Health System Resilience for Climate Change Adaptation: An Empirical Evaluation of Access and Utilization in Western Province, Zambia

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public

Statement of Contributions

This dissertation consists of four manuscripts that have been submitted for publication and one policy brief. The manuscripts are organized as Chapters 2, 3, 4, and 5, while the Policy Brief serves as Chapter 6. All work was conducted under the supervision of Dr. Zahid A. Butt at the University of Waterloo.

Research presented in Chapter 2 (Study no. 1)

This research was conducted by Cameron B. Chiarot as the lead author. Cameron B. Chiarot was responsible for study conceptualization, methodology, formal analysis, data curation, visualization, and drafting the original manuscript. Mr. Abu Yousuf Md Abdullah was responsible for the GIS models and producing estimated travel distances. Dr. Zahid A. Butt, the supervisor, provided overall guidance and intellectual input. Dr. Craig R. Janes, a Co-Principal Investigator (Co-PI) on the project grant, contributed to the intellectual input, as did all other co-authors (Abu Yousuf Md Abdullah, Fastone Goma, Massauso Phiri, Douglas Singini, and Richard Zulu).

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Research presented in Chapter 6 (Policy Brief, Phase I)

This document was authored by Cameron B. Chiarot. The Policy Brief served as a synthesis of the preceding dissertation chapters, translating the key research findings into a preliminary assessment (Phase I) and a future research and policy roadmap (Phase II). Dr. Zahid A. Butt, the supervisor, and the dissertation committee members—Dr. Craig R. Janes and Dr. Abel Torres-Espin—were integral to the review of this chapter. The document is not a manuscript and was not submitted for publication.

As the doctoral student and lead author, Cameron B. Chiarot was responsible for the primary contributions to conceptualizing the study design, conducting data collection and analysis, and drafting the Policy Brief Preliminary Assessment (Phase I) and the Policy Brief Supplemental Document (Technical Methodology and Future Research: Phase II).

Chiarot CB. Policy Brief, Preliminary Assessment (Phase I): Optimizing Access to Health Centres for an Equitable Future.

This document is an unpublished work, intended to serve as the foundation for a future external funding application. Potential funding agencies for this research include the Canadian Institutes of Health Research (CIHR), the Bill & Melinda Gates Foundation, and the Wellcome Trust.[a]

[a] Potential funding agencies for this research include the Canadian Institutes of Health Research (CIHR), the Bill & Melinda Gates Foundation, and the Wellcome Trust. The rationale for targeting these agencies and their specific funding opportunities are as follows: CIHR: As a Canadian-led project, CIHR is a natural fit. We would specifically target the CIHR Project Grant, which supports health research that addresses complex health challenges like the one presented here. Bill & Melinda Gates Foundation: This foundation has a strong focus on global health and health systems in low-income countries. We would seek funding through their Grand Challenges in Global Health initiative, which prioritizes innovative and scalable solutions for persistent health problems. Wellcome Trust: The Wellcome Trust's mandate includes supporting research that tackles urgent health challenges. We would apply to their Health Systems Research or Global Health funding streams, which are specifically designed to fund interdisciplinary work that combines data science, geospatial analysis, and policy.

Abstract

Background Achieving Universal Health Coverage (UHC) in low- and lower-middle-income countries (LMICs) is jeopardized by the convergence of climate-related shocks and chronic health systems stressors. In Western Province (WP), Zambia, a vast, rural, and remote area characterized by the Barotse Floodplain, progress toward UHC is hindered by the interplay between seasonal flooding variations and pre-existing challenges such as low health facility density and geographic barriers to accessing and utilizing essential primary health care services. A significant gap exists in the empirical evidence necessary to quantify these adverse synergistic interactions, improve routine surveillance systems that currently lack reliable population denominators, and develop dynamic models to assess the impact of shocks and stressors on health service utilization.

Objectives This dissertation develops and applies a comprehensive methodological framework to empirically evaluate access to and utilization of essential health services in WP, Zambia. It endeavors to (1) define and measure the dimensions of access, encompassing supply- and demand-side conditions within the context of spatial and temporal parameters; (2) establish an innovative methodology for generating population denominators to enhance disease surveillance and epidemiological metrics; (3) quantify the synergistic impacts of environmental and systemic challenges on service utilization through a novel *econosyndemic* framework; and (4) model health system resilience dynamically by forecasting utilization patterns and evaluating the effects of various shocks and stressors over time. Furthermore, this dissertation concludes with a policy brief, representing a preliminary policy assessment (Phase I) that employs a location-allocation model to optimize the current health facility network for geographical efficiency, thereby identifying existing access gaps and redundancies within the system. This initial optimization serves as a foundation for a proposed multi-stage framework designed to generate actionable investment strategies by integrating health system capacity, cost considerations, and evolving population needs into future analyses (Phase II). Ultimately, this work offers an integrated, evidence-based framework aimed at strengthening health system resilience as a vital climate change adaptation strategy, thereby advancing the overarching objective of ensuring equitable access to healthcare for vulnerable populations.

Methods This dissertation, grounded in comprehensive research, comprises four empirical studies in addition to a policy analysis. Study no. 1 employed a cross-sectional design utilizing geospatial analysis of 220 health facilities (centres and posts) to assess access through metrics such as facility density, population growth, travel durations, and personnel distribution. Study no. 2 introduced and applied an innovative Spatially Defined Catchment Area and Population Under Rooftop (SCSO-PUR) methodology, leveraging satellite data to establish denominators for 321 health facilities, as exemplified in a malaria surveillance epidemiological case study spanning 2017 to 2024. Study no. 3 presented and quantified the *econosyndemic* framework within an ecological longitudinal study of 62 health centres and posts from 2017 to 2023, employing beta regression and structural equation models (SEM) to analyze the interaction between flood exposure and health system capacity concerning maternal and child health, as well as overall general utilization (i.e., outpatient visits). Study no. 4 utilized time-series forecasting and an Interrupted Time Series (ITS) analysis on the same dataset to measure the dynamic effects of three distinct shocks—the 2019 drought, the 2021 COVID-19 pandemic, and the 2023 complex flood event[b]—on overall utilization, namely outpatient visits. The Policy Brief, Preliminary Assessment (Phase I), employed a Set Covering Problem (SCP) model on the network of 321 facilities to optimize geographic coverage and identify system-wide efficiencies.

Findings Geographic access constitutes a primary barrier, with projected declines in facilities per capita and estimated mean travel times ranging from 6.6 to 13.9 hours. A substantial proportion of the population (26.4%, exceeding 322,000 individuals) resides beyond the World Health Organization's recommended two-hour travel time to a comprehensive Health Centre. The SCSO-PUR methodology has demonstrated feasibility in establishing standardized denominators, thereby elucidating previously obscured spatial-demographic disparities in malaria risk. The *econosyndemic* framework has been empirically validated; notably, the interaction between high flood depths and health system stressors was found to significantly disrupt essential services, including antenatal care (ANC) and facility-based births. The Interrupted Time Series (ITS) analysis indicates that various shocks yield distinct and quantifiable impacts on overall utilization patterns, ranging from immediate declines (drought) to paradoxical increases (COVID-19) and

[b] Characterized by an unusual 'double-peak' where floodwaters receded and then rose to a second, later peak, deviating from the typical single-peak annual flood cycle.

gradual recoveries (i.e., complex flood event). Lastly, the health system optimization analysis uncovers significant spatial redundancy; specifically, while comprehensive geographic coverage could be theoretically achieved with only 46 of the 321 existing facilities, this would entail accepting travel times of up to 7.5 hours, thereby underscoring a crucial trade-off between efficiency and equitable access.

Conclusion This dissertation provides a comprehensive, empirically grounded framework for understanding and strengthening health system resilience in a climate-vulnerable setting. It demonstrates that the adverse synergistic interaction between environmental shocks and systemic supply- and demand-side stressors creates an *econosyndemic* that dynamically and inequitably disrupts access to and utilization of essential health services. The novel methodologies developed offer scalable, data-driven tools for ministries of health to transition from reactive to proactive, evidence-based planning. The findings provide a clear policy directive: building health system resilience for climate adaptation requires targeted, context-specific interventions that address underlying vulnerabilities in infrastructure and geographic accessibility.

Dissertation Keywords Access and Utilization, Climate Change Adaptation, Econometrics, Environmental Shocks, Epidemiology, Geospatial Analysis, Global Health, Health Economics, Health Management Information Systems, Health System Resilience, Health System Stressors, Health Systems, Infectious Diseases, Location-Allocation, Malaria, Maternal and Child Health, Micro- and Macro-Economics, Equality and Equity, Regression Modeling, Routine Health, Information Systems, Structural Equation Modelling, Sub-Saharan Africa, Supply- and Demand, Side Conditions, Syndemic Theory, Universal Health Coverage, Western Province, Zambia

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Dedication

To my Mums

Mary M. Chiarot and in memoria di Clelia Castaldi

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List of Abbreviations

ABM	Agent-Based Model
AIC	Akaike Information Criterion
AICC	Corrected Akaike Information Criterion
ANC	Antenatal Care
AOR	Adjusted Odds Ratio
ARIMA	Autoregressive Integrated Moving Average
B	Births
BIC	Bayesian Information Criterion
CBD	Central Business District
CFI	Comparative Fit Index
CHA	Community Health Assistant
CI	Confidence Interval
CIHR	Canadian Institutes of Health Research
CHW	Community Health Worker
Co-PI	Co-Principal Investigator
CSO	Central Statistical Office
DEM	Digital Elevation Model
DHIS2	District Health Information System 2
ETS	Exponential Smoothing
FIML	Full Information Maximum Likelihood
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
GLPK	GNU Linear Programming Kit
GIS	Geographic Information System
GRID3	Geo-Referenced Infrastructure and Demographic Data for Development
HIM	Hydrodynamic Inundation Model
HMIS	Health Management Information System
HQP	Highly Qualified Personnel
HRSL	High Resolution Settlement Layers
HSC	Health System Capacity
HSO	Health System Optimization
HTS	Hierarchical Time Series
IHACRES	Identification of unit Hydrographs And Component flows from Rainfall, Evaporation and Streamflow data
ITS	Interrupted Time Series
k-NN	k-Nearest Neighbor
LA	Location-Allocation

List of Abbreviations (continued on next page)

LICs	Lower-Income Countries
LMICs	Lower-Middle-Income Countries
LULC	Land Use and Land Cover
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCLP	Maximal Covering Location Problem
MFL	Master Facility List
MLR	Robust Maximum Likelihood
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
PHC	Primary Health Care
PGR	Population Growth Rate
PUR	Population Under Rooftop
RCMRD	Regional Centre for Mapping of Resources for Development
RHIS	Routine Health Information Systems
RMSE	Root Mean Squared Error
SCP	Set Covering Problem
SCSO	Spatially Defined Catchment Area
SD	Standard Deviation
SDG	Sustainable Development Goal
SE	Standard Error
SEM	Structural Equation Model
SEV	Socioeconomic Vulnerability
SSA	Sub-Saharan Africa
UHC	Universal Health Coverage
UN	United Nations
USGS	United States Geological Survey
VIF	Variance Inflation Factor
WHO	World Health Organization
WP	Western Province
WRA	Women of Reproductive Age
ZEP	Zambezi Ecohealth Partnership

List of Methodologies

Chapter No.	Methodology	Description
Chapter 2	**Geospatial Analysis** • Law of Cosines • Population Projections • Descriptive Analytics	Examined the theoretical framework of access through the lens of population dynamics, facility distribution, and estimated travel times in a health systems context.
Chapter 3	**Novel Method** • Spatially Defined Catchment Area • Population Under Rooftop **Regression** • Beta-Binomial Regression	Developed a novel methodology to create population-adjusted denominators for routine health data, enabling robust analysis of disease proportions while accounting for overdispersion and spatial heterogeneity.
Chapter 4	**Regression** • Beta Regression Mixed-Effects Models • Structural Equation Modelling (SEM)	Provided the first quantitative evidence for the *econosyndemic* framework by modeling the synergistic interactions between climate shocks and health system stressors on health utilization outcomes.
Chapter 5	**Econometrics** • Time-Series Forecasting • Hierarchical Time Series (HTS) • Interrupted Time Series (ITS)	Dynamically forecasted health utilization and quantified the inferential impacts of major shocks over time, demonstrating the multi-model approach required to assess health system resilience.
Chapter 6	**Location-Allocation Optimization** • Set Covering Problem (SCP) • Advanced Optimization Modelling	Employed optimization techniques to identify the most efficient health facility network for universal coverage and outlined a roadmap for future optimization strategies to improve equitable access.

Epigraph

> *True health system resilience requires a dual focus: fortifying against the external shocks of tomorrow while relentlessly addressing the internal stressors of today*

— Cameron B. Chiarot

Preface

This dissertation was motivated by the ongoing challenge of achieving Universal Health Coverage (UHC) in regions vulnerable to climate impacts, with particular emphasis on the unique context of Western Province, Zambia. In this setting, the intersection of acute environmental shocks, such as variation in seasonal flooding, and persistent health system stressors results in a complex array of barriers that disproportionately affect rural and remote communities. The objective of this research was to transcend mere problem description and to develop a comprehensive, multi-dimensional empirical framework to measure, model, and ultimately mitigate the effects of these challenges on essential health services.

To achieve this, the research is presented as a cohesive narrative across four empirical studies and a concluding policy brief preliminary assessment (Phase I). This dissertation traces a logical path from problem identification to a proposed solution. The journey begins in Chapter 2 (Study no. 1) by establishing a foundational, empirically grounded understanding of *access* in Western Province, Zambia, quantifying the profound geographic and logistical challenges faced by the predominantly rural and remote population. Recognizing that any deeper analysis was hindered by a critical data gap, Chapter 3 (Study no. 2) introduces a novel methodological solution—the Spatially Defined Catchment Area and Population Under Rooftop (SCSO-PUR) methodology—to create the reliable population denominators necessary for robust surveillance and epidemiological metrics for empirical analysis and reporting.

With this new tool in hand, Chapter 4 (Study no. 3) proposes and empirically tests a novel theoretical framework I term the *econosyndemic*, quantifying—for the first time—the adverse synergistic interaction between climate shocks and health system stressors. The subsequent chapter, Chapter 5 (Study no. 4), introduces a dynamic temporal dimension by applying advanced time-series and interrupted time-series analyses to assess the health system's distinct responses to various real-world shocks, thereby providing a nuanced perspective on its resilience. Ultimately, the dissertation concludes with Chapter 6 (Policy Brief: Preliminary Assessment), which integrates

the evidence from all prior studies to develop a forward-looking health system optimization model, translating complex research findings into a practical and actionable framework for policymakers.

Methodologically, this work aims to contribute by integrating a diverse array of techniques—from geospatial analysis and satellite data processing to advanced econometrics and operations research. Importantly, this research was conceived not merely as an academic exercise but as a project with direct policy relevance. I hope that the frameworks, methods, and findings presented herein offer valuable tools and evidence to the Zambian Ministry of Health and other global health stakeholders engaged in developing more resilient and equitable health systems amidst the challenges posed by climate change and internal health system stressors ∞

Chapter 1

Introduction

1.1 Global Imperative for Resilient Health Systems

The pursuit of Universal Health Coverage (UHC), a fundamental component of the Sustainable Development Goals (SDGs), signifies a worldwide commitment to ensuring that all individuals have access to essential health services without incurring financial hardship.[1–4] This aspirational objective relies on the presence of robust, equitable, and responsive health systems capable of addressing the diverse needs of their populations.[2,4] Nonetheless, in recent decades, progress towards this vital goal has been increasingly threatened by a convergence of complex and often intersecting crises that reveal the profound vulnerabilities of health systems globally, particularly within low- and lower-middle-income countries (LMICs).[5] These threats are multifaceted; they appear as both acute shocks—sudden, large-scale events such as the COVID-19 pandemic or extreme weather events—and chronic stressors, which include long-standing, corrosive challenges such as inadequate infrastructure, systemic workforce shortages, fragile supply chains, and substantial geographic and financial obstacles to accessing essential health services.[6–10]

Recent global health crises have repeatedly demonstrated the stark reality of health system vulnerability. The 2014–2016 Ebola outbreak in West Africa served as a devastating reminder of how a single pathogenic threat can overwhelm fragile health systems, leading to catastrophic consequences that extend far beyond the direct mortality of the virus itself.[11] The collapse of routine health services resulted in a secondary wave of excess mortality from untreated conditions like malaria, HIV, and maternal complications, revealing how fragile governance and underfunded public health capacity can cripple a system's ability to perform its most essential functions.[11] The COVID-19 pandemic scaled this lesson to a global level, demonstrating that even well-resourced

health systems in high-income countries were ill-prepared to manage the simultaneous pressures of a novel pathogen, severe supply chain disruptions, a strained workforce, and the uninterrupted needs of patients with chronic conditions.[12] These events, shocks and stressors have made it unequivocally clear that a health system's strength cannot be measured solely by its performance under stable conditions, but by its capacity to function under constraint.[13,14]

Climate change has become a significant and widespread threat multiplier amid these challenges.[15] It is a gradual yet escalating force that induces new acute shocks—such as increased frequency and severity of floods, droughts, and heatwaves—and worsens existing chronic stressors, for example, by changing the geographic distribution of vector-borne diseases and endangering food and water security.[16] The World Health Organization (WHO) has officially acknowledged this issue by establishing an operational framework aimed at developing climate-resilient and low-carbon health systems, which underscores the importance of incorporating climate adaptation into routine health planning.[17] This global agenda, further institutionalized through initiatives such as the Alliance for Transformative Action on Climate and Health (ATACH), redefines the resilience mandate, calling for a transition from episodic crisis management to an ongoing approach of addressing the "everyday" stressors intensified by climate change.[18–20]

In response to this complex and converging threat landscape, health system resilience has transitioned from an aspirational concept to a central organizing principle within global health policy and practice.[13,21–23] Although definitions differ, a consensus has emerged that characterizes resilience as a dynamic attribute. It is broadly recognized as the capacity of health system actors, institutions, and populations to effectively prepare for, absorb, adapt to, and ultimately transform in the face of crises, while maintaining essential functions and fostering learning for future improvement.[11,22] This perspective advances beyond the simplistic notion of "bouncing back" to a pre-crisis state, instead emphasizing an ongoing process of learning and development.

Leading conceptual frameworks have further refined this definition. Blanchet and colleagues (2017) introduced a governance-oriented model that delineates three core capacities: absorptive capacity, defined as the ability to withstand shocks using existing resources and buffers without significant system change; adaptive capacity, the capacity to make proactive adjustments to

processes and reallocate resources in response to a changing environment; and transformative capacity, which refers to the fundamental reconfiguration of system structures, functions, and feedback loops in response to recurring or extreme stressors.[22] This tiered framework underscores that resilience is not a singular attribute but a collection of nested capabilities that function across different scales and temporal horizons.

Furthermore, researchers have increasingly viewed health systems as complex adaptive systems, where resilience is an emerging property rather than a deliberately designed outcome.[19] This perspective is important because it shifts the focus to the system's natural capacity to learn and reorganize. The most influential frameworks divide this capacity into three key capabilities: absorptive capacity, which involves withstanding shocks using existing resources; adaptive capacity, the ability to proactively adjust processes and reallocate resources; and transformative capacity, the ability to fundamentally reconfigure system structures in response to major stressors.[22] This dissertation is fundamentally an empirical investigation of climate change adaptation through the framework of these capacities. While all three are relevant, the research primarily focuses on measuring the outcomes of the health system's adaptive capacity. It aims to answer: When faced with a recurring climate shock like flooding and a chronic stressor such as low health facility density, how does the system adapt its service delivery? And what are the effects of that adaptation on the population? The subsequent studies do not merely describe the shocks and stressors; they quantify the effects of the system's adaptive responses—whether successful or not—using the measurable indicator of health service utilization.

Notwithstanding this conceptual richness, quantifying resilience remains a considerable challenge. A systematic review conducted by Biddle and colleagues (2020) identified a rapid proliferation in resilience research, yet highlighted the absence of standardized indicators and methodologies.[13] There exists a persistent risk that resilience metrics may merely serve as proxies for system robustness in stable conditions, thereby failing to encapsulate the dynamic performance under stress, which constitutes the core of the concept. Furthermore, resilience is not a value-neutral construct; its pursuit must be inherently aligned with the objectives of equity, trust, and accountability to ensure that the most vulnerable populations are not disadvantaged during crises.[24]

This dissertation is positioned firmly within the global context. It undertakes the challenge of empirically examining these intricate dynamics in WP, Zambia—a lower-middle-income country striving for UHC while confronting a formidable combination of climate-related shocks and chronic health system stressors. Concentrating on lived experiences within a single, highly vulnerable region, this dissertation comprises a series of research studies that aim to transcend broad conceptualizations and offer a detailed, quantitative comprehension of how resilience manifests—or fails to manifest—at the forefront of delivery of essential health services.

1.2 Conceptual and Theoretical Foundations

To thoroughly investigate the complex interplay of factors that influence health system performance under conditions of stress, it is imperative to move beyond traditional, public health models that typically examine risk factors in isolation. Such approaches are insufficient for capturing the dynamic and interactive nature of the challenges faced by health systems in contexts such as WP, Zambia. Consequently, this dissertation is based on a theoretical framework that explicitly integrates complexity and interaction, beginning with syndemic theory and extending it through an innovative, quantitatively testable model.

The syndemic framework, initially conceptualized by medical anthropologist Merrill Singer, presents a compelling alternative paradigm.[25] A syndemic is a combination of the terms 'synergy' and 'epidemic,' formulated to describe the interaction of two or more concurrent epidemics or health conditions within a particular population, resulting in a combined disease burden that exceeds the aggregate of their individual impacts.[26–31] The theory is underpinned by three core principles: the clustering of multiple diseases or health conditions; the synergistic interactions among these conditions, which may be biological, social, or psychological; and the proposition that these deleterious interactions are primarily driven by detrimental social factors such as poverty, inequality, and structural violence.[29,32,33] By redirecting emphasis from individual diseases to the overarching social and structural determinants that facilitate their interaction, syndemic theory offers an essential perspective for analyzing health disparities.[27]

Building upon this foundation, this dissertation introduces and empirically tests a novel theoretical contribution: the *econosyndemic* framework. This framework extends syndemic theory from its traditional focus on individual-level, bio-social interactions (e.g., substance abuse, violence, and HIV) to the system-level interplay between macro-level shocks and micro-level stressors (refer to Chapter 4). An *econosyndemic* is defined by the adverse synergistic interaction between broad, macro-level conditions (such as climate change-induced flooding, pandemics, economic crises or geopolitics) and localized, micro-level health system conditions, which include both supply-side stressors (e.g., low facility density, workforce shortages, supply-chain disruption, financing constraints) and demand-side stressors (e.g., long travel times, socioeconomic vulnerability). This framework hypothesizes that the impact of a shock like a flood is not uniform; rather, its effect on health service utilization is conditional upon the pre-existing capacity and stressors of the local health system, producing spatially and temporally uneven patterns of disruption.

1.2.1 Syndemics: From Qualitative Concept to Quantitative Evidence

A primary critique of the broader syndemics literature is that its central claim of synergy, although conceptually compelling, has often been described using qualitative or ethnographic methods, with a limited amount of rigorous quantitative testing.[34–38] Many early quantitative studies depended on a "sum score" or "syndemic index" approach, where the number of co-occurring health conditions experienced by an individual is summated.[36,39,40] Although these studies consistently showed that a higher score was linked to worse health outcomes, this method mainly measures the additive effect of multiple risk factors;[d] it indicates a strong association but does not, by itself, provide statistical evidence of synergy.[38]

A core contribution of this dissertation is to address this methodological gap by moving beyond the additive measurement of co-occurring health conditions to the explicit testing of multiplicative, synergistic effects through statistical interactions.. An additive relationship assumes that the

[d] While Singer's framework did not specify statistical methods, quantitative researchers operationalize synergy by testing for effect modification. In this context, the absence of synergy is represented by an additive model, where the combined effect of two factors is simply the sum of their individual effects. Synergy, by contrast, is tested by assessing for a multiplicative effect, which is typically accomplished by including a statistical interaction term in a regression model. A significant interaction term, as found in our analysis, provides empirical evidence for a non-additive, synergistic relationship (refer to Chapters 3 and 4).

combined effect of two factors is simply the sum of their individual effects. In a standard regression model, this would be represented as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

where Y is the health outcome of interest, and X_1 and X_2 are the predictor variables (e.g., health conditions or risk factors), β_0 is the intercept, β_1 and β_2 are the regression coefficients for each predictor, and ϵ is the error term.

In this additive model, the effect of factor X_1 on the outcome Y is always β_1, regardless of the level of factor X_2.[41] In contrast, synergy implies an interactive or multiplicative relationship, where the combined effect is greater than the sum of its parts. The effect of one factor is conditional on the level of another. The most direct way to test for this is by including a multiplicative interaction term in the regression model given by:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 \times X_2) + \epsilon$$

In this regression model, statistical evidence for synergy is determined by the significance of the interaction term β_3. This is formally tested by assessing the null hypothesis that $\beta_3 = 0$ (e.g., using a Wald test), or by examining whether the 95% confidence interval for the coefficient contains the null value of zero. If this interval does not contain the null value of zero, it provides evidence that the relationship between X_1 and Y is conditional on the value of X_2. The total effect of X_1 is no longer constant but is now $(\beta_1 + \beta_3 X_2)$.[41,42] By operationalizing the *econosyndemic* framework through this and other advanced quantitative methods, this dissertation explicitly tests for these synergistic effects.

The following quantitative approaches are central to this dissertation's methodology, whereby several modelling strategies are employed, including generalized linear mixed-models, structural equation models, and econometric models.

Generalized Linear Mixed-Models Testing for Synergistic Interactions (Study no. 3) To directly test for synergy, this research uses beta regression mixed-effects models that incorporate formal interaction terms as described above. This enables a direct statistical test of the hypothesis that the combined effect of a shock (e.g., high flood depth) and a stressor (e.g., low health facility density) on a health utilization outcome is significantly different from—and greater than—the sum of their individual effects.

Structural Equation Models Modeling Complex Causal Pathways (Study no. 3) To examine the underlying mechanisms of the *econosyndemic*, Structural Equation Models (SEM) are used. SEM goes beyond simple associations to test hypothesized causal pathways and feedback loops. This approach models and measures both the direct and indirect effects of unobserved, latent constructs—such as "Health System Capacity" and "Socioeconomic Vulnerability"—on health service use, offering a more detailed, systems-level view of the interacting factors.

Econometric Models Quantifying the Dynamic Impact of Shocks (Study no. 4) To provide a robust, quasi-experimental estimate of the causal impact of specific shocks over time, Interrupted Time Series (ITS) analysis is employed. This approach is utilized to accurately measure both the immediate (level) and sustained (trend) changes in service utilization following a discrete event (e.g., a drought, a pandemic policy change, or a major flood), effectively isolating the shock's impact from underlying seasonal and secular trends. By implementing these rigorous methodologies to assess synergy, this dissertation offers the empirical evidence necessary to comprehend how interacting shocks and stressors ultimately influence the population's capacity to engage with the health system—a concept intrinsically grounded in the principle of access.

1.2.2 Concept of Access: Theoretical Concept to Empirical Measure

The fundamental premise of the entire dissertation revolves around the critical concept of access to healthcare. The operationalization of Universal Health Coverage (UHC) necessitates a clear and empirically substantiated comprehension of access; however, the term itself is renowned for its complexity and multidimensionality.[1] As examined in Study no. 1, the notion of access has been articulated through various theoretical frameworks (refer to Chapter 2). The behavioural model,

for example, concentrates on the predisposing, enabling, and need-based attributes of individuals that influence their utilization of services.[43–45] More elaborate health systems frameworks, such as the one proposed by Penchansky and Thomas (1981), define access as a "fit" between the system and the patient, encompassing five principal dimensions: availability, accessibility, accommodation, affordability, and acceptability.[46,47] Levesque and colleagues (2013) further refined this conceptualization by articulating access at the intersection of health system characteristics and the population's abilities to perceive, seek, reach, pay for, and engage with services.[48,49]

A common theme across these frameworks is the crucial role of the spatiotemporal dimensions of access—space (geography) and time (travel duration)—which are particularly salient in rural areas like Western Province (WP), Zambia.[49] However, the complex nature of access poses a notable measurement challenge, as capturing all dimensions at once with a single empirical metric is difficult.[49] Consequently, this dissertation draws a clear conceptual and methodological distinction between access as the potential or opportunity to use services, and health service utilization as the empirical measure of "realized access" (refer to Chapter 2).[49] While access indicates the possibility of care, utilization reflects its actual occurrence. By examining utilization—the number of outpatient visits, facility-based births, or malaria diagnoses—this research uses a robust, measurable, and policy-relevant proxy to empirically explore how populations actively engage with the health system amid the interacting shocks and stressors of an *econosyndemic* (refer to Chapter 3).

1.3 Research Setting: Western Province, Zambia

The theoretical framework of this dissertation is empirically grounded in the unique context of Western Province (WP), Zambia. The Republic of Zambia (Zambia) is a landlocked southern African nation with a 2022 census estimated population of 19.6 million and a national poverty rate of 60.0%.[50,51] Administratively divided into 10 provinces and 117 districts, Zambia is an LMIC striving to achieve UHC through financing reforms, yet its health expenditure remains modest, projected at 6.34% of GDP for 2024 (figure 1.1).[52]

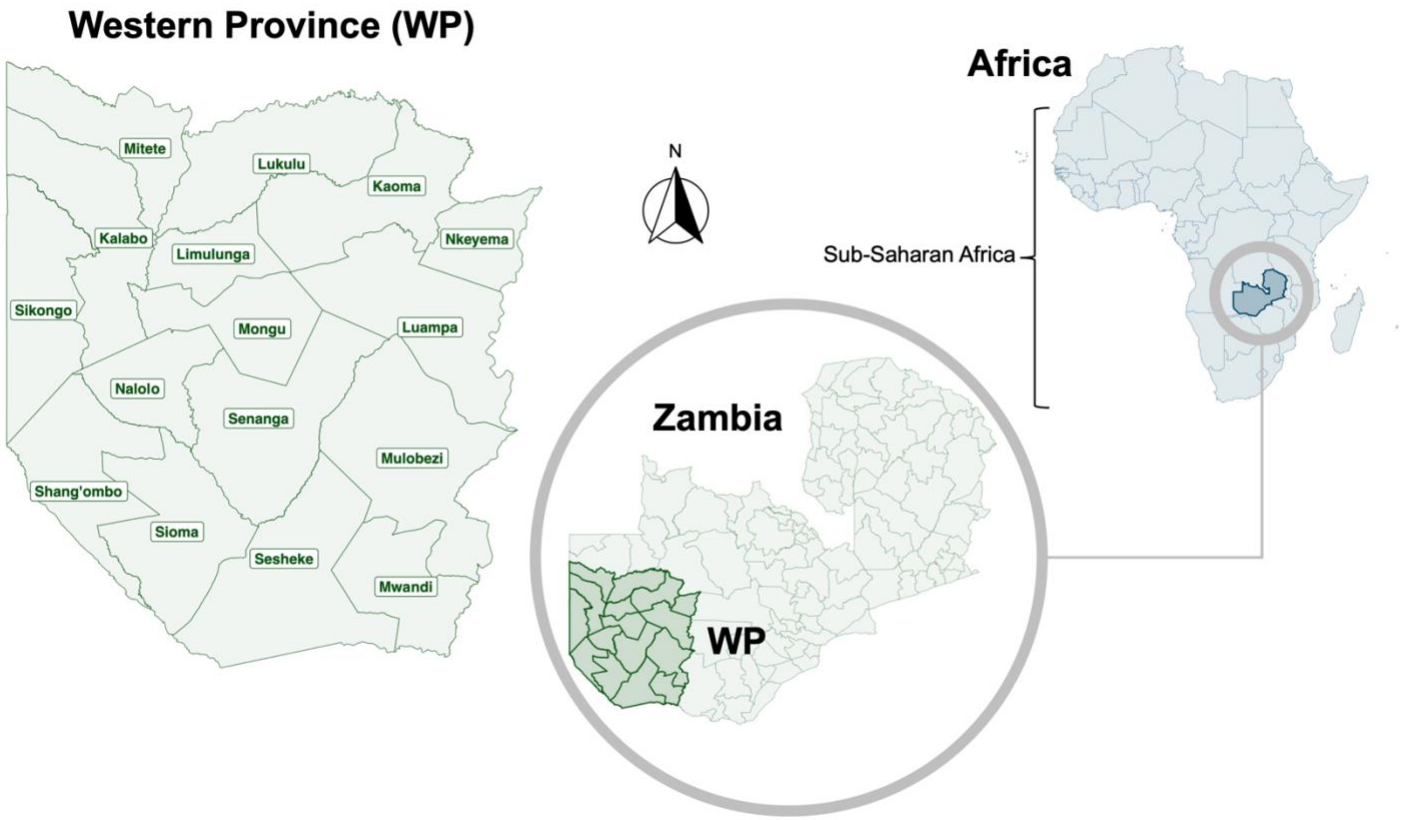


Figure 1.1 Maps of Western Province (WP), the Republic of Zambia, and the continent of Africa.

Western Province, the largest province by area and historically recognized as Barotseland, exemplifies the intersecting challenges confronting many rural health systems.[53] Its geography and ecology are predominantly characterized by the Barotse Floodplain, an extensive wetland of the upper Zambezi River. This landscape is dynamic rather than static, exhibiting a hydrological system with significant seasonal inundation that can exceed 10,000 square kilometers, effectively transforming terrestrial regions into expansive inland seas and isolating entire communities for extended periods.[54] The annual flood cycle serves as a recurrent, climate-induced environmental disturbance that fundamentally influences the lives and livelihoods of the local population.[53]

The socio-demographic profile of WP is characterized by its extensive geographical coverage and predominantly rural setting.[55] With an estimated population of 1.36 million distributed across 16 administrative districts, it ranks among the regions with the lowest population densities nationally.[49,50,56] Notably, more than 80% of this population resides in rural and remote areas, frequently inhabiting small, scattered settlements where walking constitutes the principal mode of transportation.[50] This circumstance renders geographic distance a significant chronic stressor and a primary obstacle to accessing healthcare services.

The healthcare infrastructure in Zambia is organized into a hierarchical system, with primary care services provided via a network of Health Centres that deliver comprehensive primary health services, and smaller Health Posts that offer fundamental first aid and basic primary care.[49,56,57] As of 2024, there were 344 such facilities operational in the Western Province.[58,59] Nonetheless, this network is under considerable strain. As demonstrated in Study 1, the province suffers from a low density of health facilities, a challenge expected to intensify as population growth surpasses infrastructure development (refer to Chapter 2). Although WHO recommends that travel time to essential health services should not exceed two hours, the average unimpeded walking time from a community centre to the nearest health facility in WP ranges between 6 and 13 hours, significantly exceeding this global standard (refer to Chapter 2).[49,60]

Western Province was selected as the study setting for several compelling reasons. Firstly, Zambia's dedication to UHC requires an empirically grounded comprehension of the obstacles to service utilization. Secondly, the province's pronounced rurality and dependence on walking

render it an illustrative case study for the effects of geographical access barriers. Lastly, the predictable yet fluctuating characteristics of the Barotse Floodplain offer a natural experiment for exploring the interplay between a recurring climate shock and the chronic stressors faced by an under-resourced health system.

For the people of WP, these challenges are not merely abstract, system-level issues; rather, they manifest as tangible, life-altering realities. For a pregnant woman in a remote village, an impassable flooded plain may separate her from a qualified birth attendant, transforming a manageable risk into a potential tragedy. Similarly, for a child suffering from a severe fever, the distance to the nearest clinic can determine whether timely treatment for malaria is administered or a life-threatening delay occurs. It is within this complex interplay of a dynamic environmental shock and the persistent stressors of distance, poverty, and an overwhelmed healthcare system that the *econosyndemic* discussed in this dissertation is situated.

1.4 Data Sources and Methodological Approach

The empirical analyses that constitute the foundation of this dissertation are facilitated through the integration of multiple, diverse data sources, each contributing a vital component to the overall understanding. The methodological approach is characterized by its amalgamation of these datasets to address notable data challenges and to enable a refined, population-adjusted examination of health service utilization.

The primary source of data on health service utilization is Zambia's national Routine Health Information System (RHIS), specifically the Health Management Information System (HMIS), which operates on the District Health Information System 2 (DHIS2) platform.[61–66] The HMIS serves as an essential tool for data-driven planning and resource allocation within Zambia, providing monthly, facility-level data for a broad range of health services.[65,67] This dataset supplies the fundamental numerators for the utilization metrics examined in this dissertation. Nonetheless, similar to many systems in LMICs, it encounters limitations, including issues related to data quality, completeness, and, most notably, the lack of reliable population data for the catchment areas served by each facility.[66,68–72]

To construct the requisite population denominators and to model the geographic and environmental context, this research utilizes several other key sources. Geospatial and population data include the official Zambia Master Facility List (MFL) for health facility locations and characteristics; official catchment population totals obtained from the Central Statistical Office (CSO); and, critically, high-resolution, satellite-derived gridded population estimates from Meta's High Resolution Settlement Layers (HRSL).[58,73–75] The HRSL data offer granular, disaggregated demographic counts at the level of individual rooftop structures.[75] Ultimately, environmental data concerning the primary environmental shock—flooding—were derived from the outputs of the LISFLOOD-FP hydrodynamic inundation model, which provides monthly estimates of floodwater depth across the study region (refer to Chapter 3).[76,77]

1.4.1 Denominator Challenge and Solution

A fundamental challenge in leveraging RHIS data for robust epidemiological analysis is the "denominator problem." Without accurate, localized, and demographically disaggregated population data for each health facility's catchment area, it is impossible to move beyond simple case counts to calculate service utilization rates or proportions. This limitation severely hampers the ability to make meaningful comparisons across facilities or over time and can mask significant underlying inequities in access and health outcomes (refer to Chapter 3).

This dissertation introduces a core methodological innovation developed in Study no. 2—the Spatially Defined Catchment Area and Population Under Rooftop (SCSO-PUR) methodology to address this critical gap. This novel approach resolves the denominator problem by integrating disparate data sources. It employs an iterative, proximity-based algorithm to assign the granular, demographically-disaggregated HRSL rooftop populations to their nearest health facilities, constrained by the official total catchment population provided by the CSO. Consequently, this results in the creation of a unique, spatially explicit, and demographically detailed catchment area for each health facility within the province, thereby providing the reliable denominators essential for all subsequent analyses and epidemiological metrics (refer to Chapter 3).

1.4.2 Proportion Centrality

The successful generation of reliable denominators is not merely a technical exercise; it constitutes a critical methodological step that enables more sophisticated and equitable analysis. By addressing the denominator issue, the analyses in this dissertation are able to transcend basic and potentially misleading counts of patient visits or disease cases. Instead, the principal metric employed throughout this research is the proportion.

Proportions—a fundamental element of contemporary epidemiology—offer numerous advantages.[78–84] They provide a standardized, population-adjusted metric that enables valid and meaningful comparisons of health service utilization across diverse geographic regions (which may possess significantly different population sizes) and across various temporal periods (as populations expand and evolve). This is crucial for accurately identifying high-risk populations, monitoring temporal trends, and assessing the true impact of interventions and shocks.[83] The specific utilization outcomes examined as proportions throughout this dissertation include key indicators for malaria (for both the general population and children under five), maternal and child health (proportions of antenatal care visits and facility-based births among women of reproductive age), and general utilization (the proportion of the population engaging in outpatient visits). This approach ensures that the findings are robust, comparable, and directly pertinent to the equitable distribution of public health resources.

1.5 Dissertation Overview

The preceding sections have established the global context of health system resilience, the theoretical and methodological foundations of this research, and the specific socio-ecological and health system challenges present in WP, Zambia. This confluence of factors gives rise to the central problem that this dissertation seeks to address.

1.5.1 Problem Statement

The interaction between recurrent environmental shocks, exemplified by the annual flooding of the Barotse Floodplain, and the chronic, pre-existing stressors of the health system in WP, Zambia, produces an *econosyndemic* that disrupts the utilization of essential health services. Such disruption undermines progress toward UHC and endangers the mitigation of existing health disparities. Nonetheless, the dynamic, synergistic, and geographically heterogeneous nature of this relationship remains insufficiently understood and has not been empirically quantified, thereby creating a significant gap in the evidence necessary to develop effective, context-specific interventions aimed at constructing a more resilient health system.

1.5.2 Overarching Research Objective

The primary aim of this dissertation is to empirically examine and quantify the *econosyndemic* impacting health service utilization in WP, Zambia, with the purpose of informing the development of a more resilient and equitable health system.

1.5.3 Dissertation Conceptual Map

To visually articulate the structure and intellectual scope of this research, a conceptual co-word network diagram is presented as Figure 1.2. This diagram serves as a map for the entire dissertation, delineating the interrelations among the core concepts, contextual factors, specific topics, and methodologies that underpin the five constituent studies (i.e., Study no. 1-5). The network was constructed from a corpus of key terms identified across the dissertation, with the spatial arrangement of the nodes determined by a force-directed algorithm that places highly interconnected concepts in closer proximity.

The thematic groups, represented by colour, exemplify the interdisciplinary nature of the dissertation: Core Concepts (blue) such as *Health System Resilience* and *Access & Utilization* constitute the fundamental pillars; Contextual Factors (purple) like *Climate Change Adaptation* and *Syndemic Theory* offer the broader theoretical perspective; Specific Topics (yellow) including

Malaria, *Maternal & Child Health*, and *General Utilization* signify the primary health outcomes and research areas; and Methodologies (green) such as *Geospatial Analysis*, *Structural Equation Modelling*, and *Time-Series Forecasting* indicate some of the analytical techniques employed. The size of each node reflects its centrality within the network, with larger nodes representing the principal conceptual hubs. This figure visually emphasizes the integration of health systems science with climate adaptation, advanced quantitative methods, and syndemic theory within the dissertation to address the complex public health challenges in WP, Zambia.

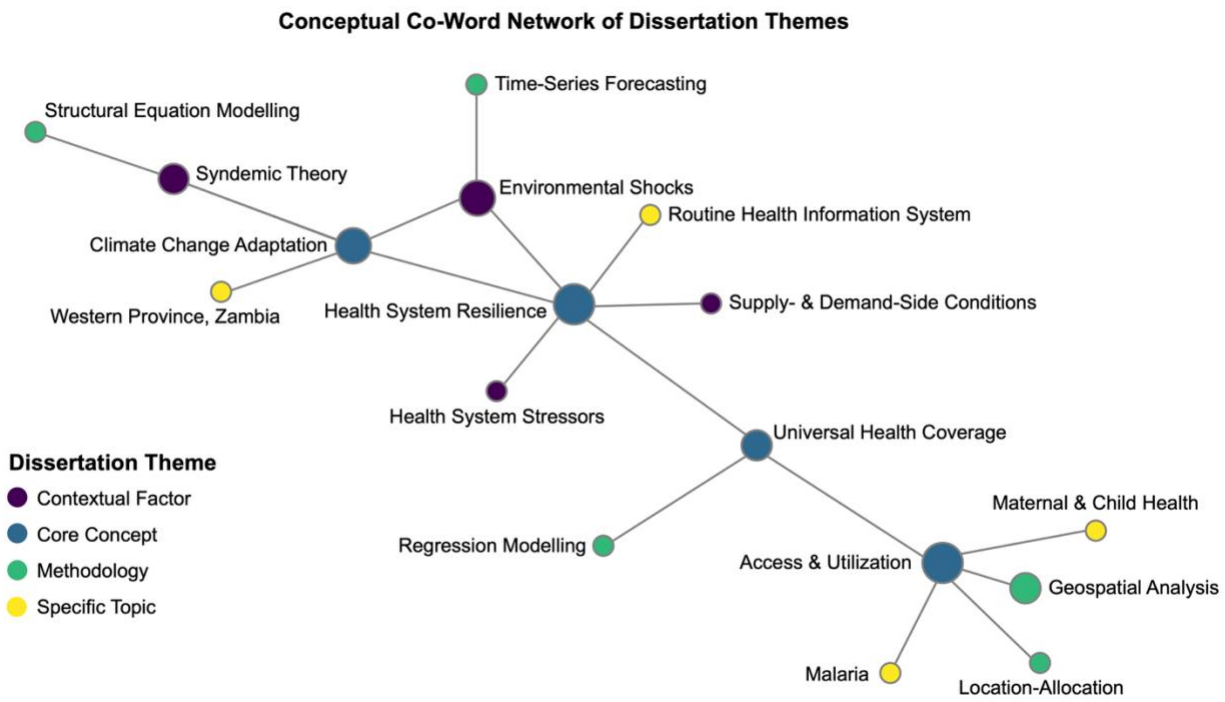


Figure 1.2 Conceptual network of dissertation themes. This figure offers a visual representation of the dissertation's conceptual framework via a co-word network analysis. The network delineates the interrelations among core concepts, contextual factors, specific topics, and methodologies that underpin this research. It was assembled from a corpus of key terms identified within the dissertation's abstracts and keyword list. Each term is depicted as a node—represented by a colour-coded circle—and the relationships between them are illustrated by edges or connecting lines. The spatial configuration of the nodes was determined using the Fruchterman-Reingold (‘*fr*’) layout algorithm, a force-directed model that positions highly interconnected nodes in closer proximity, thereby elucidating the underlying structure of the conceptual framework. The visual attributes of the nodes convey specific information: colour indicates the thematic group to which each concept belongs. These thematic groups encompass Core Concepts (the central pillars of the research), Contextual Factors (influencing conditions and theories), Specific Topics (the primary subjects of investigation), and Methodologies (the analytical approaches employed). The size of each node correlates with its centrality—specifically, degree—indicating its relative significance within the network. Larger nodes, such as "Health System Resilience" and "Access and Utilization," signify the principal conceptual hubs of the dissertation. This figure underscores the interdisciplinary nature of the research, visually connecting health systems science with climate adaptation, geospatial analysis, and syndemic theory to address intricate public health challenges in Western Province, Zambia.

1.6 Summary of Constituent Studies and Objectives

To address the overarching research objective, this dissertation comprises five distinct yet interconnected studies, each designed to build upon the previous, collectively establishing a comprehensive empirical narrative. Spanning theoretical framing, methodological innovation, quantitative analysis, and policy application, each study addresses a specific objective that contributes to the overarching aim of the dissertation.

1.6.1 Chapter 2: Concept of Access (Study no. 1)

The objective of this foundational study is to empirically evaluate the concept of access as a critical dimension of UHC within the specific context of WP. This study synthesizes the complex theoretical literature on access into a unified framework and subsequently employs a cross-sectional survey and analysis of health facility data to identify and quantify key explanatory variables that represent chronic supply- and demand-side stressors. By examining health facility density, travel times, and the distribution of highly qualified personnel, and projecting these metrics against population growth, this chapter establishes the baseline of systemic stress, thereby revealing a concerning trend of declining facilities per capita that paves the way for all subsequent analyses.

1.6.2 Chapter 3: Proportions (Study no. 2)

The objective of this methodological study is to develop and apply a novel approach to address the fundamental "denominator problem" that plagues routine health information systems in many LMICs. This chapter introduces the Spatially Defined Catchment Area and Population Under Rooftop (SCSO-PUR) methodology, an innovative technique that integrates satellite-derived population data with official health system records to create reliable, demographically-disaggregated population denominators for individual health facility catchment areas. Using malaria surveillance as a case study, this research demonstrates the feasibility and value of the

methodology, providing the essential tool needed to calculate the population-adjusted proportions that are the core outcome metric for the dissertation.

1.6.3 Chapter 4: Adverse Interactions (Study no. 3)

The objective of this core empirical chapter is to formally test the dissertation's central hypothesis by quantifying the proposed *econosyndemic*. This study employs an ecological longitudinal analysis of maternal health (i.e., antenatal care), child health (i.e., births), and general utilization (i.e., outpatient visits) of first-level (i.e., primary health care) health services to investigate the adverse synergistic interactions between seasonal flooding (the shock) and health system capacity (the stressor). Through the application of beta regression with interaction terms and structural equation modelling, this chapter provides the first quantitative evidence of the *econosyndemic* in operation, demonstrating that the impact of climate shocks on health service utilization is not uniform but is significantly conditioned by underlying, pre-existing health system vulnerabilities.

1.6.4 Chapter 5: Forecasting Utilization (Study no. 4)

The objective of this study is to incorporate a dynamic, temporal dimension into the analysis by forecasting health service utilization and evaluating the impacts of shocks over time. This chapter employs a multi-model econometric approach, initially benchmarking several time-series models—including autoregressive integrated moving average (ARIMA), seasonal ARIMA, Exponential Smoothing (ETS or Error, Trend, Seasonality), and Prophet—to ascertain the most accurate forecasting method. A Hierarchical Time Series (HTS) analysis is utilized to examine spatial disparities in WP. Subsequently, Interrupted Time Series (ITS) analysis is applied to quantify the specific, inferential effects of three distinct shocks—a drought, the COVID-19 pandemic, and a complex flood event[e]—on service utilization. The findings provide a detailed, data-driven understanding of health system resilience, demonstrating how the system responds variably to different types of disruptions.

[e] Characterized by an unusual 'double-peak' where floodwaters receded and then rose to a second, later peak, deviating from the typical single-peak annual flood cycle.

1.6.5 Chapter 6: Policy Brief Health System Optimization (Study no. 5)

The objective of this comprehensive translational study is to convert the cumulative empirical findings of the dissertation into actionable policy recommendations. It is organized into a Phase I Policy Brief and a Phase II Future Research segment. This chapter employs a location-allocation framework, specifically a Set Covering Problem (SCP), to evaluate the geographic efficiency of the existing health facility network within WP. By identifying the minimum number of facilities required to ensure universal population coverage under various travel time constraints, the analysis provides insight into spatial redundancies and access deficiencies. The culmination of this work is the development of a multi-stage Health System Optimization (HSO) framework, designed to guide strategic investment decisions, reduce inequalities and inequities, and enhance population access to comprehensive primary care. The Phase II Future Research section lays the groundwork for a potential external funding application, which is elaborated in Chapter 6.

1.7 Dissertation Contributions

1.7.1 Urgency and Significance

This dissertation is presented at a critical juncture for global health. The research responds directly to an urgent need, situated at the convergence of three defining forces of our time: the accelerating and palpable impacts of climate change on vulnerable communities; the renewed global focus on health system preparedness and resilience in a post-COVID-19 world; and the final, decisive push to achieve the ambitious targets of the SDGs.[85–88] By addressing the complex interplay of these forces within a single, deeply contextualized case study, this work seeks to make a significant and multifaceted contribution to theory, methodology, and policy.

1.7.2 Key Contributions for Stakeholders

The significance of this dissertation lies in its four primary contributions, each targeted to a specific audience within the broader global health landscape:

For Health Systems Theorists This dissertation introduces and, for the first time, empirically validates the *econosyndemic* framework. This innovative model offers a new, quantifiable perspective for analyzing the complex, synergistic interaction between large-scale environmental shocks and chronic, localized health system stressors. By moving beyond linear, single-cause analyses, it provides a more robust theoretical foundation for understanding health system performance and fragility in the Anthropocene.

For Global Health Methodologists and Data Scientists This research presents the SCSO-PUR methodology, a novel and scalable solution to the enduring "denominator problem" that has historically constrained the analytical capabilities of routine health data in LMICs. This methodological advancement enhances the potential for more sophisticated, population-adjusted, and equitable analysis of health service utilization, providing a replicable instrument that can be adapted to various other contexts.

For Climate and Health Researchers These studies offer some of the initial quantitative, longitudinal data from a vulnerable African context regarding the specific ways in which climate shocks and persistent system stressors interfere with vital health services. By elucidating intricate, geographically diverse patterns of disruption and resilience, the findings advance the understanding from merely illustrating that climate change affects health to elucidating how these effects are mediated by the capacity of the underlying health system.

For Zambian Policymakers and Global Health Practitioners This dissertation translates complex empirical findings into an actionable Health System Optimization (HSO) framework. This is not merely an academic exercise; it is a data-driven roadmap designed to guide tangible policy decisions. It provides the evidence base for strategic investments in health infrastructure that can simultaneously improve efficiency, enhance equity, and build a more climate-resilient health system in WP and, by extension, in similar settings across the globe.

1.7.3 Path Forward and Dissertation Structure

Ultimately, this dissertation constructs a comprehensive, evidence-based narrative that traces the complete trajectory of the research process—encompassing theoretical conceptualization, methodological innovation, rigorous empirical testing, and direct policy application. It aims not only to diagnose a complex problem but also to enhance the analytical tools and empirical insights necessary for the development of solutions. The structure of this work is designed to guide the reader logically through this process. Following this introductory chapter, the dissertation proceeds as follows: Chapters 2 through 6 present the five constituent studies as self-contained manuscripts, each addressing its specific research objective. Chapter 7 offers a comprehensive discussion and synthesis, integrating the key findings from all five studies to articulate the overarching contribution to knowledge, examine broader policy implications, and delineate a clear agenda for future research.

1.8 Concluding Remarks

This dissertation presents a distinctive and innovative examination of the intricate relationship between environmental shocks and vulnerabilities within health systems in a rural, climate-sensitive setting. It advances beyond conventional single-factor analyses to offer a comprehensive, quantitative understanding of how these adverse, synergistic interactions—referred to here as the *econosyndemic*—generate geographically variable patterns of disruption and resilience. By initially addressing fundamental methodological challenges and subsequently employing a multi-model approach, this research bridges the divide between theoretical frameworks and empirical evidence.

1.9 Forward

The content herein is not solely an academic endeavour but also furnishes compelling evidence supporting a paradigm shift towards data-driven, context-specific strategies intended to enhance local health system capacity. The findings illustrate that effective interventions must be customized

to concurrently address both acute shocks and ongoing stressors. Ultimately, this dissertation contends that the pursuit of UHC in an era marked by climate uncertainty necessitates a profound commitment to establishing the measurable, proactive, and genuinely resilient health systems that the future of WP, Zambia, demands.

Chapter 2

Concept of Access

2.1 Overview

Background The concept of access is critical for the operationalization of universal health coverage (UHC), which is especially relevant in rural and remote communities of lower-income countries (LICs) to lower-middle-income countries (LMICs) where high-priority health needs are in great demand. The objective of the present study was to empirically evaluate the concept of access in one such context. To gain insights into the health systems approach to the concept of access, a cross-sectional study design using a health facility questionnaire was conducted in eleven study districts of Western Province, Zambia. Additional variables were extracted from the Zambia Master Facility List.

Methods Using a combination of descriptive statistics, geospatial analysis, and modelling, we evaluated population growth, health facilities (n=221), travel time, and highly qualified personnel (HQP).

Findings Our projections indicate a 48.59% decline in total health facilities per 10,000 population by 2032, suggesting demand is outpacing supply. Estimated average walk times from a central business district to a health facility ranged from 6.64 to 13.9 hours. Analysis of HQP revealed that Community Health Workers and nurses were the most common providers, with only two doctors available across the study districts.

Conclusion We summarized numerous concept of access frameworks into three distinct approaches in the context of space and time. The health systems approach was the most comprehensive, and findings from our study underscore the importance of crucial explanatory

variables that may be used to empirically measure health service utilization as a critical dimension of UHC.

2.2 Introduction

Operationalizing universal health coverage (UHC) may vary between low- to lower-middle-income nations, but there is a consensus that the goal is to ensure access to essential healthcare services.[1] Access to essential healthcare services is especially critical for high-priority health needs, including women's and children's health, infectious diseases, and non-communicable diseases.[89] Specifically, access to healthcare services has been demonstrated to be an essential determinant of health and well-being, especially evident in rural and remote communities where there may be an array of supply-side and demand-side barriers and challenges in the context of spatial (i.e., space) and temporal (i.e., time) dimensions.[4] Prior to the development of policy aimed at operationalizing UHC, nations must first fully consider and apply an agreed-upon understanding the concept of access.[3] Access to essential healthcare services involves identifying a complex concept system of supply-side and demand-side conditions and challenges across space and time.[90] There have been numerous attempts to articulate the concept of access, many of which are well documented in published literature; however, there remains minimal agreement on what constitutes the critical components to be included in a concept of access theoretical framework.[46]

Developed a half century ago, and perhaps one of the most cited concept of access frameworks is what has been termed the "behavioural model" of health service utilization.[44] Underlying objectives of the behavioural model included the ability to understand the reasons why families use health services and to define and measure equitable access.[43] From conception, the behavioural model focused on the family as the unit of analysis; however, an updated model emphasized the individual.[43] The shift from family to the individual was a direct result of not being able to develop a series of robust measures that accounted for the potential heterogeneity at the individual level.[43,44] The primary strength of the behavioural model is that it considers the determinants of health in the context of the external environment, which is relevant in low- and lower-middle-income countries where access to essential healthcare services is a crucial component for achieving UHC.[45,91–93] Second, 'customer satisfaction' as a component of the behavioural framework can be empirically measured.[94] However, the limitations of the behavioural model are the inability to capture the overlap among multiple health determinants and the failure to consider the supply-side and demand-side conditions in the context of space and time.[95]

What we term a "health systems framework" is considered more comprehensive, as it considers the supply-side (e.g., high-quality personnel, technology, medical consumables, infrastructure, and facilities) and demand-side (individuals, caregivers, communities, and populations) conditions.[46,48,96,97] One of the most cited is a taxonomic framework comprising five components: 'availability', 'accessibility', 'accommodation', 'affordability', and 'acceptability'.[46,94] Embedded in the taxonomic components, the concept of access is conceived as the interface between potential users (i.e., demand-side) and healthcare providers (i.e., supply-side) influenced by characteristics of actors who supply as well as those who utilize the health system (i.e., 'realized access').[94] A decade later, the critical components of the health system approach emphasized the 'availability of resources', 'utilization power' (i.e., user), and 'resistance' (i.e., barriers that the users may experience during health-seeking behaviour).[97] The strength of the health system approach is its utility in empirically measuring the health system's performance (e.g., utilization may be measured as 'realized access').[98] The primary limitation of the health system approach is a failure to fully include the dimensions of space and time. While the health systems framework effectively captures supply- and demand-side factors and their interaction, it typically does not explicitly incorporate geographic distance or travel time as fundamental components within its core structure, unlike spatially-explicit models.

A more targeted "technology model" for the concept of access was developed to assess the ability to access and utilize health technologies, including vaccines and health-related products.[99] Further, the technological model was used extensively to evaluate health technologies in the context of rural and remote communities of low- to lower-middle-income countries.[99] Many health-related technologies, due to a variety of barriers, never reach the hands of the end-user, which suggests challenges with supply-side conditions. If the technologies did reach the hands of the end-user, there were often challenges with utilization (i.e., technologies that were not used for the desired intention, suggesting challenges with demand-side conditions). The primary limitation of the technology access framework is that it is not a 'one-size-fits-all', as health-related technologies can substantially differ by product or service offering.[99] The second limitation is that the framework may be too complex to be useful for others, as there may not be enough detail about the different activities or actors involved in a specific health-related technology.[99] The final limitation of the technology framework is that it does not consider the dimensions of space and

time, which are highly relevant when considering supply-side and demand-side conditions in rural, remote communities of low-income countries (LICs).

Several authors have criticized the current concept of access models as being confusing, highly theoretical, and absent of empirical evidence.[97,98,100] We aim to strengthen the current literature by developing a unified and comprehensive framework categorized into three approaches: behavioural, health systems, and technological. Further, we summarized the three approaches with cross-cutting components and added the dimensions of space and time (figure 2.1). The proposed unified theoretical framework of approaches addresses the current literature's limitations and gaps.

The objective of the present study was to investigate potential explanatory variables that may be used to empirically evaluate the components of the unified concept of access framework, with a focus on the health systems approach. To achieve this objective, we chose Western Province, Zambia, Africa, as the study setting. Western Province was chosen for three reasons: i) Zambia, considered before 2023 as a LIC (reclassified in 2023 to lower-middle), is striving toward UHC where operationalization requires an empirically-based understanding of the barriers to access and utilization of essential health care services; ii) greater than 90% of the population resides in remote communities where the primary mode of travel is walking; iii) eleven districts of Western Province are located in and adjacent to the Barotse Floodplain, which is susceptible to variations in seasonal flooding due, in part, to the impact of climate change; and iv) numerous physical barriers have a profound and negative impact on access and utilization of essential healthcare facilities and services, resulting in an increase in the burden of disease.

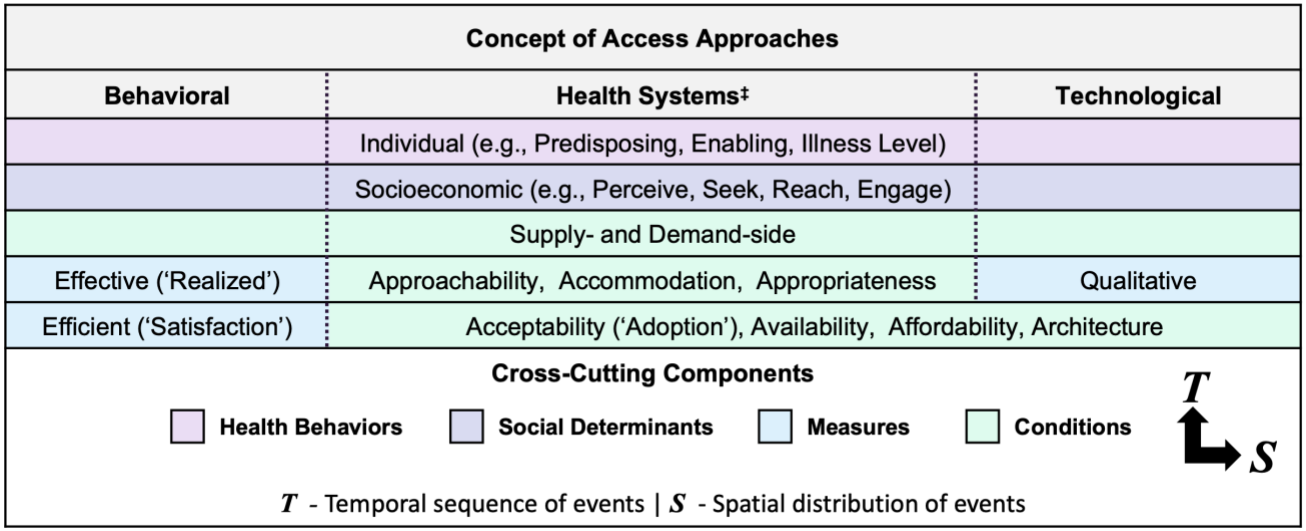


Figure 2.1 A unified theoretical framework for the concept of access. The framework is comprised of three approaches with corresponding cross-cutting components. The supply- and demand-side conditions are to be considered in the spatial (S) and temporal (T) dimensions. ‡The purpose of the present study was to investigate the Health Systems approach and the relevant cross-cutting components.

