Incorporating seasonal flooding into frameworks modelling geographical access to health services

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Submitted in accordance with the requirements of the degree of

Master of Science by Research

The University of Leeds

School of Geography

September 2021

Acknowledgements

Thanks simply *must* go first to my incredible supervisors, Dr. Mark Smith and Dr. Tom Willis. Even in the daunting face of my long emails and even longer PowerPoint presentations, both have tirelessly guided and supported me throughout this project. What started off as an undergraduate exercise in delineating roads and trying not to get a repetitive strain injury became *this project* thanks to their enthusiasm in letting me explore ideas, their expertise in helping me shape said ideas into methods, and their knack for knowing when to reel me back in so I didn't lose focus! It goes without saying that the Guinness World Record for *Best Supervisor* is a shared title between them.

Secondly, I'd like to thank my family. They have no absolutely no clue what it is I do, but they blindly love and support and tell me I'm the best anyway. Visits home also never had panic-inducing questions about how the thesis write-up was going – *bonus*!

I'd also like to thank my PGR buddies: Sophie Tankard, who has been a continuous source of support and great conversations which have kept me sane; Adam Hartley, for his endless kindness; and Chris Stringer, friend extraordinaire who revolutionised my life by showing me how to make aesthetic graphs in Excel.

Finally, immense thanks and gratitude are dedicated to Ewan McLaughlin, Samantha Ravenscroft, and Lydia Richardson. When the worst experience of my life occurred and threatened my academic progress, their unwavering love and support throughout the proceeding months ensured I was able to continue to succeed academically whilst recovering. This thesis simply wouldn't have been possible without them, and I feel so blessed to call them my best friends.

Abstract

Seasonal floods are an important barrier to healthcare access in low-income countries, with recognised implications of increased morbidity and mortality. Effective interventions require detailed understanding of how flood inundation alters patterns and magnitudes of inaccessibility through space and time. Despite recognition of the importance of seasonal floods, few have previously modelled their impacts on geographic access. This study developed a new framework for incorporating quantitative measurements of floodwater depth and velocity into network analysis and cost-distance algorithms. The new approach directly calculates flood hazard to vehicular and walking access as it changes through space and time, permitting more realistic representation of floods as a barrier without substantially inflating data requirements or relying on inappropriate assumptions from urban, high-income regions. The new approach was demonstrated in the Barotse Floodplain, a large African floodplain in Zambia. Floodwater variables were obtained from a hydrodynamic model, and all other inputs were sourced from freely-available datasets or manually delineated. Monthly scenarios were produced between October 2017 and October 2018, capturing the spatio-temporal impacts of one annual flood event on access to healthcare and specifically to maternal services. Access was shown to dynamically change through space and time as the seasonal floodwave passed through the floodplain, with substantial drops in access experienced at the peak of the floods. The new approach provided unprecedented, detailed information regarding the onset, duration, and cessation of flood impacts. Previous static approaches were shown to be unable to recreate the dynamism of access under floodwaters. The use of a hydrodynamic model is advantageous over satellite-derived flood extents and has the potential to predict future impacts of climate change on access. This research has demonstrated the importance of modelling spatio-temporal variability in access for regions affected by seasonal flooding and the framework can be applied to other regions to aid in intervention planning and build future health system resilience. Future research should continue to reduce the gap in knowledge of how floods affect access, integrate qualitative and quantitative data to address access through an interdisciplinary approach, and investigate what scale of data are needed for accurate results at different areal units.

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Abbreviations

BRE	Barotse Royal Establishment
2SFCA	Two-step floating catchment area method
e2SFCA	Enhanced two-step floating catchment area method
3SFCA	Three-step floating catchment area method
EmOC	Emergency obstetric care
FME	Feature Manipulation Engine
FW	Walking through floodwaters
GIS	Geographical information system
h	Human height
H	Water depth
H_{max}	Maximum water depth threshold
HRSL	High resolution settlement layer
HV	Depth-velocity product
HV_c	Critical depth-velocity stability criteria
ITCZ	Intertropical Convergence Zone
m	Human weight
MMR	Maternal mortality ratio
MWS	Maternity waiting shelter
NFW	Not walking through floodwaters
OSM	OpenStreetMap
PPR	Provider-to-population ratio
UN	United Nations
V	Velocity
V_{max}	Maximum velocity threshold
WHO	World Health Organisation
4WD	Four wheel-drive

CHAPTER 1

INTRODUCTION: *Outline of the research*

1.1. Rationale

The ability of populations to access healthcare is critical for improving health outcomes, reducing inequity, and meeting the United Nation's Sustainable Development Goal of good health and wellbeing for all. In low-income countries, geographical barriers to healthcare facilities have been linked with poor service uptake and worsened health outcomes (Gabrysch *et al.,* 2011a; Lohela *et al.*, 2012; Zegeye *et al.,* 2014; Kenny *et al.,* 2015; Wong *et al.,* 2017; Tegegne *et al.,* 2018; Gammino *et al.,* 2020; Stone *et al.,* 2020). Modelling geographical access is essential for identifying populations not served adequately by facilities, recognising the most impactful variables, and to plan interventions that allocate limited resources for the greatest cost-benefit (e.g., Fisher and Lassa, 2017; Ihantamalala *et al.,* 2020; Ngana and Karyawati, 2021; Pereira *et al.,* 2021).

Floodwaters are key barriers in low-income countries with distinctive seasonal climates (Schoeps *et al.,* 2011; Blanford *et al.,* 2012; Berendes *et al.,* 2014; Makanga *et al.,* 2017; Brottem and Coulibaly, 2019; Schmitz *et al.,* 2019; Joseph *et al.,* 2020). The impacts of floods can persist for extensive amounts of time, restricting healthcare access (Espinet Alegre *et al*., 2020; Ngana and Karyawati, 2021), isolating entire populations (Makanga *et al.,* 2017), causing medical supply shortages (Phalkey *et al.,* 2012; Iimi and Rajoela, 2018), and hindering referrals between facilities (Nhemachena *et al.,* 2011; Phalkey *et al.*, 2012); all of which increase morbidity and mortality that could have otherwise been preventable in the dry season. Despite recognition (Oppong, 1996; Nhemachena *et al.,* 2011; Phalkey *et al.,* 2012; Makanga *et al.,* 2017; Munthali *et al.,* 2017) that floods have significant impacts on access, there is a critical dearth of literature that considers the impacts of floods on access to healthcare in low-income countries. Few studies have directly considered the impacts of floods on access (Blanford *et al.,* 2012; Fisher and Lassa, 2017; Makanga *et al.,* 2017; Hierink *et al.,* 2020), and no study has yet coupled a hydrodynamic model with an access model to investigate how access changes spatio-temporally over the duration of a flood event. Nearly all previous studies have presented access as a spatially and temporally static contrast between a dry and wet scenario (e.g., Blanford *et al.,* 2012), using maximum flood extents only to represent floodwaters.

Consequently, there is limited understanding of the relationship between actual floodwater variables and access, and no representation of how access changes in the key transition stages of flood rise and flood recession.

The lack of understanding on how floods affect access to healthcare is a critical problem. Floods exert multiple influences on access by not only limiting the ability of populations to reach care, but also potentially reducing the quality of care provided such as by impacting the distribution of important medicines (e.g., antiretrovirals) and preventing timely referrals (Veenstra *et al.,* 2010). These impacts cannot be mitigated against without knowledge on how floods impact access through space and time, particularly during flood rise and recession stages which previous work has not studied. Additionally, climate change will alter the magnitude, timing, and extent of fluvial floods (Arnell and Gosling, 2014; Kling *et al.,* 2014; Nka *et al.,* 2015) which in turn will impact the health outcomes of rural floodplain populations who are already vulnerable. Health systems need to be resilient to the effects of climate change in order to prevent progress stagnating or undoing. The ability to explicitly model changes in access under flooding is consequently crucial now as well as in the future to continue with progress made towards health equity. For models to be effective in achieving this, an interdisciplinary approach is needed that is able to integrate environmental science into geographic access models.

1.2. Aims and objectives

The aim of this study was to create a geospatial framework that quantifies the spatio-temporally variable impacts of flooding when modelling geographical access to healthcare in low-income countries. The Barotse Floodplain located in Western Province, Zambia was selected as the first case study application to demonstrate the new approach which is generalisable to other regions. Three objectives were defined to guide the research:

O1: To create novel network and raster models that incorporate quantitative measurements of water depth and velocity when assessing vehicular and walking access.

O2: To demonstrate the new approach by modelling monthly changes in access across an entire hydrological year for a large African floodplain using hydrodynamic model outputs representative of a real annual flood event.

O3: To assess the spatio-temporal impact of flooding on access to both general and maternal healthcare for the Barotse Floodplain, Zambia.

The research aim and objectives build upon four key research gaps identified in the health access literature. First, quantitative measurements of floodwater depth and velocity are directly incorporated into the geospatial framework; previous research in low-income countries has either ignored floodwater impacts, or solely considered flood extent as a barrier. Second, the new framework incorporates stability criteria for vehicles and humans to more accurately assess the safety of moving through floodwaters. To the author's knowledge, this is the first instance of these being used in access models. Third, the case study outlined here assesses access for thirteen months, documenting access in the dry season and throughout an annual flood event. Previous studies that considered access with a temporal component were nearly all limited to modelling access as one dry and one wet season scenario, ignoring changing spatio-temporal dynamics. Finally, this study is the first to apply access models specifically to a large African floodplain.

1.3. Thesis outline

Chapter 2 addresses the existing literature which underpins this research, spanning disciplines to discuss: (i) the characteristics of large African floodplains and their populations; (ii) the theories of health access; (iii) the GIS (geographic information system) methods used to assess access; (iv) human and vehicular instability criteria; and (v) the work of previous studies which have incorporated precipitation and flooding into their methodologies. A new geospatial framework is then proposed in Chapter 3 which address the gaps identified in the literature review through the specific incorporation of floodwater variables and stability criteria. The Zambezi case study is also introduced, and the application of the new methodology to model access to general and maternal healthcare is described. Chapter 4 reports the results from the Zambezi case study, focusing on the spatio-temporal influence of floodwaters on the monthly variation of populations attempting to reach healthcare. The new methodology is also compared with previous approaches to demonstrate its advantages and the additional insights into access it provides. The results are further discussed in Chapter 5 with comparisons made to previous studies to emphasise the importance and usefulness of modelling spatio-temporal impacts of flooding in the new methodology. The limitations of the study and recommendations for future research directions are also discussed in this chapter. Chapter 6 summaries the body of the thesis by presenting the key findings.

CHAPTER 2

LITERATURE REVIEW: *Health access and modelling geographical variables*

Section 2.1 describes the characteristics of large African floodplains, focusing on flood pulses and their importance to the local livelihoods. In Section 2.2, access to healthcare is then reviewed in the entirety of its theoretical framework, with a focus on geographical variables. The effects of flooding and precipitation on access are explicitly described to emphasise the importance of considering these variables. Section 2.3 introduces the current common methodologies used to measure geographical access, ranging from most simple to complex. Euclidean distances and cost-distance algorithms are then compared as these are the most commonly-used methods in low-income or data-sparse regions. Finally, Section 2.4 considers the incorporation of flooding and precipitation into access models. Instability of both vehicular and human movement is described to provide knowledge on how floodwater variables can be used to determine hazard. The current state of knowledge is then explicitly reviewed in Section 2.5 to show how few studies have attempted to account for seasonality effects on access, and that a critical gap in knowledge persists regarding how dynamic floodwaters cause access to change over space and time. To conclude, Section 2.6 provides a concise summary of the entire literature review.

2.1. Characteristics of large African floodplains

African floodplains often cover substantial areas of flat land adjacent to rivers and experience a minimum of one seasonal flood pulse per hydrological year (Welcomme, 1975; Gaudet, 1992). A floodplain is considered large when its extent at peak inundation exceeds 1,000 km^2 (Gaudet, 1992), but the inundation dynamics of floodplains varies considerably and some may contract as much as 85% in areal inundation extent during the dry season (Gaudet, 1992; Adams, 1993; Cohen Liechti *et al.,* 2016a; Thompson *et al.,* 2017). Nearly every African river has a fringing floodplain, but the largest floodplains have formed due to geologic impediments that have obstructed discharge (Welcomme, 1979). The presence of a barrier, such as a resistant outcrop, forces floodwaters backwards into extensive flat plains which creates seasonal flood extents that rival the area of the largest lakes (Welcomme, 1979).

Strongly seasonal variations in precipitation cause many African rivers to exhibit seasonal discharges which cause overbank flooding (Welcomme, 1979; Gaudet, 1992; Charlton, 2008). Variability in precipitation and discharge determines flood extent and depth, leading to annual variations in the size of floods (Welcomme, 1979; Zimba *et al.,* 2018). Flow patterns and flood pulses differ between floodplains due to complexity in factors such as river length, climate, underlying geology and soil, upstream catchment size, and the number, complexity and synchronicity of tributaries (Welcomme, 1975; Charlton, 2008). The delayed arrival of floodwaters is a common characteristic shared between African floodplains; floodwaters often arrive downstream many months after peak rainfall due to the length of many African rivers (Welcomme, 1979; Cai *et al.,* 2017; Thompson *et al.,* 2021). For example, before dams modified flows in the Kafue Flats, Zambia, floodwaters would peak in the dry season month of May, after the rainy season between November and March (Howard, 1991). Consequently, some floodplains even experience multiple flood pulses per year: one flood pulse resulting from local rainfall, and a second caused by overspill of delayed discharge arriving from upstream (Welcomme, 1975; Welcomme, 1979). The hydrology of large African floodplains is complex which leads to difficulties in establishing their water regimes, but floods typically persist from weeks to multiple months with the average inundation time estimated to be six months annually (Marchand, 1987).

Large floodplains have complex negative relief features which are highly significant in determining the behaviours of floodwaters (Adams, 1993; Lewin and Ashworth, 2014). Negative relief features influence surface water depths and velocities as well as groundwater; consequently, even minor variations alter the spatio-temporal distribution of floodwaters across a floodplain (Welcomme, 1979; Lewin and Ashworth, 2014). The topography of a floodplain is not permanent as sediment from fluvial and non-fluvial sources may infill depressions over very long timescales (Lewin and Ashworth, 2014). Negative relief features are additionally important to local populations as they provide diverse ecological habitats, including for fish and mammals (Lewin and Ashworth, 2014). They can even influence transmission of diseases like malaria; in non-flood months, depressions that retain water can provide viable anopheline habitats (Smith *et al*., 2013).

Local African communities are dependent on floodplains and their regular inundation (Marchand, 1987; Thompson and Polet, 2000; Schuijt, 2002; Schuijt, 2005; Rebelo *et al.*, 2010; Moritz *et al.,* 2016; Cai *et al*., 2017; Laborde *et al*., 2018). These communities typically have subsistence-based economies which gives floodplain resources a high local value (IUCN, 2003). Floodplains offer a source of food, water, and building materials which are important to livelihoods, and it is the dynamism and characteristics of floodplains and their floods which maintains these (Marchand, 1987). Floodplains are pulse-stabilised ecosystems whose continuous wet and dry cycles prevent a climatic climax community; this maintains high productivity, and thus high numbers of fish and mammals which are traditional key sources of food and income (Marchand , 1987; Junk *et al*., 1989; Acreman, 1996).

Despite the importance of floodplains for local communities, decision-makers commonly view large African floodplains as economically worthless due to ignorance regarding the ecosystem services they provide (Marchand, 1987; Schuijt, 2002; Schuijt, 2005). Floodplains are often seen as having an “excess” of water (Howard, 1991; Adams, 1993) and thus large African floodplains are increasingly under threat due to the potential they afford large hydropower production and irrigation schemes (Gaudet, 1992; Movik *et al.*, 2005; Schuijt, 2005; Fynn *et al.,* 2015). Due to the strong interrelationship between floodplains and local populations, any variation in seasonal flood characteristics directly impacts livelihoods (Moritz *et al*., 2016). The construction of dam and irrigation projects would alter hydrology, modify the timing and magnitude of floods, and affect river system continuity and sediment transfer dynamics (Adams, 1993; Charlton, 2008; Beilfuss, 2012). Consequently, the impact to floodplains and their populations would be significantly detrimental.

2.2. Theoretical framework of access to healthcare

2.2.1. Overview

Achieving equitable access to healthcare is important for maintaining and improving the health of populations. Access can be most broadly defined as the ability of populations to reach healthcare; however, access is a complex concept with multiple dimensions to consider. The World Health Organisation (WHO, 1978, p. 58) defined accessibility as “…*the continuing and organised supply of care that is geographically, financially, culturally, and functionally within easy reach of the whole community. The care has to be appropriate and adequate in content and in amount to satisfy the needs of people and it has to be provided by methods acceptable to them.”*

Penchansky and Thomas (1981) defined five dimensions of access that theoretically satisfy this definition: availability (provision of enough services to meet everyone’s needs), accessibility (geographic barriers impeding populations from reaching services), accommodation (whether populations deem health services and their delivery suitable for them), affordability (financial costs to use services), and acceptability (satisfaction with care quality). As human decision-making underpins the entire access to healthcare framework, Thaddeus and Maine (1994) proposed that there are three key phases in healthcare access: (1) the decision to seek care; (2) the ability to reach care; and (3) the delay in receiving treatment. The five dimensions of access (Penchansky and Thomas, 1981) and the variables influencing them form complex interrelationships that affect each of these three phases (Figure 2.1).

The uptake of health services can be affected by either spatial (physical and geographical) or aspatial (sociocultural and socioeconomic) variables (Khan and Bhardwaj, 1994), and access can either be measured as realised or potential. Realised access analyses actual real-world uptake of health services, such as by recording travel times of actual journeys. Potential access models the barriers that could be impeding access and estimates travel times (Khan and Bhardwaj, 1994; Andersen, 1995).

This research investigates only the accessibility dimension of access (also referred to as geographic, physical, or spatial accessibility) and solely considers spatial factors when modelling potential access to healthcare. Throughout the study, human decision-making is assumed to weigh in favour of seeking care, and only the second phase of Thaddeus and Maine's (1994) framework concerning the ability to reach care is considered. Healthcare is also used in this study to refer exclusively to medical care administered by professionals. Complete health is considered to be comprised of physical, mental, and social health (WHO, 1978) and so medical care is only one component of healthcare (Gulzar, 1999).

2.2.2. Geographic accessibility

In the first and second phases of delay (Thaddeus and Maine, 1994), geographical accessibility is critical in determining whether a person seeks care and whether a person can reach care. Spatial barriers act as a significant impediment to the uptake of services; this has been well-demonstrated in the literature (e.g., Gage and Calixte, 2006; Gage, 2007; Mpembeni *et al*., 2007; Kyei *et al*., 2012; Mwaliko *et al*., 2014; Tatem *et al*., 2014; Hanson *et al.,* 2015; Vora *et al*., 2015; Ruktanonchai *et al.*, 2016; Hanson *et al*., 2017; Wong *et al*., 2017). For example, Gabrysch *et al*. (2011a) found that increased distance to a healthcare facility in rural Zambia was significantly associated with the likelihood of institutional births decreasing by 29% (p<0.05). Meanwhile, Tanser *et al*. (2006) found healthcare facility usage declined logistically as travel times increased in rural South Africa (p<0.0001), and Ruktanonchai *et al.* (2016) found that increased geographic inaccessibility had the strongest association with reducing all maternal care usage in five countries (Burundi, Kenya, Rwanda, Tanzania, and Uganda). These examples demonstrate the distance decay effect: a decrease in healthcare system usage as barriers to geographic accessibility increase.

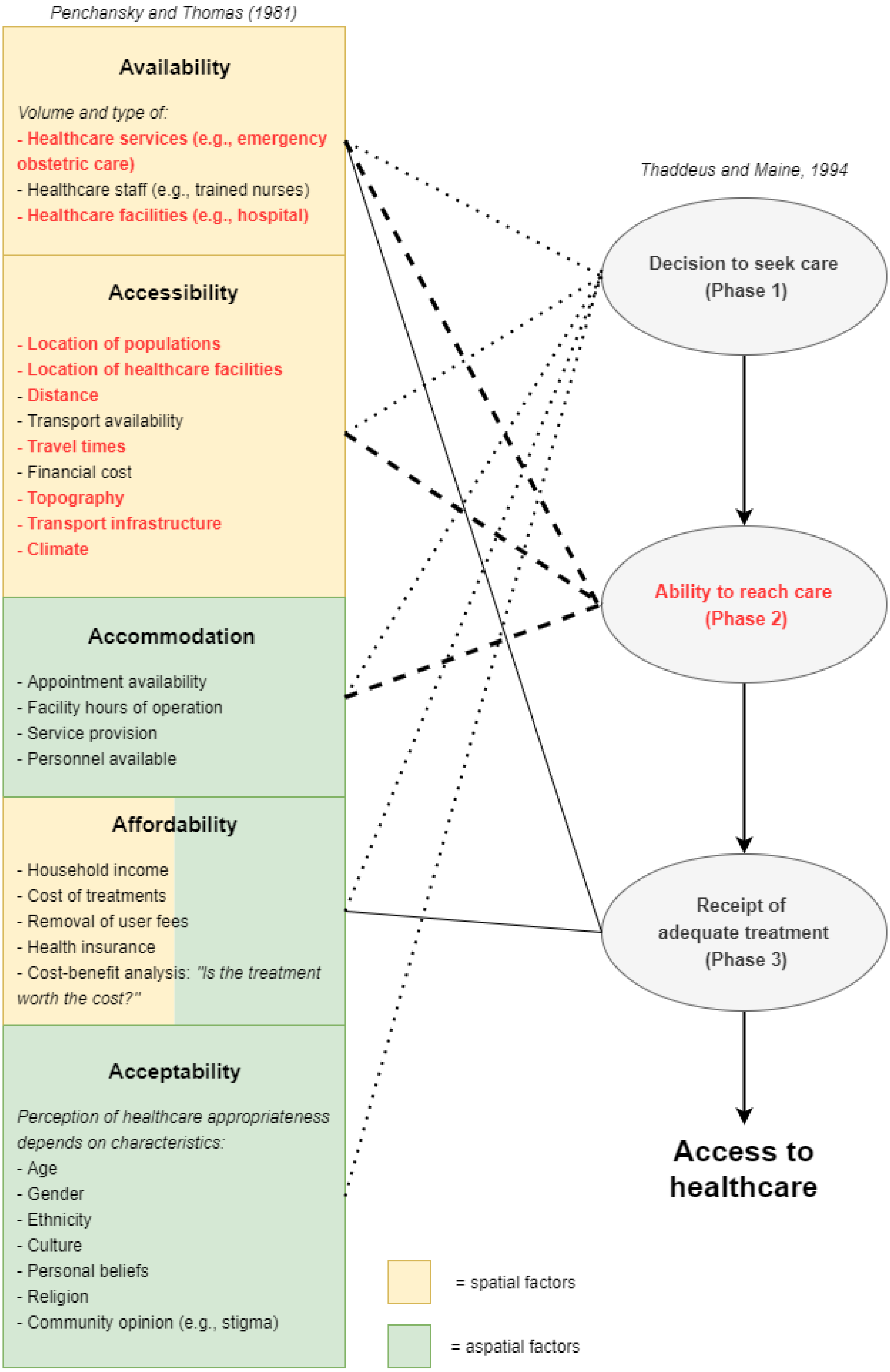


Figure 2.1. Conceptual diagram outlining the key variables influencing access to healthcare, according to the classical frameworks of Penchansky and Thomas (1981) and Thaddeus and Maine (1994). Text in red indicates the health aspects this thesis covers.

Variables important in explaining geographical accessibility include travel distance, road network infrastructure and conditions, topography, available modes of transport, and climate (Kironji *et al.,* 2018; Huot *et al.,* 2019; Dawkins *et al.*, 2021). These factors aggregate into an accumulated travel time which often exerts multiple influences on human decision-making by forming complex interrelationships with other variables such as finance (Thaddeus and Maine, 1996; Simkhada *et al*., 2008; Karra *et al*., 2016). If transport is too expensive and walking too arduous due to difficult terrain and subsequent long travel times, a person will simply not be able to reach a healthcare facility irrespective of whether they want to. Consequently, the interpretation of potential geographic access is complicated, as the other factors involved in healthcare-seeking behaviour (see Section 2.3.4) must be considered to prevent erroneous conclusions.

Travel distance refers exclusively to the total distance between a population and a healthcare provider. Distance typically forms complex interrelationships with other spatial variables which can compound its effect, so distance preferably should not be considered alone. Topographies such as deserts, wetlands, and mountains can increase travel times or force travel along longer distances due to their impassibility (Gage and Calixte, 2006; Alegana *et al.*, 2012; Blanford *et al.,* 2012; Sturrock *et al*., 2014; Khatri and Karkee, 2018; Dumitrache *et al.,* 2020). Terrain slope alone is able to reduce walking accessibility by increasing the relative travel time to walk a given distance (Tobler, 1993; Fogliati *et al.*, 2015; Márquez-Pérez *et al*., 2017). Temporal topographic effects, such as precipitation and flooding, can act as temporary barriers for parts of the year thereby complicating journeys and travel times (see Section 2.3.3). Access to a motorised vehicle is associated with improved geographic accessibility as a person becomes able to travel longer distances to reach healthcare (e.g., Comber *et al.,* 2011; Gabrysch *et al*., 2011a). However, in low-income areas such as rural sub-Saharan Africa, very few households have access to their own motorised vehicle and public transport can be unscheduled and incomplete in coverage (Gabrysch *et al*., 2011a; Dos Anjos Luis and Cabral, 2016). Instead, journeys often take place on-foot and thus long distances and travel times act as common barriers to healthcare access.

Road network infrastructure conditions describe whether paths, roads, and bridges are in good traversable condition. Poor conditions can further impede walkers and prevent motorised vehicles from driving along theoretically optimum routes, thus compounding distance and increasing travel times (Le Roux *et al*., 2019). All-weather (also referred to as all-season) roads are arguably a key infrastructure for improving healthcare accessibility in rural areas (Espinet Alegre *et al.,* 2020). An all-weather road is paved with surface materials that are resistant to precipitation (i.e., the materials do not become saturated and waterlogged), maintained in good condition, and thus operable all year-round (Blanford *et al*., 2012; Mikou *et al.,* 2019; Stone *et al.*, 2020). Such characteristics are important in countries with significant wet seasons. Vora *et al.* (2015) found that access to an all-weather road was positively correlated with institutional births for rural women in two states in India, which experiences an annual monsoon.

2.2.3. Effects of flooding and precipitation

The effects of climate on geographical accessibility are primarily dictated by precipitation and flooding, both of which have severe impacts on access. For countries with high percentages of unpaved roads (such as most of the sub-Saharan Africa region), heavy precipitation can render most of the roads unusable due to waterlogging (Laurance *et al.*, 2014; Le Roux *et al.,* 2019; Stone *et al*., 2020). Even on paved road surfaces, precipitation causes increased risk of hydroplaning (e.g., Atubi and Onokala, 2009) and increased braking distances, both of which reduce safe travel speeds and thus increase journey times. Very high precipitation rates can cause surface flooding on roads which necessitates their closure, forcing travel along alternative routes, negatively influencing the connectivity of the network, potentially increasing congestion, and thus increasing travel times. In extreme scenarios, excess precipitation and flooding can cause wide swathes of land to become inaccessible, subsequently isolating local populations constrained by the floodwaters (Howard, 1991; Makanga *et al*., 2017; Espinet Alegre *et al.,* 2020; Roder-DeWan *et al.,* 2020).

Accessibility to a wide range of services can be affected including schools, shops and markets (Nhemachena *et al., 2011*; Cai *et al*., 2017), which further compounds poverty (Espinet Alegre *et al.,* 2020). However, the impacts on healthcare accessibility are immediately more critical as geographical access is hindered and the provision of quality care is reduced (e.g., Nhemachena *et al.,* 2011; Phalkey *et al.,* 2012). Morbidity and mortality often increase as a result of reduced accessibility during floods; for example, missed appointments for chronic illnesses (e.g., HIV) or medicine stock-outs (e.g., of antiretroviral drugs) lead to worsened health outcomes and shortened life expectancies (Schatz, 2008; Lankowski *et al.,* 2014; Espinet Alegre *et al.,* 2020). Injuries and health emergencies that were time-critical result in fatalities in the wet season despite them otherwise being treatable in the dry season. Those most impacted by floods are usually already vulnerable, such as the rural poor who already face long travel times to their nearest healthcare facility.

2.2.4. Non-geographic variables affecting access

Decisions to seek healthcare and the ability to reach healthcare facilities are underpinned by numerous theoretical concepts regarding influential socioeconomic and sociodemographic factors in addition to the geographical factors discussed (Penchansky and Thomas, 1981; Thaddeus and Maine, 1996; Gabrysch and Campbell, 2009; Levesque *et al.,* 2013). It is beyond the scope of this study to incorporate and discuss all of these factors in detail. However, to dismiss them entirely would ignore substantial contextual information that explains the unquantifiable aspects of geographical access related to human-decision making, which are critical to understanding and interpreting results (Simkhada *et al.,* 2008; Gabrysch *et al*., 2011a). Failure to give consideration to all potentially influential factors could cause misleading interpretation of results and thus misrepresentation of the true nature of geographic accessibility for policy-makers (Gabrysch *et al.,* 2011a).

Perceived accessibility, finance, and social influences (e.g., stigma) are key to influencing decisions to seek care (Thaddeus and Maine, 1994). Essentially, a person is either motivated or demotivated to seek care based upon how difficult they believe it will be to attend a healthcare facility (both geographically and economically) and whether they believe their local community will view them negatively. If the route to healthcare is deemed too difficult or too costly, healthcare-seeking may be restricted to only serious illnesses and critical injuries (Thaddeus and Maine, 1994). Social influences vary geographically due to differing local sociocultural traditions surrounding modern medicine and healthcare usage. Perceived impression of healthcare facilities is also an influential social factor; this includes whether a person believes a healthcare facility will offer advantages over traditional medicine, and perceived quality of care, which has been shown to be a strong influence affecting healthcare-seeking behaviours (Thaddeus and Maine, 1994; Gage, 2007).

Healthcare-seeking journeys are not concluded until the receipt of appropriate treatment. A person may have overcome travel obstacles to reach a healthcare facility, but waiting times for treatments, referral times between facilities and services, poor quality of care, understaffing, and medicine stock-outs can all lead to delays in receiving appropriate treatment for a health condition (Thaddeus and Maine, 1994; Phalkey *et al*., 2012; Penfold *et al*., 2013). These final delays can be critical, resulting in mortalities that would otherwise have been prevented with adequate, timely treatment (Thaddeus and Maine, 1994; Hanson *et al*., 2015). For example, Nassoro *et al*. (2020) found that 19 of 35 maternal deaths at a Tanzanian referral hospital in 2018 were due to these final delays in referrals from facilities, in receiving treatment, and inadequate skills of staff.

Strong feedback loops can emerge between the variables involved in each phase of this conceptual healthcare access framework. For example, the effects of precipitation and flooding have long-term impacts on the health-care seeking behaviours of populations in addition to the short-term implications already described. For those who have travelled despite floods and overcome significant obstacles to reach a healthcare facility, there is an expectation that the healthcare received will be of quality to have made the arduous journey worthwhile. Receipt of poor healthcare quality, thus, causes dissatisfaction and potentially a perception that healthcare quality is poor year-round. This discourages future healthcare-seeking for the individuals and the experience may also be communicated so that entire communities can be deterred from seeking care (Thaddeus and Maine, 1994; Gage, 2007; Ruktanonchai *et al*., 2016; Mupwanyiwa *et al*., 2020).

2.3. Modelling geographical accessibility

2.3.1. Overview of GIS methods

There are a variety of methods used in the literature to measure geographic access to services. Most broadly, these can be grouped into four categories: (1) simple Cartesian measures; (2) provider-to-population ratios; (3) gravity-based measures; and (4) cost-distance and network analysis. Any method and the data used in models of geographic accessibility all influence the outcome and can bias the results. The potential sources of this bias necessitate close consideration of the data and methodology used at every stage of the research process.

2.3.1.1. Simple Cartesian measures

Euclidean (also commonly referred to as straight-line or linear) and Manhattan distances (also known as taxicab geometry) are the two simplest access measures employed in the literature (Figure 2.2). Euclidean distances are simply a straight-line plotted between point A (e.g., the centre of a population) and point B (e.g., a healthcare facility). As Euclidean distances ignore topography to assume a homogeneous isotropic surface, they can be readily applied anywhere which has made them historically popular for studies in low- and middle-income countries where the data required to operate more complex GIS methods can be difficult to source or of unusable quality (e.g., Noor *et al*., 2003; Målqvist *et al.,* 2010; Gabrysch *et al*., 2011a; Gabrysch *et al.,* 2011b; Kyei *et al.,* 2012; Mwaliko *et al.,* 2014; Hanson *et al.,* 2015). Manhattan distances are slightly more complex as they measure the distance between point A and point B based on the absolute difference in length between their Cartesian coordinates (Apparicio *et al.,* 2017). Due to the differences in how they are calculated, Manhattan measures will always produce a greater distance value than Euclidean measures for the same sets of points (Apparicio *et al.,* 2017).

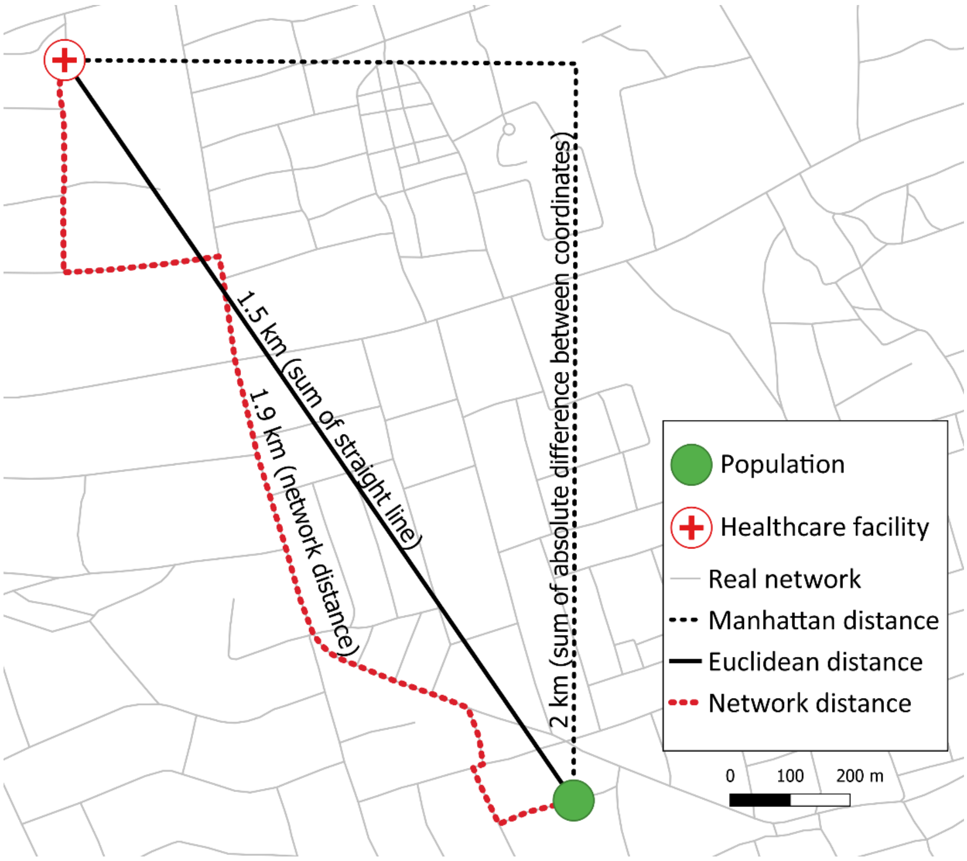


Figure 2.2. Euclidean and Manhattan distance measures compared against the shortest network distance calculated between a healthcare facility and a populated area in Mongu, Zambia. Adapted from Apparicio *et al*., (2017).

2.3.1.2. Provider-to population ratios

Provider-to-population ratios (PPR; also known as supply ratios) have been used as a measure of geographical accessibility since before the 1970s (Maina *et al.,* 2019). In a PPR, the numerator represents a value for an indicator of a health system (e.g., hospitals, available hospital beds) and the denominator denotes the population size computed for an area (Rekha *et al.,* 2017). Areas border one another and are representative of a geographic unit such as countries, states, or another user-determined geographic boundary (Rekha *et al*., 2017). PPRs can be compared for all areas to assess discrepancies in the healthcare system and to identify areas under- or over-served by the healthcare system (Rekha *et al.,* 2017). PPRs are popular as the data required to create them are usually readily-accessible and they require no GIS expertise to create (Guagliardo, 2004). Values arising from PPRs are also easily interpreted by policy-makers (Guagliardo, 2004) and consequently the format is often used to report values resulting from gravity models.

2.3.1.3. Gravity models

Gravity models estimate interactions between populations and providers by combining both accessibility and availability (supply of services), considering the effects of distance and the attractiveness of services (Rekha *et al*., 2017). Gravity models use a distance decay function to represent the fact that nearby providers are more accessible than those located further away (Luo and Wang, 2003). In the simplest gravity models, demand and competition effects are not considered. The limitations of early, basic gravity models have spawned a series of descendants attempting to improve upon the gravity model concept. The two-step floating catchment area method (2SFCA), enhanced two-step floating catchment area method (e2SFCA), and three-step floating catchment area method (3SFCA) are the most noteworthy of the descendants.

The 2SFCA method (Luo and Wang, 2003) improved upon earlier gravity models by explicitly considering travel times as its threshold, rather than assuming that all providers were equal in accessibility provided they were located within a threshold distance of a population centroid. 2SFCA is a systematic and consistent approach whose results are more easily interpreted by policy-makers than earlier gravity models as they are in the familiar PPR ratio format (Luo and Wang, 2003). 2SFCA also considers population movement across geographic boundaries, which earlier gravity models did not do.

The e2SFCA method (Luo and Qi, 2009) is a derivative of the 2SFCA method which incorporates a distance decay function to further emphasise distances between providers and populations (Luo and Qi, 2009; Heywood *et al*., 2011). The use of a distance decay function further discretises a population's catchment into travel time intervals permitting higher resolution quantification of the differences in accessibility between travel time intervals in one catchment, rather than using dichotomous travel time measures for catchment coverage (i.e., providers are either within the threshold or they are not) (Luo and Wang, 2003, Luo and Qi, 2009). Access within a catchment is no longer assumed to be uniform, and the discretisation is a closer analogue to the continuous distance measures used in traditional gravity models which are theoretically optimal (Luo and Qi, 2003). eS2FCA results are also reported in the familiar PPR format.

The 3SFCA method was developed from the 2SFCA and e2SFCA methods and differs in that it considers competition effects between facilities (Rekha *et al*., 2017). This consequently models the demand supply of healthcare in addition to the supply side, reducing overestimation of demand (Wan *et al*., 2012).

2.3.1.4. Cost-distance and network analysis

Cost-distance and network analysis are commonly used in the literature to measure distance and/or travel time between two locations, normally populations and services (e.g., Tanser *et al*., 2006; Bailey *et al*., 2011; Blanford *et al.,* 2012; Gething *et al.,* 2012; dos Anjos Luis and Cabral, 2016; Ruktanonchai *et al.,* 2016; Makanga *et al*., 2017; Ihantamalala *et al*., 2020). In addition to health services, cost-distance and network analysis have been used to assess geographic access to food, education, parks and recreation, religious establishments, and other services (Larsen and Gilliland, 2008; Hallet and McDermott, 2011; Mulrooney *et al.,* 2017; Abd El Karim and Awawdeh, 2020). The methods are also applied in other fields such as landscape ecology (Pérez-Espona *et al.,* 2008; Etherington, 2016), archaeology (Taliaferro *et al.,* 2010; White, 2015), and infrastructure planning (de Lima *et al.,* 2016; Ghandehari Shandiz *et al.,* 2018).

Principally, cost-distance analysis uses a raster-based model and network analysis uses a vector-based model (Delamater *et al.,* 2012; Nesbitt *et al*., 2014). Whilst methodological differences exist between the two types, the underlying principles of the algorithms are the same (Delameter *et al*., 2012): raster and vector are simply alternative ways of representing geographical data (Figure 2.3). In both analyses, geographical accessibility is typically computed by calculating the path of least resistance, or least geographical cost, between two locations (Ruktanonchai *et al.,* 2016) using an algorithm such as Dijkstra's Shortest Path (Dijkstra, 1959). The resulting path represents the ideal route to take in terms of minimum distance or travel time (Tanser *et al.,* 2006).

