dissertation are readily extendible and applicable to other countries, help shed light on the production of health inequalities in high-burden settings, and useful to suggest potential mitigation measures.

Other particular strengths of this dissertation include the utilization of some of the newest data (e.g., MAP's friction surface and data from the Gridded World Population (Revision 11)) and emerging, open-source tools (e.g., OpenStreetMap and R) in methodologically rigorous ways. In Study 2, I used a holdout approach to test the performance of different modelling methods for poverty mapping. When there was no one-size-fits-all solution, a data-driven approach can help identify the best method to be employed in specific applications. The computationally intensive simulation approach in Study 3 enabled me to assess the extent to which the current distribution of hospitals efficiently and equitably serves the population, and how this distribution could be optimized.

Despite these strengths, there are limitations to this dissertation. Those related to the geospatial analytical approaches adopted have been discussed in Chapters 5-7. Firstly, an important limitation of this work is the reliability of the secondary data used. In particular, the MFL data may be somewhat incomplete and inaccurate. This can be expected as the number and location of facilities is a dynamic situation, and therefore the task to accurately geo-reference all health facilities is resource-intensive. In the Tanzanian list, for instance, it was noted that some health facilities located in remote areas are accessible only on foot or on motorbike, which has implications on the ability of the fieldworker to travel to these health facilities for data collection to update the MFL [6]. This limitation predominantly leads to underestimation of travel time to lower/primary level facilities, as hospitals in the study countries are typically accessible by road. The collection of MFL data in SSA are further discussed in Section 8.3.1.

Secondly, a conceptual challenge was the definition of what signifies “long travel” or “poor accessibility” between point A and point B. In Study 4, for instance, I have only kept to the relative difference in travel time between subpopulations. Yet it is worth noting that consensus on this matter among researchers and policymakers, including the WHO, is yet to be established (see Section 8.3.1 for further discussion).

Thirdly, the categorization of “hospital” versus “not a hospital” to indicate the provision of adequate care for childbirth has two potential issues. First, misclassification; since some hospitals may not meet the minimal practice recommended for childbirth (such as those proposed by Campbell and colleagues – at least BEmONC capacity, with facilitated referral to a CEmONC facility capable of the other two signal functions – caesarean-section and blood transfusion [7]), and conversely, some non-hospitals may qualify. The results of a systematic review published in 2013 showed 66% of hospitals in SSA lack electricity [8]. In Malindi District, Kenya, Echoka and colleagues found that of the 50 health facilities assessed (comprising 3 hospitals and 47 non-hospitals), none met the WHO requirement for emergency obstetric care [9]. In a general environment where hospitals often do not meet all the requirements needed to provide adequate childbirth care at the CEmONC functionality level, it may be reasonable to assume that non-hospitals are less subject to misclassification (as hospitals), and that their true capacity to provide adequate childbirth care was indeed low. Hence, our estimates of travel time to the nearest hospital (as an indicator of physical accessibility to adequate childbirth care) are prone to underestimation. Second, even if both types of misclassification were negligible, hospitals differ in a wide range of aspects/”characteristics”, such as the quality and content of care provided, availability of medical supplies and commodities, bed capacity, the extent of overcrowding, opening hours, staffing configurations and their attitude. These nuances have been overlooked in this dissertation (all hospitals are assumed to have an equivalent capacity and offer identical care), when many of them have practical implications on the geographic distribution of “good quality care”.

Fourthly, we only focused on the disparities of physical accessibility and utilization at the national level, and our results may therefore not be generalizable at smaller geographic scales, such as in an intra-urban setting. This is because the variability in physical accessibility (as distance or travel time) to the nearest hospital in such a setting may not differ substantially between the poor and non-poor, and thus may not be expected to have a substantial contribution to the variability in the uptake of health services. However, evidence from a recent review demonstrates that health service provision in urban settings in many LMICs is inequitable, often failing to serve the poor and informal communities [10]. Such failure typically involves systematic differences in staffing patterns, availability of services and standards of care between communities, leading to health inequity in an intra-urban setting [10]. The use of better population data, facility data and mixed-methods studies combining quantitative and qualitative research approaches to identify relevant factors beyond physical accessibility are recommended for future research.