2.3 Methods

2.3.1 Study Setting

Western Province, one of 10 provinces of Zambia, is divided into 16 administrative districts and based on the 2023 census, there was an estimated population of 1.36 million.[100] Approximately 80.6% of people live in remote communities where access to health facilities may present many barriers, including travel distance and time.[54,101] Through financing reforms, the Zambian healthcare system aims to achieve UHC; however, as a lower-middle-income nation, Zambia's health expenditure in 2024 is expected to be only 6.34% of GDP.[102]

The infrastructure of the Zambian health system is organized around four levels of hospital care, Health Centres, and Health Posts. Responsible for providing essential health care services, Health Centres provide primary care, while Health Posts deliver basic first aid and some primary care services.[59] Health facilities in each district are managed by a district health director (DHD) and a district health information officer (DHIO) operating from one dedicated district health office. In 2023, there were a total of 320 health facilities operating in the 16 districts in Western Province. For the present study, 11 of the 16 districts were chosen as study districts given the vast spatial distribution of the population, proximity to the floodplain, and extensive variations in seasonal flooding.

2.3.2 Study Design and Participants

The eleven study districts out of the 16 in Western Province were purposefully chosen for this study. This selection was based on specific criteria relevant to the study objective: the vast spatial distribution of the population within these districts, their proximity to the Barotse Floodplain, and the extensive variations in seasonal flooding experienced in these areas. This purposeful sampling allowed for an in-depth evaluation of access challenges in a context characterized by significant geographic barriers. To gain insights on the dimensions of space and time in the context of supply-side and demand-side conditions, a cross-sectional study using a health facility questionnaire was

conducted during the month of July 2022 in the 11 study districts. The health facility questionnaire was adapted from the World Health Organization's Harmonized Health Facility Assessment (HHFA), a comprehensive survey used to assess supply-side conditions, including capacity and availability of services based on quality standards. The study questionnaire contained 46 questions relevant to supply-side conditions, including the number and type of health facilities, the number of highly qualified personnel per facility, types of service utilities, equipment for cold chain, and type and quantity of medical supplies. Before administering the questionnaire, the directors of the eleven study districts were briefed on the study design and objective. Based on their knowledge of Health Centres and Health Posts, the district information officers were selected as study participants and were asked to complete the questionnaire using an online data collection, management, and visualization platform.[103] Participant responses were received for 212 of the 221 health facilities surveyed (response rate = 95.5%). Raw response data were exported from the online platform using a comma-separated values file (*.csv), and organization and cleaning were completed using an advanced spreadsheet software program.[104]

2.3.3 Ethics Approval

Ethical approval for this study was obtained from the University of Waterloo Human Research Ethics Board (ORE-43883), the University of Zambia Biomedical Research Ethics Committee (Ref. No. 2472-2021; renewed February 9, 2024), the National Health Research Authority in Zambia (Ref. No. NHRA000009/10/07/2022), and the Provincial Ministry of Health, Western Province. Permissions were granted for the secondary analysis of de-identified data stored in the national HMIS.

2.3.4 Data Sources and Analysis

Participant response data obtained from the questionnaire used for analysis included: i) name of district, ii) name of health facility, and iii) number of highly qualified personnel (HQP) at each health facility (i.e., doctor, nurse, midwife, community health worker (CHW), or community health assistants (CHAs)) (refer to Appendix A). In addition to the questionnaire, detailed information for health facilities was obtained from the Master Facility List (MFL) of 2023, an

open-source online database.[58,59] The MFL contained the facility name by province, district, constituency, and ward. Facilities are categorized by location (i.e., urban, or rural), facility type (i.e., level of care), ownership (e.g., Ministry of Health or Faith-Based), head count, census (Central Statistics Office Zambia (CSO)), and latitude and longitude coordinates (measured in decimal degrees). To validate health facilities by study district, we cross-referenced the questionnaire and the MFL, yielding n=220 for our analysis (tables 2.1 and 2.2).

Population per health facility was analyzed using the MFL census data from the past three decades (i.e., 2000, 2010, and 2023).[50] The distinct time periods (2000-2010, 2010-2023, and 2023-2032) were chosen based on the availability of decadal census data from the Zambia Statistics Agency. The historical periods align with available census years, while the 2023-2032 period projects forward a decade from the most recent census. While these periods are not uniform in length, using the existing census data was necessary for empirical comparison and projection based on available historical population data.[50] Population Grow Rates (PGR) provided by the Census of Population and Housing for each district were used to calculate 2032 population projections using the geometric change method: $P_t = P_0(1 + r)^t$, where P_t was the projected population, P_0 was the initial population (2023 census), r was the PGR (10-year average), and t was the period (i.e., 10 years).[50,100] To assess the change in health facilities per capita over time, we calculated percent difference for three distinct periods (i.e., 2000 to 2010, 2010 to 2023, and 2023 to 2032). The analysis of health facilities per capita and the projected decline were based on the number of physical health facilities listed in the MFL and verified through the questionnaire. For the purpose of this study and projection, a facility was counted if it was physically listed as operational in the data sources. This analysis did not account for potential changes in the quality of care or functionality of these facilities over the study period due to data limitations.

Table 2.1 Indicators and parameters used in the study.

Indicator	Parameters / Data Used	Source
Population Growth	• Census • District-level PGRs	• Zambia Statistics Agency
Health Facilities	• Health Centres (Rural/Urban) • Health Posts (Rural/Urban)	• HF Questionnaire • MFL
Travel Time	• Geo-codes of CBDs and HFs • Walk speed (5 km/hr) • Road network data • Land use and land cover (LULC) • Digital Elevation Model (DEM) • Flood level data	• HF Questionnaire • MFL • Google maps • OCHA • RCMRD • USGS
Highly Qualified Personnel	• Doctors • Nurses • Midwives • CHWs • CHAs	• HF Questionnaire • MFL

Abbreviations: CBD – Central Business District, **CHA** – Community Health Assistant, **CHW** – Community Health Worker, **DEM** – Digital Elevation Model, **HQP** – Highly Qualified Personnel, **HF** – Health Facility **LULC** – Land Use/Land Cover, **MFL** – Master Facility List, **OCHA** – United Nations Office for the Coordination of Humanitarian Affairs, **PGR** – Population Growth Rate, **RCMRD** – Regional Centre for Mapping of Resources for Development, **USGS** – United States Geological Survey

Table 2.2 Number of health centres and health posts by study district.

Study Districts (n=11)	Health Centres n (%)	Health Posts n (%)	Total Facilities n (%)
Kalabo	12 (11.5)	19 (16.2)	31 (14.0)
Limulunga	9 (8.7)	10 (8.5)	19 (8.6)
Lukulu	13 (12.5)	12 (10.3)	25 (11.3)
Mitete	3 (2.9)	8 (6.8)	11 (5.0)
Mongu	20 (19.2)	19 (16.2)	39 (17.6)
Nalolo	9 (8.7)	8 (6.8)	17 (7.7)
Senanga	8 (7.7)	10 (8.5)	18 (8.1)
Sesheke	9 (8.7)	10 (8.5)	19 (8.6)
Shang'ombo	6 (5.8)	4 (3.4)	10 (4.5)
Sikongo	7 (6.7)	8 (6.8)	15 (6.8)
Sioma	8 (7.7)	9 (7.7)	17 (7.7)
Totals	**104 (100)**	**117 (100)**	**221 (100)**

For the geospatial analysis of the population and health facilities, latitude and longitude coordinates for Health Centres and Health Posts were plotted on a static Google map of Western Province, Zambia. The geospatial analysis was completed using the open-source integrated development environment (IDE) R coding and RStudio visualization software (R Core Team and the R Foundation for Statistical Computing).[105] To access Google Maps via the R software environment, Google Cloud Application Programming Interfaces (APIs) and a registered API key were used (Google LLC, Googleplex, Mountain View, California, United States). Specifically, the Google Cloud APIs used for all the geospatial analysis included the following: Directions, Distance Matrix, Geocoding, Geolocation, Maps Elevation, Maps SDK for iOS, Maps Static, Places, Roads Static. The geospatial analysis using the R software was conducted on a computer running macOS Sonoma, version 14.2.1 (Apple Inc., Cupertino, California, United States).

For calculating travel distance, a physical location in the central business district (CBD) was chosen based on centrality. Using a series of static Google maps, the latitude and longitude coordinates were obtained for each location in the CBD (table 2.3).

Table 2.3 Latitude and longitude coordinates measured in decimal degrees for an assigned location in the central business district for each of the eleven study districts.

Study District	Central Business District	Latitude	Longitude
Kalabo	Kalabo District Hospital	-14.992960	22.680738
Limulunga	Limulunga District Health Office	-15.129840	23.147292
Lukulu	Lukulu District Health Office	-14.373841	23.238124
Mitete	Mitete Town Council	-14.392003	23.241764
Mongu	Mongu Post Office	-15.271136	23.127936
Nalolo	Nalolo District Hospital	-15.539212	23.115475
Senanga	Senanga District Council	-16.109060	23.296967
Sesheke	Sesheke Civil Centre	-17.480947	24.294144
Shang'ombo	Shang'ombo Town Council Civic Centre	-16.319420	22.105857
Sikongo	Sikongo Police Station	-15.034735	22.151424
Sioma	Sioma Town Council	-16.604332	23.504906

To generate a series of travel distance estimates, we developed a series of travel models. In our study setting of WP, walking is the primary mode of transportation, especially evident in rural and remote communities in and adjacent to the Barotse Floodplain, where road infrastructure is nearly absent.[54] Further, the Barotse Floodplain is characterized by an extremely flat terrain with a near-homogeneous land use; therefore, land use and slope data were not considered variables in the first set of travel models.[54] Typically, an average walk speed of 5 km/hr[f] is used in the absence of

[f] While a standardized walking speed of 5 km/hr is used for baseline modeling, it is critical to acknowledge that this does not fully capture the dynamic reality of travel in the Barotse Floodplain, a point reinforced by the broader Zambian literature.[107] Actual travel patterns are dictated by the annual flood cycle, which transforms the landscape and the lived experience of the floodplain's hydrology.[53] During the dry season, movement is primarily on foot, but at the peak of the flood, canoe travel becomes dominant. This can paradoxically create direct waterways and, in some cases, improve access between certain points compared to the dry season or transitional flood periods. This 'ground-truthing' context is essential for interpreting utilization patterns, as access is not static. For a detailed geospatial analysis of these seasonal flood impacts on travel to maternal healthcare facilities in this region, see Mroz et al. (2025).[77]

topographical impedances, which we used in our travel models for estimating travel time.[54,106–110] However, Tobler's Function and Naismith's Rule would be appropriate in travel models to estimate average travel time when an incline is present.[111] Given our study setting, the first travel model we developed was based on the law of cosines using the following expression:

$$d = \text{acos}(sin\ \varphi_1 \cdot\ sin\ \varphi_2 + cos\ \varphi_1 \cdot\ cos\ \varphi_2 \cdot cos\ \Delta\lambda) \cdot R$$

where φ is latitude, λ is longitude, and R is the radius of the Earth (i.e., mean radius = 6,371 km).

The second model we used was the Minkowski distance with varying orders of p, where p was an integer between two points:

$$X = (x_1, x_2, \dots, x_n)\ and\ Y = (y_1, y, \dots, y_n) \in \mathbb{R}^n$$

The final Minkowski expression used was defined as:

$$D(X,Y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}}$$

where D is distance and the Minkowski integers $p = 1$ and $p = 2$ are equivalent to Manhattan and Euclidean distances respectively. Using equation 3, we developed three Minkowski travel distance models using the Minkowski integers: $p = 1$, $p = 1.5$, and $p = 2$ (figure 2.2).

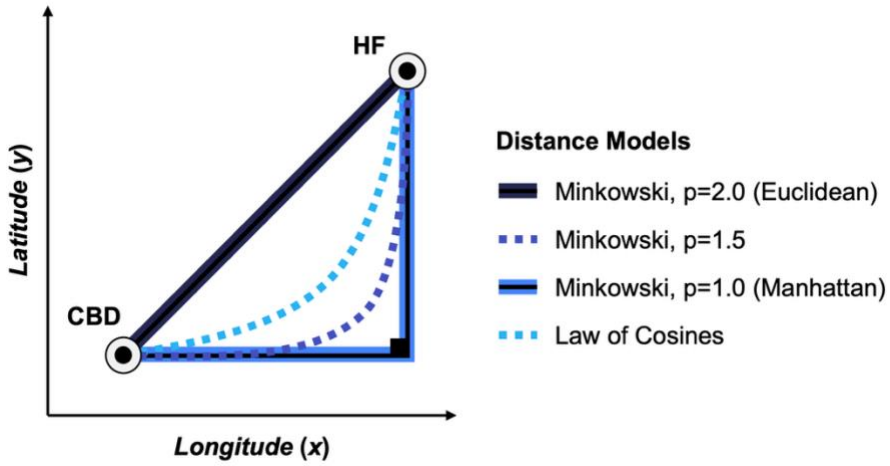


Figure 2.2 Schematic of models for estimating travel distance from the Central Business District (CBD) to a Health Facility (HF) using latitude and longitude coordinates.

In the second set of travel models, we accounted for varying speeds across land uses and land cover (LULC) while using the road network. To achieve this, we ran a cost-friction analysis using a Geographic Information System (GIS) based network analysis. To generate the travel distance and time estimates using the road network and LULC features, we employed the Closest Facility analysis in ArcGIS.[112] The closest facility analysis was selected as health-seeking populations prioritize their closest (based on route distance) health facilities after considering the available health services they seek. The analysis involved estimating the cost of travel (based on distance and time) between the CBDs and facilities and identifying the closest facility for each CBD based on route distance. Upon review of existing literature on Zambia and other study regions having similar geographic and geomorphic settings, a walking speed of 5 km/hr was used to estimate the distance of travel.[54,107,109] However, it is worth noting that as distance remains fixed (i.e., from origin to destination), our findings of the distance between a CBD and its closest health facility are scalable to provide travel time based on any walking speed. For this study, average travel time was based on a walk speed of 5 km/hr using the following equation: $V = d/t$, where V was the assumed travel speed in kilometers per hour, d was the estimated travel distance in kilometers, and t was time in hours. The travel models and walk speed are based on best-case scenarios, which assume zero impedance (i.e., 'generalized costs').

The data used for this analysis was selected based on several considerations and sources. First, we developed a detailed road, CBD, and health facility network for the study region (figure 2.3). The OpenStreet road network dataset was downloaded from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA).[113] The network dataset was processed to carry out the necessary topological corrections to ensure that all the roads and pathways were properly connected at junctions, no gaps or overlaps existed between the roads and required elevation adjustments and impedance (or restrictions) were incorporated into the network layer.

Second, we considered a detailed LULC map of the study region, the digital elevation model (DEM), and the flood level map to identify the elevation and impedance adjustments. The LULC map for the year 2016 derived from processing Sentinel-2 imageries was retrieved from the Africa Geoportal website by the Regional Centre For Mapping Of Resources For Development (RCMRD).[114] LULC maps that create travel hindrance, especially walking, are mainly attributable to geographic features or barriers.[54,107,109] Therefore, despite being from 2016, the open-source LULC map provided us with the required information on the major LULC categories that must be considered as impedance within the network. As can be seen from Figure 2.4a, the study region comprises a homogeneous LULC condition, mainly dominated by vegetation, grasslands, and croplands, with a relatively scarce presence of open water or water bodies. Furthermore, a DEM for the study region was downloaded from the website of the United States Geological Survey (USGS).[115] Figure 2.4b shows that the study region is a relatively flat terrain devoid of sharp elevation changes that could provide notable impedance. However, after retrieving and processing the flood level data for Zambia developed by the World Food Programme (Advanced Disaster Analysis and Mapping),[116] we noted that flood levels must be considered as the geophysical impedance for our network analysis. Consequently, the flood was added as an impedance or restriction in the road network layer (figure 2.4c). Specifically, the network analysis was set to prefer roads that were not flooded as people travelled from CBDs to the health facilities. Additionally, as the primary mode of travel used was walking, the cut-off distance imposed was 100 km, which implied that any facility 100 km away from the CBD was excluded.

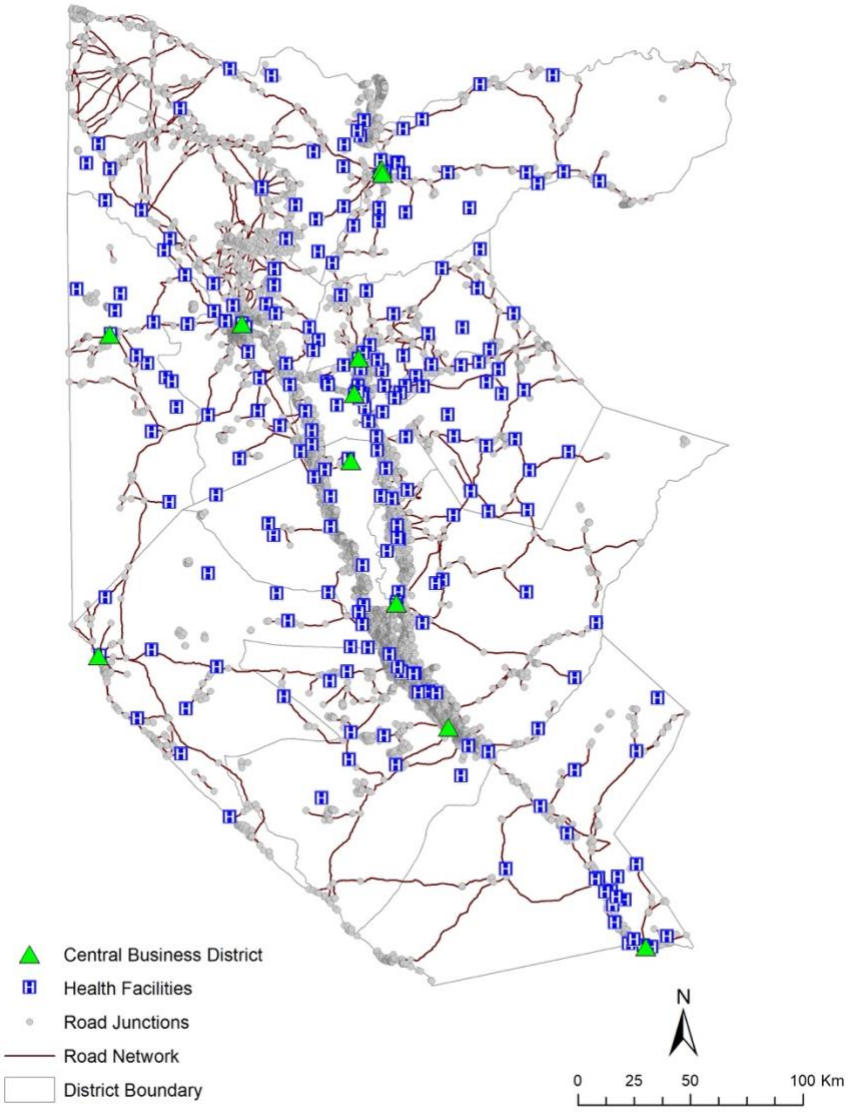


Figure 2.3 GIS-based road network for cost-friction analysis to estimate the distance and travel time to the closest facility from each central business district.

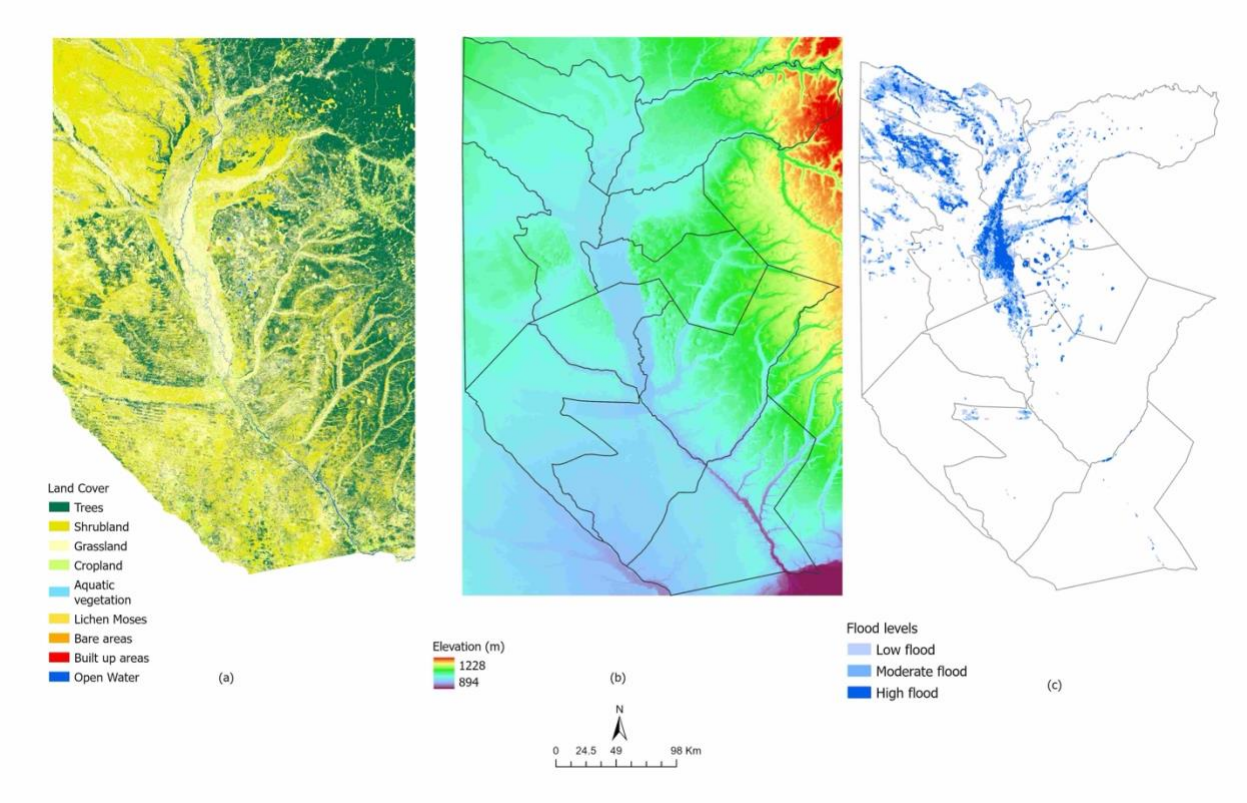


Figure 2.4 The travel impedance features considered in the GIS-based network analysis.

2.4 Results

A total of 221 health facilities were plotted on a static map using latitude and longitude coordinates, and it was observed that most of the Health Centres (n=104) and Health Posts (n=117) were concentrated in and adjacent to the Barotse Floodplain. Further, it was observed that health facilities resided along the Barotse River, and the spatial distribution was greater in remote communities (i.e., appearing that remote communities are underserved). The highest concentration of health facilities was observed in the Mongu district, where Mongu, the capital of Western Province, is located. An uneven resource allocation was observed when we assessed health facilities per catchment population (i.e., based on the 2023 census) for the eleven study districts (figure 2.5).

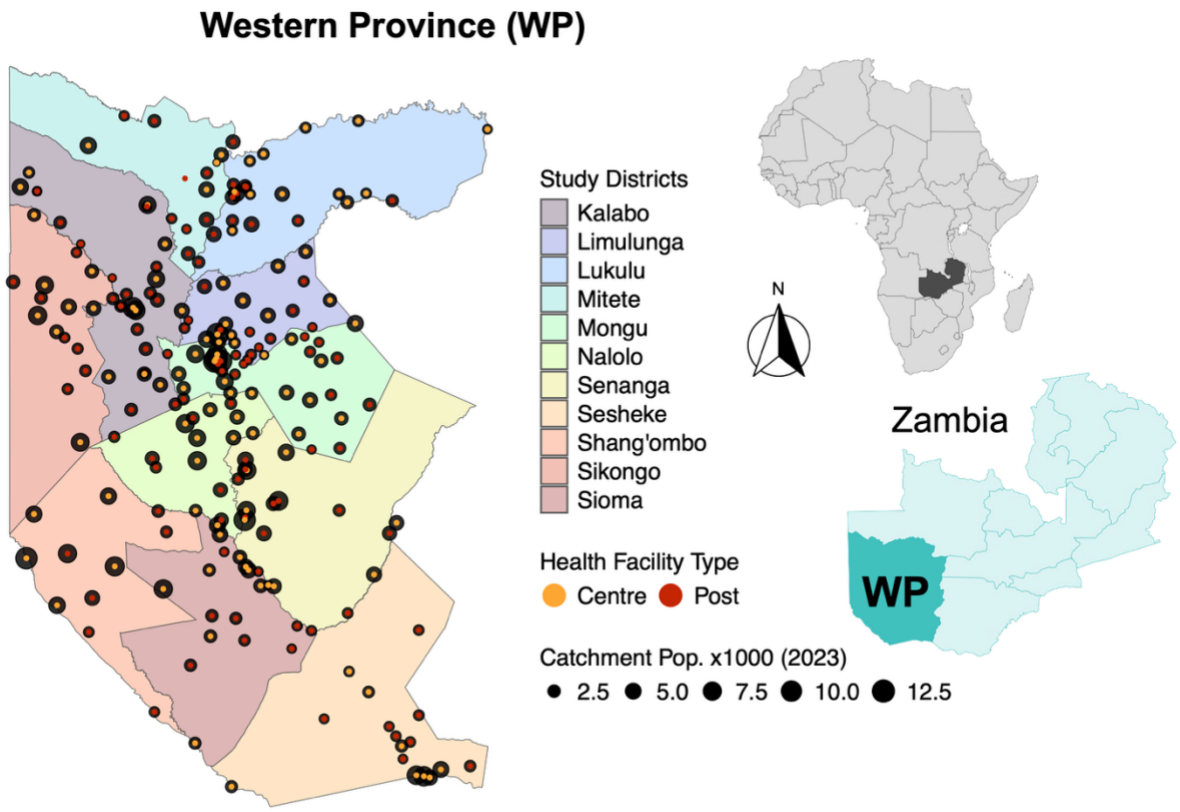


Figure 2.5 Geospatial distribution of study district health facilities by type and catchment population in Western Province (WP), Zambia.

Investigating the physical infrastructure (i.e., the number of health facilities) over time, we noted that there was minimal change during the period between 2000 and 2022; therefore, the number of health centres and health posts was assumed constant. Investigating the historical and predicted changes in total physical health facilities per 10,000 population, we observed a steady decline from 2000 to 2032 across all study districts (figure 2.6). It was also determined that the districts of Lukulu and Sesheke are projected to have the greatest decline in health facilities per 10,000 by 59.9% and 60.4%, respectively (Table 3). More striking was that all study districts are projected to witness a double-digit decline in total health facilities per 10,000 population by 2032 (table 2.4).

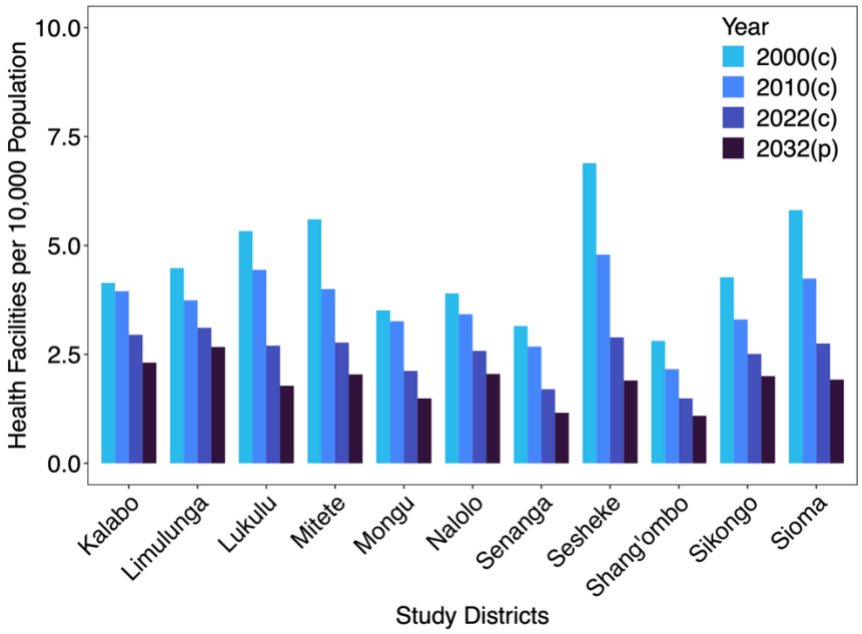


Figure 2.6 Total number of health facilities per 10,000 population by census year © and projections (p) for each of the study districts.

Table 2.4 Historical and projected percent change of total health facilities (Health Centres plus Health Posts) per capita by study district. Historical values were based on census data (c), and projected (p) values on district population growth rates.

	Percent Change (%) of Health Facilities Per Capita			
Study Districts (n=11)	**2000-2010 (c)**	**2010-2022 (c)**	**2022-2032 (p)**	**2000-2032**
Kalabo	-4.48	-25.34	-21.88	-41.68
Limulunga	-16.34	-16.96	-14.26	-28.80
Lukulu	-16.73	-39.21	-34.05	-59.91
Mitete	-28.53	-30.71	-26.31	-48.94
Mongu	-7.21	-34.87	-29.79	-54.27
Nalolo	-12.31	-24.54	-20.73	-40.18
Senanga	-14.87	-36.69	-31.79	-56.81
Sesheke	-30.49	-39.65	-34.36	-60.39
Shang'ombo	-23.10	-31.16	-26.67	-49.52
Sikongo	-22.78	-23.81	-20.34	-39.31
Sioma	-27.10	-35.18	-30.13	-54.71
Averages	**-18.54**	**-30.74**	**-26.39**	**-48.59**

When we assessed health facilities (i.e., number and type), we observed that the Sesheke district had the most total facilities (8.35 per 10,000 population) and the Shang'ombo district had the least (3.70 per 10,000 population). Regarding health facility allocation, we observed that the districts of

Lukulu, Sesheke, and Sioma had the most Health Centres. In contrast, the districts of Limulunga, Sesheke and Sioma had the most Health Posts (figure 2.7).

The results of our four unimpeded travel distance models revealed that the minimum and maximum average estimated travel walk time from a CBD to a health facility took between 6.64 (law of cosines) and 13.9 hours (Minkowski, $p = 1$ or Manhattan) respectively. Overall, the law of cosines model resulted in the shortest average estimated walk times, whereas Minkowski with an integer of $p = 1$ (i.e., Manhattan) resulted in the longest average estimated walk times. Of the study districts, the shortest average estimated walk times, based on the law of cosines model, were observed for Nalolo (6.64 hours), Sikongo (6.67 hours), and Limulunga (6.71 hours), whereas the longest average estimated walk times were observed for Sesheke (9.81 hours), Shang'ombo (9.12 hours), and Kalabo (11.45 hours) (figure 2.8).

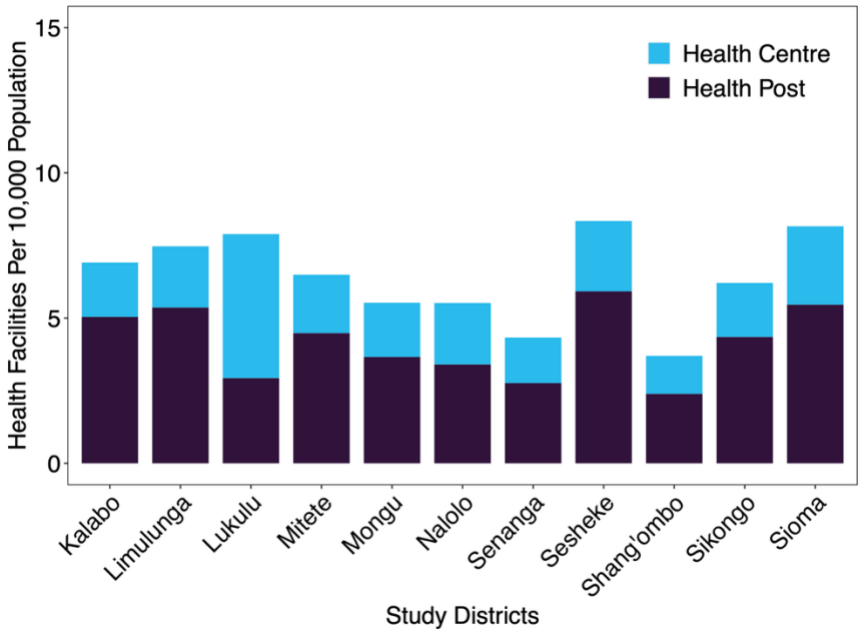


Figure 2.7 Number and type of health facilities per 10,000 catchment population.

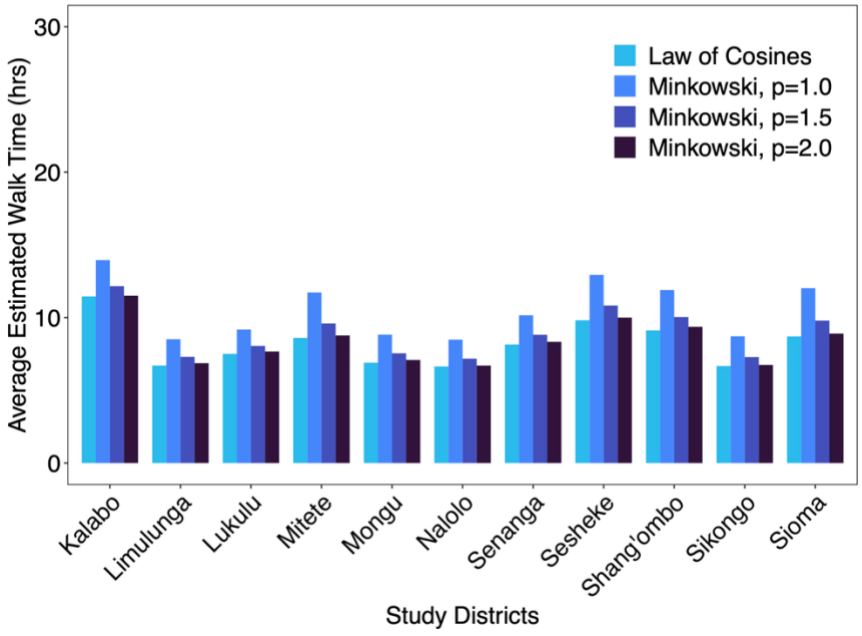


Figure 2.8 Modelled average unimpeded estimated walk time from a CBD to a health facility by study district.

Based on the law of cosines model, it was determined that the average estimated travel time from a central point of the CBD to a health facility took longer for Health Posts (8.66 hrs) than Health Centres (7.74 hrs). It was determined that the average estimated travel time to a Health Post for the Nalolo district took the longest (13.32 hrs). The shortest average estimated travel time from a CBD to a Health Centre or a Health Post was 4.81 hrs and 5.07 hrs for the districts of Nalolo and Lukulu, respectively (table 2.5). While standardized benchmarks for acceptable walking time to health facilities can vary depending on context, travel times exceeding 1-2 hours are often considered a significant barrier to access in many public health assessments. Our estimated average walk times, ranging from 6.64 to 13.32 hours, suggest substantial geographic impedance to accessing health facilities for populations relying on walking as their primary mode of transport in the study area.

The results from the impedance and GIS-based network analysis provided a similar finding. On average, the distance between a CBD and its closest facility was 32 km, having a travel time of 6.4 hours. The shortest average estimated travel time from a CBD to a health facility was 3.5 minutes (i.e., Sikongo Police Station to the Sikongo Rural Health Centre), and the longest estimated travel time was 88 minutes (i.e., Mongu Post Office to the Nalolo District Hospital). Based on the existing available road network, geophysical impedance imposed, and the distance cost cut-off applied, health facilities (i.e., health centers and posts) within a reasonable walking distance (<10 km) were found for only four CBDs (Lukulu District Health Office, Mongu Post Office, Nalolo District Hospital, and Sikongo Police Station).

Table 2.5 Estimated unimpeded average (avg.) travel walk time from a CBD to a health facility calculated using the law of cosines distance model.

Study Districts (n=11)	Health Centres avg. hrs (n)	Health Posts avg. hrs (n)	Totals avg. hrs (n)
Kalabo	8.50 (12)	13.32 (19)	11.45 (31)
Limulunga	6.57 (9)	6.83 (10)	6.71 (19)
Lukulu	9.76 (13)	5.07 (12)	7.51 (25)
Mitete	8.90 (3)	8.49 (8)	8.60 (11)
Mongu	6.26 (20)	7.57 (19)	6.90 (39)
Nalolo	4.81(9)	8.69 (18)	6.64 (17)
Senanga	7.82 (8)	8.41 (10)	8.15 (18)
Sesheke	9.77 (9)	9.86 (10)	9.81 (19)
Shang'ombo	8.38 (6)	10.22 (4)	9.12 (10)
Sikongo	6.66 (7)	6.68 (8)	6.67 (15)
Sioma	9.32 (8)	8.16 (9)	8.71 (17)
Total Avg.	**7.74 (104)**	**8.66 (117)**	**8.22 (221)**

When we assessed the supply-side condition of highly qualified personnel (HQP), it was determined that Community Health Workers (CHWs) were the most common providers of essential healthcare services for Health Centres and Health Posts, while nurses were the second most common (figure 9a, b). Our analysis also revealed that, excluding district medical directors (primarily administrative), the total number of doctors was 2 for all 221 health facilities across the eleven study districts. When HQP was expressed per 10,000 population, it was determined that Kalabo (3.85), Lukulu (5.38) Nalolo (4.84), and Sioma (4.31) had the greatest supply of staff for Health Centres (figure 2.9c). When we analyzed HQP per 10,000 population for Health Posts, it was determined that the districts of Mitete (5.54), Nalolo (6.03), and Sesheke (3.91) had the greatest supply of staff who provided essential healthcare services (figure 2.9d).

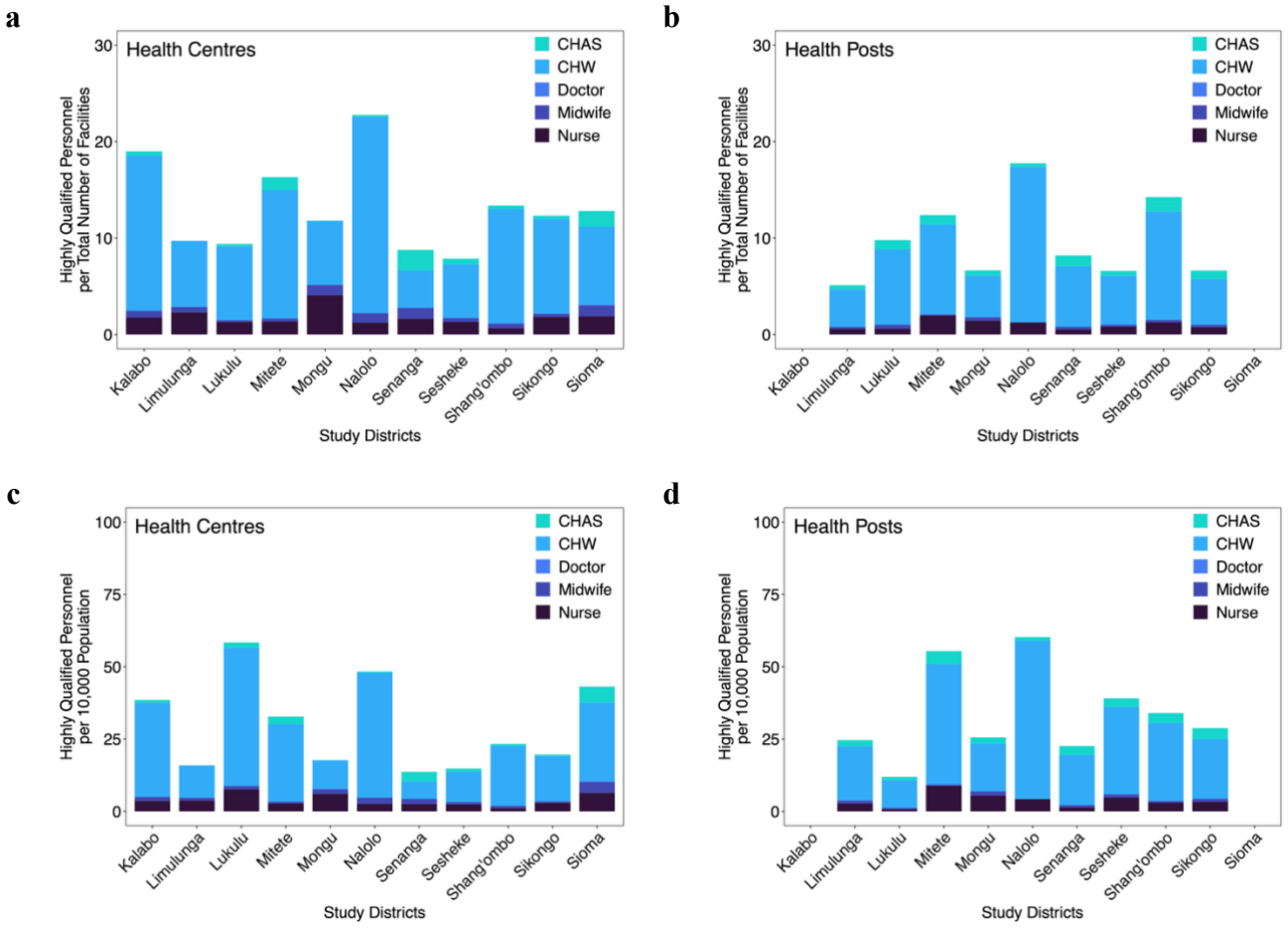


Figure 2.9 Highly qualified personnel (HQP) by study district. (a) Total number of highly qualified personnel per total number of Health Centres, (b) Total number of highly qualified personnel per total number of Health Posts, (c) Total number of highly qualified personnel per 10,000 population staffed at Health Centres, and (d) Total number of highly qualified personnel per 10,000 population staffed at Health Posts. Community Health Assistants (CHAs) and Community Health Workers (CHWs). CHW is an overarching category of positions and includes CHAs and community health volunteers (CHVs). The CHW is a paid position and requires six to twelve months of training. The CHVs may receive a stipend, require six weeks of training, and report to CHAs.

2.5 Discussion

This study empirically evaluated key dimensions of access to essential healthcare services in rural Western Province, Zambia, using a health systems framework in the context of space and time. Our findings highlight significant challenges related to the availability of physical facilities per capita, projected to decline substantially by 2032. Furthermore, the estimated long travel times by walking emphasize the considerable geographic barriers faced by the population. The distribution and type of highly qualified personnel also indicate potential disparities in the availability of skilled healthcare providers.

We present a case highlighting the health systems approach to access in the lower-middle-income country of Zambia. Our study investigated potential explanatory variables that could be used in empirical studies to measure components of the health systems approach. Results from the present study facilitated the identification of potential explanatory variables that could be used in advanced statistical and econometric modelling techniques to empirically measure the health systems approach of the concept of access, including health service utilization (i.e., underutilization, maximum benefit, or overutilization). We identified and classified potential explanatory variables as supply- or demand-side conditions in space and time dimensions. In the context of space, the supply-side conditions that we found relevant for measuring health system utilization include the number and type of health facilities and the number and type of HQP. In the context of time, we found that supply-side conditions may include the change in the number and type of health facilities and HQP. For health system planning and preparedness, resource allocation is crucial. In our study, the number of physical facilities did not change during the past two decades; however, the population increased, resulting in a decrease in facilities per capita. Future investigation would be to statistically model utilization rates to determine if the resource allocation is associated with underutilization resulting in less-than-ideal health outcomes.

Demand-side conditions in the context of space may include the size of the catchment population, mode of transportation (i.e. walking), travel distance, and travel barriers (e.g., lack of road networks or climate change events, such as flooding). Recommended variables that may be

sensitive to time and related to demand-side conditions may include the change in the size of the catchment population and the change in the type of travel barriers (e.g., dry season versus wet season). For example, Schuurman and colleagues employed a vector-based GIS network analysis to model catchment populations in non-urban areas based on travel time in rural British Columbia.[117] Schuurman and colleagues found that their modelling tool was useful for defining true catchment and travel time to specific health services.[117] Investigating the impacts of variation in seasonal flooding in the Barotse Floodplain of Western Province, Mroz and colleagues found that the changes in the monthly distribution of floodwaters negatively impacted access to health facilities.[54] Investigating the geographical access to maternal health facilities in Mozambique, Makanga and colleagues found that variation in seasonality was an important consideration when evaluating access to health facilities for maternal care.[101] In our study, we developed a series of unimpeded travel models with the aim of estimating best-case walk travel time from the CBD to a health facility. In a similar study, Shahid and colleagues found that the Euclidean (Minkowski, $p = 2$) and Manhattan (Minkowski, $p = 1$) metrics tend to underestimate and overestimate road distance and travel time respectively.[118] Our findings are consistent with prior literature, which empirically supports our access framework and the explanatory variables that we have proposed that may be key metrics for assessing utilization.

Despite the challenges in conducting a GIS-based network analysis to find the travel time between CBDs and health facilities with geographic impedance, we have employed open-source spatial datasets to understand the health accessibility in the study area. Our findings suggest that although the study area's land use and cover and elevation are relatively homogeneous, a substantial travel time between each CBD and health facilities is noted due to a dilapidated road network. We found that the travel time for most CBDs was over 1 hour, which was consistent with the findings from the past study in Zambia, which suggested that less than 25% of the population resides within 15 km (or 3 hours of travel time by walking) from critical health services.[107] However, our GIS analysis is not without limitations. It is important to note that the closest facility analysis employed in this study was based on the publicly available geospatial datasets. Although the sources of these datasets have been carefully selected to maintain the highest quality and reliability, a variation in results could be found in studies that aimed to generate geospatial datasets.

Although our results yielded discrete supply- and demand-side explanatory variables relevant to our study setting, these variables may be important considerations in contexts outside of lower-middle-income countries. For example, our study setting was in remote communities of Western Province, where greater than 90% of the population resides and where the dimensions of space and time may present numerous challenges leading to underutilization of the health system. Challenges that may exist in space and time are not unique to Western Province; instead, these challenges are relevant to most rural and remote communities. For example, in a study by Gibson and colleagues, the research objective was to investigate the use of mobile clinics for vulnerable populations where geographic barriers were encountered.[119] In their study, Gibson and colleagues could not accurately measure utilization due to the limited ability to identify other sources of healthcare utilization by the patient before accessing the mobile clinic visitations.[119] This study highlights the importance of the temporal and spatial dimensions when empirically measuring access and health service utilization.[119]

Our study was unique in that we developed a unified concept of an access framework that aimed to provide guidance when investigating health service utilization. A strength of our research study is that we critically analyzed a tranche of literature to distill the concept of access into three approaches to empirically investigate health service utilization. Our theoretical framework is relevant for countries striving to achieve UHC; however, our study has limitations. First, the explanatory variables we propose as proxies for measuring utilization are not necessarily generalizable to all study contexts. We propose these variables as possible metrics for measuring utilization in rural and remote communities of Western Province, Zambia. Still, the type of HQP, for example, was specific to Zambia's healthcare system. Second, our questionnaire had some missingness, including geocoordinates, health facility name, and the number of HQP for two study districts. To compensate for the level of missingness, we cross-referenced several variables with the Zambia MFL. Third, our travel models were specific to the study setting, where the Barotse Floodplain is exceptionally flat, and land use is near-homogeneous. In this context, our travel models assumed an average walking speed of 5 km/hr, which is typically used when topographical impedances are void. However, our models did not consider physical barriers, such as variation in seasonal flooding, which are important to consider in other geographical contexts. Fourth, the objective of our study was to highlight the importance of the dimensions of space and time when

investigating the concept of access; however, our study did not explore space and time variables using geospatial analysis. Geospatial analysis, using various techniques, would add great value when empirically evaluating access and utilization of essential health services in rural and remote communities. Arambepola and colleagues (2021) employed advanced geospatial models to investigate children's vaccine coverage in the lower-middle-income country of Zambia.[120] Further, the geospatial models developed by Arambepola and colleagues (2021) identified that greater than 25% of children had not received certain vaccines.[120] This study highlights that when investigating the concept of access, it is crucial to evaluate it empirically, and geospatial modelling is one additional technique that permits fine-scale analysis to accurately predict utilization.[120] Finally, our concept of access framework is theoretical, and we have only identified potential explanatory variables. Future research will investigate these explanatory variables with the dependent variable as health system utilization (e.g., vaccinations) using advanced regression and econometric modelling techniques.

2.6 Conclusion

The objective of this study was to identify and evaluate potential explanatory variables that can be used to empirically measure access within a health systems framework, using the rural and remote communities of Western Province, Zambia, as a case study. Our findings go beyond a theoretical discussion by providing concrete evidence of the barriers to achieving UHC in the context of a lower-middle-income nation. We empirically demonstrated that the availability of health infrastructure, specifically the number of health facilities, is severely strained per capita.

The implications of our findings highlight the critical importance of grounding access frameworks on empirical data. Our analysis revealed significant geographic barriers, including lengthy average walk times to the nearest health facility, which pose substantial obstacles for communities that depend on walking as the primary mode of transportation. Furthermore, our assessment of highly qualified personnel indicated a system heavily dependent on CHWs and nurses, who serve all health facilities in the study districts. These findings—the facility-to-population ratio, travel times, and healthcare workforce composition—are the key variables this study aimed to identify.

In conclusion, this study supports the health systems approach by using these variables to empirically measure the concept of access. While we acknowledge that no single access framework is universally correct, our research from Western Province, Zambia, highlights that the utility of any framework depends on its application to tangible, context-specific challenges in both space and time. The data from this study provides a clear policy directive: addressing the significant gaps in physical infrastructure, geographic accessibility, and the availability of highly qualified personnel is crucial for the effective operationalization of UHC in Zambia and similar settings.

Chapter 3

Proportions

3.1 Overview

Background Routine Health Information Systems (RHIS) and Health Management Information Systems (HMIS) in sub-Saharan Africa are essential for disease surveillance but often lack reliable population denominators. This limitation hampers the ability to accurately calculate disease rates and monitor trends. Malaria remains a leading cause of illness and death among children under five, and this data gap particularly impacts its surveillance.

Methods To address the lack of denominators in the HMIS, we developed an innovative methodology—spatially defined catchment area (SCSO) and population under rooftop (PUR)—using high-resolution satellite-derived population data to define individual health facility catchment areas. We applied this approach to estimate malaria-confirmed case proportions across 321 health facilities in Western Province, Zambia, from January 2017 to June 2024, using an ecological longitudinal study design. A beta-binomial regression model was utilized to analyze spatial and temporal variations in malaria risk.

Findings The average proportion of malaria-confirmed clinical cases was 6.17% at the facility level and 5.80% at the district level, indicating substantial geographic variability. Children under five years had significantly lower odds of confirmed malaria compared to the general population (OR=0.770, 95% CI: 0.697–0.850), although this pattern varied by district. Strong seasonal trends were observed, with peaks occurring from December to April.

Conclusions Our findings show that integrating satellite-derived population data is feasible for creating denominators used in routine HMIS case data. The SCSO-PUR methodology provides

standardized, population-adjusted metrics that enhance traditional numerator-only reporting and reveal important spatial-demographic disparities in disease risk. This adaptable approach offers a scalable solution to strengthen surveillance for malaria and other health indicators in low- and lower-middle-income countries.

3.2 Introduction

Malaria remains a significant global health challenge, with approximately 249 million cases and 608,000 deaths reported worldwide in 2022.[121,122] Children under five years old in sub-Saharan Africa (SSA) bear a disproportionately high burden of malaria, accounting for over three-quarters of malaria-related mortality.[123,124] In Zambia, malaria continues to be a leading cause of outpatient visits, hospitalizations, and deaths, particularly impacting vulnerable groups such as children and pregnant women.[125] Although considerable progress has been made through preventive interventions—including insecticide-treated nets, indoor residual spraying, and artemisinin-based combination therapies—malaria transmission persists unevenly across geographic regions and demographic groups.[125] This highlights the need for high-quality, spatially defined data and appropriate metrics to inform subnational surveillance and to guide targeted interventions effectively.

Health Management Information Systems (HMIS) are central in tracking disease patterns and informing public health interventions in many low- and middle-income countries, including Zambia.[72,126] However, these systems are primarily designed to report service delivery counts, such as the number of confirmed clinical cases of malaria, effectively only providing the numerator for some epidemiological metrics. A critical gap exists because HMIS lacks the corresponding denominator—population risk—which is required for calculating meaningful rates or proportions that can be used for observing spatial and temporal trends.[127,128] This limitation is well recognized across various disease surveillance contexts, including malaria, immunization coverage, and maternal and child health, undermining global efforts to achieve Sustainable Development Goal (SDG) 3, specifically Target 3.3, which aims to end epidemics of malaria and other communicable diseases by 2030.[85,87,129]

While official sources like the Zambia Master Facility List (MFL) may provide official catchment population estimates from the Central Statistical Office (CSO), these figures often rely on infrequent and outdated census projections, lack fine-scale demographic disaggregation, and may not accurately represent the true populations served by each facility. Therefore, it is impossible to calculate age-specific indicators, such as the proportion of children under five with malaria, using

these data alone. Conversely, modern geospatial datasets, such as Meta's Data for Good High Resolution Settlement Layers (HRSL), provide granular demographic estimates for individual rooftop structures but do not assign these rooftops to any health facility catchment area.[74,75] To address this critical data gap, we developed and applied a novel methodology—the Spatially Defined Catchment Area (SCSO) and Population Under Rooftop (PUR)—that re-engineers catchment areas by synergizing these disparate data sources.

Several strategies address denominator limitations, including census-derived population projections, proximity-based methods like Thiessen polygons, and cost-distance models.[127,128,130–135] While these approaches offer advantages, they often depend on coarse or outdated data, failing to adequately capture dynamic population movements or fine-scale variations in healthcare access.[127] A recent scoping review of methods used to estimate catchment populations highlighted this concern, emphasizing the reliance on numerator-only indicators in SSA and stressing the urgent need for scalable, replicable methods to estimate catchment populations accurately.[127] To address this critical gap, we developed a novel spatially defined catchment area (SCSO) methodology, utilizing high-resolution satellite-derived estimates of population under rooftops (PURs).[74,75] These PURs consist of estimates of population demographics disaggregated by sex (i.e., male or female) and age (children under five years, youth, and women of reproductive age).[74] The SCSO-PUR methodology allocates populations to their nearest health facility, constructing empirically grounded denominators that enable meaningful calculations of disease proportions, such as the proportion of children under five who test positive for malaria within health facility catchments. This method represents a significant advancement from raw numerator counts to standardized, population-adjusted metrics, facilitating valid comparisons across regions, time, and demographic groups.

To address this critical data gap, this study introduces and applies the SCSO-PUR methodology to estimate malaria risk among children under five and the general population across the 16 administrative districts in the Western Province (WP), Zambia. Our method uses official total population counts as a constraint while aggregating detailed, rooftop-level demographic data to construct, for the first time, demographically-stratified denominators for each health facility. In this context, we implement an ecological longitudinal study design with spatial analysis from

January 2017 to June 2024 and apply beta-binomial regression models to rigorously examine spatial-temporal variations in the proportions of malaria-confirmed clinical cases. By demonstrating the application of the SCSO-PUR methodology to generate previously unavailable, population-adjusted health metrics, this research provides an adaptable and generalizable solution applicable across diverse contexts where accurate denominators are lacking, ultimately contributing to health surveillance systems and alignment with SDG 3.3 and 3.8 targets.[86]

3.3 Methods

3.3.1 Study Setting

Zambia is a landlocked country in Southern Africa, with an estimated population of 19.6 million, according to the 2022 census, and a national poverty rate of 60%.[50] Western Province (WP), the largest province by land area, has one of the lowest population densities, with approximately 1.36 million residents, over 80% of whom live in rural and remote areas.[49,50] In 2022, the Zambia Ministry of Health reported that WP had 344 operational health facilities across its 16 administrative districts (figure 3.1).[58,59]

3.3.2 Ethics Approval

Ethical approval for this study was obtained from the University of Waterloo Human Research Ethics Board (ORE-43883), the University of Zambia Biomedical Research Ethics Committee (Ref. No. 2472-2021; renewed February 9, 2024), the National Health Research Authority in Zambia (Ref. No. NHRA000009/10/07/2022), and the Provincial Ministry of Health, Western Province. Permissions were granted for the secondary analysis of de-identified data stored in the national HMIS.

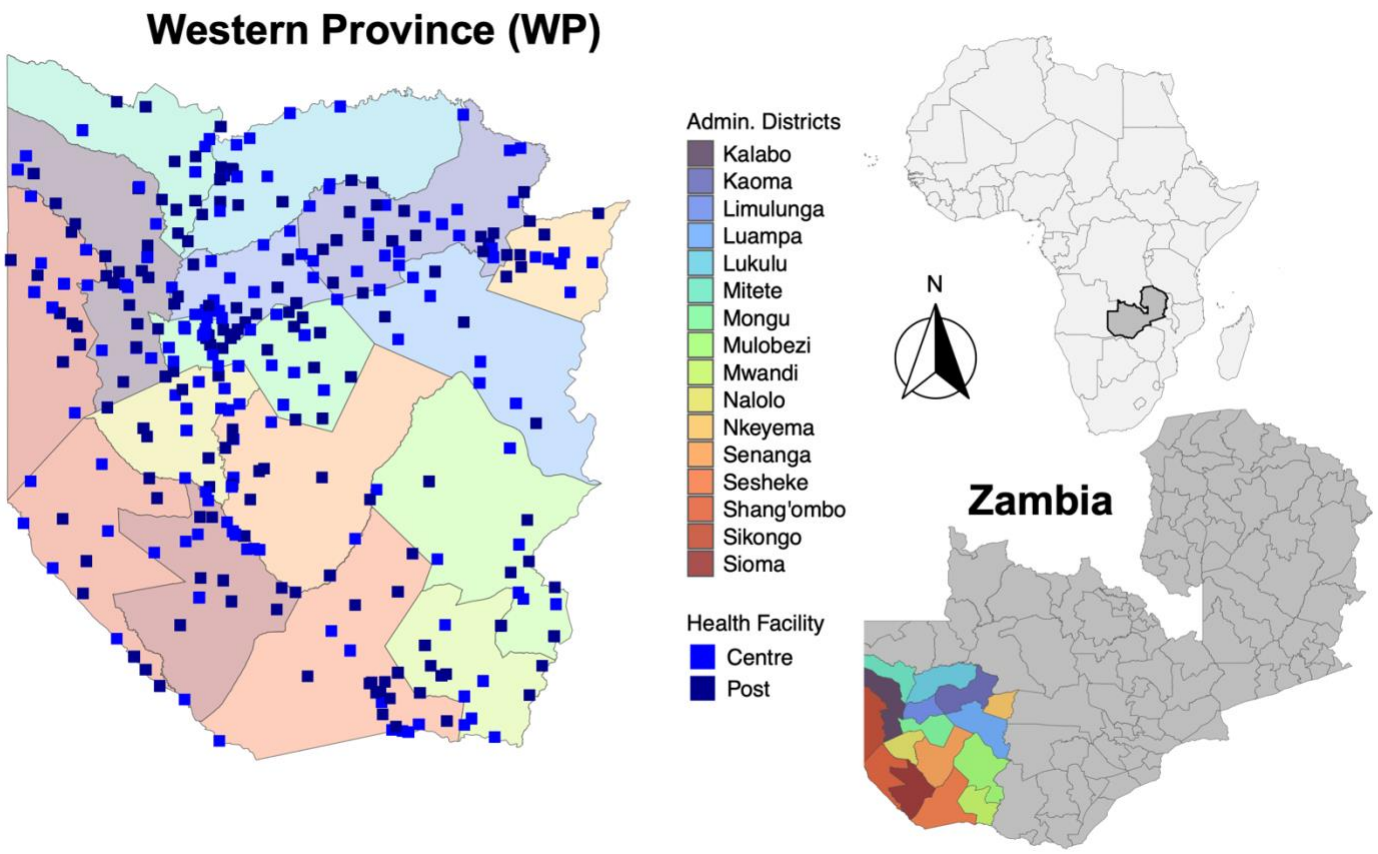


Figure 3.1 Map of health facility locations and administrative boundaries in WP, Zambia.

3.3.3 Data Sources

Data on health facilities, including their geocoordinates and official catchment population estimates, were obtained from the Zambia Master Facility List (MFL) and the Central Statistical Office (CSO), respectively.[51,58] The CSO estimates provided a single total population count for each facility's service area. For the 8.2% of facilities with missing CSO catchment population estimates, values were imputed using k-nearest neighbour (k-NN) single imputation (k=14, k selected based on the correlation of ρ=0.83 between the observed and imputed values). These imputed values were subsequently used as the population constraint (CSO_m) in the catchment definition algorithm.

High-resolution gridded population data were obtained from Data for Good at Meta. These High Resolution Settlement Layers (HRSL) use satellite imagery and census data to create 30×30 m population grid tiles disaggregated by demographic groups, including children under five years of age. For this study, each populated grid tile was treated as a Population Under Rooftop (PUR) unit, providing the detailed demographic building blocks for our analysis. To create a geographic boundary for the study, we used administrative district geocoordinates from Geo-Referenced Infrastructure and Demographic Data for Development (GRID3) to filter the nationwide HRSL dataset to include only PURs located within Western Province.[136] Estimates were adjusted to 2020 baselines using national population totals provided by the United Nations (UN).[137] To harmonize with the 2023 Zambian census, we adjusted the HRSL data using district-specific population growth rates (PGR) through the geometric projection formula: $P_t = P_0(1 + r)^t$ where P_t is the projected population, P_0 is the baseline population, r is the annual growth rate, and t is the time in years.[138] These PGRs were used to project annual PUR estimates for each grid cell for the study period (2017–2024), ensuring that denominators were dynamic over time.

Monthly confirmed malaria clinical case data were extracted from the Zambia Health Information Management System (HMIS) using the District Health Information System 2 (DHIS2) platform.[65] The dataset spanned from January 2017 to June 2024 (90 months) and included confirmed

outpatient malaria clinical cases stratified by health facility for children under 5 years old and the general population.