A vector-based model uses edges (lines) and nodes (points) to construct the road network, with the remainder of the geographical plane denoted as undefined (Delameter *et al*., 2012). Travel can only occur along edges and time penalties can be introduced at nodes to represent delays such as turn and stop impedances (Heywood *et al*., 2011; Delameter *et al*., 2012). The construction of a vector network closely mimics its real-world counterpart (Heywood *et al*., 2011; Delameter *et al.,* 2012) and so they are after seen as a more realistic representation of true road network connectivity. Vectors have attribute tables which permit the storage of multiple entities of information about each edge such as geographical coordinates, road type, road surface material, speed limits under different conditions, etc. The expansiveness of the vector attribute table allows complex calculations of impedance values assigned to edges. However, this also requires the modeller to clearly document all the rules in their vector-based model that determine travel along the edges and nodes (Delamater *et al*., 2012; Wong *et al*., 2017). Failure to do so could misrepresent connectivity and thus lead to misleading conclusions about geographical accessibility.

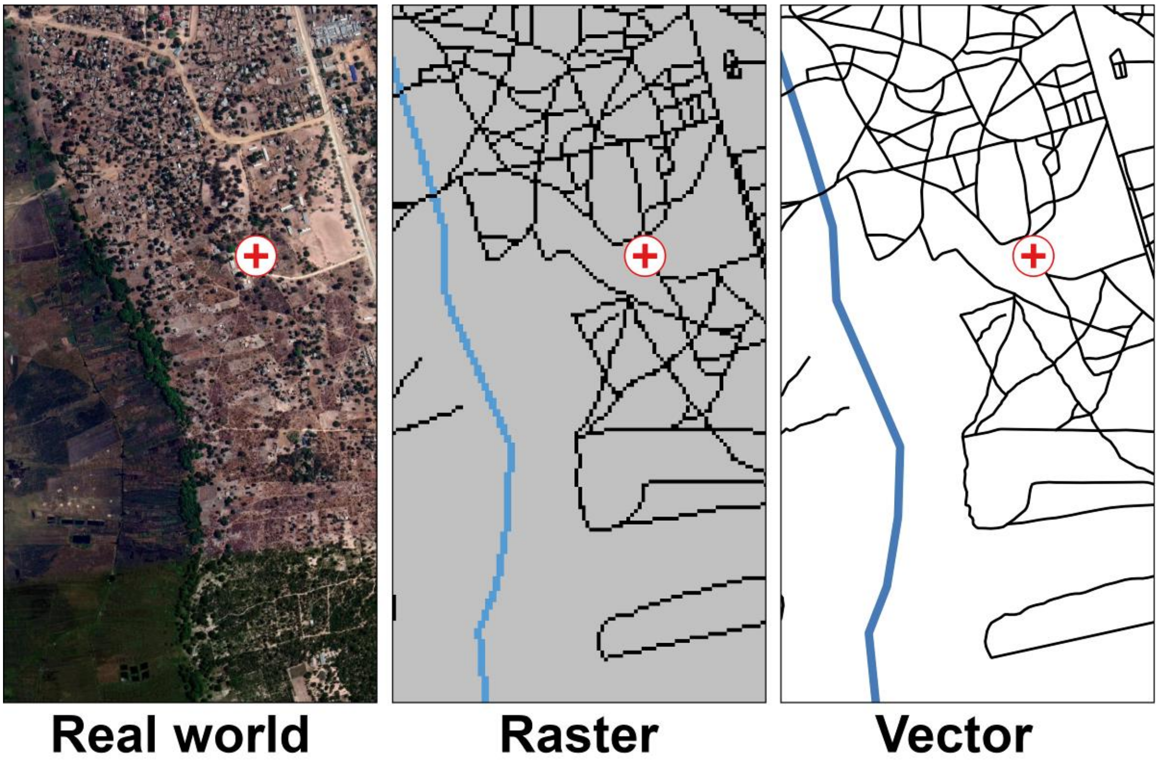


Figure 2.3. A comparison of vector- and raster-based representations of an area in Limulunga, Zambia. Note that in the vector model, white represents an undefined plane which cannot be traversed. Comparatively, in the raster model, the same area is represented in grey as it can be traversed.

In a raster-based model, travel is determined by cell proximity on an impedance surface (also known as a friction surface or cost surface) (Delamater *et al.,* 2012). An impedance surface is a grid of cells with impedance values determining the ease of geographical movement through each cell (Gething *et al*., 2012). Typically, the higher the impedance value, the less accessible the cell is to move through geographically, and vice versa. Waterbodies are typically assigned impedance values representative of total inaccessibility (e.g., Makanga *et al*., 2017) to deter any attempts to route through waterbodies. The impedance surface used in a raster-based model can only display data for one attribute: total surface impedance. However, total surface impedance can be calculated from as many variables as desired by combining multiple different raster layers representing different impedance variables (e.g., land-use, slope, roads) (Alegana *et al*., 2012; Ruktanonchai *et al*., 2016). Spatial data can be classified into four types: ordinal, nominal, ratio, and interval. Critically, a total surface impedance must contain only ratio-scaled values (e.g., travel time) that represent the real world as these values are multiplied in order to derive shortest paths. Consequently, using arbitrary values that are not ratio-scaled results in meaningless measurements (Medrano, 2021).

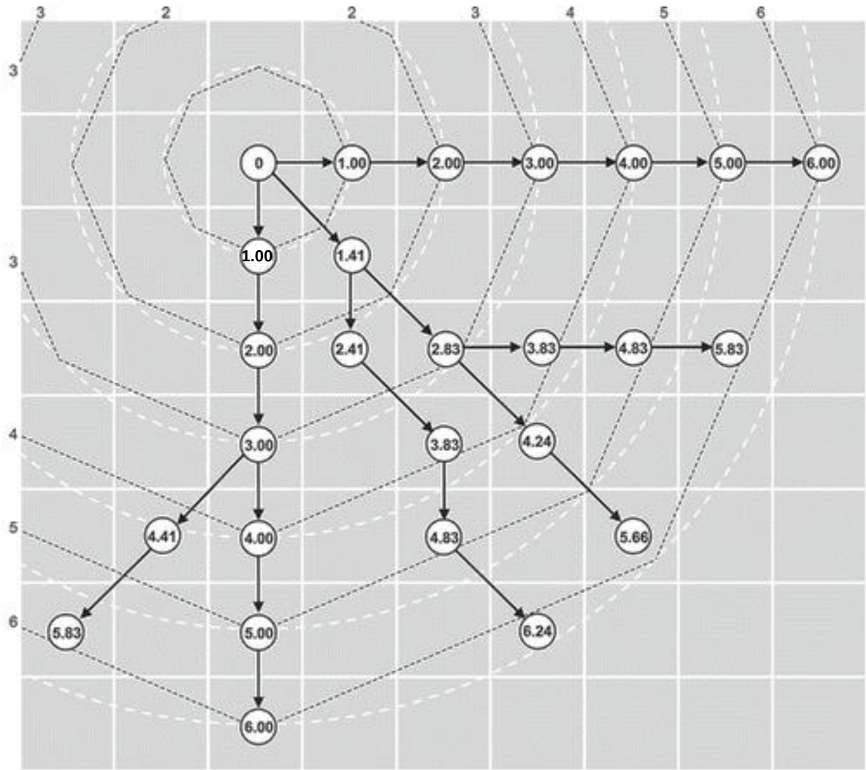


Figure 2.4. Conceptual diagram of the "zigzag" problem, taken from Tomlin (2010, p. 1,396). The white dashed lines represent radial propagation (or true distance) whilst the black dashed line illustrate the error in distance estimates caused by octangular propagation. The total error here is a 3.81% overestimate of cost.

In most raster cost-distance algorithms, movement is constricted to occur into any one of the eight adjacent cells through either horizontal, vertical, or diagonal movement (Tomlin, 2010). Due to the directional limitation imposed, propagation is octangular and paths created generate unintentional anisotropic measurements, unless they are completely straight in one of the eight directions (Tomlin, 2010). These anisotropic measurements are caused by the 45° movements that occur between cells where propagation would ideally be radial (Tomlin, 2010; Figure 2.4). This geometrically distorts paths and imparts an elongation error on measurements of distance, leading to overestimations of travel costs by as much as 8.24% if measured between octangular corners (Goodchild, 1977; Tomlin, 2010; Medrano, 2021). Increasing cell resolution is relatively ineffective for this problem, although highly heterogeneous surfaces are affected less due to the occurrence of true anisotropic movements (Tomlin, 2010). Instead, the addition of arcs that connect non-adjacent cells allows propagation into 16 cells rather than 8, which produces a result closer to true radial propagation (Figure 2.5; Tomlin, 2010; Medrano, 2021). More arcs can be added to permit propagation into greater numbers of cells to further reduce geometric distortion, but doing so increases computational processing times (Medrano, 2021); Huber and Church (1985) found that 16-cell propagation was most optimal in reducing elongation errors relative to its processing time.

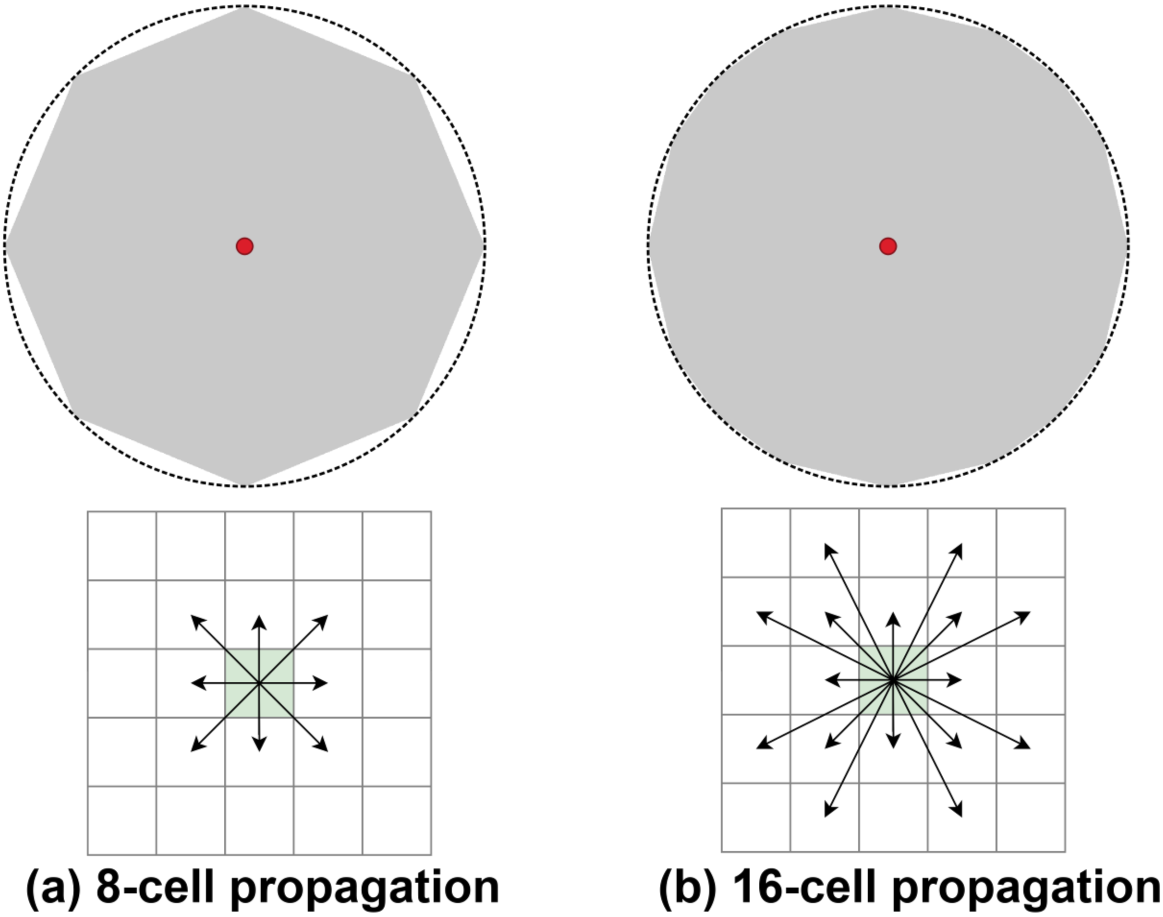


Figure 2.5. A comparison of the differences between 8-cell and 16-cell propagation. In (a), moves can only be made into directly adjacent cells in either the orthogonal or diagonal directions. This results in significant deviations away from true radial distance (black dotted line). In (b), "*knight's move*" can be made into cells that are not directly adjacent, but are within two cells horizontal and one cell vertical (or vice versa) distance; the cost in non-adjacent cells is the measurement resulting from the connecting arc (black arrow). As a result of the additional cell movement potential, unintentional anisotropic variations in grid paths are reduced, minimising travel time overestimates. Consequently, 16-cell propagation is a closer representation of true radial propagation than 8-cell propagation.

A geographical access model may represent travel as unimodal (one transport mode only) or multimodal (multiple transport modes used). More data are required to create multimodal models in order to parameterise travel times to appropriately represent the realities of populations using different combinations of transport. Unimodal models are, thus, easier to create as they only require data and rules to be provided and established for one mode of transport. In low- and middle-income countries, multimodal models typically represent movement more realistically, provided the model set-up is appropriate to the study area and the data are accurate. This is because household car ownership (for example, in sub-Saharan Africa) is usually low and journeys to healthcare are typically a combination of walking to the nearest road in order to access public transport or a taxi (e.g., Rudolfson *et al.*, 2020).

2.3.1.5. Units of measure

Access models use a variety of units to represent geographical accessibility. As described earlier, gravity models and their variants typically use PPRs to convey results, whilst Cartesian measures and cost-distance algorithms represent results in units of distance, travel time, or financial cost (Penchansky and Thomas, 1981; Vadrevu and Kanjilal, 2016).

Distance is the most commonly used unit (Wong *et al*., 2017) whilst financial cost is rarely utilised and is typically reserved for studies looking at the interrelationship between geographic and financial accessibility. In healthcare applications looking solely at potential geographic access, either distance, time, or both are acceptable to use. However, there is a stronger argument to opt for travel times as the unit of measure where possible as time often better represents a true journey traversed compared to distance alone. This is especially true for journeys over complex, difficult terrains across otherwise short distances (Vadrevu and Kanjilal, 2016). Additionally, in the health literature, time thresholds to access care are used to distinguish increased morbidity and mortality outcomes for serious conditions, such as a two-hour time limit from postpartum haemorrhage to mortality in the absence of medical intervention (World Health Organisation *et al*., 2009). Consequently, denoting geographical accessibility results in units of time allows better interpretability in the context of health.

2.3.2. Comparison of GIS methods

2.3.2.1. Appropriateness of Euclidean distance measures

There remains long-running, ongoing debate surrounding the usage of Euclidean distance measures and whether they are a trustworthy proxy for real travel distance (Målqvist *et al*., 2010;

Gething *et al.,* 2012; Salonen *et al*., 2012; Nesbitt *et al.,* 2014). As Euclidean distance measures assume isotropy, they do not consider heterogeneity in surface impedance (Delameter *et al*., 2012). Consequently, they ignore the reality of terrain and the difficulties potentially experienced in traversing it (Gabrysch *et al*., 2011a). Euclidean measures underestimate the effects of terrain in influencing distance and time to reach a healthcare facility (Figure 2.6). For example, Ihantamalala *et al.* (2020) found that Euclidean distance results consistently underestimated the recorded travel times by ~31 minutes (40.5% underestimation) when compared with a raster-based cost-distance algorithm which underestimated travel times by an absolute maximum of ~22 minutes (29.8% underestimation). As a result of its underestimation, the Euclidean approach overestimated the percentage of population with access to a healthcare facility in an hour by almost 20%.

However, Nesbitt *et al*. (2014) compared Euclidean distances to both network- and raster-based cost-distance algorithms and reported that, whilst it comparatively underestimated travel distances, it did predict the odds of healthcare facility use. Consequently, Nesbitt *et al*. (2014) concluded that, with consideration of context appropriateness, Euclidean distance measures could be reasonably used as a proxy especially for rural low-income settings where available input data is not available or of sufficient quality, or where cost or computational restrictions prevent more sophisticated GIS techniques. Regardless, for areas where waterlogged or flooded land constitutes an important component of the topography, Euclidean distance measures are completely inappropriate (Figure 2.7). The homogeneous isotropic assumption cannot consider topological features and would route a straight-line directly through impassable water bodies. Such results would be completely implausible and misleading.

Whilst Euclidean distance measures have generally fallen out of favour in more recent studies (Delamater *et al*., 2012), new studies are still being published where Euclidean distance is the primary or sole method for assessing geographic accessibility (e.g., Kyei *et al*., 2012; Hanson *et al*., 2015; Hanson *et al*., 2017; Togawa *et al*., 2020; McGuire *et al*., 2021). Commonly-cited reasons justifying the usage of Euclidean distance measures are a lack of high quality data, and the cost and computational demands of more sophisticated GIS techniques. However, the strength of this reasoning has substantially diminished over the last decade due to: (1) the availability of numerous free GIS software (e.g., QGis with a user-friendly interface and as many capabilities as ESRI's ArcGIS) (Nesbitt *et al.*, 2014; dos Anjos Luis and Cabral, 2016); (2) the availability of high-resolution satellite imagery which can be used to check and correct datasets, fill-in missing data, or even create entire new topological datasets (e.g., Google Earth Pro has very-high resolution composite imagery and permits delineation of topological features) (dos Anjos Luis and Cabral, 2016; Makanga *et al*., 2017); (3) the existence of freely-available, easy-to-operate tools that run more complex geographical accessibility analyses with minimal user set-up required (e.g., AccessMod and Fisher and Lassa's (2017) interactive modelling tool) (Ray and Ebener, 2008; Alegana *et al*., 2012; Ihantamalala *et al.*, 2020; Rudolfson *et al*., 2020); and (4) the increasing availability of open-access topological data (e.g., OpenStreetMap, DIVA-GIS) (Ruktanonchai *et al.,* 2016, Ihantamalala *et al*., 2020, Rudolfson *et al.,* 2020).

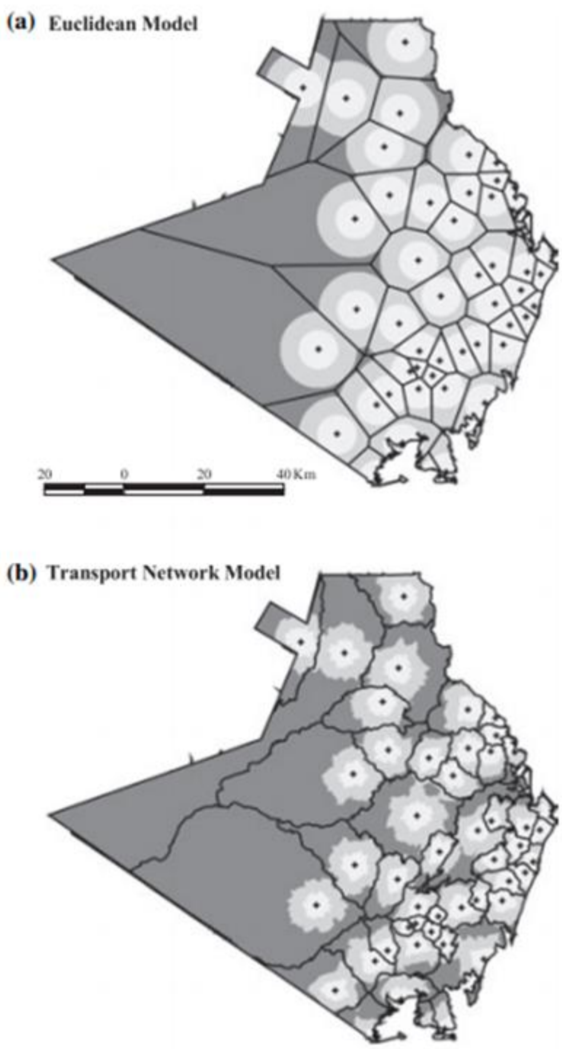


Figure 2.6. Comparison between a Euclidean approach and network-based approach for identifying variations in geographic accessibility, taken from Noor *et al*. (2006: p. 193).

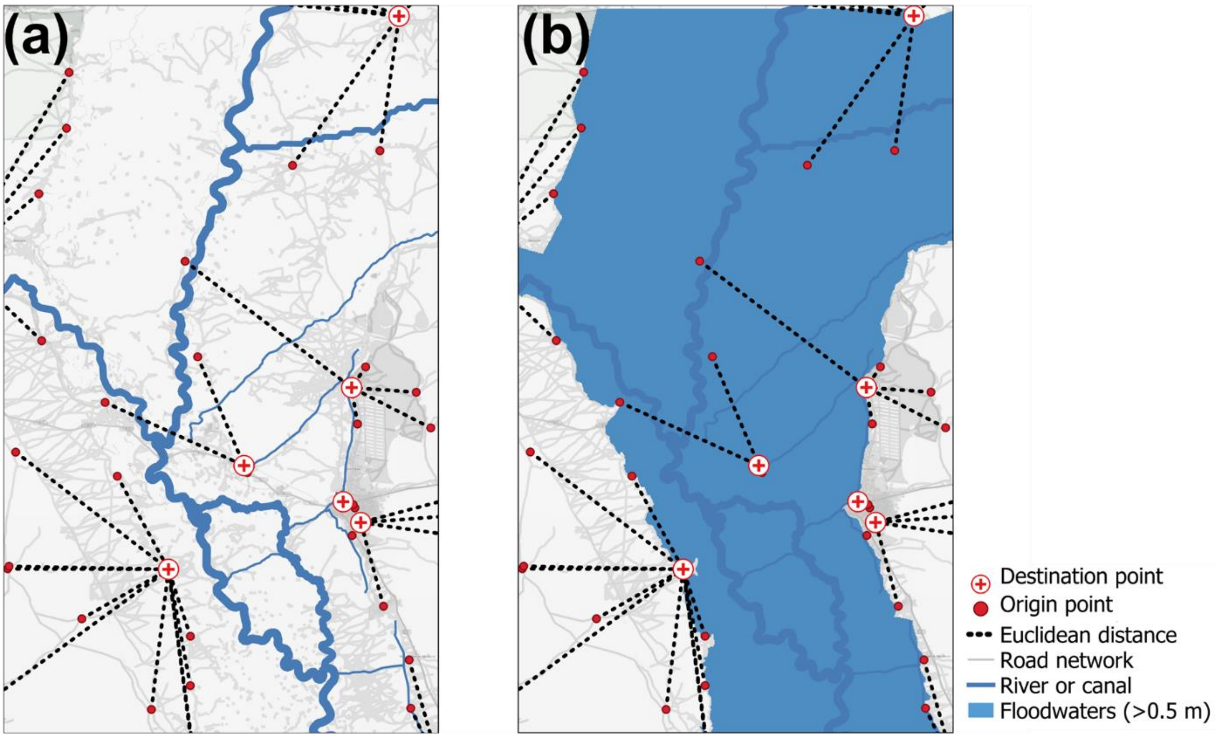


Figure 2.7. Euclidean distances calculated for the Barotse Floodplain in (a) October 2017 and (b) March 2018. Due to their isotropic assumption, the resulting measurements (black dashed lines) are the same in both months as the Euclidean distance paths generated have ignored the roads, waterbodies, and any floodwaters present.

2.3.2.2. Vector- or raster-based models?

There remains discussion in the health literature about whether vector-based or raster-models are more appropriate for measuring geographical accessibility (Delamater *et al.*, 2012). Principally, neither is universally better than the other approach. Both raster- and vector-based models operate using the same assumption that the most optimal route is the path of least resistance. The choice of which approach to use is a decision that needs to be made for each independent study. It depends upon the mode(s) of transport being assessed (e.g., mechanised or non-mechanised transport), the characteristics of the study area (e.g., topography), and data availability and quality. All variables pertaining to the study area must be considered with regards to the advantages and limitations of the vector- and raster-based approaches (Nesbitt *et al.,* 2014).

In low- and middle-income countries, raster-based models are commonly applied because they are preferable for areas where walking is the most common mode of transport and, unlike in vector-based models where movement is bound to edges, movement can occur anywhere (Blanford *et al.,* 2012; Delamater *et al.,* 2012; Neutens, 2015). Consequently, raster-based models better represent the ability of a person to walk off-road to their destination. In urban areas or high-income countries where car ownership is widespread, vector-based models provide the most accurate travel times and simulation of car journeys which are bound to the road network. A raster-based approach is as geographically appropriate as a vector-based approach for analysing geographical accessibility; exactly mimicking real-world geography of roads is not a necessity for accurate, reliable results provided impedance is adequately accounted for (Heywood *et al.,* 2011; Mulrooney *et al.,* 2017).

2.3.2.3. Unimodal or multimodal cost-distance algorithms?

Decisions on whether to operate a unimodal or multimodal model require critical consideration of the data requirements, advantages, and limitations of each model type in specific relation to the study area. A multimodal model may theoretically produce results that are more representative of true journeys undertaken in a rural, low-income area. However, if the data used are inadequate or unreliable, the results will be subject to significant uncertainty. Accurate data on travel times for all modelled transport modes are needed to calibrate journey times in a model. Additional data for multimodal models is needed on typical journeys the population take, what percentage of the population travel in the way the model suggests, and what delays are experienced when switching between transport types (e.g., waiting times for public transport). These data are typically obtained through surveys which are time- and resource-intensive (e.g., Gething *et al.,* 2012; Ihantamalala *et al.,* 2020). Consequently, a multimodal model is not inherently superior to a unimodal model if the additional data required are not available or of the quality needed.

2.3.2.4. Criticisms of cost-distance algorithms

Some authors (e.g., Geurs and van Wee, 2004) categorise cost-distance algorithms as simple approaches due to their inability to consider supply and demand and competition effects like advanced gravity models. Cost-distance algorithms also cannot account for the personal preferences of populations, including the social factors and perceptions of healthcare that can encourage populations to either ignore healthcare or to seek it beyond their nearest facility. However, in data-limited regions, cost-distance algorithms are usually the most complex models that could be feasibly operated (Nesbitt *et al*., 2014). Arguably cost-distance algorithms are excellent for low-income and middle-income countries as: (1) their data requirements are minimal relative to their research power; (2) competition is normally not as influential due to fewer services being present (Neutens, 2015); and (3) the model user can control the complexity of the model by varying the inputs, parameters, and modes of transport used to create the impedance surface.

2.4. Incorporation of flooding and precipitation

This section explains flood hazard experienced when walking or driving, and reviews existing attempts to incorporate flooding and precipitation into transport models. Sections 2.4.1 and 2.4.2 first review the literature on human instability and vehicular instability, which underpins the use and choice of stability criteria in the new network- and raster-based models. Section 2.5 then explicitly summarises methodologies from studies situated in high-and low-income countries which have incorporated flooding and precipitation, and critically reviews the variation in approaches from simple to most complex.

2.4.1. Human instability

When walking through floodwaters, the human body is subject to five key forces acting upon it vertically (gravitational force, buoyancy force, and the ground's normal reaction force) and horizontally (drag force of floodwaters, and the frictional force between a person's feet and the ground) (Abt *et al*., 1989; Xia *et al*., 2014a). Human instability occurs when the balance of forces shifts so that the hydrodynamic forces of floodwaters overwhelm the ability of a person to stand upright. There are two main mechanisms of human instability: toppling (moment) and sliding (frictional) instability (Figure 2.8; Keller and Mitsch 1993; Jonkman and Penning-Rowsell, 2008; Cox *et al*., 2010; Chanson *et al*., 2014; Xia *et al*., 2014a; Martínez-Gomariz *et al*., 2016a; Shu *et al*., 2016a). Toppling occurs where the moment drag force of floodwaters exceeds the moment force of a person's effective mass (Abt *et al*., 1989; Chanson *et al*., 2014; Xia *et al*., 2014a; Shu *et al.,* 2016a). Sliding occurs when the drag force of floodwaters exceeds the frictional resistance between a person's feet and the ground (Nanía, 1999; Chanson *et al*., 2014; Xia *et al*., 2014a; Shu *et al.,* 2016a). Toppling is most common in deep floodwaters with lower velocities, whilst sliding is more common in shallow waters with high velocities such as urban flash floods (Chanson *et al*., 2014; Shu *et al.,* 2016a). There is a third, less common hydrostatic mechanism known as floating where if water depths exceed a person's height, toppling and sliding no longer apply (Jonkman and Penning-Rowsell, 2008).

The risk of instability for a person in floodwaters changes over space and time, reflective of changes in the hydrodynamic properties of floodwaters as well as topographical changes underfoot (Xia *et al*., 2014a; Xia *et al*., 2014b). Floodwater depth (*h*) and velocity (*v*) are the key hydraulic properties commonly considered when investigating human instability (Martínez-Gomariz *et al*., 2016a), but fluctuations in water depth and velocity in addition to flow turbulence are also influential hazards (Chanson *et al*., 2014). Non-hydraulic factors also influence stability including: the temperature and visibility of water; any debris present in the water or on the ground; the surface material, its frictional resistance, and slope; weather and lighting; and a complex variety of human characteristics such as height and weight, age, disabilities and health, clothing, additional weight carried, previous experience in floodwaters, and emotions (Foster and Cox, 1973; Karvonen *et al*., 2000; Xia *et al*., 2014a; Xia *et al.,* 2014b; Martínez-Gomariz *et al*., 2016a; Arrighi *et al*., 2017; Bignami *et al*., 2019; Chen *et al*., 2019).

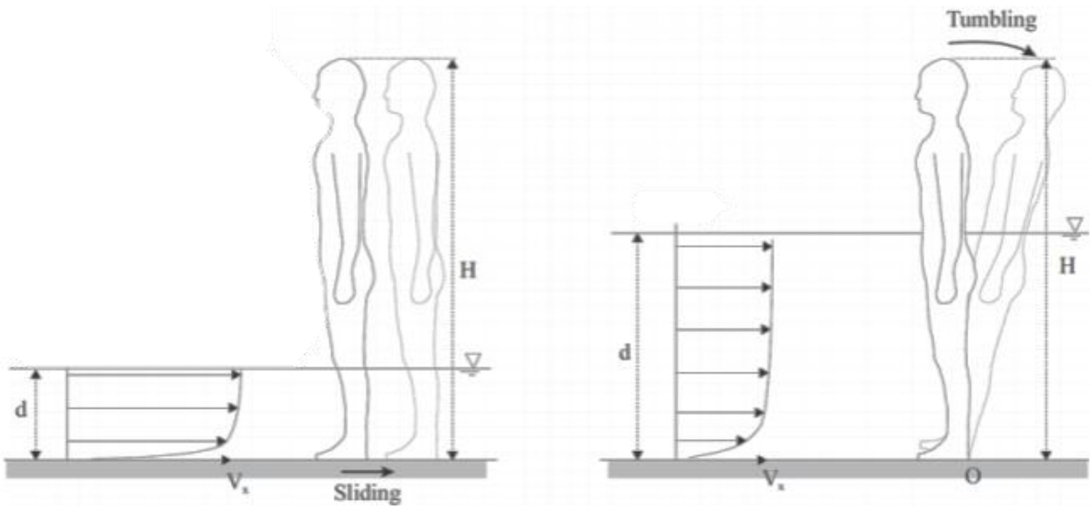


Figure 2.8. Sketch of sliding and toppling (tumbling) instability. *d* represents flow depth (m), V_x represents a depth-averaged velocity (m s^{-1}), *H* represents human height (m), and O represents forces acting at the bottom of the body. Source: Chanson *et al.* (2014: p. 3).

Numerous studies have investigated human instability from toppling and sliding to define stability criterion (e.g., Cox *et al.,* 2010; Chanson *et al.,* 2014; Milanesi *et al*., 2015). Stability criteria (hv_c) are the product of floodwater depth and velocity that causes instability (Jonkman and Penning-Rowsell 2008). Xia *et al*. (2014a) classifies these studies and their stability criteria into two groups: (1) regression relationships created from subjecting real humans (or a representative monolith) to a variety of flows in flume experiments (e.g., Abt *et al*., 1989; Karvonen *et al*., 2000; Figure 2.9), and (2) empirical or theoretical formulae from mechanics-based analyses with experimental data (Keller and Mitsch, 1993; Lind *et al*., 2004; Jonkman and Penning-Roswell, 2008).

Figure 2.9. Photographs of a human subject in a flume tank subject to floodwaters with a depth of 1.07 m and a velocity of 1.0 m s^{-1}. The human subject stands on a steel grate wearing safety clothing and equipment and has clear visibility in and out of water, all of which has the potential to influence their behaviour in simulated floodwaters relative to reality. Source: Karvonen *et al.* (2000: p. 49).

In (1) the experimental regression approach, the product of water depth and velocity that led to the instability of a person is related to the product of that person's height and weight. An equation describing the linear regression of all the experimental data is then created which estimates hv_c as a function of effective mass (Xia *et al*., 2014a). The regression relationships produced are highly dependent on a study's test subjects and conditions in the flume (Xia *et al*., 2014a). Relationships produced for monoliths will typically have lower stability criteria as real humans are able to adjust their stances relative to floodwater flow in order to become more stable (Xia *et al*., 2014a). Conditions in flumes are also usually optimum (for example, good visibility and lighting, and warm water temperatures) which Xia *et al*., (2014a) states can cause the criteria to be optimistic. Karvonen *et al*. (2000) pioneered good, normal, and bad equation variants that attempted to account indirectly for the impact of these non-measured conditions on stability (Figure 2.10). Finally, human test subjects in a flume are repeatedly exposed to different variations of flows over numerous tests, which may bias criteria towards optimistic values as participants learn to maintain stability (Xia *et al*., 2014a; Martínez-Gomariz *et al.,* 2016a).

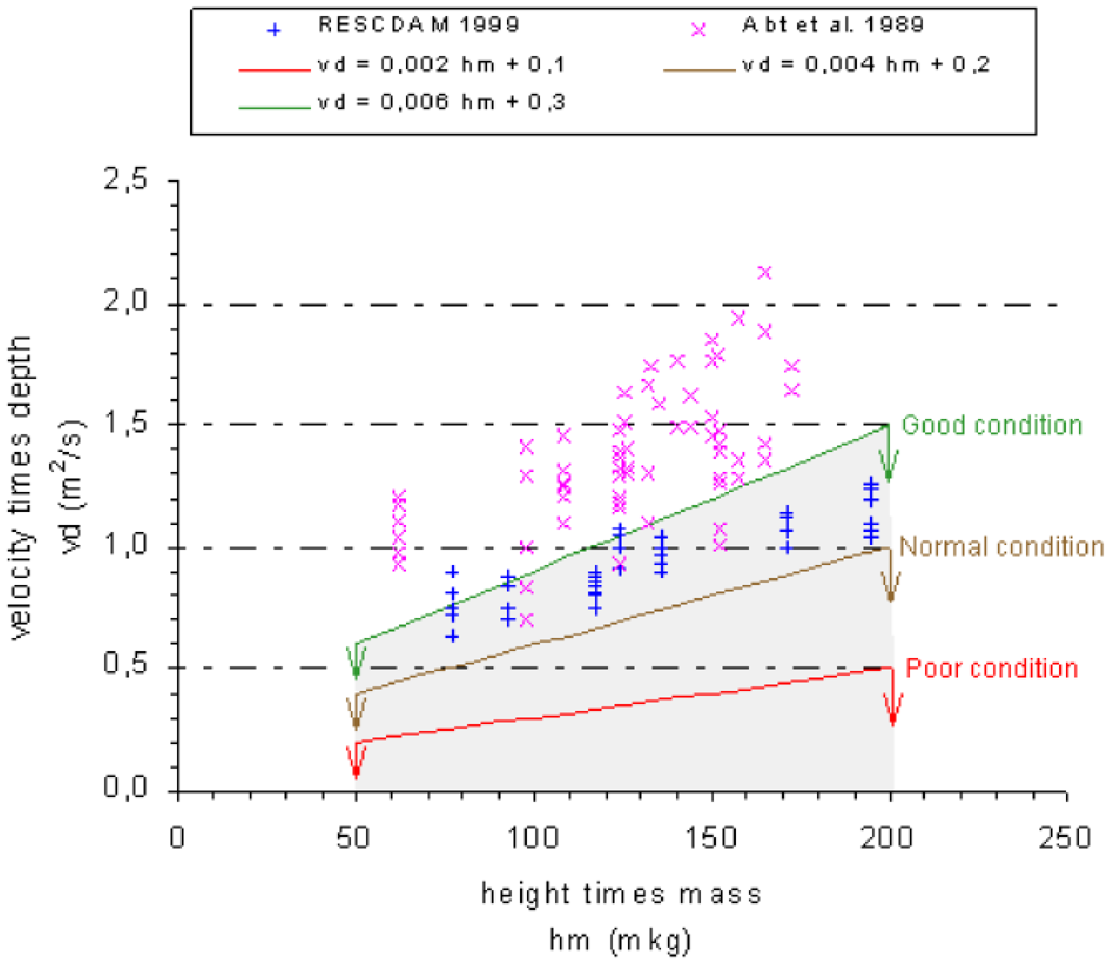


Figure 2.10. Karvonen *et al.* (2000)'s equations describing stability criteria in different conditions, plotted against experimental data of participants' loss of stability obtained from both their study (RESCDAM) and Abt *et al.* (1989). Taken from Karvonen *et al.* (2000: p. 52).

In (2), formulae derived from mechanics-based analyses are created that solely relate stability to hydrodynamic variables, ignoring non-hydraulic factors such as human height and weight (Xia *et al*., 2014a). These formulae heavily simplify human bodies and flow conditions; human bodies are represented as cylinders, and uniform velocity profiles are typically assumed (Xia *et al*., 2014a). The formulae observe the forces acting on a representative cylinder that cause toppling or sliding instability (Xia *et al*., 2014a), and are sensitive to friction and drag coefficients (Xia *et al*., 2014a). In addition to these limitations, buoyancy force is also neglected which makes criteria recommended by these formulae unsuitable for precisely assessing instability in floodwaters. Rather, they are most suitable for use in initial assessments of hazard (Xia *et al*., 2014a).

In reality, hv_c values differ depending on the characteristics of floods; for example, urban flash floods with shallow water depths and high velocities have a different hv_c relative to floodplain floods, which have higher water depths, low or negligible velocities, and persist for longer durations. Additionally in riverine floodplains, depending on a singular hv_c to determine flood hazard may be inappropriate due to these characteristics. Sole consideration of the depth-velocity product (hv) may underestimate true flood hazard; the combination of a large water depth with a negligible velocity produces a low hv below the hv_c which fails to recognise that deep flows independently are hazardous (Quirogaa *et al.,* 2016). Consequently, Témez (1992) proposed additional thresholds in addition to hv_c based upon floodplains with low floodwater velocities (Martínez-Gomariz *et al*., 2016a; Martínez-Gomariz *et al*., 2016b). Témez (1992) recommended an absolute maximum depth (H_{max}) of 1 m, an absolute maximum velocity (V_{max}) of 1 m s^{-1} in addition to a hv_c of 0.5 m^2 s^{-1} which is a commonly recommended and used threshold (Abt *et al*., 1989; Martínez-Gomariz *et al*., 2016a). Whilst Témez (1992)'s stability criterion values have been criticised as excessively restrictive in studies observing urban floodwater hazards where measured stability consistently exceeds these criterion (Martínez-Gomariz *et al*., 2016a; Martínez-Gomariz *et al*., 2016b), the values are considered reasonable in floodplains (Martínez-Gomariz *et al*., 2016a).

2.4.2. Vehicular instability

A vehicle in floodwaters is subject to a gravitational force, a frictional force between its tyres and the road surface, and a lift, drag, and buoyancy force from floodwaters (Xia *et al*., 2014c; Xia *et al*., 2011a; Xia *et al*., 2011b; Figure 2.11). As with humans, vehicles in floodwaters experience instability when the hydrodynamic forces exceed a stability threshold (Martínez-Gomariz *et al*., 2018). Assessing vehicular instability is simpler than human instability as there are fewer non-hydraulic variables to consider (i.e., ability to adapt does not apply), but still remains challenging, particularly for instability in moving vehicles. Consequently, there remains substantial disagreement about critical combinations of depth and velocity (Martínez-Gomariz *et al*., 2018). Studies examining floodwater impacts on vehicles have been limited (Xia *et al.,* 2011b; Bignami *et al*., 2019b) and have primarily investigated incipient velocities (i.e., the value of velocity required to cause instability) of idealised vehicles (stationary and water-tight) on flat surfaces in flumes, with constant drag and friction coefficients applied (Shu *et al*., 2011; Xia *et al*., 2011b; Xia *et al*., 2014c; Martínez-Gomariz *et al.,* 2018).