Fifthly, the modes of transport used by people according to their wealth and how these affect travel times have implications on the conclusion related to wealth and travel time and hospital birth that are drawn in this dissertation. The approach I used to estimate travel time between the population and hospitals assumes the "least cost" – i.e., the use of the fastest transport mode. On roads where cars can pass, for instance, a driving speed is assumed even though a given individual may walk. For low-SES people, the assumption that the fastest transport is used may not hold true. Previous studies have revealed certain relationships between poverty and the mode of transportation used when people care seeking from health facilities. In Congo [11], Kenya [12] and Zambia [13], but not in Uganda [13], poorer women tend to be more likely to walk to seek care instead of using motorized means of transportation. The general tendency for poorer individuals in low-income settings to walk was not accounted for in this dissertation. Such tendency may underestimate travel time for the poor in the analyses in Study 3 and Study 4. The true gap in accessibility by wealth may thus be wider than that reported in Study 3; and the true negative effect of long travel time on hospital-based childbirth may be stronger than the effect estimated in Study 4. Existing transportation patterns by SES should be considered in future travel time estimation, as well as in the design of policy efforts to address transportation challenges faced by all, but particularly by the poor.

Finally, residual confounding may occur if confounding is still present after the inclusion of an explanatory variable has been included in the model nominally adjusted for its effect. In Study 4, we found that increases in utilization of hospital childbirth care is associated with improvements in SES (higher SES) and travel time (shorter travel time). However, both SES and travel time are correlated with certain unobserved variables that could be the underlying causes of underutilization – e.g., social or cultural reasons, lack of access to information, suboptimal standard/quality of care and etc., which may be more prevalent in rural poor communities. This means that the modelled increase in hospital-based childbirth achieved by improving SES and travel time might have been overestimated.

8.3 Lessons learnt and recommendations

8.3.1 Data and measurement

At the time of this research, I was only able to access publicly available geo-referenced MFLs comprising all health facilities from both the government and non-government sectors in four countries in SSA. Compilation of a country MFL is strongly recommended, and its benefits detailed in Section 3.3.1.1, but the cost of compilation and keeping such data up-to-date remains a challenge in low-resource settings. An exciting new release in July 2019 by the Kenya Medical Research Institution and global partners made a major contribution to filling this gap [14]. This effort involved geo-coding a comprehensive list of 98,745 public and private-not-for-profit health facilities across the continent. Information on the facility type and ownership are also included. This extensive list has been made publicly and freely available online. Such useful and informative resource will become an essential tool to assess effective planning, coordinating and delivery of health services in the future.

The authors of this list, however, excluded facilities in the private-for-profit sector since they are typically located in urban centres, accessible only to those able to afford them, unregulated and often do not feature in MoH commodity distribution systems [15]. Exclusion was further due to a pragmatic consideration of the difficulties with enumeration within the private sector, and the complexity of its structural and organizational system. Indeed, the decision-making process of the type of facility to enumerate in an MFL is complex. The type of services that the MFL should represent is a major consideration, yet the data sources that can be used to identify a facility and gather facility information poses limitations in practice [16]. In Kenya, for example, one of the objectives of the MFL is to have an inventory of every facility that is "available to see patients, whether public or private" [16]. In addition, the recent development of the Rwandan MFL was also determined to include all private health facilities, and where it was not possible to get data from private facilities from the usual data sources, targeted visits were made to collect data directly from health facility representatives under the coordination of MFL administrators [17].

In Haiti, the 2010 earthquake prompted an urgent need for the creation of a comprehensive geo-coded MFL. At the time, private health facilities provided 75% of the country's health services, and their inclusion in the MFL was thus essential. The establishment of the proposed MFL corresponded to the development of an online facility registry service [16]. This registry required private health facilities to register to be able to provide health services in the country. This requirement spurred private health facilities to supply relevant information [18]. On the other hand, in the Philippines, the original MFL limited the types of private health facilities inclusion to private hospitals only, since they are licensed and thus easily identifiable [19]. This was not the case with lower-level private health facilities, making them challenging to profile, validate and keep up-to-date [16].

Over the last two decades, the private sector has grown rapidly as a key provider of health services in many countries in SSA [20], [21]. I echo the call of Maina and colleagues for the need to include private sector providers in future MFLs following improvements in their enumerations and auditing at the national level, particularly BEmONC and CEmONC facilities as they are essential to safe motherhood and newborn survival [14]. Private institutions and professional networks in LMICs are strongly encouraged to provide data about facilities [16]. Motivations for their engagement include access to facility data, improvements in business processes, potential expansion of business based on MFL information and enhancement of service/product offerings [16].