3.3.4 Spatially Defined Catchment Area (SCSO)

Using spatial proximity and population data, we developed an innovative methodology to estimate individual health facility catchment areas based on the spatial location of PURs. Our five-step approach integrates known variables from the Zambia MFL with the Data for Good HRSL gridded datasets and requires (figure 3.2):[65,74]

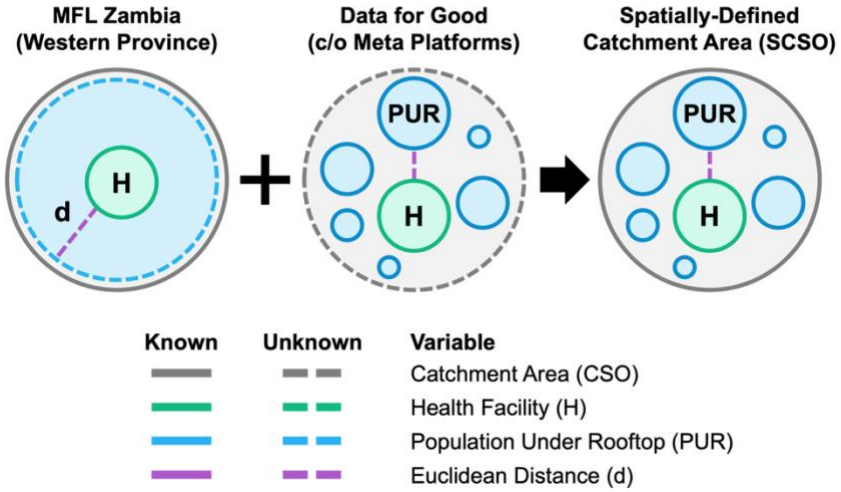


Figure 3.2 Schematic overview of the Spatially Defined Catchment Area (SCSO) and PUR methodology used to generate spatially defined catchment areas for each health facility. The SCSO-PUR methodology integrates facility locations from the Zambia Master Facility List (MFL) with Data for Good's high-resolution population grids.

For the purposes of this methodology, each populated 30×30 m grid cell from the HRSL dataset was treated as an individual PUR unit, characterized by its geocoordinates and disaggregated demographic counts.

Step 1 Data Cleaning and Preparation Geographic coordinates (i.e., latitude and longitude) were cleaned and validated for all health facilities and PURs. Data were filtered by province and district to ensure geographic consistency.

Step 2 Distance Matrix Computation Euclidean distance between each PUR and health facility was calculated using validated geographic coordinates. The distance between a PUR ($\mathcal{P}$) and a health facility (H) was determined by:

$$d(\mathcal{P}_n, H_m) = \sqrt{\left(x_{H_m} - x_{\mathcal{P}_n}\right)^2 + \left(y_{H_m} - y_{\mathcal{P}_n}\right)^2}$$

where $\left(x_{\mathcal{P}_n}, y_{\mathcal{P}_n}\right)$ and $\left(x_{H_n}, y_{H_n}\right)$ represent the geocoordinates (x = longitude and y = latitude) of a PUR and a health facility, respectively. The distances were compiled into a matrix $D = \left[d_{m,n}\right]$ representing the spatial relationship between the health facilities and PURs.

Step 3 Spatial Sorting and Iterative Aggregation For a health facility m, the Euclidean distances to all PURs within its district were sorted in ascending order. Euclidean distance was selected to define proximity-based catchments, as the goal was to spatially allocate rooftops to meet a population target rather than model complex travel behaviour. An iterative summation process was then used to collect the nearest PURs into a spatially defined catchment area ($SCSO_m$) for each facility. The aggregation of PURs continued until the sum of their populations approximated the official CSO catchment population estimate for that facility (CSO_m), within a small tolerance threshold τ to account for data noise.[g] This process effectively disaggregates the single CSO population total into a spatially explicit collection of PURs with detailed demographic characteristics.

Step 4 Assignment of Demand-Side Attributes Each PUR within an $SCSO_m$ included estimated demographic characteristics, including sex (male, female), age groups (children under 5 years, youth aged 15–24 years, and women of reproductive age aged 15–49 years).

[g] The design of the SCSO-PUR methodology is based on the fundamental assumption that the primary population constraint, derived from the catchment population estimates provided by the Central Statistical Office (CSO), is sufficiently precise to serve as the basis for the spatial allocation of Population Under Rooftops (PURs). We recognize that this reliance creates a structural dependency whereby potential misestimation or misallocation of the original CSO totals could introduce systematic bias into the adjusted denominators and consequent health metrics. Although a comprehensive measurement error analysis was beyond the scope of this study, future research will adopt a mixed-methods approach to formally evaluate this bias. Upon estimation, a sensitivity analysis will be performed by perturbing the core CSO denominators (e.g., ±10–20%) to assess the robustness of key findings, such as the spatial heterogeneity of malaria risk.

Step 5 Spatially Defined Output The final output consisted of spatially defined, demographically characterized catchment areas $SCSO_m$ for each health facility. Subsequent healthcare utilization and access equity analyses utilized these catchment areas. This methodology enhances traditional health facility catchment definitions by integrating spatial proximity and demographic representativeness, enabling more precise assessments of service coverage and population needs.

3.3.5 Study Design

An ecological longitudinal study design was employed, incorporating spatial analysis from January 2017 to June 2024. The outcome variable was defined as the proportion of confirmed clinical cases of malaria, calculated by dividing the number of confirmed cases by the population estimate, determined by the SCSO-PUR methodology, for each demographic group (specifically, children under 5 years of age and the general population), aggregated at the health facility level. For this study, health centres and health posts, both rural and urban, were included, resulting in a total of 321 health facilities.

3.3.6 Statistical Analysis

To address seasonal variation, the calendar time was transformed into a continuous variable and included seasonal harmonic terms using sine and cosine transformations:

$$\text{time}_{\sin} = \sin\left(\frac{2\pi t}{12}\right) \text{ and } \text{time}_{\cos} = \cos\left(\frac{2\pi t}{12}\right)$$

Model Justification and Response Variable Handling To account for the proportional nature of the outcome and the evident overdispersion in the data, we employed a beta-binomial regression model with a logit link, using the glmmTMB package in R.[139] The beta-binomial distribution extends the standard binomial by introducing a dispersion parameter that allows the success probability to vary across observations, thereby addressing extra-binomial variability due to unmeasured heterogeneity.[140] This approach was preferred over a binomial generalized linear mixed model (GLMM) based on preliminary modelling that revealed overdispersion. To ensure

the correct specification of the model likelihood, we provided observation-level weights corresponding to the total number of individuals tested at each facility per month. This method preserved the original proportional structure of the data while accounting for varying precision across observations. Given the bounded nature of the outcome variable (proportions in (0,1)), alongside evidence of overdispersion, seasonality, and the inclusion of a random effect variable (i.e., health facilities), we employed a beta-binomial GLMM with a logit link. This was implemented using the generalized linear mixed models template model builder (glmmTMB) package in R within the RStudio.[105,139,141] For the model, let Y_{ijt} denote the count of confirmed clinical malaria cases at a health facility i, district j, for the demographic group k, and time t. Let n_{ijt} represent the estimated PUR (denominator) for that facility-demographic-time combination. The beta-binomial model assumed:

$$Y_{ijt} \sim \text{Beta-Binomial}\left(n_{ijt}, \mu_{ijt}, \theta\right)$$

with:

$$\begin{aligned}\text{logit}\left(\mu_{ijt}\right) = \ & \beta_0 + \beta_1 \cdot \text{district}_j + \beta_2 \cdot \text{demographic}_k + \beta_3 \cdot t \\ & + \beta_4 \cdot \text{time}_{sin} + \beta_5 \cdot \text{time}_{cos} + \beta_6 \cdot \left(\text{district}_j \times \text{demographic}_k\right) + u_i\end{aligned}$$

where $u_j \sim \mathcal{N}(0, \sigma_u^2)$ is a random intercept for the health facility i, representing the unmeasured health facility-level variation. In this model, β_0 the intercept (reference: Kalabo district, general population), β_1 estimates the fixed effects for a district, β_2 estimates the effects of demographic group (children <5 yrs versus the general population), β_3 estimates the effect of the linear time (in months), β_4 and β_5 captures the seasonal variation using sine and cosine terms, and β_6 represents the interaction effects between district and demographic group. The facility-level random intercept accounts for repeated observations within health facilities. The dispersion parameter θ governs the degree of overdispersion in the beta-binomial distribution, where smaller values indicate greater overdispersion. To model overdispersed binomial outcomes, we specified a beta-binomial distribution for the response variable. The probability mass function (PMF) of the beta-binomial

distribution, which forms the basis of the likelihood function used for maximum likelihood estimation, is given by:[139,142]

$$P(Y = y) = \binom{N}{y} \cdot \frac{B(y + \alpha, N - y + \beta)}{B(\alpha, \beta)}$$

where $B(.,.)$ is the beta function, $\alpha = \mu \cdot \phi, \beta = (1 - \mu) \cdot \phi$, and $\phi = 1/\theta - 1$, with θ as the dispersion parameter, this formulation allows the variance of the outcome to exceed the mean, addressing the overdispersion frequently observed in HMIS data. The full likelihood is constructed as the product of PMFs across all n observations:

$$\mathcal{L}(\mu, \theta \mid y, N) = \prod_{i=1}^{n} \binom{N_i}{y_i} \cdot \frac{B(y_i + \alpha_i, N_i - y_i + \beta_i)}{B(\alpha_i, \beta_i)}$$

This likelihood function was maximized using maximum likelihood estimation (MLE) with the glmmTMB package in R to obtain fixed-effect estimates, the facility-level random intercept variance, and the beta-binomial dispersion parameter θ.

Computation of District-Specific Demographic Effects Interaction terms between district and demographic groups allow for district-specific estimation of the effect of being a child under five years old. Odds ratios for children in each district were computed by exponentiating the sum of the main effect for children under 5 years and the respective district-specific interaction coefficient:

$$OR_{\text{children, district}} = \exp\left(\hat{\beta}_{\text{children}} + \hat{\beta}_{\text{district} \times \text{children}}\right)$$

This approach enabled the identification of districts where children under 5 years old had relatively higher or lower odds of confirmed malaria than the general population.

Model Fit and Assumptions We evaluated model fit and diagnostic assumptions using the DHARMa package in R, which conducts simulation-based residual diagnostics for generalized

linear mixed models.[143] The residuals exhibited an approximately uniform distribution, showing no strong evidence of temporal autocorrelation or zero inflation. However, residual plots revealed the presence of heteroscedasticity or non-constant variance of residuals across the predicted range. A slightly curved pattern in the residuals versus fitted values also indicated potential mild misspecification of the linear predictor. Despite these patterns, fixed-effect estimates remained stable, and no violations were deemed severe enough to compromise model interpretability. Additional diagnostic tests confirmed that dispersion and residual uniformity fell within acceptable bounds. Comparison with a standard binomial GLMM revealed significant overdispersion in the data, further justifying the use of the beta-binomial distribution. Lastly, potential multicollinearity among time terms was assessed using pairwise correlation coefficients, with no concerning levels detected. Seasonal harmonic terms and linear time trends contributed independently to model fit, and their inclusion enhanced the residual structure.

Model Selection Maximum likelihood estimation was used to estimate fixed effects, the variance of random intercepts σ_u^2 and the dispersion parameter θ in the beta-binomial regression models.[140] We compared nested and interaction-based models to determine the optimal model structure. This comparison included a simple model with only district and time covariates and three base models featuring distinct interaction terms: Base Model 1 – Demographic × Time, Base Model 2 – District × Time, and Base Model 3 – District × Demographic. Each specification incorporated fixed effects for district, demographic group, and time (linear and harmonic), along with a random intercept for the health facility. Model performance was evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which reward goodness-of-fit while penalizing model complexity. Base Model 3 (District × Demographic) provided the best balance between model fit and parsimony, with an AIC of –76,097.4 and a BIC of –75,792.4. In contrast, Base Model 1 (Demographic × Time) yielded an AIC of –75,720.8 and a BIC of –75,523.0, while Base Model 2 (District × Time) reported an AIC of –75,804.6 and a BIC of –75,507.9. Although the model without interaction terms achieved the lowest AIC and BIC (AIC = –76,173.5; BIC = –75,976.8), it lacked the capacity to examine subgroup effects, particularly district-level differences in malaria risk between children under 5 years and the general population. The final model selected for inference included a District × Demographic interaction. This specification allowed

demographic effects to vary geographically, capturing meaningful spatial heterogeneity in pediatric malaria risk.

Statistical Inference Model coefficients were exponentiated to derive odds ratios (ORs) and 95% confidence intervals. District-specific ORs comparing children under five years to the general population were calculated using linear combinations of main effects and interaction terms. Estimated marginal means (EMMs) and pairwise contrasts were generated using the emmeans package, facilitating the interpretation of within-district comparisons.[144]

Missingness The outcome variable contained substantial missing data, particularly in the child demographic group, where the missing rate exceeded 80% in several districts. In the HMIS source data, missing values were coded as 'NA'; however, the system does not differentiate between a true zero (i.e., no cases reported) and a lack of data entry. We conservatively treated all 'NA' entries as missing to avoid falsely imputing zero incidence. No imputation was performed. Instead, we relied on the default method for handling missing data through listwise deletion in the glmmTMB, which excludes observations with missing outcome or predictor values from the model.[139] A chi-squared test confirmed that missingness was significantly associated with both district and demographic groups ($p < 0.001$), indicating that the data were not Missing Completely at Random (MCAR). However, we assumed a Missing at Random (MAR) mechanism since the missingness was primarily due to observed covariates. The MAR assumption should be interpreted cautiously, as violations could bias findings if missingness is associated with unmeasured determinants such as health system capacity or geographic remoteness. Model estimates should, therefore, be interpreted cautiously, particularly for children under five years, due to the high proportion of missing observations in this subgroup. All statistical analyses were conducted in R (v4.3.1) and RStudio (Version 2024.12.1+563) using the following packages: glmmTMB, TMB, emmeans, and DHARMa.[105,139,141,143–145]

3.4 Results

3.4.1 Study Population and Health Facility Coverage

A total of 321 health facilities across 16 administrative districts in WP were included in the analysis. These health facilities served a combined population of approximately 1.23 million people, including 224,688 children under five years (table 3.1). The number of health facilities per district ranged from 10 in Luampa to 41 in Kaoma. The spatially defined SCSOs and PURs revealed substantial variation in population density and demographic composition across districts. For example, Mitete and Sikongo had the highest average number of children per rooftop (3.30 and 2.03, respectively), suggesting higher concentrations of young children per household structure (figure 3.3).

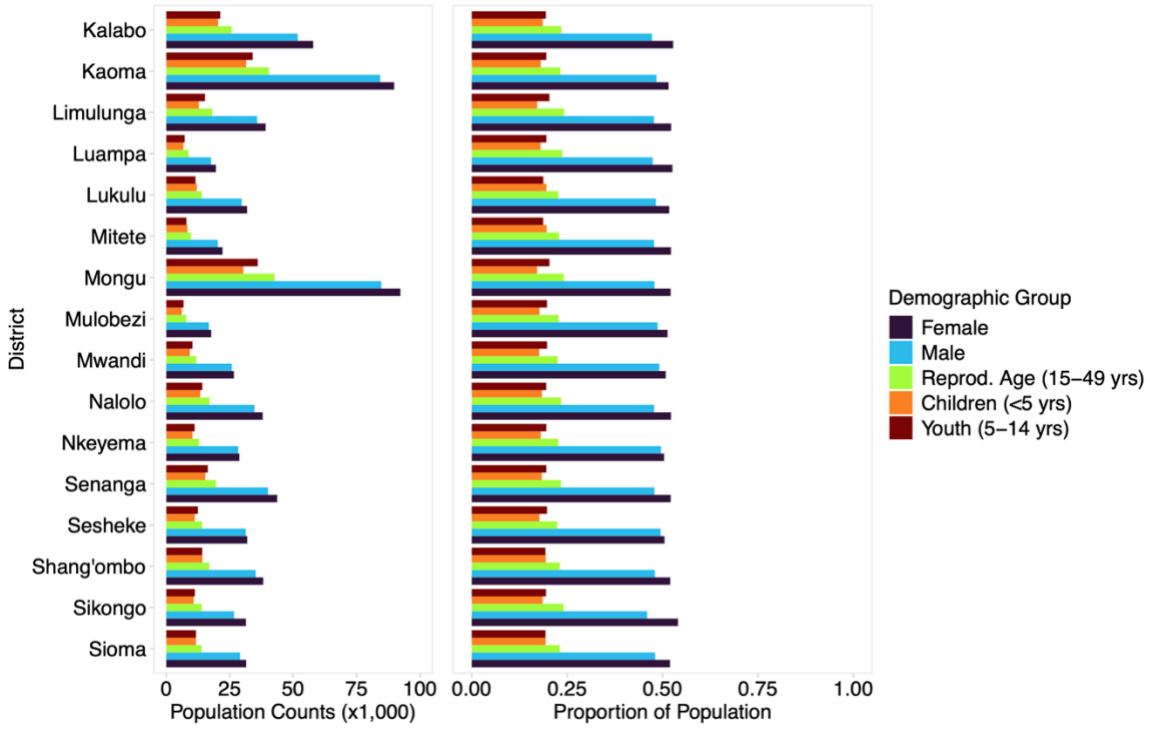


Figure 3.3 Demographic composition of the Population Under Rooftops (PURs) across the 16 administrative districts of WP. The bar chart displays total population counts (left panel) and relative proportions (right panel) by sex and age group.

3.4.2 Demonstration of Spatially Defined Catchment Area

Figure 3.4a presents a random sample of 60 health facilities across WP, each overlaid with their respective SCSOs and PURs, demonstrating the application of the SCSO-PUR methodology. The resulting catchment areas differ in geographic extent and shape, reflecting both the density and distribution of surrounding rooftop populations and variations in facility placement across urban and rural settings. Figure 3.4b provides a detailed view of the SCSO-PUR methodology, utilizing a random subsample of six health facilities. For each facility, the spatial boundaries of the catchment area are displayed alongside the PUR (in this example, the estimated number of children under five). The visualizations reveal compact, densely populated catchments—such as those around the Kaoma Urban Health Centre—and broader, more sparsely populated ones, like the Lui-Wanyau Health Post. These panels illustrate how the SCSO-PUR method considers both spatial proximity and population need, enabling precise characterization of service coverage and establishing a basis for denominator-based health metrics at the facility level.

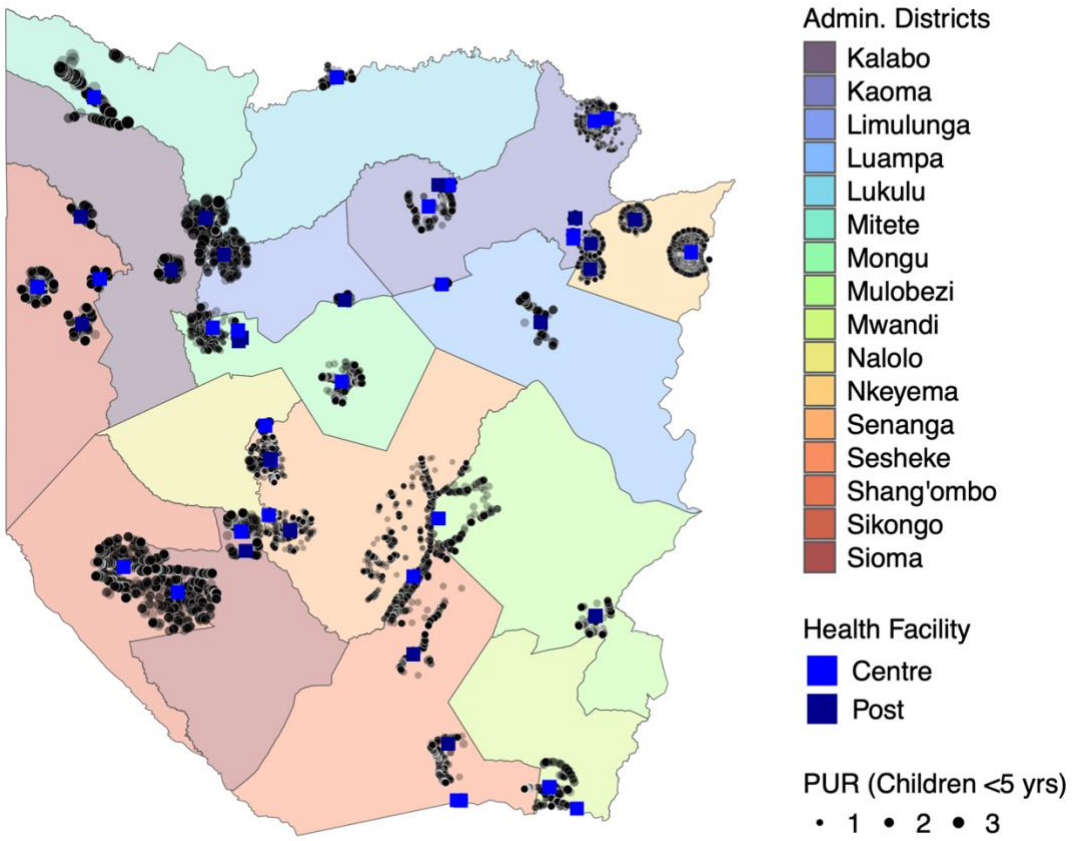


Figure 3.4 Spatially defined catchment areas (SCSOs) for a random sample of 60 health facilities. Each health facility catchment consists of PURs, specifically children under five years old. The figure illustrates the variation in catchment size and shape based on local population density and facility distribution.

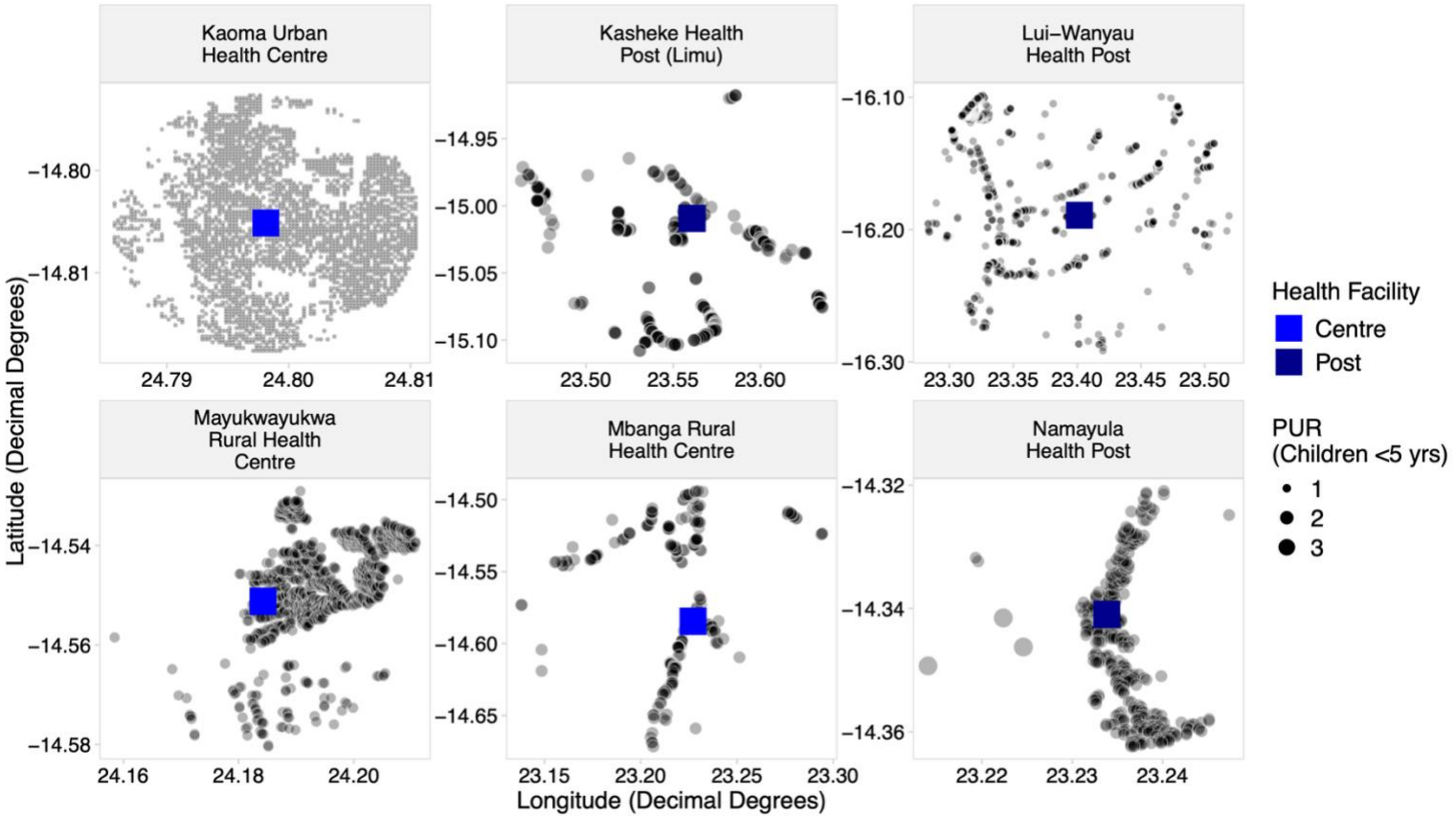


Figure 3.5 Zoomed-in visualization of six randomly selected facilities showing spatially defined catchments. Facilities located in densely populated regions have smaller, more compact catchments, while those in rural areas encompass larger, less densely populated catchment areas.

Table 3.1 Summary statistics for health facilities, demographics, and average Population Under Rooftop (PUR).

			Demographic Group		Population Under Rooftop (PUR)	
Districts (N=16)	**Number of Health Facilities**	**Number of Rooftops**	**General Population**	**Children <5 yrs**	**Ave. General Population**	**Ave. Children <5 yrs**
Kalabo	29	12,662	109,671	20,420	8.66	1.61
Kaoma	41	31,505	174,148	31,501	5.53	1.00
Limulunga	25	7,874	74,922	12,854	9.52	1.63
Luampa	10	5,046	37,237	6,717	7.38	1.33
Lukulu	20	8,188	61,548	12,040	7.52	1.47
Mitete	13	2,525	42,452	8,326	16.81	3.30
Mongu	35	26,541	176,934	30,342	6.67	1.14
Mulobezi	14	5,455	34,486	6,124	6.32	1.12
Mwandi	14	5,357	52,450	9,283	9.79	1.73
Nalolo	17	7,003	72,792	13,404	10.39	1.91
Nkeyema	12	14,339	57,115	10,335	3.98	0.72
Senanga	19	17,482	83,772	15,365	4.79	0.88
Sesheke	22	11,868	63,217	11,213	5.33	0.94
Shang'ombo	14	7,720	73,422	14,248	9.51	1.85
Sikongo	16	5,312	58,074	10,794	10.93	2.03
Sioma	20	7,106	60,551	11,722	8.52	1.65
Totals	**321**	**175,983**	**1,232,791**	**224,688**	**-**	**-**
Averages	**20**	**10,999**	**77,049**	**14,043**	**8.23**	**1.52**

Note: Rooftops refer to satellite-derived estimates of structures indicative of human settlements. Data represent 321 health facilities (Centres and Posts) across 16 administrative districts of Western Province, Zambia. The columns 'Ave. General Population' and 'Ave. Children <5 yrs' represent the district-level average number of people in that demographic category per identified rooftop structure.

Table 3.2 Health facility reporting by district.

District	Health Facilities (n)	Observations (n)	% of Total Observations
Kalabo	29	5,220	9.03
Kaoma	41	7,380	12.77
Limulunga	25	4,500	7.79
Luampa	10	1,800	3.12
Lukulu	20	3,600	6.23
Mitete	13	2,340	4.05
Mongu	35	6,300	10.90
Mulobezi	14	2,520	4.36
Mwandi	14	2,520	4.36
Nalolo	17	3,060	5.30
Nkeyema	12	2,160	3.74
Senanga	19	3,420	5.92
Sesheke	22	3,960	6.85
Shang'ombo	14	2,520	4.36
Sikongo	16	2,880	4.98
Sioma	20	3,600	6.23
Totals	**321**	**57,780**	**100.00**

Note: One observation represents a single health facility-month (i.e., one facility reporting for one month). Health facilities were observed for up to 90 consecutive months (i.e., January 2017 to June 2024). Percentages indicate the share of total observations contributed by each district.

The completeness of health facility reporting comprised 57,780 facility-month observations over 90 months (from January 2017 to June 2024) (table 3.2a). Kaoma, Mongu, and Kalabo provided the most observations, accounting for nearly one-third of the data.

3.4.3 Malaria Risk Across Districts

The overall average malaria-confirmed case proportion was 6.17% at the facility level and 5.80% at the district level (table 3.2b). However, these aggregate figures mask substantial geographic heterogeneity. Lukulu (10.56%) and Luampa (9.99%) had the highest mean malaria-confirmed proportions at the facility level, while Mwandi (2.11%) and Nalolo (3.97%) recorded the lowest. This pattern persisted at the district level, with Lukulu and Luampa again reflecting the highest risk (10.85% and 9.62%, respectively). In contrast, Sesheke (3.39%), Shang'ombo (3.14%), and Mwandi (2.14%) exhibited consistently lower proportions.

3.4.4 Predictors of Malaria Risk

Results from the beta-binomial regression model demonstrated significant spatial, temporal, and demographic variations in malaria-confirmed cases (table 3.3a). Compared to Kalabo (Ref.), individuals in Luampa (OR = 1.977; 95% CI: 1.313–2.978; p= 0.001) and Lukulu (OR = 1.861; 95% CI: 1.342–2.580; $p < 0.001$) had significantly higher odds of confirmed malaria. In contrast, significantly lower odds were observed in Mwandi (OR = 0.315; 95% CI: 0.204–0.486; $p < 0.001$), Nalolo (OR = 0.666; 95% CI: 0.469–0.946; $p = 0.023$), and Sesheke (OR = 0.664; 95% CI: 0.469–0.940; $p = 0.021$). Demographic differences were also significant. Children under five years had 27% lower odds of malaria-confirmed cases than the general population (OR = 0.770; 95% CI: 0.697–0.850; $p < 0.001$), even after adjusting for district, seasonality, and time. Temporal effects were pronounced. Seasonal harmonic terms were significant, with the sine term (OR = 1.996; 95% CI: 1.957–2.036; $p < 0.001$) and cosine term (OR = 1.575; 95% CI: 1.548–1.603; $p < 0.001$) capturing strong annual seasonality aligned with known transmission periods. A slight downward linear trend in malaria risk was also detected over time (OR = 0.997; 95% CI: 0.997–0.998; $p < 0.001$).

Table 3.3 Proportions of malaria-confirmed cases by district, summarized at the facility and district levels.

District	Facility-Level				District-Level			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Kalabo	0.0626	0.0231	0.0287	0.1158	0.0601	0.0384	0.0055	0.1571
Kaoma	0.0797	0.0271	0.0265	0.1479	0.0740	0.0490	0.0087	0.1885
Limulunga	0.0734	0.0310	0.0157	0.1672	0.0671	0.0449	0.0089	0.1595
Luampa	**0.0999**	0.0221	0.0599	0.1270	**0.0962**	0.0724	0.0054	0.2969
Lukulu	**0.1056**	0.0530	0.0427	0.2636	**0.1085**	0.0575	0.0287	0.2652
Mitete	0.0659	0.0206	0.0405	0.1089	0.0651	0.0323	0.0151	0.1520
Mongu	0.0531	0.0373	0.0062	0.1365	0.0568	0.0437	0.0071	0.1973
Mulobezi	0.0630	0.0278	0.0197	0.1032	0.0577	0.0579	0.0018	0.2418
Mwandi	**0.0211**	0.0183	0.0036	0.0597	**0.0214**	0.0220	0.0019	0.0952
Nalolo	0.0397	0.0190	0.0098	0.0814	0.0384	0.0309	0.0019	0.1204
Nkeyema	**0.0812**	0.0377	0.0339	0.1521	**0.0767**	0.0484	0.0091	0.1984
Senanga	0.0585	0.0269	0.0117	0.1051	0.0583	0.0468	0.0042	0.1797
Sesheke	0.0410	0.0320	0.0053	0.1360	0.0339	0.0375	0.0013	0.1586
Shang'ombo	0.0331	0.0214	0.0028	0.0724	0.0314	0.0288	0.0006	0.1162
Sikongo	0.0467	0.0203	0.0139	0.1069	0.0405	0.0269	0.0031	0.1276
Sioma	0.0479	0.0303	0.0143	0.1398	0.0425	0.0356	0.0041	0.1575
All Districts	**0.0617**	**0.0360**	**0.0028**	**0.2636**	**0.0580**	**0.0493**	**0.0006**	**0.2969**

Shading reflects the average malaria-confirmed case proportion:
Low (≤ 0.03) Moderate (0.031–0.07) High (> 0.07)
Bold values highlight the highest district- and facility-level mean proportions.

Note: Facility-level values reflect the average malaria-confirmed case proportions for each facility across all observed months (i.e., 90 months between the period January 2017 to June 2024. District-level values represent average monthly proportions aggregated across all facilities. All Districts reflects unweighted pooled summaries across the study area.

Table 3.4 Adjusted effects of district, demographics, and time on the odds of confirmed malaria cases.

Predictor	Estimate	OR	95% CI	P value
(Intercept)	-2.879	0.056	(0.045, 0.069)	<0.001 ***
District				
Kalabo (Ref.)	-	1.000	-	-
Kaoma	0.253	1.288	(0.968, 1.713)	0.082
Limulunga	0.255	1.291	(0.949, 1.756)	0.104
Luampa	0.682	**1.977**	(1.313, 2.978)	0.001 **
Lukulu	0.621	**1.861**	(1.342, 2.580)	<0.001 ***
Mitete	0.140	1.151	(0.781, 1.695)	0.478
Mongu	-0.198	0.820	(0.613, 1.097)	0.182
Mulobezi	0.151	1.163	(0.805, 1.680)	0.422
Mwandi	-1.155	0.315	(0.204, 0.486)	<0.001 ***
Nalolo	-0.407	0.666	(0.469, 0.946)	0.023 *
Nkeyema	0.306	**1.358**	(0.922, 1.999)	0.121
Senanga	0.032	1.033	(0.739, 1.444)	0.849
Sesheke	-0.410	0.664	(0.469, 0.940)	0.021 *
Shang'ombo	-0.680	0.507	(0.338, 0.759)	0.001 **
Sikongo	-0.348	0.706	(0.493, 1.012)	0.058
Sioma	-0.292	0.747	(0.530, 1.051)	0.094
Demographic				
General Population (Ref.)	-	1.000	-	-
Children under 5 years	-0.261	0.770	(0.697, 0.850)	<0.001 ***
Time	-0.003	0.997	(0.997, 0.998)	<0.001 ***
Sine (Seasonal)	0.691	1.996	(1.957, 2.036)	<0.001 ***
Cosine (Seasonal)	0.455	1.575	(1.548, 1.603)	<0.001 ***

Shading reflects the adjusted odds ratio (OR):
Strong protective (< 0.70) Neutral (0.70–1.30) Elevated risk (> 1.30)
Bold text highlights the highest ORs of confirmed malaria.

OR = Odds Ratio; CI = Confidence Interval; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
Reference categories (*Ref.*): *Kalabo district* and *general population*.

Model: Beta-binomial regression using *glmmTMB*; **Link function:** Logit; **Family:** Beta-binomial; **Random intercept: (health facility):** Variance = 0.3166; SD = 0.5627; **Intraclass Correlation Coefficient (ICC):** 0.088; **Dispersion parameter:** 0.0612; **Model fit:** AIC: -76097.4, BIC: -75792.4; **Log-likelihood:** 38085.7; **Deviance:** -76171.4; **Residual degrees of freedom:** 28018.

Note: Odds ratios and 95% confidence intervals derived from a beta-binomial regression model using a logit link. The model includes fixed effects for district, demographic group, and seasonal/time variables, with a random intercept for health facility.

3.4.5 Effect Modification by Demographic and District

A statistically significant interaction was observed between the district and demographic group (table 3.3b), which tests how the pediatric malaria risk varies relative to the reference district, indicating that the overall effect of age was not uniform geographically. In most districts, children under five had significantly lower malaria odds than the general population. For example, children in Mulobezi (OR = 0.400; 95% CI: 0.300–0.534; $p < 0.001$) and Luampa (OR = 0.509; 95% CI: 0.404–0.642; $p < 0.001$) experienced markedly lower odds. However, two districts exhibited a reverse pattern. In Kaoma, children under five had 44% higher odds of confirmed malaria compared to adults (OR = 1.446; 95% CI: 1.289–1.623; $p < 0.001$), and in Mwandi, odds were more than double (OR = 2.094; 95% CI: 1.247–3.518; $p = 0.005$) (figure 3.5). These exceptions suggest localized dynamics that may reflect differences in healthcare access, testing practices, or transmission intensity. District-specific odds ratios comparing children to the general population further reinforced this spatial-demographic heterogeneity (table 3.3c). While most districts showed statistically protective associations for children, the outliers demand targeted programmatic attention.

3.4.6 Temporal and Spatial Trends in Malaria Risk

Modelled temporal trends confirmed strong seasonality in malaria transmission (figure 3.6). Peaks occurred during the wet season months of December through April, with declines during drier periods. Although the amplitude and timing varied, these patterns were consistent across most districts. The general population consistently showed higher predicted malaria risk than children under five, except in Kaoma and Mwandi, where children were at greater risk.

The choropleth map of predicted monthly malaria risk visually summarized the spatiotemporal patterns by demographic group (figure 3.7). Notably, areas of persistent high risk—such as Luampa and Lukulu—exhibited elevated malaria risk across nearly all months. In contrast, low-risk districts like Sesheke and Sioma maintained relatively stable predicted risk levels.

Table 3.5 Interaction effects between district and demographic group on malaria odds. Relative odds ratios for children <5 years compared to the general population of the same district.

Predictor	Estimate	OR	95% CI	P value
Kalabo × General Population (Ref.)	1.000	1.000	-	-
Kaoma × Child	0.369	**1.446**	(1.289, 1.623)	<0.001 ***
Limulunga × Child	-0.327	0.721	(0.610, 0.852)	<0.001 ***
Luampa × Child	-0.675	0.509	(0.404, 0.642)	<0.001 ***
Lukulu × Child	-0.258	0.773	(0.678, 0.880)	<0.001 ***
Mitete × Child	-0.324	0.723	(0.555, 0.943)	0.017 *
Mongu × Child	-0.310	0.733	(0.642, 0.837)	<0.001 ***
Mulobezi × Child	-0.915	0.400	(0.300, 0.534)	<0.001 ***
Mwandi × Child	0.739	**2.094**	(1.247, 3.518)	0.005 **
Nalolo × Child	-0.481	0.618	(0.455, 0.840)	0.002 **
Nkeyema × Child	0.084	1.088	(0.940, 1.259)	0.257
Senanga × Child	-0.600	0.549	(0.422, 0.714)	<0.001 ***
Sesheke × Child	-0.665	0.514	(0.367, 0.722)	<0.001 ***
Shang'ombo × Child	-0.319	0.727	(0.453, 1.164)	0.184
Sikongo × Child	0.006	1.006	(0.796, 1.271)	0.961
Sioma × Child	-0.632	0.531	(0.368, 0.768)	<0.001 ***

Shading reflects the adjusted odds ratio (OR):
Strong protective (< 0.60) Moderate protective (0.60–0.85) Neutral (0.86–1.15) Elevated Risk (> 1.15)
Bold text indicates the highest ORs of confirmed cases of malaria.

OR = Odds Ratio; CI = Confidence Interval; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
Reference group (*Ref.*): *General population* in *Kalabo district*.

Note: Odds ratios represent the statistical interaction effect. A *p*-value tests whether the effect of being a child (<5 years) in each district is significantly different from the effect in the reference district (Kalabo). It does not represent the significance of the final child vs. general population comparison within that district (see Table 3c). Reference group: General population in each district. Estimates derived from the full beta-binomial regression model with interaction terms and using a logit link.

Table 3.6 District-specific odds ratios comparing children <5 years to the general population.

Predictor	OR	95% CI	P value
Kalabo (Ref.)	0.770	(0.697, 0.850)	<0.001 ***
Kaoma	**1.114**	(1.050, 1.181)	<0.001 ***
Limulunga	0.555	(0.485, 0.635)	<0.001 ***
Luampa	0.392	(0.318, 0.484)	<0.001 ***
Lukulu	0.595	(0.546, 0.648)	<0.001 ***
Mitete	0.557	(0.436, 0.712)	<0.001 ***
Mongu	0.565	(0.517, 0.616)	<0.001 ***
Mulobezi	0.308	(0.235, 0.404)	<0.001 ***
Mwandi	**1.613**	(0.969, 2.684)	0.066
Nalolo	0.476	(0.356, 0.636)	<0.001 ***
Nkeyema	0.838	(0.753, 0.933)	0.001 **
Senanga	0.422	(0.331, 0.539)	<0.001 ***
Sesheke	0.396	(0.287, 0.548)	<0.001 ***
Shang'ombo	0.559	(0.353, 0.887)	0.014 *
Sikongo	0.775	(0.626, 0.958)	0.019 *
Sioma	0.409	(0.287, 0.583)	<0.001 ***

Shading reflects the adjusted odds ratio (OR):
Strong protective (< 0.60) Moderate protective (0.60–0.85) Neutral (0.86–1.30) Elevated Risk (> 1.30)

Bold text highlights the highest ORs of confirmed malaria in children <5 years compared to the general population.

OR = Odds Ratio; CI = Confidence Interval; *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
Reference group (*Ref.*): *General population* in each district.

Note: Odds ratios compare children under five years to the general population within each district. These estimates are derived from the full beta-binomial model by combining the main and interaction effects. A *p*-value here tests whether the odds ratio is significantly different from 1.0. Estimates derived from the full beta-binomial regression model with interaction terms and using a logit link.

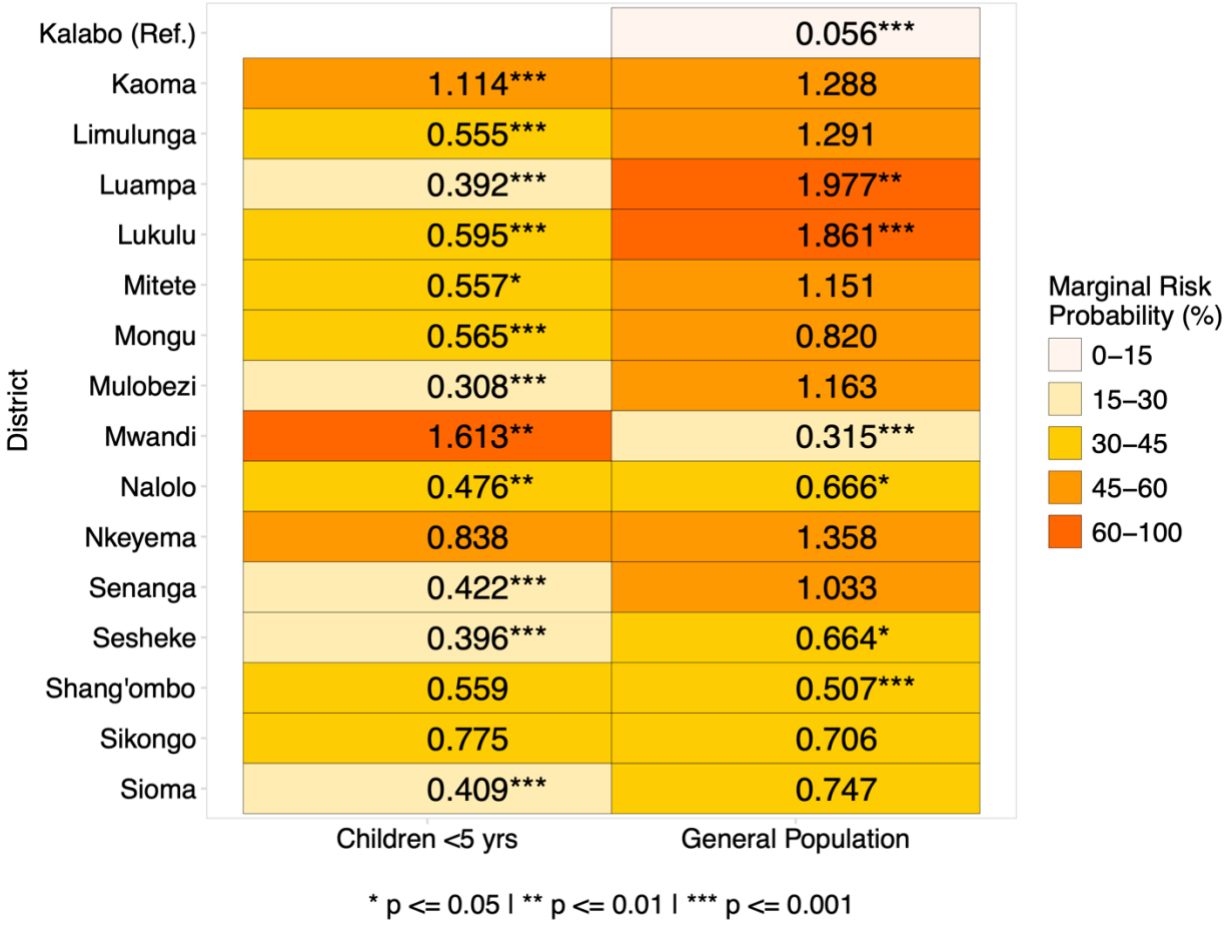


Figure 3.6 Heatmap plot comparing adjusted odds ratios of confirmed malaria cases for children under five years versus the general population across all 16 administrative districts. Odds ratios are derived from a beta-binomial regression model with a district-demographic interaction term. See Table 3.3c for corresponding values and significance levels. Odds ratios are derived from a beta-binomial regression model with a district-demographic interaction term.

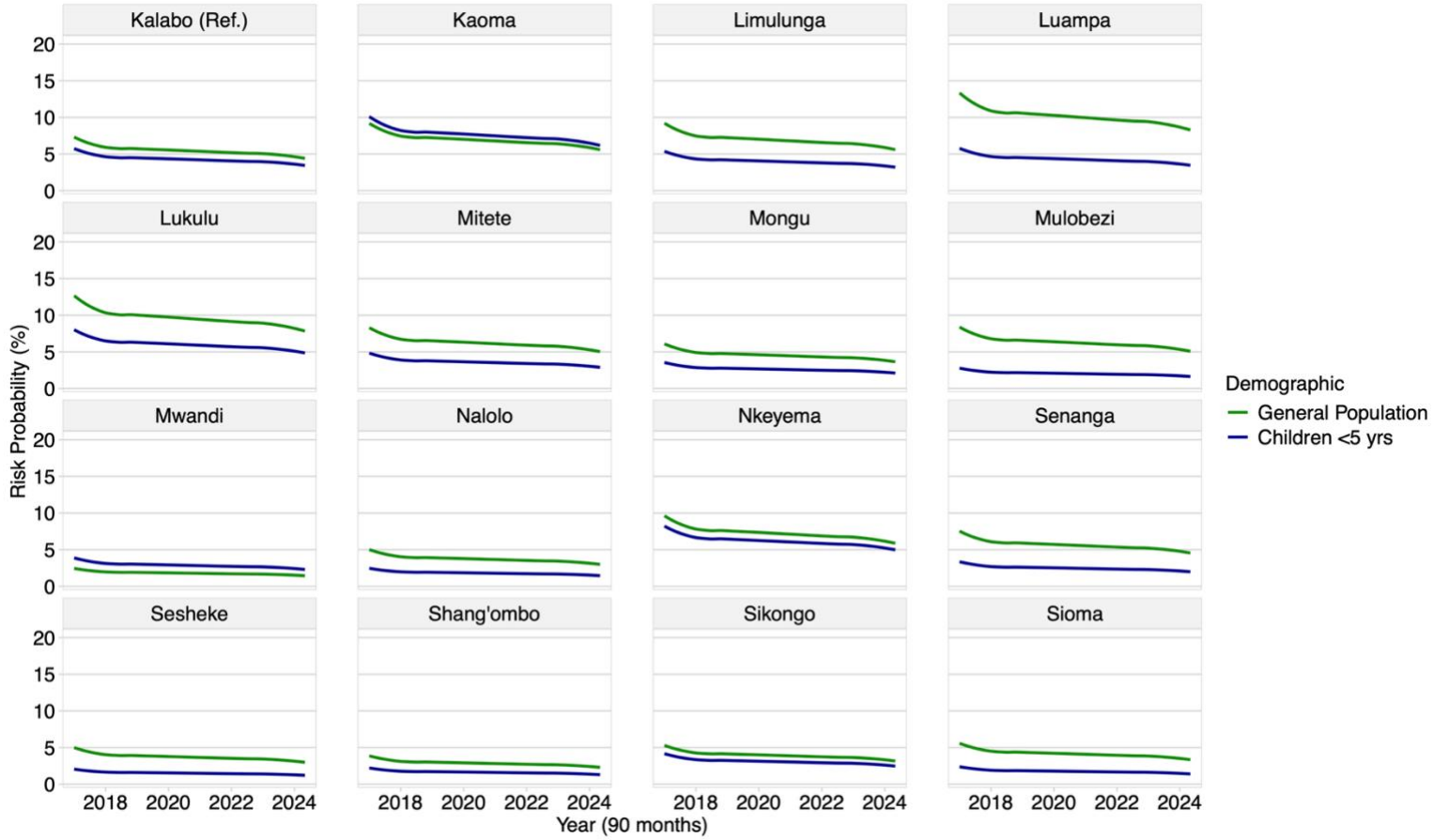


Figure 3.7 Modelled temporal trends in malaria risk by demographic group and district. Time series plots illustrate the predicted risk probabilities of confirmed malaria cases over time for children under five and the general population. Seasonal peaks correspond with known transmission periods (December–April). Each panel represents an individual district.

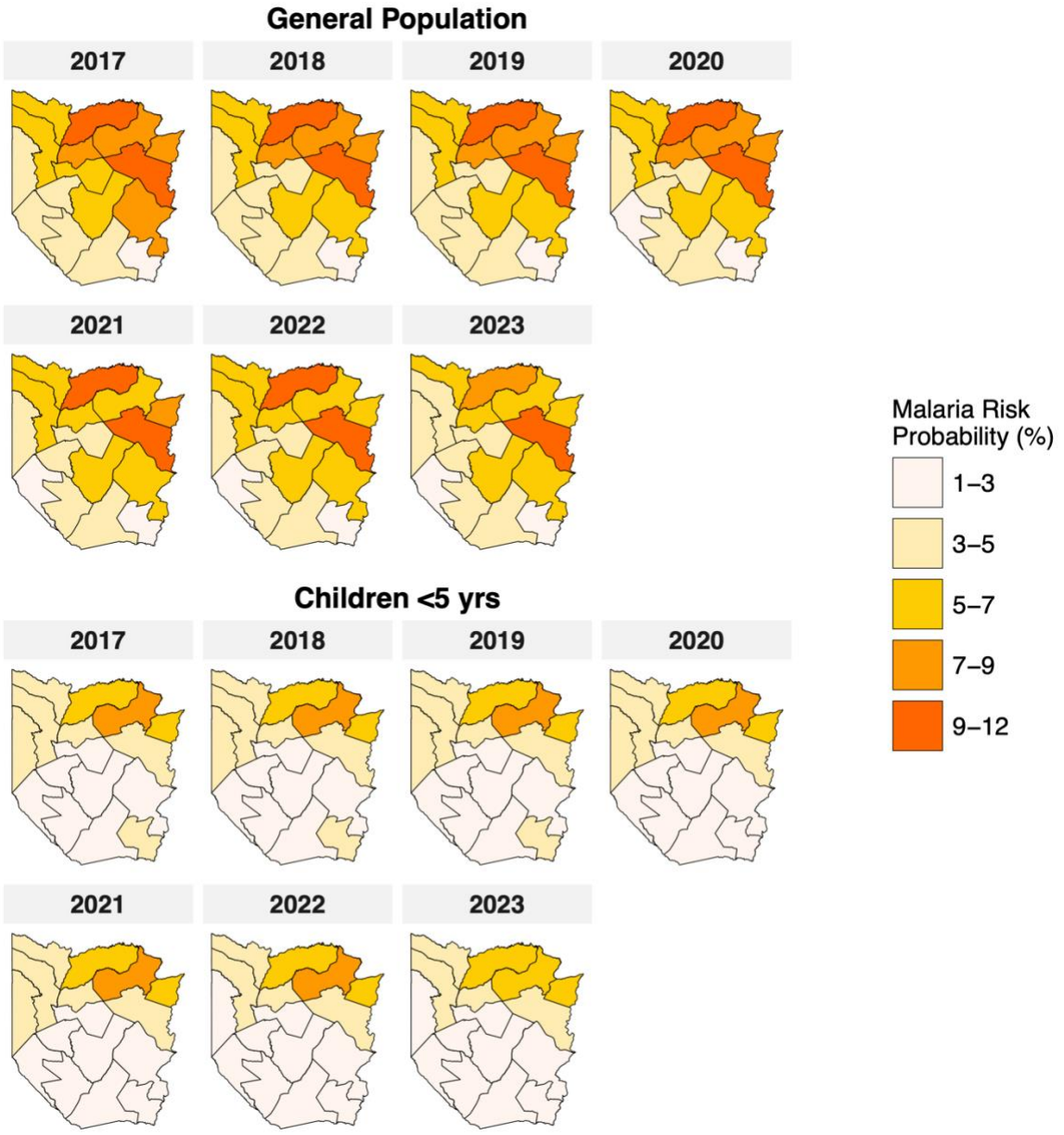


Figure 3.8 Spatiotemporal choropleth map of predicted malaria risk by demographic group and administrative district over time. Warmer colours indicate higher predicted probabilities. Notable demographic differences are observed in Kaoma and Mwandi, where children show increased risk levels.

3.5 Discussion

The central contribution of this study is the development and application of a novel methodology—the SCSO-PUR—designed to resolve a fundamental challenge in public health surveillance: the absence of reliable, disaggregated population denominators in routine health information systems. By applying this method to malaria surveillance data in Western Province, Zambia, we demonstrated its ability to generate previously unavailable, population-adjusted metrics. These metrics, in turn, revealed significant spatial, demographic, and temporal heterogeneity in malaria risk. This included key insights that were previously obscured by numerator-only reporting, such as the significantly lower odds of malaria among children in most districts, but an elevated pediatric risk in outlier districts like Kaoma and Mwandi, underscoring the need for such granular surveillance.

3.5.1 Strengths and Limitations

The primary strength of this study is the development and application of a novel methodology that solves a fundamental denominator problem in routine health surveillance. By creating a scalable process to generate demographically disaggregated denominators where none previously existed for rate calculations, the SCSO-PUR methodology enables a more robust and granular analysis of disease burden from standard HMIS data. Rather than merely refining an existing denominator, our approach creates a usable one by synergizing official, but non-disaggregated, population totals with detailed, but unassigned, geospatial demographic data. This allowed for the calculation of age-specific malaria proportions and odds ratios that were previously impossible to compute, offering critical insights into risk dynamics that numerator-only reporting obscures. This novel methodology effectively addresses a crucial gap identified by Johnson et al. (2025), who emphasized the urgent need for scalable and replicable methods to estimate accurate facility-level denominators.[127,146–148] The SCSO-PUR approach thus aligns strongly with global targets under SDG 3, specifically Target 3.3, which aims to end epidemics of malaria and other communicable diseases by 2030.[149] Critically, the methodology demonstrated in this study is both scalable and adaptable, allowing for direct integration into existing HMIS platforms such as District Health Information Software 2 (DHIS2). However, practical implementation will require addressing

several technical considerations, including computational demands, GIS expertise, and the regular updating of geospatial population data.[146,147,150–153] We demonstrated the use of the SCSO-PUR method using the case of malaria surveillance, but our approach provides a methodology that is applicable to other disease contexts, including immunization coverage, maternal health, and tuberculosis surveillance.[154–157]

While the methodology represents a significant advancement, several limitations must be acknowledged. Our use of Euclidean distance to define proximity does not account for real-world travel barriers like road networks or terrain; future work could incorporate cost-distance measures to refine catchment definitions. Second, the methodology relies on satellite-derived population estimates, which carry potential errors from imagery resolution and the modelling algorithms used to classify buildings and estimate inhabitants. Finally, our analysis was constrained by considerable missingness in the HMIS-reported malaria data for children under five, and while we assumed a Missing at Random (MAR) mechanism, any systematic reporting gaps could still introduce bias. Additionally, residual diagnostic analyses revealed mild heteroscedasticity and potential minor misspecifications in the linear predictors, indicating caution in interpreting model precision. Despite these minor issues, fixed-effect estimates remained robust and stable, and model diagnostics were generally satisfactory. Furthermore, the lack of ecological and vector-related data limited the interpretation of spatial variability observed in malaria risk, which might reflect underlying ecological determinants or vector habitats influencing transmission intensity. Incorporating these variables in future research could enhance the causal interpretation of the observed geographic disparities.

3.5.2 Interpretation of Case Study Findings

The observed protective association for children in most districts may reflect focused pediatric testing, diagnosis, and treatment under national malaria control policies, particularly in highly endemic areas.[130,158–161] Conversely, districts showing elevated pediatric malaria risk suggest underlying gaps in service delivery, geographic barriers, or distinct epidemiological patterns that warrant targeted investigation and tailored interventions.[130,162] The optimal statistical model included an interaction term between districts and demographic groups, reinforcing the necessity

of spatially defined, subgroup-specific analyses. This granularity offers crucial insights into malaria risk dynamics that are typically obscured by aggregated, numerator-only health indicators.[135,150,163,163,164]

3.5.3 Implications for Health Systems and Policy

From a public health policy perspective, the findings underscore the critical necessity of strengthening routine HMIS reporting to clearly distinguish between zero cases and missing reports, particularly for pediatric subpopulations. Geographically targeted malaria interventions may be warranted in districts such as Luampa and Lukulu, which have consistently been identified as high-risk regions throughout the study period. Moreover, the observed district-level demographic differences suggest the need for nuanced intervention strategies that are responsive to local epidemiological and health system contexts.

Future research directions may involve testing the operational feasibility of and validating the SCSO-PUR methodology within national HMIS platforms, possibly through pilot studies that assess practical scalability and sustainability. Furthermore, our methodology has the potential to be integrated into national HMIS systems such as DHIS2, provided the data infrastructure supports geospatial inputs and local capacity exists for updating spatial layers over time. In addition, integrating complementary sources of community-level survey data or active case detection could enhance validation efforts and address existing data gaps, further refining estimates of malaria burden and healthcare access inequities.

Although malaria served as a demonstration case, the SCSO-PUR methodology is broadly generalizable and holds significant potential for health systems strengthening. It can be applied to any health indicator tracked in HMIS systems that lacks denominator data, including maternal and child health indicators (e.g., antenatal care coverage, immunization rates), other infectious diseases (e.g., tuberculosis case detection rates), and chronic disease prevalence.[155–157,165,166] By providing ministries of health and global partners with the tools to calculate localized, population-adjusted metrics, this approach enhances the ability to accurately monitor health trends, target interventions to high-burden areas, and allocate resources more equitably. The operationalization of this

methodology within national HMIS platforms like DHIS2 could fundamentally improve the precision of subnational health surveillance, aligning with the goals of Universal Health Coverage (UHC) and the achievement of health-related Sustainable Development Goals.[86,149]

3.6 Conclusion

The SCSO-PUR approach fundamentally transforms the potential of routine HMIS data by providing a practical, scalable, and adaptable solution to the challenges of denominator estimation. Demonstrated here using malaria surveillance in WP, Zambia, this methodological innovation can be broadly generalized across various health indicators and geographic settings. While malaria served as a demonstration case, the SCSO-PUR methodology is broadly applicable to other diseases and surveillance needs where accurate denominators are essential. As global health systems strive to improve accountability, effectively target interventions, and advance toward SDG 3 targets, methods such as the SCSO-PUR offer essential tools for enhancing the quality of disease surveillance, improving resource allocation, and promoting health equity.

Chapter 4

Adverse Interactions

4.1 Overview

Background In low- and lower-middle-income countries, progress towards Universal Health Coverage is threatened by climate-related shocks and chronic health system stressors. While the disruptive effects of individual factors are known, there is a critical gap in empirical evidence quantifying their adverse synergistic interactions. This study introduces and empirically measures the econosyndemic framework, which suggests that adverse interactions between climate-related shocks (e.g., flooding) and health system stressors (e.g., low facility density) disrupt essential health care services. We quantify this effect in Western Province, Zambia, a flood-prone region with barriers to utilizing health facilities.

Methods We conducted a longitudinal ecological study from October 2017 to October 2023 using data from 62 health facilities across seven administrative districts. We used beta regression mixed-effects models to investigate interactions between flood exposure and health system capacity on three utilization outcomes: antenatal care (i.e., trimester visits), births, and general utilization (i.e., outpatient visits). We complemented this approach with structural equation models (SEM) to examine pathways involving latent constructs of health system capacity and socioeconomic vulnerability.

Findings: High flood depth was associated with a reduced likelihood of ANC visits (AOR=0.731, 95% CI 0.620 to 0.862) and facility births (Adjusted Odds Ratio, AOR=0.923, 95% CI 0.859 to 0.992). Importantly, we identified strong adverse synergistic interactions. The impact of health facility density on births was amplified in vulnerable districts (e.g., Sikongo: AOR=297.4,

$p<0.001$). The SEMs explained a substantial portion of outcome variance (R^2 up to 65.2%) and confirmed that health system capacity and vulnerability were predictors of service utilization.

Conclusions This study provides quantitative evidence of an econosyndemic within a climate-affected health system. The findings demonstrate that the interaction between climate shocks and health system stressors causes inequitable disruptions to essential health services. Building health system resilience as a strategy for climate change adaptation requires targeted, context-specific interventions that address these underlying systemic vulnerabilities.