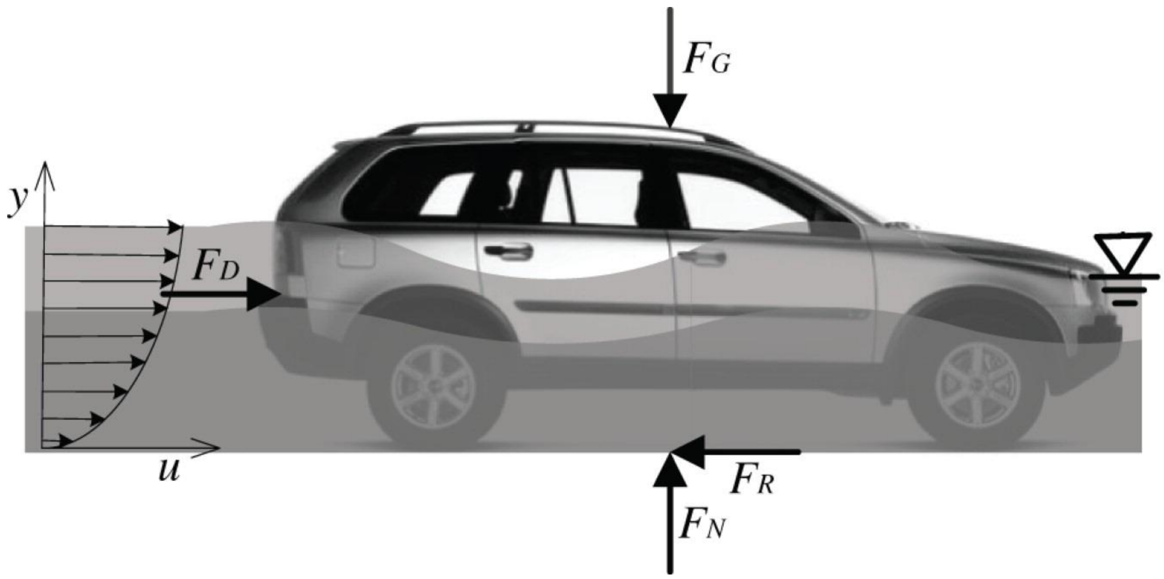


Figure 2.11. Forces acting upon a vehicle partially-submerged in floodwaters. F_D represents drag force, F_N represents the normal reaction force from the ground, F_R represents a frictional force between the car's tyres and the ground, and F_G represents a combination of the gravitational force and buoyancy force. *y* is floodwater depth (m), and *u* is floodwater velocity (m s^{-1}). Source: Shu *et al.* (2011: p. 710).

It is widely acknowledged that floodwater depth and velocity are the primary hydrodynamic variables determining stability for a vehicle (Mens *et al.*, 2008; Teo *et al*., 2013). Combinations of both shallow water depths and high velocities, and high water depths with low velocities are hazardous (Teo *et al*., 2012). Experimental studies have shown that where floodwaters are below a model vehicle's height, incipient velocities increase as floodwater depths decrease (Mens *et al*., 2008; Teo *et al*., 2012; Xia *et al*., 2014c). In contrast, if floodwaters are above a vehicle's height, incipient velocities increase with increases in floodwater depths (Mens *et al*., 2008; Teo *et al*., 2012; Xia *et al*., 2014c). However new hydrodynamic and chassis designs of vehicles increase vehicular buoyancy, so new studies are needed on modes of vehicular instability (Shand *et al.,* 2010). Slope also modifies incipient velocities which are reduced on steeper gradients (Teo *et al*., 2012; Xia *et al*., 2014c).

Instability criteria are different for every vehicle and vary spatio-temporally with floodwaters, but can be summarised as the combination of a vehicle's characteristics and the forces acting upon it (Wright *et al*., 2010). A vehicle's height, weight, chassis height, aerodynamics, sealing capacity, and tyre condition (age, tread depth, pressure) influence its susceptibility to floodwaters forces (Xia *et al*., 2011b; Teo *et al*., 2012). For example, Teo *et al*. (2012) considers chassis height to be a particularly key variable due to increased buoyancy (and thus instability) when water depths reach a vehicle's chassis. Additionally, Teo *et al*., (2012) and Xia *et al*. (2014c) showed that the same vehicle can experience different thresholds of incipient velocity based upon their orientation relative to oncoming flow; vehicles positioned perpendicular to oncoming flow experienced greater drag forces acting on the increased surface area, thus lower incipient velocities were needed to cause instability. Regardless of this complexity, experimental studies at most have calculated incipient velocities for a maximum of three vehicle models (facing oncoming flow) representative of a small (or compact) passenger vehicle, a large passenger vehicle, and a four-wheeled drive (e.g., Shand *et al*., 2010). Existing criteria are consequently unsuitable for development into generalised methodologies for calculating instability of any vehicle with different characteristics (Martínez-Gomariz *et al.,* 2018). However, in their comprehensive review on vehicular instability, Martínez-Gomariz *et al.* (2018) cited that the safety criteria in the Australian Rainfall and Runoff Project (Shand *et al.,* 2010) were the most suitable and best available reference on the basis that nearly all newly-published experimental data points on instability continued to fall outside of the boundaries of the stability criteria proposed (Figure 2.12).

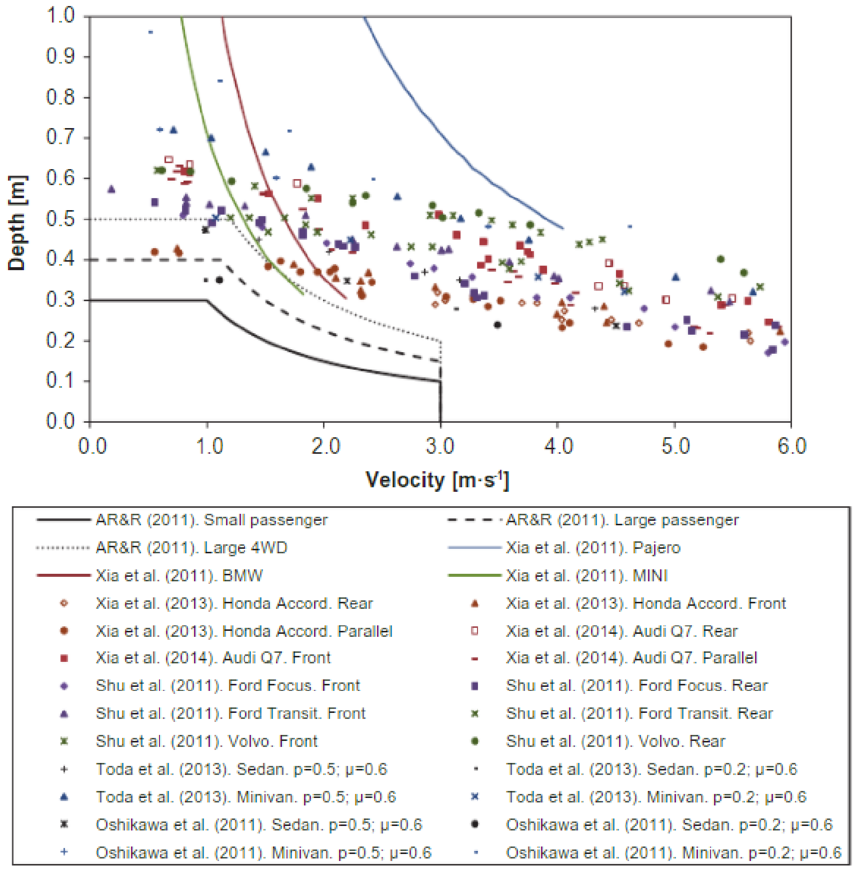


Figure 2.12. The Australian Runoff and Rainfall (AR&R) stability criteria compared against all theoretical and experimental data independently generated since its publication. The points plotted refer to measured instability for different types of vehicles. No instability data fall below the criterion for large four-wheeled drive (4WD) vehicles or small passenger vehicles. Only two instability data from Toda *et al*. (2013) and Oshikawa *et al.* (2011) fall below the criterion for large passenger vehicles. Source: Martínez-Gomariz *et al.* (2018: p. 821).

2.5. Research gaps

Few studies have attempted to model floodwater impacts on healthcare access in low-income countries, causing research gaps to exist on how intermediate changes in floodwaters affect access, and how to incorporate floods into geographic access models. Previously, limited computational power and inadequate data prevented modelling flood impacts on access at sufficient temporal and spatial resolution. These limitations have since sufficiently resolved and novel studies have pioneered approaches for representing flood hazard. However, these are limited to network-based approaches applicable only to studying the impacts of short-duration, urban floods on car usage in high-income countries with predominantly paved infrastructure. An approach is needed that is suitable to the assumptions of floods in low-income regions with predominantly informal, unpaved rural roads. A literature review was conducted through which two broad research gaps were identified. Section 2.5.1 discusses the research gap in accounting for floodwaters in low-income regions, and Section 2.5.2 explores the research gap in using hydrodynamic model outputs to represent floods in geographic access models.

2.5.1. Accounting for floodwaters in low-income regions

Due to the sheer complexity of variables involved and the spatio-temporal dynamic nature of floodwaters, accounting for the effects of floodwaters on access has been challenging. Few studies (Blanford *et al*., 2012; Makanga *et al*., 2017; Ihantamalala *et al*., 2020) have considered the impact of precipitation and/or flooding on geographical access in low-income countries, despite widespread acknowledgement in the literature that significant drops in accessibility occur between the dry and wet season (e.g., Schatz, 2008; Gabrysch *et al*., 2011a; Vora *et al*., 2015; Espinet Alegre *et al*., 2020; Stone *et al*., 2020). A failure to account for the impacts of precipitation and flooding on access leads to modelled scenarios that overestimate true geographical accessibility, resulting in overly-optimistic estimates. These "dry season" scenarios have limited value in assessing geographic access as they are static (i.e., the model's impedances do not change over space or time), cannot detect seasonal vulnerabilities in access and thus cannot represent access for more than a limited duration of a hypothesised typical year. Critically, these studies offer insubstantial information that could be of use or incorporated into health policy planning (Makanga *et al*., 2017).

Of the few studies to consider precipitation and/or flooding, most consider their study areas to be temporally and spatially static. Blanford *et al*. (2012) attempted to represent differences in access caused by seasonal effects in Niger, but were limited in creating static maps of "dry" and "wet" season access. In the wet season scenario, the differences compared to the dry season scenario purely arose because Blanford *et al*. (2012) uniformly reduced travel times across the entire of Niger, and assumed documented seasonal waterbodies were impassable in the wet (but not the dry) season. There was no consideration of real-world data and no incorporation of precipitation or flooding variables to determine where impacts were occurring.

Makanga *et al*. (2017) vastly improved upon previous research by explicitly incorporating empirical records of precipitation and flood extent into impedance surfaces for their region of interest in south Mozambique. They modelled monthly seasonal variations in access using different transport options across a 17-month timespan between March 2013 and September 2014. Critically, Makanga *et al.* (2017) demonstrated that access is not well-represented by two static scenarios of "dry" and "wet" season access, but that it fluctuates monthly. However, Makanga *et al*. (2017) used remotely-sensed flood extents (taken from the DFO Flood Observatory) and classified any land intersecting flood extent as completely impassable. This basic classification is in contrast to their approach with the precipitation data where they reduced travel times based upon precipitation depth (mm) thresholds. Flood extent data is unable to recognise water depth, and thus it is not possible to differentiate between floodwaters of 1 cm depth, and those of 1 m depth (Tsang and Scott, 2020). As a consequence, there remains limited understanding of how floodwater depth and velocity interact over space and time to determine access.

Relying on flood extent alone may be appropriate for considering spatio-temporal changes in access at the country-level. However, to date no studies have considered whether smaller areal units require higher-resolution representations of floodwater variables to adequately model flood impacts on access. There remains no geospatial model adapted for use in low-income/data-limited regions that is able to incorporate quantitative floodwater measurements. This is a critical shortcoming as government officials require information on healthcare access for specific populations they have already identified as underutilising healthcare, such as communities living on large African floodplains.

2.5.2. Use of hydrodynamic model outputs

In both vector- and raster-based access models those who consider floodwater impacts consider flood extent alone (e.g., Blanford *et al.,* 2012; Reuben and Lowry, 2016; Makanga *et al.,* 2017; Hierink *et al.,* 2020). Hydrodynamic models have been used before as a source of data on floodwater variables, but their usage has been restricted to network analysis for smaller areal units (e.g., towns or cities) in high-income regions (Albano *et al.,* 2014; Yin *et al.*, 2016; Coles *et al.,* 2017; Green et al., 2017). In these studies, floodwater depths obtained from hydrodynamic modelling are incorporated into the network analysis; velocity outputs have been seldom used in network analysis studies due to difficulties in incorporating depth-velocity products whilst the existing knowledge (Section 2.5.3) on appropriate values remains uncertain. To date, no study has used hydrodynamic model outputs in a raster cost-distance access model operated for a low-income region.

The simplest use of a hydrodynamic model has been to use the floodwater depth outputs to generate polygons representative of an area of impassable floodwaters (Coles *et al.,* 2017; Green *et al.,* 2017). To do this, a water depth threshold is defined and any floodwaters exceeding the threshold are retained in the model as impassable polygons. The water depth threshold is most commonly set as between 0.25 and 0.3 m based on air inlets of small passenger vehicles (Yin *et al.,* 2016; Coles *et al.,* 2017; Yu *et al*., 2020); however, a threshold of 0.5 or 0.6 m may be used when modelling emergency vehicles (Kramer *et al.,* 2016; Yin *et al*., 2017). These thresholds can also be defined from criteria in the vehicular instability literature.

As discussed previously in relation to flood extents, any roads intersecting a floodwater polygon are assumed inaccessible. Roads are assumed either completely inaccessible or completely accessible at ordinary speeds. This binary representation has been criticised as unrealistic (Pregnolato *et al.,* 2017; Tsang and Scott, 2020). The presence of floodwaters below a threshold will still reduce safe travel speeds along an otherwise open road. As a result, Pregnolato *et al.* (2017) created a depth-disruption function to relate floodwater depths to safe travel speeds based on available data from observational, experimental, and modelling studies in the literature. This depth-disruption function or an adaptation of it has been used in subsequent studies coupling flood models with traffic models (e.g., Kasmalkar *et al.,* 2020; Wang *et al.,* 2020).

The most advanced use of hydrodynamic model outputs in a network access model was Pyatkova *et al.* (2019) who coupled an InfoWorks 1D-2D model with a traffic supply-and-demand model to assess spatio-temporal variations in network access every ten minutes during a flood event in Marbella, Spain. Pyatkova *et al.,* (2019) defined a water depth threshold of 0.3 m for road closure and defined all roads intersecting floodwaters (of depths between 0.1 to 0.3 m) a safe travel speed of 20 km h^{-1}. Pregnolato *et al.* (2019)'s depth-disruption function was not used by Pyatkova *et al.,* (2019) due to the function not being validated by measured data. The study of Pyatkova *et al.* (2019) was novel in dynamically integrating spatio-temporal changes in floodwaters with the network, rather than relying on static flood scenarios as in previous research. Consequently, Pyatkova *et al.* (2019) were able to assess the duration of flood impacts on the network, calculating the occurrence and persistence of road closure over the duration of the >3 hour flood event.

As demonstrated by Pyatkova *et al.* (2019), the incorporation of flood variables from a hydrodynamic model greatly improved research power by capturing disruption patterns, identifying tipping points in floods impacts on the network, and revealing the roads most vulnerable to impact. Evans *et al.* (2020) were even able to consider the implications on future network resilience resulting from climate change by modelling predicted floods under different climate change scenarios. However, these approaches are not directly and appropriately applicable to low-income regions. These studies all assume cars as the predominant mode of transport, which is not necessarily an appropriate assumption in low-income regions where household car ownership may be substantially lower. Additionally, the study areas are urban with paved roads and flood characteristics representative of flash floods persisting for shorter durations and thus the modelling is specific to these characteristics and cannot be directly applied to floodplain floods in rural areas. Finally, the methodologies used are complex with high data requirements, and data constraints are a key reason behind the operation of cost-distance algorithms in low-income regions. As a result, there is a need to adapt existing models commonly-used in low-income regions so that they can capture the influence of floodwater variables as they impact access over space and time whilst otherwise maintaining low data requirements and suitable assumptions on study area characteristics.

2.6. Chapter summary

Geographic access is an important component in the ability of populations to receive healthcare. GIS can be used to model geographic access, and there are numerous specific methods available. The methods used in low-income countries tend to be simpler due to data constraints and different assumptions than those in high-income regions. Whilst precipitation and flooding have been recognised as severely impacting access in countries with seasonal climates, few have modelled their effects on potential geographic access. Failing to model changes in access under floods and considering access to be temporally static limits the ability of health policy planners to identify interventions. Floodwaters differ across space and time, and their impacts on vehicular and human instability can be represented through the use of instability criteria as derived from experimental studies. Floodwater depth and velocity can be generated using hydrodynamic models, to provide inputs by which flood hazard can be assessed throughout a flood. Traffic models operated in a few novel studies have used hydrodynamic outputs and have demonstrated greater research power in identifying spatio-temporal vulnerabilities in access. However, these models are unsuitable for operation in low-income regions where data availability is limited, and methodological assumptions are not appropriate. As a result, there is a need to adapt existing vector- and raster-based methodologies used in data-limited regions so that floodwater variables can be incorporated quantitatively. This study proposes the framework by which to achieve these new geospatial models so that the spatio-temporally variable impacts of floods on access to healthcare can be assessed for low-income countries.

CHAPTER 3

METHODS: *A new geographical access framework that models floodwater impacts*

This chapter focuses on the development of the vector- and raster-based geospatial models that are able to incorporate floodwater variables into their predictions of geographical accessibility. Section 3.1 first introduces the Barotse Floodplain field site that will be used to demonstrate the method which is generalisable to regions with similar flood and environmental characteristics, such as other floodplains. Section 3.2 then describes all the data that were created or acquired in order to operate the models for the Barotse Floodplain case study. Sections 3.3 and 3.4 explicitly explain the general procedure involved in the new approaches, including the outputs that are derived. Finally, Section 3.5 states how the new approach was applied to the Barotse Floodplain demonstration site, including the performance of a sensitivity analysis to derive approach parameter values and the access scenarios modelled.

3.1. The Barotse Floodplain

3.1.1. Floodplain characteristics

The Barotse Floodplain is located within the Upper Zambezi valley, Zambia (Figure 3.1). It is a large African floodplain, extending approximately 160 km in length and 30 km in width, reaching ~60 km wide around Mongu (Pollard and Cousins, 2008; Zimba *et al.,* 2018). The floodplain is extremely flat with elevation differences of ~5 m between the east and west escarpments, and ~30 m from north to south; this results in generally slow-moving floodwaters. The floodplain begins at Lukulu where the Kabompo River joins the Zambezi at an elevation of 1192 m above sea level (a.s.l.) and ends in the south at Senanga at an elevation of ~900 m a.s.l. (Zimba *et al.*, 2018). In total, the floodplain covers 5,500 km^2 of land, although total inundated area can be as great as ~10,750 km^2 if tributary floodplains (such as the Luena Flats) are included (Zimba *et al.,* 2018; Hardy *et al.,* 2019; Willis *et al., in press*).

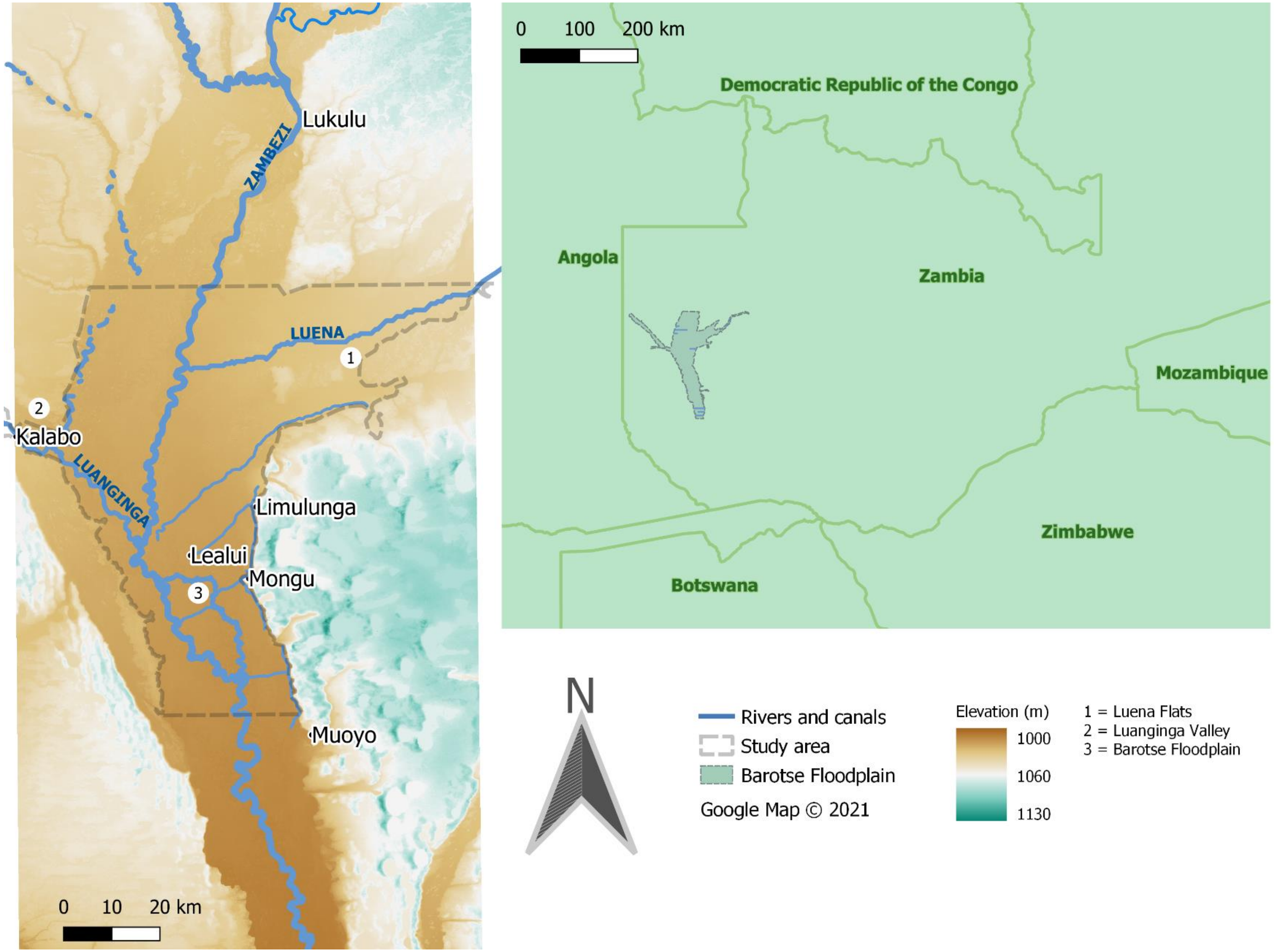


Figure 3.1. Map of the Barotse Floodplain and its major waterbodies, and the floodplain's location within Zambia.

The floodplain has formed due to basalt that has resisted downcutting below Senanga at Ngonye Falls. The resistant basalt has created a narrow valley which forces floodwaters to form behind it when the Zambezi experiences peak discharge (Zimba *et al*., 2018; Hardy *et al*., 2019). The Upper Zambezi's discharge exhibits a strongly seasonal pattern, reflective of the high inter-annual variability in precipitation caused by the movements of the Inter Tropical Convergence Zone (ITCZ) (Beilfuss, 2012; Hardy *et al.,* 2019). Average annual evapotranspiration is ~1560 mm, and average annual precipitation is ~830 mm; however, floodplain inundation is predominantly determined by rainfall in the upper catchments where the average annual precipitation is ~1400 mm (Beilfuss 2012; Cai *et al*., 2017; Chikozho and Mapedza, 2017). The floodplain has low runoff efficiency, low drainage density, and high aridity, which attenuates flows downstream causing the annual persistence of floodwaters between February and June (Beilfuss, 2012; Cohen Liechti *et al*., 2014a; Cohen Liechti *et al.,* 2014b; Kling *et al*., 2014).

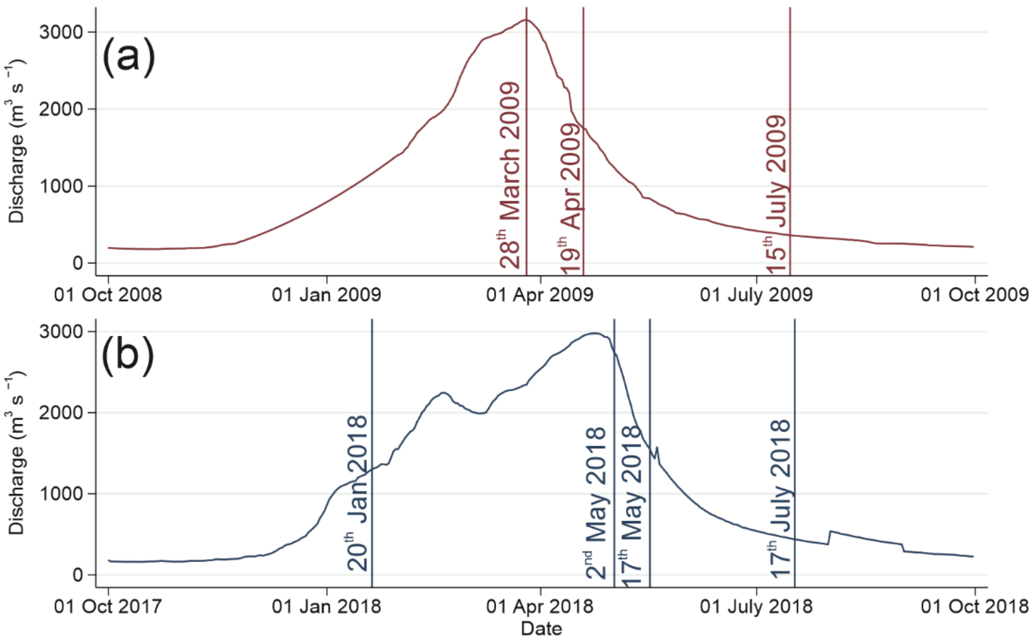


Figure 3.2. Hydrographs of the Zambezi River's discharge in the hydrological years of (a) 2009 and (b) 2018 as recorded by the Lukulu river gauge. Source: Willis *et al.,* (*in press*).

Inundation extent remains strongly correlated with channel discharge ($R^2 = 0.89$) as no dams have been constructed above the floodplain (Zimba *et al*., 2018; Figure 3.2). Floodwaters begin to rise in December, and there is a delay of approximately two months between peak rainfall in the upstream catchment and peak inundation (Cai *et al.,* 2017). The floodwaters extend annually to the floodplain escarpment, exhibit low velocities, and are mostly vegetated rather than open water (Hardy *et al*., 2019). The annual floods improve upon the otherwise low fertility of the aeolian-transported Kalahari sands by interspersing them with alluvium (Pollard and Cousins, 2008; Cai *et al.,* 2017; Estrada-Carmona *et al*., 2020). There is little forest on the floodplain and vegetation is mostly composed of grassland species (Mwanangombe, 2010; Hardy *et al*., 2020).

3.1.2. Sociocultural characteristics

The Barotse Floodplain is inhabited by the native Lozi people who depend on the floodplain for their livelihoods (Chikozho and Mapedza, 2017). The population of the Barotse Floodplain has seldom been investigated and there are large discrepancies between the few available estimates. A population of ~250,000 has been commonly cited (e.g., Rajaratnam *et al.,* 2015); however, Cai *et al.* (2017) doubted the validity of this figure and estimated a population closer to ~33,000 based upon counting houses observed in satellite imagery. Consequently, there is some uncertainty regarding the number of people living on the floodplain. This study estimates the population of the Barotse Floodplain to be ~44,600 using the High Resolution Settlement Layer (HRSL) of population density (see Section 3.2.2); this figure represents an estimate for 2021, using the values from the most recent Zambian census in 2010 adjusted with UN estimates of population growth at national level.

The Lozi exhibit transhumance which further complicates obtaining accurate population estimates for the floodplain; at the peak of the floods, the Lozi move to drier, higher ground until the floodwaters have receded. This seasonal movement is dictated by the Barotse Royal Establishment (BRE) – the traditional governance of the floodplain – on behalf of the *Litunga* (the king of Barotseland). Each year, the BRE announce a date for the *Kuomboka*, a historical festival where the Lozi vacate the floodplain for higher grounds (Flint, 2006). Kuomboka typically occurs in either late March or early April, and it is forbidden in Lozi law for the common people to leave before the Litunga (Flint, 2006; Mwanangombe, 2010). During Kuomboka, the Litunga embarks onto the water in a barge paddled by a hundred men, followed then by Lozi people in their dugout canoes (Figure 3.3). The Lozi return to the floodplain in a festival called *Kufuluhela* (again led by the Litunga) once floodwaters have begun to recede, normally in July or August (Flint, 2006; Mwanangombe, 2010).

Settlements are scattered across the floodplain; villages are built on manmade mounds of dirt (locally known as *suubas*) to prevent them being inundated (Mwanangombe, 2010; Cai *et al*., 2017; Chikozho and Mapedza, 2017). Traditional sources of income and food are livestock rearing, recession farming, fishing, and general usage of available floodplain resources (Cai *et al.,* 2017; Chikozho and Mapedza, 2017). The Lozi rely on their traditional knowledge of the floodplain to assist them with these activities.

Figure 3.3. A photograph taken during Kuomboka, showing the Litunga's state barge (called Nalikwanda) being paddled whilst the Lozi people follow in their dugout canoes. Image by Brugger (2008).

3.1.3. Canal network

There are over 3,000 canals on the Barotse Floodplain which form a critical network due to their high cultural and use value (Cai *et al.,* 2017; Estrada-Carmona *et al*., 2020). Traditionally, canals have a wide range of uses from transportation to farmland drainage and there are no restrictions on who can use them. Prior to colonialism and during Barotseland's time as a British protectorate, the BRE were solely responsible for delegating responsibility for the maintenance of the canals (World Bank, 2013). The canals act as a hydraulic extension on the floodplain and require continuous maintenance after flood recession to remove sediments, clear blockages, and reshape sections modified by geomorphic processes (Shastry *et al.,* 2020). Local governance from the BRE was effective in completing these maintenance tasks and keeping the canals in an operable state. However, since Zambian independence and the incorporation of the Barotse Floodplain as part of Western Province, authority over the canals has shifted to national government organisations. Chikozho and Mapedza

(2017) proposed that this change in governance is the primary reason why canals on the floodplain are now inoperable due to excess sedimentation and blockages. Whilst a World Bank project restored the major canals (Muoyowamo, Musiamo, Lubitamei, Fisheries, and N'gobala) in 2013/14, most canals that are important to local livelihoods remain in disrepair (World Bank, 2013; BRLi and NIRAS, 2014).

3.1.4. Transportation

Land transport on the floodplain is arduous. Little economic development and road building took place during the colonial period, and the road network on the floodplain remains disconnected, informal, and unmapped. The majority of roads are unpaved, in poor conditions, and only accessible by four-wheeled drive vehicles (BRLI and NIRAS, 2014). During the dry season, movement is either on foot or by slow vehicles; journeys can easily take an entire day to complete (Flint, 2006). Water transport by boat or canoe is also used where possible using the canal network (Chikozho and Mapedza, 2017). During the wet season, fluvial transport is usually the only reasonable mode of transport (Flint, 2006; Chikozho and Mapedza, 2017). Whilst both dugout canoes and oxen-carts are evidently influential local modes of transport, neither were modelled in this study due to a lack of data to characterise their usage, and a lack of suitable methods for incorporating boats into access models.

The Barotse Floodplain Causeway was completed in 2016, extending the Great West Road between Mongu to Kalabo. The construction of the road was a key development for the floodplain as previously no road connected between the two banks of the floodplain, and access to Kalabo was consequently very difficult.

3.1.5. Health challenges

The key health concerns on the floodplain relate to Zambia's efforts to reduce maternal mortality and HIV incidence. In 2018, the maternal mortality ratio (MMR) for Zambia was estimated to be 252 per 100,000 live births averaged over data from the preceding seven years (ZSA, MoH, and ICF, 2019). This ratio continues to exceed the Millennium Development Goal Target of 162.3 per 100,000 live births by 2015, and remains above the 2021 target set by Zambia itself to reduce MMR to 100 deaths per 100,000 live births (MoH, 2016). In previous studies, Western Province has had the highest MMR compared to any other province in Zambia (MCD and MoH, 2013; Singini, 2015) and increasing the number of births at facilities is encouraged as a mitigation strategy. Western Province also has one of the highest rates of HIV incidence in Zambia, with approximately 15% of the population estimated to be afflicted (Rajartnam *et al.,* 2015).

Efforts to reduce both maternal mortality and HIV incidence on the Barotse Floodplain are threatened by the difficulties experienced by floodplain populations in accessing healthcare. Most healthcare facilities are located on the floodplain escarpment, forcing populations to travel substantial distances with little adequate transport infrastructure (BRLi and NIRAS, 2014). For the few facilities located on the floodplain itself, there are difficulties in maintaining the medical supply chain due to the regular impassability of floods and poor network infrastructure (BRLI and NIRAS, 2014).

3.2. Description of input data

3.2.1. Healthcare facilities

Geolocation information on the operational healthcare facilities on or surrounding the Barotse Floodplain was downloaded from the Zambia Master Health Facility List (MoH, 2019). According to the list, the data were last updated in November 2019. Only non-private, correctly geolocated facilities that were within the study area were retained. Information on facility type (Table 3.1) and maternal services provided (Table 3.2) were recorded from the 2012 List of Health Facilities in Zambia (MoH, 2012).

3.2.2. Population density

Population density data were obtained from the High Resolution Settlement Layer (HRSL), a freely-accessible gridded dataset with the highest spatial resolution currently available of 30 m (1 arcsecond). The population density data were estimated using a binary top-down modelling approach where census data were proportionally attributed to buildings identified through convolutional neural networks (CNN) operating on 0.5 m resolution DigitalGlobe satellite imagery. The HRSL contains density estimates for both the entire population and by specific demographic. The HRSL was updated in August 2021 and the data for Zambia were downloaded in August 2021.

The Lozi exhibit transhumance in response to the annual floodwave, however the HRSL data was not modified to represent this. Instead, the HRSL data was used to assume that the population was static due to difficulty in ascertaining how many of the Lozi are either present or absent on the floodplain each month. Resolving this limitation was not possible in the absence of further data to characterise the Lozi’s movements (see Section 5.4.3).

Table 3.1. Information on the healthcare system surrounding the Barotse Floodplain, Zambia. Adapted from MoH (2012). Note that in the modelling, mini hospitals, first level hospitals, and second level hospitals were categorised together as "hospitals." There are also third level hospitals in Zambia, but as there are none surrounding the floodplain they are not included here.

Facility type	Description	Typical services offered	Typical catchment size
Health post	Lowest level of health care, usually positioned to serve communities that are otherwise far from the nearest health centre.	Basic first aid	1,000 to 7,000 in urban areas 3,500 in rural areas
Health centre	Can be either rural or urban. Urban health centres serve larger numbers of the population.	First aid, delivery, preventative care (e.g., HIV counselling and testing, prevention of mother to child HIV transmission)	30,000 to 50,000 in urban areas 10,000 in rural areas
Mini hospital	A new initiative, these act as an intermediate between health centre and hospital, providing a range of primary healthcare services like a first level hospital. Designed to alleviate burden on access to first level hospitals.	Medical, surgical, obstetric, preventative care, and diagnostics. More complicated, specific health problems are referred to the first level hospitals.	N/A
First level hospital	Hospitals serving at the district level.	Medical, surgical, obstetric, and diagnostic services. Populations are referred to first level hospitals from health centres and mini hospitals.	80,000 to 200,000
Second level hospital	Hospitals serving at the provincial level.	General surgery, paediatrics, obstetrics, gynaecology, dental, psychiatric, and intensive care services. Populations are referred to second level hospitals from first level hospitals.	200,000 to 800,000

Table 3.2. Description of key maternal services offered by healthcare facilities in Zambia.

Maternal service	Description	Supplementary notes
Delivery site	A healthcare facility able to provide a trained/skilled birth attendant to assist during labour.	
Emergency obstetric care (EmOC)	The provision of medical care able to assist with life-threatening obstetric complications such as haemorrhage, a ruptured uterus, and eclampsia.	EmOC can be either basic or comprehensive, depending on the presence of specific signal functions (Tembo *et al.,* 2017). The 2012 facility list makes no reference to signal functions, so EmOC is assumed to be at least basic for all facilities.
Maternity waiting shelter	Accommodations provided for pregnant women so that they can remain close to a delivery site in anticipation of labour.	

3.2.3. Waterbodies and floodwater variables

A polyline shapefile provided by Willis *et al.* (*in press*) outlined the positions and average widths of rivers and canals on the floodplain. A LISFLOOD-FP hydrodynamic model (Bates and De Roo, 2000) run for the Barotse Floodplain (Willis *et al., in press*) at monthly timesteps between October 2017 and October 2018 provided floodwater depth and velocity magnitude rasters with a spatial resolution of 100 m.

The flood event in 2018 was significant due to it being one of the largest experienced in recent years. Its extent and water levels have been compared to the 2009 flood event (Willis *et al., in press*) whose extent was estimated to be 35% greater than an average flood (Cai *et al.,* 2017). However, the event was neither extreme nor unusual, instead reflecting a larger-than-average but still normal fluctuation in the extent, timing, and magnitude of the annual flood wave. Consequently, whilst the use of modelled 2018 data may produce a more pessimistic representation of access during flood months than is average, any findings are still within the bounds of normality and thus relevant.

The LISFLOOD-FP model domain was set-up by Willis *et al.,* (*in press*) to include all canals, major river channels, and river gauges, and was configured to represent the hydrological processes on the floodplain. Inflow boundary conditions were obtained from river gauges maintained by the Water Resources Management Agency (WARMA), and the model assumes flows over the floodplain are mostly subcritical and low velocity (Willis *et al., in press*). A high-resolution TanDEM-X1 digital elevation model (DEM) obtained for 2016 (Wessel *et al*., 2018) with a spatial resolution of ~12 m and a vertical accuracy rating on the floodplain of ~2 m (Böer *et al*., 2008) was resampled to 100 m and used as the terrain data (Willis *et al., in press*). The model was calibrated using gauge data and remotely-sensed flood extents from Landsat (30 m spatial resolution), and a variance-based sensitivity analysis related the input parameters to the model results (Willis *et al., in press*). The calibrated model was then used to provide the floodwater depth and velocity rasters representative of detailed processes occurring on the floodplain (Willis *et al. in press*). Willis *et al.,* (*in press*) showed the model to perform best during the flood peak in 2018 (goodness of fit, $F^2 = 0.62$) with lower performance in intermediate flood stages ($F^2 = 0.10$). For further details on the hydrodynamic model, see Willis *et al.* (*in press*).

3.2.4. Road network

3.2.4.1. Delineation

No complete network dataset was available for the Barotse Floodplain. Remotely-sensed image classification of roads was also not possible due to the spatial resolutions of freely-available satellite imagery being too coarse and thus unsuitable for detecting community-level tracks that predominate the floodplain. Google Earth and Microsoft Bing Maps composite imagery are both very high resolution (<5 m), were collated recently, and have excellent coverage of southern Africa (Lesiv *et al.,* 2018). Neither can be used for remotely-sensed image classifications as they only contain data of the visible spectrum and original band numbers have been modified (Hu *et al*., 2013; Malarvizhi *et al.,* 2016; Fatemi and Gholinejad, 2019). However, the use of composite satellite imagery to manually delineate infrastructure has been used before successfully, including for the Barotse Floodplain (Cai *et al.,* 2017). Consequently, Google Earth and Microsoft Bing Maps were used to create a new, complete network dataset for the Barotse Floodplain through manual delineation of visible roads (Figure 3.4).

The majority of the delineation was completed between October 2019 and April 2020, but the study area was expanded and additional gaps in network coverage were delineated between April 2021 and June 2021. The entire dataset was then checked again in July 2021 to ensure completion and validity before its usage. Google Earth was primarily used for delineation due to its imagery being typically more recent (Lesiv *et al.*, 2018). For the Barotse Floodplain, Microsoft Bing Maps images originated in 2014, whilst most Google Earth images were dated as 2019 or later. Microsoft Bing Maps images normally complemented interpretation, but were relied upon solely where Google Earth imagery was degraded. Google Maps and OpenStreetMap data were used to identify highways and major roads. For the few floodplain roads documented on OpenStreetMap, these were used to validate that delineation efforts were working successfully.