Two findings from Study 1 in this dissertation were insightful to the subsequent studies in this dissertation. Firstly, the systematic review identified many studies that did not adequately capture distance/travel time to a capable childbirth care provider. Measures such as straight-line distance to the nearest health facility captures neither the reality of travel duration or the level of care that can be expected. In Study 3 and Study 4, I specifically used estimated travel time to the nearest hospital as a measure of physical accessibility to skilled childbirth care. However, modelled estimates and others obtained in a similar manner (e.g., using the WHO's AccessMod, a standalone software to model how physically accessible existing health services are to the target population) have their limitations as discussed in earlier chapters. Estimating/modelling travel time in LMICs is still in its early stages of development. Some work to map the actual travel route in a LMIC setting is already in the pipeline [22], and can be a useful resource to validate current travel time estimation procedures in future research.

Secondly, Study 1 did not find conclusive evidence to suggest the existence of a critical threshold at which distance or travel time can be deemed "too long" to deter the utilization of skilled care for childbirth. Indeed, consensus on this front among researchers, policymakers and the WHO is weak. Living at a place of residence within 1 hour of maternity and perinatal care specialists, given available transport facilities and reasonable assumption about access and personal mobility, has been suggested as an indicator of the healthiness of the lived environment by the WHO [23]. Confusingly, the WHO also considered having “basic and comprehensive facilities available within 2-3 hours” as a “reasonable standard” in a handbook on monitoring emergency obstetric care [24]. Meanwhile, Measure Evaluation has proposed a 2-hour “by the most common mode(s) of transportation” as a cut-off [25]. The 2 hours benchmark has certain clinical bases as it is considered the average time between onset of untreated severe postpartum haemorrhage and death [6]; but the scientific evidence is incomplete and further research is needed to guide health planning and policymaking.

8.3.2 Health service provision

8.3.2.1 Equitable access to health services

Equity of quality healthcare provision is a major cornerstone of universal health coverage (UHC), and a crucial aspect of health system performance [26], [27]. While it is logical that high-cost interventions are more readily available in urban areas because of higher population density and good presence of existing infrastructure, the efficiency objective leaves the rural and often poorer populations with long travel to health services. Emergency referral has been proposed as a remedy of this gap in service provision, dealing particularly with complications arising at PHC facilities [28]. In practice, however, timely referral is not feasible in many situations in LMICs due to the long distances between primary and referral facilities, unpaved roads, dysfunctional emergency transport, high costs of provision and slow recognition of complications [19], [29], [30]. Recommendations, guidelines and sectoral strategies exist to emphasize the importance of bringing lifesaving maternal health services and women closer to each other, and strengthening the referral mechanism; spatial tools for evaluation and better planning of health facility locations (such as those developed in Study 3 of this thesis) are also available, and are becoming more affordable due to technological advancements. There is, however, little to no discretionary oversight of inequitable service provision in settings similar to those studied in this dissertation. The practical challenge of providing costly interventions in poor low-density areas aside, resource distribution is also a matter of political priority. In Study 3, for example, we found that hospital care provision has the tendency to be too pro-rich for optimal efficiency in Nigeria. This finding is somewhat in line with the political and economic drivers of facility locations that have been suggested by researchers since the 1980s [31]–[33], including the ability of the catchment population to pay [34], proximity to the Government Reservation Areas (the abodes of the colonial elite but have since been inherited and expanded by local Nigerian elite [35]), and government support due to economic motives and political reasons [31], [36]. A situation in which certain groups have dominated the economic and/or power dynamics, and use them to appropriate resources does not engender a healthy population (and peaceful co-existence and development). Nonetheless, authorities that do not have the ability to implement equitable provision seem to remain under-supported, and those that do not foster equitable provision are not held accountable.

Until recently, there has not been any standardized measures for geographic or physical accessibility to maternal health services, hindering the growth of the evidence base in this area. In a July 2019 publication, three new indicators for the physical accessibility to EmONC services were proposed by Ebener and colleagues. These are (i) proportion of pregnant women able to access any EmONC health facility within a given travel time, (ii) proportion of pregnant women able to access CEmONC health facility within a given travel time and (iii) proportion of referral linkages between BEmONC facilities to their nearest CEmONC facilities [37]. Applying WHO's AccessMod tool, the author showed that, for instance, 88% of the population in Malawi live within 2 hours from their nearest BEmONC facility [27]. Methods used in Study 3 and Study 4 in this dissertation are particularly useful for the calculation of the proposed indicators in equity-related analyses. Future studies applying these standardized indicators to better contextualize inequality of maternal and newborn healthcare provision and its effect on inequitable service uptake in the population are highly recommended to inform performance gaps in current systems.