4.2 Introduction

The health effects of climate change are increasingly unevenly distributed, directly threatening progress towards Universal Health Coverage (UHC) and the resilience of health systems in the world's most vulnerable regions. Health system resilience refers to the ability of health systems to prepare for and respond to shocks and stressors.[5,14,167,168] Shocks to health systems may include adverse effects of climate change, infectious diseases, economic crisis, and geopolitics, whereas stressors involve supply- and demand-side conditions.[14] Health system resilience seeks to ensure access to health facilities regardless of crises, enabling equitable utilization of essential health services to improve health outcomes and reduce disease burden.[169] As a foundation for health system resilience, countries must ensure equitable access to health facilities, which is especially vital for rural and remote communities in low- to lower-middle-income countries (LMICs).[5,7,169]

In LMICs, acute environmental shocks such as seasonal flooding are accelerating in frequency and severity, undermining efforts to improve essential services, including maternal and child health.[170,171] These climate-driven shocks do not occur in isolation; instead, they interact with chronic, pre-existing health system stressors—such as inadequate infrastructure, supply bottlenecks, and geographic barriers to care—exacerbating health inequities and system fragility.[23,172,173] Health system resilience, often defined as the ability to absorb, adapt, and transform in response to such shocks while maintaining essential functions, is vital for progress towards UHC amid climate uncertainty.[87,174,175]

Western Province (WP), Zambia, exemplifies a microcosm of these intersecting challenges, where climate-related shocks in the form of variation in seasonal flooding converge with chronic health system stressors, including low facility density and significant geographic barriers to care.[176] The region is primarily covered by the Barotse Floodplain, an ecosystem that experiences extensive annual inundation, often exceeding 10,000 km², isolating communities.[53,54] With more than 80% of its population residing in rural areas, pre-existing barriers to care are substantial; unimpeded average walk times from community centres to the nearest health facility, for instance, range from 6 to 13 hours.[49] These distances far exceed the two-hour travel time threshold recommended for accessing essential health services, which equates to a maximum walking distance of

approximately 10 km under optimal conditions.[60,89,177–179] While previous research has documented the impact of flooding on health in the region, its effects on the utilization of routine maternal (e.g., antenatal care) and child health services remain less understood.[180] This convergence of a recurring environmental shock with chronic, underlying health system stressors makes WP an ideal setting for empirically investigating their adverse synergistic effects on access to health facilities and utilization of first-level health care services.

Traditional analytical approaches that examine single risk factors in isolation are often insufficient to capture the complex dynamics that drive health outcomes in such settings.[181] While syndemic theory offers a powerful conceptual starting point, emphasizing how co-occurring diseases and social conditions interact to produce an excess burden of disease, its application has several limitations.[25,26,30] A primary critique is that the fundamental assertion of a synergistic interaction is infrequently subjected to empirical testing capable of quantifying the magnitude of such an interaction effect; the majority of studies remain descriptive or qualitative.[28,34] Furthermore, the theory has traditionally focused on individual-level, bio-social interactions (e.g., substance abuse, violence, and HIV) rather than the system-level interplay between environmental shocks and health infrastructure.[25,26,182] Finally, while equitable access is a core principle of UHC, as a concept, it is notoriously difficult to measure in a way that captures the critical dimensions of space and time.[1,48,49] Health service utilization, by contrast, offers a practical and measurable proxy for *realized access*, providing the necessary empirical outcome to investigate how populations engage with health systems under varying structural conditions.[49]

This study introduces, defines, and applies a novel theoretical framework, which we refer to as an econosyndemic. Building upon syndemic theory, we define an econosyndemic by integrating two core concepts. The foundation is rooted in economic theory, which describes the interplay between broad, macro-level shocks (e.g., climate change, economic crises) and localized, micro-level stressors (e.g., supply- and demand-side barriers to care). The ‘syndemic’ component refers to the adverse synergistic interaction between these economic and environmental conditions, which can produce an excess burden on a health system, leading to inequitable outcomes.[30,183] As conceptualized in Figure 4.1, these adverse interacting conditions are hypothesized to produce spatially and temporally uneven impacts on health system functioning and, ultimately, on health

service utilization. In this framework, we conceptualize Health System Resilience not as a prerequisite for Universal Health Coverage, but as a demonstrated property of it. We posit that a system achieving high levels of UHC is robust; HSR is the measure of that system's capacity to maintain its functions and progress towards UHC when subjected to a shock.

Therefore, this study aimed to empirically test the econosyndemic framework and quantify its effects on health service utilization in WP, Zambia. Using six years of longitudinal data from 62 health facilities across seven flood-prone districts, we investigated the adverse synergistic interactions between anticipated flood exposure, health system capacity, and geography. We employed a robust, two-part analytical approach, using beta regression mixed-effects models to test specific interaction effects and structural equation models to examine latent system-level pathways. The analysis focused on three essential service utilization outcomes: antenatal care (ANC) trimester visits, health facility births, and general utilization (i.e., outpatient visits). We hypothesized that the adverse interaction between climate shocks and chronic system stressors would produce spatially and temporally uneven patterns of service disruption, providing the first quantitative evidence of an econosyndemic process in this fragile, climate-affected health system.

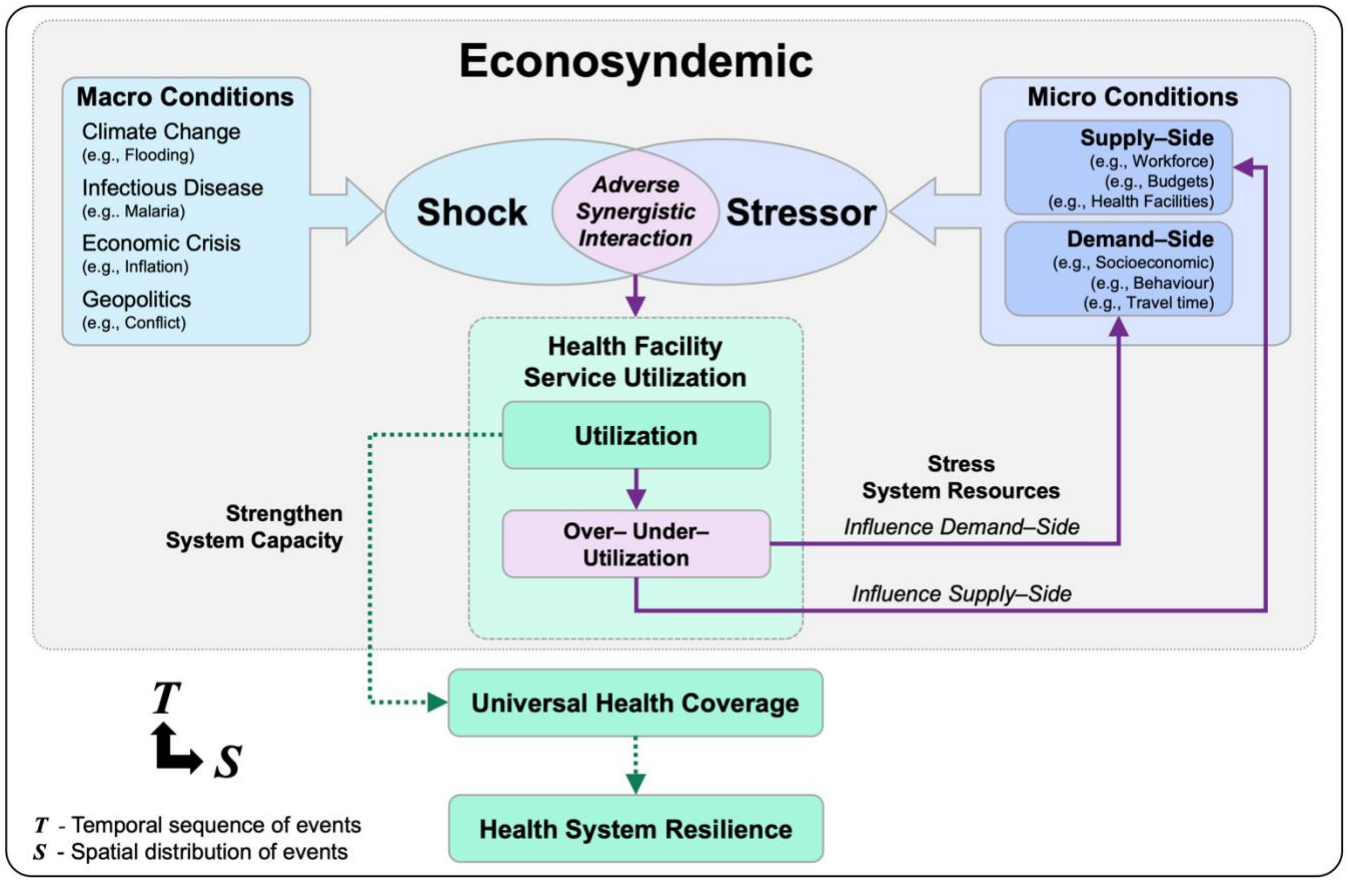


Figure 4.1 The econosyndemic conceptual theoretical framework. An econosyndemic outlines the hypothesized adverse synergistic interactions between broad macro–level conditions (e.g., climate change manifested through flooding and economic crises) and specific micro–level conditions, which include supply–side factors like the quantity of health facilities, as well as demand–side factors such as travel time. These interactions may influence the utilization of health facility services, potentially resulting in either over–utilization or under–utilization relative to need, thereby ultimately impacting progress towards Universal Health Coverage (UHC) and, consequently, the demonstrated resilience of the health system.

4.3 Methods

4.3.1 Study Design and Setting

Zambia is a landlocked country in Southern Africa, with an estimated population of 19.6 million, according to the 2022 census, and a national poverty rate of 60%.[184] Western Province is divided into 16 administrative districts, and based on the 2022 census, there is an estimated population of 1.36 million.[56,184] The spatial distribution of the population is vast, with approximately 80% residing in rural and remote communities.[50] In this setting, barriers, such as shocks and stressors, to access and utilization of essential health care facilities and services exist. In 2022, the Zambian Ministry of Health (MOH) reported that WP had 344 operational health facilities across its administrative districts.[59] Western Province is dominated by the Barotse Floodplain of the Zambezi River and characterized by extensive and variable seasonal flooding.[53,54] This study employed a longitudinal ecological design to analyze health service utilization across 62 public primary health facilities (i.e., centres and posts) where monthly flood exposure data were available, out of 344 operational facilities in WP (figure 4.2). The facility-month served as the primary unit of analysis over a 73-month study period, from October 2017 to October 2023. The final analytic dataset was restricted to facilities with monthly flood exposure data.

4.3.2 Ethics Approval

Ethical approval for this study was obtained from the University of Waterloo Human Research Ethics Board (ORE-43883), the University of Zambia Biomedical Research Ethics Committee (Ref. No. 2472-2021; renewed February 9, 2024), the National Health Research Authority in Zambia (Ref. No. NHRA000009/10/07/2022), and the Provincial Ministry of Health, Western Province. Permissions were granted for the secondary analysis of de-identified data stored in the national HMIS.

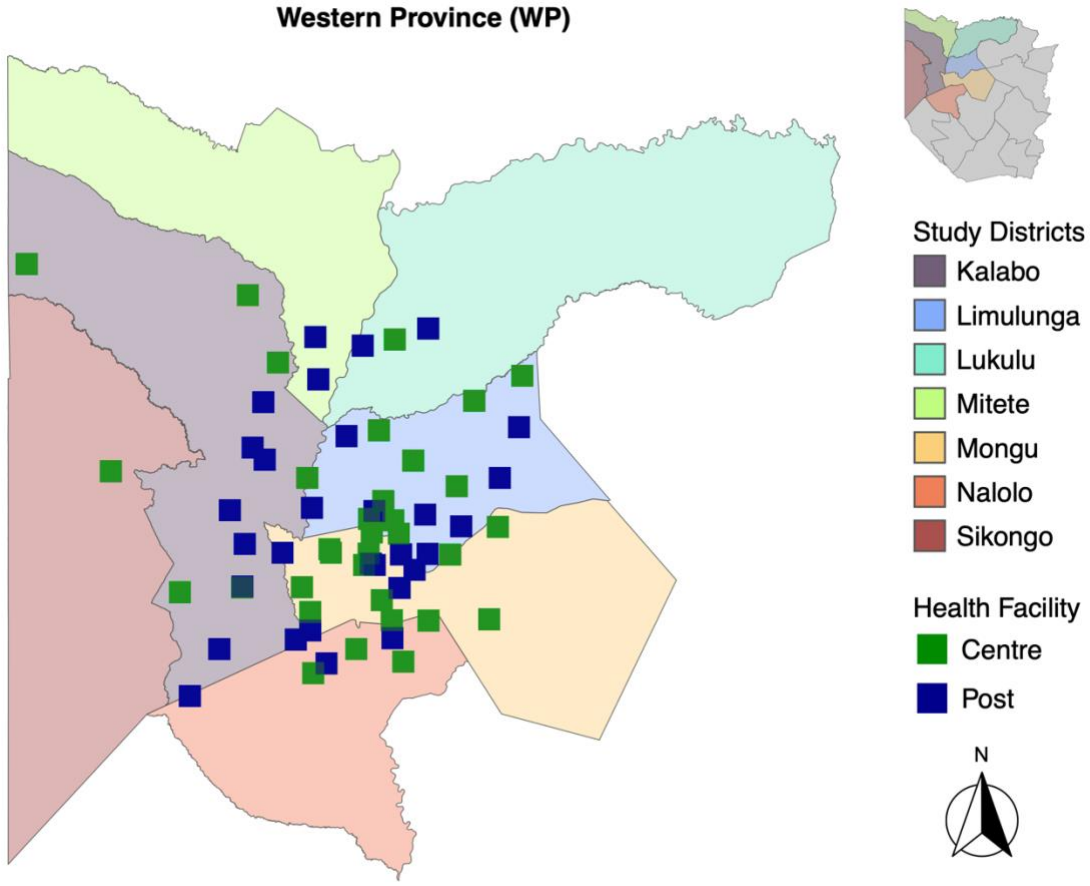


Figure 4.2 Map of health facility locations and administrative boundaries in WP, Zambia. The health facilities, which include rural and urban health centres and posts (n = 63), are situated within the administrative districts of WP (study districts, n = 7).

4.3.3 Data Preparation and Cleaning

Prior to analysis, the dataset was prepared by addressing outliers and missing data. As a form of outlier analysis, any outcome proportions reported as greater than 1.0 were considered implausible and removed from the analysis. Missing data were handled using a complete-case analysis for each of the three outcome-specific models. This conservative approach was chosen because non-reported values ('NA') in the source HMIS data are ambiguous, making it impossible to distinguish between zero visits and a failure to report. Consequently, the missing at random (MAR) assumption, which underpins standard imputation techniques, could not be confidently met. While we acknowledge that multiple imputation is often recommended for its robustness in handling missing RHIS data, we opted for complete-case analysis to avoid introducing potential bias from imputing values of unknown meaning.[68] Missingness rates varied by outcome: approximately 11% of facility-months were missing facility births data, 5% were missing general outpatient utilization data, and a higher proportion were missing ANC data (24% for 1st trimester and 41% for 3rd trimester visits). The use of one-month lead and lag flood indicators also resulted in the systematic loss of the first and last months of data for each facility. All statistical modelling and data processing were conducted using R (version 4.3.1), primarily with the *glmmTMB*, *AICcmodavg*, *DHARMa*, and *ggeffects* packages.[105,139,185–187] Assumptions were assessed using the *DHARMa* package by examining simulation-based residuals for uniformity, heteroscedasticity, and overdispersion. Final model outputs, presented in Tables 4.2, 4.3, and 4.4, report logit-scale coefficients, standard errors, 95% confidence intervals, AORs, and *p*-values. Predicted marginal effects were computed using the *ggeffects* package to aid in interpretation and visualization.[185]

4.3.4 Outcome Variables

Longitudinal data on health service utilization were primarily derived from Zambia's Health Management Information System (HMIS).[65] Three distinct health service utilization outcomes were modelled as proportions. First, the proportion of health facility births was calculated by dividing the monthly number of reported deliveries by the estimated population of women of

reproductive age (WRA, 15-49 yrs) in the health facility's catchment area[h], as shown in $Y_{ijk}^{\text{birth}} = B_{ijk}/\text{WRA}_{ijk}$ where Y_{ijk}^{birth} is the monthly proportion of health facility births, B_{ijk} is the number of births at health facility k, in district j, at time i, and WRA_{ijk} is the number of WRA living in a health facility catchment area. Second, antenatal care (ANC) was represented by the proportions of first and third trimester visits, which were converted from reported percentages by dividing by 100, $Y_{ijk}^{\text{ANC1}} = \text{ANC1}_{ijk}/100$, $Y_{ijk}^{\text{ANC3}} = \text{ANC3}_{ijk}/100$ where Y_{ijk}^{ANC1} and Y_{ijk}^{ANC3} are proportions of first and third trimester health facility visits, and ANC1_{ijk}, ANC3_{ijk} are the reported percentages of first and third trimester visits. Third, the rate of general utilization was calculated from the raw monthly count of outpatient visits. To prepare this rate for beta regression modeling and aid interpretation, it was scaled to a value between 0 and 1, creating a pseudo-proportion represented as $Y_{ijk}^{\text{util}} = \text{U}_{ijk}/1000$ where Y_{ijk}^{util} is the scaled general utilization (i.e., outpatient visits) proportion, and U_{ijk} is the monthly general utilization visits at health facility k, in district j, and at time i. Any outcome proportions reported as greater than 1.0 were considered implausible and removed from the analysis. Because the beta distribution is defined on the open interval (0, 1), we applied a continuity transformation to any observed proportions of exactly 0 or 1. This was done using the Smithson and Verkuilen approach $y_{ijk}^{*} = Y_{ijk} \cdot (n-1) + 0.5/n$, a necessary step for beta regression modelling. Here, y_{ijk}^{*} is the transformed proportion, constrained to an open interval (0,1), Y_{ijk} is the original proportion (possibly 0 or 1), and n is the total number of observations used for the transformation.

4.3.5 Predictor Variables and Covariates

Health facility catchment areas To accurately estimate population denominators and model geographic access, we developed and applied a novel methodology: the Spatially Defined Catchment Area (SCSO). This approach addresses the common limitation of routine health information systems, which often lack reliable, demographically disaggregated population data for health facility service areas. The full details of the SCSO and Population Under Rooftop (PUR)

[h] The methodology used to define health facility catchment areas and their population denominators is detailed in the 'Predictor Variables and Covariates' subsection below. This novel SCSO-PUR methodology is the subject of a separate manuscript (Chiarot et al., manuscript submitted for publication).

methodology are described in a separate manuscript (Chiarot et al., manuscript submitted for publication). The methodology integrates two key data sources: non-disaggregated total catchment population estimates for each health facility from the Central Statistical Office (CSO), and high-resolution, satellite-derived gridded population data from Meta's High Resolution Settlement Layers (HRSL).[75,188] Each populated 30×30 m grid cell from the HRSL dataset was treated as a Population Under Rooftop (PUR) unit, providing granular demographic counts (e.g., WRA). The SCSO for each health facility was constructed using an iterative aggregation algorithm. First, the Euclidean distance was calculated between every PUR and every health facility in the study area. Then, for each facility, the algorithm began aggregating the nearest PURs, continuing until the sum of the populations of the collected PURs matched the official CSO total population estimate for that facility's catchment area. This process effectively disaggregates the single CSO population number into a spatially explicit and demographically detailed service area. For this study, the population-weighted centroid of the resulting PUR cluster served as the starting point for travel time calculations (refer below). Population denominators for women of reproductive age (WRA, 15-49 yrs) were derived from the aggregated PUR data within these newly defined catchment areas.

Population adjustments To account for dynamic changes in catchment area populations over time, denominators were adjusted using district-specific annual Population Growth Rates (PGRs) calculated using the 2010–2020 Zambia Statistics Agency estimates (i.e., 10-yr district averages).[50,51] For years prior to the 2022 baseline, population estimates were decompounded using:

$$P_{d,y} = \frac{P_{d,2022}}{(1 + r_d)^{(2022-y)}}$$

where $P_{d,y}$ is the estimated catchment population in district d for year y, r_d is the annual population growth rate in district d, and $P_{d,2022}$ is the population in 2022 (baseline year). For the 2023 projections, estimates were compounded from the 2022 baseline using:

$$P_{d,y} = P_{d,2022} \cdot (1 + r_d)^{(y-2022)}$$

These adjustments were applied to all population denominators, including total population and WRA.

Floodwater hydrology The Barotse Floodplain is one of the great wetlands of sub-Saharan Africa, located on the Zambezi River in WP. While the floodplain itself receives approximately 830 mm of average annual precipitation, its extensive inundation, which can exceed 10,000 km², is predominantly driven by precipitation in the upper sub-catchments, where annual totals are approximately 1,400 mm. To capture these dynamics, we used outputs from the LISFLOOD-FP, an advanced hydrodynamic model designed for flood inundation simulation.[189] The modelling workflow, specifically developed for this region, used the IHACRES model to generate river discharge hydrographs from climate data.[76,77] These hydrographs were then used as inputs for the LISFLOOD-FP model to simulate floodwater hydrology for the retrospective period of October 2017 to October 2023. The model generated monthly outputs of floodwater dynamics, including water depth (m), as 900 m resolution rasters. From this modelled data, flood exposure was derived and categorized as *Low* (<0.2 m; *reference*), Medium (0.2–0.4 m), and High (>0.4 m). A one-month lead version of this variable was used in the regression models to capture the effects of anticipated flooding.

Travel distance and time Several covariates were constructed to account for geographic and temporal factors. Geographic access was modelled using travel time, which was estimated by calculating the straight-line distance between the population-weighted centroid of a catchment area and its health facility using the Law of Cosines given by:

$$d_{ij} = R \cdot \arccos\big(\sin(\phi_i)\sin\big(\phi_j\big) + \cos(\phi_i)\cos\big(\phi_j\big)\cos\big(\lambda_j - \lambda_i\big)\big)$$

where d_{ij} is the distance between point i (PUR centroid) and point j (health facility), ϕ is the latitude (radians), λ is the longitude (radians), and R is the Earth's radius ≈ 6,371 km. This distance was then divided by a walking speed of 5 km/hr to estimate travel time in hours $T_{ij} = d_{ij}/v$ where T_{ij} is the estimated walking time between a PUR i and a health facility j in hours, d_{ij} is the travel distance (km), and v is the walking speed.[190] Travel time was then categorized as 0–2 hours

(*reference*) and 2–5 hours. The >5 hours travel time category was excluded from the regression analysis because it contained too few facility-month observations to allow for stable model estimation.

Seasonality and temporal trends To adjust for seasonality and underlying temporal trends, the models included a linear time trend representing the number of months since the study start and two harmonic terms, calculated as the sine and cosine of the month number given by:

$$time_{sin} = \sin\left(\frac{2\pi t}{12}\right) \text{ and } time_{cos} = \cos\left(\frac{2\pi t}{12}\right)$$

District-level health facility supply was measured using two continuous indicators: the number of facilities per 1,000 WRA and the number of facilities per 1,000 general population. The administrative district was included as a factor variable, with *Kalabo* district as the *reference* category.

4.3.6 Statistical Analysis

Beta Regression Each of the three outcome measures was modelled separately using beta regression mixed-effects models with a logit link, an approach well-suited for proportion data that is often skewed, heteroscedastic, and bounded between 0 and 1.[142] The outcome, y^*_{ijk}, was assumed to follow a beta distribution $y^*_{ijk} \sim \text{Beta}(\mu_{ijk}, \phi)$ where μ_{ijk} is the mean of the beta distribution for observations i, j, k, and ϕ is the precision (i.e., inverse of dispersion) parameter with a mean μ_{ijk} and a precision parameter ϕ. The variance of the distribution is a function of these two parameters, given by $\text{Var}[Y_{ijk}] = \mu_{ijk}(1 - \mu_{ijk})/1 + \phi$. The model's linear predictor was related to the mean via the logit link function defined as $\text{logit}(\mu_{ijk}) = \log(\mu_{ijk}/1 - \mu_{ijk})$. The general structure for each model included fixed effects for the covariates and a random intercept for each health facility to account for repeated measures and unobserved facility-level heterogeneity given by $\text{logit}(\mu_{ijk}) = \beta_0 + \mathbf{X}_{ijk}\boldsymbol{\beta} + u_{0k}$ where $\beta_0$is the intercept, $\mathbf{X}_{ijk}$ is the row vector of covariates (e.g., district, time, flood depth, and seasonality), $\boldsymbol{\beta}$ is the column vector of the fixed-effect coefficients, and $u_{0k} \sim \mathcal{N}(0, \sigma_u^2)$ is the health facility-level random intercept. Model parameters

were estimated by maximizing the log-likelihood function using $\log L(\mu, \phi \mid y_1, \ldots, y_n) = \sum_{i=1}^{n} \log f(y_i \mid \mu_i, \phi)$. For each outcome, we first fit a main-effects model including district, flood exposure (lead 1-month), travel time, the relevant health facility density metric, and the time trend and seasonality terms. Subsequently, two-way interaction terms were tested based on theoretical relevance. These included interactions between flood and district, flood and travel time, district and health facility supply, and, for the ANC model only, an interaction between flood exposure and ANC visit type (first vs. third trimester visits). Final model selection was guided by the corrected Akaike Information Criterion (AICc), with a preference for models with the lowest AICc, while also considering theoretical coherence and parsimony.

Statistical inference Beta regression models were based on a two-sided significance level of $\alpha = 0.05$. For each predictor, final model outputs include the logit-scale coefficient, standard error (SE), adjusted odds ratio (AOR), and the corresponding 95% confidence interval (CI) and *p*-value. An association was considered statistically significant if the *p*-value was less than 0.05 and the 95% CI for the AORs did not include 1.0.

Structural Equation Modelling To complement the beta regression analyses, Structural Equation Models (SEMs) were used. This approach was chosen to formally test the hypothesized pathways of the econosyndemic framework by examining both the direct and indirect relationships between environmental shocks, latent health system constructs, and health service utilization outcomes. By modelling unobserved latent constructs for *Socioeconomic Vulnerability* (SEV) and *Health System Capacity* (HSC), SEM allows for a more nuanced analysis of how these system-level conditions mediate the effects of observable predictors on service uptake. Three separate SEMs were developed, each corresponding to one of the primary outcomes: ANC trimester visits, health facility births, and general utilization. All SEMs were specified with a measurement component, defining the latent variables, and a structural component, linking variables in hypothesized causal pathways. The models were estimated in R using the *lavaan* package.[191] We employed a robust maximum likelihood estimator (MLR) to account for potential non-normality in the data and used Full Information Maximum Likelihood (FIML) to handle missing data efficiently. Model fit was assessed against established thresholds for goodness-of-fit indices: a Comparative Fit Index (CFI) > 0.90, a Root Mean Square Error of Approximation (RMSEA) < 0.08, and a Standardized Root

Mean Square Residual (SRMR) < 0.08. The time series for this aggregated analysis was initiated in January 2018 to align with the start of the calendar year, differing slightly from the facility-level analysis, which began in October 2017 (i.e., 476 district-month observations from January 2018 to August 2023).

The measurement component of the SEMs defined two exogenous latent constructs: SEV and HSC, with variable definitions provided in Table 5. Across all three models, SEV was consistently specified as a single-indicator latent variable measured by the proportion of the health facility catchment population with an average walking travel time of 2–5 hours; this measurement model is given by $\text{Travel}_k^{(2\text{-}5\text{hr})} = 1 \cdot \text{SEV}_k + \varepsilon_k^{\text{Travel}}$ where $\text{Travel}_k^{(2\text{-}5\text{hr})}$ is the proportion of health facility-catchment pairs in district k with travel time between 2 and 5 hours, SEV_k is the latent variable for socioeconomic vulnerability for district k, and $\varepsilon_k^{\text{SEV}}$ is the error term for the SEV_k indicator. The measurement of HSC was adapted based on the specific outcome. For the ANC and health facility births models, HSC was indicated by two observed variables: the number of health facilities per 1,000 WRA and the number of health facilities per 1,000 general population given by $\text{HF}_k^{\text{WRA}} = \lambda_2 \cdot \text{HSC}_k + \varepsilon_k^{\text{WRA}}$, $\text{HF}_k^{\text{Gen}} = \lambda_3 \cdot \text{HSC}_k + \varepsilon_k^{\text{Gen}}$ where HF_k^{WRA} is the observed indicator, which is the number of health facilities per 1,000 WRA in district k, λ_2, λ_3 are the factor loadings, HSC_k is the latent variable, and $\varepsilon_k^{\text{HSC}}$ is the unique measurement error term for the HF_k^{WRA} indicator. In contrast, for the general utilization model, HSC was defined using only a single indicator—the number of health facilities per 1,000 general population—as this denominator is more applicable to non-maternal health services which is defined by $\text{HF}_k^{\text{Gen}} = 1 \cdot \text{HSC}_k + \varepsilon_k^{\text{Gen}}$ where HF_k^{Gen} is the number of health facilities per 1,000 general population in district k, HSC_k is the latent variable HSC in district k, and $\varepsilon_k^{\text{Gen}}$ is the unique measurement error term for the HF_k^{Gen} indicator. For general utilization, only the general population-based health facility density was used as an indicator for HSC. The structural component of each SEM specified the relationships between the latent constructs (SEV and HSC), the observed covariates, and the respective health service outcome. In each model, the direct effects of SEV, HSC, standardized flood depth (z-score, with a one-month lead), a linear time trend (months since start), and seasonal harmonic terms (sine and cosine) on the outcome were estimated simultaneously. Three distinct structural models were developed: the first evaluated the pathways influencing the proportion of ANC trimester visits given by:

$$Y_{ijk}^{\text{ANC}} = \beta_0 + \beta_1 \cdot \text{SEV}_k + \beta_2 \cdot \text{HSC}_k + \beta_3 \cdot \text{FloodDepth}_k + \\ + \beta_4 \cdot t_{ij} + \beta_5 \cdot \sin(t_{ij}) + \beta_6 \cdot \cos(t_{ij}) + \varepsilon_{ijk}^{\text{Y}}$$

where Y_{ijk}^{ANC} is the proportion of ANC trimester visits at health facility i, in month j, in district k, β_0 is the intercept, SEV_k, HSC_k are the latent variables as defined above, FloodDepth_k is the standardized flood water depth in district k, t_{ij} is the months since the study start (time covariate), $\sin(t_{ij}), \cos(t_{ij})$ are the harmonic terms capturing the seasonal variation, $\varepsilon_{ijk}^{\text{Y}}$ is the residual error term for ANC trimester visits; the second assessed predictors of health facility births given by:

$$Y_{ijk}^{\text{Births}} = \beta_0 + \beta_1 \cdot \text{SEV}_k + \beta_2 \cdot \text{HSC}_k + \beta_3 \cdot \text{FloodDepth}_k + \\ + \beta_4 \cdot t_{ij} + \beta_5 \cdot \sin(t_{ij}) + \beta_6 \cdot \cos(t_{ij}) + \varepsilon_{ijk}^{\text{Y}}$$

where Y_{ijk}^{Births} is the proportion of health facility births at facility i, in month j, in district k, and $\varepsilon_{ijk}^{\text{Y}}$ is the residual error for births. All other model variables are described above; and the third modeled the factors affecting general utilization given by:

$$Y_{ijk}^{\text{Util}} = \beta_0 + \beta_1 \cdot \text{SEV}_k + \beta_2 \cdot \text{HSC}_k + \beta_3 \cdot \text{FloodDepth}_k + \\ + \beta_4 \cdot t_{ij} + \beta_5 \cdot \sin(t_{ij}) + \beta_6 \cdot \cos(t_{ij}) + \varepsilon_{ijk}^{\text{Y}}$$

where Y_{ijk}^{Util} is the proportion of general utilization (i.e., outpatient visits) at health facility i, in month j, in district k, and $\varepsilon_{ijk}^{\text{Y}}$ is the residual error for general utilization. All other model variables are described above. The standardized path coefficients (β) from these models are reported in Table 4.6, with the path diagrams illustrated in Figures 4.12, 4.13, and 4.14. All data processing, visualization, and statistical analyses were conducted using R statistical software (version 4.3.1).[105]

4.4 Results

4.4.1 Health Facility Observations

The final analytic dataset consisted of 4,473 facility-month observations from 62 health facilities across seven districts. Descriptive statistics for all study variables are detailed in Table 4.1. Among complete cases, the mean proportion of 1st trimester ANC visits was 40.9% (SD = 26.3%), while facility-based births averaged 1.0% of the WRA population (SD = 0.6%). Most facility-months (95.2%) corresponded to catchment areas with an average travel time of 0–2 hours to the nearest health facility.

4.4.2 Beta Regression Modelling

Antenatal care Several factors were significantly associated with the probabilities of ANC trimester visits (Table 4.2). Compared to low flood depth (lead 1 month), high flood depth was associated with lower odds of ANC visits (AOR = 0.731, 95% CI [0.620, 0.862], $p < 0.001$). Among the seven administrative districts and relative to *Kalabo*, Limulunga district demonstrated notably higher odds of ANC visits (AOR = 1.518, 95% CI [1.046, 2.203], p = 0.028). A significant negative temporal trend was observed, with each additional month associated with slightly lower odds of ANC visits (AOR = 0.994, 95% CI [0.993, 0.996], $p < 0.001$), a pattern visualized in Figure 4.4 . Seasonality also contributed, with the cosine component of the harmonic term showing an association (AOR = 0.923, 95% CI [0.879, 0.970], $p = 0.001$). The interaction between ANC visit type and flood depth was not statistically significant (Figure 4.3), and the spatio-temporal distribution of predicted probabilities are shown in Figure 4.5.

Table 4.1 Descriptive statistics of health facility-month observations.

Variable and Level Statistic	N	Percent	Mean	SD	Median	IQR Range
Outcome (Proportion)						
ANC First Trimester	3,405	--	40.90	26.30	33.30	(20.00 – 53.80)
ANC Third Trimester	2,625	--	36.80	22.60	33.30	(18.80 – 50.00)
HF Births	3,984	--	1.00	0.60	0.90	(0.60 – 1.30)
General Utilization (i.e., Outpatient)	4,254	--	0.02	0.01	0.02	(0.01 – 0.02)
Administrative District						
Kalabo	994	22.2	--	--	--	--
Limulunga	1,349	30.2	--	--	--	--
Lukulu	213	4.8	--	--	--	--
Mitete	142	3.2	--	--	--	--
Mongu	1,207	27.0	--	--	--	--
Nalolo	497	11.1	--	--	--	--
Sikongo	71	1.6	--	--	--	--
HF Type						
Health Centre	2,343	52.4	--	--	--	--
Health Post	2,130	47.6	--	--	--	--
HF per						
1,000 WRA	3,479	--	1.16	0.26	1.25	(0.90 – 1.31)
1,000 Gen. Pop.	3,479	--	0.28	0.06	0.30	(0.22 – 0.32)
Time Period						
Months Since Study Start	4,473	--	35.00	20.00	35.00	(17.00 – 53.00)
Flood Category (Current)						
Low (<0.2 m)	567	12.7	--	--	--	--
Medium (0.2–0.4)	2,268	50.7	--	--	--	--
High (>0.4 m)	1,638	36.6	--	--	--	--
Flood Category (Lead 1 Month)						
Low (<0.2 m)	504	11.3	--	--	--	--
Medium (0.2–0.4 m)	2,331	52.1	--	--	--	--
High (>0.4 m)	1,638	36.6	--	--	--	--
Travel Time to HF						
0–2 hrs	4,260	95.2	--	--	--	--
2–5 hrs	213	4.8	--	--	--	--
Avg. Travel Time (minutes)	4,473	--	64.10	42.30	58.60	(31.80 – 94.80)
Avg. Travel Distance (km)	4,473	--	5.30	3.50	4.90	(2.60 – 7.90)

Note: Statistics are presented as n (%) for categorical variables. For continuous variables, statistics are presented as Mean (SD) and Median (IQR; Q1 - Q3), unless otherwise specified in the 'Level Statistic' column (e.g., proportions presented as percentages). 'N' for continuous variables represents the count of non-missing facility-month observations for that variable. The study period encompasses October 2017 to October 2023.

Abbreviations: ANC, Antenatal Care; **Gen. Pop.**, General Population; **HF**, Health Facility; **IQR**, Interquartile Range; **N**, Number of observations; **SD**, Standard Deviation; **WRA**, Women of Reproductive Age (15–49 years).

Table 4.2 Beta regression mixed–effects of factors associated with ANC trimester visits.

Predictor	Estimate (log–odds)	SE	95% CI	AOR	95% CI	P value
(Intercept)	0.286	0.160	(–0.027, 0.600)	1.332	(0.973, 1.821)	0.073
ANC Visit Type (20+ yrs)						
First Trimester (*Ref.*)	--	--	--	--	--	--
Third Trimester	–0.155	0.083	(–0.318, 0.008)	0.856	(0.728, 1.008)	0.062
Flood Depth (Lead 1 Month)						
Low (<0.2 m) (*Ref.*)	--	--	--	--	--	--
Medium (0.2–0.4 m)	–0.093	0.064	(–0.218, 0.032)	0.911	(0.804, 1.032)	0.145
High (>0.4 m)	–0.313	0.084	(–0.478, –0.148)	**0.731**	(0.620, 0.862)	<0.001***
Administrative District (n = 7)						
Kalabo (*Ref.*)	--	--	--	--	--	--
Limulunga	0.418	0.190	(0.045, 0.790)	**1.518**	(1.046, 2.203)	0.028*
Lukulu	0.355	0.337	(–0.304, 1.015)	1.427	(0.738, 2.760)	0.291
Mitete	–0.063	0.400	(–0.846, 0.720)	0.939	(0.429, 2.055)	0.875
Mongu	–0.120	0.197	(–0.506, 0.266)	0.887	(0.603, 1.304)	0.541
Nalolo	0.338	0.242	(–0.137, 0.813)	1.402	(0.872, 2.254)	0.163
Sikongo	–0.240	0.541	(–1.300, 0.819)	0.787	(0.273, 2.269)	0.657
Travel Time (Walk 5 km/hr)						
0–2 hrs (*Ref.*)	--	--	--	--	--	--
2–5 hrs	–0.345	0.325	(–0.982, 0.292)	0.708	(0.375, 1.339)	0.288
Time Period						
Months since start	–0.006	0.001	(–0.007, –0.004)	**0.994**	(0.993, 0.996)	<0.001***
Sine (Harmonic)	0.045	0.032	(–0.017, 0.107)	1.046	(0.983, 1.113)	0.155
Cosine (Harmonic)	–0.080	0.025	(–0.129, –0.031)	**0.923**	(0.879, 0.970)	0.001**
Interaction Term: Visit Type × Flood Depth						
First Trimester × *Low* (*Ref.*)	--	--	--	--	--	--
Third Trimester × Medium	–0.044	0.092	(–0.225, 0.136)	0.956	(0.799, 1.145)	0.628
Third Trimester × High	–0.015	0.095	(–0.201, 0.172)	0.986	(0.818, 1.188)	0.879

Note: Results from a beta regression mixed–effects model. **AOR**, Adjusted Odds Ratio; **CI**, Confidence Interval; **SE**, Standard Error; ***Ref***., Reference Category; **ANC**, Antenatal Care measured as trimester visit type (i.e., First or Third) among women of 20+ years of age.

Levels of Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

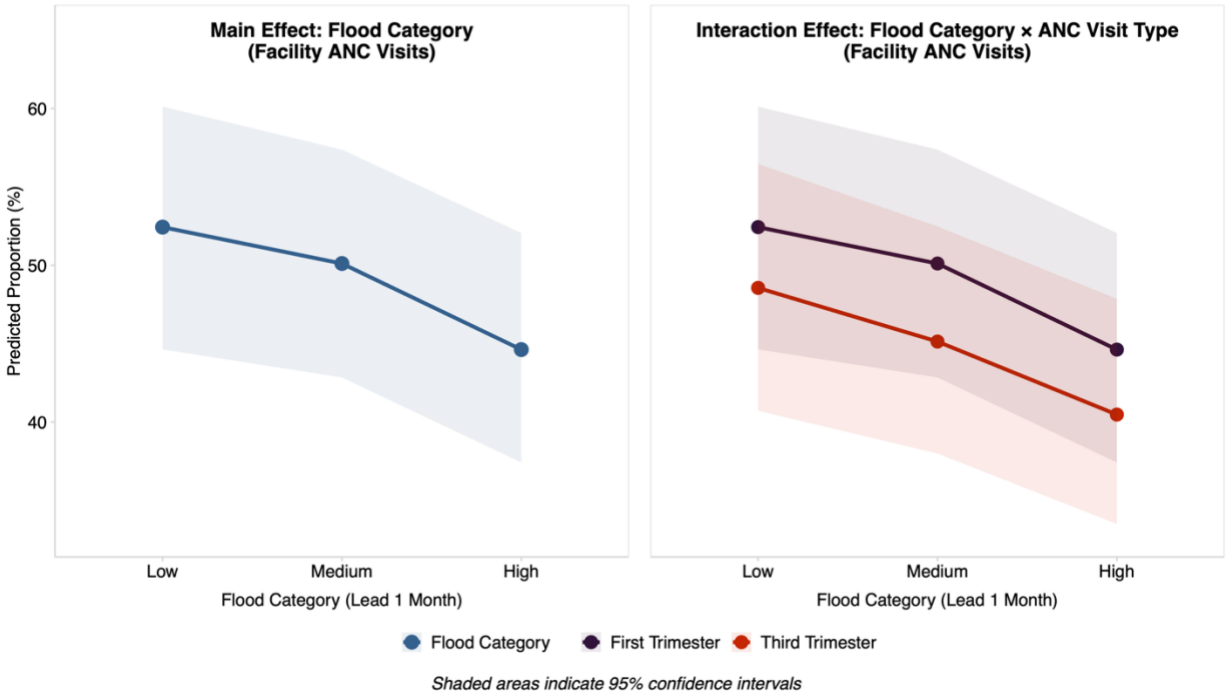


Figure 4.3 Predicted proportions of antenatal care (ANC) trimester visits based on flood category and their interaction with visit type. It presents the predicted proportions as a percentage of health facility-based trimester visits (i.e., First Trimester vs. Third Trimester), derived from the beta regression mixed–effects model. The left panel illustrates the main effect of the flood category (lead 1 month for low, medium, and high floodwater depth categories) on trimester visit type. The right panel demonstrates the interaction effect between flood category and ANC visit type. The predicted proportions are shown with shaded areas representing 95% confidence intervals.

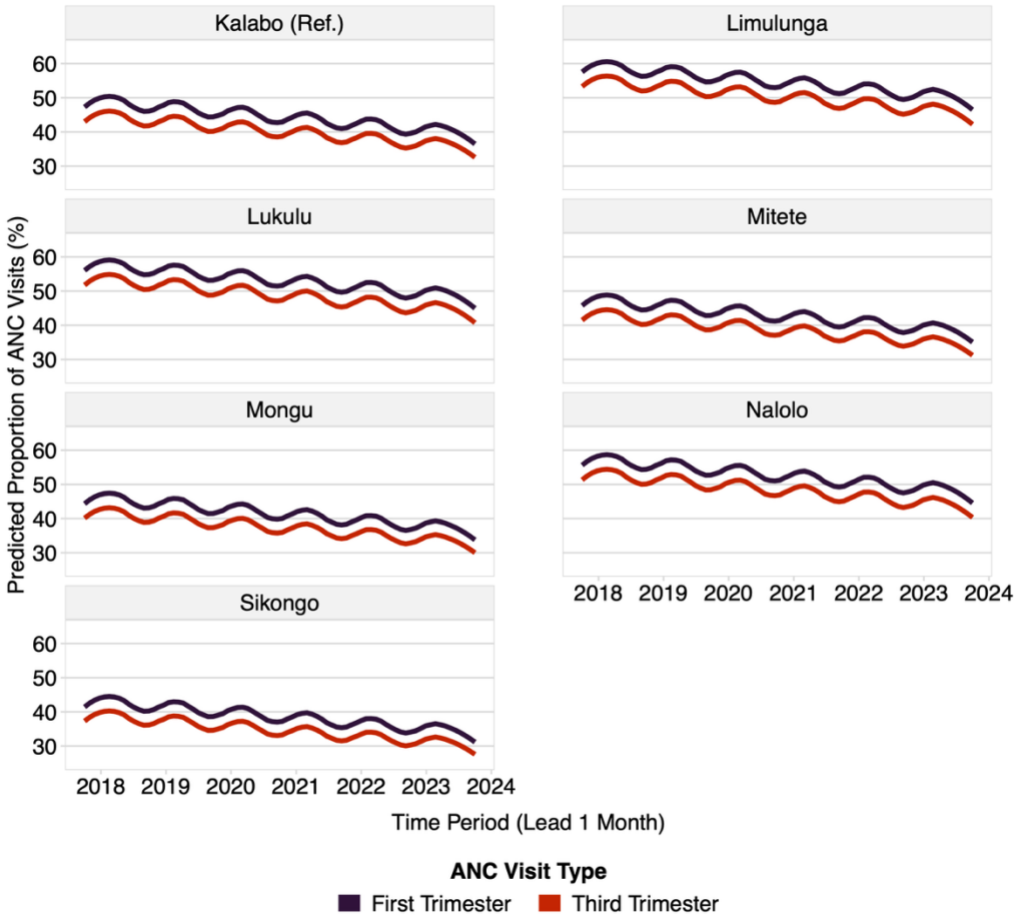


Figure 4.4 Predicted time trends of Antenatal Care (ANC) visit probabilities by district and trimester. The predicted proportion of ANC trimester visits (%) over the study period (October 2017 – October 2023, with x–axis labels extending to 2024 for trend visualization) is presented for each of the seven study districts (*Kalabo* [*Ref.*]). Trends are shown separately for First and Third Trimesters, derived from the beta regression mixed–effects model (Table 4.2).

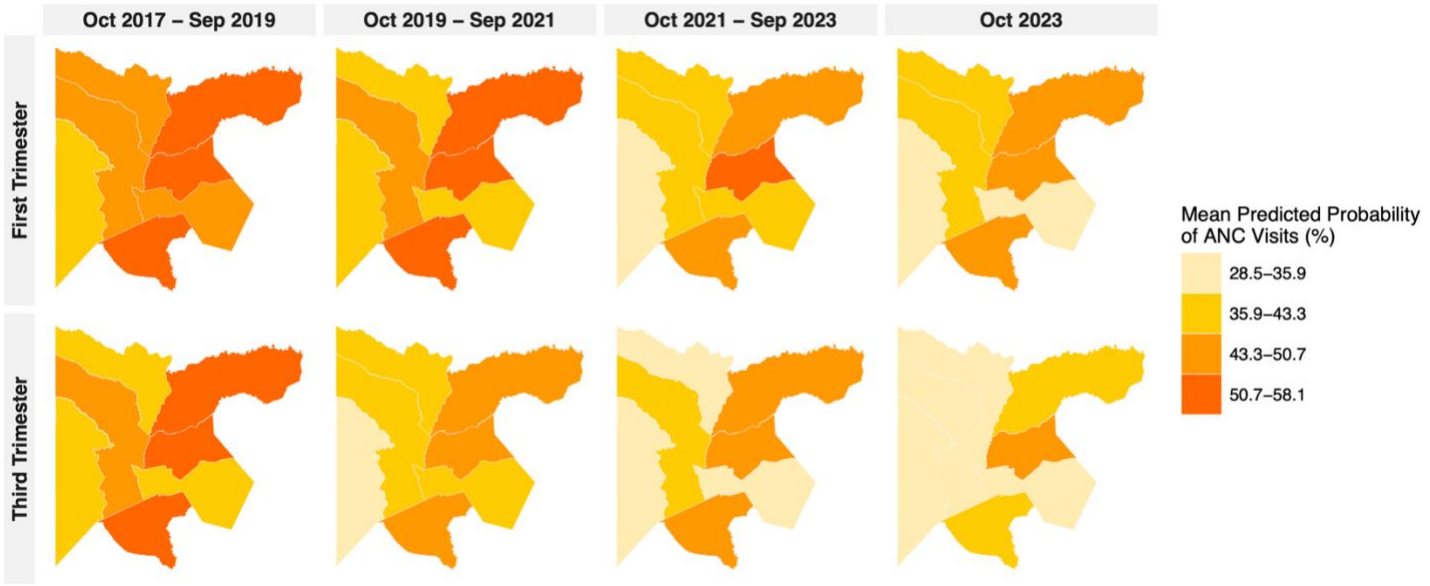


Figure 4.5 Spatio–temporal distribution of Antenatal Care (ANC) trimester visits. The mean predicted probability of ANC first and third trimester visits (%) across the seven study districts over four time periods: October 2017 – September 2019, October 2019 – September 2021, October 2021 – September 2023, and October 2023 are presented. Mean predicted probabilities were derived from the beta regression mixed–effects model (Table 4.2). The legend indicates the ranges for mean predicted probabilities (%). Legend colour bands are based on equal intervals across the range of predicted probabilities.

Health facility births Factors influencing the proportion of births in health facilities are detailed in Table 4.3. Administrative district was a strong predictor; compared to *Kalabo*, Lukulu (AOR = 0.144, 95% CI [0.025, 0.821], $p = 0.029$) and Sikongo (AOR = 0.007, 95% CI [0.000, 0.104], $p < 0.001$) had significantly lower odds of health facility births. As illustrated in Figure 4.6, high flood depth was associated with modestly lower odds of facility births compared to the low flood category (AOR = 0.923, 95% CI [0.859, 0.992], $p = 0.029$). Both sine ($p < 0.001$) and cosine ($p = 0.003$) harmonic terms indicated significant seasonal effects, with temporal trends visualized in Figure 4.7. The main effect of health facilities per 1,000 WRA was not significant ($p = 0.640$). However, the interaction between district and health facility density was significant for Lukulu (AOR = 3.921, $p = 0.047$) and Sikongo (AOR 297.4, $p < 0.001$), indicating that the effect of health facility supply varied significantly by district (Figure 4.6). Notably, the magnitude of the interaction effect in Sikongo was exceptionally large. The spatio-temporal distribution of predicted probabilities is shown in Figure 4.8.

Table 4.3 Beta regression mixed–effects analysis of factors associated with HF births.

Predictor	Estimate (log–odds)	SE	95% CI	AOR	95% CI	P value
(Intercept)	–3.570	1.812	(–7.121, –0.018)	**0.028**	(0.001, 0.982)	0.049*
Admin. District (n = 7)						
Kalabo (*Ref.*)	--	--	--	--	--	--
Limulunga	–0.499	1.099	(–2.653, 1.655)	0.607	(0.070, 5.235)	0.650
Lukulu	–1.935	0.887	(–3.672, –0.197)	**0.144**	(0.025, 0.821)	0.029*
Mitete	0.064	0.969	(–1.835, 1.962)	1.066	(0.160, 7.113)	0.948
Mongu	–0.285	0.666	(–1.591, 1.020)	0.752	(0.204, 2.774)	0.668
Nalolo	–0.483	0.674	(–1.804, 0.838)	0.617	(0.165, 2.312)	0.474
Sikongo	–4.954	1.373	(–7.645, –2.262)	**0.007**	(0.000, 0.104)	<0.001***
HF / 1,000 WRA (District–Year specific)	–0.626	1.338	(–3.248, 1.995)	0.534	(0.039, 7.353)	0.640
Flood Depth (Lead 1 Month)						
Low (<0.2 m) (*Ref.*)	--	--	--	--	--	--
Medium (0.2–0.4 m)	0.021	0.025	(–0.029, 0.071)	1.021	(0.972, 1.073)	0.408
High (>0.4 m)	–0.080	0.037	(–0.153, –0.008)	**0.923**	(0.859, 0.992)	0.029*
Travel Time (Walk 5 km/hr)						
0–2 hrs (*Ref.*)	--	--	--	--	--	--
2–5 hrs	–0.080	0.217	(–0.505, 0.345)	0.923	(0.603, 1.412)	0.712
Time Period						
Months Since Start	–0.006	0.003	(–0.012, 0.001)	0.994	(0.988, 1.001)	0.108
Sine (Harmonic)	–0.064	0.016	(–0.095, –0.033)	**0.938**	(0.910, 0.968)	<0.001***
Cosine (Harmonic)	–0.059	0.020	(–0.098, –0.021)	**0.943**	(0.907, 0.979)	0.003**
Interaction Term: District × HF / 1,000 WRA						
Kalabo × HF /1,000 WRA (*Ref.*)	--	--	--	--	--	--
Limulunga × HF / 1,000 WRA	0.270	0.799	(–1.295, 1.835)	1.310	(0.274, 6.268)	0.735
Lukulu × HF / 1,000 WRA	1.366	0.689	(0.017, 2.716)	3.921	(1.017, 15.120)	0.047*
Mitete × HF / 1,000 WRA	0.222	0.787	(–1.320, 1.764)	1.248	(0.267, 5.834)	0.778
Mongu × HF / 1,000 WRA	–0.093	0.395	(–0.868, 0.681)	0.911	(0.420, 1.976)	0.813
Nalolo × HF / 1,000 WRA	0.305	0.533	(–0.740, 1.349)	1.356	(0.477, 3.854)	0.568
Sikongo × HF / 1,000 WRA	5.695	1.702	(2.359, 9.031)	**297.4**	(10.6, 8360.7)	<0.001***

Note: Results from a beta regression mixed–effects model. **AOR**, Adjusted Odds Ratio; **CI**, Confidence Interval; **SE**, Standard Error; **HF**, Health Facility; **WRA**, Women of Reproductive Age (15–49 yrs); ***Ref.***, Reference Category.

Levels of Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

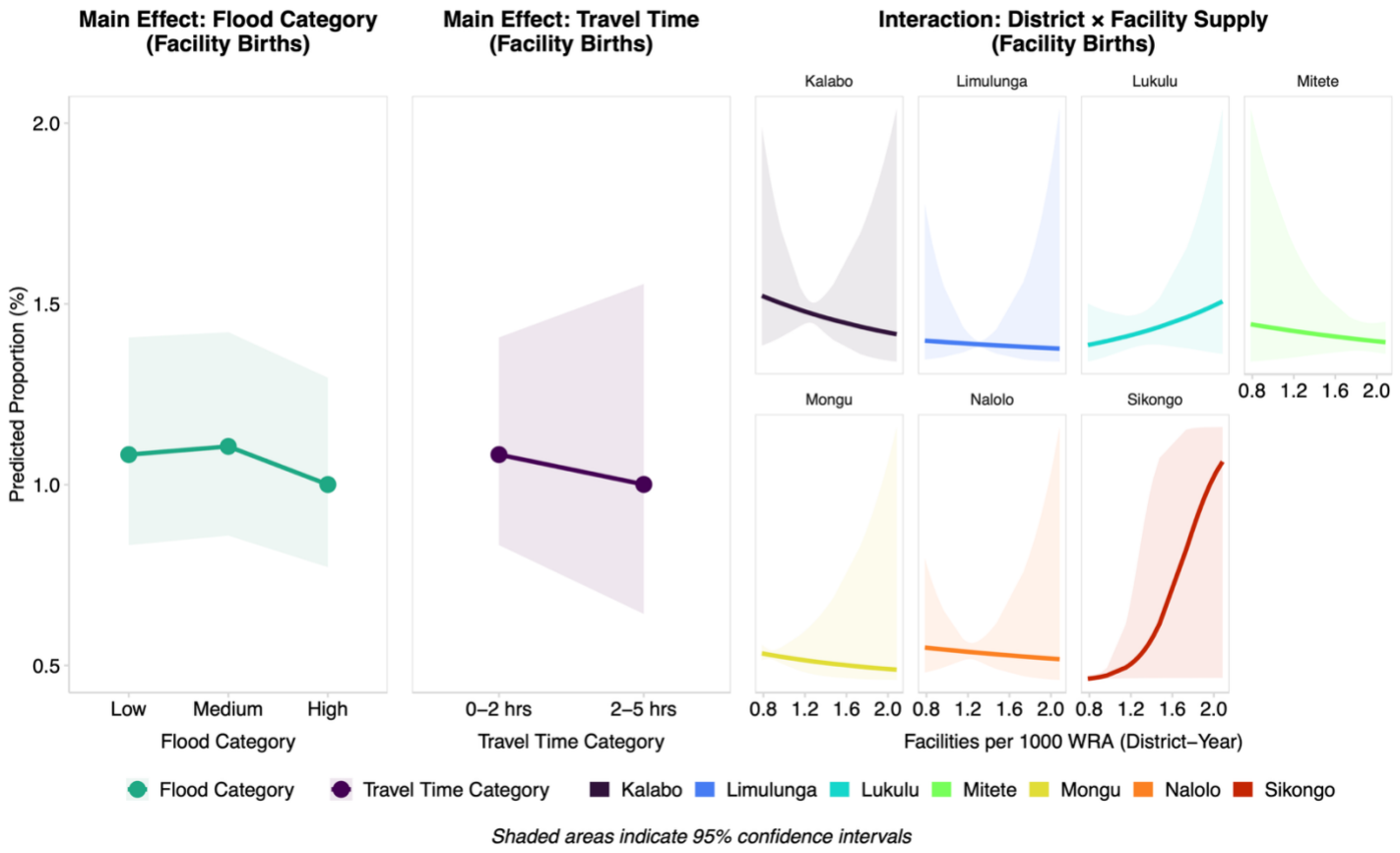


Figure 4.6 Predicted proportions of health facility births categorized by flood category, travel time, and the interaction effect of the district with health facility supply. The predicted proportions (%) of health facility births were derived from the beta regression mixed-effects model (detailed in Table 4.3). The left panel displays the main effect of flood category (i.e., Depth: Low [<0.2 m], Medium [0.2–0.4 m], High [>0.4 m]) on health facility births. The middle panel illustrates the main effect of travel time category (i.e., Walk speed: 0–2 hrs, 2–5 hrs) on health facility births. The right panel depicts the interaction effect between the administrative district and health facility supply (i.e., health facilities per 1,000 Women of Reproductive Age [15–49 yrs], district–year) on the predicted proportion of facility births. Predicted proportions are presented with shaded areas representing 95% confidence intervals where applicable.

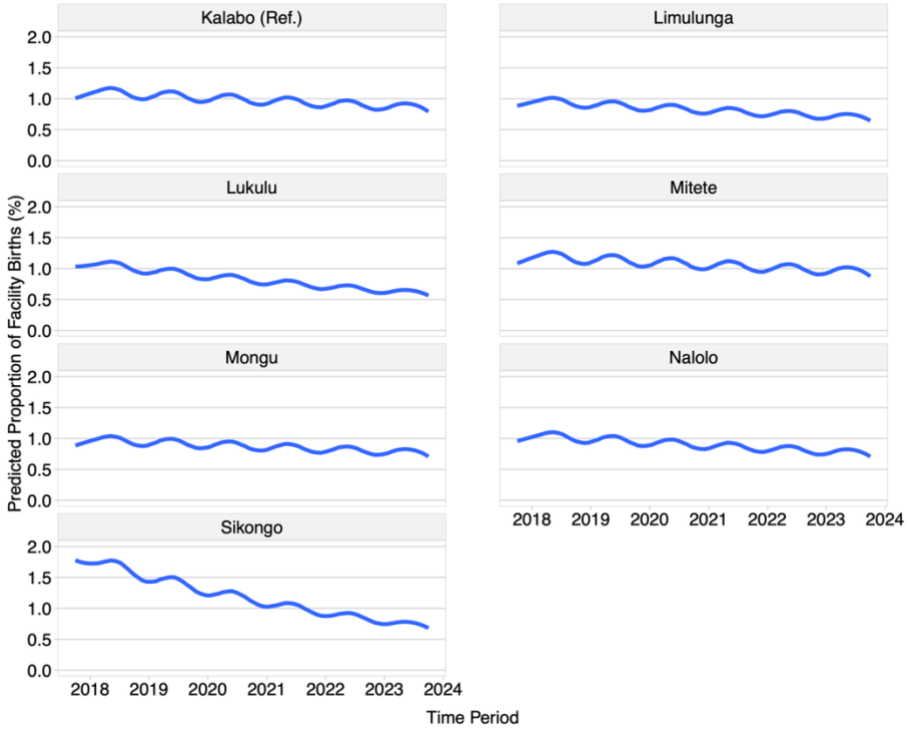


Figure 4.7 Predicted temporal trends for health facility birth probabilities by administrative district. It shows the predicted proportion of health facility births (%) over the study period (October 2017 – October 2023, with x–axis labels extending to 2024 for trend visualization) for each of the seven study districts: *Kalabo* (*Ref.*), Limulunga, Lukulu, Mitete, Mongu, Nalolo, and Sikongo. These probabilities were derived from the beta regression mixed-effects model (see Table 4.3). The y–axis denotes the predicted proportion of facility births (%).

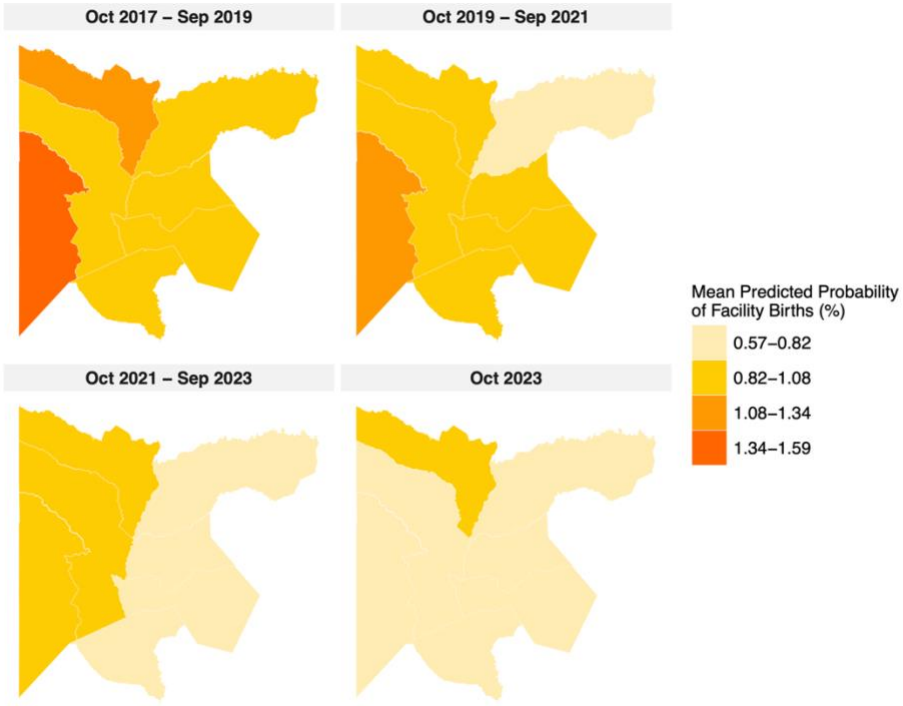


Figure 4.8 Spatio-temporal distribution of the mean predicted probabilities for health facility births. The mean predicted probability of health facility births (%) across the study districts over four distinct time periods: October 2017 – September 2019, October 2019 – September 2021, October 2021 – September 2023, and October 2023. These probabilities were derived from the beta regression mixed–effects model (Table 4.3). Legend color bands are based on equal intervals across the range of predicted probabilities.