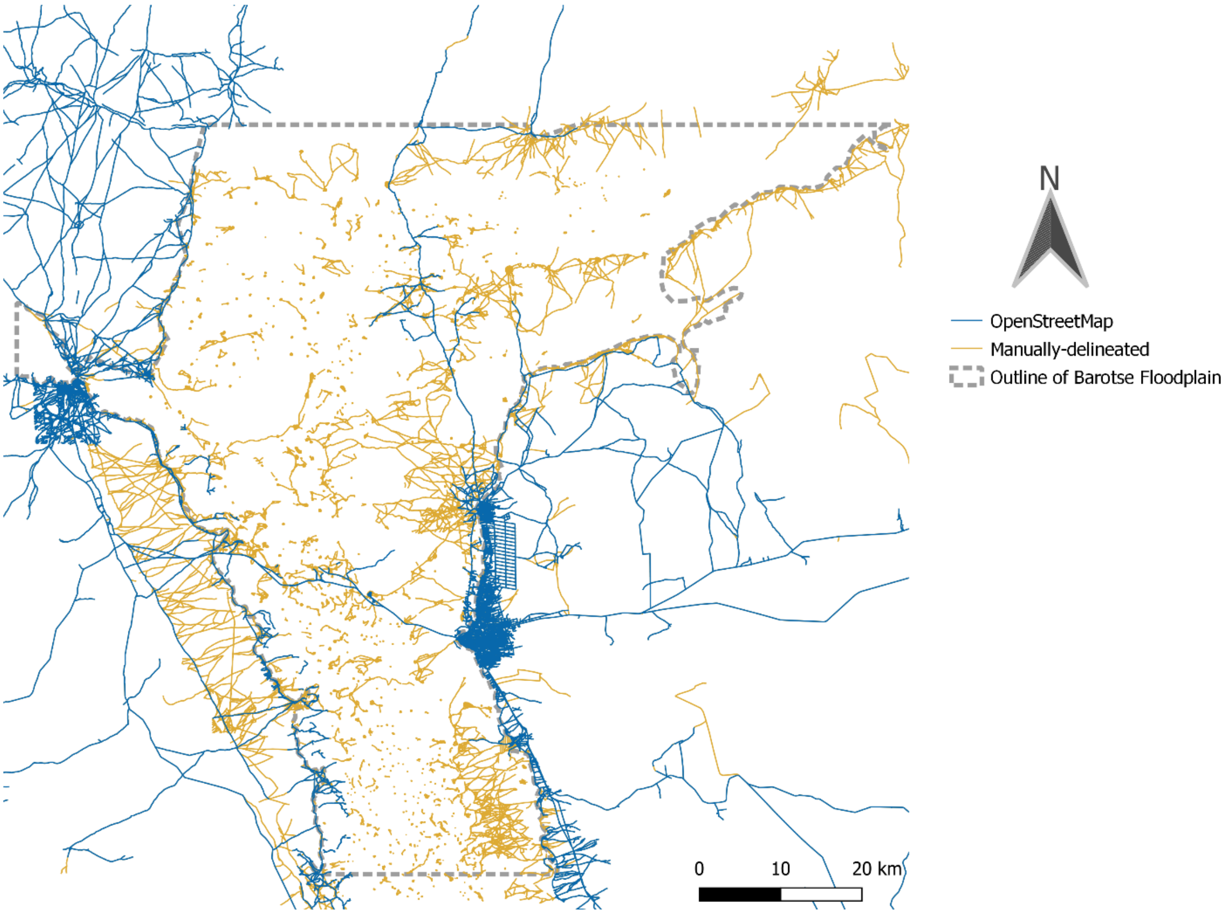


Figure 3.4. The roads network dataset used as inputs, as created by combining OpenStreetMap data with manually-delineated data.

A systematic approach for delineation was used which assigned an ID to each network edge based upon the following road type classifications: (1) primary road; (2) secondary road; (3) track; (4) uncertain track; (5) elevated highway; (6) bridge/water crossing. Polygons were used to enclose areas of dense track interconnectivity to speed-up delineation by assuming full road connectivity within. The polygons were then divided into 100 m^2 grid tiles, converted to polylines with the track classification attribute, and merged with the network dataset. Bridge and water crossings were delineated as points which were then buffered to 100 m; any road within was assigned the attribute and considered always accessible unless the surrounding roads were flooded.

No distinction was made between paved and unpaved major roads, although tracks were always unpaved. Uncertain tracks were those where reasonable doubt prevented confident delineation, such as difficulty in differentiating tracks from canals filled with sediment which appear visually similar on images. Uncertain tracks were subject to further analysis using historical images in Google Earth Pro, where they were either retained in the dataset as tracks or removed if significant doubt persisted. The inability to extract Z-coordinates for roads prevented creating a three-dimensional network beyond identifying roads that were already known to be elevated.

3.2.4.2. OpenStreetMap

OpenStreetMap contained network data for beyond the floodplain escarpment. These data were downloaded in March 2021 and gaps in coverage were manually delineated in June 2021. The data were recoded to match the classification assigned to the delineated Barotse Floodplain roads (Table 3.3). The OpenStreetMap data were then merged with the Barotse Floodplain data, and conflating roads were removed.

3.2.4.3. Speed limit classifications

Each road in the network-based model is assigned a speed limit based upon its road type classification (Table 3.4). The Road Traffic (Speed Limits) Regulations (2020) were used to assign these speed limits to network edges, assuming the limits listed for ordinary motor vehicles. Tracks assumed the unpaved (Second Schedule) speed limit regulations, whilst primary roads and highways assumed the paved (First Schedule) speed limit regulations. Minor roads were assigned a speed limit value that was the midpoint of the paved and unpaved speed limit regulations. Bridges and water crossings on the floodplain were assumed to have a reduced speed limit in absence of measured data (Table 3.4).

3.2.4.4. Validation

For network analysis, a topologically correct network that appropriately represents edge connectivity is vital (Heywood *et al.,* 2011). Consequently, an extensive validation procedure was undertaken. Network completeness was ascertained by manually checking that all roads had been delineated. Topological, geometrical, and classification errors were corrected using FME Workbench 2020.2. Healthcare facilities were snapped to the nearest transport network edge if they were determined to be within proximity, and nodes were ensured to be located only at endpoints, intersections, speed limit changes, and healthcare facilities.

Table 3.3. Reclassification of OpenStreetMap data.

OpenStreetMap classification	Recode
Trunk	Primary road
Primary	Secondary road
Secondary	Secondary road
Tertiary	Secondary road
Track	Track
Residential	Track
Unclassified	Track
Service	Track
Path	Track
Footway	Removed in network model (track in walking model only)
Steps	Removed in network model (track in walking model only)

Table 3.4. Speed limits assigned to roads in the network-based model.

Road classification	Speed limit (km hr^{-1})
Primary road	80
Secondary road	50
Track	30
Elevated highway	120
Bridge/water crossing	15

3.3. Network-based model

FME Workbench 2020.2 was used to create an automated network-based model that directly considers the impact of floodwater variables on road network accessibility (Figure 3.5). The model developed is capable of computing accumulated cost surfaces (aggregated travel times distributed over space), service areas (catchments of facilities), binary network accessibility (operational status of a road), origin-destination cost matrices (every path computed between origins and destinations), and closest facilities (the closest facility for given points). Either distance or travel time can be used as the cost metric. QGis Desktop 3.16.6 with GRASS 7.8.5 was used to post-process and display the data. Section 3.3.1. provides overview on how the model generally operates with specific reference to the modelling of spatio-temporal variations in access to healthcare. Section 3.5.2. explicitly describes the scenarios that were assessed using the model.

3.3.1. Procedure

3.3.1.1. Set-up and calculating travel times

Inputs (see Section 3.2) and parameters (Table 3.5) were first defined for each network model run. In all model runs with different inputs and parameter sets, the general procedure was the same. The network was first converted into a series of points at every 100 m interval. The points extracted the cell values from the underlying floodwater rasters to generate lists of the water depths and velocities intersecting each unique edge. The absolute maximum water depth and velocity value was then determined and forced as a new attribute for each edge.

The speed limits defined for each road type were assumed representative of travel conditions in the dry season, before floodwater impact had been considered. The impact of floodwaters on the network was considered through a series of conditional statements to derive updated travel speed weights (*w*) for the network at each flood timestep (Figure 3.6).

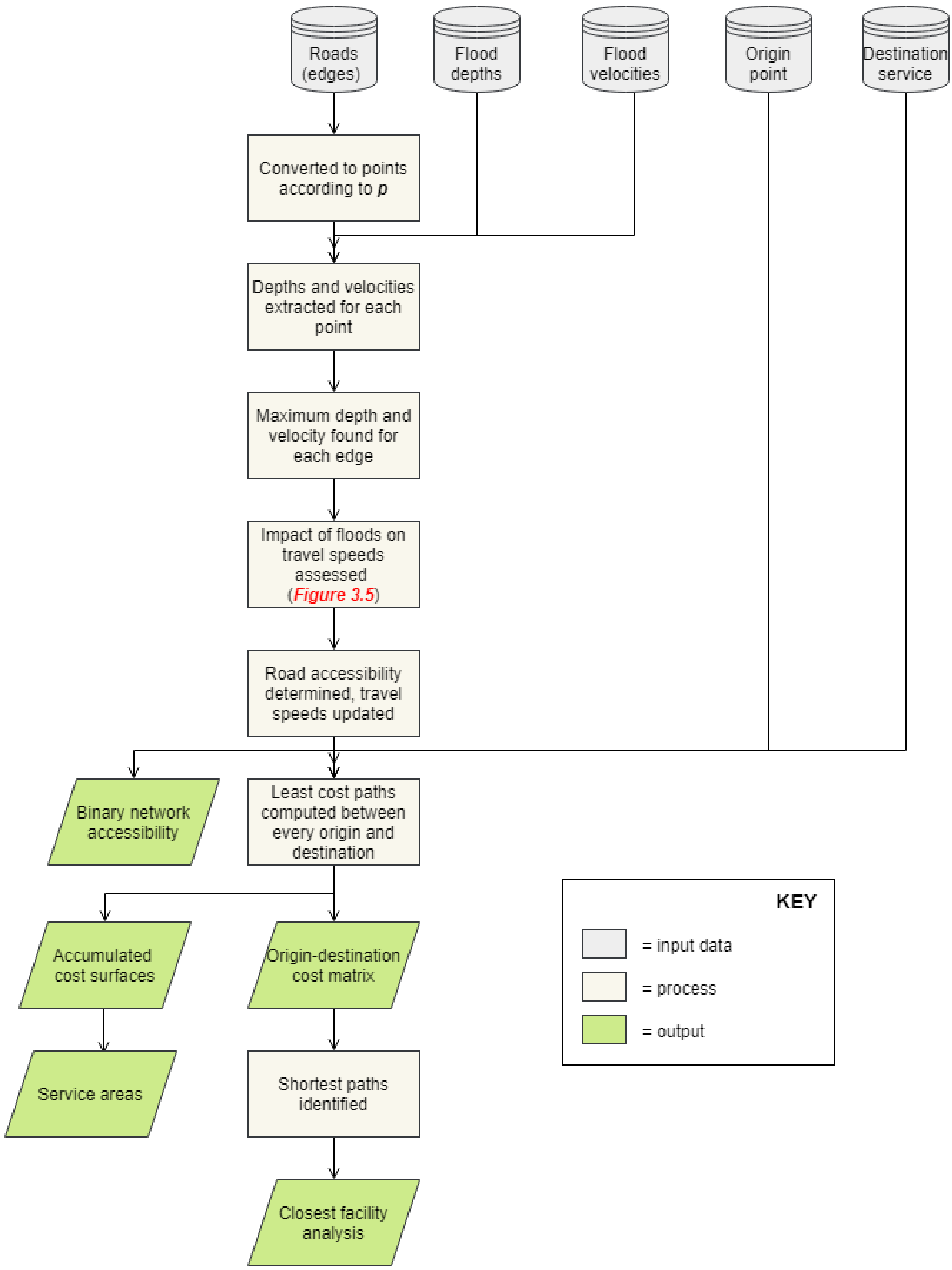


Figure 3.5. Simplified flow diagram of the vector model framework.

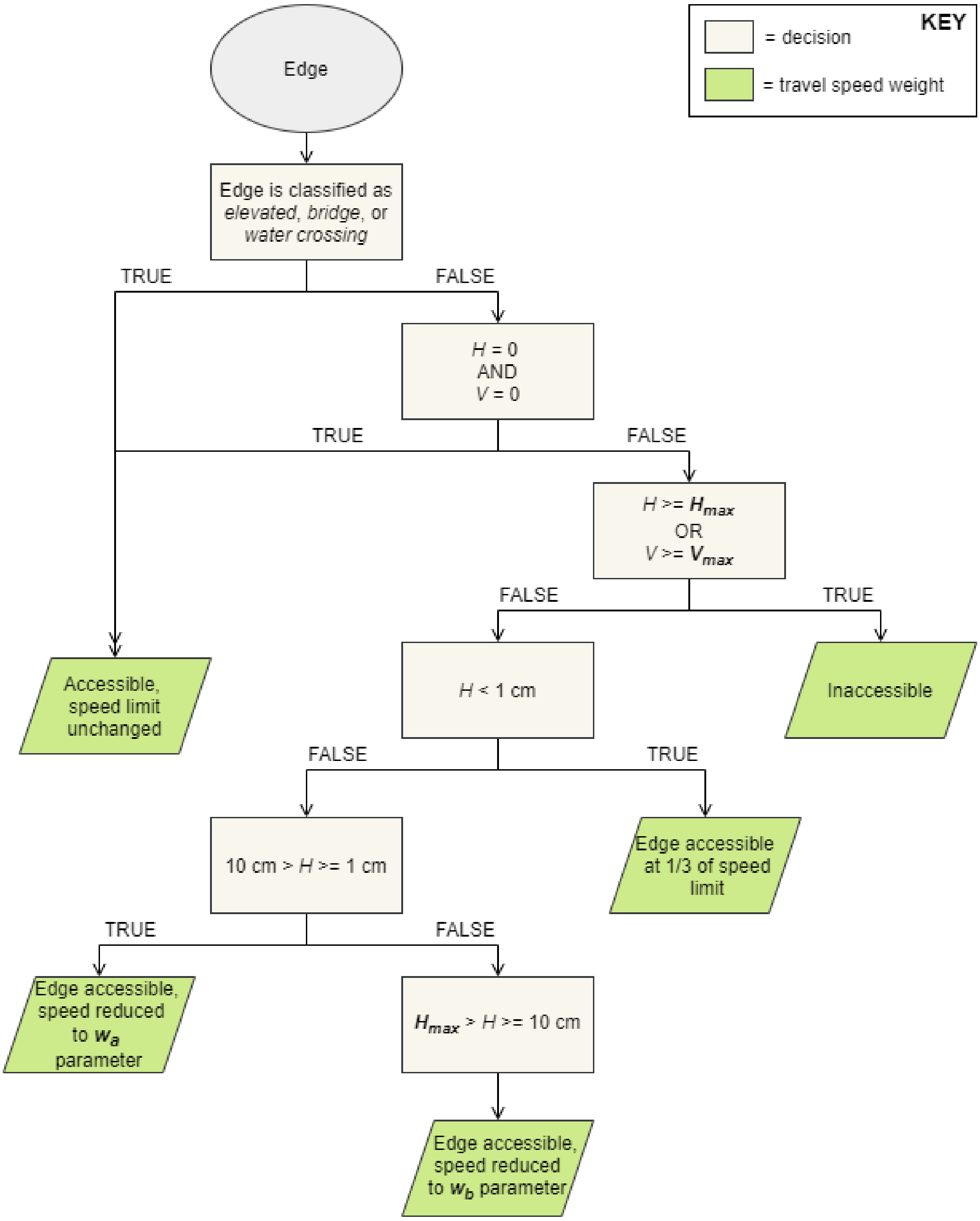


Figure 3.6. Decision tree outlining how the network-based model decides on speed weights for edges intersecting floodwaters.

The conditional statements make a number of assumptions, specifically that: (i) the maximum floodwater values extracted are representative of accessibility across the entirety of each edge; (ii) drivers have omniscient knowledge of floodwater properties; (iii) drivers will drive through floodwaters (parameter settings permitting) where deemed safe to do so; (iv) water depth and velocity are the only variables dictating travel safety through floodwaters; and (v) drivers always drive on wet roads and through floodwaters safely and at appropriate speed. Travel times along each edge were then calculated for input into the network model analyses.

3.3.1.2. Accumulated cost surfaces

Accumulated cost surfaces were created for each monthly timestep, representing accumulated travel times from healthcare facilities along network edges. Edges were first assessed to determine if they were connected to a healthcare facility and that a direct path could be routed. Any disconnected edges had their travel times overwritten to the infinite value as used by the flooded edges. Dijkstra's algorithm was used to calculate least-cost paths which were output as travel time vertices. Each vertex also contained the unique healthcare facility ID that produced the minimum travel time at that location. Interpolated travel time vector surfaces were then created, with isochrones built at 5 minute intervals. A buffer with a distance standard of 1 km was created around the connected edges, and the cost surfaces were clipped to this buffer. Geometries of the clipped cost surfaces were dissolved and collected to form multipart polygons based on the isochrones intervals. Zonal statistics can then be calculated on the area or populations living within each travel time isochrone.

3.3.1.3. Service areas

Dynamic service areas for each monthly timestep were created based on the corresponding accumulated cost surfaces. Thiessen polygons were generated around the travel time vertices, and then dissolved by unique healthcare facility IDs. The resulting service area polygons were then clipped by a 1 km buffer of the network considered accessible within a 60 minute driving threshold.

3.3.1.4. Binary network accessibility

A binary representation of network accessibility was created for each timestep in every scenario. Edges with an infinite travel time were classified as inaccessible whilst all other edges were classified as accessible regardless of whether floodwaters had modified their overall travel speeds. Summary statistics produced can then be interpreted to demonstrate monthly changes in network accessibility and connectivity over the duration of a flood event for each scenario.

Table 3.5. Parameters in the network-based model. Note that w_a, w_b, H_{max}, and V_{max} can be disabled so that driving through floodwaters is not permitted.

Parameter	Units	Definition	Appropriate values
p	m	The interval at which edges are divided into points for sampling the flood raster data	Value should be the same resolution as the highest resolution floods raster
w	km hr^{-1}	The travel speed limit applied to an edge	Dependent on road type and restrictions. Absolute maximum legal limit in the world is 140 km hr^{-1}
w_a	km hr^{-1}	A reduced speed limit when travelling through floodwaters between 1-10 cm depth	Below 10 km hr^{-1}
w_b	km hr^{-1}	A reduced speed limit when travelling through floodwaters greater than 10 cm depth, but below H_{max}	Below 8 km hr^{-1}
H_{max}	m	Maximum water depth threshold. Water depths greater than the threshold are completely impassable	< 0.3 m for passenger vehicles 0.5 – 0.6 m for 4WD
V_{max}	m s^{-1}	Maximum velocity threshold. Velocities greater than the threshold are completely impassable	Appropriate value dependent on H. Absolute maximum of 2.0 m s^{-1} if H = 0.5 m

3.3.1.5. Origin-destination cost matrix

An origin-destination cost matrix was performed for each monthly timestep to calculate the shortest paths and closest facilities between points representing origin facilities and every demand location (e.g., population) (see Section 3.5.2 for case study specifics). If points (representative of facilities or locations) intersected a floodwater value greater than H_{max}, they were considered inaccessible and removed from the dataset. Otherwise, points were snapped to the nearest network if they were within a 100 m radius. Only the points on the network were used in each origin-destination cost matrix. A closest facility analysis was then performed using the databases to extract the shortest path route and the travel time to the nearest facilities for each demand location. Points which could not be routed to were designated as having no viable form of network access to a healthcare facility.

3.4. Raster-based model

FME Workbench 2020.2 was used to create an automated workflow for generating impedance surfaces that directly consider the impact of floodwater variables on walking accessibility to healthcare facilities (Figure 3.7). The impedance surfaces generated are suitable for input into any cost-distance algorithm in any GIS environment. QGis Desktop 3.16.6 with GRASS 7.8.5 was used in this study to compute accumulated cost surfaces, service areas, origin-destination cost matrices, and closest facilities. Section 3.4.1 provides an overview on how the model generally operates with specific reference to the modelling of spatio-temporal variations in access to healthcare. Section 3.5.2 explicitly describes the scenarios that were assessed using the model.

3.4.1. Procedure

3.4.1.1. Set-up and impedance surface creation

Inputs (see Section 3.2.) and parameters (Table 3.6) were first defined for each scenario. In all model runs with different inputs and parameter sets, the general procedure was the same. Waterbodies were first buffered according to their average width, and then converted to a waterbodies impedance surface with a 10 m spatial resolution. The road network was then converted to a roads impedance surface. Elevated roads, bridges, and water crossings were always prioritised for representation in the resulting 10 m raster cells. As the Barotse Floodplain is extremely flat with a near-homogeneous land use, slope and land use were not considered in the impedance surface creation.

A floodwater impedance surface was then created (Figure 3.8). Floodwater depth (*H)* and velocity (*V*) were first considered independently of each other. If cell *H* was greater than H_{max}, the cell was classified as inaccessible. If cell *V* was greater than V_{max}, the cell was classified as inaccessible. *H* and *V* were then considered together by multiplying their cell values together to create depth-velocity products (*HV*) for each cell. An empirical equation (Karvonen *et al.,* 2000) was used to determine the critical depth-velocity product (HV_c) at which a simulated person would experience toppling instability when walking through floodwaters (equation 3.1). A simulated person was defined based upon human height (*h*) and weight (*m*) parameters.

$$HV_c = 0.004hm + 0.2$$

(equation 3.1)

Calculated *HV*s were then compared against the HV_c:

(1) If cell *HV* was greater than the HV_c, the risk of toppling instability was deemed high and the cell classified as inaccessible

(2) If a cell contained a *HV* but which did not exceed HV_c, it was considered accessible at a reduced walking speed

(3) If a cell contained no *HV* (*HV* = 0), it was considered not flooded and accessible as usual

It is clearly inappropriate to assume that a simulated person will always attempt to walk through floodwaters. Consequently, the V_{max} and H_{max} parameters, and the empirical equation are optional. When this option is turned off, all cells containing floodwaters are classified as inaccessible.

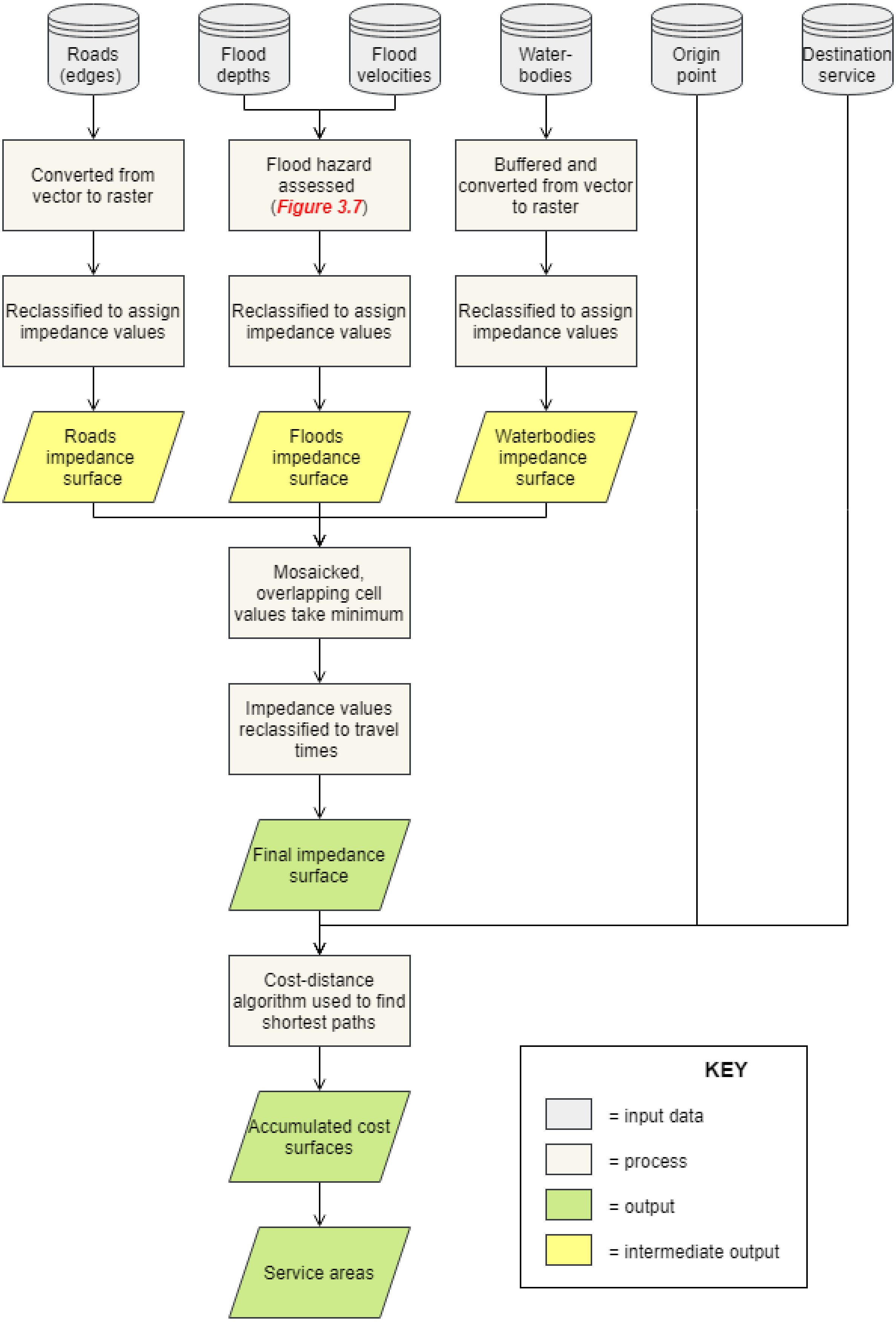


Figure 3.7. Simplified flow diagram of the raster model framework.

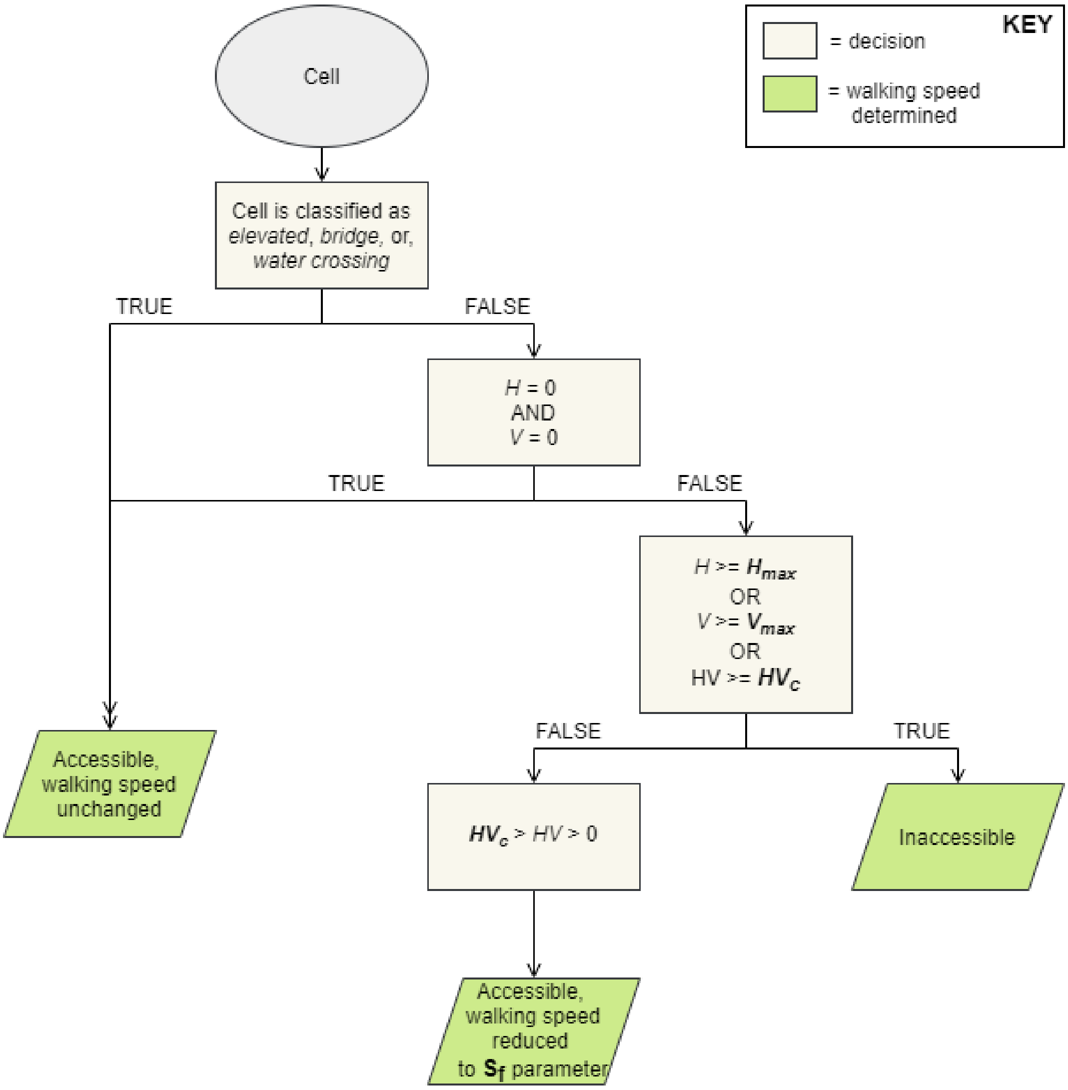


Figure 3.8. Decision tree outlining how the raster-based model decides on cost values (walking speeds) within each cell of an impedance surface.

The floodwaters impedance surface was then resampled from 100 m to 10 m using nearest neighbour interpolation; this resampling was deemed appropriate as the floodwaters raster was now nominal data coded numerically. The roads, permanent waterbodies, and floodwaters surfaces were then mosaicked together to form a final impedance surface with 10 m cell resolution. Cell value conflict was resolved by prioritising representation in the following order: (1) elevated roads; (2) inaccessible floods; (3) flooded but accessible conditions; (4) unflooded roads; (5) off-road areas. It was assumed that any cell classified as elevated road was permanently above the floodwaters; this assumption was appropriate for the Barotse Floodplain where the only elevated road is the causeway which was purposefully elevated above the annual floods. Cell values were assigned based on the travel time (in seconds) it would take to walk across 10 m at a defined walking speed (see Section 3.5.2). Inaccessible cells were removed from the final output so that they cannot be routed through in cost-surface algorithms. The impedance surfaces were then input into QGis to complete the raster analyses.

3.4.1.2. Accumulated cost surfaces and closest facility analysis

Minimum isotropic accumulated cost surfaces were calculated from healthcare facilities to populations. Movement was considered in 16 directions rather than 8 to increase output accuracy. A closest facility analysis was then performed by extracting the minimum travel time for a population to identify its nearest facility.

3.4.1.3. Service areas

Cost allocation outputs were produced which specified the nearest healthcare facility (based on the minimum aggregated travel time) for each cell. These were used to generate service area polygons across the entire study area. Service areas were discretised into time travel thresholds, with the key threshold being walking access within 2 hours as an indicator of timely access to healthcare services.

Table 3.6. Parameters in the raster-based model. Note that the parameters used to determine hazard of floodwaters can be turned off so that walking through floodwaters is not permitted.

Parameter	Units	Definition	Appropriate values
r	m	The resolution desired for the final impedance surface	Varies. Dependent on overall size of impedances surface and resolutions of input datasets.
Hmax	m	Maximum water depth threshold. Water depths greater than the threshold are completely impassable	Absolute maximum of 1 m
Vmax	$m\ s^{-1}$	Maximum velocity threshold. Velocities greater than the threshold are completely impassable	Absolute maximum of 1 $m\ s^{-1}$
h	m	Height of a simulated human	Dependent on characteristics of simulated human (e.g., child or adult). Averages are recommended
m	kg	Mass of a simulated human	Dependent on characteristics of simulated human (e.g., child or adult). Averages are recommended
S	$km\ hr^{-1}$	Walking speed within a cell	Dependent on topography characteristics within a cell. 5 $km\ hr^{-1}$ recommended as the average walking speed of an abled individual in the absence of topographical impediments
S_f	$km\ hr^{-1}$	Walking speed through floodwaters	Must be lowest walking speed parameterised. Absolute maximum of 2 $km\ hr^{-1}$, 1 $km\ hr^{-1}$ recommended
K	n/a	Karvonen equation variant	Default is the “normal” variant. Can be changed to “good” or “poor” variant depending on conditions in simulated floods

3.5. Application to the Barotse Floodplain

This section explains how the new framework as described prior was applied specifically to model access in the Barotse Floodplain. Section 3.5.1 outlines the sensitivity analysis which was conducted in order to derive appropriate parameters of H_{max} and V_{max} for both the network- and raster-based models. Section 3.5.2 then describes the access scenarios modelled, including the parameter values and inputs used in each scenario.

3.5.1. Sensitivity analysis

A one-at-a-time sensitivity analysis was performed to investigate the effects of changing H_{max} and V_{max} respectively for both the network and raster models. Two scenarios were investigated: a dry season scenario and a wet season scenario. The dry season scenario was based on the flood model outputs from the first timestep, October 2017. The wet season scenario was based on the outputs from the sixth timestep, March 2018, which had the overall greatest mean water depth of any timestep. Mean accumulated cost was chosen as the response variable to aggregate changes in travel times across the entire floodplain. The results of the sensitivity analysis were used to inform the choice of appropriate H_{max} and V_{max} values used in the modelling.

3.5.1.1. Network-based model

The range of appropriate values was determined for a four-wheel drive vehicle. The upper bound of H_{max} was set to 0.6 m. The upper bound of V_{max} was determined to be 2.0 m s^{-1} but only if H_{max} was no greater than 0.5 m (Martínez-Gomariz *et al.,* 2018); however, none of the flood rasters contained velocity values that exceeded 1.2 m s^{-1}. Standard values for H_{max} and V_{max} were set to 0.5 m and 1.0 m s^{-1} respectively. Parameter values were varied in increments of ±10% of their standard values. A total of 40 model runs were completed with seven runs per H_{max} scenario and 13 runs per V_{max} scenario.

The dry season was insensitive to changes in H_{max} and V_{max}, reflecting the lack of floodwaters on the floodplains and that the presence of permanent waterbodies was already accounted for with existing bridges and elevated roads. The wet season was sensitive to changes in H_{max} and V_{max} (Figure 3.9). Decreases in both parameters increase mean travel time; however, the output was only sensitive to V_{max} values between -100% to -80% of the standard value. A V_{max} of 0.0 m s^{-1}, or -100% of the standard was the most sensitive value and increased travel times by ~34%. This is expected as the value marks an assumption change where travel through floodwaters is restricted to completely static waterbodies. H_{max} was the most sensitive parameter; the output was sensitive to all changes, but particularly those within ±40% of the standard value. The floodplain escarpment was the primary location of uncertainty, with changes in mean travel time predominantly occurring there.

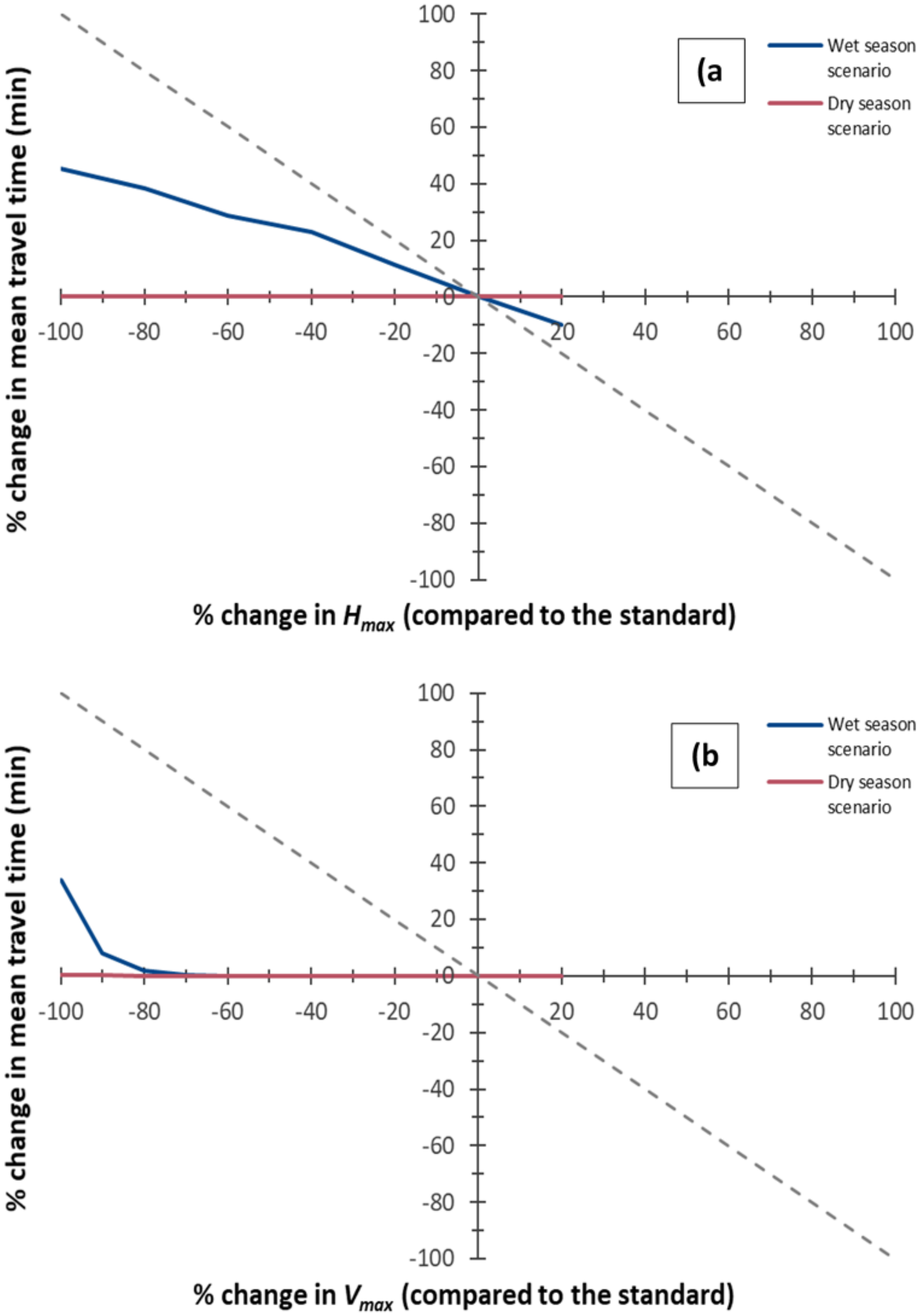


Figure 3.9. Sensitivity of the network-based model to changes in (a) H_{max} and (b) V_{max}.

3.5.1.2. Raster-based model

For the sensitivity analysis, the Karvonen *et al.* (2000) empirical equation was turned off so that the effects of H_{max} and V_{max} alone could be isolated. The upper bounds of H_{max} and V_{max} were set to 1.0 m and 1.0 m s^{-1}, and the standard values to 0.5 m and 0.5 m s^{-1} respectively. Parameter values were varied in increments of ±10% of their standard values. A total of 44 model runs were completed with an equal number of runs for H_{max} and V_{max}. Three variations of the output variable were observed: (1) count of null cells; (2) mean accumulated cost of "always accessible" cells; and (3) mean accumulated cost of all cells. For (3), nulls were converted to a value of 113,352 seconds which was the maximum accumulated cost obtained in any run; this permitted them to be included appropriately in raster calculations.

The dry season was insensitive to changes in H_{max} and V_{max} due to the lack of floodwaters resulting in negligible influence from the floodwater parameters. The wet season was sensitive to changes in H_{max} and V_{max} (Figure 3.10); decreases in both parameters increased the null cell count and mean accumulated cost of all cells. The mean accumulated cost of "always accessible" cells (i.e., cells that are not nullified in any run of their scenario) was insensitive to H_{max} and V_{max}, indicating that the impact of the parameters on nulls predominates the response of overall cell access; consequently, the floodplain is most sensitive to changes in the parameters as flood inundation causes nulls to occur there. The changes that did occur for "always accessible" cells were highly localised at floodplain boundaries and indirectly caused by nulls since at lower H_{max} and V_{max} values, fewer cells were nullified and thus more optimal paths were able to be routed, thereby reducing mean accumulated costs of cells at these areas.

Overall, mean accumulated cost of all cells and null count were more sensitive to H_{max} than V_{max}. A 100% decrease in H_{max} increases overall mean accumulated cost by ~42% whilst a 100% decrease in V_{max} increases overall mean accumulated cost by 32%. Additionally, the response variables were sensitive to any change in H_{max} but were insensitive to changes in V_{max} above the standard value. Decreases in H_{max} and V_{max} of 100% (or values of 0.0 m and 0.0 m s^{-1}) respectively produced the most sensitive response in overall mean accumulated cost; this was expected as these particular parameter values represent an assumption change where walking through flooded cells is not permitted.