8.3.2.2 Better spatial planning of health facilities

Although inequitable distribution of hospitals favouring richer urban places was seen in all study countries, Kenya is the only country where the wealth gap in travel time cannot be closed even if all hospitals were strategically relocated. To a certain extent, this indicates an insufficient number of hospitals relative to the geographic spread of the population. Kenya has a relatively high proportion (95%) of non-hospitals among all facilities (see Section 8.6.1), and may present a good opportunity to strategically upgrade existing health centres where the density of hospitals is low to improve physical accessibility for poor and remote populations. In Tanzania, the number of hospitals per capita/land area is also low, and the overall travel time to the nearest hospital long compared to the other three countries. Although the equity gap in travel time to the nearest hospital can be closed in Tanzania, it comes at the high cost of doubling the overall travel time across the whole population (finding from Study 3). The Tanzanian government has shown a commitment to expanding service provision by adding PHC facilities and deploying more health workers [38]. But with 97% of the country's health facilities being dispensaries/health centres/clinics (see Section 8.6.1), the situation in Tanzania may also be seen as an opportunity to strategize where to upgrade existing facilities, deploy health workers and extend the services offered to their catchment population. On this front, we recommend approaches such as the simulation used in Study 3 in this dissertation for optimal location selection for upgrading.

For Kenya, Tanzania and other similar situations, the simulation used in Study 3 is best applied with specific information pertaining to the practicality of building/upgrading a hospital in a particular location, such as jurisdiction/zoning policies, compatibility with the surrounding environment, land ownerships, the nearby transport infrastructure, availability/consistency of electricity supply and etc. In practice, a few candidate sites can be selected/shortlisted based on these criteria, and the expected overall travel time and equity gap can then be calculated and compared. Adopting a mixed-methods approach of computational accessibility models with the qualitative information that reveals the true feasibility of facility site selection can help reduce uncertainty and optimize locational selection regarding the spatial patterns of service provision.

8.3.2.3 Obstetric emergency referral

Countries that deliver health services via a PHC-based model, such as those studied here, require not only quality and evidence-based services at their frontline facilities to ensure safe childbirth, but also a functional referral mechanism to link women from where they first seek care to the place where the type of care necessary to meet their health needs is available. Concerns of low capacity and low-quality care at PHC facilities in SSA have been discussed earlier (Section 2.1.4). The inter-facility referral capacity in SSA countries is also generally weak, rendering, specifically, timely use of adequate care for those who attend their nearest PHC facility for childbirth [19].

Among the four countries included in this dissertation, this issue is most apparent in Malawi. In Malawi, most women attend a facility for childbirth (as FBD is near universal in Malawi, see Section 7.4.1), usually one that is within good proximity, and they likely stay there for childbirth, whether or not the facility can adequately serve their needs (since the percentage of hospital birth approximately levels with that in the other three countries, and the effect of time on hospital birth strong). Assuming an equal need for hospital-based childbirth care across the whole population, it appears as though rural women who seek care for birth from their local PHC facilities are not effectively referred upward in the health system when that need arises. To a certain extent, this is also demonstrated in the difference in caesarean-section rates between urban area (12%) and rural area (5%) as shown in the 2015-16 Malawi DHS [39].

Unless good referral infrastructure is in place, and in view of the urgency and unpredictability of maternal complications, the inequities in utilization of hospital birth as seen here have serious implications for women living in underserved areas. Despite a high overall FBD rate, maternal mortality in Malawi are relatively high compared to the other study countries – 634/100,000 livebirths in 2015 versus 510 in Kenya, 814 in Nigeria, 398 in Tanzania and 546 across the whole of SSA. Promoting universal facility childbirth within a PHC-based service delivery model without a functional referral mechanism potentially creates a fragmented system, stratifying women into tiered benefits that leaves the poor and remote with inadequate healthcare provision [40].

The Malawi Emergency Obstetric and Newborn Care Needs Assessment in 2014 sampled 464 health centres (out of 489 in the country) [41], and found that 370 (or 80%) lacked the capacity to perform obstetric surgery. Although these facilities mostly had a functioning mode of communication on site, over 80% did not have a functioning motor vehicle ambulance or motorcycle ambulance. The median distance to the nearest facility that had obstetric surgical capacity was 34 km; in some districts, the median distance was over 50km [41]. A new study published in 2019 looked at the practice of inter-facility referrals in rural Tanzania, and found that lateral referral to a facility of the same level (e.g., both the sending and receiving facilities are health centres) is common [42]. In some cases, lateral referral is due to geographic proximity and convenience, without understanding and consideration for the level of care provided at the receiving facility [43]. This process may unnecessarily lengthen the time needed for a patient to reach the appropriate level of care, or fail to link the patient to the level of care required, thereby missing the objective of the referral system.