General Utilization The analysis of general utilization (Table 4.4) revealed several associations. Paradoxically, both medium (AOR = 1.126, $p < 0.001$) and high (AOR = 1.340, $p < 0.001$) flood depth categories were associated with higher odds of General Utilization compared to the low flood category (Figure 4.9). Relative to *Kalabo*, Mitete district had higher odds (AOR = 1.755, p = 0.014), while Mongu had lower odds (AOR = 0.740, $p = 0.018$) of general utilization. Increased density of health facilities per 1,000 general population was associated with lower odds of the measured utilization outcome (AOR = 0.040, $p = 0.004$). Strong temporal and seasonal trends were observed (Figure 4.10). The interaction between high flood depth and district was significant for Mitete ($p = 0.011$) and Mongu ($p = 0.041$), indicating differential effects of flooding by district (Figure 9). The spatio-temporal distribution of predicted probabilities are shown in Figure 4.11.

Table 4.4 Beta regression mixed–effects analysis of factors associated with general utilization.

Predictor	Estimate (log–odds)	SE	95% CI (log–odds)	AOR	95% CI (AOR)	P value
(Intercept)	–7.152	0.362	(–7.861, –6.442)	**0.001**	(0.000, 0.002)	<0.001***
Flood Depth (Lead 1 Month)						
Low (<0.2 m) (*Ref.*)	--	--	--	--	--	--
Medium (0.2–0.4 m)	0.119	0.030	(0.059, 0.178)	**1.126**	(1.061, 1.195)	<0.001***
High (>0.4 m)	0.293	0.034	(0.226, 0.360)	**1.340**	(1.254, 1.433)	<0.001***
Administrative District (n = 7)						
Kalabo (*Ref.*)	--	--	--	--	--	--
Limulunga	0.068	0.080	(–0.089, 0.224)	1.070	(0.915, 1.251)	0.396
Lukulu	0.061	0.136	(–0.205, 0.327)	1.063	(0.815, 1.387)	0.652
Mitete	0.563	0.228	(0.116, 1.009)	**1.755**	(1.123, 2.743)	0.014*
Mongu	–0.301	0.127	(–0.550, –0.052)	**0.740**	(0.577, 0.949)	0.018*
Nalolo	–0.056	0.100	(–0.251, 0.139)	0.946	(0.778, 1.149)	0.574
Sikongo	–0.353	0.245	(–0.833, 0.127)	0.703	(0.435, 1.136)	0.150
Travel Time (Walk 5 km/hr)						
0–2 hrs (*Ref.*)	--	--	--	--	--	--
2–5 hrs	–0.231	0.119	(–0.465, –0.002)	0.793	(0.628, 1.002)	0.052
Facilities / 1,000 Gen. Pop. (District–Year specific)	–3.228	1.128	(–5.439, –1.016)	**0.040**	(0.004, 0.362)	0.004**
Time Period						
Months Since Start	–0.004	0.001	(–0.006, 0.000)	**0.996**	(0.994, 0.997)	<0.001***
Sine (Harmonic)	0.077	0.009	(0.059, 0.095)	**1.080**	(1.061, 1.100)	<0.001***
Cosine (Harmonic)	0.039	0.007	(0.024, 0.053)	**1.039**	(1.025, 1.054)	<0.001***
Interaction Term: Flood Depth × District						
Low × *Kalabo* (*Ref.*)	--	--	--	--	--	--
Medium × Limulunga	–0.034	0.039	(–0.110, 0.042)	0.966	(0.896, 1.042)	0.377
High × Limulunga	0.012	0.039	(–0.065, 0.088)	1.012	(0.937, 1.092)	0.764
Medium × Lukulu	0.005	0.068	(–0.127, 0.137)	1.005	(0.880, 1.147)	0.941
High × Lukulu	0.102	0.068	(–0.031, 0.234)	1.107	(0.970, 1.264)	0.132
Medium × Mitete	–0.106	0.084	(–0.270, 0.059)	0.900	(0.763, 1.061)	0.209
High × Mitete	–0.219	0.086	(–0.389, –0.050)	**0.803**	(0.678, 0.951)	0.011*
Medium × Mongu	–0.005	0.041	(–0.085, 0.075)	0.995	(0.918, 1.078)	0.896
High × Mongu	–0.085	0.041	(–0.166, –0.004)	**0.919**	(0.847, 0.996)	0.041*
Medium × Nalolo	–0.049	0.052	(–0.151, 0.052)	0.952	(0.860, 1.053)	0.340
High × Nalolo	–0.083	0.052	(–0.185, 0.020)	0.921	(0.831, 1.020)	0.114
Medium × Sikongo	–0.005	0.115	(–0.230, 0.220)	0.995	(0.795, 1.246)	0.967
High × Sikongo	–0.025	0.117	(–0.254, 0.204)	0.975	(0.776, 1.226)	0.830

Note: Results from a beta regression mixed–effects model. **AOR**, Adjusted Odds Ratio; **CI**, Confidence Interval; **SE**, Standard Error; **Gen. Pop.**, General Population; ***Ref.***, Reference Category.

Levels of Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

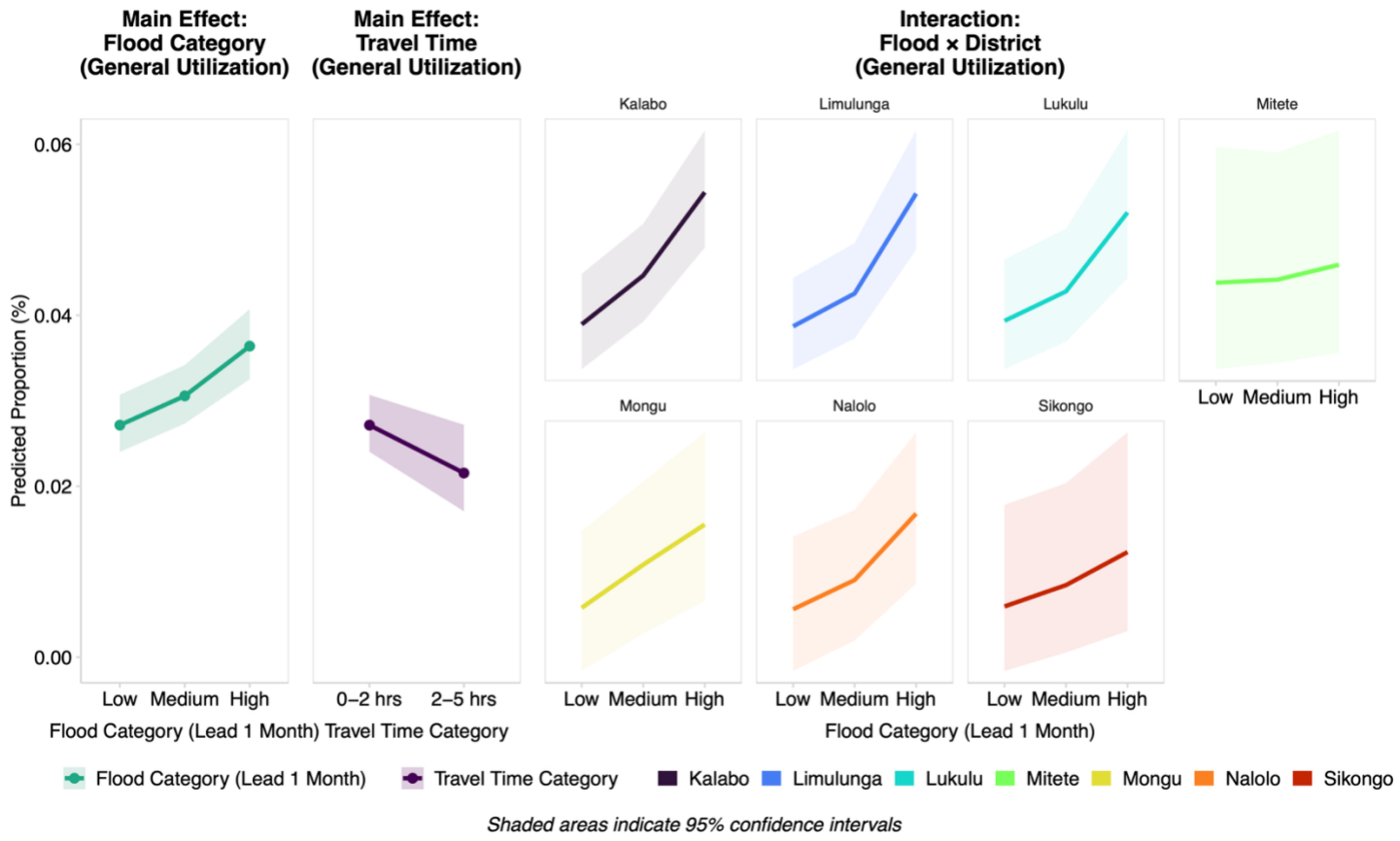


Figure 4.9 Predicted proportions of general health facility utilization based on flood category, travel time, and the interaction effect of flood with administrative district. The predicted proportions (%) of general health facility utilization (i.e., outpatient) were derived from the beta regression mixed–effects model (detailed in Table 4.4). The left panel displays the main effect of flood category (i.e., Depth: Low [<0.2 m], Medium [0.2–0.4 m], High [>0.4 m]) on general utilization. The middle panel illustrates the main effect of travel time category (i.e., Walk speed: 0–2 hrs, 2–5 hrs) on general utilization. The right panel depicts the interaction effect between flood category (lead 1 month) and administrative district on the predicted proportion of general utilization, showing separate lines for each district to illustrate predicted utilization across flood categories (Low, Medium, High). Predicted proportions are represented with shaded areas indicating 95% confidence intervals where applicable.

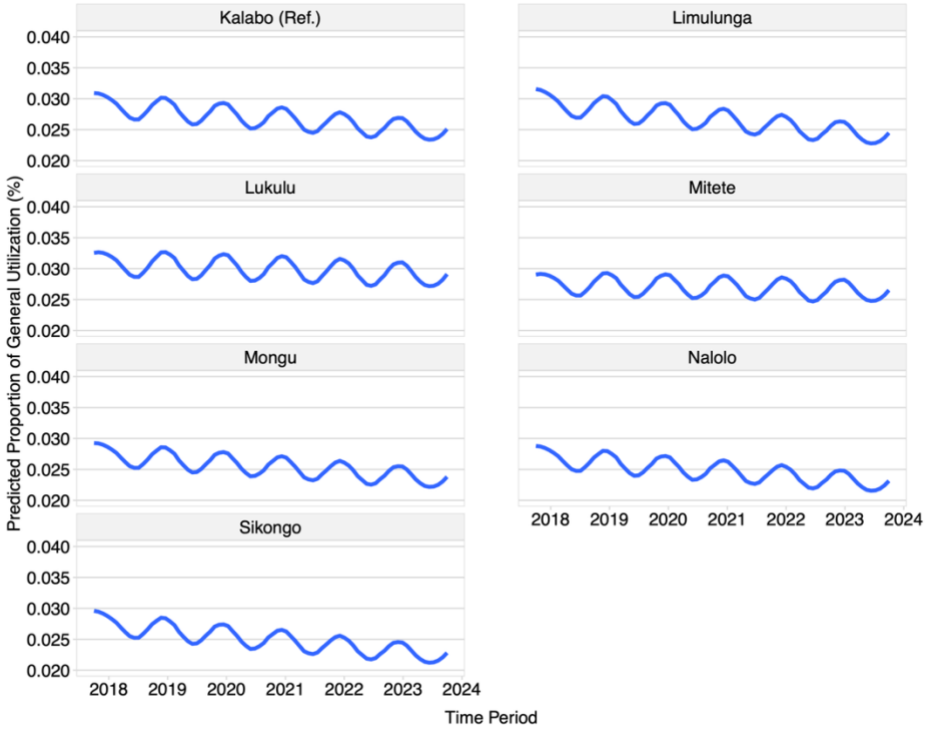


Figure 4.10 Predicted time trends of general health facility utilization probabilities by administrative district. The predicted proportion of general health facility utilization (%) over the study period (October 2018 – August 2023, with x–axis labels extending to 2024 for trend visualization) is detailed for each of the seven study districts: *Kalabo* [*Ref.*], Limulunga, Lukulu, Mitete, Mongu, Nalolo, and Sikongo. Probabilities were derived from the beta regression mixed-effects model (Table 4.4). The y–axis represents the predicted proportion of general utilization (%).

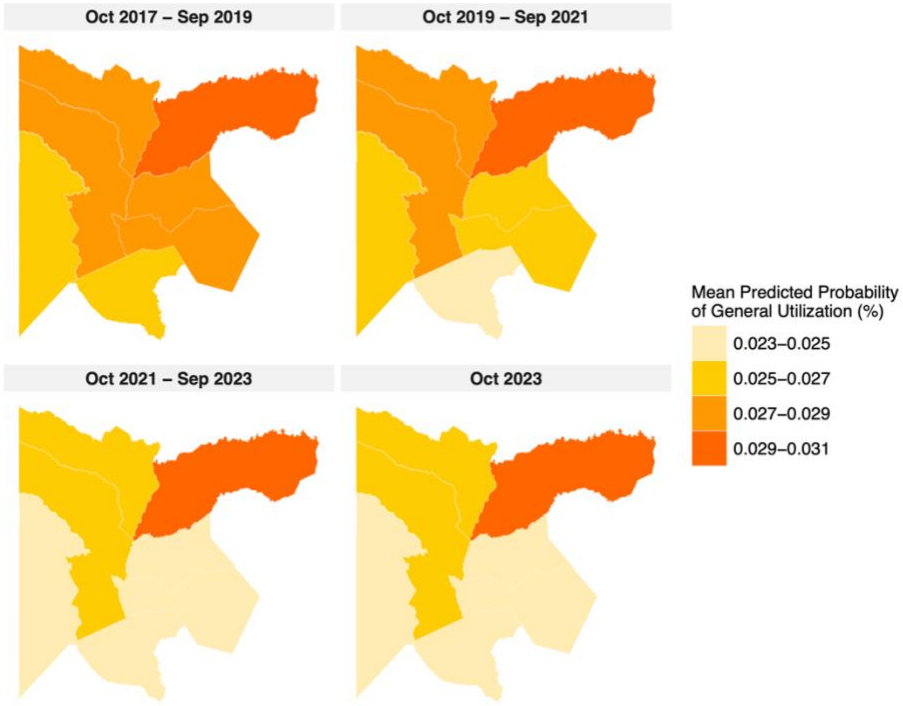


Figure 4.11 Spatio–temporal distribution of mean predicted probabilities for general health facility utilization. The mean predicted probability of utilizing general health facilities (%) across the study districts spans four distinct time periods: October 2017 – September 2019, October 2019 – September 2021, October 2021 – September 2023, and October 2023. Probabilities were derived from the beta regression mixed-effects model (Table 4.4). The legend provides the ranges for these mean predicted probabilities (%). Legend color bands are based on equal intervals across the range of predicted probabilities.

4.4.3 Structural Equation Models

To investigate direct and indirect factors influencing health service utilization, three SEMs were developed, with variable definitions in Table 4.5 and standardized path coefficients in Table 4.6. The analyses were based on 476 district-month observations. The overall fit for each specified SEM model was evaluated and found to be adequate. The measurement aspect of the SEMs was defined by two latent exogenous constructs: SEV and HSC. In all models, SEV was indicated by Travel Time (2–5 hrs). For the ANC and health facility births models, HSC was indicated by both WRA- and general population-based facility density measures; for the general utilization model, HSC was indicated by the general population metric alone. The standardized covariance between SEV and HSC was not statistically significant in any model.

Antenatal Care The structural model for Antenatal Care (ANC) trimester visits (Figure 4.12) explained 26.8% of its variance ($R^2 = 0.268$). Higher SEV ($\beta = 0.164$, $p < 0.001$) and higher HSC ($\beta = 0.232$, $p < 0.001$) were both associated with increased ANC trimester visits. Standardized flood depth did not show a significant direct effect ($p = 0.956$).

Health Facility Births For health facility births, the model accounted for 43.8% of the variance ($R^2 = 0.438$) (figure 4.13). A negative linear time trend and significant seasonal effects were the most prominent influences ($\beta = –0.606$, $p < 0.001$). The direct effects of flood depth, SEV, and HSC on facility births were not statistically significant.

General Utilization The SEM for general utilization explained 65.2% of its variance ($R^2 = 0.652$) (figure 14). Higher SEV was associated with lower utilization ($\beta = –0.169$, $p < 0.001$), whereas higher HSC was strongly linked to an increase in utilization ($\beta = 0.239$, $p < 0.001$). Floodwater depth did not demonstrate a statistically significant direct effect ($p = 0.726$).

Table 4.5 Description of variables and constructs used in the structural equation models.

Variable (Category and Name)	Type	Role in SEM	Description
Outcomes			
Antenatal Care (ANC) Trimester Visits	Observed	Endogenous	Mean predicted probability of combined first and third trimester visits (derived from beta regression model)
HF Births	Observed	Endogenous	Mean predicted probability of health facility–based deliveries (derived from beta regression model)
General Utilization (i.e., Outpatient)	Observed	Endogenous	Mean predicted probability of health facility utilization (derived from beta regression model)
Observed Predictors			
Flood Depth (z–score)	Observed	Exogenous	Standardized mean flood water depth (m) with a 1–month lead
Time Period & Seasonality			
Months Since Start	Observed	Covariate/Exogenous	Linear time trend since Oct. 2017
Sine (Harmonic)	Observed	Covariate/Exogenous	Seasonal sine term (12–month cycle)
Cosine (Harmonic)	Observed	Covariate/Exogenous	Seasonal cosine term (12–month cycle)
Latent Indicators			
Socioeconomic Vulnerability (SEV)			
Travel Time (2–5 hrs)	Observed Indicator	Indicator for SEV	Proportion of health facility catchment areas with average travel time (2–5 hrs)
Health System Capacity (HSC)			
Health Facilities per 1,000 WRA	Observed Indicator	[(a)]Indicator for HSC	Number of health facilities per 1,000 WRA
Health Facilities per 1,000 General Population	Observed Indicator	Indicator for HSC	Number of health facilities per 1,000 General Population
Latent Constructs			
Socioeconomic Vulnerability (SEV)	Unobserved	Exogenous	Representing SEV indicated by average travel time (2–5 hrs)
Health System Capacity (HSC)	Unobserved	Exogenous	[(a)]Representing HSC indicated by health facility density

Note: **(a)** The Health System Capacity construct is indicated by both 'Health Facilities per 1,000 Women of Reproductive Age' and 'Health Facilities per 1,000 General Population' in the Structural Equation Models for Antenatal Care Trimester Visits and Health Facility Births. In the SEM for General Utilization, HSC is indicated only by 'Health Facilities per 1,000 General Population'.

Abbreviations: **ANC**, Antenatal Care; **SEV**, Socioeconomic Vulnerability; **HSC**, Health System Capacity; **WRA**, Women of Reproductive Age (15–49 years); **SEM**, Structural Equation Model; **HF**, Health Facilities (Centers & Posts)

Table 4.6 Standardized structural path coefficients from structural equation models.

Variable Path and Description	ANC Model (β [P value])	HF Births Model (β [P value])	Gen. Utilize Model (β [P value])
Factor Loadings (Standardized β)			
Socioeconomic Vulnerability (SEV)			
SEV ← ~ Travel Time (2–5 hrs)	1.000 [--] (f)	1.000 [--] (f)	1.000 [--] (f)
Health System Capacity (HSC)			
HSC ← ~ HF per 1,000 WRA	0.978 [--] (f)	1.192 [--] (f)	[--]
HSC ← ~ HF per 1,000 Gen. Pop.	**1.020** [<0.001]***	0.837 [0.285]	1.000 [--] (g)
Structural Model			
Paths to ANC Trimester Visits			
Flood Depth (z–score) → ANC Visits	0.005 [0.956]	[--]	[--]
SEV → ANC Visits	**0.164** [<0.001]***	[--]	[--]
HSC → ANC Visits	**0.232** [<0.001]***	[--]	[--]
Months Since Start → ANC Visits	**-0.349** [<0.001]***	[--]	[--]
Sine (Harmonic) → ANC Visits	**0.117** [0.024]*	[--]	[--]
Cosine (Harmonic) → ANC Visits	**-0.206** [0.005]**	[--]	[--]
Paths to Health Facility Births			
Flood Depth (z–score) → HF Births	[--]	–0.002 [0.982]	[--]
SEV → HF Births	[--]	–0.026 [0.282]	[--]
HSC → HF Births	[--]	0.008 [0.748]	[--]
Months Since Start → HF Births	[--]	**–0.606** [<0.001]***	[--]
Sine (Harmonic) → HF Births	[--]	**–0.222** [<0.001]***	[--]
Cosine (Harmonic) → HF Births	[--]	**–0.193** [0.006]**	[--]
Paths to General Utilization			
Flood Depth (z–score) → Gen. Utilize	[--]	[--]	0.019 [0.726]
SEV → Gen. Utilize	[--]	[--]	**–0.169** [<0.001]***
HSC → Gen. Utilize	[--]	[--]	**0.239** [<0.001]***
Months Since Start → Gen. Utilize	[--]	[--]	**–0.383** [<0.001]***
Sine (Harmonic) → Gen. Utilize	[--]	[--]	**0.582** [<0.001]***
Cosine (Harmonic) → Gen. Utilize	[--]	[--]	**0.229** [<0.001]***
Latent Variable Covariances (Standardized)			
SEV ~~ HSC	-0.016 [0.588]	0.009 [0.587]	0.002 [0.955]
Model Fit: R^2 (Variance Explained)			
ANC Trimester Visits	0.268	[--]	[--]
HF Births	[--]	0.438	[--]
Gen. Utilize	[--]	[--]	0.652

Note: β represents fully standardized coefficients (derived from Std.all in *lavaan* R code summary output).

Levels of Significance: P values are shown in brackets [ ], * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The notation [--] in a P value cell indicates it is not applicable for that parameter (e.g., for factor loadings fixed for model scaling or for single–indicator latent variables where the indicator's R^2 is 1.0). **(f)** Denotes a factor loading derived from an unstandardized loading that was fixed at 1.0 for model scaling purposes, or a standardized loading that is 1.0 because it is for a single indicator of a latent variable where that indicator's R^2 is 1.0. **(g)** In the General Utilization Model, the Health System Capacity latent variable is indicated by "HF per 1,000 General Population" only; "HF per 1,000 WRA" is not an indicator for HSC in this specific model configuration. Variable names used in the "Parameter Path and Description" column correspond to the more detailed variable descriptions provided in Table 5.

Abbreviations: ANC, Antenatal Care; **Gen. Utilize**, General Utilization; **HF**, Health Facility (Centers and Posts); **HSC**, Health System Capacity; **SEV**, Socioeconomic Vulnerability; **WRA**, Women of Reproductive Age (15–49 years); **Gen. Pop.**, General Population.

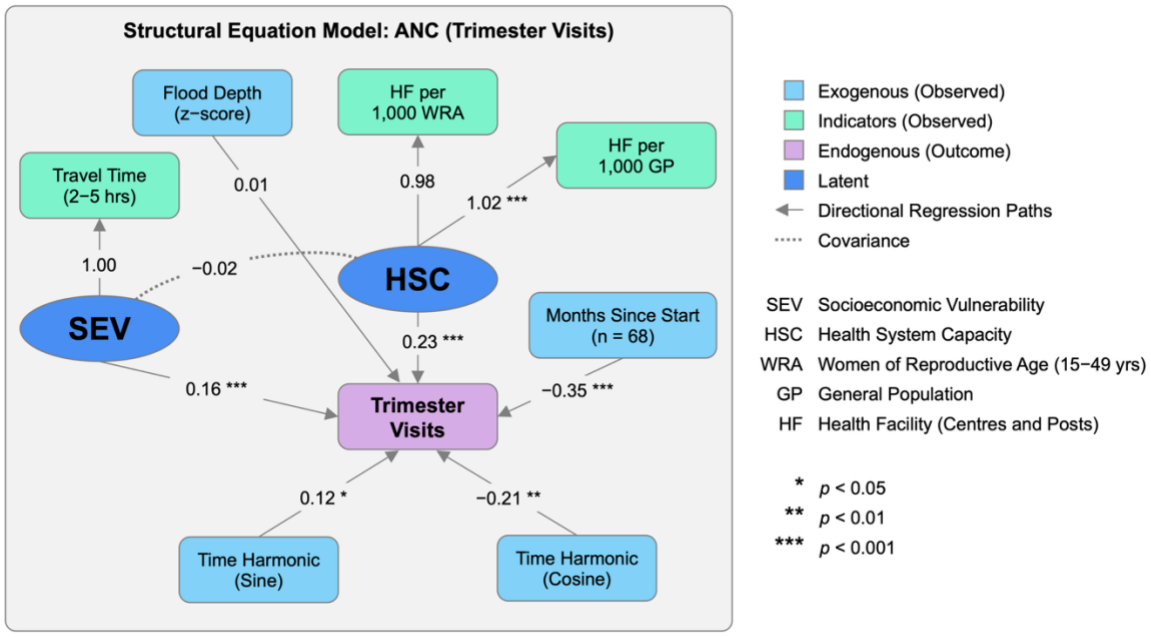


Figure 4.12 Structural equation model path diagram for Antenatal Care combined trimester visits (First and Third).

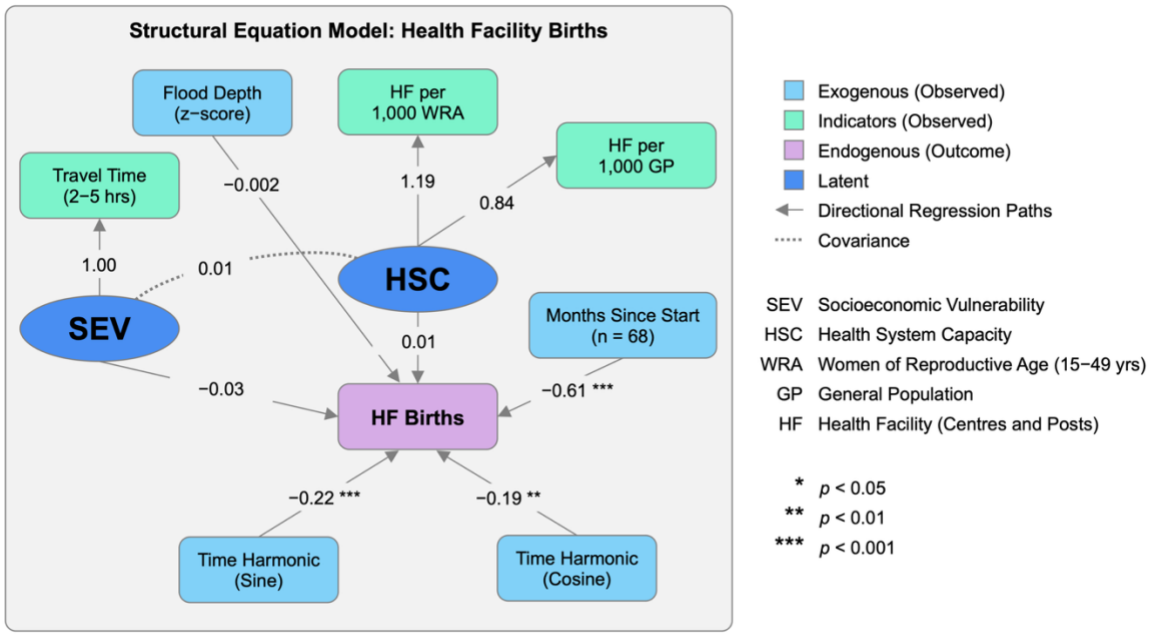


Figure 4.13 Structural equation model path diagram for health facility births.

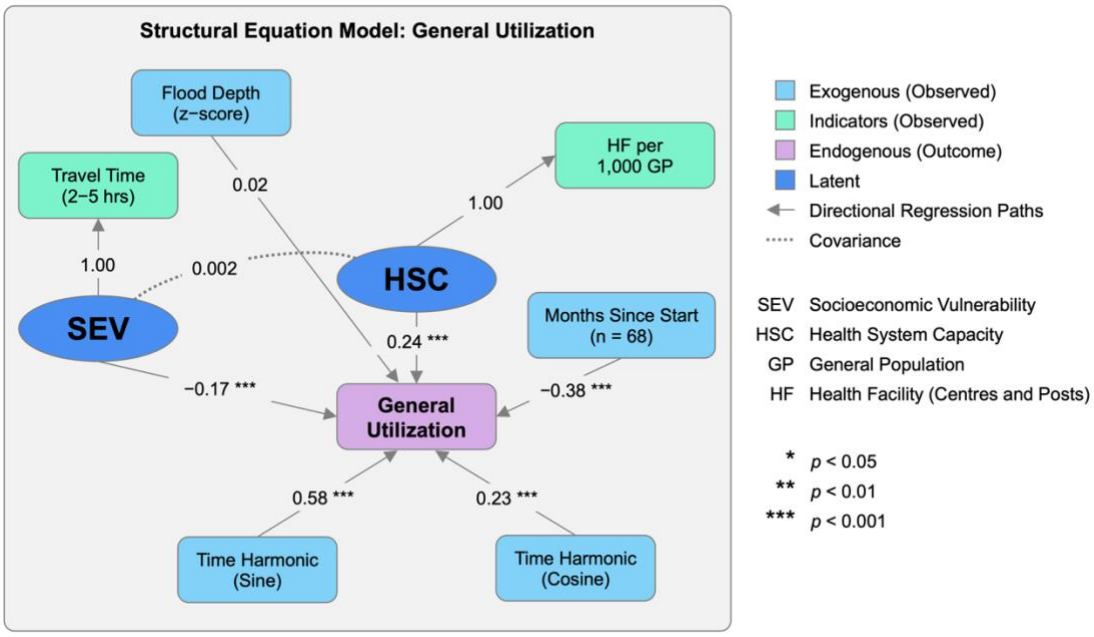


Figure 4.14 Structural equation model path diagram for general health facility utilization (i.e., Outpatient).

4.5 Discussion

To the best of our knowledge, this study introduces the first quantitative evidence of an econosyndemic within the health system of Western Province (WP), Zambia. Our results illustrate that the effects of climate shocks are not uniform; rather, they are significantly conditional upon the underlying capacity of the health system. The most compelling evidence of this is a powerful synergistic interaction affecting facility births, where the protective effect of higher health facility density was markedly amplified in the most vulnerable districts. This effect was most pronounced in Sikongo district, which exhibited an exceptionally large adjusted odds ratio. This is likely a result of the district's very low baseline rate of facility births, where even a modest absolute improvement in utilization produces a dramatic relative effect. This key finding is corroborated by a series of related effects: increased exposure to seasonal floods is associated with a decline in antenatal care (ANC) trimester visits, while, paradoxically, general utilization of services increases in some regions and decreases in others. Collectively, these findings confirm that the interaction

between climate-related shocks and chronic stressors results in heterogeneous patterns of service disruption, leading to both under-utilization and over-utilization relative to actual needs.

Our finding that high seasonal flood exposure was associated with a reduction in both ANC trimester visits and health facility births was strongly supported by a consistent and growing body of international research. This evidence confirms that flooding acts as a critical barrier to accessing essential maternal and newborn health services. Research from other flood-prone regions offers direct parallels; in Bangladesh, for example, studies have shown that the odds of receiving ANC from skilled providers and having institutional deliveries were significantly lower in flood-affected areas, with the impact being more severe in areas experiencing recurrent floods.[192] Similarly, women from households displaced multiple times by extreme weather events were found to be substantially less likely to receive adequate ANC.[193] This relationship is powerfully corroborated by research conducted in our specific study setting, the Barotse Floodplain of WP. A recent GIS-based study demonstrated that as floodwater levels increased, the proportion of women with walking access to their nearest delivery site within two hours dropped from 55% to just 29%.[54] At the flood's peak, an estimated 65% of women were unable to walk to any delivery site at all, providing a clear mechanism for the statistical association we identified. Qualitative studies further highlight the severe consequences of this access barrier, documenting the absence of skilled birth attendants and clean delivery spaces in flood relief camps, which places mothers and their newborns at significant risk.[194,195]

In contrast to the decline in the utilization of maternal health services, our study revealed a paradoxical increase in general outpatient utilization during periods of high flood exposure.[i] The most plausible explanation for this finding is that the heightened burden of infectious, waterborne, and vector-borne diseases during and after flooding creates a surge in care-seeking that outweighs the concurrent challenges of physical access. This phenomenon is well-documented in disaster

[i] The observed paradoxical increase in utilization may be partially confounded by the arrival of additional, unobserved resources that typically enter the local health system during major flood events. These resources, which may originate from federal government disaster relief, non-governmental organizations (NGOs), or external agencies, could contribute to motivating increased care-seeking by providing free temporary medical supplies, mobile clinical support, or disease testing. Since these efforts are not recorded in the routine HMIS data, they were excluded as a variable in the current analysis. Future mixed-methods research should incorporate a qualitative component to evaluate the role and timing of external agency support in influencing local health-seeking behaviors during acute shocks.

epidemiology. For example, a multi-year analysis of national health data in Cambodia found that floods were significantly associated with increases in consultations for skin diseases and acute respiratory infections.[196] Similarly, research following floods in Pakistan highlights the mechanisms driving this trend, noting that contamination of water sources and poor hygiene in displaced settings lead to a higher incidence of infectious diseases, particularly among children.[195] A systematic review focused on sub-Saharan Africa further corroborates the strong association between flooding events and a range of adverse health outcomes, including increased morbidity from communicable diseases.[197] Our finding aligns with existing evidence suggesting that floods may severely restrict access to time-sensitive or complex care like childbirth. However, they simultaneously increase the overall demand for community-level essential health services.

Beyond these principal effects, the primary contribution of our study resides in empirically demonstrating the econosyndemic framework. The strong interaction observed for facility births provides robust quantitative evidence supporting the concept of an econosyndemic. Specifically, the positive influence of increased health facility density on the rate of facility births was notably amplified in the most socioeconomic vulnerability (SEV) districts. This confirms that the impact of a climate shock is not uniform but is conditional upon the underlying social and health system contexts, a principle extensively discussed in the climate and health literature.[198,199] Our findings are consistent with conceptual models that conceptualize vulnerability to climate hazards as a function of exposure, sensitivity, and adaptive capacity, which differ across various geographic and demographic settings.[200] By demonstrating that enhancing a key health system component—namely, facility density—provides the greatest protective benefit in the most vulnerable regions, our study offers empirical support for the principle that targeted strengthening of health systems constitutes a vital form of climate adaptation capable of advancing health equity.[197,201] This evidence underscores the foundational principle of the econosyndemic framework: that focusing solely on individual conditions is inadequate, as it is the interaction between the environmental shock and the system's capacity that ultimately determines health outcomes.

Further reinforcing the econosyndemic model, our analysis revealed a strong heterogeneous interaction for general utilization. While flooding was associated with an overall increase in health-seeking behaviour, this effect was markedly attenuated in certain administrative districts. This

finding demonstrates that the community and health system response to a climate shock is not uniform and can be influenced by local context in complex ways. The geographic variation in vulnerability is a well-established concept, with studies indicating that susceptibility to flood impacts can vary substantially even among neighbouring communities, based on underlying socioeconomic and environmental factors.[202,203] Although our model did not explicitly identify the specific factors driving this dampening effect, such heterogeneity suggests that unmeasured local characteristics—such as differences in population density, health-seeking behaviours, or the capacity of local health facilities to manage surges in outpatient visits—may modify the impact of a large-scale environmental shock. This contrast between reduced maternal care and increased general utilization may also reflect underlying gendered priorities in health-seeking during a crisis, though our ecological data does not allow for a direct test of this hypothesis. This finding offers additional evidence against a one-size-fits-all approach to interpreting climate impacts, emphasizing the importance of geographically nuanced analysis to understand how and why different segments of a health system respond differently to the same shock.[204]

The results derived from our SEMs further substantiate the econosyndemic framework by emphasizing the fundamental importance of latent, system-level constructs. Our observation that both Health System Capacity (HSC) and SEV serve as robust direct predictors of health facility utilization confirms that foundational structural conditions are primary determinants of access to essential first-level health services. This observation corroborates extensive scholarly literature highlighting that a health system's capacity to endure shocks is dictated by its intrinsic resilience and the susceptibility of the population it serves.[16,205] By operationalizing and quantifying these latent constructs, our research transcends the analysis of individual variables to empirically demonstrate that these broader systemic characteristics ultimately influence health outcomes amid environmental challenges.[197,206] This serves as a compelling rationale for policy initiatives to prioritize not merely discrete interventions, but the enhancement of overall systemic capacity and the alleviation of socioeconomic vulnerabilities as central strategies for climate adaptation.[207,208]

A key finding of this study is how the role of flooding differs between our two analytical models, which, when taken together, provide a deeper insight into the econosyndemic process. While the beta regression models identified flooding as a significant predictor of service disruption, the

SEMs reveal that this effect is not direct. Instead, the SEMs empirically demonstrate that the flood's impact is mediated through the system's underlying conditions—namely, HSC and SEV.[9,209] In this model, the flood acts less as a direct cause of health service disruption and more as a catalyst that exposes and exacerbates pre-existing weaknesses in health system capacity and magnifies underlying SEVs.[205] This finding is arguably the most direct validation of our study's central hypothesis, shifting the focus from shock to systemic conditions that determine the resilience of a community and the health system.

4.5.1 Strengths and Limitations

This study possesses multiple notable strengths. Its foremost contribution lies in the novel application and empirical validation of the econosyndemic framework within a climate-vulnerable health system. It advances beyond mere descriptive studies by quantifying the crucial interaction between a climate-related shock and chronic health system stressors. The analysis utilizes a substantial, multi-year longitudinal dataset encompassing an entire province, thereby enhancing the generalizability of our findings within this region. Moreover, a robust two-part analytical methodology—integrating beta regression mixed-effects models to test specific interactions with structural equation models to explore latent system-level pathways—offers a comprehensive and methodologically rigorous evaluation of these intricate relationships.

Nevertheless, it is imperative to interpret our findings considering several limitations. First, the ecological study design precludes inferences at the individual risk level, and the observational nature of the data prevents establishing causal relationships. Second, the flood exposure variable, derived from advanced hydrodynamic modelling, was applied at the district level and may obscure finer-scale, localized variations in flood intensity and impact. Third, relates to our finding of a declining temporal trend in ANC visits, which contrasts with national survey data.[55,210] High-quality data from the Zambia Demographic and Health Surveys (ZDHS) indicate that ANC coverage in Western Province is not only high but has actually increased between the 2018 and 2023–24 surveys.[55,210] This discrepancy likely highlights a key challenge of relying solely on routine HMIS data, which was the only longitudinal data source available for this analysis. The difference may stem from several factors, including variations in reporting completeness over time

within the HMIS, or fundamental differences between administrative data that tracks facility-level service provision and population-based surveys that measure patient-reported outcomes. While a formal data triangulation study was beyond the scope of this project, future research could aim to integrate these distinct data sources to provide a more comprehensive understanding of service utilization trends. Fourth, methodologically, our choice to model the general utilization outcome using beta regression warrants discussion. While the ANC and facility birth outcomes are true proportions, general utilization is a rate. We transformed this rate into a pseudo-proportion to maintain a consistent analytical framework and allow for the interpretation of all main effects as odds ratios, which aids in comparing outcomes. We acknowledge that a count-based model, such as a negative binomial regression, represents a more conventional approach for this type of data. However, given that our primary interest was in the direction and significance of the interaction effects within the econosyndemic framework, we believe this approach provides a reasonable and interpretable approximation of the underlying relationships. Fifth, the exceptionally large odds ratio observed for the interaction in Sikongo district, while directionally consistent with our hypothesis, should be interpreted with caution. Such extreme estimates, accompanied by a wide confidence interval, can be statistical artifacts of low event counts in specific strata and suggest that while the protective effect is strong, its precise magnitude is difficult to estimate. Finally, the analysis relies on routine HMIS data, which, despite its benefits, may be influenced by concerns related to data quality and completeness. This is particularly relevant regarding ANC outcomes, and our application of complete-case analysis for handling missing data constitutes a significant limitation. The substantial proportion of missing ANC outcomes, if not missing at random, could introduce bias into our estimates. Although methods such as multiple imputation were considered, their implementation was beyond the scope of this study; however, they represent an essential area for future methodological enhancement.

4.5.2 Health Policy and Programmatic Implications

Our findings have meaningful implications for health system planning and climate adaptation policies. The evidence of a geographically heterogeneous econosyndemic effect strongly advocates against a one-size-fits-all approach at the national level, emphasizing instead the urgent need for decentralized, data-driven, and geographically targeted interventions. For health planners,

this entails prioritizing investments in districts where the detrimental interaction between high flood risk and limited health system capacity is most evident. For instance, our results indicate that enhancing health infrastructure through increased facility density could produce substantial benefits in reducing service disruptions within the most vulnerable districts. Furthermore, these findings endorse a proactive strategy for climate adaptation. Instead of merely responding to disasters, health systems can employ predictive models such as ours to pre-position essential medical supplies, establish robust referral transport networks, and ensure that health facilities in high-risk areas are adequately staffed and equipped with ample resources, including trained health professionals and essential medicines, prior to flooding seasons. This transition from reactive to proactive measures is essential for fostering genuine health system resilience.[211] Ultimately, the methodologies employed in this study demonstrate the potential for routine spatiotemporal monitoring to function as an early warning mechanism, allowing health systems to allocate resources more effectively and safeguard essential services amidst foreseeable environmental shocks.

This study highlights several important directions for future academic research. Longitudinal investigations are essential to validate the causal pathways delineated within our models and to establish connections between observed utilization patterns and subsequent health outcomes, such as maternal and neonatal morbidity and mortality. Future analyses would be markedly improved through the integration of more granular data, including higher-resolution flood metrics, facility-specific preparedness indicators, and household-level data concerning health-seeking behaviour and socioeconomic status, thereby enabling a more precise representation of localized interactions. Methodologically, there exists scope to expand the econosyndemic framework to include other macro-level shocks, such as economic recessions, droughts, or infectious disease outbreaks or future pandemics, to deepen our understanding of how multiple systems interact to influence health outcomes. Most critically, future research must emphasize implementation science: the design, execution, and rigorous assessment—perhaps using methods like cluster randomized trials—of targeted, context-specific interventions, which our findings suggest are essential. Such efforts will be vital in developing an evidence base for effective, equitable, and sustainable climate change adaptation strategies within fragile health systems.

4.6 Conclusion

In conclusion, this study offers innovative, empirical evidence demonstrating that the complex interplay of climate-related shocks and inherent health system vulnerabilities influences health service utilization in rural Zambia. The application of the econosyndemic framework illuminates how these adverse synergistic interactions produce geographically diverse patterns of disruption and resilience. Ultimately, our findings highlight the importance of implementing targeted, context-specific strategies aimed at enhancing local health system capacity, thereby contributing to the advancement of Universal Health Coverage, which is fundamental to building resilient health systems capable of climate change adaptation.

Chapter 5

Forecasting Utilization

5.1 Overview

Background: In low- and lower-middle-income nations, advancements toward Universal Health Coverage (UHC) are progressively jeopardized by the combined effects of acute shocks, such as floods and pandemics, alongside chronic health system stressors. Although the disruptive effects of individual conditions are well understood, a significant gap exists in the empirical quantification of their synergistic interactions over time. This study employs an innovative multi-model time-series methodology to dynamically forecast health service utilization and assess the impacts of major shocks in Western Province (WP), Zambia.

Methods: We conducted a longitudinal ecological study utilizing 73 months of routine health data collected from 62 healthcare facilities, spanning October 2017 to September 2023. Initially, a comparative analysis of four time-series models—ARIMA, SARIMA, ETS, and Prophet—was performed to determine the most accurate forecasting approach. Subsequently, a Hierarchical Time Series (HTS) model was employed to generate reconciled forecasts across various administrative levels, assessing the additional value provided by an exogenous flood variable. Finally, an Interrupted Time Series (ITS) analysis using a generalized linear mixed-effects model was implemented to quantify both the immediate (level) and long-term (trend) impacts of three distinct shocks: a drought in 2019, the COVID-19 pandemic in 2021, and a complex flood event (i.e., February 2023 double-peak flood), characterized by an unusual 'double-peak' inundation pattern.

Findings The Prophet model was identified as the most accurate forecasting tool, achieving a mean absolute percentage error (MAPE) of 7.22%. The ITS analysis demonstrated that each shock distinctly affected health service utilization. The drought was associated with a significant

immediate decline in utilization (level = -0.105, $p < 0.001$), followed by a recovery trend (trend = 0.019, $p < 0.001$). The COVID-19 pandemic resulted in an immediate increase (level = 0.069, $p < 0.001$) followed by a negative trend change (trend = -0.005, $p < 0.001$). The 2023 flood event showed no immediate impact but was associated with a significant positive trend change (trend = 0.019, $p < 0.001$), suggesting a gradual recovery.

Conclusions This study provides innovative empirical evidence demonstrating that the interaction between environmental shocks and health system stressors dynamically affects health service utilization. The findings underscore the significance of adopting multi-model predictive strategies to produce early warnings and to inform targeted, data-driven interventions to strengthen health system resilience.

5.2 Introduction

The health effects of climate change are progressively diverse, presenting a direct threat to achieving Universal Health Coverage (UHC) and jeopardizing the stability of health systems in the world's most vulnerable regions.[167,168] Health system resilience—the capacity of a health system to anticipate, absorb, and adapt to shocks and stressors—is a vital component of climate adaptation strategies.[5,23] In low- and lower-middle-income countries (LMICs), health systems often face a convergence of acute, frequently unpredictable shocks, such as widespread floods and pandemics, alongside chronic, pre-existing stressors, including insufficient infrastructure and geographical barriers to essential health services. These shocks seldom occur in isolation; rather, they interact with underlying systemic vulnerabilities, resulting in disruptions and inequitable access to essential health services.[170,173] Although existing conceptual frameworks, such as syndemic theory, provide valuable insights into understanding these complex interactions, a notable gap persists in the empirical and quantitative assessment of the dynamic and synergistic effects between environmental shocks and health system stressors over time.

An effective approach to this challenge necessitates a sophisticated, multi-model strategy that extends beyond single-factor or single-model analyses. Traditional time-series methods, such as ARIMA, often exhibit limitations in managing non-linear trends, intricate seasonal patterns, and exogenous variables—attributes characteristic of health utilization data in fragile settings.[212,213] Accordingly, this study employs the Prophet model as a more robust and contemporary alternative. Prophet is a widely used forecasting algorithm suitable for time series data exhibiting pronounced seasonal effects and multiple changepoints, providing flexibility, high accuracy, and interpretability.[213,214] Furthermore, incorporating multiple models—comprising Hierarchical Time Series (HTS) models to encapsulate data across different levels of aggregation and Interrupted Time Series (ITS) analysis to methodically assess inferential effects—is crucial for a thorough and substantiated investigation.[215,216]

While equitable access remains a fundamental principle of UHC, it is notoriously challenging to measure in a manner that comprehensively captures the critical dimensions of space and time.[48,49] Consequently, this study uses general utilization, defined by monthly outpatient visits, as a

practical and measurable proxy for *realized access*. This metric is especially relevant in LMICs, where primary health facilities represent the initial point of contact for the majority of the population and function as the forefront of the health system.[49] Focusing on this measure provides valuable insights into the functionality and resilience of the frontline of the health system, where the impacts of shocks and stressors are most acutely experienced and where targeted interventions are frequently implemented.

The distinctive context of Western Province (WP), Zambia, provides an exemplary setting for the empirical investigation of these converging challenges. The region is predominantly characterized by the extensive Barotse Floodplain, an ecosystem subject to significant seasonal inundation, which, while vital for the local ecology and economic livelihoods, constitutes a recurrent environmental shock.[49,54] This acute environmental perturbation intersects with chronic stressors within the health system, including low facility density and substantial geographic barriers to care.[49] To rigorously examine these interactions, this study employs a novel analytical framework—econosyndemic—that extends beyond single-factor analysis, explicitly modelling the dynamic interplay between macro-level shocks and micro-level stressors (i.e., supply- and demand-side conditions).[j] Extending the syndemic framework, first postulated by Singer in 1996, the econosyndemic framework was conceptualized to evaluate how these interacting conditions influence health system performance and, ultimately, health service utilization over time.[k,25]

Building upon the preceding analysis, this study aims to accomplish two principal objectives. Firstly, it seeks to apply, evaluate, and interpret advanced time-series methodologies for modelling and forecasting general utilization, specifically the proportion of outpatient visits. This includes benchmarking multiple models, such as Prophet and a Hierarchical Time Series (HTS) model, to produce accurate predictions of future utilization. Furthermore, an assessment is conducted on the extent to which incorporating an exogenous variable, floodwater depth, enhances forecast precision. Secondly, this research utilizes an Interrupted Time Series (ITS) analysis to

[j] The analytical framework used in this study, defined as the econosyndemic, is described in a related manuscript submitted for publication. Chiarot, C.B., et al., 2025 (*Quantifying an econosyndemic: A longitudinal analysis of the interaction between climate shocks and health system stressors on utilization of essential health services using beta regression and structural equation modelling in WP, Zambia*).

[k] Ibid.

systematically evaluate the immediate (level) and long-term (trend) impacts of three noteworthy macro-level shocks: the 2019 drought, the 2021 COVID-19 pandemic[1], and the 2023 complex flood event (i.e., characterized by an unusual 'double-peak' where floodwaters receded and then rose to a second, later peak, deviating from the typical single-peak annual flood cycle). The results provide a comprehensive and dynamic understanding of health service utilization within a climate-vulnerable context, offering valuable insights for planning, policy formulation, and health system enhancement.

5.3 Methods

5.3.1 Study Design and Setting

This study employed a longitudinal ecological study design, using time-series analysis to examine patterns and determinants of health service utilization. This approach facilitated the assessment of temporal trends and the impacts of specific shocks on health outcomes within an existing population without the need for direct intervention. The three macro-level shocks analyzed included a drought in 2019, the COVID-19 pandemic (i.e., SARS-CoV-2), and a complex flooding event in 2023. The analysis focused on a longitudinal dataset comprising facility-month observations, with health facilities serving as the primary units of analysis. The research was conducted in Western Province (WP), Zambia, a region in Sub-Saharan Africa with an estimated population of 1.36 million in 2022.[50] Western Province is notably characterized by the Barotse Floodplain, an extensive wetland system along the Zambezi River, distinguished by seasonal flooding variations.[49,54,77] Healthcare services are provided through a network of first-level health facilities (i.e., primary health care), including health centers and health posts.[49,56] The study period

[1] The interruption date for the COVID-19 pandemic was set to January 2021. This date was chosen to model the onset of a sustained, systemic shock to the health system rather than the date of the first reported case. The first two cases in the study area of Western Province were reported significantly earlier on May 28, 2020 (Ministry of Health, Zambia. 2020, May 28. COVID-19 Daily Update. As reported by Lusaka Times). The January 2021 date, however, corresponds to the period when the pandemic's cumulative effects—including the implementation of major public health measures, widespread changes in health-seeking behaviors due to public fear, and significant policy shifts—became fully pronounced. This created a consistent and structural disruption to health service utilization. Therefore, this date is a more appropriate anchor for the Interrupted Time Series (ITS) analysis, as it marks the beginning of the stable, long-term impact that the model is designed to evaluate.

spanned from October 2017 to September 2023, covering a comprehensive temporal window of 73 months for analysis. The final analytic dataset comprised 62 public health centres and health posts across seven administrative districts within WP, where monthly flood exposure data were available.

5.3.2 Data Sources and Variables

Longitudinal data on general utilization (i.e., outpatient visits) were obtained from Zambia's Health Management Information System (HMIS), its national routine health information system.[56,217] Supplementary data for population denominators and geographic access modelling were derived from the Spatially Defined Catchment Area (SCSO) and Population Under Rooftop (PUR) methodology, which integrates official Central Statistical Office (CSO) population estimates with high-resolution, satellite-derived gridded population data from Meta's High Resolution Settlement Layers (HRSL).[m,74,75] Flood exposure data were obtained from the LISFLOOD-FP hydrodynamic inundation model, a widely used model that simulates river hydrodynamics to predict flood extent and depth, which provides average monthly outputs of floodwater dynamics, including water depth with a spatial resolution of 900 m.[54,76,77] It is important to note that the flood exposure data represents a single, district-wide monthly average for the region. As such, the variable captures the overall temporal dimension of seasonal flooding but does not account for finer-scale, localized variations in flood intensity across different districts or facility catchment areas.

The primary dependent variable was general utilization, defined as the monthly proportion of outpatient visits. The monthly proportion of outpatient visits was selected as the primary outcome to normalize utilization across health facilities with vastly different catchment population sizes and to account for population growth over the 73-month study period. This approach ensures that trends in utilization are not confounded by underlying demographic changes and maintains methodological consistency with related analyses in previous research. This proportion was calculated by dividing the monthly number of reported outpatient visits by the estimated general

[m] The SCSO-PUR methodology used in this study to calculate proportion of general utilization was described in a related manuscript submitted for publication. Chiarot, C.B., et al., 2025 (*Enhancing Routine Health Information Systems Data Using a Novel Spatially Defined Catchment Area Methodology for Estimating Denominators: A Malaria Surveillance Case Study Among Children Under Five in Western Province, Zambia*).

population within each health facility's catchment area. To ensure compatibility with the Beta regression models used in the ITS analysis, a continuity transformation was applied to the entire vector of observed proportions to constrain the data to the open interval (0,1). This adjustment, based on the Smithson and Verkuilen approach (Ferrari et al., 2004), modified the proportion as follows: $y' = y \cdot (n-1) + 0.5/n$ where y' is the transformed proportion used as the outcome variable in the model, constrained to an open interval (0,1), y is the original proportion of general utilization (i.e., outpatient visits), and n is the total number of observations used for the transformation.

Several independent variables and covariates were constructed to account for geographic, environmental, and temporal factors. The characteristics of each health facility, including its unique name, geographic coordinates (latitude and longitude), type (Health Centre or Health Post), and location classification (rural or urban), were used. The administrative district of each health facility was included as a categorical variable, with *Kalabo* district serving as the *reference* category among the seven study districts. Flood depth, derived from the LISFLOOD-FP hydrodynamic model, was measured in meters.[76] This continuous variable was also categorized into three levels: *Low* (<0.2 m; *reference*), Medium (0.2−0.4 m), and High (>0.4 m). A one-month lag version of the flood depth variable was incorporated into the exogenous variable Prophet models and the final ITS model to capture the delayed effects of flooding. Population denominators were adjusted using district-specific annual Population Growth Rates (PGRs) derived from 2010-2020 Zambia Statistics Agency estimates (Kalabo: 2.5%; Limulunga: 1.6%; Lukulu: 4.2%; Mitete: 3.1%; Mongu: 3.6%; Nalolo: 2.4%; Sikongo: 2.3%) to account for dynamic changes in catchment area populations over time.[50] Geographic access was quantified using estimated travel time, which was calculated as the straight-line distance between the population-weighted centroid of each health facility's catchment area (PUR centroid) and the health facility. The *law of cosines* was applied to calculate this distance defined by:

$$d_{ij} = R \cdot \arccos\big(\sin(\phi_i)\sin\big(\phi_j\big) + \cos(\phi_i)\cos\big(\phi_j\big)\cos\big(\lambda_j - \lambda_i\big)\big)$$

where d_{ij} is the straight-line distance between point i (PUR centroid) and point j (health facility), ϕ is the latitude (radians), λ is the longitude (radians), and R is the Earth's radius ≈ 6,371 km. This

distance was then divided by an assumed walking speed of 5 km/hr to estimate travel time in minutes, which was subsequently categorized into three levels: 0−2 hrs (*reference*), 2−5 hrs, and >5 hrs. To account for underlying temporal trends and seasonal patterns, the models included a linear time trend representing the number of months since the study start and two harmonic terms, which were calculated as the sine and cosine of the month number over a 12-month cycle. The harmonic time terms were given by: $time_{sin} = \sin(2\pi t/12)$ and $time_{cos} = \cos(2\pi t/12)$.

5.3.3 Data Preparation and Cleaning

The analytic dataset was refined to include exclusively data from the designated study period, spanning October 2017 to September 2023, and to encompass a subset of 62 health facilities distributed across the seven administrative districts where complete monthly flood exposure data was obtainable. This refinement process yielded a final dataset comprising 4,254 facility-month observations for analytical purposes. The dataset was subsequently divided into two subsets to facilitate the primary analytical components of the study: time-series forecasting and Interrupted Time Series (ITS) analysis. This approach ensured that the specific data formatting requirements of each modelling approach were satisfied without compromising the integrity of the original dataset. All facility-month observations were aggregated to generate a single monthly time series for provincial-level forecasting. As the outcome variable represented a proportion, a weighted aggregation method was employed to ensure an accurate depiction of utilization at the provincial level. First, the monthly visit count for each facility was recalculated by multiplying its utilization proportion by its corresponding population denominator. These counts were then summed across all facilities for each month. Finally, a single, aggregate provincial utilization proportion was calculated by dividing the total monthly visits by the total provincial population for that month. This approach avoids potential bias that could arise from simply averaging the individual facility proportions. District-level data were aggregated similarly for the disaggregated forecasting models. A comprehensive analysis was conducted, and observations were excluded if the primary outcome or key predictors were missing. Without a time-series imputation method, this approach ensured that all models were fitted to a complete dataset, which is essential for the stability and interpretability of regression models. The missingness rate for the primary outcome, general utilization, was approximately 5% of facility-month observations. The application of lagged flood

variables in certain analyses also necessitated the systematic exclusion of the first and last months of data for each facility.

5.3.4 Statistical Analysis

Time-Series Forecasting A comparative analysis was performed to identify the most accurate forecasting model for general utilization. Four models were evaluated: an autoregressive integrated moving average (ARIMA), a seasonal ARIMA (SARIMA), an exponential smoothing model (ETS), and an additive model that accounts for non-linear trends and seasonality (Prophet).[142,214,218] The Prophet model is based on a decomposable time series model that captures a trend, seasonality, and holidays and is given by $y(t) = g(t) + s(t) + h(t) + \epsilon_t$ where $y(t)$ is the forecasted proportion of general utilization at time t, $g(t)$ is the non-linear trend function, $s(t)$ is the seasonal component, $h(t)$ is the holiday effect component (excluded in this model), and ϵ_t is the error term. The Prophet model captures seasonality automatically using a Fourier series, so external harmonic terms were not specified for the forecasting component of the analysis. The models were trained on data from October 2017 to December 2022 and validated on a 9-month test set from January 2023 to September 2023. Forecast accuracy was assessed using three standard metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The model with the lowest MAPE was selected for further analysis. The results of this comparison are presented in Table 5.2 and visualized in Figure 5.1. The Prophet model was implemented using the default hyperparameters of the *prophet* package in R (version 4.5.1) to ensure reproducibility.[105,219]

Hierarchical Time Series To forecast general utilization across different levels of aggregation, a hierarchical time series (HTS) model was developed.[215,216,220,221] The hierarchy was defined with three levels: Level 0 represented the total for WP, Level 1 comprised four geographic quadrants, and Level 2 comprised the 62 individual health facilities. The base time series was a matrix of monthly visit counts for each facility. This hierarchy can be described mathematically as: $y_t = S\beta_t$ where y_t is a vector of the total general utilization visits at each level of the hierarchy at time t, S is the summation matrix that maps the bottom-level series to their corresponding aggregates at high levels, and β_t is a vector of the bottom-level series (i.e., individual health facility general

utilization visits) at time t. The forecast reconciliation was performed using a bottom-up (*bu*) approach, where individual facility forecasts were aggregated to generate forecasts for the higher levels of the hierarchy (figure 5.3).

Exogenous Variable Modelling To assess the impact of environmental shocks on forecast accuracy, two augmented Prophet models were developed at the district level. These models incorporated flood data as an exogenous regressor.[222,223] The Prophet model with an exogenous regressor is extended by adding a linear term for the new variable, such that the model becomes: $y(t) = g(t) + s(t) + h(t) + \beta X_t + \epsilon_t$ where $y(t)$ is the forecasted proportion of general utilization at time t, $g(t)$ is the non-linear trend function, $s(t)$ is the seasonal component, $h(t)$ is the holiday effect component (excluded in this model), β is the coefficient for the exogenous regressor, X_t is the value of the exogenous regressor (i.e., continuous floodwater depth measured in meters or a categorical dummy variable) at time t, and ϵ_t is the error term. The first model included a continuous flood depth variable, while the second used a categorical flood level variable (low, medium, and high). The forecast accuracy of these flood-augmented models was compared to a baseline Prophet model for each of the seven districts. The performance of the models, as measured by RMSE, MAE, and MAPE, is detailed in Table 4 and visualized for key districts in Figure 4.

Interrupted Time Series The immediate (level) and long-term (trend) impacts of three major interruptions on health utilization were evaluated using an interrupted time series (ITS) design.[224,225] A generalized linear mixed-effects model (*glmmTMB*) was employed, which is well-suited for longitudinal data with a hierarchical structure.[139] The outcome, general utilization, was assumed to follow a Beta distribution with a logit link function. The fixed effects in the model included a linear time trend (months since study start), and, to explicitly control for seasonal patterns, harmonic terms for seasonality (sine and cosine), and fixed effects for each of the seven administrative districts, with *Kalabo* district as the *reference*. The model also included a random intercept for each health facility to account for unobserved facility-level heterogeneity. The three primary interruptions were specified as changepoints in the time series and were modelled with both level and trend variables given by:

$$L_m = \begin{cases} 0, & \text{if } t < C_m \\ 1, & \text{if } t \geq C_m \end{cases} \text{ and } T_m = \begin{cases} 0, & \text{if } t < C_m \\ t - C_m, & \text{if } t \geq C_m \end{cases}$$

where L_m is the level variable for interruption m, T_m is the trend variable for interruption m, t is time measured as months since start, and C_m is the changepoint date (in months) for interruption m. The model's final structure is defined by:

$$logit(\mu_{it}) = \beta_0 + \beta_1(t) + \beta_2(\sin(t)) + \beta_3(\cos(t)) + \sum_{j=1}^{k} \beta_{j+3}(District_j) + \sum_{m=1}^{3} [\delta_m(L_m) + \gamma_m(T_m)] + u_i$$

where $logit(\mu_{it})$ is the log-odds of the mean general utilization proportion for facility i at time t, β_0 is the intercept, $\beta_1(t)$ is the linear time trend, where t is months since start, $\beta_2(\sin(t)) + \beta_3(\cos(t))$ are the harmonic terms used for seasonality, $\sum_{j=1}^{k} \beta_{j+3}(District_j)$ is the fixed-effects for the k districts, $\delta_m(L_m)$ is the immediate change in the level of general utilization for interruption m, $\gamma_m(T_m)$ is the change in the trend of general utilization for interruption m, and u_i is the random intercept for each health facility i. o visualize the impact of each interruption, counterfactual time series were generated by setting the relevant level and trend variables to zero for all post-intervention time points in the final model's linear predictor.[224] This approach facilitated a comparative analysis between the predicted outcomes of the factual model and a hypothetical scenario wherein a specific interruption had not occurred. The visualization of these scenarios is presented in Figure 5.6. The results of the final model, including fixed-effects estimates, 95% confidence intervals, standard errors, and p-values, are summarized in Table 5.5. This table provides the statistical evidence for the immediate and long-term effects of each interruption on overall utilization. The entire time series of general utilization and flood depth is depicted in Figure 5.5 to offer an environmental context for the ITS model.