The Luena Flats was found to exhibit a different response threshold to H_{max} and V_{max} than the Barotse Floodplain. The Barotse Floodplain was relatively insensitive to V_{max} and mostly responded to positive increases in H_{max} beyond the standard. The Luena Flats exhibited great sensitivity to changes in both lower V_{max} and H_{max} values below the standard, reflecting shallower floodwaters present than on the Barotse Floodplain.

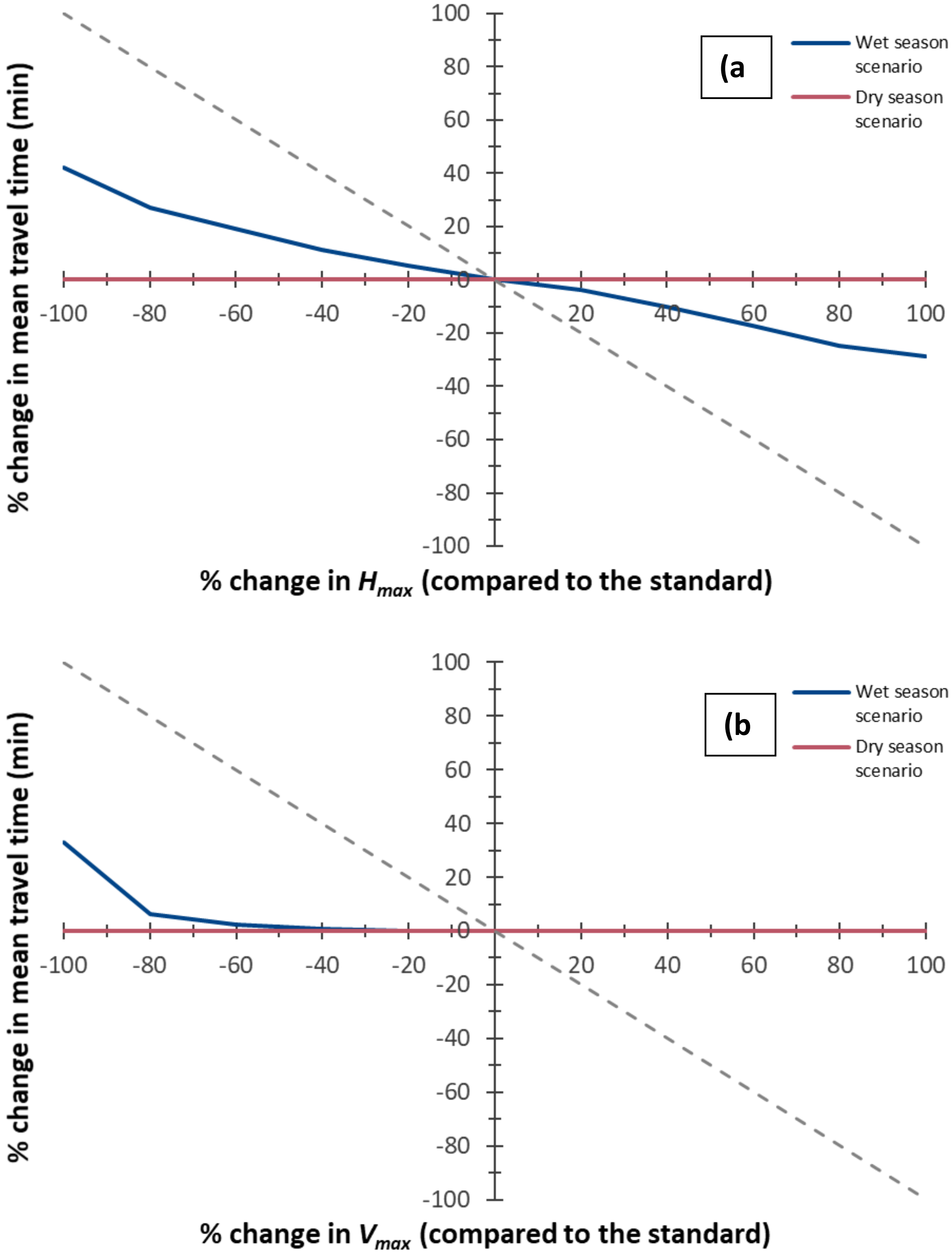


Figure 3.10. Sensitivity analysis of the raster-based model to changes in (a) H_{max} and (b) V_{max}.

3.5.1.3. Conclusions of Sensitivity Analyses

H_{max} and V_{max} values are locally variable; this was most evident in the raster model where the Luena Flats exhibited a different threshold response which emphasises the importance of site-specific analyses. The Barotse Floodplain is most sensitive to changes in H_{max} in its wet season, reflecting that the floodwaters are deep but slow-moving. The greatest source of sensitivity for both models is whether movement through floodwaters is permitted. The appropriateness of this assumption should always be a primary consideration.

3.5.2. Access scenarios

Accessibility for the entire population of the floodplain to healthcare facilities between October 2017 and October 2018 was assessed. The raster-based model was used as described in Section 3.4 to assess populations' abilities to reach hospitals, healthcare centres, and health posts (Table 3.7). Two scenarios were generated: one in which populations will walk through floodwaters (FW), and one where populations will not walk through floodwaters (NFW). Walking speeds and simulated person characteristics were assumed for an average 19 year old female (Mitsunaga and Yamauchi, 2020) to produce a resulting HV_c of 0.53 m^2 s^{-1}, more conservative than the lower boundary in Karvonen *et al*. (2000).

Access to maternal health services between October 2017 and October 2018 was then assessed using women of reproductive age as a proxy for pregnant women (Table 3.7). The raster-based model was used to assess women's ability to reach a healthcare facility with delivery, emergency obstetric care (EmOC), or maternity waiting shelters (MWS) respectively. Walking travel times were parameterised to be lower to reflect a decreased walking ability of women in their third trimester, and walking through floodwaters was not permitted in the maternal modelling as this was deemed inappropriate for heavily pregnant women potentially in or about to be in labour. The network-based model was also used as described in Section 3.3 to model vehicular referral travel times from a delivery site to the nearest EmOC site. Emergency vehicles were permitted to drive through floodwaters deemed low hazard at heavily reduced speeds.

To compare the new approach with previous approaches, a static "dry" (October 2017) and "wet" (April 2018) season scenario were created. These static scenarios used the same inputs and model parameterisation as the maternal healthcare access scenarios, but the hydrodynamic floodwater variables were substituted with floodwater extent polygons. A MODIS NRT Global Flood Product (250 m spatial resolution) was used as the remotely-sensed extent of floodwaters composited over three days between the 17th and 19th April 2018; this composite was selected for the "wet" season scenario as it was the most representative of true flood conditions visible between March and April 2018.

3.6. Chapter summary

Separate vector- and raster-based models were developed which incorporate floodwater variables to quantitatively assess their impact on vehicular and walking travel times. These models are a modification of common GIS methods already used in geographical access studies, and are suitable for operation in low-income regions. These models were demonstrated by specifically applying them in a large African floodplain to assess access to healthcare, using hydrodynamic model outputs to determine flood hazard and resulting impacts on access in a novelistic approach. Importantly, the frameworks created are not region-specific and can be used to assess access to any services in similar regions, provided the models are parameterised appropriately. A sensitivity analysis was conducted on two of the most important variables in both models, H_{max} and V_{max}, to demonstrate model parameterisation and to determine appropriate values for the model runs in the Barotse Floodplain.

Table 3.7. All access scenarios modelled alongside input datasets, and parameter settings.

	Model used	Inputs		Walking speed (km hr^{-1})				Parameters			
		Origin	*Destination*	*Road*	*Off-road*	*Flooded but accessible*	*Inaccessible*	*H_{max} (m)*	*V_{max} (m s^{-1})*	*Height (m)*	*Weight (kg)*
FW scenario	Raster	All population on Barotse Floodplain	(1) Any HF (2) Hospital only (3) Health centre or health post only	5	4	1	0	0.5	0.5	157	54
NFW scenario	Raster	All population on Barotse Floodplain	(1) Any HF (2) Hospital only (3) Health centre or health post only	5	4	0	0	0.01	*n/a*	*n/a*	*n/a*
Maternal walking scenario	Raster	Women of reproductive age on Barotse Floodplain	(1) Delivery site (2) EmOC site (3) Maternity waiting shelter	4	3	0	0	0.01	*n/a*	*n/a*	*n/a*

	Model used	Inputs		Driving speed (km hr^{-1})				Parameters	
		Origin	*Destination*	*w*	*w_a*	*w_b*	*Inaccessible*	*H_{max}*	*V_{max}*
Maternal referral scenario	Vector	Delivery site	EmOC site	See Table 3.4	8	5	0	0.5	1.0

CHAPTER 4

RESULTS: *Health access in the Barotse Floodplain*

Section 4.1 will first provide a description of the floodwave passage over the Barotse Floodplain. In Section 4.2, the ability of all populations to walk to their nearest healthcare facility and nearest hospital will then be described, with differences between the FW scenario (walking through floodwaters) and NFW scenario (all floodwaters inaccessible) stated. Section 4.3 then specifically discretises facilities by the maternal services they provide, reporting on the ability of floodplain women to reach these services. Walking access is first described, followed by the ability of delivery sites to refer patients to EmOC sites as identified through network analysis in the vector model. Note that the network-based model was only operated once to produce the vehicular referral times between delivery sites and EmOC in the maternal healthcare scenarios (Section 4.3.3). As household car ownership is rare, it was deemed inappropriate to model driving times for floodplain populations to facilities; modelling referrals between delivery sites and EmOC represented the best use of the new network-based approach to consider a key functional aspect of the healthcare system. Improvements over previous approaches are then explicitly highlighted in Section 4.4, followed by a summary of the key findings in Section 4.5.

4.1. Floodwave passage

Floodwater depths and velocities change each month in response to the passage of the annual floodwave (Table 4.1). Due to the low gradient of the floodplain, floodwaters are deep but with very low velocities; consequently, water depth is the most influential hydrodynamic characteristic of the floodwave on access. Floodwaters first appear in the Luena Flats in November 2017 (Figure 4.1), with depths below 0.3 m and velocities below 0.2 m s^1. By December, these floodwaters have increased in extent, although depths and velocities remain relatively unchanged. In the Barotse Floodplain, land adjacent to river channels has begun to inundate, with negative relief features preferentially flooded. Floodwaters have also appeared in the Luanginga Valley. Inundation is greatest in extent and depth at the southernmost part of the floodplain, at the confluence of the Zambezi and an anabranching channel.

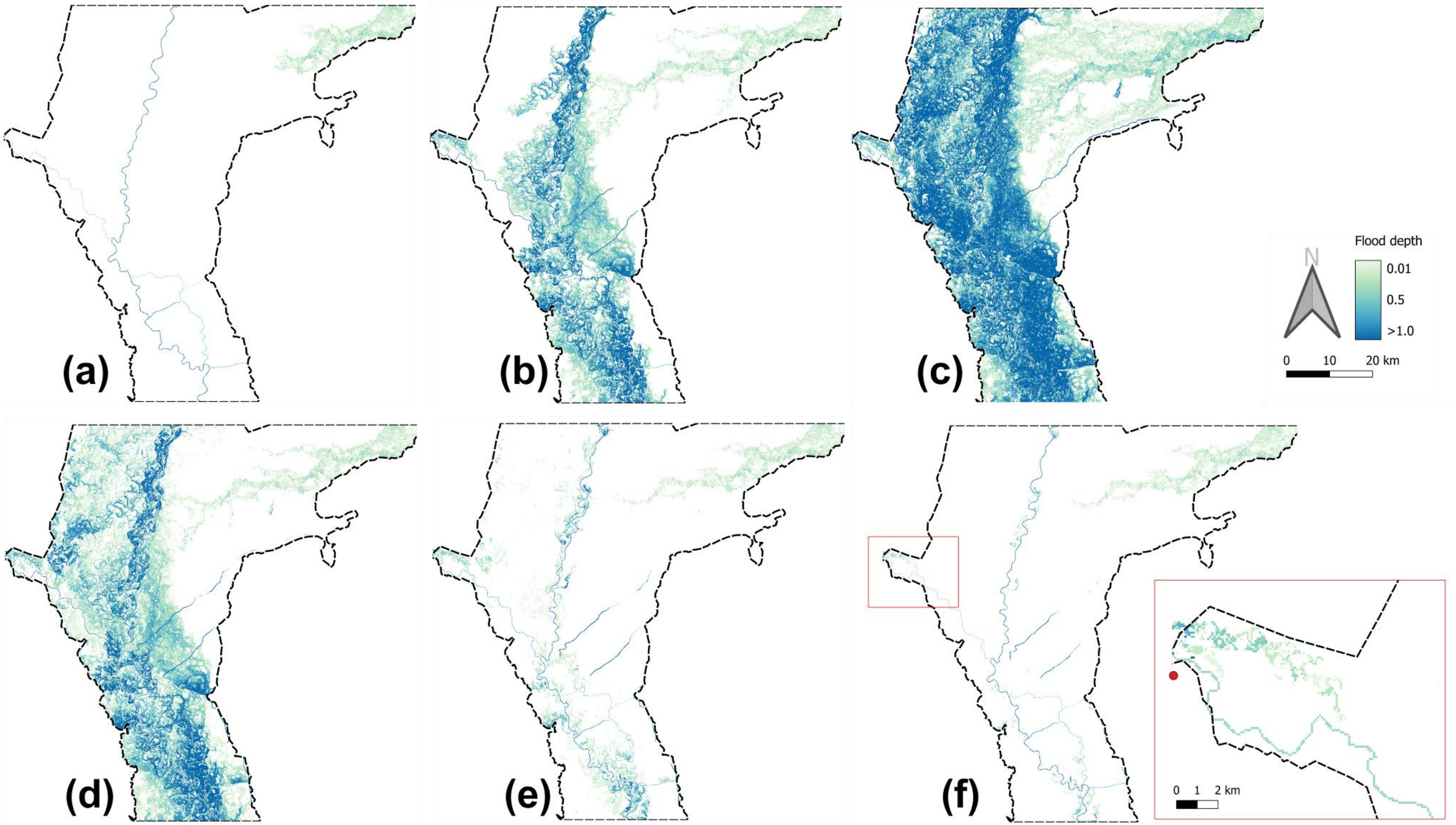


Figure 4.1. Floodwater extent and depth in (a) November 2017, (b) January 2018, (c) March 2018, (d) June 2018, (e) August 2018, and (f) October 2018. The red dot represents Kalabo Hospital.

Between January and February 2018, floodwaters expanded rapidly. Depths are greatest adjacent to the Zambezi trunk, and negative relief assemblages convey deeper floodwaters across the floodplain. Floodwater depths increase in both the Luena and Luanginga valleys; however, these depths remain lower than those on the Barotse Floodplain.

Table 4.1. Monthly average depths and velocities across the study region.

Month	Mean depth (m)	Mean velocity (m s^{-1})
October 2017	0.0098	0.0002
November 2017	0.0112	0.001
December 2017	0.0345	0.0025
January 2018	0.21	0.0189
February 2018	0.3377	0.0392
March 2018	0.5659	0.0699
April 2018	0.5497	0.0659
May 2018	0.5388	0.0641
June 2018	0.2522	0.0196
July 2018	0.0795	0.0025
August 2018	0.0352	0.001
September 2018	0.0238	0.0009
October 2018	0.0161	0.0008

The peak of the floods occurs in March and April 2018. Inundation extent is greatest, with floodwaters spanning to the escarpment across the ~90 km length of the study area. Deep floodwaters greater than 1 m span across the floodplain, although depths in the tributary valleys are lower (mostly below 0.5 m). Velocities remain low, mostly below 0.5 m s^{-1}.

Flood drawdown occurs from June 2018 onwards, with floodwaters decreasing depths *in-situ* rather than overall extent retracting. By October, the majority of floodwaters have receded, but inundation persists in the Luena Flats and Luanginga Valley; these remaining floodwaters are shallow of approximately 0.2 m depths.

4.2. General walking access to healthcare

4.2.1. Overview

The spatio-temporal distribution of floodwaters affects the ability of floodplain population to walk to healthcare facilities. Both the FW (walking through floodwaters permitted) and NFW (all floodwaters inaccessible) scenarios agree that floodwaters act as a barrier, either impeding or completely restricting walking with the consequences of increased travel times and inaccessibility (Figures 4.2-4.4). Walking access changes dynamically as the floodwave passes over the floodplain. Access is most optimal before flood onset, and decreases as the floods rise. As floodwaters increase in depth and extent, walking ability is impacted. By the peak of the floods in March and April 2018, the proportion of the population with timely access to healthcare (defined as within two walking hours) is at its lowest (31-40%) and inaccessibility is at its highest (47-66%). Those living furthest away from healthcare facilities are disproportionately most impacted. As floodwaters recede (Figure 4.1), access generally restores to pre-flood levels by the final model timestep in October 2017.

Populations living closer to the floodplain escarpment typically experience lower walking times to their nearest healthcare facility due to the greater distribution of facilities above the floodplain rather than on the floodplain. In contrast, those living closer to the Zambezi trunk experience worse accessibility; walking times are longest and these populations are impacted in more months by floodwaters which inundate the centre of the floodplain first. A few facilities are positioned on the floodplain which reduces walking times in their catchments, but these facilities are the first to be impacted by rising floodwaters. Populations located near the causeway benefit from the easier access to healthcare in major settlements such as Lealui and Mongu. Due to the sparser number of facilities, access is overall poorer in the Luena Flats. Similarly, walking access is worsened for populations located within the confinements of the Zambezi, Luanginga, and Luambimba rivers which geographically restrict access onto the escarpment.

Due to only five hospitals being located in three geographically distinct areas (Kalabo, Mongu, and Lealui), walking access to hospitals is worse and the majority of the floodplain population lack timely access. Populations in the north-west of the floodplain and in the Luanginga Valley are able to walk to Kalabo and Yuka Mission Hospital in the dry season, but their access is very vulnerable and quickly impacted in flood months due to the few connecting roads (Figure 4.1). Again, the population in the Luena Flats experiences heightened difficulties due to their nearest hospitals being located in Mongu as access is limited by waterbodies that persist for longer.

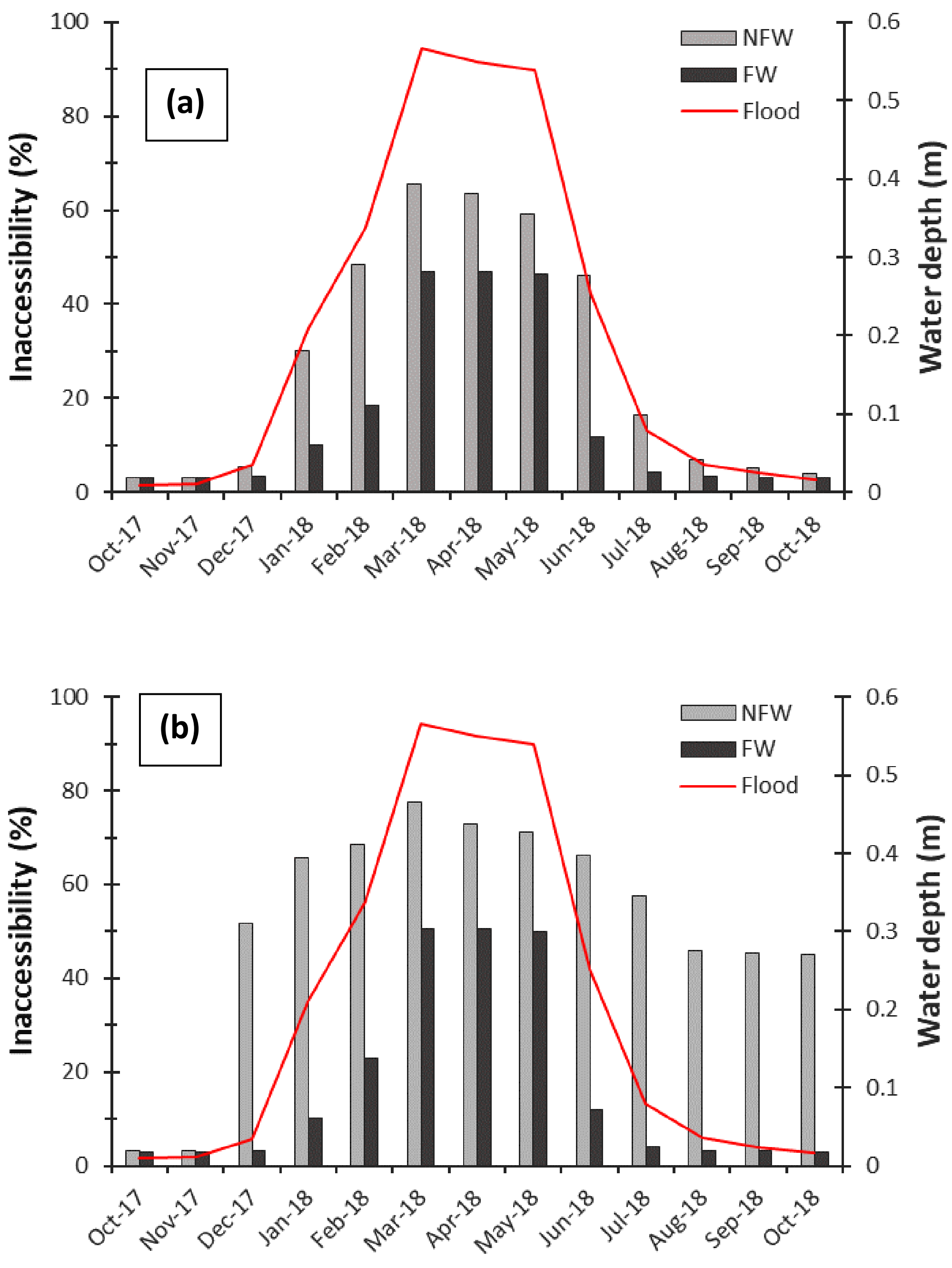


Figure 4.2. Comparison of the FW and NFW scenario monthly predictions of the percentage of the floodplain population considered unable to walk to: (a) any healthcare facility, (b) a hospital. Inaccessibility increases as floodwater depths increase each month in both scenarios.

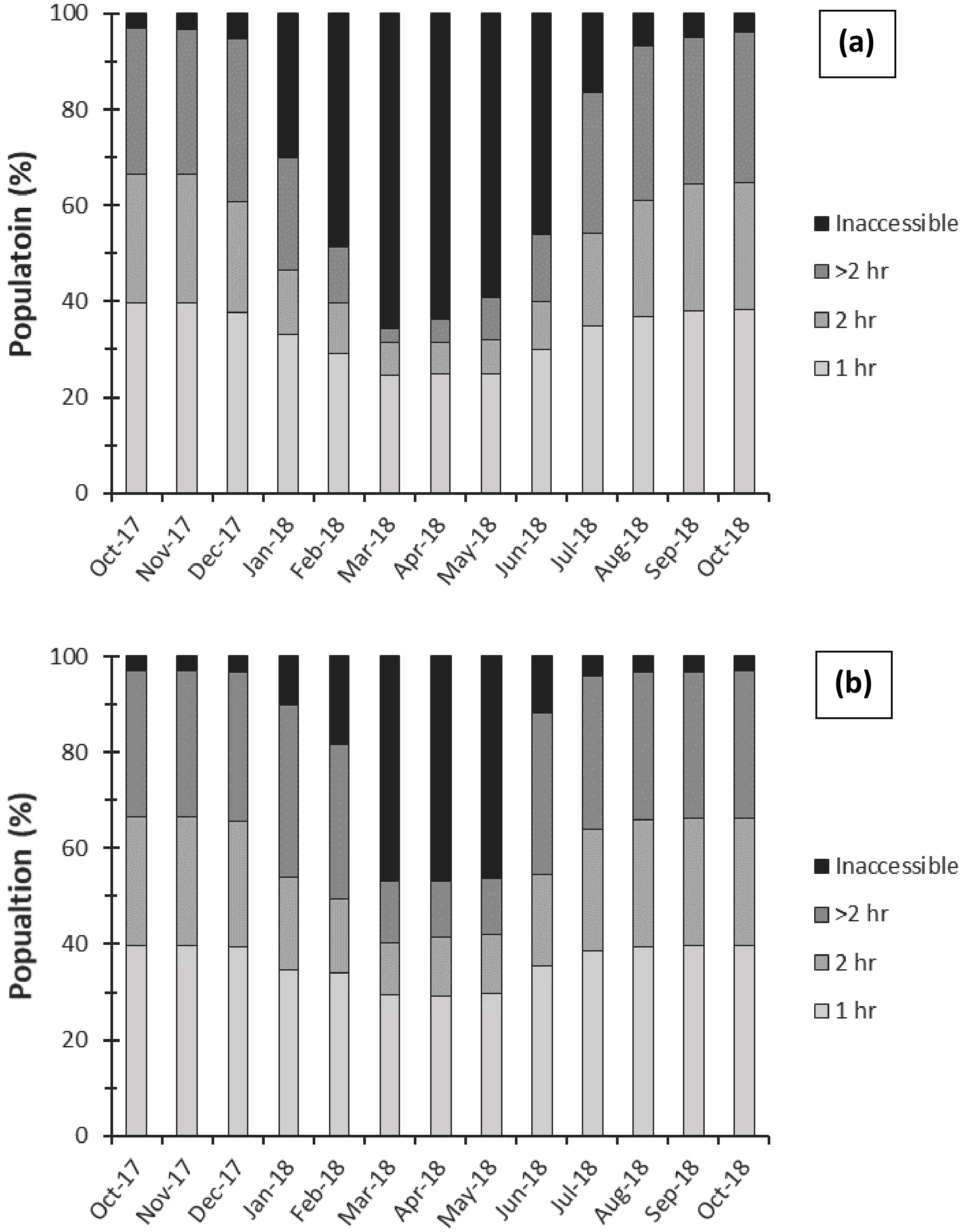
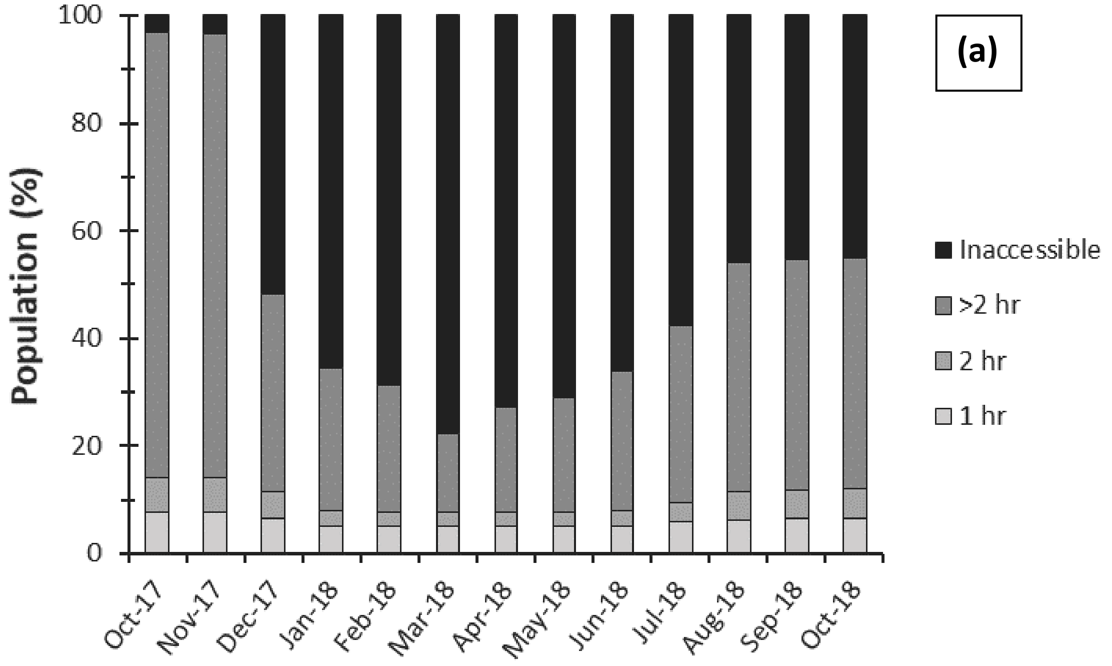


Figure 4.3. Monthly variation in the percentage of the floodplain population with walking access to any healthcare facility, compared between (a) the NFW scenario, and (b) the FW scenario.



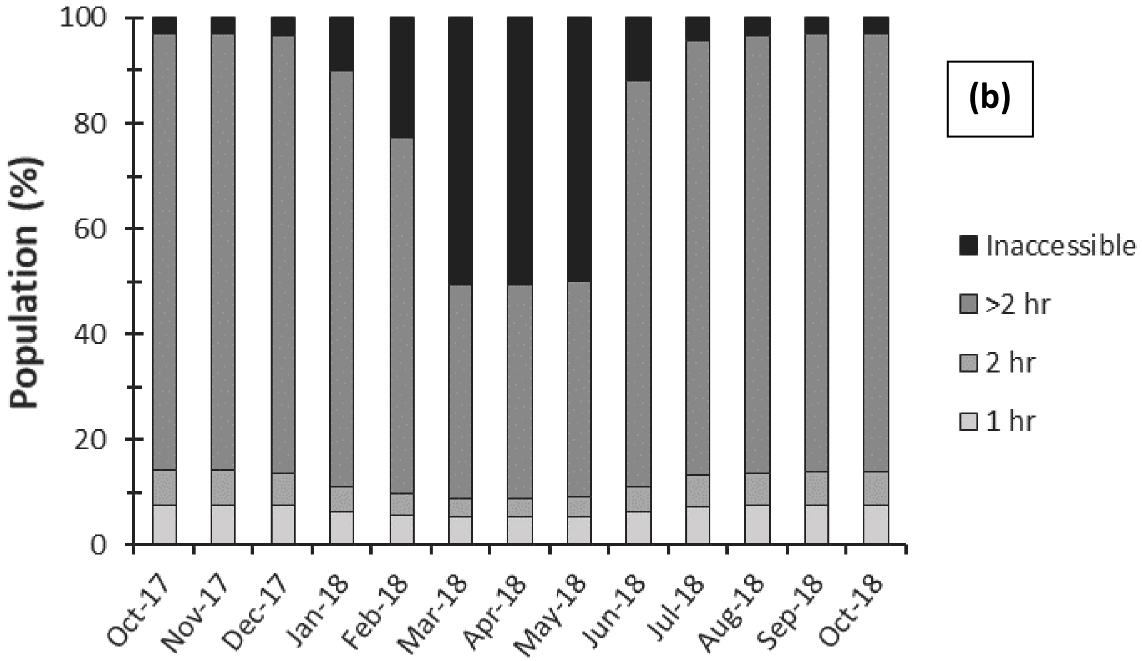


Figure 4.4. Monthly variation in the percentage of the floodplain population with walking access to a hospital, compared between (a) the NFW scenario, and (b) the FW scenario.

Both scenarios agree on the general pattern of these findings, but the ability to walk through floodwaters deemed low hazard in the FW scenario decreases the influence of shallow and low-velocity floodwaters on the accessibility of the floodplain. As a consequence, the two scenarios show different magnitudes of impact, in addition to key differences in: (1) the onset of impacts resulting from floodwaters; (2) the recovery in walking access to hospitals; and (3) the duration of peak floodwater impact. The greatest relative differences between the two scenarios' inaccessibility estimates for different facilities always occurs during the intermediate flood stages rather than at peak flood or peak dry season. The differences between scenarios do not detract from the general pattern observed nor imply one scenario has performed better than the other, but rather present two contrasting scenarios of walking access: how access may look for those able to walk through low-hazard floodwaters, and how access may look for those who cannot or do not want to wade through any floodwaters.

4.2.2. Walking access throughout the hydrological year

Walking access to healthcare facilities and hospitals is optimum in October 2017, reflecting optimal access conditions with only permanent waterbodies present on the floodplain. In the dry season 66% of the population have timely access to their nearest healthcare facility (Table 4.2), and the average walking time is 83 minutes (1.4 hours) whilst the maximum walking time is 320 (5.3 hours). The majority of facilities are either healthcare posts or healthcare facilities, and thus access to hospitals is worse (Table 4.3). Only 14% of the population can walk to a hospital within 2 hours; the average journey takes 314 minutes (5.2 hours) whilst the longest takes 1,035 minutes (17.3 hours). In October 2017, both scenarios identify only 3% of the population to be isolated and unable to walk to a healthcare facility; these populations are within the confinements of the Zambezi trunk and an anabranching channel, with no watercrossings on either channel. Consequently, these populations cannot solely walk to healthcare, it is most likely these populations use boats for at least part of their journey which can be seen navigating the channels in satellite images (Figure 4.5).

In December 2017, the NFW scenario identifies walking access to hospitals as being significantly impacted (Table 4.3, Figure 4.6). However, the FW scenario does not identify the first major impacts until January 2018 by which point the NFW scenario predicts access to have worsened again. Floodwaters have appeared by December 2017 but are shallow and limited in extent; hence whilst the NFW scenario treats them as inaccessible barriers with large implications on access, the FW scenario assumes populations are still able to walk through these shallow floodwaters to access hospitals. Both the NFW and FW scenario are in agreement that from January 2018, walking accessibility to any facility decreases monthly corresponding with rising floodwaters; their only disagreement is in the magnitude of decline. By the peak of floods in March and April 2018, both scenarios identify inaccessibility to be highest and timely access to be lowest, with walking access to hospitals for the population impacted worse than access to other healthcare facilities. Again, their only disagreement is in the magnitude of impact.

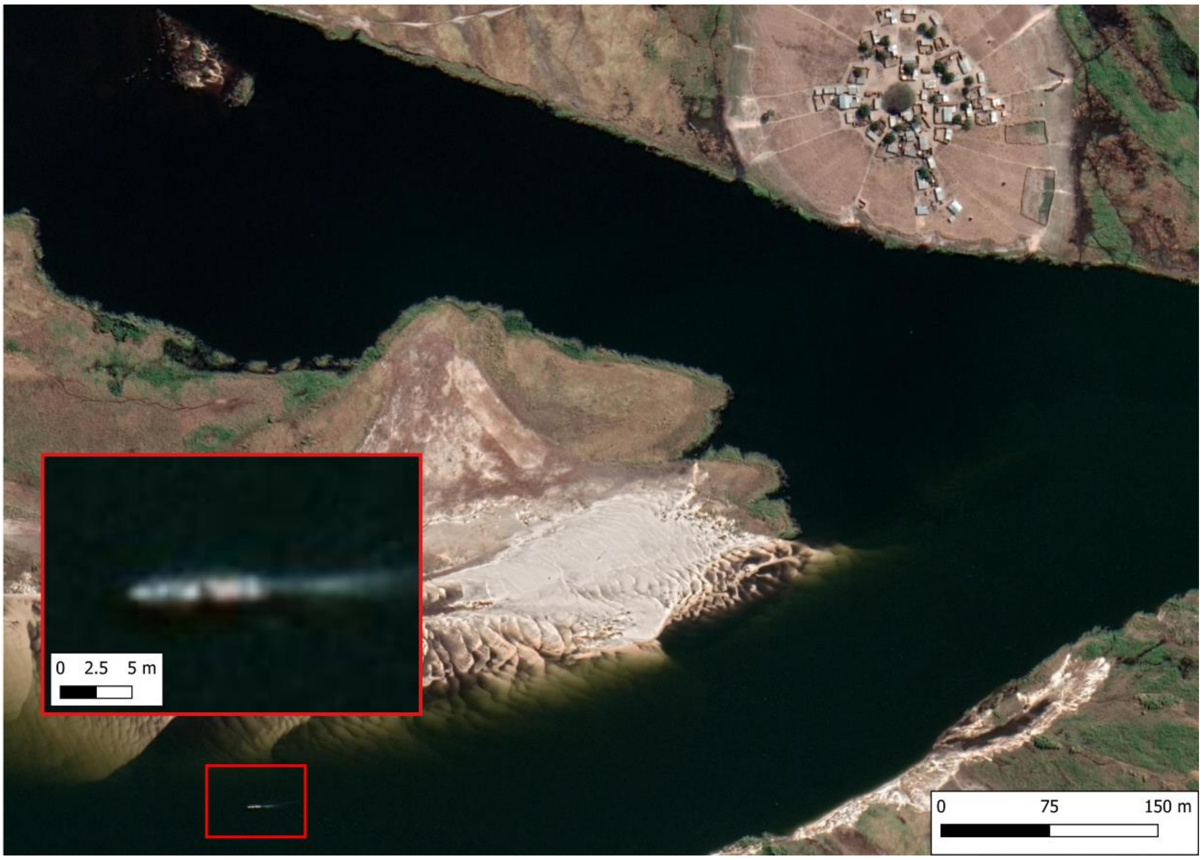
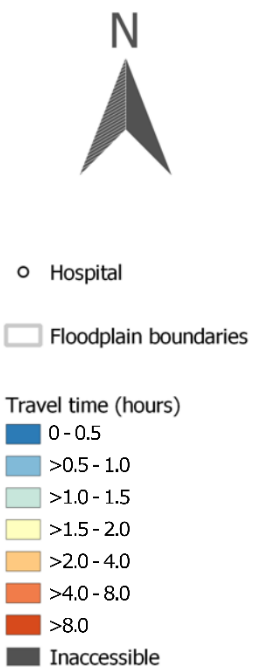


Figure 4.5. A settlement (top right) located within the confinements of the Zambezi and its anabranching channel, with no direct walking access to a healthcare facility. The population is estimated to be ~49 people, containing ~12 women of reproductive age. The settlement is built upon a *suuba* (elevated land) and is not inundated by floodwaters in 2018. A dugout canoe (bottom left) is seen moving along the Zambezi in this satellite image, as are others along this stretch of channel (not pictured here).



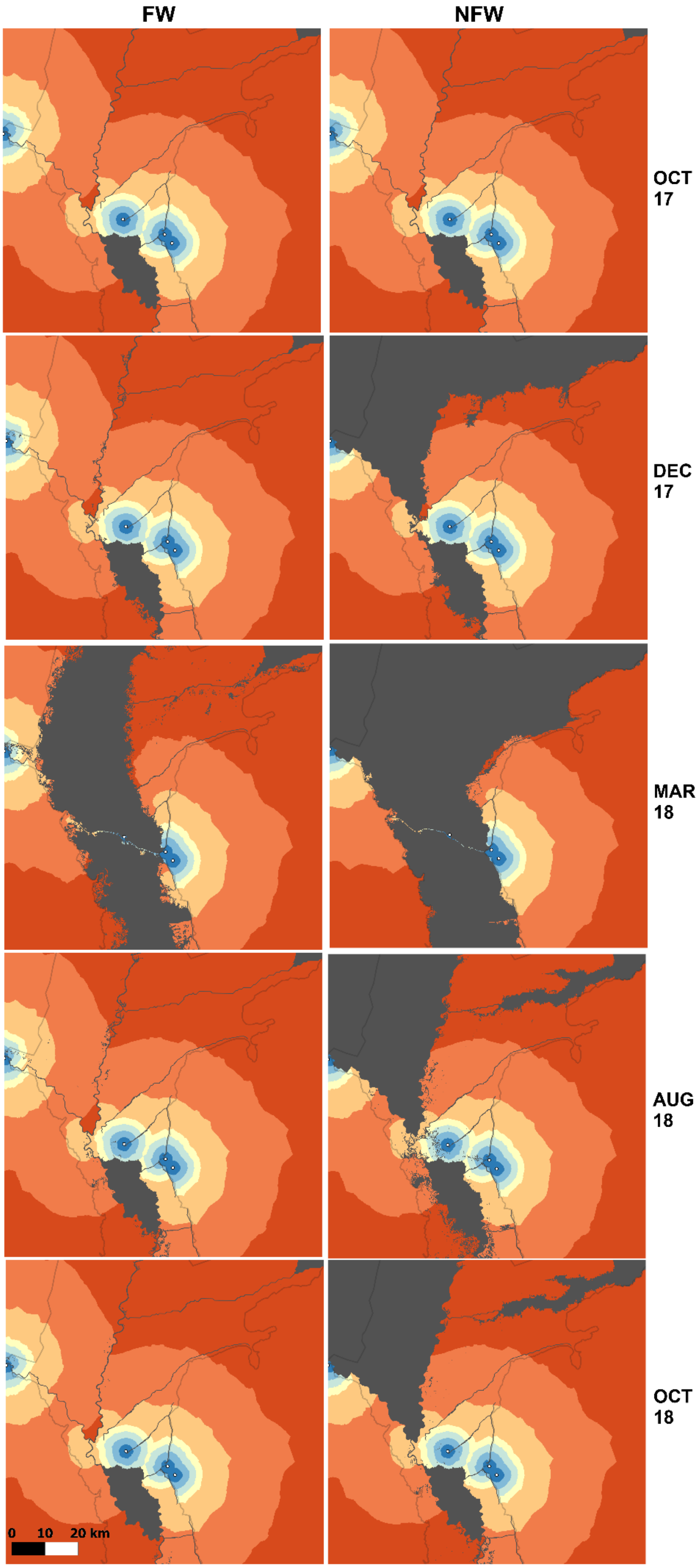


Figure 4.6. A comparison of NFW and FW monthly predictions of walking accessibility to hospitals

Access remains impacted through to May 2018 in both scenarios due to the deep and extensive floodwaters present. From June 2018 onwards, floodwater recession coincides with restorations in access to all healthcare facilities. In the NFW scenario, access to all facilities (including hospitals) has nearly restored to pre-flood levels as early as July 2018, with almost complete restoration by the final model timestep in October 2018. However, the NFW scenario identifies a slower recovery period, with access to healthcare facilities largely still recovering until around August 2018. By October 2018 in the NFW scenario, access to health posts and health centres has mostly restored but, in disagreement with the FW scenario, the NFW scenario identifies hospitals as remaining impacted. In the NFW scenario restoration to pre-flood levels has not occurred, and recovery has stagnated since August 2018.