Strengthening the referral system through provision of motor vehicle ambulances and streamlining communication process are important [44]–[47]. Although other strategies, such as improving the quality of childbirth care for timely identification of danger signs, mobilizing communities to devise back-up funds or plans for emergency transport have also been recommended, they rarely work at scale and in sustained ways [48]–[51]. From the perspective of physical accessibility, long distance would still need to be overcome. Whether or not women receive timely and adequate care for childbirth, regardless of the facility at which they first arrive, is highly dependent on the transportation network, road routability and other relevant components that facilitate inter-facility referral. Effective referral has been proposed as a priority of quality improvement at PHC facilities [19], and this may be particularly critical in settings where a PHC-based health service delivery model is adopted. Further research in referral to better understand patients' and providers' usage of the inter-facility referral systems in obstetric and other types of emergencies could improve resource allocation and optimize travel times.

8.3.2.4 Spatial equity in healthcare delivery a decentralized system

Decentralization of healthcare is perceived as a mechanism that can increase accountability, improve effectiveness and deliver accessible healthcare throughout a country. One of the objectives of the Kenya Constitution 2010, for instance, explicitly states for decentralization of healthcare to help promote social and economic development and provision of proximate and easily accessible services thorough the 47 counties in the country [52]. Devolved healthcare implementation in Kenya was marked largely by increment, expansion and improvement in health infrastructure as well as human resources for health across the countries with the resources generated in their jurisdiction. An assessment of health delivery under the devolved system found upsurge in number of health facilities, improvement in health service densities and sustained disparities in health access [53]. The number of registered health facilities increased from 8,600 to 11,000 between 2013 and 2017. Decentralization has been shown to improve access to healthcare, especially for rural areas, by decreasing distance to health facilities and has been associated with improved outcomes including decreased mortality [54]–[57].

Whilst a devolved system can address local spatial disparities in healthcare delivery, much of the evidence point to improvement in PHC. Bypassing frontline PHC facility and favouring certain providers for childbirth services irrespective of distance, especially when service fees have been removed, is common. In their investigation of local spatial clustering of maternal health utilization in the 30 wards in Siaya County in Kenya, Nyangueso and colleagues found that proximity to public referral facility was largely responsible for the spatial clustering of maternal health services utilization [58]. In areas bordering these clusters, facilities have the tendency to report a low level of maternal healthcare provision. Given reasonable physical accessibility, pregnant women appear to desire the care provided at referral facilities, and avoid care provided at their local facility.

Increasing spatial clustering in healthcare utilization due to perceived quality is harmful to spatial equity. Besides meeting more than their local demands, referral facilities also attract a substantial number of patients from neighbouring service areas, potentially leading to overstretching of services. Moreover, underutilization of local services negatively affects the cost effectiveness of local service provision, and fails the intended outcome of majority receiving healthcare within close proximity [52].The appropriate distribution of primary and comprehensive care is an essential consideration when addressing the persistent burden of maternal and newborn mortality and morbidity in LMICs. In a decentralized system, efforts and commitments at both the national and subnational levels of governance are required to ensure the provision of high-quality childbirth care to all.

Subnational governments under a decentralize system are responsible for the structural, funding and programming decision-makings of PHC and most referral care, and should ensure allocative and technical efficiency in the release of funds. The allocation of resources should be based on population and geographic size, as well as the distribution of unmet need and health outcome

[59]. Where there is inter-governmental transfer of funds involving multiple levels of governances (e.g. in Nigeria), the national government should also ensure funds are not retained at the first level of subnational governance, and that further transfers to the lower levels are appropriate. Direct allocation of funds from the national government to the lowest level of governance has also been recommended [59].

8.4 Conclusion

In conclusion, an evidence-based minimum set of practices for care during childbirth has been proposed by researchers and experts, and such standards should be universal in any given population of pregnant women. In many LMICs, the use of some facility-based care for childbirth is rapidly increasing, but a large proportion of births still occur in low-capacity facilities that are under-equipped and under-staffed, with women and newborns living in poorer and remote places – often an overlapping subpopulation – most affected. In low-density and poor areas, implementing costly interventions is a big challenge, and the local population have little means to change their reality until resources are introduced to them. Health equity analyses should consider the inequity of physical accessibility to health services by wealth/SES, as the failure to do so is victim-blaming in nature.