5.3.5 Statistical Inference

For the comparative time-series models, forecast accuracy was evaluated using RMSE, MAE, and MAPE. The model with the lowest MAPE was selected as the best-performing model. The forecast

utilization flag thresholds presented in Table 3a were defined based on the quartiles of the historical distribution of monthly general utilization from 2017-2023. For the ITS analysis, the Beta regression model was based on a two-sided significance level of $\alpha = 0.05$. For each predictor, final model outputs include the logit-scale coefficient, standard error (SE), adjusted odds ratio (AOR), and the corresponding 95% confidence interval (CI) and *p*-value. An association was considered statistically significant if the *p*-value was less than 0.05 and the 95% CI for the AORs did not include 1.0.

5.3.6 Model Diagnostics

The assessment of model assumptions was carried out through the analysis of simulation-based residuals obtained via the *DHARMa* package. The distribution of these residuals was meticulously examined to evaluate their uniformity and heteroscedasticity. Furthermore, the variance inflation factor (VIF) was determined using the *performance* package to identify potential multicollinearity among the fixed effects of the model. Notably, a diagnostic evaluation of the residuals revealed significant autocorrelation, which could not be rectified due to convergence failures encountered when an autoregressive component was incorporated. Consequently, *p*-values should be interpreted with caution, as autocorrelation can lead to an underestimation of standard errors, potentially making some results appear more statistically significant than they truly are. Therefore, the findings should be viewed as strong evidence of association rather than precise causal estimates. All data processing, visualization, and statistical analyses were performed utilizing R statistical software (version 4.3.1), predominantly employing the *prophet*, *hts*, *glmmTMB*, and *gtsummary* packages.[105,139,219,226,227]

5.3.7 Ethics Approval

Ethical approval for this study was obtained from the University of Waterloo Human Research Ethics Board (ORE-43883), the University of Zambia Biomedical Research Ethics Committee (Ref. No. 2472-2021; renewed February 9, 2024), the National Health Research Authority in Zambia (Ref. No. NHRA000009/10/07/2022), and the Provincial Ministry of Health, WP. Permission was granted for the secondary analysis of a large, de-identified administrative dataset.

Patients or members of the public were not directly involved in designing, conducting, or reporting this research.

5.4 Results

5.4.1 Descriptive Statistics

The final analytic dataset consisted of 4,254 facility-month observations, derived from a network of 62 primary care facilities across seven administrative districts in WP. The average monthly proportion of general utilization over the entire study period was 0.000189 (SD = 0.000126), with a median of 0.000179. Geographic access, measured by the average travel time to a health facility (based on straight-line distance and an assumed walking speed of 5km/hr), was 63.3 minutes (SD = 42.0). Most observations originated from rural health facilities, representing 93% of the total, with health centers and health posts comprising 52% and 48% of the data, respectively. Over the entire 73-month study period, the distribution of monthly flood severity categories was 14% for low flood exposure, 49% for medium, and 37% for high. A comprehensive summary of these descriptive statistics, stratified by each of the seven districts, is provided in Table 5.1.

5.4.2 Time-Series Forecasting

Model benchmarking The time-series forecasting analysis was conducted in three stages: a model benchmarking exercise, a hierarchical forecast, and an assessment of exogenous variables. A comparative analysis of four time-series models revealed that the Prophet model provided the most accurate forecasts for general utilization. As detailed in Tables 5.2 and 5.4, the Prophet model achieved the lowest Mean Absolute Percentage Error (MAPE) at 7.22% on the 9-month test set, which is an *excellent* forecast based on the pre-defined interpretation criteria.[221,226] In comparison, the Exponential Smoothing (ETS) model performed well with an MAPE of 13.56%, while the ARIMA and SARIMA models both yielded MAPE values of 16.30%. This superior performance of the Prophet model led to its selection for all subsequent forecasting analyses. A visual representation of the Prophet model's aggregate forecast for the entire province is presented in

Figure 5.1, which displays the model's fit on the training data and its forecast on the test set, including a 95% confidence interval.

Forecasted general utilization The Prophet model was employed to forecast overall utilization for the period from September 2023 to September 2024, with the results delineated at the district and quarterly levels in Table 5.3. A summary of the metrics and thresholds utilized for this analysis is provided in Table 5.4. The forecasts underscored notable variations in anticipated utilization across districts and quarters. For instance, several districts, including Kalabo and Limulunga, are projected to experience periods of over-utilization in Q1 2024, with forecasted percentages significantly exceeding the 0.023% threshold (figure 5.2). Conversely, districts such as Sikongo and Lukulu are consistently projected to fall within the severe under-utilization category for most of the forecasted period, exhibiting substantial negative deviations from their baseline values (tables 5.3 and 5.4).

Hierarchical Time Series Analysis The HTS model offered a coherent and reconciled forecast of provincial utilization by consolidating predictions derived from individual health facilities. This analysis validated an overarching downward trend in utilization across most regions of the province, accompanied by notable seasonal variations. The reconciled top-level forecast for the entire province achieved a Mean Absolute Percentage Error (MAPE) of 14.5% on the 9-month test set. The forecasts for WP (Level 0) and the four geographic quadrants (Level 1) are depicted in Figure 5.3, exemplifying the model's capacity to uphold logical relationships between disaggregated and aggregated projections. This furnishes a comprehensive and reconciled forecast of utilization for each of the four quadrants and the overall province of Western Province, extending through December 2024.

Table 5.1 Descriptive statistics of key variables stratified by district.

Variable	Overall	Kalabo	Limulunga	Lukulu	Mitete	Mongu	Nalolo	Sikongo
Observations (N)	4,254	948	1,335	207	125	1,083	486	701
Outcome								
General Utilization								
Proportion	0.000189	0.000192	0.000197	0.000244	0.000192	0.000178	0.000159	0.000168
Std. Dev.	(0.000126)	(0.000127)	(0.000136)	(0.000164)	(0.000106)	(0.000117)	(0.000087)	(0.000075)
Predictors								
Health Facilities								
Type								
Health Centre	2,226 (52%)	406 (43%)	704 (53%)	69 (33%)	0 (0%)	701 (65%)	276 (57%)	70 (100%)
Health Post	2,028 (48%)	542 (57%)	631 (47%)	138 (67%)	125 (100%)	382 (35%)	210 (43%)	0 (0%)
Location								
Rural	3,975 (93%)	948 (100%)	1,335 (100%)	207 (100%)	125 (100%)	804 (74%)	486 (100%)	70 (100%)
Urban	279 (7%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	279 (26%)	0 (0%)	0 (0%)
Ave. Travel Time (mins)	63.3 (42.0)	83.3 (51.7)	57.5 (34.8)	95.0 (19.3)	79.4 (9.5)	44.3 (37.0)	66.8 (37.9)	48.79 (0.0)
Flooding								
Water Depth (m)	0.37 (0.18)	0.37 (0.18)	0.37 (0.18)	0.37 (0.18)	0.37 (0.18)	0.37 (0.18)	0.37 (0.18)	0.37 (0.18)
Flood Severity (lag)								
Low	598 (14%)	139 (15%)	186 (14%)	29 (14%)	16 (13%)	149 (14%)	69 (14%)	10 (14%)
Medium	2,095 (49%)	462 (49%)	657 (49%)	104 (50%)	63 (50%)	534 (49%)	241 (50%)	34 (49%)
High	1,561 (37%)	347 (37%)	492 (37%)	74 (36%)	46 (37%)	400 (37%)	176 (36%)	26 (37%)

Note: Data are presented as *n* (%) for categorical variables and mean (standard deviation) for continuous variables. Statistics were calculated from 4,254 facility-month observations from 62 unique health facilities between October 2017 and September 2023. "Flood Severity (lag)" was based on the flood depth from the preceding month.

Table 5.2 Forecast model performance comparison for general utilization.

Model	R pkg [function]	RMSE	MAE	MAPE (%)	Description
ARIMA	*forecast* [auto.arima()]	0.000029	0.000025	16.30	Baseline autoregressive integrated moving average
SARIMA	*forecast* [auto.arima()]	0.000029	0.000025	16.30	Seasonal autoregressive integrated moving average
ETS	*forecast* [ets()]	0.000025	0.000022	13.56	Exponential smoothing
Prophet	*Prophet* [prophet()]	**0.000015**	**0.000012**	**7.22**	Additive; captures trends, seasonality, and changepoints

Note: Forecast accuracy of four time series models used to predict general health service utilization in Western Province, Zambia. All models were trained on data from Oct 2017 to Dec 2022 (n = 63 months) and tested on Jan 2023 to Oct 2023 (n = 10 months). Accuracy was evaluated on total monthly utilization (i.e., outpatient visits) across all study facilities. The Prophet model demonstrated the highest forecast accuracy (MAPE = 7.22%) on the test set and was selected for further modeling. **Abbreviations: ARIMA** Autoregressive Integrated Moving Average, **SARIMA** Seasonal ARIMA, **ETS** Exponential Smoothing, **RMSE** Root Mean Squared Error, **MAE** Mean Absolute Error, **MAPE** Mean Absolute Percentage Error (lower is ideal).

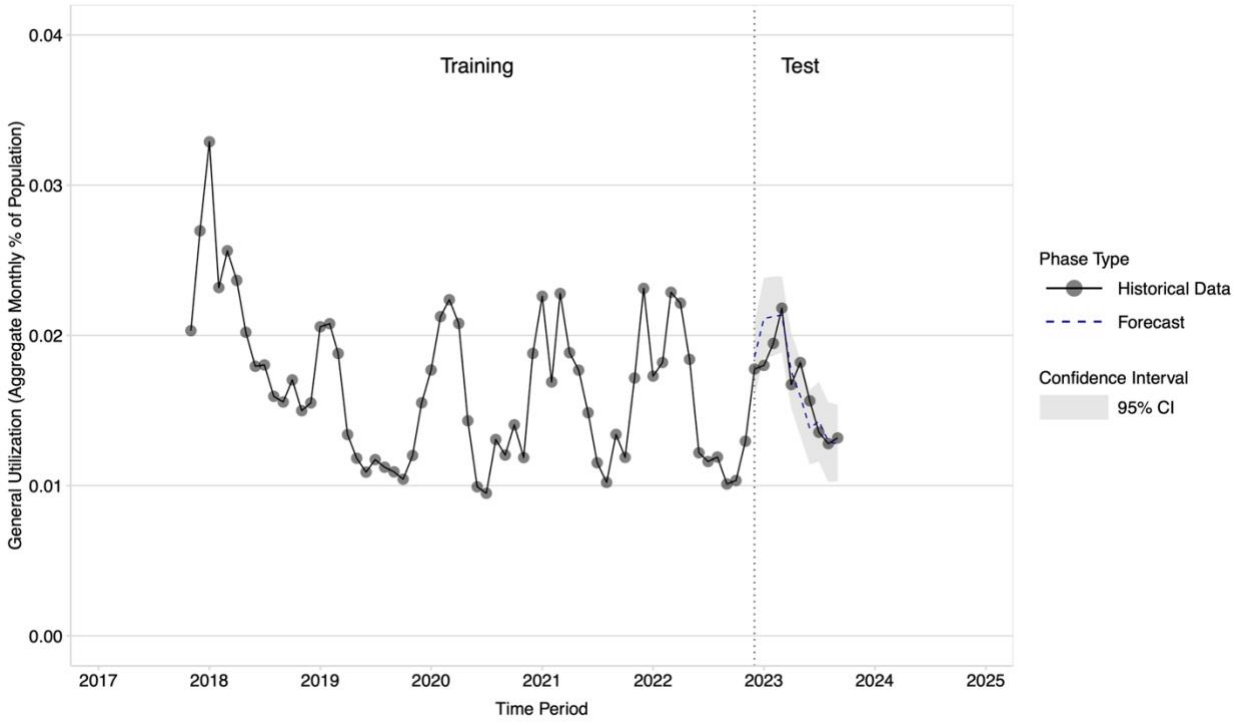


Figure 5.1 Prophet forecast of general utilization. The Prophet model forecast for aggregate monthly general utilization from October 2017 to September 2024. The model, which captures trend and seasonality, was trained on monthly data through December 2022 and evaluated using a 9-month test set from January to September 2023. The solid line shows the model's point forecast, while the shaded area indicates the 95% confidence interval.

Table 5.3 Forecasted general utilization by administrative district and quarter (September 2023 to September 2024).

Quarter–Year / Admin. District	District Pop.	Baseline (%)	Baseline Visits	Change from Baseline (%)	Forecast (%)	95% CI – Forecast %	Predicted Visits	95% CI – Predicted Visits	Forecast Utilize Flag
Q4 2023[n]									
Kalabo	48919.2	0.0209	30.3	7.1	0.0224	(0.018–0.027)	32.8	(26.1–39.1)	Utilize
Limulunga	61336.4	0.0124	22.9	10.3	0.0136	(0.010–0.017)	25.1	(18.6–31.9)	Utilize
Lukulu	9969.7	0.0144	4.7	35.0	0.0194	(0.011–0.029)	5.8	(3.2–8.6)	Utilize
Mitete	4992.5	0.0266	3.9	–2.9	0.0258	(0.017–0.035)	3.9	(2.6–5.2)	Over
Mongu	80628.8	0.0097	23.0	33.1	0.0130	(0.009–0.016)	31.4	(22.9–39.7)	Severe Under
Nalolo	25326.6	0.0143	10.9	1.2	0.0145	(0.011–0.018)	11.0	(8.4–13.5)	Under
Sikongo	5139.3	0.0070	1.1	71.3	0.0120	(0.005–0.019)	1.8	(0.8–2.9)	Severe Under
Q1 2024									
Kalabo	48919.2	0.0248	36.6	22.0	0.0303	(0.026–0.035)	44.4	(37.8–50.7)	Over
Limulunga	61336.4	0.0194	33.9	24.2	0.0241	(0.020–0.028)	44.3	(37.4–51.3)	Over
Lukulu	9969.7	0.0341	11.7	–9.4	0.0309	(0.022–0.040)	9.2	(6.5–11.9)	Over
Mitete	4992.5	0.0272	4.1	2.2	0.0278	(0.019–0.037)	4.2	(2.9–5.5)	Over
Mongu	80628.8	0.0149	37.1	29.9	0.0194	(0.016–0.023)	46.9	(38.2–55.4)	Utilize
Nalolo	25326.6	0.0189	14.7	16.1	0.0219	(0.019–0.025)	16.6	(14.1–19.1)	Utilize
Sikongo	5139.3	0.0200	3.1	–15.9	0.0168	(0.010–0.024)	2.6	(1.6–3.7)	Utilize
Q2 2024									
Kalabo	48919.2	0.0206	29.4	16.4	0.0240	(0.019–0.028)	35.2	(28.5–41.8)	Over
Limulunga	61336.4	0.0193	36.4	–1.1	0.0191	(0.016–0.023)	35.2	(28.6–42.0)	Utilize
Lukulu	9969.7	0.0174	5.1	40.9	0.0245	(0.016–0.033)	7.3	(4.7–10.0)	Over
Mitete	4992.5	0.0172	2.6	36.7	0.0236	(0.015–0.032)	3.5	(2.3–4.8)	Over
Mongu	80628.8	0.0131	32.6	12.0	0.0147	(0.011–0.018)	35.6	(27.0–44.6)	Under
Nalolo	25326.6	0.0154	12.0	0.6	0.0155	(0.012–0.019)	11.8	(9.3–14.3)	Under
Sikongo	5139.3	0.0187	2.9	3.4	0.0193	(0.012–0.026)	3.0	(1.9–4.0)	Utilize
Q3 2024									
Kalabo	48919.2	0.0157	23.9	16.9	0.0184	(0.014–0.023)	26.9	(20.2–33.4)	Utilize
Limulunga	61336.4	0.0122	23.0	–14.7	0.0104	(0.007–0.014)	19.2	(12.4–26.1)	Severe Under
Lukulu	9969.7	0.0161	3.7	–34.8	0.0105	(0.002–0.019)	3.1	(0.5–5.8)	Severe Under
Mitete	4992.5	0.0150	2.3	52.6	0.0230	(0.014–0.031)	3.4	(2.1–4.7)	Utilize
Mongu	80628.8	0.0125	29.2	–12.9	0.0108	(0.007–0.014)	26.2	(17.7–34.9)	Severe Under
Nalolo	25326.6	0.0109	7.8	14.8	0.0125	(0.009–0.016)	9.5	(7.0–12.0)	Severe Under
Sikongo	5139.3	0.0157	2.4	–32.7	0.0105	(0.004–0.018)	1.6	(0.6–2.7)	Severe Under

Note: Forecasted general utilization by administrative district and quarter (Oct 2023 – Sep 2024). Flags represent forecasted utilization levels based on percentage thresholds: **Severe Under–utilization** < 0.013%, **Under–utilization** = 0.013–0.018%, **Utilization** = 0.018–0.023%, **Over–utilization** > 0.023%. Forecasts were compared to baseline values from the equivalent quarters in 2022–2023. The forecast utilization flag thresholds presented in Table 3a were defined based on the quartiles of the historical distribution of monthly general utilization from 2017-2023 Refer to table 5.4 for equations.

[n] Observed utilization for Q4 2023, based on available data from October 2023, was as follows: Kalabo (0.017%), Limulunga (0.013%), Lukulu (0.015%), Mitete (0.020%), Mongu (0.014%), Nalolo (0.013%), and Sikongo (0.017%).

Table 5.4 Summary of forecast and translation metrics used in Table 5.3.

Model Metric	Equation and Description
Baseline Visits	$\text{Baseline \%} \times (\text{Population} \times 3 \text{ months})$
Forecast %	$\hat{y}_t = \text{Prophet prediction at time } t$
Forecasted Visits	$\text{Forecast \%} \times (\text{Population} \times 3 \text{ months})$
95% CI – Forecast % (Range)	$\hat{y}_t \in (\hat{y}_t^{\text{lower}}, \hat{y}_t^{\text{upper}}) \times \text{Population} \times 3$
95% CI – Forecasted Visits (Range)	$\text{CI \% bounds} \times (\text{Population} \times 3 \text{ months})$
Change from Baseline (%)	$\left(\frac{\text{Forecast \%} - \text{Baseline \%}}{\text{Baseline \%}}\right) \times 100$
Forecast Utilization Flag Thresholds	Severe Under (<0.013), Under (0.013–0.018), Utilize (0.018–0.023), Over (>0.023)

Note: $\hat{y}_t$ represents the predicted proportion of general utilization (i.e., visits) at time t from the Prophet model. Confidence Intervals (CI) reflect model–based uncertainty in the forecasts.

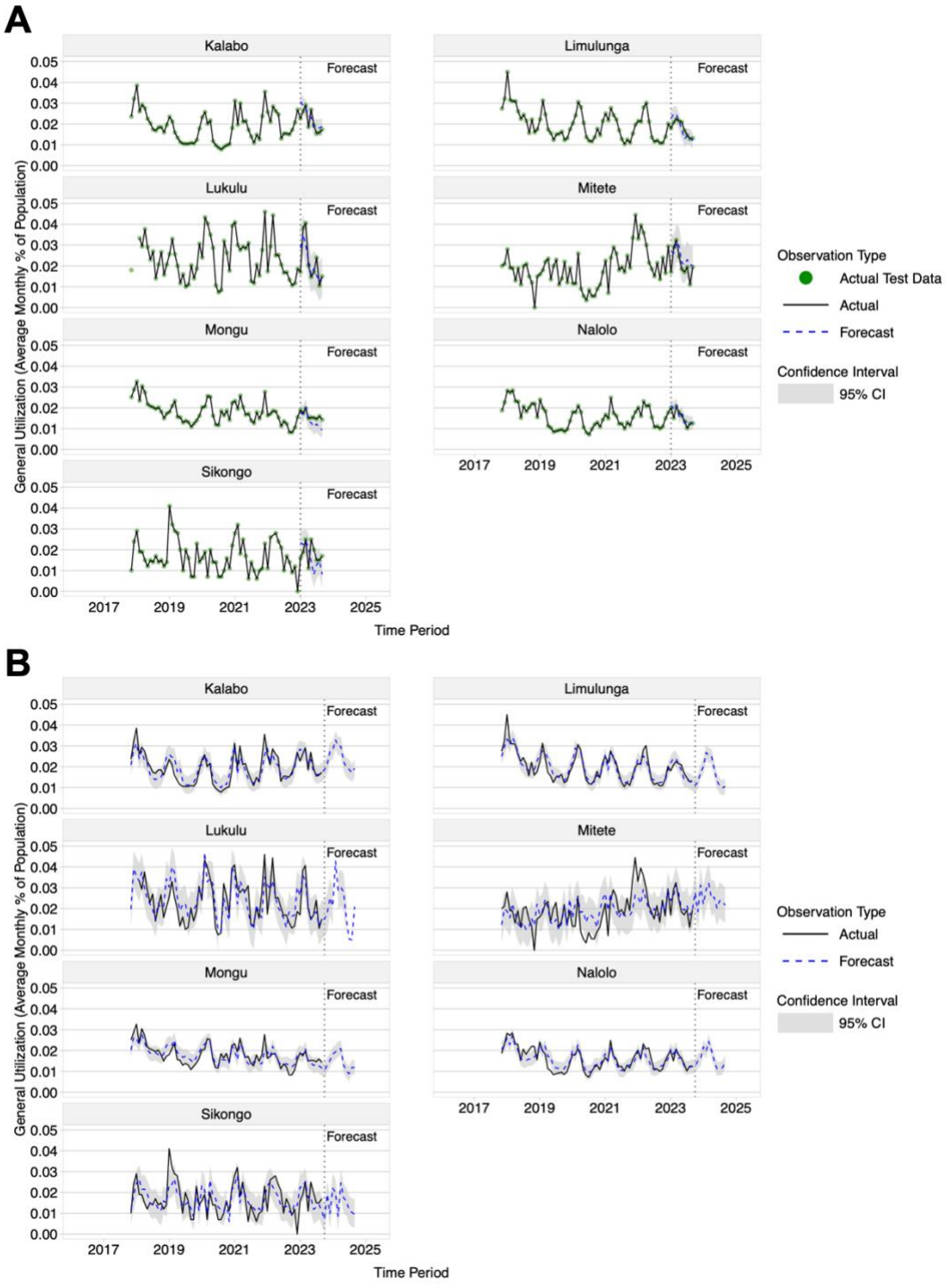


Figure 5.2 District-level forecasts of general utilization from seven individual Prophet models. Panel A shows the model validation, comparing the forecast (dashed blue line) against the actual observed data (green points) on the 9-month hold-out test set from January to September 2023. Panel B displays the full 12-month future forecast, projecting utilization trends from November 2023 to October 2024.

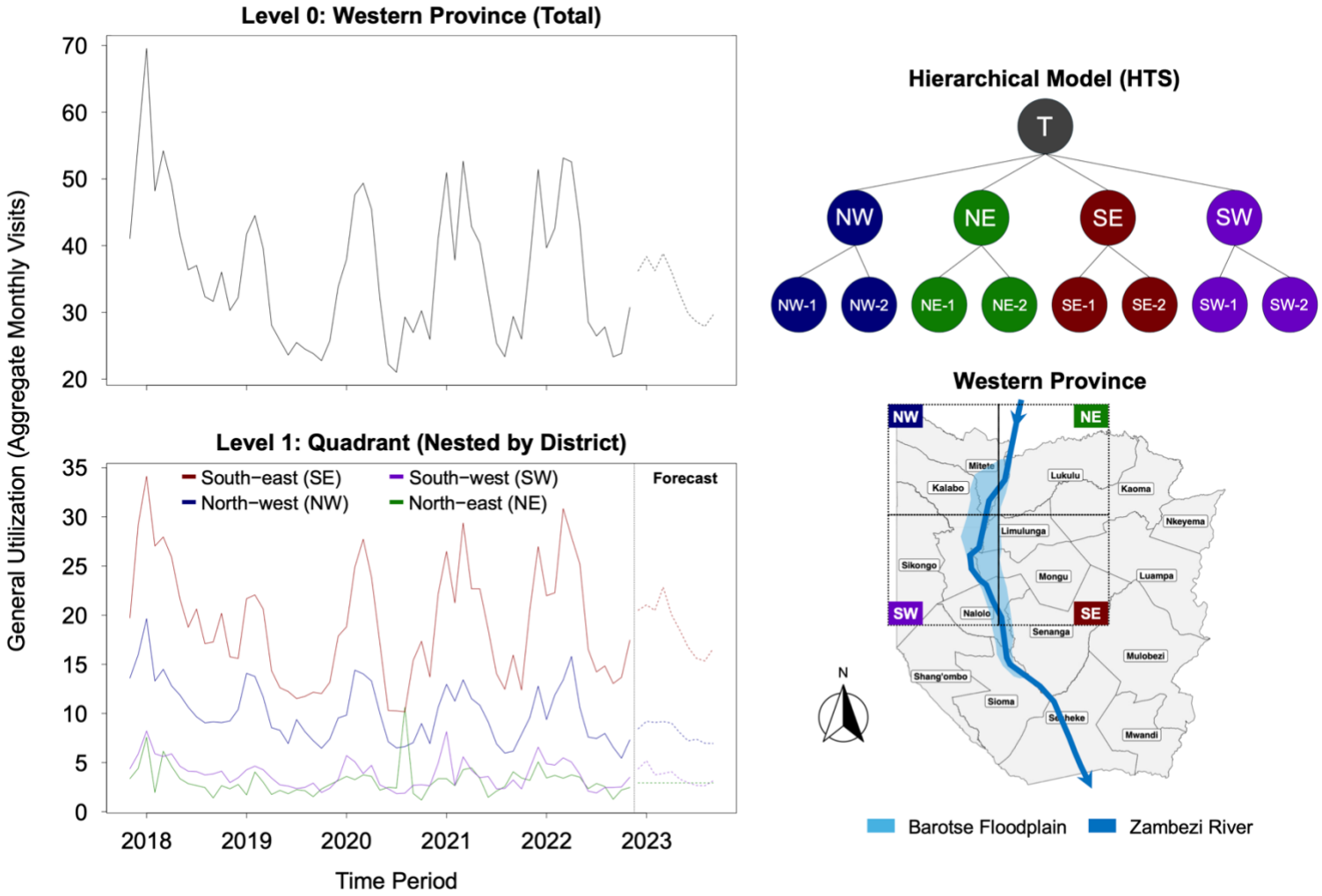


Figure 5.3 Hierarchical Time Series (HTS) forecasts of general utilization extending to December 2024. The model aggregates predictions from 62 health facilities (Level 2), which are nested within the four geographic quadrants shown on the map (Level 1).

Exogenous Variable Integration The accuracy of the Prophet model was enhanced through the inclusion of the flood variable as an exogenous regressor. As demonstrated in Table 5.4, the model incorporating the categorical flood variable outperformed the one with the continuous flood variable. For districts with a historically better performance, such as Limulunga and Kalabo, the integration of flood data yielded a *good forecast* with MAPE values ranging from 10% to 20%. Conversely, districts with a historically weaker performance, including Sikongo and Lukulu, continued to fall within the *acceptable* or *poor forecast* categories, despite the addition of the flood regressor. This observation indicates that the influence of flood exposure on utilization is not uniform and may be confounded by unmeasured district-level factors. A visual comparison of the models' performance for these districts, contrasting the baseline Prophet model with the model that includes the categorical flood regressor, is presented in Figure 5.5.

Table 5.5 Forecast accuracy of flood–augmented Prophet models by administrative district.

Model Type / Administrative District	RMSE	MAE	MAPE (%)	Interpretation
Categorical Flood Model				
Kalabo	0.0000378	0.0000290	**14.1**	Good forecast
Limulunga	0.0000295	0.0000250	**13.4**	Good forecast
Lukulu	0.0000733	0.0000566	**27.4**	Acceptable
Mitete	0.0000556	0.0000428	25.6	Acceptable
Mongu	0.0000343	0.0000285	18.0	Good forecast
Nalolo	0.0000254	0.0000207	14.2	Good forecast
Sikongo	0.0000929	0.0000777	**N/A**	Poor forecast
Continuous Flood Model				
Kalabo	0.0000448	0.0000363	18.0	Good forecast
Limulunga	0.0000307	0.0000258	13.8	Good forecast
Lukulu	0.0000753	0.0000594	29.9	Acceptable
Mitete	0.0000493	0.0000384	22.8	Acceptable
Mongu	0.0000312	0.0000256	16.3	Good forecast
Nalolo	0.0000278	0.0000225	15.8	Good forecast
Sikongo	0.0000876	0.0000714	N/A	Poor forecast

Note: Performance of Prophet models augmented with flood level as an exogenous predictor variable (i.e., Flood level as categorical [low, medium, and high] and flood depth [m] as continuous. RMSE, MAE, and MAPE (%) are shown by district. Forecasts were considered "good" when MAPE < 20%, and "acceptable" up to 50%. **Abbreviations: RMSE** Root Mean Squared Error, **MAE** Mean Absolute Error, **MAPE** Mean Absolute Percentage Error. ***MAPE Range (%) Interpretation:*** < 10 Excellent forecast, 10–20 Good forecast, 20–50 Acceptable, > 50 Poor forecast. **Bold Text MAPE %:** used in Figure 5.4. MAPE is not applicable (N/A) for Sikongo due to zero values in the test set; model performance for this district was assessed using MAE.

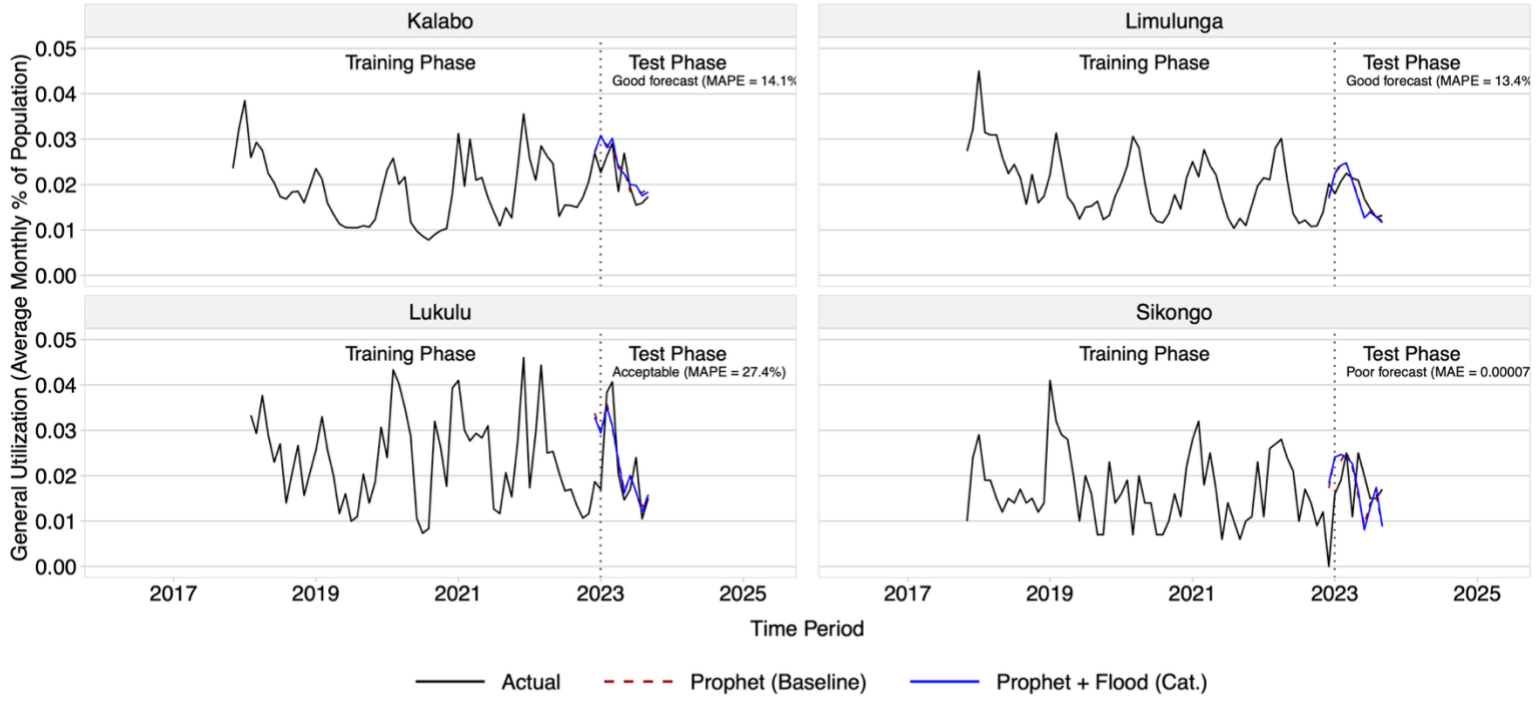


Figure 5.4 Forecast accuracy with flood regressor. Comparison of Prophet model forecast accuracy with and without the flood category as an exogenous regressor. The figure highlights two districts with good forecast performance (Limulunga, Kalabo) and two with weaker performance (Sikongo, Lukulu) to demonstrate model variability, as measured by Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The vertical dotted line indicates the transition from the training phase to the test phase.

5.4.3 Interrupted Time Series Analysis

A generalized linear mixed-effects model was employed to evaluate the influence of three major interruptions on overall utilization. The model output, which accounts for overarching temporal trends, seasonal variations, district fixed effects, and random intercepts for each health facility, is presented in Table 5.6. The findings confirmed a significant negative temporal trend in utilization throughout the study period (Estimate = -0.017, $p < 0.001$), alongside notable seasonal effects ($p < 0.001$). The three interruptions exhibited distinct impacts: the Drought (January 2019) was associated with a significant immediate decline in utilization (Level Estimate = -0.105, $p < 0.001$), followed by a significant positive change in trend (Trend Estimate = 0.019, $p < 0.001$), indicating a period of recovery. The COVID-19 pandemic (January 2021) correlated with a significant immediate increase in utilization (Level Estimate = 0.069, $p < 0.001$), succeeded by a strong negative change in trend (Trend Estimate = -0.005, $p < 0.001$), reflecting a subsequent decrease. Finally, the Complex Flood Event (i.e., February 2023 double-peak flood) demonstrated no significant immediate alteration in utilization (Level Estimate = -0.003, $p = 0.896$). Still, it was associated with a significant positive change in trend (Trend Estimate = 0.019, $p < 0.001$), suggesting a gradual recovery post-event. The time series depicting general utilization and flood depth, offering environmental context for these interruptions, is illustrated in Figure 5.5, where counterfactual analysis visually depicts the estimated impacts of each interruption. As illustrated in Figure 5.6, the observed data (points) are plotted against the model's factual prediction (solid line), representing the average expected utilization after accounting for all variables like seasonality and underlying trends. The dashed lines represent the counterfactual scenarios. Each counterfactual shows the trajectory the model would have predicted if that interruption's specific impact (i.e., its associated level and trend changes) had not occurred. For instance, the 2019 drought was associated with a significant positive change in the recovery trend (Table 5.6). Consequently, the 'No Drought' counterfactual, which projects the original, less steep pre-drought trend forward, results in a substantially lower utilization estimate in subsequent years. This analysis underscores how each event, notably the drought and COVID-19, modified the underlying trajectory of health-seeking behaviour, while the model indicates that the flood event initiated a recovery trend.

Table 5.6 Interrupted time series regression results for general utilization with fixed and random effects (October 2017 to September 2023).

Predictor	Estimate	95% CI	Std. Error	P value
(Intercept)	**–7.85882**	(–7.96585, –7.75179)	0.05461	< 0.001 ***
Administrative District				
Kalabo (*Ref.*)				
Limulunga	0.01684	(–0.11912, 0.15280)	0.06937	0.808
Lukulu	0.14297	(–0.10229, 0.38824)	0.12514	0.253
Mitete	0.02353	(–0.26861, 0.31568)	0.14906	0.875
Mongu	–0.03173	(–0.17308, 0.10962)	0.07212	0.660
Nalolo	–0.09061	(–0.26944, 0.08822)	0.09124	0.321
Sikongo	–0.04963	(–0.44929, 0.35002)	0.20391	0.808
Time				
Months since start	**–0.01737**	(–0.02145, –0.01329)	0.00208	< 0.001 ***
Sine (Harmonic)	**0.17663**	(0.16432, 0.18894)	0.00628	< 0.001 ***
Cosine (Harmonic)	**–0.02862**	(–0.04008, –0.01716)	0.00585	< 0.001 ***
Interruptions (Shocks)				
January 2019				
Drought Onset				
Level	**–0.10451**	(–0.15065, –0.05838)	0.02354	< 0.001 ***
Trend	**0.01906**	(0.01461, 0.02352)	0.00227	< 0.001 ***
January 2021				
COVID–19 Pandemic (lagged)				
Level	**0.06947**	(0.03069, 0.10824)	0.01978	< 0.001 ***
Trend	**–0.00487**	(–0.00748, –0.00225)	0.00133	< 0.001 ***
February 2023				
Complex Flood Event ("double–peak")				
Level	–0.00343	(–0.05484, 0.04798)	0.02623	0.896
Trend	**0.01957**	(0.00883, 0.03030)	0.00548	< 0.001 ***
Random Effects	**Variance**	**Std. Dev.**		
Intercept (Health Facility)	0.03784	0.19452		

Note: Results from a *generalized linear mixed–effects model* (GLMM) estimating changes in monthly general utilization as a percent of the population, based on an interrupted time series (ITS) framework with random intercepts for health facilities (n = 62). Fixed effects include overall time trends, seasonal patterns (sine and cosine harmonics), district fixed effects (*Kalabo* [*Ref.*]), and post–shock level and trend changes associated with three major interruptions: the 2019 drought, the 2021 COVID–19 pandemic (*lagged*), and the 2023 complex flood event (i.e., February 2023 double-peak flood). A Beta distribution with a logit link function was used as the outcome was a proportion. A diagnostic check of the model residuals indicated significant autocorrelation that could not be resolved due to model convergence failures; therefore, p-values should be interpreted with caution. Reported are model estimates, 95% confidence intervals (Wald), standard errors (Std. Error), and p-values for fixed effects, along with variance and standard deviation (Std. Dev.) estimates for random effects. All models were fit using the *glmmTMB* package in R. **Levels of Significance:** $p < 0.05$ *, $p < 0.01$ **, $p < 0.001$ ***

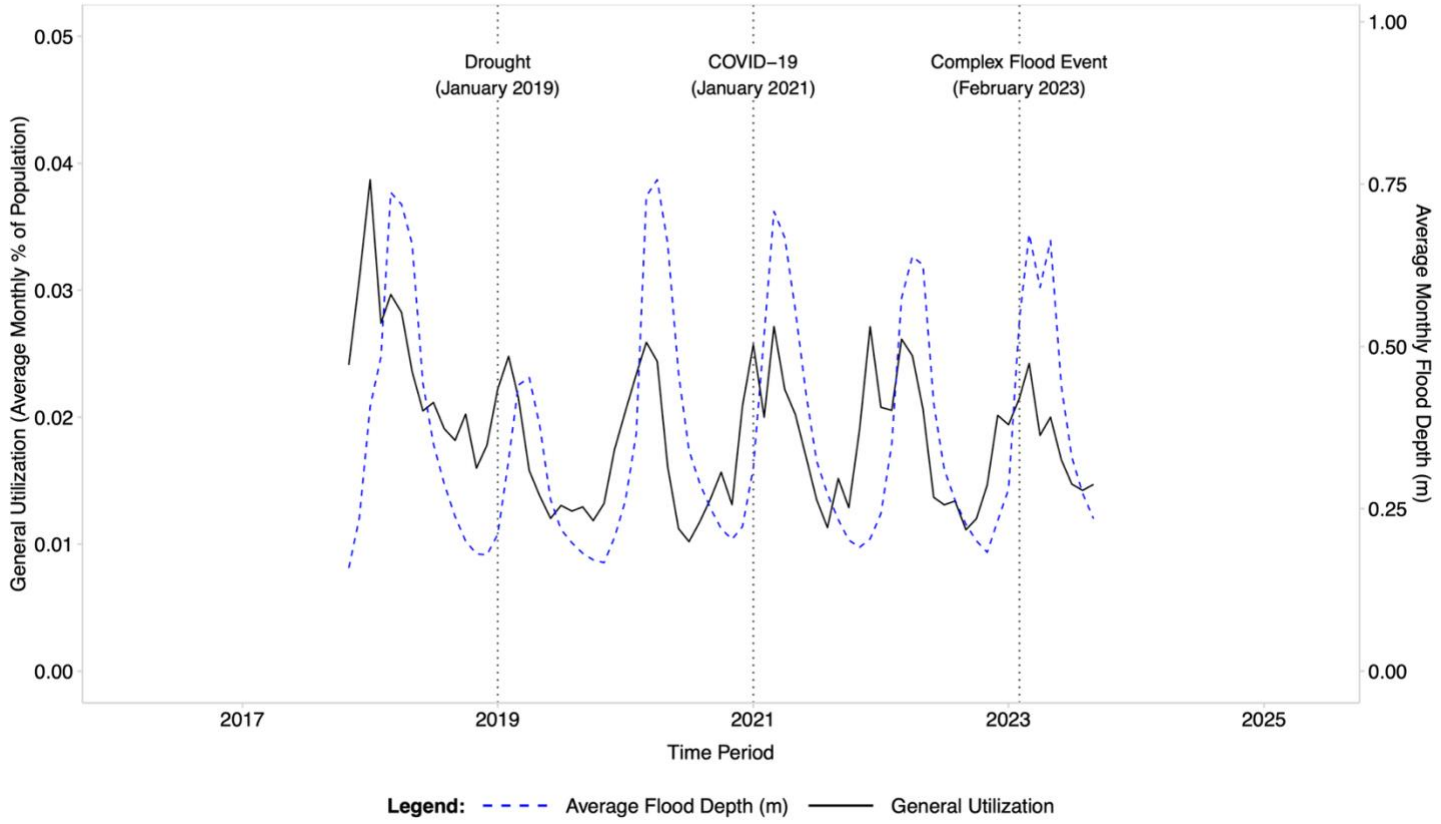


Figure 5.5 Time series of general utilization and flood depth. The observed monthly time series of general utilization and flood depth spans from October 2017 to September 2023. The solid black line represents the monthly average utilization (% of population, left axis), while the dashed blue line illustrates the average monthly flood depth (m, right axis). This plot provides environmental context for the three major interruptions—Drought (January 2019), COVID-19 (January 2021), and the Complex Flood Event (i.e., February 2023 double-peak flood)—which are analyzed in the subsequent ITS model (Figure 5.6).

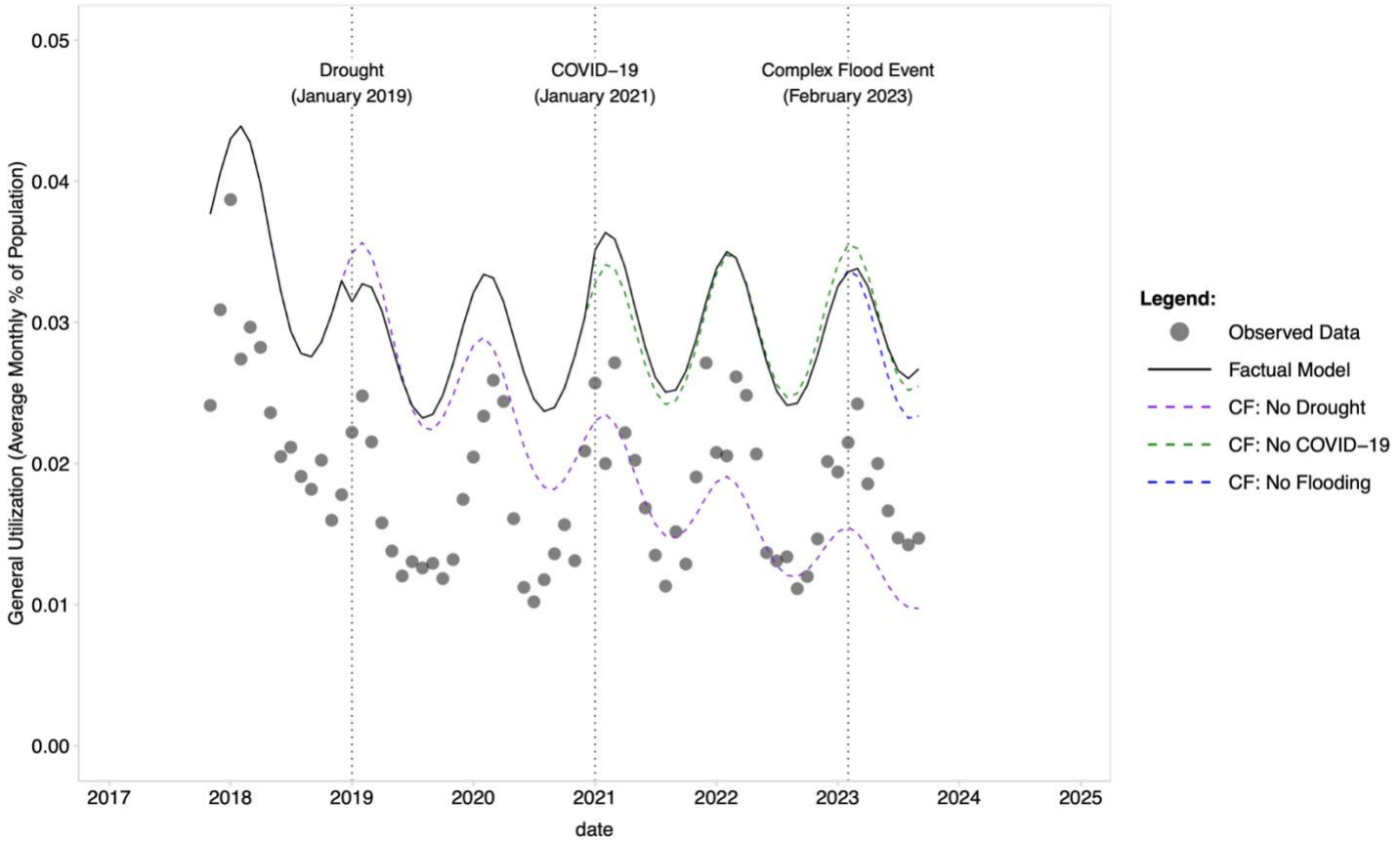


Figure 5.6 Interrupted Time Series (ITS) model of general utilization. Grey points represent the observed monthly average general utilization. The solid black line illustrates the factual prediction from the fitted model, representing the expected mean utilization. The dashed lines depict counterfactual (CF) scenarios that the model estimates would have occurred had a specific interruption's associated level and trend change not taken place. Vertical dotted lines indicate the onset of the three analyzed interruptions. This plot visualizes the immediate (level) and long-term (trend) effects of each event, with full model coefficients and 95% confidence intervals provided in Table 5.4.

5.5 Discussion

This study offers a comprehensive quantitative analysis of health service utilization in Western Province, Zambia, employing a multi-model time-series approach. The results of our forecasting and interrupted time series analyses furnish persuasive evidence of the health system's dynamic response to shocks and stressors. Our model benchmarking exercise verified the Prophet model as the most accurate forecasting tool, attaining an excellent forecast with an MAPE of 7.22% on the test set. The Hierarchical Time Series (HTS) model confirmed a prevailing downward trend in utilization and uncovered distinct spatial and temporal patterns at the quadrant level. For instance, the HTS forecasts, which are shown in Figure 3, exhibited a more stable trend compared to the steeper downward trajectory observed in the southeastern quadrant, thereby illustrating the model's capacity to capture spatial heterogeneity in trends (Figure 3). In our analysis of exogenous variables, we observed that integrating flood data notably enhanced predictive accuracy for specific districts, such as Kalabo and Limulunga, while exerting a lesser effect on others, such as Sikongo and Lukulu, thereby underscoring spatial heterogeneity in response. Most notably, our Interrupted Time Series (ITS) analysis demonstrated that the three major shocks exerted distinct and quantifiable impacts: a drought in 2019 was associated with a strong immediate reduction in utilization (Level Estimate = -0.105, $p < 0.001$) and a subsequent positive recovery trend; the COVID-19 pandemic in 2021 yielded a significant immediate increase in utilization followed by a negative trend change; and the complex flood event (i.e., February 2023 double-peak flood), while not producing a significant immediate impact, was associated with a significant positive trend change.

The aggregate findings from our forecasting and exogenous variable analyses furnish compelling quantitative evidence supporting the dynamic and spatially heterogeneous nature of health system resilience in vulnerable settings. The superior performance of the Prophet model, especially when compared with traditional methodologies such as ARIMA, corroborates an expanding body of scholarly literature that endorses flexible, machine learning-based models capable of managing non-linear trends and intricate seasonality typical of routine health data in low-resource environments.[212,228,229] This selection of the model proved essential for generating precise forecasts

within a data environment characterized by significant temporal variability. Our analysis additionally substantiated that the utility of external predictors, including flood data, in enhancing forecast accuracy varies across districts. The heterogeneous impacts of the flood regressor, which augmented predictive performance for districts such as Kalabo and Limulunga but had minimal influence on others like Sikongo and Lukulu, illustrate that the effect of macro-level shocks is highly contingent upon underlying local stressors and geographic context.[222,223] This finding reinforces the concept that a uniform approach to forecasting or intervention is unlikely to be effective and that predictive models must integrate the spatial heterogeneity of vulnerabilities within health systems.

Our Interrupted Time Series (ITS) analysis introduced an inferential perspective to these findings by demonstrating that distinct shocks produced fundamentally different system-level responses. The notable immediate decrease in utilization, followed by a recovery trajectory in response to the 2019 drought, indicates a shock that temporarily impeded access but from which the system was able to partially recover. This pattern markedly contrasts with findings from studies of the COVID-19 pandemic, which, in our analysis, correlated with a significant initial increase in utilization followed by a sustained decline. This observation is consistent with studies conducted in Ghana and Uganda, which reported complex, non-uniform effects of the pandemic on health service utilization.[230,231] Such a pattern may reflect a period of heightened health-seeking behaviour prompted by the infectious disease shock, succeeded by a *wear-out* effect or burnout in subsequent months. Conversely, the complex flood event (i.e., February 2023 double-peak flood) exhibited no significant immediate impact on utilization but was associated with a substantial positive trend change. This finding aligns with studies from Rwanda and Kenya, which utilized ITS analysis to demonstrate that certain system-strengthening interventions can induce a gradual increase in utilization over time rather than an immediate change.[232,233] These diverse responses to various shocks offer compelling evidence for a dynamic and multifaceted understanding of health system resilience, a fundamental component of the conceptual framework underpinning this study.

5.5.1 Strengths and Limitations

This study possesses multiple notable strengths. Its foremost contribution lies in the novel application of a multi-model approach. It integrates time-series forecasting, hierarchical analysis, and interrupted time series analysis to provide a comprehensive and dynamic evaluation of health system resilience. Using a substantial, multi-year longitudinal dataset encompassing 62 health facilities across an entire province also enhances the generalizability of our findings within this region, a recognized advantage over smaller-scale studies.[217,232] A further strength is our use of a unique, curated flood exposure variable derived from a hydrodynamic inundation model and utilized in peer-reviewed publications by an international research collaboration.[54,76] This provides a more precise and robust measure of environmental shock than is typically available in similar studies. Lastly, while the HMIS database can be affected by issues related to data quality and completeness, the data used for the primary outcome of general utilization in this study was relatively complete, with a low missingness rate of approximately 5%. This is a notable strength, as studies have shown that data quality can significantly impact the stability and accuracy of model estimates, especially in low-resource settings.[68] Nevertheless, it is imperative to interpret our findings considering several limitations. The ecological study design precludes inferences at the individual risk level, and the observational nature of the data prevents establishing definitive causal relationships.[49,234] Moreover, the flood exposure variable, derived from hydrodynamic modelling and applied at the district level, may obscure finer-scale, localized variations in flood intensity and impact. Finally, a diagnostic evaluation of the residuals from the ITS model revealed significant autocorrelation that could not be rectified due to model convergence failures. This is a common challenge in time-series analysis and means that the p-values from the ITS model should be interpreted with caution.[218]

5.5.2 Health Policy and Programmatic Implications

The findings of this study provide a compelling justification for policy interventions aimed at mitigating the adverse synergistic interaction between environmental shocks and pre-existing health system stressors. This strategy is central to the econosyndemic framework, which our research empirically substantiates. The evidence of geographically heterogeneous responses

strongly argues against a uniform approach to intervention, highlighting the imperative for decentralized and data-driven strategies.[235,236] For health planners, this entails prioritizing investments in districts where the detrimental interaction between elevated environmental risks and limited health system capacity is most pronounced. The predictive capabilities of our models, especially the Prophet model's capacity to deliver precise quarterly forecasts, can be harnessed to transition from reactive to proactive strategies for enhancing health system resilience.[211,237] For instance, these predictive models can function as an early warning system, enabling health systems to pre-position essential medical supplies, reinforce referral transport networks, and ensure sufficient staffing in high-risk areas in anticipation of events such as seasonal floods. Such a shift is vital for cultivating genuine health system resilience and protecting essential services amidst climate-related uncertainties.[207,208]

5.6 Conclusion and Future Research

In conclusion, this study provides innovative empirical evidence that the intricate interaction between acute environmental shocks and chronic stressors on health systems exerts a dynamic influence on health service utilization within a rural setting vulnerable to climate impacts. The employment of a multi-model time-series methodology, which integrates forecasting with Interrupted Time Series analysis, elucidates how these synergistic effects generate geographically heterogeneous patterns of disruption and resilience. Ultimately, the findings underscore the significance of implementing targeted, data-informed strategies to bolster local health system capacity, thereby contributing to the progress of Universal Health Coverage and serving as a fundamental element of climate change adaptation.[174,211] Moreover, this research delineates several critical avenues for future scholarly inquiry. Longitudinal studies are vital to validate the causal pathways outlined in our models and to establish links between observed utilization trends and subsequent health outcomes. Future research would benefit significantly from integrating more granular data, such as higher-resolution flood metrics, facility-specific preparedness indicators, and household-level information on health-seeking behaviour and socioeconomic variables. Most importantly, future investigations must prioritize implementation science: the design, implementation, and rigorous evaluation of targeted, contextually tailored interventions, which our findings suggest are indispensable.

Chapter 6

Policy Brief

6.1 Executive Summary

As part of a comprehensive Policy Brief, the Preliminary Assessment (Phase I) addresses a persistent challenge in Western Province (WP), Zambia: ensuring all residents have equitable geographic access to essential first-level health care services. Zambia's health service delivery system is structured in three tiers, with primary health care (PHC)—delivered through a network of health centres and posts—forming the first level of care. Primary health care infrastructure includes health centres and health posts (rural and urban) (figure 6.1). Primary health care aims to meet the health needs of all individuals seeking care at the community level. Community-level PHC services include integrated care, disease prevention, health promotion, and education. According to the World Health Organization (WHO), access to a first-level health facility should ideally be within two hours of travel by the primary local mode of transport.[60,89,177–179] In WP, where most people travel on foot, the WHO benchmark corresponds to a walking distance of approximately 10 km (i.e., a two-hour walk at a speed of 5 km/hr). While previous national estimates suggest that 91.5% of WP's population lives within two hours of any first-level facility, these figures mask major inequities in access to comprehensive primary health services, especially those provided by Health Centres.[60] The Phase I analysis showed that 26.4% of individuals (i.e., over 322,000 people) currently reside beyond a two-hour walking distance to their nearest Health Centre.



Figure 6.1 Salunda Health Post, Kalabo District, Western Province, Zambia. The Salunda Health Post, initially designated as the Salunda Rural Health Centre, was established circa 2013. Its development was financed through Zambia's Constituency Development Fund (CDF), a government initiative dedicated to supporting community-prioritized projects at the local level.[238] During its inception, a significant obstacle encountered by newly established facilities in Kalabo District was the lack of radio communication equipment, a vital resource for liaising with the district hospital during emergencies.[239] The health post serves a rural community in Western Province (WP), an area officially recognized for possessing some of the most constrained and underdeveloped health infrastructure within Zambia.[240] First-level health facilities such as Salunda Health Post are indispensable for delivering fundamental primary healthcare services to populations that would otherwise be compelled to undertake long journeys to access district-level hospitals. The accompanying photograph depicts a modest, utilitarian building situated within a sandy, sparsely vegetated landscape—a characteristic feature of rural health infrastructure in the remote regions of WP. The development and maintenance of health posts in Kalabo constitute part of a broader, ongoing initiative to enhance healthcare accessibility within the district. Recent projects, also funded by the CDF, have targeted the construction of housing for medical personnel, the creation of maternity annexes, and the rehabilitation of existing hospital infrastructure.[238,241] Despite these advances, community-level primary healthcare in the area continues to face significant challenges, including unreliable supply chains for medicines and equipment and difficulties in staffing and supervising community health workers—issues prevalent in Zambia's remote rural regions.[242] —Photograph Copyright © Cameron B. Chiarot (2022).

To better understand these spatial inequalities and their implications for system efficiency, this Phase I assessment applied a location-allocation framework, whereby a Set Covering Problem (SCP) model was used to optimize geographic coverage of the health facility network. Using spatial data from 321 existing Health Centres and Health Posts and more than 176,000 Population Under Rooftops (PURs), we modelled alternative facility configurations capable of providing universal coverage under varying travel time thresholds. Our findings show that full geographic coverage is theoretically feasible under a 7.5-hour walking threshold, requiring only 46 strategically located facilities. This finding reveals substantial spatial redundancy in the current health facility network. More importantly, it highlights a *last-mile* challenge: while universal health coverage (UHC) is mathematically possible, ensuring access within a reasonable and equitable time frame requires a more nuanced system redesign. This brief presents key findings from the Phase I assessment and outlines a forward-looking roadmap for Phase II. Future work will build on this foundation by integrating facility-level capacity, cost structures, and service offerings into the optimization model pipeline. The goal is to provide actionable investment strategies that reduce inequities and maximize returns in population-level access to comprehensive PHC at Health Centres.

6.2 Background

Geographic access to first-level essential health services constitutes a fundamental element of equitable health systems and is intrinsically associated with enhanced outcomes concerning maternal, child, and overall public health.[92] In Western Province (WP), physical distance, travel durations, and infrastructural constraints hinder access, particularly for rural, remote, and vulnerable populations. The World Health Organization (WHO) proposes that primary care services should be accessible within a two-hour travel period via the predominant local transportation methods. For rural and remote communities in WP, where walking remains the customary mode of travel, this criterion equates to roughly 10 km, assuming a conservative walking speed of 5 km/hr.[243]

The geographic and ecological profile of WP substantiates the application of this travel assumption. The region encompasses an area exceeding 126,000 km² and is characterized by relatively flat terrain, primarily dominated by the Barotse floodplain and open dry forests. Elevation varies from 927 to 1,249 meters above sea level, with land cover consisting of grasslands, miombo woodlands, teak forests, and Cryptosepalum thickets. (Topographic-Map, 2024; Zambezian Forests, 2024). These environments are largely permeable to pedestrian movement during dry seasons. Although seasonal flooding may pose localized access challenges, such obstacles are transient and do not compromise the applicability of the 5 km/hr travel speed assumption for most months of the year.[134] Additionally, demographic pressures vary across the province, with certain districts experiencing higher population growth rates (figure 6.2).

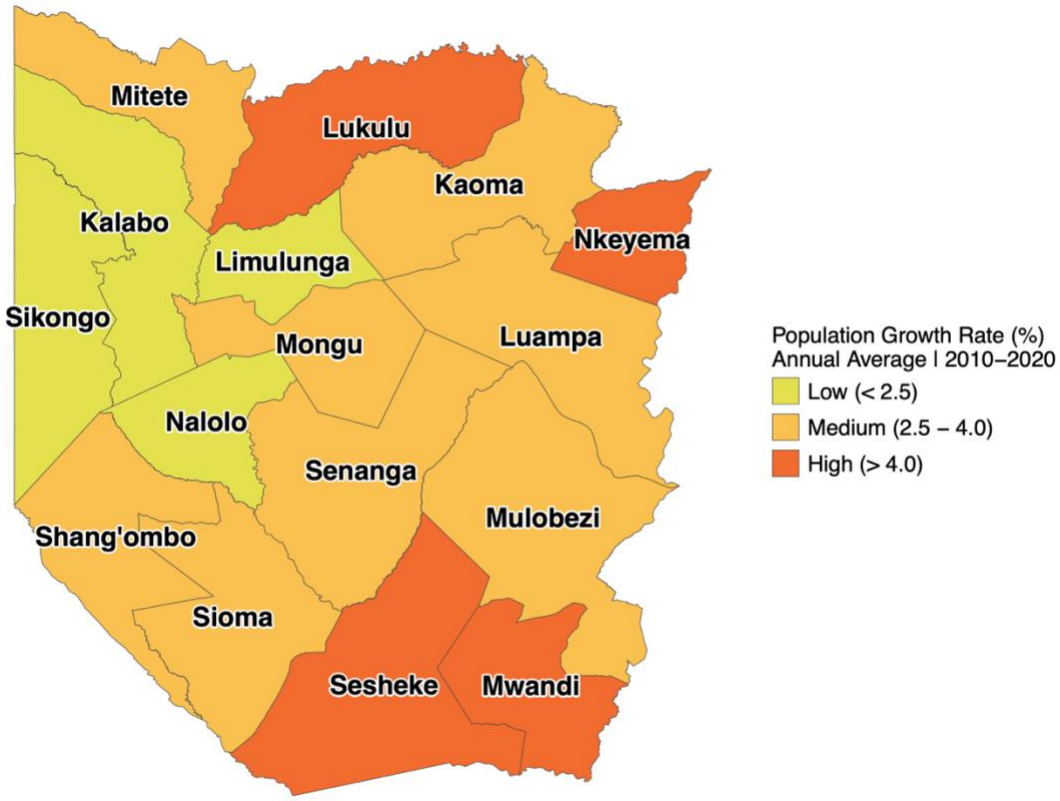


Figure 6.2 District-level population growth rates in Western Province from 2010 to 2020. The choropleth map depicts the average annual population growth rates (PGRs) for each administrative district in Western Province. Districts are categorized by their growth rate: 'Low' (≤ 2.5%, green), 'Medium' (> 2.5% to 4.0%, yellow), and 'High' (> 4.0%, red).