Table 4.2. Monthly estimates from the FW and NFW scenarios of the population with timely access to their nearest healthcare facility, and the population with no access to any healthcare facility.

Month	***Inaccessibility***				***Timely access (< 2 hrs)***			
	FW		**NFW**		**FW**		**NFW**	
	%	***n***	**%**	***n***	**%**	***n***	**%**	***n***
October 2017	3	1,032	3	1,056	66	22,780	66	22,780
November 2017	3	1,032	3	1,112	66	22,780	66	22,773
December 2017	3	1,119	5	1,828	66	22,493	61	20,810
January 2018	10	3,442	30	10,367	54	18,563	47	16,005
February 2018	18	6,337	49	16,658	50	16,991	40	13,618
March 2018	47	16,102	66	22,539	40	13,861	31	10,785
April 2018	47	16,126	64	21,832	41	14,221	31	10,797
May 2018	46	15,900	59	20,261	42	14,429	32	10,941
June 2018	12	4,079	46	15,818	54	18,680	40	13,707
July 2018	4	1,433	16	5,649	64	21,939	54	18,606
August 2018	3	1,123	7	2,355	66	22,576	61	20,911
September 2018	3	1,087	5	1,730	66	22,721	64	22,088
October 2018	3	1,042	4	1,371	66	22,766	65	22,238

Table 4.3. Monthly estimates from the FW and NFW scenarios of the population with timely access to their nearest hospital, and the population with no access to any hospital.

Month	***Inaccessibility***				***Timely access (< 2 hrs)***			
	FW		**NFW**		**FW**		**NFW**	
	%	**n**	**%**	**n**	**%**	**n**	**%**	**n**
October 2017	3	1,032	3	1,056	14	4,871	14	4,871
November 2017	3	1,032	3	1,112	14	4,871	14	4,871
December 2017	3	1,119	52	17,771	14	4,709	12	3,992
January 2018	10	3,442	66	22,513	11	3,771	8	2,778
February 2018	23	7,828	69	23,529	10	3,401	8	2,688
March 2018	51	17,357	78	26,641	9	3,034	8	2,652
April 2018	51	17,381	73	24,971	9	3,034	8	2,652
May 2018	50	17,156	71	24,415	9	3,120	8	2,652
June 2018	12	4,079	66	22,713	11	3,822	8	2,748
July 2018	4	1,433	58	19,784	13	4,530	9	3,217
August 2018	3	1,123	46	15,767	14	4,709	11	3,907
September 2018	3	1,087	45	15,544	14	4,769	12	4,071
October 2018	3	1,042	45	15,429	14	4,769	12	4,101

4.2.3. The spatio-temporal impact of floodwater variables

The differences exhibited between the FW and NFW scenarios arise due to how they incorporate floodwater depth and velocity into their model parameterisation resulting in different representations of the spatio-temporal impacts on access caused by the same floodwaters. As the NFW scenario does not allow populations to walk through any floodwater regardless of depth or velocity, it always produces an increased magnitude of impact relative to the FW scenario as it is sensitive to any cell containing a floodwater variable. Consequently, when floodwaters first appear in the Luanginga and Luena valleys in December 2017, accessibility is impacted immediately in the NFW scenario, particularly for hospitals where the inundation of roads connecting to a hand-pulled pontoon prevents large numbers of the floodplain population from reaching their nearest hospital in Kalabo. However, as these floodwaters are shallow and of low velocity, they do not act as complete barriers in the FW scenario as populations are able to walk through them albeit at a reduced walking speed;

hence the FW scenario reports the first significant impacts to access in January 2018 where floodwaters increase in extent, depth, and velocity. Similarly, as floodwaters recede, access restores more quickly in the FW scenario as the remaining floodwaters are shallow and considered traversable. The NFW scenario is sensitive to the extent of the remaining floodwaters, which must decrease in extent for estimated access to increase. As floodwaters persist in the Luanginga and Luena valleys throughout the remainder of the model duration, access to hospitals remains impacted in the NFW scenario (Figure 4.7).

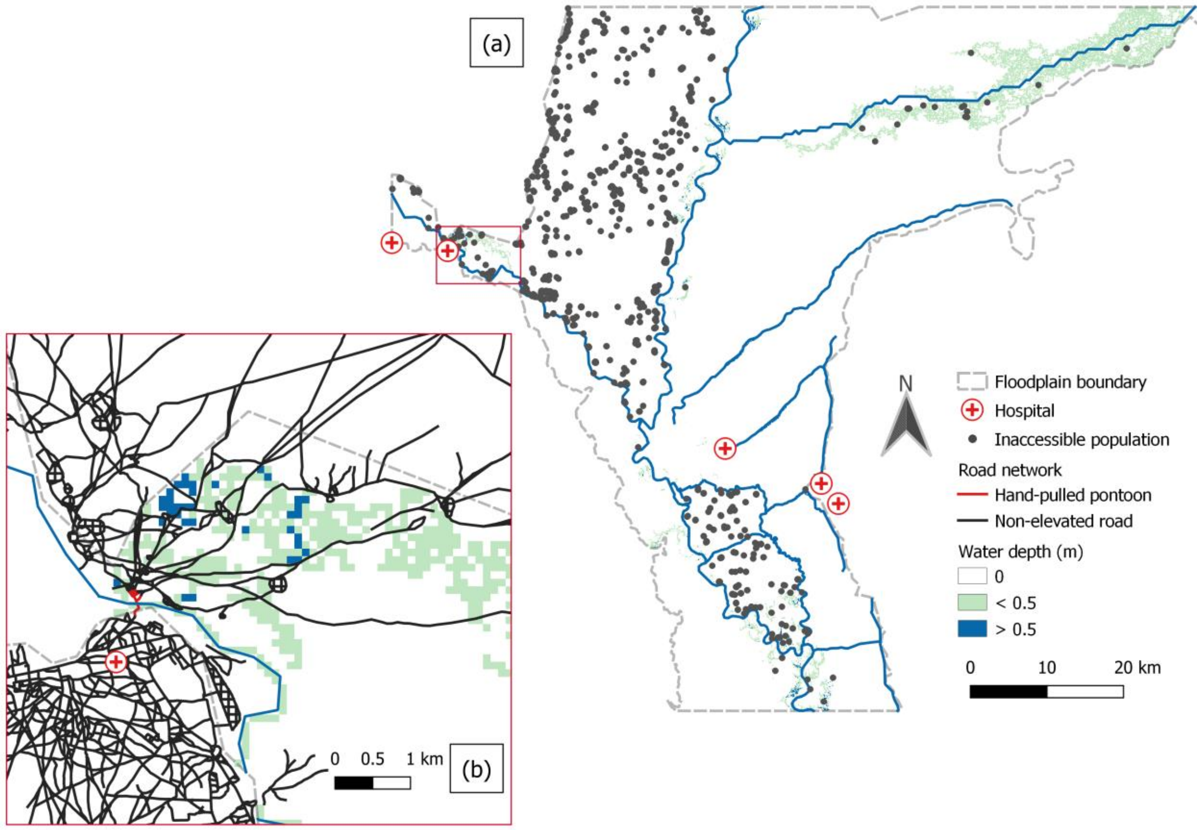


Figure 4.7. For October 2018, (a) shows floodplain populations identified in the NFW scenario as unable to reach a hospital and (b) shows persisting floodwaters in the Luanginga Valley intersecting critical roads linking to Kalabo and its district hospital.

Additionally, in the FW scenario, inaccessibility remains near-uniformly maximal between March and May 2018. However, in the NFW scenario, whilst inaccessibility remains high throughout all three months, it distinctively peaks in March. Floodwaters are most extensive in March 2018 compared with April and May, but the additional floodwaters are of shallower depths and lower velocities. Consequently, the FW scenario is only sensitive to the same hazardously deep floodwaters that persist between March and May and impacts to access remain nearly the same throughout the three months.

4.2.4. Effects of floods on health access inequity

Both scenarios agree that floodwaters disproportionately impact the populations that were located furthest away from their nearest facility in October 2017 (Table 4.4). A greater walking time in the dry season indicates an increased likelihood of being completely inaccessible at the peak of the floods. In the intermediate stages of flood rise and flood drawdown, the disproportionate impact on those furthest away is lessened. There is negligible difference in inaccessibility increases experienced between those living within 1-2 hours of a facility in October 2017, and those living beyond a 2 hour journey (Figure 4.8). Similarly, disproportionate impacts are found regarding access to hospitals (Figure 4.9); however the difference is lessened between those living within 1-2 hours and those living beyond 2 hours in October 2017.

Table 4.4. Populations who are furthest away from healthcare facilities in October 2017 experience greater inaccessibility in March 2018.

		Inaccessibility in March 2018:	
		Nearest healthcare facility (%)	*Nearest hospital (%)*
FW scenario	**1 hr**	21	15
Population with access in October 2017 within:	**2 hr**	52	46
	>2 hr	71	52
NFW scenario	**1 hr**	36	26
Population with access in October 2017 within:	**2 hr**	54	66
	>2 hr	92	82

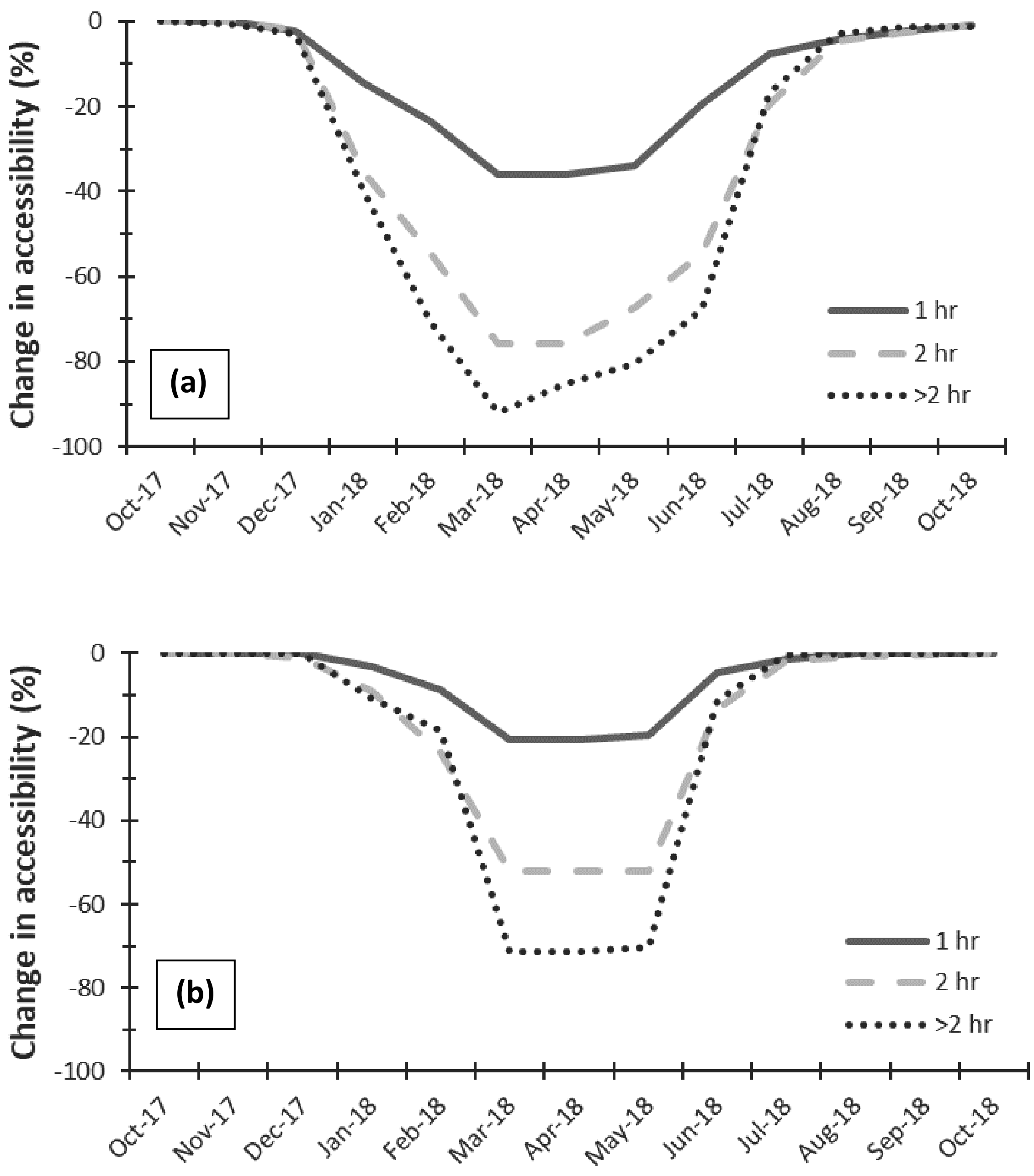


Figure 4.8. Relative monthly decreases in accessibility to the nearest healthcare facility depending on the location of the population in October 2017, compared between (a) the NFW scenario, and (b) the FW scenario.

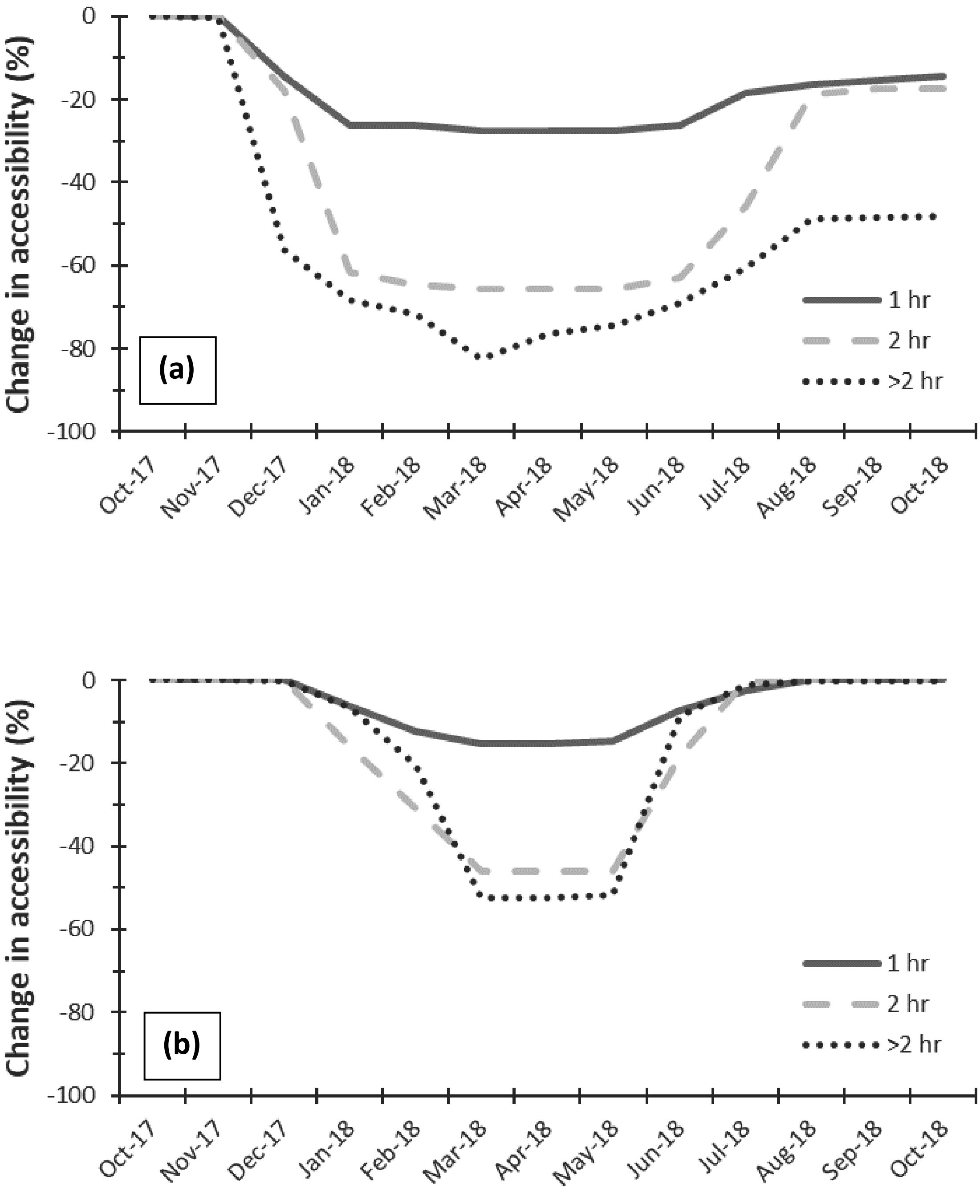


Figure 4.9. Relative monthly decreases in accessibility to the nearest hospital depending on the location of the population in October 2017, compared between (a) the NFW scenario, and (b) the FW scenario.

4.3. Access to maternal services

4.3.1. Walking access throughout the hydrological year

Potential geographic access to maternal services corresponds with the presence of floodwaters which impede the walking ability of women of reproductive age (Figure 4.10, Figure 4.11). Walking access to all maternal services is optimum before flood onset, where inaccessibility is lowest and the proportion of the population with timely access to maternal services is highest. As with access to general healthcare, walking access to maternal services generally decreases as floodwaters rise, is impacted the most at the peak of the floods, and is restored as floodwaters recede.

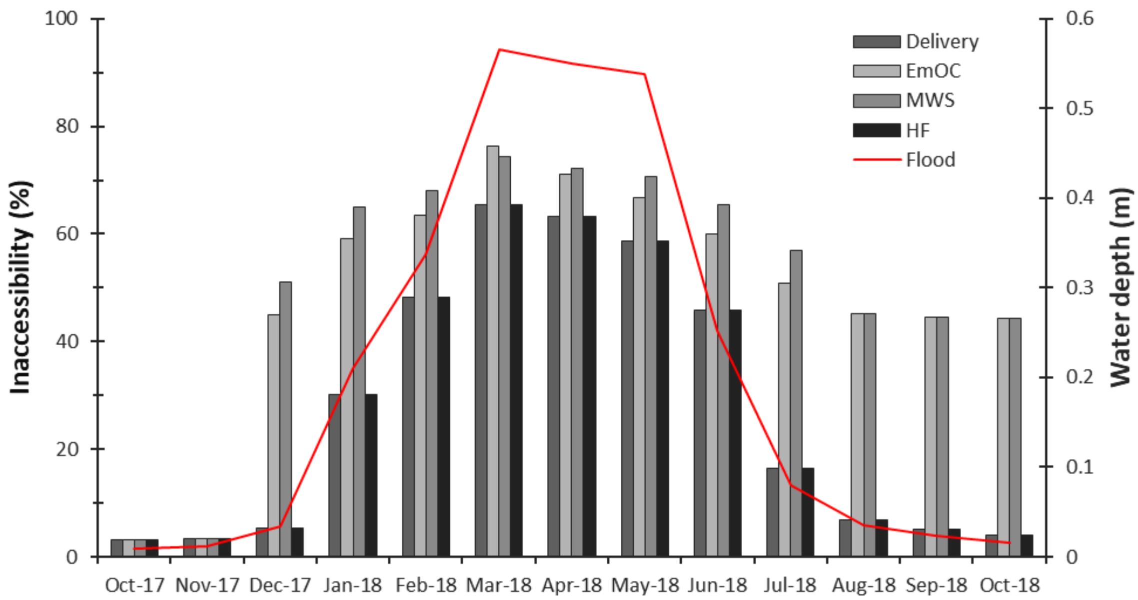


Figure 4.10. The percentage of women of reproductive age who are unable to walk to maternal services each month, alongside the monthly mean depth of floodwaters.

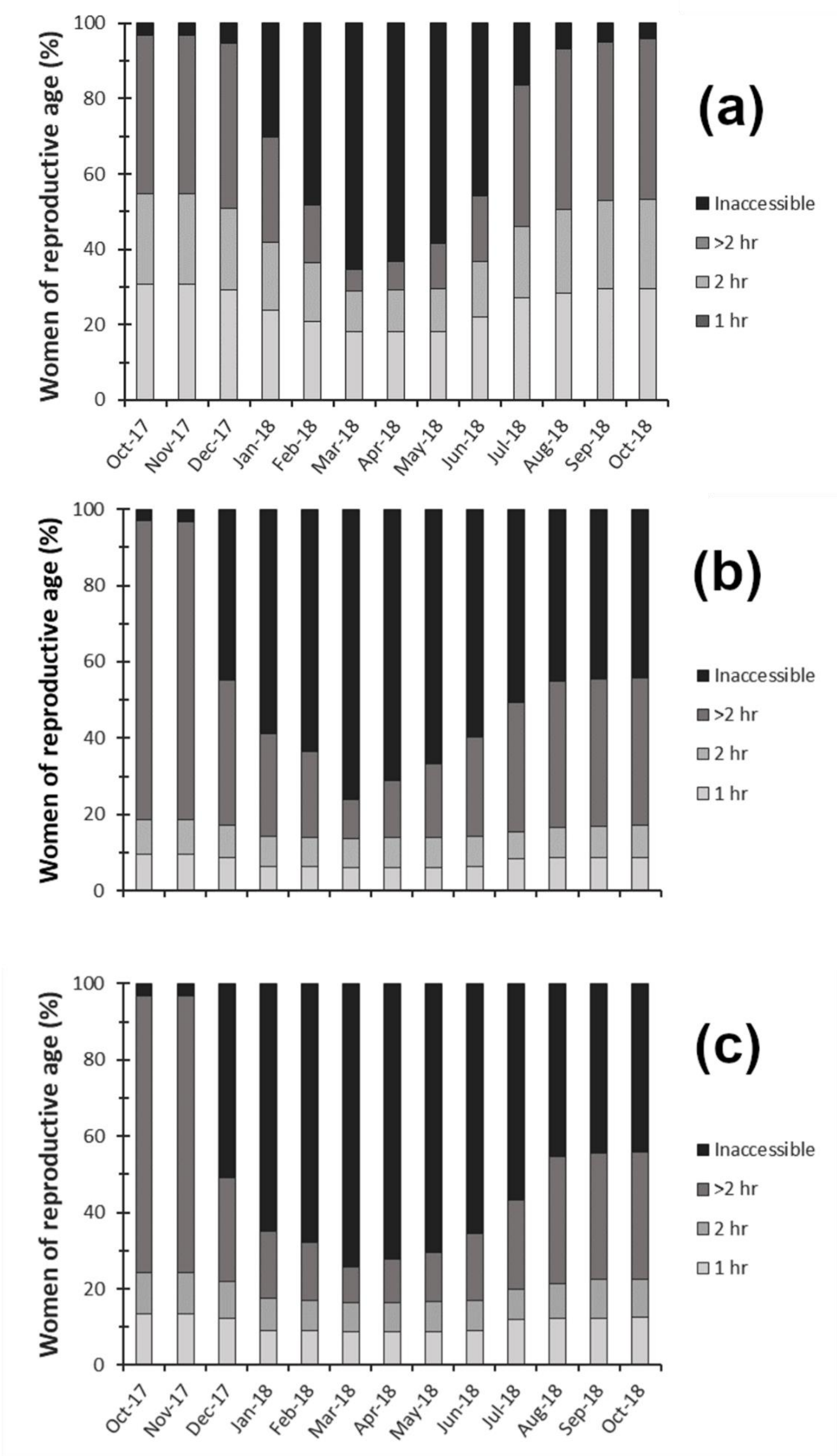


Figure 4.11. The percentage of women within each walking travel time threshold to: (a) delivery sites; (b) EmOC; (c) Maternity Waiting Shelters (MWS).

October 2017 represents the peak of the dry season. Walking access to delivery sites, emergency obstetric care (EmOC) and maternity waiting shelters (MWS) is highest; however, the proportion of the population with timely access to services is still low (Table 4.5). Half of the population have walking access to a delivery site within 2 hours, but whilst the average walking time is 109 minutes (1.8 hours), the furthest populations have to walk a maximum time of 420 minutes (7 hours). Only a quarter of the population have access to a MWS within 2 hours, and the average walking time was 251 minutes (4.2 hours) with the furthest populations walking for 845 minutes (14.1 hours). Timely access to EmOC is the worst; less than a fifth of women can walk to EmOC within 2 hours, and the average walking time was 280 minutes (4.7 hours) whilst the maximum travel time was also 845 minutes (14.1 hours).

Comparatively, March 2018 represents the peak of the wet season. Walking access to all maternal services is most severely impacted in this month, with the majority of women unable to reach services. Walking access to EmOC is most impacted, followed by MWS. Delivery sites are impacted relatively less, but still substantially. Whilst the majority of women experience increased walking times or complete inaccessibility to maternal services in the wet season, those who are already located the furthest away in the dry season are those whose accessibility is impacted most by floodwaters (Table 4.6). The proportion of the population who experience inaccessibility each month increases the further away they were from maternal services in October 2017. Evidently, floods disproportionately impact those who already experience the most difficulties walking to maternal services in a timely manner in the dry season.

Monthly inaccessibility for women to a delivery site mimics monthly inaccessibility for women to reach any healthcare facility, indicating good placement of delivery sites within the existing healthcare infrastructure. Walking accessibility is unlikely to improve significantly unless entirely new facilities were to be constructed. Fewer healthcare facilities offer EmOC or MWS which explains the increased inaccessibility for women in accessing these services.

Table 4.5. The number and percentage of women who are inaccessible and who have timely walking access to maternal services each month.

Month	***Inaccessibility***						***Timely access (< 2 hrs)***					
	Delivery		**EmOC**		**MWS**		**Delivery**		**EmOC**		**MWS**	
	%	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**
October 2017	3	256	3	256	3	256	55	4,445	19	1,507	24	1,971
November 2017	3	269	3	269	3	269	55	4,444	19	1,507	24	1,970
December 2017	5	438	45	3,654	51	4,146	51	4,121	17	1,396	22	1,788
January 2018	30	2,456	59	4,798	65	5,285	42	3,394	14	1,149	18	1,426
February 2018	48	3,929	63	5,156	68	5,527	36	2,963	14	1,140	17	1,378
March 2018	65	5,313	76	6,200	74	6,039	29	2,362	14	1,104	16	1,337
April 2018	63	5,141	71	5,787	72	5,871	29	2,363	14	1,125	16	1,339
May 2018	59	4,764	67	5,426	71	5,736	29	2,397	14	1,125	17	1,346
June 2018	46	3,728	60	4,869	66	5,327	37	2,975	14	1,148	17	1,365
July 2018	16	1,340	51	4,132	57	4,621	46	3,745	15	1,239	20	1,601
August 2018	7	562	45	3,681	45	3,681	51	4,114	17	1,356	21	1,736
September 2018	5	415	45	3,627	45	3,627	53	4,304	17	1,381	22	1,817
October 2018	4	330	44	3,600	44	3,600	53	4,328	17	1,396	23	1,838

Table 4.6. Women who are furthest away from maternal services in October 2017 experience greater inaccessibility in March 2018.

		Inaccessibility in March 2018:		
		Delivery site (%)	*EmOC (%)*	*MWS (%)*
Women with access in October 2017 within:	**1 hr**	33	17	14
	2 hr	62	35	46
	>2 hr	89	87	89

4.3.2. Spatio-temporal patterns of walking access

The patterns and magnitudes of inaccessibility to maternal services are neither spatially nor temporally uniform (Figure 4.12). Walking access to EmOC and MWS was impacted a month earlier than access to delivery sites; those located more than two hours away from EmOC and MWS accounted for the majority of the rise in inaccessibility. The first major decrease in access to delivery sites occurred in January 2018, with those located beyond two hours of walking time also accounting for a large proportion of the increase. Inaccessibility to EmOC and MWS is not reduced to pre-flood levels by the final model timestep in October 2018. Whilst walking access to delivery sites recovers for all women back to pre-flood levels in October 2018, improvements in access to EmOC and MWS stagnate from August 2018. As before, those located beyond two hours of walking account for the stagnation as they remain inaccessible.

The earlier impact and delayed recovery of access to emergency obstetric care and maternity waiting shelters is due to the limited locations of the facilities offering these services. Whilst 40 facilities offer delivery services that are accessed by the floodplain women, only ten offer emergency obstetric care and only 22 offer maternity waiting shelters. Kalabo District Hospital serves the greatest number of women in the dry season for both emergency obstetric care (45%, *n*=3,687) and maternity waiting shelters (45%, *n*=3,667). Critically, the hospital serves 3,288 women who are geographically restricted within the confinements of the Zambezi, Luambimba, and Luanginga rivers. These women are only able to access emergency obstetric care and maternity waiting shelters in Kalabo where they must first travel along roads that connect to a hand-pulled pontoon into the town. In December 2017, many of these connecting roads become inundated and the populations are unable to reach Kalabo, with no access to any other facility offering these maternal services; of the 3,288 geographically restricted women, only 3 can now access Kalabo Hospital. Consequently, the population served with EmOC and MWS by Kalabo Hospital declines 89% by December 2017 so that Kalabo Hospital serves just 5% of the total floodplain population with EmOC (n = 396) and MWS (n = 378) in December 2017. Some floodwaters still persist in the Luanginga Valley from August till October 2018, hence these same population remains cut-off (Figure 4.7, Figure 4.12).

Women also experience the greatest inaccessibility in reaching maternity waiting shelters, except in March 2018 when inaccessibility to emergency obstetric care is highest. This is due to the lack of a maternity waiting shelter on the right bank of the Luena Valley where otherwise delivery facilities and emergency obstetric care are present. The Luena Valley floods earlier than the Barotse Floodplain, and its floodwaters persist for longer, restricting use of bridges and water crossings. Thus, populations in the Luena Valley are unable to access a maternity waiting shelter for the majority of the year.

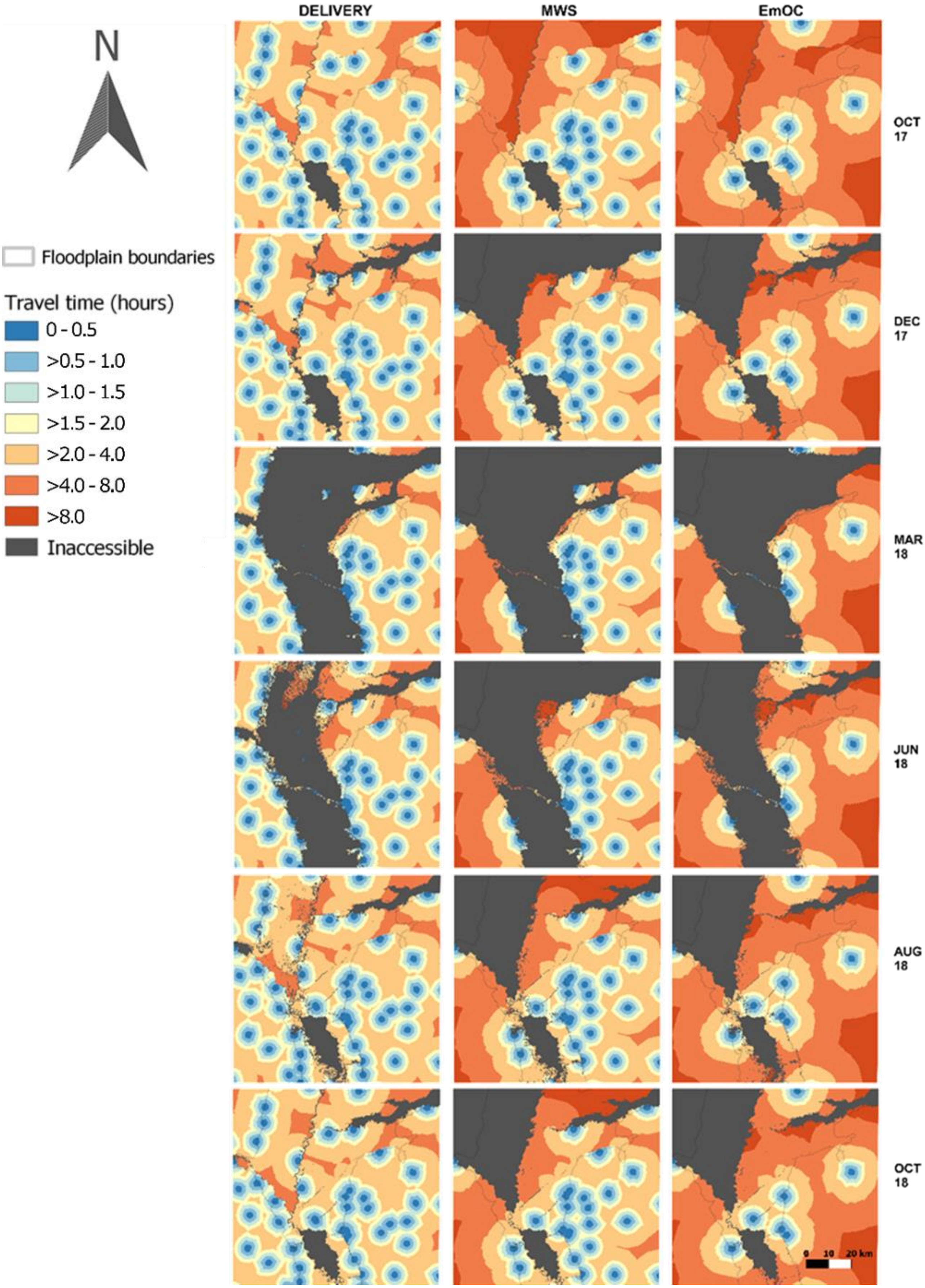


Figure 4.12. A comparison of accessibility to different maternal services in key months.

4.3.3. Potential referral coverage and referral times

Potential referral times by emergency vehicle between delivery sites and EmOC were calculated using network analysis with the vector model. Identifying potential referrals is complicated by the multiple impacts of floods on: (1) reducing the proportion of the population able to reach a delivery site; (2) altering which delivery facilities are being accessed monthly; and (3) affecting the referral abilities of delivery sites to EmOC locations. Consequently, referral coverage and referral times are only considered for facilities being accessed by populations, which changes monthly; this weights the referral results by the impact on the floodplain population.

Over the entire duration of the model, 40 healthcare facilities act as the nearest delivery site for floodplain women in at least one month of the hydrological year. 33 of these facilities can only provide delivery, whilst seven are able to offer delivery and EmOC. Of the 33 "delivery only" facilities, four have no direct road connection to a facility offering EmOC. As a consequence, these four facilities are unable to make referrals year-round.

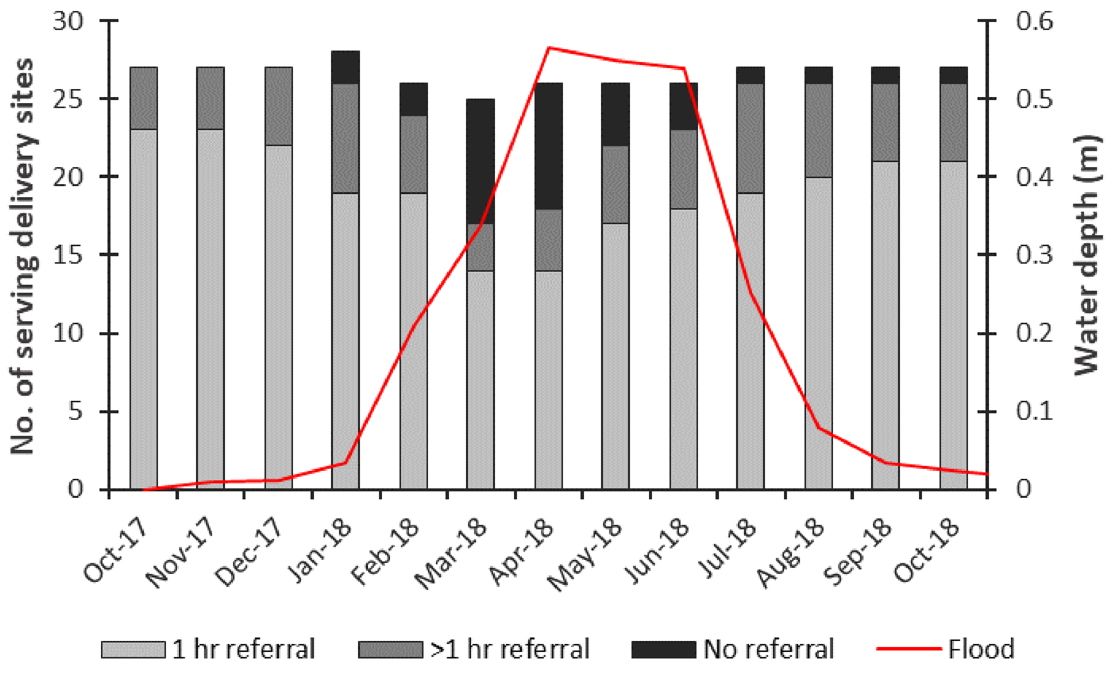


Figure 4.13. The number of healthcare facilities providing delivery services to floodplain women each month, discretised by referral capability. A "serving delivery site" refers to a facility which is being accessed by floodplain women and has a direct road connection to EmOC so referrals are possible. The number and location of these changes each month as floodwaters force populations to access different facilities. Note that delivery sites which serve the population but are unable to ever make road referrals are not considered.

Vehicular referrals between delivery sites to emergency obstetric care are impacted by floodwaters which inundate roads, either reducing safe travel speeds along them or closing them entirely with connectivity implications for the remainder of the network. The depth and extent of floodwaters impacts the number of delivery sites that can make referrals, can be accessed by floodplain populations and which have a direct road connection to an EmOC location. As floodwater mean depth increases, the number of facilities able to make a referral decreases, as does the proportion of those referrals which are within 1 hour (Figure 4.13). Facilities with the lowest referral times in the dry season typically remain consistently accessible with either negligible or no impact to their referral times throughout the hydrological year, whilst facilities with higher referral times are usually those most impacted and experience either increased referral times or a complete inability to make road referrals during the floods. This pattern reflects the impact of the locations of these facilities; urban facilities located closer to EmOC sites have fewer or no roads directly impacted by inundation, and the denser connectivity of urban roads mitigates for any closures by providing alternative routes.

Referral coverage and referral times are most optimal before flood onset in October 2017 (Figure 4.13). Of the 27 "*delivery only*" facilities serving the floodplain population in that month, all are able to make referrals and 23 had referral times within an hour. The mean referral time was 30 minutes whilst the maximum referral time was 89 minutes. Consequently, 50% of women (*n*=4,083) can be referred to EmOC within an hour whilst 14% (*n*=1,169) of women have already arrived directly to an EmOC location, resulting in 65% (*n*=5,251) of women with access to EmOC in a theoretically timely manner.

As floodwaters increase in extent and depth, the number of serving facilities able to make a referral decreases which causes increasingly greater proportions of the population to have either poor or no referral access from their nearest delivery facility. By the peak of the floods in March 2018, referral coverage and referral times were most impacted (Figure 4.14) Of the 25 "*delivery only*" facilities serving the floodplain population in that month, only 17 were able to make referrals to EmOC and 14 had referral times within an hour. The mean referral time of the remaining accessible facilities was 35 minutes, but the maximum referral time was 205 minutes. Consequently, only 16% of women (*n*=1,334) can be referred to EmOC within an hour whilst 7% (*n*=558) are already present at an EmoC location, resulting in only ~23% (*n*=1,892) having timely access to EmOC.