We also call for more research in inter-facility referrals, and discretionary oversight in performance tracking and directing and managing resources efficiently and equitably at the global, national and subnational levels. Ultimately, the issue of health is highly challenging and complex, requiring the various actors across levels and networks of governance to act in the pursuit of better health outcomes for all.

Lastly, the initial motivation of this dissertation was to ask “who (if any one) serves poor women” and “so what?”, i.e., what are the implications on women’s uptake of health services? This is a question of the equity of service provision. Disparities in health impact (e.g., uptake of services), and health outcomes (e.g. mortality and morbidity), have largely been described as the variability in individual sociodemographic characteristics, yet an individual’s uptake of services is conditioned on their service environment, which needs to be duly considered and acknowledged. The answer – e.g., “health personnel A from facility B provided care to woman C, and the outcome for her is D” – was not directly sought as it is resource-intensive to collect the relevant data at scale. Instead, I used geospatial tools and geo-referenced data to assess physical accessibility to hospitals by SES, assuming better access indicates a better service provision environment for an individual, and then tested if this was associated with a greater usage of health services (and a greater production of individual health). The overarching answers are that, “poorer women are served less optimally” and “such differentials have a significant influence on women’s uptake of hospital-based childbirth care”. Wealth inequality of service utilization indicators should be considered alongside the inequity of physical accessibility to health services by wealth. Encouragingly, methods for such considerations are becoming available.

8.5 References

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8.6 Supplementary materials

8.6.1 Lessons learnt in this dissertation

	Methodological	Kenya	Malawi	Nigeria	Tanzania
Study 1	Self-reported//modelled travel time to a provider/facility capable of providing skilled care, as an indicator of physical accessibility, is of higher standard compared to others, such as self-reported straight line distance to the nearest facility. It was not possible to identify a critical threshold for what signifies " too far" from available evidence. This is due to the many ways in which distance/travel time had been measured/analysed.	One of the most studied countries in SSA Beyond 2 km, distance had no effect on place of delivery. (Mwaliko 2014)		One of the earliest studies identified by Okafor also, in other studies not included here, examined pro-richness of health facilities distribution in Nigeria.	One of the most studied countries in SSA
Study 2	Even after account for agro-climatic factors and infrastructure/developmental predictors such as night-time light, there was some remaining spatial patterns of wealth index, and spatial methods were more appropriate than non-spatial methods. But there is no one-size-fits-all solution. It was beneficial to choose between analytical methods using a data-driven approach (holdout method).	MBG, which assumes nearer observations are more alike, performed better in Kenya, where wealth index decreases gradually over distance from Nairobi (at the global scale).	Spline, as part of a GAM, fits a smoothed surface to the data and performed better in Malawi, for which we observed spatially dispersed concentration of high wealth index.	Spline, in a GAM, fits a smoothed surface to the data and performed better in Nigeria, where wealth index presented with an overriding north-south divide (at the global scale).	Spline, as part of a GAM, fits a smoothed surface to the data and performed better in Tanzania, for which we observed spatially dispersed concentration of high wealth index.
Study 3	The simulation enabled the making of " a judgement call" about whether the system is equitable/efficient or not, without which we could only quantify current levels, and not know where the performance gaps are. The approach developed can be extended to best selection locations for adding/upgrading health facilities.	Can be considered efficient, but inequitable. The only country where the inequity gap cannot be closed even if all hospitals were strategically relocated	Can be considered efficient, but inequitable. Shortest overall travel time	Adequately efficient, but somewhat pro-rich; most hospitals per capita/land area	Can be considered efficient, but inequitable. Longest overall travel time; least hospitals per capita/land area
3a	Number of hospitals per 1,000km^2 land area	0.85	1.23	4.16	0.30
3b	Number of hospitals per 10,000 population	0.10	0.07	0.21	0.05
3c	Percentage of facilities that are hospitals versus. non-	5 versus 95	12 versus 88	11 versus 89	3 versus 97
Study 4	If the predictor variables in a model do not have a standardized unit, μ±1SD can be used as a consistent unit of change, in which case observations from the 16th, 50th and 84th percentiles are compared against one another	SES was more important than travel time, but only up to a certain degree after which the effect of SES levels off.	Travel time was more important than SES; FBD near universal (but hospital birth similar to the other three countries)	Uptake of hospital birth low among those with either a long travel time or low SES. and both factors, with their additive effect twice	Travel time was more important than SES.