6.3 Critical Gap

Current national metrics on healthcare accessibility mask significant geographic inequities, especially in access to health facilities that offer a full range of primary care services (i.e., first-level). While 91.5% of the WP population is estimated to have access to a first-level facility within two hours, this percentage drops sharply when considering access to Health Centres specifically. More than 322,000 people in WP live beyond the two-hour travel threshold to these facilities, putting them at a disadvantage for essential health services such as skilled birth attendance, immunization, and management of chronic diseases (table 6.1, figures 6.3a and 6.3b). The spatial

distribution of these underserved populations, shown for any facility (figure 6.4a) and Health Centres only (figure 6.4b), indicates that these access gaps are concentrated in often remote areas of WP. If left unaddressed, this access gap is expected to grow significantly in the coming years due to population growth, further widening inequalities (figures 6.5a and 6.5b).

Table 6.1 Baseline access metrics across health facility network optimization scenarios in WP.

Metric	Centres + Posts	Centres (x Posts)
Total Population (year)		
Current (2022)	1,223,722	1,223,722
5-yr Projected (2027)	1,449,590	1,449,590
10-yr Projected (2032)	1,724,080	1,724,080
Total number of PURs	175,983	175,983
Walking Travel Time (hours)		
Minimum	~2 min	~2 min
Maximum	7.3	9.4
Mean	0.8	1.3
Median	0.5	0.8
25th Percentile	0.2	0.2
75th Percentile	1.1	1.9
Travel Thresholds		
Within 2-hours		
Total Population (2022)	1,119,085	901,181
Total number of PURs	161,963	134,315
Proportion Population	91.5%	73.6%
Proportion PURs	92.0%	76.3%
Exceeds 2-hours		
Total Population (2022)	104,637	322,541
Total number of PURs	14,020	41,668
Proportion Population	8.5%	26.4%
Proportion PURs	8.0%	23.7%

Note: This table summarizes the baseline geographic access to first-level health facilities for the population of Western Province under two scenarios. The 'Centres + Posts' column reflects travel times to the nearest facility of any type (Health Centre or Health Post), representing basic access. The 'Centres (x Posts)' column reflects a scenario where only Health Centres are considered available, measuring access to more comprehensive primary care. All travel times are based on an assumed walking speed of 5 km/hr. **Abbreviations: PURs** Population Under Rooftops.

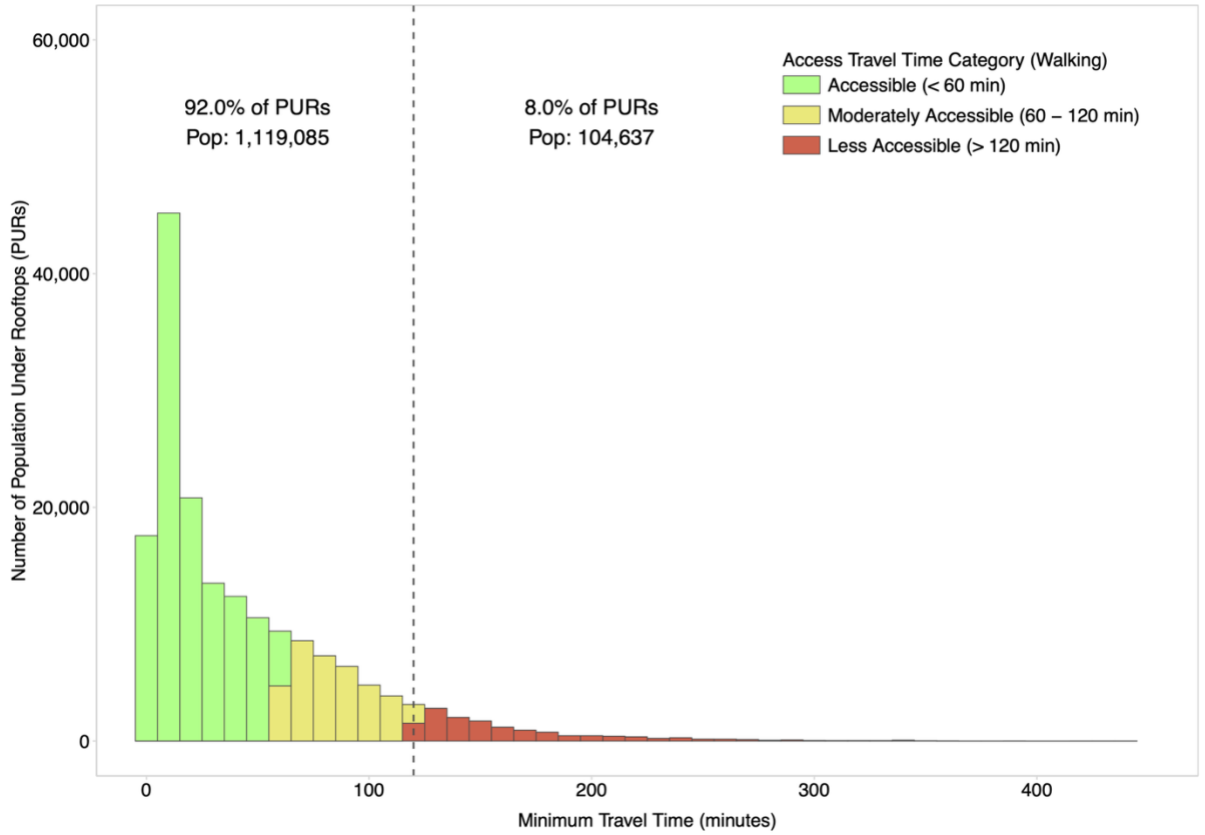


Figure 6.3a Distribution of walking travel times to the nearest health facility in Western Province (2024). The histogram illustrates the distribution of minimum walking times from Population Under Rooftops (PURs) to the closest health facility (Centre or Post). The dashed line at 120 minutes indicates the World Health Organization (WHO) recommended equitable access threshold. The green segment highlights PURs with very good access (<60 minutes), yellow indicates moderate access (60-120 minutes), and red denotes PURs with limited access (>120 minutes).

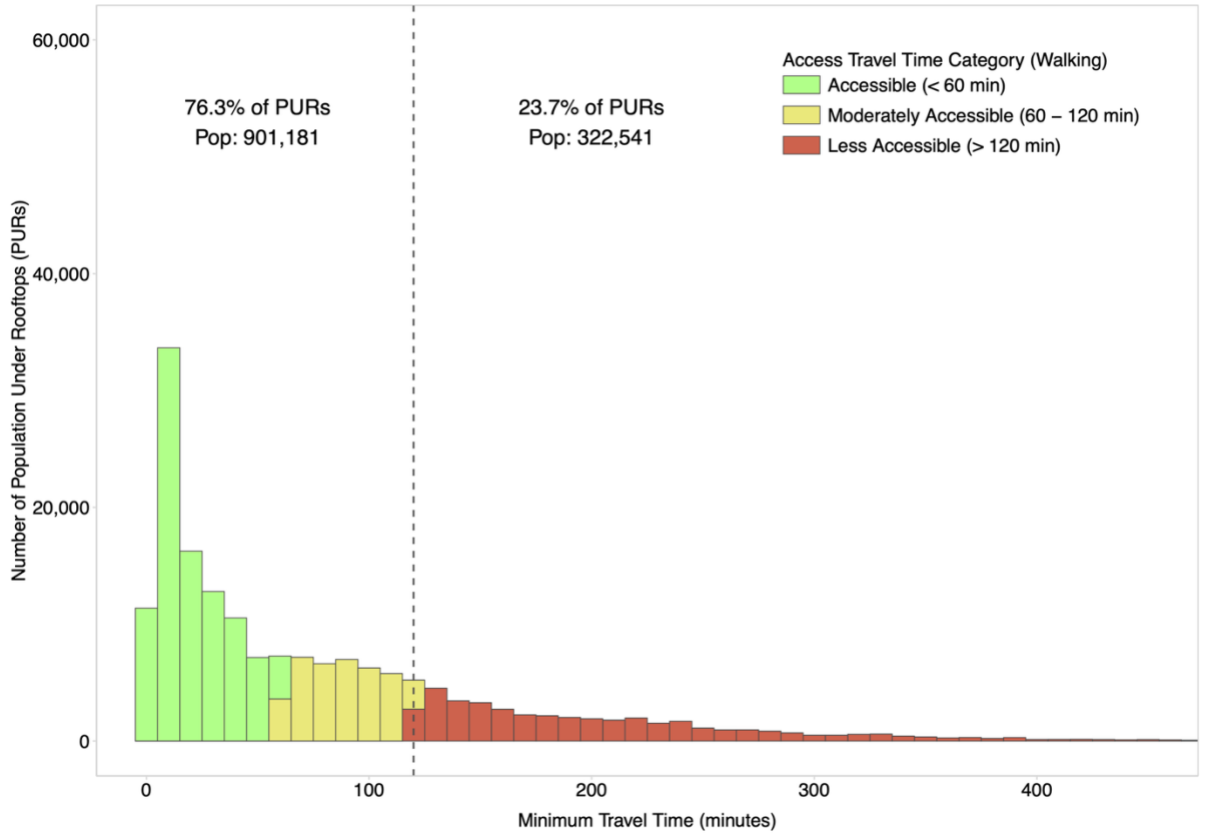


Figure 6.3b Distribution of walking travel times to the nearest Health Centre in Western Province (2024). This histogram illustrates the minimum walking travel times from Population Under Rooftops (PURs) to the closest Health Centre. The dashed line at 120 minutes indicates the World Health Organization (WHO) recommended equitable access threshold. The green segment represents PURs with very good access (≤ 60 minutes), yellow indicates moderate access (>60 to 120 minutes), and red shows PURs with limited access (>120 minutes). Unlike overall facility access, 73.6% of the population (901,181 individuals) are within 2 hours of a Health Centre, while 26.4% (322,541 individuals) live beyond this threshold, revealing a significant access gap for primary healthcare.

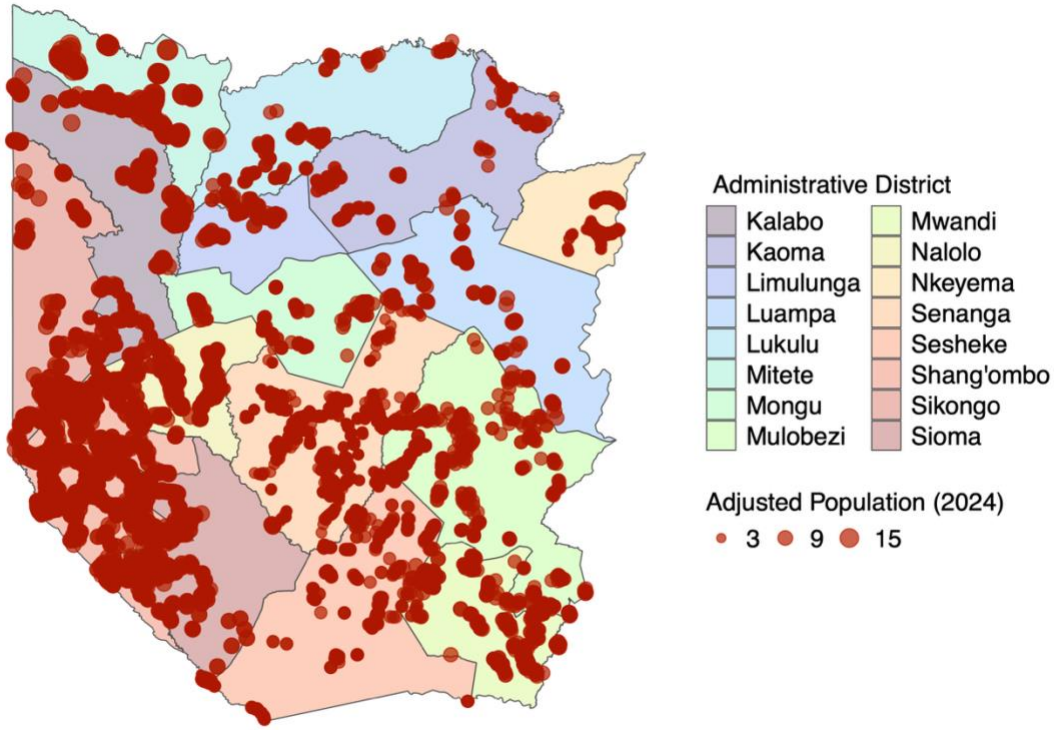


Figure 6.4a Spatial distribution of less accessible populations in Western Province (2024). The map identifies the geographical locations of populations across 16 administrative districts that are considered less accessible to health facilities (Centre or Post). Less accessible PURs are defined as those requiring more than 2 hours of walking to reach the nearest health facility. Each red point represents a PUR, with its size scaled to reflect the adjusted population at that location.

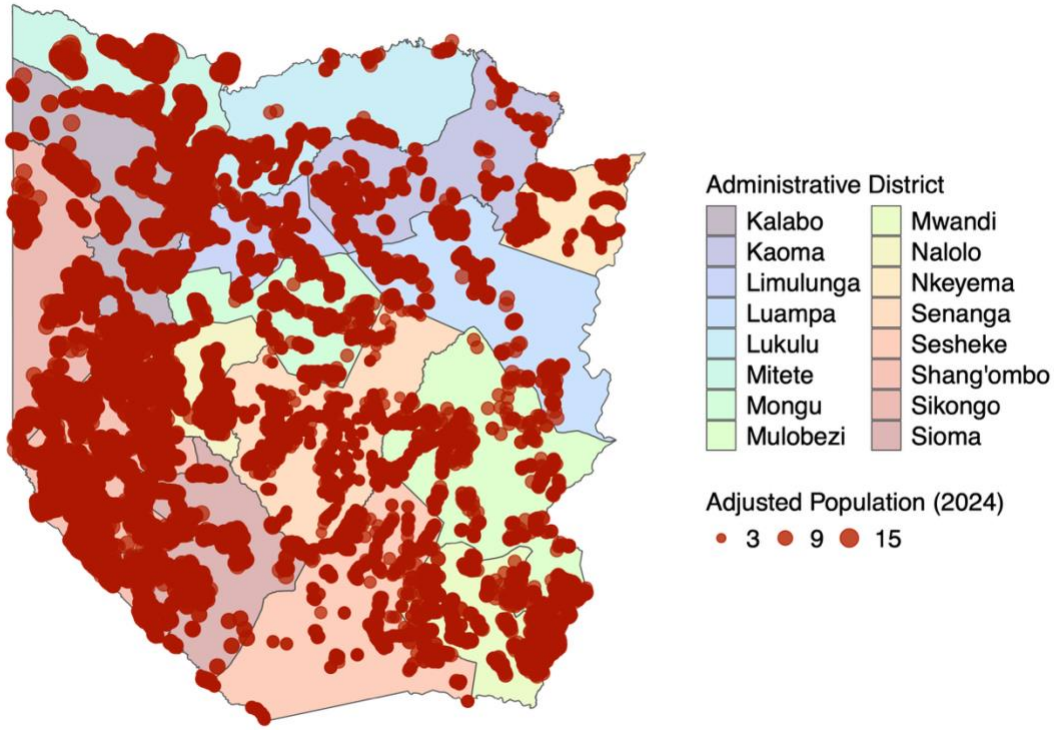


Figure 6.4b Spatial distribution of less accessible populations to Health Centres in Western Province (2024). The map highlights the geographical locations of populations in Western Province considered less accessible when only considering Health Centres. Less accessible PURs are defined as those requiring more than 2 hours of walking time to reach the nearest Health Centre. Each red point represents a PUR, with size scaled to reflect the adjusted population at that location. The map indicates that, although general access to any facility is high, a significantly larger number of populations are underserved when assessing access to comprehensive primary care at Health Centres.

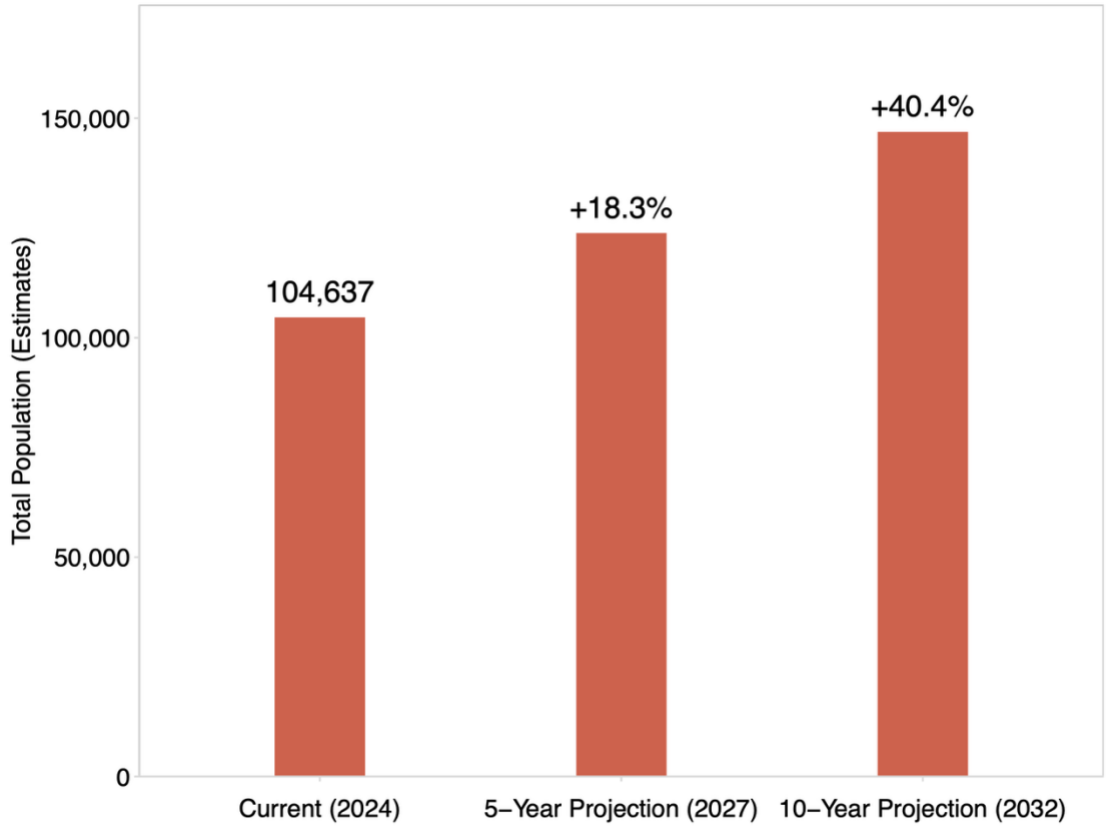


Figure 6.5a Projected growth of less accessible populations in Western Province (2024 to 2032). This bar chart illustrates the projected increase in the number of individuals classified as less accessible (i.e., >2 hours of walking travel time to the nearest health facility). This forecast emphasizes the importance of strategic health system optimization to anticipate and mitigate future access disparities driven by population growth.

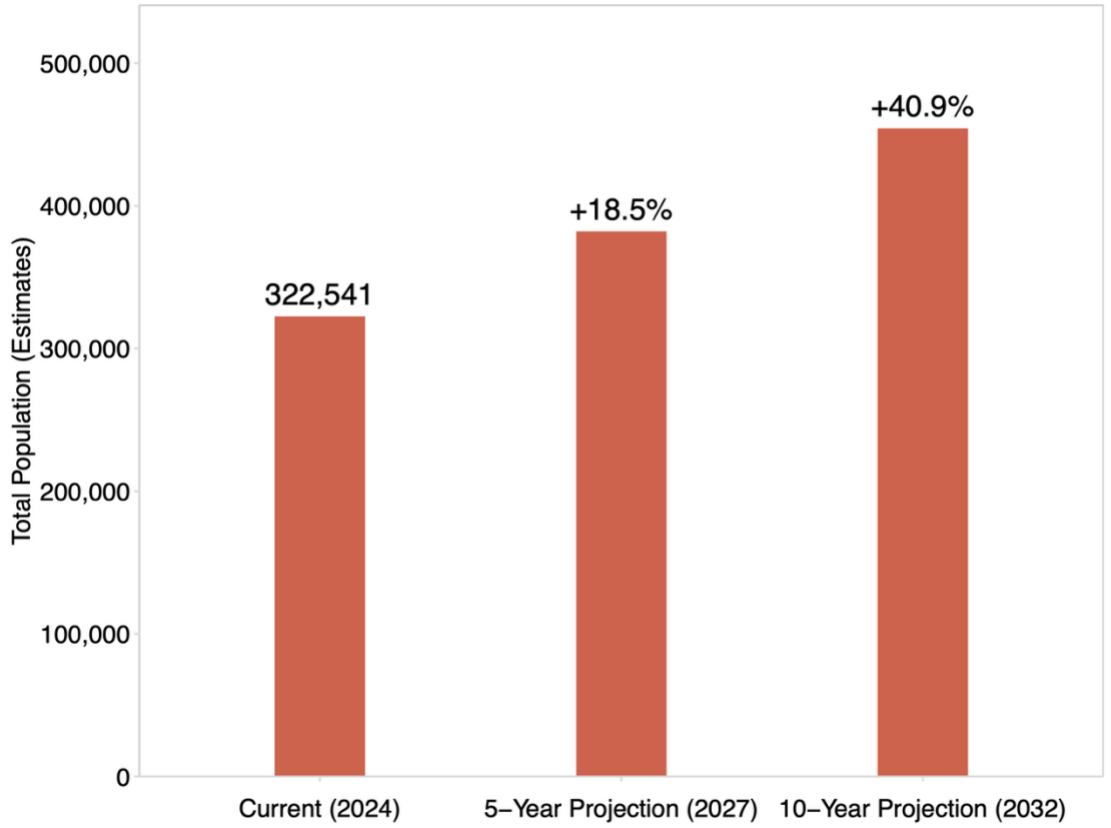


Figure 6.5b Projected growth of less accessible populations to Health Centres in Western Province (2024 to 2032). This bar chart highlights the projected increase in the number of individuals deemed less accessible (i.e., >2 hours of walking) when considering access only to Health Centres. This projection emphasizes the growing challenge of providing equitable access to comprehensive primary healthcare services for a substantial and increasing portion of the population.

Infrastructure constraints and limited data on road or trail networks exacerbate this issue. High-resolution travel time models necessitate comprehensive friction surfaces or digitized path networks, neither of which are presently accessible across all districts of WP. While prior studies have demonstrated the utility of satellite-derived footpath data in specific districts, their approach was limited to 67 facilities in 7 districts.[54] Conversely, our research encompasses 321 facilities across all 16 districts, rendering a network-free modelling strategy more suitable and scalable.

6.4 Methods

This analysis employed a location-allocation methodology, specifically utilizing a Set Covering Problem (SCP) framework to determine the minimal number of healthcare facilities required to ensure geographic coverage of all identified population clusters—represented by over 176,000 Population Under Rooftops (PURs). Walking distance was approximated using the *law of cosines* to calculate straight-line distances between each PUR and proximate health facilities, assuming a consistent walking speed of 5 km/hr.[49] This methodology aligns with large-scale accessibility studies conducted in Sub-Saharan Africa and accounts for data limitations concerning road and trail networks in WP.[132,243] The SCP model simulations evaluated multiple time thresholds, ranging from 2 hours (120 minutes) to 7.5 hours (450 minutes). For each threshold, the algorithm identified the smallest subset of the 321 available health facilities capable of providing coverage to all PURs within the designated walking time.

6.5 Key Findings

At the WHO-recommended 2-hour threshold, the analysis indicated that 14,020 PURs—equating to approximately 104,637 individuals—remain without coverage. This access gap underscores a persistent spatial inequity in the rural health system provision. As the threshold was gradually increased, health coverage improved, achieving complete geographic coverage at the 7.5-hour threshold. At this level, only 46 facilities are deemed necessary to guarantee that all PURs are within accessible distance, thereby revealing significant spatial redundancy within the current health system. The model's configuration of 46 facilities demonstrates a balanced spatial

distribution across districts, yet many PURs would still fall beyond the 2-hour benchmark (figures 6.6 and 6.7). This finding confirms that while optimization can improve efficiency, it cannot fully resolve inequities without targeted policy to improve service reach (figure 6.8).

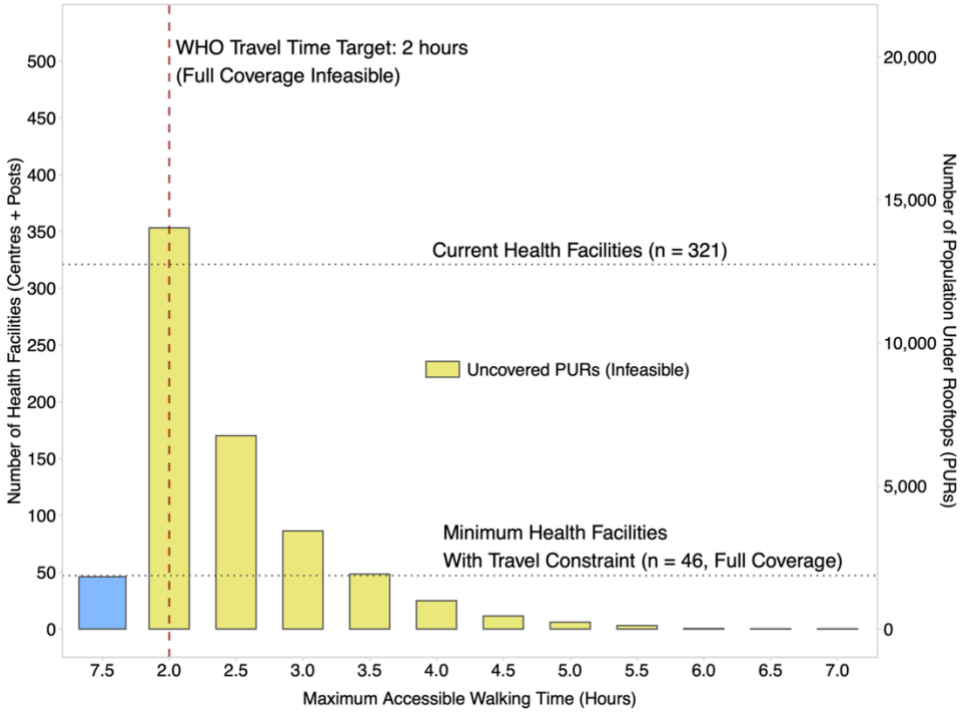


Figure 6.6 Trade-off curve for determining the optimal number of health facilities to achieve full coverage in Western Province. The chart demonstrates the trade-off between maximum accessible travel time and the minimum number of health facilities needed for full coverage. It shows that 46 health facilities can provide full coverage, but may require up to 7.5 hours of travel time in remote areas.

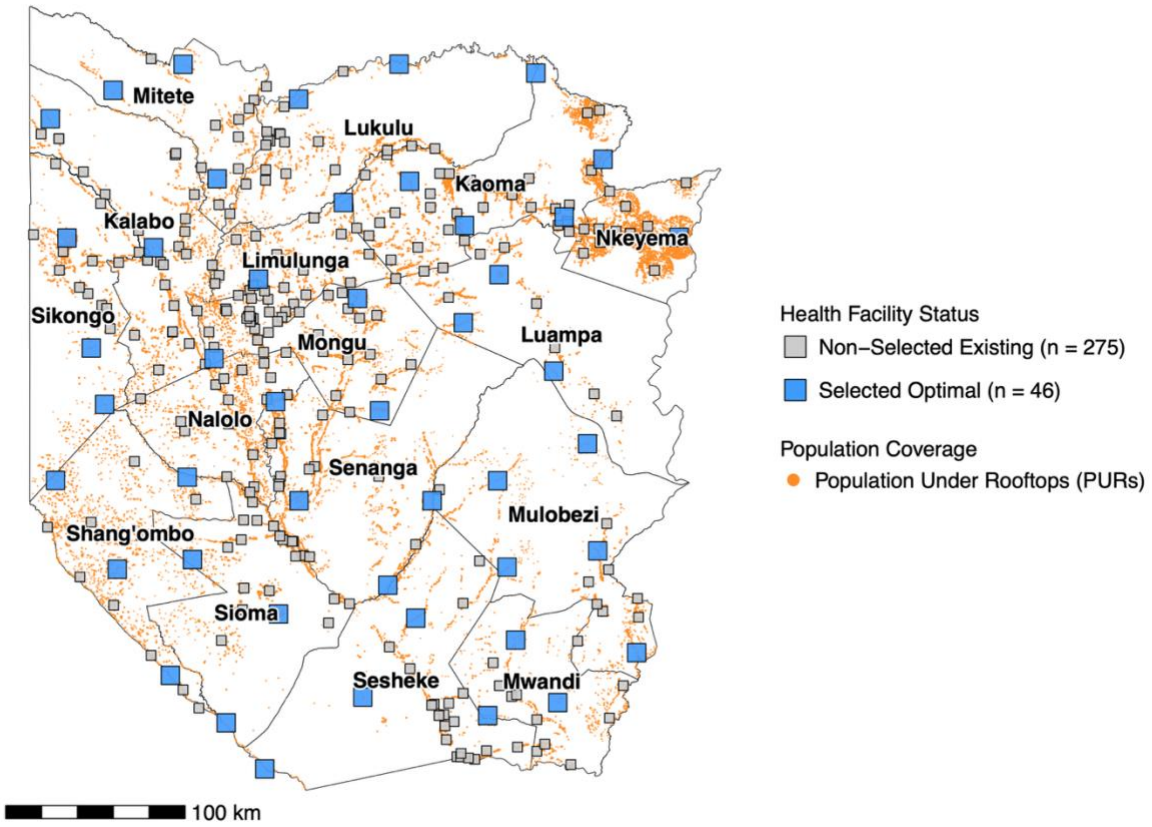


Figure 6.7 Spatial distribution of the optimized health facility network in Western Province. The map of the 16 administrative districts displays the locations of the 46 selected optimal health facilities (blue squares) compared to the 275 non-selected existing facilities (gray squares). Orange dots represent PURs, highlighting the network's extensive geographic coverage.

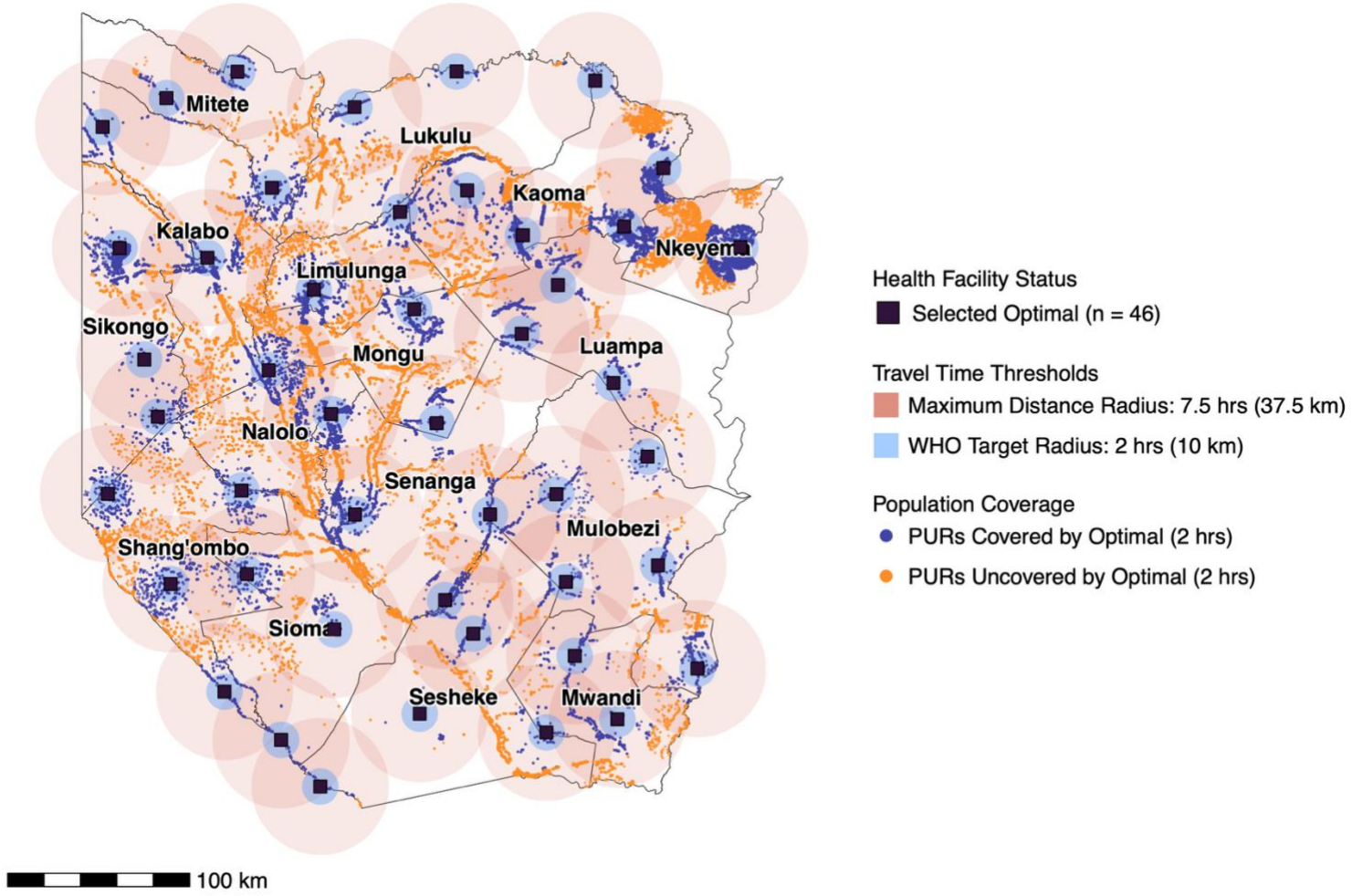


Figure 6.8 Ideal geographic coverage by the optimized health facility network in Western Province. It shows the geographic coverage of the 46 selected optimal health facilities (blue squares) with two key travel time thresholds: the WHO target of 2 hours travel time (walking, 10 km; light blue shading) and an extended maximum distance of 7.5 hours walking (37.5 km; light red shading). PURs within the 2-hour buffer are classified as *covered*, while those outside are classified as *uncovered*. This map demonstrates the spatial reach and potential service area of the optimized network under ideal conditions.

6.6 Comprehensive Optimization (Phase II)

The initial phase of the Health System Optimization (HSO) study has successfully quantified the geographic accessibility landscape in Western Province and established a critical efficiency benchmark. The Set Covering Problem (SCP) analysis demonstrated that while universal geographic access is theoretically possible with a much smaller network of 46-47 facilities, it necessitates accepting a maximum travel time of up to 7.5 hours. This finding underscores the profound challenge of achieving the WHO's 2-hour accessibility standard for all individuals, particularly for comprehensive services offered at Health Centres. This foundational work enables a transition from descriptive analysis to a prescriptive, multi-stage optimization framework designed to generate actionable, evidence-based policy recommendations.

6.7 Multi-Stage Framework

We propose a sophisticated, three-stage framework for Phase II to address the multifaceted nature of healthcare access (figure 6.9 and table 6.2). This approach moves beyond a single, province-wide optimization model to a more nuanced strategy that leverages the full breadth of findings from previous research (Studies 1-4) to inform final recommendations.

6.7.1 Stage 1: Strategic Prioritization via Composite Risk Indexing

- **Objective** To identify and prioritize health facility catchments with the highest risk or priority, specifically those facing the most severe barriers to access.
- **Methodology** A composite vulnerability index shall be developed through the normalization and integration of several key indicators at the catchment level.
- **Input Variables** The vulnerability index shall be computed utilizing specific metrics obtained from prior analyses, including: the flood impact coefficient derived from an interrupted time series (ITS) model; the average travel time determined from the HSO Phase I baseline; PURs that exceed the two-hour travel time threshold; the projected 10-

year average population growth rates by administrative district; and coefficients derived from generalized linear mixed-models that quantify the statistical impact of access barriers.

- **Process** The input variables will undergo scaling, such as normalization from 0 to 1, and will be subsequently combined using a weighted sum to generate a single Composite Vulnerability Index (CVI) for each health facility catchment area. The weights may be allocated equally or adjusted by policy priorities, such as emphasizing flood resilience.
- **Challenges and Scope** This stage requires a clear definition and justification for the weighting scheme. The primary output will be a Prioritization Heat Map of WP, visually identifying where targeted interventions are most needed.

6.7.2 Stage 2: Focused Dynamic Simulation using Agent-Based Modelling

- **Objective** To comprehend the intricate local dynamics of health-seeking behaviour within the highest-risk catchments and to evaluate the relative effectiveness of various localized policy interventions.
- **Methodology** A comprehensive Agent-Based Model (ABM) will be developed for a designated set of high-priority catchments.
- **Model Components** The ABM simulation will encompass: *Agents* (i.e., PURs: households characterized by specific locations and demographic attributes); a dynamic *Environment* integrating road networks, terrain, and temporally varying flood data; and *Institutions* (i.e., health facilities with specified capacities and service levels).
- **Agent Decision Rules** The decision-making process of an agent to seek medical care is modelled as a probabilistic function influenced by multiple factors. These include the agent's perceived severity of sickness (a stochastic variable), the travel costs—which are dependent on distance, terrain, and flood levels—and the perceived quality of the healthcare facility, such as a Health Centre versus a Health Post.
- **Challenges and Scope** This data-intensive stage necessitates detailed geospatial data such as Digital Elevation Models and road networks. A key challenge involves meticulously calibrating and validating the Agent-Based Model (ABM) against historical real-world

utilization patterns to ensure its accuracy. The outcome will provide robust evidence regarding the relative effectiveness of competing local strategies, such as mobile clinics versus facility upgrades, under specific conditions.

6.7.3 Stage 3: Informed Provincial Optimization Modelling

- **Objective** To develop a robust, efficient, and equitable province-wide health system investment and resource allocation strategy.
- **Methodology** This phase will utilize formal optimization methodologies, such as the Maximal Covering Location Problem (MCLP) or a cost-constrained Location-Allocation model, to determine the optimal placement of new facilities and the enhancement of existing ones.[o]
- **Model Formulation** The model will be constructed to optimize either the minimization of total investment costs or the maximization of population coverage within a predefined temporal framework (e.g., 2 hours to a Health Centre).
- **Model Parameters** The primary innovation lies in that outcomes derived from Stage 2 simulations will serve as direct inputs for the parameters of the Stage 3 optimization model. For instance, the anticipated *coverage benefit* of establishing a new facility in a flood-prone region will be attributed a higher weight, with the specific value of this weight established through ABM simulations.
- **Challenges and Scope** Translating the nuanced findings from the ABM into precise mathematical parameters for the formal optimization model will be a significant challenge. The final deliverable will be a spatially explicit, actionable plan for WP, rigorously justified by multiple layers of evidence.

[o] The final HSO roadmap must be part of a comprehensive strategy that acknowledges the limits of fixed infrastructure in areas characterized by sparse population density and environmental challenges. While optimal facility placement remains crucial, achieving the final equity access goals, particularly the WHO 2-hour recommendation, will require additional methods. These may include mobile outreach clinics, increasing the capacity and reach of Community Health Workers, setting up maternity waiting homes, and implementing dedicated community-managed emergency transport schemes. Incorporating these approaches into the final investment plan is vital for closing the last-mile access gaps in the most remote, climate-vulnerable regions.

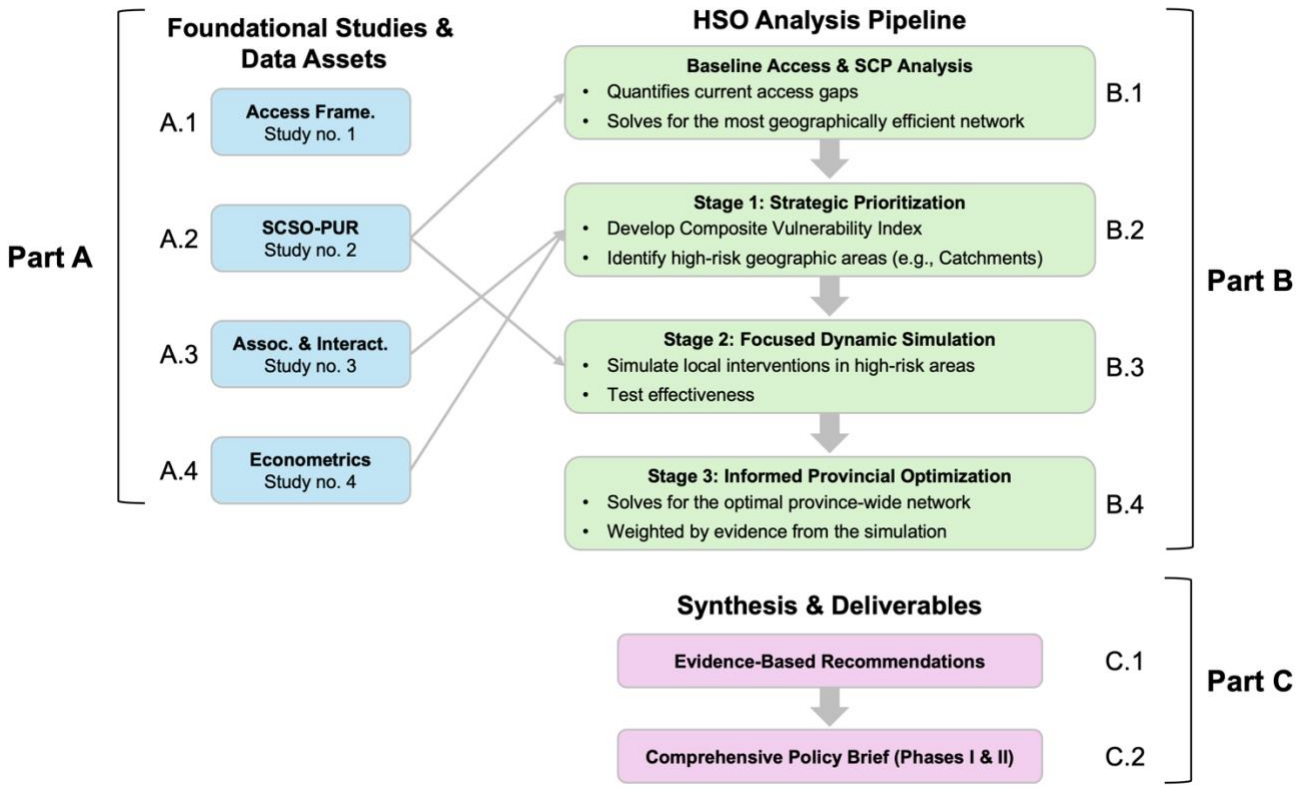


Figure 6.9 Integrated research workflow for the Health System Optimization (HSO) Policy Brief (Phases I & II). This diagram shows the integrated, multi-stage workflow designed for the HSO Policy Brief. The workflow proceeds from foundational empirical research (Part A: Blue Boxes) through a series of analyses and the optimization pipeline (Part B: Green Boxes) and concludes with the synthesis and policy recommendations (Part C: Purple Boxes). Importantly, the diagram highlights the specific dependencies where foundational studies inform subsequent analytical stages. For example, findings from the statistical analyses and econometrics of barriers to access and utilization (i.e., Studies no. 3 & 4) are direct inputs into the Strategic Prioritization (Stage 1), while the geospatial analysis using estimated granular population data (Study no. 2) is essential for both the Baseline Analysis and the agent-based simulations (Stage 2). This comprehensive approach ensures that the final policy recommendations are based on a rigorous, multi-layered evidence base.

Table 6.2 Comprehensive research workflow for the Health System Optimization (HSO) Policy Brief (Phases I & II).

Part	Key Contribution (study no.)	Method & Model	Inputs & Dependencies	Status & Outcome
A. Doctoral Dissertation Research (Empirical)				
A.1	Conceptual Framework (s.1)	Geospatial Analysis	Primary Research	Published
A.2	SCSO-PUR (s.2)	Geospatial Analysis, GLMM	Primary Research	Submitted
A.3	Statistical Associations & Interactions (s.3)	GLMM, SEM	Primary Research	Submitted
A.4	Dynamic Impact Analysis, Associations & Forecasts (s.4)	ARIMA, SARIMA, ETS, Prophet, GLMM, ITS, HTS	Primary Research	Submitted
B. Policy Brief – Health System Optimization Preliminary Assessment (Phase I & II)				
B.1	Policy Brief – Phase I: Baseline Access & SCP Analysis	Geospatial Analysis, SCP	A.2 →PUR & Facility Locations	Complete
B.2	Stage 1: Strategic Prioritization	Vulnerability Index	A.3 → Barrier Coefficients A.4 → Shock Impact (e.g., Floods) B.1 → Baseline Travel Time	Funding Proposal
B.3	Stage 2: Focused Dynamic Simulation	ABM	A.2 → Creating agents B.2 → Select vulnerable areas	Funding Proposal
B.4	Stage 3: Informed Provincial Optimization	MCLP, LA (Cost- and Capacity-constrained)	B.3 → Impact weights for optimization	Funding Proposal
C. Policy Brief – Final Report (Phase I & II)				
C.1	Evidence-Based Policy Recommendations		A.1 → Guiding Goals B.1 → Baseline B.4 → Optimal strategy for planning	Policy Brief
C.2	Comprehensive Policy Brief		Culmination of all preceding Parts	Policy Brief

Abbreviations: GLMM Generalized Linear Mixed-Model, **SEM** Structural Equation Model, **ARIMA** Autoregressive Integrated Moving Average, **SARIMA** Seasonal ARIMA, **ETS** Exponential Smoothing (aka Error, Trend, Season), **ITS** Interrupted Time Series, **HTS** Hierarchical Time Series, **SCP** Set Covering Problem, **ABM** Agent-Based Model, **MCLP** Maximal Covering Location Problem, **LA** Location-Allocation

6.8 Strengths and Limitations

A comprehensive evaluation of this HSO study necessitates acknowledgment of its methodological strengths alongside its inherent limitations. The study's primary advantages include its innovative approach and data-rich foundation. The proposed multi-stage, mixed-methods framework, which integrates statistical analysis, simulation, and formal optimization, exemplifies a novel and rigorous methodology for health systems planning. The entire analysis is founded on granular, sub-catchment level population data (i.e., PURs), offering a level of precision seldom observed in studies of comparable scale. Moreover, the research is explicitly designed to address practical policy questions by transitioning from problem identification to the development and empirical testing of potential solutions. The study's recommendations are crafted to be resilient and pertinent for future health system planning by incorporating population projections.

Conversely, the study has several inherent limitations. The quality of the model outputs is fundamentally dependent on the quality of the input data, meaning limitations in the original data, such as incomplete geographic coverage of flood gauge data, are implicitly carried into this analysis. The advanced models also rely on simplifying assumptions regarding agent behaviour and system costs; these assumptions will be stated transparently but represent an abstraction of complex reality. Additionally, this study primarily focuses on spatial and geographic barriers to access. It does not explicitly model other critical determinants, such as direct financial costs to patients, perceived quality of care, or cultural factors influencing health-seeking behaviour. Finally, while forward-looking, the final optimization provides a static *snapshot* of an optimal health system network. In practice, health systems are dynamic, and any implementation plan would require continuous monitoring and re-evaluation over time.

6.9 Preliminary Policy Recommendations

Based on the completed Phase I analysis, the following preliminary recommendations are proposed:

- **Recommendation 1** Formally recognize the significant disparity in access between basic (Health Posts) and comprehensive (Health Centres) primary care in strategic planning and resource allocation.
- **Recommendation 2** Utilize the baseline access data to prioritize immediate support for the most underserved populations, even while the complete optimization plan is being developed.
- **Recommendation 3** Acknowledge the potential for significant system-wide efficiencies, as demonstrated by the SCP analysis, and support the Phase II research required to develop a concrete optimization strategy.

6.10 Concluding Remarks

This preliminary assessment demonstrates that universal geographic coverage in WP is mathematically feasible, but meaningful access—measured by travel time to Health Centres—remains uneven. Optimizing the spatial configuration of facilities offers a powerful tool for health system improvement, but it must be integrated with practical considerations around cost, capacity, and service equity. The roadmap proposed here paves the way for targeted investment to transform health access in one of Zambia's most underserved regions.

Chapter 6: Supplemental

6.11 Background

Supplement A offers an in-depth technical overview supporting the Policy Brief Preliminary Assessment (PBPA) Phase I on Health System Optimization (HSO) in Western Province (WP), Zambia. It delineates the methodologies, data preprocessing techniques, mathematical formulations of the optimization models, and a detailed work plan for future Phase II research, including potential external funding proposals. This supplement is intended for technical reviewers, researchers, and funding agencies seeking a comprehensive understanding of the analytical framework underlying the HSO Phase I findings.

6.12 Data Sources and Pre-processing

The HSO study integrates multiple primary datasets, meticulously prepared and standardized to ensure accuracy and consistency for spatial, temporal, and demographic analysis.

Health Facility Data The health facility dataset, derived from the Master Facility List (MFL)[58] of Zambia, contains time-series information on health facilities (Centres and Posts, n=321) situated within 16 administrative districts of WP. Key variables encompass facility name, district, type, location, and geocoordinates. Data was filtered to include the most recent year available (2024).

Population Under Rooftops (PURs) Data The dataset delineates spatially defined Population Under Rooftops (PURs). Each PUR corresponds to a unique geographic coordinate accompanied by precise geolocation data and detailed demographic breakdowns. Baseline population estimates for PURs from the year 2020 were compounded to 2022 (see data standardization and projections).

Administrative Boundaries The dataset defines Zambia's administrative district boundaries, providing essential geographical context for spatial filtering.

Data Standardization and Projections District names were standardized across all datasets. Current PURs for 2022 were projected forward by 5 and 10 years (to 2027 and 2032) using district-specific 10-year average Population Growth Rates (PGRs) obtained from ZamStats (i.e., 2010-2020 average). The compounding formula was given by:

$$FV = PV(1 + r)^t$$

where FV is the future value (projected population), PV is the present value (current population), r is the annual growth rate (PGR), and t is the number of years in the future.

6.13 Comprehensive Distance Matrix Generation

A fundamental component of the HSO study is a robust understanding of travel costs from each PUR to every potential health facility in the study area. This results in massive distance matrices.

Travel Time Calculation Geodesic distances between PURs and facilities were calculated using the *law of cosines* given by:

$$d = \text{acos}(sin\ \varphi_1 \cdot\ sin\ \varphi_2 + cos\ \varphi_1 \cdot\ cos\ \varphi_2 \cdot cos\ \Delta\lambda) \cdot R$$

where d is the distance, acos is the arccosine function (inverse function of the cosine function). φ is latitude, λ is longitude, and R is the radius of the Earth equal to 6,371 km. Travel time (minutes and hours) was then derived assuming a constant walking speed of 5 km/hr.

Computational Challenge With approximately 176,000 PURs and 321 health facilities in WP, a direct cross-join leads to tens of millions of unique PUR-to-Facility pairs, exceeding typical RAM limits. To overcome the computational challenge, a chunking strategy was used. The chunking strategy was implemented using the *arrow* package in R, where chunks of distance calculations were immediately written to disk, partitioned by district, preventing the entire dataset from being loaded into RAM simultaneously. After all chunks were processed, a file system dataset object was created to permit efficient querying and manipulation directly on the computer's hard disk.

6.14 Baseline Access Assessment Methodology

Using the disk-backed distance datasets, comprehensive baseline assessments of current accessibility were performed for two distinct scenarios: access to any first-level facility and access to Health Centres only.

Identify Closest Facility per PUR For each PUR, the minimum travel time to any facility (or specific facility type) was identified from the relevant distance matrix.

Summarize Baseline Statistics The resulting data was then summarized to generate key metrics: total PURs, total current and projected populations, and travel time statistics (minimum, maximum, mean, median, 25^{th} and 75^{th} percentiles). Crucially, it quantifies the number and proportion of PURs and population falling within and beyond the 2-hour (i.e., 120 minutes) travel time threshold.

6.14.1 Part A.1: Access to All First-Level Health

This assessment evaluates access to any of the 321 Health Centres or Health Posts in WP. The total number of PURS was 175,983, with 14,020 PURs (representing 104,637 individuals) exceeding a 2-hour travel time threshold. The proportion of the population within the 2-hour travel threshold was 91.5%.

6.14.2 Part A.2: Access to Health Centres Only

This assessment examines access only to the Health Centres to understand detailed access levels to more comprehensive primary healthcare services. The total number of PURs was 175,983; the number of PURs that exceeded the 2-hour travel threshold was 41,668 (i.e., 322,541 individuals); and the proportion of the population within the 2-hour travel threshold was 73.6%.

6.15 Classical Set Covering Problem (SCP)

The classical Set Covering Problem (SCP), a variant within location-allocation optimization models, was formulated to identify the minimum set of facilities required to cover all demand points (PURs) within a given travel time threshold.

Objective Function The objective is to minimize the total number of selected candidate health facilities:

$$Minimize \sum_{j=1}^{n} x_j$$

where x_j is a binary decision variable for health facility j, and n is the total number of candidate health facilities. The decision variables were defined as:

$$x_j = \begin{cases} 1 \\ 0 \end{cases}$$

where 1 was if a health facility j is selected and 0 otherwise.

Constraints Each PUR i must be covered by at least one selected health facility. This is formulated using a binary coverage matrix A given by:

$$\sum_{j=1}^{n} a_{ij} x_j \geq 1 \quad \forall_i \in \{1, \dots, m\}$$

Where m is a binary parameter where $a_{ij} = 1$ if a health facility j can cover PUR i within the given travel time threshold, and $a_{ij} = 0$ otherwise.

Solver Implementation The optimization problem was solved using the *Rglpk* package in R, which interfaces with the GNU[p] Linear Programming Kit (GLPK) solver. A sensitivity analysis was performed by iteratively running the SCP for thresholds ranging from 120 to 450 minutes to produce the results shown in the main Policy Brief document.

6.16 Advanced Optimization & Research (Phase II)

This preliminary assessment highlights a significant opportunity for optimizing health facility networks for basic geographic access. However, a comprehensive health system optimization strategy requires deeper analytical phases to address the critical gap in access to Health Centres (comprehensive primary care) identified in the baseline assessment.

6.16.1 Advanced Optimization Modelling

The primary objective of future work is to specifically address this gap. This will involve exploring more complex optimization models that incorporate additional real-world constraints and objectives.

Maximal Covering Location Problem (MCLP) This model variant is ideal when resources are constrained. Instead of trying to cover everyone, the objective is to locate a fixed number of new or upgraded facilities to maximize the population covered within a specific service standard (e.g., the 2-hour threshold). The MCLP is given by:

$$Maximize \sum_{i=1}^{m} p_i z_i$$

and is subject to:

[p] The GNU project, an initiative by Richard Stallman to develop a free and open-source Unix-like operating system, is named with the recursive acronym GNU, which signifies 'GNU's Not Unix'

$$\sum_{j \in N_i} x_i \geq z_i \quad \forall_i \in \{1, \dots, m\}$$

$$\sum_{j=1}^{n} x_j = k$$

$$x_j \in \{0,1\} \quad \forall_j \in \{1, \dots, n\}$$

$$z_i \in \{0,1\} \quad \forall_i \in \{1, \dots, m\}$$

where p_i is the population of a PUR i, z_i is a binary variable that is 1 if PUR i is covered, and 0 otherwise, x_j is a binary variable that is 1 if a health facility j is selected, and 0 otherwise, N_i is the set of candidate health facilities that can cover PUR i, and k is the fixed number of health facilities to be located, and m is the total number of PURs, and n is the total number of candidate health facilities.

Cost-Constrained Location-Allocation Models These models explicitly integrate the financial costs associated with facility selection. The objective could be to minimize the total cost of the network while meeting certain coverage targets, or to maximize coverage within a defined budget.

Capacity-Constrained Models These models add a critical layer of realism by ensuring that selected facilities have sufficient capacity to serve the population allocated to them, preventing the model from creating solutions that would overwhelm existing or new infrastructure.

$$\sum_{i=1}^{m} p_i y_{ij} \leq C_j x_j \quad \forall_j \in \{1, \dots, n\}$$

where p_i is the population (demand) of PUR i, y_{ij} is a binary variable that is 1 if PUR i is assigned to a health facility j, and 0 otherwise, C_j is the service capacity of a health facility j, x_j is a binary variable for selecting a health facility j. This constraint ensures that the total population is assigned to a health facility does not exceed its capacity and only applies if the facility is selected $\{x_j = 1\}$.

6.16.2 Detailed Data Requirements

Successful implementation of Phase II requires specific data not fully integrated in Phase I:

- **Cost Data** Estimated construction costs for new Health Centres, renovation/upgrade costs for Health Posts, and average annual operational costs per facility type.
- **Capacity Data** Estimated patient capacities (e.g., daily or yearly visits) for existing Health Centres and Health Posts, and projected capacities for new or upgraded facilities.
- **Refined Demand Data** Potentially more granular population demand data reflecting specific service needs or demographics if relevant to capacity allocation.

6.16.3 Methodological Challenges Anticipated

Future phases may present challenges, including sourcing reliable cost and capacity data, managing the increased computational complexity of more advanced integer linear programs, and ensuring the effective integration of diverse data types into the optimization framework.

6.16.4 Preliminary Budget Outline

Securing funding is crucial for this next phase of research. A preliminary budget outline is provided below, with a detailed breakdown subject to refinement during grant application development:

- **Personnel** Principal Investigator (i.e., Scientist/Health Economist), Post-Doctoral Fellow, Doctoral Student(s), Research Assistant(s), Project Manager, and Specialized Consultants (e.g., GIS Experts).
- **Software and Computational Resources** Licenses for commercial optimization solvers, server, and cloud computing resources.
- **Data Acquisition and Licensing** Costs associated with acquiring specific cost, capacity, or refined demographic datasets.
- **Travel and Fieldwork** For data validation, stakeholder consultations, or site visits in WP and Lusaka (Capital).

- **Dissemination and Knowledge Mobilization** Support for workshops, policy dialogues, and publications.
- **Indirect Costs (Overhead)** A percentage allocated by the university/institution.
- **Contingency** (10-15%) For unforeseen expenses and adaptive research needs.

6.17 Concluding Remarks

This supplement A has detailed the preliminary assessment's robust methodology and foundational findings (Phase I), providing the technical underpinnings for the primary policy brief (Phase I and II). The meticulous data pre-processing, the generation of comprehensive, disk-backed distance matrices, and the formal application of the Set Covering Problem have produced a rigorous, evidence-based understanding of the current accessibility landscape in WP. This foundational work is not merely an academic exercise; it provides the essential, validated inputs required for the advanced optimization and simulation models outlined in the future work plan. By establishing this strong technical basis, the HSO project is well-positioned to develop comprehensive, data-driven recommendations to enhance equitable access to quality healthcare for all individuals living in rural and remote communities in WP, Zambia.

Chapter 7

Discussion

7.1 Revisiting the Central Problem

This dissertation addresses a central problem in Zambia's Western Province (WP): the disruptive interaction between seasonal environmental shocks and chronic health system stressors. This intricate dynamic impedes progress toward Universal Health Coverage (UHC) and exacerbates existing health disparities and inequities. It was hypothesized that this relationship was not merely additive but synergistic, constituting an *econosyndemic* whose dynamic and geographically variable nature had not been empirically quantified. The preceding chapters have systematically followed a structured research trajectory to address this complex problem, advancing from theoretical conceptualization and methodological innovation to empirical testing and, ultimately, policy development.

The research trajectory commenced with the deconstruction of the fundamental concept of access and the quantification of chronic stressors—including extensive travel distances and decreasing facility density—that characterize the health system landscape in WP (Study no. 1). It subsequently addressed a critical methodological obstacle by developing the novel SCSO-PUR methodology to resolve the persistent "denominator problem" in routine health data, thereby facilitating a robust, population-adjusted analysis of service utilization (Study no. 2). With these foundational elements established, the dissertation provided the first empirical evidence of the *econosyndemic* in operation, demonstrating the adverse synergistic interaction between flooding and health system capacity on maternal (i.e., antenatal care) and child health outcomes (Study no. 3). The analysis incorporated a dynamic temporal dimensions, forecasting utilization rates and measuring the distinct signatures of various shocks—drought, pandemic, and flood—to present a nuanced portrayal of health system resilience time (Study no. 4). Ultimately, the research translated these

cumulative empirical findings into a forward-looking, actionable policy framework to optimize the health system for enhanced efficiency, to reduce disparities and achieve equitable access to essential health services (Study no. 5).

This concluding chapter now synthesizes the key findings from this integrated body of empirical research. It is not a simple restatement of results, but an effort to weave the distinct themes from each study into a cohesive narrative. This chapter will first synthesize the thematic findings to construct a holistic picture of the *econosyndemic* and its consequences. It will then articulate the dissertation's primary contributions to theory, methodology, and policy. Finally, after considering the research's strengths and limitations, it will outline specific policy implications and propose a clear agenda for a future research program, concluding with a final reflection on the urgent need to build resilient and equitable health systems that the future demands.

7.2 Synthesis of Key Findings

While distinct in their specific objectives and methods, this dissertation's five studies collectively assemble a multi-layered, quantitative portrait of a health system operating under significant and compounding pressures. When synthesized, their findings move beyond a simple description of individual problems to reveal the systemic and interactive nature of the challenges in WP. This synthesis is organized around two core themes: first, the empirical validation of the *econosyndemic* framework through the dissertation's primary findings; and second, an exploration of noteworthy patterns that, while not always statistically significant, offer rich insights and generate critical hypotheses for future research.

7.2.1 Quantitative Portrait of a System Under Stress

The central argument of this dissertation—that the health system in WP is shaped by an *econosyndemic*—is substantiated by synthesizing the primary findings from Studies 1, 3, and 4. Study no. 1 initially delineated the landscape of chronic stressors, thereby establishing a quantitative baseline of systemic vulnerability. The projected decline of 48.6% in health facilities per capita by 2032 and average unimpeded walk times of up to 13.9 hours are not merely statistical

data; instead, they represent empirical indicators of a system operating at the brink of overload, where geographic distance constitutes a significant and enduring barrier to the access of essential health services.[49] This observation aligns with an extensive body of literature demonstrating that such distances directly correlate with adverse health outcomes.[244–247]

In the context of ongoing chronic stress, Study no. 3 introduced an acute and recurrent environmental shock: variation in seasonal flooding. The finding that higher flood depths correlated with a significant decrease in antenatal care (ANC) visits and facility-based births aligns with evidence from other contexts indicating that climate shocks can severely disrupt essential maternal health services.[192,248] Nevertheless, the most vital contribution was empirically validating a synergistic effect. The robust interaction effect, particularly observed in Sikongo district, demonstrated that the protective effect of health facility density was substantially enhanced in the most vulnerable regions. This phenomenon exemplifies the *econosyndemic*: the shock (flood) and the stressor (low facility density) did not merely sum their effects; they magnified them, resulting in a disproportionate risk escalation for the most marginalized populations. This quantitative validation of a synergistic interaction offers a rigorous response to critiques[249] of syndemic theory and elucidates a clear mechanism through which climate change can intensify health disparities.