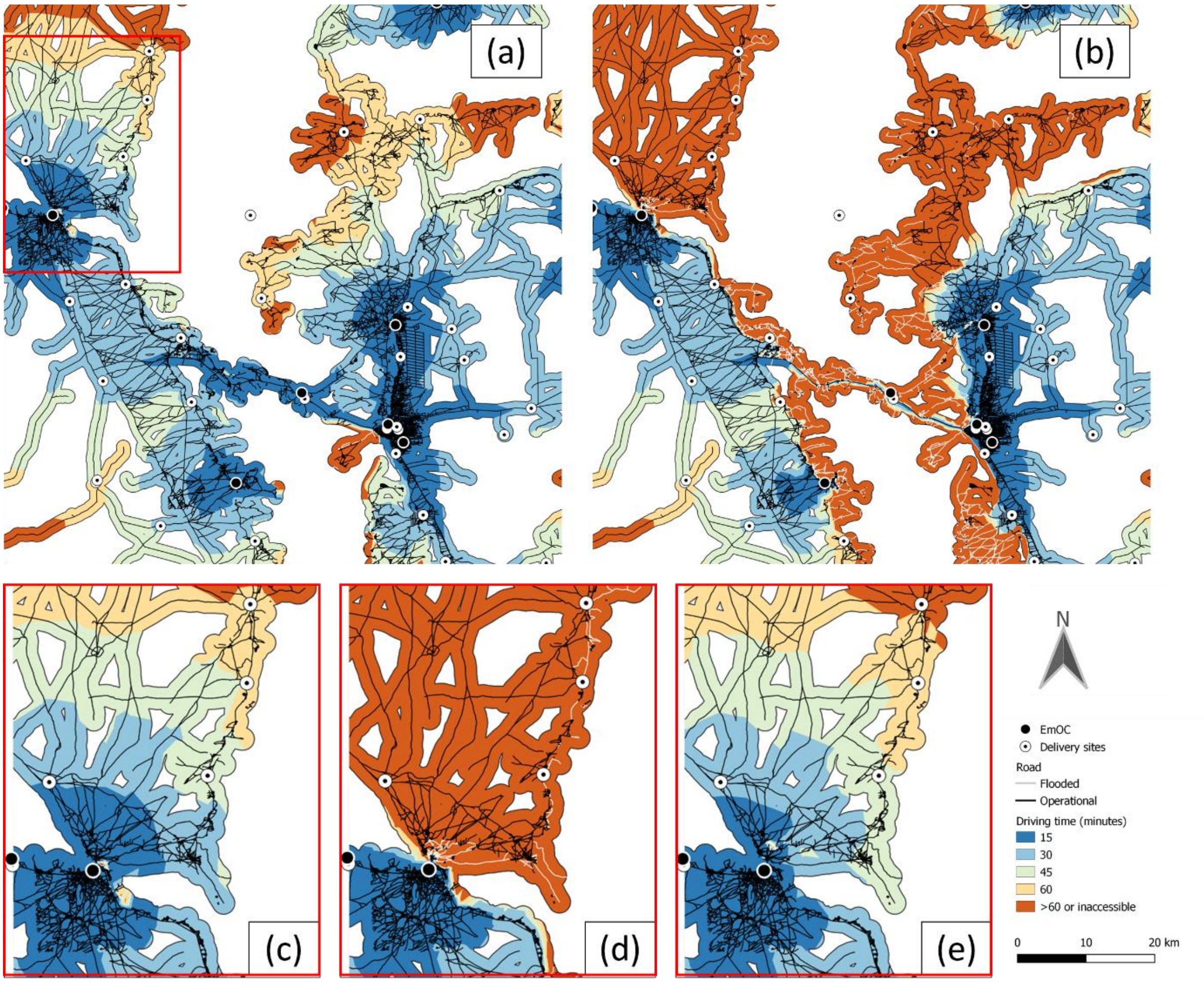


Figure 4.14. Vehicular referral times across the Barotse Floodplain between delivery sites and EmOC locations in (a) October 2017 and (b) March 2018. The inset maps (red border) show referral times specifically in the Luanginga Valley for: (c) October 2017, (d) March 2018, and (e) October 2018. Due to the presence of persisting floods in the Luanginga Valley, referral times in October 2018 remain slightly elevated.

From flood drawdown until the final modelled month, the referral system steadily recovers. By October 2018, of the 27 "*delivery only*" facilities serving the floodplain population in that month, 26 are able to make referrals; 21 of these are able to make referrals within an hour's travel time. The mean referral time was ~32 minutes, whilst the maximum travel time was 94 minutes. As small areas of floodwaters still persist, a continued impact is experienced on the network which is reflected in elevated referral times between some delivery sites and EmOC (Figure 4.14). Overall, 48% of women (n=3,874) can be referred to an EmOC within an hour whilst 13% (n=1,031) have already arrived directly at an EmOC. Consequently, 60% (n=4,905) of women have timely access to an EmOC again in the final modelled month.

In October 2018, the one facility whose referral access to an EmOC had not been restored was Lealui Rural Health Centre (RHC). This observation arises from a conflict between the geoposition of the facility and the flood model outputs. A 15 m wide water body is located approximately 250 m (Euclidean distance) from Lealui RHC. The flood model represents this waterbody as only becoming wet after flood onset, with the waters within persisting after flood drawdown (Figure 4.15). As the spatial resolution of the flood model is 100 m, this waterbody is represented as being one 100 m cell wide and it is positioned closer to the RHC than in reality. As a consequence, the waterbody intersects the two roads that connect to the RHC. By October 2018, it is likely that this results in a false representation of the facility being unable to make referrals as: (1) there are no remaining floodwaters within the vicinity of Lealui; (2) the waterbody does not, in reality, cross the two roads directly connected to the RHC; (3) the RHC is positioned less than a kilometre away from Lealui Mini Hospital (offering EmOC) with multiple possible routes; and (4) of these possible routes, the waterbody, if still impassable, would only block half as the RHC could still access the causeway to gain access to the Mini Hospital.

Whilst the detrimental impact of floods on referral coverage and referral times has some impact on population ability to reach EmOC in a timely manner, the primary reductions arise from the complete inability of populations to reach any delivery site in flood months. This is reflected in the relative monthly position of women within the referral system (Figure 4.16); as floodwaters increase, the most substantial reduction in women with timely referral access to EmOC occurs because women are unable to reach any facility, rather than because of an increase in the number of women that are at a facility with impacted referral abilities.

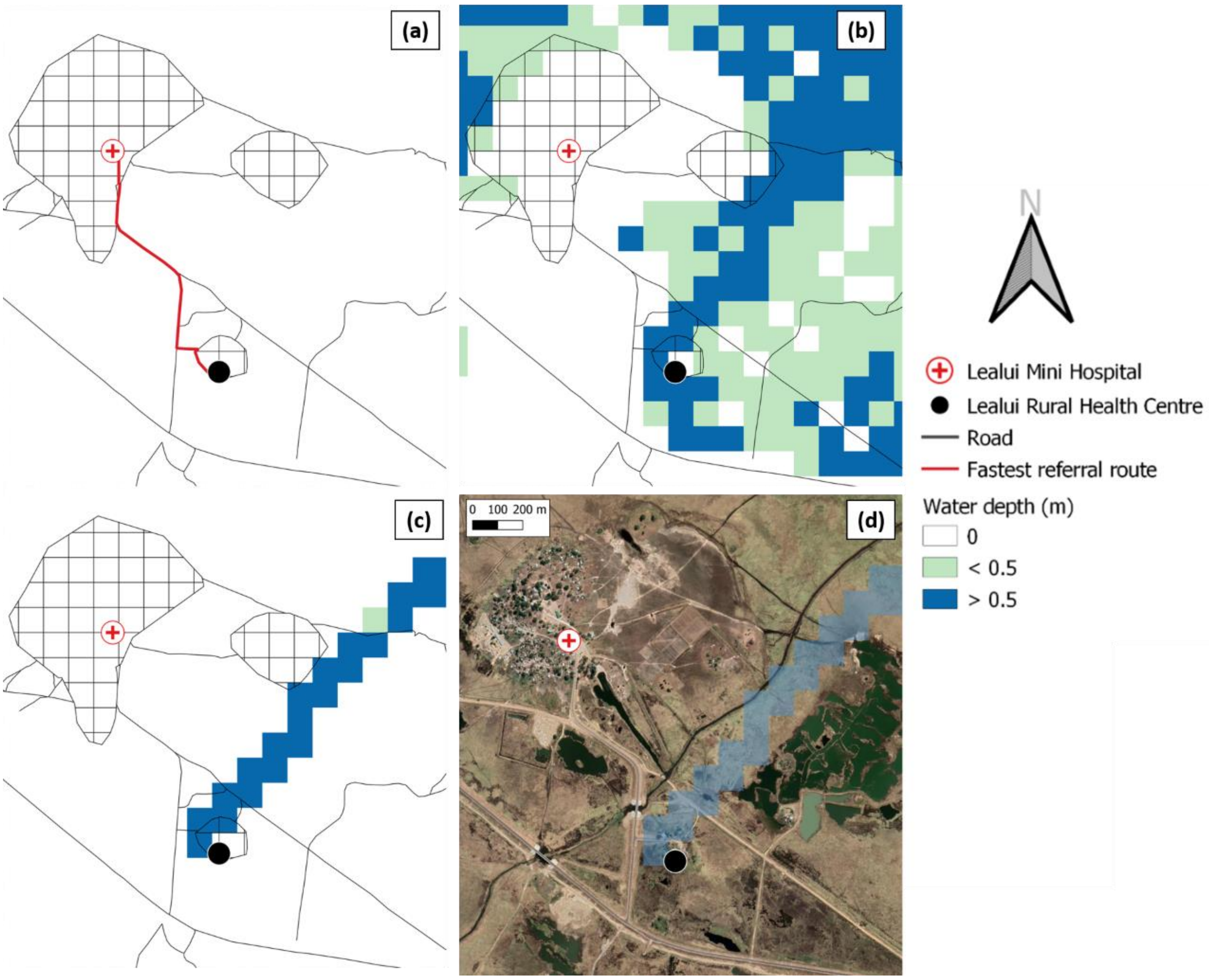


Figure 4.15. Flood presence around the floodplain settlement of Lealui in (a) October 2017, (b) March 2018, and (c) October 2018 compared with (d) a satellite image of Lealui showing the flood representation of the canal after the floods to be larger and positioned closer to Lealui Rural Health Centre than in reality, causing false intersection of connecting roads which prevents referrals to Lealui Mini Hospital.

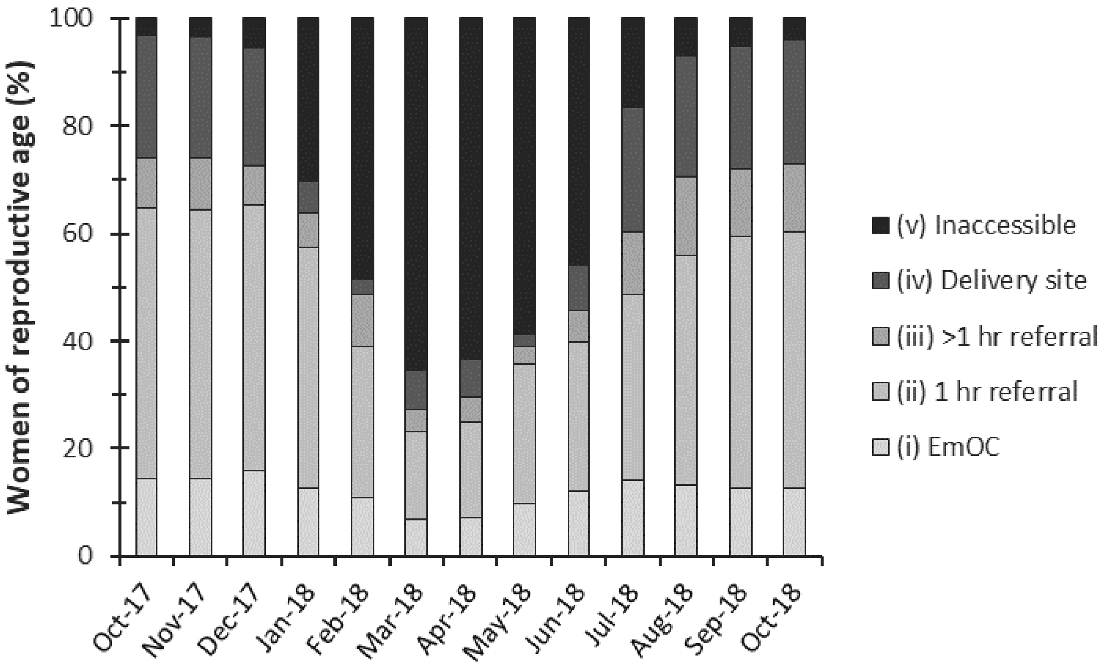


Figure 4.16. Monthly variation in the percentage of women within the different referral categories. (i) EmOC refers to women whose nearest delivery site is a facility capable of EmOC; i.e., those whom do not need a referral to another facility. (ii) 1 hr referral refers to women whose delivery site can refer to an EmOC facility within an hour's travel time. (iii) >1 hr referral refers to women whose delivery site can refer to an EmOC facility, but with a referral travel time greater than one hour. (iv) Delivery site refers to women who have arrived at their nearest delivery site which is unable to refer them to an EmOC due to inundation on the road network. (v) Inaccessible refers to women who are unable to reach any delivery site and thus unable to enter the healthcare or referral system.

4.4. Improvements over previous approaches

To demonstrate improvements over previous static approaches which used remotely-sensed flood extents, the results from the maternal access scenarios were compared against static "dry" (October 2017) and "wet" (April 2018) season scenarios created using remotely-sensed flood extents instead of hydrodynamic model outputs. Aside from the static approaches using remotely-sensed flood extents and modelling access for only two months of the year, all inputs and model parameters were kept the same as the new approach.

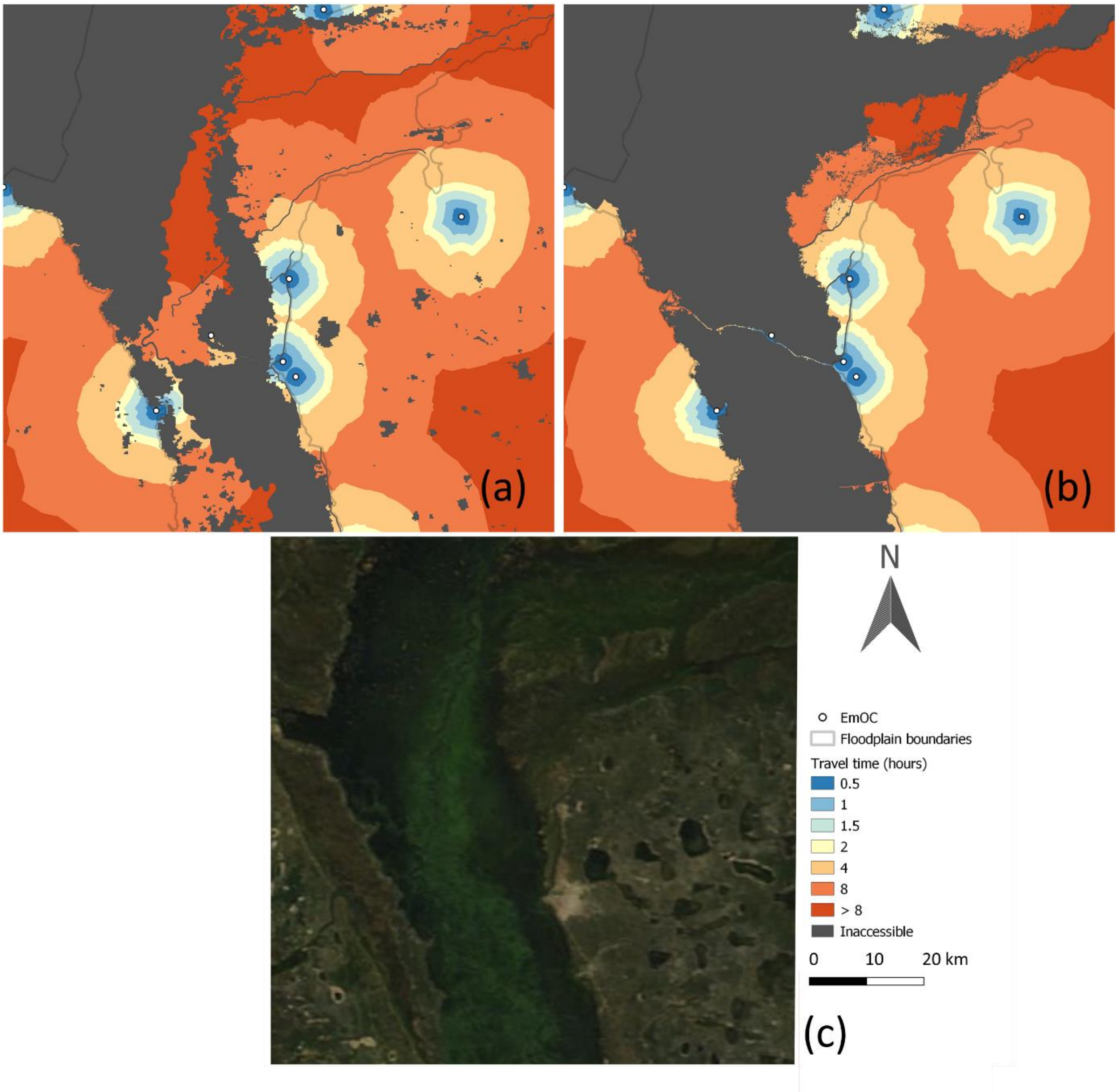


Figure 4.17. Comparison of the representations of access for April 2018 as identified by (a) previous static approaches using a flood extent layer and (b) the new approach using hydrodynamic flood model variables. (c) is a satellite image from MODIS dated the 17th April 2018, showing floodwaters in the Barotse Floodplain.

The new approach correctly identifies the entire of the Barotse Floodplain and the Luena Flats as inundated in April 2018. The previous approach identifies extensive flooding in the Barotse Floodplain, but the extent used has falsely marked areas of the floodplain as unflooded despite floods being clearly visible in MODIS imagery (Figure 4.17); affected areas are around the Zambezi channel at the central axis of the floodplain, as well as south-west at the bottom of the floodplain. Similarly, the flood extent has failed to recognise the majority of vegetated floodwaters in the Luena Flats. Floodwaters in the Luanginga Valley have been accurately detected, including those beyond the extent of the LISFLOOD-FP flood model. As a consequence, the static "wet season" scenario identifies fewer populations as being inaccessible overall (Figure 4.18, Table 4.7).

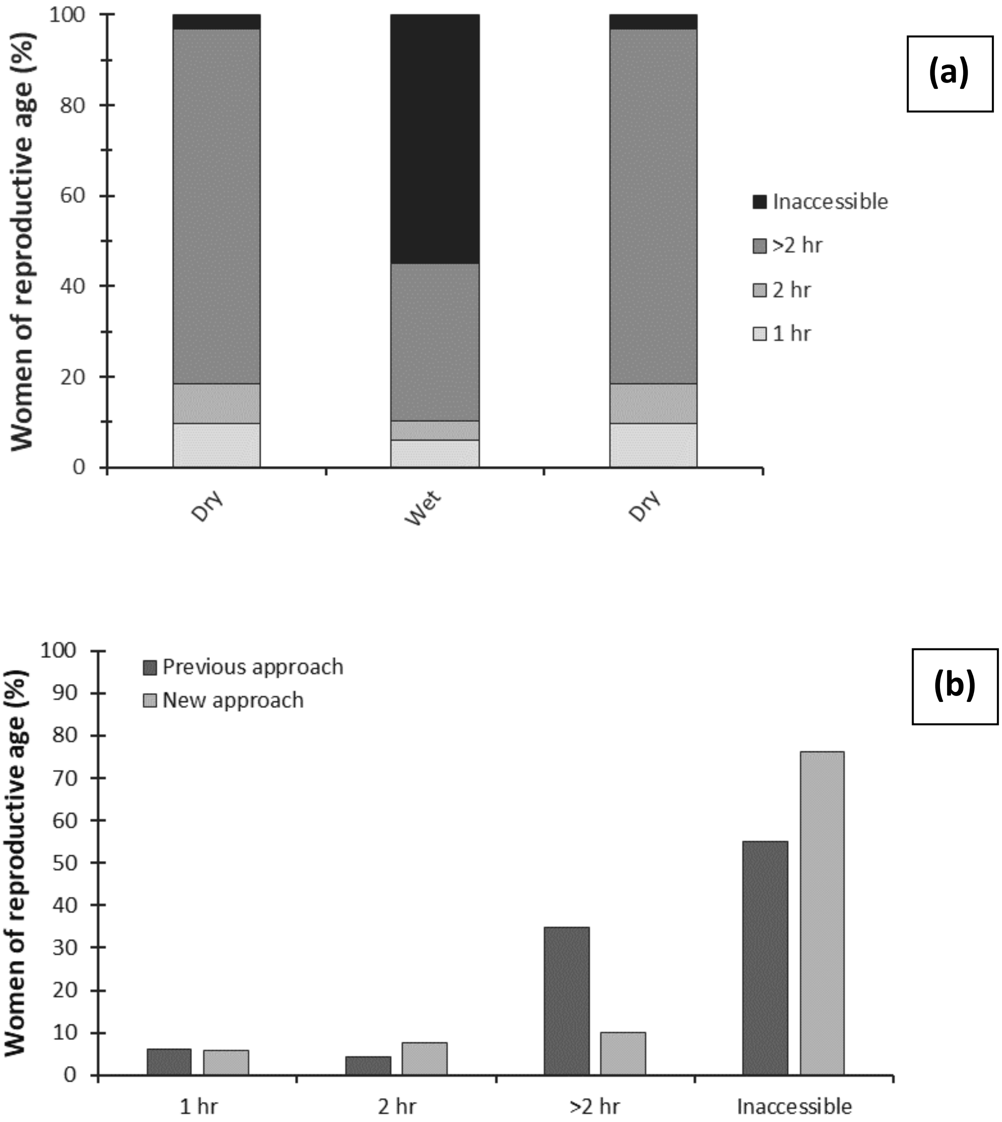


Figure 4.18. Comparison between a representative example of a spatio-temporally static previous approach, and the new approach as developed in this study. (a) shows the percentage of women within each travel time threshold to EmOC as identified using a static "dry" and "wet" season approach. The static approach has not specifically considered months, hence the "dry" season scenario is assumed to represent conditions post-floods (the second "dry" after the "wet" season); it is temporally ambiguous. (b) compares the percentage of women within each travel time threshold to EmOC between the static "wet" season scenario (previous approach) and the access scenario for March 2018 (new approach).

Table 4.7. Comparison of the previous approach (static “wet” season scenario) and the new approach (March 2018 scenario) for the ability of women of reproductive age to reach EmOC.

		Women of reproductive age			
		Previous approach		***New approach***	
		n	%	*n*	%
Walking access within:	***1 hr***	497	6	482	6
	2 hr	345	4	622	8
	>2 hr	2,818	35	825	10
	Inaccessible	4,469	55	6,200	76

The previous approach is very limited in what information it can provide on access, unlike the new approach (Figure 4.18). The “wet season scenario” indicates increased inaccessibility during flood months (55%, *n* =4,469), but it under predicts the percentage considered inaccessible relative to the new approach (76%, *n* = 6,200) by ~28% due to issues with the extent data aforementioned. The “wet season scenario” is able to identify key areas of inaccessibility, but is unable to provide much inference beyond that floodwaters are simply impacting access. For example, the “wet season scenario” correctly identifies that a large proportion of women on the north-west of the Zambezi are unable to reach EmOC in Kalabo, but it is unable to identify when the impact first occurred, for how long they persist, and when access is restored. In the new approach, however, through modelling the monthly impact on access resulting from the spatio-temporal changes of floodwaters, it can be identified that impact occurs in December 2017 due to early presence of floodwaters, and that the impact persists until the end of the model due to continued persistence of floodwaters in the Luanginga Valley. Critically, in the previous approach, the “dry season scenario” would assume the same conditions in October 2018 as in October 2017 (unless a second “dry” scenario was created, which has not been done in previous studies), and thus would be unable to identify the continued impact.

4.5. Summary of key findings

Incorporating floodwater variables into both network- and raster-based models allows detailed visualisation into how changing floodwaters over the hydrological year impacts access patterns. The raster-based model was used to quantify walking times to general healthcare and to maternal services, whilst the network-based model was additionally used in the maternal scenario to specifically calculate referral times by road between delivery sites and EmOC. Access to all facilities and maternal services is impacted most severely at the peak of the floods, but modelling monthly timesteps of the intermediate flood rise and recession stages identified further patterns regarding the onset and cessation of inaccessibility for different floodplain populations to different services. Those located on the floodplain are disproportionately impacted relative to those living closer to the escarpment, indicating floods worsen existing health access inequity in the area. Populations in the tributary valleys and on the floodplain north-west of the Zambezi were impacted earlier and for longer due to fewer services positioned close to them, and the vulnerability of key infrastructure used to access facilities. During flood months, the inaccessibility of women to reach delivery sites and to receive a timely referral (<1 hr driving time) is greatly increased compared to the dry season. The new raster-based approach was compared with an example of a typical previous static approach modelled for the area using flood extents, considering access to be represented using only a “wet” and “dry” season scenario. This comparison highlighted the inadequacy of former static dry/wet approaches in understanding access across an entire hydrological year, and the use of flood model variables was shown to recreate the extent of floodwaters seen in satellite imagery resulting in an increased proportion of the population being identified as inaccessible in April 2018 compared with the previous approach.

CHAPTER 5

DISCUSSION: *Understanding dynamic flood inundation impacts on health service access*

A new geospatial framework was created which successfully incorporated dynamic representation of floodwater inundation into network-based and raster-based models assessing vehicular and walking access to services (**Objective 1 - O1**). The new framework was applied to the Barotse Floodplain as a case study, and additional, unprecedented research power was demonstrated through modelling monthly dynamic changes in access occurring between October 2017 and October 2018 as a result of annual floodwave passage through the floodplain (**O2**). Access to all healthcare facilities and to maternal services was shown to be impacted by floodwaters as they changed through the course of the wet season, but impacts were neither spatially nor temporally uniform due to the complexity of the floodplain environment and due to the positioning of facilities in relation to the population (**O3**). Through the consideration of monthly floodwater changes, substantial impacts to access could be dated by month of onset and resolution, and populations were identified that were disproportionately more vulnerable as a result.

Section 5.1 compares this study's results of flood impacts on access with previous findings for other regions, emphasizing the importance of a spatio-temporal approach. The implications of the results and their relevance for any intervention planning on the Barotse Floodplain are then discussed, followed by an assessment of the accuracy of the framework in recreating observed access impacts on the floodplain. The section concludes by considering the parameterisation of the floodwater variables in the framework. Section 5.2 then directly compares the new framework's method with previous approaches, focusing on the usage of hydrodynamic model outputs over remotely-sensed flood extents and the appropriateness of the floodwater parameter values used. Section 5.3 describes the wider significance of the framework, its specific advantages, and how it can be used as a strategic tool. Finally, Sections 5.4 and 5.5 then discuss the limitations of the research and outline areas for future research

5.1. Evaluation of model performance

5.1.1. Impact of floods on access to care

In all scenarios, floods exerted a clear control on access to healthcare in the Barotse Floodplain by both increasing travel times and isolating populations. Access to all facilities and to all maternal services was optimum in the dry season month of October 2017 and most impacted during the peak of the floods in March 2018. The substantial decline in access observed between these two months is similar to previous study findings and anecdotal observations that floods substantially reduce access (Schatz 2008; Alderman *et al*., 2012; Makanga *et al*., 2017; Codjoe *et al*., 2020; Espinet Alegre *et al*., 2020).

In Niger, Blanford *et al.* (2012) found the proportion of the population with walking access within one hour to their nearest facility declined from 39% in their static dry season scenario to 24% in their static wet season scenario. Comparatively, in the Barotse Floodplain, the proportion of the entire population with walking access within one hour to their nearest facility declined from 40% in October 2017 to between 25-29% in March 2018 depending on the scenario (i.e., whether all floodwaters acted as total barriers). These declines are similar in magnitude, but substantially greater uncertainty exists regarding how representative the findings of Blanford *et al.* (2012) are due to their overly-simplistic method that systematically reduced all travel times to create the “wet season scenario”. Rather than explicitly model any floodwaters (even the use of remotely-sensed extents were not considered in their study), their approach assumed that the entire of Niger was uniformly affected rather than directly account for seasonal impacts occurring at a specific place and time as was performed in this study. Models that simply reduce travel speeds (e.g., Verburg *et al*., 2004; Schoeps *et al*., 2011; Blanford *et al*., 2012; Lubamba *et al*., 2013) consider changes in wet season access as a direct function of dry season impedances. Such models are of little operational use as they poorly represent the real physical processes that limit access in the real world where seasonal impacts may be highly localised as was demonstrated in this study.

In southern Mozambique, Makanga *et al.* (2017) found the proportion of pregnant women with walking access within one hour to their nearest facility declined from 46% in the month with most optimal access to 37% in the most impacted month. A direct comparison cannot be made with this figure as there were no data on pregnant women in 2018 for the Barotse Floodplain; instead, women of reproductive age were substituted in models assessing access to maternal healthcare. However, a similar pattern was observed in that 31% of women had access within one hour to their nearest facility in October 2017 which declined to 18% in March 2018.

Both this study and Makanga *et al.* (2017) modelled changes in access monthly. Makanga *et al.* (2017) modelled access changes over 17 months for Mozambique, using remotely-sensed flood extents and rasters of empirical precipitation data obtained daily between March 2013 and October 2014 to create their impedance surfaces. Any area intersected by a flood extent was considered completely impassable by Makanga *et al.* (2017), but roads with precipitation above 1 mm had their travel speeds reduced according to a threshold (Zhang *et al.,* 2011). Makanga *et al.* (2017) found that access continually changed due to precipitation over their 17-month study period, and this study also found that access in the Barotse Floodplain substantially fluctuated monthly due to floodwaters throughout the 2018 hydrological year. Substantial spatio-temporal variations in access were found in this study that could not have been represented by modelling access as a static "dry" or "wet" season scenario as with previous approaches. For example, access to facilities offering EmOC or MWS was first impacted in December 2017, a month earlier than access to delivery sites, and restoration of access to pre-flood levels similarly lagged behind the recovery of delivery sites. These variations occurred due to early floodwater development and late floodwater recession in the Luanginga and Luena Valleys, which consequently compounded access of the populations to the limited number of locations offering these services for the area. These patterns were revealed and interpreted due to the monthly temporal resolution employed in this study; one "dry" and one "wet" season result were shown to be unable to recognise the onset and duration of these impacts. Consequently, this study arrives at a similar conclusion to Makanga *et al.* (2017) that access fluctuates more than can be visualised through a "wet" and "dry" season scenario. This study emphasises the importance of considering intermediate months of flood rise and recession to derive additional information on changes in access that will be of importance for health intervention planning (Gabrysch and Campbell, 2009). Spatio-temporal incorporation of floodwater variables is necessary for adequate representation of their impact on access for a region and to produce operational outputs that highlight the most vulnerable populations, and when and where to distribute additional resources in advance to facilities whose supply chains may be restricted during flood months.

Additionally, between 47-66% of the total population on the Barotse Floodplain were estimated to become completely inaccessible at the peak of the floods in March 2018, representing a large proportion of the population being isolated, although some uncertainty exists regarding this value due to the Lozi practicing transhumance (see Section 5.4.3). Comparatively in rural Cambodia, Espinet Alegre *et al*. (2020) estimated that 27% of the population were inaccessible at the worst of flood impacts. Floodplain populations likely suffer greater vulnerability in becoming isolated due to floodwater impacts than typical in seasonally-affected rural regions because of their positioning in relation to infrastructure, but as few have directly quantified isolation in studies, this interpretation requires further studies to be conducted. Regardless, population who were already located the furthest away from healthcare facilities on the floodplain were found to be disproportionately impacted relative to those living closer, in agreement with previous findings (Schatz, 2008; Makanga *et al.,* 2017).

5.1.2. Importance of findings for the region

Access to healthcare services in the Barotse Floodplain is compounded by the annual floodwave passage. However, even in the most optimal month in the dry season, access to emergency services is poor. A benchmark was set by Meara *et al.* (2015) that 80% of populations should have timely access (defined as within 2 hours) to surgical services. The two hour threshold is important as it recognises the point at which increased morbidities typically occur in medical emergencies, such as postpartum haemorrhage, in the absence of appropriate medical intervention (WHO, 2009; Rudolfson *et al*., 2020). In October 2017, only 14% of the floodplain population have timely access to a hospital, and only 19% of women have timely access to EmOC. These values are far below the benchmark set but are also worse than aggregated national and continental averages. Ouma *et al*. (2018) estimated that 29% of Sub-Saharan Africa is unable to reach a hospital within two hours, of which 40% of Zambians lack timely access; comparatively, 86% of the Barotse Floodplain were calculated here to lack timely access. Rural populations have commonly been shown to utilise services less than their urban counterparts due to increased geographical difficulty in reaching care (Gage 2007; Kyei *et al*., 2012; Tatem *et al*., 2014; Mupwanyiwa *et al*., 2020; Vasudevan *et al*., 2020), and consequently geographic access may be also acting as a significant barrier to healthcare uptake in the Barotse Floodplain.

The inability of the population to reach emergency medical services in a timely manner even under the most optimal access conditions represents a critical concern as poor geographical access has regularly been linked to increased morbidities and mortalities (Phalkey *et al.,* 2012; Manongi *et al*., 2014; Rodrígues-Espíndola and Gaytán, 2015). Floods were shown to further compound access on the floodplain through increased travel times and inaccessibility which further worsens inequity in access to healthcare, so interventions and strategies are required to increase accessibility in the dry season whilst mitigating for the annual effects of floodwaters.

Access to maternal services was specifically modelled in this study, and the ability of women to reach maternal health services has routinely been acknowledged as an effective strategy in reducing maternal mortality (Mpembeni *et al*., 2007; Simkhada *et al*., 2008; Stone *et al*., 2020). However, decreased uptake of maternal services has been correlated with decreases in geographic accessibility (Ruktanonchai *et al*., 2016). In Zambia, Gabrysch *et al*. (2011a) found that only a third of rural Zambian births occurred in healthcare facilities due to geographical impedances, and births were less likely to occur in a facility in the wet season. Direct maternal deaths have been correlated with long travel distances (Hanson *et al*., 2015), and Stone *et al*. (2020) estimated increased neonatal and maternal deaths as a consequence of facility births being 6% lower in the wet season in Mozambique. Consequently, floods may be increasing maternal mortality during the wet season in the Barotse Floodplain by further compounding the inability of women to reach maternal services and increasing vehicular referral times between delivery sites to EmOC on the road network. The results here showing poor potential geographic access to emergency services necessitate further consideration; their interpretation with data on health services uptake and morbidities and mortalities is needed to identify the relative importance of geographic access for any future health intervention planning such as strategies aimed to reduce maternal mortalities.

Potential geographic access to other services was not analysed in this study; however, floodwater impacts will have implications for access to all services as demonstrated by the impacted ability of populations to reach any facility as floodwaters progress. In addition to maternal mortality, HIV has been identified as a key concern in Western Province and for the Barotse Floodplain. Lankowski *et al*. (2014) recognised poor geographic access was associated with poor HIV outcomes in sub-Saharan Africa in their analysis of 66 studies. Antiretroviral treatment (ART) needs to be taken daily to control HIV infection (Schatz, 2008) and access to HIV testing and counselling (HTC) services is important for diagnosing and treating patients at earlier stages of infection in addition to educating populations for the prevention of future HIV transmission. Consequently, the impacts of floods on the inability of populations to reach facilities where they can obtain ART and HTC or on the continued supply of ART medications to healthcare facilities warrants additional investigation. The framework can be used to model walking access to key HIV services and to identify facilities which are at risk of medicine stock-outs if floodwaters cut-off their road access.

5.1.3. Accuracy of the model in representing access

No studies have modelled access to any services in the Barotse Floodplain before, which prevents comparing results to previous models of the region. However, limited qualitative data exists where observations have anecdotally reported inundation patterns and impacts on access. This study's results for the Barotse Floodplain were compared with these previous findings, and overall the results recreated real access patterns well. However, these interpretations are precarious due to the lack of comparison data.

Ascertaining the accuracy of the hydrodynamic model used is important as it provided the variables that influenced the results of the access models. Large African floodplains similar to the Barotse Floodplain have complex hydrology, and limited understanding of hydrological systems and poor availability and quality of data has created difficulty in building two-dimensional models that can adequately represent them (Hughes, 1990; Beven, 2007; Tshimanga *et al*., 2011; Pedinotti *et al*., 2012; Cohen Liechti *et al*., 2014a; Cohen Liechti *et al*., 2014b; Komi *et al*., 2017; Grimaldi *et al*., 2019). Consequently, a hydrodynamic model that poorly represents floodwave passage will cause the coupled access model to poorly represent the impacts of floodwaters on access.

Generally, the hydrodynamic model used to provide floodwater variable captures the dynamics of floodwave passage well. The model best represents inundation at the peak of the floods ($F^2 = 0.62$), and modelled discharge at Senanga is similar to observed data but predicts peak discharge to occur 2 days earlier and 12% greater than recorded (Willis *et al., in press*). Performance is worse during the rise and recession of floodwaters ($F^2 = 0.1$), but this could reflect the accuracy of Landsat data (used in evaluation) as areas of "over-prediction" were close to the Zambezi and shown in ground-truthing to be dominated by vegetation which are likely to be inundated but difficult to detect (Hardy *et al.,* 2020). Regardless, inundation patterns are still similar to what has been observed and reported anecdotally. Tributary valleys are inundated earlier than the floodplain as reported by IUCN (2003), which consequently relates to the earlier onset of impact to access in the Luena Flats and Luanginga Valley. In the Luena Flats, the hydrodynamic model finds that the floodwaters persist for longer in agreement with previous observations mapped using Sentinel-1 radar images (Hardy *et al.*, 2019). The peak of the floods is modelled to occur in March 2018 as represented by the greatest mean depth in this month and the larger impact on access. Hardy *et al*. (2019) identified the average floodwave peak to occur in early April 2018, but the hydrodynamic model does find substantial flooding in both March and April with minimal difference in their extent, depths, and subsequent impact on access.

The access models reproduced key impacts from floodwaters that have been previously reported in the literature. ZVDI (2010) reported that roads connecting to Kalabo in the Luanginga Valley typically become completely impassable from December onwards due to their early inundation. This impact was well-represented in the NFW (not walking through floodwaters) and maternal access scenarios where the floodplain populations living within the river-locked, north-western Baroste Floodplain and on the Luanginga Valley were identified as unable to reach services in Kalabo from December 2017 onwards due to inundation of roads in the Luanginga Valley. The FW (walking through floodwaters permitted) scenario also recognised that these populations were unable to access services in Kalabo for many months, but it modelled inaccessibility as first occurring in January 2018 instead. Whilst early inundation of roads did increase travel times, the route was not considered completely inaccessible as depths were shallow and thus not considered hazardous. However, the FW scenario predicted restoration in access to services in Kalabo from June 2018 onwards, in agreement with ZVDI (2010) which states June is the month the roads become usable again. In contrast, the NFW and maternal scenarios continue to model the roads as impassable beyond June and October 2018 due to the persisting floodwaters that remain in the valley. Evidently, the different parameterisations of the access models causes the scenario variants to successfully capture different parts of the patterns described by ZVDI (2010). The floods in 2018 were the largest experienced by the Barotse Floodplain in recent years, which makes it difficult to ascertain whether the NFW model was conservative in predicting restoration in access, or whether it accurately represented that inundation in 2018 impacted access for longer than in typical years.

Floodwaters are still modelled as present on the floodplain in August 2018, and all access models recognise some persisting impacts on access as a result. This agrees with Del Río (2014) whose study participants reported that access on the floodplain remained impeded in August due to the presence of floodwaters. However, the NFW and FW models differ in their prediction of the relative magnitude of impact. The NFW scenarios predict an increased inaccessibility and access impact relative to the FW scenario which predicts that, whilst localised impacts to access persist, access has otherwise nearly restored to pre-flood conditions.

The differences in predictions between the NFW and FW models occurs due to their contrasting parametrisations. The NFW model represents the most conservative model, where no floodwater parameters are used and all floodwaters act as complete barriers. In contrast, the FW model calculates flood hazard and allows populations to walk through floodwaters deemed low hazard instead of considering all floodwaters to be barriers. Together, the NFW and FW represent the lower and upper boundaries respectively on flood impacts on access. This constricts uncertainty in model predictions between two values based upon alternative representations of what access may look like for populations willing to wade through floodwaters and those that are not or cannot. Cost-distance algorithms do not measure error or uncertainty in their predictions (Le Roux *et al*., 2019) so previous studies have similarly created uncertainty intervals by varying their travel speed parameters between two boundaries (Tansley *et al*., 2016; Le Roux *et al*., 2019; Schmitz *et al*., 2019; Hierink *et al*., 2020; Macharia *et al*., 2021). This approach is more beneficial in providing policy planners with a range of possible access scenarios, allowing them to assess how much uncertainty exists.

5.2. Comparison to previous approaches

5.2.1. Use of hydrodynamic model outputs instead of remotely-sensed flood extents

Floodwaters cause substantial drops in accessibility and the spatio-temporal variations that occur over the course of a hydrological year are not adequately represented through consideration of just a static “dry” season and static “wet” season. As demonstrated in this study, the intermediate months are important for providing additional information regarding the onset of flood impacts on access, identifying which populations are more vulnerable and experience greater impacts relative to others, and for directly relating the changes in floodwater dynamics with changing access; this information can be directly incorporated into health plans preparing for flood impacts, such as supplying additional resources to vulnerable health facilities ahead of predicted impact. The new framework, consequently, is of greater relevance for health intervention where plans need to be designed to improve access year-round; previous static approaches are simply not robust enough for revealing the same complexities in access. As a result, representing floodwaters as they change through space and time is a significant advantage but data are required to achieve this. To model floodwater changes, floodwater data needs to be representative and reliably available at an appropriate temporal resolution.

Previous studies that have considered floodwater impacts on access have relied on flood extents from satellite imagery. Most notably, Makanga *et al*. (2017) took daily remotely-sensed flood extents and incorporated them into their spatio-temporal access model for southern Mozambique. Flood extents have been used previously as they are can be freely- and readily-obtained from different sources, and can be made available as early as a week after a flood event has occurred (Sharma *et al*., 2016). However, flood extents from satellites are subject to observational biases which are rarely mentioned in studies who assume that their flood extents are entirely representative of actual flood extents.

Optical sensors are sensitive to cloud cover, and both optical and radar sensors experience difficulty in detecting vegetated waters. Post-processing methods exist to reduce bias, but extents derived will still retain some bias and consequently miss real sections of flooding (Bernhofen *et al*., 2018). Dense cloud presence in the rainy season and vegetated floodwaters were identified as significant barriers to the collection of regular flood extents for the Barotse Floodplain. Both Zimba *et al*. (2018) and Cai *et al*. (2017) reported difficulty in obtaining cloud-free imagery due to persistent cloud coverage in the rising stage and peak of the floodwaters. Similarly, this study recognised extensive cloud cover in MODIS imagery for March and April 2018. Even though MODIS has a temporal resolution of 1-2 days which has been claimed as temporally adequate for collating information in the rainy season (Chen *et al*., 2013, Zimba *et al*., 2018), readily-available extent from NASA's NRT (near real-time) flood maps (produced from MODIS imagery) were unavailable for the entire duration of March 2018 because of persistent cloud cover. The first extent available that represented peak floodwaters was only obtained between the 15^{th}-17^{th} of April 2018, the first days to have no cloud cover above the floodplain. This extent then missed real flooding (identified in observations of the corresponding satellite image) in the central axis of the floodplain and in the Luena Valley, likely due to these waters being vegetated which is a known systematic limitation in the production of the extent products (Nigro *et al.,* 2014). When compared against the access models using hydrodynamic model inputs, the access models using the extent were shown to underestimate inaccessibility and overestimate the proportion of the population with timely access to healthcare. As a consequence, observational biases (Mateo-Garcia *et al.,* 2021) limit the current usefulness of using satellite-derived flood extents as a reliable source of floodwater information for input into spatio-temporal access models. The data quality may be poor or entirely non-existent during the rainy season when obtaining accurate floodwater information is most crucial.

Hydrodynamic models are not subject to the same observational biases, can provide reliable flood information (if accurate) at the temporal resolution of the modeller's choosing, and also provide floodwater depths and velocities which can be used to better assess flood hazard rather than assuming all floodwaters are equally inaccessible (Smith *et al.,* 2015; Trinh and Molkenthin, 2021). Movement through floodwaters is complicated due to the different forces exerted on a body or car through space and time, and weighting shallow waters as equally impactful on driving and walking abilities simplifies reality. The usage of outputs from LISFLOOD-FP in this study incorporated real-world flood complexity into the access results, and the sensitivity analysis revealed that depth was more important than velocity in the floodplain for controlling access on the floodplain. Consequently, the use of a flood model as demonstrated in this study clearly offers new advantages in identifying which flood variables are more important in affecting access and in modelling flood hazard for different scenarios and population characteristics.

The approach using hydrodynamic model inputs also offers predictive capabilities as potential future floods can be modelled (Jha and Afreen, 2020; Mudashiru *et al.,* 2021). Whilst mapping observed extents provides information on past floods, hydrodynamic models can be used to simulate future flood scenarios (e.g., Robi *et al.,* 2019; Liew *et al.,* 2021); obtained floodwater variables from these future scenarios can be incorporated into geographic access models and used to inform future decision-making about impacts to health access, and could even potentially be used to create early warning systems. The ability to predict flood impacts in addition to modelling those that have already occurred in the past is becoming increasingly more important. Over the next decade, climate change will alter the prevalence, magnitude, and timings of floods (Zimba *et al.,* 2018; Chomba *et al.,* 2021 IPCC, 2021); this threatens health system resilience and necessitates approaches that can assess where flood impacts may worsen the ability of populations to reach care, prevent referrals from occurring, and hinder healthcare facilities from receiving the equipment and medicines they require to provide good quality of care.

In the short-term, the Covid-19 pandemic has emphasised the importance of having a spatio-temporal modelling approach that considers floodwater impacts. Low-income, rural areas have already been identified as containing additional access challenges which limits abilities to strategise and respond to pandemics and epidemics (Porter, 2002; Espinet Alegre *et al.,* 2020; Ogunkola *et al.,* 2020); seasonal rain and floods are one such substantial challenge. For example, Mensah *et al.* (2019) found that healthcare facilities in Madagascar which were able to maintain a continuous supply of measles vaccines in the rainy season had the fewest number of unvaccinated children within their catchments. Additionally, low-income regions such as sub-Saharan Africa are disproportionately burdened by the Covid-19 pandemic, particularly as their mitigation strategies for other diseases such as malaria, HIV, and tuberculosis have become further strained (Elebesunu *et al.,* 2021; Ogunbiyi, 2021; Tessema and Nkengasong, 2021). The framework developed here could be used to manage Covid-19 response in low-income countries affected by seasonal flooding through the continuous modelling and quantification of predicted flood impacts on access. This could be of use for: (1) assessing vaccine uptake, including the ability of populations to reach vaccination centres and for health facilities to receive vaccine deliveries; (2) ensuring Covid-19 patients can access appropriate treatment and can be referred if they need specialist care (Denhard *et al.,* 2021); (3) preventing disruption in access to critical health services and provision of resources for other diseases, such as antimalarial and antiretroviral medicines, to ensure morbidities and mortalities do not increase (Weiss *et al.,* 2020b; Assefa *et al.,* 2021; Hamer, 2021).

It is recognised that creating a hydrodynamic model to couple with an access model represents a significant undertaking due to the additional time investment and considerations required to set up and parameterise such a model, especially in data-limited regions where sufficient hydrological and topographical information may not be of good temporal and spatial quality to be able to adequately represent floodwave passage (Karim *et al.,* 2011). These limitations are becoming less restrictive, particularly due to the provision of free and low-cost topography data (Mukolwe *et al.,* 2016), and methodological innovations such as sub-grid modelling which allows representation of features smaller than the resolution of DEMs in data-restricted areas (Neal *et al.,* 2012; Fernández *et al.,* 2016; Shastry *et al.,* 2020); for example, canals on the Barotse Floodplain were modelled using the sub-grid approach (Willis *et al., in press*). Global flood models (GFMs) are a potential alternative source of hydrodynamic data; advancements in computing power and the availability of global data have facilitated their rapid recent development (e.g., Yamazaki *et al.,* 2017; Allen and Pavelsky, 2018), permitting simulations within reasonable costs and time (Ward *et al.,* 2015). However, as with any model, an access model's outputs are only as good as its inputs so an access model run with outputs from an ill-representative model would not be more advantageous. GFMs have accuracy and resolution limitations that have been well-documented in the literature which limit their current application (Sampson *et al.,* 2015; Sampson *et al.,* 2016; Trigg *et al.,* 2016; Hoch and Trigg, 2019); as a result, the use of flood extents remain likely to be the main form of incorporating flood data into access models for now. Thus, optimising abilities to obtain flood extents reliably at sufficient temporal and spatial resolutions is important.

The Landsat-based approach of TropWet (Hardy *et al*., 2020) has been recently developed showing greater accuracy in distinguishing between open and vegetated waters in grassland environments. The Landsat archive has greater spatial resolution than MODIS and more accurately represents inundation (Chen *et al*., 2013), although its revisit period is longer at 16-days. Such a tool could be used to take advantage of the Landsat archive and provide more accurate flood extents across seasonal timespans for incorporation into spatio-temporal access models; for example, computing geographic access over multiple years to derive an average baseline of flood impact. The results produced would be analogous to those created in the NFW scenario and would be vastly superior to the static approaches using extents more afflicted by observational biases, even if the same level of complexity in modelling hazard as derived in this study is not obtainable.

5.2.2. Walking through floodwaters

Nearly all studies who incorporate satellite-derived flood extents consider the extents to represent impassable waterbodies. Hierink *et al*. (2020), however, obtained flood extent shapefiles from Sentinel-1 for two tropical cyclone events that occurred in Mozambique and modelled access before and after cyclone impact. In some scenarios representing one week after cyclone impact, Hierink *et al*. (2020) modelled all flooded areas as being passable with walking speeds of 1.5 km hr^{-1} without consideration of the relative hazard of floodwaters; no additional hydrodynamic information beyond extent was used to assess flood risk. The new framework developed in this study directly considers flood depth and velocity when assessing hazard. This better represents the realities of floodwaters whose hazard is neither spatially nor temporally uniform. In this study, where populations were modelled to walk through floodwaters when allowed, a lower walking speed of 1 km hr^{-1} was used; this was chosen to be lower than the self-reported floodwater walking speeds in Kaneda *et al*., (2014) which were between 1.2 and 2.4 km hr^{-1}. Hierink *et al*. (2020) were the first to model changes in geographic access after a disaster, but their approach in allowing all floodwaters to be traversable during flood recession does not recognise any continued hazard as the new framework is capable of. As a consequence, the framework is also of relevance for modelling geographical access throughout disasters with a flooding element.

5.2.3. Comparison of floodwater parameters with those used in hazard mapping

As floodwater depths and velocities have never been incorporated into cost-distance algorithms previously, it is not possible to compare the framework's method for assessing floodwater safety using them as variables. However, hydrodynamic model outputs have been used to make flood hazard maps previously (Poretti and De Amicis, 2011; Aronica *et al*., 2012; Moya Quirogaa *et al*., 2016), including for the lower Mono basin in Togo, West Africa (Ntajal *et al*., 2016) and for the Chipembe Dam in Mozambique (Álvarez *et al*., 2017). These studies represent the closest analogue available to which the new framework for incorporating floodwater variables into cost-distance algorithms can be compared to assess the wider applicability of the approach. Different floodwater parameter settings alter the representation of floodwater hazard, and thus vary representations of access; this was evidenced in the differences between the FW and NFW access scenarios. Consequently, it is necessary to ensure that these parameters are locally-appropriate to the region which they are being applied to.

A sensitivity analysis was used in this study to investigate how changing the H_{max} (maximum water depth threshold) and V_{max} (maximum velocity threshold) altered access model behaviour. The 0.5 m H_{max} and 0.5 m s^{-1} V_{max} derived in this study were also commonly used to denote the boundary of low hazard in other flood hazard studies including for a riverine floodplain in Bolivia (Moya Quirogaa *et al*., 2016) and the surrounding area of Chipembe Dam in northern Mozambique (Álvarez *et al*., 2017). This suggests these H_{max} and V_{max} values may be widely applicable, likely as they are sourced from the human instability literature and thus represent absolute upper boundaries of human stability.

This study used a HV_c (critical depth-velocity criteria) of 0.53 m^2 s^{-1} based on the calculation of the Karvonen equation under normal conditions for the typical height and weight of a Zambian girl. Álvarez *et al*. (2017) stated *HV*s (depth-velocity products) above 0.5 m^2 s^{-1} constituted high hazard and *HV*s needed to be below 0.25 m^2 s^{-1} to be considered low hazard, thus this study applied a HV_c deemed to be too hazardous according to their hazard determination. HV_c derived experimentally have ranged between 0.6 to 2 m^2 s^{-1} (Jonkman *et al*., 2008), and a HV_c of 0.5 m^2 s^{-1} has been typically recommended as an upper threshold distinguishing low hazard. As a result, Álvarez *et al*., (2017)'s choice of HV_c is conservative, although this is not a limitation; HV_c derived from flume experiments represent idealised conditions of flood hazard (Abt *et al*., 1989; Xia *et al*., 2014a) so opting for lower values may reduce perceived risk of overestimating stability in floodwaters. Moya Quirogaa *et al*., (2016) ignored HVc entirely, stating that the usage of *HV*s alone was inappropriate in their floodplain due to the deep floods and low velocities of floodwaters. Instead, Moya Quirogaa *et al*., 2016 relied on floodwater depth alone to determine hazard.

Evidently, the choice of HV_c or whether to use it at all differs depending on location as well as the modeller's personal perception of hazard, but this study agrees with Moya Quirogaa *et al*. (2016) that considering HV_c alone is inappropriate in floodplain environments where deep depths and low velocities can produce *HV*s misrepresentative of hazard. The framework developed in this study is robust in using H_{max}, V_{max}, and HV_c to comprehensively ensure access is accounted for. All three are parameterisable and optional which gives the new framework flexibility and widens its applicability.

5.3. Importance of the new framework

The results show that national-scale evaluations of access may mask subnational variations in access for complex environments such as floodplains, and are thus of limited use for identifying and resolving geographical access issues. Precise representation of access at smaller scales is necessary as health interventions are typically operationalised at provincial or district level (Roder-DeWan *et al*., 2020). Consequently, the framework created in this study is significant as it provides a method in which flood impacts on access can be represented with a high level of spatio-temporal detail, providing an operational tool for this health access modelling niche. Increasing the spatial and temporal resolution of access models is arguably of more relevance for health intervention planning as approaches can be developed more strategically to mitigate inequity for the most vulnerable populations. Through modelling access spatio-temporally, more evidence is provided to justify decisions, such as where investments of limited resources will yield the greatest cost-benefit.

Stark contrast in geographical access and subsequently health service uptake has been identified between urban and rural areas (Hosseinpoor *et al.,* 2007; Fisseha *et al.,* 2017; Debie *et al.,* 2019; Kpienbaareh *et al.,* 2019), and this study has further compiled evidence that populations exposed to annual flooding experience disproportionate inequity in accessing care due to the impact of floods. If interventions are to be designed which can reduce inequity for those affected by seasonal floods, producing higher spatial and temporal representations of access is necessary. This framework developed is thus a tool for achieving this, and represents a significant advancement of access modelling for low-income regions which are where the majority of floods with substantial impacts on health occur. The framework has been demonstrated for the Barotse Floodplain where it has provided novel understanding of health access, but the framework can be employed widely to other regions.

5.3.1. Raster-based model

As far as the author is aware, this study represents the first time that floodwater variables from a hydrodynamic model have been incorporated into a cost-distance algorithm to assess access to healthcare. Through direct representation of flood hazard as revealed by water depth and velocity, the new approach is able to assess flood impacts on access as a function of human stability. This has permitted more precise representation of how changes in floodwaters across space and time directly impact access, when compared to previous approaches.

Whilst the framework was specifically applied to the Barotse Floodplain as a case study, the framework has global significance. The framework is of relevance for any region which experiences substantial flooding, and its approach can (and should) be adapted to suit the data requirements and characteristics of different locations. In the absence of available hydrodynamic inputs, the framework is still able to incorporate floodwater extent, and all travel time and floodwater parameters can be modified as deemed appropriate for a study region. Whilst the framework was developed with consideration to the characteristics of large African floodplains, other flood events can be considered. For example Moya Quirogaa *et al*., (2016) assessed flood risk for an inland riverine flood event for a Bolivian floodplain in South America, whose flood characteristics consisted of deep depths, low velocities, and a duration of a few days. With a sensitivity analysis to determine appropriate parameterisation of floodwater parameters, and obtaining data at a higher temporal resolution, the framework could be appropriately applied for similar events in South American floodplains. Hence, the new framework has wide applicability, and its usage does not need to be restricted to modelling just healthcare access; it can be used to model access to any service of interest.

5.3.2. Vector-based model

Hydrodynamic model outputs have been used in network analysis before, but never in a rural, low-income and data-limited region such as the Barotse Floodplain. The framework developed in this study provides a methodology for incorporating floodwater variables into network analysis operational in low-income, data-limited regions. The network-based model features functions of the more sophisticated approaches operated in high-income regions as it is able to account for flood impacts through both closure of roads and reduced speeds along roads using both depth and velocity information. However, unlike the methods operated in urban, high-income regions, the new vector framework is simplified and its assumptions are appropriate for it to be used in rural, unpaved environments. Consequently, the new network-based framework allows researchers in low-income and data-restricted study regions to experience increased research power in being able to locate specific vulnerabilities in network infrastructure and to assess the onset and persistence of flood impacts in relation to their study interest.

Network analysis has been historically underutilised in low-income environments as studies have focused on the ability of populations to arrive at facilities; as populations typically rely on multiple forms of transport, a raster-based model is normally deemed more appropriate for being able to represent travel off-road. However, network analysis has advantages for investigating the operational side of healthcare systems (e.g., Bailey *et al.,* 2011; Chowdhury *et al.,* 2018). In this study, vehicular referral times to emergency care were investigated. The modified network analysis approach could also be used to investigate the effects of floods on medical supply deliveries. Facilities could be identified which may become unable to receive deliveries during flood months and are thus at risk of stock-outs which would have detrimental impacts on patients (e.g., HIV patients reliant on ART). Consequently, the development of the vector-based framework in this study allows exploration of infrastructure- and system-functioning of health facilities.

5.4. Limitations

5.4.1. Data constraints

Difficulty was experienced in obtaining suitable datasets to be used in both the raster- and vector-based models. This is not a limitation caused by the framework, but instead reflects the wider issue in acquiring GIS data for health studies in low-income regions as noted previously (Makanga *et al*., 2016a). In this study, data constraints pertained to the acquirement of roads, bridges and water crossings, and health services data.

No complete dataset existed that detailed the **road network** of the Barotse Floodplain. OpenStreetMap contained relatively good coverage of roads beyond the floodplain escarpment but gaps still existed; very little of the informal, community-level tracks on the floodplain were detailed (Figure 3.4). As a consequence, all roads had to be delineated from composite satellite images sourced from Google Earth and Bing Maps. Makanga *et al*. (2016b) also found large gaps in OSM coverage in

Mozambique and similarly resorted to manual delineation of roads; the approach is common in low- and middle-income data regions where large areas of roads have gone undocumented (Laurance *et al*., 2014). Generally, there was good availability of images but composite datasets vary in quality, particularly in dynamic environments, and some images were unusable. Occasionally, images suitable for delineating roads within an area could not be obtained in either Google Earth or Bing Maps which incurred uncertainty in identifying road presence within small areas across the floodplain.

Additionally, difficulties were experienced in distinguishing between sandy tracks and canals infilled with sediment due to their visual similarity, and elevated roads could not be detected. Overall, however, the solution of delineating roads was successful in producing the most complete road network dataset to be used in both vector- and-raster based access models. Manual digitisation has been facilitated as an approach due to it becoming easier and cheaper with the availability of high-resolution and recent composite satellite images (Makanga *et al*., 2016a; Makanga *et al.,* 2016b), but doing so still represents a significant burden experienced in low- and middle-income data-sparse regions. The increasing availability of high-resolution satellite imagery has facilitated attempts to automatically delineate roads using machine and deep learning approaches (Miao *et al.,* 2015; Wang *et al.,* 2016; Singh *et al.,* 2020; Soni *et al.,* 2021); the potential for such approaches to be adapted and rolled out across data-sparse rural regions in the future would help substantially reduce the need for manual digitisation.

As with the road network, few data existed on the **presence of bridges and water crossings** on the floodplains. As a consequence, all waterbodies were traced in satellite imagery to manually delineate crossing locations. Bridges and water crossings have a large influence on access due to permanent waterbodies acting as significant topological barriers; in some locations, a crossing may act as the only accessible way across a river for many kilometres. Study participants in Nhemachena *et al*. (2011) specifically singled out bridges and water crossing as influential infrastructure in Limpopo, South Africa as, when seasonally inundated, access was restricted across them to schools, shops, and healthcare centres. Whilst all bridges and water crossings identified on satellite imagery were recorded, some uncertainty remains regarding whether all were captured. Blanford *et al*. (2012) experienced similar difficulties with collating information on the presence of bridges due to a lack of data.

It has been continually noted that there is a lack of **information on the geolocation of facilities in Africa and the services they offer**. This has historically limited the application of access modelling (Blanford *et al*., 2012; Ouma *et al*., 2018; Ebener *et al*., 2019; Weiss *et al*., 2020a). An increase in the creation and availability of up-to-date master health facility lists (e.g., Maina *et al*., 2019) has helped to reduce limitations regarding knowledge of the location of primary healthcare facilities. For example, the Zambian Ministry of Health website maintains a master health facility list which was last updated in 2019 and this provided the location of all facilities on and surrounding the floodplain, distinguished by health system level; comparison with previously recorded data from field investigations confirmed that these were accurate. However, the master facility list provided no information on the services offered by each facility. The only available services data identified originated from a 2012 report (MoH, 2012) which contained gaps in service data for newly-built facilities. This limited the ability of the study in considering access to specific services, as was also concluded as a limitation in Blanford *et al*., (2012).

This study modelled access of women to EmOC, but the results are subject to large uncertainties. Firstly, it is not known whether additional EmOC sites were added to the floodplain since 2012. Secondly, what constitutes EmOC is vague in the 2012 list. EmOC sites can be either basic or comprehensive depending on how many of eight signal functions (Table 5.1) they offer (Gabrysch *et al.,* 2011b). As a result, the sites listed as offering EmOC cannot be distinguished. Ebener *et al*., (2019) recommended three indicators be modelled to comprehensively assess access to EmOC: the proportion of women with timely access to (1) any EmOC and (2) comprehensive EmOC; and (3) the proportion of timely referral linkages between basic and comprehensive EmOC sites. In this study, it was only possible to model the first indicator without further data to discretise EmOC sites into categories. Tatem *et al*., (2014) similarly recognised that a lack of service data hampered their ability to advance beyond simplistic models of general access to healthcare as specific scenarios could not be precisely explored without adequate information on the services provided at healthcare facilities.

Table 5.1. Classification of basic and emergency obstetric care based upon the signal functions available. Adapted from Gabrysch *et al.* (2011b).

Basic emergency obstetric care (BEmOC)
• Injectable antibiotics
• Injectable oxytocics
• Injectable anticonvulsants
• Manual removal of placenta
• Manual removal of retained products
• Assisted vaginal delivery
Comprehensive emergency obstetric care (CEmOC)
All of the above plus:
• Caesarean section
• Blood transfusion

5.4.2. Unimodality of approach

Whilst vehicular and walking access were considered in the case study, the two were considered separately in unimodal network- and raster-based models. In the network model, considering vehicular access alone was deemed appropriate for the purpose of modelling referral times in emergency vehicles between delivery sites and EmOC. However, rural, low-income populations have been commonly found in previous studies to rely on multiple modes of transport in order to access healthcare.

In the Barotse Floodplain, oxen-carts and boats have additionally been used as modes of transport across the region (Shela, 2000; Del Río, 2014; Rajaratnam *et al*., 2015), but these were not considered in the study due to a lack of data on their usage which could be used to create and justify a multimodal approach. Oxen-carts have similar slow travel speeds to walking and are also constrained by the presence of floodwaters, so their explicit representation was not deemed necessary. However, boats are commonly used on the floodplain (Shela, 2000; Rajaratnam *et al*., 2015), and these are able to navigate areas not accessible by walking. For example, in Del Río (2014), farmers reported that it was necessary to own a canoe to be able to navigate through the floodplain in the wet season across floodwaters and canals. In all scenarios, 3% of the population were recorded as always being unable to access healthcare due to being river-locked within the confinements of the Zambezi and an anabranching channel; no bridges were on either waterbody. However, these populations likely do have access to healthcare by substituting part of their journey with the use of dugout canoes. Consequently, assuming that canals and waterbodies act only as impassable barriers in the absence of a water crossing is inaccurate; they are known to facilitate transportation.

From the outset of this study, it was recognised that incorporation of boats as a form of access in the framework would be useful, but this was difficult to execute. Multimodal models require correct parameterisation in order for their results to be representative, and the lack of qualitative data collection on community behaviours and transportation habits caused uncertainty in deciding what was appropriate. Important considerations include: (1) identifying whether populations rely solely on a boat for an entire journey, or whether boats are combined with other modes of transport; (2) determining the appropriateness of any assumptions, such as whether it is reasonable to assume populations have a canoe readily-available that can be used to navigate floodwaters positioned kilometres away from their settlement; and (3) establishing household prevalence of boat ownership, and usage patterns (i.e., whether boats are used equally in all months). Implementing canoe transport into the raster-based framework also required additional knowledge on what water depth clearances are needed for a canoe to be able to use floodwaters, and for data to identify vegetated waters which act as barriers to canoe travel.

A dearth of research exists on boat access modelling (e.g., Salonen *et al.,* 2012; Makkonen *et al.,* 2013; Webster *et al.,* 2016; Chen *et al.,* 2017) despite that boats have been identified as a common mode of transport in many communities globally (Oppong, 1996; Schmid *et al.,* 2001; Salonen *et al.,* 2012; Makkonen *et al.,* 2013; Chen *et al.,* 2017). As with any multimodal model, the incorporation of boats into the raster-based framework required many additional considerations to be made (e.g., Tenkanen *et al.,* 2015). This substantial piece of research in itself was beyond the scope of this project. It was thus deemed more appropriate to keep the raster-based framework as unimodal currently to prevent incurring uncertainty that could not be adequately accounted for.

5.4.3. Transhumanance behaviours of the population

This study calculated a new estimate of the population of ~44,600 which is substantially lower than the most commonly-cited estimate of ~250,000. However, the Lozi exhibit transhumance, which creates difficulty in ascertaining their location at different months throughout the year. In this study, the population locations and densities derived from the HRSL dataset were assumed to remain static and consistent throughout the year despite it being known that the Lozi vacate the floodplain for portions of the year. Characterising movements of populations that are nomadic or exhibit transhumance is difficult, as was similarly reported as a limitation in Blanford *et al*. (2012) in Niger. In the absence of qualitative data to understand where people vacate to and how many remain on the floodplain and in what months, it was not possible to represent access with direct consideration of the dynamic movements of the Lozi. However, the greatest uncertainty in estimates of the Lozi population on the floodplain can be constrained due to the characteristics of Lozi movements. The BRE announces the Kuomboka festival each year, which dictates when Lozi will vacate the floodplain after their Litunga; this festival is typically held in March or April, although it may not take place at all if sufficient rain has not fallen and floodwaters are deemed shallow. In 2018, the Kuomboka festival was held on April 21st (Chabala, 2018) and Kufuluhela (the festival celebrating the return of the Lozi to the floodplain) was held on the 20th August (Lusaka Times, 2018). Consequently, for the scenarios modelled, uncertainty in population estimates is greatest between April and August.

Some populations will always remain on the floodplain, such as fishermen who reside isolated on floodplain levees to take advantage of fish (e.g., Lungu and Hüsken, 2010), so identifying access issues in all months remains important for targeting these populations. Future efforts are needed to obtain an accurate estimate of the population as it changes throughout the year as it is important for planning healthcare interventions and assessing health system usage. Floodplain settlements appear to have village "twins" which the Lozi vacate to, which necessitates an interdisciplinary mixed qualitative and quantitative methods approach that can understand these movements and map them. A new census is also currently underway which could be used to estimate the floodplain population again for 2021 provided the Covid-19 pandemic does not further impact its progression.

5.4.4. Validation of travel times and consideration of other access variables

Only potential geographic access was considered in this study, and the modelled travel times were not compared with actual travel times; this prevented ascertaining how representative the modelled travel times are of real journeys, and whether the parameterisation of the access models was appropriate. Van Duinen *et al*. (2020) compared the results from two different access models in Kenya with real travel times and found that the more conservative approach (Munoz and Källestål, 2012) better represented real travelled times than the less conservative approach (Ouma *et al.,* 2018). The availability of real travel times would have been useful in this study for further evaluating the success of the FW and NFW scenarios.

Populations are modelled as immediately starting healthcare journeys at the onset of a medical complication (i.e., no stage one delays), traveling at the same consistent speeds, and omnisciently knowing the fastest route to take. Modelled travel times are thus optimistic. Access is modelled to the nearest facility only, and all facilities are assumed to offer the same quality of care and to be adequately staffed. This may misrepresent access as populations may walk further if they perceive care to be better or more suitable at another facility (Penfold *et al*., 2013; Roder-DeWan *et al*., 2020; Mupwanyiwa *et al*., 2020), and availability of qualified staff may vary throughout a region which influences service provision (Fogliati *et al*., 2015; Faruk *et al*., 2020). In the Barotse Floodplain, participants surveyed by Pasqualino *et al*. (2016) reported issues with quality of care received at some facilities such as inconsistent provision of ART, and stated that some facilities were only staffed by untrained community health workers. Populations are also assumed to receive appropriate care immediately on arrival, ignoring potential further delays in being treated by staff.

Measured walking speeds have been shown to vary throughout the day and in different weather conditions (Witt, 2012) but these were not accounted for. In general, the use of an average walking speed does not represent the multiple influences that affect the walking ability of a person (Bosina and Weidmann, 2017). Some populations, such as women in labour, may not be able to walk at all (Gabrysch and Campbell, 2009). The position of cars and humans in relation to oncoming flow was not modelled despite that instability may occur at lower thresholds depending on the orientation of oncoming flow (Teo *et al.,* 2012; Xia *et al.,* 2014c). Current understanding of how instability thresholds are modified based on slope and flow orientation remain incomplete for accounting for this effect. Walking times were also not reduced in the wet season due to a lack of data to parameterise the effects of precipitation on walking speeds. No discretion was made in either model about how floodwater impacts are likely to differ between paved and unpaved surfaces. Additionally, the 100 m spatial resolution of the hydrodynamic model is also a limitation as LISFLOOD-FP assumes flat topography within a cell, resulting in a constant cell water depth; this could obscure local depressions within the cell, such as wheel ruts, which could impede access.

Modelled referral times assumed that emergency vehicles were present at every location and immediately available to make referrals; this is a large assumption as these vehicles are rarely available in sub-Saharan Africa due to high running costs and their usage for other tasks in addition to transporting patients (Chen *et al*., 2017). Vehicles were also assumed to be able to navigate along sandy tracks at the same travel speeds as other tracks, despite sandy terrain offering poor traction (Sinkala *et al*., 2014). Communication between facilities is needed to arrange referrals (Ebener *et al*., 2019), and all facilities were assumed to have operational communications equipment; failure or lack of equipment delaying or preventing referrals may not have been accounted for (Speranza, 2010).

5.5. Future work

This section outlines future research that has been identified for consideration in this study. Section 5.5.1 considers the scales used to model geographic access, and highlights the limited understanding on what resolution of input datasets are needed to produce accurate results with access models. Section 5.5.2 explains the lack of research on boat models, and describes some considerations integral to their incorporation into future access studies. Finally, Section 5.5.3 discusses the necessity in incorporating both qualitative and quantitative methods in an interdisciplinary approach to provide a complete overview of access to care which would establish the relative importance of each access variable (including geographic access).

5.5.1. Scale of approach

Geographical access models have been operated at larger continental to global (Ouma *et al.,* 2018; Weiss *et al.*, 2020a), national (Epstein *et al.,* 2020; Macharia *et al*., 2021), and sub-national scales (Chen *et al*., 2017) but no study has ever explicitly considered the scale of inputs required to obtain representative access results with the best trade-off between accuracy and research burden. In this study, significant time investment was required in order to obtain a complete roads dataset and the hydrodynamic model outputs used are highly specialised; both are beyond what could be reasonably expected in every future operation of the framework. However, it is unknown to what extent the high-resolution results in this study could be recreated using lower resolution datasets. Can specific datasets (such as the geolocation of water crossings) be identified which are more influential on successful results than others which should thus be prioritised for collection? To operate the new framework over larger areas such as Western Province, it would be inconceivable to expect the same high-level of inputs to be used; the data and computational costs would be substantial. As a consequence, investigating the scale of approach necessary for operating geographic access models at different areal units is highlighted as a key area of future research that will help researchers optimise their geographic access methods.

5.5.2. Boat modelling

Boats can be an important mode of transport on floodplains and for travelling along canals and rivers, which makes them important to consider when modelling access as was determined in this study. However, there is currently a dearth of research modelling boat accessibility (Makkonen *et al*., 2013; Webster *et al*., 2016). The few studies completed where boats are modelled as a form of transport have been limited to the Peruvian Amazon, where a version of network analysis is completed assessing boat access on the fluvial network (Salonen *et al*., 2012; Tenkanen *et al*., 2015; Webster *et al*., 2016). Access modelling specific to boats is thus a gap in the literature, and future work should investigate how boats can be incorporated into cost-distance algorithms, outlining key variables that must be considered and incorporated; such research would facilitate appropriate representation of boats as a form of travel for regions such as the Barotse Floodplain.

5.5.3. Integration of qualitative and quantitative approaches

Health access is a complex concept, constituting multiple dimensions of access including socio-demographic, socio-economic, and geographical variables (Penchansky and Thomas, 1981; Thaddeus and Maine, 1994). All access variables are influential in affecting human decision-making, and in the ability of populations to seek and reach appropriate care (e.g., Jammeh *et al.,* 2011; Mpimbaza *et al.,* 2017; Adedokun *et al.,* 2017). Studies that solely consider one dimension of access are limited in the conclusions that can be derived as access cannot be fully interpreted and understood without identification of all influential variables (Eklund and Mårtensson, 2012). For example, in this study, the impact of floods on geographic access was investigated. It was already identified that floods can exert a dual effect on health access by preventing populations reaching care and impacting health system functioning by impeding referrals and causing medicine stock-outs; this in turn leads to poor perception of care which negatively affects utilisation in all months. The study's framework modelled potential geographic access and revealed that floods have a substantial detrimental impact on the *potential* ability of populations to walk to care, and that referrals were impeded. However, this can only explain part of the dual effect identified. Without qualitative data obtained on service and medicine provision, and community perceptions of quality of care, it is not possible to completely understand how influential floods are in impacting health access in the Barotse Floodplain. Such data is not quantifiable and requires sophisticated qualitative techniques developed in the social science disciplines to survey staff, patients, and populations to obtain information on their perspectives and lived experiences of health access (e.g., Chibwana *et al.,* 2009; Eide *et al.,* 2018; Marhatta *et al.,* 2021). Obtaining this information supplements any results from a geographic access model by interpreting whether floods impact particular population subgroups and whether specific socioeconomic and sociodemographic characteristics can be linked to perceptions of floods or related to utilisation patterns.

Integration of qualitative data also improves the execution of geographic access models. Information on the health needs of populations can be used to plan where and how geographic access models should be operated as part of targeted strategies to address key health priorities (e.g., reduction of maternal mortality) rather than merely modelling access to any primary healthcare facility. Qualitative information can also be used as inputs and as part of model parameterisation. For example, this study would have benefited from qualitative data on nomadic population movements and the prevalence and usage of different transport on the floodplain; with such data, a more regionally-specific multimodal model could have been developed for assessing Lozi access to healthcare. Collaboration with local communities and organisations can also help by validating modelled travel to develop geographic access models that are representative of real journeys (Van Duinen *et al.,* 2020).

To conclude, future work should aim to take advantage of health access as an interdisciplinary concept by fully integrating qualitative and quantitative data and techniques. Access and utilisation can be complicated by regionally- and community-specific factors (such as community beliefs, perception of care, and stigma), and so consideration of these factors helps tailor intervention plans that are most suitable to the needs of specific communities. The health access discipline can also benefit from approaches and knowledge from wider fields, as was demonstrated through this study operationalising knowledge from the hydrology, geospatial, and hazard management fields in its framework. For the most effective health access policies to be developed and successfully implemented, comprehensive knowledge of all factors relevant to health access are needed which necessitates an interdisciplinary mixed methods approach. This study's framework has greatly improved representation of floods as a barrier, but future work is now needed to determine the relative importance of floods on health system utilisation for regions.

CHAPTER 6

CONCLUSION: *towards a new understanding of floodwater impact on access*

Annual floods are common in low-income countries with seasonal climates. Regular floodwave passage through floodplains supports local livelihoods with the provision of ecosystem resources. However, assessing how floods impact access to healthcare for these and other populations affected by floods has been hindered by the lack of models able to represent the spatio-temporal dynamics of flood inundation on accessibility. This shortcoming has limited the ability of previous studies to identify vulnerable populations, to assess the resilience of health system functioning, and to understand how floodwater variables impact access. To better represent and ultimately resolve existing health inequity, an approach was needed that could explicitly model changes in access under flooding. This study has provided a new geospatial framework that is able to address this important research gap. The new framework precisely models the spatio-temporally variable impacts of floodwaters on geographic access. An interdisciplinary approach was used to determine changing flood hazard by relating floodwater depth and velocity variables to mechanisms of human and vehicular instability.

The new framework was successfully demonstrated in the Barotse Floodplain, Zambia. Monthly changes in access to healthcare were modelled to provide completely novel information on how annual floodwave passage impacts access to general and maternal services between October 2017 and October 2018. This represents the first such implementation of this approach. Dramatic variations in geographic access through space and time were revealed to occur as a result of the seasonal floods. This was expected based on previous identification from WARMA that this was a problem on access to healthcare, but access had never been explicitly modelled before. The proportion of the population without timely access (within two hours) to healthcare is increased at the peak of the floods, with accessibility to emergency care (hospitals and emergency obstetric care) impacted the worst. Hydrodynamic variables were shown to exert a strong control on the potential ability of populations to reach healthcare, and access asynchronously varied with floodwaters depending on flood stage, the location of settlements, and the position of facilities and services within the landscape. Substantial declines in potential access were observed between the peak dry and peak flood months, as has similarly been reported in previous studies. However, dynamic spatio-temporal variations in access observed in the intermediate flood rise and flood recession months were also seen which could not be recreated using previous static scenarios of “dry” and “wet” season access, emphasising the need to move away from such simple representations.

The framework is widely applicable to other regions affected by seasonal flooding. Its assumptions are appropriate to the characteristics typical in low-income regions, and its data requirements are not substantially beyond what is already expected to operate simple network analysis or a raster cost-distance algorithm. It is advantageous in using parameters to alter the representation of floods as a barrier, allowing the representation of flood hazard to vary based upon context and regional characteristics. In this study, the same floodwater inputs were used to produce two different representations of access in each month: one in which populations could walk through floodwaters deemed low hazard, and one in which all floodwaters acted as impassable barriers. This created an upper and lower uncertainty boundary on access measures, which would be of use to intervention planning to consider uncertainty in access scenarios. Additionally, the framework benefits health intervention planning by allowing floodwater variables to represent real events and updating access as it changes under floodwaters. This provides additional research power for applications such as: identifying health facilities whose catchments are most vulnerable to flood impact; measuring the number of months communities are unable to reach healthcare; and recognising roads whose inundation would have the greatest detriment to the resilience of the referral system. The framework also has uses beyond health access modelling. Access to other services could be modelled, and the ability to use hydrodynamic model outputs allows predictions to be made about expected changes in access under climate change and in disaster situations.

Improved representation of floodwaters in geographic access models was achieved in the framework created in this study. However, modelled access is simplified by: assuming populations access their nearest facility only; ignoring other influential access variables; and being restricted to modelling access with one mode of transport only. Key limitations pertaining explicitly to the case study are the assumption that population is static throughout the year despite the Lozi practicing transhumance, and the lack of consideration of canoes and oxen as a mode of transport. These limitations reflect existing issues regarding how to best model populations exhibiting transhumance and the dearth of research on boat modelling. Both are proposed as areas for future research that uses an interdisciplinary approach to identify this information and relate it to access. Additionally, it is unknown what scale of inputs are required in order to balance geographic access model accuracy with computational and data burden. Future work should contrast access results obtained for the same region using different resolutions of input data.

It is recognised that qualitative and quantitative data must be interpreted to contextualise all access factors as they pertain to a region. Whilst in the Barotse Floodplain floods are identified as causing a substantial decline in accessibility, the results of the geographic access model alone are inadequate for determining the actual effect floods are having on real-word health service utilisation. To take geographic access results and operationalise them into an effective health policy, additional research is needed to determine the relative importance of geographic access as an influential access variable in relation to other non-measured variables such as quality of care, gender, and education. Where possible, future work should contextualise the results of geographic access models within the wider access framework.

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