Furthermore, the paradoxical finding in Study no. 3 of a surge in general utilization (i.e., outpatient visits) during floods, likely driven by an increased burden of waterborne (i.e., malaria) and other infectious diseases, adds another layer of complexity.[248,250] This suggests that a single shock can simultaneously suppress the utilization of some essential services (time-sensitive maternal care) while increasing the demand for others (acute primary care). This dual pressure places immense strain on a system already defined by the workforce shortages identified in Study no. 1. The health system's response is further complicated by the dynamic and varied nature of shocks, as revealed in Study no. 4. The distinct "signatures" of the drought (an immediate drop in utilization), the COVID-19 pandemic (an immediate surge), and the complex flood (a delayed recovery trend) demonstrate that the system's adaptive capacity is tested in different ways by different crises. The surprising surge in utilization following the COVID-19 shock, for instance, may reflect a period of heightened health awareness or specific public health messaging, a finding that contrasts with

evidence of service disruption in other settings but underscores the importance of context-specific analysis.[251,252]

Collectively, these findings provide a clear depiction. The healthcare system in WP is not merely confronting a series of isolated issues. Instead, it manages a synergistic network of interconnected risks, wherein the effect of any individual shock is either intensified or mitigated by the persistent underlying stressors of geographical remoteness, vulnerability, and resource deficiency. This constitutes the quantitative representation of the *econosyndemic*.

7.2.2 Patterns and Emergent Hypotheses

A comprehensive analysis of the data uncovers several noteworthy patterns that, although not consistently reaching the conventional threshold for statistical significance in the primary models, offer valuable insights and generate essential hypotheses for future research. These observations enrich the main findings and underscore the complexity inherent in the health system's adaptive processes.

One of the most compelling patterns emerged from the analysis of antenatal care (ANC) in Study no. 3. Although the final model did not test for a formal interaction between visit type and time, the descriptive trends in the predicted probabilities indicated a potentially steeper decline in ANC third-trimester visits over time compared to first-trimester visits. This observation, although not statistically confirmed as a differential effect, may suggest important underlying dynamics in the continuum of care. It generates several plausible hypotheses: this could be a function of escalating socioeconomic barriers, where the cumulative cost and time of multiple visits become prohibitive for vulnerable households.[253–255] Alternatively, it may reflect supply-side constraints, whereby a poor-quality experience during an initial visit—such as long wait times or a lack of supplies—disincentivizes return for subsequent appointments.[46,47] This pattern underscores the fragility of sustained engagement with the health system and warrants a dedicated qualitative investigation.

The Structural Equation Models (SEMs) in Study no. 3 also revealed a crucial nuance. The direct path from "Flood Depth" to the health utilization outcomes was not statistically significant,

suggesting the flood's impact is not direct but is mediated through the system's underlying "Health System Capacity" and "Socioeconomic Vulnerability." This finding strongly supports the theoretical structure of the *econosyndemic* framework, which hypothesizes that a shock does not act in a vacuum but exerts its force by exploiting pre-existing vulnerabilities and testing the limits of system capacity.

Furthermore, the econometric analyses in Study no. 4 highlighted considerable spatial heterogeneity. The observation that incorporating flood data (continuous variable) as a regressor enhanced forecast precision in certain districts (i.e., Limulunga, Kalabo) while providing limited benefit in others (e.g., Sikongo) underscores that the relationship between shock and utilization is not uniform. This indicates that communities' social vulnerability and adaptive capacity may vary significantly across the province, thereby influencing the localized impact of a province-wide shock.[256–258] Likewise, the Hierarchical Time Series (HTS) model demonstrated distinct long-term utilization trajectories across different geographic quadrants, suggesting the presence of underlying spatial patterns in health system performance or demographic trends that are obscured by provincial averages. Collectively, these findings advocate for a decentralized strategy in health planning and resilience enhancement.[259]

This point is powerfully illustrated by the pattern of pediatric malaria risk inversion found in Study no. 2. While children under five generally had lower odds of confirmed malaria, the risk was significantly inverted in Kaoma and Mwandi districts. This generates a hypothesis of "localized epidemiological traps," where a unique confluence of local factors—perhaps specific vector habitats, gaps in pediatric-specific interventions, or distinct diagnostic practices—creates pockets of intense risk for children that defy province-wide trends and require targeted, sub-district-level investigation.[260–263]

The distinct system responses to different shocks in Study no. 4 suggest a "hypothesis of shock typology." The system's reaction appears to be dictated by the nature of the shock itself. Logistical shocks that primarily impact physical and economic access, such as the 2019 drought, led to an immediate suppression of services. In contrast, informational and perceptual shocks, like the 2021 COVID-19 pandemic, prompted an initial surge in utilization, possibly driven by heightened health

awareness, employment or fear, followed by a decline.[q] This distinction is critical for preparedness, suggesting that health systems must plan for fundamentally different behavioural and access-related responses depending on the type of crisis anticipated.[6,11,264]

The optimization model in Study no. 5 revealed a tension between efficiency and resilience. The finding that universal geographic coverage could theoretically be achieved with only 46 facilities implies substantial spatial redundancy in the current network. This leads to a "hypothesis of efficiency versus resilience." While seemingly inefficient, the current network may possess a hidden resilience; its redundancy could provide a crucial fail-safe during localized disruptions like a washed-out road, where a nearby, "redundant" facility becomes the only accessible point of care. An optimized, leaner network might be more efficient under normal conditions but far less resilient to the shocks that define the region. This highlights a fundamental policy trade-off between optimizing for routine performance and planning for crisis response.

Ultimately, the geospatial analysis conducted in Study no. 5 served as a compelling visual instrument. The mapping of populations beyond the two-hour threshold for accessing health centres transcends mere statistics, offering a definitive policy tool for identifying specific clusters of underserved communities. This approach is consistent with an expanding body of scholarly literature that underscores the significance of Geographic Information Systems (GIS) and spatial analysis as pivotal instruments for the equitable planning of health services and the allocation of resources. Collectively, these eight significant patterns enhance the primary findings of the dissertation and establish a robust foundation for future research inquiries.

Finally, a critical pattern emerges from the tension between different levels of care, which can be termed the “health post Paradox.” Study no. 5 starkly illustrates this by showing that while

[q] The interruption date for the COVID-19 pandemic was set to January 2021. This date was chosen to model the onset of a sustained, systemic shock to the health system rather than the date of the first reported case. The first two cases in the study area of Western Province were reported significantly earlier on May 28, 2020 (Ministry of Health, Zambia. 2020, May 28. COVID-19 Daily Update. As reported by Lusaka Times). The January 2021 date, however, corresponds to the period when the pandemic’s cumulative effects—including the implementation of major public health measures, widespread changes in health-seeking behaviors due to public fear, and significant policy shifts—became fully pronounced. This created a consistent and structural disruption to health service utilization. Therefore, this date is a more appropriate anchor for the Interrupted Time Series (ITS) analysis, as it marks the beginning of the stable, long-term impact that the model is designed to evaluate.

geographic access to *any* first-level facility is high at over 91%, coverage for comprehensive services offered only at health centres drops significantly to under 74%, creating a substantial "comprehensive care gap." This generates a crucial hypothesis: the strategic expansion of health posts, while successful in improving metrics of basic geographic reach, may inadvertently mask or even perpetuate inequities in access to the quality and scope of care required for better health outcomes, such as skilled birth attendance. With the health system's heavy reliance on Community Health Workers (CHWs) and nurses who primarily staff these posts, as noted in Study no. 1, a tiered system may be forming. In this system, many rural populations have nominal geographic access but lack practical clinical access to the higher-level services concentrated in harder-to-reach health centres. This paradox suggests that optimizing for geographic coverage alone, without explicitly considering the level of care, is insufficient to achieve true health equity.

7.3 Knowledge Expansion

Through its integrated series of studies, this dissertation makes several novel and significant contributions to knowledge across the fields of health systems research, global public health, and climate and health science. The contributions are not confined to a single domain but are multifaceted, spanning theory, methodology, empirical evidence, and policy.

7.3.1 Theoretical Contribution

The primary theoretical contribution of this work is the development and, for the first time, the empirical validation of the *econosyndemic* framework. While syndemic theory has provided a powerful lens for understanding co-occurring, individual-level health conditions, this dissertation extends the concept to the health system level. It offers a new, quantifiable model for analyzing the complex, synergistic interplay between large-scale environmental and social shocks and the chronic, localized stressors that define a health system's capacity. By demonstrating that the impact of a flood is conditional upon the pre-existing strength of the health infrastructure, this research moves beyond linear, single-cause analyses to provide a more robust theoretical foundation for

understanding health system performance and fragility in the Anthropocene.[r] It provides a structured way to conceptualize and test how climate change and other macro-level forces interact with local vulnerabilities to produce inequitable health outcomes.

7.3.2 Methodological Contribution

This research makes two key methodological contributions. First, it introduces the SCSO-PUR methodology, a novel and scalable solution to the persistent "denominator problem" that has long constrained the analytical potential of routine health data in LMICs. This methodological innovation enables more sophisticated, population-adjusted, and equitable analysis of health service utilization, providing a replicable tool adaptable to numerous other contexts lacking granular census data. Second, the dissertation enhances the quantitative application of syndemic theory. Employing advanced statistical techniques—specifically interaction terms in mixed-effects models and Structural Equation Modelling—advances beyond merely documenting the co-occurrence of risk factors to formally testing the synergistic interactions central to the theory. This offers a rigorous methodological framework for future research to quantify syndemic processes.

7.3.3 Empirical Contribution

This dissertation offers initial quantitative, longitudinal evidence from a vulnerable Sub-Saharan African setting concerning the specific interactions between climate shocks and chronic system stressors that disrupt essential health services. The empirical findings of the dissertation reveal nuanced and geographically diverse patterns of disruption and resilience. It demonstrates that a single shock can produce divergent effects across different health services, suppressing maternal care and increasing demand for emergency primary care. Additionally, it illustrates that various shocks—such as drought, pandemic, and flood—generate distinct temporal "signatures" in utilization patterns. Moving beyond merely documenting the impacts of climate change on health and explaining how these impacts are mediated by the capacity of the underlying health system, this research provides a detailed and context-specific body of evidence vital for understanding the real-world dynamics of climate change and health.

[r] Period in time during which human activity has been the dominant influence on climate and the environment.

7.3.4 Health Policy Contribution

Finally, this dissertation translates complex empirical findings into an actionable Health System Optimization (HSO) framework. This is not merely an academic exercise; it is a data-driven roadmap designed to guide tangible policy decisions. By employing location-allocation modelling to identify access gaps and system inefficiencies, the HSO framework provides an evidence base for strategic investments in health infrastructure that can concurrently enhance efficiency, promote equity, and foster a more climate-resilient health system. This work presents a practical instrument for Zambian policymakers and global health practitioners, illustrating how advanced spatial analytics can be utilized to design health systems better equipped to serve their populations in an era characterized by increasing environmental and social instability.

7.4 Strengths and Limitations

A comprehensive assessment of this dissertation necessitates a balanced consideration of its methodological strengths and inherent limitations. The research was meticulously designed to be rigorous and innovative; however, like all empirical endeavours, it is subject to constraints that influence the interpretation of its findings.

7.4.1 Strengths and Limitations of the Overall Research Design

Strengths

Integrated, Multi-Faceted Approach The primary strength of this dissertation resides in its integrated, multi-faceted approach. The manuscript-based format permits an in-depth and focused examination of five distinct yet complementary research questions, collectively constructing a comprehensive narrative.

Substantial Longitudinal Dataset The research is underpinned by a substantial, longitudinal dataset spanning several years, thereby affording the statistical power necessary to identify temporal trends and the effects of shocks—an advantage that surpasses more conventional cross-

sectional designs. Moreover, the innovative synthesis of multiple, disparate data sources—including routine health information, high-resolution satellite population data, and sophisticated hydrodynamic flood models—signifies a noteworthy methodological advancement, facilitating a more holistic analysis than could be achieved with any single data source alone.

Innovative Synthesis of Data Sources A notable strength of this dissertation lies in its innovative synthesis of diverse data sources. The research is supported by the meticulous integration of routine health information from the Zambian HMIS, high-resolution satellite-derived population data, and advanced hydrodynamic flood models.[65,74,76] This intricate data fusion represents a significant methodological progression, enabling a more comprehensive and detailed analysis than would be possible with any individual data source. Thus, it supplies the comprehensive, multi-layered dataset necessary to empirically evaluate the *econosyndemic* framework.

Novel Theoretical and Methodological Contributions Beyond merely synthesizing existing data, a primary strength resides in the development of innovative theoretical and methodological contributions. The establishment of the *econosyndemic* framework introduces a novel and quantifiable perspective for health systems analysis. At the same time, the formulation of the SCSO-PUR methodology provides a practical and scalable solution to a pervasive challenge in global health research. Advanced quantitative techniques—including the formal testing of interaction terms, Interrupted Time Series (ITS) analysis, and location-allocation modelling—enhance the rigour of the empirical findings. Ultimately, the dissertation's explicit translational focus, culminating in the Health System Optimization (HSO) framework, guarantees that this research extends beyond academic inquiry to address tangible policy and planning challenges in WP, Zambia and comparable contexts.

Methodological Triangulation A significant strength of this dissertation is the use of methodological triangulation, not just across the five studies, but within them. For instance, Study 4 did not rely on a single time-series model but benchmarked four distinct methods (ARIMA, SARIMA, ETS, and Prophet) before deploying an Interrupted Time Series analysis. Similarly, Study no. 3 complemented its regression analysis with Structural Equation Modelling to test latent pathways. This multi-model approach demonstrates exceptional rigour, ensuring that the core

findings are robust and not merely an artifact of a single statistical technique, thereby strengthening the validity of the conclusions by showing they hold under different analytical assumptions.

Translational and Policy-Grounded Focus The research design is also strengthened by being deeply grounded in policy and partnership. Including the Policy Brief (Study no. 5) as an integral chapter transforms the dissertation from a purely academic exercise into a work of translational science. This practical orientation is further reinforced by the established partnership with the Zambian Ministry of Health, which ensures that the research questions are policy-relevant and that the findings are positioned for tangible uptake. This stakeholder engagement elevates the research from a passive analysis to an active contribution to real-world health systems planning.

Limitations

A comprehensive assessment of this dissertation necessitates a balanced consideration of its methodological strengths and inherent limitations. The research was meticulously designed to be rigorous and innovative; however, like all empirical endeavours, it is subject to constraints that influence the interpretation of its findings and define the scope of its conclusions.

Ecological Study Design The most significant is the ecological study design. All analyses were conducted at an aggregated, facility- or district-level, which means the findings describe population-level trends and cannot be used to make inferences about individual-level risk. This carries a potential for ecological fallacy, where conclusions about individuals are incorrectly drawn from group-level data.[265,266]

Reliance on Routine Health Information System Data The research extensively utilizes data from the Routine Health Information System (RHIS), specifically from the Zambian HMIS and its District Health Information System 2 (DHIS2) platform.[s] While the SCSO-PUR methodology was conceived to improve this data, the fundamental numerators remain vulnerable to the well-documented, inherent challenges associated with routine data collection in low-resource settings.

[s] The DHIS2 open-source software platform was developed via a global collaboration between Health Information Systems Programme (HISP), the University of Oslo and the University of the Western Cape.

Although the Zambian HMIS offers valuable data for planning purposes, it is known to encounter notable limitations related to data quality, including issues such as incomplete data, inaccuracies in data entry, and delays in reporting.[68,69,71,242] These issues are often exacerbated by human resource constraints, such as a lack of trained personnel in data analysis, and infrastructural deficits, like limited internet access in rural areas, which can impede timely data transmission and effective use.[56] For example, the considerable amount of missing data concerning ANC outcomes necessitated a complete-case analysis, which may introduce bias if the data missingness is not entirely random.

Simplifying Assumptions The models employed rely on several simplifying assumptions. Travel time calculation, a key variable, was based on straight-line (Euclidean) distance and an assumed constant walking speed. While this is a common and necessary approach in data-scarce environments, it does not account for real-world barriers like terrain, road quality, or seasonal impediments not captured by the flood model.[267] Similarly, the optimization models in Study no. 5 are based on geographic access and do not yet incorporate other critical real-world constraints such as facility capacity, service quality, or the financial costs of construction and operation.[46,268,269]

Exclusion of Other Health Sectors The analysis is constrained by its exclusion of the private and informal health sectors. Dependence on official data from the public health system results in the study not considering the role of private clinics, faith-based facilities, traditional healers, or informal drug vendors, which form a substantial part of the healthcare landscape in rural and remote communities of WP, Zambia. This omission may result in an incomplete representation of overall health-seeking behaviours, as a perceived decrease in public facility utilization during a shock might indicate not only access barriers but also a transient shift towards more accessible informal providers—a dynamic not encapsulated within this research.

Lack of Key Supply-Side Variables An additional limitation pertains to the scope of predictor variables incorporated within the models. The analyses predominantly concentrate on geographic accessibility, population density, and the influence of environmental shocks. Nonetheless, they do not include vital facility-level, supply-side variables that substantially affect the quality and

capacity of service delivery. Data regarding factors such as the operational costs of facilities[t], the specific number and cadre of healthcare personnel at each site, or the availability and stock levels of essential medical supplies were unavailable for inclusion in the longitudinal models. Accordingly, the models consider all facilities of a given type (e.g., health centres) as homogeneous units. This simplification conceals the reality that a well-staffed, fully stocked facility provides a fundamentally different level of care than one facing persistent shortages. This unmeasured heterogeneity implies that some of the variation in service utilization currently attributed to geographic or temporal factors could be influenced by these unobserved supply-side constraints. This issue is particularly salient for the Health System Optimization (HSO) framework in Study no. 5, as a truly comprehensive model would need to weigh not only a facility's location but also its operational capacity and cost-effectiveness.

Static Nature of Key Health System Stressors Although the dissertation encompasses a longitudinal approach, many of the fundamental stressors within the health system examined remain relatively constant throughout the study period. For instance, the quantity and geographical distribution of physical health facilities did not undergo substantial changes over 73 months. While the ratio of facilities to population was modelled dynamically through growth projections, the analysis is not positioned to draw definitive causal inferences regarding the impact of infrastructural modifications, such as the construction of new clinics. The research excels in analyzing the interaction between static stressors and dynamic shocks but is less capable of evaluating the effects of policy-driven, dynamic changes within the health system.

Limited Direct Generalizability Finally, although the findings are solid within the specific context of WP, their direct applicability to other environments should be regarded with caution. The characteristics of the environmental shock—namely, a predictable, seasonal floodplain—and the structure of the health system are distinctive to this region. While the theoretical frameworks and methodological approaches possess broad relevance, the particular empirical outcomes may not be transferable to areas with differing ecological, social, or health system features, which is a

[t] A per-capita budget estimate was initially developed to serve as a proxy for facility-level resources. This variable was subsequently excluded from the final regression models after preliminary analysis indicated a high potential for multicollinearity with population-based covariates.

common challenge in health services research where local context significantly influences outcomes.[270]

7.4.2 Econosyndemic Framework

Strengths

Theoretical Novelty A primary strength of the *econosyndemic* framework is its theoretical novelty and its capacity to conceptualize health system performance beyond linear, single-cause explanations. Extending syndemic theory to the systems level provides a structured model for analyzing the synergistic interplay between macro-level shocks and chronic, micro-level stressors.

Conceptualizes Dynamic Resilience Crucially, the framework is not limited to describing system failure. Its inclusion of a dynamic feedback loop—labelled "Strengthen System Capacity"—is a significant theoretical advance, conceptualizing resilience as an adaptive process. This component posits that a system can learn from navigating crises, allowing positive gains in Universal Health Coverage to be reinvested, thereby enhancing its capacity to mitigate future shocks. This moves beyond a static view of vulnerability and provides a more holistic and optimistic model of how health systems can evolve.

Provides a Structure for Quantifying Synergy A key strength of the *econosyndemic* framework is that it provides a structure for quantifying synergy, moving beyond the descriptive accounts that have often characterized syndemic research.[34] The framework's central hypothesis—that shocks and stressors interact to produce a total effect greater than the sum of their individual effects—is explicitly testable. This was empirically demonstrated in Study no. 3, where using statistical interaction terms in mixed-effects models provided a formal method for measuring this synergy.[49] The finding that the protective effect of health facility density was significantly amplified in the most vulnerable, flood-prone districts provided direct, quantitative evidence of this synergistic process. By employing these advanced statistical methods, the framework offers a rigorous and replicable approach for researchers to empirically validate and measure the magnitude of syndemic interactions within a health system.

Limitations

Nascent and Untested A primary limitation is that the *econosyndemic* framework, as a newly proposed concept, is nascent and has not yet undergone extensive peer review. Unlike traditional syndemic theory, which has been debated, applied, and refined across diverse contexts for decades, the *econosyndemic* framework's theoretical underpinnings have not yet been widely tested or critiqued by the broader scientific community.[30] Its novelty is a core strength, but this also means its constructs and hypothesized pathways lack validation from repeated application by different research groups in varied settings. This dissertation serves as its first empirical test, and further research will be required to establish its robustness and generalizability.

Intensive Data Requirements Despite its theoretical strengths, the *econosyndemic* framework exhibits certain limitations, chiefly pertaining to the challenges encountered during its empirical implementation. This framework necessitates extensive data collection, involving the integration of longitudinal health, environmental, and geospatial data, which are frequently limited in low-resource settings, thereby potentially restricting its broad applicability.

Ambiguity in Definitions Although the framework's differentiation between acute "shocks" and chronic "stressors" is theoretically beneficial, these categories may become indistinct in practice, as a sustained shock such as a drought can develop into a chronic stressor.

Empirical Focus on Negative Impacts Most importantly, while the framework theoretically accounts for positive, adaptive feedback, the empirical scope of this dissertation was necessarily focused on quantifying the more immediate, disruptive, and negative synergistic interactions. Measuring the long-term, system-strengthening feedback loop would require a much longer time series and data on policy and investment responses to crises, which were beyond the purview of this research. Therefore, the primary limitation is not a flaw in the theory itself, but a boundary on its current empirical validation, which sets a clear agenda for future research to quantify these adaptive pathways.

Primary Outcome is Utilization Additionally, the framework as applied in this dissertation is limited by its reliance on health service utilization as the primary outcome. While utilization serves as a powerful and practical proxy for "realized access", it does not capture the full spectrum of health system performance or population health.[49] This focus necessarily excludes other critical domains, such as direct health outcomes (e.g., changes in maternal or neonatal mortality), the quality of care provided, or the patient experience, including the financial hardship associated with seeking care. As such, while the framework effectively models how shocks and stressors impact whether a person reaches a facility, it is less equipped in its current application to measure what happens after they arrive, a crucial dimension of equitable healthcare.[47]

7.5 Policy and Programmatic Implications

The cumulative findings of this dissertation offer a compelling, evidence-driven mandate for action. By transcending mere problem identification to a quantitative comprehension of their synergistic and dynamic characteristics, this research establishes a basis for targeted, context-aware, and proactive policy measures. The implications range from local health planning in WP to broader global health and climate adaptation strategies.

7.5.1 Ministry of Health and Provincial Health Planners

Prioritize Targeted and Strategic Infrastructure Investment: The evidence overwhelmingly argues against a uniform approach to health system strengthening. The HSO framework from Study no. 5, which identified a significant comprehensive care gap affecting over 322,000 people, provides a clear roadmap. The most urgent policy implication is to use this evidence to prioritize upgrading existing health posts to fully resourced health centres or constructing new ones, specifically in the geographically underserved areas identified in the analysis. Furthermore, the powerful synergistic effect found in Study no. 3 suggests that such investments will yield the greatest return in building resilience precisely in the most vulnerable, flood-prone districts like Sikongo. This provides a data-driven rationale for moving beyond simple efficiency metrics to an equity-focused investment strategy.

Integrate Climate Data into Routine Health Planning: The forecasting work in Study no. 4 demonstrates that health service utilization is not only seasonal but can be predicted with a high degree of accuracy. The Zambian Ministry of Health (MOH) should institutionalize the use of climate and environmental data—such as forecasted flood extent—as a key input for proactive resource allocation. By using predictive models, provincial health offices can anticipate periods of heightened demand (e.g., for flood-related illnesses) and suppressed access (e.g., for maternal care), allowing them to pre-position essential medicines, deploy mobile outreach teams, and reinforce staffing in high-risk areas before the peak of the flood season.

Address the "Last Mile" through community-based platforms: The extreme travel times quantified in Study no. 1 confirm that, for many remote communities, even an optimized network of fixed facilities will remain difficult to reach. This highlights the critical necessity of enhancing community-based health platforms. This entails investing in the training, equipping, and support of Community Health Workers (CHWs), who are often the sole accessible source of care. Policies designed to improve the retention of skilled health workers in these remote areas are also of paramount importance.[271]

7.5.2 Global Health Policy and Climate Adaptation

The challenges identified in WP are not unique; instead, they represent a microcosm of the threats facing vulnerable health systems globally in an era of increasing climate instability. Therefore, this dissertation's findings extend beyond local recommendations for WP, Zambia, and offer several key implications for the broader fields of global health policy and climate adaptation strategy. By providing empirical evidence of the *econosyndemic* process, this research informs a necessary shift away from isolated, reactive interventions toward more integrated, proactive, and systems-based approaches to building global health resilience.

Adopt a Systems-Based, Syndemic Approach to Climate Adaptation This dissertation's primary theoretical contribution—the *econosyndemic* framework—has broad implications for global health policy. It argues that effective climate adaptation is not about building flood-proof clinics in isolation but about strengthening the entire health system's capacity to manage interacting

shocks and stressors. Global health funders and national governments should adopt this systems-level perspective, designing and funding interventions that simultaneously address infrastructure, workforce, supply chains, and data systems as an integrated whole.

Invest in Data Systems as a Core Climate Adaptation Strategy The success of this dissertation's analyses hinged on overcoming data limitations through the SCSO-PUR methodology. This highlights a critical, often overlooked point: robust, localized, and disaggregated data are a prerequisite for effective climate adaptation. Investing in strengthening national RHIS, integrating them with geospatial and climate data platforms, and building local capacity for advanced analytics is not a mere technical exercise but a fundamental strategy for building resilient health systems that can learn and adapt to environmental change.

Scale Up the Use of Optimization Science in Health Planning The application of location-allocation modelling in Study no. 5 exemplifies the significant potential of operations research and optimization science to enhance the effectiveness and fairness of health infrastructure investments in settings with limited resources.[272] International health collaborators and national health authorities should endeavour to expand the utilization of these methodologies, transitioning from informal or politically motivated facility placement to a more systematic, evidence-driven strategy that optimizes population health outcomes per financial resource allocated.

7.6 Directions for Future Research

This dissertation, while comprehensive, opens several important avenues for future inquiry (figure 7.1). The findings and limitations of this work naturally point toward a clear agenda for subsequent research that can deepen, broaden, and validate the conclusions presented here.

7.6.1 Deepening the Analysis

The subsequent logical progression is to expand upon the Health System Optimization framework formulated in Study no. 5. The existing model emphasizes the optimization of geographic access; however, a more advanced analysis should incorporate additional layers of complexity. Future

research should concentrate on developing cost-constrained and capacity-constrained location-allocation models. This would necessitate collecting detailed data regarding the costs associated with constructing and upgrading facilities and their operational capacities to generate an optimization plan that is not only geographically efficient but also economically viable and practically feasible. Integrating a formal cost-benefit analysis would facilitate a direct comparison of the return on investment for various strategies, such as establishing new Health Centres versus reinforcing community-based outreach programs.

Furthermore, the noteworthy trend of a steeper decline in ANC third-trimester visits warrants a dedicated investigation. Future research should employ qualitative methods, such as in-depth interviews with women and healthcare providers in WP, to explore the lived experiences and decision-making processes behind this pattern. This would help uncover whether the decline is driven by socioeconomic barriers, perceptions of care quality, or other demand-side factors not captured in the quantitative data.

7.6.2 Broadening the Scope

Within Zambia

A comparative analysis employing a natural experiment may represent a pivotal direction for future research. Expand the analytical scope to encompass the entire province by utilizing the non-floodplain districts of WP as a natural experiment. This approach would directly extend the findings of this dissertation while addressing one of its principal limitations. Studies no. 3 and no. 4 were necessarily concentrated on the subset of 62 health facilities situated within the Barotse Floodplain, as this was the region for which detailed hydrodynamic data were accessible.

Future work should aim to replicate these longitudinal models for the health facilities situated in the districts outside this flood-prone zone. By treating the non-floodplain districts as a robust comparison group, this quasi-experimental design would allow for a more rigorous isolation of the specific effects of seasonal flooding. It would enable the disentanglement of the hydro-climatic

shock of inundation from other province-wide shocks (e.g., the COVID-19 pandemic, drought) and chronic stressors that affect the entire province.

This comparative analysis would be a powerful test of the *econosyndemic* framework's specificity. If the synergistic interactions and dynamic signatures of disruption are significantly attenuated or absent in the non-floodplain areas, it would provide compelling evidence that seasonal flooding is the principal driver of the *econosyndemic* process in this context. Conversely, if similar patterns of system fragility and service disruption are observed in the absence of major flooding, it would generate a powerful new hypothesis: that other, less visible chronic stressors—such as economic vulnerability, agricultural cycles, or systemic resource limitations—are the dominant factors shaping health system resilience across the entire province. Such a finding would have profound implications, suggesting that while flooding is a dramatic and visible shock, the underlying vulnerabilities of the health system are pervasive and require a much broader set of interventions beyond climate-specific adaptations.

Beyond Zambia

The entire research program could be replicated in other regions facing different types of recurrent environmental shocks, such as drought-prone areas (e.g., Afghanistan, Pakistan, Bangladesh) or regions susceptible to extensive flooding (e.g., Niger, India, Pakistan, and Bangladesh).[192,195,273–276] Such comparative work would be invaluable for testing the *econosyndemic* framework's external validity and understanding how different shocks interact with local health system characteristics to shape health outcomes.

This dissertation's theoretical and methodological frameworks possess considerable potential for application beyond the immediate context. Future research should aim to implement the *econosyndemic* framework and the SCSO-PUR methodology to other health outcomes and geographical settings. In WP, this could include examining the effects of shocks and stressors on outcomes such as child nutrition, vaccination coverage, or the management of chronic diseases such as HIV and tuberculosis.

7.6.3 Validating at the Individual Level

Finally, it is crucial to address the primary limitation of this dissertation: its ecological design. While the population-level findings are robust, they do not capture individual-level heterogeneity in risk and behaviour. Future research should aim to validate these findings through studies at the individual level. For instance, a prospective cohort study design could follow a group of pregnant women throughout a flood season, collecting detailed data on their health-seeking behaviours, travel patterns, and health outcomes. Such research would furnish the detailed, patient-specific evidence necessary to confirm the mechanisms hypothesized within this dissertation and to facilitate the development of more precise, person-centred interventions.

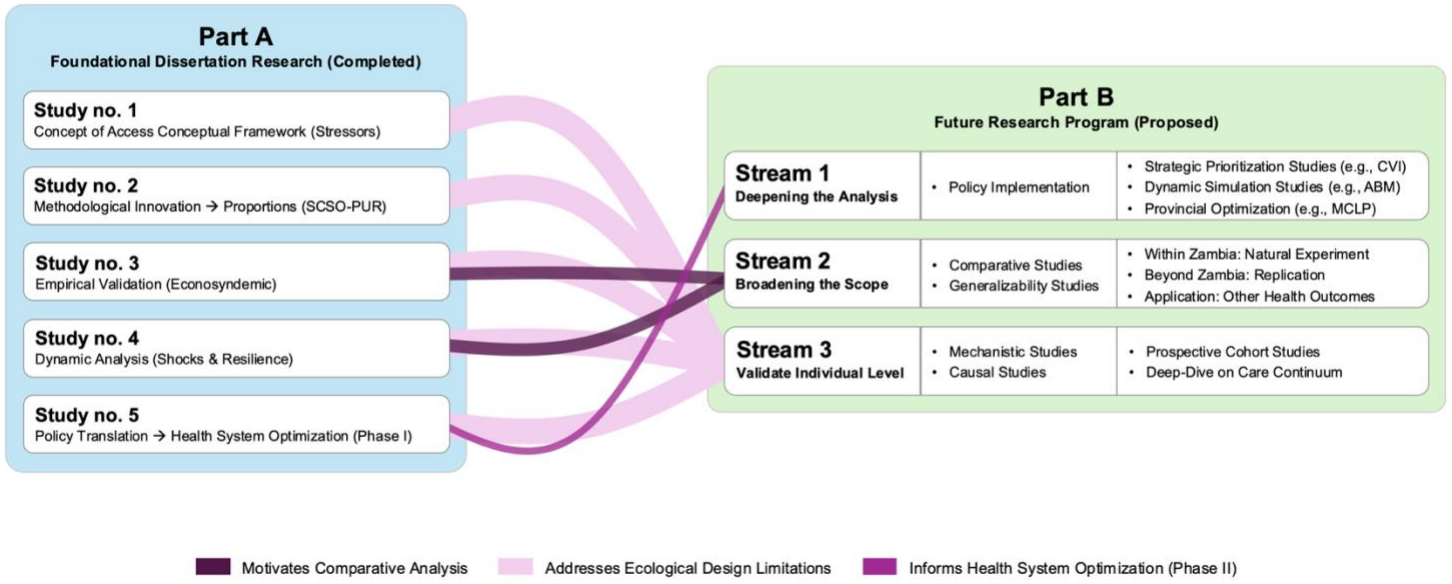


Figure 7.1 An integrated framework for a future research program. This figure delineates the conceptual connection between the foundational dissertation research (Part A) and the proposed future research initiative (Part B). Part A encapsulates the five completed studies, which furnish the essential empirical evidence, theoretical frameworks (e.g., *econosyndemic*), and methodological innovations (e.g., SCSO-PUR) that underpin subsequent inquiry. Part B outlines three distinct yet interconnected streams of the proposed research program: Stream 1 emphasizes policy implementation science to enhance analysis; Stream 2 aims to expand the scope via comparative and generalizability studies; and Stream 3 endeavours to validate findings at the individual level through mechanistic and causal investigations. The colour-coded arrows symbolize the direct dependencies between the two components, with the legend elucidating how specific foundational studies underpin comparative analyses, address the primary ecological design limitations, and directly inform the subsequent phase of the Health System Optimization (HSO) research. Ultimately, the diagram offers a comprehensive roadmap, illustrating a logical and evidence-based progression from the completed dissertation to a broader, multifaceted research endeavour. **Abbreviations: CVI** Composite Vulnerability Index, **ABM** Agent Based Model, **MCLP** Maximal Covering Location Problem.

7.7 Concluding Remarks

This dissertation has presented a novel and rigorous examination of the complex relationship between environmental shocks and health system vulnerabilities in a rural, climate-sensitive setting. It has moved beyond conventional, single-factor analyses to offer a comprehensive, quantitative understanding of how adverse, synergistic interactions—termed an *econosyndemic*—generate geographically variable patterns of disruption and resilience. This research has bridged the divide between abstract theoretical frameworks and concrete empirical evidence by confronting fundamental methodological challenges and employing a multi-model approach.

The work herein is not solely an academic endeavour; it provides compelling evidence for a paradigm shift toward data-driven, context-specific strategies designed to strengthen local health system capacity. The findings illustrate that effective interventions must be tailored to address acute shocks and chronic stressors concurrently. Ultimately, this dissertation argues that pursuing Universal Health Coverage in an era defined by climate uncertainty requires a profound commitment to establishing the measurable, proactive, and genuinely resilient health systems that the future of WP and countless similar regions demands.

Epilogue

After months immersed in geospatial data, regression models, and health system metrics, the enduring lesson from my time in Zambia isn't found in a dataset. It resides in the remarkable character of its people. During two month-long trips for fieldwork and collaboration, the recurring observation—from the bustling provincial capital of Mongu to the most remote rural health posts of Western Province—was the profound resilience of the Zambian people. In a nation grappling with high poverty levels and increasing climate change pressures, there is a steadfast determination not just to survive, but to carve a way forward.

This spirit was most vivid in the small moments that data can never capture. During a two-day research expedition to conduct fieldwork, which took us through the beautiful countryside of Western Province, including the southern part of the Liuwa Plain National Park, our first visit was to the Mishulundu Health Post and the Kalabo District Health Office.[u] Upon arrival, I observed several health professionals hanging a health promotion banner for a child polio vaccination campaign.[v] I asked if I could assist in hanging the banner, which was pleasantly greeted with an astounding “yes, please.” On our next stop, I recall a brief conversation with a mother at the Salunda Health Post. She had walked with her child to wait for hours in +40 °C heat to seek the

[u] The research expedition lasted for two days, during which a distance of 500 kilometers was travelled, entailing a twenty-hour drive, and approximately 13,291 square kilometers were covered. Liuwa Plain in western Zambia possesses one of the most longstanding conservation histories in Africa, originating in the late 19th century when the King of Barotseland designated his subjects as the guardians of the reserve.

[v] The health promotion banner originates from the Zambian Ministry of Health, specifically the Kalabo District Health Office. Kalabo is a district situated in the Western Province of Zambia, where the Lozi language is predominantly spoken. The vaccination campaign was occurring at the Mishulundu Health Post. The primary message on the banner was: “Silelezo ya banana babasika kwanisa lilimo ze keta lizoho kwa butuku bwa liweyenga," which, when translated from Lozi, means "Protection for children who have not yet reached five years of age from the disease of Liweyenga." Liweyenga is the traditional Lozi name for poliomyelitis; although the modern or clinical term employed in Lozi is frequently a direct adaptation of the English term ("butuku bwa polio"), many languages retain traditional, descriptive names for diseases. The term "Liweyenga" is understood within the Lozi language to indicate a condition characterized by withering, thinning, or wasting away, particularly of the limbs—a description that accurately corresponds to the most severe and identifiable symptom of poliomyelitis (polio).

care she needed. She was kind, soft-spoken, and genuine, graciously letting me photograph her with her child—a lasting moment that was truly special.[w]

These individual stories, repeated in countless forms across the province, represent the human face of the resilience this dissertation aims to understand and support. They turn abstract ideas like "access" and "utilization" from academic terms into real, everyday challenges faced with inspiring fortitude.

The models and analyses in this document provide a framework for enhancing a health system to make it more efficient and equitable. However, no system can be truly effective without acknowledging the human capacity at its core. This research aims to offer a technical solution and advocate for a health system worthy of the people it serves. I sincerely hope that this work contributes, in some small way, to building a future where the resilience of the Zambian people is matched by the strength and reliability of the essential health services they rely on θ

[w] A special thank you is extended to Dr. Mwimanenwa Njungu and Dr. Inonge Milupi for their efforts in translation.

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Appendix A: Health Facility Questionnaire

No.	Question Stem
1	What district?
2	**Health Facility:**
2a	Name of facility (health centre or health post)?
2b	Name of additional health posts responsible for?
3	Distance from District Centre (est.)?
4	Estimated Catchment Pop (based on old census) Dec 2021 (Centers include health posts that they serve)?
5	Headcount?
6	How many zones?
7	How many zones severely affected by flooding?
8	How many zones sometimes affected by flooding?
9	Where do people in affected zones move (Stay in catchment or move to another one)?
10	Number of doctors?
11	Number of clinic officers?
12	Number of nurses?
13	Number of midwives?
14	Number of environmental health workers?
15	Number of community health workers (CHWs)?
16	Number of Community Health Assistants (CHAS)?
17	Number of overnight or inpatient beds?
18	Number of maternity delivery beds?
19	Maternity waiting shelter?
20	**Communications:**
20a	Available communications:/Landline
20b	Available communications:/Cell
20c	Available communications:/Radio
20d	Available communications:/None
21	Smartcard laptop present?
22	Ambulance service nearby (within 2 hours)?
23	**Source of electricity:**
23a	Source of electricity:/Grid
23b	Source of electricity:/Generator
23c	Source of electricity:/Solar
23d	Source of electricity:/None
24	**Source of water:**
24a	Source of water:/Piped
24b	Source of water:/Borehole
24c	Source of water:/Dug well
24d	Source of water:/Rainwater collection

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24e	Source of water:/Surface water
24f	Source of water:/No water source
24g	Source of water:/other
24h	Other
25	Sanitation:
26	Emergency obstetric care available?
27	Functioning refrigerator for vaccines present?
28	Basic childhood vaccines available?
29	Are ORs available?
30	Are COVID-19 vaccines available?
31	Is TB diagnosis available?
32	Is malaria diagnosis available?
33	HIV testing available?
34	Is ARV prophylaxis for women and newborns available?
35	Are ARTs available for adults?
36	Is pregnancy testing available?
37	Are blood glucose tests available?
38	Is diagnosis of cervical cancer available?
39	Does facility stock basic antibiotics for childhood respiratory infections?
40	Does facility stock pain medications?
41	Does facility stock supplements for pregnant women?
42	Does facility stock medications for labor and delivery (oxytocin)?
43	Does facility stock micronutrient supplements for children?
44	Does facility stock medications for TB (e.g., isoniazid)?
45	Does facility stock medications for malaria (e.g., Coartem)?
46	How does facility provide data for uploading to the HMIS?

Appendix B: Curriculum Vitae

CAMERON B. CHIAROT

BSc (Hon) | MBA | PhD (c)

LinkedIn: www.linkedin.com/in/cameronchiarot | GitHub: https://cbchiarot.github.io/

EDUCATION

2021 – current	PhD Candidate, Doctoral Program in Health Economics, Epidemiology, and Biostatistics, School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Thesis: *Health System Resilience for Climate Change Adaptation: An Empirical Evaluation of Access and Utilization in Western Province, Zambia*.
2015 – 2017	MBA, with Distinction (Dean's List), Economics, Finance, and Healthcare Systems, Schulich School of Business, York University (Toronto, Ontario, Canada). Course Thesis: *Health and Economic Impacts of Influenza in Ontario: A Proactive Forecasting and Prevention Approach in Decreasing the Incidence Rate*.
1996 – 2000	BSc (Honors), Psychology (Neuroscience), University of Western Ontario (London, Ontario, Canada). Thesis: *Fos Expression Induced by Intraventricular Injection of Neurotrophin-3 (NT-3) in the Paraventricular Nucleus (PVN) of the Hypothalamus in the Rat*.

CREDENTIALS

2006 – 2007	Executive Leadership Development Program, Healthcare Management, Rotman School of Management, University of Toronto (Toronto, Ontario, Canada).

PROFESSIONAL DEVELOPMENT (INSTRUCTOR)

2021 – current	Centre for Teaching Excellence, University of Waterloo. Modules completed: Preparing to TA (CTE1210), Teaching Online Basic Skills (CTE1406), Giving and Receiving Feedback (CTE1106), Supporting Student Mental Health (CTE2259), More Feet on the Ground, Unit 2A (CTE2259), LEARN for TAs (CTE6550), and Effective Lesson Plans (CTE1202).
2021 – current	Fundamentals of University Teaching (FUT), University of Waterloo. Enrolled in the program.

2021 – 2021	Education and Development, Conestoga College Institute of Technology and Advanced Learning. Micro-Credentials Completed: Teaching and Services at Conestoga (EDEV0670), Active Learning Leading to Assessment to Conestoga (EDEV0650), Understanding Outcomes-Based Curriculum (EDEV0640), and Conestoga's LMS and Technologies for Teaching (EDEV0660).

ACADEMIC POSITIONS

2024 – current	**Sessional Lecturer** (Contract, Part-Time), School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Graduate course: Health Economics and Public Health (HLTH 632). Course offering for the Master of Public Health program.
2021 – 2024	**Professor** (Part-Time Faculty), School of Health & Life Sciences, Conestoga College Institute of Technology and Advanced Learning (Kitchener, Ontario, Canada). Undergraduate course: Financial Practices for Healthcare Organizations (FIN8230); Engaging Collaboration in Health Care Management (MGMT8165); and Entrepreneurship in Health Care (ENTR8260).
2021 – 2023	**Teaching Assistant** (Contract), Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Undergraduate courses: Global Health (HLTH 401); Contemporary Issues in Health: The Wicked Problem of Climate Change (HLTH 473); Social Determinants of Health (HLTH 260); An Introduction to Health Neuroscience (HLTH 290). Graduate courses: Applied Machine Learning and Artificial Intelligence in Public Health (HLTH 650); Quantitative Methods and Analysis (HLTH 605B).
2022 – current	**Graduate Student Supervisor & Mentor**, Graduate Research Assistant (MSc), School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada).
2024 – current	**Graduate Research Studentship** (Contract), School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Supervisors: Dr. Craig R. Janes (2024-2025), Dr. Zahid A. Butt (2025).
2023 (Fall)	**Instructional Aide**, AccessAbility Services, University of Waterloo, School of Public Health Sciences, Faculty of Health, University of Waterloo. Graduate course: Quantitative Methods and Analysis (HLTH 605B).
2023 (Spring)	**Graduate Research Assistantship** (Contract), School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Supervisor: Dr. Kelly Anthony

2022 (Fall)	**Proctor** (Volunteer), School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Undergraduate course: Aging & Health (HLTH 201).
2021 – 2022	**Graduate Student Representative (GSR)** (Volunteer), School Advisory Committee on Appointments (SACA), School of Public Health Sciences, Faculty of Health, University of Waterloo (Waterloo, Ontario, Canada). Advertised position: Assistant Professor, Health Informatics.
2000 – 2002	**Research Associate** (Full-Time), Medical Imaging, Sunnybrook Research Institute, Sunnybrook Health Sciences Centre, Healthcare Service Provider – Quaternary Hospital Care (Toronto, Ontario, Canada).
1995 – 2000	**Research Assistant** (Internships and Practicums), Department of Anatomy and Cell Biology, Faculty Medicine and Dentistry, University of Western Ontario (London, Ontario, Canada), Department of Psychology and Neuroscience, Faculty of Social Science, University of Western Ontario (London, Ontario, Canada), Institute for Medical Sciences, Department of Physiology, Faculty of Medicine, University of Toronto (Toronto, Ontario, Canada), Department of Obstetrics & Gynecology, Faculty of Medicine, St. Joseph's Hospital and Lawson Health Research Institute, University of Western Ontario (London, Ontario, Canada), Department of Physiology, Faculty of Medicine, University of Western Ontario (London, Ontario, Canada).

NONACADEMIC POSITIONS

2018 – 2021	**Founder,** Waterloo Health Network, Health Service Provider/Research and Development (Kitchener, Ontario, Canada).
2007 – 2021	**Consultant**, CDG Inc., Healthcare Consulting, Strategic Planning and Regulatory Affairs (Medical Device Technology) (Kitchener, Ontario, Canada).
2017 – 2018	**Senior Consultant & Executive Director (Interim)**, Mississauga Halton Local Health Integration Network, Healthcare Provider – Primary Care Services (Oakville, Ontario, Canada). *Budget*: $5 M
2013 – 2015	**Chief Innovation Officer & Member of the Executive Team,** Health Sciences Centre, Healthcare Service Provider – Tertiary Hospital Care and Trauma Centre (Winnipeg, Manitoba, Canada). *Budget*: $10 M

2012 – 2012	**Associate Director & Ex Officio**, Hotchkiss Brain Institute, University of Calgary, Academic Research Centre – Brain Health, Neurology and Neuroscience (Calgary, Alberta, Canada). *Budget*: $100 M
2010 – 2012	**Senior Manager**, Strategy & Asset Management, CML Healthcare Inc., Healthcare Service Provider – Diagnostic Imaging and Laboratory Diagnostics (Mississauga, Ontario, Canada). *Budget*: $30 M
2002 – 2007	**Senior Manager**, Pre-Clinical Research Program, Princess Margaret Hospital, University Health Network, Healthcare Service Provider – Quaternary Hospital Care (Toronto, Ontario, Canada). *Budget*: $40 M

AWARDS

Fall 2025	Graduate Research Studentship, School of Public Health Sciences, Faculty of Health, University of Waterloo. Dr. Zahid A. Butt	$9,500
Spring 2025	Graduate Research Studentship, School of Public Health Sciences, Faculty of Health, University of Waterloo. Dr. Craig R. Janes	$10,000
Winter 2025	Graduate Research Studentship, School of Public Health Sciences, Faculty of Health, University of Waterloo. Dr. Craig R. Janes	$10,000
Fall 2024	Graduate Research Studentship, School of Public Health Sciences, Faculty of Health, University of Waterloo. Dr. Craig R. Janes	$9,500
Spring 2024	Graduate Research Studentship, School of Public Health Sciences, Faculty of Health, University of Waterloo. Dr. Craig R. Janes	$9,500
Winter 2024	Graduate Research Studentship, School of Public Health Sciences, Faculty of Health, University of Waterloo. Dr. Craig R. Janes	$9,000
Spring 2022	Faculty of Health Teaching Assistant Award, Issued by, School of Public Health Sciences, Faculty of Health, University of Waterloo	$500

SCHOLARSHIP[x]

2004 – current	ResearchGate, Research Interest Score: 190, Citations: 391, h-index: 6, Reads: 750, Recommendations: 14.
2004 – current	Google Scholar, Citations: 498, h-index: 5, i10-index: 5.

PEER-REVIEWED PUBLICATIONS

1. **Chiarot, C.B.**, Janes, C.R., Dubin, J.A., Goma, F., Grépin, K.A., Torres-Espin, A., Larkin, Y., Mroz, E.J., Smith, M.W., & Butt, Z.A. (*Under review*). Quantifying an econosyndemic: A longitudinal analysis of the interaction between climate shocks and health system stressors on utilization of essential health services using beta regression and structural equation modelling in WP, Zambia.

2. **Chiarot, C.B.**, Janes, C.R., Torres-Espin, A., Grépin, K.A., & Butt, Z.A. (*Under review*). Enhancing Routine Health Information Systems Data Using a Novel Spatially Defined Catchment Area Methodology for Estimating Denominators: A Malaria Surveillance Case Study Among Children Under Five in Western Province, Zambia.

3. **Chiarot, C.B.**, Janes, C.R., Goma, F., Grépin, K.A., Torres-Espin, A., Mroz, E.J., Smith, M.W., & Butt, Z.A. (*Under review*). Health System Resilience: Quantifying the Dynamic Impact of Environmental Shocks on Health Service Utilization using an Interrupted Time Series and Time-Series Forecasting Approach in Western Province, Zambia.

4. **Chiarot, C.B.,** Janes, C.R., Goma, F., Grépin, K.A., Hotchkiss, D.R., Mroz, E.J., Torres-Espin, A., Smith, M.W., & Butt, Z.A. (*In preparation*). Disentangling Climate Shocks from Systemic Stressors: A Longitudinal, Quasi-Experimental Study of the Maternal Continuum of Care in Western Province, Zambia.

5. **Chiarot, C.B.,** Butt, Z.A., Goma, F., Torres-Espin, A., & Janes, C.R. (*In preparation*). Uncovering spatial inequities in primary health care access: A location-allocation analysis for advancing Universal Health Coverage and health system resilience in Western Province, Zambia.

6. Mroz, E.J., Trigg, M., Willis, T.D.W., Johnston, L., Janes, C.R., Singini, D., Njungu, M., Liu, J., Thomas, C., **Chiarot, C.B.**, Smith, M.W. (*In preparation*). Climate change-driven hydrological changes reshape maternal healthcare access on a large African Floodplain.

7. **Chiarot, C.B.**, Janes, C.R., Abdullah, A.Y.M., Goma, F., Phiri, M., Singini, D., Zulu, R., & Butt, Z.A. (2025). Evaluating the Concept of Access as a Critical Dimension of Universal Health Coverage in the Context of Rural Communities of Western Province, Zambia. SSM-Health Systems, Dec 1; 5. DOI: https://doi.org/10.1016/j.ssmhs.2025.100106

8. Liyanage, S., Saqib, K., Khan, A.F., Thobani, T.R., Tang, W-C., **Chiarot, C.B.**, AlShurman, B.A., & Butt, Z.A. (2022). Prevalence of Anxiety in University Students during the COVID-

[x] Scholarship was last updated on 03x25.

19 Pandemic: A Systematic Review. Int. J. Environ. Res. Public Health, 19(1):62. DOI: https://doi.org/10.3390/ijerph19010062

9. Jaffray, D.A., Moseley, D., Chow, J., Kim, S., Ansell, S., Wilson, G., & **Chiarot, C.B.** (2006). WE-D-330A-09: An Image-Guided Irradiator for Pre-Clinical Radiation Therapy Studies. Med. Phys., 33:2241-2241. DOI: https://doi.org/10.1118/1.2241750

10. **Chiarot, C.B.**, Siewerdsen, J.H., Haycocks, T., Moseley, D.J., & Jaffray, D.A. (2005). An innovative phantom for quantitative and qualitative investigation of advanced x-ray imaging technologies. Phys. Med. Biol., 50(21):N287-97. DOI: https://doi.org/10.1088/0031-9155/50/21/N01

11. Hardy, P.A., Ridler, A.C., **Chiarot, C.B.**, Plewes, D.B., & Henkelman, R.M. (2005). Imaging articular cartilage under compression--cartilage elastography. Magn. Reson. Med., 53(5):1065-73. DOI: https://doi.org/10.1002/mrm.20439

12. Marxen, M., Thornton, M.M., **Chiarot, C.B.**, Klement, G., Koprivnikar, J., Sled, J.G., & Henkelman, R.M. (2004). MicroCT scanner performance and considerations for vascular specimen imaging. Med. Phys., 31(2):305-13. DOI: https://doi.org/10.1118/1.1637971

13. Wagner, G.F., De Niu, P., Jaworski, E., Radman, D., & **Chiarot, C.** (1997). Development of a dose-response bioassay for stanniocalcin in fish. Mol. Cell. Endocrinol., 128(1-2):19-28. DOI: https://doi.org/10.1016/s0303-7207(97)04009-4

PUBLISHED ARTICLES

1. **Chiarot, C.B.** (2004). Cone-Beam Computed Tomography – An Integrated Vision for Guiding Therapy at Princess Margaret Hospital. Princess Margaret Hospital, University Health Network News, Toronto, Ontario, Canada.

2. **Chiarot, C.B.**, & Jaffray, D.A. (2004). The STTARR Program –Taking a Closer Look at Therapy Response through Cellular, Pre-clinical, and Clinical Imaging. Industrial Research Assistance Program (NRC-IRAP) News Article. Canada.

3. **Chiarot, C.B.** (2003). A 'Guided' Success Story. Princess Margaret Hospital, University Health Network News, Toronto, Ontario, Canada.

4. **Chiarot, C.B.** (2003). The Image-Guided Therapy Facility and the Radiation Medicine Program. Princess Margaret Hospital, University Health Network News, Toronto, Ontario, Canada.

5. **Chiarot, C.B.**, Belliveau, D.J., & Ossenkopp, K-P. (2000). Fos Expression Induced by Intraventricular Injection of Neurotrophin-3 (NT-3) in the Paraventricular Nucleus (PVN) of the Hypothalamus in the Rat. Honors Thesis. The University of Western Ontario, London, Ontario, Canada.

6. **Chiarot, C.B.** (2000). The effects of G-Induced Loss of Consciousness: A physiological basis. University Library, University of Western Ontario, London, Ontario, Canada.

ABSTRACTS & CONFERENCES

1. **Chiarot, C.B.** (2022). Achieving Health System Resilience: An Econosyndemic Approach. 10th Zambia Health Research Conference. Mulungushi International Conference Centre, Lusaka, Zambia.

2. **Chiarot, C.B.** (2022). Achieving Health System Resilience: An Econosyndemic Approach. Research Advisory Committee. Liseli Lodge & Conference Centre, Mongu, Western Province, Zambia.

3. **Chiarot, C.B.**, Phiri, M.M., & Zulu, R. (2022). Health Facility Questionnaire: Progress Report, Preliminary Analysis and Needs Assessment. Research Advisory Committee. Liseli Lodge & Conference Centre, Mongu, Western Province, Zambia.

4. Siewerdsen, J.H., Paul, N., Wong, R., **Chiarot, C.B.**, Patsios, D.A., Rao, A.T., Chung, T.B., Moseley, D.J., & Jaffray, D.A. (2004). Nodule detectability in chest CT: Delving the low-dose limits. 90th Scientific Assembly and Annual Meeting. The Radiological Society of North America. McCormick Place, Chicago, Illinois, USA.

5. **Chiarot, C.B.**, Siewerdsen, J.H., Haycocks, T., Moseley, D.J., & Jaffray, D.A. (2004). An innovative phantom for quantitative/qualitative investigation of advanced x-ray imaging technologies. 46th Annual Meeting and Exhibition. American Association of Physicists in Medicine. David L. Lawrence Convention Center, Pittsburgh, Pennsylvania, USA.

6. **Chiarot, C.B.**, Marxen, M., Satomi, J., Sled, J.G., & Henkelman, R.M. (2001). Microcomputed tomography of the renal vasculature in mice. Imaging Network Ontario. Crowne Plaza Don Valley Hotel, Toronto, Ontario, Canada.

7. **Chiarot, C.B.**, Marxen, M., Satomi, J., Sled, J.G., & Henkelman, R.M. (2001). Microcomputed tomography of the renal vasculature in mice. High Resolution Imaging in Small Animals: Instrumentation, Applications, and Animal Handling. Double Tree Hotel and Executive Meeting Center, Rockville, Maryland, USA.

8. Satomi, J., **Chiarot, C.B.**, Henkelman, R.M., terBrugge, K., Wallace, M.C., & Letarte, L. (2001) Angioarchitecture in a murine model of hereditary hemorrhagic telangiectasia. Annual Meeting of the AANS. Toronto, Ontario, Canada.

9. Satomi, J., **Chiarot, C.B.**, Henkelman, R.M., terBrugge, K., Wallace, M.C., & Letarte, M. (2001). Angioarchitecture in a murine model of hereditary hemorrhagic telangiectasia. The 5th Annual Meeting of the AANS/CNS and ASITN. Hawaii, USA.

10. **Chiarot, C.B.**, Belliveau, D.J., & Ossenkopp, K-P. (2000). Fos Expression Induced by Intraventricular Injection of Neurotrophin-3 (NT-3) in the Paraventricular Nucleus (PVN) of the Hypothalamus in the Rat. Annual Honors Thesis Poster Presentation. University of Western Ontario, London, Ontario, Canada.

11. Davey, V.A., Bateman, R., **Chiarot, C.B.**, & Gagnon, R. (1999). The effects of NG-Nitro-L-Arginine Methyl Ester (L-NAME) on placental embolization (EMB). Department of Obstetrics and Gynecology Annual Research Awards Day. University of Western Ontario, London, Ontario, Canada.

12. Davey, V.A., **Chiarot, C.B.**, Homan, J., & Gagnon, R. (1999). Hemodynamics and metabolic responses to fetal placental embolization in the fetal sheep. The 46th Annual Meeting of the Society for Gynecologic Investigation, Atlanta, Georgia, USA.

13. Davey, V.A., Bateman, R., **Chiarot, C.B.**, & Gagnon, R. (1999). The effects of NG-Nitro-L-Arginine Methyl Ester (L-NAME) on placental embolization (EMB). The 46th Annual Meeting of the Society for Gynecologic Investigation, Atlanta, Georgia, USA.

14. Davey, V.A., **Chiarot, C.B.**, Homan, J., & Gagnon, R. (1999). Hemodynamics and metabolic responses to fetal placental embolization in the fetal sheep. The 25th Annual Meeting of the Fetal and Neonatal Physiological Society, Lake Arrowhead, California, USA.

15. Davey, V.A., Bateman, R., **Chiarot, C.B.**, & Gagnon, R. (1999) The effects of NG-Nitro-L-Arginine Methyl Ester (L-NAME) on placental embolization (EMB). The 25th Annual Meeting of the Fetal and Neonatal Physiological Society, Lake Arrowhead, California, USA.

16. Wagner, G.F., Niu, P., Jaworski, E., Radman, D. & **Chiarot, C.B.** (1997). Development of a dose-response bioassay for stanniocalcin in fish. The Canadian Society of Zoologists 36th Annual Association Meeting, University of Western Ontario, London, Ontario, Canada.

INVITED GUEST LECTURES

1. **Chiarot, C.B.** (2025). Research Dissemination (Health Service Utilization), Various venues: Ministry of Health (Lusaka), Provincial Ministry of Health (Western Province), University of Zambia, and the Zambia National Public Health Institute (ZNPH), Republic of Zambia (Lusaka and Western Province).

2. **Chiarot, C.B.** (2023). Global Health: The Concept of Access. Graduate course: 'Selected Topics' (HLTH 620), School of Public Health Sciences, Faculty of Health, University of Waterloo, Waterloo, Ontario, Canada.

3. **Chiarot, C.B.** (2023). Global Health: The Concept of Access. Undergraduate course: 'An Introduction to Health Neuroscience (HLTH 290), Faculty of Health, University of Waterloo, Waterloo, Ontario, Canada.

4. **Chiarot, C.B.** (2022). Achieving Health System Resilience: An Econosyndemic Approach. Undergraduate course: 'An Introduction to Health Neuroscience (HLTH 290), Faculty of Health, University of Waterloo, Waterloo, Ontario, Canada.

ACKNOWLEDGEMENTS

1. Zheng, J., Perkins, G., Kirilova, A., Allen, C., & Jaffray, D.A. (2006). Multimodal contrast agent for combined computed tomography and magnetic resonance imaging applications. Invest. Radiol., 41(3):339-48. DOI: https://doi.org/10.1097/01.rli.0000186568.50265.64

2. Rink, A., Vitkin, I.A., & Jaffray, D.A. (2005). Suitability of radiochromic medium for real-time optical measurements of ionizing radiation dose. Med. Phys., 32(4):1140-55. DOI: https://doi.org/10.1118/1.1877832

OTHER INFORMATION

Citizenship:	Canadian
Place of Birth	Toronto, Ontario
Languages:	English (Fluent), French (Basic)
Programming languages:	R and RStudio, SAS, Python (Basic), APIs, CMS, VS
Databases	DHIS2, HMIS Zambia, GRID3, HDX
LinkedIn:	More than 2400 followers
Global Health Experience	United Kingdon, United States, Zambia (WP)
Accomplishment:	Published photographer (Black & White)